Entrepreneurship and the Racial Wealth Gap*

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Abstract

Entrepreneurship promotes wealth accumulation. However, Black households face significant barriers to entrepreneurship, operating fewer and smaller businesses. We formalize a general equilibrium model of entrepreneurship choice and wealth accumulation in which Black households experience adverse distortions as entrepreneurs and as workers. Disciplined by micro and macro data, our model matches the observed racial wealth gap well and captures the correlation between wealth and entrepreneurship. We find that distortions faced by Black entrepreneurs are the key factor for understanding the racial wealth gap across the wealth distribution. Our analysis also indicates that addressing racial disparities in the US can substantially increase output.

Keywords: Racial wealth gap, entrepreneurship, incomplete markets, wealth accumulation, financial frictions, wealth inequality

JEL Codes: E21, J15, D31, D52

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1 Introduction

Racial wealth inequality in the United States is striking. Figure 1 shows that the average net worth of Black households from 2001 to 2019 was equal to $133,600, while the average White household held $811,900. In other words, Black households held 83.6% less wealth than their White counterparts. Beyond racial disparities, overall wealth inequality is also high: the top 10% of households hold 73.0% of total wealth. Entrepreneurs, owners-managers of businesses, are over-represented at the top of the wealth distribution, and an established literature has highlighted the central role of entrepreneurship in understanding overall wealth inequality. At the same time, Black households exhibit one-third the entrepreneurship rates of White ones, and the median Black-owned firm is 2.9 times smaller than its White counterpart. This paper asks: What is the contribution of disparities in entrepreneurship to the racial wealth gap?

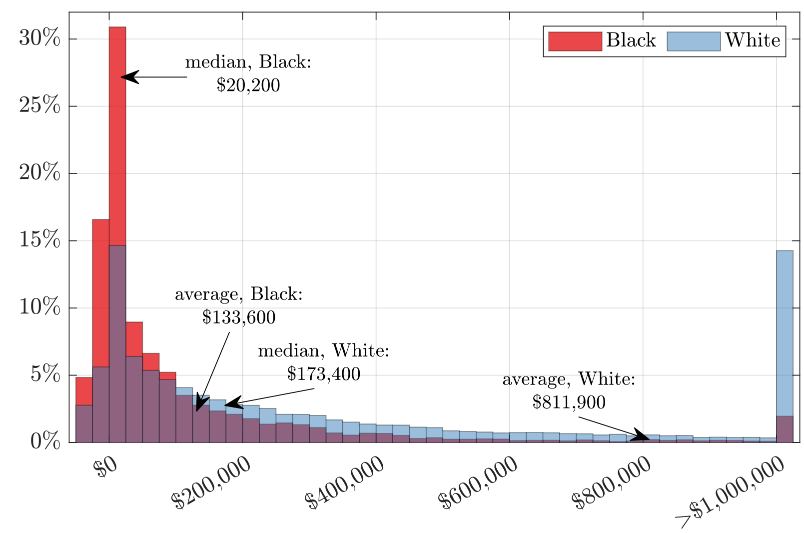


Figure 1: Histogram of wealth for Black and White households, 2001-2019

Notes: This figure plots the histogram of wealth for Black and White households, using data from 2001 to 2019. Values are adjusted to 2019 dollars. *Source*: SCF.

Using the Survey of Consumer Finance data from 1989–2019, we document a large and stable racial gap in average household wealth and across different wealth percentiles. Additionally, the wealth gap is accompanied by stable racial gaps in entrepreneurship rates and firm size. The positive correlation between wealth and entrepreneurship is remarkably similar for Black and White households, reflecting that, regardless of race, wealthy households are more likely to be entrepreneurs. To understand the extent to which entrepreneurship matters for the racial wealth gap, we use non-linear Blinder–Oaxaca decompositions, and find that entrepreneurship explains, in the correlational sense, a sizable share of the racial wealth gap and more so at the top of the wealth distribution. Additional factors affecting the decision to become an entrepreneur, such as education and labor income, are also important for the wealth gap, but more so for poorer households. Furthermore, using the Panel Survey of Income Dynamics, we demonstrate that entrepreneurship correlates with wealth mobility, increasing the probability that Black and White households will move up along the wealth distribution. This empirical analysis, while informative, is not causal. It neglects the dynamic effects of entrepreneurship on wealth accumulation and the dynamic selection into entrepreneurship. To overcome these limitations, we build a structural model.

Our main contribution is to develop and quantify an incomplete-market, general-equilibrium model of wealth accumulation that features dynamic choice between employment and entrepreneurship, along with differences in economic outcomes between Black and White households. In the model, Black and White households have identical preferences and beliefs, but Black households are subject to distortions that hinder their income generation both as workers and as entrepreneurs. Since households are infinitely lived, the model generates strong intergenerational wealth persistence.

The heart of our model is the prospective entrepreneur's decision to leave the labor market and start their own business. The model captures the dynamic selection into entrepreneurship by wealth and labor market earnings, such that wealthier and higher-income households are more likely to choose entrepreneurship. We model race-specific distortions such that Black households face: lower labor income conditional on own productivity (labor income distortion); more volatile income process (labor income risk distortion); and lower profits conditional on business productivity (entrepreneurship distortion). Labor market distortions are externally calibrated using labor income moments, while the entrepreneurship distortion is internally calibrated. These distortions imply that Black and White households differ in how they sort into entrepreneurship. We model the distortions as steady-state features to replicate the stability of racial wealth and entrepreneurship disparities in the data.

The model replicates the racial wealth gap as an untargeted moment (83.4% in the model vs. 83.6% in the data) and also generates the salient correlations between wealth, entrepreneurship, and race, thus allowing us to analyze counterfactual scenarios that shed light on the extent to which observed differences in entrepreneurial outcomes help us understand the racial wealth gap. We then use it to analyze the importance of entrepreneurship in accounting for the racial wealth gap and report four main findings.

First, our main result is that current distortions faced by Black entrepreneurs are the major factor accounting for racial wealth differences. Removing these distortions reverses the sign of the average racial wealth gap, making Black households more than 4.9% wealthier on average than White households. Moreover, the median racial wealth gap would also fall drastically from a baseline of 79.5% in our calibrated model to only 24.1%.

Second, the entrepreneurship distortion also has important macroeconomic consequences, as removing it alone increases output by 4.8%. This result is mainly due to a relative reallocation of resources from White-owned to Black-owned firms, as Black-owned firms can now realize their full potential.

Third, we analyze policies targeted at reducing the racial wealth gap by subsidizing Black entrepreneurship. We find that one cannot evaluate their effectiveness by the level of Black entrepreneurship that they generate. We thus conclude that parity in entrepreneurship rates is not enough. That is because ongoing labor market distortions push Black households into entrepreneurship; thus, subsidies can close the racial entrepreneurship gap while there is still a large racial wealth gap present. This highlights the importance of analyzing labor market and entrepreneurial outcomes, and their distortions, together, since one is the outside option for the other. Furthermore, we consider profit, revenue, and capital subsidies and find that the last is the most effective, since it is more helpful to relatively larger Black-owned firms.

Last, we show that even under favorable conditions, it would take more than 150 years for the racial wealth gap to close, since it takes time for Black households to become entrepreneurs, grow their firms, accumulate profits, and break into the top of the wealth distribution. The combined results highlight the centrality of entrepreneurship in explaining the racial wealth gap and in studying policies targeting it.

Because our model distortions are reduced-form modeling tools that, in reality, map into frictions and institutional barriers (such as discrimination, differences in access to education, differences in social capital, etc.), our model tells us which distortion matters and not which root cause drives any particular distortion. Thus, thinking beyond the model, these frictions and barriers matter for the racial wealth gap if they are the fundamental drivers of the entrepreneurship distortion rather than labor market distortions.

1.1 Related literature

This work is primarily related to works on drivers of the racial wealth gap in the macroeconomics literature. Aliprantis, Carroll, and Young (2022) and Ashman and Neumuller (2020) model exogenous labor income gaps, and White (2007) does so through differences in human capital accumulation. All of these conclude that observed differences in labor earnings can generate large racial wealth gaps. Entrepreneurs' income includes both dividends and wages paid to the entrepreneur, but labor income only includes the latter. We clearly separate entrepreneurial and labor income and find that it is the former that is crucial for understanding the racial wealth gap. In related work, İmrohoroğlu, Kumru, and Lain (2025) find that crime has little bearing on the racial wealth gap precisely because it mainly affects low-income households. Thus, our contribution relative to this literature is to isolate, model, and highlight the importance of entrepreneurship choices.

Closest to our work are Lipton (2022) and Boerma and Karabarbounis (2023), who also model differences in entrepreneurship and firm ownership between Black and White households. Compared to Lipton (2022), we model distortions in the labor market and entrepreneurship jointly and allow for endogenous firm creation, thereby enabling us to examine changes in firm ownership over time and assess the contribution of equilibrium forces to these changes. Boerma and Karabarbounis (2023) focus on heterogeneous beliefs arising from historical exclusion as the primary friction driving the racial wealth gap. In their framework, the gap persists because Black households internalize historical trauma as pessimism, reducing their willingness to invest in risky assets. In contrast, we isolate the role of current structural distortions in both labor and output markets. Our framework highlights active market wedges that depress both the selection of high-income Black workers into entrepreneurship and the intensive margin (firm-level employment or profitability) of Black-owned firms. By explicitly modeling the positive selection of high-income earners into entrepreneurship, we demonstrate how labor market distortions deplete the pool of potential Black entrepreneurs, a channel distinct from the belief-driven mechanism. Moreover, our work complements the analysis in Catherine, Lu, and Paron (2024) for non-entrepreneurs and the work of Kondo et al. (2025), which highlights the importance of those with zero wealth.

This paper is motivated by the literature documenting barriers faced by Black entrepreneurs. Most of the literature so far has focused on credit barriers for Black entrepreneurs.[1] More recently, Bento and Hwang (2022) and Tan and Zeida (2024) use rich panel data and tools from the misallocation literature to study the different barriers faced by Black entrepreneurs. Our paper complements these works by demonstrating the consequences of racial gaps in entrepreneurship for wealth accumulation.

Conceptually, our modeling of the entrepreneurship choice under a credit constraint follows from the seminal work of Evans and Jovanovic (1989), which underpins much of the subsequent literature on entrepreneurship and wealth inequality, notably Cagetti and De Nardi (2006). Most closely related to our paper are works that incorporate group-specific distortions into such frameworks and study their implications for sorting into entrepreneurship, including Morazzoni and Sy (2022) and Goraya (2023). We extend the sorting mechanism in these earlier models by introducing two-sided heterogeneity: both workers and entrepreneurs exhibit heterogeneous ability, with a positive correlation between permanent income and entrepreneurial ability. This correlation allows the model to capture that entrepreneurial entry occurs predominantly among the asset-rich—standard

[1] Studies have found that Black entrepreneurs face lower approval rates for credit (Blanchflower, Levine, and Zimmerman, 2003; Blanchard, Zhao, and Yinger, 2008; Cavalluzzo and Wolken, 2005; García and Darity Jr, 2021); face higher interest rates (Dougal et al., 2019; Hu et al., 2011); get access to smaller loans (Atkins, Cook, and Seamans, 2022; Bates and Robb, 2016); have a harder time raising start-up capital and apply for loans less often, fearing they would be denied (Fairlie, Robb, and Robinson, 2022).

in the literature—and also among high-earning, more educated individuals, a salient feature of the data that earlier models abstract from by modeling only one dimension of ability heterogeneity or assuming independence across dimensions. By capturing this empirically relevant correlation, our framework is better suited to evaluate policy prescriptions that influence occupational sorting, since such policies affect incentives on both the worker and entrepreneur sides.

Finally, another sector that has received attention is the housing market, including its importance for the racial wealth gap (e.g., Flippen, 2004; Faber and Ellen, 2016; Kermani and Wong, 2021; Gupta, Hansman, and Mabille, 2022; Higgins, 2023). Since housing wealth is more concentrated in the middle of the wealth distribution and Black households are poorer on average, housing represents a higher share of Black-owned wealth, while private businesses represent a higher share of White-owned wealth.[2] Thus, disregarding housing wealth actually increases the average racial wealth gap between Black and White households from 83.6% to 88.5%, which leads us to focus on entrepreneurship.

The paper proceeds as follows. Section 2 presents stylized facts regarding disparities in wealth, and entrepreneurship in the US and documents empirical evidence in support of our proposed mechanism. Section 3 develops our model. Section 4 calibrates the model and discusses its fit. Section 5 demonstrates the role of gaps in entrepreneurial outcomes in generating the racial wealth gap and its macroeconomic implications, and analyzes the effects of entrepreneurship subsidies. Section 6 analyzes counterfactual scenarios about the future of the racial wealth gap and the potential role of wealth transfers. Section 7 concludes.

2 Race, wealth, and entrepreneurship in the US: empirical evidence

This section presents empirical evidence that guides our analysis of the relationship between entrepreneurship and the racial wealth gap. We document that (1) there is a substantial and stable racial wealth gap; (2) entrepreneurs are disproportionately represented among the wealthy, both among Black and White households; and (3) Black households are three times less likely to be entrepreneurs, and Black-owned firms are significantly smaller than their White-owned counterparts. Using a non-linear Blinder–Oaxaca decomposition, we argue that entrepreneurship choice and factors affecting it account, in the correlational sense, for a large share of the racial wealth gap. We further demonstrate how, from a dynamic perspective, entrepreneurship is a vehicle for upward wealth mobility. These empirical patterns on the relationship between wealth, entrepreneurship,

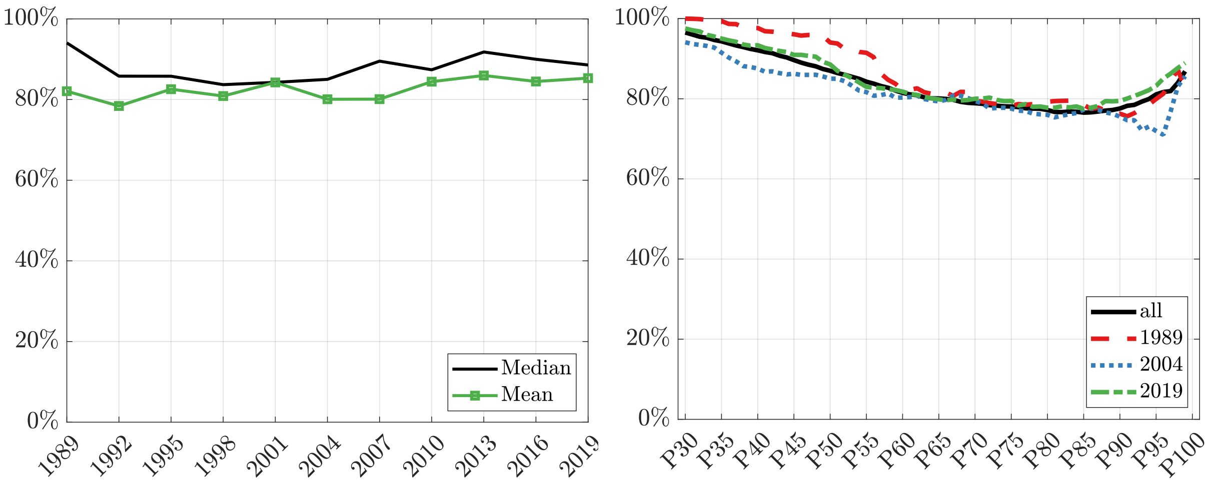
[2] From 2001 to 2019, housing wealth (net of housing debt) represented 52.1% and 31.6% of the wealth held by Black and White households, respectively. For private business, these shares were 12.2% and 21.4%.

and race will discipline our analysis and allow us to evaluate the model developed in the following sections. We provide additional evidence on labor market differences between Black and White households in Appendix B.

Our primary data sources are the Survey of Consumer Finances (SCF) and the Panel Survey of Income Dynamics (PSID). We mostly use the SCF to examine wealth and entrepreneurship and use the PSID to examine labor markets, and when a panel structure is necessary. We view these surveys as complementary sources. The SCF oversamples wealthy households to focus on the top of the wealth distribution, while the PSID is well-suited for the bottom of the income distribution. Importantly, the PSID added an extra sample in the 1990s to better capture the increase in minority households since its inception, which means that the sample size of Black households is substantial. In both surveys, the unit of observation is a household. We restrict our sample to households where the main respondent identifies as Black or White, excluding all households that also identified as of Latino or Hispanic origin. Since we are interested in fitting our model to current gaps in wealth and entrepreneurship, we focus on the period between 2001 and 2019 to calibrate the model.

2.1 The racial wealth gap

We define wealth as total assets minus total liabilities of a household and wealth gaps as $1-\widehat{w}^B/\widehat{w}^W$ with $\widehat{w}^i$ denoting a statistic of the wealth distribution (average, median, etc.) for households of race i. The average and median racial wealth gaps are reported in Figure 2A. Since the 1980s, these gaps have been stable and hovered between 80% and 90%, averaging 83.6% and 88.4% for the average and median gaps, respectively, since 2001.



(A) Mean and median

(B) At given wealth percentiles

Figure 2: The racial wealth gap

Notes: Wealth gaps are defined as $1-\widehat{w}^B/\widehat{w}^W$, where $\widehat{w}^i$ denotes a measure of household wealth such as the average, median, or a particular quantile for households of race i. Panel (A) shows the average (median) racial wealth gap between Black and White households. Panel (B) shows the racial wealth gap at each percentile of wealth by comparing the distribution of wealth of Black and White households, separately. Panel (B) shows the results using the whole sample over 1989-2019, or for specific years. *Source*: SCF 1989-2019.

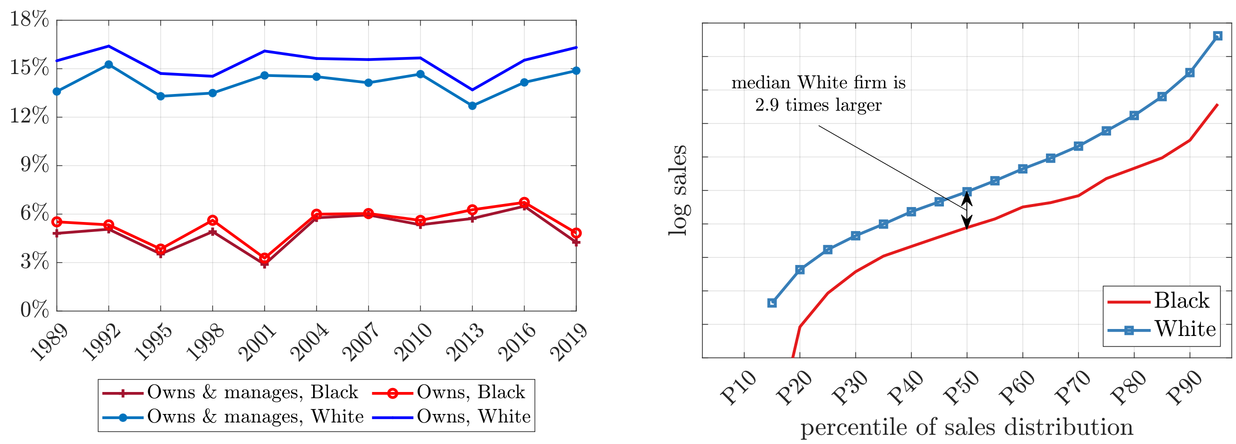
The finding of a sizable and recently stable racial wealth gap is well documented in the literature. Kuhn, Schularick, and Steins (2020) extended the SCF further back in time and document that the wealth gap has been more or less stable in the last seventy years. Derenoncourt et al. (2024) go even further back to the 1860s and report that there was significant progress in closing the gap in the fifty years after the Emancipation, from an extremely high level in 1860, and also some progress from 1920 to 1950. However, progress has stalled since then.

