Entrepreneurship and the Racial Wealth Gap*

Daniel Albuquerque † Tomer Ifergane ‡

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Abstract

Entrepreneurship promotes wealth accumulation. However, Black households face significant barriers, operating fewer and smaller businesses compared to White households. We propose and evaluate a general equilibrium model of entrepreneurship choice and wealth accumulation in which Black households experience adverse distortions as entrepreneurs and workers, both affecting entrepreneurship choice. We discipline the model using U.S. microdata, and find that it matches well the observed racial wealth gap and the correlation between wealth and entrepreneurship. We find that distortions faced by Black entrepreneurs are the key factor for understanding the average racial wealth gap and play a significant role in determining the median gap. Our analysis also indicates that addressing racial disparities in the U.S. 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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†Bank of England, daniel.albuquerque@bankofengland.co.uk

‡Ben-Gurion University - Dept. of Economics, London School of Economics - Centre for Macroeconomics, iftomer@gmail.com

1 Introduction

Racial wealth inequality in the United States is striking. Figure 1 shows that the average Black household's net worth from 2001 to 2019 was equal to $133,600, while the average White household held $811,900. In other words, Black households held 83.5% less wealth. Overall wealth inequality is also high: the top 10% of households hold 73.2% of total wealth. Entrepreneurs, those who own and manage a business, 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 (Quadrini, 2000; Castaneda, Diaz-Gimenez, and Rios-Rull, 2003; Cagetti and De Nardi, 2006). At the same time, entrepreneurship rates are almost three times higher for White households than for Black ones and the median Black-owned firm is 3.4 times smaller. However, the degree to which disparities in entrepreneurial outcomes contribute to the racial wealth gap remains understudied.

This paper studies to what extent observed differences in entrepreneurial outcomes help us understand the racial wealth gap. Our main contribution is developing an incomplete market model of wealth accumulation featuring a choice between being a worker or an entrepreneur, and differences in economic outcomes between Black and White households. In the model, households save to smooth income fluctuations and also to alleviate financial

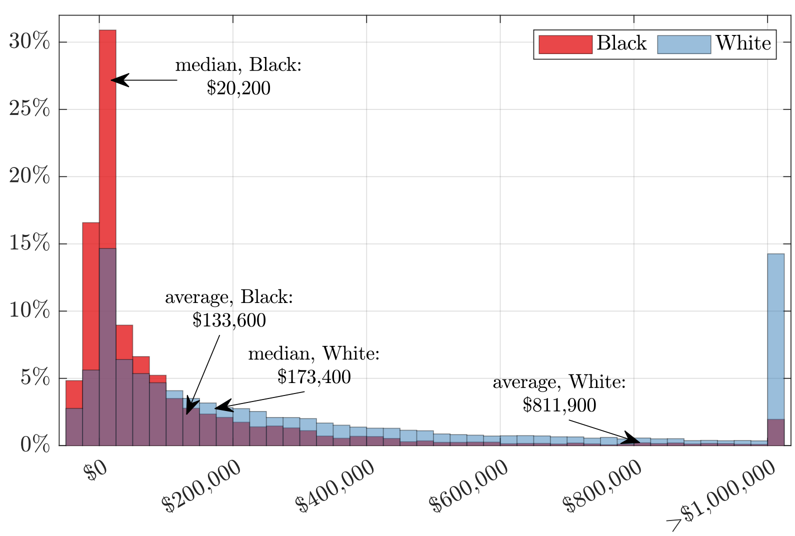


Figure 1: Histogram of wealth for Black and White households, 2001-2019

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.

constraints faced by entrepreneurs. Because starting a firm is a choice, households sort into entrepreneurship based on their wealth and their income-generating ability in the labor market and as entrepreneurs. As households are infinitely lived, the model generates strong intergenerational persistence of wealth.

We assume that Black and White households have identical preferences and beliefs. We introduce three forces that distort the entrepreneurship choices of Black households to generate the observed differences in entrepreneurial outcomes by race. Because the desirability of entrepreneurship is determined both by expected profits and the forgone labor income, we consider *distortions* affecting both margins. These distortions (i) reduce the wage conditional on employment of Black workers (*labor income distortion*), (ii) lower the attachment rate of Black workers to the labor market and increases their labor income risk (*labor income risk distortion*), and (iii) reduces the size of Black-owned firms, controlling for productivity (*entrepreneurship distortion*). These distortions are a reduced form modeling tool which, in reality, map into frictions and institutional barriers such as discrimination, different access to education, different social capital, etc. Thus, our model remains agnostic regarding their root causes but allows us to examine their margins of influence.

To motivate our theoretical approach, and lend it empirical discipline, We present five stylized facts on racial disparities in wealth, entrepreneurship, and income. Using the Survey of Consumer Finances (SCF) and the Panel Survey of Income Dynamics, we document that: (1) The racial wealth gap has been sizeable and stable over the last 30 years. Both the average and median racial wealth gaps have hovered between 80% and 90%. (2) Entrepreneurship rates are increasing in wealth regardless of race. However, (3) Black households are almost three times less likely to be entrepreneurs and operate smaller firms. Moreover, (4) Black households face a racial wage gap when employed, and experience weaker attachment to the labor market. Thus, their labor income is lower and riskier. (5) Labor income is also positively correlated with entrepreneurial entry, both for Black and White households.

Informed by these five facts, our empirical strategy quantifies the model distortions in two steps. First, labor income processes are estimated from the data separately for Black and White households. These processes include permanent and transitory components with race-specific parameters that lead to different levels of labor income when employed and different exposures to income risk. Second, the entrepreneurship distortion faced by Black entrepreneurs is calibrated internally in the model to match the lower entrepreneurship rate of Black households. Reassuringly, our quantitative strategy yields an entrepreneurship distortion close to that of Tan and Zeida (2024), who estimate it directly from firm-level data. The estimated entrepreneurship distortion would have been much smaller without a worse outside option for Black entrepreneurs. Thus, incorporating distortions in the labor market as well as for entrepreneurs is essential to this exercise. The resulting calibrated model does an excellent job in capturing the racial wealth gap, generating an untargeted average racial wealth gap of 82%, compared to 83.5% in the data. It also replicates the increasing and similar entrepreneurship rates conditional on wealth for Black and White households.

Our main result is that current distortions faced by Black entrepreneurs are the major factor accounting for the average racial wealth gap: if removed, we estimate that the racial wealth gap would be reversed and Black households would be more than 20% wealthier on average than White households. Furthermore, the median racial wealth gap would also fall by more than 30 percentage points (p.p.). In contrast, labor market distortions mainly affect the median racial wealth gap, which falls by more than 50p.p., while the average racial wealth gap moves by 8p.p. Moreover, because higher labor income pushes households out of entrepreneurship, we find that lower labor market distortions can actually reduce the representation of Black households among the top 10% of the wealth distribution. The results highlight the importance of tackling the adverse conditions faced by Black entrepreneurs for reducing the racial wealth gap.

Using the model we also estimate the output cost of racial disparities. We find that removing the entrepreneurship distortion increases output by 5.4%. In this counterfactual, the primitive distributions of firm and labor productivity remain unchanged. This result is mainly due to a relative reallocation of resources from White firms to Black-owned firms as Black owned firms can now expand to their optimal size. There is an additional sorting effect as some White households switch from entrepreneurship to wage work. Removing all the distortions together yields an output increase of 10.9%. The magnitude of this result is reminiscent of the result in Brouillette, Jones, and Klenow (2021), who analyse the sorting of households across occupations and find similar numbers. The results highlight that policies targeted at addressing racial disparities may have large macroeconomic impact.

Given our finding on the importance of entrepreneurship, we explore the ability of subsidies targeted at Black entrepreneurs to lower the racial wealth gap, without addressing the fundamental distortions. We find that while subsidies can be quite effective in closing the gap in entrepreneurship rates, their impact on the racial wealth gap is limited. That happens because as long as Black workers still face discrimination in the labor market which worsens their outside option, the subsidies necessary to close the entrepreneurship gap are smaller than the existing entrepreneurship distortion. In this scenario, even though entrepreneurship rates are similar, Black-owned firms are still significantly smaller due to the remaining distortions they are facing. Thus, to close the racial wealth gap merely with entrepreneurship subsidies it is necessary to generate Black entrepreneurship rates that are way above the current one for White households. This result highlights the importance of modeling the interaction between distortions experienced by workers and entrepreneurs.

Our final exercises analyze the transition towards an equilibrium without racial inequality. The model indicates that even if we were to remove all the distortions today current disparities in wealth and firm ownership are such that closing the average racial wealth gap would take 150 years. While it takes only 50 years for entrepreneurship rates to converge, convergence in wealth is slower because entrepreneurs need time for their firms to grow, and yet more time to accumulate profits from these larger firms, to finally catch up with the wealthiest White entrepreneurs.

While wealth transfers do not impact the long-run distribution of wealth in the model by assumption, we ask whether they can help close the racial wealth gap faster when accompanied by social change, i.e., removing the fundamental distortions. We find that a wealth transfer that immediately closes the average racial wealth gap has a transitory impact, as the gap re-emerges and only closes completely after 150 years - as was the case without transfers. Intuitively, closing the racial wealth gap via transfers does not equalize income sources, since White-owned firms are still larger and more profitable. However, if the wealth transfers were combined with the expropriation of ownership on the larger firms in the economy, results could differ.

Related literature This work relates to four strands in the literature. It is primarily related to works on drivers of the racial wealth gap in the macroeconomics literature. Aliprantis, Carroll, and Young (2019) and Ashman and Neumuller (2020) model exogenous labor income gaps, and White (2007) does so through differences in human capital accumulation. All of them conclude that observed differences in labor earnings can generate large racial wealth gaps. While we also find that labor earnings differences are important, we highlight that their interaction with entrepreneurship choices is crucial for understanding the racial wealth gap and, in particular, differences at the very top of the wealth distribution.

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, thus allowing us to consider changes in firm ownership over time and to assess the contribution of equilibrium forces to it. Boerma and Karabarbounis (2023) focus on the ability of heterogeneous beliefs and historical exclusion of Black households from markets to generate a persistent racial wealth gap via entrepreneurship choices. The main difference between our paper and Boerma and Karabarbounis (2023) is that we model exogenous distortions, allowing us to maintain an agnostic view of the underlying causes of disparities in entrepreneurial outcomes. Moreover, the racial wealth gap in our setting is stable, in line with the data presented in Section 2. In addition, since we are concerned with entrepreneurship choice, which interacts with labor market outcomes, we model an equilibrium labor market and target the positive correlation between labor income and entrepreneurial entry, documented in the data.

Second, our paper also contributes to the growing body of work leveraging tools from the misallocation literature to study disparities in outcomes. The seminal work is Hsieh et al. (2019), who examine the effects of race and gender specific distortions on occupational sorting in the US over time. Directly related to us are works studying entrepreneurship disparities between groups. The most relevant among those are Bento and Hwang (2022) and Tan and Zeida (2024), who use rich panel data to study the different barriers faced by Black entrepreneurs. Our paper complements these works by mapping their results on entrepreneurship into consequences for wealth accumulation. Other works include Morazzoni and Sy (2022) and Goraya (2023), who study barriers to female entrepreneurs and lower castes entrepreneurs in India, respectively.

Third, our paper builds on works documenting the racial wealth gap and its implications for welfare. Early studies include Higgs (1982) and Margo (1984). More recently, 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. Ganong et al. (2023) and Brouillette, Jones, and Klenow (2021) highlight how differences in wealth translate into welfare effects.

Fourth, our paper is motivated by the literature documenting barriers faced by Black entrepreneurs. 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).

More broadly, our work is informed by the extensive empirical literature concerning differences in other socioeconomic outcomes between Black and White households. The outcome that has arguably received the most attention is the gap in labor income, and Lang and Lehmann (2012) review the findings of this literature.[1]

Another outcome that has received attention is disparities in 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). 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 83.5% to 88.5% leading us to focus on entrepreneurship.

The paper proceeds as follows. Section 2 presents stylized facts regarding disparities in wealth, entrepreneurship, and income in the U.S. Section 3 develops our model. Section 4 calibrates the model and discusses its fit. Section 5 demonstrates the role of disparities in entrepreneurship in generating the racial wealth gap and its macroeconomic implications, and analyses the effects of entrepreneurship subsidies. Section 6 analyses counterfactual scenarios about the future of the racial wealth gap and the role of wealth transfers. Section 7 concludes.

2 Five facts on race, wealth, income, and entrepreneurship in the U.S.

This section presents five stylized facts that guide our analysis of the contribution of entrepreneurship to the racial wealth gap. We document that (1) there is a substantial and

[1] See Blanchet, Saez, and Zucman (2022) for evidence of the gap in capital income, which is similar to that on wealth; 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.

[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%.

stable racial wealth gap; (2) entrepreneurs are disproportionately represented among the wealthy, both among Black and White households; (3) Black households are three times less likely to be entrepreneurs and Black-owned firms are smaller than their White counterparts; (4) Black households also earn lower labor income and have a weaker labor market attachment; and (5) labor income correlates with entrepreneurial entry. These empirical patterns on the relationship between wealth, entrepreneurship, labor income, and race will discipline our analysis and allow us to evaluate the model developed in the following sections.

