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Consumption Insurance among Blacks and Whites

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Consumption Insurance among Blacks and Whites

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Abstract

We document relevant racial differences in the degree consumption insurance against shocks: Blacks appear to be less insured. We probe these results by performing a double/debiased lasso estimation of the treatment effects of a health shock, and we find that such effects are both larger and more long-lasting for Blacks than for Whites. With the help of a toy model, we show that, having a lower life expectancy, Blacks save less and, as a consequence, are less insured than Whites against both income and health shocks.

JEL classification: E21, D12, C3
Keywords: Consumption, Insurance, Inequality, Savings, Life Expectancy.

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1 Introduction

The aim of this paper is to investigate the differential in the degree of insurance against shocks among Blacks and Whites. Insurance against income and health shocks plays a fundamental role on household well-being as uninsured shocks might draw households to extreme consequences. See Jappelli and Pistaferri [2010] for an extensive discussion on the literature.

in determining income and consumption dynamics, and hence the evolution of inequality in the long run. Economic inequality remains one of the major challenges for policy-makers and economists. In recent years there has been a burgeoning literature in this area. Starting from Piketty and Saez [2003], several authors have documented and investigated the rising income, and wage inequality, in the US and other countries (see Autor et al. [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, 2016], Blundell [2014],Chetty et al. [2014a]). Given that consumption is tightly related to permanent income and it is a driver of individual utility more than income itself, a related literature has also stressed the importance of focusing on consumption inequality (see for example Blundell and Preston [1998], Meyer and Sullivan [2003], Krueger and Perri [2006], Blundell et al. [2008], Attanasio et al. [2014], Aguiar and Bils [2015], Attanasio and Pistaferri [2016], Blundell et al. [2016]).

A stream of the literature, close in spirit to the current paper, has investigated the existing differences in earnings levels between Black and White individuals in the US (see, for example, Chetty et al. [2014b], Blau and Beller [1992], Card and Krueger [1992], Heckman et al. [2000], Bayer and Charles [2018], Chay and Lee [2000], Heywood and Parent [2012], Oaxaca and Ransom [1994], Peoples and Talley [2001], Card and Krueger [1993]). However, the current paper focuses on a relatively unexplored areas, i.e. racial differences in the degree of insurance against shocks, by using 20 years of PSID data (1999-2017). We argue that such differences in the degree of insurance have mainly to do with lower savings and wealth accumulation among the Blacks, which in turn can be rationalized via a toy model of life expectancy. We show that the Blacks have on average 8 years shorter life expectancy than the Whites, hence they save less, accumulate less wealth, and are hence less prepared to deal with shocks (e.g. health shocks) when they hit. As a consequence, the drop in consumption witnessed by a black individual after a health shock is way larger than that experimented by a white individual, even if the corresponding drop in income is comparable.

This is confirmed by the application of the Commault [2022] model for partial insurance, which is reported in Section 4, and following a causal approach in Section 5 on the effects of health shocks on consumption which we perform through a double lasso procedure in the spirit of Chernozhukov et al. [2018]. Importantly, we show that while the impact of a health shock on income (and unemployment probability) is indistinguishable across race, the impact on consumption is around 65% larger for Blacks. Close to our paper, Ganong et al. [2020] use bank data matched with voter registry and firm-wide wage changes data in order to estimate the transmission of unexpected income shocks into consumption by race. They, too, link race differentials in the degree of insurance against shocks to the different amount of wealth held by Blacks and Whites. However, differently from them, our focus lies in the income and consumption reaction to health shocks.

The remainder of the paper is organized as follows: Section 2 investigates racial differences in life expectancy and a toy model to link those to saving behavior. Section 3 presents the data and a descriptive analysis of the different sources of insurance for Blacks and Whites. Section 4 presents the model for insurance against income shocks, and the relative results. Section 5 is devoted to the presentation of the double/debiased lasso results for health shocks. Section 6 concludes. Appendix A provides further information on the construction of the dataset. Appendix B reports additional descriptive statistics on the health shocks. Finally, in Appendix C we present the results of the Blundell et al. [2008] model which confirms the results of the Commault [2022] model, i.e. Blacks are more exposed than Whites to income shocks.

2 Inequality in Life Expectancy

As we will show in the data analysis part, Blacks save less and own less wealth than the Whites. In this Section, we aim at addressing the question why is that the case. We believe that a shorter life expectancy and a lower rate of return are part of the explanation. We show, using an extremely stylized model, that a life expectancy differential like the one observed for the cohorts of interest and a plausibly lower rate of return deliver predictions in terms of savings and wealth accumulation in line with those observed in the data.