Figure 2B compares the wealth gaps at different percentiles of the separate Black and White wealth distributions. We do this exercise either by pooling together the whole sample from 1989-2019 or by looking at specific years only. The figure shows that the racial wealth gap is higher at the bottom of the wealth distribution, falls until the 80^{th}-85^{th} percentile, and then starts rising again. Regardless of the wealth statistic one chooses to examine, it is clear that: the racial wealth gap is sizable, it is not localized in a particular part of the distribution, and it has remained virtually unchanged for the past three decades.

2.2 Racial differences in entrepreneurship

A long-standing strand of the economic literature has emphasized the importance of entrepreneurship for understanding overall wealth accumulation and wealth inequality (Quadrini, 2000; Castaneda, Diaz-Gimenez, and Rios-Rull, 2003; Cagetti and De Nardi, 2006). To understand whether entrepreneurship is also essential for accounting for the racial wealth gap we start by exploring if there are differences in entrepreneurship between Black and White households. As we argue below, the answer is a clear yes.

We define an entrepreneur as a household that owns and actively manages a private business. Households that own a business but do not manage it are not considered entrepreneurs to exclude households that made a portfolio choice of investing in a private business but are otherwise not engaged in entrepreneurial activity. Figure 3A plots the entrepreneurship rates over the last 30 years according to the SCF. It shows that there is a racial gap in entrepreneurship rates, which has been stable and sizable, around 9 p.p. (5.2% for Black households vs 14.2% for White ones), over the last three decades.[3] That is, Black households are nearly three times less likely to be entrepreneurs than White ones.



(A) Entrepreneurship rates

(B) Firm size distribution

Figure 3: Entrepreneurship rates and outcomes

Notes: Panel (A) reports the share of Black and White households that are entrepreneurs according to two definitions: (i) owns a private business; (ii) owns and actively manages a private business. Panel (B) reports the percentiles of the distribution of log revenue of Black and White-owned firms separately. There is no information for the lower percentiles because some firms do not report positive sales. *Source*: SCF.

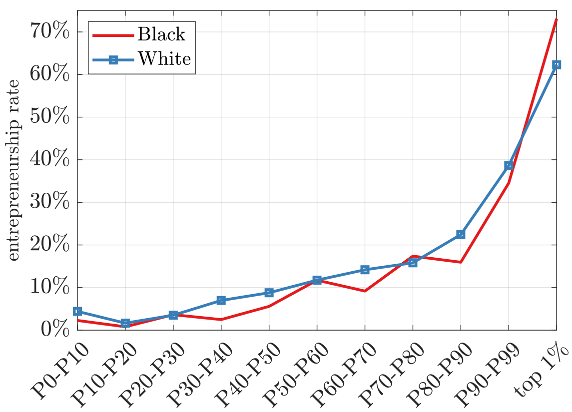
Our findings align well with those of Fairlie and Meyer (2000), who use census data from 1910 to 1990 to document the longer trends of Black and White self-employment rates. They find: (i) a stable gap in entrepreneurship; (ii) that Black households have a third of the rate of entrepreneurship of White households; and (iii) that entrepreneurship rates were 4.1% and 11.4% in 1990 for Black and White households, respectively. These results are qualitatively similar to

[3]Results are also reported for the alternative "owns a business" definition as well and are similar. Our measure is more restrictive and results in a smaller gap in entrepreneurship rates.

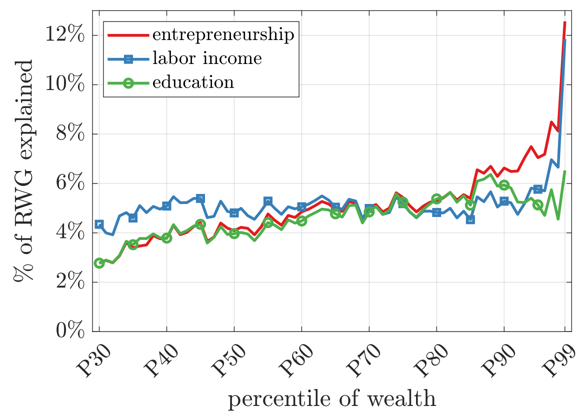
ours, while using a different data source and definition of entrepreneurship.[4]

On top of differences in entrepreneurship rates, Figure 3B shows that there are also differences in outcomes conditional on being an entrepreneur. Using information from firm owners in the SCF we can calculate the implied revenue distribution for firms. We find that the median White-owned firm is 2.9 times larger than the median Black-owned firm, and the difference seems relatively stable throughout the firm-size distribution. This result is important for our choice of distortion that reduces the demand equally for Black firms of all sizes and pushes their size distribution down relative to that of White firms, as we discuss in Section 3.2.

2.3 Entrepreneurship and wealth



(A) Entrepreneurship rates by wealth fractiles



(B) non-linear Oaxaca-Blinder decomposition of the RWG

Figure 4: Correlations between Entrepreneurship and the RWG

Notes: Figure 4A shows the share of Black and White households that are classified as entrepreneurs (i.e., those that own and manage a business) in different fractiles of the overall wealth distribution (e.g., "P10-P20" denotes those between the 10^{th} and 20^{th} percentiles). Figure 4B displays how much each variable can explain the RWG at each percentile of the Black vs White wealth distributions, according to the non-linear Blinder–Oaxaca decomposition from Section 2.3.1. It shows how much the RWG widens when removing the highlighted variable from the Probit. "Entrepreneurship" is a dummy for being an entrepreneur, "education" are dummies for high-school and college completion, and "labor income" is wage income. *Source*: SCF, 2001-2019.

Having established that there are large differences in wealth and entrepreneurship between

[4] Bento and Hwang (2022) find a closing racial gap in entrepreneurship rates, defining entrepreneurship as self-employment and using data from the Survey of Business Owners and the Current Population Survey. In Appendix C we use data from the PSID to investigate the stability of the entrepreneurship gap under different definitions of entrepreneurship and a longer sample. We reconcile our findings with those of Bento and Hwang (2022) by showing that there has been a closure of the gap in self-employment, but not under more strict notions of entrepreneurship, e.g. incorporated firms, which we argue are the most relevant ones for wealth accumulation.

Black and White households, we investigate whether the latter can help explain the former. This is not a straightforward question since entrepreneurship is correlated with many other variables, like labor income, education and innate ability.

We start by establishing a simple fact; entrepreneurship is positively correlated with wealth. Figure 4A, reports that the correlation between entrepreneurship and wealth is strong regardless of race. Furthermore, entrepreneurship rates conditional on wealth are surprisingly similar between Black and White households. More than 60% of Black or White households in the top 1% of the overall wealth distribution are classified as entrepreneurs, while in the bottom half the corresponding figure is less than 10%. Interestingly, the average racial wealth gap between Black and White workers (79.4%) and between Black and White entrepreneurs (75.1%) are quite similar to the overall racial wealth gap of 83.6%. However, White entrepreneurs hold 45.3% of White-owned wealth, while Black entrepreneurs hold only 25.3% of Black-owned wealth, which is explained by a lower entrepreneurship rate among Black households. As entrepreneurs are wealthier than the average population and Black households are less likely to become entrepreneurs, this creates a phenomenon of missing Black entrepreneurship wealth that helps explain the large racial wealth gap.

2.3.1 Non-linear Blinder–Oaxaca decomposition

Given this correlation, we now turn our attention to unpacking the statistical relationship between entrepreneurship and wealth in the data by employing a non-linear Blinder (1973) – Oaxaca (1973) (BO) decomposition. For comparison, we also examine the contribution of labor income and education towards the racial wealth gap.

We are interested in explaining differences in the outcome variable $y_j =$ wealth of household j between Black and White households. The original BO framework can be limiting because it assumes a linear relationship between the explanatory variables X_j and the outcome variable y_j (Barsky et al., 2002). However, it could be that differences at the top and the bottom of the wealth distribution have different causes, and a non-linear BO decomposition allows one to capture that. This type of exercise follows the methodology of DiNardo, Fortin, and Lemieux (1995) and has been used extensively in the literature on racial differences, e.g., Barsky et al. (2002), Altonji, Bharadwaj, and Lange (2012), Luo (2021), and Sabelhaus and Thompson (2023) (see Fortin, Lemieux, and Firpo, 2011, for a comprehensive discussion on decomposition methods).

The idea of the non-linear BO decomposition is to re-weight the population of White households to match the conditional distribution of a set of explanatory variables for Black households.[5]

[5] We do the re-weighting on the White distribution for two main reasons. First, for variables like labor income, in many datasets there would be several White households with higher labor income than the highest labor income for Black households. Thus, it would not be possible to re-weight the Black distribution to match the highest percentiles

Let ω_j^W be the weight of White household j in the sample, and let $\widehat{p}_j$ be the estimated probability of household j being Black given controls X_j. Then, the re-weighting is given by

$$\widehat{\omega}_j^W = \omega_j^W \times \frac{\widehat{p}_j}{1-\widehat{p}_j}. \tag{1}$$

To implement the re-weighting scheme while controlling for many variables at the same time we rely on a Probit model (Fortin, Lemieux, and Firpo, 2011).[6] Therefore, we estimate a Probit of an indicator of whether a household is Black on a set X_j of variables, which include labor income, a dummy for entrepreneurship, education dummies, and also controls for gender and age. This gives us

$$\widehat{p}_j = \Phi\big(\widehat{\beta}' X_j\big) \tag{2}$$

where $\Phi(x)$ is the cumulative density function of the standard normal distribution. This allows us to calculate the re-weighting scheme in Equation (1).

To isolate the impact of a single variable, we remove one explanatory variable at a time from the Probit, perform the re-weighing in Equation (1), and calculate how the RWG at each percentile changes, while still controlling for all the other variables. Figure 4B shows the change in the percentage of the racial wealth gap that is explained when removing the highlighted variable. The percentages might seem small, but this is because all explanatory variables are highly correlated with each other, and we are isolating the impact of each of them at a time. Taken together, the variables explain a large share of the racial wealth gap (70.7% of the mean, 66.9% of the median), thus one should focus on the relative ranking of the variables in isolation.

Viewed in isolation, labor income is the variable that explains the most of the racial wealth gap at the bottom of the wealth distribution, up to the 65$^{\text{th}}$ percentile. From that point up to the 80$^{\text{th}}$ all three variables – entrepreneurship, labor income, education – have equal importance. At the top, we see that entrepreneurship becomes the most important variable, from the 85$^{\text{th}}$ to the 97$^{\text{th}}$ percentile. Somewhat surprisingly, labor income becomes almost as important as entrepreneurship at the 98$^{\text{th}}$ and 99$^{\text{th}}$ percentiles as well. In the end, because entrepreneurship has a more significant role at the top percentiles, it means that entrepreneurship is more important in accounting for the average racial wealth gap as well: without entrepreneurship, our Probit decomposition explains 8.6% less of the average racial wealth gap, compared to only 7.9% less without labor income.

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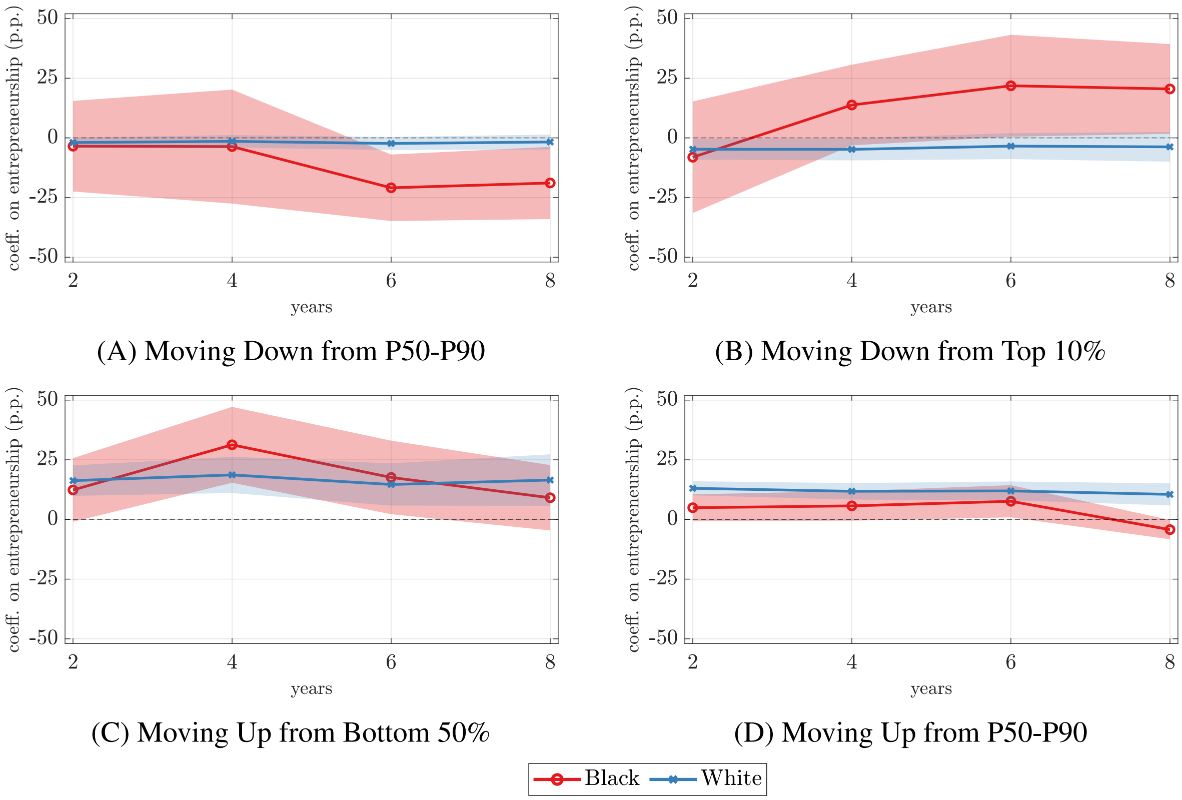
of the White distribution. Second, one potential reason why the joint distribution of (X_j, y_j) is different for Black and White households is discrimination, which can keep, for example, the returns to education lower for Black households. Thus, in this scenario, one can interpret the White distribution as the "normal" estimate, to which the Black distribution would converge to in the absence of discrimination.

[6] When isolating the effect of a single variable, one could do the re-weighting non-parametrically by creating bins of the variable in question and re-weighting them. Because we want to control for many variables at the same time that would mean creating a multi-dimensional bin structure which can easily become unfeasible due to the large number of bins.

2.3.2 Entrepreneurship and wealth mobility



(A) Moving Down from P50-P90

(B) Moving Down from Top 10%

(C) Moving Up from Bottom 50%

(D) Moving Up from P50-P90

Figure 5: Entrepreneurship and wealth mobility

Notes: This figure plots the estimated $\widehat{\gamma}^{j}_{g}$ coefficients on entrepreneurship in Equation (3), i.e., the correlation of entrepreneurship with the probability of a household moving up or down from its current wealth group to the next one, in the horizon given by the x axis. The wealth groups are the bottom 50%, P50-P90, and the top 10%. For example, in Panel 5C being an entrepreneur for Black households is correlated with a higher transition rate of 12.4p.p. from the bottom 50% to P50-P90 at a 2-year horizon. All the point estimates and average transition rates are reported in Table A.2. Other controls include age, gender, education, employment status, wealth percentile, labor income percentile, and year fixed effects. Confidence intervals are 95% and standard errors are clustered at the household level.

The framework from the previous section, while informative, has two possible drawbacks. First, it is only correlational, and uninformative on causality. Second, it misses dynamic effects, for example, entrepreneurs in the bottom 50% of wealth might not be wealthier than the non-entrepreneurs in the same part of the distribution, but entrepreneurship enables them long-term upward mobility. The structural model developed in the next section is able to deal with both issues when performing counterfactuals.

But first we investigate whether entrepreneurship is correlated with wealth mobility in the data.

To do so, we use PSID data to estimate the following regression

$$\mathbb{1}\{g \to \tilde{g}\}^i_{j,t,t+h} = \alpha^i_{t,g} + \gamma^i_g \times \text{entrep}^i_{t,g} + \beta^i_g X^i_{j,t,g} + \varepsilon^i_{j,t,g} \tag{3}$$

where $\mathbb{1}\{g \to \tilde{g}\}^i_{j,t,t+h}$ is an indicator function that equals one if household j of race i was in wealth group g at time t and group $\tilde{g}$ at time $t+h$, and $X^i_{j,t,g}$ are controls. Figure 5 plots the estimated coefficients $\widehat{\gamma}$ for $g \in \{\text{bottom 50\%, P50-P90, top 10\%}\}$.

Panels (C) and (D) show that entrepreneurship is associated with an increase in upward mobility for Black and White households, both from the Bottom 50% to P50-P90, and from the P50-P90 to the top 10%. Panels (A) and (B) tell a slightly different story. Black entrepreneurs have lower downward mobility rates from the P50-P90, but higher ones from the top 10% at longer horizons compared to non-entrepreneurs. White entrepreneurs also have higher downward mobility both from the P50-P90 and the top 10%. Some of the estimated coefficients are quite large. For example, being an entrepreneur for Black households is correlated with a higher transition rate of 12.4p.p. from the bottom 50% to P50-P90 at a 2-year horizon, when the average transition rate for Black households between those groups is 10.2%. However, notice the wide confidence intervals, especially for Black households, given their lower entrepreneurship rate and lower sample size at the top of the wealth distribution. All point estimates and average transition rates are reported in Table A.2.

We interpret the combined results as suggestive that entrepreneurship is associated with higher upward wealth mobility for both Black and White households across the wealth distribution, which is something the BO decomposition did not capture, and thus its importance could be even higher for explaining wealth differences. Moreover, there is some evidence that entrepreneurship within the top 10% might be riskier for Black entrepreneurs than for White ones, which could be indicative of additional barriers to entrepreneurship which, if removed, would further increase the importance of entrepreneurship for Black wealth accumulation. To explore these questions, we turn to our model next.

3 Model

Our model utilizes the workhorse incomplete markets model à la Bewley-Imrohoroglu-Huggett-Aiyagari set in general equilibrium. We augment it with a dynamic discrete entrepreneurship choice under a financial friction and decreasing returns to scale production technology, as in Evans and Jovanovic (1989). This allows for a non-degenerate distribution of firms and positive profits for an owner-manager entrepreneur. Our modeling approach is motivated by the works of Quadrini (2000), Castaneda, Diaz-Gimenez, and Rios-Rull (2003), and Cagetti and De Nardi (2006), which show how entrepreneurship can be used to model wealth concentration and mobility. We also include a rich, estimated labor income process featuring permanent, transitory, and non-employment shocks.[7]

3.1 Environment

Time t is continuous. There exists a unit mass of households that differ in race $i \in \{B, W\}$, where B denotes Black and W denotes White. The mass of households of each race is denoted by m^i, which is exogenous and fixed. Households are identical ex ante, but Black households are subject to race-specific distortions that we explain in detail below. In the end, these distortions make Black households worse off relative to White households, both as entrepreneurs and as workers.

