On the Black-White Gaps in Labor Supply and Earnings over the Lifecycle in the US*

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Abstract

In the US economy, Black men, on average, receive lower wages than White men, and the difference increases over the working life. The employment rate and the number of hours worked are also lower for Blacks, but the gap is nearly constant. Together these facts suggest that on-the-job human capital accumulation might explain the diverging wages. However, the wage gap and its evolution over the lifecycle cannot be explained by differences in accumulated experience or educational attainment for the cohort we analyze. Instead, the combination of experience and test scores measured at ages 17-22 accounts for the wage gap and its growth. We propose an on-the-job human capital accumulation model with heterogeneity in the initial human capital endowment and the lifelong ability to accumulate human capital, and endogenous labor supply at the extensive and intensive margins to explain the evolution of the Black-White wage gap over the lifecycle. We discipline the distribution of the ability to accumulate human capital using the power of test scores to predict earnings growth in the data. We find that if the pre-market distributions were the same for Blacks and Whites, the racial gap in hourly earnings would be closed by 84%, with the remaining gap opening throughout life due to higher labor supply amongst White men. That is, the unequal conditions with which men in the two groups enter the labor market are likely to be the key determinant of the differences over the lifecycle.

Keywords— Inequality, Lifecycle; Racial gap; Human capital; Wage gap; Employment gap; Labor supply decision.

JEL Codes— J15, J24, J31, J64.

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1 Introduction

Inequality is a major concern globally and in the US, more specifically.[1] Today, more than 50 years after the civil rights movement, the median Black-White earnings gap is as large as in 1950 (Bayer and Charles 2018). At the same time, the median net wealth of White households is almost seven times greater than that of Black households, and labor income differences alone account for nearly half of the racial wealth gap (Ashman and Neumuller 2020).

A fact that receives less attention is that the racial gap in earnings widens over the lifecycle. Moreover, a racial gap exists not only for earnings but also for employment and hours worked among the employed.[2] In the National Longitudinal Survey of Youth 1979 (NLSY), at age 25, when most people have completed their education and are already active in the labor market, the Black-White gap in annual mean earnings conditional on working is \$11,433.[3] In other words, Black men earn 26% less than their White counterparts. By age 45, the gap is about \$37,317 or 40%. On the other hand, in terms of the employment rate, at age 25, Black men have a 14 percentage points lower employment rate than Whites, while at age 45, this difference is 13 percentage points. For hours worked per week among the employed, the racial gap at ages 25 and 45 is around 3.6 and 2 hours, or 8% and 4%, respectively.

The fact that the racial gap in earnings increases with age, while the gap in employment and hours worked is comparably flat, suggests that the accumulation of human capital on the job can be a crucial ingredient in understanding the differences between Black and White men in the labor market. However, the Black-White gap in earnings growth can only be partially explained by the difference in accumulated experience between the two groups. Instead, the racial differential in earnings growth virtually disappears when we jointly control for accumulated experience and results in the Armed Services Qualification Test (AFQT), a test meant to measure cognitive ability, from the NLSY.[4] Moreover, a major concern in this context is the endogenous determination of earnings and experience, i.e., the stock of accumulated labor supply decisions over the lifecycle.

We propose an on-the-job human capital accumulation model with endogenous labor supply at the extensive and intensive margins. The model features a learning-by-doing human capital

[1] For instance, an opinion poll by the Pew Research Center documents that nearly half of Americans consider inequality a 'very big problem', while concerns in Europe tend to be even higher. See Wike (2013).

[2] Ritter and Taylor (2011) study the Black-White unemployment rate gap and provide a statistical discrimination theory to explain the gap. Antecol and Bedard (2004) highlight the importance of experience in accounting for the Black-White earnings gap. Bowlus and Eckstein (2002), Decreuse and Tarasonis (2021), and Borowczyk-Martins, Bradley, and Tarasonis (2017) study equilibrium search models with discrimination in which wages and unemployment rates are endogenous. Butler and Heckman (1977) put forth the idea that governmental transfer programs are more likely to reduce the incentives to work for low-skilled workers. Holzer, Offner, and Sorensen (2005) attribute much of the decline in employment of low-educated Black men to the increase in incarceration and the stricter enforcement of child support. Another explanation for racial differences in job-finding rates is network effects (Holzer 1987, Tenev 2018).

[3] Throughout the paper, we use wage, earnings, and income interchangeably. Empirically, we focus on labor earnings, defined as wages and salary, while abstracting from capital income. All gaps are computed from our main sample, described in Section 2. All monetary values are expressed in 2018 US dollars.

[4] See Borghans, Golsteyn, Heckman, and Humphries (2016) for a discussion on what achievement tests, like the AFQT, measure.

accumulation technology with heterogeneity in the ability to accumulate human capital and the value of not working.[5] Agents enter the model at age 23 with an initial level of human capital, which evolves endogenously over the lifecycle, and a constant ability to acquire new human capital. We refer to the initial conditions with which agents enter the model/labor market as pre-market factors. There is heterogeneity in these pre-market factors both within and between racial groups. Each period, agents choose whether to be employed or not and how many hours to work if employed. The labor supply decision crucially depends on two factors. The first is the relative payoff of earning income in the current period versus enjoying the value of not working. Secondly, work also has a dynamic payoff in the form of higher human capital in the future. Differences in work and earnings may arise from differences in the characteristics with which agents enter the model or because of differences in the preference parameters that control the trade-off between work and leisure.

We calibrate the model in two stages. In the first stage, we rank men of both racial groups into deciles according to AFQT scores from the data and let the ability to acquire new human capital on the job vary on the relative ranks. We proxy initial human capital using wages at age 23 in the data and target lifecycle earnings profiles for each decile of AFQT scores, irrespective of race, to infer ability levels and the parameters governing the human capital production function. In the second stage, we calibrate the preference parameters of the extensive and intensive labor market decisions to match employment and hours worked profiles by race and AFQT ranks. Despite its parsimonious structure, the model can replicate the main patterns of earnings, employment, and hours worked for Blacks and Whites that we observe in the data. We then use the calibrated model to run several experiments to understand what drives the racial disparities we see in the data.

We show that equalizing pre-market factors without allowing for endogenous responses to labor supply reduces the racial gap in total earnings from 46% to 25%. When allowing labor supply to respond to the counterfactually assigned pre-market factors, the gap reduces further to 15%. Despite the differences in hourly wages dropping by 84%, the employment gap only halves.

On the other hand, if Black men had the same preference parameters as Whites, i.e., the differences in labor supply conditional on AFQT/ability level would disappear, the gap in hourly wages would only decrease by 7%. The implications of the results from our experiments are twofold. First, the racial gap in earnings and its increase over the lifecycle are crucially related to pre-market differences, i.e., the initial levels of human capital and the ability to accumulate it. Therefore, the most relevant source of racial inequality in labor market outcomes is likely to stem from factors such as neighborhood effects, family endowments, resources and investments, schooling quality, or access to further education. Second, conditional on these differences in pre-market factors, the labor supply gap is nonetheless of quantitative importance. While we model these frictions as preference parameters, they could reflect discrimination, given that the literature has documented the existence of discrimination against Blacks in the labor market. We also do not account for the fact that racial discrimination in the labor market reduces the

[5] Our framework features heterogeneity in pre-market factors as in Huggett, Ventura, and Yaron (2006, 2011), a fixed cost of working similar to Erosa, Fuster, and Restuccia (2016b), and a human capital accumulation function resembling the learning-by-doing case in Blandin (2018).

incentives to acquire skills before entering the labor market (Phelps 1972).

There is an extensive literature that studies racial differences in the labor market.[6] One of the primary pursuits of the literature is to establish how much of the racial differences observed in the labor market are due to racial discrimination and how much is generated by the fact that Blacks and Whites enter the labor market with different distributions of skills. Using reduced-form approaches, Neal and Johnson (1996), Johnson and Neal (1998), and Luo (2021) show that AFQT scores account for a significant portion of the differences in earnings among young Black and White men. Similarly, Carneiro, Heckman, and Masterov (2005a,b) point toward how the gaps in skills with which young men enter the labor market are formed early in life.

We contribute to the literature looking at racial gaps by adding a dynamic perspective to understand not only how pre-market factors can explain levels but also the widening of racial earnings gaps over the lifecycle. Importantly, we combine heterogeneity in the ability to acquire human capital with the idea that employment is necessary to gain experience, which generates future earnings growth.[7] The crucial question we address is how existing differences when entering the labor market affect lifecycle earnings and labor-supply profiles.[8] We highlight the interplay between pre-market conditions, labor supply, and the dynamic accumulation of human capital throughout the lifecycle.[9]

Our results align with the literature that discusses the importance of pre-market factors for the wage gap. However, they should not be interpreted as evidence that discrimination may not be relevant to Black-White disparities in the labor market.[10] Given that there is evidence

[6] See Altonji and Blank (1999), Pager (2007), Charles and Guryan (2011), and Lang and Lehmann (2012) for reviews of this literature. Bayer and Charles (2018) provide an account of the evolution of the racial earnings gaps over the last decades.

[7] Our paper also relates to the literature on how career interruptions determine the differences between men and women in the labor market. See, for example, Attanasio, Low, and Sánchez-Marcos (2008), Guner, Kaygusuz, and Ventura (2011), Low and Sánchez-Marcos (2015), or Adda, Dustmann, and Stevens (2017). Another related article about the gender gap is Lazear and Rosen (1990), which discusses the possibility that the gender gap arises due to differences in promotions using a job-ladder model.

[8] Urzúa (2008) estimates a model to explain how unobserved cognitive and non-cognitive abilities generate the observed differences in educational choices and labor market outcomes at the beginning of Black and White men's working lives. Lang and Manove (2011) use a discrimination model to explain why Black men obtain more education than their White counterparts, conditional on cognitive ability measures. Assuming higher uncertainty about Black men's productivity, a form of statistical discrimination, Oettinger (1996) shows that the earnings differences between Blacks and Whites over the lifecycle widen due to Black men's lower job mobility, which prevents them from reaping the associated wage gains.

[9] Wu (2007) estimates a structural model based on the Ben-Porath (1967) structure of human capital accumulation to address the gender and race gaps over the lifecycle while taking labor supply as given. In contrast, we endogenize labor supply at the extensive and intensive margins to account for and explain the differences in accumulated experience.

[10] It is important to note that labor market discrimination could disincentivize acquiring education and human capital before entering the labor market. There is an extensive literature dedicated to the detection of discrimination. One strand of this literature uses indirect inference to measure discrimination. Eckstein and Wolpin (1999) explain the challenges of doing so. Altonji and Pierret (2001) propose a methodology to test for employer learning and statistical discrimination but find no evidence of racial discrimination. Charles and Guryan (2008) test Becker's employer prejudice theory and find that one-fourth of the Black-White wage gap is explained by prejudice. Fryer, Pager, and Spenkuch (2013) present evidence consistent with employers statistically discriminating by race while learning about actual productivity over time. Field experiments are also used to document the existence of racial discrimination in the labor market. Bertrand and Mullainathan (2004), Pager, Bonikowski, and Western (2009), and Nunley, Pugh, Romero, and Seals (2015) use different interventions to measure the extent of discrimination at different stages of

of racial discrimination in the labor market, it is likely that there also exists discrimination in many other aspects of life that are crucial to determining the set of conditions with which Black men enter the labor market.

The paper proceeds as follows. In Section 2, we present the data and empirical facts. In Section 3, we specify the model with on-the-job human capital accumulation and labor supply decisions and discuss the chosen parameters and model fit. In Section 4, we conduct counterfactual experiments to understand the drivers of the racial gaps. Section 5 summarizes our main findings and discusses future research venues.

2 The Data

In order to be able to follow individuals over their lifecycles, we rely on the National Longitudinal Survey of Youth 1979 (NLSY). The NLSY started in 1979 with 12,686 men and women born between 1957-64. Therefore, individuals are aged 14-22 at the beginning of the panel. Individuals were interviewed annually from 1979-1994 and biennially after that. We restrict the sample to non-Hispanic US-born Black and White men aged 23-54 years who are not in full-time education. Our sample comprises 66,164 observations across 2,451 men, of which 308 are Black and 2,143 are White. We use the NLSY sampling weights to correct for oversampling of certain groups.

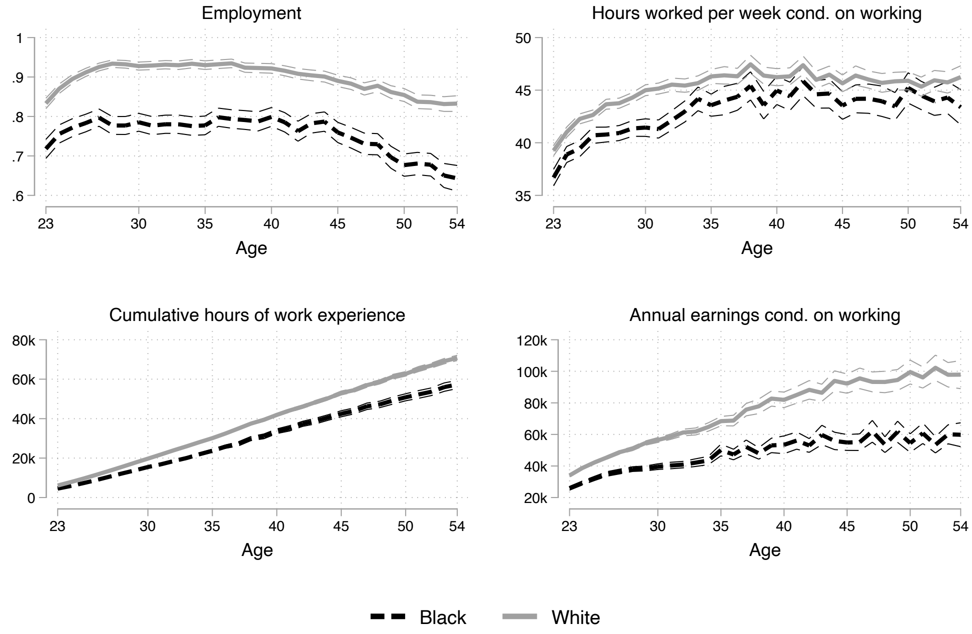
Using the NLSY, we reconstruct weekly work histories, including hours worked. We define two labor market statuses: employed and non-employed. Therefore, the non-employed comprise the unemployed and those out of the labor force. Similarly to Blandin (2018), we define as employed any individual working at least 500 hours and 25 weeks in a given calendar year. All others are considered non-employed. We define hours worked as the sum of hours worked across all weeks, which we construct using the work history files of the NLSY. Labor market earnings are wage and salary income earned from all jobs over a year. Finally, we compute hourly wages as total annual earnings divided by yearly hours.

