

Race and Economic Well-Being in the United States

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June 2022

Abstract

We construct a measure of consumption-equivalent welfare for Black and White Americans. Our statistic incorporates life expectancy, consumption, leisure, and inequality. Based on this incomplete list of factors, welfare for Black Americans was 43% of that for White Americans in 1984 and rose to 59% by 2019. Going back further in time (albeit with more limited data), the gap was even larger, with Black welfare equal to just 29% of White welfare in 1940. On the one hand, there has been remarkable progress for Black Americans: the level of their consumption-equivalent welfare increased by a factor of 26 between 1940 and 2019, when aggregate consumption per person rose a more modest 5-fold. On the other hand, despite this remarkable progress, the welfare gap in 2019 remains disconcertingly large. The gap appears even larger when we make rough attempts to incorporate omitted factors such as morbidity, incarceration, and unemployment.

***Brouillette**: Stanford University; **Jones** and **Klenow**: Stanford University and NBER. We are grateful to Armelle Grondin, Arjun Ramani, and Chloe Shrager for superb research assistance, and Julian Reif for a very helpful discussion.

1. Introduction

An enormous literature has documented large and persistent differences in economic outcomes by race in the United States. These outcomes include income, earnings, wealth, education, life expectancy, morbidity, access to good neighborhoods and other public goods, unemployment, and incarceration.

Across these different measures, some differences are huge. Average wealth for Black Americans was just 16% of that of White Americans in 2019 (Derenoncourt, Kim, Kuhn and Schularick, 2022). Incarceration rates were 5-6 times higher for Black Americans than for White Americans in 2005 (Mauer and King, 2007). Other differences appear to be smaller. For example, average earnings by Black Americans were 77% of that for White Americans in 2019 (Chetty, Hendren, Jones and Porter, 2020). Average life expectancy was even closer, reaching 95% in recent years (National Center for Health Statistics, 2022).

It is hard to compare these measures because they are in different units. Put differently, if you could magically close one of these gaps, which one would you choose? To answer this question, and to think about policy priorities more generally, one needs to somehow put these outcomes into common units.

In addition, notice that it is not the average gap across different measures that we should care about. Instead, these gaps cumulate: the economic well-being of Black Americans is reduced by low consumption, low life expectancy, high morbidity, and high rates of incarceration. The overall loss of welfare is much larger than from any individual component.

The goal of this project is to make progress by putting some key outcomes into common units and showing how they cumulate. Following Jones and Klenow (2016), we combine several factors into a single utility-based welfare metric. We incorporate micro data on consumption, mortality, and leisure to estimate consumption-equivalent welfare by race over time.¹

¹Falcattoni and Nygaard (2022) look at welfare across U.S. states and incorporate education and housing, but do not concentrate on patterns by race.

Relative to the long list of economic outcomes mentioned above, we make progress but are unable to include everything, usually because it is not clear in the literature how to convert some outcomes into consumption-equivalent units. For example, conventional utility functions do not depend on wealth and education once consumption, leisure, and mortality have been included. This is not to say that there are no additional channels whereby wealth or education matter for welfare. Because they are omitted from standard utility analysis, however, we do not have a body of empirical work that tells us quantitatively how these forces should enter.

In some extensions we make rough attempts to incorporate morbidity, unemployment, and incarceration rates. These are included as extensions rather than in our main measure because of data limitations that we will discuss below. We stress, however, that one should view our main measure, and even these extensions, as arriving at an incomplete welfare accounting.

With these caveats in mind, we can summarize our findings as follows. Our main analysis begins in 1984 and runs through 2019. We find a large welfare difference at the end of our sample: consumption-equivalent welfare for Black Americans was only 59% of the level for White Americans in 2019. The gap was even larger historically: relative welfare was only 43% in 1984. The good news is that there was substantial progress over the past 35 years; the bad news is that the remaining gap is much larger than the gaps in consumption, earnings, or life expectancy alone would suggest. The largest contributor to the remaining gap is consumption, closely followed by life expectancy. Consumption and life expectancy contribute the bulk of convergence in recent decades. Of much lesser importance were changes in mean leisure and within-group inequality in consumption and leisure.

The large role played by life expectancy may come as a surprise given that life expectancy for Black Americans, at 75.9 years, is 95% of that for White Americans (at 79.6 years) in 2019. This illustrates the importance of using a consumption-equivalent metric: because each year of life is worth roughly 5 years of con-

sumption according to the standard calibration in the literature, a 4-year gap in life expectancy is actually worth around 20% of annual consumption.

With less detailed data we can go back several decades before 1984. We use decennial Census data and data from the American Community Surveys to impute consumption from 1940 through 2019. This cruder measure of welfare fairly tracks our more detailed main measure from 1990 onward. We estimate that Black consumption-equivalent welfare was only 29% of White welfare in 1940, but rose substantially in the 1950s and 1960s due to gains in life expectancy.

In our more speculative extensions, we find that differences in morbidity, incarceration, and unemployment could contribute importantly to Black-White welfare differences. A common measure of Quality-Adjusted Life Years (QALYs) from a National Institute of Health Survey, for example, implies Black vs. White welfare was 40% in 2018, compared to 60% without incorporating morbidity differences. Unlike life expectancy gaps, morbidity gaps do not exhibit a downward trend, at least over 1997 to 2018. Meanwhile, the share of the adult population incarcerated is more than a percentage point higher for Black than for White Americans in recent decades. If there is (say) zero flow utility in prison, then this would be equivalent to lowering consumption by almost 6% for Black Americans. Unemployment rates also differ sharply by race, being 1 to 15 percentage points higher for Black than White labor force participants, depending on the exact measure and year. Not counting time unemployed as leisure shaves about one percentage point off the fraction of time spent in leisure for the average Black person, which in turn lowers their consumption-equivalent welfare about one percentage point as well.

We also provide welfare calculations by Latinx ethnicity since 2006, which is when the breakdown of mortality by Latinx origin first becomes available. We also compute the consequences of Covid-19 for welfare in 2020. The pandemic reduced consumption-equivalent welfare by more than 20% for Black and Latinx Americans in 2020 versus 2019; the reduction for White Americans was 12%.

The rest of the paper is organized as follows. In Section 2 we lay out our consumption-equivalent welfare framework. Section 3 describes the datasets and data patterns for life expectancy, consumption, leisure, and inequality. Section 4 discusses how we calibrate key parameters in the utility function, while Section 5 presents our welfare results from 1984 to 2019. In Section 6 we report findings with Census data going back to 1940. Section 7 discusses some extensions, such as adjusting for morbidity, incarceration, and unemployment. Section 8 concludes.

Literature review. Our paper relates to a number of recent studies. Margo (2016) documents Black-White income differences going back to 1870, and finds slow convergence except for a quickening in the 1940s and 1960s. Bayer and Charles (2018) dissect Black-White earnings differences since 1940, and find convergence from 1940 to 1970 and then divergence afterward. Chetty, Hendren, Jones and Porter (2020) document Black-White earnings and employment gaps from 1989 to 2015, and report lower rates of upward mobility and higher rates of downward mobility for Black workers. Derenoncourt and Montialoux (2021) connect a sharp narrowing in the Black-White earnings gap in the late 1960s and the early 1970s to the extension of the minimum wage to predominantly-Black occupations. Aizer, Boone, Lleras-Muney and Vogel (2020) trace a significant narrowing of the earnings gap during World War II to war contracts. Karger (2021) looks at the lifetime earnings of Black versus White males, and finds substantial convergence early in the century but then little afterward.

Cook (2014) provides evidence that violence against Black Americans hindered their patenting activity. Hsieh, Hurst, Jones and Klenow (2019) trace Black-White occupational and earnings gaps to barriers in the labor market and to human capital accumulation.² They find that human capital barriers fell in the 1960s and 1970s, but progress has stalled since then. They emphasize that

²Monge-Naranjo and Vizcaino (2018) document the occupational distribution of Hispanic workers in the U.S., and how it has moved into skilled occupations but still lags behind the overall workforce.

reducing barriers not only reduces wage inequality but also raises overall economic growth by mitigating the misallocation of talent and underinvestment in human capital.

Derenoncourt, Kim, Kuhn and Schularick (2022) document the Black-White wealth gap from 1860 to 2020. They find the fastest convergence from 1860 to 1910, but that progress came to halt in the mid-20th century and gaps widened in recent decades. They see Black wealth trending toward only 20% of White wealth (both in per capita terms), driven in part by differences in rates of return.

Boerma and Karabarbounis (2021) model barriers and how they influence racial gaps in occupations, income, and wealth. They, too, see a major role for differences in risky investments and rates of return in contributing to the Black-White wealth gap. They argue that policies promoting Black entrepreneurship would be more effective at reducing the long-run wealth gap than would one-time reparations.

Meara, Richards and Cutler (2008) document large gaps in life expectancy by race and education. Case and Deaton (2015, n.d.) underscore the recent decline in life expectancy for White men, in particular those with less education. Although not their focus, they report that life expectancy has continued to climb for Black Americans, narrowing the gap with White Americans. Chetty, Stepner, Abraham, Lin, Scuderi, Turner, Bergeron and Cutler (2016) use income from tax records and deaths from the Social Security Administration to establish the positive correlation between income and life expectancy at age 40, suggesting that welfare gaps are reinforced by combining these differences.

Higgins (2022) finds that Black Americans spend a lower share of income on housing, and argues that this pattern reflects residential segregation. Black Americans often live in worse neighborhoods than White Americans, in part due to redlining restrictions and other historical forms of discrimination. Our consumption measure does incorporate differences in expenditures on housing but is surely incomplete in capturing access to public goods such as parks and good neighborhoods. Moreover, Fogli and Guerrieri (2019) and Higgins (2022)

emphasize how residential segregation can lead to persistent inequality through its effect on human capital investments and wealth, respectively.

In addition to the quality of housing and neighborhoods, consumption prices may differ across locations in ways correlated with race. Diamond and Moretti (2021) show that consumption wages are lower in more expensive cities, in particular for less educated workers. Butters, Sacks and Seo (2022) establish that Black Americans pay several percentage point higher prices per unit than White Americans in the AC Nielsen scanner data.

Neither our baseline measure nor our extensions capture neighborhood quality or price differences, primarily because of data limitations. Our measures of relative welfare therefore likely understate both the current gap as well as the historical progress that has been made. We hope that future research will incorporate these and other forces.

2. Expected Utility Framework

Our formulation of lifetime expected utility for an individual of race i is

$$U_i = \sum_{a=0}^{100} \beta^a S_{ia} \times \mathbb{E} [u(c_{ia}, \ell_{ia})].$$

Here a indexes age, $0 < \beta \leq 1$ is the discount factor, S_{ia} is the probability a person survives from birth to age a , c is consumption, and ℓ is leisure. While it is common and most natural to think of applying this equation over time for an individual, we instead apply it to summarize the consumption, leisure, and mortality rates in a cross-section of people at a point in time. This is analogous to how life expectancy is measured by demographers: it is a summary of the cross-section of mortality rates that prevail in a given year. In this sense, our utility function has the following interpretation: consider an individual alive in some year, and suppose that individual lived his or her entire life traveling through the cross-section of consumption, leisure, and mortality rates that pre-

vail in that year. Expected utility would be U_i . In our benchmark calculations that follow, we assume $\beta = 1$, so the only discounting across ages/people in the cross-section occurs because of mortality.

To implement our consumption-equivalent welfare calculation, let $U_i(\lambda)$ denote expected lifetime utility for an individual of race i if consumption is multiplied by a factor λ at each age:

$$U_i(\lambda) = \sum_{a=0}^{100} S_{ia} \times \mathbb{E}[u(\lambda c_{ia}, \ell_{ia})]$$

By what factor λ must we adjust the consumption of all White Americans to make them indifferent between living in the conditions prevailing for Black Americans and their own? That consumption adjustment satisfies

$$U_W(\lambda) = U_B(1). \quad (1)$$

Denoting the sampling weight of an individual j of race i and age a as ω_{ia}^j , and the number of individuals of the same race and age as N_{ia} , we replace the expectation operator with the estimate provided by the sample mean:

$$U_i(\lambda) = \sum_{a=0}^{100} S_{ia} \sum_{j=1}^{N_{ia}} \omega_{ia}^j u(\lambda c_{ia}^j, \ell_{ia}^j).$$

We assume that flow utility takes the following form:

$$u(c, \ell) = \bar{u} + \log(c) + v(\ell)$$

where flow utility from leisure ℓ features a constant Frisch elasticity:

$$v(\ell) = -\frac{\theta\epsilon}{1+\epsilon} \times (1-\ell)^{\frac{1+\epsilon}{\epsilon}}.$$

Here $\epsilon > 0$ is the Frisch (compensated) elasticity of labor supply, and $\theta > 0$ is a weighting parameter. Finally, denote average flow utility for an individual of

race i and age a as:

$$u_{ia} \equiv \sum_{j=1}^{N_{ia}} \omega_{ia}^j u(c_{ia}^j, \ell_{ia}^j).$$

Solving for the scaling constant in equation (1) under these assumptions, we obtain:

$$\log(\lambda) = \frac{1}{\sum_{a=0}^{100} S_{Wa}} \times \sum_{a=0}^{100} [u_{Ba}(S_{Ba} - S_{Wa}) + S_{Wa}(u_{Ba} - u_{Wa})]. \quad (2)$$

This equation tells us that White Americans would need to have lower consumption to have the same lifetime utility as Black Americans to the extent that the latter have lower life expectancy and flow utility.

