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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 stochastic general equilibrium heterogeneous-agents model. 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, intergenerational transfers, and race. Our model predicts that equalizing earnings is by far the most important mechanism for permanently closing the racial wealth gap. One-time wealth transfers have only transitory effects unless they address the racial earnings gap, and return gaps only matter when earnings inequality is reduced.

Keywords: Racial Inequality, Wealth Dynamics
JEL Classification Codes: D31, D58, E21, E24, J7

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1 Introduction

In the United States, the average wealth of a Black-headed household is less than 20 percent that of a white-headed one. This racial wealth gap has motivated researchers to identify the factors that contribute to it and policymakers to craft proposals for eliminating it. While many racial disparities likely play a part in sustaining the racial wealth gap, what is still not well understood is which factors are most important. Which factors, if removed, would have the most potential to generate sizeable and long-lasting reductions in the gap? Identifying these primary mechanisms driving the racial wealth gap is critical for efforts to close it. After all, the wealth gap is just as large today as it was in 1962, before Civil Rights era legislation was enacted to remove barriers to economic advancement.

This paper uses a heterogeneous agents dynamic stochastic general equilibrium model to study transition paths from today's economy to a future steady state with racial equality.[1] Studying transition paths allows us to understand which factors could close the wealth gap over decades rather than centuries.

Our model incorporates rich household heterogeneity that allows the model to speak to the relative importance of the key mechanisms proposed for closing the racial wealth gap. Households in the model (i) have a life cycle as in De Nardi (2004) in which they work, retire, and face increasing mortality risk; (ii) receive idiosyncratic earnings shocks over their lifetimes; (iii) may give or receive intergenerational transfers; and (iv) are heterogeneous in terms of wealth, earnings, expected bequests, and returns on capital. We allow all of these factors to differ by race.

We find that eliminating the earnings gap is by far the most important factor for achieving sustained convergence in Black and white wealth. This finding brings a new perspective to the literature on the racial wealth gap, most of which has sought to explain the racial wealth gap using statistical models that predict wealth as a function of contemporaneous variables. The general conclusion from those efforts is that the scope for earnings to explain the wealth gap is quite limited. Formal statistical analyses have contributed to the conventional wisdom that a 40 percent earnings gap is too small to generate an 80 percent wealth gap:[2] A large racial gap in expected wealth remains after conditioning on earnings (Barsky et al. (2002)) and additional variables (Blau and Graham (1990), Altonji and Doraszelski (2005), Thompson and Suarez (2015)).[3] Some see this as evidence that the earnings gap cannot be a primary driver of the wealth gap (Hamilton et al. (2015), Darity et al. (2020)) and argue that transfers are instead the most important factor (Hamilton and Darity (2010)).

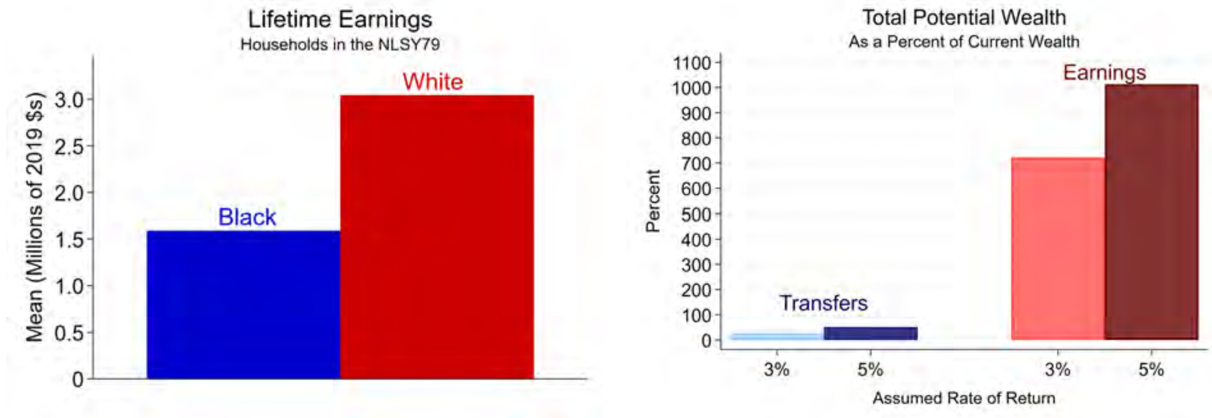
Explanations for the racial wealth gap that rely on static methods fail to capture the fundamentally dynamic nature of wealth accumulation. Wealth is the result of past saving, which depends on past and expected future earnings, financial returns, as well as the initial distribution of wealth.

[1]The model is in the spirit of Bewley (1986), Imrohoroğlu (1989), Huggett (1993), and Aiyagari (1994).

[2]See the discussions in Menchik and Jianakoplos (1997) and Barsky et al. (2002).

[3]When multivariate regression coefficients estimated from a sample of Blacks are used to predict white wealth (via the Oaxaca-Blinder decomposition), most estimates in the literature explain less than one-third of the wealth gap (Scholz and Levine (2002)).

Examining the data with an eye toward dynamics makes the importance of earnings clear. Thompson and Sablehaus (2022) show that the lifetime earnings gap between Black- and white-headed households explains the majority of the wealth gap, and Figure 1a shows that the lifetime earnings gap is large enough to account for the wealth gap at a point in time. Also, the flow of potential wealth from earnings over the life cycle is 20-26 times the flow from transfers (Figure 1b).[4]



(a) By Race

(b) Relative to Transfers

Figure 1: Lifetime Earnings

Note: The left panel shows the sum of household earnings from ages 18-60 for Black- and white-headed households in the National Longitudinal Survey of Youth 1979 (NLSY79). The right panel shows results from Feiveson and Sabelhaus (2018) on transfers compounding over the life cycle at an assumed rate together with a similar exercise compounding earnings using data from the 2019 Survey of Consumer Finances (SCF) together with data from the NLSY79. Details on both figures are provided in Appendix B.

From a theoretical standpoint, there is no compelling reason to expect that the earnings gap and the wealth gap should be of similar size. An observation of flows over a narrow time window need not offer insights into what causes stocks of variables to be different. In the long run of dynamic macroeconomics models, the earnings and wealth gaps can differ substantially. This is best illustrated by Ashman and Neumuller (2020), who compare racially unequal steady states within an incomplete markets life-cycle model with risky income endowments.[5] The main methodological advance of this paper is to study transitions instead of just steady states. This is important because the dynamics in the model are long-lived, which underscores the necessity of studying transitions. Even supposing that the economy were on a path to racial earnings and wealth equality in the long run, it does not follow that this convergence should be discernible empirically within a few decades. Given the tremendous inequality in initial conditions, it could be many years before wealth and earnings gaps close sufficiently to measure progress in the data (Derenoncourt et al. (2022)).

Our paper contributes to the new but growing literature studying the racial wealth gap with dynamic models of household saving, traditionally used in macroeconomics to study inequality.[6]

[4]This ratio for the US, based on the 2019 SCF and NLSY97 as described in Appendix B, is similar to the ratio for Norway, based on administrative data as calculated in Black et al. (2020).

[5]See White (2007) for another example but with complete insurance markets and two representative household dynasties.

[6]Some examples include Ashman and Neumuller (2020); Boerma and Karabarbounis (2021); Tan and Zeida

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 wage processes on data from the National Longitudinal Survey of Youth 1979 (NLSY79), a sample born between 1957-1964. 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 gap can be wildly different, with significant progress toward equality emerging anywhere from a few generations to centuries.

The earnings gap between Black and white households is a key ingredient of our model. For the purposes of our investigation, it is critical only that an earnings gap exists, but it is not crucial *why* it exists. The latter is a complex and important area to explore in future research (Gordon et al. (2021); Altonji et al. (2021); Gayle et al. (2015)), but an elaborate construction of all the possible mechanisms underlying the earnings gap would detract from the point of this paper. In addition to earnings differences, the baseline experiments also have racial differences in intergenerational transfers and in rates of return on savings.

Predictions from the calibrated model over the years 1962 to 2019 match 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 data 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. The simple bequest structure in the model also endogenously produces expected inheritances and inter-vivos transfers that are in line with estimates from the literature.

After validating the model on the endogenous outcomes described above, we conduct a series of numerical experiments showing that the earnings gap is by far the most important mechanism for closing the wealth gap. We first conduct a bounding exercise where we feed into the calibrated model two paths for the earnings gaps. Along the first path the earnings gap disappears immediately, while along the second path the earnings gap is permanent for hundreds of years. The trajectory of the wealth gap is extremely responsive to the path of the earnings gap. When the earnings gap closes immediately, the massive initial disparities in wealth are nearly eliminated after 70 years. But when the earnings gap is permanent, the earnings gap never closes.

We then show that a permanent earnings gap dominates all other mechanisms. We implement a one-time wealth redistribution in the model and find that equalizing wealth without changing the earnings gap has no long-term effect on the wealth gap: Within 50 years the wealth gap returns to its initial level. We also find that the wealth gap is unresponsive to return gaps of even massive magnitudes when the earnings gap is permanent at the level observed over recent decades.

(2022); and Nakajima (2022).

The dominance of a permanent earnings gap does not imply that other mechanisms cannot matter, only that the earnings gap must close sufficiently for other factors to make meaningful contributions to the wealth gap. In our model, any permanent income differences by race will lead to a long-run racial wealth gap. In the long run, return gaps will produce non-trivial wealth gaps, even after the earnings gap has been completely removed.[7]

Given the importance of earnings, we consider a path where this gap is gradually narrowed by equalizing education outcomes generation by generation. We suppose that newborn households have the same distribution across race of either attainment (i.e., highest degree) or achievement (i.e., standardized test scores), and gain the race-specific wage premia associated with each. The long-run wealth gaps are still relatively large even after these reforms are fully implemented; completely equalizing the distribution of attainment would reduce the long-run wealth gap to 67 percent, and equalizing achievement would reduce the gap to 27 percent. Along the transition path, the generation-by-generation roll-out adds 50 years relative to the path with immediate earnings equalization for all.

We conclude by considering our educational reforms in combination with a one-time wealth transfer. These experiments serve as bounds representing the most optimistic scenario for an endogenous earnings response to wealth transfers. In both of these cases, a large wealth gap quickly re-emerges after the transfers, emphasizing that a long-run change to the racial wealth gap requires closing the earnings gap.

2 Model

The model features overlapping generations of households each having a life cycle. Households choose consumption, savings, and, while they are young, hours.

Demographics and the life cycle There is 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 $j \in \{B, W\}$. Households have a life cycle. They are born at age $\underline{a}$ and face increasing mortality risk as they age. Any household that survives to $\bar{a}$ dies with certainty at the end of the period. At age a_b households receive a bequest b (which may be \$0), and they retire at age a_r where $a_b < a_r < \bar{a}$.

The earnings process and retirement Each household is endowed with one unit of discretionary time. Until age a_r, households divide this time between working market hours, h, and consuming leisure, ℓ. Households have labor productivity $\Phi(a)\exp(\varepsilon)$, where $\Phi(a)$ is a deterministic age-earnings profile and ε is a shock that follows an AR(1) process in logs

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

[7] In Boerma and Karabarbounis (2021), for example, return gaps take the form of persistent differences in beliefs about entrepreneurial success.

Labor income is equal to the product of hours worked and labor productivity, $h \times \Phi(a) \times \exp(\varepsilon)$. At retirement, labor productivity is fixed at $\bar{\varepsilon}$, the value of ε in the last period of working life. When a household retires it receives 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.

Asset market Households cannot insure against labor productivity shocks, but they can save in an asset that 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 experience different shock histories.

Transfers and inheritances 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 given as a bequest to age a_b households. Because it is infeasible to track every parent/descendent link through perpetuity, we pool these bequests across all deceased households of the same race and redistribute them to surviving same-race households of bequest age according to a lottery. Note that because we will assume that households have "warm-glow" preferences for bequeathing wealth, they have exactly the same motivation to amass an estate for the bequest pool as they would if their wealth were transferred to a descendant.

Preferences Households have preferences over consumption, leisure, and warm-glow from leaving an estate. We assume the following functional forms:

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

The functional form for utility over bequests, $z(k')$, comes from De Nardi (2004). The parameter θ_1^b controls the overall strength of preference for the size of bequests, while θ_2^b controls how strongly bequests are a luxury good. This warm-glow specification serves two purposes. First, it allows the model to speak to the role of inheritance differences for maintaining the wealth gap. Second, it generates a thick right tail in the wealth distribution. Reproducing the high degree of US wealth inequality requires adding features to the standard incomplete markets environment (De Nardi and Fella (2017)), and warm-glow is a parsimonious way of achieving this.[8]

[8] Cagetti and De Nardi (2008) point to three main features that, when added to the baseline model, can generate a thick right tail as observed in the wealth distribution seen in the data: bequests, heterogeneous rates of return on capital, and heterogeneity in the earnings process for the richest. It has been shown that one can generate a thick-tailed wealth distribution using capital income risk (Hendricks (2007), Benhabib et al. (2015)), an extremely high wage reached with very low probability (Castañeda et al. (2003)), or voluntary bequests (De Nardi (2004), De Nardi and Yang (2014)). See Stachurski and Toda (2019) and Sargent et al. (2020) for recent developments in this literature.

