LIFE-CYCLE INEQUALITY: BLACKS AND WHITES DIFFERENTIALS IN LIFE EXPECTANCY, SAVINGS, INCOME, AND CONSUMPTION*

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Abstract

Life expectancy for Blacks is about 8 year shorter than for Whites. A shorter life expectancy, in line with the theoretical prediction of a simple model, determines a much lower amount of savings and wealth accumulation and therefore a lower degree of insurance. This, in turn, contributes to persistent racial differentials in life-cycle consumption. Starting from the same position in the consumption distribution Blacks end up in a lower percentile than Whites after a few decades. This is particularly marked for those Blacks who start at the top of the consumption distribution, where Whites are much more persistent. We document these facts using 40 years of PSID data (1981-2017).

JEL classification: E21, E63, D12, C3

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1 Introduction

Economic inequality is one of the major contemporary challenges for policy-makers and economists. In recent years there has been a burgeoning of the literature in this area. Starting from Picketty and Saez (2003), several authors have investigated the rising income, wage, and consumption inequality in the US and other countries (e.g. Autor et al. (2008), Blundell, Pistaferri and Preston (2008), Bonhomme and Robin (2009), Primiceri and Van Rens (2009), Heathcote et al. (2010), Atkinson et al. (2011), Auten et al. (2013), Attanasio and Pistaferri (2014 and 2016), Blundell (2014), Chetty (2014a and 2014b)). Further, several scholars have underlined that it is crucial to study consumption inequality, as well as income inequality, in order to speak to households' well-being: consumption is linked to the permanent component of income and as such of great interest in the long-run (see for example Blundell and Preston (1998), Meyer and Sullivan (2003), Krueger and Perri (2006), Attanasio, Hurst and Pistaferri (2012), Aguiar and Bils (2015), Bludell, Pistaferri and Saporta-Eksten (2016)).

A number of authors have also investigated the existing differences in both earnings and consumption levels between Black and White individuals in the US, often suggesting that these differentials are due to the quantity and quality of schooling individuals have access to (e.g. Blau and Graham (1990), Blau and Beller (1992), Card and Krueger (1992 and 1993), Oaxaca and Ransom (1994), Chay and Lee (2000), Heckman et al. (2000), Peoples and Talley (2001), Charles et al. (2009), Heywood and Parent (2012), Bayer and Charles (2018)).

However, much less attention has been devoted to the distinguishing feature of the current paper: the differentials in both income and consumption persistence across the distribution between Blacks and Whites in the US over the life-cycle.

The present paper is positioned in the framework of life-cycle models, such as Katona (1949), Modigliani and Brumberg (1954, 1980), Friedman (1957). Life-cycle models allows distinguishing between a permanent and a transitory income component. In these models, indeed, individuals save to face income shocks and to sustain consumption in later life (after retirement). Savings rates are influenced by the permanent income of the individual and not by his disposable income as a whole. In this framework, De Nardi et al. (2018) have recently stressed the importance of adopting a rich modellization of income dynamic (i.e. by accommodating features such as non-normality and non-linearity, as well as age-dependence of the income processes) in order to obtain a better fit to the data.

Consumption heterogeneity along the distribution, as well as heterogeneous consumption responses to income shocks, have also been analyzed (Parker and Vissig-Jorgenses

(2009), Attanasio and Weber (2010), Misra and Surico (2014), De Giorgi and Gambetti (2017)). In an intergenerational perspective, Chetty et al. (2014b) found that income mobility is lower in commuting zones with a higher share of Black residents, which suggests that there are relevant racial differences in income mobility.

Further, Chetty et al. (2018) examine the racial differences in the degree of parent-children income persistence and find that the main drivers of such differences are geographical segregation of the Blacks and lower marriage rates among the Blacks, which lead, in turn, to having often only one income instead of two in the household.

However, to the best of our knowledge, the study of life-cycle racial differences in earnings persistence and how these differences are transmitted to consumption persistence has not been carried out until now. We do this in the current paper building on the work of Blundell, Pistaferri and Preston (2008) and Kaplan and Violante (2014).

We set off with some exploratory data analysis.

A few facts stand out. First, in each quintile, average consumption and income of the Blacks lie below the average (within-quintile) of the Whites and this differences does not disappear with age. Second, when estimating persistence and transition probabilities across different quintiles, it clearly emerges that Blacks are more persistent than Whites at the bottom of both income and consumption distributions. Conversely, they are less persistent than Whites at the top of both income and consumption distributions, i.e. they exhibit a higher risk of falling back into the lower quintiles. Consumption dynamics over the life-cycle are quite heterogeneous, in particular Blacks and Whites have very different degrees of persistence at the top and bottom of the distributions. As far as this observation is concerned, controlling for a standard set of observables such as age, gender, education and occupation wipes away most of the differences in income, but not those in consumption persistence, in particularly at the top. For consumption, the bottom quintile dynamics are fully accounted for by a few observables (e.g. single-parent/female-head household, age and education), but at the top of the distribution the same observables do not close the gap, i.e. Blacks seem to be less insured against income fluctuations, in particular at the top. Blacks at the top of the consumption distribution tend to be in non-managerial occupations (differently from Whites), and it appears that the income risk (volatility and dispersion) involved in any occupation is around 25% higher for the Blacks. Third, we observe that Blacks are more exposed than Whites to income shocks, which then reverberates into their consumption patterns. For example, Blacks have on average less cash savings than the Whites, even within the same consumption quintile. Similarly, Blacks spend on average less than the Whites for health insurance premiums and hence they are likely to suffer from worse coverage when hit by a health shock. Further, Blacks are more often in single-parent (or single) households and on average receive substantially lower transfers from all sources. All these facts suggest that Blacks are more exposed than Whites to an unexpected income shock. These stark facts motivate our research questions.

We first show that a trivial life-cycle model with differential life-expectancy is able to capture the main feature of the hypothesized mechanisms, i.e. lower savings and wealth accumulation for the Blacks leading to higher consumption risk. Then we apply the model developed by Blundell et al. (2008) and estimate the degree of partial insurance against permanent and transitory income shocks separately by race. From the estimation results it emerges that Blacks are less insured than Whites against both permanent and temporary income shocks. Indeed, in any consumption quintile, the median stock of savings held by the Blacks is way lower than that held by the Whites, and this difference is particularly evident in the top consumption quintile. Such findings are consistent with lower life-expectancy of Blacks; for our cohorts this is on average about seven to ten years lower than for Whites. This fact, other things equal, makes the Blacks more exposed to permanent and transitory income shocks, given the lower buffer of savings and a lower overall degree of insurance than the Whites.

The paper proceeds as follows: Section 2 describes inequality in life expectancy and its implications for savings, with the help of a toy model. Section 3 presents the data. Section 4 presents the application of the partial insurance model by Blundell et al. (2008) to our case. Section 5 provides an overview of racial differences in life-cycle income and consumption levels, as well as evidence of income and consumption persistence (e.g. quintile-quintile and rank-rank regressions). Section 6 presents some robustness checks. Finally, Section 7 presents a counterfactual analysis and Section 8 concludes. Appendix A provides further information on the construction of the dataset, whereas Appendix B presents additional descriptive statistics and empirical results.

2 Inequality in Life Expectancy

We start off the analysis by discussing and presenting evidence related to differential life-expectancy between Blacks and Whites in the population. We also make use of a simple model to have a sense of the implications in terms of saving rates of the observed differential.

2.1 Estimated Life Expectancy

Our cohorts of interest in the PSID are born between 1917 (i.e. individuals who are 64 in 1981, the first year that we consider in our sample) and 1997 (i.e. individuals who are 20 in 2017, the latest year in our sample). According to the United States Life Tables prepared by Arias and Xu (2019), for those born in 1930 the life-expectancy differential Whites to Blacks is of 14 years overall, in 1940 is of 11 years, in 1950 is of 8 years, in 1960 and 1970 of 7 years, then in 1980 is 6.4 years, and in 1990 is 7 years. Overall given the distribution of year of birth in our data, a life-expectancy difference of 8 years is in line with the figures; and we will work under that benchmark of 8 years difference in life-expectancy at birth.[1] We take the measure at birth as widely available and so to avoid making assumption on the specific individual and household decision-making process. We note that this could be a reasonable approximation, as male differentials are substantially larger all the way to the 1980's and 1990's. Females' life-expectancy is higher than males' and this is true in particular for the Blacks. We also note that the gap in life-expectancy is not closing at a fast rate: it shrunk by 45% between 1930 and 1950 and only by 20% in the last two decades, and due to current circumstances at the time of COVID-19, that gap is potentially getting larger.[2]

In Figure 1, we report the estimated life expectancy, by race, from 1920 to 2017. It is apparent from this Figure that life expectancy of Whites has been consistently between 15 and 5 years longer than that for Blacks, even if, as mentioned above, this difference has shrunk over time.

This marked difference in life-expectancy, of about 8 years, is a crucial piece in our analysis of consumption behavior over the life-cycle and we will see below how we think about it in terms of consumption and savings.

2.2 A Simple Model

We will try here to give a sense of the magnitude of the effects of life-expectancy differences in terms of saving rates and stock of savings between Blacks and Whites. At the same time we will add another crucial parameter to that decision-making process and therefore model

[1] One might want to start from differences in life-expectancy around age 18/20, when some of the financial decisions are taken and so to take into account concerns regarding low life-expectancy due to infant and child mortality. One might also want to consider male-female differential and its role in the household decision process.

[2] We know from recent CDC work that the mortality rates and overall deaths have been proportionally much larger among minorities in the US. With Blacks dying at a rate almost double that of Whites (`https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/racial-ethnic-minorities.html`)

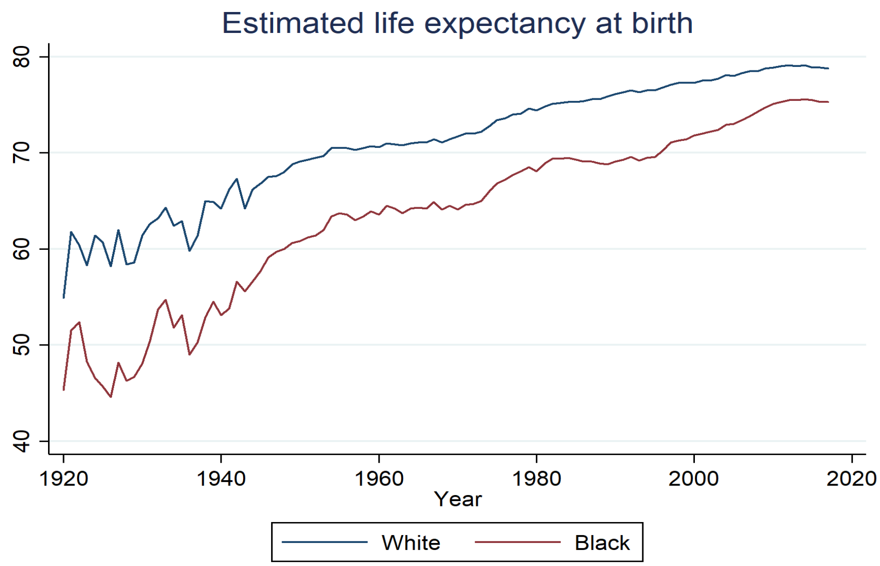

Figure 1: Estimated life expectancy at birth, by race. Data from the National Center for Health Statistics, Centers for Disease Control and Prevention (Arias and Xu (2019)).

all the mechanics through the interactions of two fundamental parameters in a life-cycle model of consumption: i. life expectancy, and ii. (gross) rate of return. We purposedly use a basic off-the-shelf model of consumption without uncertainty. This is to establish a benchmark and see how far we get with a really basic model. Let's introduce some notation. An individual maximizes lifetime consumption c subject to an inter-temporal budget constraint, we abstract from labor supply and fix the income per working period to $y_t = y_0$ where $t = 0$ indicates the first period of adult life, let's say 18 years of age. The agent works until retirement, i.e. for $L = 45$ periods, and lives for a total of T^j periods with $j = W, B$ and $T^W > T^B$.

The allocation of consumption is then chosen according to the maximization of lifetime utility.

$$\begin{aligned} argmax_{c_t^j} \quad & \sum_{t=0}^{T^j} \beta^t U\left(c_t^j\right) \\ s.t. \quad & \sum_{t=0}^{T^j} \frac{c_t^j}{(R^j)^t} \leq \sum_{t=0}^{L} \frac{y_t}{(R^j)^t}. \end{aligned}$$

We fix Blacks' and Whites' incomes to be the same and to follow the same profile. In the data, conditional on a small set of $X's$, this is a plausible starting point. Blacks and Whites have the same working life of $L = 45$ years (start working at 18 and retire at 63 in line with the literature (see for example FRED data)). Whites die at age 80, while Blacks at age 72.

Assuming a CES utility with $RRA = \theta$ and common discount factor β, we find that:

$$
\begin{aligned}
c_0^j &= \frac{1 - \left(\beta R^{1-\theta}\right)^{\frac{1}{\theta}}}{1 - \left(\beta R^{1-\theta}\right)^{\frac{T^j}{\theta}}} \frac{1 - R^{-L}}{1 - R^{-1}} y_0 \\
c_t &= (\beta R)^{\frac{t}{\theta}} c_0.
\end{aligned}
$$

We can then solve savings (and consumption) profiles varying our parameters of interest: i. difference in life-expectancy, and ii. gross interest rates. It is important to note that in these models what matters in terms of consumption and savings evolution over the life-cycle is the discounted (gross) rate of return, so that aside for the initial level of consumption c_0 one cannot parse out R, and β. In Figure **??** below we present a series of scenarios characterized by the difference in life-expectancy $T^W - T^B = 0, 8, 12$ and gross returns on assets $R^W = 1.07$ for Whites, while we vary it for Blacks ($R^B = [1.02, 1.07]$); finally, we fix $\theta = 1.5$, and $\beta = .995$. For the difference in gross returns we base our scenarios on the existing literature on asset allocations (for example Badu et al. (1999) write: *...We find that Black households are significantly more risk averse in their choice of assets. Further, we find that Black households typically pay higher rates for several types of credit instruments, even though they self identify as conducting significantly more extensive searches in the financial markets...*).

What is immediately visible for Figure 2 is that the combination of difference in life-expectancy and returns on asset contribute substantially to the accumulation of savings earlier in life. The larger the differences, the larger the saving rate gap. Below we will show that, in the data, the wealth of White individuals is on average 3.5 times larger than the wealth of Black people. The number is matched by this simple model when the life-expectancy differential is 8 years and the differential in the rate of return is around 3pp.

This "trivial" model appears able to fit an important starting point for the current paper. Given a life-expectancy difference of 8 years, as in our cohorts, and gross rate of return differential of 3pp, we can fully explain the differential saving stocks between Blacks and Whites. What does this mean in terms of consumption persistence will become clear throughout the rest of the paper.

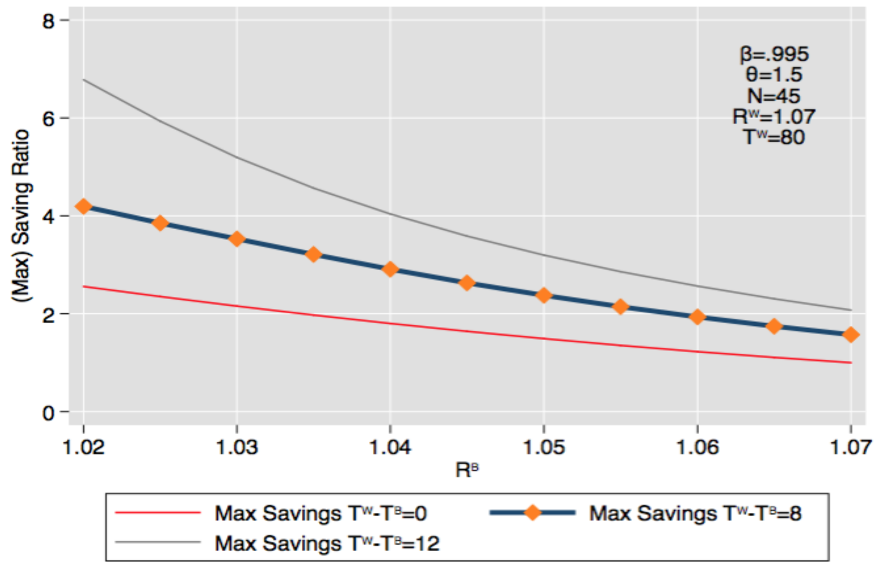

Figure 2: Model Simulations for Different Life-expectancies and (gross) Interest Rates

3 Data

We use data from the Panel Study of Income Dynamics (PSID), a longitudinal survey conducted by the University of Michigan. The PSID began in 1968 with two samples: the Survey of Economic Opportunity (SEO) sample focused on low income families, while the Survey Research Center (SRC) sample interviewed a nationally representative selection of families. Members of these households became PSID "sample members" and were surveyed annually until 1997 (each yearly survey is called a "wave"), after which they were surveyed biannually. Furthermore, all lineal descendants of original sample members become sample members themselves and were independently followed and surveyed once they started their own families. Due to budgetary constraints, in 1997 the PSID dropped approximately 25% of its sample households, with reductions made mainly to the SEO subsample.

The PSID collects a wide range of variables, including information on demographics, income, and consumption. Most data is collected at the household level, though information for PSID-defined household "heads" and "wives" is also gathered. A limited selection of questions are asked about other family members. Typically, a family head is the male in a married pair with primary financial responsibility for the family. A wife is the female counterpart of the married couple. Females only qualify as heads in single adult households (single males can also be heads, of course). If a female head marries a man, he becomes the new head and the woman's classification changes to 'wife.'

3.1 Building the Dataset

To create our dataset for the analysis, we append together all waves from 1968-2017. The full PSID dataset contains 1,856,953 individual-year observations. We limit our sample to the SEO and SRC samples, eliminating individuals from the Immigrant and Latino surveys (two other surveys conducted by the PSID that we do not use due to limited data availability). We also include only current heads, since they are the individuals with the richest and most consistent set of observables over time. As there is one head per household, our analysis is therefore effectively at the household level.

We also create a consistent race indicator for all individuals. The PSID asked heads to identify their race in every wave. For all heads, we assign race as the mode value of race from all reported years. Due to the limited sample size of some reported races, we only keep individuals identifying themselves as Black or White. Our full sample, using all waves of data, includes 457,286 individual-year observations. In our main regression analysis, however, we define a base year of 1981 - so only individuals present in the 1981 wave and beyond are included. This brings us to 219,956 individual-year observations (from waves 1981-2017). The choice of 1981 as the base year is merely dictated by sample size considerations. We have also repeated the analysis using different base years.

3.2 Family Income

The PSID consistently asks respondents to report their household's total monetary income, defined as the sum of the taxable income of the head and wife, the total transfers of the head and the wife, the taxable income of other family unit members, and the transfer income of other family unit members. Beginning with the 1994 wave, the measure also includes total family Social Security income. For prior years, when Social Security was not already included in family income, we added in separate measures of Social Security income to family income. Before 1994, family income in the PSID data is bottom-coded. Any negative or zero values are recoded to $1. Because this practice occurs for many years, we apply the same rule to the remaining years of data. To convert nominal incomes to real terms, we divide the nominal measure by the Consumer Price Index (CPI). In order to create a per capita measure, we then divide total family income by an Adult Equivalent scale, given by:

$$AE = 1 + 0.7(A - 1) + 0.5K \tag{1}$$

where A is the number of adults in the household and K is the number of children in the household. This scale assigns a value of 1 to the first household member, of 0.7 to each other adult in the household and 0.5 to each child. [3]

Our measure of real adjusted family income (TFA) is

$$TFA_i = \left(\frac{Nominal\ Family\ Income \times 100}{CPI \times AEscale} \right). \tag{2}$$

We multiply Family income by 100 to preserve the scale of the variable given that CPI is equal to 100 in the base year.

3.3 Consumption Imputation

For all years besides 1973, 1988, and 1989, the PSID asks respondents to report the monetary value of their family's consumption of food at home, food away from home, and food stamps. Therefore, household expenditures on food consumption are consistently recorded throughout the entire period. Then, beginning in 1999, households are also asked to detail their spending on a wide array of goods, such as utilities, transportation costs, and healthcare. Unfortunately, spending on clothing, vacations, entertainment, and other similar discretionary spending is only available since 2005.

Since much consumption spending information is not available prior to 1999, we use an approach developed by Blundell et al. (2008) that imputes household consumption using a demand function derived from other variables consistently present in the PSID. Specifically, the method uses spending on food, socio-demographic information (state, age, number of children, maximum education, marital status, disability, etc...), and price controls to predict non-food consumption (defined as total expenditures on rent equivalents, home insurance, electricity, heat, water/sewage, miscellaneous utilities, car insurance, gas, parking, bus/train, cabs, other transport, school fees, other school costs, childcare, health insurance, hospital care, doctors, and drugs). The idea is to estimate the relationship between consumption variables and the consistently reported demographic variables and food payments in later years, and use this relationship to predict consumption expenditure in earlier years.

Let n_{it} be our non-food consumption measure, defined as total expenditures on rent equivalents, home insurance, electricity, heat, water/sewage, miscellaneous utilities, car insurance, gas, parking, bus/train, cabs, other transport, school fees, other school costs, childcare, health insurance, hospital care, doctors, and drugs. Since consumption can

[3]This scale, which is sometimes called the "Oxford scale", has been first proposed by the OECD in 1982. We also probe the robustness of the results to the chosen scale.

sometimes take on the value of zero, instead of taking the log of consumption we consider the Inverse Hyperbolic Sine transformation, defined as:

$$IHS(n_{it}) = \ln\left(n_{it} + \sqrt{n_{it}^2 + 1}\right) \tag{3}$$

The model consists of the following regression, estimated using data from waves 1999-2017:

$$IHS(n_{it}) = Z_{it}\beta + p_t\gamma + g((f_{it};\theta)|\mu_{it}) \tag{4}$$

Z represents an array of dummy variables for our various demographic covariates: race, state, age, number of children, maximum education, employment, marital status, home-owner status, self-employment, and disability. We also include continuous covariates for total number of hours worked and total number of family members. We add p for price controls: the yearly CPI and the CPIs for food at home, food away from home, and rent. The polynomial function *g(.)* includes food expenditures, *f*, and μ is an error term, with θ measuring the importance of the different types of food expenditure. f_{it} stands for food at home, food away from home and food stamps, for individual i in year t.

Once the demand function is estimated for years 1999-2017, we use the coefficients to predict non-food consumption in all waves, including the earlier years. Total imputed consumption is then found for each household-year by adding their actual food consumption to the imputed non-food consumption. First we recover imputed non-food consumption from the Inverse Hyperbolic Sine transformation, and then we add actual food consumption:

$$c_{hat} = exp\{Z_{it}\hat{\beta} + p_t\hat{\gamma} + g(f_{it};\hat{\theta})\} \tag{5}$$

$$c_{IHS} = \left(\frac{c_{hat}^2 - 1}{2 \times c_{hat}}\right) \tag{6}$$

$$Nominal\ Imputed\ Consumption = \hat{c} = f_{it} + c_{IHS} \tag{7}$$

Since all consumption expenditures are reported at the household level, we divide this value by the Adult Equivalent scale. We also use a CPI adjustment to convert consumption into real terms:

$$Real\ Imputed\ Consumption = TCP_i = \left(\frac{\hat{c} \times 100}{CPI \times AEscale}\right) \tag{8}$$

As we will see later, we also probe our results using actual consumption expenditure whenever possible.