In the top-left panel of Figure 1, we see that the employment gap between Black and White men is around 15 percentage points at the beginning of the lifecycle and remains relatively constant for most of the working life. In the top-right quadrant, we see a similar pattern for hours worked conditional on employment. As a consequence of the constant gaps in both the extensive and intensive margins of labor supply, we see in the bottom-left quadrant that Black men accumulate less work experience throughout their lives. In the bottom-right quadrant, we see that the earnings gap conditional on working is relatively small at younger ages but increases steadily throughout the lifecycle.[11]

the job application process. Giulietti, Tonin, and Vlassopoulos (2019) use a similar setup to evaluate the responses that Blacks are given from state service providers such as local libraries.

[11]In Appendix Figure B.1, we show that the same pattern holds both for annual and log hourly labor income.

Figure 1: Employment, hours worked, cumulative experience, and annual earnings over the lifecycle by Black and White men.



Notes: The dashed black lines are labor market outcomes of Black men. The solid gray lines are labor market outcomes of White men. Annual earnings are expressed in 2018 US$. The thin lines are 95% confidence intervals.

The Role of Experience in the Black-White Gaps

It is helpful to focus first on the potential determinants of the growing earnings gap to assess the Black-White gaps in labor market outcomes that we observe in Figure 1. The constant gaps in labor supply mechanically generate a growing gap in accumulated experience. Given that experience is a determinant of productivity, it is natural to inquire whether the increasing difference in accumulated experience between Blacks and Whites explains the growing gap in earnings.

We present two pieces of evidence indicating that experience alone cannot account for the gap in earnings. First, we apply the test for parallelism developed by Heckman, Lochner, and Todd (2006) on hourly and annual labor income. The idea is to perform non-parametric tests of whether the earnings-experience profiles are parallel across race groups. Let r represent the race of an individual. We test whether $E(y_i|x_i, r = White) - E(y_i|x_i, r = Black) = constant\ across\ x_i \in \{10, 20, 30\ years\}$. We select the experience levels at which the hypothesis is tested to be at least two bandwidths apart from the other experience levels so that the non-parametric estimates are independent of each other.[12] In Table 1, we show the differences between White and Black men in terms of hourly earnings (second column) and annual absolute earnings (third column) at 10, 20, and 30 years of experience. The gaps appear to be widening, and the non-parametric test confirms that the slopes are unlikely to be parallel.

[12]As in Heckman et al. (2006), we choose the bandwidth to be five years and a quartic kernel for the weights. For the test details, we refer to Appendix C in Heckman et al. (2006).

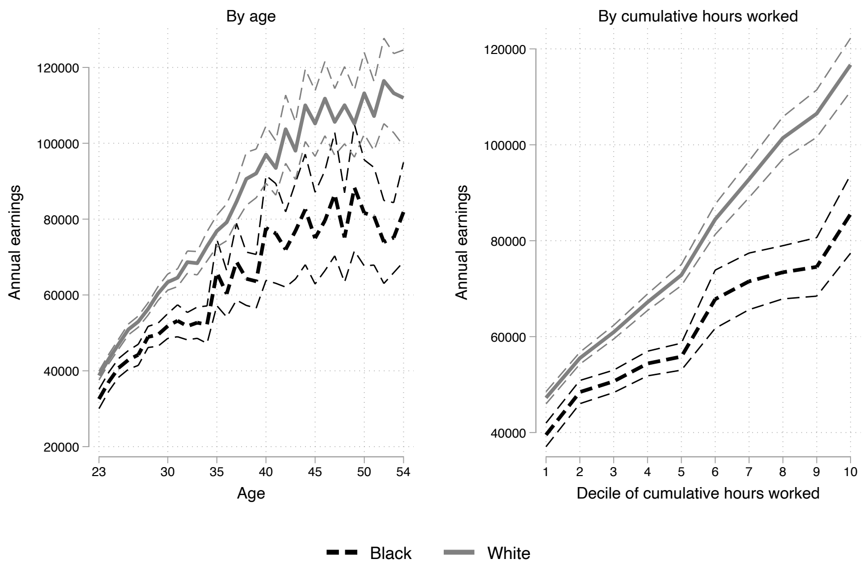
Table 1: Test of parallelism in earnings experience profiles between Black and White men.

	Difference White - Black	
Experience in years	Hourly wage	Annual earnings
10	5.196	13,883
20	10.241	27,008
30	12.894	31,686
p-value	<0.001	<0.001

Notes: The test statistics for parallelism are computed following Appendix C in Heckman et al. (2006). Annual earnings are expressed in 2018 US$ and experience is measured in weeks worked.

Second, in Figure 2, we show that the gap in earnings is also increasing when we compare Blacks and Whites that never experience a non-employment spell. In the left panel, we show that mean annual earnings diverge by age and in the right panel by decile of cumulative hours worked even when we restrict our sample to men employed continuously since age 23. In Appendix Figures B.3 and B.4, we show that the gap in average annual earnings also widens within every educational group, except for those with less than high school education, for whom the sample size is small (and wage growth generally is benign). Therefore, the widening gap in Figure 2 cannot be attributed solely to differences in the education of Black and White men.

Figure 2: Mean annual earnings over the lifecycle for Black and White men that do not experience any non-employment spell.



Notes: The sample is restricted to individuals for whom we do not observe a single non-employment spell after age 23. The x-axis on the left panel represents age, while it represents the decile of cumulative hours worked between ages 23 and 54 on the right panel. The dashed black line represents the mean earnings for Black men. The solid gray line represents the mean earnings for White men. Annual earnings are expressed in 2018 US$. The thin lines are 95% confidence intervals.

Are Differences in AFQT Scores a Candidate to Explain Black-White Gaps?

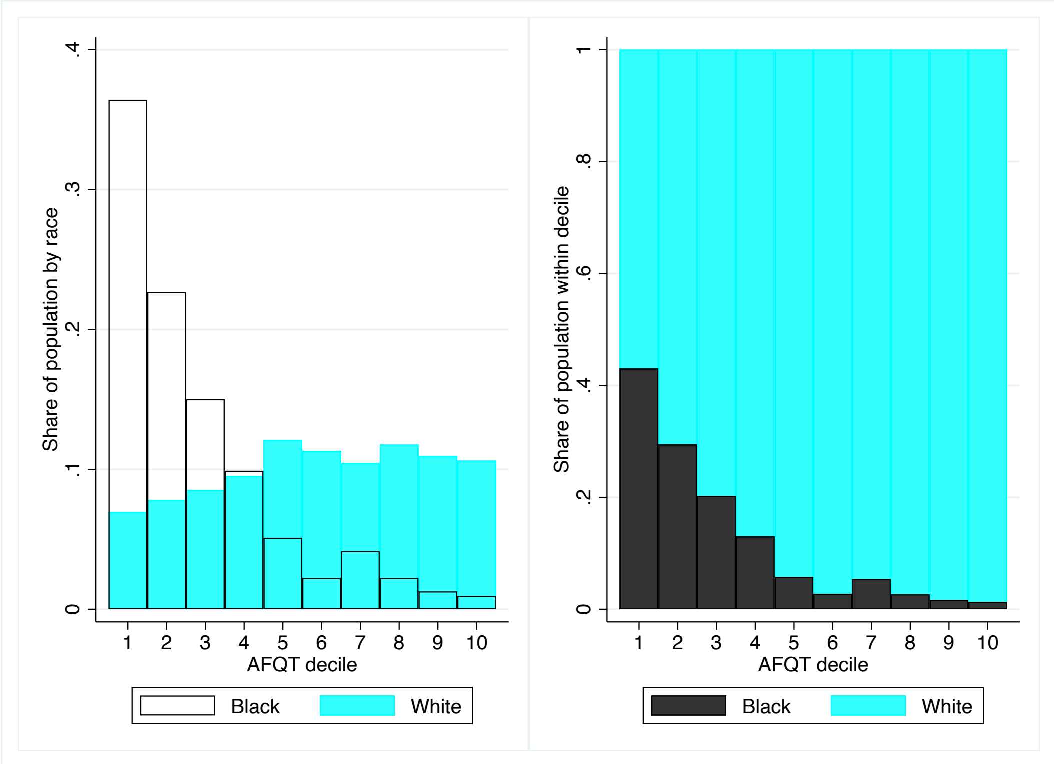
We have established that the differences in accumulated experience and education degrees cannot account for the Black-White gaps in earnings and earnings growth. Now, we turn our attention to another candidate to account for the differences in labor market outcomes between the two groups. In 1980, NLSY respondents completed the Armed Forces Qualification Test (AFQT), a collection of cognitive tests commonly used in the literature to approximate cognitive ability.[13] Neal and Johnson (1996) show that controlling for AFQT scores in a wage regression accounts for most of the Black-White gap in hourly wages observed for young adults in the cross-section. In what follows, we classify men into deciles according to AFQT scores and illustrate the differences between race groups. Using deciles has the advantage of not imposing strong assumptions about absolute test scores that have no natural scale and location. Then, we assess whether the difference in AFQT scores can help account for the Black-White gaps in earnings and earnings growth.

Figure 3 presents the distribution of AFQT deciles for Black and White men. In the left panel, each race sums to one, giving an idea of the within-race distribution of AFQT scores. On the right side, each decile sums to one across both races, exhibiting the relative share of each race group within each decile. We can see that White men tend to have higher AFQT scores while Black men are overrepresented in the lower deciles of the AFQT score distribution. In Appendix Figure B.5, we see that this is not solely driven by the fact that average educational attainment amongst Black men is lower, as the same pattern holds qualitatively within groups of similar educational attainment.[14]

[13]See, for instance, Cawley, Conneely, Heckman, and Vytlacil (1997) for an extensive discussion. Individuals take ten tests split into science, arithmetic, word knowledge, paragraph comprehension, numerical operations, coding speed, auto and shop knowledge, mathematics knowledge, mechanical comprehension, and knowledge of electricity. The AFQT score is based on four of the ten tests, i.e., arithmetic reasoning, mathematics knowledge, word knowledge, and paragraph comprehension. Given that the tests are administered at different ages to the respondents, we correct for this fact by using the methodology developed by Altonji, Bharadwaj, and Lange (2012).

[14]The education levels are based on the highest level of education achieved throughout life. The distributions in Appendix Figures B.5 and B.6 rely on the assumption that cognitive abilities are not directly affected by educational attainment at very late stages since some surveyed men have not achieved their highest level of education at the time they took the test.

Figure 3: Distribution of AFQT deciles by race.



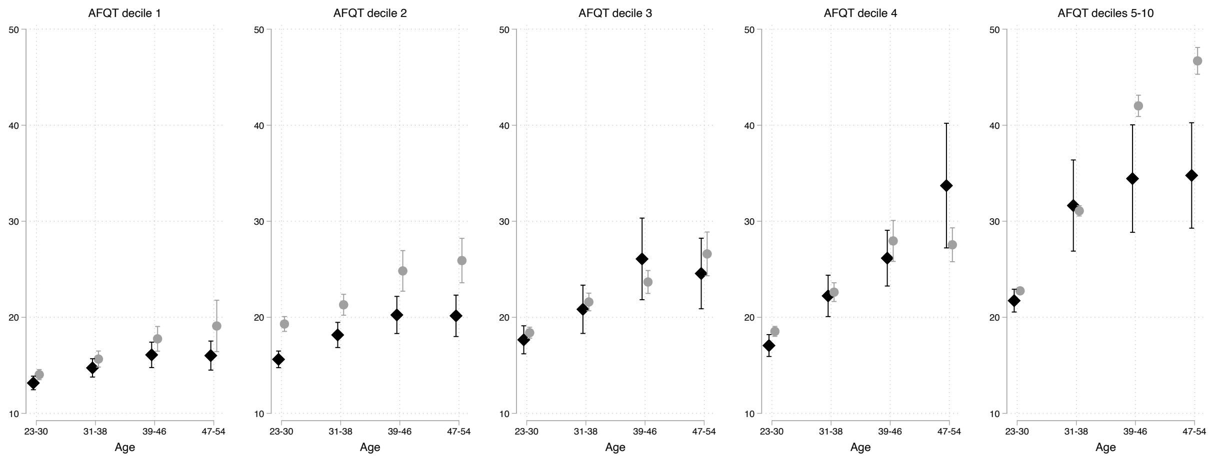
Notes: AFQT deciles are computed across both Black and White men. In the left panel, each race sums to one indicating the overall distribution for each race. In the right panel, each decile sums to one across both races indicating the racial distribution within each decile.

In Figure 4, we plot hourly earnings for Black and White men over the lifecycle within each of the bottom four AFQT deciles and deciles 5-10 together.[15] We can see that wage levels and growth increase with AFQT scores. Within all but the second and top deciles, the level and growth of hourly earnings are similar between race groups. We also see a divergence later in the lifecycle in the top deciles. This is because Black men are relatively more likely to be in the fifth and sixth deciles and consequently experience lower wage growth. Only within the second decile do we see hourly wages of White men that are significantly higher than for Black men, which could indicate the presence of wage discrimination amongst this subgroup.[16]

[15]For higher deciles, the sample of Black men is very small, making the plot too noisy.

[16]Similar patterns persist when restricting the sample to continuously employed Black and White men in Appendix Figure B.7.

Figure 4: Hourly earnings conditional on working by race for AFQT deciles over the lifecycle.



Notes: Hourly earnings in 2018 US$ conditional on working. Black diamonds represent the mean of Black men. Gray dots represent the mean of White men. Deciles 5th to 10th are aggregated due to sample sizes. The thin lines are 95% confidence intervals.

In Table 2, we regress hourly earnings on race, experience, and the interaction of race and experience for the first to the fifth AFQT deciles. The estimated coefficients indicate that the dummy for Blacks is insignificant for AFQT deciles 1-5, which includes 90% of Black men in the whole sample. That is, in the bottom half of the skill distribution, AFQT scores and experience can largely account for the Black-White gaps in hourly wages. Only for the second AFQT decile do we find evidence for differential returns to work experience, with the return to one year of work experience appearing to be 40% lower for Black men.[17] In Appendix Figures B.8 and B.9, we provide further evidence for the correlation between wage levels, returns to experience, and AFQT scores. We also show that this relationship is similar for AFQT deciles 1-5 within race groups.

