The Dynamics of the Racial Wealth Gap

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Abstract: What drives the dynamics of the racial wealth gap? We answer this question using a dynamic general equilibrium heterogeneous-agents model that matches racial differences in earnings, wealth, bequests, and returns to savings. Our calibrated model endogenously produces a racial wealth gap matching that observed in recent decades along with key features of the current cross-sectional distribution of wealth, earnings, and race. Our model predicts that equalizing earnings is the quickest way to close the racial wealth gap, with much smaller roles for bequests or returns to savings. One-time wealth transfers have only transitory effects unless they address the racial earnings gap.

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1 Introduction

In 1962 in the United States, average Black household wealth was less than one-fifth that of whites. This wealth gap was the consequence of centuries of violence and discrimination toward African Americans, often in the form of government policy. Perhaps surprisingly, this racial wealth gap is just as wide today as it was in 1962 depsite the passage of legislation aimed at eliminating the most egregious obstacles to Black wealth accumulation, such as discrimination in education and in the labor, housing, and credit markets.

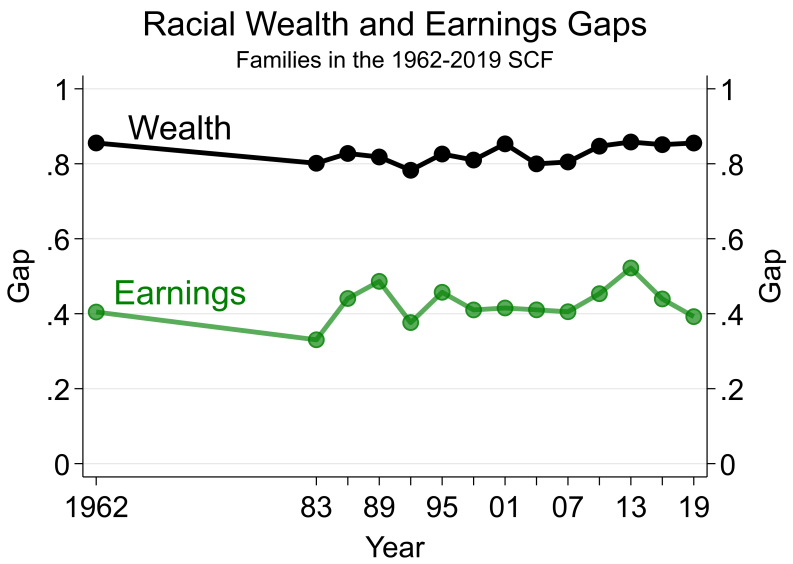


Figure 1: Racial Wealth and Earnings Gaps
Note: We define the racial wealth and earnings gaps as one minus the ratio of Black to white means for families. Wealth and earnings are both measured in this figure using the 1962 Survey of Financial Characteristics of Consumers (SFCC) and the 1983-2019 waves of the Survey of Consumer Finances (SCF). Details are provided in Section 3.1 and Appendix A.

What is behind the persistence of the racial wealth gap over recent decades? And what types of policies would change its trajectory?

This paper studies how responsive the racial wealth gap is to differences in three broad mechanisms: household earnings, the return to saving, and intergenerational transfers. Our analysis is based on a heterogeneous agents dynamic stochastic general equilibrium model in the spirit of Bewley (1986), Aiyagari (1994), and Huggett (1993) with features capable of generating a right-skewed wealth distribution (De Nardi (2004)). Agents in the model (i) have a life cycle in which they work, retire, and face increasing mortality risk; (ii) receive idiosyncratic earnings shocks along their life cycle; (iii) may give or receive intergenerational transfers; and (iv) are heterogeneous in terms of wealth, earnings, expected bequest size, and returns on capital.

A unique feature of our analysis is that we solve for model transition paths and study their behavior in the presence or removal of heterogeneity in earnings, bequests, or returns on capital. Wealth accumulation is an inherently dynamic process, which limits the usefulness of documenting

cross-sectional relationships between variables like earnings, educational attainment, and wealth at a point in time. A dynamic analysis allows us to study how causal relationships interact over time, and to uncover how the wealth gap response to these mechanisms may not be detected by cross-sectional analysis over short time intervals.

Our approach and results stand in contrast to the cross-sectional literature that tends to find that the earnings gap cannot explain a large percentage of the racial wealth gap.[1] The importance of a long-run view is supported by Ashman and Neumuller (2020), which in a similar modelling environment compares racial wealth gaps across steady states and finds that earnings (and to a lesser degree intergenerational transfers) account for a large fraction of the wealth gap in the long run. Ashman and Neumuller (2020), however, do not solve for transitions from one steady state to another, and steady state analysis is silent as to how long it will take to see meaningful equalization of economic opportunity or which policies will more rapidly achieve that end. We show that, in fact, these dynamics tend to be very long-lived, so that focusing on the transition path offers a more policy-relevant characterization of the effects of interventions. Our analysis indicates that wealth will be unequal for a long time: Even under our most optimistic scenarios, the wealth gap takes over half a century to close.[2]

We use the 1962 Survey of Financial Characteristics of Consumers (SFCC) to initialize the Black and white wealth distributions in the model and estimate race-specific lifetime wage processes on data from the National Longitudinal Survey of Youth 1979 (NLSY79), a sample born between 1957-1965. We then feed the calibrated model a path for earnings that begins with the racial gap estimated in the NLSY79 and simulate the evolution of the racial wealth gap arising under different transition paths to a distant steady state in which there is no earnings gap and expected outcomes are independent of race. Importantly, while all paths lead to the same terminal steady state, the persistence of the racial wealth can be wildly different, with significant progress toward equality appearing anywhere from a few generations to centuries.

In addition to earnings differences, the baseline experiments also have racial differences in bequests and in rates of return on savings. The simple bequest structure in the model produces expected inheritances and inter-vivos transfers that are in line with estimates from the literature.[3] The return gap, which is a consequence of closing our model, is small and shown in a later section to be of negligible consequence for our baseline wealth gap paths.[4]

[1] The cross-sectional literature has found that a large racial gap in wealth remains after conditioning on earnings (Barsky et al. (2002)). Moreover, regression models have a difficult time explaining the wealth gap even after conditioning on variables in addition to earnings (Blau and Graham (1990), Altonji and Doraszelski (2005), Thompson and Suarez (2015)). When multivariate regression coefficients estimated from a sample of blacks are used to predict white wealth, most estimates in the literature explain less than one-third of the wealth gap (Scholz and Levine (2003)).

[2] Technically, the gap only completely disappears in the limit. Here we use the word "close" to mean Black mean wealth is more than 95 percent of mean white wealth.

[3] By initializing the model to the large wealth differences observed in 1962, the model endogenously produces racial differences in intergenerational transfers of the same magnitude as observed in the data in terms of both bequests and inter vivos transfers (Avery and Rendall (2002), Smith (1995), Menchik and Jianakoplos (1997), Wolff (2002)).

[4] Empirical measures of a racial return gap find that over recent decades it is small, if it exists at all (Gittleman and Wolff (2004), Wolff (2018)).

Next we validate our model by comparing its predictions over the years 1962 to 2019 with their analogs in the data. The time series of the racial wealth gap endogenously generated by the model is very close to the one observed in the SCF between 1962 and 2019 (79 percent in the model compared to 82 percent in the data). In addition, the model endogenously reproduces a relationship between earnings and wealth by race throughout this time period that is consistent with a central finding from the cross-sectional literature on the wealth gap (Barsky et al. (2002)): There is a large racial gap in wealth even after conditioning on earnings.

Our first contribution is to show that the persistence of the racial wealth gap is highly responsive to the assumed path of the racial earnings gap. We begin with a bounding exercise that contrasts two paths, one arising from a "quasi-permanent" earnings gap and one where the gap instantly vanishes in 2022. In the permanent case, the racial wealth gap remains unchanged until the earnings gap is finally removed, while under the immediate closure case the wealth gap nearly converges within one century.[5]

We then use the NLSY79 to estimate how much the earnings gap would be reduced from equalizing racial differences in either educational attainment (degree completion) or educational achievement (labor market skills) and then simulate education reforms where the estimated earnings gap reductions roll out over generations, beginning in 2022. Because reforms only affect the earnings of newborn households, the transitional period for the wealth gap is stretched by an additional 50 years relative to the immediate closure case. Moreover, because neither reform closes the earnings gap completely, a wealth gap remains post-reform. Equalizing educational attainment reduces the earnings gap by 25 percent and eventually moves the wealth gap from 79 percent to 66 percent. Equalized achievement has a much larger effect, reducing the earnings gap by 76 percent and pushing the wealth gap down to 26 percent.[6] These experiments highlight that even under optimistic scenarios, closing the racial wealth gap may take considerable time.

Our second contribution is to show that, as long as the earnings gap persists, racial differences in returns to capital or intergenerational transfers have limited effects on the wealth gap. Transition paths resulting from a permanent earnings gap are almost identical, even for implausibly large return differences.[7] In contrast, when imposing the same return gaps on the immediate earnings closure path, we find that large return gaps can result in sizeable differences in the wealth gap. For example, when earnings are equalized but the return to white household's savings is 25 percent larger, a wealth gap of 14.5 persists. We conclude that return gaps can matter for the racial wealth

[5] To be clear, we use "permanent" earnings gap to refer to a path where the current gap level persists for many centuries before closing abruptly. This mimics the effect of a permanent wealth gap for all but the end of the transition because our OLG structure implies that distant events have no affect on current decisions. For brevity, we will label a "quasi-permanent" exercise as "permanent."

[6] We interpret the differences between equalized attainment and achievement as evidence that Black and white children attend different schools. These differences could arise from the interaction of de facto neighborhood segregation by race with local-financing of public schools. Fernández and Rogerson (1998) explore the welfare consequences for school financing reform in a model without race, and Aliprantis and Carroll (2018) explore income transitions in a racially-segregated model of neighborhoods with educational externalities.

[7] This is true even in our largest return gap case, which assumes white households get 10 times the return of Black households.

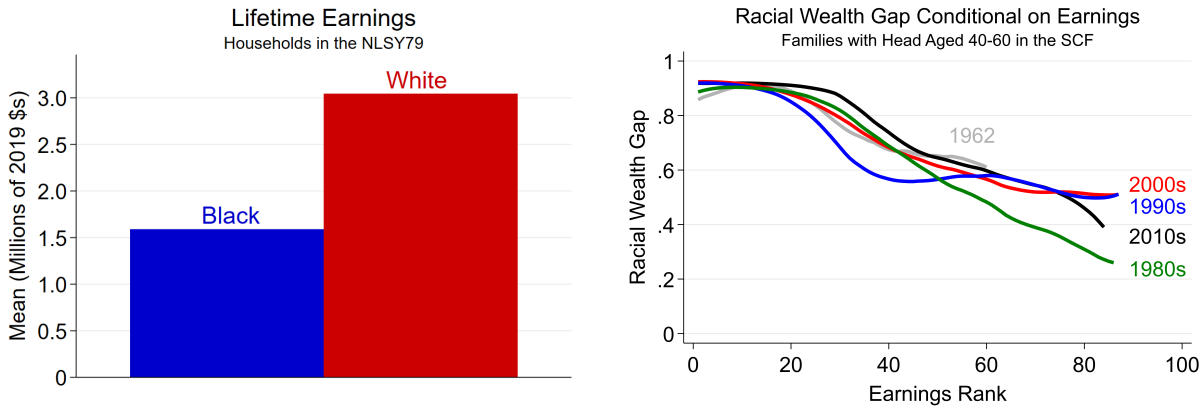
gap, but not in environments with substantial earnings inequality. We also conduct an experiment that equalizes the expected bequests received by Black and white households. Given the disparities in mean wealth, this implies some transfer policy from the estates of white households to Black heirs. Under the permanent earnings gap path, equalizing bequests reduces the racial wealth gap from 79 percent to 58 percent.

Our final contribution is to study a version of reparations centered on one-time direct payments to Black households. We run an experiment in which we counterfactually eliminate racial inequality in wealth distributions while holding the level of aggregate wealth constant. We find that if one-time wealth transfers do not change the racial earnings gap, such transfers are not effective, with the racial wealth gap reverting to its initial level within 50 years. These results indicate that efforts to equalize the racial wealth gap will deliver only short-lived benefits if they do not address the racial earnings gap.

When taken together, the above results indicate that policies closing the racial earnings gap will have the largest effect on closing racial differences in wealth. This conclusion may be somewhat surprising to readers who have approached this topic solely from the cross-sectional literature, but it is consistent with recent literature finding that earnings are the primary driver of the wealth distribution (Ashman and Neumuller (2020), Kaymak et al. (2020), Black et al. (2020)). This conclusion is also consistent with three pieces of empirical evidence. First, the earnings gap over a lifetime is sufficiently large to support the racial wealth gap. Figure 2a shows that in the NLSY79 average white lifetime earnings is almost twice that of Black lifetime earnings. Second, lifetime earnings have a much larger effect on potential wealth than intergenerational transfers. Using lifetime earnings to repeat an exercise that has been used to quantify the importance of transfers for the racial wealth gap (Gale and Scholz (1994), Wolff and Gittleman (2014), Feiveson and Sabelhaus (2018)), we find that when compounded over the lifecycle, earnings sum to 20-28 times more of current wealth than do intergenerational transfers.[8] Third, Figure 2b shows that among middle-aged households in SCF, the gap between Black and white wealth is declining in earnings.

Our findings focus attention on the factors behind the gap between Black and white earnings. Potential sources of earnings differences include differences in human capital through education, segregated job market networks, and labor market discrimination (whether statistical or taste-based). One set of policies along these lines would aim to equalize opportunity within public education, since pre-market factors influenced by education are strong predictors of wages and employment (Neal and Johnson (1996), Nielsen (2020), Keane and Wolpin (1997), Lee and Seshadri (2019)) and skill-biased technical change has placed growing penalties on remaining racial differences in education (Bayer and Charles (2018)). Additional policies likely to improve the relative labor market outcomes of African Americans would address incarceration (Neal and Rick (2014)), discrimination in the labor market (Kline et al. (2021), Bertrand and Mullainathan (2004), Nunley et al. (2015)), labor market attachment (Ritter and Taylor (2011), Daly et al. (2019)), and persistent residential segregation (Aliprantis and Richter (2020), Chetty et al. (2016), Bayer et al. (2008), Fogli and

[8] See Appendix B for details.



(a) Lifetime Earnings

(b) Wealth Gap Conditional on Earnings

Figure 2: Earnings and Wealth
Note: See Appendix B for details on these figures.

Guerrieri (2019), Aliprantis and Carroll (2018)).[9] Within this paper, one should view the earnings gap as the result of all these factors, and policy enacted to mitigate any particular factor would be expressed as a reduction in the earnings gap.

2 Model

The economy is populated by a unit continuum of households divided between Black and white in time-invariant fractions s and $1-s$, respectively. We denote a household's race by $j \in \{B, W\}$. Each household is endowed with one unit of discretionary time to allocate between leisure ℓ and hours working in the market h. Households value consumption, c, leisure ℓ, and accumulating wealth, k, to leave as bequests and have the same period utility functions $u(c, \ell)$ and $z(k')$.[10]

Households have a life cycle: They are born at age $\underline{a}$, face increasing mortality risk as they age, and die with certainty by age $\bar{a}$. At age a_b households receive a bequest b, and retire at age a_r where $a_b < a_r < \bar{a}$. Households have labor productivity $\Phi(a)\exp(\varepsilon)$, where $\Phi(a)$ is a deterministic age-earnings profile. Productivity at retirement is $\bar{\varepsilon}$, and while working ε follows an AR(1) process in logs

$$\log(\varepsilon') = \rho_\eta \log(\varepsilon) + \eta' \qquad \eta \sim \mathcal{N}\left(0, \sigma_\eta^2\right).$$

When a household dies, there is a transfer of $(1-\nu)k$ to a newborn household of the same race. Because newborn households begin their life cycle at working age, this can be interpreted as an inter-vivos transfer from childhood. The remaining νk is pooled with the assets of other deceased households of the same race and then distributed to surviving same-race households of bequest age.

Households cannot insure against labor productivity shocks, but they can save in an asset that

[9] We see household formation, as studied in Gayle et al. (2015) for example, as a consequence more than a cause of these other factors.

[10] We present the household's problem in recursive form, so we denote next period variables with a prime symbol.

returns $1+R$ units of consumption tomorrow. Because households cannot perfectly insure away income risk, they adjust their personal savings to smooth consumption. This behavior generates a distribution of wealth as households experiencing different shock histories. During retirement, households receive a benefit Ω, which is indexed to the household's labor productivity in its last period of working life and is funded by a tax τ on labor earnings.

A stand-in firm purchases effective labor and rents capital from households. The key model ingredient for our analysis is the earnings gap between Black and white households. For the purposes of our investigation, it is critical that an earnings gap exist, but less crucial why it exists. The latter is a complex and important area to explore in future research, but an elaborate construction of the possible mechanisms would detract from the point of this paper. To generate a racial gap in earnings, we adopt a simplifying assumption that the firm cannot distinguish between Black and white workers until it hires them. Once the firm has hired workers, it pays white workers their marginal product of labor and Black workers only a fraction $\varphi(B) < 1$ of theirs.[11] As a result, the firm earns profits equal to $[1-\varphi(B)]\, wN_B$ (Appendix D illustrates this detail.). These profits are rebated to white households through a dividend that is proportional to their wealth, $D(k)$.[12] The firm produces output according to a Cobb-Douglas production function $Y = AK^{\alpha}N^{1-\alpha}$ where aggregate capital is $K = K_B + K_W$ and aggregate effective labor is defined analogously. Capital depreciates at a constant rate δ, and the return on capital paid by the firm is the marginal product of capital minus the depreciation rate, $R = r - \delta$.