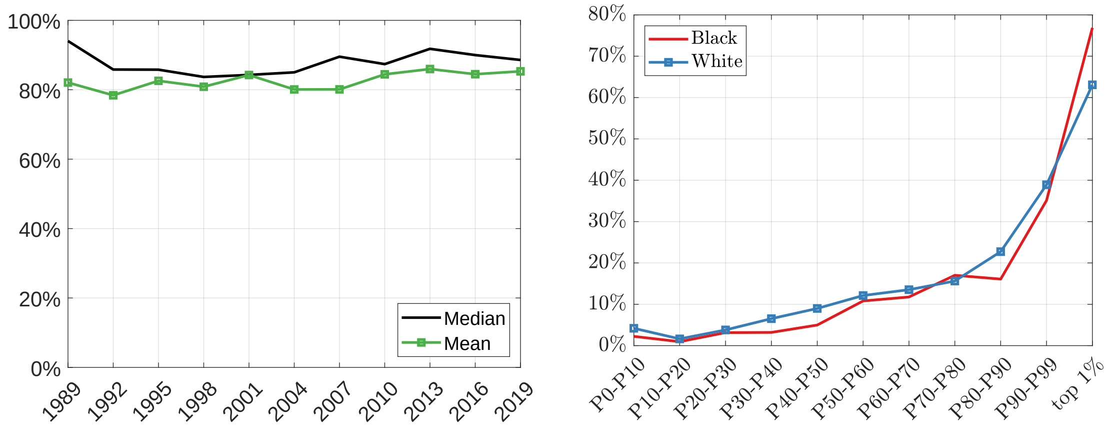
Our primary data sources are the Survey of Consumer Finances (SCF) and the Panel Survey for Income Dynamics (PSID). We mostly use the SCF to examine wealth and entrepreneurship and the PSID to examine labor income. We view these surveys as complementary sources. The SCF oversamples wealthy households to focus on the top of the wealth distribution, while the PSID is well-suited for the bottom of the income distribution. 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 Latinx or of Hispanic origin. Since we are interested in fitting our model to current gaps in wealth and entrepreneurship, we will focus on the period between 2001 and 2019 to calibrate the model.

2.1 Fact 1: the racial wealth gap is sizable and stable

We define wealth as total assets minus total liabilities of a household. The average and median wealth racial wealth gaps are shown in Figure 2A. Since the 1980s, these gaps have been stable and hovered between 80% and 90%, averaging at 83.5% and 88.1% for the average and median gaps, respectively, since 2001. The finding of a sizable and recently stable racial wealth gap is well documented in the literature (e.g., in the aforementioned works of Kuhn, Schularick, and Steins, 2020; Derenoncourt et al., 2024). Figure 2A is consistent with their findings.

2.2 Fact 2: wealth and entrepreneurship are correlated

We define an entrepreneur as a household who owns and actively manages a private business, as documented by the SCF. 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. Results



(A) The racial wealth gap

(B) Entrepreneurship rates by wealth fractiles

Figure 2: Wealth and its correlation with entrepreneurship

Notes: Panel (A) shows the average (median) racial wealth gap between Black and White households, defined as one minus the average (median) wealth of a Black household divided by the average (median) wealth of a White household. In other words, $1-\hat{w}^B/\hat{w}^W$, where $\hat{w}$ can denote either average or median wealth. Panel (B) shows the share of households of a given race that are classified as entrepreneurs in different fractiles of the overall wealth distribution, where, for example, "P10-P20" denotes those in between the 10^{th} and 20^{th} percentiles. A household is classified as an entrepreneur if it owns and actively manages a private business. *Source*: SCF.

are also reported for the alternative "owns a business" definition as well and are similar. Ultimately, our measure is more restrictive and results in a smaller gap in entrepreneurship rates.

Figure 2B plots entrepreneurship rates across the overall wealth distribution for both Black and White households and illustrates that the correlation between entrepreneurship and wealth is strong regardless of race.[3] 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%. Figure 2B also demonstrates that entrepreneurship rates conditional on wealth are surprisingly similar for both Black and White households.

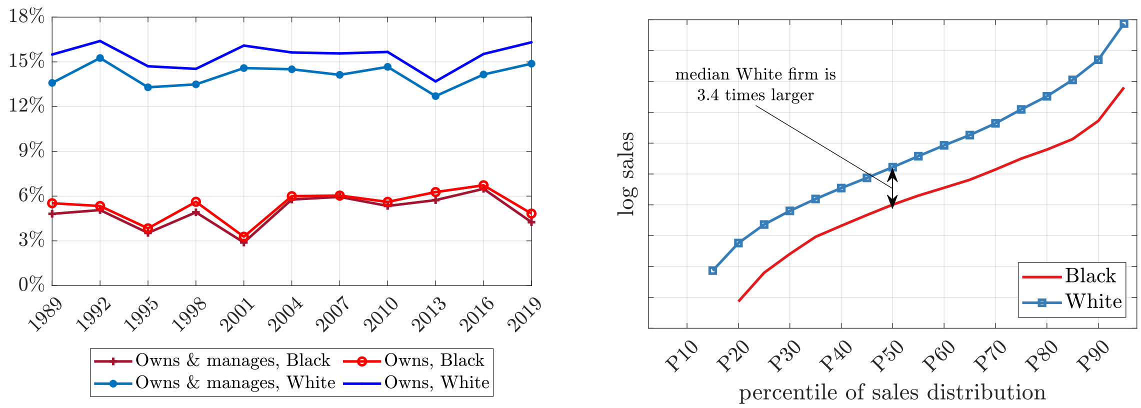
Interestingly, the average racial wealth gap between Black and White workers (75.6%) and between Black and White entrepreneurs (79.4%) are quite similar to the overall racial wealth gap of 83.5%. However, White entrepreneurs hold 45.3% of White-owned wealth. In contrast, Black entrepreneurs hold only 25.3% of Black-owned wealth, which is mostly

[3] Figure A.2 presents a similar pattern for other definitions of entrepreneurship in the SCF and the PSID.

explained by a lower entrepreneurship rate among Black households.[4] 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.

Entrepreneurs' significant role in contributing to overall wealth and their comparatively lower importance in accounting for Black-owned wealth jointly indicate that entrepreneurship is crucial in narrowing the racial wealth gap. To further investigate this, we now turn our attention to disparities in entrepreneurial outcomes.

2.3 Fact 3: racial disparities in entrepreneurial outcomes



(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.

Figure 3A plots entrepreneurship rates in the last 30 years according to the SCF. It shows that the gap in entrepreneurship rates has been stable and sizable, around 9 p.p. (5.2% vs 14.2%), over the last three decades.

Our findings align 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

[4]The intensive margin contributes in the other direction. Black entrepreneurs are wealthier relative to Black non-entrepreneurs than their White counterparts are relative to White non-entrepreneurs.

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

To further investigate the robustness of the stable gap in entrepreneurship rates, we turn to the PSID, which has a larger sample and longer history than the SCF. Figure A.1 in the Appendix plots the entrepreneurship rate over time of Black and White households, according to three alternative definitions available in the PSID: (i) self-employment; (ii) ownership of a business; (iii) ownership of an incorporated business. The first two definitions might lead one to conclude that the gap in entrepreneurship rates is shrinking. Figure A.1 documents a decrease in business ownership by White households and an increase in self-employment rates among Black households.

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). Turning our attention towards the owners of incorporated businesses, a definition of entrepreneurship that is more closely related to wealth accumulation,[5] results in a similar picture in the PSID to the one emerging from the SCF, with Figure A.1 demonstrating a stable entrepreneurship gap since at least the mid-1970s.

This reconciles our stable gap in entrepreneurship rates with the results from Bento and Hwang (2022), who find a closing gap on self-employment rates, using data from the Survey of Business Owners, and the Current Population Survey. We conclude that the notion of entrepreneurship that is relevant for our purposes has indeed shown a stable gap between Black and White households.

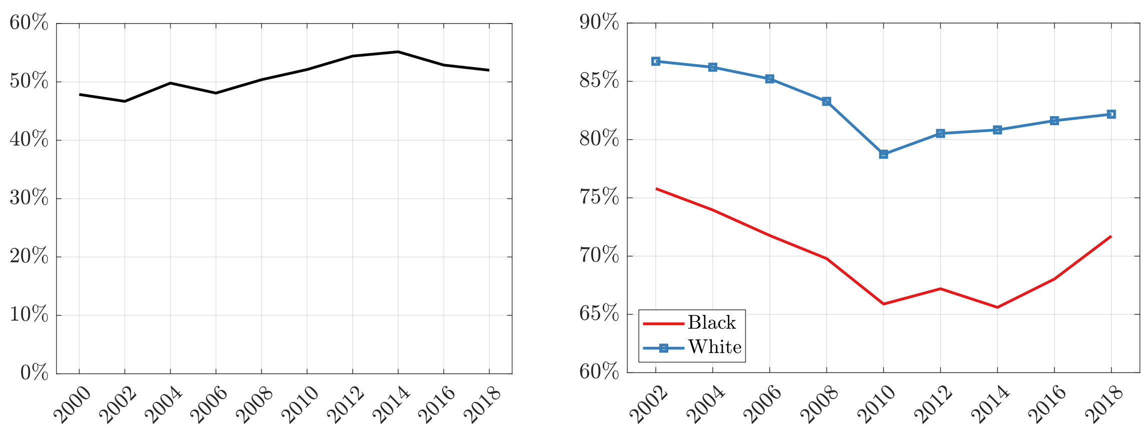
On top of differences in entrepreneurship rates, Figure 3B shows that there are also differences in outcomes conditional on being an entrepreneur. Using information from firm owners in the SCF we can calculate the implied distribution of revenues of firms owned by Black and White households. We find that the median White-owned firm is 3.4 times larger than the median Black-owned firm, and the difference seems stable throughout the firm-size distribution.

There has been a long literature on the different outcomes and barriers faced by Black

[5]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 (see Levine and Rubinstein, 2017).

and White entrepreneurs, and most of it has focused on the barriers in access to credit for Black entrepreneurs (see Related Literature). However, recent evidence from Tan and Zeida (2024) suggests that, while extra financial constraints play a role, the most important barrier is lower consumer demand for products of Black-owned firms. Figure 3B is in line with this finding. The distribution of revenue of Black-owned firms is shifted downwards compared to that of White-owned firms. Lower demand for all Black-owned firms or other factors that limit Black entrepreneurs from realizing their full potential across the board can explain this permanently smaller size across the distribution. Additional credit constraints, in contrast, would not affect larger, better-capitalized, Black-owned firms, and those firms would be able to catch up with their White-owned counterparts. This does not seem to be the case, and our modeling strategy will allow us to match the patterns in Figure 3B.

2.4 Fact 4: Black households have worse labor market outcomes



(A) The racial wage gap

(B) Employment rates

Figure 4: 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. Due to its panel structure, the PSID allows us to compare changes in income over time for the same household, which will be important for calibrating the income process imputed to the model.

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 4A 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 imputed to the model's labor income distortion. 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 4A, we also document a gap in employment rates in Figure 4B. 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. In the next section, we incorporate this gap in employment rates into our income process 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). 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 single 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.

2.5 Fact 5: labor income and entrepreneurship choice are correlated

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	All	Black	Black	Black
percentile of income	0.031^{***}	0.012^{**}	0.009^{*}	0.022^{***}	0.019^{**}	0.013
	(0.002)	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)
percentile of wealth	0.031^{***}	0.042^{***}	0.039^{***}	0.018^{*}	0.019^{*}	0.016
	(0.003)	(0.003)	(0.004)	(0.007)	(0.009)	(0.009)
education			0.147^{***}			0.243^{***}
			(0.031)			(0.059)
Year FE	No	Yes	Yes	No	Yes	Yes
Demographics	No	Yes	Yes	No	Yes	Yes
Emp. Status	No	Yes	Yes	No	Yes	Yes
R-Squared	0.011	0.031	0.032	0.008	0.018	0.020
Observations	63,459	63,453	62,973	25,259	25,255	25,066

Table 1: Entrepreneurship entry and income

Notes: This table reports the results of estimating Equation (1) 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. *Source*: PSID, 2001-2019.

In the next section, we model entrepreneurship as an endogenous choice. Thus, labor market conditions will affect the entrepreneurship decision and entrepreneurial outcomes. Therefore, it is important to capture any possible correlation between labor income and the entrepreneurship decision present in the data.

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

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

where α_t denotes a year fixed effect, and $X_{i,t}$ is a vector of household-level controls, 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 2.3.

Table 1 reports the result of estimating Equation 1 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). The point estimates show that moving up one percentile group is correlated with a 0.03p.p. increase in the probability of entry, when the average entry rate over the sample is 1.7%.

A similar picture emerges for both Black and White households when we control for year fixed effects and demographics (columns 2 and 5). However, when education is included (columns 3 and 6) the coefficient on income becomes statistically insignificant, while that of education is highly significant. We interpret this result as suggestive that underlying human capital generates a positive correlation between labor income and the propensity to become an entrepreneur.[6] This correlation motivates our modeling in the next section, where we assume a positive correlation between starting entrepreneurial productivity and the permanent component of labor income.