Production A stand-in firm purchases effective labor and rents capital from households. 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, $R = r - \delta$.

Firm profits and dividends To generate a racial gap in earnings, we adopt a simple form of wage discrimination. 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.[9] As a consequence of wage discrimination, the firm earns profits equal to $[1 - \varphi(B)]\, wN_B$. (Appendix D illustrates this detail.)

There are several options for how to treat these profits. In the baseline, we choose to rebate the profits to white households through a dividend that is proportional to their wealth, $D(k)$. 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; however, this is not the case. Alternative treatments of firm profits, including returning them lump sum to white households, or lump sum to all households, and discarding them via wasteful government spending, produce transition paths that are nearly identical to the baseline. There are two reasons for this. First, relative to average income, the dividend is small, owing in large part to the low relative population share of Black households. Thus, the premium to white savings is also very small. Additionally, in most of our exercises, the earnings gap diminishes over time, which shrinks the return gap even further. As we show in Section 5.2.2, in the presence of a substantial earnings gap, racial differences in the return of capital have a negligible effect on the transition path, while in the absence of an earnings gap, return differences require considerable time to produce significant gaps in wealth.

Household problem 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

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

subject to

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

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

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

3 Calibration and Data

We conduct a series of numerical exercises to quantify the contribution of racial disparities to the path for the wealth gap. Specifically, we want to understand how changes in the earnings gap affect the path of the wealth gap, and how those changes compare with those from return and bequest gaps.

We initialize the calibrated model so that its wealth distribution matches the 1962 data. Then we compute transitions from this initial condition to a long-run steady state in which all Black and white households are identical in all respects, meaning that is there is no racial gap in labor income, no difference in bequest schedules or returns on savings, and therefore no difference in the conditional wealth distributions across race.

3.1 Calibration

We calibrate the model to a long-run steady state in which all processes are independent of race. Some of the parameters of the model are estimated from the data (either by ourselves or by others in the literature); The remainder are calibrated using simulated method of moments or set to standard values from the literature. Table 1 reports the parameter values used in our calibrated model.

Preferences We set the intertemporal elasticity of consumption to $\gamma = 2.0$, a standard value in the literature. The remaining utility parameters are jointly calibrated so that the model matches moments from the data. $\beta = 0.59$ sets the capital-output ratio to 0.6 (equivalent to an annualized level 3.0). θ_h is calibrated to 1.27 so that households spend 30 percent of discretionary time working on average. The parameters governing the warm-glow term, θ_1^b and θ_2^b, are 1.41 and 0.10, respectively. These values produce a wealth Gini of 0.66 and put 12.4 percent of households on the borrowing limit.

Production The total factor productivity (TFP) parameter A normalizes period output of 1. We follow the literature and set capital share of income to $\alpha = 0.36$. Capital depreciates at an annualized rate of 5 percent, which implies that investment is 15 percent of output in annual terms.

Intergenerational transfers 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 inheritance pool.

The fraction of a deceased household's estate that flows into the bequest pool, ν, is 75 percent, which is in line with estimates from studies of the SCF. 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) generate a ν of 0.76 in the 1996-2016 SCF.

Mortality 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).[10] 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 converges slowly to the white schedule. Differences between the implied wealth gap path from this exercise and the one in the baseline are inconsequential.

Table 1: Calibration for Baseline Steady State with 5-Year Periods

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

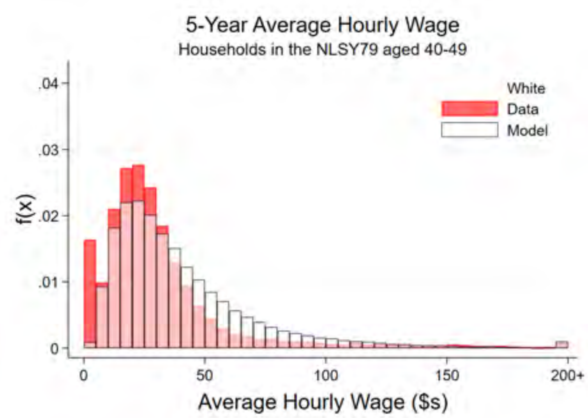
Labor income process We measure household wages over the life cycle using the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 sample was born between 1957 and 1964 and has been followed with annual (1979-1994) and biennial (1996-2016) surveys. Respondents were aged 14-22 at the date of the 1979 survey and aged 51-60 at the date of the 2016 survey. To measure household hourly wages in the NLSY79, we divide annual household earnings 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.

Figure 2a shows the age-wage profiles, $\varphi(j) \times \Phi(a)$, estimated from the NLSY79 under a specification of a quadratic function of age with $\varphi(Black) = 0.58$. Taking the mean wage in each household's category for age and race summarized by these estimates as given, we use maximum likelihood to estimate the parameters $\widehat{\rho}_\eta = 0.77$ and $\widehat{\sigma}_\eta = 0.67$.

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

In Appendix A.3 we replicate our NLSY79 analysis with the Panel Study of Income Dynamics (PSID, ISR (2018)). We find a persistence parameter that is nearly identical across samples (0.77 versus 0.74), while our variance parameter is higher in the NLSY79 than in the PSID (0.67 versus 0.44). Our estimated labor income process from the NLSY79 is also consistent with estimates from other studies. A comparable estimation using the PSID in De Nardi (2004) finds a variance parameter of $\widehat{\sigma}_\eta = 0.55$, which is between our estimates in the NLSY79 and PSID. And while the implied five-year estimate using the PSID in Floden and Lindé (2001) of $\widehat{\sigma}_\eta = 0.33$ is lower than all of our estimates, this difference is in the direction expected based on differences in sample selection, time periods, and heterogeneity by education.[11]

(a) Mean Wage by Age and Race in the NLSY79



(b) White-Headed Families

Figure 2: Wages by Age and Race in the NLSY79 and Estimated Model
Note: The left panel shows the age-wage profiles estimated from the NLSY79 that are used to calibrate the model. The right panel shows the cross-sectional fit of the estimated wage process together with the data in the NLSY79. See Appendix A for details.

Our estimated labor income process also captures key features of the cross-section in the data. Figure 2b shows the fit of the estimated wage process along with data for households with white heads aged 40-49. Our parsimonious specification captures the overall shape of the distributions, including the very long right tail of the white distribution. We choose to account for selection into 0 hours by imputing a minimum wage, which produces many very low-wage observations in the data. Examination of the distributions in Figure 2b and Table 2 shows that the long right tail of the distribution is a stronger force than the many low-wage observations, having the effect of pulling the distribution in the model up relative to the distribution in the data.

[11]For example, we include households with top- and bottom-coded wages to control for the extensive margin of employment; Floden and Lindé (2001)'s sample is heads of the same household in the PSID, while households in our sample are based on all individuals in the NLSY79; their sample time period is from 1988 to 1992 and ours is from 1979 to 2016; and their age-wage profiles are education- and occupation-specific, while ours are race-specific.

Table 2: Moments of the Black and White Wage Distributions

			25th Pctl	Median	Mean	90th Pctl
Wages ($s)	White	Model	20	32	41	79
		Data	16	25	32	58
	Black	Model	12	19	24	45
		Data	7	16	20	39

Note: This table reports moments of the Black and white wage distributions in the estimated process used in the calibrated model along with the distributions found in the NLSY79, in both cases for households with head aged 40-49. See Appendix A for details.

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

Government 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.

1962 Wealth Distribution We measure the distribution of wealth 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), along with the SCF+ from 1963 to 1977, which comprises archival data from historical waves of the SCF (Kuhn et al. (2020)).

We measure the racial wealth gap as

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

and measure the racial earnings gap analogously. Wealth is the SCF net worth variable, which includes home equity, individual retirement accounts (IRAs), and many other financial/nonfinancial assets and debts.[12] Earnings in the SCF are 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.

Initiating the model requires starting from a wealth distribution over productivity, age, and race. One issue for estimating such a wealth distribution is the fact that racial categories have changed since the time of the 1962 SFCC, so it is nontrivial to map groups in the survey onto racial groups under today's definition. Appendix A.1.1 presents additional data work justifying our choice to treat the "nonwhite" group in the 1962 SFCC as the equivalent of today's "Black" racial group.

Another issue for estimating an initial wealth distribution has to do with the sparseness of the data. Because the 1962 SFCC has only 2,557 households, we do not have an observation for every

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

possible household type in the model– this is especially problematic for Black households. If we restricted the initial model distribution to only households observed in the 1962 data, this sparsity would induce spurious transitional dynamics for some initial periods as the model's stochastic processes populated the missing types.

To avoid this outcome, we instead use kernel density techniques to smooth the initial distribution of wealth within race and age groups in the 1962 SFCC. Age groups are chosen to maximize sample size while grouping similar distributions. Representative age groupings based on mean wealth by age and race are displayed in Figure 3. Because the wealth distribution of Black-headed households is much more compressed than for white-headed households, fewer Black groupings are required. The groupings are 20-44 and 45-94 for Black-headed families, and 20-24; 25-29; 30-34; 35-39; 40-44; 45-55; 55-79; and 80-94 for white-headed households.

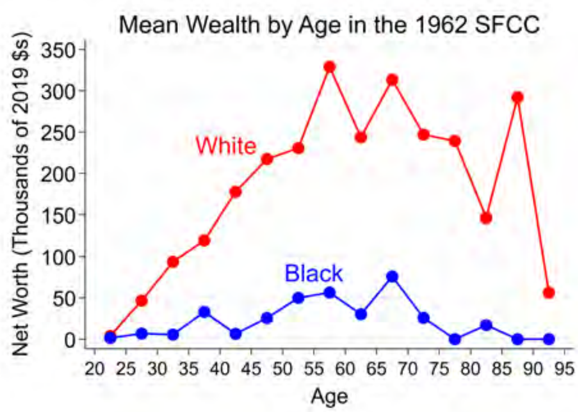


Figure 3: Wealth by Age and Race in the 1962 SFCC
Note: This figure shows mean net worth in the 1962 Survey of Financial Characteristics of Consumers (SFCC) by age and race groups. See Appendix A for details.

The resulting initial wealth distribution used in the calibration matches the distribution in the data; key moments are compared in Table 3. The model distribution is generally similar but shifted slightly to the right compared to the data; the white (Black) mean is \$205,000 (\$30,000) in the model compared to \$188,000 (\$27,000) in the data. Importantly, the model distribution captures the extremely long right tail of the wealth distribution well, with the 90th percentiles of the white (Black) model distributions being \$383,000 (\$97,000) compared to \$342,000 (\$89,000) in the data.

Table 3: Moments of the Initial Black and White Wealth Distributions

			25th Pctl	Median	Mean	90th Pctl
Wealth ($1,000s)	White	Model	23	79	205	383
		Data	8	60	188	342
	Black	Model	0	0	30	97
		Data	0	4	27	89

Note: This table reports moments of the Black and white wealth distributions used to initialize the model along with the distributions found in the 1962 Survey of Financial Characteristics of Consumers (SFCC). See Appendix A for details.

Another way of assessing the fit of the initial wealth distribution is to look at the over- and under-representation of Black households in various parts of the wealth distribution. Table 4 shows that the over-representation of Black households below the median of the wealth distribution is accurately captured by the distribution used to calibrate the model, as is the under-representation of Black households in the top quartile of the distribution. While the distribution used for model calibration slightly over-represents the share of Black households in the bottom quartile of the wealth distribution, this is not the best metric of fit because the CDF is so steep at low levels of wealth.

Table 4: Percent Black by Quartile of Wealth

	All	Bottom 25%	Bottom 50%	Top 25%
Data (1962 SFCC)	9.1	21.8	17.6	1.6
Model	11.5	31.9	19.5	1.8

Note: This table reports moments of the Black and white wealth distributions used to initialize the model along with the distributions found in the 1962 Survey of Financial Characteristics of Consumers (SFCC). We set the model's time-invariant share of Black households to 11.5 percent because the share of Black residents in the US was 10.5 percent in the 1960 Census and 12.6 in the 2010 Census. See Appendix A for details.

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

4 Model Validation

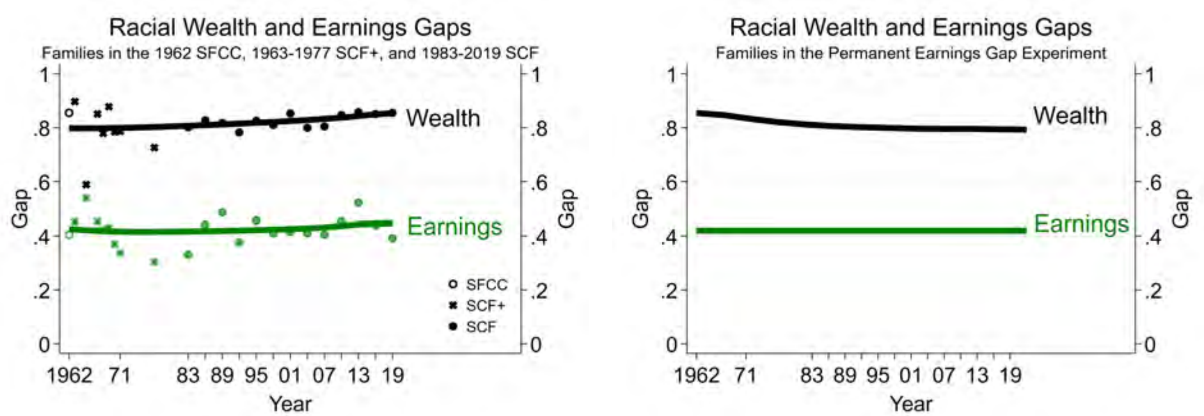
Before using the model to explore counterfactual wealth gaps, we first ask: Is the calibrated model consistent with the wealth gaps we have observed? To answer this question, we feed in the sequence of observed earnings gaps and compare the model's racial wealth gap to that in the data, both in terms of the time series and the joint distribution of race, earnings, and wealth in a given cross-section.