To formalize the household's problem recursively, define the state vector as wealth k, labor market productivity ε, age a, and race $j \in \{B, W\}$. The Bellman equation is

$$V(k,\varepsilon,a,j) = \max_{c,k',h} \left\{ u(c,h) + \psi_a \beta \mathbb{E}\left[V\left(k',\varepsilon',a+1,j\right)\right] + (1-\psi_a)\, z\left(k'\right) \right\}$$

subject to

$$\begin{cases} c + k' & \leq (1-\tau)\,\varphi(j)\Phi(a)\, e^{\varepsilon} wh & +(1+R)\,k + D(k,j) & \text{when} \quad a < a_r \quad \text{and} \quad a \neq a_b; \\ c + k' & \leq (1-\tau)\,\varphi(j)\Phi(a)\, e^{\varepsilon} wh & +(1+R)\,k + D(k,j) + b & \text{when} \quad a = a_b; \\ c + k' & \leq \Omega\varphi(j)\Phi(a)\, e^{\bar{\varepsilon}} w & +(1+R)\,k + D(k,j) & \text{when} \quad a \geq a_r \end{cases}$$

where ψ_a is the conditional probability of surviving from age a to $a+1$.

The warm-glow specification for utility over bequests, $z(k')$, serves two purposes. First, it allows the model to speak to the role of inheritance differences for maintaining the wealth gap (Menchik and Jianakoplos (1997)). Second, warm-glow generates a wealth distribution in our model with a thick tail. It is well-known that baseline overlapping generations general equilibrium models with

[11] All households have perfect foresight in this model. Consequently, Black workers know that they will be paid lower effective wages when they make their hours decisions.

[12] We allocate the dividends in this manner in order to close the model. One may legitimately worry that our results are strongly affected by this choice since it increases the effective rate of return for white households. The dividend is small, however, owing in large part to the much smaller Black population share. As a consequence, our numerical results are very similar if we discard profits instead (e.g., via wasteful government spending).

heterogeneous agents do not generate realistic wealth distributions (De Nardi and Fella (2017)).[13]

3 Quantitative Analysis

We explore transitions from a wealth distribution matching the data in 1962 to a *racial-equality stationary equilibrium*, in which there is no gap in labor income, no difference in bequest schedules by race, and no difference in the conditional wealth distributions across race. Each experiment will explore how the various features of the model contribute to the path for the wealth gap.

3.1 Data

We measure the joint distribution of earnings and wealth at a point in time using the triennial Survey of Consumer Finances (SCF), which began in 1983 and has been most recently released for 2019. We also use a precursor to the SCF, the 1962 Survey of Financial Characteristics of Consumers (SFCC) and the 1963 Survey of Changes in Family Finances (SCFF), which we refer to as the 1962 SCF.[14] We measure the racial wealth gap as

$$1 - \frac{\text{Mean Black Wealth}}{\text{Mean White Wealth}}$$

and measure the racial earnings gap analogously. We measure wealth in the SCF as net worth, which includes home equity, Individual Retirement Accounts (IRAs), and many other financial/nonfinancial assets and debts.[15] We measure earnings in the SCF as total family income from wages and salaries. Our SCF sample consists of families with heads or respondents who are (i) either Black or white and (ii) aged 20-100. All financial variables are converted to 2019 dollars.

We measure household wages over the life cycle using the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 sample was born between 1957 and 1964, and has been followed with annual (1979-1994) and biennial (1996-2016) surveys. Respondents were aged 14-22 at the date of the 1979 survey and aged 51-60 at the date of the 2016 survey. We measure household hourly wages in the NLSY79 as annual household earnings divided by annual household hours, where household earnings are the wage and salary income of the respondent and their spouse/partner, and household hours are the total hours worked by the respondent and their partner.

Appendix A provides the details on our data work, and Appendix B documents facts in the data.

[13] Alternative approaches to generating a thick-tailed wealth distribution include capital income risk (Hendricks (2007), Benhabib et al. (2015)) or an extremely high wage reached with very low probability (Castañeda et al. (2003)).

[14] Appendix A elaborates on our choice to use only the 1962 SCF and none of the nearby years in the SCF+ (Kuhn et al. (2020)). See Derenoncourt et al. (2021) for further historical data on the racial wealth gap.

[15] The full list is available at https://www.federalreserve.gov/econres/files/Networth%20Flowchart.pdf.

3.2 Calibration

We begin by calibrating the model to a long-run steady state in which all processes are independent of race. Parameters of the model are either estimated from the data (by ourselves or by others in the literature); calibrated using simulated method of moments; or set to standard values from the literature.

3.2.1 Functional Forms

We specify preferences over consumption, leisure, and the warm-glow from bequests as

$$u(c,h) = \frac{c^{1-\gamma}}{1-\gamma} + \theta_h \log(1-h) \qquad \text{and} \qquad z(k') = \theta_1^b \frac{\left(\theta_2^b + k'\right)^{1-\gamma}}{1-\gamma}.$$

The functional form for z comes from De Nardi (2004), and allows for bequests to be a luxury good. Under this specification, θ_1^b controls the overall strength of preferences for bequests while θ_2^b affects how strongly bequests are a luxury good.

3.2.2 Parameters

Table 1 shows the parameters used in our calibrated model. We set $\gamma = 2.0$, the capital share of production $\alpha = 0.36$, and the depreciation rate of capital $\delta = 0.25$, which implies that investment is 15 percent of annual output. By rebating the firm's profits back to white households, we assume in our baseline experiment that white households face a return that is typically 1.22 times Black households' return.

The parameters governing the transfer of wealth across generations are set in order to capture the stylized facts in Hendricks (2001). We set the bequest age $a_b = 7$, which corresponds to ages 50-54. Bequests b to middle-age households take one of three values: 70 percent receive no bequest, 28 percent receive a small amount b_2, and 2 percent receive a large amount b_3, where b_3 is set to 70 percent of the middle-age inheritance pool. We set $\nu = 0.75$; Avery and Rendall (2002) calculate ν to be 0.78 using lifetime inheritances in the 1989 SCF, and the individual-level data on transfers received in Feiveson and Sabelhaus (2019) generates a ν of 0.76 in the 1996-2016 SCF.

The survival probabilities ψ_a are estimated using data on all-gender survival probabilities for white individuals in Table 20 of Arias et al. (2016).[16] Appendix E shows the mortality rates used in a robustness check in which the mortality schedule for black households begins at the one measured in the data and then convergences slowly to the white schedule. Differences between the implied wealth gap path from this exercise and the one in the baseline are inconsequential.

[16] Arias et al. (2016) is a Centers for Disease Control National Vital Statistics Report and we use estimates representing age-specific 2012 survival probabilities.

Table 1: Calibration for Baseline Steady State

Model Parameter	Estimated Value		Model Parameter	Chosen Value
ρ_η	0.77	NLSY79	γ	2
σ_η	0.67	NLSY79	α	0.36
ν	0.75	Avery and Rendall (2002)	δ	0.25
$Pr(b_1)$	0.70	Hendricks (2001)		
$Pr(b_2)$	0.28	Hendricks (2001)		
$Pr(b_3)$	0.02	Hendricks (2001)		

Moment	Targeted Moment	Calibrated Moment	Model Parameter	Calibrated Value
$\overline{K}/Y$	0.60	0.60	β	0.59
Y	1.0	1.0	A	2.25
H	0.30	0.31	θ_h	1.27
$\Gamma(k=0)$	0.13	0.124	θ_1^b	1.41
Gini of Wealth	0.82	0.66	θ_2^b	0.10
Government surplus	0	0	τ	0.17
Avg. replacement rate	0.40	0.40	Ω	0.16

Note: The estimated age-wage profile $\Phi(a, j)$ is shown in Figure 3, and the estimated mortality schedule ψ_a is taken from Arias et al. (2016).

We estimate ρ_η and σ_η using the NLSY79, with Appendix A.2.3 describing the estimation in detail. We use race-specific quadratic functions of age to estimate Φ as the mean of wages in each household's category for age and race, shown in Figure 3. Taking the Φ's as given, we then use maximum likelihood to estimate the parameters $\widehat{\rho}_\eta = 0.77$ and $\widehat{\sigma}_\eta = 0.67$. Appendix A.3 replicates our analysis with the Panel Study of Income Dynamics (PSID); our persistence parameter is nearly identical across samples, while our variance parameter is higher in the NLSY79 than in the PSID. The $\widehat{\sigma}_\eta = 0.55$ estimate on the PSID in De Nardi (2004) is between our estimates in the NLSY79 and PSID; the implied five-year estimate in Floden and Lindé (2001) of $\widehat{\sigma}_\eta = 0.33$ using the PSID is lower than all of our estimates.[17]

We finish by jointly calibrating the remaining parameters so that the model matches moments from the data. Targeting a capital/output ratio of 0.6 (equivalent to a capital/output ratio at an annual rate of 3.0) generates a model discount factor of $\beta = 0.59$. The total factor productivity (TFP) parameter A being 2.25 produces a five-year output of 1, which serves to normalize units. For the labor supply choice, θ_h is calibrated to 1.27 in order to match an average hours of work equal to 30 percent of discretionary time. We calibrate θ_1^b and θ_2^b to 1.41 and 0.10, respectively,

[17] Differences between our estimates and the estimates in Floden and Lindé (2001) are likely driven by sample selection (we include top- and bottom-coded households to control for the extensive margin of employment; their sample is heads of the same household in the PSID while households in our sample are based on all individuals in the NLSY79), sample time period (their sample is from 1988 to 1992 and ours is from 1979 to 2016), and age-wage profiles (theirs are education- and occupation- specific while ours are race-specific).

which yields a wealth Gini of 0.66 with 12.4 percent of households are at the borrowing limit.

The tax rate on labor income is 17.0 percent. This clears the government budget constraint when the retiree benefit parameter, Ω, implies a replacement rate of 40 percent of last period labor earnings.

Figure 3: Mean Wage by Age and Race in the NLSY79

Initiating the model requires that we have a starting wealth distribution over productivity, age, and race. We estimate this distribution using kernel density techniques to smooth the initial distributions of wealth within race and age groups in the 1962 SCF. Age groups are chosen to maximize sample size while grouping similar distributions. We chose age groups based on mean wealth by age and race, which are displayed in Figure 4. We chose the age groups 20-44 and 45-94 for Black-headed families, and for white-headed households we chose the age groups 20-24; 25-29; 30-34; 35-39; 40-44; 45-55; 55-79; and 80-94.

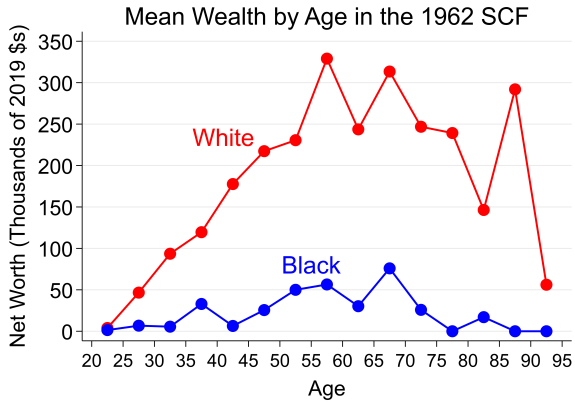
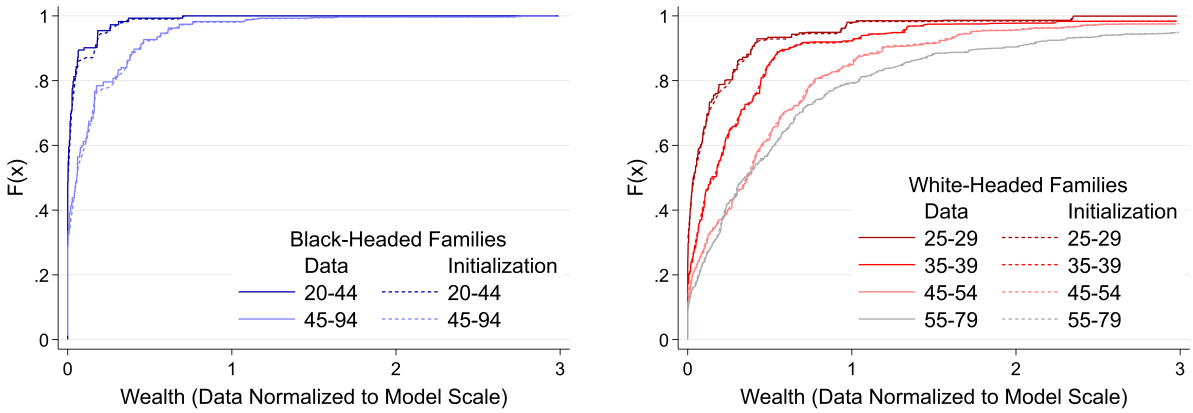


Figure 4: Wealth by Age and Race in the 1962 SCF

Figure 5 shows the best fitting kernel density approximations to the raw data for some of these groups. What is immediately apparent is that African Americans had much lower wealth in 1962 than their white counterparts. While it is relatively rare for white families to possess model wealth

over 1, essentially no Black families have this level of wealth. The comparison is even more unequal if we look at wealth levels like 0.5.



(a) Black-Headed Families

(b) White-Headed Families

Figure 5: Wealth by Age and Race in the 1962 SCF

In the model, income and age will be correlated with wealth through the endogenous savings decisions of households. For the initial joint distribution of productivity, age, and wealth, we assume productivity and age follow their invariant distributions while wealth is independently distributed according to the estimated conditional distributions of wealth by age and race

3.3 Model Validation

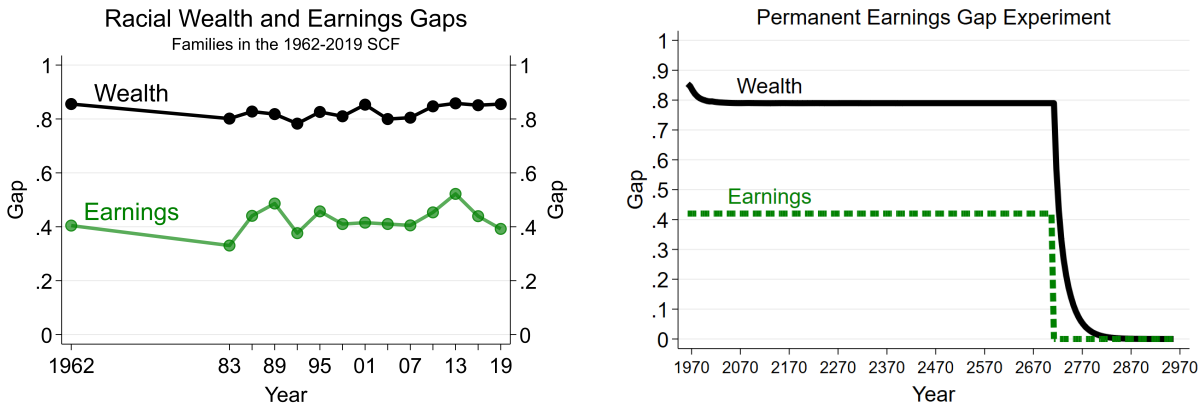
Before using the model to make predictions about counterfactual outcomes, we first ask: Does the model make reasonable predictions about outcomes we have observed? To answer this question, we feed a sequence of earnings gaps that matches what we have observed in the data. Then we compare the data to what the model predicts about the racial wealth gap, both in terms of the time series and the joint distribution of race, earnings, and wealth in a given cross section.

We capture the data on the earnings gap with a sequence of exogenous earnings gaps $\{\varphi(B)_t\}_{t=1}^{T}$ where $\varphi(B)_t = 0.42$ for $t = 1, \ldots, 150$, or until the year 2712.[18] In this case, as shown in Figure 6b, the earnings gap is effectively permanent for households in the present (and for many generations in the future). Throughout the paper we refer to this transition path as one with permanent earnings differences.

Given a sequence of earnings gaps consistent with what we have observed in the data, the model predicts an endogenous wealth gap that is nearly identical to what we have observed in the data. At the beginning of the path there is a small decline in the wealth gap. This is because the model

[18] Appendix B presents this empirical fact, along with all of the additional facts from the main text, in greater detail. We do not take a stand on the factors behind the earnings gap. They could range from persistent differences in human capital, lower employment, household composition, higher incarceration rates, or racial bias. We discuss interpreting the labor income gap in the conclusion.

does not start in a steady state, and such initial dynamics will be featured in all of our subsequent exercises. But Figure 6b shows that after these initial few periods, the model endogenously settles at a wealth gap that is very close to the one in the data.



(a) Data (b) Model

Figure 6: Racial Wealth and Earnings Gaps in the Data and Model

Given a sequence of earnings gaps consistent with what we have observed in the data, the model also predicts a cross-sectional relationship between earnings, wealth, and race that is qualitatively similar to the relationship in the data. Figure 7a shows that the racial wealth gap remains even after conditioning on earnings, a fact that has received considerable attention in the literature. While a cross-sectional perspective might see this pattern in the data as a puzzle, our model suggests that this relationship should not be a surprise. Figure 7b shows that the model predicts this relationship as a byproduct of the dynamics of the racial wealth gap. The model predicts that in the years 2017-2021, the racial wealth gap will still remain conditional on earnings.

(a) Data (b) Model

Figure 7: Wealth by Earnings and Race in the Data and Model
Note: Model data in the right panel have been annualized.

3.4 The Earnings Gap

Given the validation of the model's predictions just presented, we now proceed to study the contributions of mechanisms by conducting numerical experiments in which we alter some mechanisms in the model to produce counterfactual predictions.