3.4 Quintiles

To measure consumption and income mobility over the life-cycle, we group individuals into quintiles based on two different measures: Adult Equivalent (AE) imputed consumption (TCP) and AE family income (TFA). For each of these two measures, we order *all* individuals by their consumption (or income) and assign quintiles based off their position in this *national* ranking for each year, i.e. this measure responds to perhaps the more interesting question of how are different groups faring in the national socio-economic distribution. Another potentially interesting ranking is that based of within group mobility which we will not consider in this paper.

Note that in the PSID there is an over-representation of Blacks with respect to their prevalence in the US population. Indeed, Black individuals constitute on average more than 34% of our sample, whereas, according to the 2010 census, Black people constitute around 14% of the total US population. Hence, in order to avoid bias given by the fact that our lowest income and consumption quintiles could be mechanically filled by Blacks due to their high number, we use weights to ensure that population shares are adequately represented. This means that a weight equal to 1.3 is given to each Whites observation, whereas a weight of 0.4 is given to each Blacks observations. In the following, we call these weights "census weights". Census weights are used in the current paper in all the analyses in which Blacks and Whites are considered together, for example in the construction of income and consumption quintiles.

4 Differential Savings, Insurance and Health

We begin our empirical analysis by assessing whether there are substantive differences between Blacks and Whites in terms of savings and wealth accumulation.

4.1 Savings and Wealth Accumulation

In the previous section we have shown through a simple model that differences in life expectancy imply sizeable differences in saving rates and wealth accumulation. We begin the analysis by investigating whether there are relevant racial differences in the amount of wealth, savings and/or income from wealth.

We compute wealth as the sum of seven asset types: imputed value of farm or business, imputed value of cash savings, imputed value of real estate other than home, imputed value of stocks, imputed value of vehicles, imputed value of other assets, value of home equity net of debt. This wealth measure is divided by the Consumer Price Index (CPI), in order to obtain a measure of wealth in real terms.

Panel (a) of Figure 3 plots the extensive margin for wealth holding, i.e. the percentage of individuals having positive wealth across consumption quintiles. Differences between Blacks and Whites households are between 2-7pp across all the consumption quintiles. However, from the panel (b), it is striking that, among people with a positive wealth, Blacks own far less of it than Whites, and this is particularly evident in the top TCP quintile. Wealth accumulated by Blacks is on average 3-7 times smaller than that accumulated by the Whites. Such a differences while extremely large are reasonable, even if we suppose that income processes do not vary according to race, given the racial differential in life expectancy. As shown in Section 2, the shorter life-expectancy and higher returns on assets can explain these differences.

Panel (a) Panel (b)

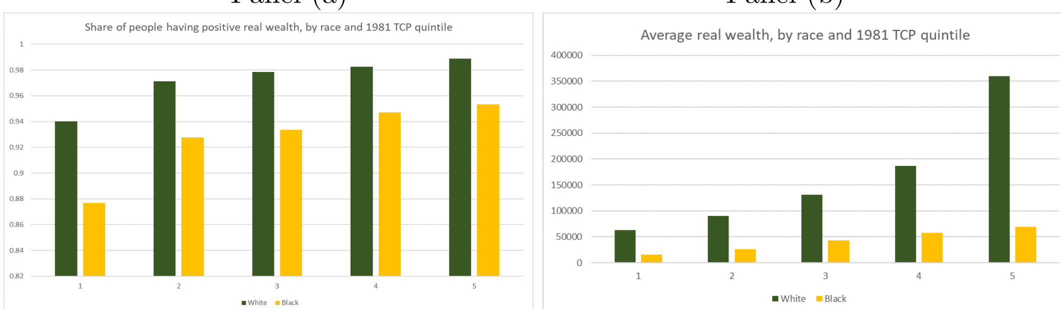

Figure 3: Panel (a): extensive margin for wealth (in real terms): share of people having positive real wealth, by 1981 TCP quintile. Panel (b): intensive margin, wealth by 1981 TCP quintile, people with zero wealth have been excluded. Wealth is computed as the sum of seven asset types: imputed value of farm or business, imputed value of cash savings, imputed value of real estate other than home, imputed value of stocks, imputed value of vehicles, imputed value of other assets, value of home equity net of debt. This wealth measure is divided by the Consumer Price Index (CPI), in order to obtain a measure of wealth in real terms. Data on wealth are available for the years 1989, 1994 and 1999-2017.

Panel (a) Panel (b)

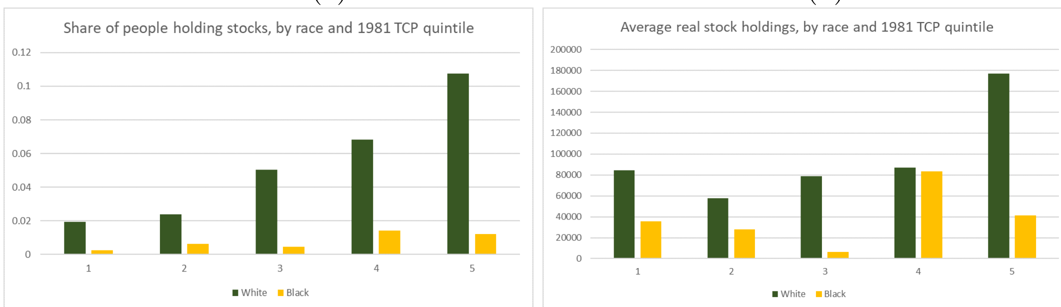

Figure 4: Average value of stock holdings in US dollars divided by CPI, by race and by 1981 TCP quintile Panel (a): extensive margin for real stock holdings. Panel (b): intensive margin for real stock holdings, people with no stocks have been excluded. Data for the 1999-2017 period.

Similarly to what we did earlier for total wealth, in Figure 4 we show the intensive and extensive margin for stock holdings. A few remarks are in order. First, there are huge racial differences in the percentage of households holding stocks. For example, in the top 1981 TCP quintile only, more than 10% of Whites households hold stocks, whereas only around 1% of Blacks households do. Second, there are also relevant differences in the amount of stocks held. In the top 1981 TCP quintile, a White individual holds on average 180'000 US dollars in stocks, whereas a Black individual only holds around 40'000 US dollars. These differences in stock holdings are suggestive of large differential returns on assets and this difference is particularly relevant at the top TCP quintile. Given the very low probability of holding stocks in the bottom 3 quintiles (below 5pp), especially for Blacks (below 2pp), we shouldn't be surprised of the intensive margin for the bottom 4 quintiles showing some non-monotonic relation.

Panel (a) Panel (b)

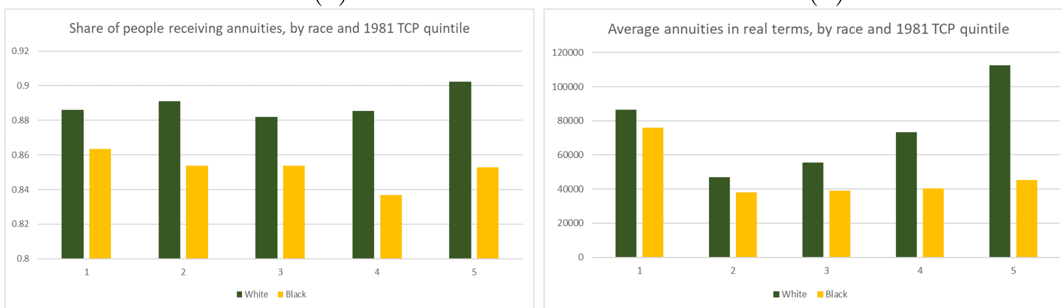

Figure 5: Panel (a) extensive margin for receiving annuities. Panel (b) intensive margin. People receiving no annuities have been excluded from Panel (b). Data for the 1999-2017 period.

In the PSID data the variable "annuities" is defined as follows. After a first filter question: "Did you receive any income in previous year from other retirement pay, pensions, or annuities?", then the sub-question "Then, how much of this was from annuities or IRAs?" gives the numeric value of our variable of interest. An annuity is commonly defined as a financial product that pays out a fixed stream of payments to an individual. These financial products are often used to ensure having a stable income stream during retirement age, as well as to avoid the risk of outliving one's savings. From Figure 5, we find evidence of significant racial differences, not only in the share of individuals receiving annuities, but also, among those receiving it, in the average yearly amount received. From Panel (a), the share of people receiving annuities is around 4pp higher among Whites in each consumption quintile. Further, from Panel (b), it emerges that among people who receive annuities, Whites in the top 1981 TCP quintile receive an average amount which is more than double than that received on average by Blacks in the same consumption quintile.

To wrap up: we find substantial racial differences in the amount of savings and wealth accumulation. In particular, the ratio of wealth held by Whites versus Blacks increases as hypothesized along the consumption distribution, and in general appears to be at least 3-7 times higher for Whites than for the Blacks.

4.2 Insurance

The results of the previous section point to a huge difference in the amount of savings and wealth of Whites and Blacks. This is suggestive of a potential important difference in the level of consumption insurance achieved. More specifically we conjecture that even for households in the same top quintile, Blacks have a lower degree of partial insurance than Whites: having then a more volatile consumption with potentially larger downfalls. In order to test this hypothesis, we adopt the framework developed by Blundell et al. (2008).

In line with that work, we disentangle the permanent and transitory income component and we allow the variances of the permanent and transitory factors to vary over time. Further, we assume that the permanent component follows a random walk. Suppose log income, $\log Y_t$ can be decomposed into a permanent component P and a mean-reverting transitory component v. Then the income process for an household i is:

$$\log Y_t = Z'_{i,t}\varphi_{i,t} + P_{i,t} + v_{i,t} \tag{9}$$

where Z is a set of observable income characteristics such as demographic, education, race and other variables. We allow the effect of these characteristics to shift with calendar time and we also allow for cohort effect. The impact of the deterministic effects $Z_{i,t}$ on log income and (imputed) log consumption is removed by separate regressions of these variables on year and year-of-birth dummies, and on a set of observable family characteristics (dummies for education, race, family size, number of children, region, employment status, residence in a large city, outside dependent, and presence of income recipients other than husband and wife). As in Blundell et al. (2008), we then work with the residuals of these regressions. We assume that the permanent component follows the following process:

$$P_{i,t} = P_{i,t-1} + \zeta_{i,t} \tag{10}$$

where $\zeta_{i,t}$ is serially uncorrelated and the transitory component $v_{i,t}$ follows an MA(q) process, whose order is established empirically. We are interested in assessing how income shocks differently transmit to consumption for Blacks and Whites households. We write unexplained change in log consumption as:

$$\Delta c_{i,t} = \phi_{i,t}\zeta_{i,t} + \psi_{i,t}\varepsilon_{i,t} + \xi_{i,t} \tag{11}$$

where $c_{i,t}$ is the log of real consumption net of its predictable components. We allow permanent income shocks ($\zeta_{i,t}$) to have an impact on consumption with a loading factor of $\phi_{i,t}$. On the other hand, the impact of transitory income shocks $\varepsilon_{i,t}$ is measured via the factor loading $\psi_{i,t}$. The random term $\xi_{i,t}$ represents innovations in consumption that are independent of those in income (this may capture measurement error in consumption, preference shocks, etc.). Our aim is to estimate $\phi_{i,t}$ and $\psi_{i,t}$, which are our insurance parameters. In case of full insurance, they would be both equal to zero, whereas in case of no insurance they would be both equal to 1. These parameters are estimated by diagonally weighted minimum distance.

	Whites	Blacks
ϕ	0.7687***	0.7959***
	(0.0650)	(0.1182)
ψ	0.1026***	0.1699***
	(0.0322)	(0.0550)

Table 1: Degree of partial insurance of Blacks and Whites towards permanent vs transitory income shocks. Bottom 0.5% of consumption has been trimmed.

The parameter ϕ represents the degree of insurance with respect to permanent income shocks, whereas the parameter ψ stands for the degree of insurance with respect to transitory income shocks. In both cases, the lower the value of the parameter, the higher the degree of partial insurance, the smoother the consumption profile and the smaller the consumption responses to both types of income movement. From Table 1, it emerges that Blacks are less insured than the Whites, both with respect to transitory and to permanent shocks. This is likely to explain the remaining differences in consumption persistence between Blacks and Whites, in particular at the top of the distribution. Different racial degrees of partial insurance are likely to be at the root of racial differences in persistence across the consumption distribution. However, these differences in the estimated coefficients for partial insurance across race are not statistically different from each other, neither for the permanent nor for the transitory shock coefficient. This has been verified by performing 100 bootstrap replications of the estimation presented above. While the parameters are not statistically different from each others, those differences are economically quite substantial in particular for the transitory component. Indeed, a 1 USD temporary shock translates into a 17 cents consumption fall for Blacks, whereas it only translates into a 10 cents consumption fall for Whites. A permanent shock has clearly a much large impact on consumption, as predicted by the theory, on both Blacks and Whites, with 1 USD of permanent fall in income pushing down consumption by 80 and 77 cents for Blacks and Whites respectively. Notice that the variance of the two components are very similar for Blacks and Whites, confirming the validity of our original assumptions on similar income processes between Blacks and Whites after controlling for a few demographic and labor market characteristics.

	Whites	Blacks
Var of permanent component	0.0395	0.0509
Var of transitory component	0.0432	0.0586

Table 2: Variance of the permanent and of the transitory income component, by race. Bottom 0.5% of consumption has been trimmed.

This suggests that Blacks and Whites are subject to similar shocks during their life-cycle, but what determines their different degree of positional persistence in the consumption distribution is how they react to these shocks (i.e. drawing from their savings or reducing consumption permanently). Note that the similarity in income variances between Blacks and Whites is not merely a consequence of the modellization adopted, but is instead a feature present in the data. A simple descriptive statistics shows that the overall cross-sectional standard deviation of log wages, which can be considered as a rough measure of income volatility, is equal to 1.28 for the Blacks and to 1.59 for the Whites, i.e. these standard deviations are rather close (Households with zero wage have also been included, as having the value of 1, in this computation).

4.2.1 Sources of Insurance for Whites and Blacks

When hit by a shock, an individual may resort to one or more of three main sources of insurance, i.e. social or government insurance, family insurance and self-insurance.

While the previous section provide some insights on how much insurance is achieved by Blacks and Whites, it doesn't directly decompose the contribution to the final nexus income-consumption mediated by all the possible sources of insurance. We here investigate those different sources. As far as family insurance is concerned, we are not able to precisely estimate how much this channel accounts for in case of a shock for Blacks and for Whites. However, based on some descriptive evidence in our data, we can deduce that Blacks in general have a lower access to this insurance channel. Indeed, Blacks usually have more out-of-wedlock children and they also on average get married more times during their lifetime than Whites. It appears that with multiple and changing family ties the fundamental for informal insurance aren't particularly solid. Just to provide an example, in the top consumption quintile, 20% of Blacks are divorced, whereas only 10% of Whites are. Further, Blacks are less likely than Whites to receive an inheritance and, when they do, the average amount is substantially lower.

Finally, as far as social or government insurance is concerned, it is not straightforward that Blacks have more access to it than Whites. It is plausible that the poorer Black households somehow lack knowledge of the administrative procedures which are necessary to obtain social security transfers, and hence are less likely than the (equally poor) White households to obtain them.

Panel (a) Panel (b)

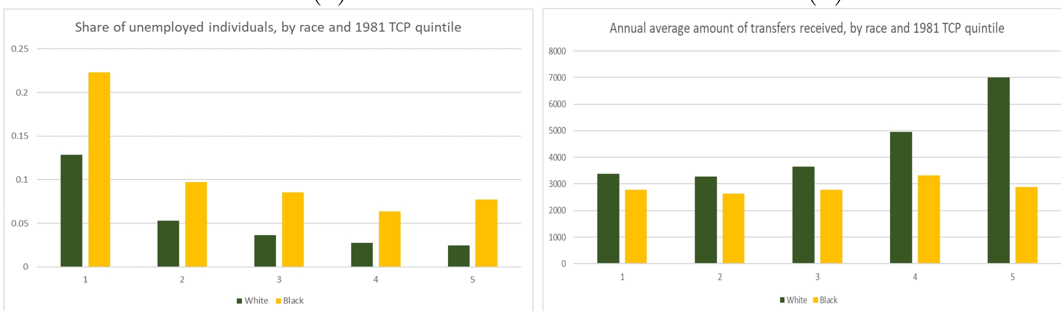

Figure 6: Panel (a): percentage of people who are currently unemployed and looking for a job, by race and by 1981 TCP quintile. Data for 1981-2017. Panel (b) average amount of transfers that households have received in a year, either from public or private sources, by race and 1981 TCP quintile. Data for 1981-2017.

In Panel (a) of Figure 6, we report the share of unemployed households, by race and 1981 TCP quintile, in order to assess whether there are relevant racial differences in the probability of being hit by an income shock. From this Figure, we deduce that, in general, the share of unemployed households is higher for the Blacks than for the Whites. In order to obtain an overview of how much support can Blacks and Whites households receive in case they are hit by a shock, in Panel (b) of Figure 6, we report the average amount of transfers (this time including both private and public sources) received in a year. From this panel we notice that this average amount of transfers is higher for Whites than for Blacks in any TCP quintile, and in particular at the top, where the average amount is more than double for the Whites than for the Blacks.

As far as other external channels of insurance against income shocks are concerned, there is a large literature on racial differences in credit market access. Just to mention some examples, Arrow (1998) claims that credit market is one of the many aspects in which economic discrimination may manifest itself, and Blanchflower et al. (2003) find evidence that, all other relevant factors being equal, Black-owned small businesses are around twice as likely to be denied credit than White-owned ones. Dymski and Mohanty (1999) further suggests that one of the reasons why Blacks have lower access to the credit market may be that there are fewer bank branches in the urban areas which are mostly populated by Blacks. As an important point, on average, the interest rate paid by Whites on their first mortgage is 5.61%, whereas that paid by Blacks is 5.87%. This is consistent with the findings by Cheng et al. (2015), who claim that Black borrowers on average pay about 29 basis points more than comparable Whites borrowers, even after controlling for mortgages characteristics. Further, Cheng et al. (2015) report that the median mortgage amount for Blacks is 105'000 US dollars, while for Whites is 120'000 US dollars; this is consistent with our hypothesis that Blacks have a harder time in accessing the credit market than Whites. Moreover, Blacks seem to prefer long-term mortgages (30-year-loans) than Whites (71% vs 57.8%, Cheng et al. (2015)). Similarly, on the basis of more detailed data, Bayer et al. (2016) show that African-American and Hispanic borrowers were respectively 103 percent and 78 percent more likely to receive high-cost mortgages for home purchases before the Great Recession, even after controlling for individual credit scores and other risk factors. Moreover, Blacks have been more exposed to foreclosures than Whites during the crisis (Bayer et al. (2017)).

4.3 Exposure to Health Shocks

In order to dig further into the issue of the different degrees of insurance for Black and White households, we analyze whether Blacks and Whites have different degree of health insurance and whether they react differently to a health shock.

Panel (a) Panel (b)

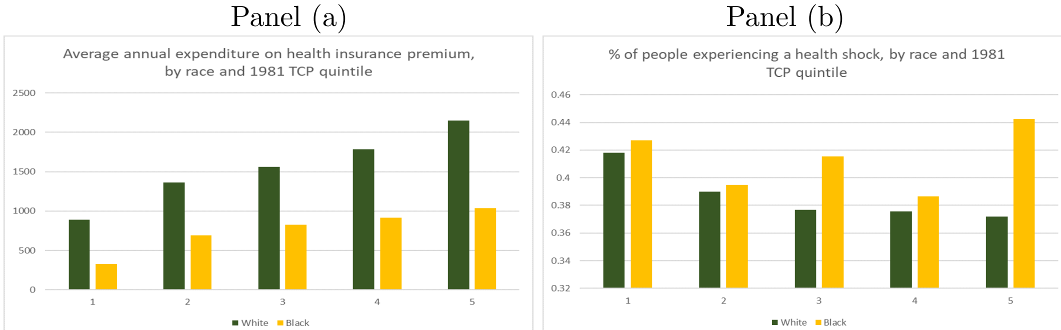

Figure 7: Panel (a): average annual amount (in US dollars) of expenditure for health insurance at the family level, by race and by 1981 TCP quintile. PSID data for the period 1999-2017. Panel (b): share of households being affected by an health shock. An health shock is defined as insurgence of any of the nine major health problems recorded in the PSID in the period 1999-2017.

As a first exploratory analysis, in panel (a) of Figure 7 we report the average expenditure on health insurance, by race and by 1981 TCP quintile. This information is available in the PSID from 1999 onwards. The amount paid by Whites for health insurance each year is on average way higher than the amount paid by the Blacks and the difference widens in the upper part of the consumption distribution. This is a first supporting evidence to the claim that Blacks are less insured than Whites against health shocks, even when they are at the top of the consumption distribution.

From panel (b) of Figure 7, we get evidence that Blacks are more exposed than Whites to health shocks, and that this difference is particularly evident at the top 1981 consumption quintile. In particular, the probability of being hit by any of the following diseases, asthma, arthritis, cancer, diabetes, high blood pressure, heart attack, heart disease, lung disease, stroke, is in general higher for Blacks and particularly so at the top of the consumption distribution where 44% of Blacks compared to 37% of Whites are hit by any of those health shocks. In order to get further insights on the impact of health shocks on income and consumption, for the survey years for which we have detailed information on individual health status (i.e. 1999-2017), we run an event study by race, in order to assess the impact of a health shock (i.e. a stroke) on both income and consumption.

Given the small number of events, we perform the analysis for the overall sample and not just for the top consumption quintile.

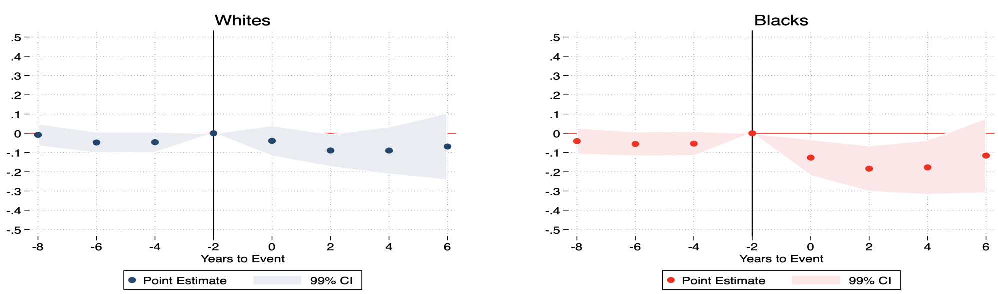

Figure 8: Results of the event study on the impact of a stroke on log consumption, separately for Blacks and Whites households. People who suffered more than one stroke during the period 1999-2017 have been excluded from the sample. The x-axis reports the time to the event, recall that the PSID is bi-annual since 1997. Data for 1999-2017. Standard errors have been clustered at the individual level. In the regression we control for age (non-parametrically), gender, survey year, education dummies, and TFA.

In Figure 8 we report the results of an event study, in which the health shock is represented by the individual having a stroke. For individuals with multiple strokes we define the event as the first one in time. The survey year prior to the stroke is normalized to zero, and then we estimate the impact of the health shock on different time horizons, i.e. two, four and six actual years after the event (recall the PSID is biannual since 1997). Before time zero, i.e. in years -2, -4, -6 and so on, we should find no statistically significant impact of the shock, since these are the placebo years, and that appears to be true for both Blacks and Whites.