[17]In Appendix Table B.1, we show the analogous results for deciles 6-10. The Black dummy becomes positive and significant for deciles 7, 8, and 10. However, in these deciles, the shares of Black men are very low. For some of the top AFQT deciles, we find that the returns to experience are smaller for Black men. However, the inferences are usually based on less than 30 observations within these deciles.

Table 2: Regressing hourly earnings conditional on working on race and cumulative labor market experience for AFQT deciles 1-5.

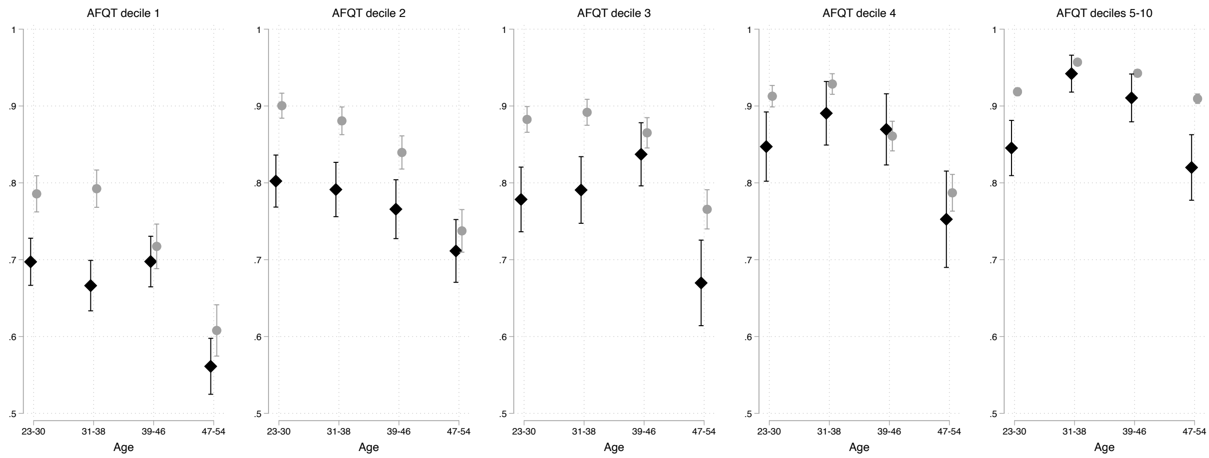
Deciles 1-5	(1)	(2)	(3)	(4)	(5)
Black dummy	0.3137	-0.2925	0.5165	-1.7880	1.6343
	(0.7078)	(1.0862)	(1.2054)	(1.4069)	(1.7063)
Work experience (years)	0.3011***	0.5203***	0.4080***	0.5078***	0.5690***
	(0.0450)	(0.0748)	(0.0451)	(0.0416)	(0.0506)
Work experience x Black	-0.0433	-0.2037**	-0.0221	0.1782	0.0114
	(0.0535)	(0.0868)	(0.0881)	(0.1181)	(0.1340)
Constant	14.4745***	11.6656***	17.5199***	15.8240***	18.0268***
	(0.9618)	(1.1841)	(0.8774)	(0.8553)	(0.8853)
Mean	15.64	22.03	21.76	23.17	25.83
Share Black	0.197	0.114	0.076	0.050	0.023
Observations	2873	3180	3088	3299	3926
R-squared	0.08	0.09	0.08	0.10	0.08
Region fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: AFQT deciles are indicated in the column headings. Work experience is measured by weeks worked and enters the regression in terms of years of work experience. The estimation technique is OLS. Robust standard errors in parenthesis. *p<0.1,**p<0.01,***p<0.01.

There are two important limitations to this regression analysis. First, experience, the accumulated stock of labor supply, is endogenous to the returns to work, i.e., wages, and, hence, is likely to be affected by AFQT scores. Second, the analysis in Table 2 does not spell out the mechanism through which higher AFQT scores are associated with both higher levels and earnings growth. Note that Neal and Johnson (1996) focus on the level of hourly wages at the beginning of the working life, while Figure 4 and Table B.1 (and Appendix Figures B.8 and B.9) indicate that AFQT scores are also crucial to explain earnings growth over the lifecycle.

In the next section, we set up a learning-by-doing human capital accumulation model with endogenous labor supply at the extensive and intensive margins to address these limitations. We allow for heterogeneity in the ability to accumulate human capital across agents. That is, given the same investment in human capital on the job, some agents increase their human capital more than others. Because earnings levels and growth are strongly correlated with AFQT scores, we assume that this heterogeneity in the ability to accumulate human capital is related to the variation in AFQT scores we observe in the data. Moreover, in Figure 5, we show that even within AFQT deciles, employment rates tend to be lower for Black men. Therefore, we require a model that can explain wage growth for different ability levels, while at the same time allowing for differences in employment rates across race groups.

Figure 5: Employment rates over the lifecycle by race and AFQT deciles.



Notes: Employment rates are the share (in %) of individuals employed within a race-AFQT decile group. Black diamonds represent the mean of Black men. Gray dots represent the mean of White men. Deciles 5th to 10th are aggregated due to sample sizes. The thin lines are 95% confidence intervals.

3 The Model

Utility-maximizing agents live for $j = 1, \ldots, J$ discrete periods. The value of being alive in period $J + 1$ is normalized to zero. Generally speaking, parameters associated with human capital accumulation are universal, while preference parameters are race specific and indexed by $r \in \{\text{Black, White}\}$.

Upon entering the model, each agent draws a realization of their initial level of human capital (h_1) and permanent ability level (a). Ability plays a crucial role in determining an agent's proficiency in accumulating human capital (h): low-ability agents accumulate less human capital per hour worked.

Each period, agents are endowed with one unit of time, which they can distribute between staying at home or working. The utility of working agents (u^W) is given by:

$$u^W(h, n) = \omega \cdot h \cdot n + \psi^r \cdot h \cdot \frac{(1-n)^{1-\gamma^r}}{1-\gamma^r},$$

where ω is the exogenous wage rate, h is the level of human capital, n is the fraction of available hours that the agent works, ψ^r is the weight of leisure in the utility function, and γ^r determines the curvature of the utility of leisure. We define the utility of staying at home (u^H_j) in terms of age j as:[18]

$$u^H_j(h, \kappa) = \frac{\psi^r}{1-\gamma^r} \cdot h^{\eta^r} \cdot e^{(\kappa_0^r + \kappa_1^r \cdot j + \kappa_2^r \cdot j^2 + \kappa)},$$
$$\kappa \sim N(0, 1).$$

where η^r determines the curvature, which could be interpreted as efficiency in the production of

[18]We calibrate the model to the data of one cohort; hence, age and time are equivalent.

stay-at-home utility. κ_0^r, κ_1^r, and κ_2^r are the age-dependent deterministic components, and κ is the realization of an i.i.d. shock with mean zero and a normalized standard deviation equal to 1 drawn every period. We use a polynomial of degree two in age to replicate the shape of the employment rate we observe in the data. The fact that the utility of staying at home depends on age can be interpreted as proxying factors that affect labor supply and change over the lifecycle, such as household composition, health, or networks.

We express the problem solved by the agents in recursive form and indicate any value associated with the subsequent period by marking it with a prime. Let us denote the value of staying at home as $H_j(h, \kappa; a)$, the value of working as $W_j(h, \kappa; a)$, and the decision to work or stay at home as:

$$V_j(h, \kappa; a) = \max\{W_j(h, \kappa; a), H_j(h, \kappa; a)\}.$$

The value of staying at home is given by:

$$\begin{aligned} H_j(h, \kappa; a) = \quad & u_j^H(h, \kappa) + \beta \mathbb{E}_{\kappa'} V_{j+1}(h', \kappa'; a), \\ \text{s.t.} \quad & h' = (1-\delta)h, \end{aligned}$$

where β is the discount factor. The value of working is given by:

$$\begin{aligned} W_j(h, \kappa; a) = \max_{h,n} \quad & u^W(h, n) + \beta \mathbb{E}_{\kappa'} V_{j+1}(h', \kappa'; a), \\ \text{s.t.} \quad & h' = (1-\delta)h + an^{\phi}, \\ & 0 \leq n \leq 1. \end{aligned} \tag{1}$$

The function h' defines how human capital evolves over the lifecycle. The parameter ϕ defines the curvature of human capital next period with respect to time spent working. We assume that human capital depreciates at a constant rate δ. We model human capital accumulation as a learning-by-doing technology. The labor supply decision trades off less leisure today versus more income today and higher human capital in the future. The following section describes how we set race-specific and universal model parameters. Appendix Section A describes the algorithm we use to solve the model.

3.1 Model Parameterization

A model period is one year, and the lifespan stretches from age 23 to 54, i.e., 32 years. The discount rate $\beta = \frac{1}{1+i}$ is defined as a function of the interest rate (i), which is set to 4%. The time an individual has available each period is normalized to one and can be interpreted as 5,824 hours (16 hours per day for 52 weeks). The wage rate ω is also normalized to one.

We parameterize the model in two stages. In the first stage, we take labor supply from the data as given. Then we determine pre-market factors and the human capital production function by targeting lifecycle wage profiles by AFQT deciles independent of race. In the second stage, we calibrate the preference parameters governing labor supply decisions by targeting employment and hours worked profiles by race and AFQT deciles over the lifecycle.

First-Stage Calibration

We start by sorting all men in our sample, irrespective of race, into AFQT deciles. We treat AFQT as a proxy for the ability (a) to accumulate human capital (h), as described in Equation (1). We assume ability is influenced by pre-market factors and remains fixed throughout life. Hence, we need to calibrate ability levels $a \in \{a^1, \dots, a^{10}\}$ and initial levels of human capital $h_1 \in \{h_1^1, \dots, h_1^{10}\}$, a pair (a^d, h_1^d), for each AFQT decile $d \in \{1, \dots, 10\}$. We calibrate the ten initial levels h_1 outside the model by taking average wages at age 23 for each of the ten AFQT deciles. We report the levels of h_1 in Appendix Figure B.10 and separately by race in Appendix Figure B.11. It stands out that initial hourly wages are reasonably similar across AFQT deciles, except for the bottom decile, for which they are lower. When looking at initial wages by race, no clear patterns emerge in terms of differences across AFQT deciles.

Then, we use the human capital function of Equation (1) and the observed data on employment and hours worked to generate simulated wage profiles for each AFQT/ability decile. We settle for the parameters that minimize the squared distance between these simulated wage profiles and their counterpart in the data.[19]

Identification comes from the relationship between labor supply, wage growth, and the differences in this relationship across ability deciles. Consider two agents with equal ability but different wage growth. If the agent with higher wage growth works more hours, this helps pin down ϕ, the parameter governing how current labor supply translates into future wage growth. Next, picture two agents with equal ability, one working while the other is idle. This comparison helps discipline δ, the depreciation rate of human capital. Finally, consider two agents with equal labor supply but differential wage growth. If the agent with higher wage growth is in a higher AFQT decile, this comparison tells us about their differences in ability levels. These stylized comparisons exemplify how we identify the twelve free parameters in the first stage. In Table 3, we report the parameter values that minimize the squared distance between the simulated wage profiles and the data.

[19] We report the average squared distance for each AFQT/ability decile in Appendix Table B.2.

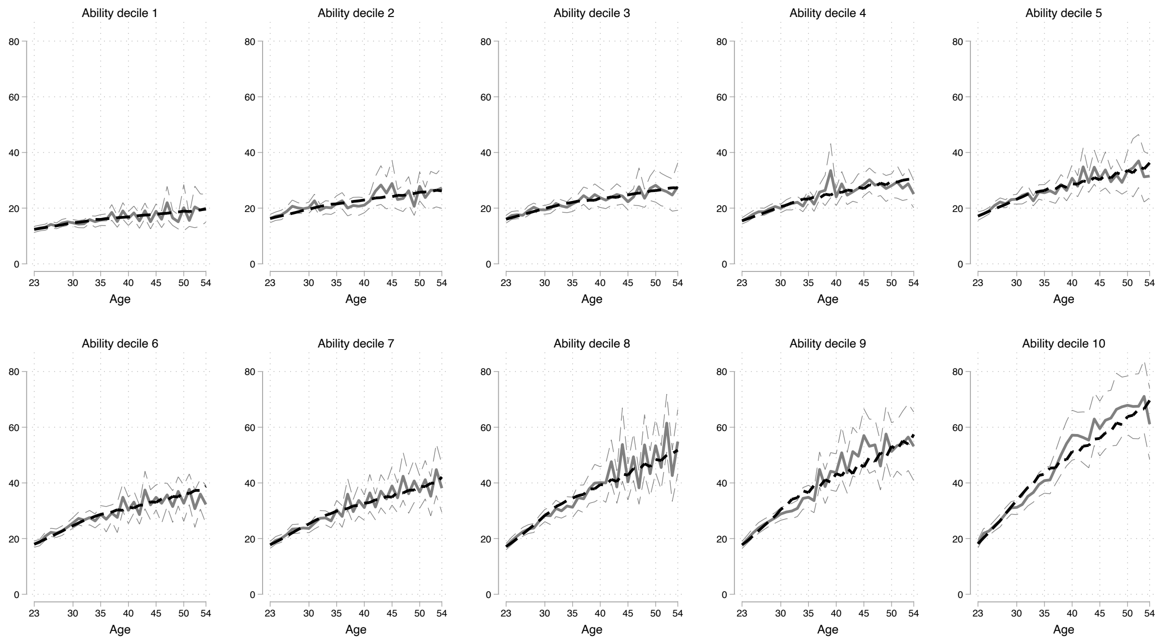
Table 3: First-stage parameters.

Curvature of $h'(h, n)$ with respect to n	ϕ	0.93
Human capital depreciation	δ	0.00014
Ability levels and initial human capital for AFQT deciles		
First	(a^1, h_0^1)	(0.037, 0.423)
Second	(a^2, h_0^2)	(0.047, 0.556)
Third	(a^3, h_0^3)	(0.052, 0.548)
Fourth	(a^4, h_0^4)	(0.07, 0.528)
Fifth	(a^5, h_0^5)	(0.073, 0.587)
Sixth	(a^6, h_0^6)	(0.089, 0.615)
Seventh	(a^7, h_0^7)	(0.1, 0.608)
Eighth	(a^8, h_0^8)	(0.165, 0.585)
Ninth	(a^9, h_0^9)	(0.172, 0.606)
Tenth	(a^{10}, h_0^{10})	(0.245, 0.62)

Notes: The parameters in this Table are obtained by minimizing the squared distance between the model-generated moments and their counterparts in the data using the TikTak algorithm (Arnoud, Guvenen, and Kleineberg 2019). For each AFQT decile, we target five moments that define an age profile: average wages at ages 24-31, 32-39, 40-47, and 48-54. The model-generated moments are computed using the human capital accumulation function described in Equation (1) and the individual observed hours worked in the data.