We investigate the importance of the earnings gap by studying two starkly different scenarios shown in Figure 8: an optimistic case in which the earnings gap instantly vanishes starting in 2022 and a pessimistic case where, as above, the earnings gap stays at 0.42 until the year 2712. In the second case, the earnings gap is effectively permanent for households in 2021 (and for many generations in the future). This highlights a difference between our model and one with infinitely-lived households (or equivalently dynasties if altruism is perfect). Here households do not internalize the utility of future generations, so even though they have perfect foresight about the future path of the earnings gap, there is no feedback from gap changes centuries in the future to the present. Thus, current household's decisions do not respond to changes in the distant future.[19]

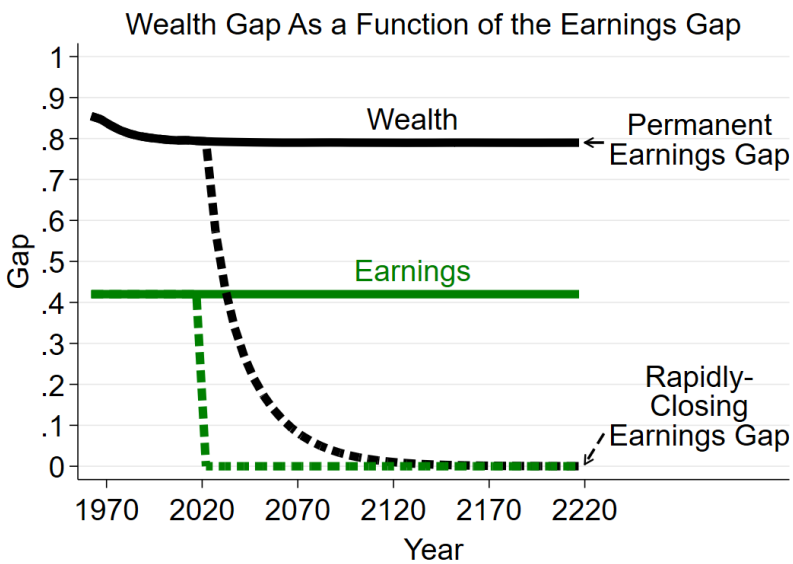


Figure 8: The Wealth Gap by Earnings Equality

Figure 8 plots the earnings and wealth gaps over the next 200 years in these two cases. The wealth gap paths under the two cases could not be more different. In the case of a permanent earnings gap, the wealth gap stabilizes at 79 percent and does not change until the earnings gap finally closes. In the optimistic case of a rapidly-closing earnings gap, once the earnings gap is removed, the wealth gap rapidly declines. Of course, "rapidly" is only accurate relative to the pessimistic scenario. Even under this best-case where earnings gaps vanish instantly, mean Black wealth takes 80 years to reach 95 percent of mean white wealth. This result should serve as caution

[19] If we impose that the interest rate is constant at the initial value over the entire transition, the dynamics of the wealth gap barely change because life cycle considerations dominate savings behavior. Details of this experiment are available upon request.

to policymakers: Wealth gap transitions are going to evolve slowly.

3.5 Educational Reforms

The bounding exercises above illustrate the enormous potential equalizing earnings can have for closing the wealth gap. In the interest of making this point as plain as possible, we have intentionally chosen not to muddle the analysis by explicitly modelling any specific cause of the earnings gap. The truth is that there are many factors contributing to the earnings gap, but regardless of the composition of their contributions, in a dynamic model of savings like this one the persistence of the racial wealth gap will depend fundamentally upon the persistence of the earnings gap. To give some sense for policy-relevant changes to the earnings gap, we consider much of the earnings gap might close if we attribute some of the earnings gap to the unequal distribution of educational attainment and achievement by race.[20]

In the NLSY79, white respondents have significantly higher educational attainment (ie, degree completion) and educational achievement (ie, test scores). Both attainment and achievement are likely to be components of the pre-market factors found to be important for racial gaps in labor market outcomes (Keane and Wolpin (2000), Cameron and Heckman (2001)), including wages (Neal and Johnson (1996)), lifetime earnings (Nielsen (2015)), and intergenerational income mobility (Bhattacharya and Mazumder (2011), Davis and Mazumder (2018)).[21]

This previous literature motivates our educational reform exercises, in which we narrow the earnings gap in the model beginning in 2022. Unlike in the bounding exercises where the earnings gap vanished for all ages at once, we will roll the educational reform out over generations. Initially, only the newborn Black households realize a smaller earnings gap, and they maintain this earnings gain for the rest of their lives. All other Black households continue with the pre-reform gap value. Over time the reform is realized by all Black households, as old generations die and are replaced by a newborn generation.

To measure the fraction of the earnings gap that could be closed by education reform, we estimate how much of the lifetime earnings gap in the NLSY79 can be accounted for by racial differences in attainment and achievement. To do this, we assign earnings for Black households given the counterfactual white distribution of educational attainment or achievement as the average earnings of Black households at a given level of treatment times the white share at each level of educational treatment. Formally, for attainment or achievement treatments D and earnings Y, we compute the counterfactual mean earnings as

$$\mathbb{E}[Y_i(D^W)|\text{age}_i, \text{race}_i = B] = \sum_{a=1}^{A} \mathbb{E}[Y_i|d_i = a, \text{age}_i, \text{race}_i = B] Pr[d_i = a|\text{age}_i, \text{race}_i = W]. \quad (1)$$

[20] These educational differences can be attributed to decades of purposeful under-resourcing of Black communities, i.e, structural racism.

[21] Measurement issues for both attainment and achievement are especially pronounced for discerning trends (Bayer and Charles (2018), Heckman and LaFontaine (2010), Nielsen (2017), Bond and Lang (2013)).

For the treatment D defined as attainment, $A = 3$ and the three levels we consider are less than high school, high school diploma, and BA or higher. For the treatment D defined as achievement, $A = 20$ so that the levels we consider are the ventiles of AFQT test score ranks.

Figure 9 shows lifetime earnings over the life cycle in the data and after adjusting for attainment or achievement following Equation 1. By age 60, educational achievement can explain 76 percent of the racial gap in lifetime earnings, while educational attainment can explain only 25 percent of the gap. Notice that the earnings gap remains wide even conditional on age; the earnings gap is not simply due to the fact that in a given cross section, Black households will tend to be younger. These findings are suggestive that apart from large differences in the certified level of education the labor market premium is conferred on graduates is not equal by race. This would be consistent with, for instance, the interaction of de facto neighborhood segregation by race with local financing of public education.

Figure 9: Education-Adjusted Lifetime Earnings in the NLSY79

The transitions for equal attainment and equal achievement scenarios are plotted in Figure (10. As one would expect, equalizing skills has a roughly fives times larger effect on wealth gap. In either case, progress comes slowly as the generation rollout of reform adds an additional 50 years to wealth gap relative to conferring the same earnings gain on all households immediately.

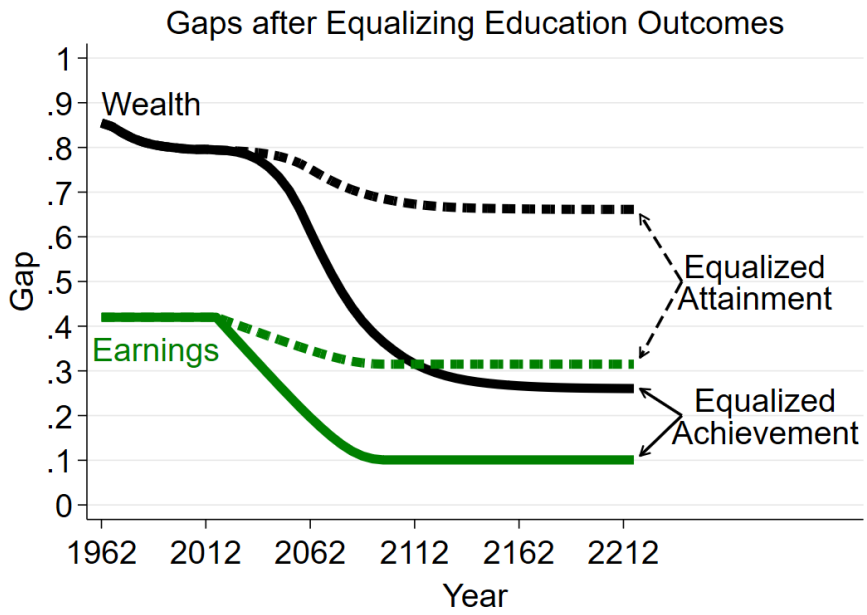


Figure 10: The Wealth Gap by Earnings Equality

3.6 The Return Gap

A racial gap in the returns to capital is thought to be one of the key factors that helped to generate the 1962 racial wealth inequality used in our analysis. Historical examples that contributed to a return gap include limiting credit in Black areas (Aaronson et al. (2017), Faber (2020)), subsidizing housing in white areas (Rothstein (2018), Baradaran (2017)), white flight and blockbusting (Akbar et al. (2020)), and theft by means of predatory housing financing such as contract sales (George et al. (2019), Coates (2014)).

In more recent decades, a return gap would most likely have appeared as differences in the risk/return composition of portfolios (Bartscher et al. (2021), Kuhn et al. (2020)), rather than different returns on the same types of assets, with housing being one potential exception.[22] This return gap, however, is hard to find in the data. The most compelling evidence indicates that rates of return have been similar for Black and white households over recent decades (Wolff (2018), Gittleman and Wolff (2004)).[23]

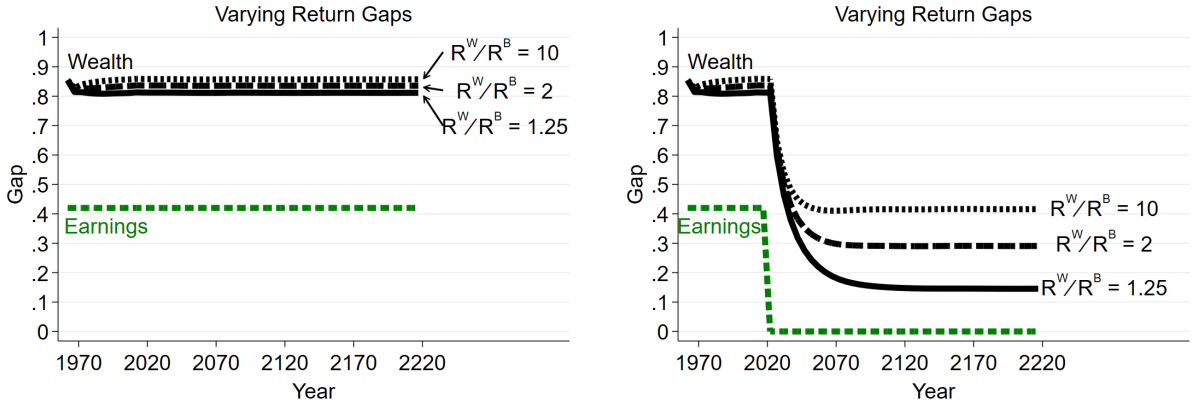
The evidence on a potential return gap is far from conclusive, though. The possibility of a mis-measured return gap is one reason we do not dispose of the firms' profits in the baseline experiment, which generates a non-trivial return gap so that white returns are typically 1.22 times

[22] Bayer et al. (2016) provide evidence consistent with differential returns on housing; the mechanism is concentration of initial wealth in housing, residential segregation, and a recession generating a shock to the housing sector. Such a mechanism could be amplified by continued discrimination in the housing market (Christensen and Timmins (2018), Turner et al. (2013), Courchane and Ross (2019)) together with differential returns by neighborhood racial composition (Collins and Margo (2003), Howell and Korver-Glenn (2020)).

[23] Boerma and Karabarbounis (2021) explores how capital income risk can impact the racial wealth gap.

Black returns.[24] The possibility of a mis-measured return gap also motivates us to re-run the bounding exercises from Section 3.4, under three counterfactual return gaps (in addition to the gap created by dividends): one where the return for Black households is 80 percent of the return for white households, one where it is 50 percent, and one where it is 10 percent. In light of the empirical evidence available (Wolff (2018), Gittleman and Wolff (2004)), we believe that even the 80 percent case is "generous." The additional cases are meant to further illustrate the limitations of return gaps for driving the wealth gaps in the model, rather than to approximate reality. For example, we consider the 10 percent case, in which white households earn 10 times the return of their Black counterparts, far too large to be plausible. As evidence bounding the type of return heterogeneity we find plausible, Kaymak et al. (2020) find that in recent waves of the SCF, the top 0.1 percent of the income distribution enjoys a rate of return that is 3.4 times the rate on the assets of the bottom 90 percent of the distribution. In each experiment the return gap is eliminated in the year 2712, so that the economy can reach the racial equality steady state.

When the earnings gap is permanent, including a return gap has very little effect on the wealth gap. This is illustrated in Figure 11a. Recall that when there is no return difference, the model settles into a gap of 79 percent. In contrast, with Black returns at 80, 50, and 10 percent of white returns, the wealth gap is 81 percent, 84 percent, and 86 percent, respectively. This lack of sensitivity of the wealth gap in this scenario is due partly to the fact that Black households earn much less so there is a only a small wealth base for the return difference to interact with. The second factor comes from the life-cycle structure of the model. Because households live a finite number of periods and have no meaningful connection to periods far in the future, return differences, which could compound many times in an infinitely-lived or dynastic framework, are limited here.



(a) Permanent Earnings Gap

(b) Rapidly-Closing Earnings Gap

Figure 11: The Wealth Gap by Return and Earnings Gaps

These results do not imply that return differences are of no consequence, but rather that they

[24] As noted earlier, if instead of being redistributed this dividend is disposed of, the results of our numerical experiments do not change.

are secondary to the earnings gap in importance. Contrast the results under a permanent earnings gap with those under immediate closure, which are shown in Figure 11b. The figure shows that return gaps limit the longer run convergence of the wealth gap. While the baseline case with a small earnings gap effectively eliminates the wealth gap, the 80 percent return case leaves a gap of 14.5 percent, and in the most extreme case, there is a still a 41.6 percent gap remaining. Taken together, the results from our experiments with a return gap indicate that this mechanism could play some role in maintaining the wealth gap. However, we again stress that even the weakest return difference considered here quite unlikely given empirical evidence to date. We conjecture that plausible return difference (should they exist) would have only a small effect on the future gap and even then only after the earnings gap has been greatly reduced.

3.6.1 The Bequest Gap

Our model points to the difference in Black and white earnings as a strong force keeping average racial wealth levels from converging. We interpret this result as being consistent with the evidence in the data and the literature suggesting that earnings are the primary driver of the racial wealth gap. For instance, the raw magnitudes of potential wealth flows from earnings are much larger than from transfers. Running an accounting exercise similar to that in Feiveson and Sabelhaus (2018), but with lifetime earnings, reveals that earnings can account for 20-28 times more of current wealth than intergenerational transfers.[25]

Further, evidence from the US shows the importance of labor income as the major driver of total income (Kaymak et al. (2020)), and evidence from administrative data in Norway points to a much larger role for earnings in driving the wealth distribution than for inheritances (Black et al. (2020)). The literature generally finds that inheritances can account for at most 20 percent of the racial wealth gap in the US (O'Flaherty (2015)). For example, Menchik and Jianakoplos (1997) find that financial inheritances account for 10 to 20 percent of the gap; an estimate with more recent data is 12 percent (McKernan et al. (2011)). Nevertheless, the mechanism of intergenerational transfers is still put forward in policy discussions as a primary driver of the racial wealth gap.[26]

We investigate the role of intergenerational transfers for sustaining the racial wealth gap in our model, since the bequest structure also perpetuates the wealth gap. In the model, even though Black and white households have the same structural preferences for leaving bequests, the unequal nature of the initial wealth distribution produces long-lasting differences in bequests for two reasons. First, because mean wealth is higher for white households, the pool of bequests will be larger for them. Second, because leaving bequests is a luxury good, white households on average have a stronger incentive to accumulate wealth.

To disentangle the effect of inheritances from that of earnings, we run a counterfactual in which, beginning in 2022, the Black and white bequest pools are joined, and all middle-aged households draw from this joint pool. We keep the same probabilities over the bequest lottery as before, but

[25] For more detail on this exercise, see Fact 7 in Appendix B.
[26] See Hamilton and Darity (2010).

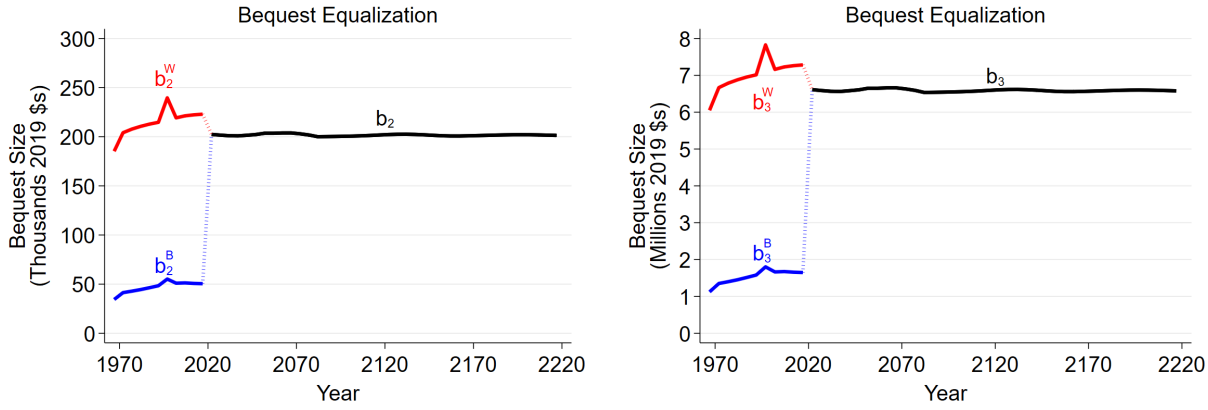
now the bequest sizes themselves are equal for both races. This avoids transitory complications in the bequest paths arising from heterogeneous inheritance probabilities. The earnings gap is set to the same permanent path as in the pessimistic bounding case; it remains at its initial value of 0.42 until 2712 when it vanishes, allowing the model to reach the racial equality steady state.

Table 2 reports bequest sizes by race for model period 2017-2021, just before the bequest pools are combined. The expected bequest for a white household is 4.4 times that for a Black household. These bequests, produced endogenously by our model, are consistent with the evidence of large differences across race found in the literature. Menchik and Jianakoplos (1997) and Wolff (2002) find a ratio of about 3 times, and Avery and Rendall (2002) and Smith (1995) find ratios closer to 5.[27] For lifetime inheritances, Avery and Rendall (2002) find a ratio of 6-7 times.

Table 2: Model Bequests in 2017-2021
As a Share of Average Wealth

	Black	White	$Pr(b = b_m)$
b_1	0	0	0.70
b_2	0.27	1.21	0.28
b_3	8.96	39.57	0.02
$E(b\|b > 0)$	0.85	3.77	–

Figure 12 plots the two positive bequest values over the first 200 years of the transition. From the plots it is immediately apparent that the policy experiment considered here would represent a massive reallocation of wealth from the estates of white households to Black households.



(a) Medium-Sized Bequests (b_2)

(b) Large Bequests (b_3)

Figure 12: Bequests

[27] Thompson and Suarez (2015) find a ratio of 3 conditional on receiving an inheritance.

As one would expect, removing racial inequality in bequests speeds the rate of convergence of the wealth ratio; however, after approximately 50 years the gap stops closing and settles at 58 percent until 2712 when the earnings gap closes and the model reaches the racial equality steady state. Given that the wealth gap is 79 percent in 2021, bequests equalization alone reduces it another 22 percentage points. This suggests we can assign 27 percent of the model gap in 2017-2021 to differences in bequests.[28] This finding is consistent with the steady state analysis in Ashman and Neumuller (2020).