However, the negative impact of the stroke on consumption is about -10%, not statistically significant, for Whites with a cumulated effect over the 8 years since the event of -31% (again not statistically different from 0), whereas for Blacks the negative effects are much larger (twice the magnitude) and statistically different from 0 at the 1% level. The cumulative post-event effects is about -68% (significant at the 1% level). Importantly the difference in the cumulated effect between Blacks and Whites is large, with a differential drop of 30% of yearly consumption, this difference is statistically different from 0 at 5% level (we build this test by bootstrap with 300 replications).

Finally, to probe the results we estimate the following models on income and consumption responses to all health shocks, and lags for the health shocks and for the interactions with race directly:

$$\begin{aligned} ln(TCP_{i,t}) &= \alpha + \beta_1 Shock_{i,t} + \beta_2 Black_{i,t} + \beta_4 Shock_{i,t} * Black_{i,t} + \varepsilon_{i,t} \\ ln(TFA_{i,t}) &= \alpha + \delta_1 Shock_{i,t} + \delta_2 Black_{i,t} + \delta_3 Shock_{i,t} * Black_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{12}$$

	(1) LTCP	(2) LTFA	(3) LTCP	(4) LTFA
Shock	-0.0565***	-0.0858***	-0.0721***	-0.0530***
	(-10.21)	(-7.95)	(-14.65)	(-4.72)
$Shock_{t-1}$	YES	YES	YES	YES
$Shock_{t-2}$	YES	YES	YES	YES
$Shock_{t-3}$	YES	YES	YES	YES
Black	-0.457***	-0.787***	0	0
	(-36.99)	(-23.72)	(.)	(.)
Shock*Black	-0.0235*	-0.0352	-0.0170*	-0.00857
	(-2.49)	(-1.41)	(-1.98)	(-0.44)
$Shock_{t-1} * Black$	0.0166	-0.0817***	0.0312***	-0.0456*
	(1.78)	(-3.33)	(3.59)	(-2.30)
$Shock_{t-2} * Black$	-0.00319	-0.0123	-0.00126	0.0122
	(-0.35)	(-0.50)	(-0.14)	(0.59)
$Shock_{t-3} * Black$	-0.0425***	0.0397	-0.0457***	0.0410*
	(-4.40)	(1.50)	(-5.17)	(2.04)
Constant	8.510***	9.639***	8.396***	9.339***
	(1150.82)	(679.48)	(2382.59)	(1162.64)
P-value of coeff test	0.0013	0.0444	0.0120	0.9713
N	67304	67304	67304	67304

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Consumption and Income responses to health shocks. Standard errors clustered at the individual level. Data for 1999-2017. In Columns (3)-(4), we control for individual fixed effects.

The measure of health shock here is a dummy taking value 1 if, from period $t-1$ to period t, the indivdual records to have a major health problem that he/she had not reported in the previous survey year. As major health problems, we consider the following nine: asthma, artritis, cancer, diabetes, high blood pressure, heart attack, heart disease, lung disease and stroke.

The estimation results of these models are reported in Table 3. From these estimates, we deduce that a health shock has a negative contemporaneous impact on both total family income and consumption. This emerges from all the estimations in Table 3.

Further, the interaction term between the Black dummy and the health shock at time t, when statistically significant, has a negative estimated coefficient in all the model specifications, thus suggesting that Black households face a more negative impact on the health shock on their consumption. This negative impact of the interaction term between race and the health shock appears to be long-lasting, i.e. in some model specifications (estimations (1) and (3)) the estimated coefficient is negative and statistically significant six years after the health shock has taken place. In Table 3 we also report the value of the test for the hypothesis that the sum of the coefficients for all the interaction terms between shock and race is equal to zero. We are able to reject this null hypothesis in the first three model specifications, but not in the last one. In particular, the cumulated effect of the shock on consumption is particularly large for Blacks, as we have seen in the event study, with an overall negative impact 3/5pp.

4.4 Implications

The above evidence has direct implications in terms of life-cycle consumption and income dynamics. The downfall risk for Black people is much higher than for White people. Given that savings accumulation and insurance ability appear much lower for Black individuals and their exposure to health shock is much higher, the probability of moving down in the consumption distribution in principle might be much higher. This is the implication we will investigate in the next section.

5 Life-Cycle Consumption and Income Dynamics

We turn now our attention to life-cycle dynamics. In the previous sections, we have documented that Black individuals have a lower wealth accumulation and savings and they are less insured against shocks. Here we try to understand the implications in terms of life-cycle dynamics. More specifically we try to depict racial differences in terms of movements over the life-cycle within the income and consumption distribution. First we document the evolution of average consumption for the quintiles of the consumption distribution. Second, we measure the tail persistence, i.e. the probability of remaining in the bottom and top quintiles of the distribution. Third, we use rank-rank regression to assess in which part of the distribution individuals starting from a given percentile end up. In all the results and Figures presented in this Section, each individual in a given year is assigned to the income/consumption quintile (or percentile, for the rank-rank regressions), according to her position in the overall income/consumption distribution of that particular year. Our aim here is to describe the short and long-term movements along the national distribution.

5.1 Life-Cycle Profiles

In Figure 9, we show the life-cycle consumption profile for Blacks and Whites in the five quintiles. The lines represent the average consumption for White and Black individuals within the same baseline quintile as of 1981. This provides information about life-cycle evolution of consumption between the two groups and given their starting point.

It is apparent from the graphs that the consumption profile of the Whites is always higher than that of the Blacks, in any of the considered quintiles. Differences are smaller when the head of the household is young (i.e. in his 20s or 30s). On the contrary, this difference appears to grow with age, especially in the bottom and in the top consumption quintiles. This behavior for the difference is in fact consistent with the differential asset accumulations we have documented earlier.

Figure 10 reports the results for life-cycle income. As for consumption, the life-cycle income profile of the Whites is always higher than that of the Blacks in every quintile. Again, the distance between the profiles of the two groups appears roughly to grow with age.

So while consumption of White individuals in the top quintile does not fall at older ages, income does. This suggests an important role for wealth to keep consumption high. The income and consumption profiles reported in Figures 9-10 are divided by the (income, resp. consumption) quintiles to which the individual belonged in 1981.

Figure 9: Life-cycle consumption profile for racial groups in the different TCP quintiles. The reference year for the division into consumption quintiles is 1981. Data for the 1981-2017 period.

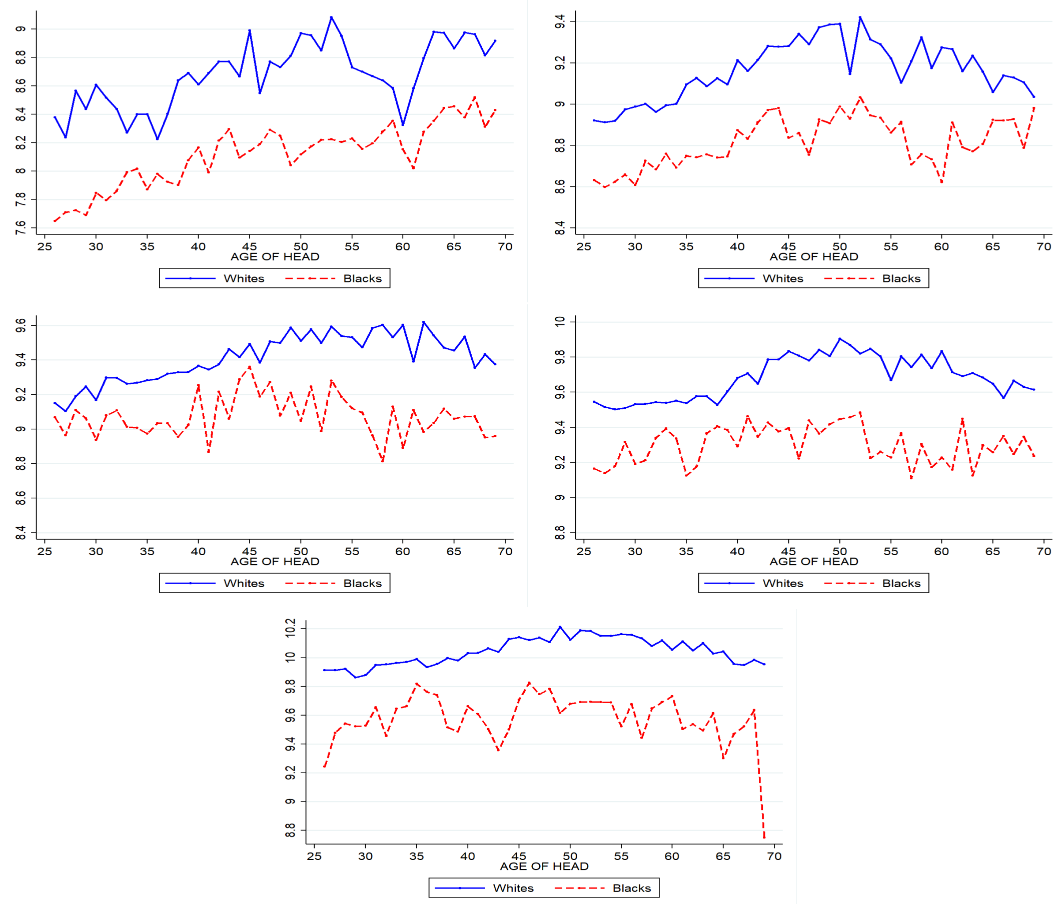

Figure 10: Life-cycle family income profile for racial groups in the different TFA quintiles. The reference year for the division into consumption quintiles is 1981. Data for the 1981-2017 period.

Given the highlighted life-cycle profiles it is natural to ask how much mobility there is across quintiles as people get older. We will approach such question in a couple of ways: i. through Persistence Probabilities; and ii. Rank-Rank analysis.

5.2 Persistence Probabilities

We study the persistence probabilities in the bottom and top quintiles, those are natural focal points being the tails of the distribution. More specifically we construct the probability of staying in the bottom quintile for a household first observed in the bottom quintile, and the probability of staying at the top if the household begins at the top. While the analysis of average mobility - i.e. the persistence in any given quintile - is interesting as well, it could mask important heterogeneity for the two natural focal quintiles: bottom and top. Our rank-rank analysis in the next section will partially cover the overall distributional dynamics.

As mentioned we set 1981 as a base year, using all (Blacks and Whites) households present in the PSID at that time as our fixed sample, i.e. a standard panel of households over time. We then analyze the transition probabilities for each household for every survey-year up to 2017. Therefore, we are able to capture a substantial part of the life-cycle, as our typical household head is 42 years old in 1981.

To compute persistence probabilities we proceed as follows. Conditional persistence in the top quintile is defined as the coefficient β_5 in the following regression model:

$$\begin{aligned} Q5_{it} = \alpha &+ \beta_2 Q2_{i1981} + \beta_3 Q3_{i1981} + \beta_4 Q4_{i1981} + \beta_5 Q5_{i1981} + \gamma_1 Age_{it} + \gamma_2 AgeSq_{it} \\ &+ \gamma_3 Gender_{it} + \gamma_4 Industry_{it} + \gamma_5 Edu_{it} + \gamma_6 QuintileRank_{i1981} + \epsilon_{it} \end{aligned} \tag{13}$$

Similarly, we estimate conditional persistence in bottom quintile via the following regression (the coefficient of interest is β_1 here):

$$\begin{aligned} Q1_{it} = \alpha &+ \beta_1 Q1_{i1981} + \beta_2 Q2_{i1981} + \beta_3 Q3_{i1981} + \beta_4 Q4_{i1981} + \gamma_1 Age_{it} + \gamma_2 AgeSq_{it} \\ &+ \gamma_3 Gender_{it} + \gamma_4 Industry_{it} + \gamma_5 Edu_{it} + \gamma_6 QuintileRank_{i1981} + \epsilon_{it} \end{aligned} \tag{14}$$

where QK_{it} is a dummy variable taking value 1 if individual i is in the Kth (income, resp. consumption) quintile at date t and zero otherwise. Further, QJ_{i1981} is a dummy equal to 1 if individual i was in the (income/consumption) quintile J in 1981, our base year. $Gender_{it}$ is a dummy for being female, Edu_{it} is a categorical variable corresponding to different maximum education bins; namely, these four education bins are: (i) 0-11 grades, (ii) high school or 12 grades plus some nonacademic training, (iii) college dropout, (iv) BA degree, or college or professional degree. $Industry_{it}$ stands for the individual's industry of employment. Further, $QuintileRank_{it}$ stands for the uniform rank (i.e. position) of the individual in the income/consumption distribution *within* the (income/consumption) quintile in 1981. The inclusion of this variable among our controls allows us to avoid biases due to the different positions of Blacks and Whites within the same quintile. It is possible, for example, that the Blacks are more often close to the bottom threshold of the top quintile than the Whites. For this reason, they could be mechanically more likely to fall out of it if hit by a shock, and hence to exhibit a lower degree of persistence. By including the within-quintile rank among the regressors, we purge our results from this effect.

Figure 11 plots the estimated persistence probabilities. Several interesting findings emerge. First, Whites are more persistent at the top while Blacks are more persistent at the bottom for both consumption and income. Second, differences in income persistence between Whites and Blacks tend to disappear in the long run. On the contrary differences in persistence in the consumption distribution are permanent. For Blacks the downfall risk is much higher, in the long-run around 40% of Whites are still in the top consumption quintile, while for Blacks the corresponding figure is around 5%. On the contrary, at the bottom of the distribution racial differences in consumption persistence do not seem to be significant. Third, differences in the persistence at the top of the income distribution are much smaller than for consumption. Still the probability of remaining at the top of the income distribution is higher for Whites but the differential is substantially smaller. The findings square with the implication discussed in the previous sections. Black people have lower savings, and are less insured, and this can explain the fall from the top of the consumption distribution.

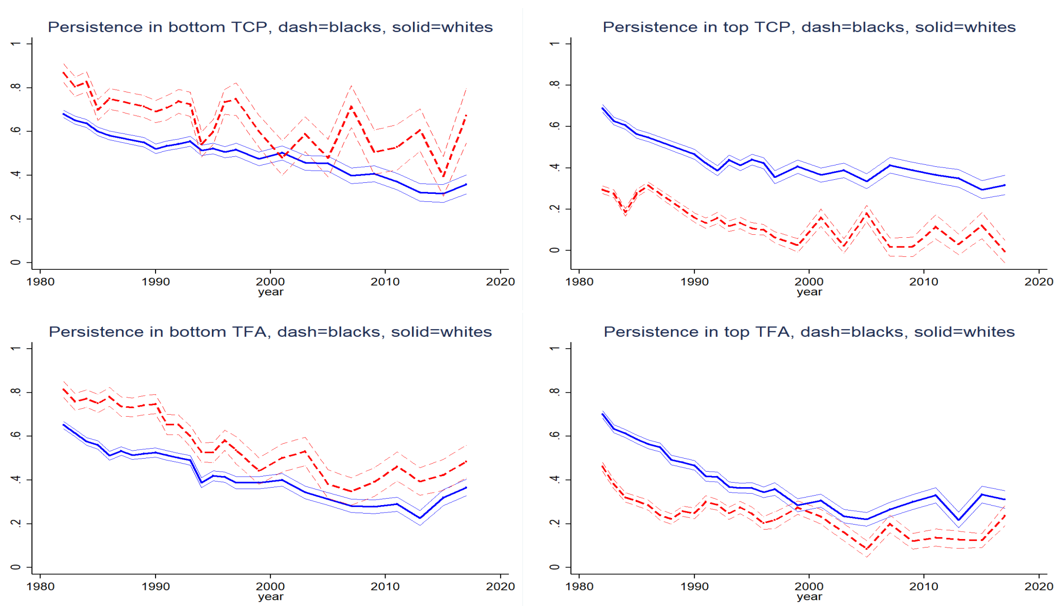

Figure 11: Persistence at the bottom/top TCP/TFA quintiles. OLS regressions, controls: quintile rank, age, age squared, gender, education, industry. Census weights are used to construct the quintiles. Period 1981-2017.

We argue that the observed differences in persistence at the top of consumption distribution between Blacks and Whites are due to their different degree of insurance against permanent shocks. Indeed, in the analysis presented in the previous Sections, we show that the stock of savings held by Blacks is way lower than that held by Whites and this difference is particularly striking at the top quintile. This implies that, if a Blacks individual is hit by a negative income shock, then she is forced to reduce her consumption level. Permanent and transitory income shocks translate into much larger falls in consumption due to the lack of insurance.

5.3 Rank-Rank Regressions

In order to obtain insights on the differences in the degree of income and consumption persistence of Blacks and Whites along the overall distribution, we perform a rank-rank analysis in the spirit of Chetty et al. (2018). The idea is to estimate the mean (income/consumption) percentile in which an individual ends up given that she was in a given (income/consumption) percentile in the base year. For example, we may consider individuals who were in the 10th lowest income percentile in 1981. In which income percentile do they end up on average in, say, 2011? The rank-rank analysis allows us to answer such questions, separately by race, and to provide a simple graphic intuition of the results. We aim at assessing whether Black and White individuals ended up in different income and consumption percentiles, either starting from the top, middle, or the bottom of the distributions, after 10, 20 and 30 years from the base year (1981). We perform this analysis separately by race, both in an unconditional, i.e. without control variables, and in a conditional version, i.e. with control variables, and for both income and consumption.

In Figure 12, we report the results of the unconditional rank-rank regressions. On the x-axis we have the percentile in 1981 while on the y-axis we report the percentile in 1991 (first row), 2001 (second row) and 2011 (third row) covering then 10-20-30 years transitions. The left column refers to the income distribution and the right column to the consumption distribution. Several interesting findings emerge. First, in all of the panels of the figure, the blue line (Whites) is above the red line (Blacks). Thus, for any possible origin percentile of the income and the consumption distribution, the average destination percentile of Blacks lie below the destination percentile of Whites. White people tend to be more persistent at the top of the distribution, both in terms of consumption and income, relative to Black people no matter the length of the period considered. Just to provide an example, from the upper left panel of Figure 12 we see that if a Black individual was in the 100th (top) income percentile in 1981, then on average she will end up in the 60th income percentile after ten years. On the contrary, a White individual being in the 100th (top) income percentile in 1981 will end up on average in the 80th income percentile after ten years.

Second, and complementing the first result, Black people above the 20th percentile in 1981 are expected, on average, to end up in a lower percentile. On the contrary only

White people above the median are expected to end up in a lower percentile.

Third, there is a quantitative difference between the income and consumption distribution at the top of the distribution. Indeed when considering the 100th (top) percentile, it can be noted that the difference between Blacks and Whites is always larger for consumption than for income. Such differences are in line with our previous findings, i.e. that Blacks are unconditionally less persistent than Whites at the top of the income distribution. For example, if we look closely at the upper right panel of Figure 12, we deduce that a White individual being in the top consumption percentile in 1981 will end up on average above the 80th consumption percentile in 1991, whereas a Black individual being in the top consumption percentile in 1981 will end up on average below the 60th consumption percentile in 1991.

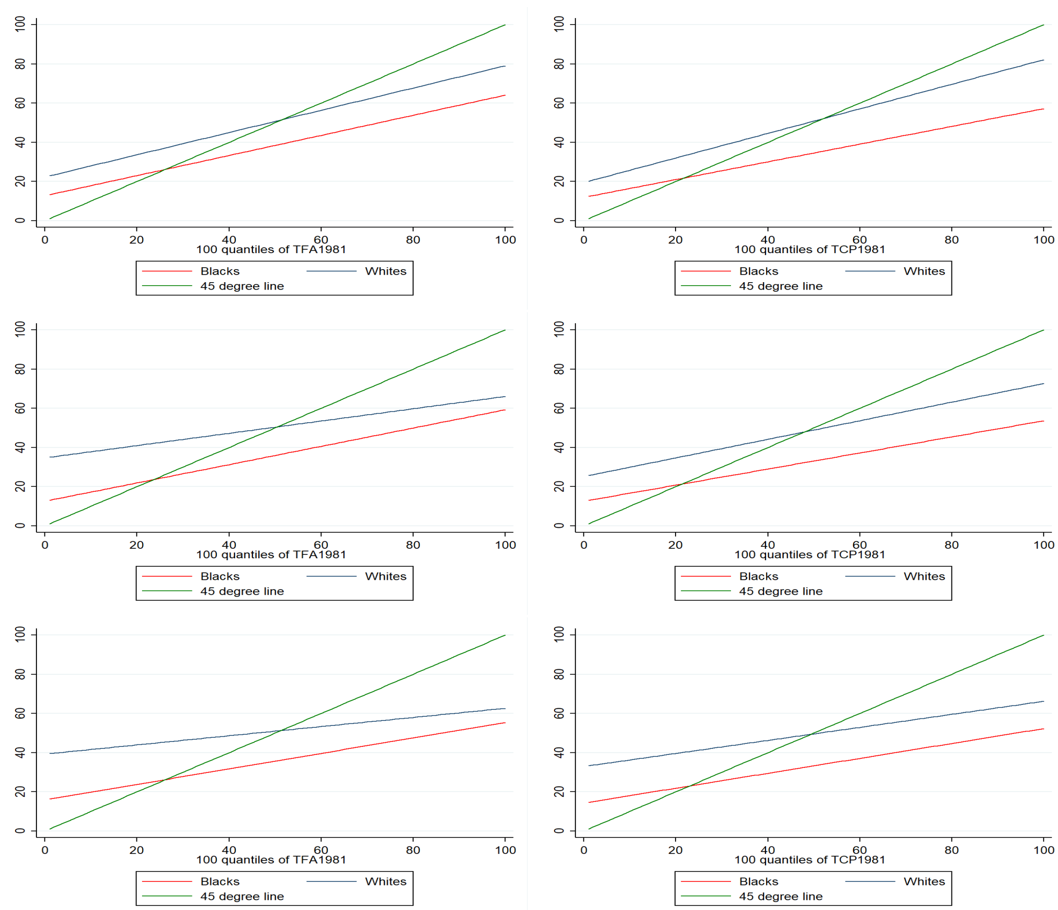

Figure 12: Average TFA (on the left) and TCP (on the right) consumption rank in a fixed year (1991, 2001, 2011) for an individual who was in each income or consumption percentile in 1981, by race. These results are unconditional, i.e. no control variables have been considered. Solid stands for Whites, dash for Blacks.