2.1 Estimated Life Expectancy

Our cohorts of interest in the PSID are born between 1935 (i.e. individuals who are 64 in 1999, 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] Importantly, the gradient of life-expectancy across education categories (as a proxy for permanent income) is much lower for Blacks than for Whites (see for example Hummer and Hernandez [2013]) which is consistent with a life-expectancy gap that doesn't close at high level of consumption. We take the measure at birth as widely available and so to avoid making assumptions 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 as we will show below.

2.2 A Simple Model

Here we provide a sense 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 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 purposely use a basic off-the-shelf model of consumption without uncertainty. This is useful to establish

[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`)

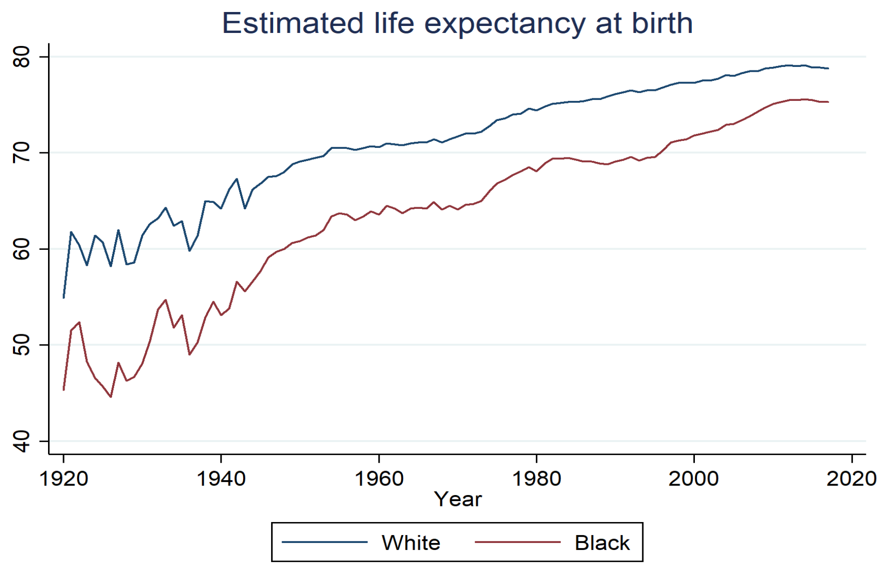

Figure 1: Estimated life expectancy at birth, by race. Data from the National Center for Health Statistics, Centers for Disease Control and Prevention Arias and Xu [2019]).

a benchmark and see how far we get with the simplest model.

Let us 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, 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 $T^W > T^B$ (where B stands for Blacks and W for Whites).

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

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

We fix Blacks' and Whites' incomes to be the same and to follow the same profile, this is because we are only interested in the role of life-expectancy and secondarily rate of returns. 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.

We assume a CES utility with $RRA = \theta$ and common discount factor β. It should be clear that we are abstracting from explicit differences in the discount factor β, curvature θ, and bequest motives. Importantly Altonji et al. [2000] state that

> *[... Several studies, including those mentioned above, have found large wealth differences even after controlling for differences between blacks and whites in average income and other factors. For example, Blau and Graham [1990] conclude that as little as one quarter of the wealth gap can be attributed to racial differences in income and demographic variables...] [...They tentatively suggest that the race difference in the wealth models is not driven primarily by inter vivos gifts and inheritances...]*

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

We can then assess how savings and consumption profiles vary depending on our parameters of interest: difference in life-expectancy and 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 2 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...*). Similarly, Menchik and Jianakoplos [1997] suggests that blacks have a lower rate of return on assets, in particular because of the composition as we show in the previous sections. For the benchmark gross returns (1.07) we use the long-term figures suggested in Jordà et al. [2017].