Households are infinitely lived, and we consider them as dynasties. This choice is equivalent to households having perfect "warm glow" motives towards their offspring and leaving bequests, implying a high persistence of wealth outcomes. All households can save and accumulate wealth a subject to a borrowing constraint $a \geqslant \underline{a}$. Assets are rented as productive capital to firms and, in equilibrium, total capital stock equals the total net asset position of households.[8]

Households sort themselves into either entrepreneurs or workers based on their productivity as workers z_L, the productivity of their business z_F, their assets a, and the distortions they face. Workers face uninsurable idiosyncratic shocks to their labor productivity z_L, and the per-productivity-unit wage rate w is determined in general equilibrium.

Labor productivity z_L. Idiosyncratic labor productivity $z_{L,t}$ is modeled similarly to the jump-drift process of Kaplan, Moll, and Violante (2018), augmented with employment and non-employment status. All parameters are race-dependent. The process for labor productivity is given by

$$z_L(l, z_P, z_T) = l \times e^{z_P + z_T}, \tag{4}$$

where $l \in \{0, 1\}$ is the employment status, z_P is the permanent component of log income, and z_T is the transitory component, all of which are idiosyncratic. This mapping is independent of race; however, the stochastic processes governing the evolution of all components do depend on race as follows.

We assume l is a Poisson jump process where $\lambda^i_{ll'}$ denotes the rate at which households of race i switch from employment status $l \in \{0, 1\}$ to $l' \in \{0.1\}$. The permanent and transitory components

[7]Our entrepreneurship choice model is consistent with recent empirical evidence by Bhandari et al. (2024) who use administrative data for the US and highlight the importance of pecuniary incentives, instead of preference-based heterogeneity, in explaining entrepreneurial entry, especially so for larger businesses.

[8]Negative asset positions are debt owed to other households. We assume that capital and debt yield the same net return.

follow a jump-drift process given by:

$$\begin{aligned} dz_P &= -\mu_P^i z_P dt + dJ_P^i, \\ dz_T &= -\mu_T^i z_T dt + dJ_T^i, \end{aligned} \tag{5}$$

where dJ_j^i is an idiosyncratic jump process with an arrival rate of λ_j^i, in which case z_j is redrawn from a normal distribution with mean zero and variance $(\sigma_j^i)^2$, $j = \{P,T\}$.

We also assume that the government taxes all labor, capital, and profit incomes in the model at a flat rate $\bar{t}$ to finance an income floor T, which we calibrate according to the literature and discuss in Section 4.3.

Entrepreneurial productivity z_F. Entrepreneurs hire labor and capital in markets to produce a single homogeneous final consumption numeraire good. Each entrepreneur operates a firm with a decreasing returns to scale technology, and its capital choice is subject to a collateral constraint such that they cannot utilize more capital than $\lambda_{CC} \times a$ where a is their asset holding. Additionally, entrepreneurs are heterogeneous with respect to their idiosyncratic productivity z_F, which evolves stochastically. The mass of entrant entrepreneurs is endogenously determined by workers, who have a business idea at rate η, and then decide whether to start a firm or not, given their asset level a, their permanent and transitory income components, their employment status, and their race at the time of idea arrival. Ideas cannot be stored or traded. Entrepreneurs exit at an exogenous rate λ_D and return to the worker pool.

Recent evidence from Bhandari et al. (2024) demonstrates that entrepreneurs are primarily high-wage earners. In Appendix B.2 we use the PSID to show that entrepreneurial entry is positively correlated with labor income. Because we aim to accurately capture how distortions in the labor and entrepreneurship markets affect a household's decision to become an entrepreneur, our model must account for the positive correlation between labor income and entrepreneurial entry. Since higher labor-income households need higher compensation to forgo their labor income and start a business, we assume a positive correlation between permanent income z_P and initial productivity as an entrepreneur.[9] Specifically, we assume an isoelastic mapping $z_F = \psi(z_P)$ between the productivity of prospective entrant entrepreneurs and their permanent income z_P given by:

$$\log\left(\psi(z_P) - \underline{z}_F\right) = \Psi_1 \log\left(z_P - \Psi_0\right), \tag{6}$$

[9] One possible way to interpret the correlation between the permanent component of labor productivity and initial productivity as an entrepreneur is that there is an unobservable, unmodeled human capital that determines both. Indeed, when looking at the PSID, the correlation between entrepreneurial entry and labor income disappears once we control for education, which we interpret as a proxy for human capital.

with $\underline{z}_F$ denoting the lower bound of the entrepreneurial productivity distribution, which we normalize to unity, and $\Psi_0, \Psi_1 \geqslant 0$. Note that this implies $\psi(z_P) = \underline{z}_F + (z_P - \Psi_0)^{\Psi_1}$ for $z_P \geqslant \Psi_0$. To implement this, we preclude workers with $z_P < \Psi_0$ from becoming entrepreneurs. In Section 4.3, we demonstrate that this entry process successfully replicates the positive gradient between labor income and entrepreneurial entry.

3.2 Racial disparities

Following the misallocation literature, we treat racial disparities as *distortions* faced by otherwise identical households or firms and consider them as fundamentals. Since distortions are only identified in relative terms, we set all White households' distortions to zero and calibrate Black households' distortions either directly using microdata or using our model. The model is then able to map them into racial gaps in wealth and entrepreneurship similar to those in the data. We model the following three distortions:

(1) Labor-income level distortion τ_L^B. A proportional labor productivity distortion lowers the effective productivity of a worker with labor productivity z_L:

$$\underbrace{z_L}_{\text{true productivity}} \quad \longrightarrow \quad \underbrace{(1-\tau_L^i)z_L}_{\text{distortion-adjusted productivity}} \quad , \qquad i \in \{B, W\}.$$

Labor income then equals $w(1-\tau_L^i)z_L$. In section 4.2, we calibrate $\tau_L^B \in [0,1]$ to the Black–White median wage gap, conditional on employment.

(2) Labor-income risk distortion. Black and White households face Markov income processes with distinct transition rates and shock variances for all components (permanent, transitory, and non-employment). Panel estimates we discuss below imply higher earnings volatility and longer non-employment spells for Black workers, strengthening their precautionary saving motives. We estimate these stochastic processes directly from the microdata in a procedure detailed in Section 4.2.

(3) Entrepreneurship distortion τ_y^B. Entrepreneurs produce output y with technology $y = z_F k^\alpha h^\beta$ and $\alpha + \beta < 1$, where k denotes capital, h labor, and z_F productivity. We assume they hire factors to maximize perceived profits given by

$$(1-\tau_y^i)\, z_F k^\alpha h^\beta - wh - rk, \quad \text{s.t.} \quad k \leqslant \lambda_{CC} a.$$

even though their true output is given by $y = z_F k^{\alpha} h^{\beta}$. Thus, while this distortion does not directly reduce the output of Black entrepreneurs, it leads them to hire less capital and labor for given wealth a and firm productivity z_F. This particular modeling strategy is motivated by our own findings reported in Figure 3B, demonstrating a persistent gap in firm size between Black and White-owned firms even at the top of the firm-size distribution. In other words, the barriers that prevent Black-owned firms from achieving parity of outcomes with their White-owned counterparts are systemic and not specific to small firms. This distortion is a reduced-form way to capture the fact that Black entrepreneurs are generating lower profits, while assuming no innate differences in productivity ex ante. We calibrate τ_y^B internally to match moments related to the joint distribution of wealth, race, and entrepreneurship, which are discussed in Section 4.3.

Two implications of this modeling strategy are noteworthy. First, having a positive entrepreneurship distortion $\tau_y^B > 0$ implies that Black-owned businesses are sub-optimally small, have lower profits controlling for productivity, and that reallocation of capital and labor towards Black-owned firms would increase output.

Second, if one believes that differences in access to financial markets are the reason Black-owned firms are less profitable, our model would generate a similar underutilization of capital by Black-owned firms. However, in the model, they utilize less capital than is optimal for them, but in a way that does not distort their capital or labor intensity. Interestingly, recent work by Tan and Zeida (2024) finds, using data from the Kauffman survey, that Black-owned businesses are less profitable and rejects the hypothesis that it is primarily due to distortions in capital markets. They attribute these differences to consumer discrimination rather than to financial factors alone.

To conclude our discussion of distortions, it is worthwhile to emphasize that we do not interpret the estimated distortions as quantifying the direct discrimination that a Black household faces in a specific market. For example, the estimated distortion in wages is 50.9%. This figure could be partially attributed to discrimination in access to high-quality education throughout childhood, which leads to different educational choices and, ultimately, lower wages in adulthood. However, this strategy enables us to quantify the extent to which each distortion influences steady-state wealth gaps without committing to a single root cause.

Moreover, when we perform counterfactual exercises in which we remove the distortions, our interpretation is not that discrimination in that particular market has ceased, but that any discrimination or barrier leading to the observed distortion has ceased. Finally, suppose distortions in both the labor and entrepreneurship dimensions are partially due to the same root cause (e.g., education). In that case, our exercise remains helpful in quantifying how much of the convergence in wealth between Black and White households would result from the closing of the gaps in entrepreneurial or labor outcomes.

Having described the environment, the components affecting the entrepreneurship choice, and the racial distortions, in what follows, we state the decision problems faced by workers and entrepreneurs. For clarity, we state the value functions in their steady-state forms, referring to constant prices and omitting time derivatives.

3.3 Workers

Workers choose how much to consume c and save, subject to a borrowing limit. They receive a business idea allowing them to start a firm at an exogenous rate η. When the idea arrives, workers face the discrete choice of whether to use the idea to start a firm or not.

Let $V(a, z_P, z_T, l, i)$ denote the value of being a worker with asset level a, permanent income component z_P, transitory income component z_T, employment status l, and race i. The worker faces the following problem:

$$\rho V(a, z_P, z_T, l, i) = \max_c \Big\{ u(c) + V_a s_V(a, z_P, z_T, l, i) \tag{7}$$

$$+ \eta \max\{F(a, \psi(z_P), i) - V(a, z_P, z_T, l, i), 0\} + A_L^i V(a, z_P, z_T, l, i) \Big\},$$

subject to the borrowing limit $a \geqslant \underline{a}$, where $u(c) = c^{1-\gamma}/(1-\gamma)$ denotes flow utility from consumption; γ is the coefficient of relative risk aversion; ρ is the discount rate; $F(a, \psi(z_P), i)$ is the worker's expected value from becoming an entrepreneur after receiving an idea and starting a business with productivity $z_F = \psi(z_P)$; $V_a = \partial V(a, z_P, z_T, l, i)/\partial a$; and A_L^i denotes the generator for the stochastic process governing the income process, via the three independent stochastic processes that govern (z_P, z_T, l), described above. The law of motion for assets $\dot{a} = s_V(\cdot)$ is

$$s_V(a, z_P, z_T, l, i) = w z_L (1 - \tau_L^i)(1 - \bar{t}) + (1 - \bar{t} I_{a>0})(r - \delta)a - c + T, \tag{8}$$

where w denotes the wage per distortion-adjusted labor productivity unit, $r - \delta$ the net return for asset holdings, with r being the rental rate of capital and δ its depreciation rate.[10] All household incomes are taxed at a rate $\bar{t}$ conditional on being positive. Thus, $I_{a>0}$ is an indicator that equals one if $a \geqslant 0$, and zero otherwise. This assumption implies that capital income is taxed and debt repayments are not deductible. Households receive a lump-sum transfer benefit of T, which generates an income floor in our model. Note that other income sources are non-negative by construction.

[10]For brevity we suppress the dependence of $z_L(l, z_P, z_T) = l \times e^{z_P + z_T}$ in what follows.

3.4 Entrepreneurs

The entrepreneurs' optimization problem is:

$$
\begin{aligned}
&(\rho+\lambda_D)F(a,z_F,i) \qquad (9)\\
&\quad = \max_c \left\{ u(c) + F_a s_F(a,z_F,i) + \lambda_D \mathbb{E}^i[V(a,z_P,z_T,l,i)] + (\mu_F z_F)F_{z_F} + \frac{(z_F\sigma_F)^2}{2} F_{z_F z_F} \right\},
\end{aligned}
$$

with the associated law of motion of assets $\dot{a} = s_F(\cdot)$ given by

$$
s_F(a,z_F,i) = (1-\bar{t})\,\pi(a,z_F,i) + (1-\bar{t}I_{a>0})\,(r-\delta)a - c. \qquad (10)
$$

Entrepreneurs are subject to the same borrowing limit $a \geqslant \underline{a}$ as workers. Note that $\pi(a,z_F,i)$ denotes true realized profits, which are affected by τ_y^B only through the firm's input choice.

Firms die with rate λ_D, in which case the household becomes a worker again, and $\mathbb{E}^i[V(a,z_P,z_T,l,i)]$ is the expected value of this transition, where expectations are taken with respect to (z_P,z_T,l) over the distribution $n^i(z_P,z_T,l)$ which is the stationary distribution induced by the exogenous race-dependent income process described in equation (4).[11] We assume that following the exogenous exit, entrepreneurs are reintroduced into the labor force, with labor productivity and employment status redrawn from $n^i(z_P,z_T,l)$.[12,13]

3.5 Production

Firms produce a single homogeneous final consumption good y by renting physical capital k and distortion-adjusted labor h from households using a production function $y = z_F k^\alpha h^\beta$, with $\alpha+\beta < 1$. The entrepreneurship distortion, ${\tau_y}^i$, reduces the firm's perception of its own productivity or, alternatively, the firm's perception of output prices. Profits are:

[11] The model does not allow for endogenous firm exit, thus it does not capture the option value of closing a firm. However, the continuation value after firm exit is significantly higher for White than for Black entrepreneurs, since they return to a better labor market. This influences the decision to start a firm as a worker, consistent with the findings of Catherine (2022).

[12] The stationary distribution of workers over (z_P,z_T,l) is different from $n^i(z_P,z_T,l)$, given by the exogenous income process, due to differences in entry decisions. Thus, this assumption simplifies the numerical implementation. Quantitatively, the transition rates across labor statuses within workers dominate those between workers and entrepreneurs, making the two distributions approximately the same.

[13] One might worry that this assumption on labor productivity after exit incentivizes households to enter entrepreneurship to redraw their (z_P,z_T,l). However, in the calibrated version of the model, this is not a significant concern, as high z_L households are much more likely to enter entrepreneurship. Furthermore, ideas arrive approximately every twenty-three years on average, and firms exit at a rate of approximately every ten years on average, rendering this incentive negligible.

$$\pi(a,z_F,i) = z_F k(a,z_F,i)^{\alpha} h(a,z_F,i)^{\beta} - wh(a,z_F,i) - rk(a,z_F,i), \tag{11}$$

where due to the distortion ${\tau_y}^i$, factors are chosen according to

$$\{h(a,z_F,i),k(a,z_F,i)\} = \underset{\{h,k\}}{\arg\max}(1-\tau_y^i)z_F k^{\alpha} h^{\beta} - wh - rk, \quad \text{s.t. } k \leqslant a\lambda_{CC}, \tag{12}$$

and a denotes the asset position of the entrepreneur. For firms with a non-binding collateral constraint, the first order conditions are given by

$$\left(1-{\tau_y}^i\right)\alpha z_F h^{\beta} k^{\alpha-1} = r, \tag{13}$$

$$\left(1-{\tau_y}^i\right)\beta z_F h^{\beta-1} k^{\alpha} = w. \tag{14}$$

If the credit constraint is slack and the entrepreneurship distortion $\tau_y^B = 0$, these first-order conditions imply that profits are a share $(1-\alpha-\beta)$ of the total output of each firm. However, when the collateral constraint binds, production decisions reflect lower capital intensity due to its higher shadow price. Let $\mu_{CC}(a,z_F,i)$ denote the Lagrange multiplier of the collateral constraint. When the collateral constraint binds, μ_{CC} ensures that $k(a,z_F,i) = \lambda_{CC}a$, otherwise, $\mu_{CC} = 0$. Thus, factor quantities are chosen according to:

$$h(a,z_F,i) = \left(\left(1-{\tau_y}^i\right)z_F\right)^{\frac{1}{1-\alpha-\beta}} \left(\frac{\alpha}{r+\mu_{CC}(a,z_F,i)}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{1-\alpha}{1-\alpha-\beta}} \tag{15}$$

$$k(a,z_F,i) = \left(\left(1-{\tau_y}^i\right)z_F\right)^{\frac{1}{1-\alpha-\beta}} \left(\frac{\alpha}{r+\mu_{CC}(a,z_F,i)}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}} \tag{16}$$

Firms are each owned by a single entrepreneur and differ in their productivity z_F. Conditional on staying in business, z_F follows a random growth process with average growth rate μ_F and variance σ_F^2 given by:

$$dz_F = \mu_F z_F dt + \sigma_F z_F dB, \tag{17}$$

on the support $z_F \in [\underline{z}_F, \infty)$, where $\underline{z}_F$ is a reflective barrier, and dB_t denotes a Brownian motion process. Note that while this process governs productivity, it is not the sole factor governing firm size, since the collateral constraint also plays a role when it binds. Thus, a new firm can grow due to productivity shocks or by the owner saving to relax the collateral constraint.

While it is not possible to obtain an analytical solution to the exact distribution of z_F, we can use an asymptotic result (Gabaix, 2009) stating that as $z_F \to \infty$ its stationary distribution $f(z_F)$ has a Pareto right tail with parameter ζ that depends on $\mu_F, \sigma_F^2, \lambda_D$ (see details in Appendix F.1). We later use ζ to calibrate the dispersion of top wealth in the economy. Note that if the productivity distribution has a tail parameter of ζ, then equation (15) implies that the firm-size distribution in terms of labor is also a Pareto with a tail parameter equal to $\zeta(1-\alpha-\beta)$ for firms with a slack borrowing limit.

3.6 Equilibrium

The model economy has three markets: assets, labor, and goods. In general equilibrium, these three markets clear, with total net asset positions in the economy equal to the firms' capital demand, total distortion-adjusted labor supplied by households equal to the total amount of labor demanded by firms, and total output produced equal to the total amount of output consumed and invested in capital accumulation. Additionally, the government operates its transfer scheme under a balanced budget. For conciseness, a formal statement of the equilibrium definition and market-clearing conditions in the economy is relegated to Appendix D. A detailed solution algorithm is given in Appendix E.

4 Calibration

This section details the calibration procedure and reports the model fit and performance. We proceed in three steps: (*i*) externally set parameters from the literature, (*ii*) use microdata to estimate the income process, and (*iii*) internally calibrate the remaining parameters to match key moments related to entrepreneurship, wealth, and labor income.

The model delivers an excellent fit to the data. It reproduces, as *untargeted* moments, an average racial wealth gap of 83.3% and a median gap of 79.5% (vs 83.6% and 88.4% in the data, respectively). It also matches empirical patterns, showing that entrepreneurship is concentrated at the top of the wealth distribution for Black and White households. Finally, consistent with the data, Black-owned businesses are systematically smaller than White-owned ones, with the median Black-owned business earning in profits only 44.3% (vs 39.9% in the data) of what its White-owned counterpart earns.