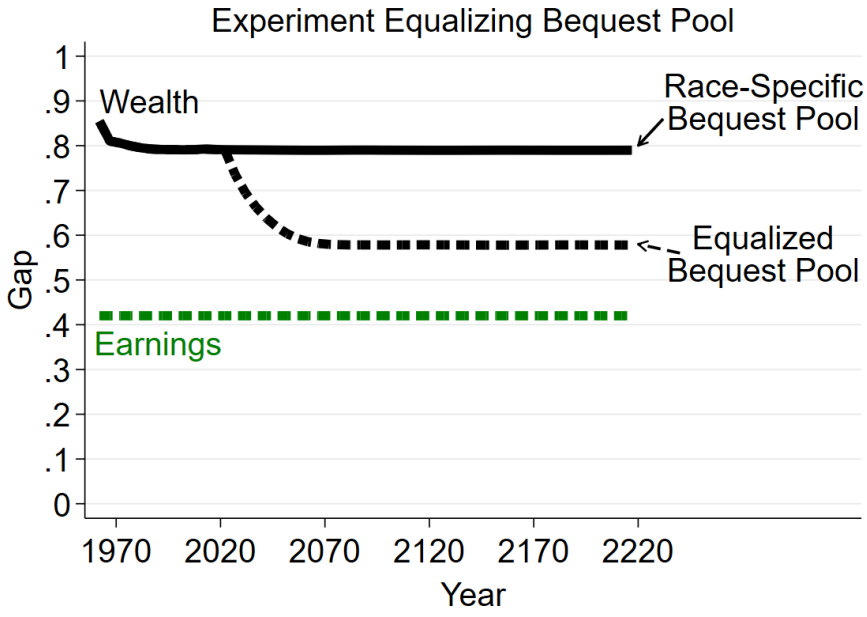


Figure 13: The Transition Path for Bequests under the Baseline

3.7 Reparations As a One-Time Wealth Transfer

The analysis in this paper is focused on the questions of how to close the racial wealth gap, both quickly and permanently. These economic questions are part of the much larger political question: Should the US do anything to address the racial wealth gap, and if so, what?

Public opinion is changing toward the first part of this question, with wider recognition of the injustices caused by racism and their ongoing consequences. In recent years the case for reparations has gained increasing attention (Coates (2014)), and in 2019 a resolution was introduced in the US House of Representatives to establish a commission to study and develop reparations proposals (US Congress (2019)).[29] In 2020, video of the murder of George Floyd, together with protests and

[28] Appendix F shows that equalizing inter-vivos transfers in our model would have smaller effects on the wealth gap than equalizing bequests.

[29] Local efforts have also been made. Two examples include Evanston, Illinois' enactment of a reparations program to compensate Black families that suffered harm from past policies and the University of Virginia's funding of scholarships in compensation for owning slaves.

discussions around the Black Lives Matter movement, rapidly changed public opinion on race in the US in 2020 (Cohn and Quealy (2020)). While a consensus public "narrative" has yet to be reached in the US about the problem of racial inequality (Loury (2006)), the country appears its closest yet to facing the problem.

The above discussion is largely about the social welfare function we should adopt; that is a political question and not an economic one. Even assuming society chooses to implement reparations policies, the form they might take involves a number of possible perspectives (O'Flaherty (2015)). One approach is for the entire society to take responsibility for the situation of poor Black citizens, acknowledging that the present circumstance is a consequence of an ethically indefensible past (Loury (2006)). One prominent proposal is to create a trust to assist in the educational and economic empowerment of African-Americans (Robinson (2000)), while another calls for direct cash payments to verifiable descendants of slaves and those who have identified as Black (Darity and Mullen (2020)).

Our model is well-suited to evaluate the consequences of these programs. Specifically, we study how a program of one-time cash payments would affect the racial wealth gap over time. We again suppose that the earnings gap is effectively permanent and repeat our pessimistic bounding exercise from Section 3.3; however, in 2022, the wealth distribution of black households is equalized to that of white households by a system of transfers that keeps aggregate wealth constant. Our results are meant to be illustrative of the potential effects of such a program. We do not attempt to model any political or social obstacles to implementation, nor do we explore the finer details of how one would make these payments (should we tax white households to pay transfers to Black households or should we directly transfer ownership of financial assets?).

The resulting wealth gap path is plotted in Figure 14. Equalizing wealth without equalizing earnings has no long-term effect on the wealth gap: Within 50 years the wealth gap returns to its initial level. Our results again emphasize the importance of policies aimed at reducing the earnings gap in addition to the wealth gap if the goal is to have lasting effects.

One obstacle to the interpretation of this last experiment is that wealth could very well feed back into earnings, which we assume does not happen in the experiment. Despite this simplifying assumption, we still consider this experiment to be an informative exercise. The best empirical evidence currently available suggests that wealth is not the primary driver of earnings (Chetty et al. (2020)), and recent evidence on feedback from wealth to earnings via college attendance (Bulman et al. (2021)) and neighborhood effects (Aliprantis et al. (2021)) suggests that these mechanisms are relatively weak.[30] While the evidence is far from conclusive, and there are additional mechanisms like job-search insurance (Pilossoph and Wee (2021), Algan et al. (2003), Bloemen and Stancanelli (2001)) and capital for entrepreneurship (Doorley and Pestel (2016)) through which wealth could affect earnings, it is worth recalling that all of these mechanisms point to the importance of earnings.[31]

[30] See Fox (2016) for additional evidence.

[31] The empirical evidence from historical examples of this kind of large wealth transfer in the US is also consistent with our results (Bleakley and Ferrie (2016), Ager et al. (2019)).

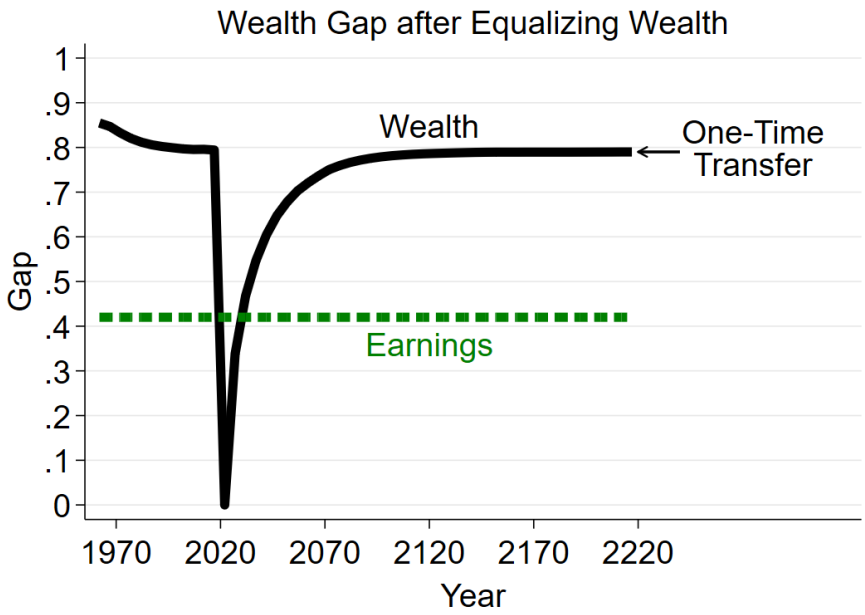


Figure 14: The Wealth Gap by Earnings Equality

4 Conclusion

This paper uses a heterogeneous agents dynamic stochastic general equilibrium model to study mechanisms that can generate the type of persistent Black-white wealth inequality documented in the data. Our analysis provides a dynamic perspective to the literature studying the racial wealth gap. Our model is able to explain key features of the racial wealth gap across both time and individuals given the tremendous wealth inequality at the start of the period we examine, as well as differences in bequests, earnings, and returns to savings. Our model attributes the slow convergence of the racial wealth gap primarily to persistent differences in earnings.

Our results underscore the importance of understanding the sources of continued differences in earnings between Black and white households. We take our findings as evidence that policies aimed at reducing the earnings gap would be most effective at eliminating the racial wealth gap.

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A Appendix: Details on Data Work

A.1 The Survey of Consumer Finances (SCF)

We measure the joint distribution of earnings and wealth at a point in time using the triennial Survey of Consumer Finances (SCF), which began in 1983 and has been most recently released for 2019. We also use a precursor to the SCF, the 1962 Survey of Financial Characteristics of Consumers (SFCC) and the 1963 Survey of Changes in Family Finances (SCFF), which we refer to as the 1962 SCF.[32]

Our SCF sample consists of families with heads or respondents who are (i) either Black or white and (ii) aged 20-100. It is not entirely obvious how to define "Black" in the 1962 SCF. In the 1962 SCF the surveyor assigned household heads to one of three mutually exclusive categories: "White," "Nonwhite," or "Not Ascertained." We interpret the "Nonwhite" group in the 1962 SCF as being identical to the "Black or African American" group under the 1997 US Office of Management and Budget Classification Standards (OMB (1997)) for defining race. Appendix A.1.2 describes this interpretation in detail.

In the SCF we measure wealth as net worth, which includes home equity, Individual Retirement Accounts (IRAs), and many other financial/nonfinancial assets and debts.[33] In the SCF we measure earnings as total family income from wages and salaries.[34]

For 1989-2019 we obtain wealth and earnings in real 2019 dollars from the "Summary Extract Public Data" files. For 1983 and 1986 we obtain wealth and earnings in nominal dollars from the Edited and Imputed Version of the Stata format "Full Public Data Sets." For 1962 we obtain wealth and earnings in nominal dollars from the "Full Public Data Set," but a major difference from subsequent waves of the survey is that we must construct our own net worth variable in terms of total assets minus total debts. We construct total assets and total debts from the list of component variables according to the SCF definitions to match the net worth programs for 1983 onwards.

Since the CPI-U-R series only goes back to 1977, we deflate nominal values in 1962 using the CPI-U and nominal values in 1983 and 1986 using the CPI-U-R. The financial variables already converted to real 2019 dollars in the 1989-2019 "Summary Extract Public Data" files were deflated by SCF staff using the CPI-U-R.

A.1.1 The SCF+

Kuhn et al. (2020) construct and analyze the SCF+, an additional series of annual SCF data sets from 1949-1971, along with 1977, currently available from the ICPSR. We do not use the SCF+ because it is a survey with distinct features from the waves of the SCF posted on the Federal Reserve

[32] In the SCF+ constructed by Kuhn et al. (2020), the racial differences in the 1962 SCF are not outliers relative to nearby years. Below we discuss our reasons for using only the 1962 SCF and none of the nearby years in the SCF+.

[33] The full list is available at https://www.federalreserve.gov/econres/files/Networth%20Flowchart.pdf.

[34] The sources of earnings are the head, wife, and other family members in 1962; the respondent and spouse in 1983-1986; and anyone in the family in 1989-2016.

Board's website, which are the waves we use in our analysis.[35] The distinct features of the SCF+ raise a separate set of concerns relative to the 1962 and 1983-2016 SCF surveys, with the 1962 SCF being the most direct precursor to the subsequent 1983-2016 SCF surveys. For example, coverage of SCF+ variables is incomplete across survey years, with some variables reported in bins or not at all in some years. Moreover, the analysis in Kuhn et al. (2020), as well as our own replication, confirms that our inference from the 1962 data is consistent with the SCF+.

A.1.2 Racial Categories in the 1962 SCF

Mapping previous racial and ethnic categories in the US Census to the currently-used categories is a convoluted process (Pratt et al. (2015)). Aside from the issues this fact raises about how we interpret racial statistics (Zuberi (2001)), this fact also raises a measurement issue for our analysis.

Mapping race from the 1983-2016 waves of the SCF to current racial categories is not straightforward because the surveys convolute race and ethnicity. We assign race to families based on the race of the survey respondent, who must choose one mutually exclusive choice. In 2016, for example, respondents are asked which category best describes them among "white, Black or African-American, Hispanic or Latino, Asian, American Indian or Alaska Native, Hawaiian Native or other Pacific Islander, or another race."

Mapping race in the 1962 survey to current racial categories is less straightforward than choosing the mapping for later waves. Race was determined in the SCF by the surveyor in 1962, which simplifies our task relative to respondents choosing their racial identity (Dahis et al. (2019)).[36] The 1962 SCF labels the family head as being one of three mutually exclusive categories: "White," "Nonwhite," or "Not Ascertained." In our analysis we interpret these categories in terms of the current US Census Bureau categories established by the 1997 US Office of Management and Budget Classification Standards (OMB (1997)).

Of the weighted sample in the 1962 SCF, white, nonwhite, and not ascertained respondents make up, respectively, 79.5, 9.5, and 11.0 percent of the sample. In the 1960 census, white and Black individuals are, respectively, 88.6 and 10.5 percent (US Census (1961)). Thus, the numbers would be reasonable if marginally white groups – white groups by today's terms that were historically viewed as being white in a marginal or inferior way, such as Jews, Greeks, Italians, and Irish (Painter (2015)) – combined with Hispanics to form the 11.0 percent of "not ascertained" family heads in the 1962 SCF. The remaining share of "nonwhite" respondents in the 1962 SCF corresponds closely with the share of Black individuals in the US population at the time.

With these considerations in mind, we interpret "nonwhite" in the 1962 SCF as meaning "Black" in today's terms and we interpret "white" and "not ascertained" in the 1962 SCF as meaning "white" in today's terms. Relevant data show that these appear to be reasonable interpretations. Nearly all of the US population was either white or Black in the 1960 Census. Of the nonwhite

[35] See https://www.federalreserve.gov/econres/scfindex.htm.
[36] Race became self-identified starting in the 1989 SCF.

population in the 1960 census, 92.1 percent were "Negro" (US Census (1961)).[37] Although the Hispanic origin question was first introduced in the 1970 census, Gratton and Gutmann (2000) have used other variables, such as birthplace, maternal birthplace, mother tongue, and having a Spanish last name, to impute how respondents to censuses before 1970 would have responded to the Hispanic origin question had it been posed in those earlier censuses. Figure 15 shows the results of their analysis; it is likely that about 3 percent of the US population was Hispanic in 1960.

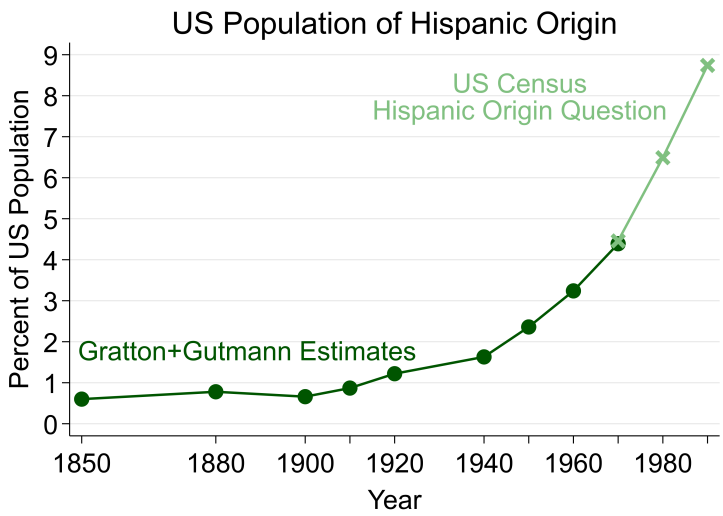


Figure 15: Hispanic Population in the US over Time

Evidence on educational attainment also supports our choices for mapping the racial categories in the 1962 SCF to today's racial categories. BA attainment would be higher than expected if "not ascertained" family heads were mapped to "Black." This can be seen by looking at levels (Figure 16) or ratios (Figure 17).

[37] The 1960 Census questionnaire asked if each person was "White, Negro, American Indian, Japanese, Chinese, Filipino, Hawaiian, Part Hawaiian, Aleut, Eskimo, (etc.)?"

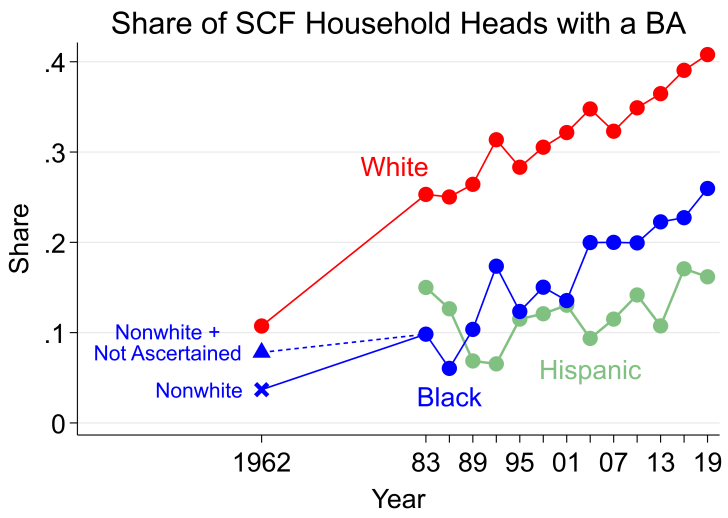


Figure 16: Educational Attainment in the SCF

Focusing on ratios, our interpretation of "nonwhite" respondents in the 1962 SCF as being Black, and only those respondents, implies trends of educational attainment that are consistent with the trends in other data sets that more precisely and consistently defined "Black" as a category. In contrast, if we were to interpret respondents in both the "nonwhite" and the "not ascertained" groups as being Black, the 1962 SCF would imply unrealistic rates of educational attainment for Blacks in 1962. To see this formally, we estimate a regression where the dependent variable is the ratio of Black to white BA attainment, the independent variable is year, and we use both the CPS and SCF data from 1963 onward. In terms of the errors from this regression, the error for the 1962 SCF prediction would have a z-score of 2.1 or 11.4 if we measured Black as, respectively, either "nonwhite" or "nonwhite + not ascertained."