To ease notation, define survival rates normalized by White life expectancy:

$$s_{ia} \equiv \frac{S_{ia}}{\sum_{a=0}^{100} S_{Wa}} \quad \text{and} \quad \Delta s_{Ba} \equiv \frac{S_{Ba} - S_{Wa}}{\sum_{a=0}^{100} S_{Wa}}.$$

Further denote average lifetime utility from consumption and leisure as:

$$\mathbb{E} \log(c_i) \equiv \sum_{a=0}^{100} s_{Wa} \sum_{j=1}^{N_{ia}} \omega_{ia}^j \log(c_{ia}^j) \quad \text{and} \quad \mathbb{E} v(\ell_i) \equiv \sum_{a=0}^{100} s_{Wa} \sum_{j=1}^{N_{ia}} \omega_{ia}^j v(\ell_{ia}^j).$$

Finally, denote average lifetime consumption and leisure as:

$$\bar{c}_i \equiv \sum_{a=0}^{100} s_{Wa} \sum_{j=1}^{N_{ia}} \omega_{ia}^j c_{ia}^j \quad \text{and} \quad \bar{\ell}_i \equiv \sum_{a=0}^{100} s_{Wa} \sum_{j=1}^{N_{ia}} \omega_{ia}^j \ell_{ia}^j.$$

Substituting these definitions into equation (2), we obtain the following de-

composition of consumption-equivalent welfare:

$$\begin{aligned}
\log(\lambda) &= \sum_{a=0}^{100} \Delta S_{Ba} \times u_{Ba} && \text{Life expectancy} \\
&+ \log(\bar{c}_B) - \log(\bar{c}_W) && \text{Consumption} \\
&+ v(\bar{\ell}_B) - v(\bar{\ell}_W) && \text{Leisure} \tag{3} \\
&+ \mathbb{E} \log(c_B) - \log(\bar{c}_B) - [\mathbb{E} \log(c_W) - \log(\bar{c}_W)] && \text{Consumption inequality} \\
&+ \mathbb{E} v(\ell_B) - v(\bar{\ell}_B) - [\mathbb{E} v(\ell_W) - v(\bar{\ell}_W)] && \text{Leisure inequality}
\end{aligned}$$

Notice here that λ is an *equivalent* variation in that it adjusts the consumption of White Americans so that their welfare equals that of Black Americans. A *compensating* variation can be analogously defined, instead adjusting the consumption of Black Americans to equalize welfare across race. In the quantification of this welfare calculation in Section 5, we report the geometric average of the equivalent and compensating variations.

The expression in equation (3) simplifies into an even more intuitive form under a few conditions. Suppose (i) consumption is constant across ages, (ii) consumption is lognormally distributed with variance σ^2 , and (iii) leisure is the same for all individuals within each race. With these assumptions, the above decomposition becomes:

$$\begin{aligned}
\log(\lambda^{simple}) &= \frac{e_B - e_W}{e_W} \times [\bar{u} + \log(\bar{c}_B) + v(\bar{\ell}_B) - \sigma_B^2/2] && \text{Life expectancy} \\
&+ \log(\bar{c}_B) - \log(\bar{c}_W) && \text{Consumption} \\
&+ v(\bar{\ell}_B) - v(\bar{\ell}_W) && \text{Leisure} \\
&+ (\sigma_B^2 - \sigma_W^2)/2 && \text{Consumption inequality}
\end{aligned}$$

The percentage difference in life expectancy ($e_i \equiv \sum_{a=0}^{100} S_{ia}$) between the two groups matters for consumption-equivalent welfare, with the difference weighted by the average flow utility of one of the groups. With log utility and lognormal shocks, the variance of consumption in the cross-section reduces welfare by the

usual factor of 1/2. Finally, a 1% difference in life expectancy is approximately equal to a \bar{u} percent difference in consumption in a year, provided we normalize $\bar{c} = 1$ and the $v(\ell)$ and σ^2 terms are small.

3. Datasets

Our consumption-equivalent welfare calculation requires micro data on survival rates, consumption, and leisure. We draw on three sources: the U.S. Centers for Disease Control and Prevention (CDC) Life Tables, the U.S. Department of Labor’s Consumer Expenditure Survey (CEX) and the U.S. Census Bureau’s Current Population Survey (CPS).

Racial definitions

In all of the data sources we use, we follow the 1977 Office of Management and Budget (OMB) standards for race and ethnicity. Those standards define four racial groups (White, Black, Native American, and Asian or Pacific Islander) and treat Latinx origin as ethnicity, distinct from race.

In 1997 the OMB revised its standards to allow respondents to report two or more racial groups. From 1997 on, therefore, we treat multiple-race observations as fractional and divide each observation’s sampling weight by the number of groups reported for that observation. Because Latinx origin is not consistently reported over time in some of our data sources, and because the CDC only started publishing Life Tables by Latinx origin in 2006, our definition of Black and White Americans includes Americans of Latinx origin. For the period in which non-Latinx Black and non-Latinx White Americans are consistently classified, we will report additional results for those sub-groups.

Survival rates

Our data on survival rates comes from the CDC’s Life Tables, which are available for the Black and White population since 1890.³ The 1950 and 1960 (but not 1940) Life Tables cover only White and “non-White” Americans. The 1970 Life Tables include data for both Black and non-White Americans, so we adjust the survival rates for non-White Americans in 1950 and 1960 to make them more comparable with data for Black Americans in 1940 and from 1970 onward.

Starting in 2018, the CDC stopped publishing Life Tables for Black and White Americans irrespective of Latinx origin. Therefore, from 2018 onward we calculate survival rates using individual death records from the mortality data files of the CDC’s National Vital Statistics System (NVSS).⁴ Each record contains information on the deceased’s gender, race, and age. We then use the CDC’s bridged race population estimates to determine the population at risk by gender, race and age from 2018 onward.⁵

Figure 1 plots life expectancy at birth for Black and White Americans from 1984 to 2019. Black Americans had about 6 fewer years of life expectancy in 1984 and around 3.7 fewer years in 2019. Lifespans diverged from 1984 to the the mid-1990s before converging sharply through the early 2010s. Life expectancy has leveled-off or fallen for both White and Black Americans in the last decade. Case and Deaton (2015, n.d.) attribute this stagnation to “deaths of despair” (suicide, opioid overdoses, and alcohol-related chronic illnesses).

Consumption

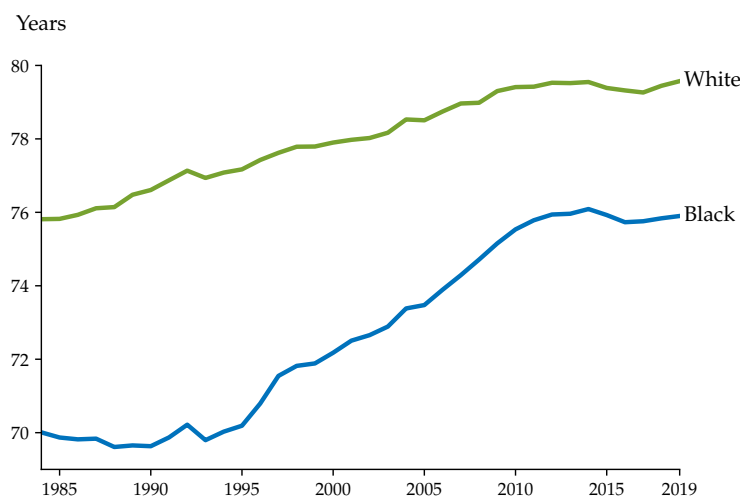
Our consumption data comes from the CEX interview samples. For each year from 1984 to 2019, a rotating panel of about 20,000 households are interviewed about their expenditures on hundreds of items for up to four quarters. The survey ask about total household expenditures on each item, but the survey

³https://www.cdc.gov/nchs/products/life_tables.htm

⁴https://www.cdc.gov/nchs/data_access/vitalstatsonline.htm#Mortality_Multiple

⁵<https://wonder.cdc.gov/Bridged-Race-v2020.HTML>

Figure 1: Life expectancy at birth by race



Note: Author calculations using data from the CDC.

contains the race, age, gender, and educational attainment of each household member.

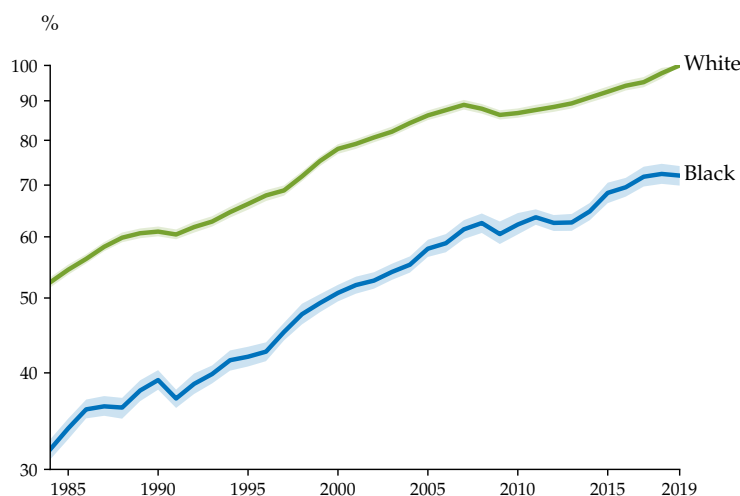
Our measure of household expenditures includes housing (rent paid by renters and self-reported rental equivalence for homeowners). To arrive at a measure of individual consumption, we divide household spending evenly among household members.⁶

As is well-known, consumption expenditures from the CEX do not aggregate to personal consumption expenditures in the National Income and Product Accounts (NIPA); see Aguiar and Bils (2015) for example. We therefore re-scale total individual consumption in the CEX such that it aggregates to NIPA personal consumption expenditures per capita in each year from 1984 to 2019.

Figure 2 plots consumption per capita for Black and White Americans when

⁶Three possibly important sources of consumption that are absent in the CEX surveys are food stamps, medicaid and medicare expenditures. To approximate how accounting for those would impact our baseline results, for each program, we use data on total U.S. National Income and Product Account expenditures in 2019 which we allocate across racial groups based on reported participation in the 2019 American Community Survey. Doing so raises Black welfare from 59% to 63% of White welfare in 2019.

Figure 2: Consumption per capita by race



Note: Author calculations using data from the U.S. Consumer Expenditure Surveys (CEX). Consumption for White Americans is normalized to 100 in 2019 and the vertical axis is plotted on a logarithmic scale. The shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples.

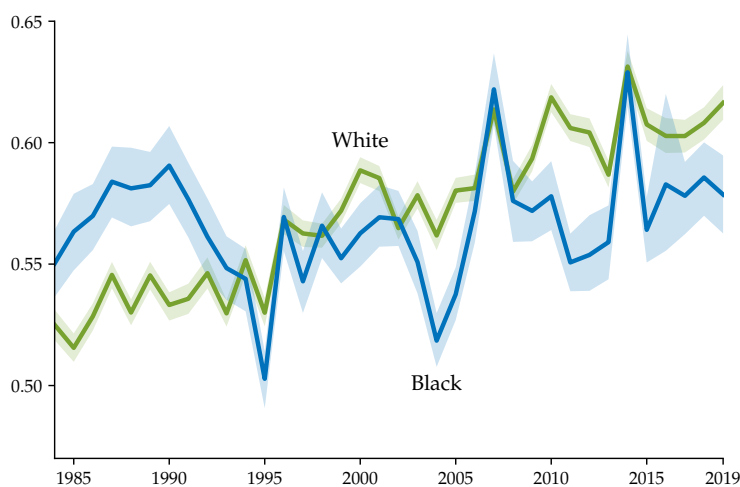
White consumption is normalized to 100 in 2019. Consumption per person was about 39% lower for Black Americans in 1984, but only 29% lower in 2019. Notice that here (and elsewhere possible) we provide bootstrapped 95% confidence intervals. The bands are typically narrow and sometimes hard to see as a result.⁷

Figure 3 displays the standard deviation of log nondurable consumption across people within a group by year. Consumption dispersion is choppy across years due to modest sample sizes, especially for Black Americans. The standard deviations for both groups hover around 0.6. If consumption is lognormally distributed, then with log utility such inequality lowers consumption-equivalent welfare by 18% for each group.⁸

⁷This is in line with the results of Fernández-Villaverde and Krueger (2007) who also perform bootstrap simulations in the CEX to assess the precision of consumption life cycle profile estimates. They find that those estimates are precise with tight confidence intervals.

⁸In the case of additively separable utility from consumption and lognormally distributed consumption, the loss in consumption-equivalent welfare from behind-the-veil inequality is the coefficient of relative risk aversion times the variance of log consumption divided by two.

Figure 3: Standard deviation of log consumption by race



Author calculations using data from the U.S. Consumer Expenditure Surveys (CEX). For our inequality measures, we use nondurable consumption in order to avoid the overstatement that would otherwise arise from the lumpiness of durable spending. The shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the CEX.