4.1 Externally calibrated parameters

We begin by setting a small set of parameters to standard values from the literature. The coefficient of relative risk aversion is set to $\gamma = 1.5$, a conventional choice in the wealth inequality literature. The annual depreciation rate of capital is set to $\delta = 4.8\%$ following Hubmer, Krusell, and Smith (2021), and the firm exit rate to $\lambda_D = 0.10$, consistent with estimates of average business survival. The volatility of firm productivity growth, σ_F, is chosen such that the largest, financially uncon-

Table 1: Estimated parameters for the labor productivity process

Parameter	Symbol	Black households	White households
Labor income distortion	τ_L^B	50.9%	0.0%
Mean reversion, permanent	μ_P	0.71%	0.01%
Mean reversion, transitory	μ_T	64.2%	83.8%
Volatility of jumps, permanent	σ_P	0.67	0.68
Volatility of jumps, transitory	σ_T	0.33	0.22
Jump rate, permanent	λ_P	0.05	0.04
Jump rate, transitory	λ_T	0.77	3.67
Jump rate, employment → non-employment	λ_{10}	15.4%	10.0%
Jump rate, non-employment → employment	λ_{01}	31.5%	44.2%

Notes: This table reports the estimated parameters of the processes for the components of labor income productivity z_P and z_T, and labor status l. All transition rates are at an annual frequency.

strained firms display a log profit volatility of 12%, in line with empirical evidence (e.g., Gabaix, 2011).[14] We also normalize the lower bound $\underline{z}_F = 1$.

These externally calibrated values pin down broad features of household preferences, capital dynamics, and firm survival, before introducing race-specific distortions or targeted calibration moments.

4.2 Income process estimation

Labor income process estimation. Using data from the PSID from 2001 to 2019 we separately estimate the parameters governing the income processes for Black and White workers. The parameters τ_L^B, λ_{01}^W, $\lambda_{10}^W, \lambda_{01}^B$ and λ_{10}^B are calculated directly from the data, while the remaining ones are estimated via Simulated Method of Moments (SMM). Table 1 reports the estimated parameter values. For a detailed explanation of the estimation procedure, see Appendix B.3.

Resulting labor income process. The labor income distortion $\tau_L^B = 50.9\%$ is calculated as the gap between Black and White households in median weekly labor income when employed, without controlling for other variables such as family structure and education, since we do not model these explicitly. We consider both male- and female-led households, which makes our measure slightly higher than those reported by Bayer and Charles (2018).[15]

[14]For unconstrained firms, profits are proportional to $z_F^{1/(1-\alpha-\beta)}$, so if $\log(z_F)$ has volatility σ_F, then log profit volatility equals $\sigma_F/(1-\alpha-\beta)$.

[15]We acknowledge that by using such a measure for τ_L^B, our labor income distortion encompasses not only labor market discrimination but also differences in household composition, thereby making it stronger. This conservative measure strengthens the results in the next section regarding the relative importance of entrepreneurship versus labor income in explaining the racial wealth gap.

Table 2: Internally calibrated parameters

Parameter	Symbol	Value
Entrepreneurship distortion	τ_y^B	62.88%
Capital share, production function	α	0.3
Labor share, production function	β	0.39
Discount rate	ρ	10.26%
Borrowing limit	$\underline{a}$	0.13
Collateral constraint	λ_{CC}	3.18
Idea arrival rate	η	4.40%
Tail of z_F process	ζ	5.84
Tax rate	$\bar{t}$	11.35%
Minimum permanent labor income for entry into entrepreneurship	Ψ_0	0.67
Elasticity of initial firm productivity to permanent labor productivity	Ψ_1	0.52

Notes: This table summarizes all internally calibrated parameter values.

The resulting income process features a more persistent permanent component for White households, where persistence is given by $1-\mu_P^i$. However, the values for volatility and jump rates are similar, with persistent shocks estimated to arrive on average every 20 to 23 years. The estimated transitory process differs significantly by race. White households face more frequent shocks, but these are less volatile and dissipate quicker than the transitory shocks faced by Black households. Finally, Black households are estimated to face a lower probability of finding a job when non-employed, and also a higher probability of losing a job when employed, resulting in a higher non-employment rate in labor markets.[16]

4.3 Internal calibration and targeted moments

The internally calibrated parameters are set to target key moments related to the interaction between wealth, entrepreneurship, income, and race. Most of the moments we target are aggregate ones, independent of race. The only exceptions to this are that we also target the entrepreneurship rate among Black households and the share of wealth held by entrepreneurs of each race. The model has eleven internally calibrated parameters: the entrepreneurship distortion τ_y^B, the production function parameters α and β, the discount rate ρ, the borrowing limit $\underline{a}$, the collateral constraint λ_{CC}, the idea arrival rate η, the tail parameter of the z_F distribution ζ, the tax rate $\bar{t}$, and the entry process parameters Ψ_0 and Ψ_1. These parameters and their values (summarized in Table

[16]The non-employment rate for Black and White households is equal to $\lambda_{10}^B/(\lambda_{10}^B+\lambda_{01}^B) = 32.8\%$ and $\lambda_{10}^W/(\lambda_{10}^W+\lambda_{01}^W) = 18.5\%$, respectively. These rates include both non-participation and unemployment.

2) are set to target twelve moments reported in Table 3.[17] Although most parameters affect mainly one or two targeted moments to a first order, we stress that all the targeted moments summarized in Table 3 are jointly determined by all parameters.

Wealth moments. We follow the literature by targeting a net return on wealth ($r-\delta$) of 4% annually and a capital-to-annual-output ratio of 3. We also target the share of households with negative assets (10.5%), the share of wealth held by the 50^{th} to 90^{th} percentiles of the wealth distribution (24.9%), and the share held by the top 10% (73.0%). Our model delivers an excellent fit to all those targets, as shown in Table 3.

The key parameters affecting these include ρ, which governs the desire of households to hold assets, λ_{CC}, and α, which determine the capital demand of firms. The share of households with negative net wealth is primarily pinned down by the borrowing limit $\underline{a}$,[18] and top wealth concentration is mostly driven by $\zeta(1-\alpha-\beta)$ which controls the skewness of firm profits.

Entrepreneurship moments. We target the overall household entrepreneurship rate in the SCF, which is 12.7%. Additionally, to capture the correlation between entrepreneurship and wealth, we target the share of wealth held by Black-owned and White-owned entrepreneurs, which are 25.6% and 46.2%, respectively. These moments are central to our analysis, and we assign them higher weights when evaluating the model fit.[19] To discipline our entrepreneurship distortion τ_y^B, we also target the entrepreneurship rate among Black households of 5.2%.

The idea arrival rate $\eta = 4.4\%$ is the chief determinant of the overall entrepreneurship rate in the model. Combined with $\lambda_D = 10\%$, these parameters imply an upper bound on the entrepreneurship rate, which occurs if all ideas result in entry, of $\frac{\eta}{\eta+\lambda_D} = 30.6\%$.[20] This bound implies that many households endogenously choose not to become entrepreneurs after idea arrival.

Our model ultimately delivers an aggregate entrepreneurship rate of 13.7% in the model compared with 12.7% in the data. This overstatement of the entrepreneurship rate is primarily due to a slight overshoot in White entrepreneurship rates (15.5% vs. 14.2% in the data) and an undershoot of the Black entrepreneurship rate (4.5% vs. 5.2% in the data). Note that these differences imply that our model slightly overstates the racial gap in entrepreneurship rates (9 percentage points in the data, vs. 11 percentage points in the model).

However, this overstatement of the extensive margin gap in entrepreneurship is accompanied by

[17] Our distance metric is the mean squared relative weighted error such that $MSRE = \sum_{j=1}^{12}\left(\frac{S_j^{model}-S_j^{data}}{S_j^{data}}\right)^2 \frac{\omega_j}{\sum_{k=1}^{12}\omega_k}$, where S_j^{model} and S_j^{data} correspond to the value of the j^{th} moment in the model and the data, and ω_j is its weight. The resulting model achieves $MSRE = 4.9\times 10^{-3}$.

[18] We set $\underline{a} = 0.13$, equal to 18% of median labor income in the model.

[19] These three moments: aggregate entrepreneurship rate, and the share of wealth held by Black and White entrepreneurs, receive a double weight $\omega_j = 2$; all other moments receive unit weight $\omega_j = 1$.

[20] The entry process function ψ further limits this number by precluding low permanent income households from entry.

Table 3: Summary of targeted moments and model fit

Targeted moment	Source	Data	Model
Net return $(r-\delta)$	literature	4.0%	4.0%
Capital to output ratio	literature	3.0	3.0
Wealth share of those in P50-P90 percentiles	SCF	24.9%	25.0%
Wealth share of the Top 10%	SCF	73.0%	71.7%
Share of households with negative net wealth	SCF	10.5%	10.3%
Entrepreneurship rate, all households	SCF	12.7%	13.7%
Entrepreneurship rate, Black households	SCF	5.2%	4.5%
Share of group wealth held by entrepreneurs, Black households	SCF	25.6%	23.2%
Share of group wealth held by entrepreneurs, White households	SCF	46.2%	44.3%
$ER_{P50-P90}/ER_{P0-P50}$	PSID	2.6	2.8
$ER_{P90-P100}/ER_{P0-P50}$	PSID	5.8	6.1
Ratio of benefits T to median wage	literature	33.0%	29.4%

Untargeted moment	Source	Data	Model
Average racial wealth gap	SCF	83.6%	83.3%
Median racial wealth gap	SCF	88.4%	79.5%
Entrepreneurship rate, White households	SCF	14.2%	15.5%
Wealth of avg. ent. to avg. household, Black	SCF	4.9	5.1
Wealth of avg. ent. to avg. household, White	SCF	3.2	2.9
Ratio of median profits of Black- vs White-owned firms	SCF	39.9%	44.3%

Notes: This table summarizes the targeted moments and reports the model's fit with respect to each, as well as the model's overall fit. $ER_{P50-P90}/ER_{P0-P50}$ denotes the relative entry rate into entrepreneurship of households in the P50-P90 of the labor income distribution, relative to those in the P0-P50, and analogously for $ER_{P90-P100}/ER_{P0-P50}$. All data coming from the SCF/PSID refers to averages over the 2001-2019 period.

a slight understatement of the intensive margin along which entrepreneurship contributes to wealth and, primarily, White wealth. In particular, the average White entrepreneur in our model is slightly less affluent than their worker counterparts, compared to what the data implies (2.9 times richer in the model, vs. 3.2 times richer in the data). Overall, these gaps are not substantial and suggest that our model effectively captures the correlation between wealth, race, and entrepreneurship, and the relative importance of entrepreneurial wealth.

Note that since the model underestimates the importance of White entrepreneurship in explaining wealth inequality among the White population, our model is also prone to underestimating the role of entrepreneurship in accounting for racial wealth inequality.

Income and entry decision moments. We use entry rates by income from the PSID to target entry dynamics. As discussed in the previous section, the PSID data reveals a positive correlation between income and entry into entrepreneurship. Denote the average entry rate into entrepreneurship in labor income fractile j by ER_j. We target the ratio $ER_{P50-P90}/ER_{P0-P50} = 2.6$ and also $ER_{P90-P100}/ER_{P0-P50} = 5.8$ to capture the correlation between labor income and entry rates. The resulting model delivers a good fit with $ER_{P50-P90}/ER_{P0-P50} = 2.8$ and $ER_{P90-P100}/ER_{P0-P50} = 6.1$. These values are primarily influenced by our entry process parameters Ψ_0 and Ψ_1.

Our final targeted moment is an income floor of 33% of the median household income, in line with other studies (e.g., see Straub, 2019). To obtain this, we calibrate a simplified tax system under a balanced budget with a single parameter $\bar{t} = 11.35\%$, and achieve an income floor such that the benefit T is equal to 29.4% of the median household's pre-tax labor income, slightly undershooting the targeted 33% but well within reasonable bounds.

Notice that we calibrate the Pareto tail of the productivity distribution to $\zeta = 5.84$, implying that the firm-size distribution in our model has a tail of $\zeta(1-\alpha-\beta) = 1.81$ (with $1-\alpha-\beta = 0.31$).[21] Moreover, our calibration internally sets decreasing returns to scale of $\alpha+\beta = 0.69$, in line with the literature, with $\alpha = 0.30$ and $\beta = 0.39$. These values do not directly map to the empirical factor shares, as the empirical labor share also includes the labor income of CEOs and partners, which in our model are labeled as profits. Thus, to be empirically sensible, our value for β should be strictly below the empirically observed payroll share (53.3% for the US in 2010-2012 according to Elsby, Hobijn, and Şahin (2013)).

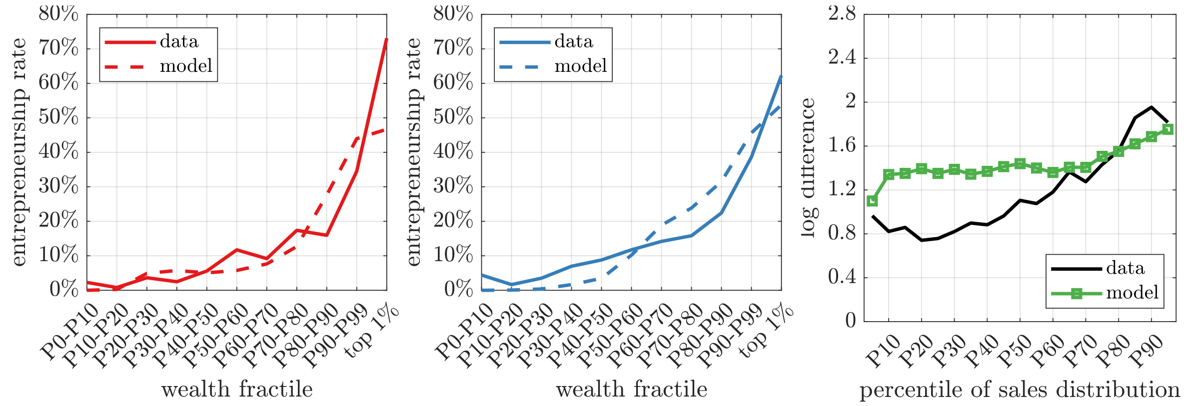
4.4 Model Validation

This section outlines several validation checks we conduct to ensure our model is suitable for the analysis that follows. Critically, we verify that our model indeed captures the racial wealth gap, the correlation between entrepreneurship and wealth, and racial differences in business performance.

The model generates a large and untargeted average racial wealth gap (83.3% in the model vs 83.6% in the data) consistent with the data. It also delivers a median racial wealth gap of 79.5%, compared to 88.4% in the data. These results indicate that the model can account for nearly the entire average racial wealth gap, although it somewhat underestimates the median. Given the high concentration of wealth in the US, this is not surprising: entrepreneurship is likely to explain most of the right tail of the wealth distribution. Therefore, racial differences in entrepreneurship choices and their determinants can account for a significant portion of the average racial wealth gap. However, other factors, not modeled here, might be necessary in governing the median gap.

The correlations between entrepreneurship and wealth, overall and by race, are untargeted in

[21] Empirically, the firm-size distribution is considerably more skewed (e.g., Axtell, 2001). However, modeling the firm-size distribution and wealth inequality as joint phenomena requires taking a stance on ownership structures and portfolio choices, which lies beyond the scope of this paper (for an example that includes human capital wealth, see Aoki and Nirei (2017)).



(A) Entrepreneurship rate, Black households

(B) Entrepreneurship rate, White households

(C) Difference in log(size) of firms

Figure 6: Untargeted entrepreneurship moments - model validation

Notes: This figure evaluates the model's performance by comparing untargeted entrepreneurship outcomes to the data. Panels (A) and (B) report the share of entrepreneurs among Black and White households within each wealth fractile of the overall wealth distribution. Panel (C) displays the log differences in firm size, measured as revenue, between White-owned and Black-owned firms, conditional on their revenue fractile. For example, P50 displays the log size difference between the median White-owned and Black-owned firms in the data and the model. Lower percentiles are shown as missing in the data because some firms do not report positive sales. Source: SCF, 2001-2019.

our calibration. Figures 6A and 6B show that our model accurately captures this correlation for both Black and White households. This validation exercise is both crucial and reassuring, as the primary goal of the paper is to understand the role that entrepreneurship plays in understanding wealth and, specifically, wealth differences across races.

Previously, when discussing Figure 3B we indicated that there is a constant gap in the size of White-owned firms vs Black-owned firms. We conjectured that our entrepreneurship distortion τ_y^B would be able to deliver a constant difference in size. In contrast, a distortion in collateral constraint would cause Black-owned firms with wealthy owners to converge with their White counterparts. Figure 6C supports our modeling choices and indicates that the entrepreneurship distortion indeed delivers a constant difference across the size distribution of Black vs White-owned firms. The resulting gap is broadly consistent with the empirically observed gap, and its overall magnitude and slope are similar. Moreover, compared to its White-owned counterpart, the median Black-owned business is substantially less profitable both in the model and in the data. The median Black-owned business delivers to its owner only 44.3% (vs 39.9% in the data) of the profits of its White-owned counterpart.

To conclude this section, our model successfully captures the racial wealth gap, the correlation between wealth and entrepreneurship, and the stark differences in outcomes between Black and White entrepreneurs.

5 Results

5.1 Decomposing the racial wealth gap

With the quantified model at hand, we now explore the role of entrepreneurship choices in determining racial wealth outcomes. Recall that the model allows for Black and White households to differ in outcomes due to the distortions faced by Black workers (labor income and a labor income risk distortion) and Black entrepreneurs (entrepreneurship distortion), both of which affect the entrepreneurship choice. To disentangle the effects of the two, we conduct a comparative statics exercise in which we equalize the conditions faced by Black households to those faced by White ones for workers only, for entrepreneurs only, or for both.

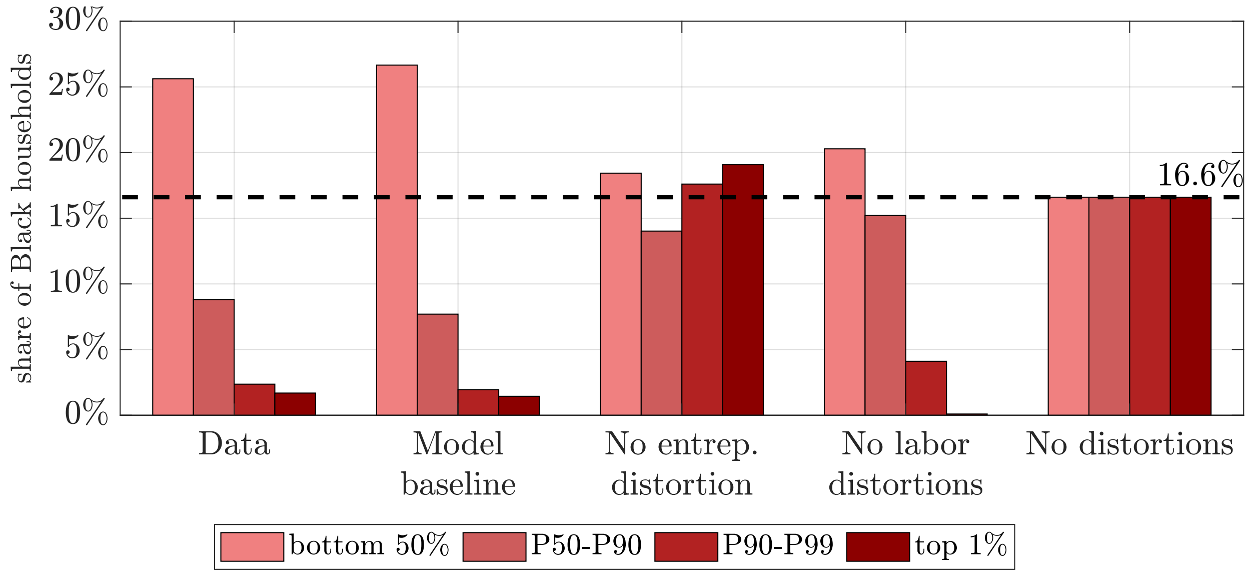


Figure 7: Racial representation along the wealth distribution

Notes: Each bar shows the share of Black households within a fractile of the wealth distribution. The first set of bars reports SCF data. The baseline case corresponds to our calibrated model. The next three sets of bars correspond to counterfactual scenarios in which the entrepreneurship distortion, labor market distortions, and all distortions are removed.