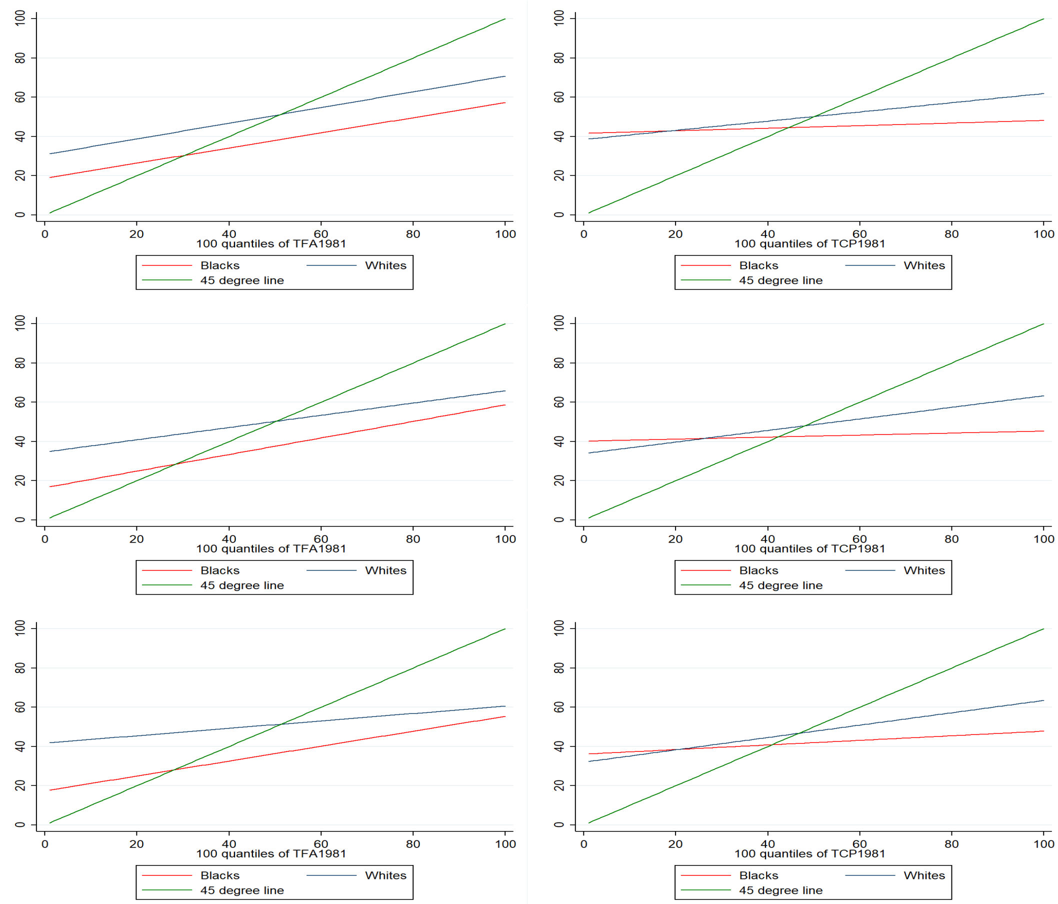

Figure 13: In this Figure we represent the average residual TFA (on the left) and residual TCP (on the right) consumption rank in a fixed year (1991 in the upper panels, 2001 in the middle panels and 2011 in the bottom panels) for an individual who was in each income or consumption percentile respectively in 1981, 1991 or 2001, by race. Residual TFA has been obtained by regressing TFA on a set of controls (age, age squared, gender, occupation, education) and taking the residual terms. Similarly, residual TCP has been obtained regressing TCP on the same set of controls. Solid stands for Whites, dash for Blacks.

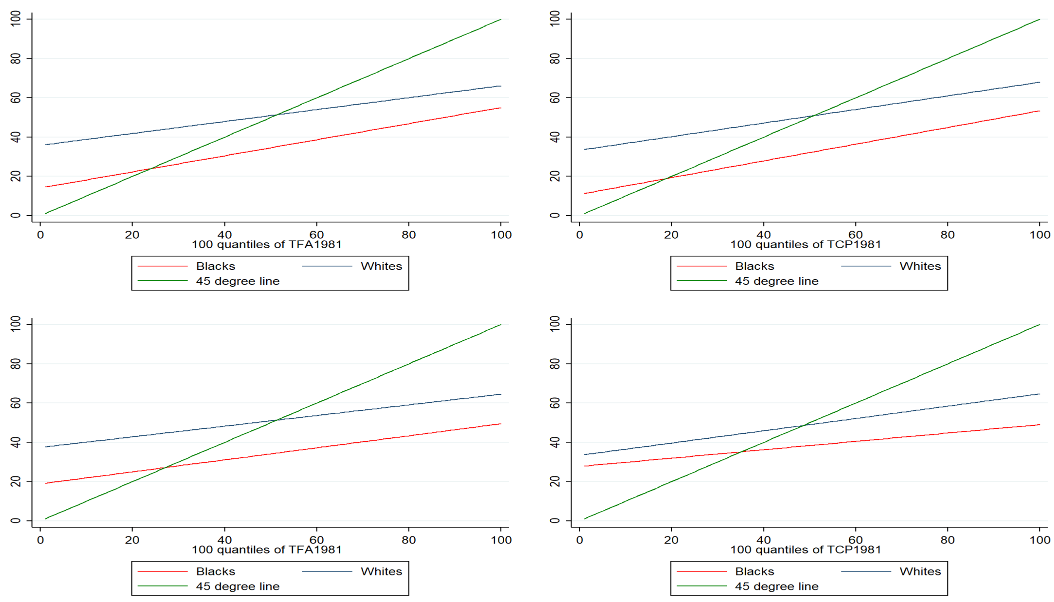

Figure 14: Long-term rank-rank regressions (1981-2017). In this Figure we represent the average TFA (on the left) and TCP (on the right) consumption rank in a fixed year (2017) for an individual who was in each income or consumption percentile 36 years before (i.e. in 1981), by race. In the first row we use unconditional regression in the second conditional regressions. Solid stands for Whites, dash for Blacks.

In Figure 13, we replicate the analysis of Figure 12, but considering residual income and residual consumption as the variables on the basis of which the percentiles are constructed. This means that first we regress income, respectively consumption, on a set of control variables (i.e. age, age squared, gender, education and industry of occupation), then the estimated residuals of this regression are ranked for each year of the analysis. As far as the income distribution is concerned, the results are similar to those obtained in the unconditional rank-rank regression. The the average destination percentile of White people is always higher than that of Black people. However for the consumption distribution the results are slghtly different. Indeed the differences at the bottom of the distribution disappear. Destination percentiles at the bottom are extremely similar for Blacks and Whites individuals. On the contrary the differences appear to be marked at the top at the distribution where the average percentile of White individuals is much higher than the average percentile of Black individuals. In general both the blue and red line for consumption flatten substantially. This suggests a tendency towards the median of the within-race distribution independently on the initial percentile. However the tendency is higher for the distribution of Black individuals (red line flattens more) and this amplifies the difference at the top of the distribution. The result again confirms our previous finding: persistence at the top of the distribution is higher for White people even when controlling for observable characteristics.

Finally, in Figure 14 we report the results of long-run rank-rank regression, i.e. we report the average destination percentile in 2017 by fixing the origin percentile in 1981. The figure confirms our previous findings, showing even wider differences in the average destination percentile between Blacks and Whites. In particular, in the long-run, racial differences are more evident at the bottom of the income and consumption distribution, where they become as wide as at the top of it.

To summarize, these rank-rank regressions show that, in general, Blacks exhibit a higher degree of downward mobility than Whites. Indeed, Blacks starting at the top of the consumption distribution (i.e. in the 100th percentile) end up on average below the 60th consumption percentile after 10 years, whereas Whites end up on average above the 80th percentile. These results hold both unconditionally and conditionally on a set of explanatory variables (age, gender, education, industry). This means that the Blacks are disproprotionately exposed to downward mobility in the upper part of the distribution, even after controlling for observable characteristics, but not for savings (see the next section).

5.4 Controlling for Savings

The main conclusion from the previous sections is that Black individuals are disproportionately exposed to downward mobility in the upper part of the distribution. This result squares with the prediction discussed in Section 4 that the lower amount of savings and wealth accumulation determines a substantially higher downfall risk for Blacks. To test whether savings can explain the differences in the estimated life-cycle dynamics we repeat the analysis above controlling also for the individual savings. We add as a control variable in the persistence regression and in the rank-rank regressions the value of savings at each year t. Given that complete information on savings has only been collected in the PSID since 1999, this analysis is only be performed for the years 1999-2017. Hence, we use here 1999 as a reference year. This means that this analysis is performed on a subsample of our dataset, which contains 82'145 individual-year observations. Figure 15 reports the results. When controlling for savings, the differences between Blacks and Whites in the rank-rank regressions virtually disappear, the two lines being extremely close (right panel). This difference is not due to the different sample used. Indeed, when performing the same analysis on the same sample without controlling for savings, differences are wide (left panel).

Also in terms of persistence, the differences are substantially mitigated compared to the estimates reported in Figure 13. Due to a shorter life expectancy and a lower return on asset, Blacks save, on average, much less than Whites and cumulate also much lower wealth; at the same time they seem to under-insure their health taking up lower premium plans. This translates into a much lower degree of insurance against negative shocks. For Blacks this generates a much higher downward mobility in the consumption distribution.

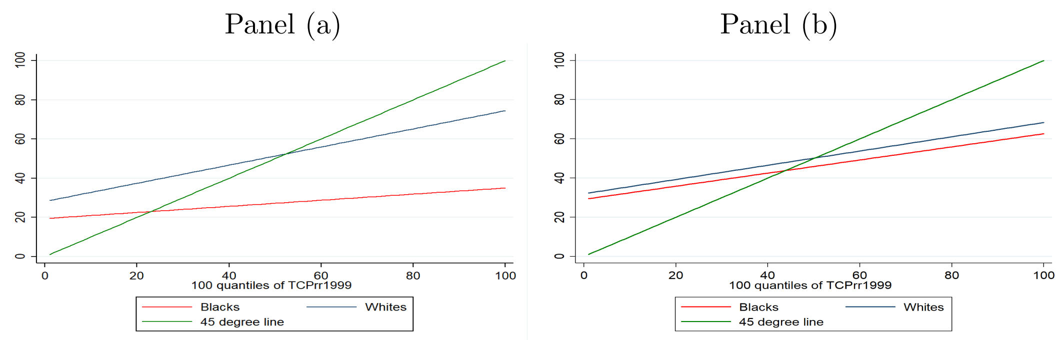

Figure 15: Rank-rank regression (1999-2017). In this Figure we represent the average residual TCP consumption rank in 2017 for an individual who was in each residual consumption percentile in 1999. Blue stands for Whites, red for Blacks. Residual consumption has been obtained regressing TCP on a set of controls (age, age squared, gender, occupation, education) and taking the residual terms. In Panel (b) we include savings as a control. Here savings are defined as home value equity and cash savings.

6 Robustness checks

In this section, we discuss a series of robustness checks that we performed. All the graphs relative to the robustness checks are reported in Appendix B.

6.1 Actual Consumption

As far as persistence probabilities are concerned, we re-estimated them by using actual consumption data (for years from 1999 onwards) instead of our measure of imputed consumption. In this case, too, the Blacks/Whites differences in consumption persistence at the top of the distribution do not disappear, even after the industry of employment has been included among the controls. Further, we estimate positional persistence in the top consumption quintile by using different sets of control variables. In particular, we exploit geographical information (four US macro-regions), explore non-linearities in the impact of the number of children and investigate the role of household wealth (i.e. estimated house value). However, none of these variables totally closes the gap between Blacks and Whites positional persistence at the top.

6.2 Equivalence Scale

As a further check, we estimate persistence by adopting a different equivalence scale than the one in the main body of the paper. This means that we compute Total Family Income or Consumption by dividing total family income/consumption by an alternative equivalence scale, i.e., the Square Root Scale. The formula applied here is the following:

$$SR = \sqrt{\text{Number of people in the household}} \tag{15}$$

The results of the previous sections are confirmed, in the sense that persistence differences between Blacks and Whites, both at the bottom and at the top of the income distribution, almost disappear once a standard set of explanatory variables is included in the quintile-quintile regression. The behavior of consumption is the same as in the previous Sections, with persistence differences not disappearing at the top of the consumption distribution.

7 Counterfactual Analysis

In this Section, we present a simple counterfactual exercise, i.e. we estimate the impact of being Black on the amount of savings held, cosumption, and income by giving to Blacks the same age, gender, education, industry distribution of Whites. We restrict this analysis to households being in the top consumption quintile, since it is the main focus of our research. In essence, the exercise allows us to make some headway on the determinants of the large differences in savings between Blacks and Whites, and in particular whether some unobservables including individual life-expectancy are crucial determinants of such differences. From this counterfactual analysis summarized in Figure 16 we deduce that the gap between the savings distributions of Whites and Blacks isn't closed by observables, in fact the role of the residuals appears extremely large as on average there is a very large gap between the true and counterfactual distribution. This once more is consistent with the role of unobservable to the econometrician life-expectancy (among other possible unobservables). Similarly, observables do not fully close the gaps in the distributions of Consumption and Income to a lesser extent. This counterfactual analysis is in line with our hypothesized crucial role of life-expectancy in defining saving rates, wealth accumulation and therefore consumption, while income gaps between Blacks and Whites, while large, are somewhat explained by observable characteristics.

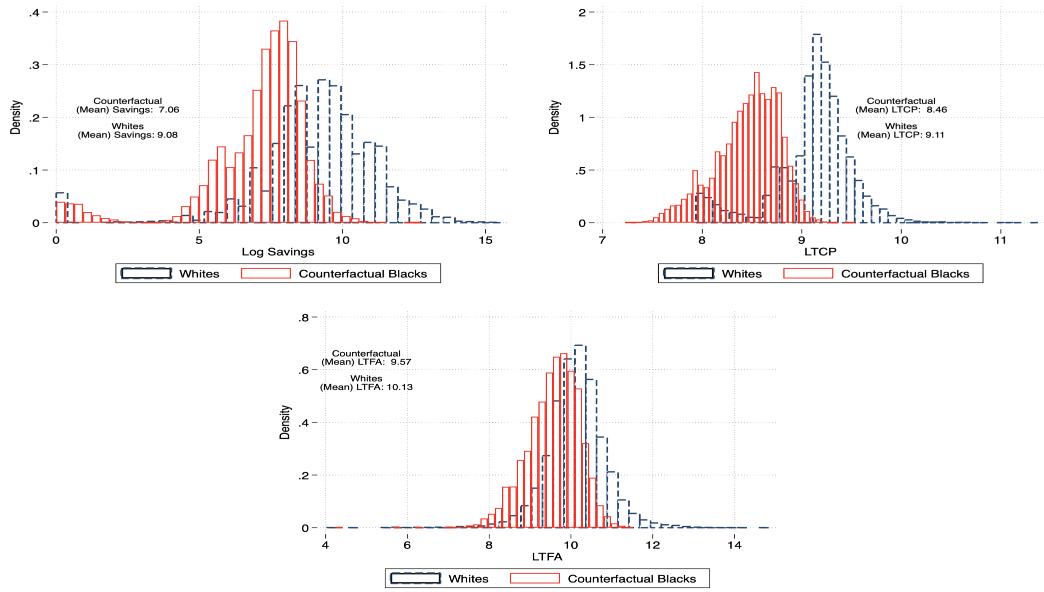

Figure 16: Impact of being Blacks on log savings, based on the estimation of the difference between the actual savings distribution of the Whites and the counterfactual distribution of savings of the Blacks had they had the same characteristics of Whites in terms of age, education, gender, and occupation. Top TCP quintile in 1981 only. Data for 1999-2017.

8 Policy Implications and Conclusions

Our analysis strongly points towards the lack of insurance for Blacks as a main driver of racial differentials in the consumption dynamics. It is well known and confirmed here that Blacks and Whites differ substantially in their amount of savings and wealth, it is however novel that we show how those differences persist even when comparing Blacks and Whites with initially similar levels of consumption. The lack of insurance in face of both permanent and temporary shocks, such as health shocks, makes Blacks more vulnerable and in fact more prone to downfalls in the consumption distribution. While a standard analysis of mobility would probably show Blacks to be more mobile, the reality is that they are more mobile downwards and not upwards, both in the short and long run. Differential life-expectancy, about 8 years for our cohorts, seems to us to contribute substantially to such a life-cycle profile. While understanding where such differences in the life span are coming from is beyond the scope of the current paper, policy action to improve the access to insurance could be promoted.

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Appendix A: Data

Sample Selection

As explained in Section 3.2, to create our dataset, we append together all waves from 1968-2017. The full PSID dataset contains 1,856,953 individual-years. We limit our sample to the SEO and SRC samples, eliminating households from the Immigrant and Latino surveys. We also include only current heads, since they are the households with the richest and most consistent set of observables overtime. We also create a consistent race indicator for all households. The PSID asked heads to identify their race in every wave. For all heads, we assign race as the mode value of race from all reported years. Due to the limited sample size of some reported races, we only keep households identifying themselves as Black or as White. Our full sample, using all waves of data, includes 457,286 individual-year observations. In our main regression analysis, however, we define a base year of 1981 - so only households present in the 1981 wave and beyond are included. This brings us to 342,679 individual-year observations (from waves 1981-2017).

Variable Definition

Demographics

Over time, the PSID has altered how it collects educational data. From 1968 until 1990, households reported educational buckets; afterwards education was given in yearly denominations. To create a consistent education status, we assign households to the four categories used by Attanasio and Pistaferri: 1) 0-11 grades completed, 2) High school degree or 12 grades plus nonacademic training, 3) College dropout (some college), and 4) BA degree or college and advanced/professional degree. Heads report educational information every year in the period 1968-2017. To account for missing data, we generate a new variable for each individual that contains their maximum education status attained.

The PSID allows for five different classifications for marital status: married, single, widowed, divorced, separated, and married with spouse absent. We use these same definitions in our analysis.

Another demographic variable of interest is disability status. The PSID asks households if they have "any physical or nervous condition that limits the type or amount of work" they can do. We use an affirmative answer to this question as an indicator for presence of a disability.

To define employment status, we create a binary variable. households who report that they are working or temporarily laid off are considered employed. The PSID also includes a variable on self-employment. We define as self-employed only those households who report being exclusively self-employed, not those who indicate they are employed by themselves and by someone else.

Information is also present on total hours worked, defined as the total annual hours worked for money on all jobs, including overtime. We replace two wild codes in the data with missing values.

Consumption

For all waves of the survey except 1973, 1988, and 1989, the PSID consistently collects information on food consumption. Starting in 1968, interviewees are asked to provide their *annual* expenditures on food used at home. This value includes the cost of food delivered to the home, but excludes alcohol and cigarette consumption and excludes expenditures from food stamps. Then in 1994, the question switches to a *varying time* unit form. The interviewees themselves choose the time frequency to report at, whether it be weekly, monthly, or yearly. Therefore, we convert expenditures to annual values by multiplying the reported values by the appropriate constant based off the given time unit (i.e. by 12 if the time unit is monthly, by 52 if the time unit is weekly, etc...). Post 1994, if an individual reports $0 spent on food at home, we set their home food expenditures to 0 regardless of the time unit. In addition, food delivery expenditures become a separate variable beginning in 1994, so we have to manually add these values to our measure of food-at-home consumption.

The PSID follows a similar format to collect information on food away from home. With the exception of 1973, 1988, and 1989, households provide the dollar value of annual expenditures spent on food away from home between 1968-1993. Money spent on meals at school or work is excluded. Then in 1994, the question switches to a varying time unit format. We use an identical procedure as described above to convert expenditures to annual values.

Though the PSID asks respondents questions about food stamps in every wave except 1973, they change the wording on the questionnaire. Between 1968-1979 respondents are asked about the amount they saved by using food stamps in the previous year, calculated as the dollar value of food bought with stamps minus the amount spent to purchase the food stamps. Then from 1980 -1993 they are asked about the dollar value of stamps they received in the previous year. In 1993 and in subsequent waves, the PSID also asks about the value of food stamps received, but with a varying time unit. For our own measure, we use the annual values up until 1992, and the time varying values from 1993 on. If an individual reports $0 received in food stamps, we set their food stamp expenditures to 0. For the year 1993, if the *time-varying* value is missing, we fill it in with the *annual* value. Since the time frame of collection for food stamps does not align with the time frame for collection of other food expenditures (i.e. most food expenditure questions are asked about current food consumption, while food stamps are reported for the prior year) we assign food stamp values to the year of the wave they were collected in.

To create a total food consumption measure, we add together the expenditures for food at home (and food delivery when this is separate), food away from home, and food stamps for each wave.

We noticed the presence of dramatic outliers in total food consumption. These come from later waves of the survey, and we suspect were due to errors in the time unit reporting. For instance, if the correct time unit for food expenditures is monthly, but it is coded as weekly, we would multiply the value by 52 instead of the correct 12 to achieve the annual amount. To correct for extreme outliers, we drop the top 0.1 percentile of food consumption each year.

Our rent equivalent measure combines values for both renters and homeowners. We define homeowners as households who report a non-zero positive house-value. We create a rent equivalent by taking 6% of this house-value. For those who do not report a positive house-value, the PSID provides annual rent payments from 1968-1993. Then for 1993-2017, rent is given in varying time units, defined by the interviewee. To convert these payments to an annual rent, we multiply the reported rent by the appropriate constant based off the given time unit (i.e. by 12 if the time unit is monthly, by 52 if the time unit is weekly). This procedure applies to interview years 1993-2011. In all waves, rent values can be either positive or 0.

This leaves us with some missing values. In 1993, if an individual does not report a positive house-value, but is also missing *time-unit* rent information, we fill in the value of rent given in the *annual* variable when applicable. We are only able to do this in 1993 because this is the only year that includes both the annual and the time-varying rent variables. Furthermore, the PSID includes another variable that indicates the interviewee's self-reported house-status. For households with missing house-values and missing rent information but who self-report that they are not renters or homeowners, we set their rent equivalent to 0. In 1978, some households claim an annual rent of $768 but also report they are not homeowners or renters. Communication with the PSID indicated that 768 was a wild code in that year. The rent equivalents for these households are therefore also set to 0.

In summary, our analysis includes one measure of rent equivalent. For people with positive house-values, we take 6% of this value. For people without positive house-values, we generate an annual version of their reported rent payments (whether the payments are positive or 0). For households missing information on both house-value and rent payments and who self-report being neither homeowners nor renters, we set their annual rent equivalent to 0.

The PSID asks about amounts paid for utilities such as electricity, water and sewage, gas and other heating fuel, and miscellaneous utilities. We convert all quantities to an annual measure by multiplying the reported value by the appropriate time constant.

PSID transportation variables are all reported at the monthly level. For the month of the interview, respondents are asked how much they paid for parking expenses, gas, bus and train, cab, and other transportation costs. We again annualize these values. households also provide their car insurance payments for all family vehicles per year.

Annual school-related expenses (such as tuition, books, computers, tutors, room/board, uniforms, and other school related expenses) are asked of households regarding the previous year. Families are also asked how much they paid for childcare in the previous year. This question is one of the few consumption measures asked beginning in 1970, but in earlier years it is only asked to families with working female heads or wives. In the waves relevant to our purposes (1999 and on), all families are asked about childcare costs.

We also use various healthcare expenditures in our analysis. For instance, the PSID asks households how much they pay for health insurance premiums for all health insurance coverage in their family. This includes amounts both paid directly and automatically deducted from pay. Furthermore, information is also collected regarding out-of-pocket costs paid for nursing homes, hospital bills, doctors' visits, outpatient surgery, dental bills, prescriptions, in-home medical care, and specialty facilities. Healthcare costs correspond to the prior two year period, so we divide reported values in half to get annual values.

The final consumption variable we use in our analysis is home insurance. Interviewees provide their total yearly homeowner's insurance premium.

Missing Data

For all variables, whenever an individual gives an answer of "Don't Know" or "Not Available" (indicated with specific codes in the PSID data), we set this value to missing at first. Unfortunately, the systematic presence of missing values would eliminate a large number of observations from our consumption imputation. To make sure these observations are still included, for each categorical demographic variable we create a new group to identify households with missing information. For example, all households missing marital status information are assigned the code 999 for the marital status variable, so they are grouped together in the imputation. This procedure applies to marital status, maximum education, state, number of children, employment status, self-employment status, disability status, and homeowner status. For continuous variables (such as age, expenditures, and income), missing values remain missing.