Leisure

Our leisure estimates are derived from hours worked in the CPS for each year from 1984 to 2019. We define leisure as the fraction of total waking hours that are not spent on market work over the year:

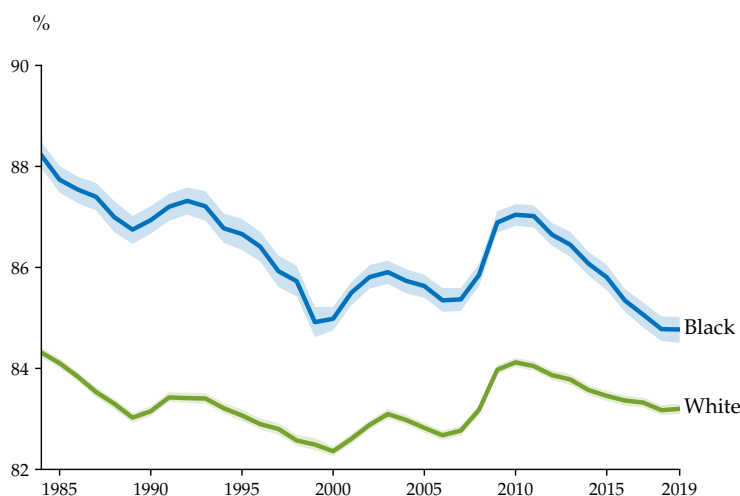
$$\ell \equiv \frac{5,840 - \text{hours worked in the year}}{5,840}.$$

We obtain 5,840 total hours available as the product of 16 hours per day and 365 days.⁹ In a rough attempt to account for the division of non-market work, we divide hours worked per year equally among individuals between 25 and 64 years old within each household.¹⁰ For household members outside of this age range, we make no adjustment. The resulting split in leisure time between men

⁹We use 366 days for leap years and assume 8 hours a day of sleep.

¹⁰Aguiar and Hurst (2007) and Erosa, Fuster, Kambourov and Rogerson (2017), among many others, document that women typically spend more time on home production than men.

Figure 4: Leisure by race



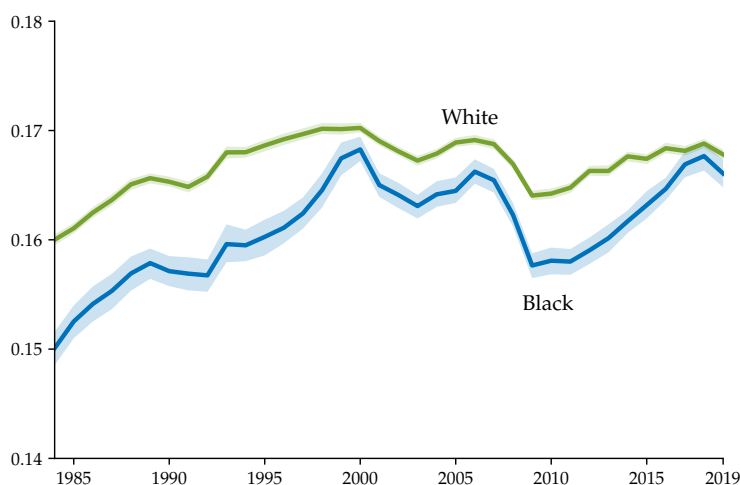
Author calculations using data from the U.S. Current Population Surveys (CPS). The shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the CPS.

and women is similar to that found in Aguiar and Hurst (2007), who carefully delineate leisure from home production work in time-use surveys.

Figure 4 shows that leisure is about four percentage points higher for Black Americans than for White Americans in 1984, but only around two percentage points higher in 2019. There are sizable fluctuations in between, with leisure rising notably for both groups in the 2008–2009 Great Recession and its aftermath. In our extensions in Section 7, we consider the possibility that unemployment yields less utility than other non-work time. This may matter for our comparisons given that unemployment rates are uniformly higher in the CPS for Black Americans than for White Americans over our sample. Incarceration rates are also higher for Black men than for other groups, so we will likewise explore the effect of treating incarceration as providing much lower flow utility.

Figure 5 compares the standard deviation of leisure across individuals within groups. Just as for consumption, unequal leisure lowers average utility from due to diminishing marginal utility from leisure. Leisure inequality is similar across

Figure 5: Standard deviation of leisure by race



Note: Author calculations using data from the U.S. Current Population Surveys (CPS). The shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the CPS.

racial groups, especially at the end of the sample.

4. Calibration

The three key parameters to be calibrated are: the Frisch elasticity ϵ , the utility weight on leisure θ , and the intercept in flow utility \bar{u} . We provide our baseline parameter values here, but explore robustness to alternative parameter values in Section 5.3 below.

We consider a Frisch elasticity of labor supply of 1.0, which implies that the disutility from working rises with the square of the number of hours worked. This is a compromise between Hall (2009), who advocates for a Frisch elasticity of 1.7, and Chetty, Guren, Manoli and Weber (2013), who recommend a value closer to 0.5.

We use the first-order condition for the labor-leisure choice to calibrate the weight on leisure in the utility function. The corresponding static first order

condition is $u_\ell/u_c = w(1 - \tau)$, where w is the real wage and τ is the marginal tax rate on labor income. With logarithmic utility from consumption and a constant Frisch elasticity, this implies $\theta = w(1 - \tau)(1 - \ell)^{-1/\epsilon}/c$. The marginal tax rate τ is borrowed from Barro and Redlick (2011), who report a value of 0.353 for the United States in 2006. Consumption per person in 2006 is obtained from NIPA table 2.4.5 where we subtract insurance from total personal consumption expenditures to obtain a value of \$33,716 in 2012 dollars. Average earnings and leisure are calculated directly from the CPS, where we restrict on prime-age workers (25-55 years old) and obtain values of \$37,716 in 2012 dollars and 0.71, respectively. This delivers a value of $\theta = 8.8$.

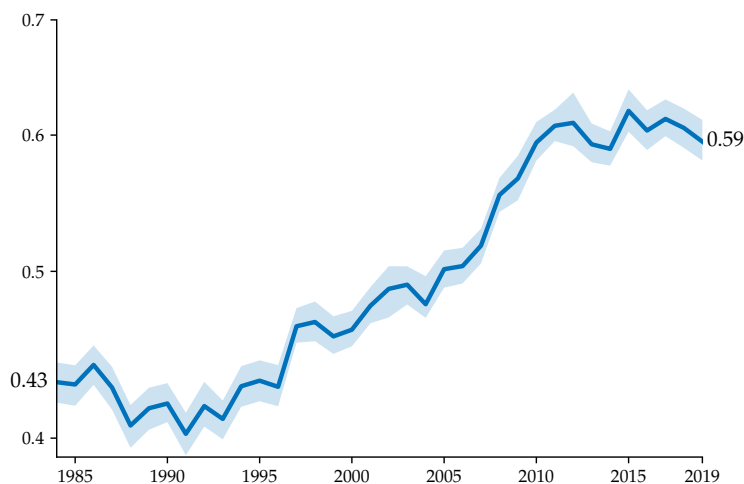
The intercept in flow utility, \bar{u} , is critical for valuing differences in mortality. The U.S. Environmental Protection Agency (2020) recommends \$7.4 million for the value of remaining life in 2006 dollars for those age 25 to 55. Hall, Jones and Klenow (2020) use this figure when valuing lives at risk from COVID-19. Matching this number leads to $\bar{u} = 6.02$ when consumption per capita is normalized to 1.0 in 2019. This means that \bar{u} has a natural interpretation for our utility function: one additional year of life is valued at $\bar{u} = 6.02$ years of 2019 consumption.

5. Welfare

We combine our ingredients into a single measure of consumption-equivalent welfare as described in Section 2. Figure 6 plots Black versus White welfare from 1984 through 2019. The initial level in 1984 is surprisingly low at 43%. It rises to around 60% from the mid-1990s to the early 2010s. The gap between Black and White Americans remains disappointingly wide.

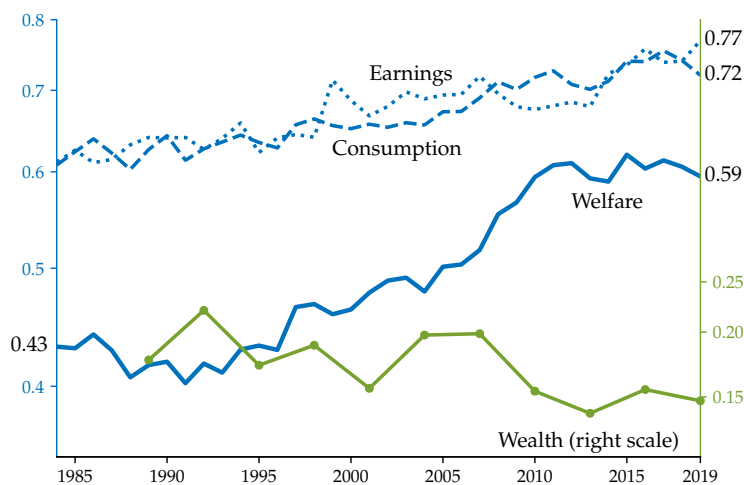
Figure 7 also plots consumption in the CEX, earnings in the CPS, and wealth in the Federal Reserve's Survey of Consumer Finances (SCF) for Black relative to White Americans for comparison (Aladangady and Forde, 2021). Earnings includes wages, salaries, business income, and farm income before taxes and transfers. Black relative earnings was notably higher than Black relative welfare

Figure 6: Consumption-Equivalent Welfare, Black vs. White Americans



Note: The figure shows the consumption-equivalent welfare for Black relative to White Americans from 1984 to 2019, computed according to equation (3). The shaded area represents the 95% confidence interval from 1000 bootstrap samples of the CEX and CPS.

Figure 7: Consumption-Equivalent Welfare, Black vs. White Americans



Note: The figure shows the consumption-equivalent welfare for Black relative to White Americans from 1984 to 2019, computed according to equation (3). For comparison, we also show the corresponding relative consumption, earnings and wealth level. The earnings series is from the CPS and includes wage, salary, business and farm income, before taxes and transfers. The wealth series is from the SCF and corresponds to total net worth.

until the 2010s. In contrast, Black relative wealth is significantly lower throughout the period, actually declining in recent years to just 15 percent. This illustrates the contribution of life expectancy (versus earnings and wealth) to gaps in welfare.

Table 1 and Figure 8 decompose the drivers of the overall welfare differences using the expression in equation (3). The two biggest contributors are life expectancy and consumption. Leisure, inequality in consumption, and inequality in leisure contribute surprisingly little to both levels and trends.

Table 1: Welfare decomposition

	λ	$\log(\lambda)$	— <i>Decomposition</i> —				
			LE	c	$\sigma(c)$	ℓ	$\sigma(\ell)$
2019	0.59	-0.52	-0.27	-0.29	0.02	0.02	0.00
2000	0.46	-0.77	-0.42	-0.39	0.01	0.02	0.00
1984	0.43	-0.84	-0.40	-0.46	-0.02	0.03	0.01

Note: The last five columns report the additive decomposition in equation (3), where σ denotes the inequality terms.

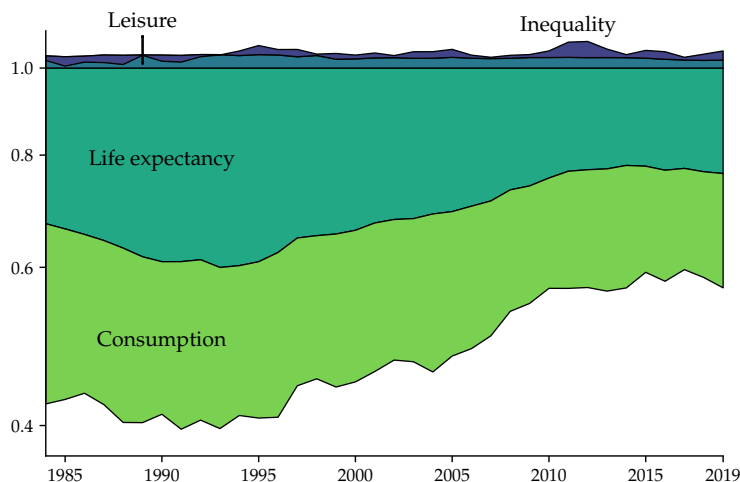
We next examine welfare growth rates in Table 2 by applying equation (3) over time. From 1984 to 2019, Black consumption-equivalent welfare grew 3.26% per year, faster than their earnings growth of 2.01% per year. For White Americans, welfare also rose more quickly than earnings (2.29% vs. 1.35% per year). Cumulating this growth over time, Figure 9 shows that consumption-equivalent welfare grew by a factor of 3.1 for Black Americans from 1984 to 2019, and by a factor of 2.2 for White Americans.

Table 2 also decomposes the contributions to growth rates. From 1984 to 2019 the biggest contributor was consumption growth at 2.25% for Black Americans and 1.78% for White Americans.¹¹ Life expectancy was the next most important at 1.20% per year for Black Americans and 0.77% for White Americans.¹²

¹¹It is not surprising that consumption growth does not track earnings growth perfectly. See for example Krueger and Perri (2006) or Heathcote, Storesletten and Violante (2013).

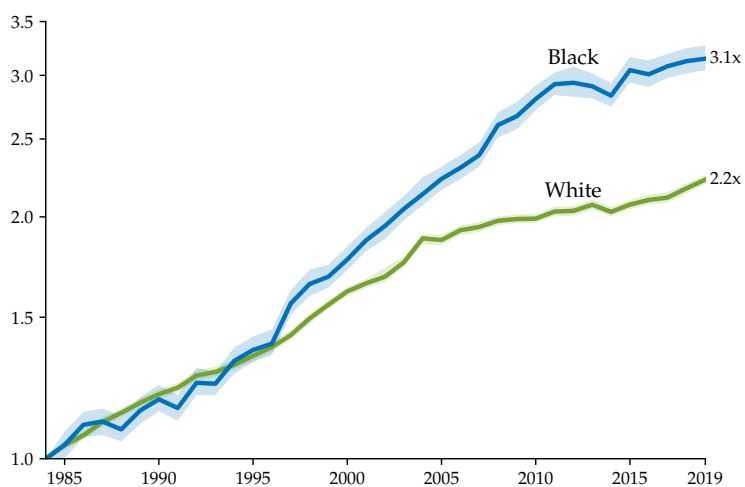
¹²Becker, Philipson and Soares (2005) similarly found that rising life expectancy was a major contributor to “full income” growth in the U.S. and other other countries in recent decades.