Before discussing the results, it is instructive to consider the non-trivial effects of removing the distortions on wealth outcomes. Removing the entrepreneurship distortion makes Black entrepreneurs richer on impact. These existing entrepreneurs, in turn, demand more labor and capital, raising factor prices. Ultimately, these forces alter the sorting patterns into entrepreneurship for both Black and White households. Thus, without the entrepreneurship distortion, the continuing labor market distortions imply that Black households are more likely to choose entrepreneurship, which improves their wealth outcomes. Note, however, that it is harder for these households to accumulate wealth in the labor market.

The labor market distortions are more complex. Removing the labor income distortion raises the labor income of Black households, improving their ability to accumulate wealth as workers. Simultaneously, removing the labor income risk distortion reduces the precautionary saving motive of Black households, as it reduces their earnings risk. Both of these changes, all else being equal, make entrepreneurship less desirable to Black households and likely depresses wealth accumulation. Two caveats are in order: first, removing labor market distortions increases the quantity of distortion-adjusted labor available for hire, thereby lowering wage income overall; second, having households spend more time in high-permanent-income states enables them to receive more high-quality ideas. Both of these forces make entrepreneurship more desirable so the results are not ex-ante obvious.

Table 4: The racial wealth gap and entrepreneurship outcomes

	Entrepreneurship rates			Racial wealth gap	
	Black	White	gap (W-B)	Average	Median
Data	5.2%	14.2%	9.0%	83.6%	88.4%
Model	4.5%	15.5%	11.0%	83.3%	79.5%
No entrepreneurship distortion	20.9%	13.0%	-7.9%	-4.9%	24.1%
No labor market distortions	0.2%	16.4%	16.2%	73.9%	38.8%
No distortions	14.0%	14.0%	0.0%	0.0%	0.0%

Notes: This table reports each counterfactual scenario, the entrepreneurship rate of Black and White households, the gap between them, and the average and median racial wealth gap. The entrepreneurship gap is expressed as the difference in entrepreneurship rates between the groups. For comparison purposes, the baseline model and the SCF data are also reported.

Figure 7 and Table 4 report how counterfactual changes in the distortions influence the racial wealth gap and the representation of Black households along the wealth distribution. All these counterfactuals are general equilibrium exercises where all quantities and prices adjust to the shocks, and the distribution of households is the new stationary distribution resulting from the updated household policy functions.

Strikingly, Figure 7 show that removing the entrepreneurship distortion alone flips the sign of the steady-state racial wealth gap, nearly eliminates the over-representation of Black households at the bottom of the wealth distribution, and even creates an over-representation of Black households at its top. As Table 4 reports, in this counterfactual scenario, the racial wealth gap is -4.9%. That is, the average Black household is 4.9% wealthier than the White one, and the entrepreneurship rate among Black households is 7.9 p.p. higher than for White households.[22]

[22] Even though Black households are wealthier on average, we cannot conclude that their welfare is higher since they still face labor market distortions. See Brouillette, Jones, and Klenow (2021) for a study that measures the welfare gap between Black and White households.

Removing the entrepreneurship distortion also reduces the median racial wealth gap from 79.5% to 24.1%. One might wonder: why does the median racial wealth gap respond at all to the entrepreneurship distortion, which affects mainly the right tail of the distribution? Two factors contribute to this effect on the median. First, when we equalize the conditions faced by Black entrepreneurs, Black entrepreneurship is more profitable, all else being equal. Thus, Black workers have a greater incentive to save more, thereby better capitalizing on emerging opportunities. Second, wealth outcomes persist over time. Children of wealthy entrepreneurs are more likely to be wealthier even when they are not entrepreneurs themselves.[23] All figures reported in Table 4 are steady state figures, and mask the long transition period it would take to converge to them, which is treated in Section 6.

In comparison, equalizing the conditions faced by Black workers helps alleviate poverty among Black households. However, it also leads to a severe reduction in Black entrepreneurship. Because the entrepreneurship distortion remains in place, Black households almost never enter entrepreneurship (a Black entrepreneurship rate of only 0.2%) and instead stay in the labor market, with less than 0.1% of Black households in the top 1%. The median wealth gap declines to 38.8% and the average to 73.9%, the latter remaining relatively close to the baseline. On both statistics, reducing the entrepreneurship distortion is more meaningful for reducing the racial wealth gap than reducing the labor market distortions.

These results illustrate how entrepreneurship, a phenomenon concentrated at the top of the wealth distribution, plays a pivotal role in determining racial wealth outcomes throughout the distribution. To eliminate the racial wealth gap, one must target entrepreneurship outcomes and achieve equal representation of Black households among the very wealthy. This result is informative for emphasizing which channels are key to closing the racial wealth gap. Policy interventions targeting the entrepreneurship distortion are promising, while policies that focus on the labor market outcomes of Black households are less effective in achieving this goal. When addressing poverty alleviation among Black households, focusing on labor market outcomes is a suitable approach. However, policies targeting labor market outcomes alone can even exacerbate the under-representation of Black households among the wealthiest. Such under-representation could even reduce the political influence of Black households (Bartels, 2009) and ultimately may have unintended social consequences.

[23] These counterfactual shifts on the relative wealth of Black compared to White households occur without much change in the overall wealth distribution as shown in Table A.1 in the Appendix. This happens because the first-order determinant of overall wealth dispersion is the stochastic process governing income dispersion from profits, which remains unchanged in all scenarios.

5.2 The macroeconomic implications of racial distortions

To understand the significance of these racial distortions to macroeconomic outcomes we utilize the aggregate production function representation of our model economy to decompose the role of the distortions on macroeconomic aggregates. The aggregate production function is as follows

$$\log Y = \underbrace{\alpha \log K + \beta \log N + (1-\alpha-\beta)\log m_F}_{\text{factor quantities}} + \underbrace{\beta \log\left(\mathbb{E}(z_L(1-\tau_L))\right)}_{\text{agg. labor productivity}} + \underbrace{\log(\text{TFP})}_{\text{agg. productivity}}. \tag{18}$$

Thus, aggregate output Y is a constant-returns-to-scale production function of the aggregate capital stock, K, the aggregate number of workers N, and the number of firms m_F. It also depends on aggregate labor productivity $\mathbb{E}(z_L(1-\tau_L))$, or the distortion-adjusted labor input provided by a worker, and total factor productivity (TFP). Labor productivity is affected by the labor income distortion, and by the labor income risk distortion governing the distribution of z_L among Black households. TFP is also endogenous in our model, as it is affected by the entire distribution of firm-level productivity, the distortions, and the financial frictions, accounting for endogenous sorting patterns that determine entry into entrepreneurship and entrepreneurs' savings choices.

Table 5: The effects of distortions on aggregate quantities

Distortions removed	Y	K	N	m_F	$\mathbb{E}(z_L(1-\tau_L))$	TFP
Entrepreneurship	4.8%	5.1%	-0.8%	5.0%	1.5%	1.4%
All	11.0%	10.4%	-0.4%	2.7%	11.5%	2.6%

Notes: This table reports for each variable the percentage deviations with respect to the baseline.

Removing the entrepreneurship distortion increases steady-state GDP by 4.8%. This is primarily due to a higher demand for capital and labor by existing and new entrant Black-owned firms, even though the primitives governing firm productivity are unchanged. Removing the distortion increases the overall number of firms and implies a reallocation of factors from White-owned to Black-owned firms in relative terms. Observe that higher labor demand also leads some high z_L White workers to remain in the labor market, increasing economy-wide labor productivity. Changes to the entry decision, ultimately manifest as changes to the TFP, which is positively influenced by the higher quality of entrants in the model economy.

Furthermore, removing all distortions raises steady-state GDP by 11.0%. This increase suggests substantial potential gains from policies aimed at addressing the root causes of racial disparities in outcomes. While this number is large, it is not extraordinary. In a similar exercise, but using different models and distortions, Hsieh et al. (2019) consider removing frictions that prevent efficient sorting across occupations and report an increase in steady-state GDP of 9.9%. The results suggest that our estimates are well within the bounds suggested by the literature, providing further support for the critical role of efficient occupational sorting in economic conditions.

5.3 Evaluation of policies targeting the racial entrepreneurship gap

Table 6: Policy counterfactuals - subsidizing Black entrepreneurship

	Entrepren. rate		Racial wealth gap		$\frac{E[l^B]}{E[l^W]}$	Tax rate	Subsidy rate
	Black	White	Average	Median			
Baseline	4.5%	15.5%	83.3%	79.5%	7.4%		
Profit subsidy	13.5%	15.3%	68.2%	76.9%	5.1%	2.7%	57.4%
Revenue subsidy	16.7%	15.1%	56.8%	69.0%	8.8%	2.7%	23.2%
Capital subsidy	16.9%	15.1%	41.7%	50.8%	10.4%	2.7%	59.8%

Notes: This table reports entrepreneurship and wealth outcomes following a subsidy aimed at stimulating Black entrepreneurship. The tax rate represents the additional labor income tax t_w necessary to fund the subsidy policy, and $E\left[l^B\right]/E\left[l^W\right]$ represents the average size of a Black-owned business relative to a White-owned one, as measured by labor. Denoting the subsidy on profits, revenue and capital by s^i_π, s^i_y, s^i_k, respectively, the firms' problem in Equation (12) with all subsidies becomes $\{h(a,z_F,i),k(a,z_F,i)\} = \arg\max_{\{h,k\}}\left[(1+s^i_y)(1-\tau^i_y)z_F k^\alpha h^\beta - wh - (1-s^i_k)rk\right]$, subject to $k \leqslant a\lambda_{CC}$, and profits are given by $\pi(a,z_F,i) = (1+s^i_\pi)\left[(1+s^i_y)y(a,z_F,i) - (1-s^i_k)rk(a,z_F,i) - wh(a,z_F,i)\right]$.

We now ask: Is it possible to address the racial wealth gap without addressing its root causes? This question is of interest since, while profound social change may be slow, there may be scope for policy interventions. We consider subsidies to either profit, revenue, or capital for Black entrepreneurs,[24] all funded with a higher labor income tax on all workers.[25] We compute new steady states in which each of these subsidy programs has an identical fiscal cost fixed at 1.0% of our baseline GDP. The fiscal cost is chosen for illustrative purposes only. Results are reported in Table 6.

The main result from this exercise is that subsidy policies, even very generous ones, are ineffective in eliminating the racial wealth gap, despite being able to increase the Black entrepreneurship rate to as high as 16.9%, higher than the White entrepreneurship rate. As Table 6 shows, the size ratio between Black and White owned firms $E\left[l^B\right]/E\left[l^W\right]$ is still such that the average Black-owned business is between ten and twenty times smaller than its White-owned counterpart.[26] Thus, the

[24] Boerma and Karabarbounis (2023) also highlight the effectiveness of policies that increase the rate of return of entrepreneurship for Black households.

[25] Shifting the funding burden to White workers only does not meaningfully affect the results. If anything, it makes supporting Black entrepreneurship slightly harder, as Black workers would not be taxed and would therefore be less inclined to become entrepreneurs.

[26] The average size of Black businesses falls with the profit subsidy, which might seem puzzling at first. This happens because the subsidy stimulates entry of less productive households with lower z_P which leads to firms with lower initial productivity z_F.

subsidies are not enough to entirely offset the impact of the entrepreneurship distortion. This is clearest when examining the revenue subsidy, which is the closest to a negative entrepreneurship distortion.[27] Black entrepreneurship rates increased to 16.7% as a result of a revenue subsidy of 23.2%, while the entrepreneurship distortion remains more than 60%, so Black-owned firms are still inefficiently smaller. Ultimately, this exercise implies that without deep social change, it is possible that a policy that is successful in equalizing entrepreneurship rates could fail to close the racial wealth gap.

These small wealth effects might seem puzzling at first. However, they are the result of existing labor market distortions, which make the outside option for Black entrepreneurs worse, thus enabling policymakers to close the entrepreneurship rate gap while simultaneously having a net positive distortion faced by Black entrepreneurs. If there were no labor market distortions acting as a countervailing force, the relationship between the racial wealth gap and the gap in entrepreneurship rates would be more direct. Thus, ignoring labor market distortions could lead one to overestimate the impact of policies targeted at equalizing entrepreneurship rates on the racial wealth gap. Once the interaction between labor market outcomes and entrepreneurship outcomes is properly considered, closing the racial wealth gap with policies targeted at entrepreneurs is not possible without Black entrepreneurship rates overshooting those of their White counterparts. In other words, as long as the distortions are still in place, parity in entrepreneurship rates is not enough to close the racial wealth gap.

Finally, of the policies considered, we find that the capital subsidy is the most effective policy. It causes the largest reduction in both the average and median racial wealth gaps, and the largest increase in the relative size of Black-owned firms. Notice that, because collateral-constrained firms cannot increase their capital input even if the subsidy reduces their costs, most of the benefits of this policy accrue to the larger, better capitalized, Black-owned firms, which are typically owned by wealthier individuals. This finding suggests that policies aimed at helping larger Black-owned firms catch up with the largest White-owned firms may be more successful in reducing the racial wealth gap than policies targeting small firms.

6 The dynamics of the racial wealth gap

So far, we have compared different steady states in the model. However, the speed of change also matters. Thus, we now investigate how long it would take to close the part of the racial wealth gap accounted for by our model, from the initial steady state calibrated to the 2001-2019 US economy. All scenarios studied in this section take into consideration general equilibrium effects

[27] The comparison is not exact since the revenue subsidy affects the choice of capital and labor, and the profits given those choices, but the distortion affects only the choice of inputs, as explained in Section 3.

under perfect foresight and hold the population composition constant.

We begin by studying the case in which all distortions are removed immediately. In this case, it takes between 150 and 200 years for the average racial wealth gap to close, as Panel (A) of Figure 8 shows, and 100 years to close the median racial wealth gap (Panel (B)). The primary result of this exercise is that wealth convergence occurs gradually. In other words, the initial conditions play a powerful role in shaping the transition, as from $t = 0$ onward, there are no exogenous distortions imputed to the model. The second main result is that convergence between Black and White households occurs more rapidly at the lower end of the distribution than at the upper end. The median racial wealth gap closes faster than the average one. Moreover, Panel (C) shows that Black households only achieve equal representation at the top 1% of the wealth distribution and reach their population weight of 16.6% after 150 years, in line with the closing of the average racial wealth gap.

Both results above may seem particularly puzzling, given the faster convergence in entrepreneurship rates shown in Panel (D), which occurs in less than 100 years. However, even though removing the distortions increases the current and future profits of existing Black-owned firms and incentivizes the creation of new ones, it takes time for new entrant firms to grow to their optimal size and equal that of their White-owned counterparts. Panel (E) reports that the profitability of Black and White-owned firms is equalized only after 150 years. Finally, panel (F) reports the increased share of Black households among top-income earners. Notice that once equal representation among top-income earners is achieved, or even slightly before, the median racial wealth gap closes. Thus, the convergence of the average racial wealth gap appears to be slower, in line with convergence at the top 1% of wealth, whereas the convergence of the median racial wealth gap is faster, in line with convergence at the top 1% of the income distribution.

6.1 The effect of wealth transfers

Our final exercise is to analyze the effect of a wealth transfer using a one-time, proportional wealth tax imposed on White households, with the proceeds redistributed as a lump sum to all Black households, independent of their wealth or other characteristics. We report the results of this wealth transfer in Figure 8 for three scenarios: (i) assuming that all distortions are eliminated immediately; (ii) distortions close linearly over 100 years; and (iii) no social change occurs, which means that distortions remain unchanged.