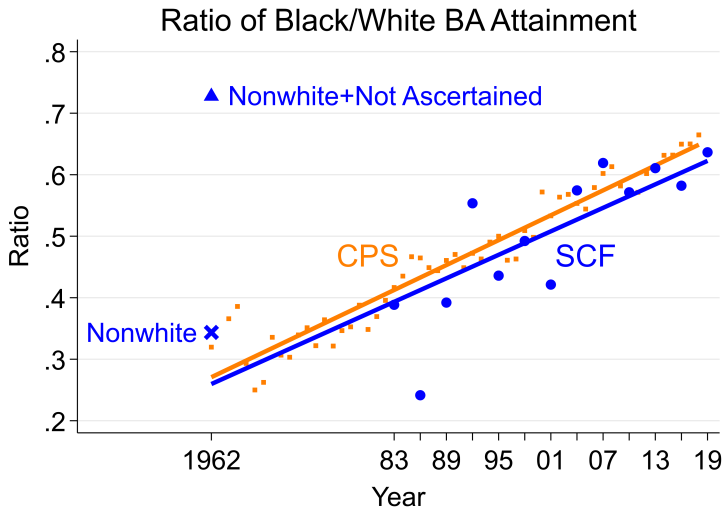


Figure 17: Educational Attainment in the SCF and CPS

A.2 The National Longitudinal Survey of Youth 1979 (NLSY79)

We measure labor market outcomes over the life cycle using the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 sample was born between 1957 and 1964, and was followed with annual (1979-1994) and biennial (1996-2016) surveys. Respondents were aged 14-22 at the date of the 1979 survey and aged 51-60 at the date of the 2016 survey. The NLSY79 has a core sample that is nationally-representative and four supplemental samples designed to oversample poor whites, Blacks, Hispanics, and military. Our analysis is based on the white respondents in the core sample and Black respondents in either the core sample or the Black supplemental sample, which follows the approach in Keane and Wolpin (2000).

There are many degrees of freedom when defining race in the NLSY79. While Black and Hispanic respondents are identified directly, the sampling frame from which white respondents are taken is non-Black/non-Hispanic. In addition to this sampling frame, we eliminate respondents from our non-Hispanic white category using their response to the first question asked about the racial/ethnic origin group with which the respondent most closely identifies. Specifically, we eliminate respondents in the non-Black/non-Hispanic sample from the white category if they respond that their origin is Black, Chinese, Filipino, Hawaiian or Pacific Islander, Indian-American or Native American, Asian Indian, Japanese, Korean, Vietnamese, Chicano, Mexican, Mexican-American, Other Hispanic, Other Spanish, Other, or None. This definition yields 3,379 white males in the original sample, consistent with Cunha and Heckman (2016). We assign race to each household based on the race of the respondent.

We measure respondents' educational attainment in the NLSY79 in terms of three levels: less than high school, high school diploma, or BA/college degree. We follow Bhattacharya and Mazumder (2011) and measure attainment primarily using information on years of completed schooling by age 26. Alternatively, measuring attainment using information on respondents' highest degree received would result in 7.6 percent fewer observations, and creates discrepancies for an additional 4.1 percent of respondents in our sample. In the case of a discrepancy between these measures, we use information about the highest degree as follows: For those who report receiving a college degree while completing 15 or less years of schooling, we assign *college degree*. For those who report not receiving a college degree while completing 16 or more years of schooling, we assign *high school diploma*. And we assign *less than high school* to those likely to have received a GED; this group reported "high school diploma (or equivalent)" in terms of their highest degree received, but have 11th grade or lower as their highest grade completed. We assign educational attainment to each household based on the attainment of the respondent.

Achievement is measured in the NLSY79 by the Armed Forces Qualifying Test (AFQT). In 1980, when the NLSY79 sample was aged 15 to 23, respondents were paid $50 to take the Armed Services Vocational Aptitude Battery (ASVAB). More than 94 percent of the samples used in our analysis, the cross-sectional and supplemental samples, completed the test at sites that included hotels, community centers, and libraries. The ASVAB consists of a battery of 10 tests, and the AFQT is based on results on four of these tests: Paragraph Comprehension, Word Knowledge,

Arithmetic Reasoning, and Mathematics Knowledge. AFQT percentile scores are reported in the NLSY79 using three normalizations. In our analysis we use the 2006 normalization, AFQT-3, that adjusts for both implementation issues and age at test.

We define household earnings in the NLSY79 as the sum of wage and salary income reported in the year preceding each survey for the respondent and their spouse/partner. We convert these earnings to 2019 dollars using the CPI-U-R, and we assign this income to households by age using the respondents' age at the survey minus one. To generate earnings over five year windows, we average each household's earnings over the observed ages in the given window.

We compute household average hourly wages over five-year windows as annual earnings divided by annual hours worked averaged over the given five-year window. Although each respondent's annual hours worked is directly reported, and so is the spouse/partner's earnings, the spouse/partner's hours worked is not reported. We impute the spouse/partner's hours worked as follows: For spouses/partners who reported zero earnings, we impute zero hours. For spouses/partners with positive earnings, we impute the spouse/partner's hours worked as the mean hours worked of opposite sex (of the respondent) respondents with positive earnings and the same race, educational attainment, and age as the spouse. We top- and bottom-code wages at $200 and $2.

A.2.1 Longitudinal Imputation of Earnings in the NLSY79

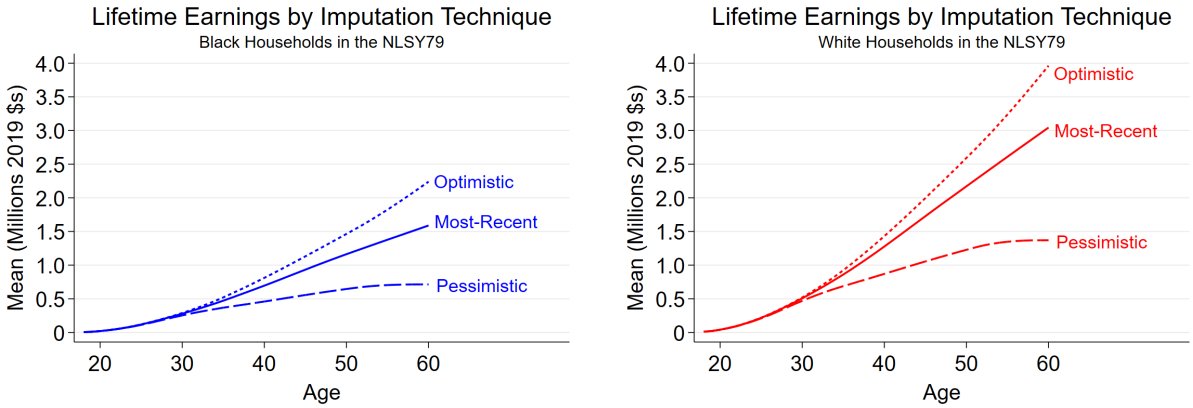
Computing lifetime earnings from ages 18-60 with the NLSY79 is complicated because the NLSY79 becomes a biennial survey in 1996. To account for the biennial nature of the NLSY79, as well as data simply missing over the life cycle, we impute missing earnings at a given age as the respondent's most recent non-missing household earnings.

Figure 18 shows lifetime earnings using our preferred most-recent imputation technique, along with versions of the optimistic and pessimistic techniques from Nielsen (2015). For a missing earnings observation at age a, our optimistic technique imputes the respondent's maximum household earnings observed between ages 18 and age $a - 1$. Our pessimistic technique analogously imputes the respondent's minimum household earnings observed between ages 18 and age $a - 1$. For this exercise we keep earnings reported as "$0."

Figures 18a and 18b show that our preferred most-recent imputation technique arrives at mean incomes by age and race closer to the optimistic technique than to the pessimistic technique. Figures 19a and 19b show that the general pattern of adjusting lifetime earnings for education hold regardless of the imputation procedure. Under our preferred most-recent imputation technique, as discussed in the main text, adjusting for educational attainment and achievement can account for, respectively, 25 and 76 percent of the age 60 racial difference in lifetime earnings. Under the optimistic imputation technique attainment and achievement account for, respectively, 24 and 71 percent of the difference. And under the pessimistic imputation technique attainment and achievement account for, respectively, 27 and 75 percent of the difference.

It is worth noting that our measure of academic achievement, AFQT-3, uses the standard psychometric method for aggregating individual test questions into the scalar index reported in the

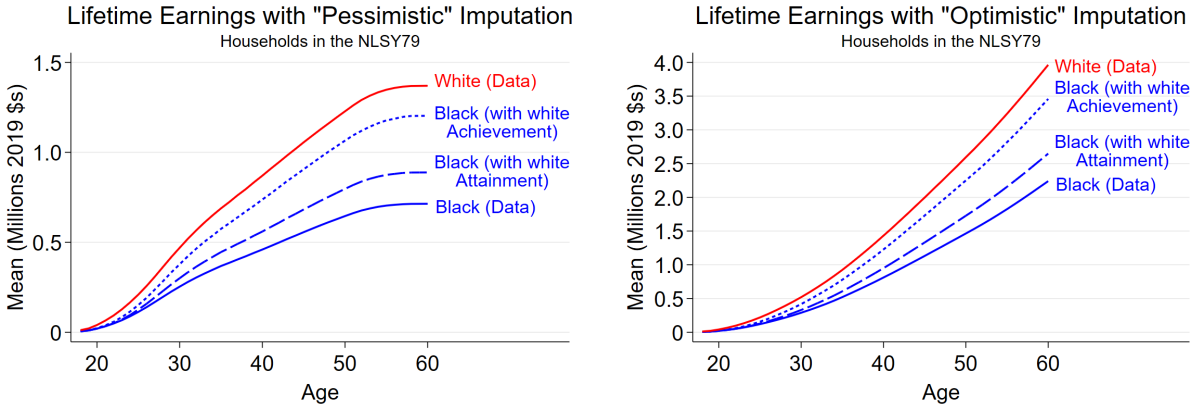
NLSY79. Item-anchored rankings that aggregate questions into a scalar index based on each item's predictiveness of economic outcomes would likely result in achievement accounting for more of the Black-white gap in lifetime earnings (Nielsen (2015)).



(a) Black Households

(b) White Households

Figure 18: Lifetime Earnings in the NLSY79 by Imputation Technique



(a) Pessimistic Imputation

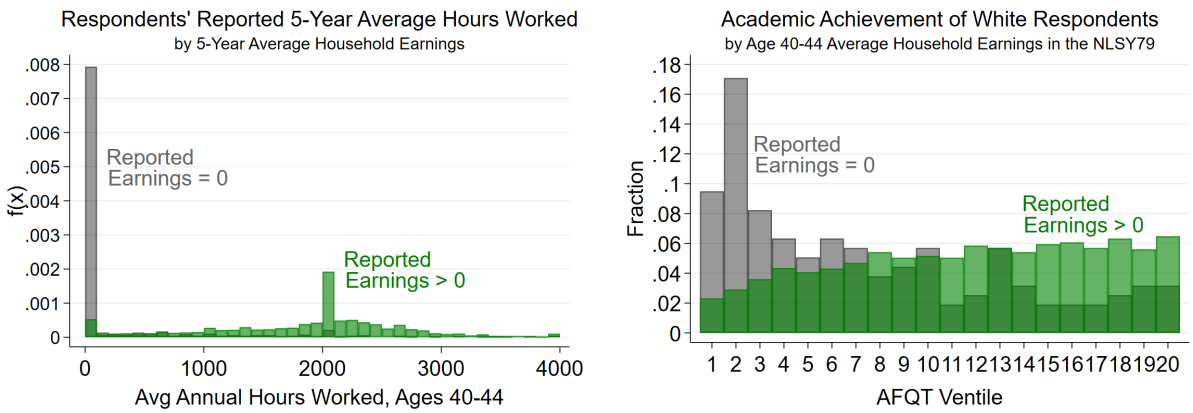
(b) Optimistic Imputation

Figure 19: Lifetime Earnings in the NLSY79 by Imputation Technique

A.2.2 Interpreting $0 Earnings in the NLSY79

Another measurement issue arises from the fact that income is underreported in large national surveys, especially in the left tail of the distribution. Labor income, or earnings, are an important component of this underreporting (Sullivan (2020), Meyer et al. (2021)). If Black households are over-represented in the left tail of the earnings distribution, then underreported earnings will most likely bias our estimates to overstate the magnitude of the racial earnings gap.

One standard approach to dealing with this problem is to treat observations above and below some bounds as missing. However, much like Bollinger et al. (2019)'s finding that missing earnings observations in the Current Population Survey (CPS) are not missing at random, we find that the $0 earnings observations in the NLSY79 are not random. Figure 20 shows that of the households in our sample reporting $0 in earnings over the 40-44 age window, 77 percent have a respondent who reported working 0 hours on average over those 5 years. As well, those who reported $0 earnings over 40-44 had disproportionately low AFQT scores.



(a) Hours

(b) AFQT

Figure 20: Lifetime Earnings in the NLSY79 by Imputation Technique

A.2.3 Estimating the Wage Process on the NLSY79

The evidence in Appendix A.2.2 indicates that earnings reported as $0 should not be treated as "missing" data in the NLSY79. When making lifetime earnings calculations using the NLSY79, we do impute unobserved earnings data as described above, but we do not adjust the reported number for any observed earnings.

When estimating the wage process, however, we do adjust reported numbers in some cases. The two changes to reported wages help us to account for selection into 0 hours. First, if 0 hours are reported and a household is below the 10th percentile of lifetime earnings, we impute the bottom-coded hourly wage, $2. One way of interpreting the sources of this small wage is as a combination of earnings in the underground economy and the value of transfers from friends or family in exchange for work (Venkatesh (2006)), or simply as a minimum wage one can possibly receive from earnings due to intrafamilial transfers (Kaplan (2012), Rosenzweig and Wolpin (1993), Rothstein (2019)). Second, among the remaining households aged 45 plus and reporting 0 hours and 0 earnings, the wage at the previous age is imputed as the wage at the current age.

Recall from the main text that household i's pre-tax wage w_i is

$$w_i(age) = \Phi(\text{age}_i, \text{race}_i) \cdot \exp(\varepsilon_i(\text{age}))$$

with

$$\varepsilon_i(\text{age}+1) = \rho\varepsilon_i(\text{age}) + \eta \qquad \text{where} \qquad \eta \sim \mathcal{N}(0, \sigma^2).$$

We use race-specific quadratic functions of age to estimate Φ as the mean of wages in each household's category for age and race. We estimate the Φ's under the constraint

$$\Phi(a, \text{Black}) = 0.58 \cdot \Phi(a, \text{white})$$

to match the earnings gap described in Fact 1. The estimated $\Phi(a, \text{Black})$ and $\Phi(a, \text{white})$ are shown in Figure 27a.

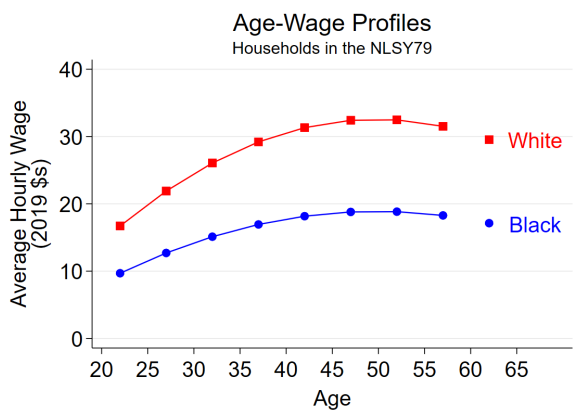


Figure 21: $\widehat{\Phi}(\text{age}, \text{race})$ in the NLSY79

Given our estimates of Φ and the data on observed earnings w, for each household we observe

$$\varepsilon_i(\text{age}) = \log\left(\frac{w_i(age)}{\Phi(\text{age}_i, \text{race}_i)}\right).$$

To specify the likelihood of the earnings process parameters, the assumption of a minimum wage $\underline{w}$ imposes that the $\varepsilon_i(\text{age})$ are censored observations from a true process

$$\varepsilon_i^*(\text{age}+1) = \rho\varepsilon_i^*(\text{age}) + \eta$$

where

$$\varepsilon_i(\text{age}) = \begin{cases} \underline{\varepsilon_i^*}(\text{age}) = \log\left(\frac{\underline{w}}{\Phi(\text{age}_i, \text{race}_i)}\right) & \text{if } \varepsilon_i^*(\text{age}) < \underline{\varepsilon_i^*}(\text{age}) \\ \varepsilon_i^*(\text{age}) & \text{if } \varepsilon_i^*(\text{age}) \geq \underline{\varepsilon_i^*}(\text{age}) \end{cases}.$$

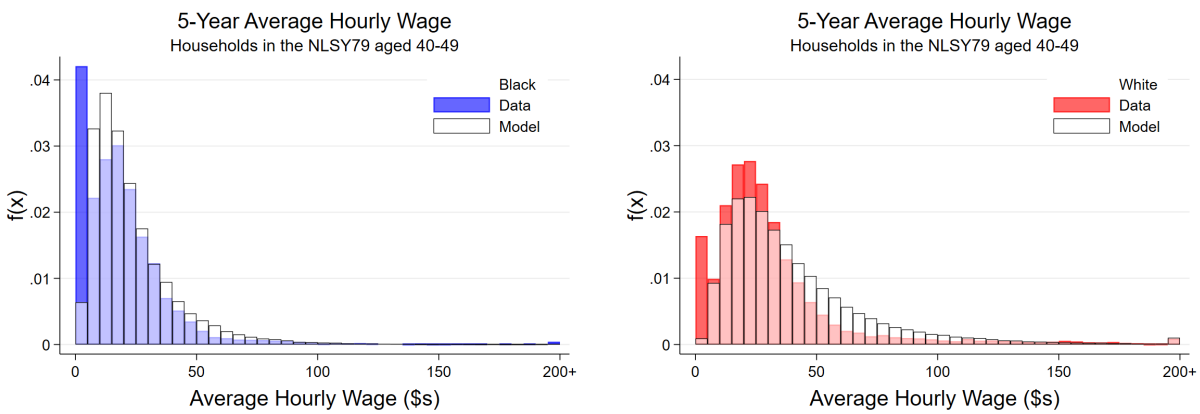
Thus, given $\Phi(a, \text{Black})$ and $\Phi(a, \text{white})$, we can estimate common ρ and σ parameters via maximum

likelihood where the log-likelihood is

$$LL(\rho,\sigma|\varepsilon) \propto \sum_{i:\varepsilon_i(1)=\underline{\varepsilon_i}(1)} \log[Pr(\varepsilon_i^*(1) < \underline{\varepsilon_i^*}(1)|\rho,\sigma,\text{race}_i)] + \sum_{i:\varepsilon_i(1)>\underline{\varepsilon_i}(1)} \log[f(\varepsilon_i(1)|\rho,\sigma,\text{race}_i)] \quad (2)$$
$$+ \sum_{\text{age}=2}^{A} \Bigg[\sum_{i:\varepsilon_i(\text{age})=\underline{\varepsilon_i}(\text{age})} \log[Pr(\varepsilon_i^*(\text{age}) < \underline{\varepsilon_i^*}(\text{age})|\rho,\sigma,\varepsilon_i(\text{age}-1),\text{race}_i)]$$
$$+ \sum_{i:\varepsilon_i(\text{age})>\underline{\varepsilon_i}(\text{age})} \log[f(\varepsilon_i(\text{age})|\rho,\sigma,\varepsilon_i(\text{age}-1),\text{race}_i)]\Bigg].$$

The estimated parameters are $\widehat{\rho} = 0.77$ and $\widehat{\sigma} = 0.67$.