Figure 8: Relative Welfare Decomposition



Note: The figure shows the decomposition of consumption-equivalent welfare for Black relative to White Americans from 1984 to 2019, computed according to equation (3). Author calculations using data from the CDC's NVSS and the Department of Labor's CPS and CEX Surveys.

Figure 9: Cumulative welfare growth by race



Note: Author calculations using a combination of data from the CDC's NVSS and the Department of Labor's CPS and CEX Surveys. The shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the CEX and CPS.

Table 2: Welfare growth between 1984 and 2019 (%)

	Welfare	Earnings	— <i>Decomposition</i> —				
			LE	c	$\sigma(c)$	ℓ	$\sigma(\ell)$
Black	3.26	2.01	1.20	2.25	-0.05	-0.09	-0.06
White	2.29	1.35	0.77	1.78	-0.18	-0.06	-0.04
Gap	0.97	0.67	0.43	0.46	0.13	-0.02	-0.02

Note: The last five columns report the additive decomposition in equation (3), where σ denotes the inequality terms.

Though dwarfed by other factors, rising inequality of consumption and leisure together subtracted between 20 and 28 basis points a year from growth for both groups. Falling leisure lowered growth 9 basis points a year for Black Americans and 6 basis points a year for White Americans.

5.1 Welfare by Latinx Origin

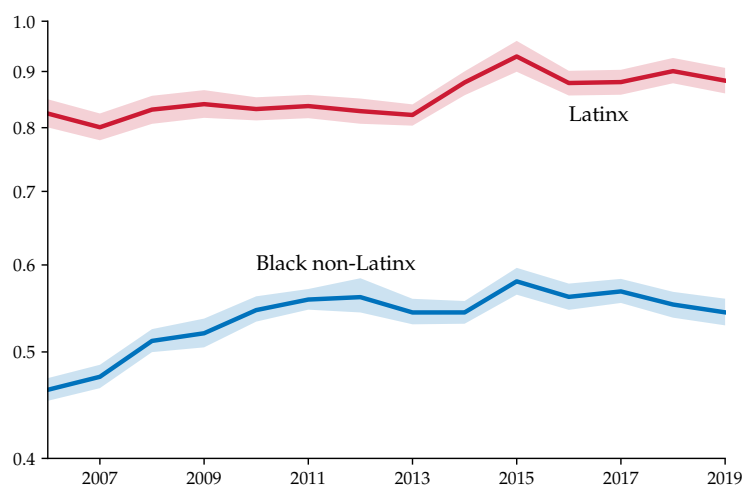
As mentioned in Section 3, the CDC only started publishing life tables by Latinx origin starting in 2006, which is why we report our results by race *and* Latinx origin from 2006 to 2019. Here, we break our results into Latinx, Black non-Latinx, and White non-Latinx. In this and the next subsection, we will simply refer to these latter two groups as Black and White.

Figure 10 plots our consumption-equivalent welfare statistic over that period for Black and Latinx Americans, both relative to White Americans. In 2019, Latinx welfare was 88% of White welfare. In contrast, the welfare of Black Americans was 54% of White welfare in 2019.

Each ingredient of our welfare calculation is discussed in the Appendix, but the main reason why the relative welfare of Latinx Americans is so much higher than that of Black Americans is their longer life expectancy. In 2019, life expectancy stood at 82.4 years old for Latinx Americans, as opposed to 79.3 and 75.5 years old for White and Black Americans, respectively.

This is often referred to as the “Latino paradox” by which Latinx Americans tend to have better health outcomes than non-Latinx Americans despite lower

Figure 10: Consumption-Equivalent Welfare relative to White non-Latinx



Note: The figure shows the consumption-equivalent welfare for Black non-Latinx and Latinx relative to White non-Latinx from 2006 to 2019, computed according to equation (3). The shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the CEX and CPS.

incomes. Consumption and leisure are comparatively similar for Latinx and Black Americans. Latinx and Black consumption per person was 39% and 34% lower than White consumption in 2019. Latinx and Black Americans spent 85% and 83% of their time endowment on leisure. See Appendix A.5 for more detail.

5.2 COVID-19 Pandemic

Some of the convergence in life expectancy we documented from 1984 to 2019 was reversed, at least temporarily, by the COVID-19 pandemic. In 2020 alone, life expectancy for Latinx, Black, and White Americans fell by 3.6, 3.0, and 1.6 years, respectively.

Table 3 reports the change in our measure of consumption-equivalent welfare between 2019 and 2020 for these groups. Since a 1% drop in life expectancy is tantamount to a roughly 6% drop in consumption, the welfare of Latinx, Black, and White Americans fell by 20%, 18%, and 12%, respectively. Not surprisingly,

the largest driver of this reversal is the sharp drop in life expectancy experienced by all groups. In addition, while Black and Latinx consumption stalled in 2020, it fell by about 5% for White Americans, reflecting the heterogeneous response of consumption during the pandemic, as has been documented by Meyer, Murphy and Sullivan (2022).

Table 3: Welfare loss in 2020 relative to 2019 (%)

	λ	$\log(\lambda)$	LE	— <i>Decomposition</i> —			
				c	$\sigma(c)$	ℓ	$\sigma(\ell)$
Black	0.83	-0.19	-0.23	0.01	0.01	0.01	0.01
White	0.87	-0.13	-0.12	-0.05	0.02	0.01	0.01
Black non-Latinx	0.82	-0.20	-0.24	0.01	0.01	0.01	0.01
White non-Latinx	0.88	-0.12	-0.10	-0.06	0.02	0.01	0.01
Latinx	0.80	-0.22	-0.25	-0.00	0.00	0.02	0.01

Note: The last five columns report the additive decomposition in equation (3), where σ denotes the inequality terms. From 2019 to 2020, Black life expectancy fell by 3.04 years while White life expectancy fell by 1.61 years.

An active literature has analyzed the differential effect of the pandemic by age and gender, and optimal mitigation policies in light of this heterogeneity. See Alon, Doepke, Olmstead-Rumsey and Tertilt (2020b) for a focus on gender, and Glover, Heathcote, Krueger and Ríos-Rull (2020) and Alon, Dzansi, Kim, Lagakos, Telli and VanVuren (2020a) for optimal policy with respect to age. There has been less work on the differential effects of the pandemic by race.

5.3 Robustness

In this section, we assess the robustness of our benchmark results to alternative assumptions and parameter values. Table 4 shows that the welfare gap between Black and White Americans is fairly robust in both the beginning and ending years of our sample to a variety of permutations.

As described in Section 2, our benchmark welfare calculation is a geometric average of *equivalent* and *compensating* variations. The second and third rows

of Table 4 make clear that averaging between these two metrics (as our baseline calculation in the first row does) has a modest effect as the two variations differ by around four percentage points.

The fourth and fifth row respectively show robustness to a discount factor of $\beta = 0.99$ as well as consumption growth of 2% per year, and dividing household consumption by the square root of the number of household members rather than by the number of household members. Both of these changes move our bottom line only about a single percentage point.

Table 4: Robustness results

	Consumption-equivalent welfare (%)	
	1984	2019
Benchmark case	43.1	59.5
Equivalent variation	44.6	60.2
Compensating variation	41.7	58.8
$\beta = 0.99$ and $g = 0.02$	41.9	59.1
Household size (square root)	45.4	57.9
NIPA PCE categories	41.4	57.7
Ages 1 and above	44.8	61.2
Ages 5 and above	44.3	60.7
$\gamma = 2$	53.2	62.7
Frisch elasticity = 0.5	43.3	59.4
Frisch elasticity = 2	43.3	59.7
Value of life = \$5m	50.2	65.1
Value of life = \$10m	36.5	53.9

Note: See the main text for a discussion of the various robustness cases.

As mentioned previously, total CEX consumption is known to fall below the consumption aggregate in NIPA. If there is differential misreporting by categories in the CEX relative to the national accounts, and the composition of the consumption basket differs by race, we might be mismeasuring the racial gap in consumption. To account for this, the sixth row of Table 4 reports our results using a consumption measure in which expenditures are re-scaled category by category using a correspondence between the CEX and NIPA PCE developed by

the BLS.¹³ Using this NIPA adjustment widens the welfare gap, relative to our benchmark results, by only 1-2 percentage points.¹⁴

To make sure that infant mortality is not driving our results, the seventh and eighth rows report our welfare calculation when utility is evaluated starting at age one or five, respectively. In contrast, the next three rows show robustness to alternative parameter values for the utility function. As mentioned above, leisure plays a relatively muted role in our calculation, which is why it is not surprising that a Frisch elasticity of labor supply of 0.5 or 2 instead of unity leaves our results almost unchanged.¹⁵ However, imposing more curvature in the utility function slightly raises the welfare of Black relative to White Americans. More precisely, we consider the following flow utility function:

$$u(c, \ell) = \bar{u} + \frac{c^{1-\gamma}}{1-\gamma} \times \left[1 + (\gamma - 1)\theta \times \frac{\epsilon(1-\ell)^{\frac{1+\epsilon}{\epsilon}}}{1+\epsilon} \right]^\gamma - \frac{1}{1-\gamma}$$

which nests our baseline specification as $\gamma \rightarrow 1$.

The last two rows of Table 4 show that the most consequential assumption in our calculation is the value assumed for the intercept \bar{u} in the utility function. We vary this intercept such that the remaining value of life for a 40-year-old in 2006 dollars is \$5 million or \$10 million instead of our benchmark value of \$7.5 million. As discussed earlier, since life expectancy is such a critical ingredient in our calculation, changing the remaining value of life to \$5 million or \$10 million respectively narrows or widens the welfare gap by about 6 to 7 percentage points both in 1984 and 2019. However, life expectancy is also an important driver of the *convergence* in living standards between Black and White Americans, which means that a larger (lower) value of life implies a faster (slower) catch-up in welfare by a little over 1 percentage point over the entire sample.

¹³<https://www.bls.gov/cex/cepceconcordance.htm>

¹⁴We do not use this adjustment as our baseline because this correspondence only covers a subset of consumption categories in the CEX and is based on a single benchmark year (2007).

¹⁵When changing this elasticity, we also re-calibrate the weight of leisure in the utility function to ensure that the optimality condition for the labor-leisure choice is satisfied.

6. Census Data back to 1940

We can extend our welfare calculations further back in time using the population Censuses for 1940, 1950, ..., 2000 and the American Community Survey annually for 2005 to 2019. An advantage of Census data is the large sample sizes relative to the CEX. For example, even in 1940 using our 1% sample, the Census data contains 1.3 million individuals versus only 31,000 in the 1984 CEX. The main limitation of the Census is that it has no data on consumption. We therefore impute consumption from Census income data.

We use the CEX to create a procedure for imputing consumption from income. More precisely, we regress CEX consumption on CEX earnings at the individual level, controlling for race, age, gender, education and family size. All variables are in percentage deviations from their annual average across individuals. We then infer consumption from earnings in the Census using the same variables and the CEX regression coefficients. We next scale up the aggregate imputed consumption expenditures to match real personal consumption expenditures per capita from NIPA. This scaling deals with the downward trend in CEX aggregate consumption relative to NIPA aggregate consumption. More details are available in Appendix A.¹⁶

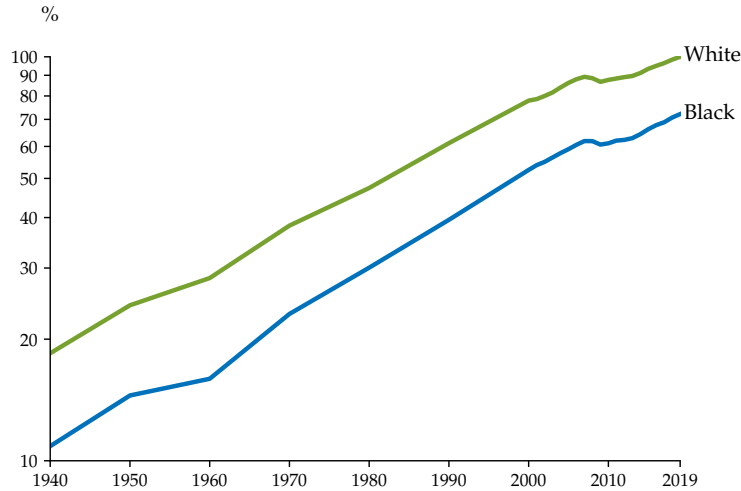
Figure 11 shows average consumption for Black and White Americans based on this procedure. While the lines look remarkably parallel, there is some catch-up: the average gap in imputed consumption between Black and White Americans is 41% in 1940, 37% in 1980, and 29% in 2019.

Figure 12 plots the levels of life expectancy at birth that we calculate from the survival rates in the CDC Life Tables in each decade back to 1940.¹⁷ There is sub-

¹⁶We do not attempt to impute consumption inequality by race because this is more difficult than imputing mean consumption by race, and within-group consumption inequality differences were small in the CEX from 1984–2019.