The scope of the wealth transfer involved is large. Each White household with a positive net asset position faces a 13.8% tax on their wealth. At the same time, each Black household receives a lump sum transfer of 6.4 times the median household's annual labor income in the model, which is 417% of the total Black household wealth. The total wealth transfers amount to 40% of the

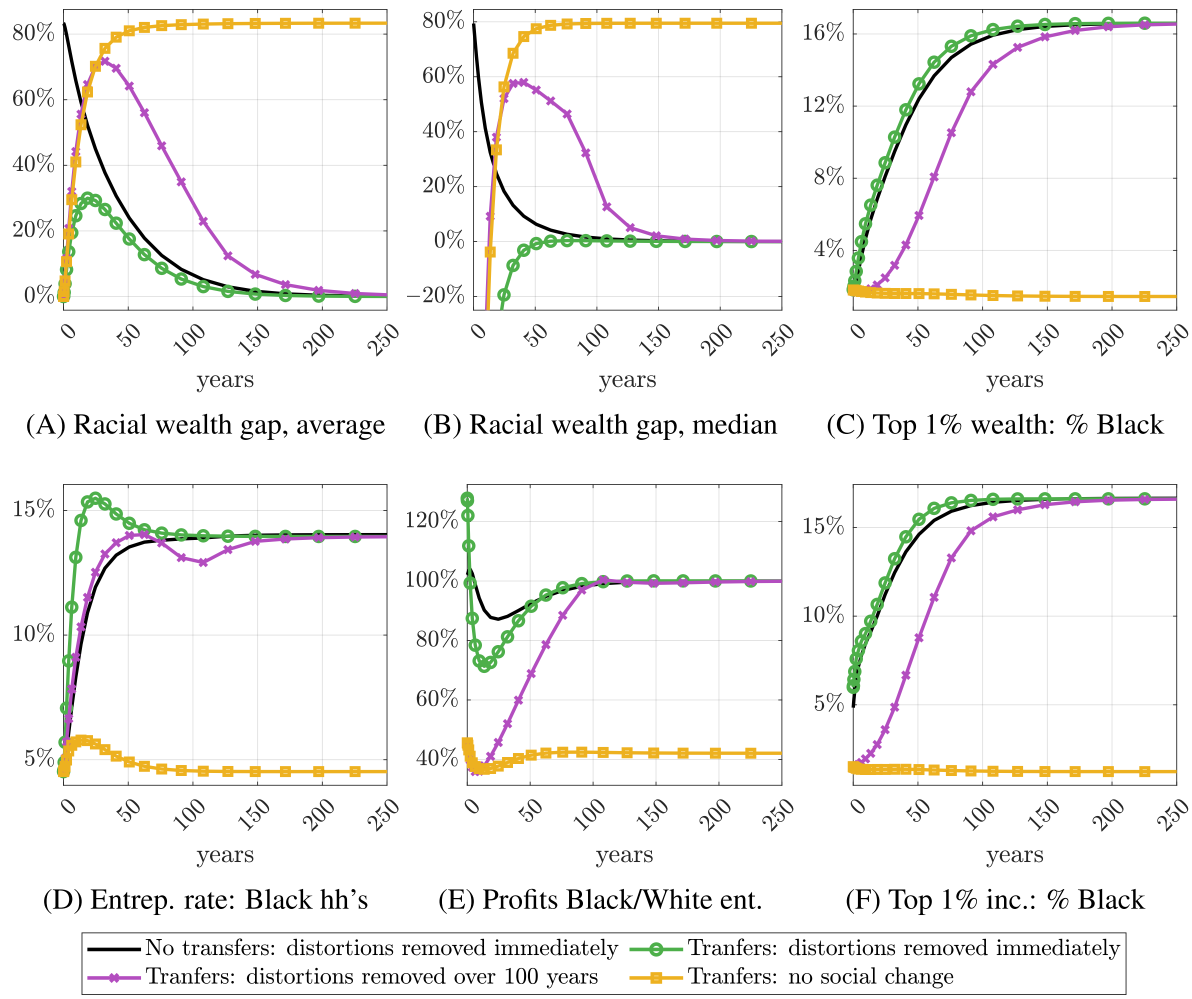


Figure 8: Closing the racial wealth gap

Notes: The solid black line shows the transition path from the steady state with distortions to a steady state without distortions, when all the distortions are removed immediately. The other three cases involve wealth transfers that close the average racial gap, assuming that: (i) all distortions are removed immediately; (ii) the distortions close linearly over the next 100 years; (iii) there is no social change and all distortions remain as they were in the initial steady state. The panels show: (A) the average racial wealth gap; (B) the median racial wealth gap; (C) the share of Black households in the top 1% of the wealth distribution; (D) the entrepreneurship rate for Black households; (E) the average profits of a Black entrepreneur relative to that of a White one; (F) the share of Black households in the top 1% of the total income distribution.

annual GDP in the model. Thus, compared to US GDP in 2019, this would result in a transfer of \$8.6 trillion.[28]

Panel (A) of Figure 8 illustrates that, in all these scenarios, the average racial wealth gap falls

[28] This number is in line with other estimates: Boerma and Karabarbounis (2023) report a corresponding number of \$10 trillion, Darity Jr and Mullen (2020) of \$8 trillion. Given the approximately 20.1 million Black households in 2019, this would amount to a transfer of approximately \$427,000 per household.

to 0% on impact by construction. It reopens shortly thereafter as Black households consume a significant portion of the transferred wealth, and income parity has not yet been achieved. In the case of transfers combined with the immediate removal of the distortions, the average racial wealth gap closes completely after 150 years, or approximately the same horizon as in the no-transfers case, albeit with an overall lower level throughout the transition period. Our main result in this section is that, while transfers help maintain a lower average racial wealth gap throughout the transition, they do not significantly impact the speed with which it converges to zero.

Panel (F) illustrates why this is the case: even though average wealth is equalized immediately, Black households' incomes remain lower than White households' after exogenous distortions are removed. In the less extreme case of distortions closing slowly, the profitability of Black-owned firms remains significantly lower than that of White-owned ones (Panel (E)), and it takes approximately 100 years for them to converge. Moreover, Black households have just received a transfer of wealth and anticipate a future income rise. Thus, they smooth out the wealth shock and consume more than their income, thereby increasing the average racial wealth gap again.

Several notes are in order. First, the median racial wealth gap reverses on impact because the transfers are proportional to White households, but lump-sum to Black households. Second, without social change, i.e., as long as the distortions remain in place, wealth transfers cannot, by construction, alter long-term wealth inequality, and the racial wealth gap reopens to its original magnitude, with most of the progress undone quickly over the course of the first 50 years. That finding is meaningful since even though the end result is an assumption in the model, the speed of convergence is instructive.

Importantly, in the above exercise, the distortions are entirely independent of the dynamics of the racial wealth gap. One might argue that wealth transfers to Black households can reduce the distortions themselves (e.g., through increased investment in education and reduced discrimination), thereby further reducing the racial wealth gap. Given this notion, one can consider the case in which all distortions close upon the transfer (and, some may argue, as a result of it) and the case in which the transfer delivers no social change as two extreme cases. In the former, transfers help alleviate all distortions immediately, making it the best-case scenario for wealth convergence. In the latter, transfers do not affect the distortions, making it the worst-case scenario. The case of slowly removing distortions in Figure 8 provides insight for a potential intermediate scenario in which social change occurs after the transfer but very gradually. Notice that even with an exogenous downward path towards zero for distortions over 100 years, the average racial wealth gap rises quickly again and, in less than 50 years, it is almost back at its original level. Thus, unless the impact of wealth transfers is such that all distortions are immediately removed, the model suggests that it is unlikely that wealth transfers could generate a virtuous cycle of reducing inequality and reducing distortions.

7 Conclusion

We develop a model of entrepreneurship and wealth accumulation that features incomplete markets and a dynamic discrete choice of entrepreneurship. In the model, Black households face adverse distortions as workers and entrepreneurs. We use US microdata to discipline the model.

Quantifying the impact of each distortion reveals that removing the entrepreneurship distortion would reverse the average racial wealth gap and almost halve the median racial wealth gap. In comparison, we demonstrate that addressing labor market distortions has a significant impact on the median racial wealth gap; however, it can hurt the representation of Black households at the top of the wealth distribution due to its influence on entrepreneurship choices. Our analysis highlights the crucial role of sorting via the entrepreneurial entry choices as a margin of influence for policies targeting racial disparities.

Our analysis suggests three lessons to inform the future policy debate. First, removing the entrepreneurship distortions increases output by 4.8%, primarily due to reallocation of factors towards Black-owned firms, indicating a substantial potential gain from policies targeting this distortion. Second, subsidy policies aimed at equalizing the entrepreneurship rates are effective at closing the entrepreneurship gap. However, they are not enough to close the racial wealth gap, as Black-owned businesses are still smaller than their White counterparts. Lastly, in all scenarios explored, the racial wealth gap is slow to close, and wealth transfers are ineffective at accelerating the speed of convergence.

The results highlight the centrality of entrepreneurship in understanding the racial wealth gap and the potential for policies that reduce barriers to Black entrepreneurship.

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Online Appendix to "Entrepreneurship and the Racial Wealth Gap"

Daniel Albuquerque and Tomer Ifergane

A Additional figures and tables

Table A.1: Overall wealth inequality

	Share of wealth held by the			
	bottom 50%	P50-P90	P90-P99	top 1%
Baseline	3.4%	25.0%	36.6%	35.0%
Counterfactual scenario - baseline without				
Entrepreneurship distortion	4.0%	25.8%	36.5%	33.7%
Labor market distortions	3.6%	24.9%	36.6%	34.9%
All distortions	3.7%	25.5%	36.6%	34.2%

Notes: This table reports the wealth distribution for the counterfactual scenarios in Section 5.1.

Table A.2: Average transition rates between wealth groups and regressions results

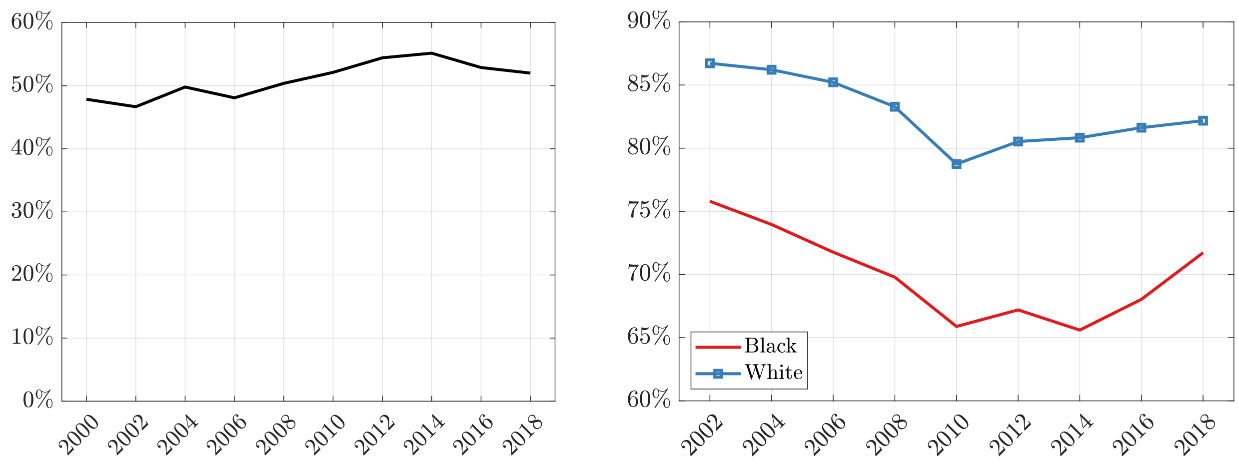
	Black households				White households			
horizon (years)	2	4	6	8	2	4	6	8
Panel A: average transition rates								
Move down from P50-P90	31.7	33.6	35.3	33.4	11.2	12.3	12.6	12.7
Move down from top 10%	70.6	72.4	82.5	85.6	25.7	28.0	29.1	31.1
Move up from bottom 50%	10.2	12.8	15.1	17.1	15.8	21.6	26.6	30.8
Move up from P50-P90	3.0	3.1	3.7	3.3	7.2	8.7	10.1	11.6
Panel B: point estimates from mobility regressions								
Move down from P50-P90	-3.5	-3.6	-20.9	-18.9	-2.0	-1.4	-2.3	-1.7
Move down from top 10%	-8.1	13.8	21.8	20.5	-4.8	-4.8	-3.4	-3.8
Move up from bottom 50%	12.4	31.3	17.6	9.1	16.3	18.7	14.7	16.5
Move up from P50-P90	4.9	5.7	7.6	-4.3	13.1	11.8	12.0	10.5

Notes: Panel A reports the average transition rates (in percentages) between wealth groups over different horizons. Panel B reports the point estimates for the dummy of entrepreneurship on the same transition rates (i.e., coefficient $\widehat{\gamma}_g^i$ in Equation (3)). Source: PSID, 2001-2019.

B Labor market outcomes

We highlighted in the main text the differences between Black and White households as entrepreneurs, which is the focus of our paper. However, there are stark differences in labor market outcomes as well which, as the outside option to entrepreneurship, are also important for our main analysis. In this Appendix we first focus on differences between Black and White households in wages conditional on employment and in employment rates. Second, we show that labor income and entrepreneurship entry are positively correlated in the data, which we argue is due to underlying human capital. Taking this into consideration is important so not to overstate the importance of entrepreneurship for the racial wealth gap. Finally, we describe in detail the estimation of the labor income process used in our model.

B.1 Differences in labor market outcomes



(A) The racial wage gap

(B) Employment rates

Figure B.1: Differences in labor income and employment rates

Notes: Panel (A) shows the racial gap in households' median labor income conditional on employment. Household labor income includes the wages of the main respondent and their spouse, and other sources, such as overtime pay, tips, bonuses, etc. Panel (B) shows the different employment rates for Black and White households. The employment rate is calculated as weeks of employment over the whole year. *Source*: PSID, 2001-2019.

Using PSID data, we calculate the gap in labor income conditional on employment between Black and White households, henceforth the racial wage gap and the gap in employment rates. As the unit of observation is a household, our measure of income includes the total labor income of the survey's main respondent and their spouse, if there is one. We include both male and female heads of household, but restrict the sample to households led by individuals between 25 and 65 years old. We also exclude any individual that reported being self-employed to only include true workers in the sample.

Figure B.1A shows the resulting racial wage gap, measured as the difference between Black and White households in the median wage per worked week in the previous year. The wage gap seems to be slightly increasing from 2000 to 2018, with an average of 50.9%. This is the measure of the racial wage gap that is imputed to the labor income distortion in the model. Notice that this is the unconditional wage gap – it does not control for any other factors, such as differences in education or household composition. Given that we do not model these differences explicitly, this is the appropriate measure to use. Thus, when we perform an exercise in the model where the labor income distortion is closing over time, we interpret it as not just the wage gap conditional on observables closing but also, for example, the convergence of educational attainment leading to convergence in wages.

On top of the gap in labor income conditional on employment displayed in Figure B.1A, we also document a gap in employment rates in Figure B.1B. While the employment rate for Black and White households naturally fluctuates with the business cycle, the gap seems relatively stable. The differences in non-employment rates are due to both a higher unemployment rate and also a higher non-participation rate for Black households. Our income process estimation incorporates this gap in employment rates to capture differences in labor market attachment between Black and White households.

Differences in labor income between Black and White workers have received considerable attention in the literature (e.g., see the review of Lang and Lehmann, 2012), and differences in employment rates have garnered more attention recently (Chandra, 2003; Bayer and Charles, 2018).[29] However, most of the literature focuses on the labor market outcomes of men. Because of the different composition of Black and White households and different employment rates between Black and White women, our headline figures differ from the literature. For example, we document larger gaps than Bayer and Charles (2018), who report a wage gap of around 40% between Black and White male workers since 1980 whereas ours is around 50%. Given the significant share of households led by women, we find it important to use our broader measure. We stress that in doing so we attribute a larger role to labor market disparities than if we were to use the alternative estimates, which is a conservative assumption.

	(1) All	(2) All	(3) All	(4) Black	(5) Black	(6) Black
percentile of income	0.012**	0.009*	0.010	0.018*	0.012	0.001
	(0.004)	(0.004)	(0.007)	(0.008)	(0.008)	(0.015)
percentile of wealth	0.043***	0.039***	0.031***	0.019*	0.016	0.001
	(0.004)	(0.004)	(0.006)	(0.010)	(0.009)	(0.009)
education		0.154***	0.187		0.245**	0.304
		(0.036)	(0.159)		(0.080)	(0.224)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Emp. status/age	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes
R-Squared	0.014	0.014	0.338	0.011	0.013	0.428
Observations	63,453	62,973	60,865	25,255	25,066	24,196

Table B.1: Entrepreneurship entry and income

Notes: This table reports the results of estimating Equation (19) either on all households (columns 1-3) or just on Black households (columns 4-6). Entrepreneurship entry is defined as not owning an incorporated business in wave t, but owning one at wave $t+1$. The regressors highlighted are the income and wealth percentile groups, and education as measured by years of schooling. Column (1) shows that moving up one percentile group is correlated with a 0.03p.p. increase in the probability of entrepreneurship entry. All specifications include employment status and age as controls, and specifications without individual fixed effects include gender as well. Standard errors are clustered at the individual level. *Source*: PSID, 2001-2019.

B.2 Labor income and entrepreneurship choice

In the model, entrepreneurship is an endogenous choice. Therefore, it is important to capture any possible correlation between labor income and the entrepreneurship decision present in the data: if those that start businesses usually have lower wages then increasing entrepreneurship might have a bigger effect on wealth than if those that start businesses were already earning higher incomes.

To investigate such correlations we use data from the PSID and regress the entry choice to become an entrepreneur on a set of observables. Entry $\text{entry}_{i,t+1}$ is a dummy variable indicating that household i did not own an incorporated business at wave t, but owns one at wave $t+1$ (there are PSID surveys every other year during this period) and estimate the following specification

$$\text{entry}_{i,t+1} = \alpha_t + \alpha_i + \beta_1 \text{income}_{i,t} + \beta_2 \text{wealth}_{i,t} + \beta_3 \text{education}_{i,t} + \Gamma X_{i,t} + \varepsilon_{i,t}, \tag{19}$$

where α_t, α_i denote year and individual fixed effects, and $X_{i,t}$ is a vector of household-level con-

[29] See Derenoncourt and Montialoux (2021) for the impact of minimum wage policies on the decline of the income gap in the 1960s and 1970s; and Althoff and Reichardt (2024) for the long-run effects of being tied geographically to the Deep South.

trols, including employment status, race, gender, and age. Education is measured in years of schooling, and income and wealth are measured as the percentile group of the household, e.g., between P50 and P51. We define an entrepreneur as the owner of an incorporated business in the PSID since it is the closest definition to our measure of choice in the SCF, as discussed in Section 2.2.

	(1) All	(2) All	(3) Black	(4) Black
percentile of income	0.013**	0.004	0.012	0.011
	(0.004)	(0.004)	(0.008)	(0.008)
wealth in P50-P95	1.291***		1.004*	
	(0.174)		(0.483)	
wealth in top 5%	5.423***		1.352	
	(0.698)		(1.455)	
education	0.145***	0.178***	0.236**	0.248**
	(0.036)	(0.036)	(0.077)	(0.082)
percentile of wealth × WORK		0.053***		0.019
		(0.005)		(0.014)
percentile of wealth × NOT WORK		0.016***		0.011
		(0.004)		(0.010)
Year FE	Yes	Yes	Yes	Yes
Empl. status/age	Yes	Yes	Yes	Yes
Individual FE	No	No	No	No
R-Squared	0.016	0.016	0.014	0.014
Observations	62,973	62,973	25,066	25,066

Table B.2: Entrepreneurship entry and income: alternative measures of wealth

Notes: This table shows the results of estimating Equation (19) either on all households (columns 1-2) or just on Black households (columns 3-4), under alternative measures of wealth. Entrepreneurship entry is defined as not owning an incorporated business at time t, but owning one at time $t+1$. The regressors highlighted are the income percentile group, education (as measured by years of schooling), and two distinct measures of wealth. In columns (1) and (3), wealth is measured non-linearly, with dummies indicating whether a household belongs in the middle of the distribution (P50-P95) or in the top 5% of wealth, as motivated by Hurst and Lusardi (2004). In columns (2) and (4), we interact the wealth percentile group with employment status, as motivated by Fairlie and Krashinsky (2012). Column (1) shows that moving up one percentile group is correlated with a 0.013p.p. increase in the probability of entrepreneurship entry. Standard errors are clustered at the household level. *Source*: PSID, 2001-2019.

Table B.1 reports the result of estimating Equation (19) either using all households (columns 1-3) or just Black households (columns 4-6). Observe that income is an important predictor of entry into entrepreneurship even when controlling for wealth (columns 1 and 4) and a long set of controls. Thus, on average, firms are started by those with higher labor income, even after controlling for wealth.

However, notice that when education is included as a control (columns 2 and 5) the statistical significance of income almost disappears. Furthermore, when individual fixed effects are included (columns 3 and 6), then statistical significance of both income and education disappear. We interpret this set of results as suggestive that underlying human capital generates a positive correlation between labor income and the propensity to become an entrepreneur. This correlation motivates our modeling choice, where we assume a positive correlation between starting entrepreneurial productivity and the permanent component of labor income. This is crucial so not to overstate the importance of entrepreneurship: many entrepreneurs had already good labor market outcomes, so starting a business is not a leap in income as it would be if one had poor labor market outcomes. However, we still find that entrepreneurship is crucial for explaining the racial wealth gap.

Finally, in Table B.2 we document that the same picture on the importance of education emerges when using different measures of wealth, motivated by Hurst and Lusardi (2004) and Fairlie and Krashinsky (2012). We do not report results including individual fixed effects for brevity, but in that case we confirmed that income and education loose their significance as well.