What is immediately visible from Figure 2, where we show the (Whites over Blacks) ratio of the max savings is that the combination of difference in life-expectancy and returns on asset contribute substantially to the accumulation of savings in life. The larger the

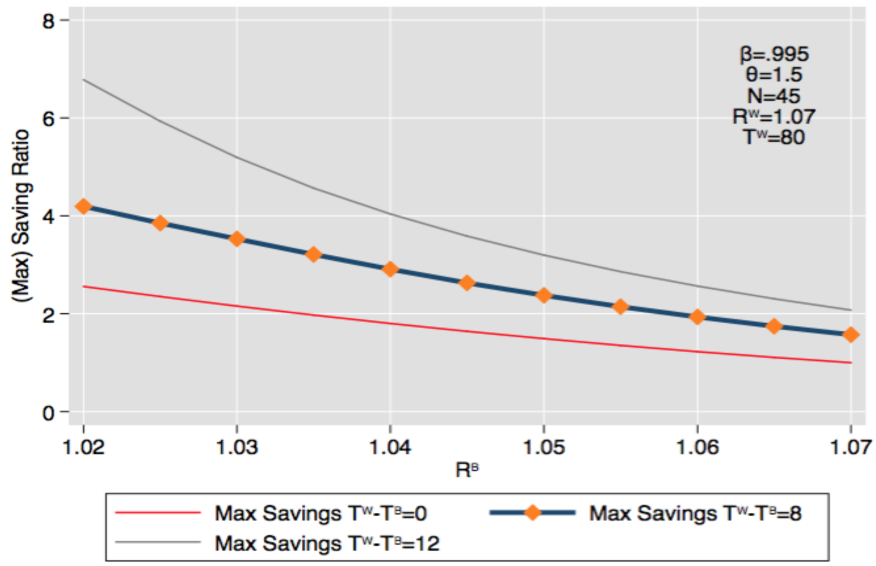

Figure 2: Model Simulations for different Life-expectancy and (gross) Interest Rates

differences, the larger the savings gap. As we have shown, 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 3 percentage points.

This simple 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 3 percentage points, we can explain (almost fully) the differential saving stocks between Blacks and Whites. in Section 4, we will analyze the role of a smaller buffer stock of savings for the Blacks in making them more exposed than the Whites to permanent and transitory income shocks.

3 Data and exploratory analysis

3.1 The PSID

We use data from the Panel Study of Income Dynamics (PSID)[3], a longitudinal survey conducted by the University of Michigan. 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.'

To create our dataset for the analysis, we append together all waves from 1999-2017. This choice is dictated by the fact that information on actual consumption is only collected starting in 1999.[4] 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 then 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, for the years under scrutiny, includes 153,592 individual-year observations.

[3]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 (mainly from the SEO subsample).

[4]In previous versions of the current paper we included older PSID waves and performed a consumption imputation to deal with the missing consumption categories, see De Giorgi et al. [2020].

3.1.1 Household 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.

Any negative or zero values are recorded to $1 in the PSID, and 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. 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 by applying a different equivalence scale (results not reported for brevity). Of course the equivalence scales take into account the household size and composition.

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. Similarly, we construct the following measure of real adjusted wealth as follows:

$$RealAdjWealth_i = \left(\frac{Nominal\ Wealth \times 100}{CPI \times AEscale} \right). \tag{3}$$

3.1.2 Household Consumption

Starting in 1999, the PSID asked its respondents the amount spent over different categories of goods, always at the household level. The expenditure categories for which we have information are the following: food at home, food out, food stamps (if used), rent, home insurance, electricity, heating, water, other utilities, car insurance, car repairs, gas, parking, bus, train, cab, other transportation, cost of school, cost of childcare, health insurance, expenditures on hospitals, doctors, and drugs. We construct our measure of actual consumption as the sum of all these expenditure categories[5]. This definition of total household consumption is the same as in Attanasio and Pistaferri [2014, 2016]. Then, similarly to what we did already in the case of total family income, we deflate this measure by CPI and we divide it by the same equivalence scale as above, in order to take adequately into account different family compositions. Real adjusted family consumption is hence defined as

$$TC_i = \left(\frac{Nominal\ Family\ Consumption \times 100}{CPI \times AEscale} \right). \tag{4}$$

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

[5] Our consumption measure is constructed as comprehensively as possible given the information available in the PSID. However, some, limited, expenditure cathegories are not covered by the survey, such as holidays and investments in durables.