Other Considerations

One peculiarity about the PSID is the discrepancy that sometimes arises between the year of the survey wave and the year that a variable is collected for. For example, in each interview the PSID asks respondents about their current house value and rent, so these values correspond to the year of the survey wave. The same pattern also arises for food consumption at home - interviewees are asked about their current expenditures on food consumption, so the value corresponds to the year of the survey. However, for some variables the PSID asks respondents about values for the prior year. For example, households report their family income for the year prior to the survey. Food stamp value is also collected for the year prior to the survey. Beginning in 1999 when the PSID includes more consumption measures, this inconsistency continues. Utilities, transportation, and car insurance costs are reported currently, and therefore apply to the year of the survey. Other consumption expenditures, such as education and childcare expenses, are reported for the prior year. In addition, healthcare costs - including drug and hospital costs - are reported for the prior *two* years. Since the time frame that the PSID uses to collect data varies for different variables, we standardize our measures of consumption and income by assigning all values in a particular interview to the year of that survey wave. For instance, all information collected in the 1995 survey wave is assigned as pertaining to the year 1995. This becomes relevant when we adjust our values by the CPI - we use the CPI of the year of the survey wave.

In our regressions, we cluster the standard errors at the family level, using our own definition of family. We consider families to be households where the identity of the head and the wife remain the same (though in the actual regressions only the heads are present). If at any point and time the identity of the head and/or wife changes (i.e. if a couple splits, if a head or wife dies, or if a previously single individual gets married), we consider this to be a new family.

We would also like to note that for all types of analysis involving consumption expenditures, we do not use data from years 1973, 1988, and 1989 since food information was not collected in those surveys. Family income, however, was collected in those years. For all analyses pertaining to income, however, we keep years 1973, 1988, and 1989 in order to increase the sample size. One more final consideration is that when values in the PSID are topcoded, we keep the topcoded values. This applies to very few observations.

Attrition

From 1968 until 1991, the PSID only interviewed households if they had been interviewed in the previous wave. People who could not be found or refused to participate in one year were lost to the survey. However, in 1992 the PSID began an effort to recontact some of these nonresponse households from previous years. Furthermore, starting in 1993, households who were nonresponsive in a particular wave were still followed for the subsequent wave. If an individual remained missing for two waves, they were then dropped. In a similar effort, 1993 marked the year when the PSID began to follow sample children who left their family units before the age of 18 to join a non-sample family. This meant that for the first time, both the head and the wife of an interviewed family could be non-sample. The family just needed one sample member in order to be interviewed, regardless of this member's relational status. Due to budgetary constraints, in 1997 the PSID dropped approximately 25% of its sample families, with reductions made mainly to the SEO subsample.

Appendix B: Additional Results

B.1 Additional Descriptive Statistics

	Whites					Blacks				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
TCP	2501.682	3833.555	4983.308	6333.018	9201.923	2359.27	3781.212	4913.272	6252.982	8654.118
	(555.879)	(323.7019)	(349.8955)	(448.0453)	(1906.936)	(571.2593)	(331.568)	(327.5802)	(459.2927)	(1760.424)
TFA	6344.553	8797.514	11194.81	13873.4	22855.34	4577.908	7685.912	10035.92	12337.08	15220.9
	(4806.653)	(6295.467)	(6415.958)	(6845.81)	(28915.88)	(3244.078)	(4516.912)	(4872.493)	(6495.513)	(7844.782)
Family size	3.420613	2.927803	2.772166	2.692308	2.398671	3.859067	2.947994	2.542725	2.166052	1.875
	(1.897873)	(1.557911)	(1.509055)	(1.399453)	(1.151326)	(2.145349)	(1.71876)	(1.42681)	(1.371033)	(1.11191)
Age	40.58217	44.56682	42.51515	42.34663	43.91944	39.23731	39.80832	39.94688	38.89299	37.55
	(19.37669)	(20.6452)	(18.42539)	(16.55795)	(15.29443)	(16.40364)	(16.00652)	(15.58562)	(14.22282)	(13.36108)
Female	0.417827	0.310292	0.255892	0.186135	0.128738	0.539896	0.371471	0.307159	0.295203	0.275
Education										
Grades 0-11	0.588235	0.356375	0.209877	0.094017	0.0299	0.392116	0.298663	0.230947	0.129151	0.075
High School	0.327731	0.385561	0.373737	0.293447	0.146179	0.357884	0.367013	0.30485	0.273063	0.233333
Some College	0.042017	0.179724	0.234568	0.271605	0.222591	0.211618	0.249629	0.316397	0.313653	0.341667
BA or higher	0.042017	0.078341	0.181818	0.340931	0.601329	0.038382	0.084695	0.147806	0.284133	0.35
Obs	357	651	891	1053	1204	964	673	433	271	120

Table B.1: Descriptive Statistics

TFA	Q1	Q2	Q3	Q4	Q5
% Whites	.43	.61	.69	.74	.83
% Blacks	.57	.39	.31	.26	.17
TCP	Q1	Q2	Q3	Q4	Q5
% Whites	.48	.55	.64	.75	.87
% Blacks	.52	.45	.36	.25	.13

Table A.2: Shares of Blacks and White households in TFA and TCP quintiles, pooled 1968-2017 data

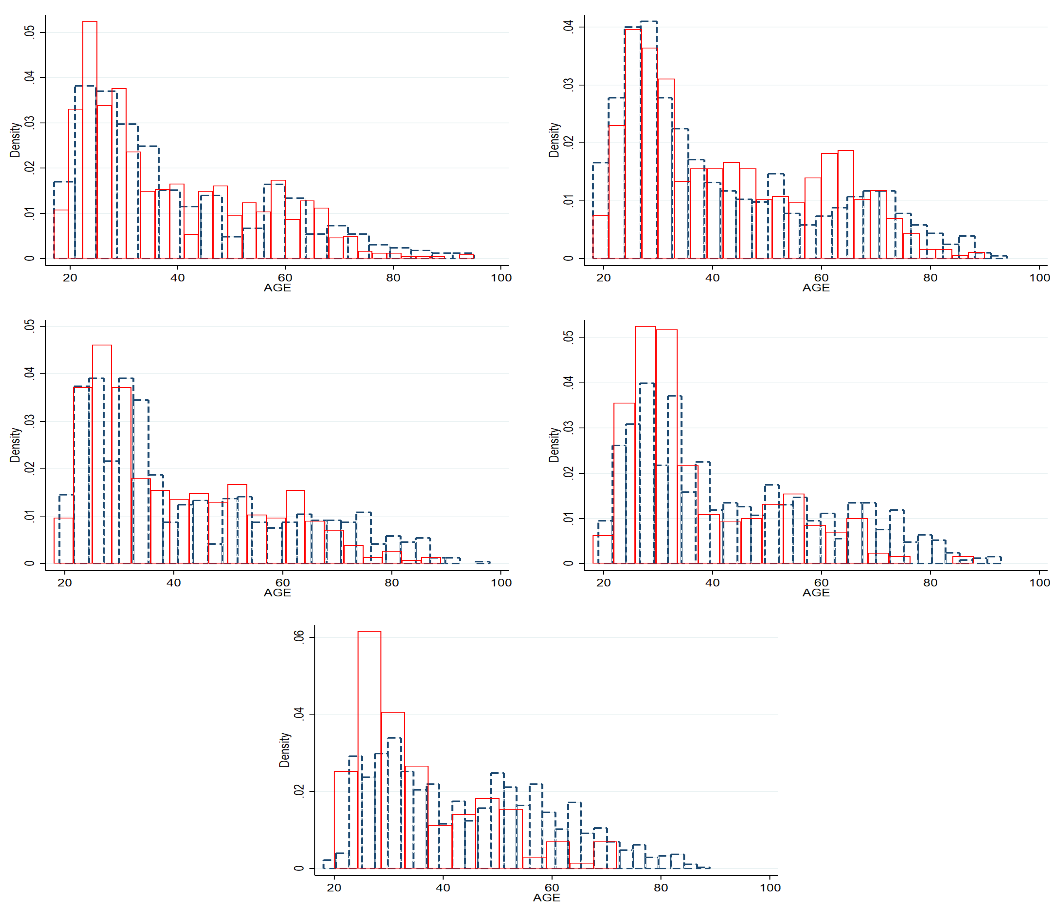


Figure A.1: *Histogram of AGE by TCP quintile and race, in year 1981. Red stands for Blacks, blue for Whites.*

t-1 \ t	1	2	3	4	5	6	7	8	9	10
1	**0.50**	0.23	0.10	0.06	0.04	0.03	0.02	0.01	0.01	0.01
2	0.19	**0.33**	0.20	0.11	0.07	0.04	0.02	0.01	0.01	0.01
3	0.08	0.18	**0.28**	0.19	0.12	0.07	0.04	0.02	0.01	0.01
4	0.04	0.08	0.17	**0.27**	0.20	0.11	0.06	0.04	0.02	0.01
5	0.02	0.04	0.09	0.17	**0.27**	0.19	0.10	0.07	0.03	0.02
6	0.01	0.02	0.04	0.09	0.18	**0.28**	0.19	0.10	0.06	0.03
7	0.01	0.02	0.02	0.04	0.09	0.18	**0.30**	0.20	0.10	0.04
8	0.01	0.01	0.01	0.02	0.04	0.09	0.20	**0.34**	0.21	0.08
9	0.00	0.01	0.01	0.01	0.02	0.04	0.08	0.20	**0.41**	0.21
10	0.00	0.00	0.01	0.01	0.01	0.02	0.03	0.06	0.20	**0.66**

Table A.3: TCP decile transition matrix between each couple of years t and t-1, data from 1968 to 2017, subsample of Whites. Actual transitions are reported.

t-1\t	1	2	3	4	5	6	7	8	9	10
1	**0.57**	0.23	0.10	0.05	0.03	0.01	0.01	0.01	0.00	0.00
2	0.25	**0.34**	0.20	0.10	0.05	0.03	0.02	0.01	0.01	0.00
3	0.12	0.23	**0.28**	0.18	0.09	0.05	0.03	0.01	0.01	0.00
4	0.06	0.13	0.22	**0.25**	0.16	0.09	0.05	0.03	0.01	0.01
5	0.05	0.08	0.14	0.20	**0.23**	0.15	0.08	0.05	0.02	0.01
6	0.03	0.06	0.08	0.13	0.21	**0.22**	0.14	0.08	0.04	0.02
7	0.03	0.04	0.06	0.09	0.13	0.20	**0.22**	0.14	0.07	0.03
8	0.02	0.03	0.05	0.06	0.09	0.13	0.20	**0.23**	0.14	0.05
9	0.01	0.02	0.04	0.06	0.07	0.09	0.13	0.21	**0.26**	0.11
10	0.02	0.03	0.02	0.05	0.06	0.07	0.08	0.12	0.21	**0.34**

Table A.4: TCP decile transition matrix between each couple of years t and t-1, data from 1968 to 2017, subsample of Blacks. Actual transitions are reported.

t-1\t	1	2	3	4	5	6	7	8	9	10
1	**0.45**	0.23	0.11	0.06	0.05	0.03	0.02	0.02	0.02	0.02
2	0.15	**0.37**	0.21	0.11	0.05	0.04	0.02	0.02	0.01	0.01
3	0.06	0.16	**0.33**	0.19	0.10	0.06	0.04	0.03	0.02	0.01
4	0.03	0.07	0.16	**0.31**	0.20	0.10	0.06	0.04	0.02	0.01
5	0.02	0.04	0.07	0.17	**0.31**	0.19	0.10	0.05	0.03	0.02
6	0.01	0.02	0.04	0.08	0.17	**0.31**	0.19	0.09	0.05	0.03
7	0.01	0.01	0.02	0.04	0.08	0.17	**0.33**	0.20	0.09	0.04
8	0.01	0.01	0.02	0.03	0.04	0.08	0.18	**0.36**	0.21	0.07
9	0.01	0.01	0.01	0.02	0.02	0.04	0.08	0.19	**0.44**	0.20
10	0.01	0.00	0.01	0.01	0.01	0.02	0.03	0.06	0.18	**0.68**

Table A.5: TFA decile transition matrix between each couple of years t and t-1, data from 1968 to 2017, subsample of Whites. Actual transitions are reported.

t-1\t	1	2	3	4	5	6	7	8	9	10
1	**0.61**	0.21	0.08	0.04	0.03	0.02	0.01	0.01	0.00	0.00
2	0.24	**0.40**	0.18	0.08	0.04	0.03	0.02	0.01	0.01	0.00
3	0.10	0.21	**0.33**	0.18	0.08	0.05	0.03	0.01	0.01	0.00
4	0.07	0.11	0.20	**0.28**	0.17	0.08	0.05	0.02	0.01	0.01
5	0.05	0.07	0.12	0.19	**0.26**	0.17	0.08	0.04	0.02	0.01
6	0.03	0.04	0.07	0.11	0.19	**0.27**	0.17	0.08	0.04	0.01
7	0.03	0.03	0.04	0.07	0.11	0.19	**0.27**	0.17	0.06	0.03
8	0.03	0.03	0.03	0.05	0.07	0.10	0.19	**0.32**	0.15	0.05
9	0.02	0.02	0.02	0.03	0.04	0.06	0.10	0.19	**0.39**	0.13
10	0.03	0.02	0.02	0.02	0.03	0.04	0.06	0.08	0.23	**0.47**

Table A.6: TFA decile transition matrix between each couple of years t and t-1, data from 1968 to 2017, subsample of Blacks. Actual transitions are reported.

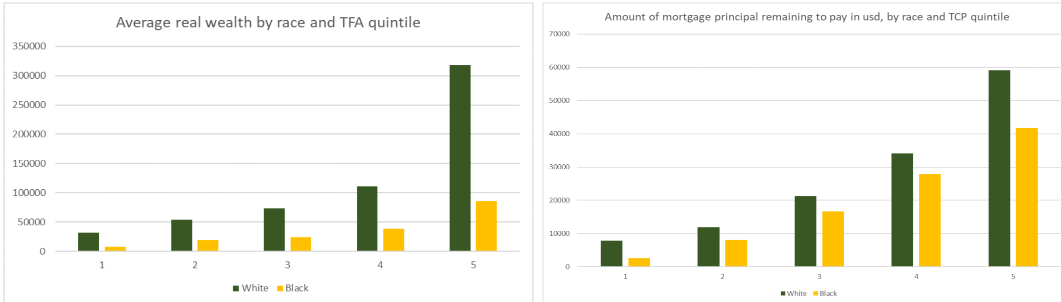


Figure A.2: left panel: Wealth by race and income quintile. Wealth data are available for 1984, 1989, 1994 and 1999-2017. Right panel: average amount of mortgage principal still remaining to pay, by race and TCP quintile, as a proxy of credit market access. These data are available from 1983 to 2017.

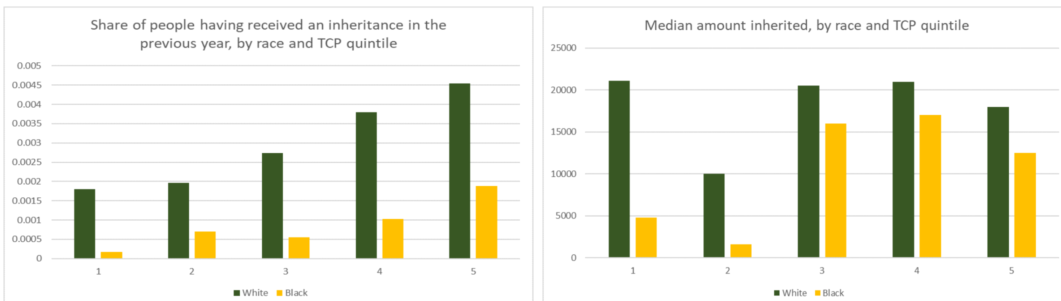


Figure A.3: Left panel: share of households who recorded to have received inheritance in the previous year, by race and TCP quintile. Right panel: median amount inherited, among those who received positive inheritance, by race and TCP quintile. This question has only been asked in 1984 in the PSID.

		NQTCP1	NQTCP2	NQTCP3	NQTCP4	NQTCP5
Firm or business	White	0.034	0.059	0.083	0.121	0.171
	Black	0.011	0.023	0.043	0.062	0.085
T-test for diff in means	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Cash savings	White	0.426	0.544	0.620	0.650	0.664
	Black	0.267	0.381	0.436	0.470	0.482
T-test for diff in means	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Real estate (no home)	White	0.048	0.069	0.111	0.153	0.214
	Black	0.017	0.041	0.058	0.091	0.126
T-test for diff in means	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Stocks	White	0.064	0.094	0.164	0.262	0.390
	Black	0.014	0.026	0.048	0.071	0.108
T-test for diff in means	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Vehicles	White	0.754	0.834	0.890	0.916	0.920
	Black	0.599	0.698	0.759	0.817	0.828
T-test for diff in means	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Other assets	White	0.065	0.096	0.135	0.164	0.195
	Black	0.043	0.071	0.087	0.098	0.117
T-test for diff in means	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Home equity net of debt	White	0.228	0.396	0.581	0.731	0.855
	Black	0.183	0.344	0.480	0.597	0.653
T-test for diff in means	P-value	0.0000	0.0000	0.0000	0.0000	0.0000

Table A.7: In this Table, we report the share of households having a positive amount of each of the seven types of assets considered, by race and by TCP quintile.

Figure A.4: Share of households having a positive amount of each of the six asset types, by race and 1981 TCP quintile, data available for the period 1999-2017. plus mention ttest always zero pvalue

Panel (a) Panel (b)

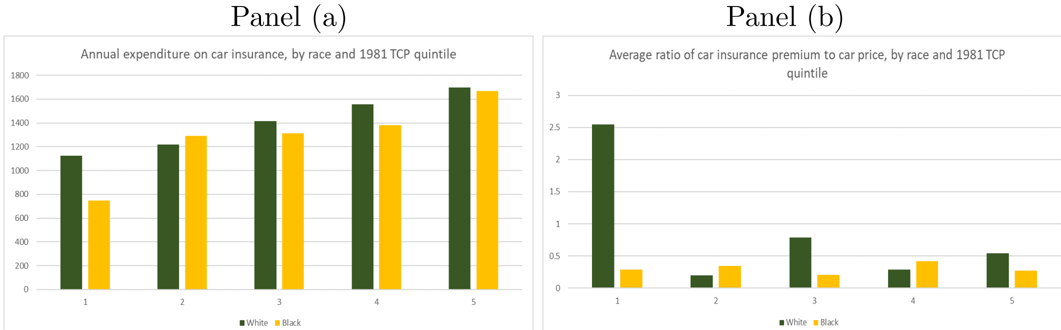
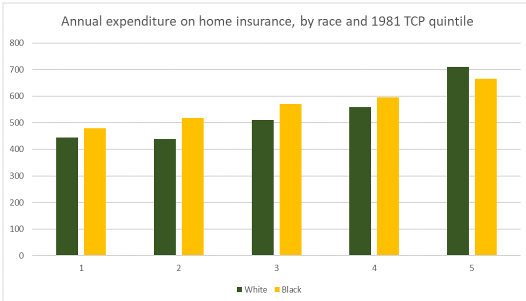
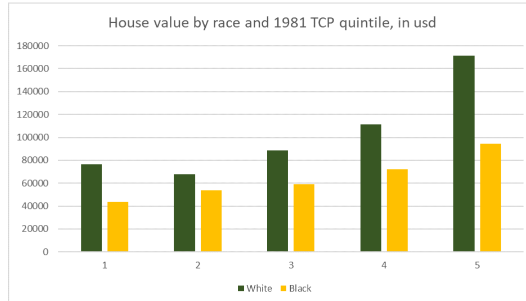


Figure A.5: Panel (a): average amount of annual expenditure on car insurance premiums, by race and 1981 TCP quintile. Data for 1999-2017. Panel (b): average ratio of annual expenditure on car insurance premiums to the car price, by race and 1981 TCP quintile. Data for 1999-2017.

Panel (a)



Panel (b)



Panel (c)

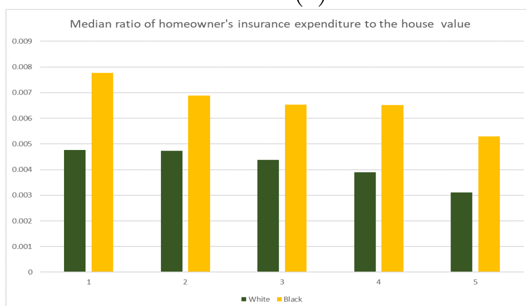


Figure A.6: Panel (a): average amount of annual expenditure on home insurance premiums, by race and 1981 TCP quintile, homeowners only. Data for 1999-2017. Panel (b): house value by 1981 TCP quintile. Only households who own a house have been included. Data for 1981-2017. Panel (c): median ratio of annual expenditure on home insurance premiums to the house value, by race and 1981 TCP quintile. Only households who own a house have been included. Data for 1999-2017.

B.2 Alternative Estimations of Persistence Probabilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	NQTCP5	NQTCP5	NQTCP5	NQTCP5	NQTCP5	NQTCP1	NQTCP1	NQTCP1	NQTCP1	NQTCP1
pastNQ1	0.00847***	-0.230***	-0.224***	-0.141***	-0.141***	0.629***	0.532***	0.510***	0.445***	0.441***
	(9.28)	(-76.99)	(-75.46)	(-52.43)	(-52.07)	(115.30)	(94.88)	(90.98)	(77.15)	(76.47)
pastNQ2	0.0155***	-0.222***	-0.218***	-0.161***	-0.160***	0.167***	0.0702***	0.0571***	0.0178***	0.0146***
	(15.61)	(-74.96)	(-74.54)	(-62.39)	(-62.22)	(50.34)	(19.86)	(16.12)	(4.94)	(4.04)
pastNQ3	0.0470***	-0.194***	-0.192***	-0.159***	-0.159***	0.0401***	-0.0583***	-0.0649***	-0.0868***	-0.0900***
	(31.45)	(-63.98)	(-63.74)	(-57.54)	(-57.39)	(29.22)	(-27.67)	(-30.63)	(-38.72)	(-39.83)
pastNQ4	0.180***	-0.0664***	-0.0661***	-0.0638***	-0.0638***	0.0153***	-0.0856***	-0.0867***	-0.0872***	-0.0904***
	(65.95)	(-18.89)	(-18.82)	(-18.72)	(-18.71)	(20.14)	(-45.87)	(-46.37)	(-46.63)	(-47.79)
pastNQ5	0.730***	0.476***	0.474***	0.439***	0.438***	0.00551***	-0.0986***	-0.0928***	-0.0672***	-0.0704***
	(217.97)	(131.03)	(130.77)	(121.80)	(121.71)	(12.97)	(-53.33)	(-50.00)	(-37.22)	(-38.51)
Race dummy	0.0484***	-0.193***	-0.184***	-0.162***	-0.164***	0.336***	0.236***	0.206***	0.192***	0.194***
	(30.70)	(-60.07)	(-57.82)	(-57.59)	(-57.84)	(88.99)	(56.69)	(50.58)	(49.88)	(50.19)
Race*NQ1	-0.0536***	0.184***	0.180***	0.161***	0.163***	-0.293***	-0.195***	-0.181***	-0.160***	-0.163***
	(-28.92)	(54.29)	(52.71)	(48.63)	(48.96)	(-39.27)	(-25.82)	(-24.18)	(-21.79)	(-22.18)
Race*NQ2	-0.0535***	0.182***	0.176***	0.157***	0.159***	-0.259***	-0.163***	-0.143***	-0.130***	-0.133***
	(-26.45)	(53.32)	(51.56)	(48.54)	(48.85)	(-43.97)	(-26.99)	(-23.92)	(-21.93)	(-22.33)
Race*NQ3	-0.0624***	0.175***	0.168***	0.151***	0.152***	-0.295***	-0.198***	-0.177***	-0.166***	-0.168***
	(-22.85)	(46.18)	(44.39)	(40.10)	(40.37)	(-63.49)	(-40.19)	(-36.38)	(-33.54)	(-33.91)
Race*NQ4	-0.104***	0.136***	0.131***	0.120***	0.121***	-0.315***	-0.216***	-0.199***	-0.192***	-0.194***
	(-19.66)	(23.65)	(22.66)	(20.55)	(20.75)	(-71.86)	(-45.99)	(-42.28)	(-39.31)	(-39.62)
Race*NQ5	-0.303***	-0.0570***	-0.0613***	-0.0607***	-0.0595***	-0.315***	-0.214***	-0.201***	-0.202***	-0.203***
	(-19.21)	(-3.68)	(-3.99)	(-4.27)	(-4.19)	(-65.31)	(-41.48)	(-37.58)	(-35.23)	(-35.50)
Age		YES	YES	YES	YES		YES	YES	YES	YES
Age squared		YES	YES	YES	YES		YES	YES	YES	YES
Gender			YES	YES	YES			YES	YES	YES
Education				YES	YES				YES	YES
Industry				YES	YES				YES	YES
N	291209	291209	291209	290646	289772	291209	291209	291209	290646	289772

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.8: This table reports the regression coefficients for one-year transitions, i.e. from 1981 to 1982. Standard errors have been clustered at the individual level.