In Figure 6, we plot the average hourly wages simulated by the model (dashed black line) and the hourly wages observed in the data (solid gray line) for all AFQT/ability deciles. The simulated wage profiles generally lie within the 95% confidence intervals of the data throughout the lifecycle, suggesting a good fit. Figure 6 helps understand the parameters calibrated in Table 3. In the model, ability (a) is a crucial factor determining human capital growth given hours worked. The initial level of human capital (h_1) determines the intercept of the wage profile. Because the intercepts of the wage profiles observed in the data are similar across AFQT/ability deciles, except for the first decile, we estimate similar $\{h_1^d\}_{i=2}^{10}$ and a lower h_1^1. We find increasing levels of ability in AFQT deciles ($\{a^d\}_{i=1}^{10}$) because wage growth in the data is increasing by AFQT decile. The calibrated curvature of the human capital function (ϕ) and the depreciation rate (δ) also play a crucial role in determining the growth of wages over the lifecycle. We calibrate a relatively high value for the curvature (ϕ), which implies almost linear wage growth and a relatively low depreciation value. One reason for this pronounced growth potential is that hourly wages keep increasing, although there is a slight decline in hours worked in the data at around age 40.

Figure 6: Mean hourly wages over the lifecycle conditional on working by AFQT/ability decile (data vs. model).



Notes: Mean hourly wages are in 2018 US$. The solid gray line represents mean hourly wages in the data. The thin dashed gray lines are the 95% confidence intervals. The black dashed line represents mean hourly wages in the first stage of the model, i.e., with labor supply taken from the data.

Second-Stage Calibration

We calibrate the twelve race-specific (six for each race group) preference parameters in the second stage. Because prices are exogenous, we calibrate each race group separately. For each race group, we target lifecycle profiles of employment and hours worked. Ideally, we would target employment and hours worked for each AFQT/ability decile. However, the number of observations in the sample does not allow us to follow this approach. Instead, we create five AFQT/ability groupings: the first, second, third, and fourth AFQT deciles and the weighted averages of the fifth to tenth deciles.[20]

The age coefficients (κ_0, κ_1, and κ_2) and the curvature of human capital in the value of not working (η) are the critical determinants of the employment decision. Conditional on employment, the amount of hours worked is crucially affected by the weight of leisure (ψ) and the curvature of leisure in the utility function of employed individuals (γ).

For each race group, we take the human capital parameters from the first stage and estimate the six preference parameters (ψ, δ, κ_0, κ_1, κ_2, and η) by minimizing the squared distance between the simulated lifecycle profiles of employment and hours worked, and their counterparts in the data. We present the calibrated parameters in Table 4 and report the average squared

[20]Note that we simulate the model for all ten ability deciles. That is, the model produces labor supply predictions for all deciles. In Appendix Figures B.13 and B.14, we present the model's fit for the fifth to the tenth AFQT/ability deciles separately. Although the moments in these deciles are not targeted directly, the model can replicate the labor supply patterns of Whites, the group for which there are enough observations to compute reliable moments.

distance between the model and the data in Appendix Table B.3.

Table 4: Second-stage parameters.

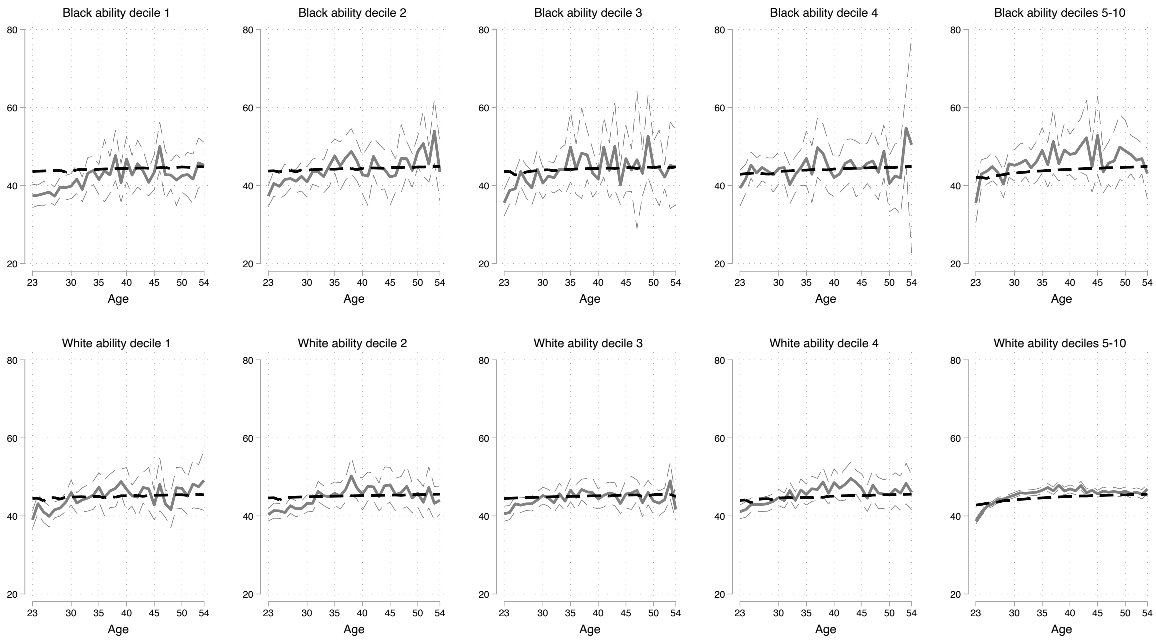
		Black	White
Weight of leisure	ψ	0.29	0.29
Curvature of leisure	γ	2.41	2.39
Intercept value of not working	κ_0	-0.21	0.45
Linear age coefficient value of not working	κ_1	0.01	-0.06
Quadratic age coefficient value of not working	κ_2	-0.002	-0.0
Curvature human capital in value of not working	η	2.14	2.31

Notes: The parameters are computed by minimizing the squared distance between the model-generated moments and their counterparts in the data using the TikTak algorithm (Arnoud et al. 2019) to minimize the squared distance between the model and data moments. We target five employment and hours worked lifecycle profiles for each race group. For each ability and race grouping, we compute the average employment rate and hours worked at ages 23-30, 31-38, 39-46, and 47-54 using both the data and the model simulation. The model-generated moments are created using the whole model structure described in Section 3 and the first-stage parameters of Table 3.

The calibrated value for the weight of leisure ψ is virtually the same for the two race groups, while the curvature of leisure η is very similar. This is because, as shown in Appendix Figure B.2, Blacks and Whites work similar hours when employed. Although the structure of our utility functions is not directly comparable to the standard ones, we calibrate a value for the curvature of leisure that aligns with the Frisch elasticity estimates in the literature.[21] We present the lifecycle profiles of hours worked from the model and the data in Figure 7.

[21] Our calibration assigns values to γ close to 2.4, which is in the range of the parameters used in the literature, typically around 2. See Chetty, Guren, Manoli, and Weber (2011), Keane and Rogerson (2012), Erosa, Fuster, and Kambourov (2016a), and Gottlieb, Onken, and Valladares-Esteban (2021).

Figure 7: Hours worked over the lifecycle conditional on employment for AFQT/ability groupings by race (data vs. model).



Notes: The solid gray lines are mean hours worked in the data. The thin dashed gray lines are the 95% confidence intervals. The dashed black line represents hours worked in the model. Ability levels 5-10 are aggregated due to sample sizes. The disaggregated plots for ability levels 5-10 are in Appendix Figure B.14.

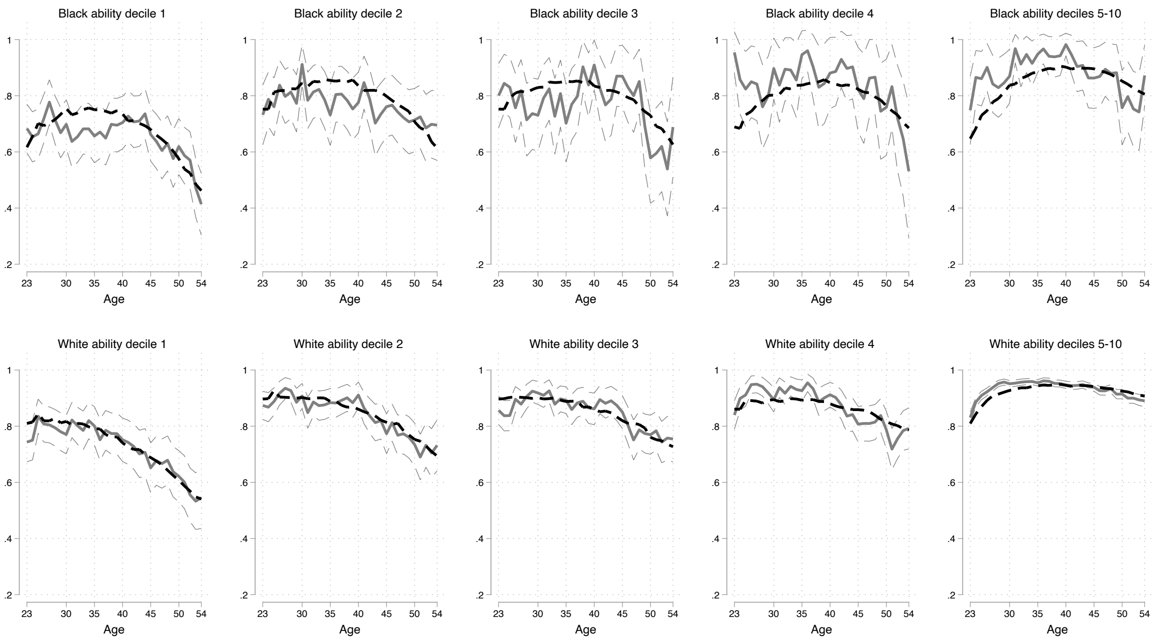
Three of the four parameters primarily determining the value of not working (κ_0, κ_1, κ_2) are identified by the age profiles in employment we see in the data. Namely, Whites have a higher employment rate across AFQT/ability deciles, and the employment rate of Blacks decreases faster over the lifecycle than that of Whites. The model achieves these patterns by assigning a lower utility of being at home to Whites at the beginning of the lifecycle. As age increases, the utility of being at home increases for both groups, but it increases faster for Whites. However, the initial difference is enough to create a wedge in human capital between the two groups such that more older Blacks find it optimal not to work than older Whites. This model feature highlights the crucial role of the first periods of the lifecycle in shaping labor market outcomes later in life. The parameter for the curvature of human capital in the home-stay utility (η) can be interpreted as a form of non-monetary opportunity cost of not working. We calibrate a similar value for Blacks and Whites, implying that the utility of staying at home increases with human capital at a similar pace for both groups. This parameter is identified by the different employment decisions related to variations in human capital levels that wage incentives cannot explain.

We present the employment lifecycle profiles generated by the model and those from the data in Figure 8. In Appendix Table B.3, we present the mean squared error between employment rate and hours worked in the data, and model moments for each ability grouping and race. In general, the model does better at replicating the model moments for White than for Black men, both for employment and hours worked.

Replicating the employment profiles by AFQT/ability groups is particularly challenging.

For Whites, the data indicates that employment decreases over the lifecycle for the lower AFQT/ability groups, while it presents a hump-shaped profile for the top AFQT/ability group. Despite its parsimonious structure, the model can replicate this pattern. Moreover, the model also reproduces that employment increases with AFQT/ability without ability entering the utility function directly.

Figure 8: Employment rates over the lifecycle by AFQT/ability decile (data vs. model).



Notes: Employment rates are the share (in %) of individuals employed within a race-ability group. The solid gray lines are the employment rate in the data. The thin dashed gray lines are the 95% confidence intervals. The dashed black line represents the employment rate in the model. Ability levels 5-10 are aggregated due to sample sizes. The disaggregated plots for ability levels 5-10 are in Appendix Figure B.13.

In Appendix Figure B.12, we present the model's fit for the mean yearly earnings for the AFQT/ability groupings by race, a set of moments we do not target. The model's yearly earnings combine endogenous hourly wages and endogenous labor supply decisions. We find that within each grouping, the model reasonably fits the lifecycle-earnings profiles, although it overpredicts yearly earnings for higher ability deciles, particularly for White men. In the model, individuals with high ability and human capital are highly incentivized to work. This re-enforcing mechanism generates a growing wedge between the data and the model for the top deciles at later ages. The result is that the model generates a higher correlation between hours worked and wages than we observe in the data for the top AFQT/ability deciles.

4 The Drivers of the Black-White Gaps

In this section, we assess the role of race-specific model fundamentals in determining the Black-White gaps over the lifecycle in earnings, employment, and hours. We start by using the benchmark calibration to compute the implied average gaps. Next, we simulate counterfactual

Black men while assigning them some parameters of White men and compute the counterfactual gaps with respect to benchmark Whites. Hence, each experiment reflects how the labor market outcomes of Black men would be if they had certain model characteristics of Whites.

Table 5 presents the results of the counterfactual experiments. The first row of Table 5 indicates the relative Black-White gap for each of the four outcomes of interest.[22] We compute the gap as

$$\text{gap}_Y = 1 - \frac{Y_{\text{Blacks}}}{Y_{\text{Whites}}}, \tag{2}$$

where Y is either the weighted mean of the employment rate (column 'Emp. rate'), the annual hours worked by the employed (column 'Hours'), the hourly wages of the employed (column 'Wage'), earnings of the employed (column 'Earnings employed'), or earnings of all agents (column 'Earnings all'). In the benchmark calibration, employed Black men earn, on average, 36.5% less than Whites. Overall, the earnings gap is 45.8%, the Black employment rate is 14.9% lower than that of Whites, employed Blacks work, on average, 1.4% fewer hours than their White counterparts, and the Black-White gap in hourly wages is 35.5%.