Variable	Mean	Std. Dev.	Min.	Max.	N
Whites					
Consumption expenditure	5986.908	3902.257	0	119611.391	12504
Total Family Income	18024.503	20297.516	-25954.205	442666.688	12504
Family size	3.122	1.522	1	9	12504
Real adjusted wealth	54778.884	241424.147	-176488.609	9792681	12504
Age	41.215	13.879	17	97	12504
Female dummy	0.206	0.404	0	1	12504
Grades 0-11	0.181	0.385	0	1	12050
High school	0.316	0.465	0	1	12050
Some College	0.233	0.423	0	1	12050
BA or higher	0.27	0.444	0	1	12050
Blacks					
Consumption expenditure	3740.475	2993.569	0	67871.937	8352
Total Family Income	8690.6	7726.440	-900.452	178739.734	8352
Family size	3.823	1.856	1	11	8352
Real adjusted wealth	11342.491	71603.453	-68034.156	1605695	8352
Age	40.156	12.195	18	96	8352
Female dummy	0.487	0.5	0	1	8352
Grades 0-11	0.317	0.465	0	1	7943
High school	0.384	0.486	0	1	7943
Some College	0.228	0.419	0	1	7943
BA or higher	0.071	0.256	0	1	7943

Table 1: Descriptive Statistics in base year 1999, by race and actual consumption quintile. Consumption expenditure is our measure of total consumption as expressed by eq. (4), Total Family Income is the variable defined by eq. (2), family size is the number of individuals in the family, age is age of the household head, wealth is real adjusted wealth as expressed by eq. (3), female is a dummy taking value 1 if the household head is a women and zero otherwise, and Education is one of the four education dummies standing, respectively, for grades 0-11, high school, some college, BA or higher degree.

In Table 1 we report the descriptive statistics for the main variables used in the present paper in the base year 1999.

3.2 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) informal insurance and self-insurance. 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 get married more times than Whites. It appears that with multiple and changing family ties the fundamentals for informal insurance aren't particularly solid. Just to provide an example, in the top consumption quintile, 24% of Blacks are divorced, whereas only 13% of Whites are. Further, Blacks are less likely than Whites to receive an inheritance and, when they do, the average amount is substantially lower. However, Busch et al. [2022] underline that within-family insurance against shocks is in general only partial in the US, as it emerges from the same PSID data that we also use.

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.

In order to dig further into the issue of the different degrees of insurance for Black and White households, we analyse whether Blacks and Whites have different degree of health insurance and whether they are differently exposed to health shocks. Further detail on the different types of health shock is reported in Section 5.

As a first exploratory analysis, in panel (a) of Figure 3 we report the distribution of annual expenditure on health insurance, by race. This information is available in the PSID from 1999 onward. The amount paid by Whites for health insurance each year is on average higher than the amount paid by the Blacks, this is evident since the distribution of the premia paid by the Blacks is shifted to the left than that of the Whites and compressed towards zero. This is a first supporting evidence to the claim that Blacks are less insured than Whites against health shocks. Further, in panel (b) of Figure 3 we find evidence that the Blacks are more exposed to health shocks than the Whites[6].

[6] However, differences in the degree of health insurance are likely not the only factor explaining differences in persistence in consumption, as Dobkin et al. [2018] indicate that health insurance doesn't effectively insure against the lost earnings from health shocks.

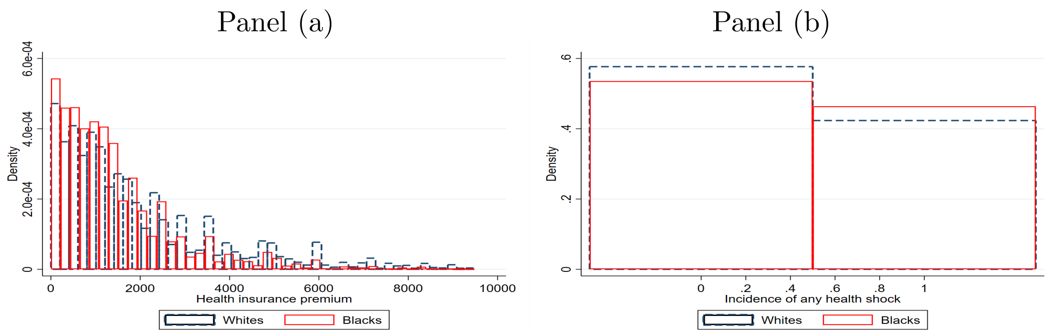

Figure 3: Panel (a): histogram of the annual amount (in US dollars) of expenditure for health insurance at the family level, by race. PSID data for the period 1999-2017, top % has been trimmed to increase readability. Panel (b): share of households being affected by an health shock, by race. An health shock is defined as insurgence of any of the nine major health problems recorded in the PSID in the period 1999-2017 (asthma, arthritis, cancer, diabetes, lung disease, heart attack, heart disease, stroke, high blood pressure).