Figure 4a shows that the earnings gap has been 42 percent since 1962; so for this test of the model, we input a constant 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.[13] From the viewpoint of households in 1962 (and for many generations thereafter) the earnings gap is effectively permanent.[14] Throughout the paper we refer to this transition path as one with permanent earnings differences.

This is a model validation exercise. We emphasize that none of the results presented below are targeted by the calibration but rather are endogenous outcomes of the calibrated model initialized to the 1962 data. In each case, the outcomes produced by the parsimonious model are strikingly close to what is observed in the data.

4.1 The Time Series of Earnings and Wealth

Given the constant earnings gap, the model predicts an endogenous wealth gap that is nearly identical to what we have observed in the data. Figure 4b shows that after a brief few periods of adjustment, the model settles to a wealth gap of 0.79.



(a) Data

(b) Model

Figure 4: Racial Wealth and Earnings Gaps in the Data and Model
Note: This figure shows mean net worth and earnings by race between 1962 and 2019. The left panel shows mean net worth in the 1962 Survey of Financial Characteristics of Consumers (SFCC), 1963-1977 SCF+, and 1983-2019 SCF along with local linear regressions. The right panel shows the model's predictions over this time period. See Appendix A for data details.

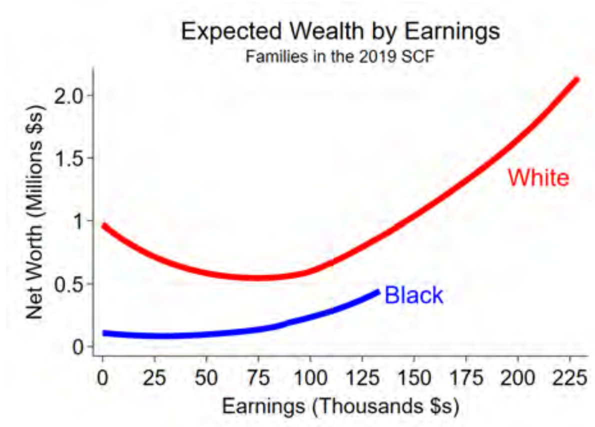
4.2 The Cross-Section of Earnings and Wealth

The model also produces the cross-sectional relationship between earnings, wealth, and race in the data. Figure 5 shows estimates of race-specific local linear regressions of wealth on earnings

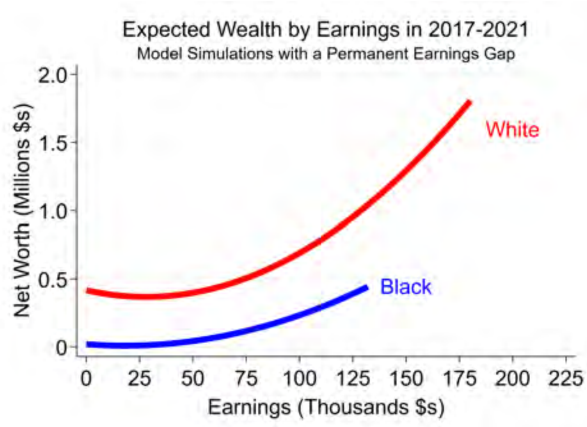
[13] Appendix B provides evidence that the earnings gap has had a slope statistically indistinguishable from 0 since 1962.

[14] After $t = 150$, we assume that the earnings gap instantly vanishes allowing the model to evolve to a racially equal steady state. Readers who are familiar with heterogeneous-agent models will recognize that because of the warm-glow utility specification, for hundreds of years this path is functionally equivalent to a permanent earnings gap.

in the 2019 SCF. The calibrated model produces a wealth gap conditional on earnings, shown in Figure 5b, that looks very similar to what we observe in the data, shown in Figure 5a.



(a) Data



(b) Model

Figure 5: Wealth by Earnings and Race in the Data and Model

Note: This figure shows local linear regression estimates of the race-specific conditional expectation functions (CEFs) of household net worth as a function of household earnings. The left panel shows estimated CEFs for the 2019 SCF, and the right panel shows model predictions for the 5-year time period 2017-2021. The model data in the right panel have been annualized.

Figure 5 illustrates the limitations of using statistical analysis of a cross-section to infer the causal relationship between the earnings and wealth gaps. A large literature has focused on how much of the racial gap can be explained, in a statistical sense, by earnings at a given point in time. This literature has found that a large racial gap in wealth tends to remain even after conditioning on earnings (Barsky et al. (2002)) and additional variables (Blau and Graham (1990), Altonji and Doraszelski (2005), Thompson and Suarez (2015)), a finding that has been interpreted as evidence that the earnings gap cannot be a primary driver of the wealth gap (Darity et al. (2020); Hamilton et al. (2015)).

The model's ability to reproduce this cross-sectional relationship between earnings and wealth by race suggests an alternative interpretation. Under this interpretation, the cross-section is a snapshot of an ongoing interaction between inflows of potential wealth, savings mechanisms, and initial conditions, and this allows for a range of relationships at a single moment in time. In particular, initial racial wealth disparities can persist well into the future for all levels of earnings – even when earnings, as we will show below, are the primary determinant of the persistence of the racial wealth gap.

4.3 Intergenerational Transfers

The model produces racial gaps in intergenerational transfers that are in line with estimates from the literature. Table 5 reports bequest sizes by race for model period 2017-2021. The expected bequest of a white household is 4.4 times that of a Black household. Using the improved techniques for measuring intergenerational transfers developed in Feiveson and Sabelhaus (2019), Thompson and Sablehaus (2022) find a ratio of expected inheritances of 4.6 between 1995 and 2018. 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.[15] For lifetime inheritances, Avery and Rendall (2002) find a ratio of 6-7.

Table 5: 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
$E(b \vert b > 0)$	0.85	3.77	–

5 Quantitative Analysis

In what follows, we conduct a series of numerical experiments in which we reduce the racial difference in one or more of the model ingredients and study how this alters the long-run level of the wealth gap as well as the persistence of the gap. Our goal in these exercises is not to generate a precise prediction about any single outcome. Instead, we hope to get a broad sense of the relative importance of the mechanisms considered here: initial conditions, earnings, returns, and wealth transfers. This decision stems from the lack of consensus about the relative importance of these factors for maintaining the racial wealth gap. As a result, we will often consider parameter values or processes that would appear unlikely to the reader in order to bound what we consider to be plausible. In doing so, these experiments should be informative to readers with their own priors over the parameterization or specification of the mechanisms under consideration.

5.1 The Wealth Gap Is Highly Responsive to the Earnings Gap

We begin by comparing the outcomes from two starkly different and extreme scenarios. In the first case, we assume that the earnings gap instantly vanishes in 2022. This endogenously removes the dividend to white households, since without a racial earnings gap, the stand-in firm no longer generates positive profits. In addition, racial differences in the bequest structure also become more equal after the earnings gap is removed; however, this occurs over time as mean wealth levels, and therefore also the size of the race-specific bequest pools, become more equal.

[15] Thompson and Suarez (2015) find a ratio of 3 conditional on receiving an inheritance. Bhutta et al. (2020) find similar median inheritance sizes conditional on receiving an inheritance, but a ratio of 3 in the likelihood of receiving an inheritance.

In the second scenario, the earnings gap is effectively permanent. Specifically, for 750 years we leave the earnings gap unchanged at its initial level. After that, the earnings gap is zero. Here it is important to point out a difference between our model with warm-glow bequests and models with infinitely lived households (or equivalently dynasties with altruism). 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, and so current households' decisions do not respond to changes in the distant future. For a sufficiently long transition, the model reaches the steady state associated with a permanent earnings gap long before we remove the earnings gap. [16,17]

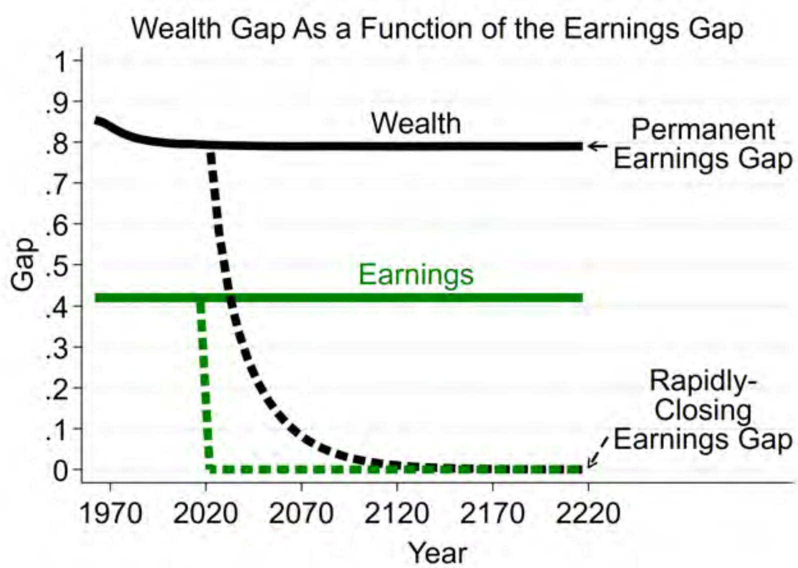


Figure 6: The Wealth Gap by Earnings Equality
Note: This figure shows model predictions of the racial wealth gap under the two scenarios of an instantaneously closing racial earnings gap (dashed lines) and a permanent earnings gap (solid lines).

Figure 6 plots the earnings and wealth gaps under the two cases. The resulting wealth gap paths could not be more different. With a permanent earnings gap, the wealth gap stabilizes at 79 percent and does not change. In contrast, the wealth gap declines when the earnings gap is not present. After 80 years, mean Black wealth is 95 percent of mean white wealth. In one sense, this experiment highlights a powerful tool for mitigating wealth disparities. On the other hand, these results are also a sobering message. Immediately erasing the earnings gap is a wildly and unrealistically optimistic scenario. Thus, under any plausible earnings gap path, the wealth gap will persist for a very long time.

[16] We acknowledge that this is a slight abuse of language since technically the earnings gap is not permanent. Nevertheless, for simplicity we will refer to such experiments as "permanent."

[17] If we impose the condition 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.

5.2 A Permanent Earnings Gap Dominates All Other Mechanisms

5.2.1 Wealth Redistribution under a Permanent Earnings Gap

In 2021, US House of Representatives bill HR40 was introduced with the goal of establishing a commission to study the effects of racial discrimination and recommend appropriate remedies, including reparations in the form of direct wealth transfers. While there is a debate about the philosophical or legal merits of direct wealth transfers (Darity and Mullen (2020)), there is also a separate empirical question: What would happen to the racial wealth gap under such a policy? Our model is well-suited to consider the consequences of large redistribution programs. We consider these consequences under a range of scenarios about the future paths of earnings and return gaps, which effectively replicate some of the scenarios one might expect in terms of how wealth transfers would alter the economy.

We begin by studying what would happen after a wealth transfer that left the earnings gap unchanged. 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. (forthcoming)) suggests that these mechanisms are relatively weak.[18] Nevertheless, the evidence is not yet 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 interact with earnings and underscore their importance.[19] If a feedback loop from wealth to earnings is strong enough, then the massive reparations experiment considered here could generate a virtuous cycle in which more equal wealth reduces the earnings gap, and that in turn mitigates the emergence of a new wealth gap. Given the possibility that wealth may feed back into earnings, we conduct experiments with a range of earnings paths in Section 5.4.

For the experiment at hand, to explore the case where a wealth transfer would not alter the earnings gap, we implement a one-time wealth redistribution on the model and document how the racial wealth gap evolves over time. Specifically, 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 details of how one would make these payments.

Equalizing wealth without equalizing earnings has no long-term effect on the wealth gap. The resulting wealth gap path is plotted in Figure 7, which shows that within 50 years the wealth gap returns to its initial level. These results emphasize the importance of policies aimed at reducing the earnings gap if the goal is to have lasting effects.

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

[19] The empirical evidence from historical examples of this kind of large wealth transfer in the US is also consistent with earnings being relatively invariant to wealth transfers (Bleakley and Ferrie (2016), Ager et al. (2019)).