3 Model

Our model utilizes the workhorse incomplete market model à la Bewley-Imrohoroglu-Hugget-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 labor income process featuring permanent and transitory components along with a labor market partici-

[6] In Table A.1 in the Appendix 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).

pation shock.

We model two groups of households, Black and White, as ex-ante identical agent types facing different market conditions. We leverage methods from the misallocation literature and introduce group-specific distortions affecting the household's problem, which we treat as fundamentals.[7] This approach allows us to model disparities in the labor and entrepreneurial outcomes and isolate the critical margin of influence on racial wealth outcomes while maintaining an agnostic view as to the underlying root causes, which potentially include discrimination, barriers to education, network effects, etc.

Next, we describe the model environment and explain our modeling of racial disparities in depth. We then state the decision problems faced by households and firms and conclude by describing the equilibrium conditions.

3.1 Environment

Time t is continuous. There exists a unit mass of ex-ante identical 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 infinitely lived, and we interpret them as dynasties. This choice is equivalent to households having perfect "warm glow" motives towards their offspring and leaving bequests, which in our setting generates intergenerational transmission of wealth and the persistence of racial wealth inequality observed in the data. All households in the model can save and accumulate wealth a subject to a borrowing constraint $a \geqslant \underline{a}$. Asset positions can be either positive or negative, and negative positions are debt owed to other households. Assets can also be rented out to firms as capital. We assume that capital and debt yield the same net return.

Households are either entrepreneurs or workers. Workers face uninsurable idiosyncratic shocks to their labor productivity z_L, affecting their income and thus consumption. Workers' labor income is proportional to their labor productivity, where the per-productivity-unit wage rate w is determined in general equilibrium. Entrepreneurs conduct all production activity in the model by hiring labor and capital to produce a homogeneous final consumption numeraire good. Each entrepreneur operates a firm with a decreasing returns to scale tech-

[7] In related works, a similar modeling approach was also used by Morazzoni and Sy (2022) to model the gap between male and female entrepreneurs, by Goraya (2023) to model gaps between members of different castes in India, and by Bento and Hwang (2022) to analyse the gap in entrepreneurship between Black and White households, but without addressing the implications for wealth inequality. All those works build on the conceptual framework of misallocation à la Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). For a comprehensive review of this literature see Hopenhayn (2014).

nology, and its capital choice is subject to a collateral constraint such that they cannot utilize more capital than a multiple λ_{CC} of their assets a. Additionally, entrepreneurs are heterogeneous with respect to their idiosyncratic productivity z_F, which evolves stochastically. Idiosyncratic shocks to z_F influence the entrepreneur's flow profit income and generate an uninsurable consumption risk. The measure of entrepreneurs is endogenously determined by workers who continuously face a discrete choice to start a firm subject to the arrival of a business idea with rate η. Entrepreneurs exit at an exogenous rate λ_D and return to the worker pool.

3.2 Racial disparities

We model three race-specific distortions: a labor income distortion, a labor income risk distortion, and an entrepreneurship distortion.

First, we model the labor income distortion as a proportional wedge in labor productivity, which we estimate as the difference in median wages between Black and White workers, conditional on employment. Each worker with labor productivity z_L generates $z_L(1-\tau_L^i)$ labor units to the firm and is paid $wz_L(1-\tau_L^i)$. Black workers face barriers preventing them from realizing their full potential in the labor market and are thus paid less after controlling for their innate productivity z_L. We normalize $\tau_L^W = 0$, and have $\tau_L^B \in [0,1]$. Therefore, our setup assumes that alleviating racial disparities in the model, i.e., setting $\tau_L^B = 0$, increases both labor income received by the worker and the amount of labor they supply. This assumption implies that our modeling of racial disparities does not result in a zero-sum game whereby one group benefits at the expense of another.

Second, we model the labor income risk distortion to capture differences in labor income risk profiles faced by Black and White workers. We use panel data to estimate two separate income processes for Black and White households, allowing us to consider differences in precautionary motives for each group. Different parameters include the transition rates between employment and non-employment, and the volatility and frequency of permanent and transitory income shocks.

Third, we model the entrepreneurship distortion as an output distortion τ_y^i faced by Black entrepreneurs. Given a production technology $y = z_F k^{\alpha} h^{\beta}, \alpha + \beta < 1$, where y is output, k is capital, h is labor and α and β are common parameters, the entrepreneur chooses inputs as if their output is given by $y(1-\tau_y^i)$. This output distortion faced by Black entrepreneurs leads them to under-produce compared to their actual productive ability. One can conceive of this distortion as Black entrepreneurs perceiving a lower output price or a lower demand for their goods. We assume that $\tau_y^W = 0$ and calibrate $\tau_y^B \in [0,1]$ internally in our model to match the gap in entrepreneurship rates between Black and White households. This distortion captures all elements that would prevent Black entrepreneurs from generating the same profits given identical productivity and financial conditions, e.g., discrimination by consumers, sectoral and geographical sorting patterns, network effects, and institutional barriers. This modeling approach is supported by the recent empirical literature on Black entrepreneurship such as (Bento and Hwang, 2022) and Tan and Zeida (2024), whose results we discuss and compare to ours in the next section. Finally, notice that while we do not model explicitly a tighter financial constraint for Black entrepreneurs, given the entrepreneurship distortion they will be less able to accumulate assets and grow out of the collateral constraint as an equilibrium result.

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. Ideas are assumed to be non-tradeable and cannot be stored. For clarity, we state the value functions in their steady-state forms, referring to constant prices and omitting time derivatives.

Let $V(a, z_L, i)$ denote the value of being a worker with asset level a, labor productivity z_L, and race i. The worker faces the following problem:

$$\begin{aligned} &\rho V(a,z_L,i) \qquad (2) \\ &= \max_c \left\{ u(c) + V_a s_V(a,z_L,i) + \eta \max\left\{\tilde{F}(a,\psi(z_L),i) - V(a,z_L,i), 0\right\} + \mathrm{A}^i_{z_L} V(a,z_L,i) \right\}, \end{aligned}$$

subject to the borrowing constraint $a \geqslant \underline{a}$, where $u(c) = c^{1-\gamma}/(1-\gamma)$ denotes flow utility from consumption, γ is the coefficient of relative risk aversion; ρ is the common discount rate; $\tilde{F}(a, \psi(z_L), i)$ is the worker's valuation of becoming an entrepreneur after receiving an idea; $V_a = \partial V(a,z_L,i)/\partial a$ denotes the partial derivative; and $\mathrm{A}^i_{z_L}$ is the generator for the stochastic process governing z_L. This generator, which is race-dependent, encodes information about expected changes in the three components governing the evolution of z_L over time: permanent productivity z_P, transitory productivity z_T, and employment status l_t, all explained in detail in the next section. The law of motion for assets $\dot{a} = s_V(\cdot)$ is

$$s_V(a, z_L, i) = wz_L^i(1-\tau_L^i)(1-t_w) + (1 - t_a I_{a>0})(r-\delta)a - c + T, \tag{3}$$

where w denotes the wage per unity of productivity, τ_L^i the labor income distortion, $r-\delta$ the net return for asset holdings, with r being the rental rate of capital and δ its depreciation rate. All households face a proportional tax rate of t_w on their labor income and a tax rate of t_a on their positive capital income. Thus, $I_{a>0}$ is an indicator that equals one if $a \geqslant 0$, and zero otherwise. Households receive a lump-sum transfer benefit of T, which generates an income floor in our model.

The quality of a business idea is governed by $\psi(z_L)$, which maps labor productivity z_L, via its permanent component z_P, into the initial productivity of an entrepreneur such that the entrant firm has $z_F = \psi(z_L)$. This mapping allows us to capture the positive correlation between labor income and entrepreneurship choice observed in the data. As discussed in Section 2.5, educational attainment seems to explain most of this correlation, so this structure allows us to interpret the permanent component of labor productivity as a proxy for human capital. We assume the following isoelastic specification for the productivity of entrants

$$\log\left(z_F - \underline{z}_F\right) = \Psi_1 \log\left(z_P - \Psi_0\right), \tag{4}$$

thus $\psi(z_L) = \underline{z}_F + (z_P - \Psi_0)^{\Psi_1}$, for $z_P \geqslant \Psi_0$, and we set $\psi(z_L) = 0$ otherwise. We calibrate Ψ_0 and Ψ_1 to match the inflows into entrepreneurship from different parts of the income distribution, with Ψ_0 determining the threshold level and Ψ_1 governing sensitivity of z_F to an increase of z_P above this threshold. When $z_P \geqslant \Psi_0$, the value of entering entrepreneurship $\tilde{F}(a, \psi(z_L), i)$ is equal to the value of being an established entrepreneur with firm productivity $z_F = \psi(z_L)$, which is given by $F(a, \psi(z_L), i)$. To preclude workers with $z_P < \Psi_0$ from becoming an entrepreneur we let $\tilde{F}(a, 0, i) = -\infty$.

3.4 Labor income

Idiosyncratic labor productivity $z_{L,t}$ is modeled according to a stochastic process similar to the jump-drift process of Kaplan, Moll, and Violante (2018), augmented with employment and non-employment status, and parameters that are race-dependent. We model labor productivity as

$$z_L^i(l^i, z_P^i, z_T^i) = l^i \times e^{z_P^i + z_T^i}, \tag{5}$$

where $l^i \in \{0,1\}$ is the employment status, z_P^i is the permanent component of log income, and z_T^i is the transitory component, all of which are idiosyncratic. We assume l^i is a jump process with a constant Poisson arrival rate. The rate at which households of race i switch from employment status l to l' is denoted by $\lambda_{ll'}^i$, which we call the participation shock. Thus, we have λ_{10}^i and λ_{01}^i for $i \in \{B,W\}$.

The permanent and transitory components follow a jump-drift process given by:

$$\begin{aligned} dz_{P,t}^i &= -\mu_P^i z_{P,t}^i dt + dJ_{P,t}^i, \\ dz_{T,t}^i &= -\mu_T^i z_{T,t}^i dt + dJ_{T,t}^i, \end{aligned} \tag{6}$$

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

Each component of log income is a mean-reverting process, similar to an AR(1) in discrete time with persistence $(1-\mu_j^i)$. However, instead of shocks arriving at every period, $z_{j,t}$ jumps with probability $\Delta t \lambda_j^i$ in an interval of time Δt. Additionally, households can also get hit with an non-employment shock, in which case their labor income is equal to zero.[8].

3.5 Entrepreneurs

The entrepreneurs' optimization problem is:

$$\begin{aligned} &(\rho+\lambda_D)F(a,z_F,i) \\ &\quad = \max_c \left\{ u(c) + F_a s_F(a,z_F,i) + \lambda_D \mathbb{E}_{z_L}[V(a,z_L,i)] + F_{z_F}(\mu_F z_F) + \frac{(z_F\sigma_F)^2}{2} F_{z_F z_F} \right\}, \end{aligned} \tag{7}$$

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

$$s_F(a,z_F,i) = (1-t_\pi)\,\pi(a,z_F,i) + (1-t_a I_{a>0})\,(r-\delta)a - c, \tag{8}$$

where t_π is a business-income tax. Entrepreneurs are subject to the same borrowing constraint $a \geqslant \underline{a}$ as workers.

Firms die with rate λ_D, in which case the household becomes a worker again, and

[8]When solving the model computationally, we assume that the transitory component z_T is equal to zero if the household is out of the labor force ($l = 0$) to economize on the state space

$\mathbb{E}_{z_L}[V(a,z_l,i)]$ is the expected value of this transition. Let $n^i(z_L)$ denote the PDF of the stationary distribution of the process described in Equation (5). We assume that following the exogenous exit entrepreneurs get reintroduced into the labor force with labor productivity and employment status re-drawn from $n^i(z_L)$.[9,10]

Conditional on staying in business, the firm's productivity z_F follows a random growth process with average growth rate μ_F and variance σ_F^2 given by:

$$dz_{F,t} = \mu_F z_{F,t} dt + \sigma_F dB_t, \tag{9}$$

on the support $z_F \in [\underline{z}_F, \infty)$, where dB_t denotes a Brownian motion process. Note that while this process governs productivity, it does not govern firm size if the collateral constraint binds. Thus, a new firm might grow not only due to productivity shocks but also via savings by its owner trying to obtain the optimal size.

3.6 Firms

Firms are each owned by a single entrepreneur and differ in their productivity level z_F. They produce a single homogeneous final consumption good y by renting physical capital k and 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 the output's price. Profits are given by:

$$\pi(a,z_F,i) = z_F \mathrm{k}(a,z_F,i)^\alpha \mathrm{h}(a,z_F,i)^\beta - w\mathrm{h}(a,z_F,i) - r\mathrm{k}(a,z_F,i), \tag{10}$$

where

$$\{\mathrm{h}(a,z_F,i), \mathrm{k}(a,z_F,i)\} = \underset{\{h,k\}}{\arg\max}(1-\tau_y^i) z_F k^\alpha h^\beta - wh - rk, \quad \text{s.t. } k \leqslant a\lambda_{CC}, \tag{11}$$

[9]The stationary distribution of workers over z_L is not $n^i(z_L)$, given by the exogenous income process, since entry into entrepreneurship differs by labor productivity. We use this assumption because it makes the numerical implementation simpler. Quantitatively, the transition rates across labor statuses within workers dominate those between workers and entrepreneurs. Thus, these two distributions are approximately the same.