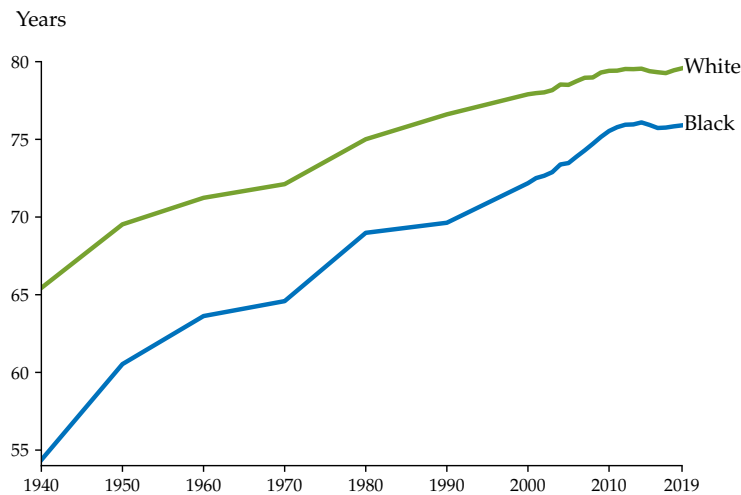
¹⁷As mentioned, the 1950 and 1960 Life Tables report data for “non-White” rather than Black Americans. In 1970, however, data for both non-White and Black Americans are observed and we use that overlap to adjust the 1950 and 1960 survival rates to make them more comparable. More precisely, we multiply the non-White survival rates in 1950 and 1960 by the ratio of Black to non-White survival rates in 1970 at each age.

Figure 11: Imputed consumption per capita by race since 1940



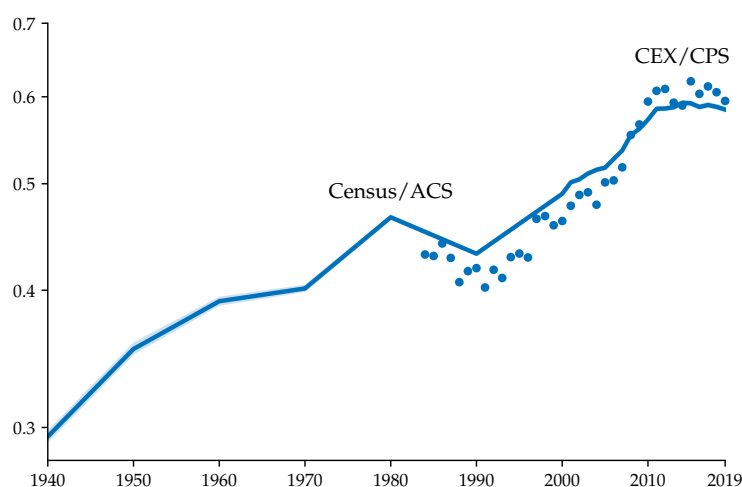
Note: Author calculations using data from the CEX, and U.S. censuses and ACS. Consumption for White Americans is normalized to 100 in 2019. While the lines look remarkably parallel, there is some catch-up: the average gap in imputed consumption between Black and White Americans is 41% in 1940, 37% in 1980, and 29% in 2019. The slightly visible shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the Census/ACS and CEX.

Figure 12: Life expectancy at birth by race since 1940



Note: Author calculations using CDC data. The life expectancy shortfall between Black and White Americans is 11 years (17%) in 1940, 6 years (8%) in 1980, and just 3.7 years (4.6%) in 2019.

Figure 13: Relative Welfare for Black Americans, 1940–2019 (White = 1)



Note: Author calculations using data from the CDC’s NVSS, and the U.S. censuses and ACS. Circles display the previous CEX/CPS results from 1984 onward for comparison; they include the inequality terms that are omitted from the Census/ACS calculation. The slightly visible shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the Census/ACS and CEX.

stantial catch-up in life expectancy over the past 80 years: the life expectancy shortfall between Black and White Americans is 11 years (17%) in 1940, 6 years (8%) in 1980, and just 3.7 years (4.6%) in 2019.

We observe hours worked in the Census/ACS, so we can incorporate leisure along with mortality and consumption. Specifically, the two variables we use to construct our measure of leisure are “usual hours worked per week” and “weeks worked last year”. In Censuses before 1980, however, the Census asked about “weeks worked last week” and an intervalled version of “weeks worked last year.” Since those definitions are also available in 1980 and 1990, we use those two years to adjust average leisure computed from the pre-1980 years. We could calculate leisure inequality but do not because it differed little by race in the CPS from 1984–2019.

Figure 13 shows our decadal welfare calculations based on Census/ACS data. For comparison, the circles show our earlier CEX-based welfare measure; the

fact that the two results are relatively close in overlapping years provides some reassurance in studying our Census-based welfare measure back to 1940.

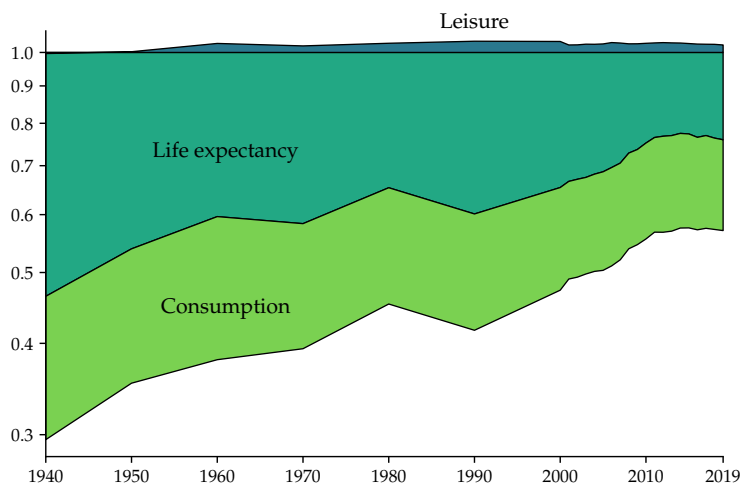
The key finding revealed by Figure 13 is the stunningly low level of Black welfare historically. In 1940, Black consumption-equivalent welfare was just 29% of that of White Americans. Recall that relative consumption in 1940 was around 59%, so the 11-year shortfall in life expectancy in 1940 played a large role. The welfare measure rose to 39% in 1960 and 47% in 1980 and reaches 58% in 2019.

Figure 14 plots the components of relative welfare over time. Differences in mortality rates far and away play the largest role, both in the levels of welfare and in the partial catch-up that has occurred over the past 80 years. Recall that the life expectancy gap fell from 17% (11 years) in 1940 to 4.6% (3.7 years) in 2019. Given that each percentage point difference in life expectancy translates into approximately a 6 percentage point difference in consumption-equivalent welfare, this explains the enormous role played by mortality differences. Consumption is the other important contributor, with about 16 percentage points of the closing of the welfare gap due to gains in consumption for Black Americans relative to White Americans. Leisure plays a minor role.

Figure 15 provides a different perspective on the past 80 years by computing the average annual growth rate of consumption-equivalent welfare for people of all races over time. To begin, the green line in the figure shows the growth rate of consumption per person, which averages 2% per year over the entire sample. In contrast, the rise in life expectancy means that consumption-equivalent welfare was growing much faster. For the entire period, the average growth rate in welfare was 3.4% per year for all races.

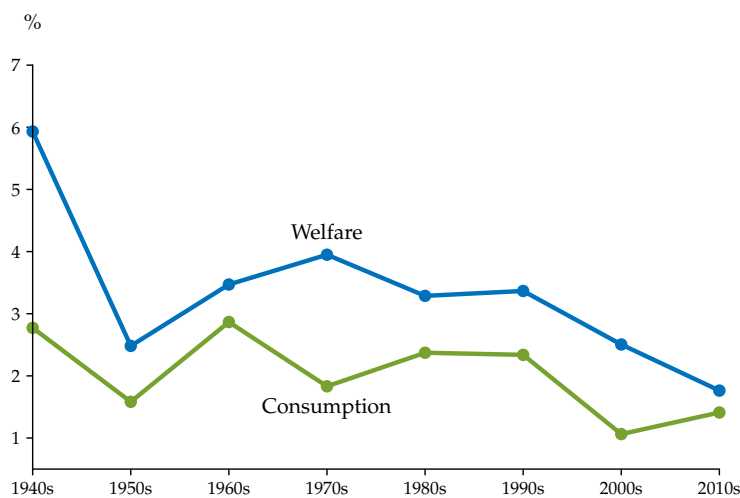
Another key fact that emerges from the figure is the appreciable slowdown in the growth rate of consumption-equivalent welfare. Between 1940 and 1980, welfare growth averaged 4% per year versus 2.8% per year since 1980 and just 1.8% per year in the 2010s (consumption growth fell more modestly from 2.3% to 1.8% over the same intervals). Put differently, the decade of the 1970s, traditionally viewed as a decade of slow growth, looks much better when life ex-

Figure 14: Decomposing Relative Welfare, 1940 – 2019



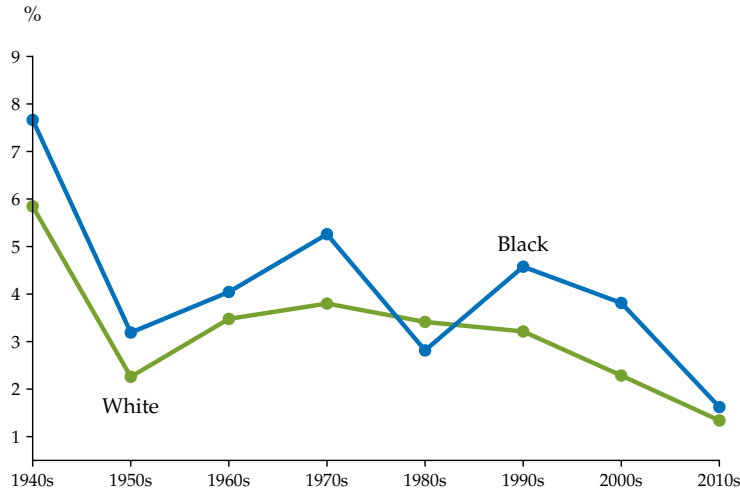
Note: Author calculations using data from the CDC's NVSS, and the U.S. censuses and ACS. The graph shows the components of consumption-equivalent welfare for Black Americans, where that for White Americans is normalized to 1.

Figure 15: Welfare and consumption growth since 1940



Note: Author calculations using data from the CDC's NVSS, and the U.S. censuses and ACS. Average annual growth rates by decade for consumption-equivalent welfare and consumption per capita for people of all races.

Figure 16: Welfare growth by race since 1940



Note: Author calculations using data from the CDC's NVSS, and the U.S. censuses and ACS. Average annual growth rates by decade for consumption-equivalent welfare. The slightly visible shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the Census/ACS and CEX.

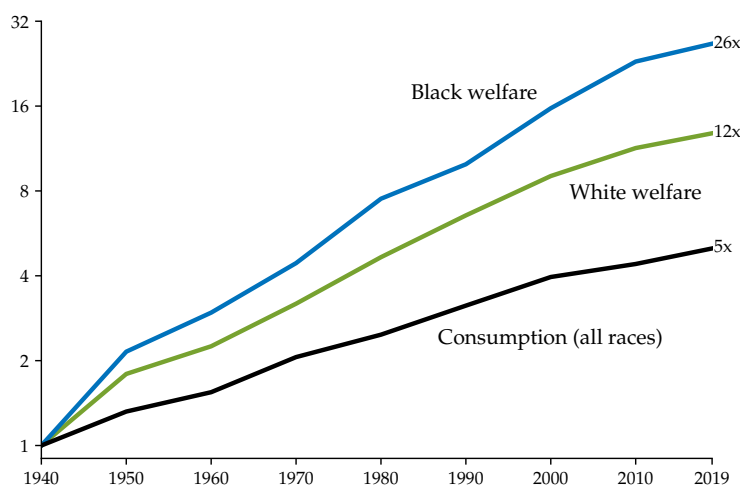
pectancy gains are included. Welfare growth is then on a downward trend for the past 50 years. From this perspective, the growth slowdown is something continually worsened throughout the last half century rather than something that developed recently. Table 5 provides more detail, noting that this slowdown is also a feature of welfare growth for Black and White Americans separately. Welfare growth by decade for Black and White Americans is displayed in Figure 16.

Table 5: Welfare growth between 1940 and 2019 (%)

	1940–1980				1940–2019			
	λ	LE	c	ℓ	λ	LE	c	ℓ
Black	5.15	2.67	2.47	0.02	4.33	2.11	2.24	-0.03
White	3.87	1.65	2.28	-0.06	3.29	1.30	2.05	-0.06
Gap	1.27	1.01	0.18	0.08	1.04	0.81	0.19	0.04

Note: Column λ is decomposed in columns LE , c and ℓ .

Figure 17: Cumulative welfare and consumption growth by race since 1940



Note: Author calculations using data from the CDC's NVSS, and the U.S. censuses and ACS. Despite the slowdown in growth, the cumulative increase in living standards is huge! 26x for Black Americans versus 12x for White Americans versus 5x for consumption. The slightly visible shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the Census/ACS and CEX.