3.2.1 Savings and Wealth

Let's turn to the third potential source of insurance against negative shocks, i.e. self-insurance via savings and wealth. If wealth accumulation for Blacks is lower than for Whites, similar health and income shocks will have very different effects. This is because Blacks are more exposed to the consequences of shocks due to a more limited buffer, and therefore the lack of self-insurance.[7]

Using an earlier sample, only composed by years 1984, 1989 and 1994, Gittleman and Wolff [2004] find no statistically significant difference in the stock of savings held by the Whites and Blacks. On the contrary, we document notable racial differences in wealth and stock of assets in our sample (1999-2017). Our results on the existence of a racial wealth gap are consistent with those by Altonji et al. [2000], who find that the racial gap in the wealth level cannot be fully explained by the distribution of income and demographic variables. However, the authors do not investigate the link of such a gap with differential consumption dynamics.

In Figure 4, we plot the extensive (left column) and intensive (right column) margins

[7] As mentioned, we compute wealth as comprehensively as we can in the PSID, summing up 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 then divided by the Consumer Price Index (CPI), in order to obtain a measure of wealth in real terms. As above, we further divide this variable by the adult equivalence scale.

of total wealth (Panel (a) and (b)) and stock holding (Panel (c) and (d)) by race. These variables are in real - per adult equivalent- terms. In Panel (a) of Figure 4, we plot the extensive margin for wealth holding, i.e. the percentage of individuals having positive wealth across consumption quintiles. This share is equal to more than 80% for the Whites, but only around 65% for the Blacks. From panel (b) it can be seen that, among people with a positive wealth, Blacks own far less of it than Whites, as their distribution is shifted to the left and compressed towards zero. Data show that wealth accumulated by Blacks is on average between 2 and 3 times smaller than that accumulated by the Whites.

When looking at the two bottom panels, we notice that the share of individuals holding stocks is lower than 10% for the Whites, but nearing 0% for the Blacks. Further, from the distribution of the amount of stocks held among those who have it, we deduce that on average Blacks hold less stocks than Whites, as their distribution is compressed towards zero. These differences in stock holdings are suggestive of large differential returns on assets and this difference is particularly relevant at the top consumption quintile.

Indeed, it is well known that the Blacks have more difficult access to credit and financial markets than the Whites. There is a large literature on racial differences in credit market access (see e.g. Arrow [1998], Blanchflower et al. [2003], Dymski and Mohanty [1999]). 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% (see e.g. Cheng et al. [2015], Bayer et al. [2016], Bayer et al. [2017]). Catherine on the other hand, investigates how age influences portfolio choices, but she does not dig into the role of race for determining such choices.

Summing up, we find substantial racial differences in the amount of savings and wealth accumulation. This is fully consistent with the toy model for life expectancy presented in Section 2. Blacks save, on average, much less than Whites and accumulate much lower wealth. Further, Blacks seem to under-insure their health: taking up lower premium plans (see Figure 3). This translates into a much lower degree of insurance against shocks and results into a much higher and longer-lasting negative impact of a health shock on consumption, as we will show in Section 5. Such results are also corroborated by the evidence provided in Section 4 where we show that transitory income shocks, in the framework of Commault [2022], have larger effects on consumption for Blacks than for Whites.