[10]One might worry that this assumption on labor productivity after exit incentivizes households to enter entrepreneurship to redraw their z_L. However, in practice, this is not a likely concern since low z_L households are precluded from entry by our assumption on the entry process $\psi(z_L)$. Also, in our calibrated model ideas arrive once every seventeen years on average, and firms exit once every ten years on average, making this incentive negligible in practice.

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

$$\left(1-\tau_y{}^i\right)\alpha z_F \mathrm{h}^{\beta}\mathrm{k}^{\alpha-1} = r, \text{ and } \left(1-\tau_y{}^i\right)\beta z_F \mathrm{h}^{\beta-1}\mathrm{k}^{\alpha} = w. \tag{12}$$

Without the credit constraint and the entrepreneurship distortion τ_y^i, these first-order conditions imply that profits are a share $(1-\alpha-\beta)$ of the total output of each firm. However, given the financial friction the production decision will 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. Thus, factor quantities are chosen according to:

$$\mathrm{h}(a,z_F,i) = \left(\left(1-\tau_y{}^i\right)z_F\right)^{\frac{1}{1-\alpha-\beta}}\left(\frac{\alpha}{r+\mu_{CC}(a,z_F,i)}\right)^{\frac{\alpha}{1-\alpha-\beta}}\left(\frac{\beta}{w}\right)^{\frac{1-\alpha}{1-\alpha-\beta}} \tag{13}$$

$$\mathrm{k}(a,z_F,i) = \left(\left(1-\tau_y{}^i\right)z_F\right)^{\frac{1}{1-\alpha-\beta}}\left(\frac{\alpha}{r+\mu_{CC}(a,z_F,i)}\right)^{\frac{1-\beta}{1-\alpha-\beta}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}} \tag{14}$$

Note that the higher is τ_y^B, the lower are the quantities of capital and labor demanded by Black-owned firms. However, actual marginal products of those factors would be higher, all else being equal, implying that a reallocation of credit and labor towards Black-owned firms in the model can be output increasing as in standard theories of misallocation.

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 (9) 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 via $\psi(z_L)$, and also the distribution of wealth, which in turn affects the 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. Thus, 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:

$$0 = -\frac{\partial}{\partial z_F}\left[f(z_F)\mu_F z_F\right] + \frac{1}{2}\frac{\partial^2}{(\partial z_F)^2}\left[(\sigma_F z_F)^2 f(z_F)\right] - \lambda_D f(z_F). \tag{15}$$

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:

$$\zeta = \frac{1}{2} - \frac{\mu_F}{\sigma_F^2} + \sqrt{\left(\frac{1}{2} - \frac{\mu_F}{\sigma_F^2}\right)^2 + \frac{2\lambda_D}{\sigma_F^2}}. \tag{16}$$

We later use ζ to calibrate the dispersion of top wealth in the economy. 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 $\tilde{\zeta} = \zeta(1-\alpha-\beta)$.[11]

3.7 Equilibrium

The model economy includes three markets: assets, labor and goods. In equilibrium, these three markets clear, with total net assets positions in the economy equal to the firms' capital demand, total 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 are relegated to Appendix C. The detailed solution algorithm is given in Appendix D.

4 Calibration

This section details the calibration procedure and reports the model fit and performance. Overall, the calibrated model is consistent with the patterns in the data. Our model generates an average racial wealth gap of 82.0% and a median racial wealth gap of 74.0%, whereas their empirical counterparts are 83.5% and 88.1%, respectively. Importantly, it captures the racial wealth gap as an untargeted moment arising from the exogenous distortions and endogenous forces.

We follow a three-step calibration strategy. First, we estimate labor income processes for Black and White households separately. Second, we externally calibrate some parameters to commonly used values in the literature. Finally, we calibrate the remaining parameters of the model internally. We do so by defining a distance metric and finding parameter

[11] The right tail of firm size is dominated by unconstrained firms, whose size is proportional to $z_F^{1/(1-\alpha-\beta)}$, as demonstrated by Equation (13). Thus, the firm-size distribution has a Pareto tail of $\tilde{\zeta} = \zeta(1-\alpha-\beta)$. For formal proofs along this line, see Carvalho and Grassi (2019) and Ifergane (2024) .

values minimizing it.

4.1 Labor income process estimation

Using data from the PSID from 2001 to 2019 we estimate the seventeen parameters governing the two income processes for Black and White workers, separately: τ_L^B, which is our labor income distortion, and $\mu_P^i, \mu_T^i, \lambda_P^i, \lambda_T^i, \sigma_P^i, \sigma_T^i, \lambda_{01}^i, \lambda_{10}^i$, $\forall i \in \{B, W\}$ which govern labor income via the permanent, transitory, and participation components. Below we briefly describe the estimation procedure. A full explanation as well as a report of the fit of the resulting process are reported in Appendix B.

Table 2: Estimated parameters for the labor productivity process $z_{L,t}$

Parameter	Symbol	Black HHs	White HHs
Labor income distortion	τ_L^B	50.9%	
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 $\rightarrow$ Non-employment	λ_{10}	15.4%	10.0%
Jump rate, Non-employment $\rightarrow$ Employment	λ_{01}	31.5%	44.2%

Notes: This table reports the estimated parameters of the processes for the components of labor income productivity $z_{P,t}$ and $z_{T,t}$, and labor status l_t. All transition rates are at an annual frequency.

First, τ_L^B, λ_{01}^W, $\lambda_{10}^W, \lambda_{01}^B$ and λ_{10}^B are directly calculated from the data. The labor income distortion $\tau_L^B = 50.9\%$ is estimated as the gap between Black and White households in median weekly labor income when employed. 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. The transition rates λ_{01}^W, $\lambda_{10}^W, \lambda_{01}^B$, λ_{10}^B are also calculated directly using monthly dating of employment status in the year prior to the survey.

Second, we use the Simulated Method of Moments (SMM) to estimate the remaining twelve parameters. We start by simulating the processes for labor income components $z_{P,t}^i$, $z_{T,t}^i$ and l_t^i without discretizing the support. We then estimate the parameters by jointly targeting moments from the PSID data. Third, using the parameters already estimated, we discretize the processes and optimize the choice of the grid points (curvature and width) by targeting the same moments used to estimate the parameters.

Table 2 reports the resulting parameter values. For the permanent component, the persistence of the process, which is $1-\mu_P^i$, is higher for White households than Black ones. 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 is quite different between races, with White households facing more frequent shocks, but which are less volatile and dissipate quicker.

Finally, Black households are estimated to face a lower probability of finding a job when unemployed, and also a higher probability of losing a job when employed. Thus, the non-participation rate in labor markets is higher for Black households.[12]

4.2 Externally calibrated parameter values

We externally calibrate the following parameters. The coefficient of relative risk aversion is set to $\gamma = 1.5$, as is conventional in the literature. We follow Hubmer, Krusell, and Smith (2021) in setting the depreciation rate of capital at 4.8%. The exit rate of firms is set to an annual value of $\lambda_D = 0.1$ which is also conventional. Finally, we set the volatility σ_F to target a profit volatility of 12% among the largest, financially unconstrained firms, which is consistent with recent estimates in the literature (e.g., Gabaix, 2011).[13]

4.3 Internal calibration procedure

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; race-dependent moments are only targeted when related to entrepreneurship. The model has eleven internally calibrated parameters summarized in Table 3. These are set to target twelve moments reported in Table 4. Our distance metric is the sum squared relative error function with equal weights on each moment $SSRE = \sum_{j=1}^{12} (S_j^{model} - S_j^{data})/(S_j^{data})^2$, where S_j^{model} and S_j^{data} correspond to the value of the j^{th} moment in the model and the data.

[12]The non- participation rate for Black households is given by $\lambda_{10}^B/(\lambda_{10}^B + \lambda_{01}^B) = 32.8\%$, whereas for White households it is $\lambda_{10}^W/(\lambda_{10}^W + \lambda_{01}^W) = 18.5\%$.

[13]Profits or labor demand of the unconstrained firms will be proportional to $z_F^{1/(1-\alpha-\beta)}$, thus if the volatility of $\log(z_F)$ is equal to σ_F, the volatility of profits is equal to $\sigma_F/(1-\alpha-\beta)$.

Table 3: Internally calibrated parameters

Parameter	Symbol	Value
Labor share, production function	α	0.31
Capital share, production function	β	0.41
Discount rate	ρ	10.1%
Borrowing limit	$\underline{a}$	0.11
Collateral constraint	λ_{CC}	3.39
Idea arrival rate	η	5.8%
Tail of z_F process	$\zeta\,(1-\alpha-\beta)$	1.50
Racial distortion on entrepreneurship	τ_y^B	0.55
Tax rate	$\bar{t}$	13.5%
Minimum permanent labor income for entry into entrepreneurship	Ψ_0	0.99
Elasticity of initial firm productivity to permanent labor productivity	Ψ_1	0.22

Notes: This table summarizes all internally calibrated parameter values.

Although most parameters affect mainly one or two targeted moments to a first order, we stress that all the targeted moments summarized in Table 4 are jointly determined as the equilibrium interaction of all parameter values. In what follows we discuss the targeted moments, the parameter values used to obtain them, and the quality of the resulting fit.

4.4 Targeted moments and resulting calibration

Wealth moments We follow the literature by targeting a net return on wealth of 4% annually and a capital-to-annual-output ratio of 3. The main parameters affecting those two moments are ρ, the discount rate, α, the share of capital in the production function, and λ_{CC}, the collateral constraint, as they jointly capture the desire of households to hold assets and the firms' demand for capital in the production process. Our model fits those targets well, achieving a net return of 3.9% and a capital-to-output ratio of 3. We also target wealth dispersion patterns from the SCF. Specifically, 11% of households have negative net asset positions, the share of wealth held by the 50^{th} to 90^{th} percentiles of the wealth distribution is 25%, and the share held by the Top 10% of the wealth distribution is 73.2%. Our model delivers an excellent fit to those targets, with 11.1% of households having negative wealth, and wealth shares of 22.6% and 74.6% for the P50-P90 and Top 10%, respectively. The key parameters affecting these wealth dispersion moments are the borrowing limit $\underline{a}$, the collateral constraint λ_{CC}, the skewness of the productivity process ζ, and the span of control of the firms, $\alpha+\beta$.

Table 4: Summary of targeted moments and model fit

Moment	Source	Data	Model
Net return	literature	4.0%	3.9%
Capital to output ratio	literature	3.00	3.00
Wealth share of those in P50-P90 percentiles	SCF	25.0%	22.6%
Wealth share of the Top 10%	SCF	73.2%	74.6%
Share of households with negative net wealth	SCF	11.0%	11.1%
Entrepreneurship rate, Black households	SCF	5.2%	5.2%
Entrepreneurship rate, White households	SCF	14.2%	11.6%
Share of wealth held by entrepreneurs, Black households	SCF	25.3%	24.7%
Share of wealth held by entrepreneurs, White households	SCF	45.3%	39.0%
$ER_{P50-P90}/ER_{P0-P50}$	PSID	2.56	2.55
$ER_{P90-P100}/ER_{P0-P50}$	PSID	5.79	5.24
Ratio of benefits to median wage	literature	33.0%	33.1%
Overall fit - SSRE			0.071

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 $ER_{P50-P90}/ER_{P0-P50}$. All the data refers to averages over the 2001-2019 period.

To obtain those targets we calibrate the discount rate to $\rho = 10.1\%$, and $\lambda_{CC} = 3.39$. We also set the borrowing limit to $\underline{a} = 0.11$ which corresponds to 14.6% of the median household labor income in the model. Finally, our calibration internally sets the degree of decreasing returns to scale to $\alpha+\beta = 0.72$, in line with the literature, with $\alpha = 0.31$ and $\beta = 0.41$. Note that these shares do not map directly to the empirical factor shares because the entrepreneurs' compensation, which in our model are labeled profits, also includes the CEO and partners' labor income in the data. Finally, we calibrate the Pareto tail of the productivity distribution to $\zeta = 5.3$ implying that the firm-size distribution in our model has a tail of $\zeta(1-\alpha-\beta) = 1.50$.[14]

Entrepreneurship moments We target the entrepreneurship rate among Black and White households in the SCF, which is 5.2% and 14.2%, respectively. We also target the

[14]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)).

share of Black-owned and White-owned wealth held by entrepreneurs, which is 25.3% and 45.3%, correspondingly. The main determinants of overall entrepreneurship rates in the model are: the idea arrival rate η, which mechanically limits the number of potential entrepreneurs; the entry process parameters Ψ_0, Ψ_1 and ζ, as they also govern the quantity and quality of potential entrants; and β, since it governs the demand for labor and thus the wage which is the outside option to starting a business. Importantly, τ_y^B is the main parameter governing the gap in entrepreneurship rates between Black and White households.