Figure 17 shows the cumulative increase in consumption-equivalent welfare. Between 1940 and 2019, nondurable consumption per person increased by a factor of 5. In contrast, consumption-equivalent welfare increased by a factor of 12, both for White Americans and for the overall population. Most remarkable of all is the factor of 26 increase in consumption-equivalent welfare for Black Americans between 1940 and 2019. It is a sign of just how low welfare was in 1940 that even this rapid growth — which averaged 4.3% per year — could still leave Black welfare at only 59% of White welfare in 2019.

7. Extensions

In this section, we explore the effect of several additional factors on consumption-equivalent welfare. These factors are more difficult to quantify, so we did not incorporate them into our baseline estimates. But each could be quite important.

First, we use CDC health surveys for morbidity to include an adjustment for quality of life (QALYs), not just quantity. Second, we consider incarceration rates, which are several percentage points higher for Black men than for White men and rose over our sample. Third, we treat unemployment as equivalent to working rather than as leisure.

7.1 Health

Our data on health status comes from the CDC's National Health Interview Survey (NHIS) for each year from 1997 through 2018.¹⁸ This survey collects information on medical conditions, physical activity, and other health behaviors through personal interviews for the civilian non-institutionalized population of the United States. Each year, approximately 35,000 households containing about 87,500 individuals are interviewed. From those interviews, we construct the Health and Activities Limitation Index (HALex) developed by Erickson, Wilson and Shannon (1995). The HALex has two ingredients, perceived health and activity limitations, which are derived from questions in the NHIS. Information on both of those are combined to construct a single health score defined on the unit line, which we then multiply by survival rates to obtain quality-adjusted life years (QALYs). Quality-adjusted life expectancy (QALE) is simply the sum of QALYs for all ages.

An important issue is how to convert the qualitative survey-based HALex measure into consumption-equivalent units. As we discuss in Appendix A.7, the HALex score ranges from 0.10 for the worst health state to 1 for the best. The traditional QALY approach simply multiplies this index by life years: so a year in the worst health state is the equivalent of 0.10 years in the best health state. Specifically, denoting the HALex for group i at age a by Q_{ia} , our lifetime utility definition for someone who's consumption is multiplied by a factor λ at

¹⁸<https://nhis.ipums.org/nhis/>

each age follows that of Murphy and Topel (2006) and becomes:

$$U_i(\lambda) = \sum_{a=0}^{100} S_{ia} Q_{ia} \times \mathbb{E} [u(\lambda c_{ia}, \ell_{ia})].$$

For the consumption equivalent variation in welfare defined by $U_W(\lambda) = U_B(1)$, we now obtain the following decomposition of consumption-equivalent welfare:

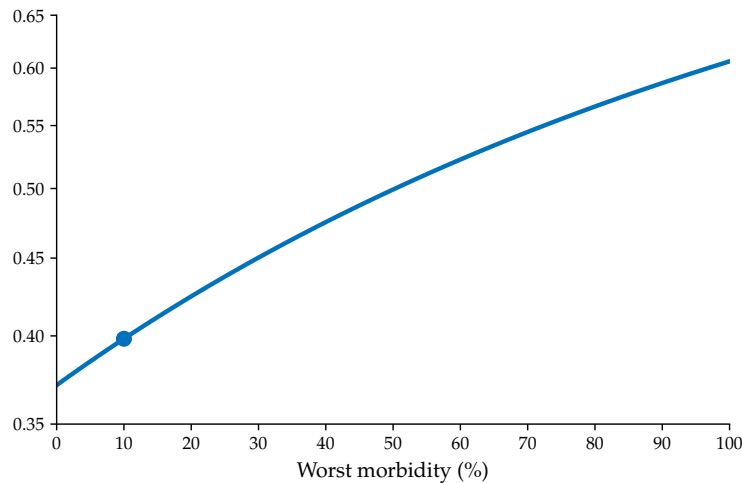
$$\begin{aligned} \log(\lambda) &= \sum_{a=0}^{100} \Delta s_{Ba} \times u_{Ba} && \text{Life expectancy} \\ &+ \sum_{a=0}^{100} \Delta q_{Ba} \times u_{Ba} && \text{Morbidity} \\ &+ \log(\bar{c}_B) - \log(\bar{c}_W) && \text{Consumption} \\ &+ v(\bar{\ell}_B) - v(\bar{\ell}_W) && \text{Leisure} \quad (4) \\ &+ \mathbb{E} \log(c_B) - \log(\bar{c}_B) - [\mathbb{E} \log(c_W) - \log(\bar{c}_W)] && \text{Consumption inequality} \\ &+ \mathbb{E} v(\ell_B) - v(\bar{\ell}_B) - [\mathbb{E} v(\ell_W) - v(\bar{\ell}_W)] && \text{Leisure inequality} \end{aligned}$$

where the flow utility intercept \bar{u} must be re-calibrated and we now have slightly different definitions for each term. The consumption, leisure and inequality terms remain almost unchanged with the exception that they are weighted by quality-adjusted life years. But most importantly, the life expectancy and morbidity terms are defined as:

$$\Delta s_{Ba} \equiv \frac{(S_{Ba} - S_{Wa})Q_{Ba}}{\sum_{a=0}^{100} S_{Wa}Q_{Wa}} \quad \text{and} \quad \Delta q_{Ba} \equiv \frac{(Q_{Ba} - Q_{Wa})S_{Wa}}{\sum_{a=0}^{100} S_{Wa}Q_{Wa}}.$$

Figure 18 shows the impact on Black vs. White welfare in 2018 of incorporating the HALex as a measure of morbidity differences. The dot in Figure 18 shows the effect of following the traditional approach and treating the HALex itself as a cardinal measure of QALYs needing no re-scaling. Under this assumption the higher morbidity of Black Americans lowers their relative welfare from 59% down to 40% in 2018. The other points on the curve in Figure 18 show the effect of stretching or compressing the HALex to range from 0 to 1 (on the left)

Figure 18: Black vs. White welfare in 2018 incorporating QALYs



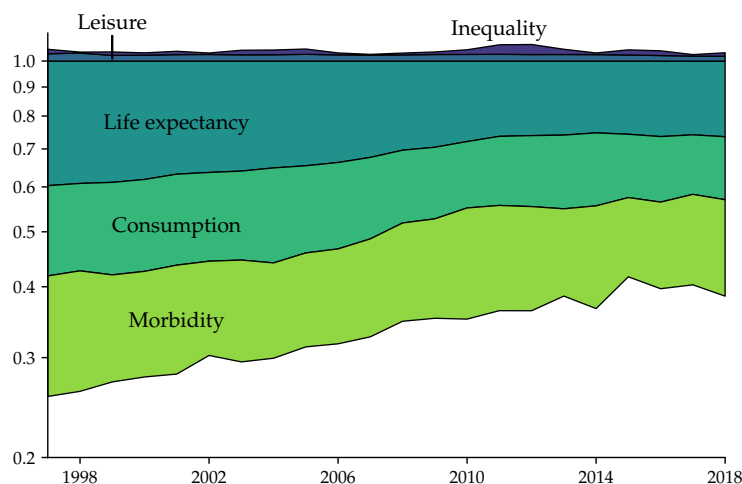
Note: The vertical axis reports the value of Black relative welfare in 2018. The blue dot treats the HALex score itself as a cardinal measure of QALYs with no rescaling. The other points in the graph show the effect of rescaling the worst health state to be the equivalent of $x\%$ of the best health state.

to not varying at all (on the right). In other words, we linearly adjust the scale so that the 0.10 worst health state is the equivalent of x percent years of life at the best state, where x is the value on the horizontal axis.¹⁹ Clearly, morbidity differences between Black and White Americans could be quite important. Our baseline calculation that ignores morbidity may understate the welfare gap substantially.

Figure 19 shows that while there has been a fair amount of convergence in Black relative to White life expectancy and consumption between 1997 and 2018, the racial gap in morbidity remained almost unchanged during that period. In fact, Figure 20 compares our baseline consumption-equivalent welfare results (dark blue line) with the results we obtain when accounting for morbidity and the gap is strikingly large.

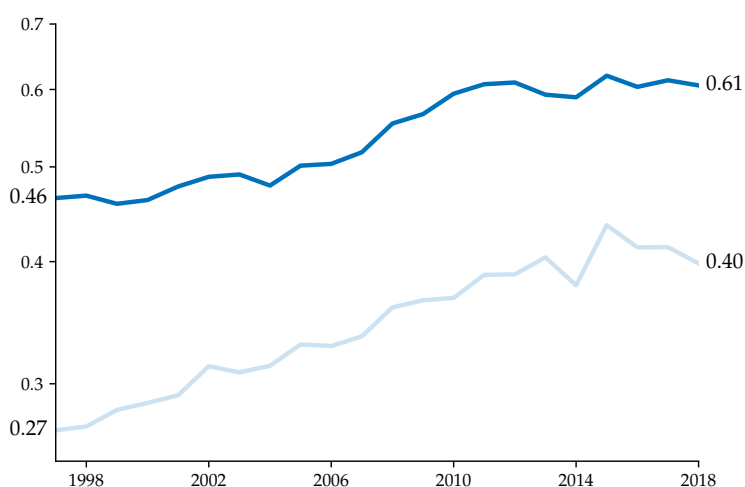
¹⁹A separate issue from the range of the HALex is whether the HALex's curvature appropriately captures QALYs.

Figure 19: Relative welfare decomposition incorporating QALYs



Note: The figure shows the decomposition of consumption-equivalent welfare for Black relative to White Americans from 1997 to 2018, computed according to equation (4). Author calculations using data from the CDC's NVSS, the Department of Labor's CPS as well as the CEX and NHIS.

Figure 20: Consumption-Equivalent Welfare incorporating QALYs



Note: The figure shows the consumption-equivalent welfare for Black relative to White Americans from 1997 to 2018, computed according to equation (2) for the dark blue line and equation (4) for the pale blue line.

7.2 Incarceration

To calculate incarceration rates by race, we use inmate population counts for adults in U.S. state and federal prisons from the National Prisoner Statistics (NPS) program of the U.S. Bureau of Justice Statistics (BJS) between 1999 and 2019.²⁰ However, the NPS does not provide inmate population counts broken down by age. We therefore use data from the National Corrections Reporting (NCR) program of the BJS from 1999 to 2019 to account for age heterogeneity in incarceration rates by race.²¹

In particular, the NCR collects data annually on inmate populations in state prisons by race and five age groups: 18 to 24 years old, 25 to 34 years old, 35 to 44 years old, 45 to 54 years old and 55 years old or older. From this, we approximate the inmate age distribution annually by race. However, in both the NPS and NCR, the inmate population for Black and White Americans is not reported irrespective of Latinx origin.

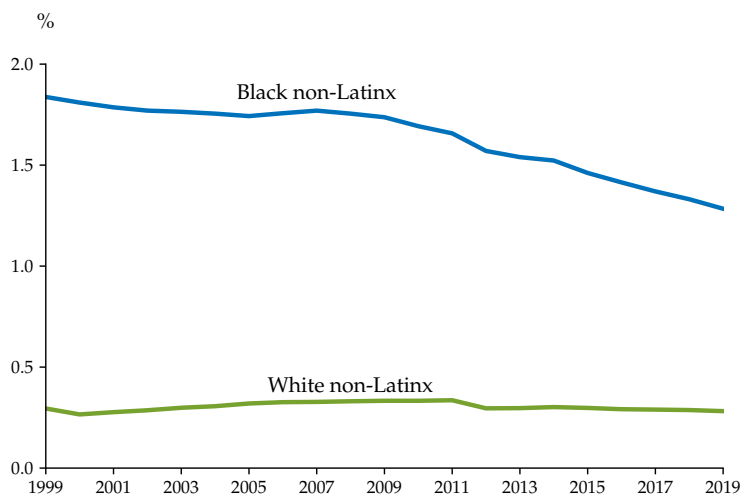
Figure 21 shows that Black non-Latinx have markedly higher incarceration rates than White non-Latinx. If flow utility is much lower while incarcerated, incarceration will subtract from Black non-Latinx welfare relative to White non-Latinx welfare.

To illustrate the potential impact of incarceration on welfare, we assume flow utility for the incarcerated population is equal to some fraction of the average flow utility for a non-incarcerated individual of the same age with a high school education or less. Figure 22 shows the resulting change in the consumption-equivalent welfare of Black non-Latinx relative to White non-Latinx in 2018. The x -axis indicates different assumed values of the flow utility adjustment when incarcerated, going from 0% (no utility while incarcerated) to 100% (no utility discount from incarceration). The figure shows that the higher incarceration rate for Black non-Latinx Americans lowered their relative welfare in 2019 by up to 6.6% in consumption-equivalent terms.

²⁰See <https://bjs.ojp.gov/data-collection/national-prisoner-statistics-nps-program>.

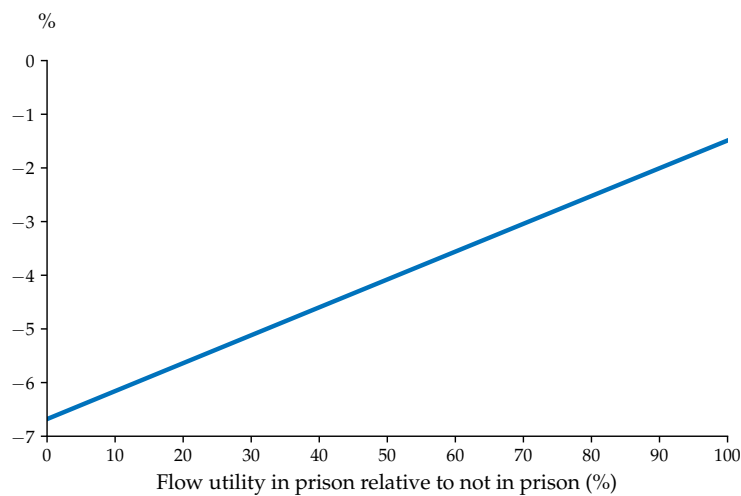
²¹See <https://bjs.ojp.gov/data-collection/national-corrections-reporting-program-ncrp>.