Figure 22 shows the fit of the estimated wage process along with data from the NLSY79 for households with heads aged 40-49. Examination of the distributions in Figure 22a shows that accounting for selection into 0 hours by imputing a minimum wage in the data produces many low-wage observations in the data. The distribution of wages from the estimated model tends to miss this left tail of the distribution; our parsimonious parameterization is unlikely to produce many values near the minimum wage. However, the estimated model does have a large left tail for Black households just above the minimum wage that is influenced by the presence of the minimum wage households. Similarly, Figure 22b shows that the estimated distribution for white households misses on the left tail of the distribution. In the case of white households, however, the estimated wage process is able to capture the long right tail of the distribution.



(a) Black-Headed Families

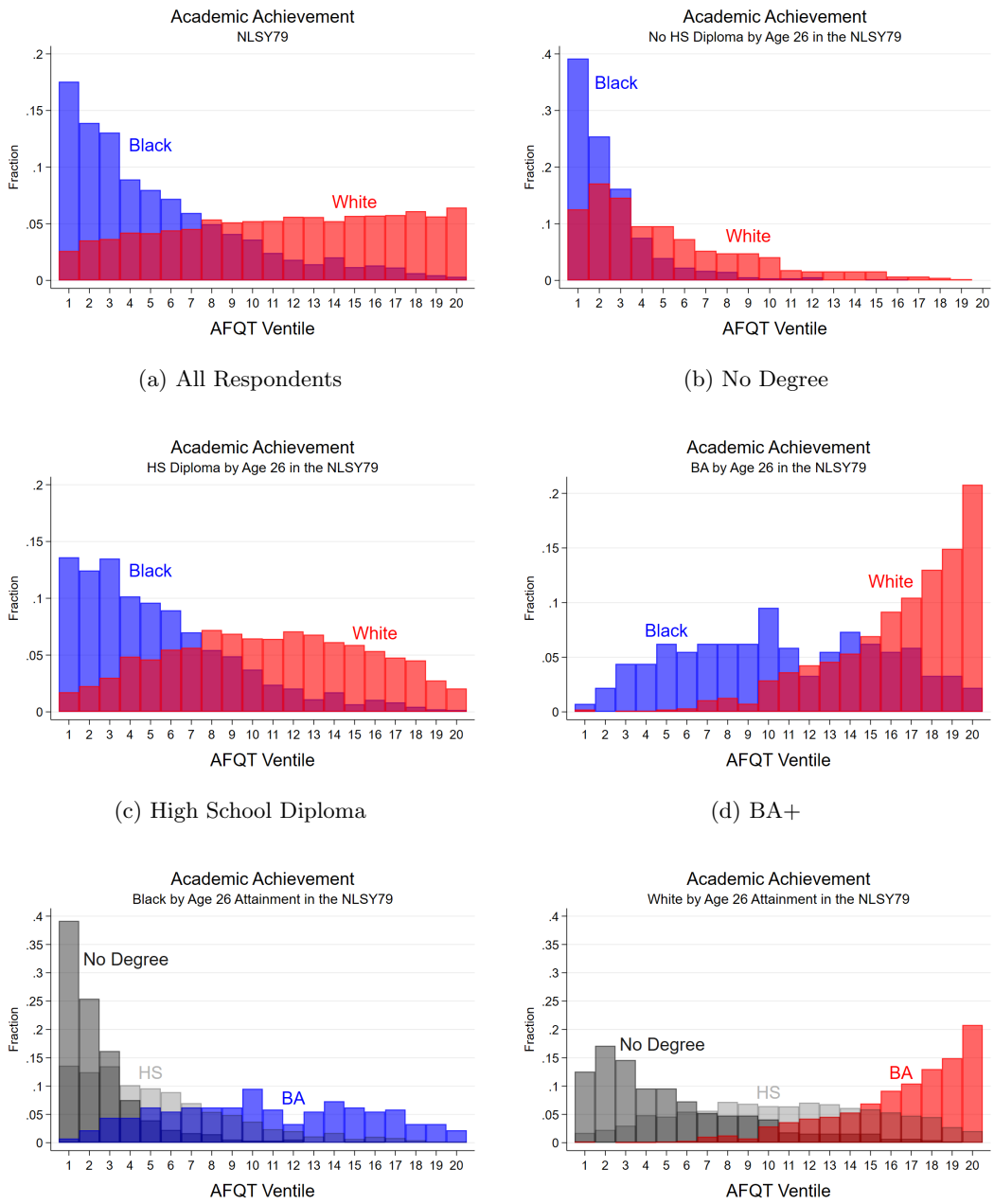
(b) White-Headed Families

Figure 22: Wages by Age and Race in the NLSY79 and Estimated Model

A.2.4 Educational Attainment and Achievement in the NLSY79

Here we present additional details about Fact 6, which is that age and educational attainment explain much less of the lifetime earnings gap than educational achievement. Figure 23a shows that academic achievement is distributed close to uniformly for white respondents, but is right-skewed

for Black respondents. Figures 23b-23d show that Black achievement lags white achievements significantly even conditional on attainment. Figures 23e and 23f shows that there is significantly more variation in achievement conditional on BA attainment for Black respondents than for white respondents; Black BA holders have a nearly uniform skill distribution, while white BA holders have a strongly left-skewed distribution of skills.



(a) All Respondents

(b) No Degree

(c) High School Diploma

(d) BA+

(e) Black

(f) White

Figure 23: Academic Achievement in the NLSY79, by Race and Attainment

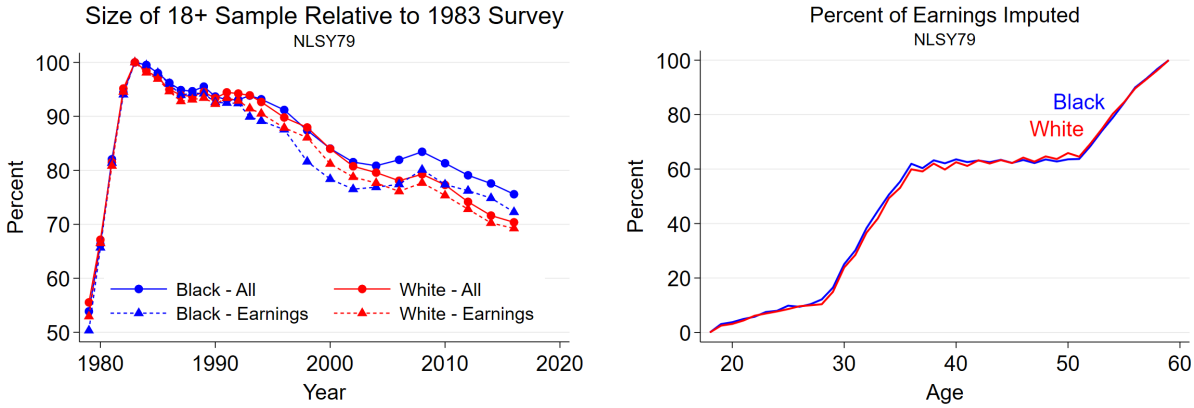
A.2.5 Attrition in the NLSY79

Our imputation procedure for unobserved earnings could generate mismeasurement in Black-white lifetime earnings gaps due to differential attrition. For example, mortality differences amplified cross-sectional earnings gaps into larger lifetime earnings gaps in the early 1900s (Karger (2020)). And in the more recent NLSY97, even in respondents' 20s there is evidence of differential mortality by race that is correlated with exposure to violence (Aliprantis and Chen (2016)).

We make two comparisons to assess the importance of attrition in the NLSY79 for our wage calculations. The comparisons suggest that racial differences in attrition are unlikely to create major biases in our life cycle analysis using the NLSY79.

First, we compare a given survey year's sample size of respondents aged 18 or older relative to the 1983 survey, the year with the largest such sample. Figure 24a shows attrition in terms of both the entire Black and white samples, as well as the Black and white samples with earnings present. Contrary to the concerns discussed above, in the most recent years the Black sample has experienced less attrition than the white sample. However, the relative share without earnings data is consistently higher for the Black sample than for the white sample. By the most recent wave reporting earnings in 2016, attrition was nearing 30 percent of the maximal sample for both the Black and white samples.

Second, we show that earnings imputation rates are similar across race. Figure 24b reports the percent of earnings that are imputed in our preferred most-recent imputation procedure. The percent of earnings imputed rises quickly after age 30, a result of the NLSY79's switch to a biennial format between 1994 and 1996. This stabilizes to a level reflecting the vast majority of imputations resulting from years not covered by the survey. After age 50 the percent imputed again rises, reflecting that the most recent survey wave reporting earnings in 2016 had respondents aged between 51 and 59.



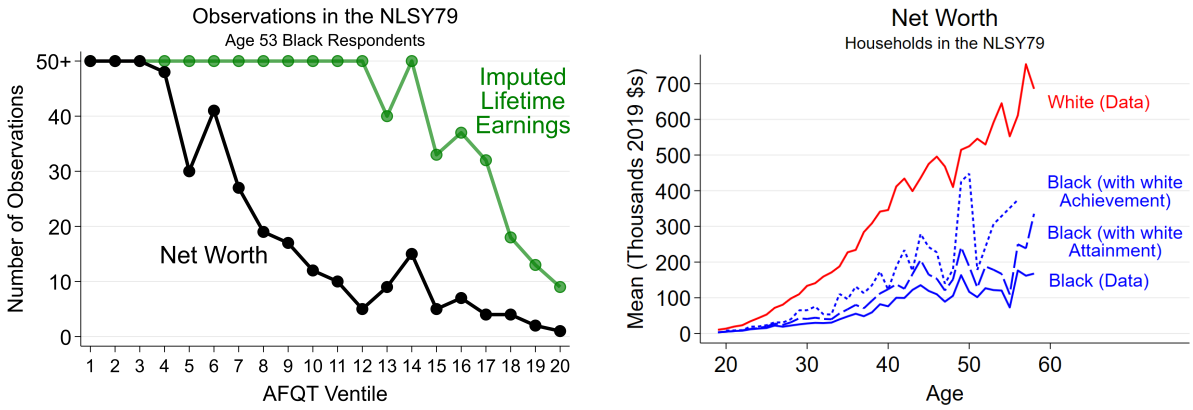
(a) Sample Size

(b) Unobserved Earnings

Figure 24: Attrition and Imputation in the NLSY79

A.2.6 Net Worth in the NLSY79

Figure 25b shows net worth calculations from the NLSY79 adjusting for educational attainment and achievement. Figure 25a shows that the sample sizes for these net worth calculations are not sufficient to provide reliable estimates; they are much smaller than the sample sizes used in the main text's estimates of education-adjusted lifetime earnings.



(a) Observations

(b) Education-Adjusted Net Worth

Figure 25: Net Worth in the NLSY79

A.3 The Panel Study of Income Dynamics (PSID)

Here we use the Panel Study of Income Dynamics (PSID) to replicate the estimation of the wage process over the life cycle specified in the main text. Relative to our use of the NLSY79, one advantage of the PSID is that it allows for researchers to control more flexibly for age and cohort effects due to the wider age range of its initial sample.[38] One advantage of the NLSY79 in our context is the ability to address selection into zero hours worked by imputing a minimum wage for those with zero hours and low lifetime earnings. The PSID sample has been followed with annual (1968-1997) and biennial (1999-2017) surveys.

The PSID has several subsamples, and our analysis is focused on the SRC and SEO samples. The SRC sample began in 1968 as a nationally-representative sample of 2,930 families designed by the Survey Research Center (SRC) at the University of Michigan, and the SEO sample consisted in 1968 of 1,872 low income families from the US Census Bureau's Survey of Economic Opportunity (SEO). The PSID has followed descendants of the original 1968 samples as they grow and split off from the original family unit. This panel structure of the PSID allows us to study life cycle wage dynamics while controlling for time or cohort effects.

We follow the sample of household heads in the PSID, defining household earnings as the sum of the previous year's total labor income for the head and their partner, if present. We define household hours worked in the year prior to the survey analogously, and define average annual earnings over 5-year age windows, $[20, 24]$, $[25, 29]$, $\ldots$, $[60, 64]$. Following the analysis of the NLSY79, we bottom code average hourly wages at \$2 and top-code wages at \$200.

Our definition of educational attainment is less straightforward. Focusing on 2017 as an example, we defined educational attainment in terms of the variable ER71538, the reference person's educational attainment.[39] If attainment is missing in ER71538, then we use the variable reporting year's of completed schooling, ER34548, to define a respondent's attainment. Defining attainment by age is where we introduce differences in measurement across households within the PSID and across the PSID and the NLSY79. We first define attainment as the highest degree received by the reference person by age 30. If this variable is missing, we measure attainment as the highest degree received by the first age at which this variable is observed.

We restrict the full sample of household heads to those with (i) the age of the head being between ages 20 and 64, (ii) the head being non-Hispanic Black or non-Hispanic white, and (iii) educational attainment being reported. Table 3 shows the sample sizes for our analysis when using the combined SRC and SEO samples, as well as when using the SRC sample alone. The

[38] While the PSID follows multiple generations, the same is true for the NLSY79. The National Longitudinal Survey of Youth 1979 Child/Young Adult (CNLSY79) sample, comprised of all children born to NLSY79 mothers, also allows researchers to observe outcomes for different birth cohorts and to track intergenerational outcomes. The NLSY79 is also capable of intergenerational linkages through questions about respondents' parents asked in the initial waves of the survey.

[39] Until 2017 the PSID defaulted to defining the head of a household as the husband in a heterosexual couple. This was updated in 2017 so that "The Reference Person ('Head' prior to 2017) of the Family Unit must be at least 18 years old and the person with the most financial responsibility for the FU." See question 76 at https://psidonline.isr.umich.edu/Guide/FAQ.aspx.

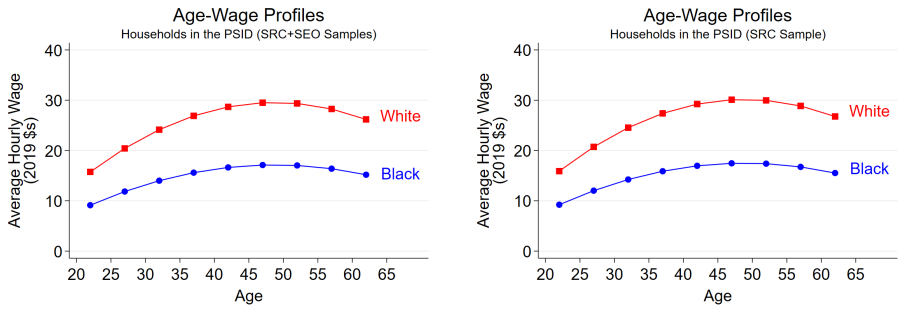
top row shows the original sample size and each subsequent row shows the additional number of observations lost when applying the sample restrictions in order from (i)-(iii). The final row shows the final sample sizes used in our analysis. Including the SEO sample nearly doubles the sample size, which is particularly important for our analysis on subsamples that include few observations in the SRC alone.

Table 3: Observations of Household Heads in the PSID by Sample Restriction

SRC+SEO, 1968-2017			SRC Only, 1968-2017		
Sample Restriction	Obs	HH	Sample Restriction	Obs	HH
Earnings and Hours Observed	278,842	26,482	Earnings and Hours Observed	164,429	14,728
Age of Head $\in [20, 64]$	–41,701	–1,765	Age of Head $\in [20, 64]$	–30,329	–1,326
Non-Hispanic Black or White	–12,272	–1,725	Non-Hispanic Black or White	–6,323	–937
Ed Attain. Present	–15	–7	Ed Attain. Present	–8	–4
Final Sample	224,854	22,985	Final Sample	127,769	12,461

We use the individual weights to account for the SEO's oversampling of low-income households and to account for attrition in both the SRC and SEO samples (Solon et al. (2015)). We include the SEO sample following the evidence in Brown (1996) that including the SEO with individual longitudinal weights better tracks the left tail of the income distribution.

To replicate our life cycle earnings analysis using the PSID, we estimate a regression of five-year average annual wages on a quadratic function of age and time fixed effects, with age and time coefficients being race-specific.[40] To adjust for sample selection into 0 hours, we adjust the wage data as we did for the NLSY79. Our adjustment is slightly different for the PSID, though, since we do not observe lifetime earnings to age 60 for all households. In the PSID, for those who report working 0 hours we adjust average hourly wages to the median of the respondent's previously-observed hourly wages. Figure 26 shows that the age-wage profiles are very similar regardless of whether we use the joint SRC and SEO sample or the SRC sample alone.



(a) PSID (SRC+SEO) (b) PSID (SRC)

Figure 26: Age-Wage Profiles in the PSID
Note: Figure displays profiles with intercepts estimated for the years 1983 and 1984.

[40] We group our year fixed effects into two-year windows for precision.