	(1) NQTCP5	(2) NQTCP5	(3) NQTCP5	(4) NQTCP5	(5) NQTCP5	(6) NQTCP1	(7) NQTCP1	(8) NQTCP1	(9) NQTCP1	(10) NQTCP1
pastNQ1	0.0566***	-0.185***	-0.187***	-0.131***	-0.131***	0.323***	0.188***	0.193***	0.154***	0.157***
	(14.15)	(-38.44)	(-38.42)	(-28.36)	(-28.29)	(32.74)	(19.47)	(20.40)	(16.29)	(16.47)
pastNQ2	0.0752***	-0.162***	-0.168***	-0.141***	-0.141***	0.148***	0.0129**	0.0273***	0.00995*	0.0120*
	(22.66)	(-37.96)	(-38.64)	(-35.30)	(-35.20)	(30.44)	(2.60)	(5.54)	(1.99)	(2.39)
pastNQ3	0.155***	-0.0842***	-0.0930***	-0.0988***	-0.0993***	0.0613***	-0.0748***	-0.0534***	-0.0459***	-0.0446***
	(38.10)	(-18.15)	(-19.71)	(-22.29)	(-22.33)	(25.44)	(-24.78)	(-17.63)	(-15.08)	(-14.60)
pastNQ4	0.301***	0.0592***	0.0481***	0.00333	0.00303	0.0258***	-0.112***	-0.0848***	-0.0482***	-0.0472***
	(59.96)	(11.36)	(9.13)	(0.65)	(0.59)	(19.67)	(-46.27)	(-33.76)	(-19.87)	(-19.43)
pastNQ5	0.574***	0.332***	0.319***	0.225***	0.226***	0.00942***	-0.131***	-0.0984***	-0.0253***	-0.0244***
	(96.57)	(55.73)	(53.68)	(40.55)	(40.55)	(12.28)	(-56.24)	(-39.40)	(-10.46)	(-10.09)
Race dummy	0.0412***	-0.186***	-0.174***	-0.146***	-0.147***	0.355***	0.236***	0.207***	0.188***	0.189***
	(30.65)	(-63.79)	(-60.18)	(-55.53)	(-55.52)	(96.72)	(57.99)	(51.20)	(49.32)	(49.45)
Race*NQ1	-0.0829***	0.140***	0.140***	0.129***	0.129***	-0.185***	-0.0684***	-0.0686***	-0.0627***	-0.0633***
	(-19.02)	(28.26)	(27.90)	(25.93)	(25.83)	(-15.41)	(-5.77)	(-5.91)	(-5.46)	(-5.49)
Race*NQ2	-0.0815***	0.138***	0.133***	0.115***	0.114***	-0.221***	-0.105***	-0.0933***	-0.0810***	-0.0813***
	(-19.75)	(29.47)	(28.10)	(25.08)	(24.87)	(-27.70)	(-13.02)	(-11.71)	(-10.24)	(-10.23)
Race*NQ3	-0.124***	0.0961***	0.0899***	0.0737***	0.0734***	-0.260***	-0.144***	-0.129***	-0.119***	-0.118***
	(-21.82)	(16.27)	(15.07)	(12.53)	(12.45)	(-40.36)	(-21.65)	(-19.67)	(-18.11)	(-18.05)
Race*NQ4	-0.204***	0.0187*	0.0137	0.00551	0.00475	-0.289***	-0.172***	-0.160***	-0.155***	-0.154***
	(-22.96)	(2.11)	(1.55)	(0.65)	(0.56)	(-46.57)	(-26.59)	(-24.95)	(-23.84)	(-23.63)
Race*NQ5	-0.324***	-0.102***	-0.107***	-0.101***	-0.101***	-0.296***	-0.177***	-0.167***	-0.173***	-0.172***
	(-17.04)	(-5.39)	(-5.67)	(-5.91)	(-5.92)	(-38.17)	(-22.09)	(-20.48)	(-20.80)	(-20.47)
Age		YES	YES	YES	YES		YES	YES	YES	YES
Age squared		YES	YES	YES	YES		YES	YES	YES	YES
Gender			YES	YES	YES			YES	YES	YES
Education				YES	YES				YES	YES
Industry				YES	YES				YES	YES
N	291209	291209	291209	290646	289772	291209	291209	291209	290646	289772

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: This table reports the regression coefficients for ten-year transitions, i.e. from 1981 to 1991. Standard errors have been clustered at the individual level.

	(1) NQTFA5	(2) NQTFA5	(3) NQTFA5	(4) NQTFA5	(5) NQTFA5	(6) NQTFA1	(7) NQTFA1	(8) NQTFA1	(9) NQTFA1	(10) NQTFA1
pastNQTFA1	0.00457***	-0.290***	-0.333***	-0.329***	-0.316***	0.682***	0.646***	0.613***	0.613***	0.608***
	(13.79)	(-126.31)	(-132.47)	(-137.15)	(-134.23)	(234.16)	(228.30)	(215.13)	(217.21)	(215.32)
pastNQTFA2	0.00433***	-0.295***	-0.334***	-0.358***	-0.344***	0.106***	0.0712***	0.0416***	0.0464***	0.0411***
	(17.17)	(-137.13)	(-141.83)	(-152.88)	(-148.94)	(80.43)	(48.80)	(27.56)	(30.77)	(26.93)
pastNQTFA3	0.0160***	-0.295***	-0.331***	-0.369***	-0.355***	0.0264***	-0.00978***	-0.0366***	-0.0288***	-0.0343***
	(31.76)	(-131.41)	(-137.36)	(-151.33)	(-146.95)	(41.15)	(-9.78)	(-33.70)	(-26.72)	(-30.85)
pastNQTFA4	0.158***	-0.167***	-0.199***	-0.253***	-0.238***	0.0123***	-0.0252***	-0.0494***	-0.0386***	-0.0441***
	(104.49)	(-64.12)	(-74.43)	(-94.41)	(-89.84)	(27.59)	(-27.11)	(-49.29)	(-38.75)	(-42.62)
pastNQTFA5	0.795***	0.456***	0.427***	0.342***	0.358***	0.00869***	-0.0304***	-0.0523***	-0.0349***	-0.0407***
	(293.34)	(130.69)	(123.44)	(102.95)	(108.92)	(17.55)	(-30.52)	(-49.15)	(-31.83)	(-35.77)
Race	0.226***	-0.106***	-0.142***	-0.157***	-0.156***	0.220***	0.181***	0.155***	0.158***	0.167***
	(62.90)	(-26.33)	(-32.79)	(-40.01)	(-40.20)	(85.09)	(66.78)	(57.04)	(59.08)	(61.58)
Race*NQ1	-0.230***	0.114***	0.143***	0.173***	0.170***	-0.116***	-0.0725***	-0.0504***	-0.0563***	-0.0651***
	(-63.57)	(26.03)	(31.85)	(40.82)	(41.08)	(-27.64)	(-17.52)	(-12.27)	(-13.81)	(-15.92)
Race*NQ2	-0.228***	0.106***	0.138***	0.176***	0.173***	-0.134***	-0.0941***	-0.0698***	-0.0775***	-0.0860***
	(-63.17)	(25.39)	(31.82)	(42.28)	(42.27)	(-38.99)	(-26.62)	(-19.92)	(-22.02)	(-24.32)
Race*NQ3	-0.231***	0.102***	0.136***	0.175***	0.171***	-0.195***	-0.155***	-0.131***	-0.138***	-0.147***
	(-62.80)	(24.20)	(30.78)	(40.67)	(40.60)	(-67.66)	(-51.39)	(-43.61)	(-45.81)	(-48.06)
Race*NQ4	-0.263***	0.0735***	0.107***	0.142***	0.138***	-0.209***	-0.168***	-0.143***	-0.150***	-0.159***
	(-60.01)	(14.80)	(21.17)	(28.68)	(28.41)	(-75.28)	(-57.46)	(-49.40)	(-51.30)	(-53.50)
Race*NQ5	-0.328***	0.00831	0.0419***	0.0886***	0.0838***	-0.215***	-0.174***	-0.149***	-0.158***	-0.166***
	(-37.85)	(0.92)	(4.65)	(10.39)	(9.92)	(-71.68)	(-55.08)	(-46.80)	(-48.81)	(-50.74)
Age		YES	YES	YES	YES		YES	YES	YES	YES
Age squared		YES	YES	YES	YES		YES	YES	YES	YES
Gender			YES	YES	YES			YES	YES	YES
Education				YES	YES				YES	YES
Industry					YES					YES
N	342679	342679	342679	342679	342679	342679	342679	342679	342679	342679

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: *Regression coefficients for one-year transitions, i.e. from 1981 to 1982. Standard errors have been clustered at the individual level.*

	(1) NQTFA5	(2) NQTFA5	(3) NQTFA5	(4) NQTFA5	(5) NQTFA5	(6) NQTFA1	(7) NQTFA1	(8) NQTFA1	(9) NQTFA1	(10) NQTFA1
pastNQTFA1	0.0481***	-0.0627***	-0.0621***	-0.0649***	-0.0617***	0.203***	0.0306***	-0.000871	-0.0000788	-0.00295
	(29.70)	(-28.59)	(-27.86)	(-29.67)	(-28.62)	(41.40)	(6.48)	(-0.19)	(-0.02)	(-0.65)
pastNQTFA2	0.103***	-0.0146***	-0.0141***	-0.0339***	-0.0308***	0.0692***	-0.102***	-0.127***	-0.117***	-0.119***
	(51.55)	(-6.13)	(-5.86)	(-14.16)	(-12.92)	(38.73)	(-38.77)	(-48.43)	(-44.73)	(-45.25)
pastNQTFA3	0.271***	0.152***	0.152***	0.121***	0.124***	0.0409***	-0.136***	-0.156***	-0.140***	-0.141***
	(85.52)	(45.53)	(45.55)	(36.44)	(37.25)	(32.87)	(-54.57)	(-62.70)	(-56.31)	(-56.61)
pastNQTFA4	0.510***	0.389***	0.390***	0.348***	0.352***	0.0240***	-0.160***	-0.176***	-0.154***	-0.154***
	(128.00)	(97.00)	(97.27)	(86.59)	(85.95)	(26.63)	(-64.42)	(-71.40)	(-62.37)	(-61.90)
pastNQTFA5	0.744***	0.623***	0.623***	0.560***	0.559***	0.0142***	-0.180***	-0.191***	-0.156***	-0.151***
	(210.19)	(168.58)	(168.43)	(145.29)	(141.31)	(20.86)	(-69.47)	(-73.91)	(-59.35)	(-56.53)
Race	0.0500***	-0.0537***	-0.0526***	-0.0588***	-0.0583***	0.480***	0.354***	0.303***	0.307***	0.309***
	(38.15)	(-30.59)	(-27.17)	(-31.34)	(-31.86)	(135.67)	(90.46)	(76.53)	(78.64)	(78.98)
Race*NQ1	-0.0804***	0.0140***	0.0130***	0.0363***	0.0357***	-0.305***	-0.169***	-0.124***	-0.137***	-0.138***
	(-36.24)	(5.58)	(4.99)	(14.05)	(14.06)	(-41.84)	(-23.71)	(-17.64)	(-19.80)	(-19.90)
Race*NQ2	-0.0968***	0.000922	-0.0000597	0.0268***	0.0247***	-0.370***	-0.240***	-0.193***	-0.209***	-0.211***
	(-32.65)	(0.30)	(-0.02)	(8.49)	(7.87)	(-74.82)	(-45.64)	(-36.70)	(-39.97)	(-40.14)
Race*NQ3	-0.162***	-0.0652***	-0.0662***	-0.0381***	-0.0404***	-0.411***	-0.283***	-0.235***	-0.252***	-0.252***
	(-32.44)	(-13.06)	(-13.15)	(-7.68)	(-8.05)	(-88.78)	(-55.83)	(-46.17)	(-49.71)	(-49.41)
Race*NQ4	-0.197***	-0.101***	-0.102***	-0.0758***	-0.0756***	-0.438***	-0.310***	-0.260***	-0.275***	-0.273***
	(-26.38)	(-13.65)	(-13.77)	(-10.43)	(-10.08)	(-99.74)	(-63.26)	(-52.68)	(-56.04)	(-54.96)
Race*NQ5	-0.199***	-0.104***	-0.105***	-0.0757***	-0.0776***	-0.461***	-0.332***	-0.280***	-0.297***	-0.295***
	(-20.89)	(-10.78)	(-10.89)	(-8.09)	(-8.04)	(-105.04)	(-66.53)	(-55.19)	(-58.58)	(-57.78)
Age		YES	YES	YES	YES		YES	YES	YES	YES
Age squared		YES	YES	YES	YES		YES	YES	YES	YES
Gender			YES	YES	YES			YES	YES	YES
Education				YES	YES				YES	YES
Industry					YES					YES
N	342679	342679	342679	342679	342679	342679	342679	342679	342679	342679

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.11: *Regression coefficients for ten-year transitions, i.e. from 1981 to 1991. Standard errors have been clustered at the individual level.*

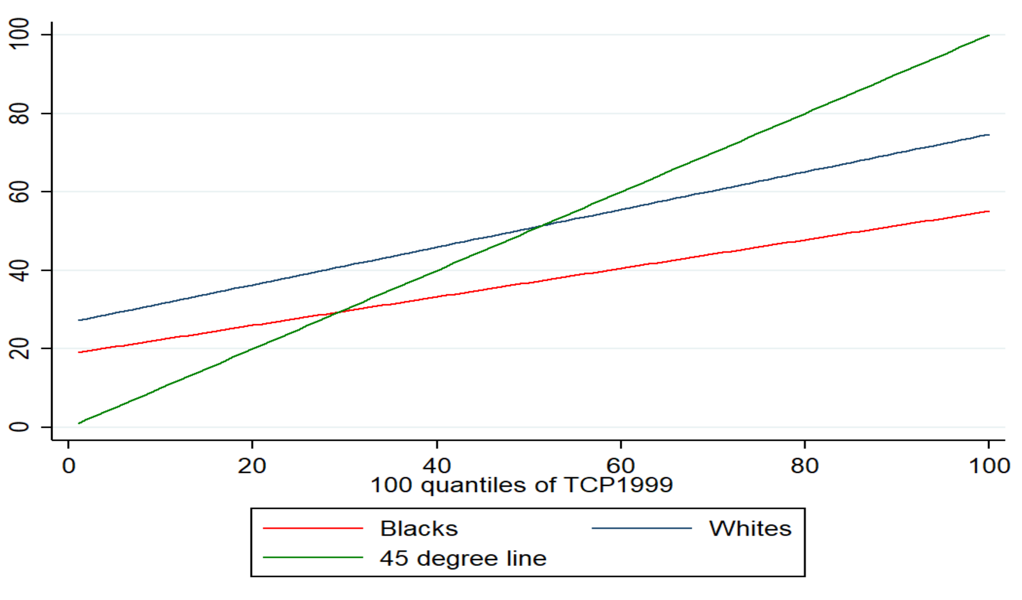


Figure A.7: This figures represents the average actual consumption rank in 2017 for an individual who was in each consumption percentile in 1999, by race. The consumption variable used to construct this figure is actual consumption, which is available from 1999 to 2017. Solid stands for Whites, dash for Blacks.

B.2.1 Persistence Probabilities with Moving Base Year

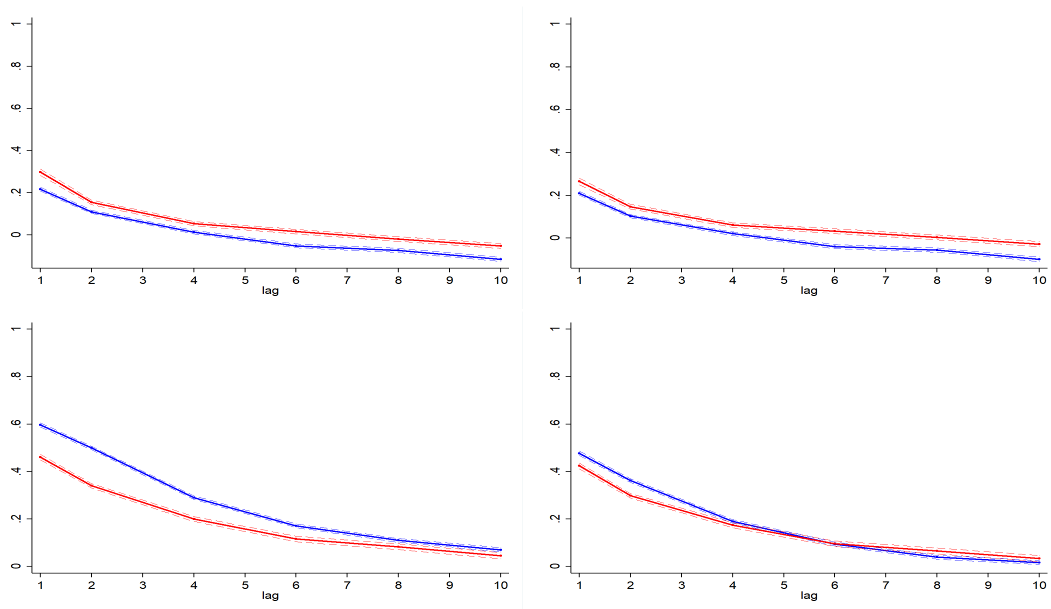


Figure A.8: *Probabilities of remaining in the bottom (upper panels) or top (bottom panels) TCP quintile between 1981 and 2017, respectively for Blacks (red) and Whites (blue). Top 1% and bottom 1% consumption have been trimmed. Persistence probabilities have been estimated for each couple of years* t *and* $t-k$ *between 1981 and 2017, where* $k = 1, 2, ..., 10$*. In the left panels we only control for year fixed effects, whereas in the right panels we also control for age, age squared, gender, education and industry of employment.*

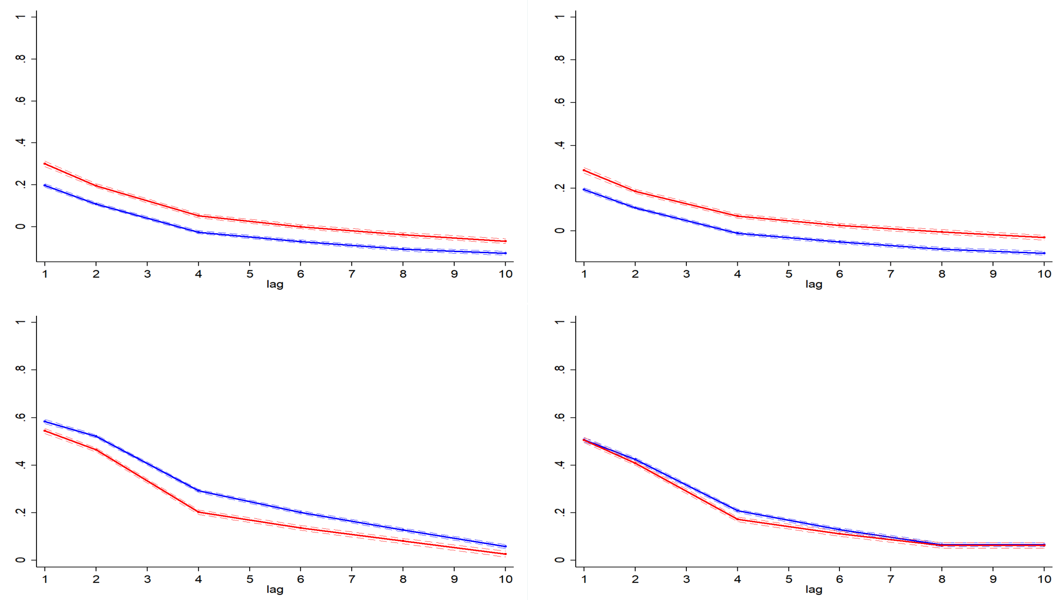


Figure A.9: *Probabilities of remaining in the bottom (upper panels) or top (bottom panels) TFA quintile between 1981 and 2017, respectively for Blacks (red) and Whites (blue). Top 1% and bottom 1% TFA have been trimmed. Persistence probabilities have been estimated for each couple of years* t *and* $t-k$ *between 1981 and 2017, where* $k = 1, 2, ..., 10$. *In the left panels we only control for year fixed effects, whereas in the right panels we also control for age, age squared, gender, education and industry of employment.*

B.2.2 Estimation of Persistence Probability with PSID Weights

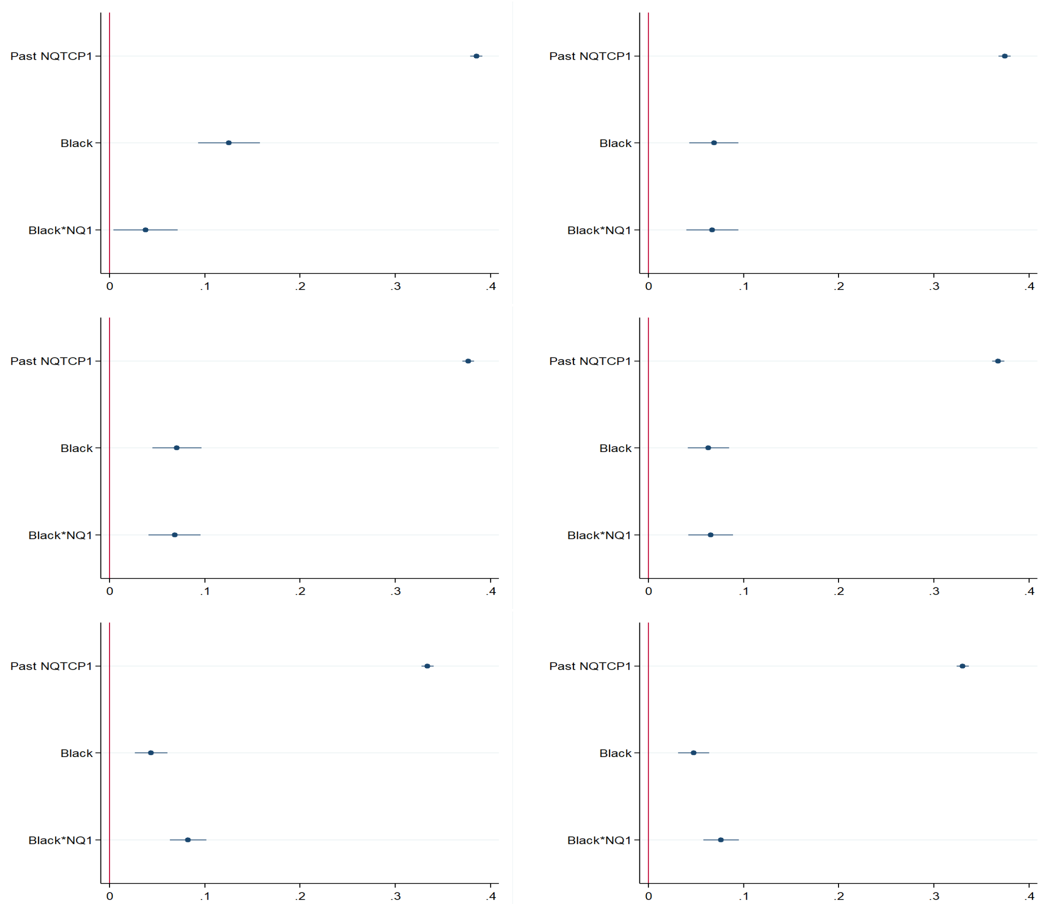


Figure A.10: OLS regressions. Dependent variable in all the estimations is the ratio of years the individual spent in the bottom TCP quintile to the total number of years the individual was in the dataset. The reference year in which past quintiles are computed is 1981. The dummy standing for past NQTCP5 and the interaction term between this dummy and the Black dummy have been omitted for collinearity. In all regressions we control for the number of years the individual has spent in the sample. 95% confidence intervals are reported. In the panels (to be read from left to right and then from top to bottom), additional controls are progressively added: (i) Years spent in the sample only, (ii) Log consumption in 1981, (iii) age, and age squared, (iv) gender, (v) education, (vi) industry.