The model delivers an excellent fit for Black entrepreneurship outcomes, with an entrepreneurship rate of 5.2% and Black entrepreneurs accounting for 24.7% of total Black-owned wealth. The main shortcoming of the model is that it understates White entrepreneurship. The entrepreneurship rate of White households is 11.6% in the model, and they control 39.0% of White-owned wealth, both lower than in the data. Because the model matches well the average wealth of an entrepreneur vs a worker (intensive margin), both for Black and White households, this means that the lower rate of White entrepreneurship (extensive margin) results in a lower share of White-owned wealth controlled by entrepreneurs in the model when compared to the data. Since the model undershoots the importance of White entrepreneurs in accounting for wealth inequality while matching well Black entrepreneurs' wealth, if anything, our model is prone to understating the importance of entrepreneurship in accounting for racial wealth inequality.[15]

We discretize the productivity process on an exponentially spaced grid and normalize the lower bound to $\underline{z}_F = 1$. We calibrate $\Psi_0 = 0.99$ and $\Psi_1 = 0.22$ to match the empirical correlation between entry and labor income.

To match the entrepreneurship rates in the model, we set the idea arrival rate to $\eta = 5.8\%$. Under this parameter value and $\lambda_D = 10\%$, the maximum possible rate of entrepreneurs out of the general population is 36.7%.[16] Because many households endogenously choose not to become entrepreneurs, we arrive at a total entrepreneurship rate of 10.6% in the model. To obtain a Black entrepreneurship rate of 5.2%, which is also the empirically observed value, our model requires that $\tau_y^B = 55.3\%$.

The value for τ_y^B might appear large but it is consistent with estimates from different

[15] The average Black entrepreneur in the data is 4.87 richer than the average Black household, irrespective of entrepreneurship status, whereas, for White households, this ratio is 3.19. In the model, these ratios are 4.75 for Black households and 3.36 for White ones.

[16] The entry process function ψ further limits this number. We allow for nine permanent income states with a unit mean (and median). A parameter of $\Psi_0 = 0.99$ means that the top five grid points can start a business conditional on getting an idea. We stress that τ_L^B is not allowed to influence idea quality in the model.

studies. The closest estimate of τ_y^B available in the empirical literature comes from Tan and Zeida (2024), who study the differential conditions faced by Black-owned businesses using tools from the misallocation literature. The authors jointly estimate a markup wedge, which affects commonly the average revenue product of all factors of production, and factor-specific distortions, affecting the average revenue product of specific factors. Using the Kaufman survey, which is a high-quality panel of firms, the authors report that the markup wedge is the single most important driver of differences between Black and White-owned firms, with point estimates ranging between -0.535 and -0.707. Translated into our model, those estimates would imply that τ_y^B ranges between 41.4% and 50.7%.[17] We thus conclude that our estimates are close to those of Tan and Zeida (2024) which is reassuring since the two works do not share data sources or methods.

Income and entry decision moments Denote the average entry rate into entrepreneurship in labor income fractile j by ER_j. We target the ratio $ER_{P50-P90}/ER_{P0-P50}$ and also $ER_{P90-P100}/ER_{P0-P50}$. In the data, we observe an increasing correlation between income and entry with $ER_{P50-P90}/ER_{-P50} = 2.56$ and $ER_{P90+}/ER_{-P50} = 5.79$. The entry process parameters Ψ_0 and Ψ_1 primarily govern these moments. The model delivers a good fit with $ER_{P50-P90}/ER_{-P50} = 2.55$ and $ER_{P90+}/ER_{-P50} = 5.24$. 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 with a single parameter such that $t_w = t_\pi = t_a = \bar{t} = 13.5\%$, and achieve an income floor of 33.1% of the median household's pre-tax labor income.

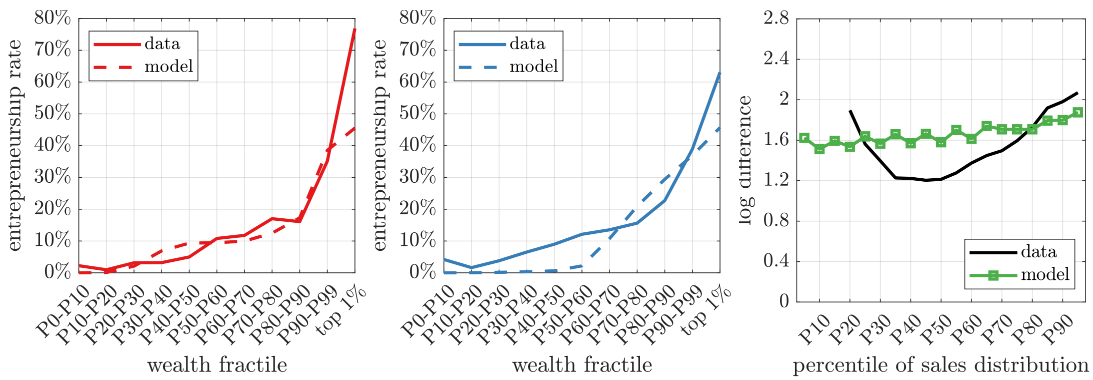
4.5 Matching the five facts using the calibrated model

The calibration strategy explicitly targets some facts described in Section 2. These facts include: the differences between Black and White households in labor market outcomes (Fact 4); the correlation between labor income and entrepreneurship entry (Fact 5); and also the gap in entrepreneurship rates, which is part of Fact 3. Importantly, we do not target the racial wealth gap (Fact 1), the correlation of entrepreneurship and wealth (Fact 2), or the disparity in revenues faced by Black-owned businesses (Fact 3). Below, we discuss our

[17] To map the estimates of Tan and Zeida (2024) to our estimates, observe that the average revenue product of capital in our model is given by $ARPK = \frac{\left(1-\tau_y{}^i\right)}{\left(1+\tau_k(a,z_F,i)\right)}\left(\frac{\alpha}{r}\right)$, and for labor $ARPL = \left(1-\tau_y{}^i\right)\left(\frac{\beta}{w}\right)$, where $\tau_k\left(a,z_F,i\right)r = \mu_{CC}\left(a,z_F,i\right)$. The common factor that would influence both the average revenue product of labor and capital is τ_y^i. Thus, using Tan and Zeida's notation of δ^μ for the markup wedge, we have that $\log\left(1-\tau_y{}^B\right) = \delta^\mu$.

model's fit to those stylized facts.

Fact 1: the racial wealth gap The model generates a large and untargeted racial wealth gap consistent with the data. The model arrives at 82.0% for the mean racial gap, compared to 83.5% in the data, and a median one of 74.0%, compared to 88.1% in the data. These results show that the model is able to account for almost the entirety of the mean racial wealth gap, but that it undershoots the median. Because wealth in the United States is heavily concentrated, this is not surprising. Entrepreneurship is likely to explain most of the right tail of the wealth distribution, and therefore racial differences in entrepreneurship and labor income are able to account for the mean racial wealth gap as well. However, other factors might also be important in the middle of the wealth distribution and, consequently, have an impact on the median racial wealth gap.



(A) Entrepreneurship rate, Black households

(B) Entrepreneurship rate, White households

(C) Difference in log(size) of firms

Figure 5: 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) shows the log differences in firm size, measured as revenue, of White relative to Black-owned firms conditional on their revenue fractile. For example, P50 shows the log differences between the median White and Black-owned firms in the data and in the model. Lower percentiles are shown as missing in the data because some firms do not report positive sales. Source: SCF, 2001-2019.

Fact 2: wealth and entrepreneurship are correlated The correlation between entrepreneurship and wealth overall and by race is untargeted. Figures 5A and 5B report that our model captures well this correlation, both for Black and White households. This is crucial, as the main goal of the paper is to understand the role that entrepreneurship plays in understanding wealth, specifically, wealth differences across races.

Fact 3: racial disparities in revenues As discussed above, we target directly the racial entrepreneurship gap with the entrepreneurship distortion τ_y^B. Reassuringly, this same distortion allows the model to also capture the magnitude of the differences between Black and White-owned firms. This element is untargeted and reported in Figure 5C. Figure 3B showed that there appears to be a constant gap in the size of White-owned firms vs Black-owned firms. When discussing the evidence and describing the model we conjectured that our entrepreneurship distortion τ_y^B would be able to deliver a constant difference in size, while a distortion in collateral constraint would see Black firms owned by wealthy individuals converge to their White counterparts. Figure 5C demonstrates that the entrepreneurship distortion does indeed deliver a constant difference across the size distribution of Black vs White-owned firms, in line with empirical evidence.

5 Results

5.1 Decomposing the racial wealth gap

With the quantified model at hand, we now explore the role of entrepreneurship in determining wealth outcomes. Recall that the model allows for Black and White households to differ in outcomes due to distortions faced by Black workers (labor income and a labor income risk distortion), and those faced by Black entrepreneurs (entrepreneurship distortion). To disentangle the effects of the two, we conduct a comparative statics exercise where we equalize the conditions faced by Black households to those faced by White ones, only as workers or as entrepreneurs. We report how those counterfactual changes influence the racial wealth gap and the representation of Black households along the wealth distribution. The results are reported in Figure 6 and in Table 5.

In an incomplete markets economy augmented with entrepreneurship choice, the impact of these distortions on entrepreneurship choices and the racial wealth gap can be complex. The entrepreneurship distortion has a clear negative effect on Black entrepreneurship. However, the labor income distortion and the labor income risk distortion operate in two different directions. On the one hand, these distortions make it harder for Black workers to accumulate wealth because of their lower income, thus making entrepreneurship less attractive given the collateral constraint. On the other hand, worse labor market conditions make the entrepreneurship route relatively more attractive than continuing as a worker, for a fixed level of wealth. Additionally, our entry process given by Equation (4) implies that

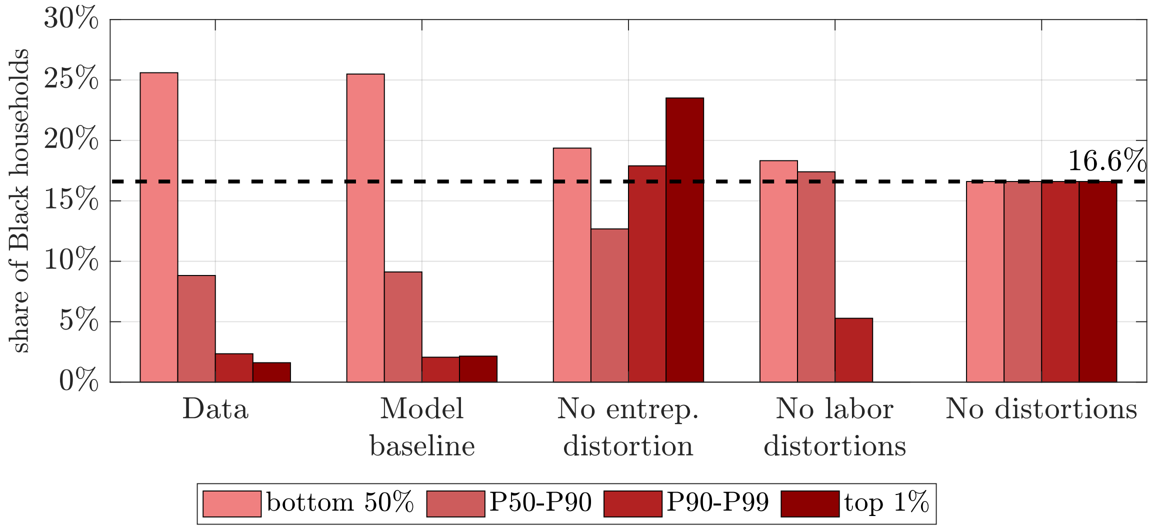


Figure 6: Racial representation along the wealth distribution

Notes: Each bar shows the share of Black households within a fractile of the wealth distribution. The first set of bars is derived from SCF data. The baseline case corresponds to our calibrated model with distortions. The next three sets of bars correspond to the two counterfactuals in which the entrepreneurship, labor, and both distortions are removed.

starting a business from the low permanent income states makes the entrant less productive initially. Thus, making entrepreneurship less attractive.

The most striking result emerging from Figure 6 is that removing the entrepreneurship distortion alone would flip the sign of the racial wealth gap in the steady state. According to our model, this would eliminate the under-representation of Black households at the bottom of the wealth distribution and create an over-representation of Black households at the top. As Table 5 reports, in this counterfactual scenario, the racial wealth gap would be -21.6%, i.e., the average Black household would be 21.6% wealthier than the White one, and the entrepreneurship rate among Black households would be 4.8 percentage points higher than for White households.[18] Observe that the median racial wealth gap would decline substantially from 73.9% to 41.6%.

One might wonder why the median racial wealth gap responds 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, Black workers can be more successful entrepreneurs when conditions are equalized. Thus, Black workers save more so they can better capi-

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

Table 5: 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%	83.5%	88.1%
Model	5.2%	11.6%	6.4%	82.0%	73.9%
No entrepreneurship distortion	15.1%	10.3%	-4.8%	-21.6%	41.6%
No labor market distortions	0.0%	12.1%	12.1%	74.0%	20.7%
No distortions	11.0%	11.0%	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

talize on emerging opportunities. Second, wealth outcomes persist over time. Having a parent who was a wealthy entrepreneur translates to a better wealth position for their children, even when they are not entrepreneurs themselves. The model captures this without having explicitly modeled a life cycle since higher entrepreneurship rates for one group imply that dynasties belonging to this group spend a higher share of their time in higher-wealth states.[19]

In comparison, equalizing the conditions faced by Black workers almost removes the over-representation of Black households at the very bottom of the wealth distribution and helps alleviate poverty. However, it would also lead to a severe reduction of Black entrepreneurship. Since the entrepreneurship distortion is still in place, Black households would not enter into entrepreneurship and instead stay in the labor market, with virtually no Black households in the top 1%. The median wealth gap declines to only 20.7%, but the average one hardly changes, declining to 74.0%. This asymmetry in the reaction of the median and average demonstrates the importance of entrepreneurship for the representation of Black households at the top of the wealth distribution.