Figure 21: Incarceration rates by race



Note: Incarceration rates are calculated from the NPS and NCR programs of the U.S. Bureau of Justice Statistics.

Figure 22: Impact of incarceration on Black non-Latinx relative welfare in 2019



Note: The effect on relative welfare is calculated by setting flow utility of incarcerated individuals to $z\%$ of the average flow utility of individuals with high school education or less, and using incarceration rates by race in each year. The x -axis shows different values of z .

7.3 Unemployment

Our baseline calculation treats unemployment as leisure. Needless to say, this may be a bad assumption and could mean our estimates overstate the relative welfare of Black Americans given their higher unemployment rates.

Surveys by Krueger and Mueller (2011) shed light on how flow utility varies with employment status. They find that the same leisure activities yield less enjoyment when a person is unemployed compared to when they are employed. They also find that those unemployed had similar hours worked in their previous jobs as employed individuals.

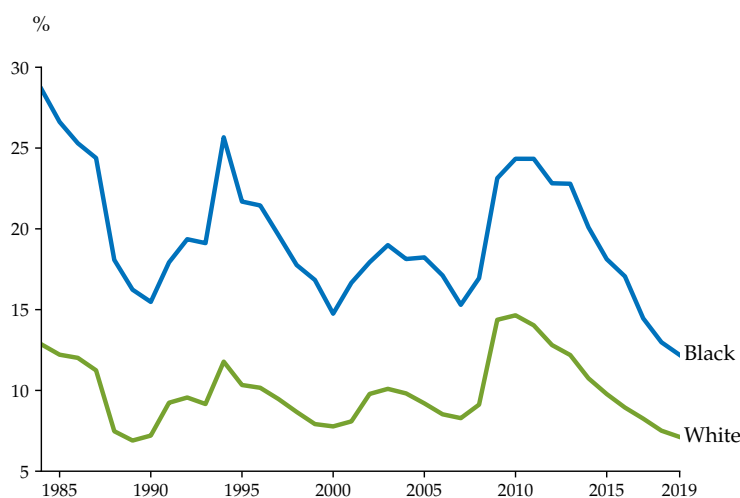
Considering these facts, we perform an adjustment where unemployed individuals have their hours worked set to full-time hours. This adjustment ensures leisure hours are no longer greater for unemployed individuals. We also consider a broad definition of unemployment, including the unemployed and marginally attached workers as well as workers who are involuntary working part-time. As illustrated in Figure 23, Black Americans face a persistently higher rate of unemployment than White Americans in our sample.

How does the unemployment adjustment to leisure impact the racial leisure gap and relative welfare? Figure 24 displays the leisure gap between Black and White Americans in percentage points before and after the unemployment adjustment. The unemployment adjustment shaves about 1 percentage points off the racial gap in leisure over the entire sample. In 2019, this adjustment reduces the gap in welfare by about 1 percent.

8. Conclusion

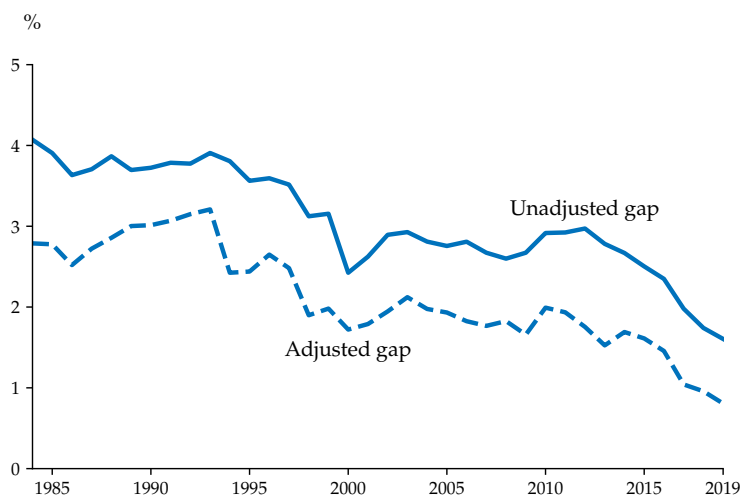
We constructed a measure of consumption-equivalent welfare for Black and White Americans. This measure allows us to gauge the relative importance and cumulative impact of gaps in consumption, life expectancy, leisure, and inequality in both consumption and leisure. According to our estimates, these

Figure 23: Broad unemployment rate by race



Note: The broad definition of unemployment includes unemployed and marginally attached workers as well as workers who are involuntary working part-time.

Figure 24: The Black-White Gap in Leisure and the Unemployment Adjustment



Note: The "unadjusted gap" shows the difference in leisure in our baseline calculation from Section 3. Adjusting for unemployment reduces the gap from 4.1 to 2.8 percentage points in 1984 and from 1.8 to 0.8 percentage points in 2019. As described in the text, our definition of leisure uses total hours worked during the year. However, since we do not observe employment status in the CPS for each individual over the entire year, the definition of leisure used for the unemployment adjustment uses total hours worked during the preceding week, where employment status is observed.

factors combined to generate welfare for Black Americans that was only 43% of that for White Americans in 1984. Black welfare rose to 59% of White welfare by 2019, driven by narrowing differences in consumption and life expectancy. Using more spotty data, we found the welfare divide was even larger in 1940, with Black welfare only 29% of White welfare in 1940. We traced this yawning gap to sizable differences in mortality.

In our extensions, we made some progress toward incorporating other important considerations such as morbidity, unemployment, and incarceration. A productive avenue for future research would be to improve on our measurement. And it would be valuable to include other considerations such as differential access to good neighborhoods and differences in prices paid by race.

We view our calculations as potentially useful for quantifying the welfare loss due to past and present discrimination, for identifying gains from reducing or eliminating misallocation that results from such discrimination, and for assessing the benefits of competing policies to reduce welfare gaps.

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A. Appendix

A.1 Survival rates

For years 1984 to 1989 and 1991 to 1996, the CDC's life tables only report survival rates up to age 85. To approximate survival rates for ages above 85, we use the fact that mortality rates increase exponentially with age after age 30, which was first documented by Gompertz (1825). More precisely, we use reported mortality rates from age 65 to 85 to estimate the coefficients α and β of the following function by race and gender:

$$m(a) = \alpha e^{\beta a}$$

where $m(a)$ is the mortality rate at age a . We can then calculate survival rates up to age 100 using the available survival rate at age 85 and the approximated mortality rates after age 85.

Since 2018, life tables stopped reporting survival rates for Black and White Americans irrespective of Latinx origin. Hence, we follow the CDC's methodology for producing life tables from death records and population estimates to make sure that our racial groups are consistent throughout our sample.²² Death records are obtained from the CDC's National Center for Health Statistics (NCHS) and the corresponding population at risk is obtained from the CDC's bridged race population estimates.^{23,24}

A.2 Consumption

To obtain our consumption measure, we closely follow the work of Aguiar and Bills (2015). In fact, our consumption aggregate corresponds to the sum of the consumption categories reported in their work, with three exceptions. First,

²²<https://www.cdc.gov/nchs/data/nvsr/nvsr61/nvsr61.03.pdf>.

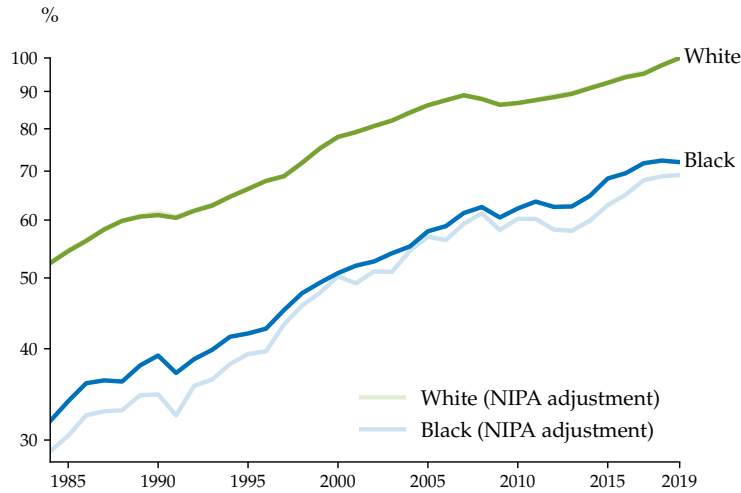
²³<https://wonder.cdc.gov/mcd.html>.

²⁴<https://wonder.cdc.gov/bridged-race-population.html>

we do not constrain our sample to 4-interview urban households and complete income reporters. Instead, we use the CEX's full sample and multiply a household's consumption by the inverse of the fraction of interviews in which it participated. However, to ensure that the standard deviation of consumption for below 4-interview households is not artificially high, we slightly adjust their consumption. In fact, we re-scale it such that within each race group, the standard deviation of *nondurable* consumption expenditures is equal to that of 4-interview households. Then, we impose a lower bound on consumption equal to \$2,000 in 2012 USD in each year. Third, we also re-scale total individual consumption expenditures such that they aggregate to NIPA real personal consumption expenditures (PCE) per capita. To do so, we first divide consumption equally among each household member. Finally, since the CEX's sample size is relatively small, we smooth the age profile of consumption within each year using a HP-filter with a penalty term of 1,600.

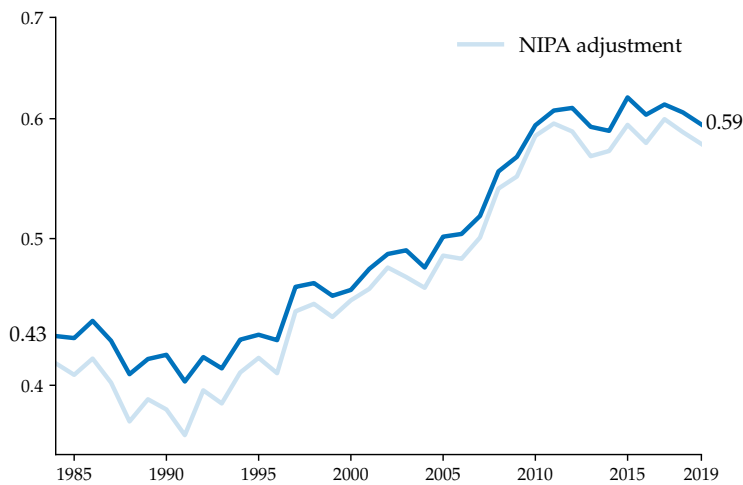
However, if there is differential misreporting of expenditures by consumption categories in the CEX relative to the NIPA PCE and the composition of the consumption basket differs for White and Black Americans, we might be mis-measuring their relative consumption. To account for this possibility, we use the correspondence between consumption categories from the CEX and NIPA PCE developed by the [BLS](#). This allows us to re-scale expenditures in the CEX such that each category aggregates to the corresponding one in the NIPA PCE. With this adjustment, we find that our baseline results slightly understate the racial gap in consumption per capita as evidenced in [Figure A1](#). In this figure, the dark lines correspond to our baseline consumption measure while the pale ones are adjusted for differential misreporting by consumption categories. [Figure A2](#) shows how this adjustment affects our welfare calculation. Instead of rising from 43% to 59% between 1984 and 2019, this adjustment would imply that the welfare of Black relative to White Americans instead went from 41% to 58%.

Figure A1: Consumption per capita by race



Note: Author calculations using data from the U.S. Consumer Expenditure Surveys (CEX) and NIPA Personal Consumption Expenditures (PCE). The dark lines correspond to our baseline consumption measure while the pale ones are adjusted for differential misreporting by consumption categories. Consumption for White Americans is normalized to 100 in 2019 for both measures and the vertical axis is plotted on a logarithmic scale.

Figure A2: Consumption-Equivalent Welfare, Black vs. White Americans



Note: The figure shows the consumption-equivalent welfare for Black relative to White Americans from 1984 to 2019, computed according to equation (3). The dark line corresponds to our baseline results while the pale one is adjusted for differential misreporting by consumption categories.

A.3 Leisure

To calculate leisure, we use information on usual hours worked per week and weeks worked per year from the CPS to obtain an estimate of hours worked per year. Then, assuming that a maximum of 16 hours per day and 365 days per year are available for work, we obtain leisure as the fraction of hours that are not spent in market work. To also account for non-market work discrepancies between genders, we divide hours worked per year equally among individuals between 25 and 64 years old within each household. The resulting split in leisure time between men and women is similar to that found in Aguiar and Hurst (2007). As for consumption, since the CPS' sample size is still somewhat small, we smooth the the age profile of leisure within each year using a HP-filter with a penalty term of 100.