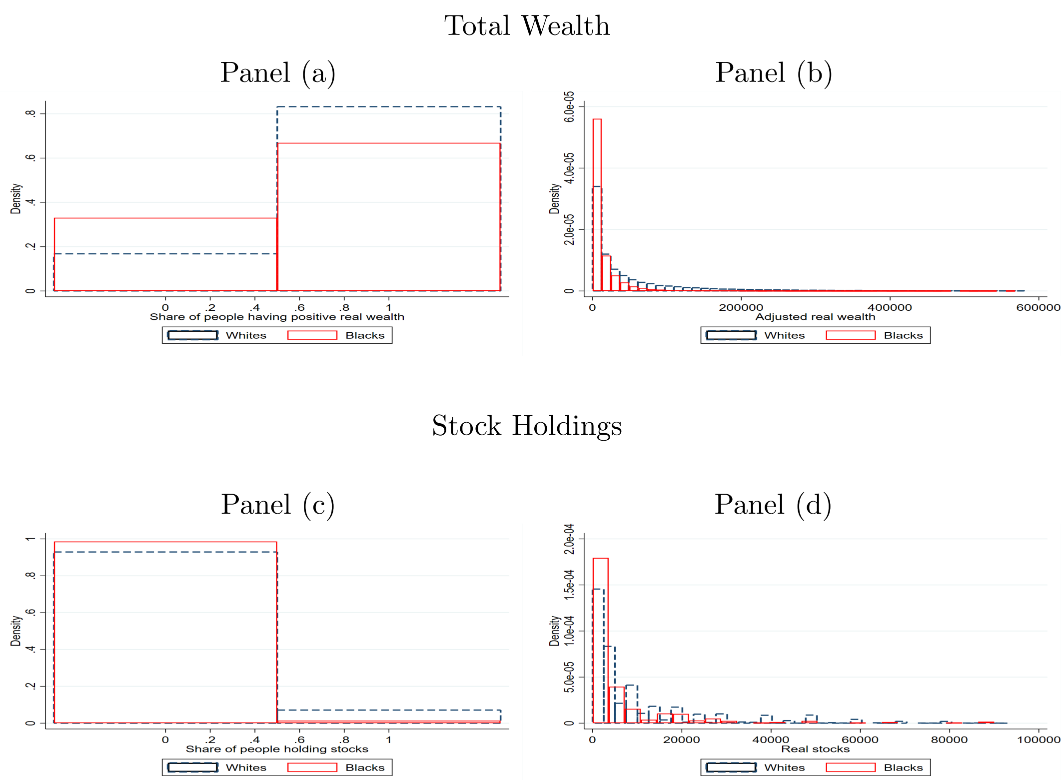

Figure 4: Total wealth: Panel (a) extensive margin: share of people having positive real wealth, by race. Panel (b) intensive margin: real adjusted wealth by race (people with zero wealth have been excluded). Wealth is computed as the sum of seven asset types: imputed value of farm or business, imputed 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. Divided by the Consumer Price Index (CPI) and adult equivalence scale. Sample 1999-2017. Stock holdings: average value of stock holdings in US dollars divided by CPI and adult equivalent scale, by race. Panel (c) extensive margin. Panel (d) intensive margin (people with no stocks have been excluded). Sample: 1999-2017. Top 1% of stocks as well as top 1% of real adjusted wealth has been trimmed in order to increase graph readability.

4 Response to Income Shocks

In this Section, we apply the model proposed by Commault [2022] to assess whether Blacks and Whites are differently exposed to transitory income shocks. The question of how much do income shocks reverberate into consumption shocks has been widely discussed in the literature. According to the complete market hypothesis, consumption is fully insured against any idiosyncratic income shocks. This hypothesis has been usually rejected in micro data (Attanasio and Davis [1996]). On the contrary, the standard permanent income hypothesis assumes that self-insurance through savings is the only mechanism that can be used to smooth income shocks. According to this latter theory, intertemporal consumption is smoothed against transitory, but not against permanent income shocks (Deaton [1992]). However, both aggregate and micro data exhibit what is called "excess smoothness", i.e. consumption is found to react too little to permanent income shocks. Further, consumption data also exhibit excess sensitivity to transitory income shocks (Hall and Mishkin [1982], Campbell and Deaton [1989], Attanasio and Pavoni [2006]. In the light of these studies, Blundell et al. [2008] for example propose a model where there is some degree of insurance, which is not necessarily full.

In the wake of Commault [2022], which expands Blundell et al. [2008], we adopt a semi-structural estimation method, that allows log-consumption to depart from a random walk. As in Blundell et al. [2008], the identification is based on instrumenting the effect of current log income growth on current log consumption growth with future log income growth, in order to filter out the contribution of the permanent shocks. Indeed, permanent shocks modify log income once and for all and are hence independent from all the future values of log income growth. However, the estimator proposed by Commault [2022] has the advantage, relative to the one proposed by Blundell et al. [2008], to be robust to a departure from the assumption that log consumption is a random walk. It is hence now allowed that past transitory shocks affect log consumption growth.

Let's present the setup of the model. The log income of household i at period t, detrended (i.e. net of demographic characteristics) is denoted as $ln(y_{it})$ and is a process with a permanent component and a transitory one:

$$ln(y_{it}) = p_{it} + \mu_{it} + \zeta_{it}^{y} \tag{5}$$

where $p_{it} = p_{i,t-1} + \eta_{it}$ is the permanent component, that is a random walk process, and $\mu_{it} = \epsilon_{it} + \theta_1 \epsilon_{i,t-1} + ... + \theta_k \epsilon_{i,t-k}$ is the transitory component, which is an MA(k) process. The shock ζ_{it}^{y} is further included to take into account measurement error. The term η_{it} is the innovation to the permanent component, whereas ϵ_{it} is the innovation term to the transitory component.