These results illustrate how focusing on eliminating the average racial wealth gap compared to the median one requires different societal shifts. To eliminate the average gap one must target entrepreneurship outcomes and generate an equal representation of Black

[19] These counterfactual shifts on the relative wealth of Black compared to White households occur despite there being very little change in the overall wealth distribution. This result, documented in Table A.2 in the Appendix, hinges on the fact that the first-order determinant of overall wealth dispersion is the stochastic process governing income dispersion from profits, which remains unchanged in all scenarios.

households among the very rich, whereas eliminating the median gap requires focusing on labor market outcomes of Black households. If one is primarily concerned with poverty alleviation among Black households then focusing on labor market outcomes is promising. However, trying to improve labor market outcomes of Black households without considering the potential adverse effect such intervention would have on entrepreneurship might lead to a society where Black households are more under-represented at the top of the wealth distribution. Such under-representation might reduce the political influence of Black households (Bartels, 2009).

5.2 The macroeconomic implications of racial distortions

Our general equilibrium model allows us to also evaluate the aggregate implications of the determinants of the racial wealth gap analyzed thus far. To do so, in Appendix E, we show how our model economy can be described using an aggregate production function of the form

$$\log Y = \underbrace{\alpha \log K + \beta \log N + (1-\alpha-\beta)\log m_F}_{\text{factor quantities}} + \underbrace{\beta \log\left(\mathbb{E}\left(z_L\left(1-\tau_L{}^i\right)\right)\right)}_{\text{agg. labor productivity}} + \underbrace{\log(TFP)}_{\text{agg. productivity}} . \quad (17)$$

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.[20] It also depends on aggregate labor productivity $\mathbb{E}(z_L\left(1-\tau_L{}^i\right))$ and total factor productivity TFP. Labor productivity is affected by the labor income distortion, which shifts the level of z_L firms can utilize in production, and by the labor income risk distortion which governs the distribution of z_L among Black households. TFP is function of the firm productivity distribution. Note that TFP is endogenous in our model since entrepreneurs can choose to enter at different levels of initial firm productivity and assets.

Table 6: The effects of distortions on aggregate quantities

Distortions removed	Y	K	N	m_F	$\mathbb{E}(z_L\left(1-\tau_L{}^i\right))$	TFP
Entrepreneurship	5.4%	5.8%	-0.6%	5.2%	2.8%	1.3%
Labor market	8.5%	8.5%	0.5%	-4.3%	11.8%	2.1%
All	10.9%	10.2%	-0.5%	4.1%	12.6%	1.6%

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

[20]Note that since population is normalized to one $N = 1 - m_F$.

Removing the entrepreneurship distortion increases steady-state output by 5.4%. This is primarily due to a higher demand for labor and capital by existing and new entrant Black-owned firms, even though the primitives governing firm productivity are unchanged. Removing the distortion implies a factor reallocation from White-owned to Black-owned firms in relative terms. Higher labor demand also leads some high z_L White workers to remain in the labor market increasing labor productivity.

Furthermore, removing labor market distortions increases output by 8.5%. This increase is mainly due to a mechanical effect arising from a higher level of aggregate labor productivity $\mathbb{E}(z_L\left(1-\tau_L{}^i\right))$ since the labor income distortion τ_L^B is set to zero.[21] In our model, Black workers earn lower wages due to this labor income distortion, and there is a one-to-one mapping between effective labor productivity $z_L(1-\tau^B)$ and labor income. However, in reality, Black households earn lower labor income because of both pure discrimination and lower productivity due to differences in, for example, education. In this sense, we interpret the output gains for the counterfactual with no labor income distortions as an upper bound.

Finally, removing all distortions raises output by 10.9%. Note that this effect is smaller than adding the output increase from removing the labor market or entrepreneurship distortions separately, indicating a strong interaction between the two changes. Hsieh et al. (2019) conduct a similar exercise, in which they remove the frictions that prevent the efficient sorting across occupations, and find that output would increase by 9.9%. While their exercise is focused solely on the labor market, it considers frictions affecting not only Black vs White household, by also female vs males. These results highlight the major macroeconomic implications of distortions and frictions that prevent the efficient sorting of households across either entrepreneurship and labor market, and within the labor market.

5.3 Evaluation of policies targeting the racial entrepreneurship gap

We now investigate the efficacy of a set of policies designed to reduce the racial wealth gap by increasing entrepreneurship rates among Black households without addressing the fundamental distortions. We consider subsidies to either profit, revenue, or capital for

[21] Note that, as in the classic Solow growth model where capital per worker and output per worker do not depend on population size, increasing z_L leads aggregate capital and output to rise by the same amount.

Table 7: Policy counterfactuals - subsidizing Black entrepreneurship

	Entrepreneurship rate		Racial wealth gap		$\frac{E[y^B]}{E[y^W]}$	Tax rate	Subsidy rate
	Black	White	Average	Median			
Baseline	5.2%	11.6%	82.0%	73.9%	7.4%	0.0%	0.9%
Profit subsidy	10.0%	11.6%	71.1%	72.4%	7.3%	1.0%	20.7%
Revenue subsidy	10.0%	11.5%	70.5%	71.7%	9.0%	0.5%	5.7%
Capital subsidy	10.0%	11.5%	69.0%	70.7%	9.3%	0.3%	19.3%

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 $E\left[y^B\right]/E\left[y^W\right]$ represents the average size of a Black-owned business relative to a White-owned one, as measure by output. Denoting the subsidy on profits, revenue and capital by s^i_π, s^i_y, s^i_k, respectively, the firms' problem in Equation (11) with all subsidies becomes $\{\mathrm{h}(a,z_F,i),\mathrm{k}(a,z_F,i)\} = \arg\max_{\{h,k\}}\left[(1+s^i_y)(1-\tau^i_y)z_F k^\alpha h^\beta - wh - (1-s^i_k)rk\right]$, subject to $k \leqslant a\lambda_{CC}$, and profits are given by $\pi(a,z_F,i) = (1+s^i_\pi)\left[(1+s^i_y)y(a,z_F,i) - (1-s^i_k)r\mathrm{k}(a,z_F,i) - w\mathrm{h}(a,z_F,i)\right]$.

Black entrepreneurs,[22] all funded with a higher labor income tax on all workers.[23] We compute new steady-states in which each of these subsidies results in an increase in the Black entrepreneurship rate from 5.2% to 10%. The results are reported in Table 7.

The main result from this exercise is that subsidy policies do not have a large impact on the racial wealth gap, even though they are able to achieve a Black entrepreneurship rate of 10% with additional tax rates ranging between 0.3-1.0% of labor income. This might seem puzzling at first, however, while the policies stimulate entry, Black-owned firms are still smaller than White-owned firms on average, as Table 7 demonstrates. Observe that the 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.[24] Black entrepreneurship rates increased to 10% using a revenue subsidy of only 5.7%, while the entrepreneurship distortion is more than 50%, so Black-owned firms are still inefficiently smaller.

It is possible to close the gap in entrepreneurship rates while having a net positive

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

[23] Shifting the funding burden to White workers only does not matter for these results. If anything, it would make supporting Black entrepreneurship slightly harder since Black workers would not be taxed.

[24] The comparison between the two is not exact because the subsidy affects the choice of capital and labor and the profits given those choices, but the distortion affects only the optimal choice of inputs, as explained in Section 3.

distortion because existing discrimination in the labor market makes the outside option of Black entrepreneurs worse. If there were no labor market distortions, the relationship between the racial wealth gap and the gap in entrepreneurship rates would be one-for-one. In turn, ignoring labor market distortions could lead one to overestimate the impact of policies targeted at equalizing entrepreneurship rates on the racial wealth gap. Thus, we conclude that, once the interaction between labor market and entrepreneurship outcomes is taken into account, closing the racial wealth gap with policies target at entrepreneurs is not possible unless the entrepreneurship rate of Black households becomes much higher than that of White households.

Finally, we find that the capital subsidy is the most effective policy among those examined. It causes the largest reduction in both the average and median racial wealth gaps, the largest increase in the relative size of Black-owned firms, and is also the cheapest. Notice that, because collateral-constrained firms cannot increase their capital input even if its cost is reduced by the subsidy, most of the benefits of this policy go towards the larger Blacked-owned firms, owned by wealthier individuals. This finding suggests that policies that help larger Black-owned firms catch-up with the largest White-owned firms might be more successful in reducing the racial wealth gap than policies that aim to improve the conditions for young, small, firms.

6 The dynamics of the racial wealth gap

In the previous section we analysed the contribution of different distortions towards closing the wealth gap by comparing different steady-states. In this section we ask: how long would it take to close the racial wealth gap?

To start, we analyze the transition dynamics of the model from the initial steady state calibrated to the US in 2001-2019 to the counterfactual one in which there are no racial distortions, by removing all of them immediately. All transitions computed are solved under perfect foresight for all agents in the model and holding the population composition constant. The results are depicted in the solid black line in Figure 7.

When the distortions are immediately removed, Panel (A) shows that it takes about 150 years for the mean racial wealth gap to close, while Panel (B) shows that it would take 100 years to close the median racial wealth gap. The first main result of this exercise is that wealth convergence occurs slowly. Alternatively, 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. Still, it takes more than a century and many generations for Black households to catch up to White ones. The second main result is that convergence between Black and White households occurs faster at the bottom of the distribution than at the top. The median racial wealth gap is faster to close than the average. Moreover, Panel (C) shows that Black households only obtain equal representation at the top 1% of wealth and reach their population weight of 16.6% after 150 years, in line with the mean racial wealth gap.

Both results above might seem particularly puzzling given the very fast convergence in entrepreneurship rates shown in Panel (4), which happens in less than 50 years. However, even though the removal of distortions increases the profits of existing Black firms (bot expected and on impact) and incentivizes the creation of new ones, it takes time for the entrant and incumbent firms to grow to their new optimal size, equal to that of their White-owned counterparts. Panel (E) shows that the profitability of Black and White-owned firms is equalized after 100 to 150 years into the transition. Thus, even though the entrepreneurship rate converges quite quickly, it takes time for newly created Black-owned firms to grow and then generate profits that are comparable to those of White-owned firms. 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. For the mean racial wealth gap, it is still necessary for firm owners to have time to accumulate the profits from their large firms, break into the top 1% of the wealth distribution, and only then accumulate enough wealth to close the average racial wealth gap.

6.1 The effect of wealth transfers

We now turn our discussion towards wealth transfers, which are set to close the average racial wealth gap at time $t = 0$. Transfers are implemented using a tax proportional to wealth imposed on White households, which is then redistributed lump-sum to all the Black households, independent of their wealth or other characteristics. We report the results of this wealth transfer also in Figure 7 for three scenarios: (i) assuming that all distortions are eliminated immediately; (ii) distortions close linearly over a hundred years; and (iii) no social change takes place, 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 13.6% tax on their wealth. At the same time, each Black household receives a lump sum transfer of 6.2 times the median household's annual labor