B.3 Wage estimation

We now explain in greater detail the estimation of the 17 parameters in the processes of the components of labor income productivity $z_{P,t}$, $z_{T,t}$ and l_t: $\{\tau_L^B, \mu_P^B, \mu_T^B, \lambda_P^B, \lambda_T^B, \sigma_P^B, \sigma_T^B, \lambda_{01}^B$, λ_{10}^B, μ_P^W, μ_T^W, λ_P^W, λ_T^W, σ_P^W, $\sigma_T^W, \lambda_{01}^W, \lambda_{10}^W\}$. Overall, we estimate moments from the data, then use Simulated Method of Moments to first estimate the parameters of the processes, and finally optimize over the choice of the grid in which to discretize the process.

The PSID from 2001 to 2019 is the source for our data moments. It is especially suited for our exercise for three main reasons. First, it is a panel dataset, which allows us to calculate moments based on wage changes over time for a given household. Second, in the 1990s the PSID added an extra sample meant to better capture minorities in the US, which means that the sample size for Black households is similar to those of White households. Finally, the PSID also asks about labor income, weeks worked, and monthly employment dating (since 2003) on the year before the survey, which will be key for the estimation of the racial wage gap conditional on employment, and also for the transition rates between employment and non-employment.

Because our unit of observation is a household, we define as "wage" the total labor income for both the main respondent to the survey and their spouse. We restrict the sample to those in working age between 25 and 65 years old, and consider both male- and female-led households. We exclude anyone that reported being self-employed to only take into account true workers. Most of the moments we calculate are based on changes in wages over time, thus we construct a single dataset with all the qualifying households that appeared in at least two consecutive waves. However, some restrictive moments require us to observe a household twice with a lag of six years (e.g., in 2011 and 2017, but not necessarily in 2013 or 2015). Our smallest sample sizes are for these moments, of 1021 for Black households and 1737 for White households (but we have 7 different combinations of 6-year spans from 2001 to 2019).

The first step in our procedure is to estimate some moments directly from the data. Because we know the labor income of each household in the year before the survey and the number of weeks worked, that allows us to calculate wage conditional on employment. The simple difference on median wage per week worked of Black and White households is our estimate for the racial wage gap, and we find $\tau_L^B = 50.9\%$. Because we do not model dimensions such as educational attainment, school quality or household composition, our measure of τ_L^B is also influenced by differences in these features between Black and White households. Furthermore, we have monthly dating of employment for households over the course of the year prior to the survey, and we use that to calculate monthly transition rates. With monthly transition rates λ_m in hand, we calculate yearly transition rates for our model with $\lambda_m = e^{-\lambda_y/12}$, and find $\lambda_{10}^B = 15.4\%$, $\lambda_{01}^B = 31.5\%$, $\lambda_{10}^W = 10.0\%$, $\lambda_{01}^W = 44.2\%$.

Second, we estimate all the other parameters jointly using a Simulated Method of Moments (SMM). The idea is to simulate the processes for $z_{P,t}$, $z_{T,t}$ and l_t for a given combination of parameters, and calculate in the model the same moments that we estimated from the data. Then we optimise over the choice of parameters to minimise the sum of squared deviations between the moments simulated from the model and those from the data. We impose the identifying assumption $\lambda_P \leqslant \lambda_T$.

The moments chosen are shown in Table B.3. There is only one moment directly related to the distribution of income across households, and that is the variance of the log of labor income. The other moments are related to the change in log labor income over time for a given household. We target the standard deviation and kurtosis of the changes over 2, 4 and 6 years, and also the fraction of households whose 2 years log changes were smaller than 5%, 10% or 20%. In total, we have 10 moments for both Black and White households for the remaining eight parameters that are left to be estimated, and we weigh all the moments equally.

The simulation involves 5000 households over a period of 1000 years to arrive at the stationary distribution, and six more years to calculate the necessary moments. The simulated process for labor income is annual, but we calculate 2, 4 and 6 years wage changes to match the data.

The estimated parameters were reported in Table 1, and the moments implied by the continuous model are shown in columns (2) and (5) of Table B.3. It shows that the model does an overall great job in matching most moments, including the high kurtosis highlighted by Guvenen et al. (2021), due to shocks not arriving at every period (Kaplan, Moll, and Violante, 2018). The model seems to undershoot the variance of log income. But, as Figure B.2 shows, the estimated model seems to

Table B.3: Labor income moments from data and model

Moments	Black Households (1) Data	Black Households (2) Model Contin.	Black Households (3) Model Discret.	White Households (4) Data	White Households (5) Model Contin.	White Households (6) Model Discret.
var(log(income))	0.67	0.56	0.53	0.64	0.57	0.52
std Δ2y	0.55	0.64	0.63	0.43	0.54	0.50
std Δ4y	0.62	0.68	0.72	0.51	0.57	0.59
std Δ6y	0.67	0.78	0.77	0.56	0.66	0.65
kurtosis Δ2y	7.0	7.5	7.7	9.9	10.5	11.1
kurtosis Δ4y	6.0	6.5	6.1	7.1	8.7	8.4
kurtosis Δ6y	5.8	5.5	5.5	7.0	7.1	7.2
share($\Delta 2y < 5\%$)	16.3%	16.6%	22.3%	20.7%	20.6%	22.0%
share($\Delta 2y < 10\%$)	29.3%	28.7%	31.6%	37.5%	36.8%	41.6%
share($\Delta 2y < 20\%$)	48.6%	48.3%	47.3%	59.3%	62.0%	66.7%

Notes: This table shows the moments for Black and White households estimated from the data, simulated by the model without a grid constraint (continuous), and simulated by the model in a specific discretized grid. The moments targeted are: variance of the log of labor income across households; the standard deviation and kurtosis of 2, 4 and 6 year wage changes; and the fraction of households that experience wage changes below 5, 10 and 20% over a 2-year period. *Source*: PSID, 2001-2019.

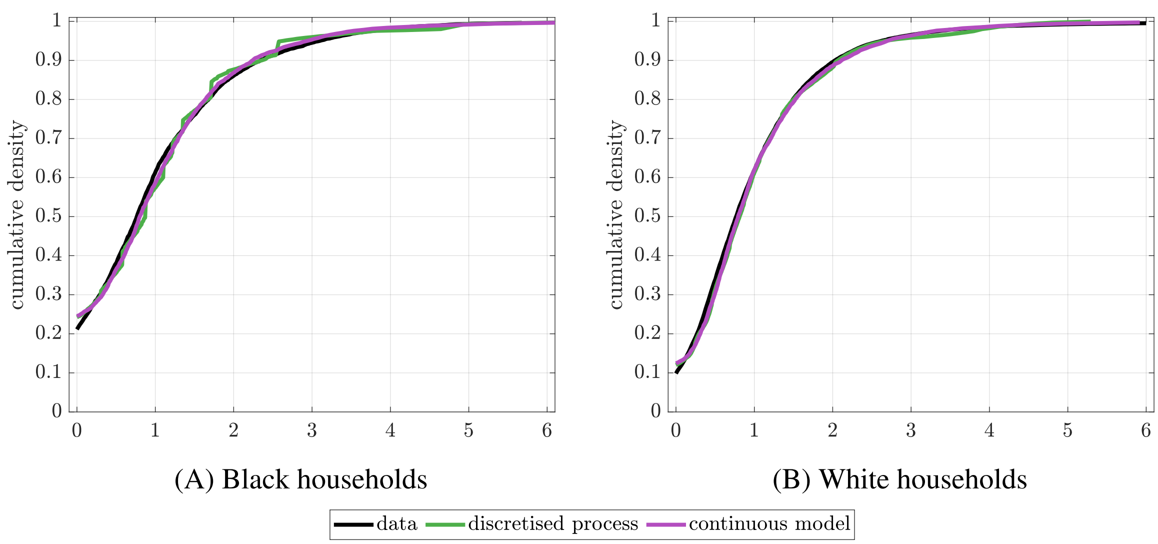


Figure B.2: CDF of log of normalized labor income

Notes: This figure shows the CDF of the log of labor income in the PSID and also in the continuous and discretized version of the estimated labor income process. Labor income has been normalised by the average labor income for each race in that year. *Source*: PSID, 2001-2019.

fit the overall distribution quite well, including the intercept with the share of households that have exactly zero labor income over the course of an year.

Third, with the estimated parameters in hand, we estimate the best grid that, given the parameters, can generate the same moments. We choose 9 grid points for permanent and 3 for the transitory component so as not to burden the numerical solution of the full model. In this step, we construct a grid for percentage deviations from the average wage, where there is a grid point exactly at zero and an equal number of grid points above and below in a symmetric fashion. We then optimise over the width of the grid points furthest away from the average and the curvature of these points (they are not uniformly distributed between zero and the points furthest away from it). The results for the moments constrained to this grid are shown in columns (3) and (6) of Table B.3. One can see that most of the moments are similar to those in columns (2) and (5), suggesting that discretizing the process does not lead to a great loss of accuracy.

C Entrepreneurship in the PSID

We now further investigate the differences in entrepreneurship rates between Black and White households using the Panel Survey of Income Dynamics (PSID). Examining the PSID enables us to verify whether the stability in the entrepreneurship gap we found in the SCF also holds over a longer time period and with different definitions of entrepreneurship. Figure C.1 plots the entrepreneurship rate over time of Black and White households. We report results for three alternative definitions of entrepreneurship: (i) self-employment; (ii) ownership of a business; (iii) ownership of an incorporated business. According to the first two definitions, the racial gap in entrepreneurship rates is shrinking. However, these definitions of entrepreneurship differ from ours as they include individuals who turned to self-employment due to a precarious situation in the labor market (Levine and Rubinstein, 2017; Fairlie and Fossen, 2018). When restricting attention to the owners of incorporated businesses, a definition of entrepreneurship that more closely aligns with our SCF-based definition and relates more closely to wealth accumulation, a similar picture emerges in the PSID and the SCF. Figure C.1 reports a stable racial gap in entrepreneurship rates going back to at least the mid-1970s. It is noteworthy that the transition rate between self-employment and ownership of incorporated businesses is small.[30]

[30]This is motivated by previous research which has shown that incorporated businesses are those most associated with entrepreneurship activities, are more likely to be present at the top of the wealth distribution, and evidence shows little switching from unincorporated businesses to incorporated ones Levine and Rubinstein (2017). We also find that transitions between non-incorporated businesses and incorporated businesses are rare in the PSID. For example, between 1969 and 1998, when the PSID was annual, the transition rate from self-employment to incorporated business was only 5.3%, and from 1999 to 2019, the two-year transition rate was 6.4%.

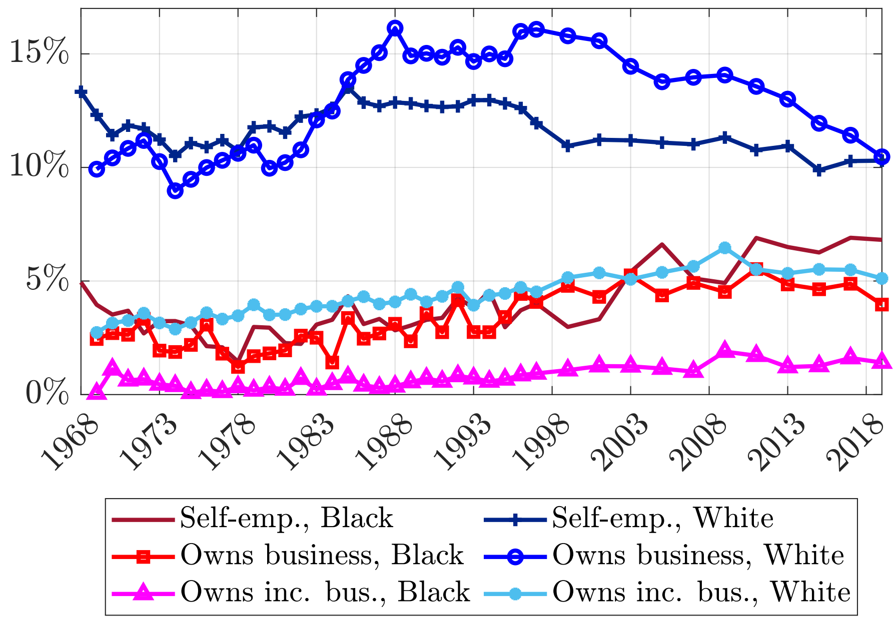


Figure C.1: Entrepreneurship rates, PSID

Notes: This figure shows the share of Black and White households over time that are entrepreneurs according to three definitions: (i) self-employed; (ii) owns a business; (iii) owns an incorporated business. Source: PSID.

D Recursive stationary equilibrium

A recursive stationary equilibrium in the model economy consists of value functions $V(a, z_P, z_T, l, i)$ and $F(a, z_F, i)$; saving rules $s_V(a, z_P, z_T, l, i), s_F(a, z_F, i)$ and the corresponding consumption policy functions $c_V(a, z_P, z_T, l, i), c_F(a, z_F, i)$; entry choice policies $I_V(a, z_P, z_T, l, i)$;[31] stationary density functions $g_L(a, z_P, z_T, l, i)$ and $g_F(a, z_F, i)$; a mass of entrepreneurs m_F; firm policy functions for capital demand $k(a, z_F, i)$ and labor demand $h(a, z_F, i)$; firm output and profit functions $y(a, z_F, i)$ and $\pi(a, z_F, i)$; rental rate of capital r; a tax rate $\bar{t}$; wage rate w; benefits T; and market aggregates, total net asset positions[32]

$$\begin{aligned} \mathbf{A}(r, w, T) = & \sum_{i \in \{B,W\}} \sum_{l \in \{0,1\}} \int_{\underline{z}_P}^{\bar{z}_P} \int_{\underline{z}_T}^{\bar{z}_T} \int_{\underline{a}}^{\infty} a\, g_L(a, z_P, z_T, l, i)\, da\, dz_T\, dz_P \\ & + \sum_{i \in \{B,W\}} \int_{\underline{z}_F}^{\infty} \int_{\underline{a}}^{\infty} a\, g_F(a, z_F, i)\, da\, dz_F \quad , \end{aligned} \tag{20}$$

[31] I_V is an indicator function that equals one if the worker chooses to become an entrepreneur and zero otherwise for each state in the worker's state space. In the main text this decision rule is replaced by the max operator for readability.

[32] We let $\underline{z}_P, \underline{z}_T$ and $\bar{z}_P, \bar{z}_T$ denote the lower and upper bounds for z_P and z_T, respectively.

total positive asset positions

$$\mathbf{A}^{+}(r,w,T) = \sum_{i\in\{B,W\}}\sum_{l\in\{0,1\}}\int_{\underline{z}_P}^{\bar{z}_P}\int_{\underline{z}_T}^{\bar{z}_T}\int_{0}^{\infty} a\, g_L\left(a,z_P,z_T,l,i\right) da\, dz_T\, dz_P \\ + \sum_{i\in\{B,W\}}\int_{\underline{z}_F}^{\infty}\int_{0}^{\infty} a\, g_F\left(a,z_F,i\right) da\, dz_F \quad , \tag{21}$$

total labor supply

$$Z_L(r,w,T) = \\ \sum_{i\in\{B,W\}}\int_{\underline{z}_P}^{\bar{z}_P}\int_{\underline{z}_T}^{\bar{z}_T}\int_{\underline{a}}^{\infty}\left(1-\tau_L^i\right)\times z_L\left(z_P,z_T,l=1\right)\times g_L\left(a,z_P,z_T,l=1,i\right) da\, dz_T\, dz_P \quad , \tag{22}$$

group-specific labor supply

$$Z_L^i(r,w,T) = \\ \int_{\underline{z}_P}^{\bar{z}_P}\int_{\underline{z}_T}^{\bar{z}_T}\int_{\underline{a}}^{\infty}\left(1-\tau_L^i\right)\times z_L\left(z_P,z_T,l=1\right)\times g_L\left(a,z_P,z_T,l=1,i\right) da\, dz_T\, dz_P\ , \tag{23}$$

total capital demand

$$K(r,w,T) = \sum_{i\in\{B,W\}}\int_{\underline{z}_F}^{\infty}\int_{\underline{a}}^{\infty} k\left(a,z_F,i\right) g_F\left(a,z_F,i\right) da\, dz_F, \tag{24}$$

total labor demand

$$H(r,w,T) = \sum_{i\in\{B,W\}}\int_{\underline{z}_F}^{\infty}\int_{\underline{a}}^{\infty} h\left(a,z_F,i\right) g_F\left(a,z_F,i\right) da\, dz_F, \tag{25}$$

aggregate profits

$$\Pi(r,w,T) = \sum_{i\in\{B,W\}}\int_{\underline{z}_F}^{\infty}\int_{\underline{a}}^{\infty} \pi\left(a,z_F,i\right) g_F\left(a,z_F,i\right) da dz_F, \tag{26}$$

which jointly satisfy the following:

1. Consumer optimization - Given prices r and w, transfers T, and the profit functions $\pi\left(a,z_F,i\right)$, the policy functions $c_V\left(a,z_P,z_T,l,i\right), c_F\left(a,z_F,i\right)$ and $I_V\left(a,z_P,z_T,l,i\right)$ solve the optimization problems given by problems (7) and (9) that are associated with the value functions $V\left(a,z_P,z_T,l,i\right)$ and $F\left(a,z_F,i\right)$. The indicator $I_V\left(a,z_P,z_T,l,i\right)$ takes the value of unity if $F\left(a,\psi(z_P),i\right) > V\left(a,z_P,z_T,l,i\right)$ and zero otherwise. Additionally, $c_V\left(a,z_P,z_T,l,i\right)$ and $c_F\left(a,z_F,i\right)$

induce the saving rules $s_V(a, z_P, z_T, l, i)$, $s_F(a, z_F, i)$ via equations (8) and (10).

2. Firm optimization - Given the rental rate r and the wage w, the policy functions for capital $k(a, z_F, i)$ and labor $h(a, z_F, i)$ are consistent with the firms solving the optimization problem (12). The functions $k(a, z_F, i)$ and $h(a, z_F, i)$ govern flow output $y(a, z_F, i)$ and profits $\pi(a, z_F, i)$ via equation (11) and the relationship $y(a, z_F, i) = z_F k(a, z_F, i)^{\alpha} h(a, z_F, i)^{\beta}$.

3. Asset market - the rental rate r satisfies the asset market clearing condition

$$\mathbf{A}(r, w, T) = K(r, w, T). \tag{27}$$

4. Labor market - the wage w clears the labor market as follows

$$Z_L(r, w, T) = H(r, w, T). \tag{28}$$

5. Transfers T are such that the government budget is balanced given the tax rates. This balanced budget rule is given by

$$T(1 - m_F) = \tag{29}$$

$$\bar{t} \times \left(\underbrace{\Pi(r, w, T)}_{\text{profit tax base}} + \underbrace{w \sum_{i \in \{B, W\}} Z_L^i(r, w, T)}_{\text{labor income tax base}} + \underbrace{(r - \delta)\mathbf{A}^+(r, w, T)}_{\text{capital income tax base}} \right),$$

note that $Z_L^i(r, w, T)$ is defined as the distortion-adjusted labor supply and that $\mathbf{A}^+(r, w, T)$ includes all income received either from renting capital to firms or lending to other households, which is consistent with no arbitrage between capital and debt.