On the other hand, the log consumption of household i at period t, detrended, is denoted as $ln(c_{it})$ and it is a flexible function of the current and past realizations of the transitory and permanent shocks and of ζ^c_{it}, a term that can be either interepreted as consumption measurement error or as a consumption-specific shifter (Commault [2022]). Hence, we can write log consumption growth as follows:

$$\Delta ln(c_{it}) = f_t(\epsilon_{it}, ..., \epsilon_{i,1}, \eta_{it}, ..., \eta_{i,1}, \zeta^c_{it}, ..., \zeta^c_{i,t-1}) \tag{6}$$

This specification encompasses the standard life-cycle model as a special case and is consistent with a wide range of models (Commault [2022]). The distributional assumptions of the model are that: (i) the shocks $\epsilon, \eta, \zeta^y, \zeta^c$ are drawn indepdently from each other, independently over time and independently across households.

In this framework, our main parameter of interest is the pass-through coefficient, denoted ϕ^ϵ, i.e. the ratio of the covariance between log consumption growth and contemporaneous transitory shock over the variance of the shock:

$$\phi^\epsilon = \frac{cov(\Delta ln(c_{it}, \epsilon_{it})}{var(\epsilon_{it})} \tag{7}$$

The quantity expressed in eq. (7) can be interpreted as the share of the variance of the transitory shock that is passed on to log consumption (Kaplan and Violante [2014]).

As far as identification is concerned, we adopt the robust estimator proposed by Commault [2022], i.e. in order to isolate the effect of the current transitory shock in current log income growth, we use future log income growth at time $t + k + 1$ $(\Delta ln(y_{i,t+k+1})$ as an instrument. Indeed, it correlates with the realization of the transitory shock at t, but not with any of the other current or past shocks that affect log consumption growth. The estimator, that is robust to whether past shocks affect log consumption, is defined as:

$$\phi^\epsilon = \frac{cov(\Delta ln(c_{it}), -\Delta ln(y_{i,t+k+1}))}{cov(\Delta ln(y_{it}), -\Delta ln(y_{i,t+k+1}))} \tag{8}$$

Provided that $k \geq 1$, this robust estimator is also immune to two effects that are mentioned in the semi-structural literature as potential sources of bias: (i) measurement error and (ii) permanent and transitory shocks being uniformly distributed over the period rather than occurring discretely once at the beginning of each period (Commault [2022]).

	Whites	Blacks
ϕ^{ϵ}	.2901***	.3506***
	(.0196)	(.0164)
N	9'627	483

Table 2: Two-year pass-through coefficient from transitory income shocks to log consumption, 1999-2017, by race

	Whites	Blacks
ϕ^{ϵ}	2559***	.3452***
	(.0032)	(.0276)
N	15'403	1'008

Table 3: Two-year pass-through coefficient from transitory income shocks to log consumption, 1999-2007, by race

By applying the above-described robust estimator on 1999-2017 PSID data, we obtain the results reported in Table 2. These results are largely in line with our expectations and show that the degree of two-year[8] pass-through from a permanent income shock to consumption is equal to around 0.29 for the Whites vs around 0.35 for the Blacks. The difference is substantial, as it implies that the same negative transitory shock of, say, one dollar, leads to a reduction in consumption by 29 cents among the Whites, but to a reduction by 35 cents, i.e. 21% more, among the Blacks. This provides evidence that the Blacks are less insured against (transitory) income shocks. A bootstrap test for the difference in coefficients (with 500 replications) shows that the difference in the estimated coefficient for the Blacks and for the Whites is statistically different from zero at a 90% (but not a 95%) confidence level. When we only use the years between 1999 and 2007, sample size is larger as the requirement for a balanced panel is less stringent. In this case, the same bootstrap test for the difference in coefficients with 500 replications shows that the difference is statistically significant at a 95% confidence level.

5 Response to health shocks

In this subsection we analyze the impact of a health shock on black and white individuals. Given the results from the previous sections, we expect a health shock to have approximately the same impact on TFA for the two groups, but to have a larger impact on TCP

[8]This is because PSID data are only collected every second year in the period of interest: 1999-2017.

for the blacks rather than for the whites. The estimation of the impact of a health shock on TFA, TCP and the probability of being unemployed is performed via the double/debiased lasso procedure proposed by Chernozhukov et al. [2018].