In the first experiment, row 'Utility home', counterfactual Blacks have the same four parameters that determine the utility of not working (κ_0, κ_1, κ_2, and η) as Whites. The gaps in this experiment do not vary much with respect to the benchmark, indicating that the differences in these four parameters play a minor role in determining the racial gaps. In the second experiment, row 'Utility employed', counterfactual Blacks have the two White parameters that shape the value of leisure when employed (ψ and γ). In this case, the gap in employment reduces to 8.7% while the gap in hours worked is reversed with counterfactual Blacks working marginally more than benchmark Whites. The overall gap in earnings reduces to 39.1%, and the earnings gap for the employed reduces to 33.2%. Notably, the gap in hourly wages barely changes. That is, the reduction in the earnings gap is primarily due to the decrease in the labor supply differences between counterfactual Blacks and benchmark Whites.

In the third experiment, named 'Utilities home & employed', counterfactual Blacks have the six preference parameters of Whites. In other words, conditional on AFQT/ability decile, the gap in employment and hours worked is zero. In this experiment, the gap in employment is almost halved, and the gap in hours is reversed. However, the gaps in earnings and hourly wages are not reduced substantially because counterfactual Blacks, on average, still enter the model with lower ability levels than benchmark Whites.

In the fifth row, 'Distribution (a, h_1)', we re-weight the sample of Blacks to have the same ability and initial human capital distribution as benchmark Whites. In this case, the hourly wage gap reduces from 35.5% to 5.7%, i.e., by 84%. This result indicates that the difference in the distribution of initial human capital and ability is the primary driver of the Black-White gap in hourly wages. The remaining difference in hourly wages, and the gap in overall earnings, is explained by the higher employment and hours worked of benchmark Whites. In the sixth row, we also equalize the initial distribution of human capital and ability, but this time we do not allow the labor supply of counterfactual Blacks to respond to the new incentives. Therefore, the gaps in employment and hours are identical to the benchmark. This experiment highlights

[22]To reflect composition effects in the counterfactual experiments, we report the racial gap on two measures of earnings: earnings of the employed and earnings of all agents.

the role of the endogenous response of accumulated experience to changes in the distribution of initial human capital and ability. Out of the total reduction in the wage gap accounted for by the initial distribution (84%), around 12% is due to the endogenous response of labor supply. In the case of total earnings, the gap remains to be 14.9%, so endogenous labor supply responses can explain about one-third of the closure of the gap in the previous experiment.

Table 5: How racial gaps respond to assigning characteristics of White men to Black men.

				Earnings	
	Emp. Rate	Hours	Wage	Employed	All
Benchmark gap	0.149	0.014	0.355	0.365	0.458
Experiments					
Utility home (κ_0, κ_1, κ_2, and η)	0.142	0.015	0.35	0.361	0.446
Utility employed (ψ and γ)	0.087	-0.005	0.334	0.332	0.391
Utilities home & employed	0.083	-0.004	0.331	0.33	0.383
Distribution (a, h_0)	0.08	0.021	0.057	0.076	0.153
Distrib. (a, h_0) - constant labor supply	0.149	0.014	0.094	0.107	0.251
Distribution & utility home	0.046	0.021	0.033	0.052	0.092
Distribution & utility employed	0.026	0.0	0.019	0.019	0.051

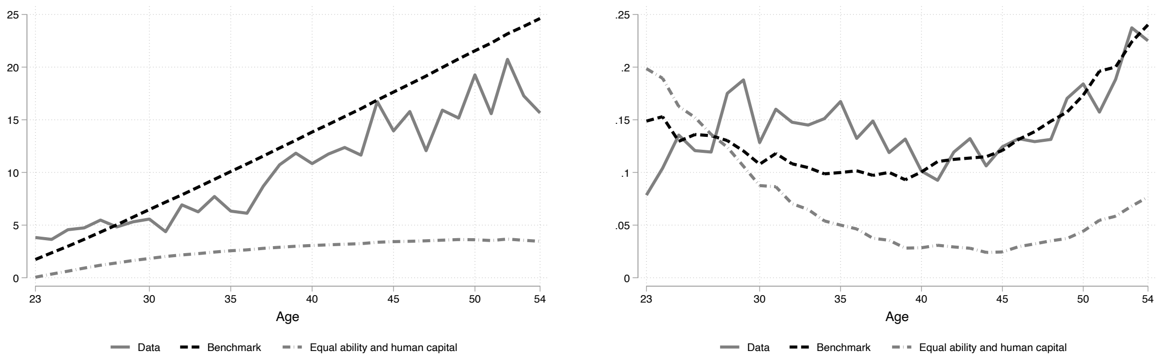
Notes: The gaps are computed as $1 - \frac{Y_{\text{Blacks}}}{Y_{\text{Whites}}}$. Column 'Emp. rate' refers to the employment gap, and 'Hours' to the hours' gap conditional on working. Column 'Wage' is the gap in hourly wages. Column 'Earnings employed' refers to the annual earnings gap of the employed, while 'Earnings all' includes those with zero earnings.

In Figure 9, we plot the racial gaps in hourly wages (left) and employment (right) over the lifecycle as observed in the data, in the benchmark model, and when both race groups enter the model with the distribution of ability and initial human capital of Whites. As discussed in Section 2, the wage gap increases dramatically over the lifecycle. The difference between the benchmark gap and the gap under identical initial conditions in the left panel indicates that the main driver of the gap's growth is the difference in pre-market factors between Blacks and Whites. When ability and initial human capital distributions are equal, the gap is zero at the beginning of the lifecycle by construction. Over time, the gap widens slightly because Whites work more than Blacks, as can be seen in the right panel, which leads to a higher accumulation of human capital.

Under equal ability and initial human capital distributions, the employment gap exhibits a U-shape and is slightly higher at the beginning of the lifecycle than in the benchmark. This is because, within race groups, employment levels at the beginning of the lifecycle tend to be lower in the higher ability deciles 5-10 than in the 2nd, 3rd, and 4th deciles. In the benchmark economy, Black agents are concentrated in the lower deciles. Instead, in the counterfactual, there is a relatively larger mass of agents in the top deciles leading to the initial rise of the gap.

Figure 9: Racial gaps over the lifecycle in the data: benchmark and counterfactual of equal initial conditions.

(a) Hourly wages (b) Employment



Notes: In the left panel, the solid gray line is the racial gap in hourly wages conditional on employment in the data expressed in 2018 US$. In the right panel, the solid gray line is the racial gap in the employment rate. The dashed black lines are the gaps from the benchmark model. The dashed-dotted gray lines are the gaps when equalizing the ability and initial human capital distribution.

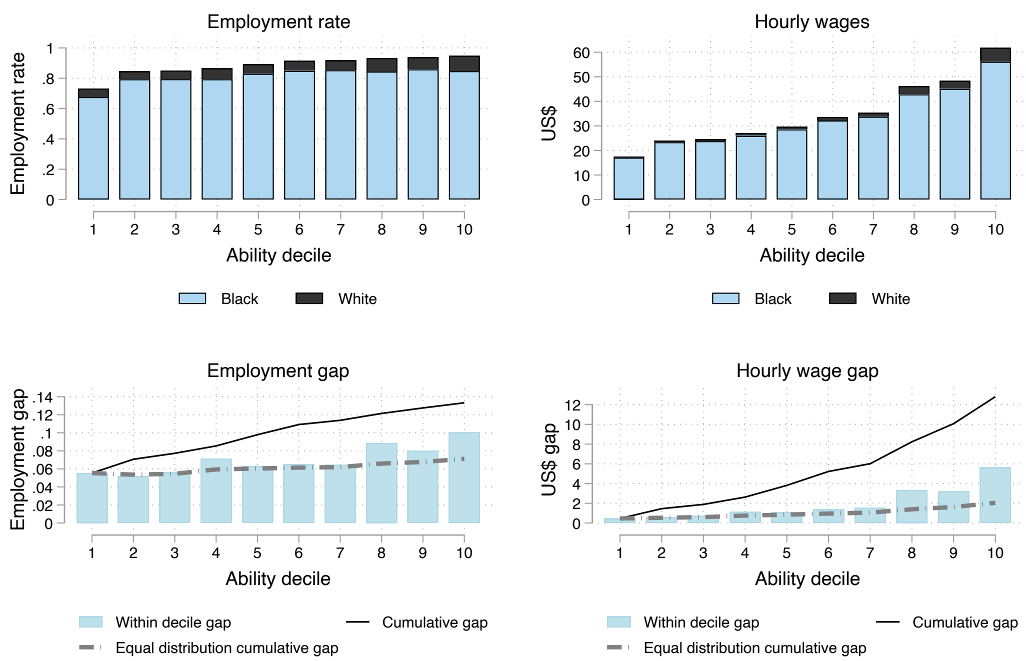
Discussion

The experiments suggest that the main driver of the wage and earnings gaps is that Black men, on average, enter the labor market with less favorable initial conditions, i.e., lower ability to acquire human capital and lower initial human capital levels. However, when we equate initial conditions, we find that the earnings gap still grows because Blacks work less than Whites, leading to lower human capital accumulation. We present the model outcomes by ability decile in Figure 10 to clarify how the model generates a growing gap even with identical initial conditions. In this illustration, we focus on employment because, conditional on working, the gap in hours worked has second-order implications.

As discussed in Section 3, we need to group the fifth to tenth AFQT deciles to construct targets due to the low number of observations for Black men. In Appendix Figure B.13, we separately compare the noisy data for the fifth to the tenth AFQT/ability deciles. The model generates profiles that are very close to the noisy estimates but also, as shown in Figure 10, an increasing employment gap in the ability level. The gap in employment in these top deciles is driven by Black agents working less at the beginning of the lifecycle, which has important implications for human capital accumulation. Since the data does not allow us to test the likelihood of this prediction, in the bottom panels of Figure 10, we present the following. The blue bars are the employment and hourly wage gaps by ability level. The solid black line indicates the average racial gap as we add deciles to the comparison. The cumulative gap g^u represents the gap between the weighted averages of the two groups of race $r \in \{b, w\}$ up until decile u. More specifically, the gap is computed between the outcomes y_d^r of ability deciles $d \in \{1, ..., u\}$ while scaling by the mass of individuals m_d^r within the respective deciles, i.e. $g^u = \frac{\sum_{d=1}^{u} m_d^w y_d^w}{\sum_{d=1}^{u} m_d^w} - \frac{\sum_{d=1}^{u} m_d^b y_d^w}{\sum_{d=1}^{u} m_d^b}$. In other words, only the first ability level is considered on the figure's left, while on the right, the average is computed across all ten ability levels. The dash-dotted gray line is the equivalent cumulative gap when Blacks enter the model with Whites' ability and initial human capital distribution. In the counterfactual, the cumulative gap is a consequence of differences in labor supply and experience only. In the benchmark case, the cumulative gap considers the differences in the relative prevalence of Blacks and Whites across ability deciles.

These figures allow us to assess how much of the main result is driven by the model's outcomes in the top ability levels. For example, the model predicts that the overall gap in hourly wages would decrease by 84% if initial conditions were equalized. If we exclude the top five ability levels (those for which the model might be underpredicting employment for Black men), the initially smaller gap would still decrease by 78% for those with ability below the median when equalizing the initial conditions. That is, the quantitative implications of the model are robust to excluding the segment of the Black population for which we have the most uncertain calibration targets.

Figure 10: Model gaps in employment and hourly wages conditional on working.



Notes: All data in these figures is simulated using the full model. Hourly wages are in 2018 US$. The top panels show levels, while the bottom panels show gaps. In the bottom panels, the bars show the gaps within each decile. The solid black line shows the cumulative gap when considering population weights. The dashed gray line is the counterfactual cumulative gap with Black men having the same ability and initial human capital distribution as White men. The cumulative gap g^u represents the gap between the weighted averages of the two groups of race $r \in \{b, w\}$ up until decile u. More specifically, the gap is computed between the outcomes y_d^r of ability deciles $d \in \{1, ..., u\}$ while scaling by the mass of individuals m_d^r within the respective deciles, i.e. $g^u = \frac{\sum_{d=1}^{u} m_d^w y_d^w}{\sum_{d=1}^{u} m_d^w} - \frac{\sum_{d=1}^{u} m_d^b y_d^w}{\sum_{d=1}^{u} m_d^b}$.

In the model, once we condition on ability and human capital level, the fundamentals that generate different labor supply between race groups are the preference parameters. However, these parameters should not be interpreted as pure differences in taste between the two groups. Labor market discrimination, which we do not model but is well documented in the literature, might determine the labor outcomes we use to calibrate these parameters. We could use the counterfactual experiments to assess how the racial gaps would look like if the totality of the difference in these parameters were caused by discrimination in the labor market. In the fourth row of Table 5, counterfactual Blacks have all the preference parameters of Whites, i.e., the gaps in employment and hours worked are zero conditional on ability level. Preference parameters account for 7% of the wage gap, 10% of the gap in earnings of the employed, and 30% of the overall earnings gap.

We provide two more measures of the potential impact of discrimination on the racial gaps in a world of identical initial conditions in the last two rows of Table 5. In the experiment 'Distribution & utility home', counterfactual Blacks enter the model with the initial conditions of Whites and with the same preference parameters that determine the utility of not working. Arguably, these parameters are the most likely candidate to capture discriminatory practices in hiring and firing. In this case, discrimination would explain 42% of the wage gap, 32% of the gap in earnings of the employed, and 40% of the overall gap. Finally, in the row 'Distribution & utility employed', we equalize the initial distribution and the two parameters that govern the utility when employed. If these were entirely driven by discrimination, one-third of the wage gap, three-quarters of the earnings gap of the employed, and two-thirds of the overall gap would be accounted for by racial discrimination in the labor market. Two features drive these greater shares. First, in a world of identical initial conditions, the gap would be smaller to begin with, so an equal reduction translates into a larger share. Second, with identical initial conditions, more Black men would not only have higher initial human capital levels but also a higher ability to accumulate human capital. Therefore, preventing them from working would translate into a larger loss of wage growth. Finally, it is worth noting that the differences in AFQT that we leverage to calibrate the ability levels might also reflect racial discrimination before men enter the labor market: in schooling, housing, health care, and legacies of historical discrimination.

5 Conclusions

In this paper, we document a relatively flat gap in employment and hours worked between Black and White men over the lifecycle while the earnings gap widens. Together these facts suggest that human capital accumulated on the job could be a key determinant of the Black-White gap in earnings. Using OLS regressions, we show that the Black-White gaps in the level and growth of earnings cannot be explained by the different levels of accumulated experience between the two groups. Instead, these gaps virtually disappear when we group men by AFQT scores and control for accumulated experience. Moreover, AFQT scores are a crucial predictor of earnings levels and growth for all individuals, irrespective of race.