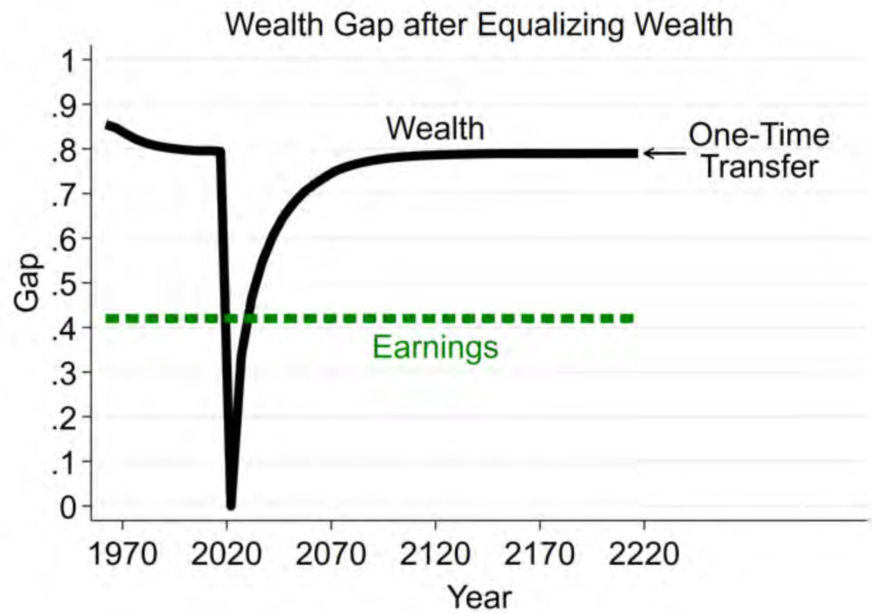


Figure 7: The Wealth Gap by Earnings Equality
Note: This figure shows model predictions of the racial wealth gap under the scenario of a one-time wealth transfer equalizing Black and white wealth distributions together with a permanent earnings gap.

5.2.2 Return Gaps under a Permanent Earnings Gap

The model does not feature significant, persistent differences in rates of return on saving by race, except for the proportional dividend of firm profits, which is small and disappears as the earnings gap closes. A racial gap in the returns to capital is an important factor leading to the 1962 racial wealth inequality used in our analysis. While there is a broad set of historical examples related to direct confiscation that helped to generate this return gap, more recently just in the realm of housing, there are examples such as limited credit in Black areas (Aaronson et al. (2017), Faber (2020)), subsidizing housing in white areas (Rothstein (2017), 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)).[20]

With the elimination of the most overt legal forms of theft, in recent decades a return gap would more likely appear 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. One potential exception would be returns to housing, with recent evidence indicating that higher income volatility for Black households drives these return gaps more than different appreciation rates (Kermani and Wong (2021)). More general return gaps, however, tend to be hard to find in the data, and the most compelling empirical evidence indicates that overall rates of return have been similar for Black and white households over recent decades (Wolff (2018); Gittleman and Wolff (2004)), as have returns

[20]Characterizing this history, Coates (2014) writes: “When we think of white supremacy, we picture COLORED ONLY signs, but we should picture pirate flags.”

on housing (Wolff (2022)).

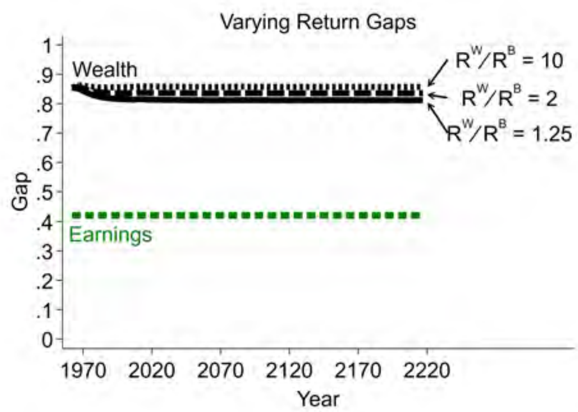
Despite a lack of clear empirical support, return differences by race are still put forward as meaningful contributors to the racial wealth gap, and with a limited supply of data on both wealth and returns in the US, it is possible that current measurements might have missed these return disparities. This leaves open the possibility that a significant return gap does exist, and so it is worthwhile to investigate how a hypothetical return gap would affect the results above.

A key question here is: what is the quantitative importance of return gaps relative to other mechanisms in the model? Understanding this question is important because equalizing earnings alone will not fully close the wealth gap when any permanent mechanism causes income to differ by race. For example, Boerma and Karabarbounis (2021) show how persistent differences in beliefs about entrepreneurial success could perpetuate some of the wealth gap even in the absence of earnings differences.

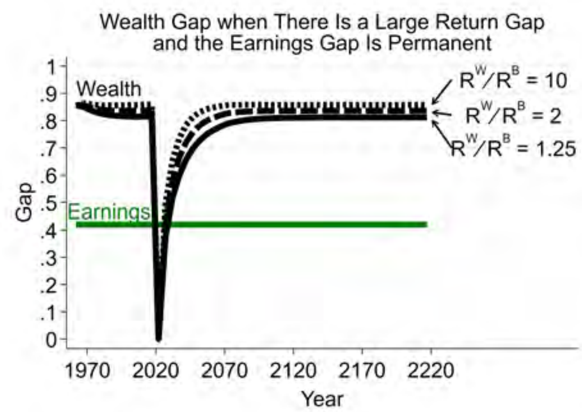
We conduct bounding exercises that use three counterfactual return gaps: a small one where the Black return is 80 percent of that for white households, a medium one where it is 50 percent, and a very large one where it is only 10 percent. It is worth pointing out that in light of the empirical evidence available (Wolff (2018); Gittleman and Wolff (2004); Wolff (2022)), even the smallest, 80 percent case is probably "generous" in terms of giving room for a return gap to matter. The additional cases are meant to further illustrate the limitations of return gaps in the model with persistent racial earnings differences, rather than to approximate reality. This is certainly the motivation behind the 10 percent case, in which white households earn 10 times the return of their Black counterparts, far too large to be plausible. For perspective, Kaymak et al. (2020) document return differences by income irrespective of race and find that in recent waves of the SCF, the top 0.1 percent of the income distribution achieve a rate of return that is 3.4 times the rate on the assets of the bottom 90 percent of the distribution.

Figure 8a plots the wealth gaps from each case. With a permanent earnings gap fixed to its baseline value, return gaps have almost no effect on the wealth gap. Recall that when there is no return difference, the model settles into a wealth 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 to the return gap is due partly to the life-cycle structure with warm-glow and partly to the fact that Black households earn so much less. Figure 8a also illustrates why our baseline results are robust to rebating profits lump-sum or proportionally (or even discarding them entirely). Firm profits are a function of the earnings gap. When the earnings gap is large, firm profits are at their maximum, but then racial return differences are nearly inconsequential. When the earnings gap is very small, and thus return differences have the most potential to affect the wealth gap, profits are zero.

Figure 8b shows that the wealth gap's lack of sensitivity to a return gap under permanent earnings differences is not affected by the initial distribution. Even under a transfer equalizing wealth, like the one described above, the wealth gap quickly re-emerges in all cases. The earnings gap simply dominates return differences.



(a) Permanent Earnings Gap



(b) Rapidly Closing Earnings Gap

Figure 8: The Wealth Gap by Return and Earnings Gaps
Note: This figure shows model predictions of the racial wealth gap under a permanent earnings gap and alternative scenarios for gaps in returns on capital and wealth transfers.

5.3 Education and the Earnings Gap

We showed above that closing the earnings gap is critical for making meaningful progress toward closing the wealth gap. However, it is difficult to assess the pace at which we might expect the earnings gap to close. On the one hand, just taking the past 60 years as precedent suggests the earnings gap should close extremely slowly, if at all. On the other hand, social awareness of and concern for the economic disadvantage of Black Americans has certainly grown since the 1960s, and one could imagine policies or private initiatives leading to rapid growth in Black Americans' earnings. In the presence of trend-altering structural changes, the historical record would be of little help for predicting the path of the earnings gap.

Given this uncertainty about the future path of the earnings gap, we explore how much the earnings gap would close if we attribute a substantial portion of it to the unequal distribution of education by race.[21] What if, for example, the American education system were equally as effective at educating Black students as white students? Or, revisiting the wealth redistribution experiment above, what if wealth transfers allowed more Black students to attend higher quality K-12 schooling or to finance their post-secondary education? How much could such changes reduce the earnings gap and how quickly would the wealth gap disappear as a result?

In measuring educational difference, we follow the tradition in the labor literature of distinguishing between educational *attainment*, or the completion of educational degrees (e.g., high school diploma, college diploma) and *achievement*, or cognitive skills as represented by a standardized test score, here measured by the Armed Forces Qualification Test (AFQT). In the 1979 National Longitudinal Survey of Youth (NLSY79), white respondents have significantly higher educational attainment and achievement. Both attainment and achievement are likely to be components of

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

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)) and intergenerational income mobility (Bhattacharya and Mazumder (2011), Davis and Mazumder (2018)).[22]

We estimate how much of the lifetime earnings gap in the NLSY79 can be accounted for by racial differences in attainment. To do so, we assume that attainment is equalized, but Black households still receive lower earnings at each level of attainment as observed in the data. That is, we assume that Black households earn degrees with the same frequency as white households, which is $Pr[d_i = a|\text{age}_i, \text{race}_i = W]$ but use the expected earnings for Black households observed in the data, which is $\mathbb{E}[Y_i|d_i = a, \text{age}_i, \text{race}_i = B]$.[23] We then compute the counterfactual mean earnings as

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

We repeat the same process for achievement, where rather than the three levels of attainment, we instead sum over 20 levels of achievement represented by the ventiles of AFQT test score ranks.

Figure 9 shows lifetime earnings by age in the data as well as after equalizing 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 after conditioning on age; the earnings gap exists not simply because in a given cross-section, Black households will tend to be younger. These findings suggest that apart from large differences in the certified level of education, the labor market premium conferred on graduates is not equal by race. This would be consistent with, for instance, the interaction of neighborhood segregation by race with local financing of public education.

[22] 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)). Likewise, the approach to measurement is important when interpreting the relationship between achievement and labor market outcomes (Nielsen (2020); Rodgers and Spriggs (1996); Ritter and Taylor (2011)).

[23] Recall that attainment levels $a = 1, 2, 3$ correspond to less than high school, high school diploma, and BA or higher.

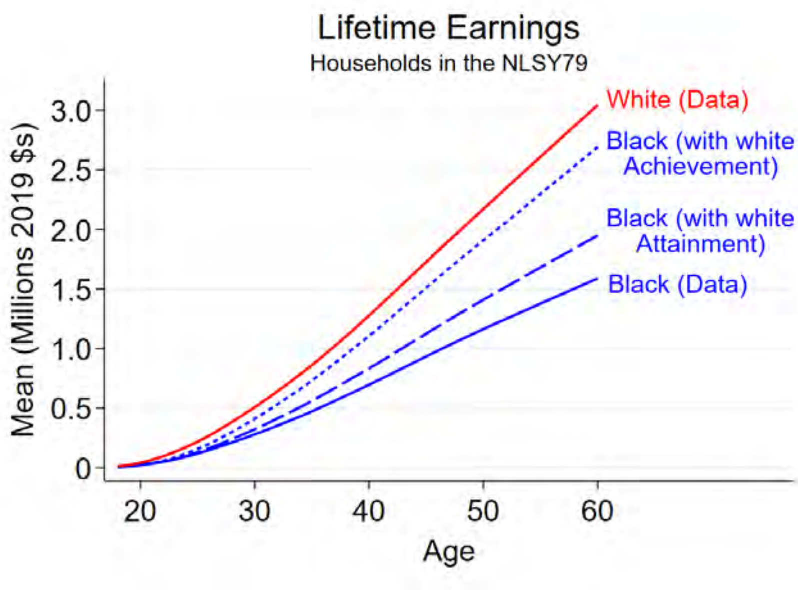


Figure 9: Education-Adjusted Lifetime Earnings in the NLSY79
Note: This figure shows the counterfactual average lifetime earnings of Black households in the NLSY79 if Black households' education outcomes were the same as white households but average earnings conditional on those outcomes were those observed in the data for Black households. See the text and Appendix A for details.

We now consider a counterfactual where, unlike in the previous bounding exercises where the earnings gap vanished instantly for all ages, an educational reform rolls out over generations. Initially, only newborn Black households realize a permanent reduction in the earnings gap, while the remaining Black households still face the pre-reform gap. Over time, as generations die and get replaced by newborns, the reform level spreads to the entire Black population.

For comparison to the bounding cases in Section 5.2, we begin the reform at the baseline 2022 wealth distribution. The wealth gap transition paths under the equal attainment and equal achievement scenarios are plotted in Figure 10. As one would expect, equal achievement has a much larger effect on the wealth gap (roughly fives times that of the equal attainment case). In both scenarios, progress occurs slowly. The generation-by-generation rollout adds 50 years to the wealth gap path with immediate earnings equalization for all.