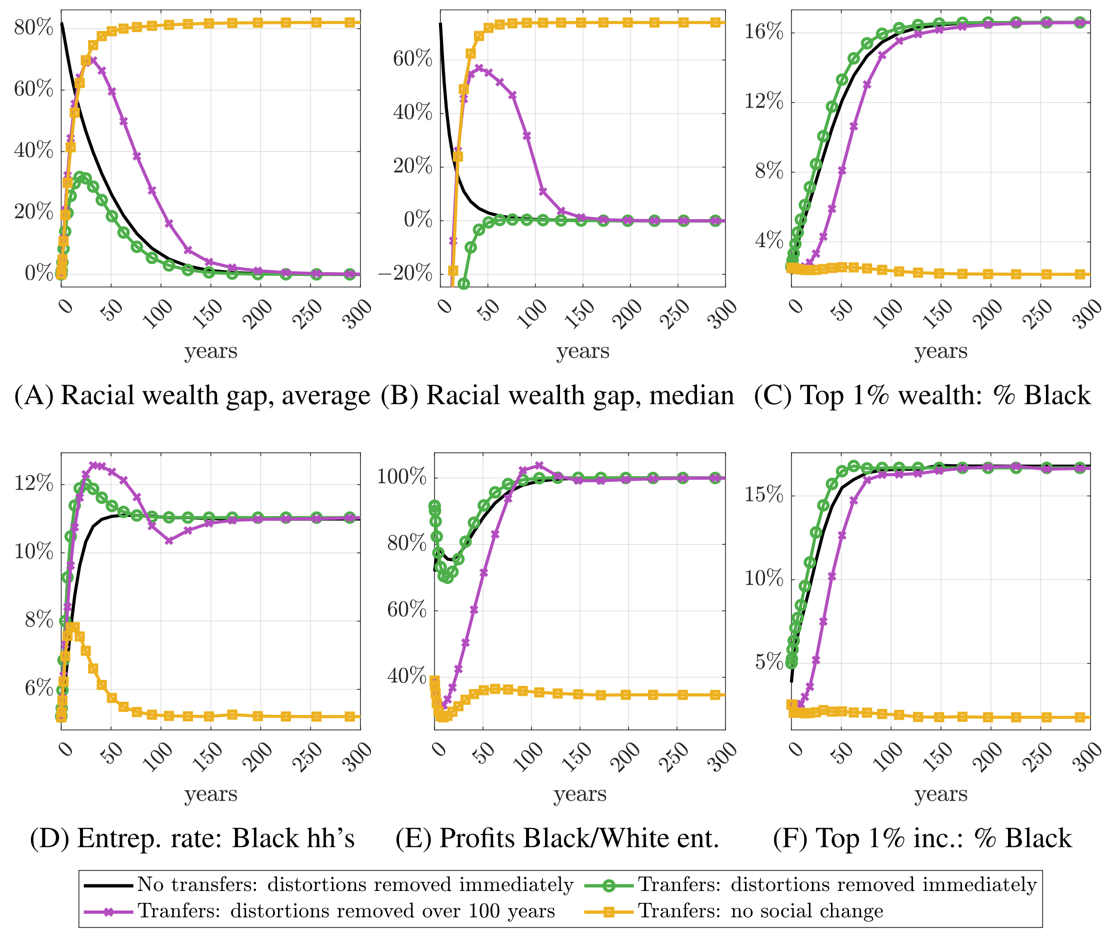


Figure 7: Closing the racial wealth gap

Notes: The solid black line shows the transition path from the steady with distortions to a steady without distortions, when all the distortions are removed immediately. The other three cases involve wealth transfers that close the average racial gap and: (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.

income in the model, which represents an increase on impact of 379% for the wealth of an average Black household. The total wealth transfers amount to 39.4% of the annual GDP in the model. Thus, compared to U.S. GDP in 2019, this would result in a transfer of $8.42 trillion.[25]

[25]This number is in line with other estimates: Boerma and Karabarbounis (2023) report a corresponding

Panel (A) of Figure 7 illustrates that, in all scenarios, the average racial wealth gap falls to 0% on impact by construction. It reopens shortly afterward as Black households consume a good portion of the transferred wealth. In the case of transfers combined with immediate removal of the distortions, the average racial wealth gap closes completely after 150 years, or the same horizon in which there were no transfers, albeit with an overall lower level throughout the transition period. Our main result in this section is that, while transfers keep the mean racial wealth gap lower throughout the transition, they do not significantly affect the speed at which the racial wealth gap converges to zero.

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

Three 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 are in place, wealth transfers cannot, by construction, change long-term wealth inequality, and the racial wealth gap reopens to its original magnitude, with most of the progress undone quickly within the first 50 years.

Finally, in our exercise the distortions are fully exogenous to the dynamics of the racial wealth gap. Arguably, it is possible that wealth transfers to Black households could cause a reduction in distortions (e.g., through more investment in education and lower discrimination), which would then help even more the reduction of the racial wealth gap. The case of slowly removing distortions in Figure 7 provides insights for this scenario. Notice that even with an exogenous downward path towards zero for distortions over 100 years, the mean 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 removed immediately on impact, the model suggests that it is unlikely that wealth transfers could generate a virtuous cycle of reduction of inequality and reduction of distortions.

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 $419,000 per household.

7 Conclusion

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

Quantifying the impact of each distortion reveals that that removing the entrepreneurship distortion would reverse the average racial wealth gap and almost halve the median racial wealth gap. In comparison, we show that addressing labor market distortions has a large impact on the median racial wealth gap, but it can have a negative impact on the representation of Black households at the top of the wealth distribution due to its effects on entrepreneurship choice. Our analysis highlights the crucial role of sorting via the entrepreneurial entry choice on racial disparities.

Our analysis suggests three lessons to inform the future policy debate. First, removing the entrepreneurship distortions increases output by 5.4%, mainly due to factor reallocation towards Black-owned firms, indicating a large potential gain from policies targeting this distortion. Second, subsidy policies aimed at equalizing the entrepreneurship rates are effective at closing the entrepreneurship gap, but they are not enough to close the racial wealth gap, as Black-owned businesses are still smaller than their White counterparts. Last, in all scenarios explored the racial wealth gap is slow to close and wealth transfers are not effective at increasing the speed of convergence.

The results point to the centrality of entrepreneurship for 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

	(1) All	(2) All	(3) Black	(4) Black
percentile of income	0.013***	0.004	0.013	0.012
	(0.004)	(0.004)	(0.007)	(0.007)
wealth in P50-P95	1.280***		1.090*	
	(0.168)		(0.451)	
wealth in top 5%	5.418***		1.483	
	(0.671)		(1.454)	
education	0.138***	0.171***	0.233***	0.246***
	(0.031)	(0.031)	(0.057)	(0.061)
percentile of wealth × WORK		0.053***		0.019
		(0.005)		(0.012)
percentile of wealth × NOT WORK		0.015***		0.011
		(0.004)		(0.010)
Year FE	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes
Empl. status	Yes	Yes	Yes	Yes
R-Squared	0.016	0.016	0.015	0.014
Observations	62,973	62,973	25,066	25,066

Table A.1: Entrepreneurship entry and income: alternative measures of wealth

Notes: This table shows the results of estimating Equation (1) 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. *Source*: PSID, 2001-2019.

Table A.2: Overall wealth inequality

	Share of wealth held by the			
	bottom 50%	P50-P90	P90-P99	top 1%
Baseline	2.8%	22.6%	33.3%	41.4%
Counterfactual scenario - baseline without				
Entrepreneurship distortion	3.0%	23.7%	33.3%	40.0%
Labor market distortions	3.0%	22.4%	33.4%	41.3%
All distortions	3.0%	23.5%	33.0%	40.4%

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

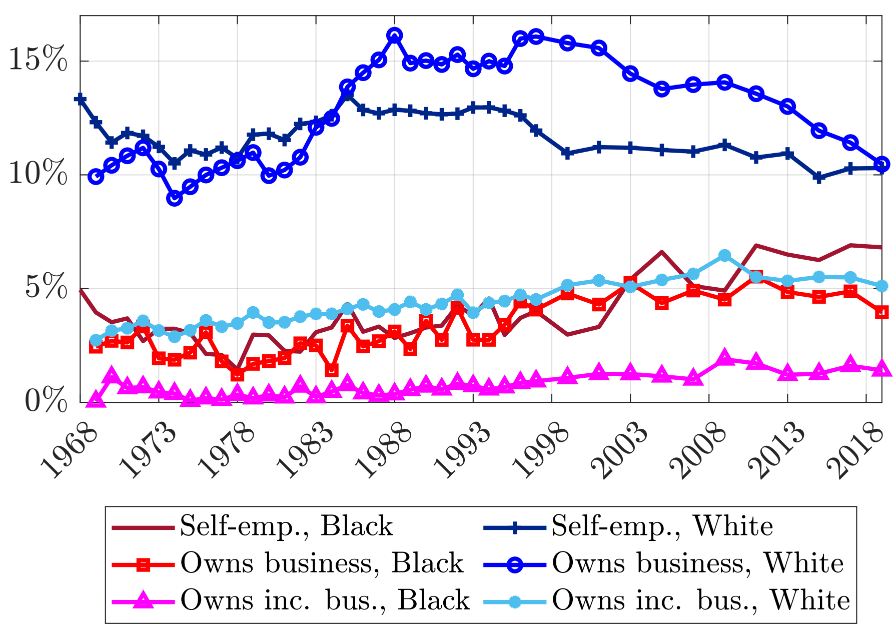
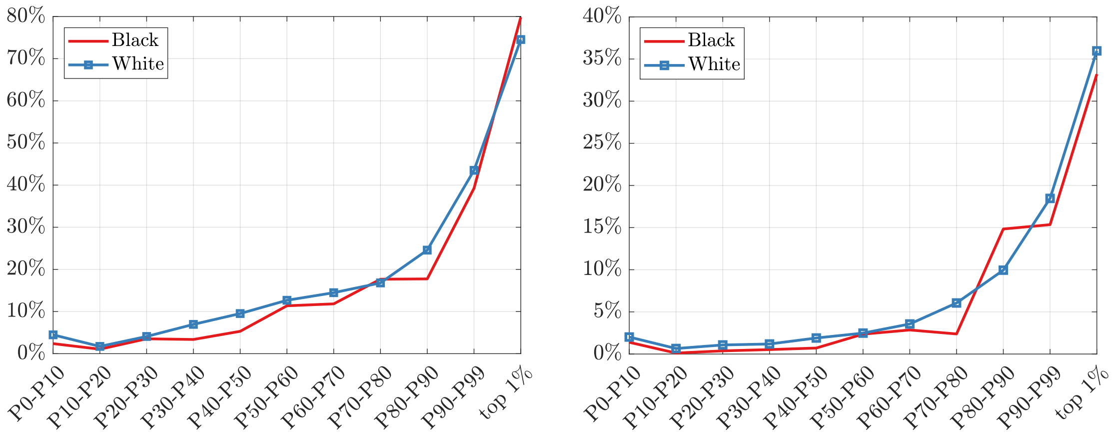


Figure A.1: Entrepreneurship rates, PSID

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.



(A) owns a business, SCF

(B) owns an incorporated business, PSID

Figure A.2: Entrepreneurship rates by wealth fractiles

Notes: This figure shows the share of households of a given race that are classified as entrepreneurs in different fractiles of the overall wealth distribution, where "P10-P20" denotes those in between the 10th and 20th percentiles of wealth, for example. A household is classified as an entrepreneurs in Panel (A) if it owns a private business, according to the SCF; and in Panel (B) if it owns an incorporated business, according to the PSID. *Source*: SCF and PSID, 2001-2019.

B Wage estimation

Here we 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 data source for the moments to be matched. It is is specially 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 they 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
$tau_L^B = 50.9\%$. 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.1. 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 2, and the moments implied by the continuous model are shown in columns (2) and (5) of Table B.1. 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.1 shows, the estimated model seems to 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

Table B.1: 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%

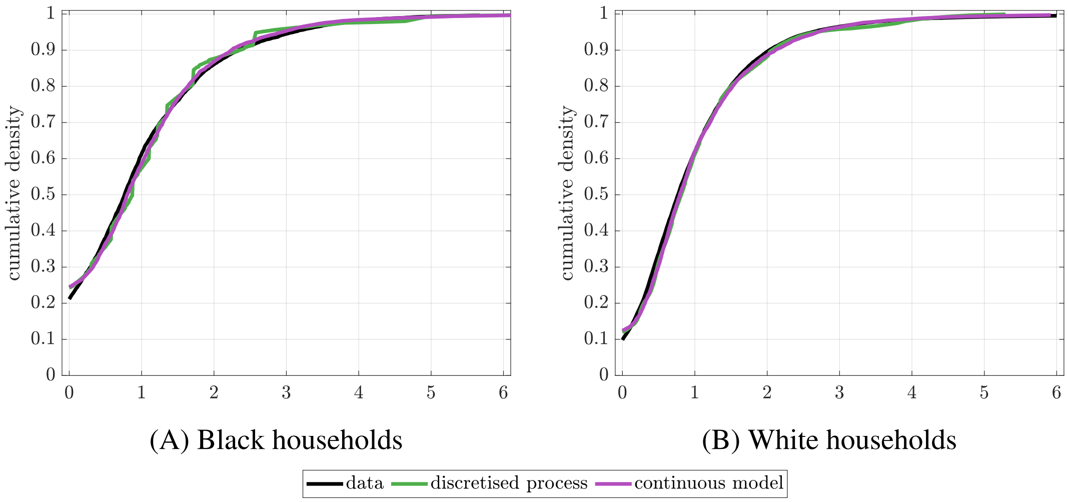
Notes: This table shows the moments for Black and White households estimated from the data, simulated by the model without a grid constraint (continuous), and simulated by the model in a specific discretized grid. The moments targeted are: variance of the log of labor income across households; the standard 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.

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.1. 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 Recursive stationary equilibrium

A recursive stationary equilibrium in the model economy consists of value functions $V(a, z_L, i)$ and $F(a, z_F, i)$; saving rules $s_V(a, z_L, i), s_F(a, z_F, i)$ and the corresponding consumption policy function $c_V(a, z_L, i), c_F(a, z_F, i)$; entry choice policies $I_V(a, z_L, i)$;[26] stationary den-

[26] 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.



(A) Black households (B) White households

Figure B.1: 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.

sity functions $g_L(a, z_L, i)$ 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; tax rates τ_a, τ_π and τ_L; wage rate w; and benefits T which jointly satisfy the following:

1. Consumer optimization - Given prices r and w, transfers T, and the profit functions $\pi(a, z_F, i)$, the policy functions $c_V(a, z_L, i), c_F(a, z_F, i)$ and $I_V(a, z_L, i)$ solve the optimization problems given by problems (2) and (7) that are associated with the value functions $V(a, z_L, i)$ and $F(a, z_F, i)$. The indicator $I_V(a, z_L, i)$ takes the value of unity if $F(a, z_F, i) > V(a, z_L, i)$ and zero otherwise. Additionally, $c_V(a, z_L, i)$ and $c_F(a, z_F, i)$ induce the saving rules $s_V(a, z_L, i)$, $s_F(a, z_F, i)$ via Equations (3) and (8).