From a human capital perspective, these results suggest there are crucial differences in pre-market factors that amplify income differences with growing experience. Because experience and earnings are endogenous to labor supply decisions, we build a structural model to study the Black-White differentials in labor market outcomes. The model features labor supply decisions at the intensive and extensive margins, a learning-by-doing human capital accumulation technology, and heterogeneity in human capital and the ability to acquire it. This heterogeneity leads to rich differences in earnings growth across agents, as observed in the data across the distribution of AFQT scores. We exploit the variation in earnings profiles across AFQT deciles to identify the heterogeneity in the ability to accumulate human capital in the model.

On average, Black men occupy lower ranks in the AFQT distribution and have lower levels of initial human capital than Whites, which translates to lower abilities to acquire human capital in the model. Our counterfactual experiments indicate that these differences in pre-market factors are crucial not only for the Black-White employment gaps but also for hourly wages. Consequently, our findings suggest that effective policy to close the gaps in the labor market should primarily be concerned about how achievement gaps are generated before adulthood. Differences in preference parameters can explain the finding that even under equal initial conditions, employment gaps persist, which generates earnings gaps. However, what we label preference parameters in the model might reflect discrimination in the real world.

Our approach ignores the potential impact governmental transfer programs and racial discrimination in hiring or offered wages might have on the incentives to work and acquire skills in the first place. We also lump initial human capital levels and ability levels together as we lack the variation to separate the two entirely. Moreover, due to the difficulty of separating educational achievement from cognitive test scores, we do not include the decision to obtain formal education or its role in signaling (e.g., Lang and Manove 2011) or occupation-specific human capital. We also abstract from incarceration, which, in particular, Black men with low education are relatively likely to experience at some point in their life (e.g., Neal and Rick 2014, Caucutt, Guner, and Rauh 2021). Finally, the paper is based on one cohort of men born between 1957-64. Patterns of labor market outcomes and pre-market conditions might have changed over time. Understanding the impact of adverse life events and structural inequality on individuals' labor market outcomes and racial gaps is an important avenue for future research.

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Appendix

A Computation

We solve the model described in Section 3 in two main steps. First, given a set of parameter values, we find the policy function for labor supply that maximizes the sum of discounted lifetime utility. Secondly, we simulate a large sample of agents that use the policy function to make labor supply decisions generating lifecycle patterns for income, hours worked, employment history, and accumulated human capital. In this section, we provide a more detailed description for each of the two main parts of the algorithm.

Finding the Policy Function for Labor Supply

Given a set of parameters and each ability decile:

1. Define a grid for human capital (h) and the value of not working (κ). For human capital we use a grid with 201 points and 101 for the value of not working.
2. Set the value of being alive at $t + 1$ to 0.
3. Proceed by backward induction. Solve from the last period J to the first period.
   (a) For each combination of human capital and the value of not working $(h, \kappa; a)$, solve the Bellman equation of not working and the Bellman equation of working.
   (b) To solve the Bellman equation of working, we find the optimal number of hours worked using the golden-section search technique.

The outcome of this procedure is a policy function that indicates the labor supply of any agent in the state space at any period of the lifecycle.

Simulate the Life of N Agents

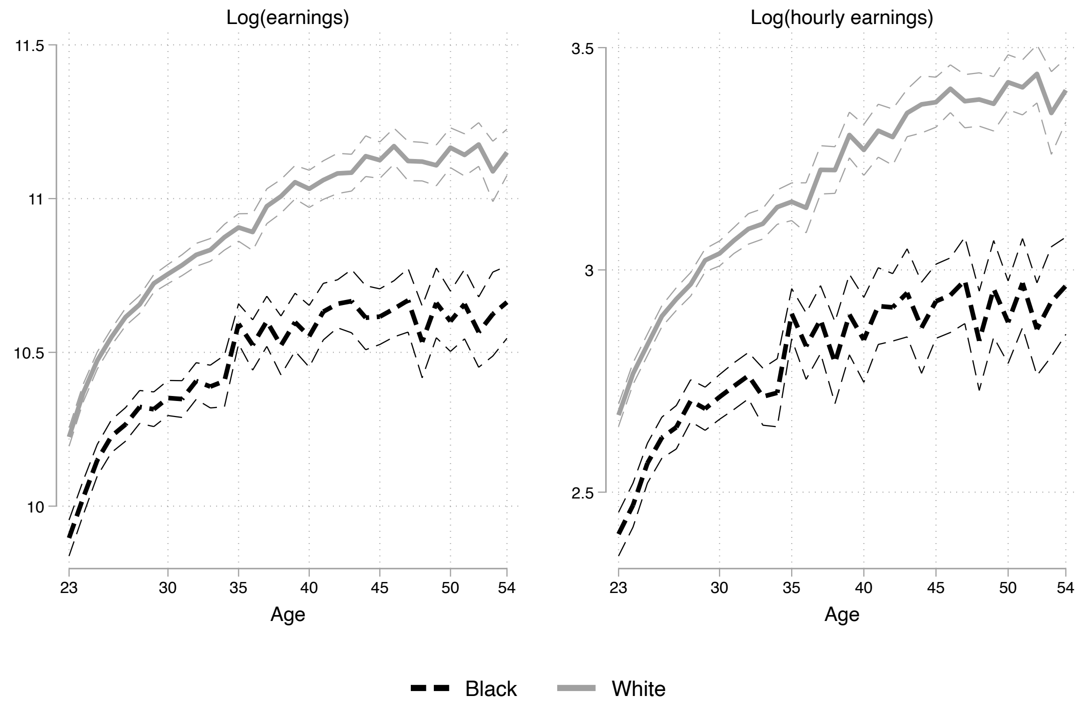
Given the policy function for labor supply:

1. Simulate a set of $N \times J$ shocks of the value of not working.
2. Assign an initial level of human capital and ability to all N agents.
3. For each agent, from the first to the last period:
   (a) Use the policy function to compute labor supply.
   (b) Given labor supply, human capital, and ability, compute the value of human capital next period.

These steps generate lifecycle profiles for hours worked and employment history for each simulated agent.

B Additional Figures and Tables

Figure B.1: Annual (left) and hourly (right) log labor income over the lifecycle.



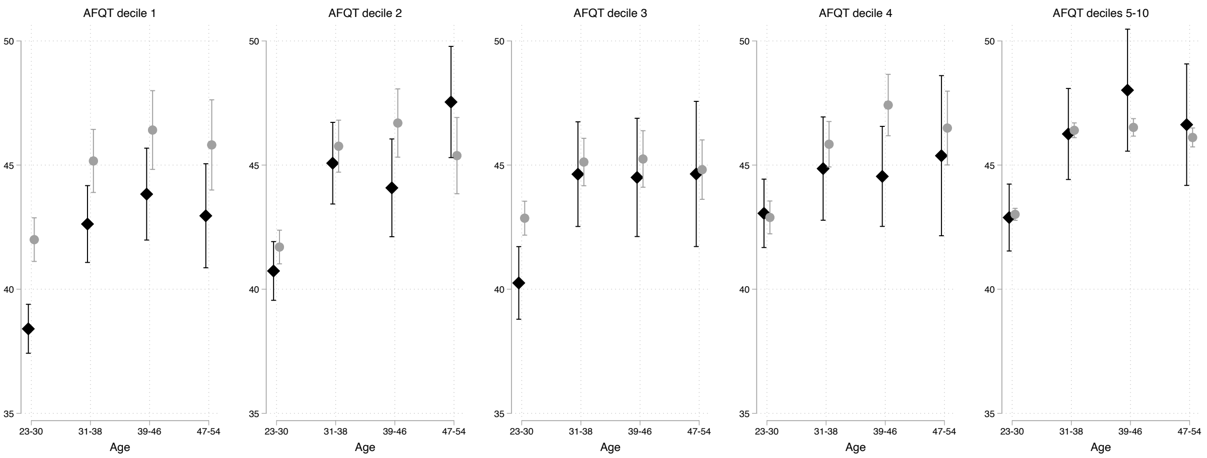
Notes: Earnings are in 2018 US$. The dashed black lines are earnings of Black men. The solid gray lines are earnings of White men. The thin lines are the 95% confidence intervals.

Table B.1: Regressing hourly earnings conditional on working on race and cumulative labor market experience by AFQT deciles.

Deciles 6-10					
	(6)	(7)	(8)	(9)	(10)
Black dummy	2.1527	5.3179***	9.5116*	3.7059	10.9889***
	(1.8411)	(1.4963)	(5.7538)	(5.7920)	(3.6672)
Work experience (years)	0.5571***	0.8475***	1.2244***	1.2027***	1.7349***
	(0.0389)	(0.0522)	(0.0678)	(0.0676)	(0.0788)
Work experience x Black	-0.5890***	-0.4524***	-0.2207	-0.6604*	-1.0025***
	(0.1265)	(0.1051)	(0.4460)	(0.3552)	(0.1759)
Constant	20.0679***	16.5291***	20.6764***	20.5754***	20.0541***
	(0.8452)	(0.9998)	(1.4762)	(1.2683)	(1.5174)
Mean	28.06	29.89	35.19	38.02	45.14
Share Black	0.011	0.015	0.009	0.009	0.004
Observations	3771	3657	4076	3620	3479
R-squared	0.09	0.13	0.15	0.14	0.20
Region fixed effects	Yes	Yes	Yes	Yes	Yes

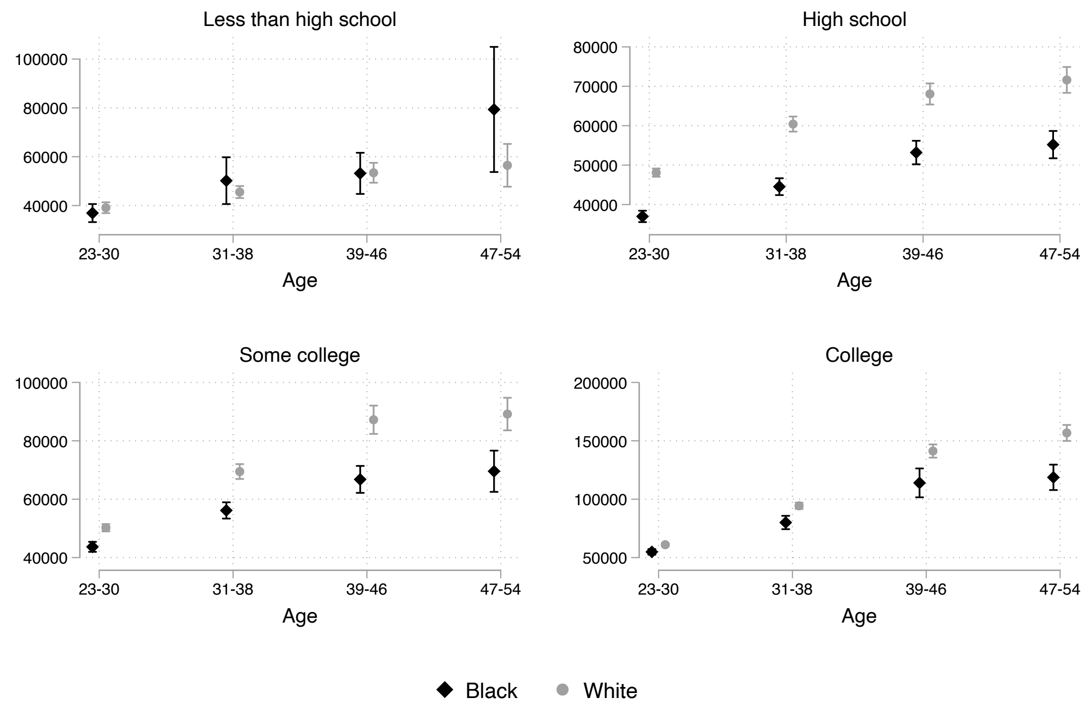
Notes: AFQT deciles indicated in the column headings. Work experience is measured by weeks worked and enters the regression in terms of years of work experience. The estimation technique is OLS. Robust standard errors in parenthesis. *p<0.1,**p<0.01,***p<0.01.

Figure B.2: Hours worked conditional on working by race for AFQT deciles over the lifecycle.



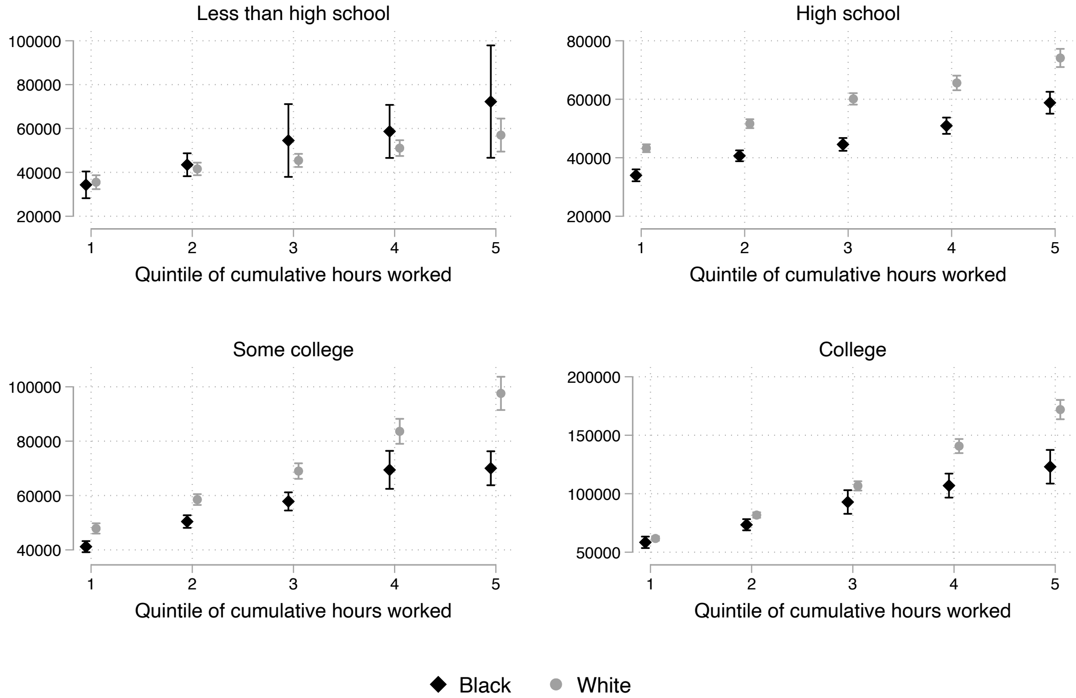
Notes: Hours worked conditional on employment. Black diamonds represent the mean of Black men. Gray dots represent the mean of White men. Deciles 5th to 10th are aggregated due to sample sizes. The thin lines are 95% confidence intervals.