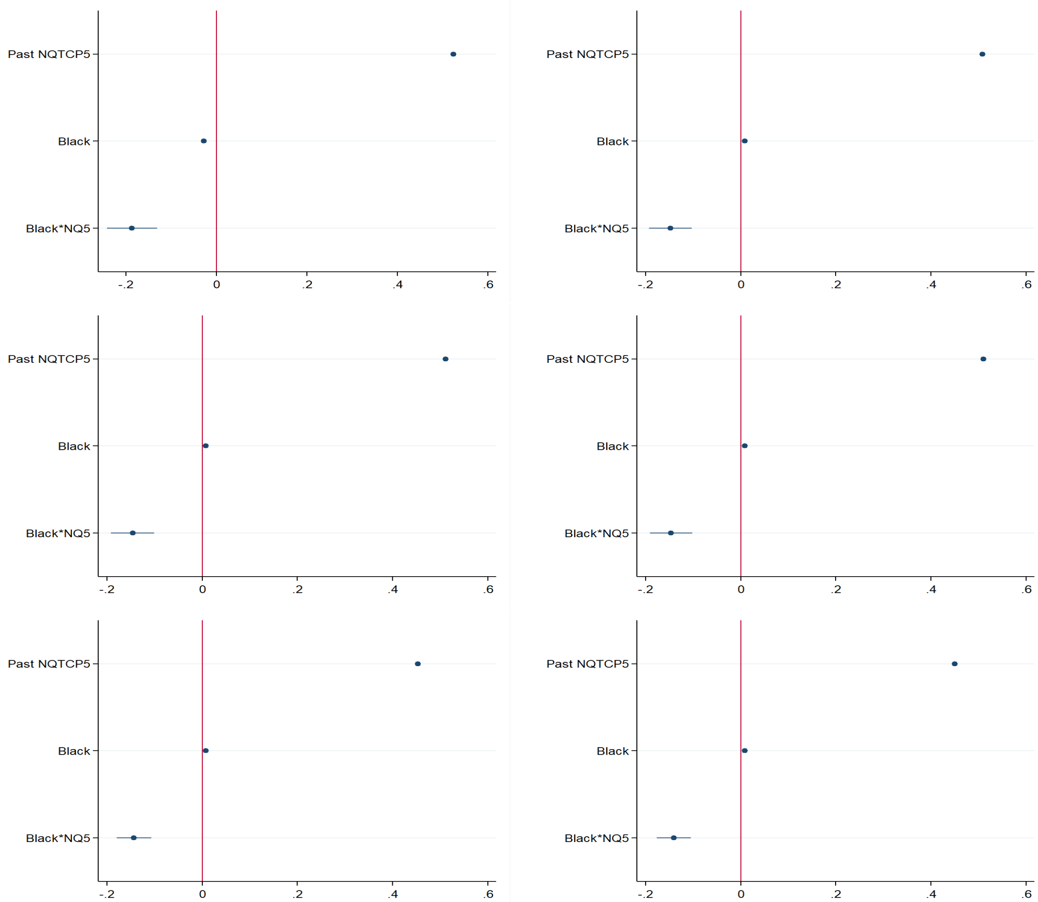


Figure A.11: OLS regressions. Dependent variable in all the estimations is the ratio of years the individual spent in the top TCP quintile to the total number of years the individual was in the dataset. The reference year in which past quintiles are computed is 1981. The dummy standing for past NQTCP1 and the interaction term between this dummy and the Black dummy have been omitted for collinearity. In all regressions we control for the number of years the individual has spent in the sample. 95% confidence intervals are reported. In the panels (to be read from left to right and then from top to bottom), additional controls are progressively added: (i) Years spent in the sample only, (ii) Log consumption in 1981, (iii) age, and age squared, (iv) gender, (v) education, (vi) industry.

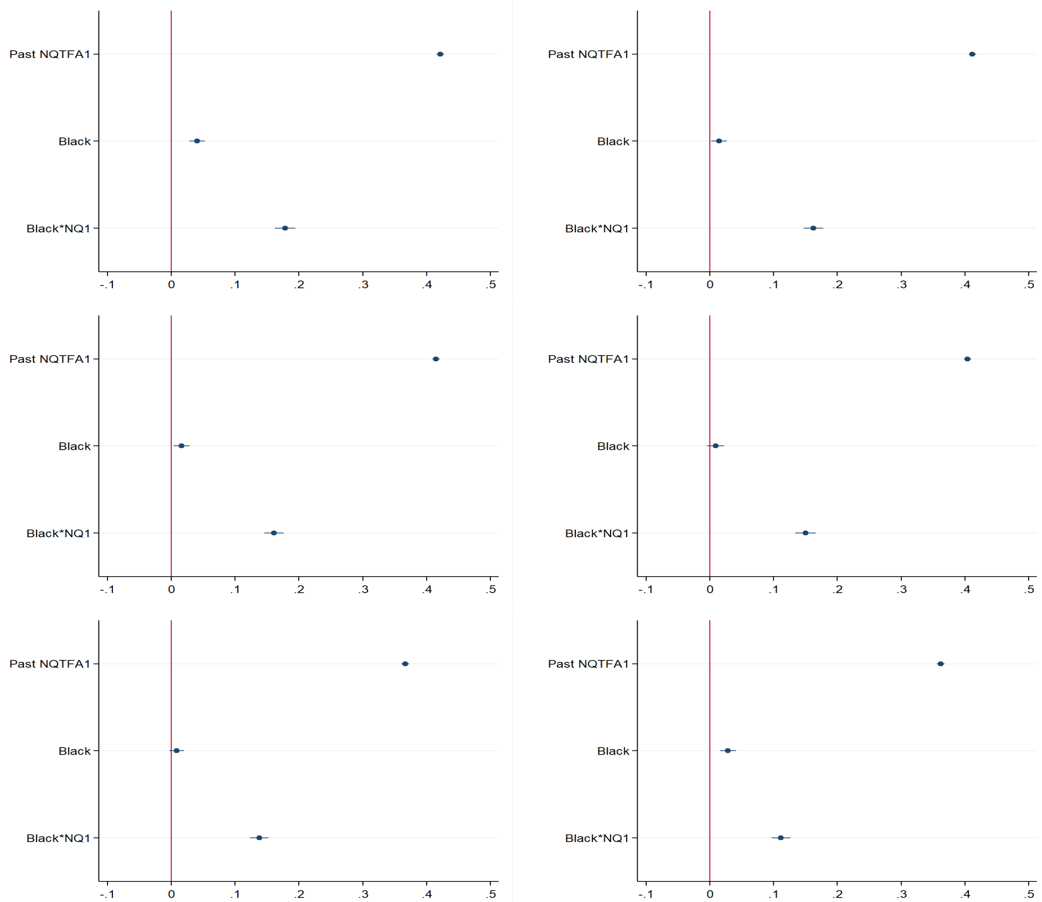


Figure A.12: OLS regressions. Dependent variable in all the estimations is the ratio of years the individual spent in the bottom TFA quintile to the total number of years the individual was in the dataset. The reference year in which past quintiles are computed is 1981. The dummy standing for past NQTFA5 and the interaction term between this dummy and the Black dummy have been omitted for collinearity. In all regressions we control for the number of years the individual has spent in the sample. 95% confidence intervals are reported. In the panels (to be read from left to right and then from top to bottom), additional controls are progressively added: (i) Years spent in the sample only, (ii) Log consumption in 1981, (iii) age, and age squared, (iv) gender, (v) education, (vi) industry.

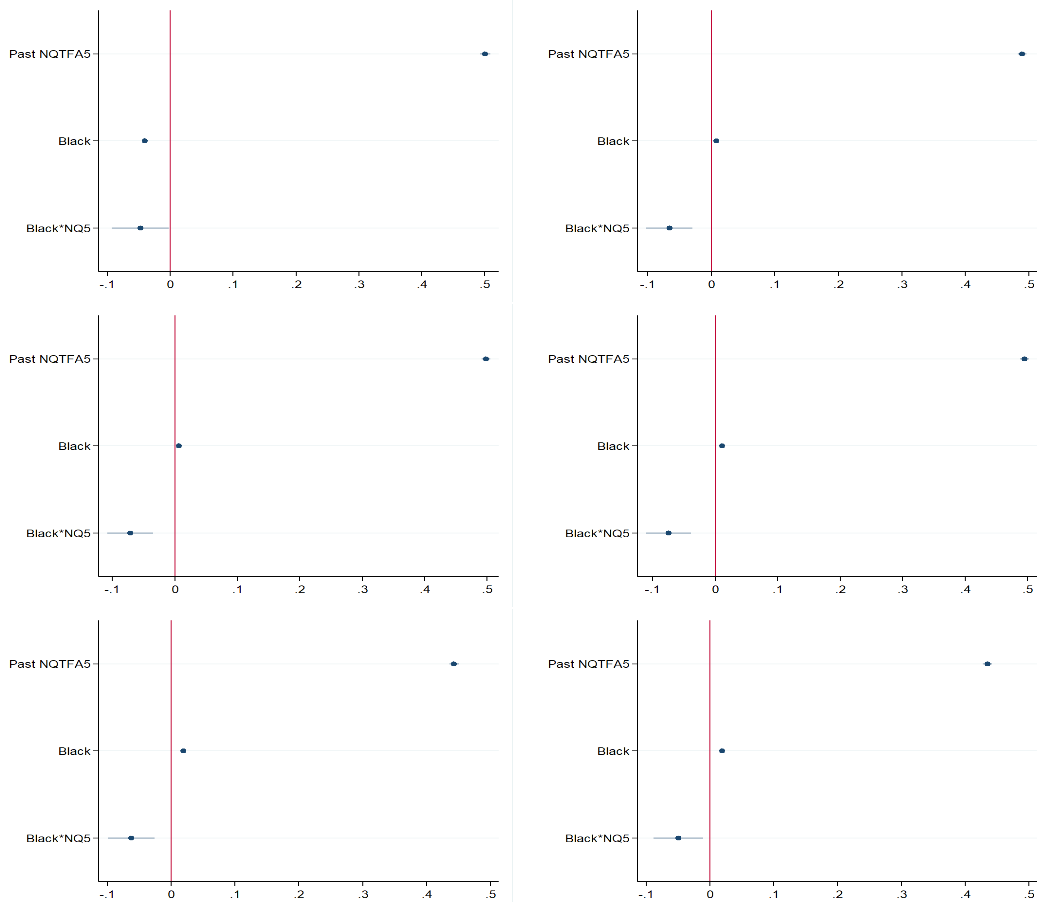


Figure A.13: OLS regressions. Dependent variable in all the estimations is the ratio of years the individual spent in the top TFA quintile to the total number of years the individual was in the dataset. The reference year in which past quintiles are computed is 1981. The dummy standing for past NQTFA1 and the interaction term between this dummy and the Black dummy have been omitted for collinearity. In all regressions we control for the number of years the individual has spent in the sample. 95% confidence intervals are reported. In the panels (to be read from left to right and then from top to bottom), additional controls are progressively added: (i) Years spent in the sample only, (ii) Log consumption in 1981, (iii) age, and age squared, (iv) gender, (v) education, (vi) industry.

B.2.3 Estimation of Persistence Probabilities with Census Weights

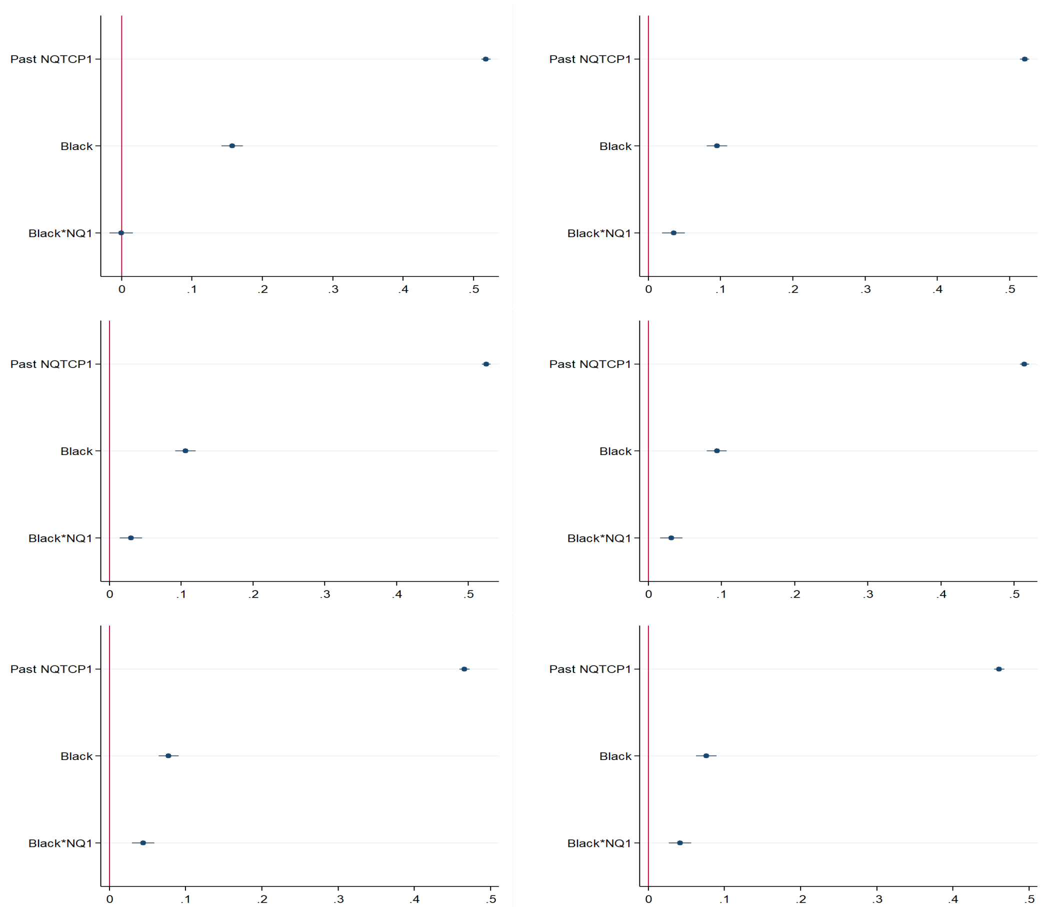


Figure A.14: OLS regressions. Dependent variable in all the estimations is the ratio of years the individual spent in the bottom TCP quintile to the total number of years the individual was in the dataset. The reference year in which past quintiles are computed is 1981. The dummy standing for past NQTCP5 and the interaction term between this dummy and the Black dummy have been omitted for collinearity. In all regressions we control for the number of years the individual has spent in the sample. 95% confidence intervals are reported. In the panels (to be read from left to right and then from top to bottom), additional controls are progressively added: (i) Years spent in the sample only, (ii) Log consumption in 1981, (iii) age, and age squared, (iv) gender, (v) education, (vi) industry.

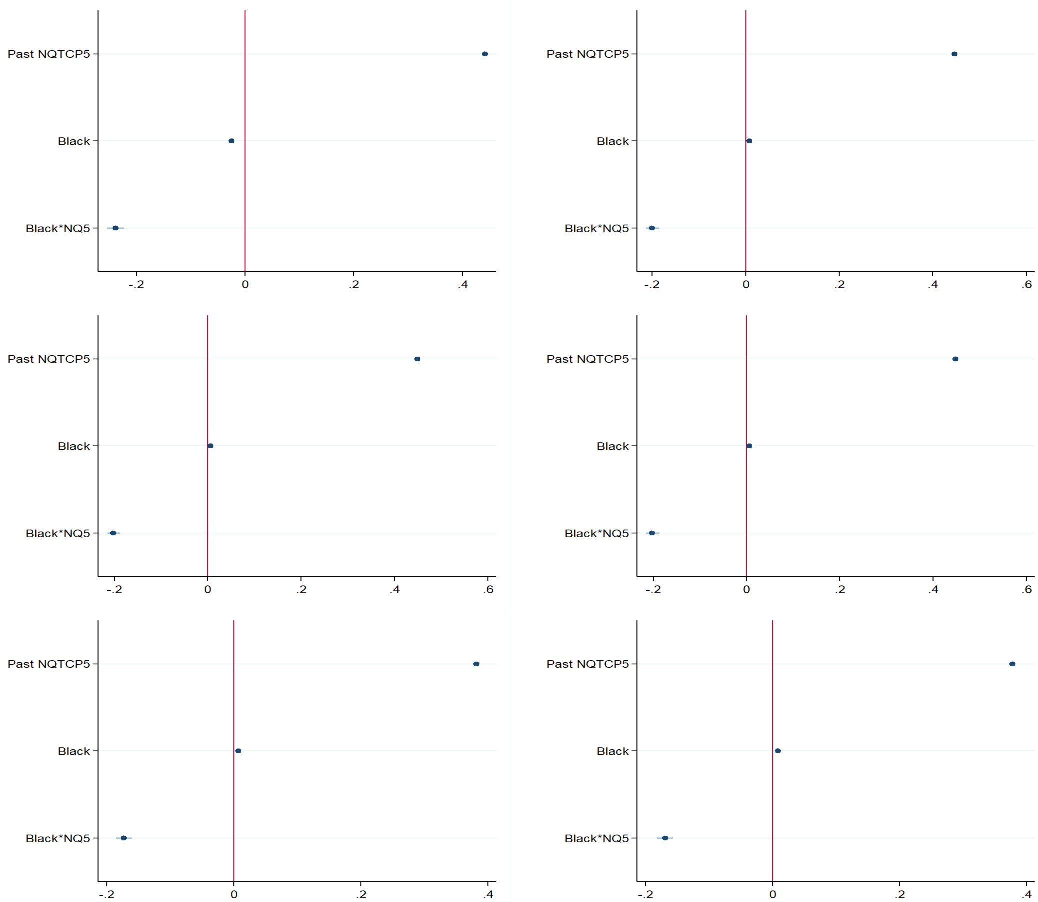


Figure A.15: OLS regressions. Dependent variable in all the estimations is the ratio of years the individual spent in the top TCP quintile to the total number of years the individual was in the dataset. The reference year in which past quintiles are computed is 1981. The dummy standing for past NQTCP1 and the interaction term between this dummy and the Black dummy have been omitted for collinearity. In all regressions we control for the number of years the individual has spent in the sample. 95% confidence intervals are reported. In the panels (to be read from left to right and then from top to bottom), additional controls are progressively added: (i) Years spent in the sample only, (ii) Log consumption in 1981, (iii) age, and age squared, (iv) gender, (v) education, (vi) industry.

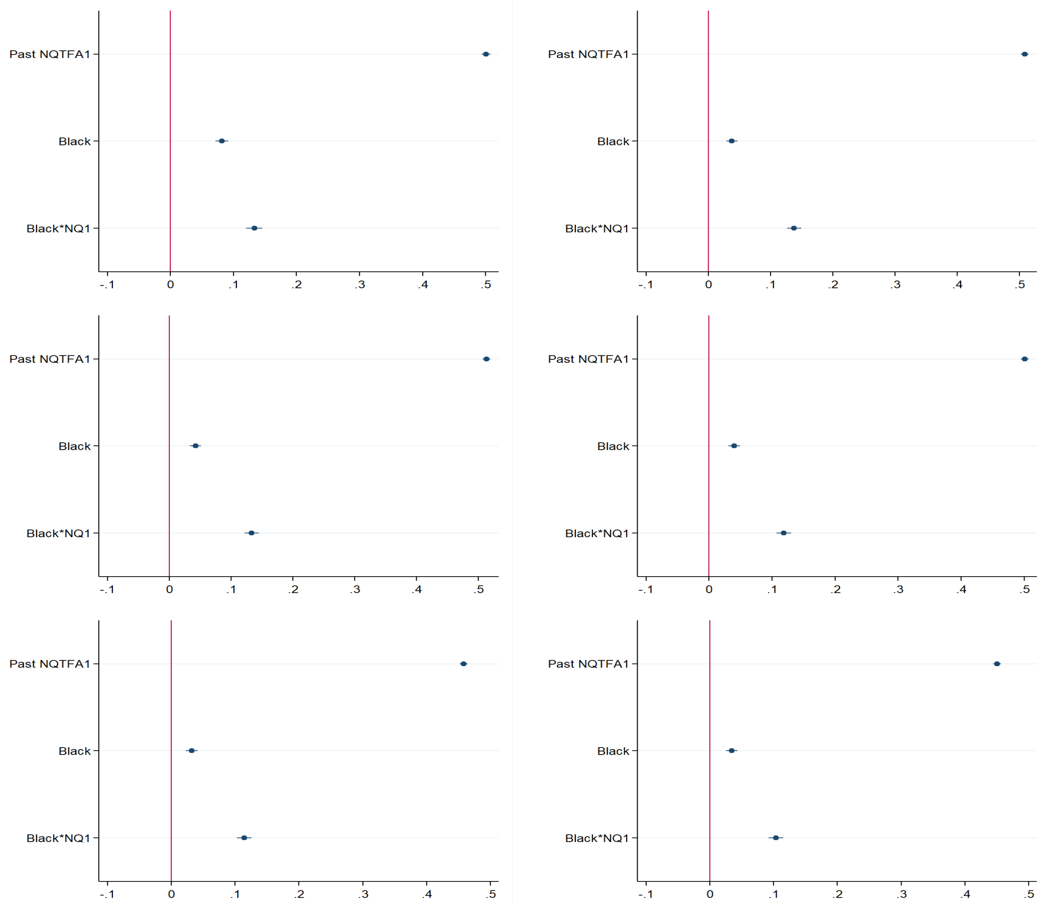


Figure A.16: OLS regressions. Dependent variable in all the estimations is the ratio of years the individual spent in the bottom TFA quintile to the total number of years the individual was in the dataset. The reference year in which past quintiles are computed is 1981. The dummy standing for past NQTFA5 and the interaction term between this dummy and the Black dummy have been omitted for collinearity. In all regressions we control for the number of years the individual has spent in the sample. 95% confidence intervals are reported. In the panels (to be read from left to right and then from top to bottom), additional controls are progressively added: (i) Years spent in the sample only, (ii) Log consumption in 1981, (iii) age, and age squared, (iv) gender, (v) education, (vi) industry.