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 (11). The functions $k(a, z_F, i)$ and $h(a, z_F, i)$ govern flow output y and profits $\pi(a, z_F, i)$ via Equation (10) and the relationship $y = z_F k(a, z_F, i)^{\alpha} h(a, z_F, i)^{\beta}$.

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

$$\underbrace{\sum_{i\in\{B,W\}}\left(\int_{\underline{z}_L}^{\bar{z}_L}\int_{\underline{a}}^{\infty} a\, g_L(a,z_L,i)\, da\, dz_L + \int_{\underline{z}_F}^{\infty}\int_{\underline{a}}^{\infty} a\, g_F(a,z_F,i)\, da\, dz_F\right)}_{\text{aggregate net asset positions}} =$$

$$\underbrace{\sum_{i\in\{B,W\}}\int_{\underline{z}_F}^{\infty}\int_{\underline{a}}^{\infty} \mathrm{k}(a,z_F,i)\, g_F(a,z_F,i)\, da\, dz_F}_{\text{capital demand}}, \tag{18}$$

where $\underline{z}_L$ and $\bar{z}_L$ denote the lower and upper bounds for z_L.

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

$$\sum_{i\in\{B,W\}}\int_{\underline{z}_L}^{\bar{z}_L}\int_{\underline{a}}^{\infty}\left(1-\tau_L^i\right) z_L\, g_L(a,z_L,i)\, da\, dz_L = \sum_{i\in\{B,W\}}\int_{\underline{z}_F}^{\infty}\int_{\underline{a}}^{\infty}\mathrm{h}(a,z_F,i)\, g_F(a,z_F,i)\, da\, dz_F. \tag{19}$$

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

$$T(1-m_F) = \underbrace{t_\pi \Pi}_{\text{income from profit tax}} + \underbrace{t_w w \sum_{i\in\{B,W\}}\int_{\underline{z}_L}^{\bar{z}_L}\int_{\underline{a}}^{\infty} z_L\left(1-\tau_L^i\right) g_L(a,z_L,i)\, da\, dz_L}_{\text{income from labor income tax}} \tag{20}$$

$$\underbrace{+t_a(r-\delta)\sum_{i\in\{B,W\}}\left(\int_{\underline{z}_L}^{\bar{z}_L}\int_{0}^{\infty} a\, g_L(a,z_L,i)\, da\, dz_L + \int_{\underline{z}_F}^{\infty}\int_{0}^{\infty} a\, g_F(a,z_F,i)\, da\, dz_F\right)}_{\text{income from capital income tax}},$$

where Π denotes aggregate profits.[27]

6. Consistency - the population densities $g_L(a,z_L,i)$ and $g_F(a,z_F,i)$ have a total mass of unity and have their stationary distributions implied by the saving rules $s_V(a,z_L,i), s_F(a,z_F,i)$ and decision rule $I_V(a,z_L,i)$ and is consistent with the following coupled KFEs (time

[27] Profits are $\Pi = \sum_{i\in\{B,W\}}\int_{\underline{z}_F}^{\infty}\int_{\underline{a}}^{\infty}\pi(a,z_F,i)\, g_F(a,z_F,i)\, da dz_F$, where $\pi(a,z_F,i) = \mathrm{y}(a,z_F,i) - w\mathrm{h}(a,z_F,i) - r\mathrm{k}(a,z_F,i)$.

indices are added here to all equilibrium objects)

$$
\begin{aligned}
\frac{\partial}{\partial t} g_L(a,z_L,i,t) = & -\frac{\partial}{\partial a}\left[g_L(a,z_L,i,t)\ \mathrm{s}_V(a,z_L,i,t)\right] + A_{z_L}^{*} g_L(a,z_L,i,t) \\
& - \eta\, \mathrm{I}_V(a,z_L,i,t)\, g_L(a,z_L,i,t) + \lambda_D\, \mathrm{n}(z_L,i) \int_{\underline{z}_F}^{\infty} g_F(a,z_F,i,t)\, dz_F
\end{aligned}
\tag{21}
$$

$$
\begin{aligned}
\frac{\partial}{\partial t} g_F(a,z_F,i,t) = & -\frac{\partial}{\partial a}\left[g_F(a,z_F,i,t)\ \mathrm{s}_F(a,z_F,i,t)\right] + A_{z_F}^{*} g_F(a,z_F,i,t) \\
& - \lambda_D\, g_F(a,z_F,i,t) + \eta\, \tilde{I}_V\left(a,\psi^{-1}(z_F),i,t\right) \tilde{g}_L\left(a,\psi^{-1}(z_F),i,t\right),
\end{aligned}
\tag{22}
$$

where $A_{z_L}^{*}$ and $A_{z_F}^{*}$ denote the adjoint operator of the infinitesimal generators of the processes governing z_L and z_F. With slight abuse of notation, $\psi^{-1}(z_F)$ denotes the inverse of the mapping in Equation (4) such that it maps the entrant's productivity into the previous value of z_L, this inverse is only defined for $z_P \geq \Psi_0$, for values below $\underline{z}_F$, we let $\psi^{-1}(z_F) = 0$. For completeness, we also define $\tilde{I}_V\left(a,\psi^{-1}(z_F),i,t\right)$ and $\tilde{g}_L\left(a,\psi^{-1}(z_F),i,t\right)$ as the functions that take the values of $I_V\left(a,\psi^{-1}(z_F),i,t\right)$ and $g_L\left(a,\psi^{-1}(z_F),i,t\right)$ when $z_F \geq \underline{z}_F$ or when $z_P \geq \Psi_0$ and are otherwise equal to zero. $\mathrm{n}(z_L,i)$ denotes the stationary pdf of the process governing z_L for group i. The mass of entrepreneurs m_F is given by

$$
m_F = \sum_{i=\{B,W\}} \int_{\underline{z}_F}^{\infty} \int_{\underline{a}}^{\infty} g_F(a,z_F,i)\, da\, dz_F. \tag{23}
$$

The masses of each race integrate such that

$$
m^B = \int_{\underline{z}_F}^{\infty} \int_{\underline{a}}^{\infty} g_F(a,z_F,B)\, da\, dz_F + \int_{\underline{z}_L}^{\bar{z}_L} \int_{\underline{a}}^{\infty} g_L(a,z_L,B)\, da\, dz_L, \tag{24}
$$

$$
m^W = \int_{\underline{z}_F}^{\infty} \int_{\underline{a}}^{\infty} g_F(a,z_F,W)\, da\, dz_F + \int_{\underline{z}_L}^{\bar{z}_L} \int_{\underline{a}}^{\infty} g_L(a,z_L,W)\, da\, dz_L, \tag{25}
$$

where m^B, and m^W are exogenously given numbers such that $m^B + m^W = 1$.

Note that for the goods market to clear, the total output produced (given by Equation (33)) 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.

D 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 C.

The solution algorithm solves a system of three equations (18), (19), and (20), in the three unknowns, r , w, and T. The algorithm follows from the definition of recursive stationary equilibrium.

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_L, z_F are constant 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_L, 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 (2) and (7).

   This will allow us to obtain the ergodic stationary distributions $g_L(a, z_L, i)$ and $g_F(a, z_F, i)$, the policy functions $c_V(a, z_L, i), c_F(a, z_F, i)$ and $I_V(a, z_L, i)$, 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 (20) to compute the government income.

6. **Clear markets** Using the results of steps 3, 4, and 5 evaluate Equations (18), (19), and (20). 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 largest discount rate 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 0.5×10^{-2} 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 in percentage deviations of the aggregate supply. The government budget is normalized in such a way that it is expressed as a percentage deviation from the government's total tax revenue.

Grid for assets We use $n = 200$ 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

3.9×10^3 unconsumed annual median labor incomes. The asset vector $\bar{a}$ is set such that it has monotonically increasing increments as follows

$$\bar{a} = (a_{\max} - \underline{a}) \frac{(0, 1, \ldots, n-1)^5}{(n-1)^5} + \underline{a}. \tag{26}$$

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 (18), (19), and (20) in 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

$$\bar{t} = t_{\max} \frac{(0, 1, \ldots, n_t - 1)^3}{(n_t - 1)^3}. \tag{27}$$

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

E 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 (13) and (14)

$$h(a, z_F, i) = \left(\left(1 - \tau_y{}^i\right) z_F\right)^{\frac{1}{1-\alpha-\beta}} \left(\frac{\alpha}{r\left(1 + \tau_k(a, z_F, i)\right)}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{1-\alpha}{1-\alpha-\beta}}, \tag{28}$$

$$k(a, z_F, i) = \left(\left(1 - \tau_y{}^i\right) z_F\right)^{\frac{1}{1-\alpha-\beta}} \left(\frac{\alpha}{r\left(1 + \tau_k(a, z_F, i)\right)}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}}, \tag{29}$$

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

$$\mathrm{y}(a,z_F,i) = \left[z_F \frac{\left(1-\tau_y{}^{i}\right)^{\alpha+\beta}}{\left(1+\tau_k(a,z_F,i)\right)^{\alpha}}\right]^{\frac{1}{1-\alpha-\beta}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}}. \tag{30}$$

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

$$K = \left(\frac{\alpha}{r}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}} \sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty}\int_{\underline{a}}^{\infty} \left[z_F \frac{\left(1-\tau_y{}^{i}\right)}{\left(1+\tau_k(a,z_F,i)\right)^{(1-\beta)}}\right]^{\frac{1}{1-\alpha-\beta}} g_F(a,z_F,i)\;\; da dz_F\;, \tag{31}$$

$$Z_L = \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{1-\alpha}{1-\alpha-\beta}} \sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty}\int_{\underline{a}}^{\infty} \left[z_F \frac{\left(1-\tau_y{}^{i}\right)}{\left(1+\tau_k(a,z_F,i)\right)^{\alpha}}\right]^{\frac{1}{1-\alpha-\beta}} g_F(a,z_F,i)\;\; da dz_F\;, \tag{32}$$

$$Y = \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}} \left[\sum_{i\in\{B,W\}} \int_{\underline{z_F}}^{\infty}\int_{\underline{a}}^{\infty} \left[z_F \frac{\left(1-\tau_y{}^{i}\right)^{\alpha+\beta}}{\left(1+\tau_k(a,z_F,i)\right)^{\alpha}}\right]^{\frac{1}{1-\alpha-\beta}} g_F(a,z_F,i)\;\; da dz_F\right]. \tag{33}$$

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

$$Y = K^{\alpha} Z_L{}^{\beta}\,\widetilde{TFP}, \tag{34}$$

where $\widetilde{TFP}$ is given by

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

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

$$Y = K^{\alpha} Z_L{}^{\beta} m_F{}^{1-\alpha-\beta}\, TFP, \tag{35}$$

with TFP given by

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

Last, we wish to separate the notions of labor quality and labor quantity. We can state effective labor input in production as $Z_L = \mathbb{E}\left(z_L\left(1-\tau_L{}^i\right)\right)N$, where N is the mass of workers, which is incidentally $1-m_F$, and $\mathbb{E}(z_L)$ is their average quality allowing for the distortions. Observe that average labor quality relates to the distortions as follows

$$E\left(z_L\left(1-\tau_L{}^i\right)\right) = \sum_{i\in\{B,W\}}\underbrace{\frac{\int_{\underline{z}_L}^{\bar{z}_L}\int_{\underline{a}}^{\infty} g_L(a,z_L,i)dadz_L}{1-m_F}}_{\text{share of workers belonging to group } i}\times\underbrace{\frac{\int_{\underline{z}_L}^{\bar{z}_L}\int_{\underline{a}}^{\infty} z_L g_L(a,z_L,i)dadz_L}{\int_{\underline{z}_L}^{\bar{z}_L}\int_{\underline{a}}^{\infty} g_L(a,z_L,i)dadz_L}}_{\text{average labor productivity in group } i}\times\underbrace{\left(1-\tau_L{}^i\right)}_{\text{distortion on group } i}. \tag{36}$$

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, ex-post, the distortions drive households that differ only in race to be exposed to different shocks and make different entrepreneurship decisions, leading to a steady state where differences in race are predictive of outcomes. Therefore, the aggregate production function in this economy can be represented as

$$Y = K^{\alpha}N^{\beta}m_F{}^{1-\alpha-\beta}\left(\mathbb{E}\left(z_L\left(1-\tau_L{}^i\right)\right)\right)^{\beta}TFP. \tag{37}$$

After taking logs, we have

$$\log Y = \underbrace{\alpha\log K + \beta\log N + (1-\alpha-\beta)\log m_F}_{\text{factor quantities}} + \underbrace{\beta\log\left(\mathbb{E}\left(z_L\left(1-\tau_L{}^i\right)\right)\right)}_{\text{labor efficiency}} + \underbrace{\log\left(TFP\right)}_{\text{aggregate productivity}} \tag{38}$$