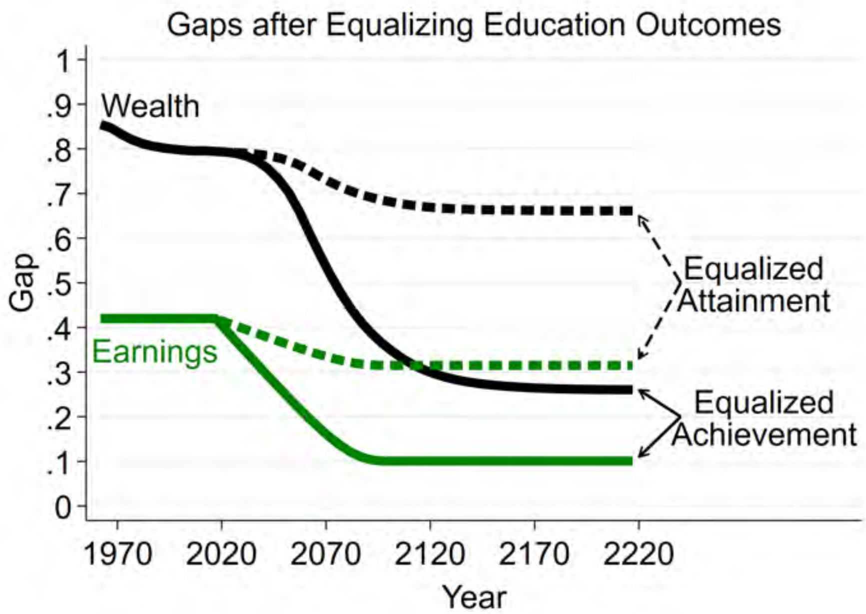
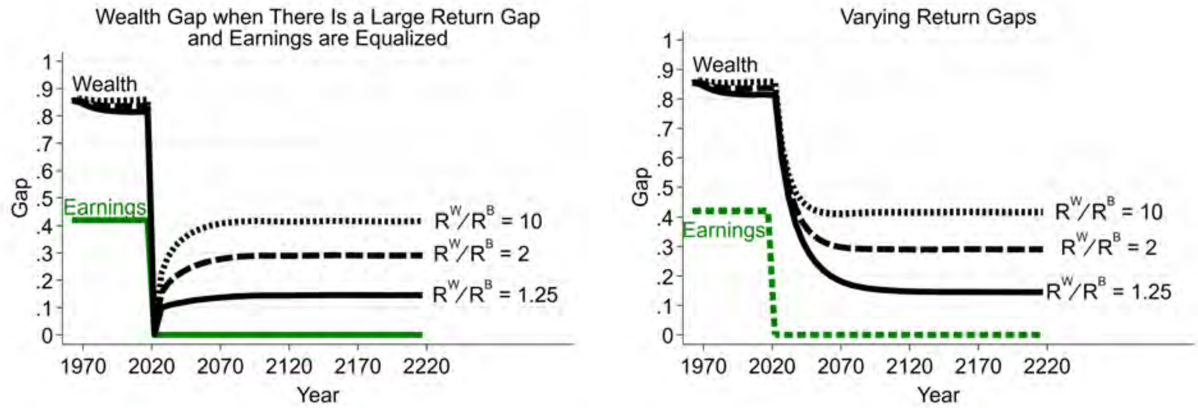


Figure 10: The Wealth Gap by Earnings Equality
Note: This figure shows model predictions of the racial wealth gap under a scenario in which newborn Black households had the same educational attainment (dashed lines) or educational achievement (solid lines) as white households.

5.4 Wealth and Returns in the Absence of an Earnings Gap

We established earlier that in the presence of a large earnings gap, return gaps have a small effect on the wealth gap and wealth transfers have a transitory effect. We now revisit these earlier exercises assuming that the earnings gap closes over time, according to the paths specified in the educational reform experiments.

Return gaps Clearly when a large earnings gap persists, return differences are of second-order importance for the wealth gap. But what about when the earnings gap is eliminated? When the earnings gap is immediately closed (shown in Figure 11), return gaps prevent the wealth gap from fully converging, and unlike in the previous case, there are significant differences in the long-run wealth gap by return gap level. A small return gap leads to a wealth gap of 14.5 percent in the long run, while the wealth gap can be as large as 41.6 percent under the most extreme return difference. Return gaps, should they exist and persist after earnings are equalized, could maintain a significant racial wealth gap. However, we again stress that even the weakest return difference considered here appears beyond the upper bound of the empirical evidence to date. Thus, it is more likely that any plausible level of return difference has only a small effect on the future wealth gap.



(a) No Earnings Gap (b) Persistent Earnings Gap

Figure 11: Transition Paths with Immediate Earnings Equality and Return Gaps
Note: This figure shows model predictions of the racial wealth gap under a scenario in which the earnings gap immediately closes in 2022 and there is a gap in the return to capital. The left panel shows this scenario in combination with a one-time wealth transfer equalizing the wealth distributions of Black and white households, and the right panel shows this scenario with no wealth transfer.

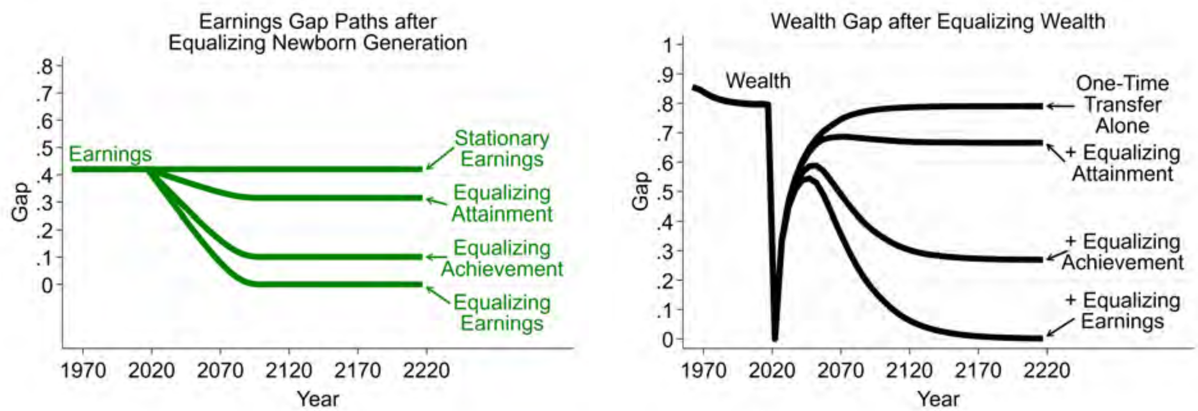
These experiments clarify how our results relate to the analysis in Boerma and Karabarbounis (2021). In that paper, households are modelled as infinitely lived dynasties, meaning that living generations internalize the return differences far out into the future long after their death. In such an environment, even small return gaps could have sizeable effects on present household savings.

In contrast, households in our model do not make decisions as if they live forever. Their horizon only extends through their expected lifetime. Consequently, there is much less scope for small return gaps to have large effects. As we showed above, this does not imply that return gaps are unimportant. On the contrary, racial differences in capital income can still cause wealth differences to accumulate slowly over generations.

Wealth Transfers Section 5.2.1 shows how rapidly wealth equalization can be undone when large earnings gaps persist. Again, we recognize that this finding is somewhat limited because of the exogenous nature of the earnings gap in the model. In the interest of making the importance of earnings 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 many factors contribute 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.

Even without endogenizing earnings, we can still provide what may be considered an upper bound on the potential changes were earnings to endogenously respond to wealth (Darity et al. (2020)) by combining the educational reform and the wealth transfer experiments. One way to interpret this exercise is that large-scale wealth transfers eliminate pecuniary barriers, making the education reform paths feasible for Black households. Like many exercises in this paper, this is highly optimistic, but it also gives the best chance to arguments in favor of a strong feedback from wealth to earnings, including those operating through mechanisms like access to capital.

Figure 12a plots the different earnings gap paths and resulting wealth gap transitions. In all cases, because reform rolls out by generation, the wealth gap begins to re-emerge over the decades following redistribution regardless of the earnings treatment. After that period, however, the wealth gap transition depends greatly upon the size of the earnings gap. If earnings are fully equalized, the wealth gap begins to rapidly diminish and virtually disappears within 100 years. If, instead, the earnings are only equalized up to the level estimated by achievement, the wealth gap still declines but levels out at 27 percent. And finally, assuming that the wealth redistribution only equalizes attainment, which would nevertheless appear to also be an optimistic scenario, the wealth gap would go to 67 percent in the long run.



(a) Earnings (b) Wealth

Figure 12: Transition Paths after a One-Time Wealth Transfer
Note: This figure shows model predictions of the racial wealth gap after a one-time wealth transfer together with various paths of earnings inequality. The left panel shows the hypothetical earnings paths fed into the calibrated model and the right panel shows the wealth gaps predicted by the model under each path of the earnings gap.

These findings yet again underscore the importance of the earnings gap for maintaining the large gap in wealth by race and highlight that we should expect the wealth gap to persist for a long time. We stress that these are intentionally optimistic assumptions about earnings equalization. As discussed earlier, in reality the likely passthrough from wealth to earnings via education would be far lower than we assume here (especially among the early generations), meaning that the wealth gap would vanish even more slowly than in these exercises. Moreover, any wealth transfer proposal is almost certainly not going to achieve immediate and complete wealth equality by race, and so again, the ensuing wealth gap, even with an endogenous earnings gap, would be even more persistent than shown here.

6 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), along with the SCF+ from 1963 to 1977, which comprises archival data from historical waves of the SCF (Kuhn et al. (2020)).

Our SCF and SFCC samples consist 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 SFCC. In the 1962 SFCC 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 SFCC 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.1.1 describes this interpretation in detail.

In the SFCC and SCF we measure wealth as net worth, which includes home equity, individual retirement accounts (IRAs), and many other financial/nonfinancial assets and debts.[24] In the SFCC and SCF we measure earnings as total family income from wages and salaries.[25]

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 the 1962 SFCC 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 onward. We obtain the SCF+ data from the data archive of Kuhn et al. (2020).

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 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 straight-

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

[25] 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.

forward 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 SFCC survey to current racial categories is less straightforward than choosing the mapping for later waves. Race was determined in the SFCC by the surveyor in 1962, which simplifies our task relative to respondents choosing their racial identity (Dahis et al. (2019)).[26] The 1962 SFCC 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 SFCC, 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 SFCC. The remaining share of "nonwhite" respondents in the 1962 SFCC 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 SFCC as meaning "Black" in today's terms and we interpret "white" and "not ascertained" in the 1962 SFCC 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 population in the 1960 census, 92.1 percent were "Negro" (US Census (1961)).[27] 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 13 shows the results of their analysis; it is likely that about 3 percent of the US population was Hispanic in 1960.

[26] Race became self-identified starting in the 1989 SCF.

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

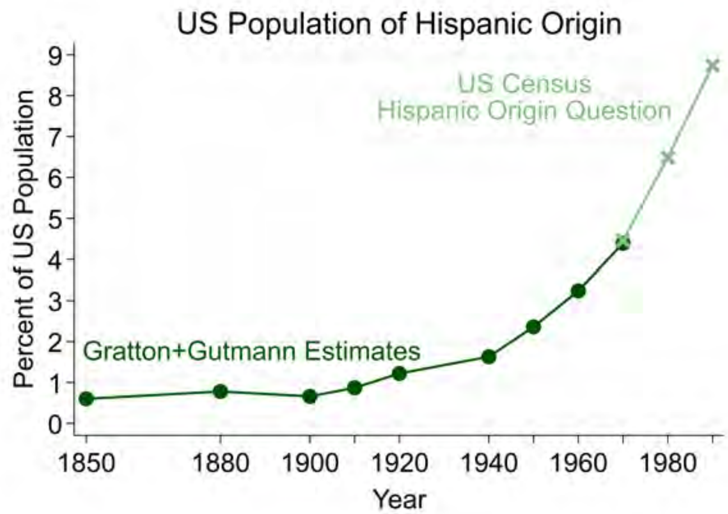


Figure 13: Hispanic Population in the US over Time

Evidence on educational attainment also supports our choices for mapping the racial categories in the 1962 SFCC 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 14) or ratios (Figure 15).

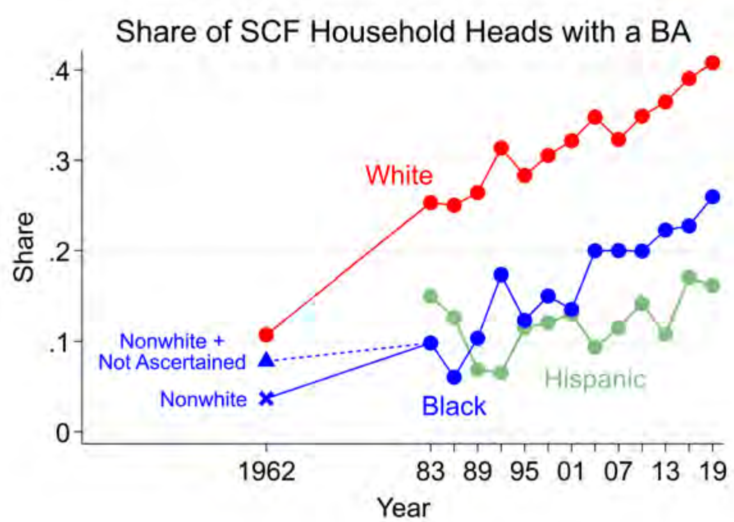


Figure 14: Educational Attainment in the SCF

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 SFCC 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 SFCC prediction would have a z-score of 2.1 or 11.4 if we measured Black as, respectively, either "nonwhite" or "nonwhite + not ascertained."