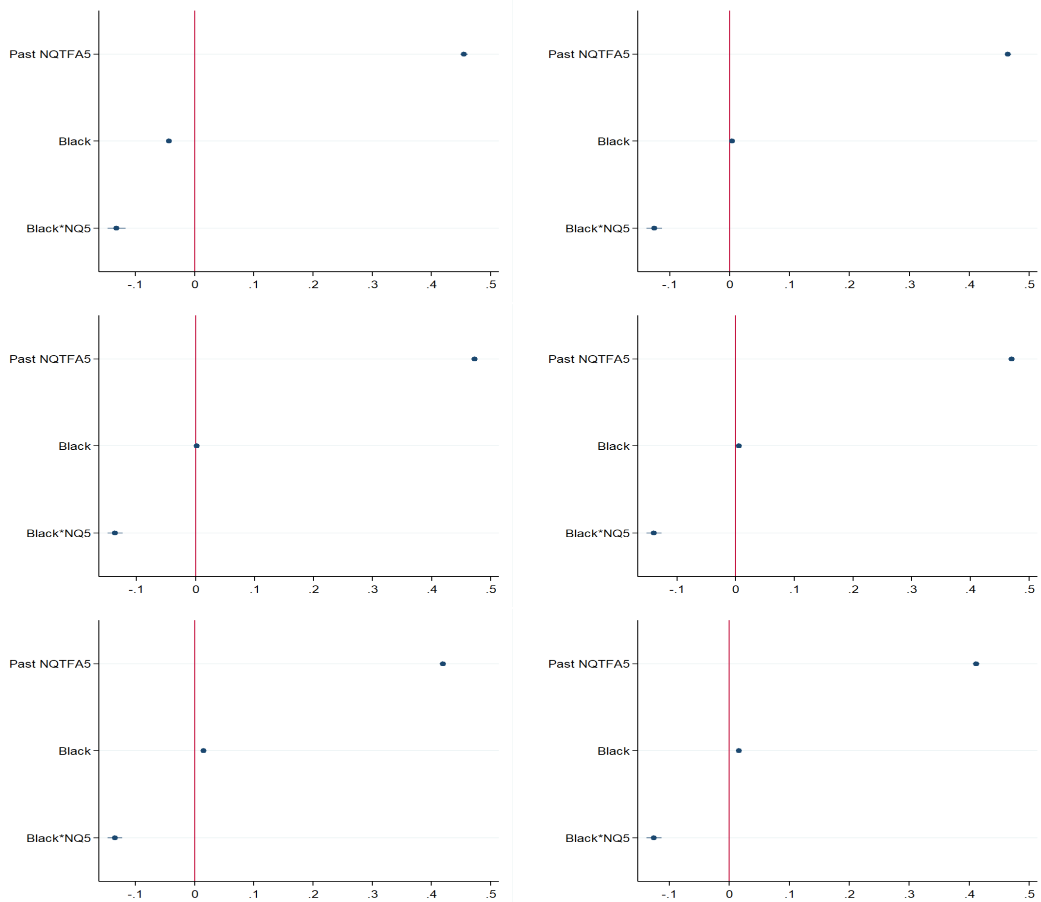


Figure A.17: OLS regressions. Dependent variable in all the estimations is the ratio of years the individual spent in the top TFA quintile to the total number of years the individual was in the dataset. The reference year in which past quintiles are computed is 1981. The dummy standing for past NQTFA1 and the interaction term between this dummy and the Black dummy have been omitted for collinearity. In all regressions we control for the number of years the individual has spent in the sample. 95% confidence intervals are reported. In the panels (to be read from left to right and then from top to bottom), additional controls are progressively added: (i) Years spent in the sample only, (ii) Log consumption in 1981, (iii) age, and age squared, (iv) gender, (v) education, (vi) industry.

B.3 Additional Evidence on Health

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	stroke	cancer	diabetes	asthma	arthritis	heart attack	heart dis	lung dis	blood press
Age	-0.00295***	-0.00314***	0.00585***	-0.00141*	0.00291***	-0.00122*	-0.00281***	0.000885*	0.0123***
	(-5.79)	(-5.43)	(8.80)	(-2.07)	(3.69)	(-2.56)	(-5.02)	(1.98)	(13.51)
Age sq	0.0000521***	0.0000614***	-0.0000195**	0.00000870	0.0000641***	0.0000375***	0.0000638***	0.00000383	-0.0000145
	(9.03)	(9.36)	(-2.73)	(1.28)	(7.59)	(6.95)	(10.21)	(0.80)	(-1.51)
Educ	-0.00428***	0.00108	-0.0124***	-0.000687	-0.0158***	-0.00429***	-0.00255	-0.00834***	-0.0108***
	(-3.87)	(0.76)	(-6.46)	(-0.33)	(-7.15)	(-3.52)	(-1.84)	(-6.98)	(-3.94)
Gender	-0.000181	0.0117***	-0.00918*	0.0242***	0.0474***	-0.0268***	-0.0132***	0.00996***	-0.0146**
	(-0.08)	(4.15)	(-2.40)	(6.01)	(10.93)	(-10.82)	(-4.92)	(4.47)	(-2.69)
Black	0.0218*	-0.0103	0.0171	0.00449	-0.00989	-0.00252	0.00168	-0.0242**	0.0996***
	(2.32)	(-1.15)	(1.22)	(0.31)	(-0.66)	(-0.28)	(0.17)	(-2.65)	(5.83)
NQTFA	-0.00612***	0.00240	-0.0146***	-0.0148***	-0.0248***	-0.00632***	-0.00816***	-0.0130***	-0.0187***
	(-4.46)	(1.56)	(-6.89)	(-6.75)	(-10.37)	(-4.48)	(-5.15)	(-9.17)	(-6.89)
Black*NQ	-0.00302	-0.00128	0.00194	0.000145	0.000268	0.000757	-0.00184	0.00478*	0.00176
	(-1.43)	(-0.62)	(0.59)	(0.04)	(0.08)	(0.38)	(-0.82)	(2.35)	(0.41)
State d	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cons	0.0793***	0.0177	-0.0272	0.137***	0.00404	0.0922***	0.117***	0.0478**	-0.166***
	(5.11)	(1.02)	(-1.15)	(5.73)	(0.14)	(5.74)	(6.33)	(3.24)	(-5.07)
N	82019	82025	82025	82030	82007	82037	82014	82028	82007

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.12: Drivers of major health problems. In this table, we regress each of the nine ilnesses recorded in the PSID on a standard set of controls. Standard errors have been clustered at the individual level. Dummies for States have been included, as well as an interaction term between the Black dummy and the quintiles in the national distribution of TFA. Data for 1999-2017. Standard errors have been clustered at the individual level.

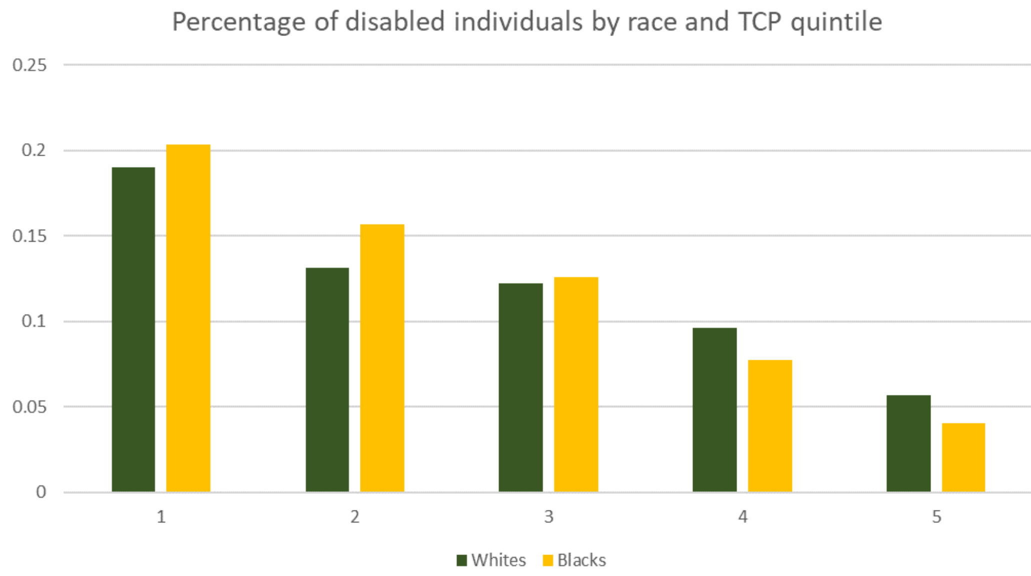


Figure A.18: *In this Figure, we report the percentage of people who are unable to work due to a physical or mental disability, by race and by TCP quintile. Data for 1968-2017.*

	(1) stroke	(2) cancer	(3) diabetes	(4) asthma	(5) arthritis	(6) heart att	(7) heart dis	(8) lung dis	(9) blood press
Age	-0.00323***	-0.00347***	0.00599***	-0.00281***	0.00235***	-0.00109***	-0.00235***	0.000295	0.0141***
	(-15.76)	(-13.76)	(17.70)	(-7.91)	(5.79)	(-4.76)	(-8.84)	(1.19)	(28.30)
Age sq	0.0000532***	0.0000643***	-0.0000180***	0.0000213***	0.0000585***	0.0000379***	0.0000584***	0.00000885***	-0.0000388***
	(26.39)	(25.89)	(-5.42)	(6.07)	(14.66)	(16.75)	(22.29)	(3.61)	(-7.92)
Edu2	-0.0171***	0.00278	-0.0335***	-0.0182***	-0.0191***	-0.0256***	-0.0271***	-0.0358***	0.00345
	(-6.98)	(0.92)	(-8.27)	(-4.28)	(-3.93)	(-9.28)	(-8.51)	(-12.02)	(0.58)
Edu3	-0.0138***	0.00265	-0.0266***	-0.000766	-0.0363***	-0.0252***	-0.0216***	-0.0434***	-0.00592
	(-5.46)	(0.85)	(-6.35)	(-0.17)	(-7.23)	(-8.87)	(-6.56)	(-14.10)	(-0.96)
Edu4	-0.0252***	0.0108***	-0.0605***	-0.0119**	-0.0754***	-0.0448***	-0.0385***	-0.0578***	-0.0412***
	(-10.42)	(3.64)	(-15.16)	(-2.83)	(-15.75)	(-16.50)	(-12.26)	(-19.69)	(-7.01)
Gender	0.00414**	0.00846***	-0.00302	0.0466***	0.0876***	-0.0192***	-0.00260	0.0299***	0.0248***
	(2.96)	(4.91)	(-1.31)	(19.16)	(31.62)	(-12.22)	(-1.43)	(17.57)	(7.27)
Black	0.0110***	-0.0212***	0.0310***	0.0141*	-0.00705	-0.00457	-0.0134**	0.00188	0.102***
	(3.35)	(-5.23)	(5.71)	(2.48)	(-1.08)	(-1.24)	(-3.13)	(0.47)	(12.78)
Black*Edu1	0.0126**	0.00419	0.00176	0.000383	-0.00104	-0.0155**	-0.0107	-0.0312***	0.0113
	(2.92)	(0.79)	(0.25)	(0.05)	(-0.12)	(-3.20)	(-1.91)	(-5.93)	(1.07)
Black*Edu2	0.00634	0.00151	-0.00189	-0.00428	-0.0286***	0.00675	0.00882	-0.0178***	-0.0406***
	(1.61)	(0.31)	(-0.29)	(-0.63)	(-3.66)	(1.53)	(1.72)	(-3.72)	(-4.23)
Black*Edu3	-0.00440	0.0122*	-0.0144*	-0.0112	-0.0128	0.00328	0.00714	-0.000378	-0.0390***
	(-1.08)	(2.42)	(-2.14)	(-1.58)	(-1.58)	(0.72)	(1.35)	(-0.08)	(-3.93)
Constant	0.0609***	0.0475***	-0.101***	0.124***	-0.0879***	0.0666***	0.0701***	0.0209*	-0.300***
	(7.93)	(5.01)	(-7.94)	(9.30)	(-5.78)	(7.72)	(7.03)	(2.24)	(-16.05)
N	79060	79062	79059	79070	79041	79074	79038	79066	79036

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.13: Drivers of major health problems. In this table, we regress each of the nine ilnesses recorded in the PSID on a standard set of controls. Standard errors have been clustered at the individual level. Dummies for States have been included, as well as an interaction term between the Black dummy and the educational level dummies. Data for 1999-2017.

B.4 Additional evidence on occupational choice

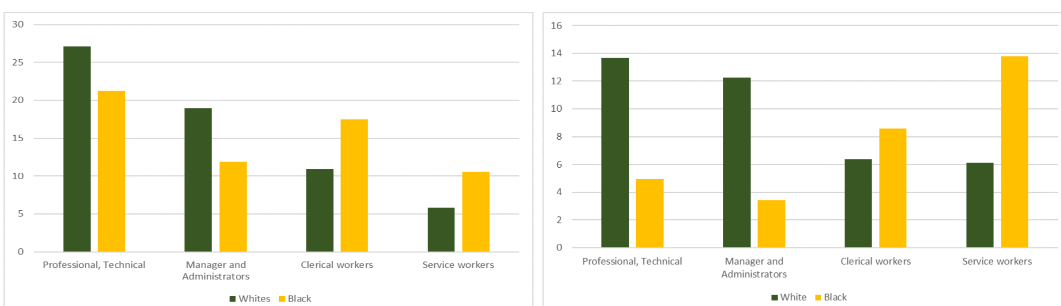


Figure A.19: Occupational choice by race in the top consumption quintile (left panel) and in the whole consumption distribution (right panel). Data for the 1968-2017 period.

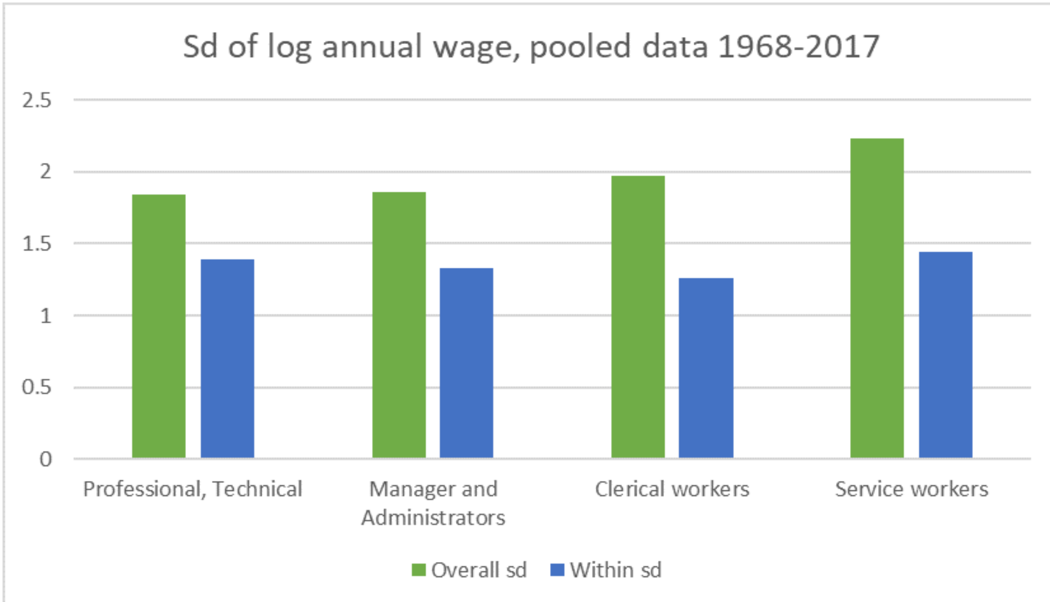


Figure A.20: Standard deviation of log wages by occupation. Overall sd has been computed on the pooled data, whereas within sd is the "time-series" standard deviation. Data for the 1968-2017 period.

	Average marginal effect of being Black
Professional, Technical, and Kindred Workers	-.0130801*** (.0012648)
Managers and Administrators, Except Farm	-.0532936*** (.0013439)
Sales Workers	-.0227845*** (.0009002)
Clerical and Kindred Workers	.002965*** (.0011318)
Craftsmen and Kindred Workers	-.0226704*** (.0010491)
Operatives, Except Transport	.0157673*** (.0009087)
Transport Equipment Operatives	.0092947*** (.0005676)
Laborers, Except Farm	.0146623*** (.0005732)
Farmers and Farm Managers	-.0165583*** (.0008184)
Farm laborers and Farm foremen	-.0001638 (.0002871)
Service workers except Private Household	.0403376*** (.0010268)
Private Household Workers	.0108431*** (.000415)
N	334519

Table A.14: Multinomial logit estimated average marginal effects for the Black dummy on occupational choice. Controls are: age, age squared, gender, number of children, civil status and education. SE are computed via the Delta method and clustered at the individual level. Data for the 1968-2017 period.

B.6 Robustness checks

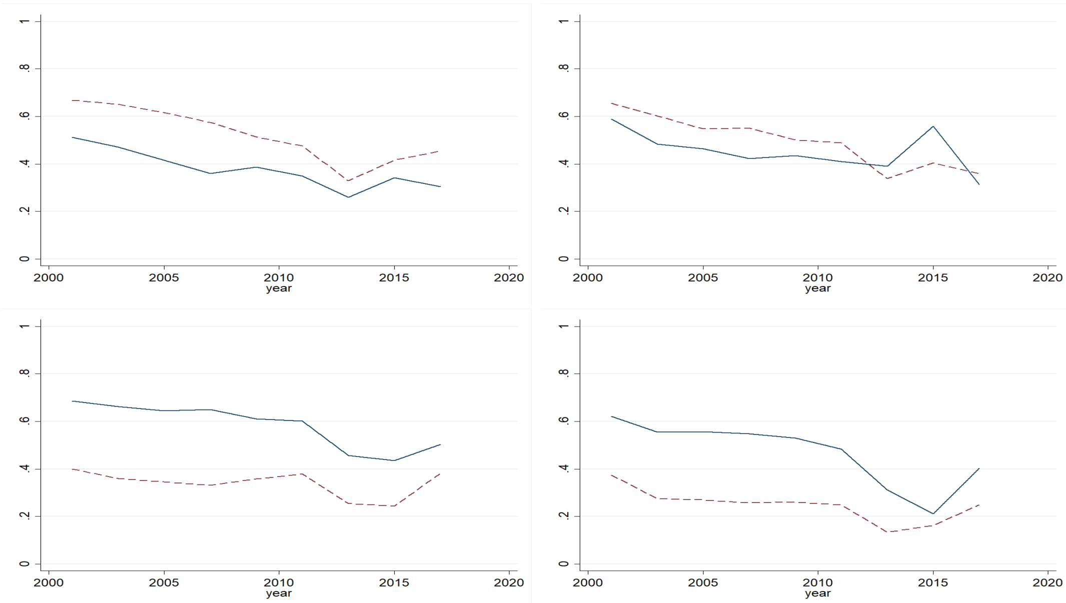


Figure A.21: *Actual consumption persistence in bottom and top quintile. Probabilities of remaining in the bottom (upper panels) or in the top (bottom panels) quintile of actual consumption over time, respectively for Blacks (dashed) and Whites (solid), without controls (left panels) and conditional on a set of control variables (right panels). Data for 1999-2017.*

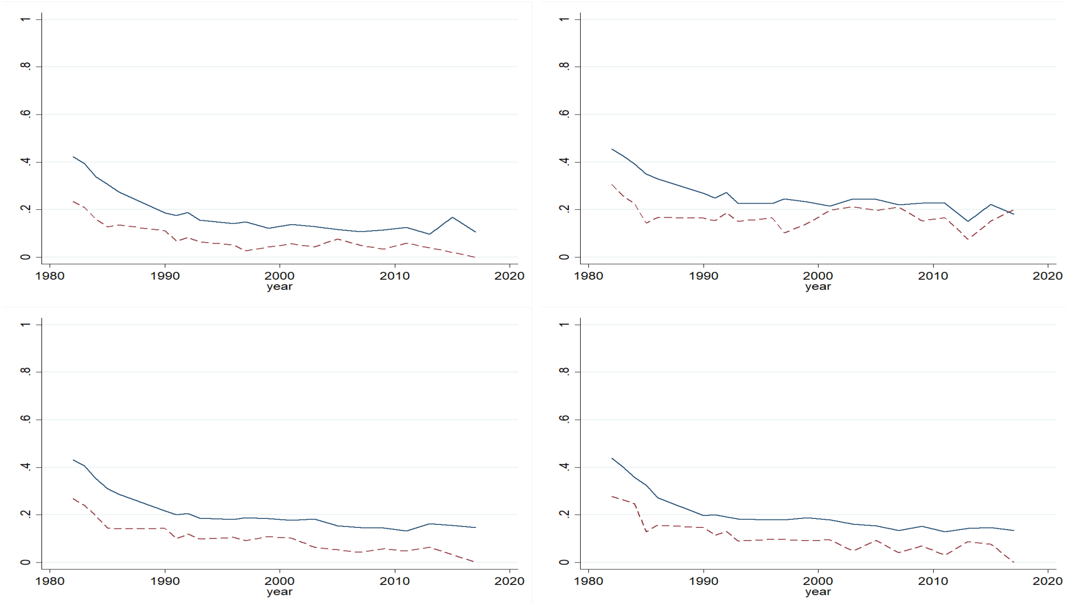


Figure A.22: *Consumption persistence in top quintile with different sets of controls. Probabilities of remaining in the top consumption quintile, by race. In the upper left panel the controls include age, age squared, gender, education and house value. In the upper right panel house value is dropped and the following controls are added: number of children, number of children squared and number of children cubic. In the bottom left panel the controls are age, age squared, gender, education, region (Northeast, North Central, West, South). In the bottom right panel controls include age, age squared, education, gender, and 52 dummies for each of the US States. Dash stands for Blacks, solid for Whites. Data for 1981-2017.*

Figure A.23: This Figure shows the probabilities of remaining in the top (left panels), respectively in the bottom TFA quintile (right panels), by race. The upper panels report actual transitions without control variables, whereas the bottom panels report staying probabilities conditional on a set of controls (age, gender, education). Dash stands for Blacks, solid for Whites. Data for 1990-2017.