A.4 Calibrating the intercept in the flow utility: \bar{u}

This section describes how to calibrate \bar{u} when we are using only part of consumption (such as nondurables). Consider an extreme version of this, where we observe Starbucks coffee purchases c^{sb} and are using this to proxy for consumption. In particular, suppose that:

$$c = \mu \times c^{sb}.$$

That is, true consumption is a “markup” μ over measured Starbucks consumption. Suppose also that lifetime utility is

$$\begin{aligned}
 V &= \sum_a \beta^a S_a u(c_a, \ell_a) \\
 &= \sum_a \beta^a S_a [\bar{u}_0 + \log(c_a) + v(\ell_a)] \\
 &= \sum_a \beta^a S_a [\bar{u}_0 + \log(\mu) + \log(c_a^{sb}) + v(\ell_a)] \\
 &= \sum_a \beta^a S_a [\bar{u} + \log(c_a^{sb}) + v(\ell_a)]
 \end{aligned}$$

where $\bar{u} \equiv \bar{u}_0 + \log(\mu)$. The VSL = \$7.4m = $V/u'(c)$ in the model where $u'(c) = 1/c$ is the marginal utility of all consumption. Rearranging, we have:

$$\begin{aligned}
 V &= \$7.4\text{m} \times u'(c) \\
 &= \frac{\$7.4\text{m}}{c} \\
 &= \frac{\$7.4\text{m}}{\mu \times c^{sb}}
 \end{aligned}$$

That is, we have to use “true” consumption to convert the VSL into utils, so that V has the units (with log utility) of “years of consumption”. Now, we can combine these two sets of equations for V and solve for \bar{u} :

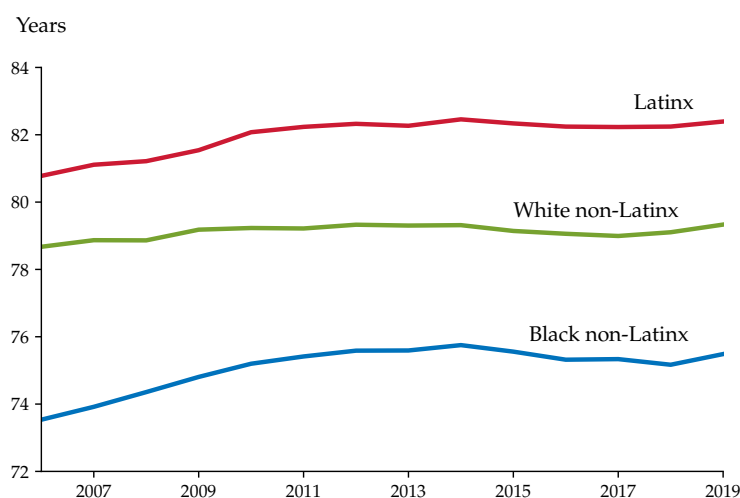
$$\bar{u} = \frac{7.4\text{m}/c_{2006} - \sum_a \beta^a S_a [\log(c_a^{sb}) + v(\ell_a)]}{\sum_a \beta^a S_a}.$$

We use a value of c_{2006} of \$31,046, which is nominal per capita NIPA personal consumption expenditures (PCE).

A.5 Welfare by Latinx Origin

In this section, we report our life expectancy, consumption and leisure statistics by race and Latinx origin since 2006. As mentioned earlier, the CDC only started

Figure A3: Life expectancy at birth by race and ethnicity



Note: Author calculations using data from the CDC.

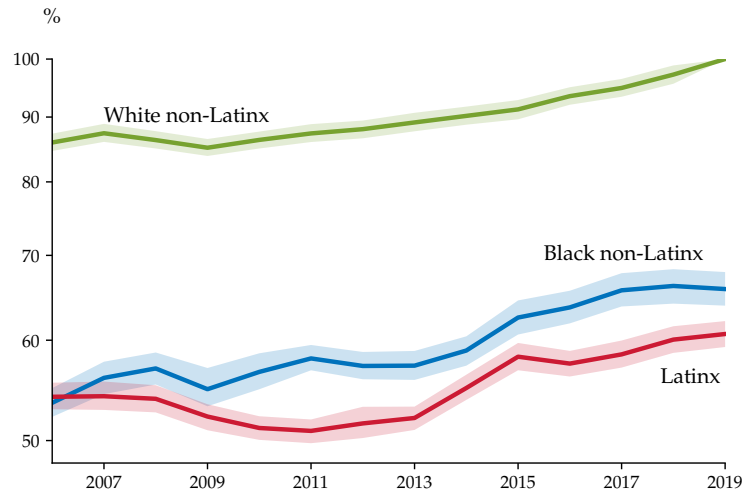
publishing Life Tables by Latinx origin starting in 2006, which is why we focus on the sample period from 2006 to 2019.

Figure A3 plots life expectancy at birth for non-Latinx Black and White, as well as Latinx Americans. What stands out of this figure is how high Latinx life expectancy is relative to the two other groups. In 2019, life expectancy at birth stood at 82.4 years old for Latinx Americans, as opposed to 79.3 and 75.5 years old for non-Latinx White and Black Americans, respectively. This is often referred to as the “Latino paradox” by which Latinx Americans tend to have better health outcomes than non-Latinx Americans, but worst socioeconomic outcomes.

In fact, looking at consumption per capita for the same three groups in Figure A4, we see that Latinx and non-Latinx Black consumption was 39% and 34% lower than non-Latinx White consumption in 2019.

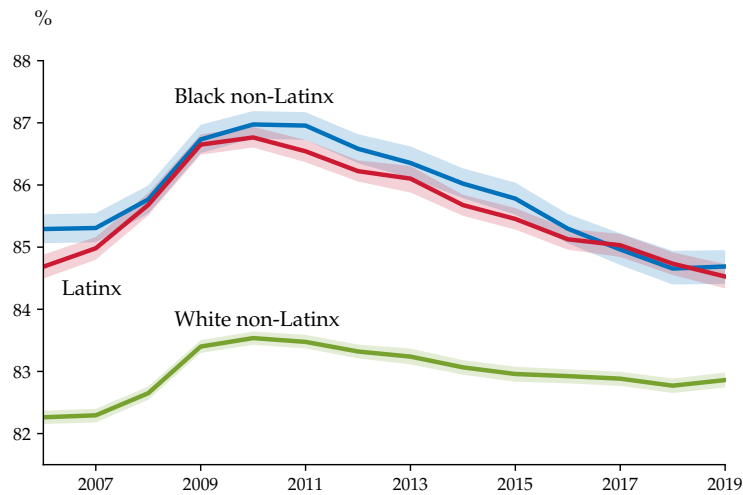
In terms of leisure, Latinx and non-Latinx Black Americans have very similar outcomes for the entire sample period. About 85% of their time endowment is spent on leisure, as opposed to 83% for non-Latinx White Americans.

Figure A4: Consumption per capita by race and ethnicity



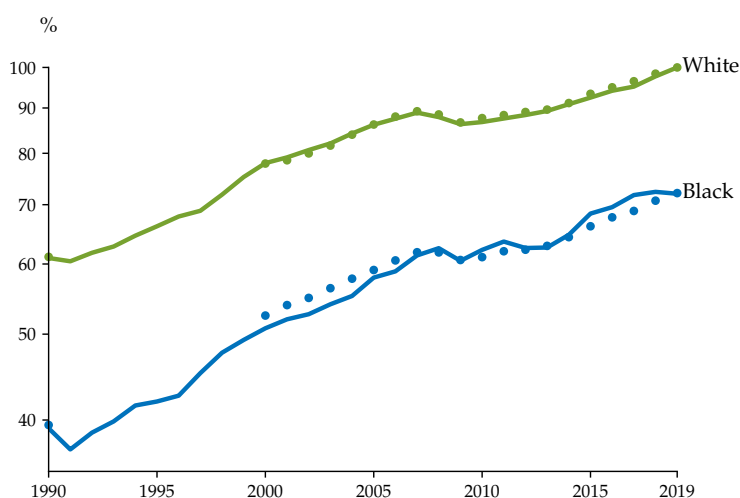
Note: Author calculations using data from the U.S. Consumer Expenditure Surveys (CEX). Consumption for White Americans is normalized to 100 in 2019 and all series are plotted on a logarithmic scale. The shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the CEX.

Figure A5: Leisure by race and ethnicity



Note: Author calculations using data from the U.S. Current Population Survey (CPS). The shaded areas represent the 95% confidence interval of each series from 1000 bootstrap samples of the CPS.

Figure A6: Consumption imputation



A.6 Consumption imputation

To impute consumption from the CEX to the U.S. censuses and ACS, we regress consumption on earnings (excluding taxes and transfers), controlling for race, gender, education, family size and age in the CEX, where all variables are in percentage deviation from their annual average. Consumption and wage and salary income are both calculated at the household level and divided evenly among family household members. Finally, we restrict the CEX estimation sample to complete income reporters.

We then use the estimated coefficients of this regression to impute consumption in the Census from household earnings (excluding taxes and transfers) as well as the race, gender, education, family size and age of household members. All Census imputation variables are constructed as they are in the CEX. Finally, we re-scale imputed consumption in the Census such that it aggregates to real personal consumption expenditures per capita from NIPA.

Figure A6 plots per capita consumption by race from 1990 to 2019 in the CEX (solid lines) and its imputed analog in the Census (dotted lines), where consumption is normalized to 100 for White Americans in 2019.

A.7 Health

For the perceived health component of the HALex, respondents are asked to self-report their overall health as excellent, very good, good, fair or poor, which defines five perceived health states. For the activity limitation component of the HALex, activities are sorted into four categories: activities of daily living (ADLs), instrumental activities of daily living (IADLs), major activities, and non-major activities. ADLs are basic personal care activities such as eating, bathing, dressing and mobility, while IADLs are slightly more involved routine activities such as household chores, doing necessary business or shopping. In contrast, a major activity represents a respondent's primary social role such as working, housekeeping, or studying, while non-major activities include all other activities that cannot be classified in the previous three categories.

Respondents are asked to report whether they are limited in performing activities in any of the above four categories. If they report being limited in multiple activity categories, they are assigned to the category that represents the greater degree of limitation. Therefore, there are six activity limitation states: not limited in any activities, limited in non-major activities, limited in major activities, unable to perform major activities, limited in IADLs and limited in ADLs.

With the five perceived health states and six activity limitation states, the HALex comprises 30 health states. A nonlinear multiattribute model was used to assign cardinal values to each health state by Erickson et al. (1995). Respectively denoting perceived health and activity limitation as PH and AL, Table 6 presents those values, which are derived from the formula in equation (A.1). Through correspondence analysis, the PH variable was assigned values of 1, 0.85, 0.7, 0.3 and 0 for the excellent to poor perceived health states and the AL variable was assigned values of 1, 0.75, 0.65, 0.4, 0.2 and 0 for the least to most

Table 6: HALex ingredients

AL\PH	Excellent	Very good	Good	Fair	Poor
Not limited	1.00	0.92	0.84	0.63	0.47
Limited – non-major	0.87	0.79	0.72	0.52	0.38
Limited – major	0.81	0.74	0.67	0.48	0.34
Unable – major	0.68	0.62	0.55	0.38	0.25
Limited – IADLs	0.57	0.51	0.45	0.29	0.17
Limited – ADLs	0.47	0.41	0.36	0.21	0.10

Note: AL and PH respectively stand for activity limitations and perceived health, which are both measured using the CDC's National Health Interview Survey (NHIS). The HALex combines AL and PH using the formula in equation (A.1), developed by Erickson, Wilson and Shannon (1995).

dysfunctional states of activity limitation.²⁵

$$\text{HALex} = 0.1 + 0.9 \times (0.41 \times \text{PH} + 0.41 \times \text{AL} + 0.18 \times \text{PH} \times \text{AL}) \quad (\text{A.1})$$

This health score has come to be widely used as way to estimate Quality-Adjusted Life Years (QALY's) in the health literature. It is also used by the CDC's health promotion and disease prevention initiatives for constructing QALYs.²⁶ Moreover, a potentially valuable feature of the HALex score is that it accounts for a respondent's subjective perception of their own health. For instance, respondents who rely on wheelchairs for mobility, but have adapted to this condition, might report themselves as healthy. In that case, the HALex score would yield higher utility than a measure that relied solely on physical limitations. Fisher, Wennberg, Stukel, Gottlieb, Lucas and Pinder (2003) looks at the relationship between the HALex and various diseases, the impact of chronic conditions on the HALex, and the impact of similar conditions on summary scores from other surveys like the Medical Outcomes Study.

²⁵Refer to the Appendix for a detailed derivation of the scaling constants in equation (A.1) and the values assigned to the PH and AL variables.

²⁶See Erickson et al. (1995), Erickson (1998) and Fryback, Dunham, Palta, Hanmer, Buechner, Cherepanov, Herrington, Hays, Kaplan, Ganiats et al. (2007), for example.

A.8 Incarceration

To calculate incarceration rates, we first use inmate population counts by race from the BJS National Prisoner Statistics Program (NPS) annually from 1999 to 2019.²⁷ However, the NPS does not provide inmate population counts broken down by age. We therefore use the BJS National Corrections Reporting Program (NCR) from 1999 to 2019 to approximate the inmate age distribution by race.

The NCR collects offender-level administrative data annually on prison admissions and releases, and year-end inmate populations.²⁸ The NCR data is publicly available from 1999 to 2019 and provides incarcerated population counts by race and five age groups, which are 18 to 24 years old, 25 to 34 years old, 35 to 44 years old, 45 to 54 years old and 55 years old or older. From this, we approximate the inmate age distribution annually by race between 1999 and 2019.

²⁷<https://www.bjs.gov/index.cfm?ty=dcdetail&iid=269>

²⁸<https://www.bjs.gov/index.cfm?ty=dcdetail&iid=268>.