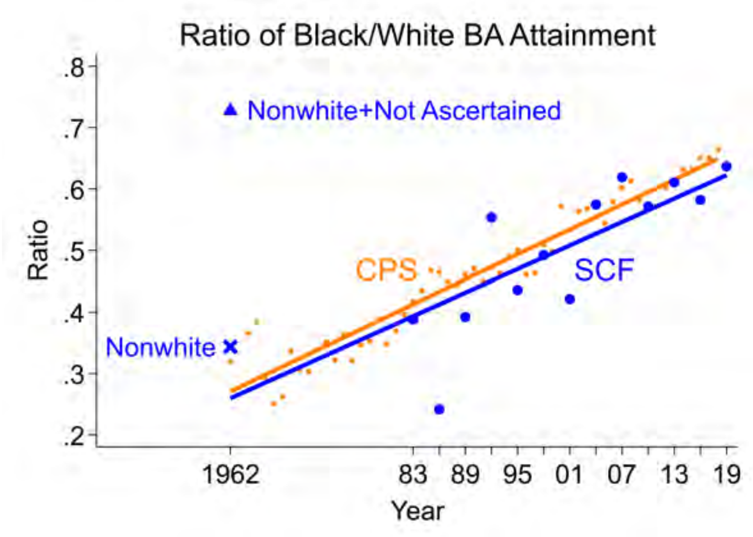


Figure 15: Educational Attainment in the SCF and CPS

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 personnel. 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 Qualification 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

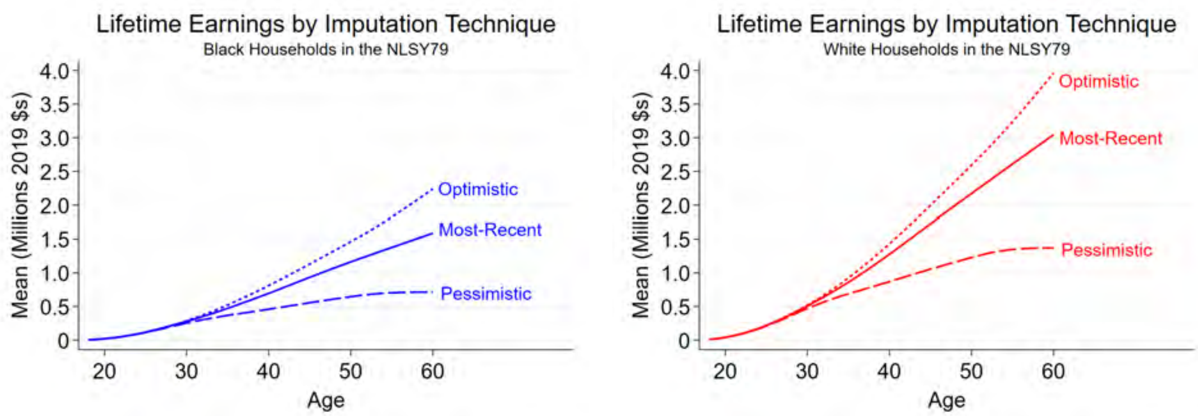
Computing lifetime earnings from ages 18-60 with the NLSY79 is complicated because the NLSY79 became a biennial survey in 1996. To account for the biennial nature of the NLSY79, as well as data simply missing over the life cycle, we impute missing earnings at a given age as the respondent's most recent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

Figure 16 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 16a and 16b 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 17a and 17b show that the general pattern of adjusting lifetime earnings for education holds 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

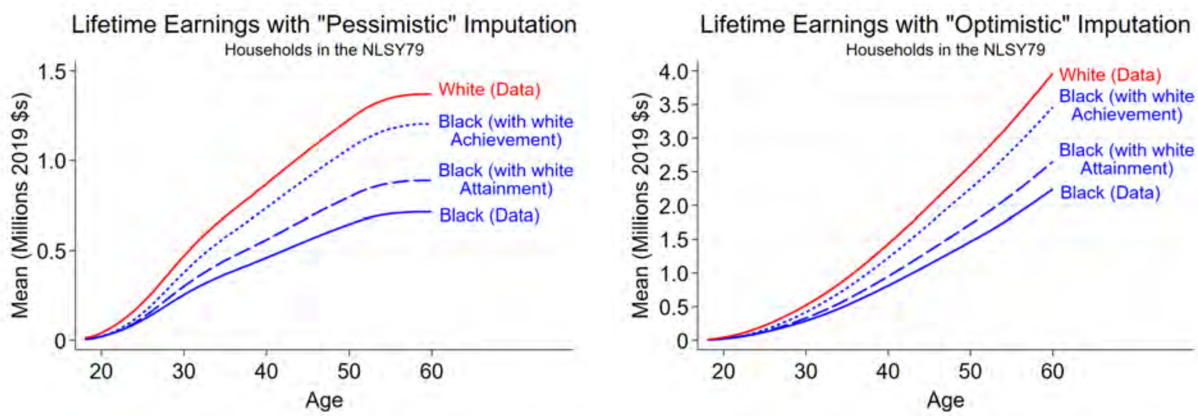
NLSY79. Item-anchored rankings that aggregate questions into a scalar index based on each item's predictiveness of economic outcomes would likely result in achievement accounting for more of the Black-white gap in lifetime earnings (Nielsen (2015)).



(a) Black Households

(b) White Households

Figure 16: Lifetime Earnings in the NLSY79 by Imputation Technique



(a) Pessimistic Imputation

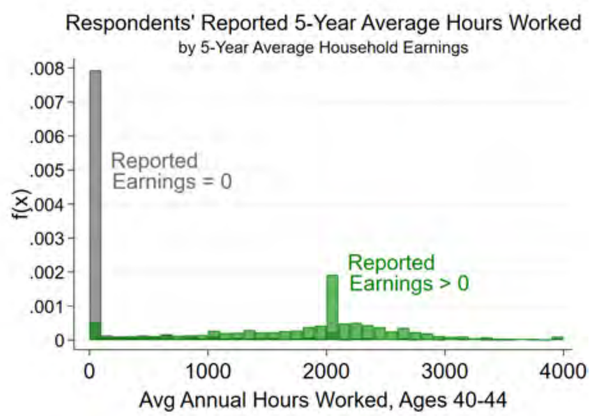
(b) Optimistic Imputation

Figure 17: Lifetime Earnings in the NLSY79 by Imputation Technique

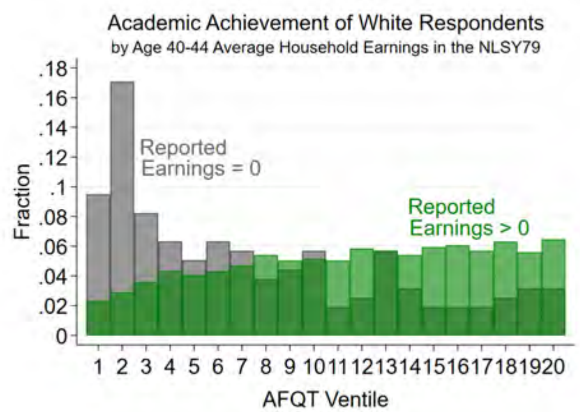
A.2.2 Interpreting $0 Earnings in the NLSY79

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 18 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 18: 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 25a.

Figure 19: $\widehat{\Phi}(\text{age}, \text{race})$ 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

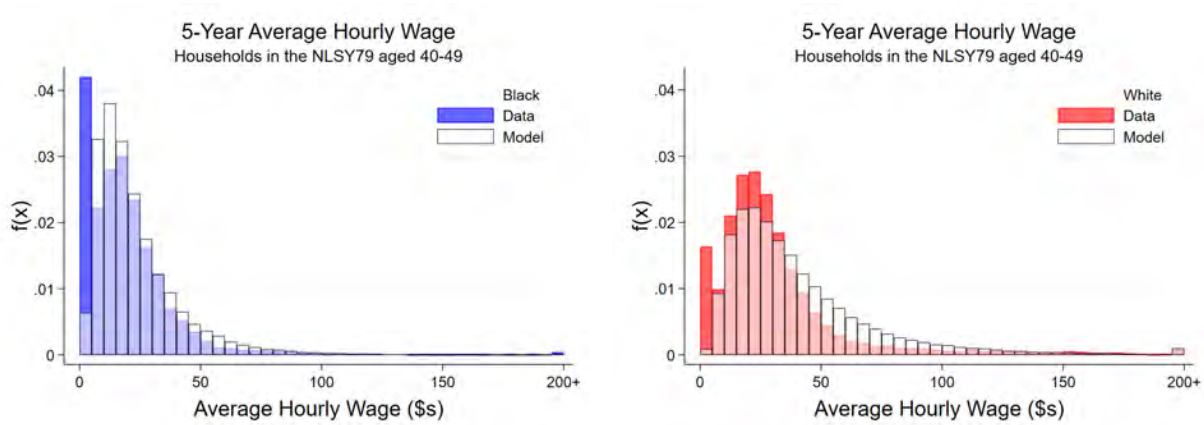
$$\varepsilon_i(\text{age}) = \begin{cases} \underline{\varepsilon_i^*}(\text{age}) = \log\left(\frac{\underline{w}}{\Phi(\text{age}_i, \text{race}_i)}\right) & \text{if } \varepsilon_i^*(\text{age}) < \underline{\varepsilon_i^*}(\text{age}) \\ \varepsilon_i^*(\text{age}) & \text{if } \varepsilon_i^*(\text{age})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

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 20 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 20a 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 20b 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.

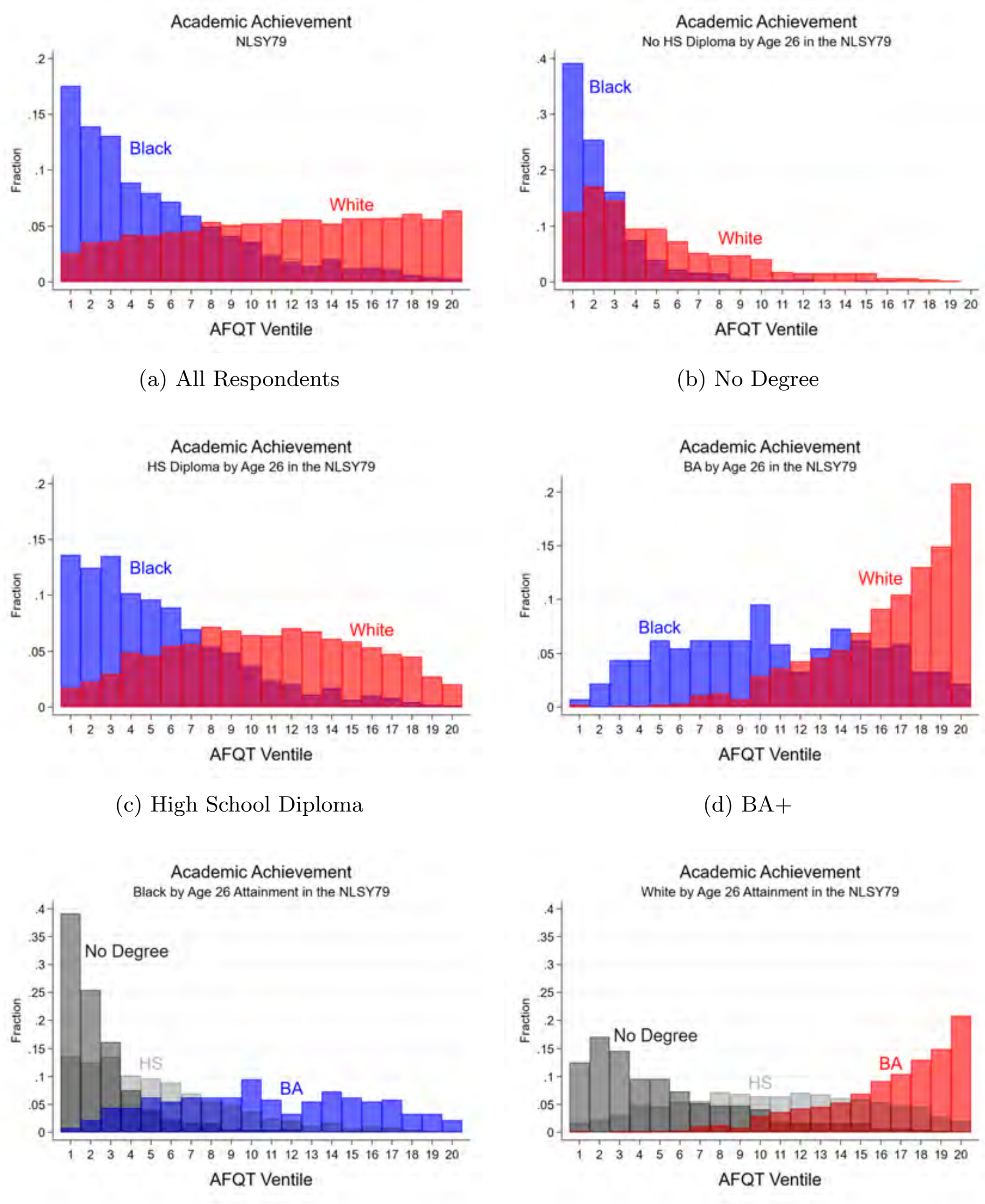


(a) Black-Headed Families (b) White-Headed Families

Figure 20: 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 21a shows that academic achievement is distributed close to uniformly for white respondents, but is rightskewed for Black respondents. Figures 21b-21d show that Black achievement significantly lags white achievement even conditional on attainment. Figures 21e and 21f show 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 21: Academic Achievement in the NLSY79, by Race and Attainment

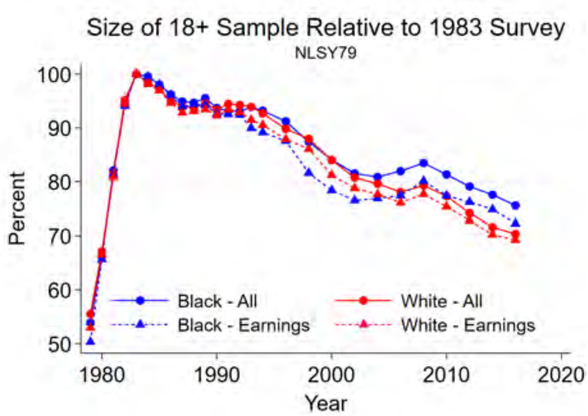
A.2.5 Attrition in the NLSY79

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)).