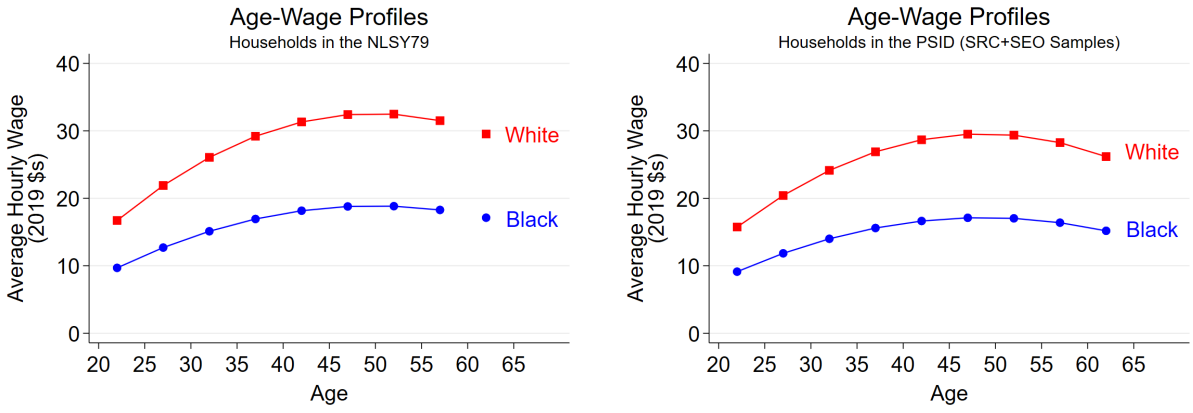
A.4 Comparing the Estimated Wage Processes in the NLSY79 and PSID

The NLSY79 and PSID are generally similar in their strengths for estimating the wage process used in our model, and as shown in Figure 27 the age-wage profiles estimated on the two samples are remarkably similar. Our judgment is that the tradeoffs between the two data sets do not create a clear case for one data set being preferred to the other.

The main reason we use the NLSY79 to estimate the earnings process used in our calibration is because household formation is slightly easier to measure in the NLSY79 than in the PSID. Because we conduct our analysis at the household level, we interpret household formation as part of the wage process. In the NLSY79, we measure household earnings as the sum of the respondent's earnings and those of his/her partner when present. Thus, formation of new households, unions, separations, and deaths of a partner are measured clearly in the NLSY79.

In the PSID we define household earnings as the sum of a household head's earnings and those of his/her partner when present. For younger ages, those who have not yet moved out of their home will not be observed as household heads in the PSID (Krolikowski et al. (2020)).[41]

Given this discrepancy in measuring household formation at young ages, it is not surprising to see in Figures 27 and 28 that the PSID generates age-wage profiles that are flatter than those we estimate in the NLSY79. This difference across the data sets could be explained by young individuals experiencing low incomes receiving their income primarily in the form of shared residence with and financial transfers from parents (Kaplan (2012), Rosenzweig and Wolpin (1993)). For example, men who did not work in the 1996 wave of the NLSY79 were 20 percentage points more likely to live with their parents than those who did work in the past year (Rothstein (2019), Table 2).

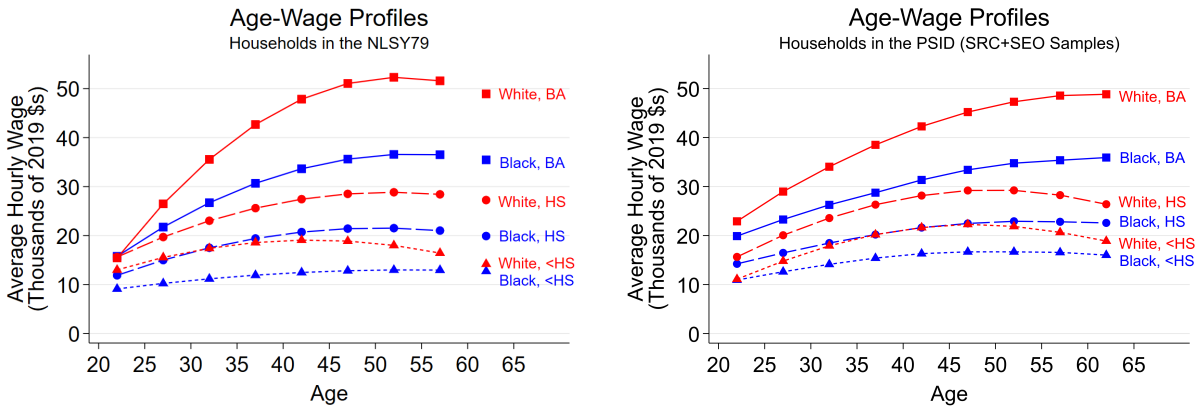


(a) NLSY79

(b) PSID (SRC+SEO)

Figure 27: Age-Wage Profiles in the NLSY79 and PSID
Note: The detached lines for age 60-64 in the NLSY79 figure indicates that those means are projections and not observations from the data. The PSID figure displays profiles with intercepts estimated for the years 1983 and 1984.

[41] After establishing their own household, household heads remain household heads in the PSID even if they move back in with their parents or other family (Altonji et al. (2021)).



(a) NLSY79

(b) PSID (SRC+SEO)

Figure 28: Age-Wage Profiles in the NLSY79 and PSID
Note: The detached lines for age 60-64 in the NLSY79 figure indicates that those means are projections and not observations from the data. The PSID figure displays profiles with intercepts estimated for the years 1983 and 1984.

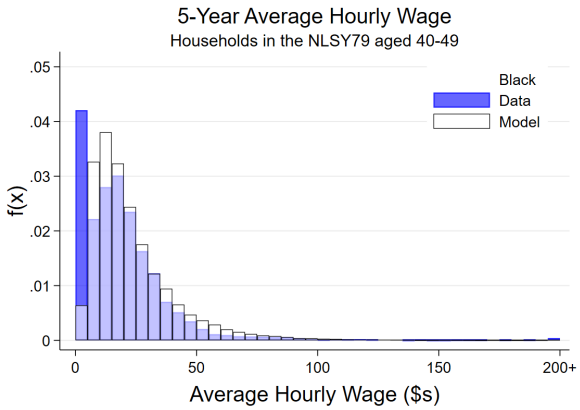
Table 4 shows the estimated ρ_η and σ_η parameters of the wage process. The parameters estimated on the PSID are remarkably similar regardless of whether we use the SRC sample only or estimate the parameters on the combined SRC and SEO samples. The persistence of the shock processes is similar across data sets. The largest difference in estimates is that the variance of the idiosyncratic shock process is higher for in the NLSY79 than in the PSID.

Figure 29 plots some data along with the estimated model to illustrate how wages are more dispersed in the NLSY79 than in the PSID. The figure shows data and estimates for households aged 40-49 by race and estimation sample. The clear difference in the data sets is that the NLSY79 has a higher share of households reporting less than $5 average hourly wages in earnings in a given 5 year window.

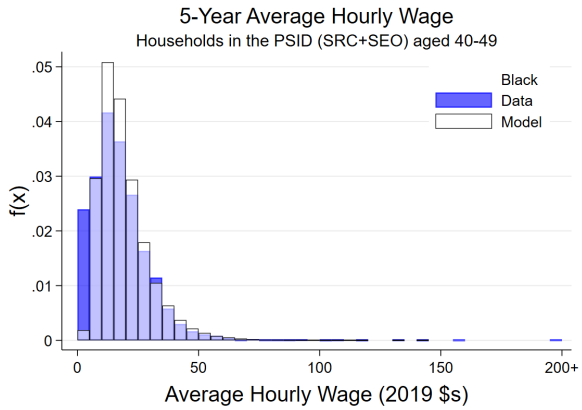
Table 4: Wage Process by Sample

Sample	Φ Estimated w/ Year FEs	ρ_η	σ_η
PSID SRC Only, 1968-2017	X	0.75	0.44
PSID SRC+SEO, 1968-2017	X	0.74	0.44
NLSY79, 1979-2017		0.77	0.67

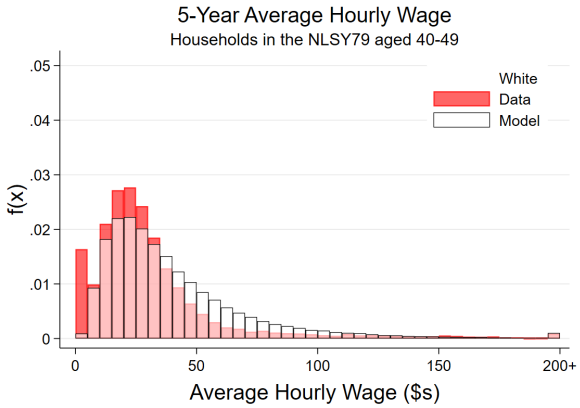
Note: This table reports the parameters of the wage process when estimated on alternative samples.



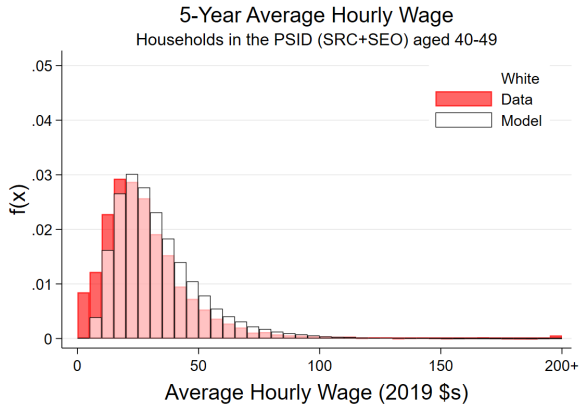
(a) Black-Headed Families



(b) Black-Headed Families



(c) White-Headed Families



(d) White-Headed Families

Figure 29: Wages by Age and Race in the NLSY79 and Estimated Model

B Appendix: Facts about the Black-White Wealth and Earnings Gaps, 1962-2019

We document seven facts from the SCF and NLSY79.

Fact 1: The earnings gap has been about 40 percent with no trend over the past 57 years.

Fact 2: The wealth gap has been about 80 percent with no trend over the past 57 years.

Figure 6a plots the wealth and earnings gaps from 1962 to 2016. Over this period, mean Black wealth averaged 17 percent of mean white wealth, resulting in a gap of 0.83. Over this same time period mean Black earnings averaged 58 percent of white earnings, resulting in a gap of 0.42. Appendix C shows that these data are consistent with the findings in several other studies using several other data sets, and also plots the ratios obtained from defining the gaps in terms of medians rather than means.

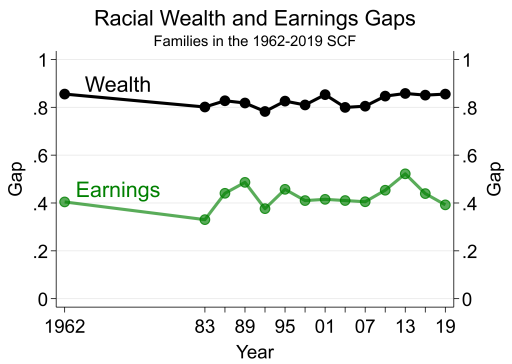


Figure 30: Earnings and Wealth Gaps

Table 5: Coefficient on Time

Time	Earnings Gap			Wealth Gap		
Period	β	$\beta\times$ 60	P	β	$\beta\times$ 60	P
1962-2019	8.8e-4	0.05	0.32	3.8e-4	0.02	0.44
1962-2007	4.0e-4	0.02	0.74	–7.6e-4	–0.05	0.22
1986-2007	–2.2e-3	–0.13	0.24	–2.2e-4	–0.01	0.86

Note: The dependent variable in the linear OLS regressions reported above is either one minus the ratio of Black to white mean income or one minus the ratio of Black to white mean wealth. The independent variable is year, where each regression is restricted to a particular subset of years.

Both gaps have been stubbornly persistent. Table 5 reports the coefficients from regressing the earnings and wealth gaps on year via OLS. None of the coefficients are statistically different from zero. This relationship is not driven by either the Great Recession or noise in the early waves of the survey. The flat earnings and wealth ratios are also consistent with Kuhn et al. (2020)'s analysis of the racial income and wealth gaps in the SCF+ going back to 1949.

Fact 3: In all decades, there is a large gap in the Black and white Conditional Expectation Functions (CEFs) of wealth conditional on earnings.

Figure 31 shows the Conditional Expectation Functions (CEFs) of wealth conditional on earnings separately for Black and white households.[42] Whatever decade of data we look at in the SCF,

[42] As shown in Barsky et al. (2002) for the 1984-1994 waves of the PSID, and as we find in our own analysis, estimating these CEFs under a quadratic OLS specification generates very similar results as semi-parametric local regressions.

we see a large gap between the Black and white CEFs. Table 6 reports these gaps as the coefficients on having a Black household head in OLS quadratic regressions of wealth on income under the restriction of households having non-negative income and being below the 95th percentile of the race-specific earnings distribution in the decade in question. Over all of the years currently available in the SCF, 1962-2019, this coefficient is –$540,000 in 2019 dollars.

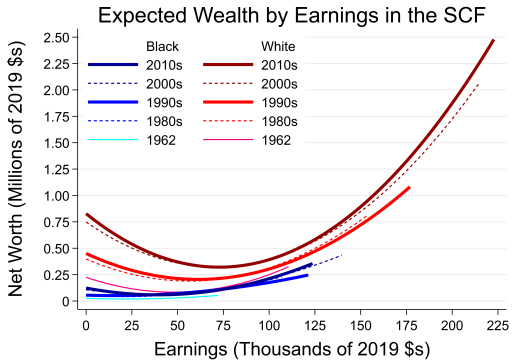


Figure 31: Conditional Expectation Functions in the Surveys of Consumer Finances (SCFs)
Note: This figure shows quadratic OLS estimates with race-specific coefficients and an indicator for race. Because of the scarcity of high earning Black families in the data, we follow Barsky et al. (2002) and restrict the sample to families with earnings below the 95th percentile of the race-specific earnings distribution during the decade in question.

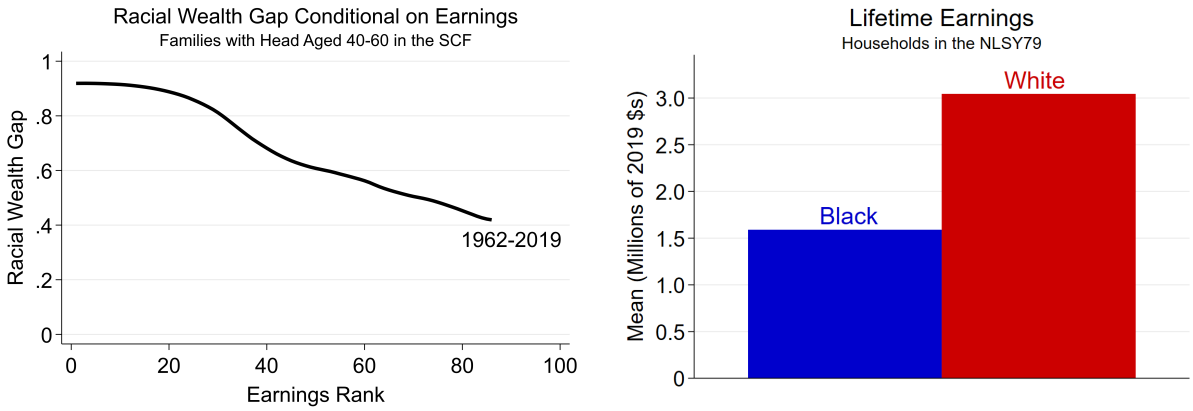
Table 6: Coeff. on Black Household Head

Time Period	β ($1,000s)	P
1962	–199	0.07
1980s	–356	0.00
1990s	–395	0.00
2000s	–642	0.00
2010s	–705	0.00
All	–540	0.00

Note: The dependent variable in the linear OLS regressions reported above is household net worth. The independent variables are earnings, earnings^2, Black, Black×earnings, and Black×earnings^2. The coefficients reported above are the coefficients on Black for all waves of the SCF occurring during the years in question.

Fact 4: The racial wealth gap is declining in earnings for those aged 40-60.

Figure 32a shows the racial wealth gap conditional on earnings predicted by estimating mean wealth conditional on earnings using race-specific local linear regressions. The racial wealth gap begins at nearly 0.9 at the lowest earnings ranks, stays nearly constant for the first quintile of earnings, and then monotonically declines to 0.4 by the 95th percentile of Black household earnings. Figure 2b in the main text shows the wealth gap as a function of the earnings ranking of households across all survey waves in the SCF, and similar results are found when estimation is on raw earnings and/or by specific decades of the survey.



(a) Wealth Gap by Earnings

(b) Lifetime Earnings

Figure 32: Earnings and Wealth Inequality

Fact 5: The lifetime earnings gap is between 78% and 205% of the racial wealth gap, with the best estimate being 173%.

There is considerable uncertainty in the measurement of lifetime earnings in the NLSY79, generated by alternative approaches to imputing missing observations longitudinally (Nielsen (2015), Nielsen (2020)) along with the known under-reporting of income in surveys in the left tail of the distribution (Meyer and Mittag (2019), Meyer and Sullivan (2003)). As we describe in Appendix A.2, our preferred approach is to impute missing observations of earnings longitudinally as the most recent previous observation. For the calculations here we treat very low earnings, whether at $0 or below the minimum wage, as accurate measurements.[43] If low-income households underreport their earnings, this will bias our estimate of the racial lifetime earnings gap as being too large.

When we simply add lifetime earnings from ages 18-60 in the NLSY79, we find the racial lifetime earnings gap to be between $656k and $1,723k depending on whether we impute missing observations using the lowest or highest previously-observed earnings. Shown in Figure 32b, our preferred estimate imputes missing earnings using the most-recent observation and finds a lifetime earnings gap of $1,456k. These pessimistic, optimistic, and most-recent imputation techniques produce estimates that represent, respectively, 78%, 205%, and 173% of the $841k cross-sectional racial wealth gap in the 2019 SCF (Bhutta et al. (2020)).

Fact 6: Age and educational attainment explain much less of the lifetime earnings gap than educational achievement.