Figure B.3: Mean annual earnings over the lifecycle conditional on working for Black and White men that experience no non-employment spells, by education groups.



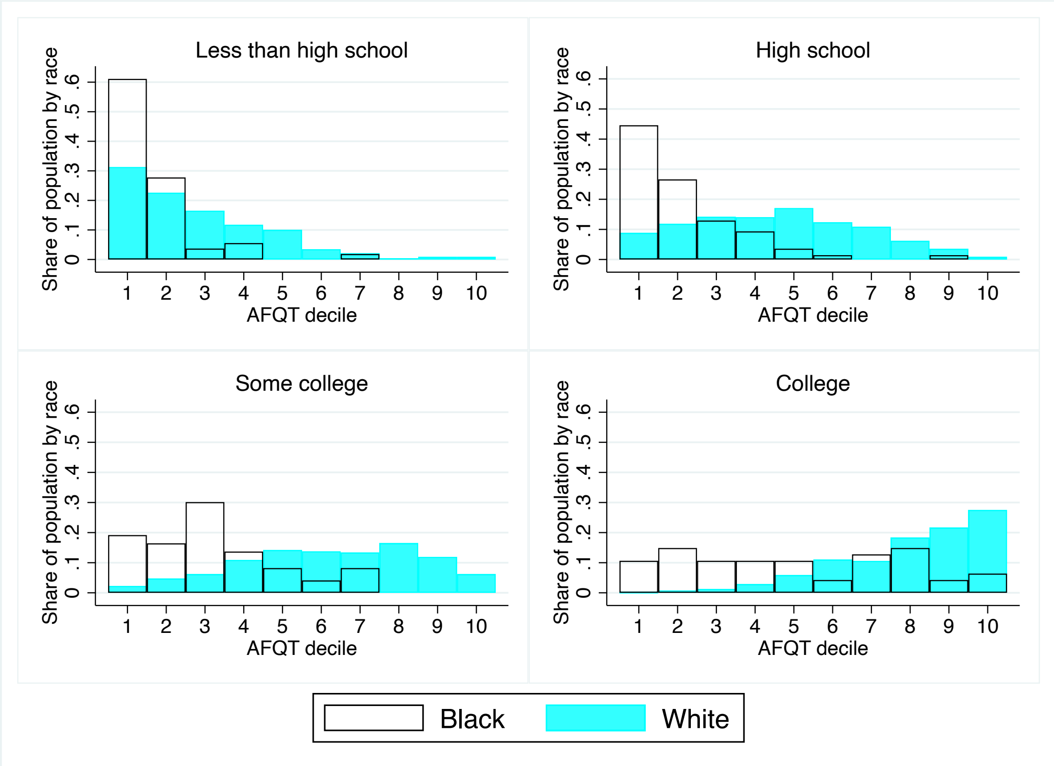
Notes: Annual earnings conditional on working are in 2018 US$. The sample is restricted to individuals for whom we do not observe a single non-employment spell after age 23. Black diamonds represent the mean of Black men. Gray dots represent the mean of White men. The thin lines are 95% confidence intervals.

Figure B.4: Mean annual earnings by cumulative hours worked conditional on working for Black and White men that experience no non-employment spells, by education groups.



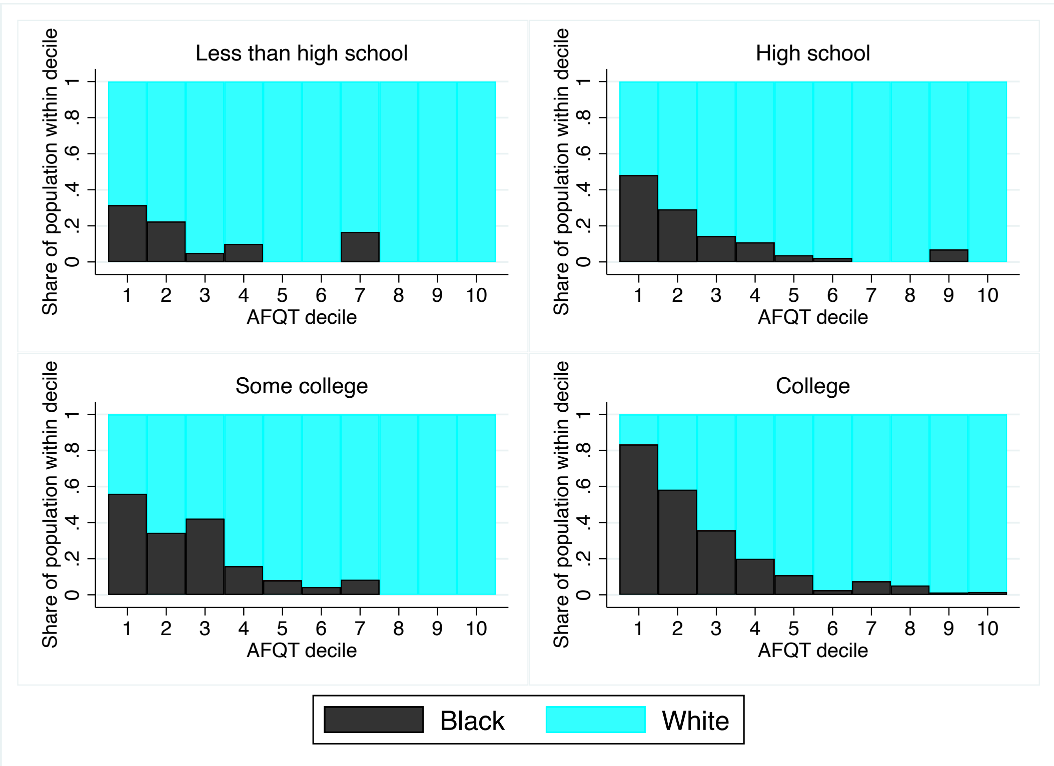
Notes: Annual earnings conditional on working are in 2018 US$. The sample is restricted to individuals for whom we do not observe a single non-employment spell after age 23. The x-axis displays the quintile of cumulative hours worked within education groups. Black diamonds represent the mean of Black men. Gray dots represent the mean of White men. The thin lines are 95% confidence intervals.

Figure B.5: AFQT score distributions by race and education (absolute).



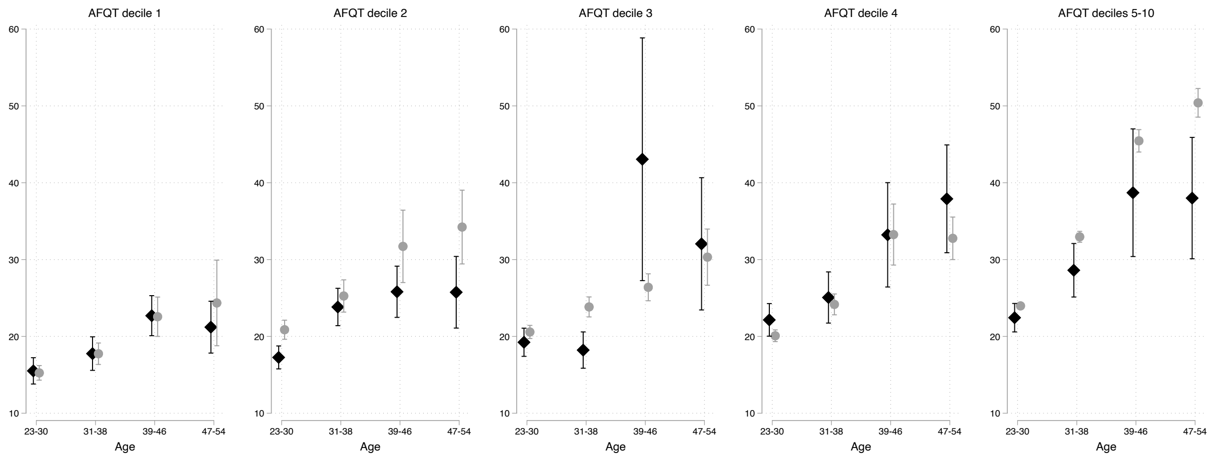
Notes: Each race sums to one within each level of education.

Figure B.6: AFQT score distributions by race and education (relative).



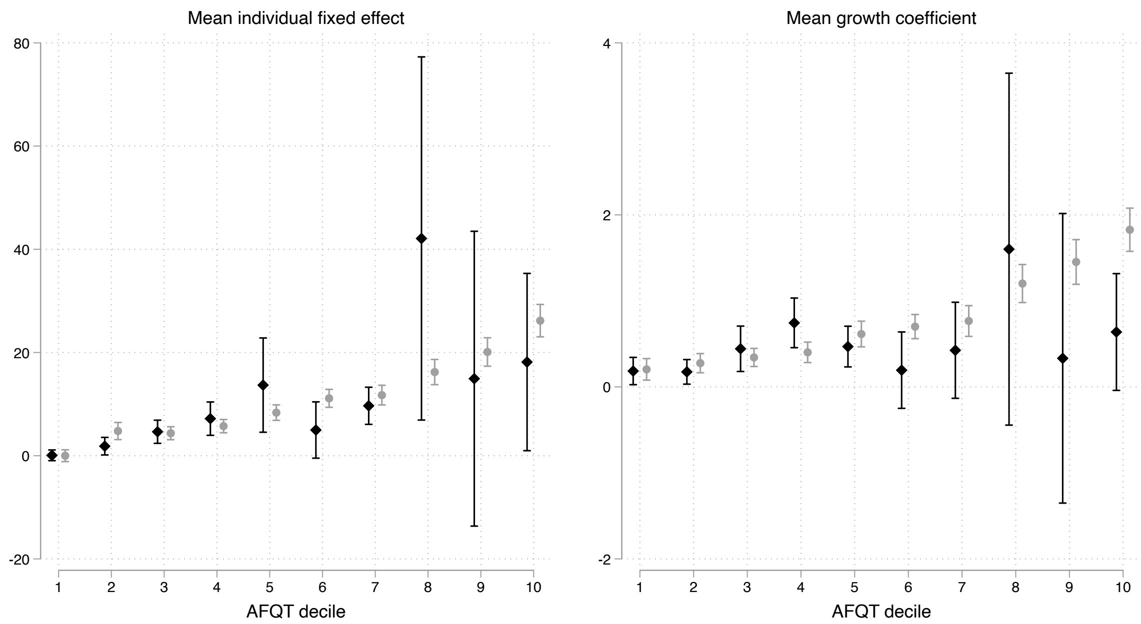
Notes: Each decile within each level of education sums to one across both races.

Figure B.7: Hourly wages conditional on working for AFQT score groupings by race over the lifecycle for men without non-employment spells.



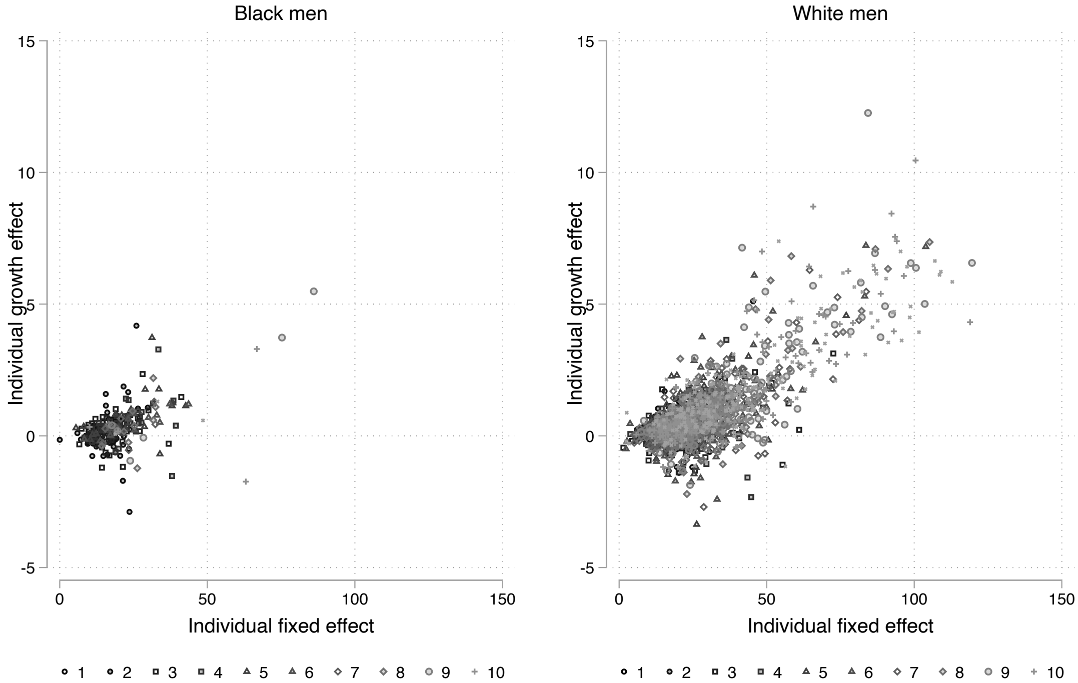
Notes: Hourly wages conditional on working are in 2018 US$. The sample is restricted to individuals for whom we do not observe a single non-employment spell after age 23. Black diamonds represent the mean of Black men. Gray dots represent the mean of White men. The thin lines are 95% confidence intervals.

Figure B.8: Mean individual fixed effect (left) and experience effect (right) for hourly wage by race and AFQT decile.