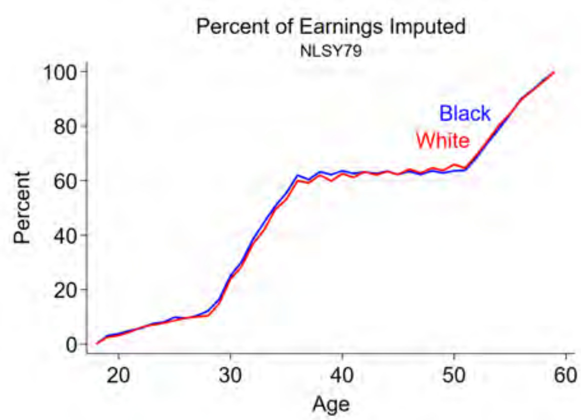
We make two comparisons to assess the importance of attrition in the NLSY79 for our wage calculations. The comparisons suggest that racial differences in attrition are unlikely to create major biases in our life cycle analysis using the NLSY79.

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 22a 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 22b 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

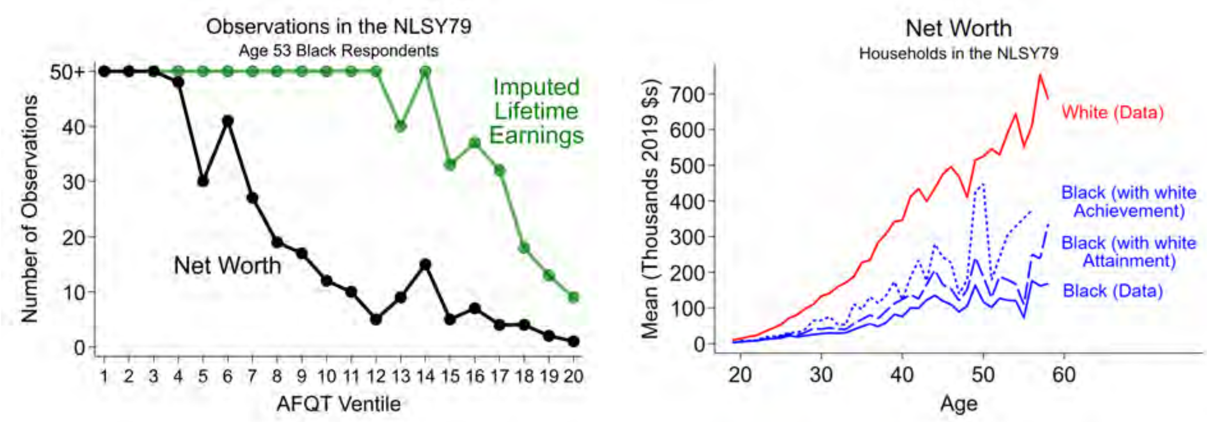


(b) Unobserved Earnings

Figure 22: Attrition and Imputation in the NLSY79

A.2.6 Net Worth in the NLSY79

Figure 23b shows net worth calculations from the NLSY79 adjusting for educational attainment and achievement. Figure 23a 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 23: 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 (ISR (2018)). 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.[28] 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.[29] 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 6 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

[28] 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.

[29] 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.

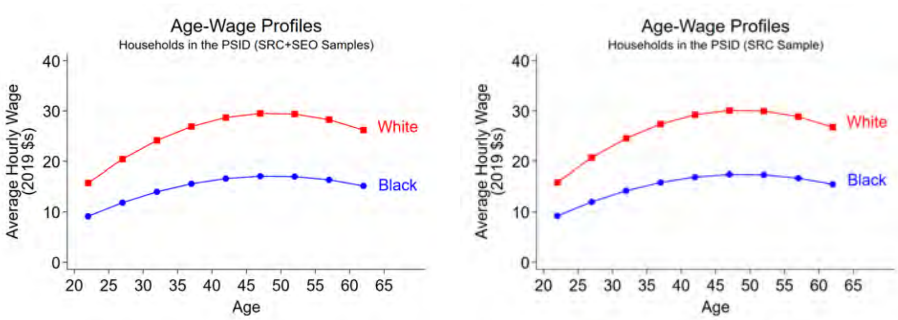
top row shows the original sample size and each subsequent row shows the additional number of observations lost when applying the sample restrictions in order from (i)-(iii). The final row shows the final sample sizes used in our analysis. Including the SEO sample nearly doubles the sample size, which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

Table 6: 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.[30] 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 24 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 24: Age-Wage Profiles in the PSID
Note: Figure displays profiles with intercepts estimated for the years 1983 and 1984.

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

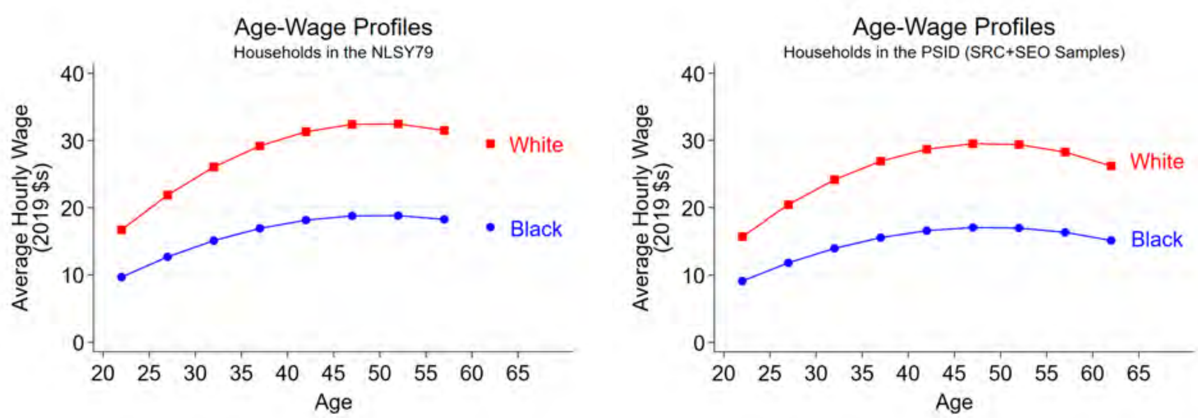
A.4 Comparing the Estimated Wage Processes in the NLSY79 and PSID

The NLSY79 and PSID are generally similar in their strengths for estimating the wage process used in our model, and as shown in Figure 25 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 that 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)).[31]

Given this discrepancy in measuring household formation at young ages, it is not surprising to see in Figures 25 and 26 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).

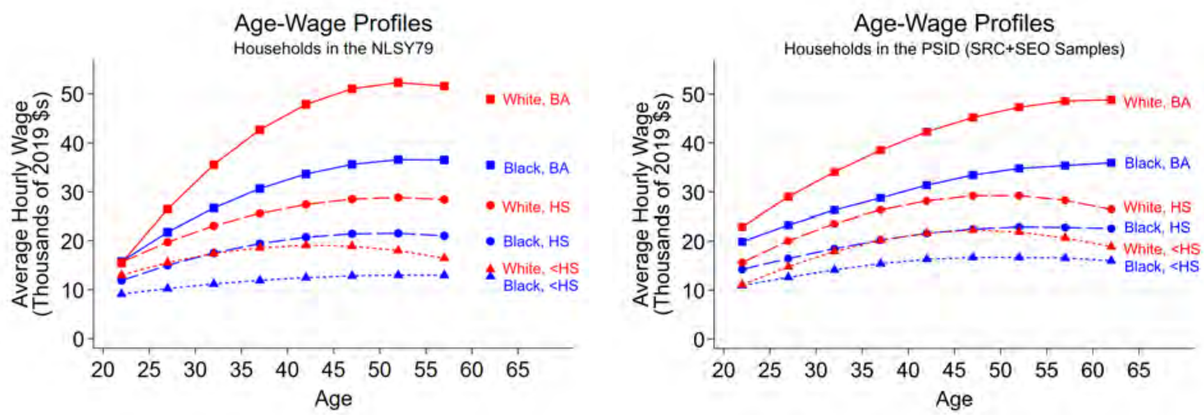


(a) NLSY79

(b) PSID (SRC+SEO)

Figure 25: 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.

[31] 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 26: 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.

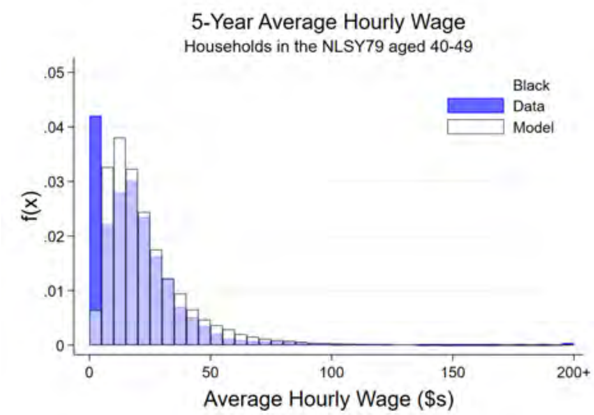
Table 7 shows the estimated ρ_η and σ_η parameters of the wage process. The parameters estimated on the PSID are remarkably similar regardless of whether we use the SRC sample only or estimate the parameters on the combined SRC and SEO samples. The persistence of the shock processes is similar across data sets. The largest difference in estimates is that the variance of the idiosyncratic shock process is higher in the NLSY79 than in the PSID.

Figure 27 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 five-year window.

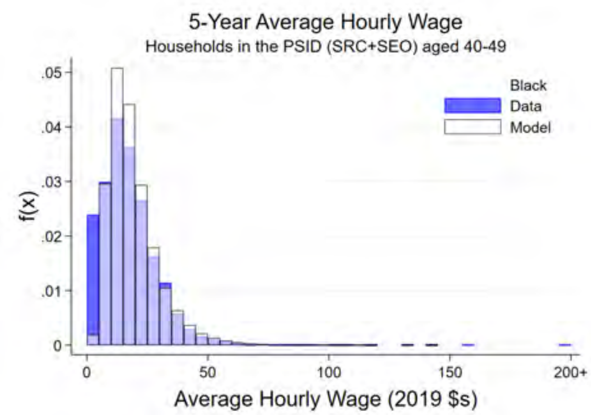
Table 7: Wage Process by Sample

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

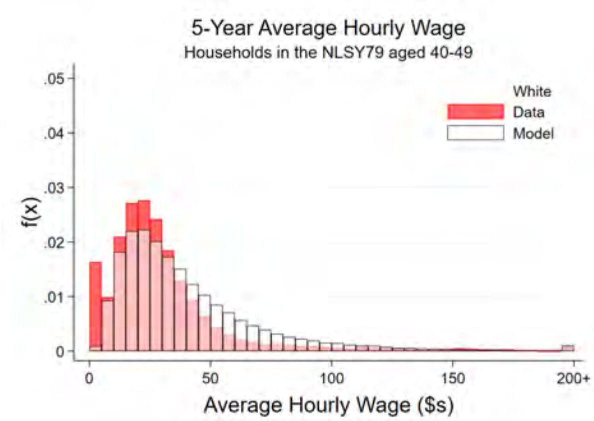
Note: This table reports the parameters of the wage process when estimated on alternative samples.



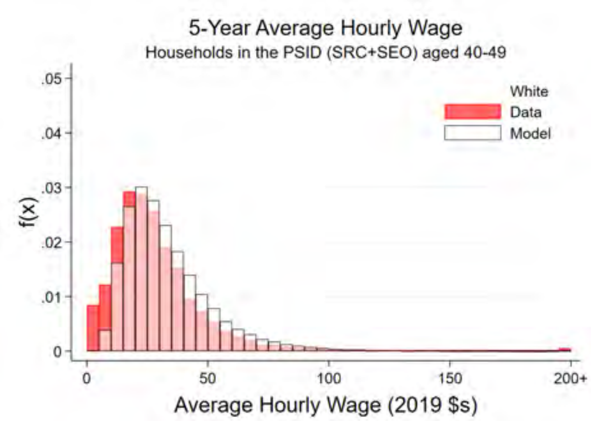
(a) Black-Headed Families



(b) Black-Headed Families



(c) White-Headed Families



(d) White-Headed Families

Figure 27: 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 28 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.