6. Consistency - the population densities $g_L(a, z_P, z_T, l, i)$ and $g_F(a, z_F, i)$ have a total mass of unity and have their stationary distributions implied by the saving rules $s_V(a, z_P, z_T, l, i)$, $s_F(a, z_F, i)$ and decision rule $I_V(a, z_P, z_T, l, i)$ induced by r, w and T, and are consistent with the follow-

ing coupled KFEs (time indices are added here to all equilibrium objects)

$$\begin{aligned}
&\frac{\partial}{\partial t} g_L(a, z_P, z_T, l, i, t) = \qquad (30)\\
&-\frac{\partial}{\partial a}\left[g_L(a, z_P, z_T, l, i, t)\ s_V(a, z_P, z_T, l, i, t)\right] + A^{i*}_L g_L(a, z_P, z_T, l, i, t)\\
&-\eta\, I_V(a, z_P, z_T, l, i, t)\, g_L(a, z_P, z_T, l, i, t) + \lambda_D n^i(z_P, z_T, l) \int_{\underline{z}_F}^{\infty} g_F(a, z_F, i, t)\, dz_F,\\
&\frac{\partial}{\partial t} g_F(a, z_F, i, t) = \qquad (31)\\
&-\frac{\partial}{\partial a}\left[g_F(a, z_F, i, t)\ s_F(a, z_F, i, t)\right] + A^*_{z_F} g_F(a, z_F, i, t) - \lambda_D g_F(a, z_F, i, t)\\
&+\eta \sum_{l\in\{0,1\}} \int_{\underline{z}_T}^{\bar{z}_T} \tilde{I}_V\left(a, \psi^{-1}(z_F), z_T, l, i, t\right) \tilde{g}_L\left(a, \psi^{-1}(z_F), z_T, l, i, t\right) \frac{d\psi^{-1}(z_F)}{dz_F} dz_T,
\end{aligned}$$

where A^{i*}_L and $A^*_{z_F}$ denote the adjoint operator of the infinitesimal generators of the processes governing the stochastic evolution of labor income via (z_P, z_T, l)[33] and z_F. With slight abuse of notation, we define $\psi^{-1}(z_F)$ as the inverse of the mapping in equation (6) such that it maps the entrant's productivity into the previous value of z_P, this inverse is only defined for $z_P \geqslant \Psi_0$, for values below $\underline{z}_F$, we let $\psi^{-1}(z_F) = 0$. For completeness, we also define $\tilde{I}_V\left(a, \psi^{-1}(z_F), z_T, l, i, t\right)$ and $\tilde{g}_L\left(a, \psi^{-1}(z_F), z_T, l, i, t\right)$ as the functions that take the values of $I_V\left(a, \psi^{-1}(z_F), z_T, l, i, t\right)$ and $g_L\left(a, \psi^{-1}(z_F), z_T, l, i, t\right)$ when $z_F \geqslant \underline{z}_F$ or when $z_P \geqslant \Psi_0$ and are otherwise equal to zero. $n^i(z_P, z_T, l)$ denotes the stationary pdf of the process governing (z_P, z_T, l) for group i. The inclusion of the $\frac{d\psi^{-1}(z_F)}{dz_F}$ term is required to ensure mass preservation when transitioning from the z_P space to z_F space.[34]

The mass of entrepreneurs m_F is given by

$$m_F = \sum_{i\in\{B,W\}} \int_{\underline{z}_F}^{\infty} \int_{\underline{a}}^{\infty} g_F(a, z_F, i)\, da\, dz_F. \qquad (32)$$

The masses of each race integrate such that

$$\begin{aligned}
&\tilde{m}^i = \qquad (33)\\
&\int_{\underline{z}_F}^{\infty} \int_{\underline{a}}^{\infty} g_F(a, z_F, i)\, da\, dz_F + \sum_{l\in\{0,1\}} \int_{\underline{z}_P}^{\bar{z}_P} \int_{\underline{z}_T}^{\bar{z}_T} \int_{\underline{a}}^{\infty} g_L(a, z_P, z_T, l, i)\, da\, dz_T\, dz_P,
\end{aligned}$$

[33]Formally, note that $A^{i*}_L = A^{i*}_{z_P} + A^{i*}_{z_T} + A^{i*}_l$ which are the individual adjoint infinitesimal generators for the stochastic processes governing the evolution of z_P, z_T, and l, respectively.

[34]Note that this derivative is well defined everywhere but at the boundary point where $z_P = \Psi_0$. We implement this numerically using a discretized state space so there's no need to treat this knife-edge case.

where $\tilde{m}^B$, and $\tilde{m}^W$ must equal the exogenous masses m^B and m^W specified in Section 3.1 and thus $\tilde{m}^B + \tilde{m}^W = 1$.

Note that for the goods market to clear, the total output produced (given by equation (43)) must equal the sum of aggregate consumption and investment in capital. This clearing condition is implied by the others since aggregate profits, labor compensations, and capital compensations constitute total income in the economy, and aggregate consumption plus gross investment is total spending.

E Solution algorithm

This appendix details the algorithm used to solve our model. The algorithm builds on the methods of Achdou et al. (2021) for continuous-time and follows along the lines of the definition of the recursive stationary equilibrium in the model economy as given in Appendix D.

The solution algorithm solves a system of three equations (27), (28), and (29), in the three unknowns (r, w, T). The algorithm follows the recursive stationary equilibrium definition in Appendix D.

1. **Initialization.** Provide a grid for assets, parameter values for the model, and initial guesses for the values of r, w, and T .

2. **Solve firm block.** Using the values of r and w solve for the firms' demand for capital and labor $k(a, z_F, i)$ and labor $h(a, z_F, i)$ and for firm profits $\pi(a, z_F, i)$.

3. **Solve household block.** Solve the household optimization problem given the guesses and the calibrated parameters using the algorithm for solving the HJB equations given in Achdou et al. (2021). Given the high dimensionality of the problem, we modify the algorithm as follows:

   (a) Provide the initial guess that the value function stays put (flow utility is constant) and solve the consumption savings problem as if all the exogenous state variables z_P, z_T, l, and z_F are fixed and not subject to exogenous stochastic processes, and the households are not allowed to choose entrepreneurship.

   (b) Use the solution to the limited problem in step 3a as an initial guess to the consumption savings problem that allows for changes in z_P, z_T, l, and z_F, but still prohibits the entrepreneurship choice.

   (c) Finally, use the solution to the limited problem in step 3b as the initial guess to the full HJBs given by equations (7) and (9) to solve the decision problem with the dynamic entrepreneurship choice.

This will allow us to obtain the ergodic stationary distributions $g_L(a, z_P, z_T, l, i)$ and $g_F(a, z_F, i)$, the policy functions $c_V(a, z_P, z_T, l, i)$, $c_F(a, z_F, i)$ and $I_V(a, z_P, z_T, l, i)$, the equilibrium masses, the savings rules, and the mass of entrepreneurs m_F, the supply of effective labor by households, and the total net aggregate asset supply.

4. **Compute capital and labor demand.** Combine the masses from step 3 with the capital and labor solutions from step 2 to obtain the aggregate capital and labor demand by the firms, given their population composition.

5. **Compute government income.** Using the tax rates and the total income in the economy, use equation (29) to compute the government income.

6. **Clear markets** Using the results of steps 3, 4, and 5 evaluate equations (27), (28), and (29). If the system is sufficiently close to zero, stop. Otherwise, update the initial guess accordingly, and repeat from 1 until convergence is achieved.

Solver. We use a quasi-Newton solver based on the Broyden method and evaluate the Jacobian of the system using finite differences. It is useful to relax the updated solution in the Newton direction such that, at the new guess, the value of $r-\delta$ lies between zero and the ρ and that w is strictly positive. We use backtracking to choose the largest relaxation parameter from a pre-specified set of values (all less than one), so the new guess is well within these bounds. If the bounds are already violated, which can occur, we use a pre-set relaxation parameter, which, in many cases, leads the algorithm to return to its normal bounds. If the solver is unsuccessful, a new guess is randomized, and the procedure begins anew.

Stopping criterion and normalizations A convergence criterion of maximum relative deviation of 10^{-3} yields fast results and performs well. All equations described in stage 6 are solved after normalization to obtain a meaningful stopping criterion. The labor and capital market clearing conditions are normalized such that they are expressed as percentage deviations of the aggregate supply. The government budget is normalized so that it is expressed as a percentage deviation from the government's total tax revenue.

Grid for assets We use $n = 250$ grid points for assets. The grid is not uniform, such that most grid points are concentrated near the borrowing constraint $\underline{a}$. The maximum value for assets is set at $a = 3,000$, corresponding to asset holdings equivalent to around 4×10^3 unconsumed annual median labor incomes. The asset vector $\bar{a}$ is set such that it has monotonically increasing increments as follows

$$\bar{a} = (a_{\max} - \underline{a}) \frac{(0, 1, \ldots, n-1)^5}{(n-1)^5} + \underline{a}. \tag{34}$$

This generates monotonically increasing increments with a grid point exactly on the borrowing constraint, which will have a positive mass of households on it.

Modifications required outside of steady state To solve for the transition dynamics as in Section 6 and Section 6.1 one needs to solve equations (27), (28), and (29) at every point in time such that for n_t periods one is required to solve $3 \times n_t$ equations given guesses for the paths of r, w and T. As shown in Achdou et al. (2021), the procedure involves solving the HJB in every period backwards from the terminal condition and using the transition matrices from every period to iterate forward on the distributions g_L and g_F from the initial condition and clear the three markets in every period. Since we solve for long horizons, we use a non-uniform grid on time as follows

$$\bar{t} = t_{\max} \frac{(0, 1, \dots, n_t - 1)^3}{(n_t - 1)^3}. \tag{35}$$

We solve in 30 increments for a total duration of $t_{\max} = 500$ years.

F Model appendix: Additional derivations

F.1 Productivity distribution in the model economy

The firm productivity distribution in the economy is given by: (i) the productivity distribution of new entrants; (ii) the exit rate λ_D; and (iii) the stochastic process in equation (17) governing the evolution of firm productivity conditional on a firm staying in operation. The distribution of new entrants is influenced by both the stationary distribution of labor income, which affects entrants' productivity through $\psi(z_P)$, and the distribution of wealth, which in turn affects potential profits and ultimately the entry decision of a prospective entrant. We impose an upper bound on the permanent component of labor productivity, which implies an upper bound on the entrant's productivity.

While it is not possible to get an analytical solution to the exact distribution of z_F, we can use an asymptotic result (Gabaix, 2009) that as $z_F \to \infty$, its distribution $f(z_F)$ has a right tail that satisfies the following Kolmogorov Forward Equation (KFE) in steady state:

$$0 = -\frac{\partial}{\partial z_F} \left[f(z_F) \mu_F z_F \right] + \frac{1}{2} \frac{\partial^2}{(\partial z_F)^2} \left[(\sigma_F z_F)^2 f(z_F) \right] - \lambda_D f(z_F). \tag{36}$$

Through guess-and-verify, one can show that $f(z_F)$ is a Pareto distribution with tail parameter ζ, i.e. $f(z_F) \propto z_F^{-(\zeta+1)}$, with:

$$\zeta = \frac{1}{2} - \frac{\mu_F}{\sigma_F^2} + \sqrt{\left(\frac{1}{2} - \frac{\mu_F}{\sigma_F^2}\right)^2 + \frac{2\lambda_D}{\sigma_F^2}}. \tag{37}$$

Note that a corollary of this tail behavior is that the right tail of the firm size distribution in terms of labor also exhibits a Pareto distribution with tail parameter equal to $\tilde{\zeta} = \zeta(1-\alpha-\beta)$. This behavior is a result of the following features. Firm size in terms of labor, for firms with lax borrowing limits, is proportional to $\left(\left(1-\tau_y{}^i\right) z_F\right)^{\frac{1}{1-\alpha-\beta}}$ as demonstrated by equation (15). Thus, in the absence of distortions, the firm-size distribution inherits the tail behavior of z_F and has a Pareto tail of ζ, then $z_F^{\frac{1}{1-\alpha-\beta}}$, has a Pareto tail of $\tilde{\zeta} = \zeta(1-\alpha-\beta)$.[35] Note that since we consider only two levels of $\tau_y{}^i$, the above statement is true within race. The distortions do not affect tail behavior, but scale the productivity distribution. Lastly, to ensure that all aggregates are well behaved and the integrals are well defined, we require that $\tilde{\zeta} > 1$ such that the firm-size distribution has a finite mean.

F.2 Aggregate production function representation of the model economy

This appendix details the exact derivation of the aggregate properties of the model economy used in Section 5. Let us begin by examining the factor demand functions for firms in Equations (15) and (16)

$$h(a,z_F,i) = \left(\left(1-\tau_y{}^i\right) z_F\right)^{\frac{1}{1-\alpha-\beta}} \left(\frac{\alpha}{r\left(1+\tau_k\left(a,z_F,i\right)\right)}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{1-\alpha}{1-\alpha-\beta}}, \tag{38}$$

$$k(a,z_F,i) = \left(\left(1-\tau_y{}^i\right) z_F\right)^{\frac{1}{1-\alpha-\beta}} \left(\frac{\alpha}{r\left(1+\tau_k\left(a,z_F,i\right)\right)}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}}, \tag{39}$$

where we have substituted in $r+\mu_{CC}(a,z_F,i) = r\left(1+\tau_k\left(a,z_F,i\right)\right)$. Thus, firm-level output $y(a,z_F,i) = z_F\, k^{\alpha}(a,z_F,i)\; h^{\beta}(a,z_F,i)$ is given by

$$y(a,z_F,i) = \left[z_F \frac{\left(1-\tau_y{}^i\right)^{\alpha+\beta}}{\left(1+\tau_k\left(a,z_F,i\right)\right)^{\alpha}}\right]^{\frac{1}{1-\alpha-\beta}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}}. \tag{40}$$

It is straightforward to explicitly derive aggregate capital K, aggregate effective labor Z_L, and aggregate output Y[36] by integrating the above three equations along the population measures as

[35] For formal proofs along this line, see Carvalho and Grassi (2019) and Ifergane (2024) .

[36] Throughout this appendix, the dependence of aggregates on prices is suppressed for conciseness.

follows:

$$K = \left(\frac{\alpha}{r}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}} \sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \left[z_F \frac{\left(1-\tau_y{}^i\right)}{(1+\tau_k(a,z_F,i))^{(1-\beta)}} \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F \;, \tag{41}$$

$$Z_L = \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{1-\alpha}{1-\alpha-\beta}} \sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \left[z_F \frac{\left(1-\tau_y{}^i\right)}{(1+\tau_k(a,z_F,i))^{\alpha}} \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F \;, \tag{42}$$

$$Y = \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}} \left[\sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \left[z_F \frac{\left(1-\tau_y{}^i\right)^{\alpha+\beta}}{(1+\tau_k(a,z_F,i))^{\alpha}} \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F \right]. \tag{43}$$

To obtain meaningful terms in the equation for Y, we transform the above equation as follows. First, observe that we can represent Y as

$$Y = K^{\alpha} Z_L{}^{\beta} \widetilde{TFP}, \tag{44}$$

where $\widetilde{TFP}$ is given by

$$\widetilde{TFP} = \frac{\sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \left[z_F \frac{\left(1-\tau_y{}^i\right)^{\alpha+\beta}}{(1+\tau_k(a,z_F,i))^{\alpha}} \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F}{\left[\sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \left[\frac{\left(1-\tau_y{}^i\right)}{(1+\tau_k(a,z_F,i))^{1-\beta}} z_F \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F \right]^{\alpha} \left[\sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \left[\frac{\left(1-\tau_y{}^i\right) z_F}{(1+\tau_k(a,z_F,i))^{\alpha}} \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F \right]^{\beta}}.$$

Second, observe that in this economy, firms are a fixed factor of production. Thus, we can multiply the terms in the integrals composing $\widetilde{TFP}$ by $\frac{1}{m_F}$ and multiply the integral itself by m_F to purge $\widetilde{TFP}$ from scale effects, we obtain

$$Y = K^{\alpha} Z_L{}^{\beta} m_F{}^{1-\alpha-\beta} TFP, \tag{45}$$

with TFP given by

$$TFP = \frac{\sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \frac{1}{m_F} \left[z_F \frac{\left(1-\tau_y{}^i\right)^{\alpha+\beta}}{(1+\tau_k(a,z_F,i))^{\alpha}} \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F}{\left[\sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \frac{1}{m_F} \left[\frac{\left(1-\tau_y{}^i\right)}{(1+\tau_k(a,z_F,i))^{1-\beta}} z_F \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F \right]^{\alpha} \left[\sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty} \int_{\underline{a}}^{\infty} \frac{1}{m_F} \left[\frac{\left(1-\tau_y{}^i\right) z_F}{(1+\tau_k(a,z_F,i))^{\alpha}} \right]^{\frac{1}{1-\alpha-\beta}} g_F\left(a,z_F,i\right) \;\; da dz_F \right]^{\beta}}.$$

Lastly, we wish to distinguish between the notions of labor quality and labor quantity. We can state effective labor input in production as $Z_L = \mathbb{E}(z_L(1-\tau_L))N$, where N is the mass of workers, which is incidentally $1-m_F$, and $\mathbb{E}(z_L)$ is their average distortion-adjusted quality. Observe that average labor quality relates to the distortions as follows

$$E(z_L(1-\tau_L)) = \sum_{i\in\{B,W\}} \underbrace{\frac{\sum_{l\in\{0,1\}} \int_{\underline{z}_P}^{\bar{z}_P} \int_{\underline{z}_T}^{\bar{z}_T} \int_{\underline{a}}^{\infty} g_L(a,z_P,z_T,l,i)\, da\, dz_T\ dz_P}{1-m_F}}_{\text{share of non-entrepreneurs belonging to group } i} \tag{46}$$

$$\times \underbrace{\frac{\sum_{l\in\{0,1\}} \int_{\underline{z}_P}^{\bar{z}_P} \int_{\underline{z}_T}^{\bar{z}_T} \int_{\underline{a}}^{\infty} z_L(z_P,z_T,l) g_L(a,z_P,z_T,l,i)\, da\, dz_T\ dz_P}{\sum_{l\in\{0,1\}} \int_{\underline{z}_P}^{\bar{z}_P} \int_{\underline{z}_T}^{\bar{z}_T} \int_{\underline{a}}^{\infty} g_L(a,z_P,z_T,l,i)\, da\, dz_T\ dz_P}}_{\text{average labor productivity in group } i} \times \underbrace{\left(1-\tau_L{}^i\right)}_{\text{distortion for group } i}.$$

We again stress that differences in the average labor productivity emerge endogenously in our model. Ex-ante, without the distortions, Black and White households are endowed with z_L drawn from the same distributions. However, the distortions lead households that differ only in race to be exposed to different shocks and make different entrepreneurial decisions, resulting in a steady state where differences in race are predictive of outcomes. Therefore, the aggregate production function in this economy can be represented as

$$Y = K^{\alpha} N^{\beta} m_F{}^{1-\alpha-\beta} \left(\mathbb{E}(z_L(1-\tau_L))\right)^{\beta} TFP. \tag{47}$$

After taking logs, we have

$$\log Y = \underbrace{\alpha \log K + \beta \log N + (1-\alpha-\beta)\log m_F}_{\text{factor quantities}} + \underbrace{\beta \log\left(\mathbb{E}(z_L(1-\tau_L))\right)}_{\text{labor efficiency}} + \underbrace{\log(TFP)}_{\text{aggregate productivity}} \tag{48}$$