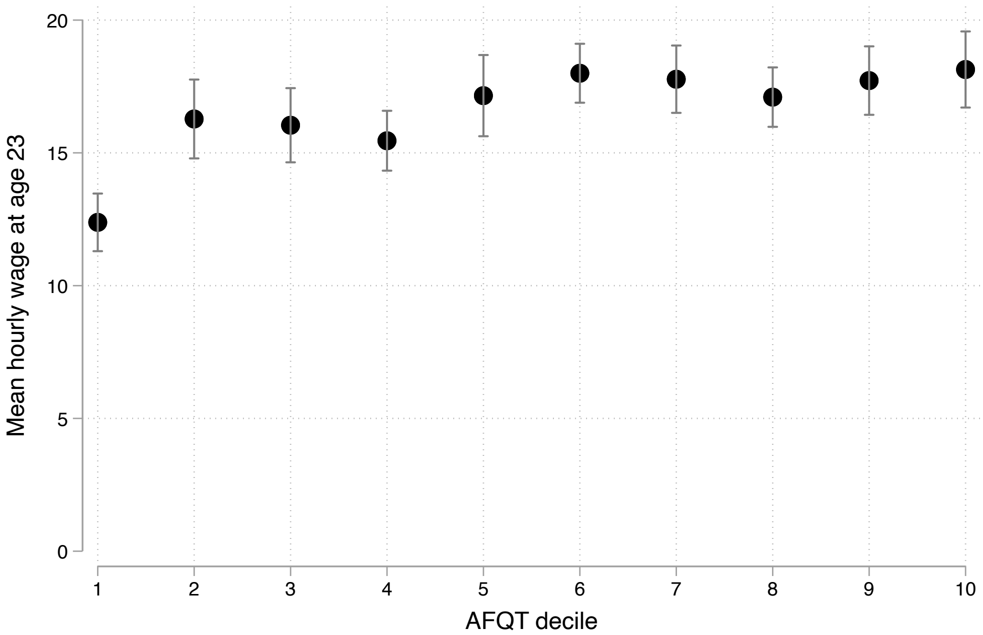
Notes: Black diamonds represent the mean of Black men. Gray dots represent the mean of White men. The left panel shows the mean individual fixed effect by race and AFQT decile obtained from a regression of hourly wages on experience and individual fixed effects. The right panel shows the mean individual growth coefficient by race and AFQT decile obtained from one regression of hourly wages on experience for each individual with at least five observations. The individual fixed effect is shifted such that the minimum mean is zero. The thin lines represent the 95% confidence intervals.

Figure B.9: Distribution of individual fixed effects (left) and experience effects (right) for hourly wage by race and AFQT decile.



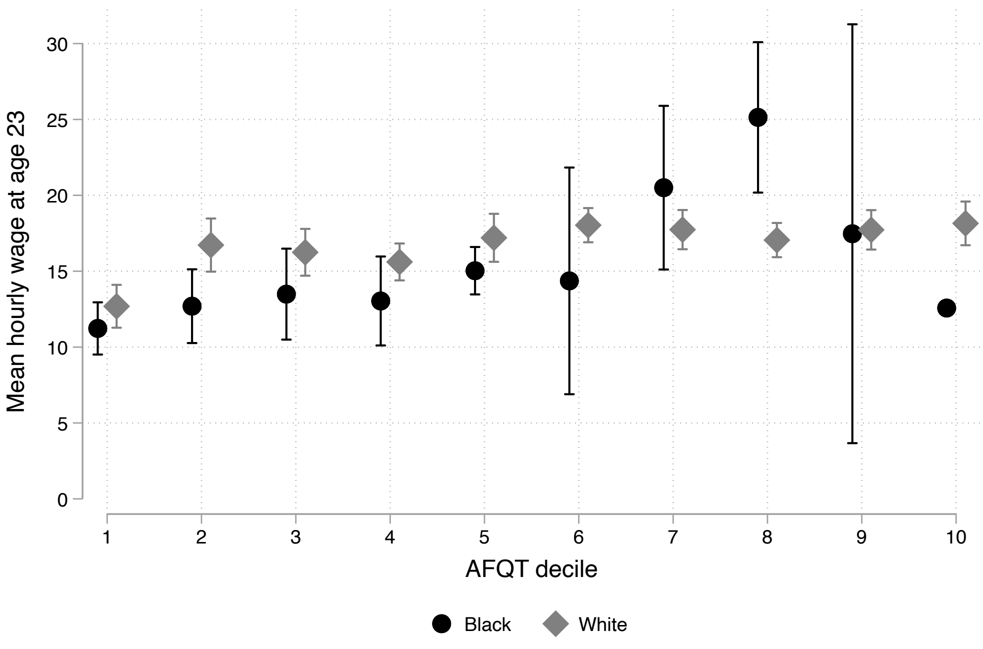
Notes: Scatter plot of Black (left) and White (right) men. The panels show the individual fixed effects obtained from a regression of hourly wages on experience and individual fixed effects on the x-axis, and the individual growth coefficients obtained from one regression of hourly wages on years of accumulated work experience for each individual for whom we have at least five observations. The individual fixed effect is shifted such that the minimum is zero. The right panel shows the sample of Black men and the left panel of White men. The legend indicates the AFQT decile of each individual.

Figure B.10: Mean hourly wages at age 23.



Notes: Mean hourly wages are in 2018 US$. The thin lines are the 95% confidence intervals. The normalized version of the means are used as initial human capital levels h_1 in the model.

Figure B.11: Mean hourly wages at age 23 for Blacks and Whites.



Notes: Mean hourly wages are in 2018 US$. The thin lines are the 95% confidence intervals.

Table B.2: First-stage squared distance between model and data moments.

AFQT/ability decile	$(\text{Model} - \text{Data})^2$
First	0.0025
Second	0.0039
Third	0.0003
Fourth	0.0058
Fifth	0.0049
Sixth	0.0072
Seventh	0.0024
Eighth	0.0081
Ninth	0.0291
Tenth	0.0180

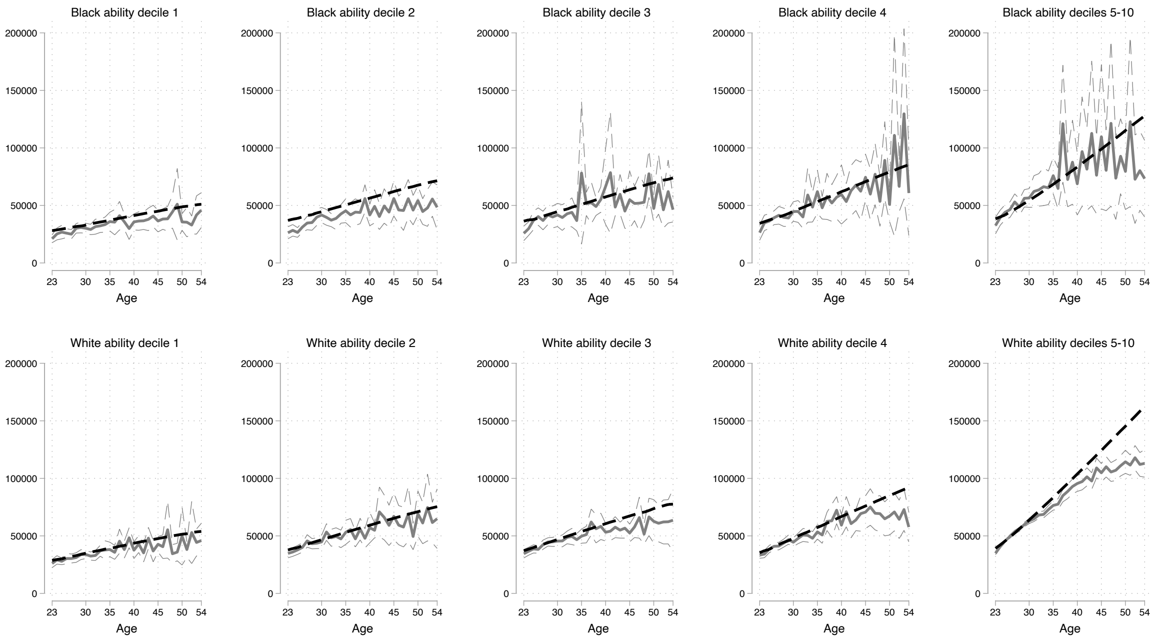
Notes: For each AFQT/ability decile, we compute the average hourly wage, in 2018 US$, at ages 23, 24-31, 32-39, 40-47, and 48-54 using both the data and the model simulation. Then, we add up the squared difference between the five model and data estimates. We use the TikTak algorithm (Arnoud et al. 2019) to minimize the distance between the model and data moments.

Table B.3: Second-stage squared distance between model moments and data moments.

	Blacks		Whites	
AFQT/Ability grouping	Emp. rate	Hours	Emp. rate	Hours
First	0.0027	0.0063	0.0006	0.0013
Second	0.0014	0.0064	0.0009	0.0002
Third	0.0008	0.0054	0.0003	0.0008
Fourth	0.0001	0.0137	0.0007	0.003
Fifth-Tenth	0.0019	0.0135	0.0005	0.0015

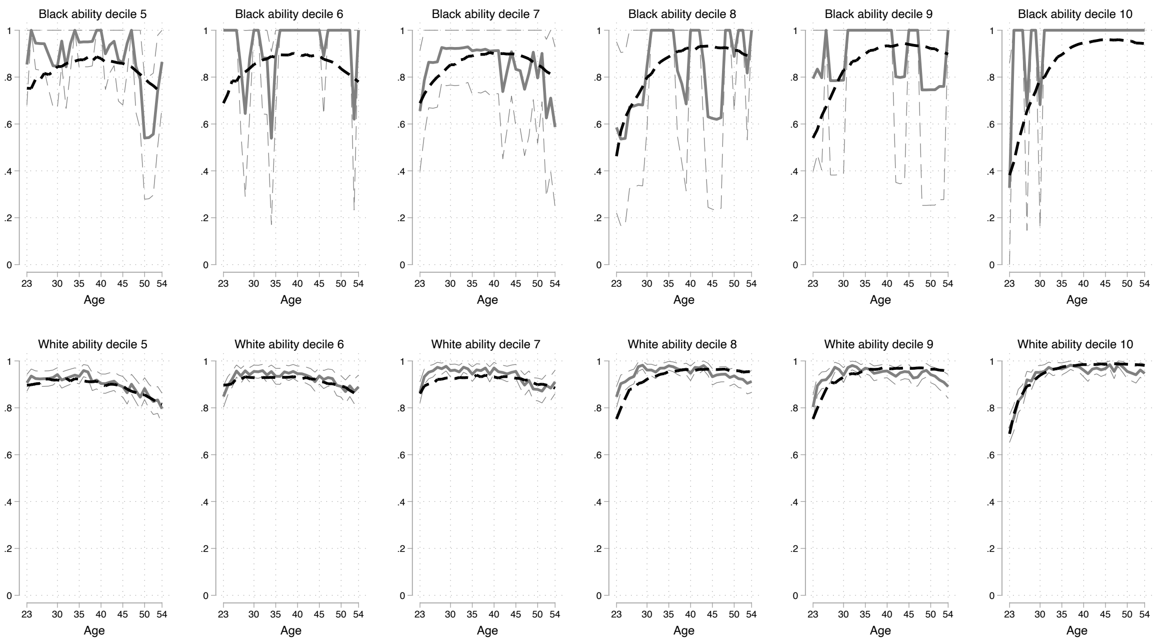
Notes: For each AFQT/ability and race grouping, we compute the average employment rate, as the share of individuals employed and hours worked, in annual hours, at ages 23-30, 31-38, 39-46, and 47-54 using both the data and the model simulation. Then, we add up the squared difference between the four model and data estimates. We use the TikTak algorithm (Arnoud et al. 2019) to minimize the distance between the model and data moments.

Figure B.12: Yearly earnings for AFQT/ability groupings by race over the lifecycle (data vs. model).



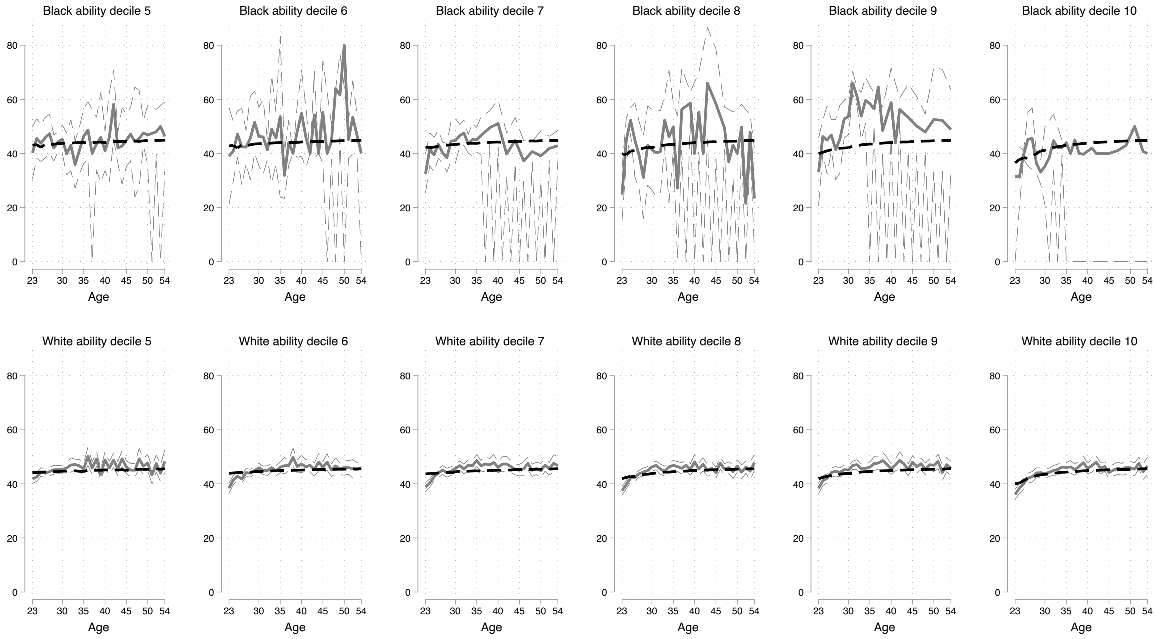
Notes: Yearly earnings in 2018 US$. The solid gray line represents yearly earnings in the data. The thin dashed gray lines are the 95% confidence intervals. The dashed black line represents the total period earnings in the model. Ability levels 5-10 are aggregated due to sample sizes.

Figure B.13: Employment rates for AFQT/ability deciles 5-10 by race over the lifecycle (data vs. model).



Notes: Employment rates are the share (in %) of individuals employed within a race-ability group. The solid gray line represents the employment rate in the data. The thin dashed gray lines are the 95% confidence intervals. The dashed black line represents the employment rate in the model.

Figure B.14: Hours worked conditional on working for AFQT/ability deciles 5-10 by race over the lifecycle (data vs. model).



Notes: Hours worked conditional on employment. The solid gray line represents mean hours worked in the data. The thin dashed gray lines are the 95% confidence intervals. The dashed black line represents hours worked in the model.