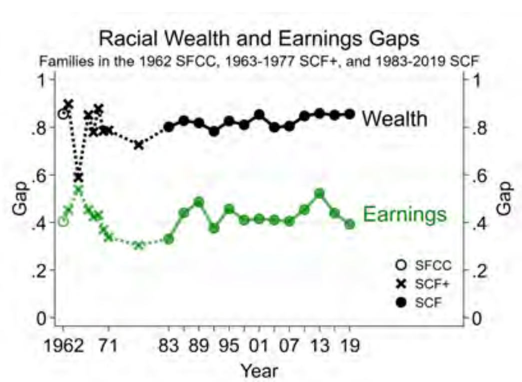


Figure 28: Earnings and Wealth Gaps

Table 8: Coefficient on Time

Time Period	Earnings Gap β	Earnings Gap $\beta\times$ 60	Earnings Gap P	Wealth Gap β	Wealth Gap $\beta\times$ 60	Wealth Gap 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 8 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 29 shows the conditional expectation functions (CEFs) of wealth conditional on earnings separately for Black and white households.[32] Whatever decade of data we look at in the SCF, we see a large gap between the Black and white CEFs. Table 9 reports these gaps as the coefficients

[32]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 results very similar to those of semi-parametric local regressions.

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 SFCC and SCF, 1962-2019, this coefficient is –$540,000 in 2019 dollars.

Figure 29: 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.

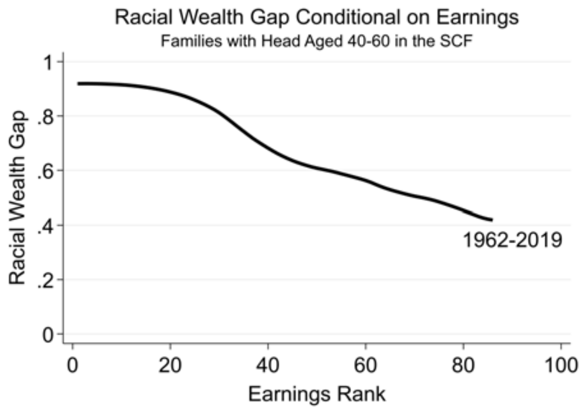
Table 9: Coeff. on Black Household Head

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

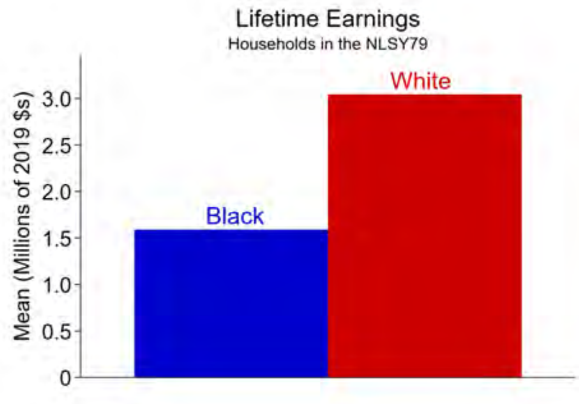
Note: The dependent variable in the linear OLS regressions reported above is household net worth. The independent variables are earnings, earnings^2, Black, Black$\times$earnings, and Black$\times$earnings^2. The coefficients reported above are the coefficients on Black for all waves of the SCF occurring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

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

Figure 30a 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. 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 30: Earnings and Wealth Inequality

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

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 underreporting 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.[33] 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 30b, 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 percent, 205 percent, and 173 percent 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

[33]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)).[34]

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

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

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 31 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 exists not simply because in a given cross-section, Black households will tend to be younger. Figure 31 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.

[34] 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)).

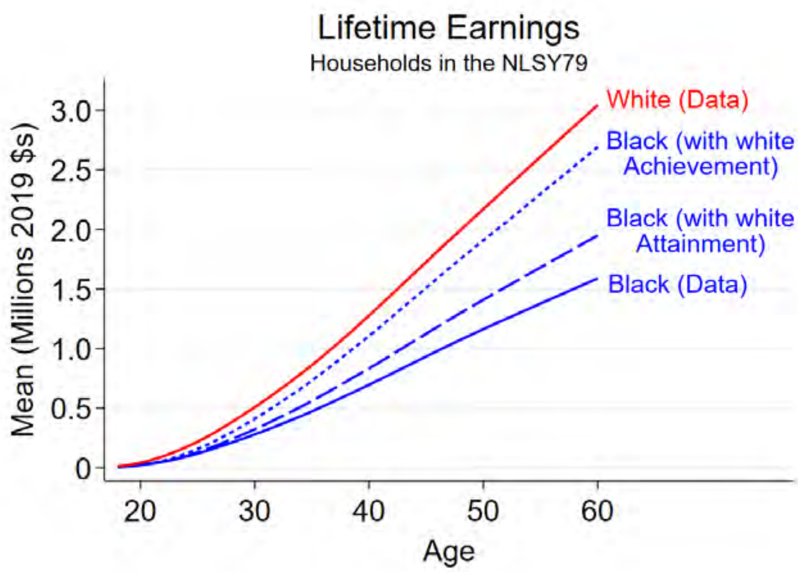


Figure 31: Education-Adjusted Lifetime Earnings in the NLSY79

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 life cycle, 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 32, and $y_i(55-60)$ in the SCF.

Figure 32: $\widehat{\Phi}(\text{age}, \text{race}, \text{education})$ in the NLSY79

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

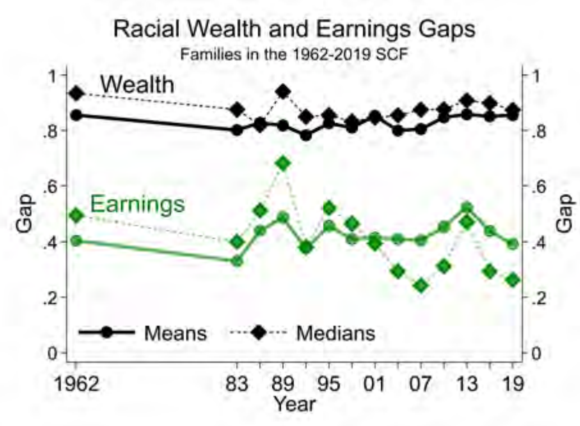
$$\sum_{a=18}^{a_{2019}} \widehat{y}_i(a)\,(1+R)^{a_{2019}-a}.$$

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.

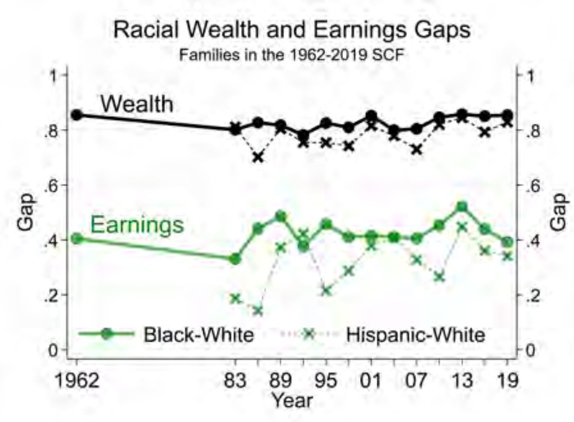
C Appendix: More on Facts 1 and 2

C.1 Means Versus Medians

Figure 33a 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 33: Measures of the Wealth and Earnings Gaps

C.2 The Hispanic-White Wealth Gap

Figure 33b 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 10 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 10: Facts 1 and 2 in the Literature

Study	Data Set	Unit of Observation	Income Gap	Wealth Gap
Labor Income (Earnings)				
This Paper	1962 SFCC, 1983-2019 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:

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

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 $\varphi(B)w^*$.

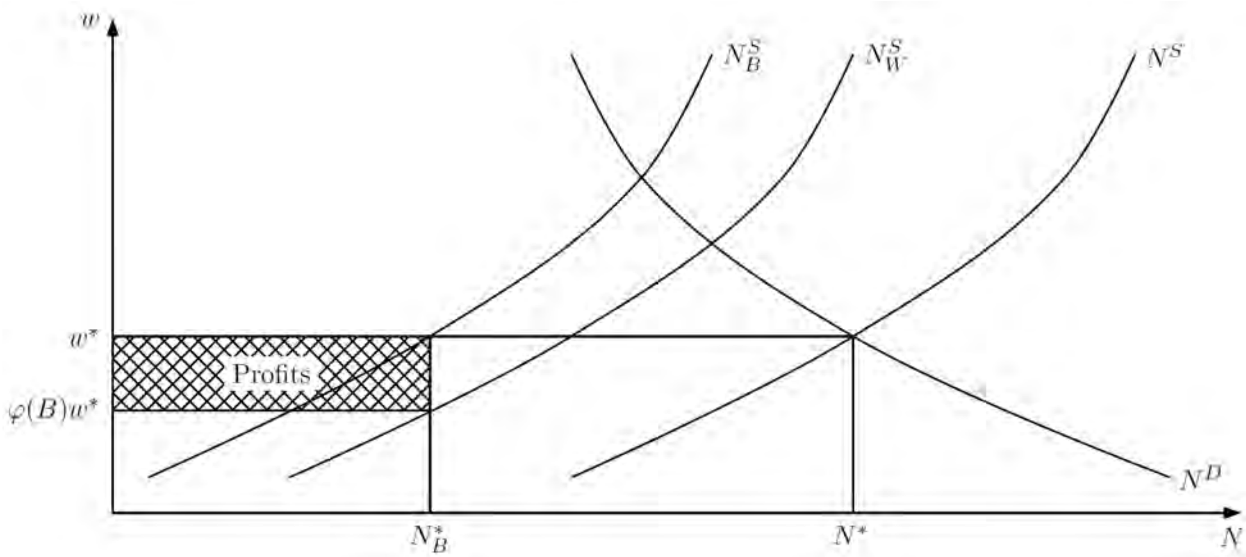
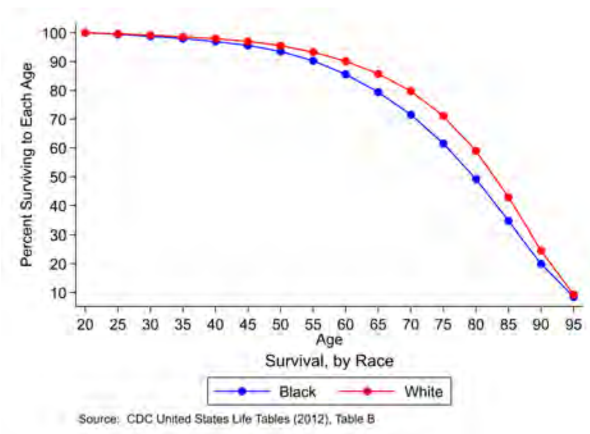


Figure 34: Profits in the Firm's Problem

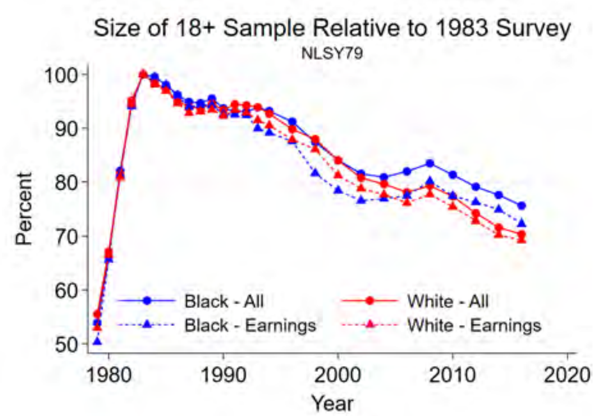
E Appendix: Mortality and Sample Attrition

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 35 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 35b, 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 35: Heterogeneous Survival Probabilities

F Appendix: Equalizing Inter-Vivos Transfers

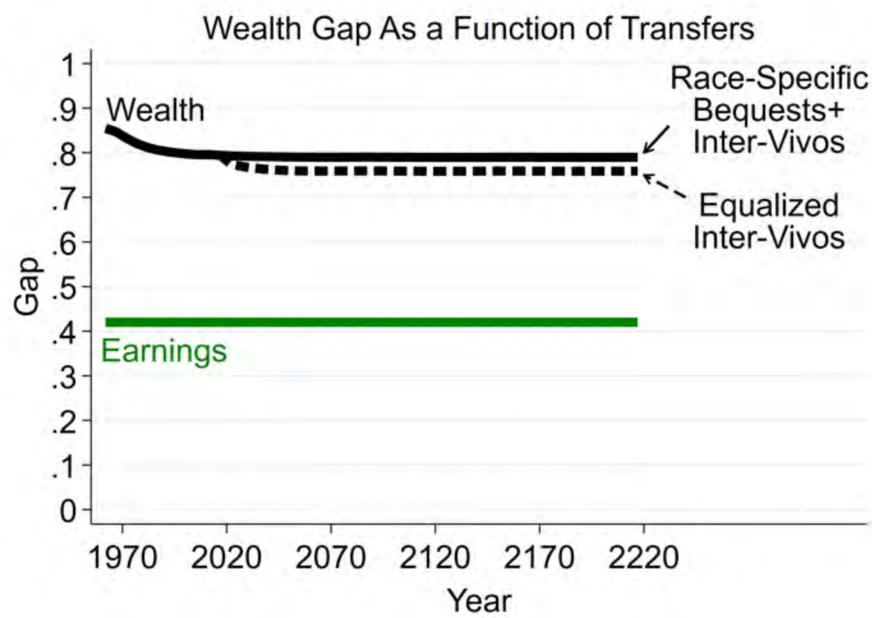


Figure 36: Equalized Inter-vivos Transfers

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 36 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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