How much can age and education help explain the lifetime earnings gap? In the 2019 SCF, white respondents are on average four years older than Black respondents. In the NLSY79, white respondents have higher educational attainment and achievement. These differences in education

[43] For the wage process, however, we adjust reported wages below $2/hour and above $200/hour to these values as bottom- and top-codes.

outcomes are of interest because of evidence that pre-market factors can explain much of the lifetime earnings of white males (Keane and Wolpin (1997)) and much of the gap in labor market outcomes between Black and white males (Keane and Wolpin (2000), Cameron and Heckman (2001)). Moreover, academic achievement as measured in standardized test scores like the AFQT are likely be a major component of the pre-market factors that appear important for racial gaps in wages (Neal and Johnson (1996)), lifetime earnings (Nielsen (2015)), and intergenerational income mobility (Bhattacharya and Mazumder (2011), Davis and Mazumder (2018)). Skill biased technological change appears to have increased the importance of achievement and attainment over time for understanding racial inequality in labor market outcomes (Thompson (2021), Bayer and Charles (2018)).[44]

To adjust for age and education, we assign earnings for Black households given the counterfactual white distribution of educational attainment or achievement as the average earnings of Black households at a given level of treatment times the white share at each level of educational treatment. Formally, for attainment or achievement treatments D and earnings Y, we compute the counterfactual mean earnings as

$$\mathbb{E}[Y_i(D^W)|\text{age}_i, \text{race}_i = B] = \sum_{a=1}^{A} \mathbb{E}[Y_i|d_i = a, \text{age}_i, \text{race}_i = B] Pr[d_i = a|\text{age}_i, \text{race}_i = W]. \quad (3)$$

For the treatment D defined as attainment, $A = 3$ and the three levels we consider are less than high school, high school diploma, and BA or higher. For the treatment D defined as achievement, $A = 20$ so that the levels we consider are the ventiles of AFQT test score ranks.

Figure 33 shows lifetime earnings over the life cycle in the data and after adjusting for attainment or achievement following Equation 3. The first result is that the earnings gap remains wide even conditional on age; the earnings gap is not simply due to the fact that in a given cross section, Black households will tend to be younger. Figure 33 also shows that by age 60, educational achievement can explain 76 percent of the racial gap in lifetime earnings, while educational attainment can explain 25 percent of the gap.

[44] We do not study the large racial gap in household hours worked, likely caused by differences in household formation, but acknowledge this mechanism as another key factor in explaining the earnings gap (Gayle et al. (2015)).

Figure 33: Education-Adjusted Lifetime Earnings in the NLSY79

Fact 7: Earnings can account for 20-28 times more of current wealth than intergenerational transfers.

In a raw sense, intrafamilial transfers across generations are large. One way to see this is to calculate the potential wealth from intrafamilial transfers. Adding both inter vivos transfers and bequests over the lifecycle, assuming that those transfers grow at a given interest rate, Wolff and Gittleman (2014) find that lifetime transfers can account for between 19 and 29 percent of current total wealth in the 1989-2007 waves of the SCF. Likewise, Feiveson and Sabelhaus (2018) calculate that lifetime transfers can account for between 26 and 51 percent of current total wealth in the 1995 to 2016 SCF, and Gale and Scholz (1994) find results of a similar magnitude.

Here we conduct a similar exercise by simulating lifetime earnings $\widehat{y}$ for households with heads aged 55-60 in the 2019 SCF. For a given age $a \in [18, 60]$, we simulate earnings $\widehat{y}_i(a)$ as $\widehat{\Phi}(\text{age}, \text{race}, \text{education}) \times y_i(55-60)$ where $\widehat{\Phi}(\text{age}, \text{race}, \text{education})$ is the race-by-education group-specific ratio of a given age's mean earnings to age $55-59$ mean earnings, and $y_i(55-60)$ is the reported earnings of households, indexed by i, aged 55-60. We estimate $\widehat{\Phi}$ in the NLSY79, with results shown in Figure 34, and $y_i(55-60)$ in the SCF.

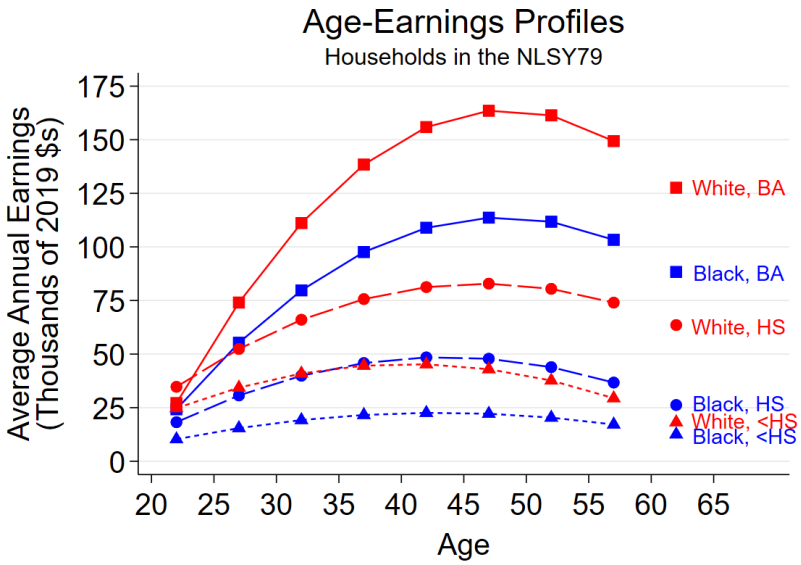


Figure 34: $\widehat{\Phi}(\text{age}, \text{race}, \text{education})$ in the NLSY79

Given our simulated earnings $\widehat{y}_i(a)$, we then calculate potential wealth from earnings as

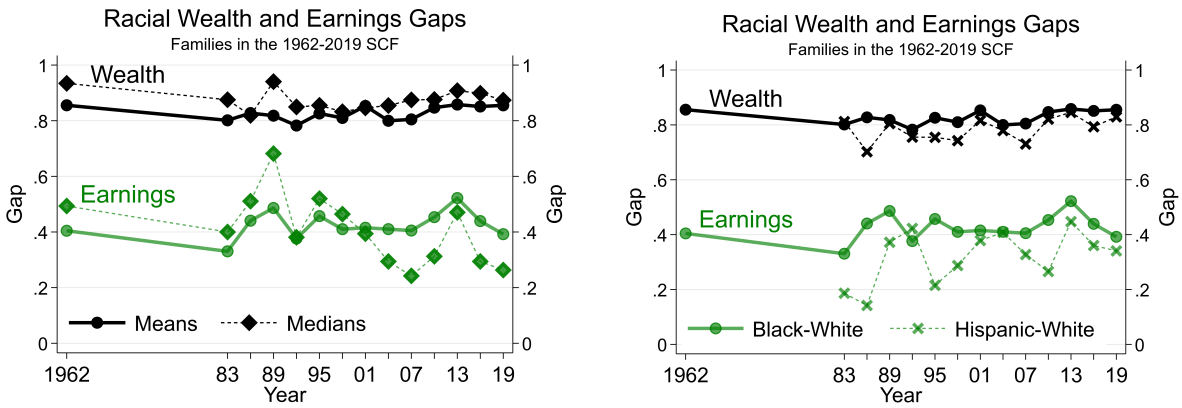
$$\sum_{a=18}^{a_{2019}} \widehat{y}_i(a)\,(1+R)^{a_{2019}-a}.$$

We find that for a real interest rate R of 3 or 5 percent, respectively, earnings can account for 723 and 1,013 percent of total wealth of 55-60 year olds in the 2019 SCF. This represents 20 to 28 times the share accounted for in the more recent transfer estimates in Feiveson and Sabelhaus (2018). This finding foreshadows the key results in our analysis, and are consistent with Menchik and Jianakoplos (1997)'s finding that inheritances can account for 10-20 percent of the racial wealth gap in the NLS76 and the 1989 SCF.

C Appendix: More on Facts 1 and 2

C.1 Means Versus Medians

Figure 35a shows that when measured in terms of medians rather than means, the wealth gap is larger and the earnings gap has a higher variance. Measured in terms of medians, the wealth gap hovers closer to 0.9. Declines in the earnings gap from 2001-2010 would appear to be driven less by improvements in the earnings of Black households and more by declines in the earnings of white households.



(a) Measuring Gaps with Means v. Medians

(b) Black Gaps v. Hispanic Gaps

Figure 35: Measures of the Wealth and Earnings Gaps

C.2 The Hispanic-White Wealth Gap

Figure 35b shows that the Hispanic-white wealth gap is not much smaller than the Black-white wealth gap. While the Hispanic-white earnings gap appears to be slightly lower than the Black-white earnings gap, this difference is not economically large in most years. We note that measurement issues can complicate a direct comparison of Black-white and Hispanic-white gaps (Duncan and Trejo (2007)).

C.3 Additional Data Sets

Facts 1 and 2 are consistent with many studies using many data sets. Table 7 shows the analogous gaps found in other studies in the literature. The wealth gap is stable across studies. The earnings gap is more sensitive than the wealth gap to the unit of observation, the time period over which it is observed, and as shown above, whether it is measured via medians rather than means.

Table 7: Facts 1 and 2 in the Literature

Study	Data Set	Unit of Observation	Income Gap	Wealth Gap
Labor Income (Earnings)				
This Paper	1962-2019 SCF	Families	0.42	0.83
Barsky et al. (2002)	1984,1989,1994 PSID	HHs with head 45-49	0.44	0.82
Bayer and Charles (2018)	1970+2000 Census; 2005-2007 ACS	Men 25–54	0.52 (median)	–
Total Income				
Wolff (2018)	1983-2016 SCF	HHs	0.52	0.82
Blau and Graham (1990)	1976+1978 NLS	Families or Individuals 24-34	0.35	0.82
Terrell (1971)	1967 SEO	Families	0.41	0.81

Note: We calculate the gap from Census data in Bayer and Charles (2018) by averaging the 1970, 2000, and 2007 values of the last row for "Earnings level gap" in Table I.

Relevant for Fact 1, Barsky et al. (2002) find an income gap of 44 percent in the 1984, 1989, and 1994 waves of the Panel Study of Income Dynamics (PSID) when focusing on households with heads aged 45-49 . Bayer and Charles (2018) provide a detailed analysis of changes in race-specific income distributions since 1940. The estimate in their paper most directly-comparable to ours is a median income gap from 1970 to 2007 of 52 percent when focusing on men aged 25-54. Most relevant for our study is Wolff (2018), who finds an average gap of 52 percent in the 1983-2016 waves of the SCF when looking at total income rather than labor income. Other studies measuring total income at different time periods found gaps closer to ours measured with labor income. Terrell (1971) found a gap of 41 percent using the 1967 Survey of Economic Opportunity and Blau and Graham (1990) find a gap of 35 percent in the 1976 and 1978 National Longitudinal Surveys of Young Men and Women.

Fact 2 is even more consistently corroborated across many studies using many data sets. Terrell (1971) found a wealth gap of 81 percent using the 1967 Survey of Economic Opportunity. Blau and Graham (1990) find a wealth gap of 82 percent in the 1976 and 1978 National Longitudinal Surveys of Young Men and Women. Barsky et al. (2002) find a gap of 82 percent in the 1984, 1989, and 1994 waves of the Panel Study of Income Dynamics (PSID) when focusing on households with heads aged 45-49. Wolff (2018) finds an average wealth gap of 82 percent in the 1983-2016 waves of the SCF.

D Appendix: The Firm's Problem

The firm maximizes profits by choosing capital and the aggregate labor input from households. It takes the prices, $r - \delta$ and w, and the earnings gap, $\varphi(B)$ for Black households as given to solve the problem:

$$\max_{K,N} AK^{\alpha} \left(N_B + N_W\right)^{1-\alpha} - (r - \delta) K - \varphi(B) w N_B - w N_W$$
$$s.t. \quad N_B + N_W = N.$$

We assume that the firm cannot distinguish between Black and white workers before hiring them. Thus at a given equilibrium wage w^*, all else equal,Black workers will have lower labor supply, since they in fact receive the lower wage $\varphi(B)w^*$.

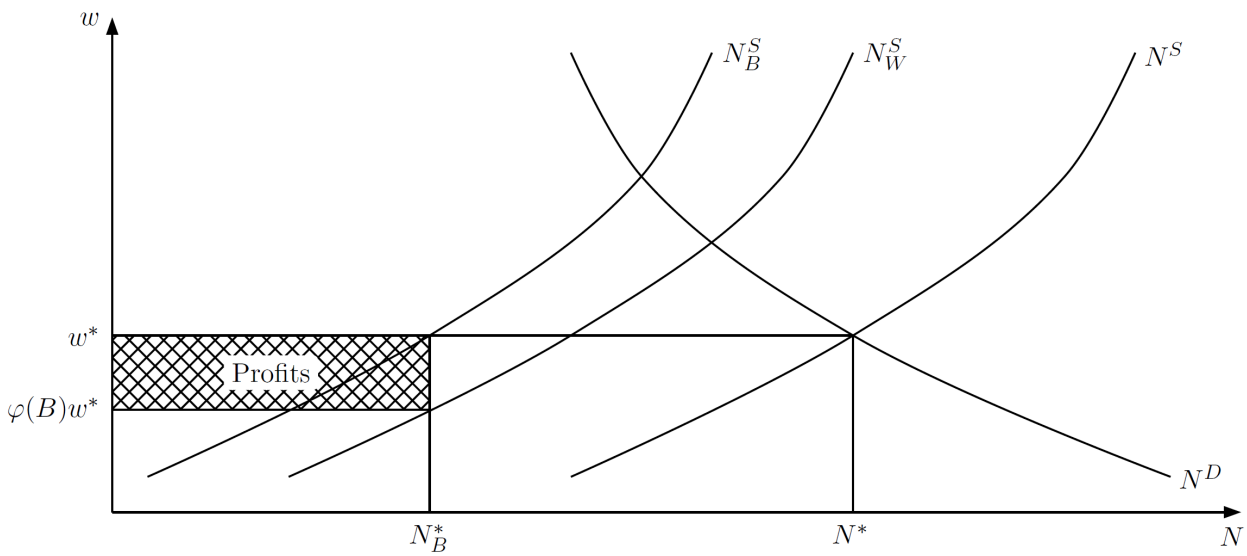
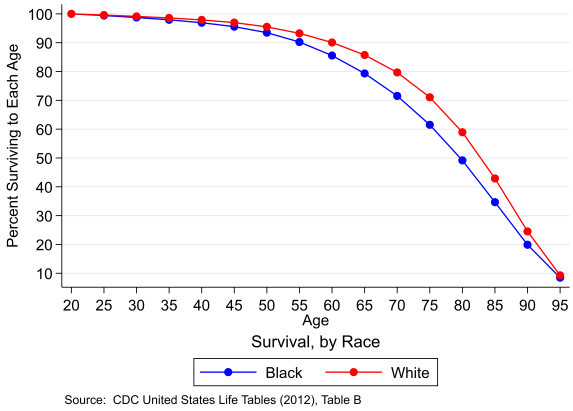


Figure 36: Profits in the Firm's Problem

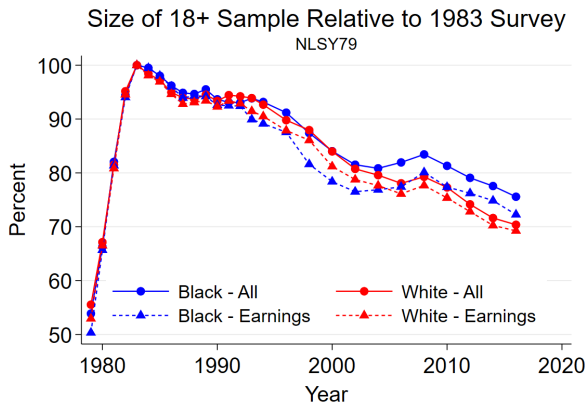
E Appendix: Mortality and Sample Attrition

The survival probabilities $\psi(a)$ used in all of the numerical exercises in the text are estimated using data on all-gender age-specific 2012 survival probabilities for whites in Table 20 of Arias et al. (2016). Figure 37 shows these survival probabilities along with those for Black individuals. We can see that survival probabilities are heterogeneous across race, especially past age 50. When we conduct a numerical experiment that includes heterogeneous mortality risk that converges at the same rate as the baseline permanent earnings gap, nothing changes qualitatively about the transition path of the racial wealth gap.

As we showed in Appendix A.2.5 and show again here in Figure 37b, it is also not the case that Black respondents are attriting more frequently from the NLSY79 on which we estimate our wage process.



(a) Heterogeneous Mortality



(b) Attrition in the NLSY79

Figure 37: Heterogeneous Survival Probabilities

F Appendix: Equalizing Inter-Vivos Transfers

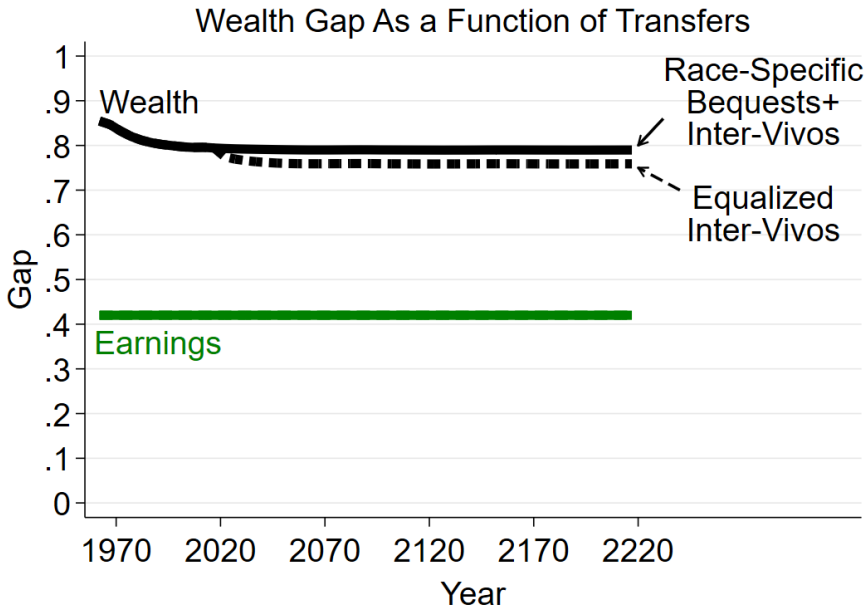


Figure 38: Equalized Inter-vivos Transfers

Here we explore the quantitative importance of inter-vivos transfers. In the model, inter-vivos transfers are represented by wealth being transferred to a newborn household of the same race when a household dies. To equalize inter-vivos transfers in our model, when a household dies, the share of its wealth going to an inter-vivos transfer (as opposed to the bequest pool) is transferred to newborn households of either race in proportion to the population shares of each race. Thus, in expectation, newborn households of either race start out with the same inter-vivos transfers. Figure 38 shows that in our model, equalizing inter-vivos transfers does not have a large effect on the transition path of the racial wealth gap.

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