Lasso is a regularization method which allows to deal with a large number of covariates by adding to the standard multivariate regression equation a penalization term. The presence of this term pushes the coefficients towards zero, so that only the most relevant covariates are kept in the model. To be precise, lasso minimizes the following quantity:

$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij}\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j| \tag{9}$$

where y_i is the outcome variable (TFA, TCP, unemployment dummy). X_i is a vector of covariates that includes age, age squared, gender, educational level dummies, year dummies). The second part of the equation, the L1 penalty, forces some of the coefficients to be exactly equal to zero when λ is sufficiently large (James et al. [2013]).

The problem when applying Lasso regression to economic research questions is that all the estimated coefficients are pushed to zero by construction. Hence, their size cannot be directly interpreted. This is why a post-Lasso approach is often adopted, in which a second stage OLS with only the relevant variables selected by the Lasso in the first stage is performed. However, another issue is that, if the variable representing treatment is not randomly assigned, the post-Lasso estimation (as well as the Lasso) will provide biased results. In our framework, the treatment variable is being hit by a health shock, which is defined as any of the nine illnesses reported in the PSID from 1999 onwards (asthma, cancer, diabetes, lung disease, hearth attack, hearth disease, stroke, high blood pressure, arthritis). This treatment variable is likely not to be randomly assigned, but to depend on individual characteristics, some of them observable (e.g. age, educational level) and some of them not (i.e. genetics or behavior). In order to avoid our estimation results to be biased by the potential endogeneity of the health shock, as mentioned above, we apply the double/debiased Lasso estimation technique proposed by Chernozhukov et al. [2018]. This method allows for robust inference in presence of many covariates and potentially many instruments.

Impact of the shock on LTCP

	(1) Whites	(2) Blacks	(3) Whites	(4) Blacks	(5) Whites	(6) Blacks
Shock	-0.0490***	-0.0541***	-0.0252***	-0.0401***	-0.0246***	-0.0391***
	(-26.22)	(-16.47)	(-18.34)	(-15.62)	(-17.90)	(-15.24)
Age	YES	YES	YES	YES	YES	YES
Age sq	YES	YES	YES	YES	YES	YES
Female dummy	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Edu dummies			YES	YES		
Wealth					YES	YES
Constant	YES	YES	YES	YES	YES	YES
Test diff in coeff	0.0000		0.0000		0.0636	
N	61281	33967	61281	33967	61281	33967

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Double/debiased lasso estimation results. Data for the years 1999-2017. Dependent variable is log of total consumption (LTCP)

The estimation results are reported in Tables 4 to 6. From these results we deduce that the impact of a health shock on log total consumption is on average larger for the Blacks than for the Whites (i.e. the drop in consumption is around 4.9% for the Whites and 5.4% for the Blacks, when we control for age and gender only). The gap even wides when we control for education (i.e. -2.5% for the Whites and -4% for the Blacks). Finally, when we control for age, gender and wealth, the drop in consumption is around -2.5% for the Whites and -3.9% for the Blacks, i.e. the gap is slightly reduced with respect to the case where we control for education, and most importatly it loses statistical significance, as shown by the results of the test for the difference in coefficients reported in Table 4. The p-value reported in the Table refers to a bootstrapped Wald test for the difference in coefficients, with 400 bootstrap replications.

In Table 5 we analyze the impact of a health shock on total family income. The negative impact of a health shock is around -8/-9% for both the Whites and the Blacks, when we only control for age and gender. This drop reduces to around -6% for both groups when we control for education and to around -5% when we control for wealth. The main finding here is that the drop in income following a health shock is never statistically significantly different for the Blacks and for the Whites, as suggested by the test for the difference in coefficients reported in Table 5. This means that, even having similar reactions to the shocks in terms of income, the Blacks withness a larger drop in their consumption. We argue that this is due to their lesser degree of insurance. Indeed, in Table 4 the difference in the coefficients stops being statistically significant once we control for wealth.

Impact of the shock on LTFA

	(1) Whites	(2) Blacks	(3) Whites	(4) Blacks	(5) Whites	(6) Blacks
Shock	-0.0919***	-0.0816***	-0.0573***	-0.0614***	-0.0446***	-0.0551***
	(-27.81)	(-17.34)	(-19.21)	(-14.47)	(-16.04)	(-13.68)
Age	YES	YES	YES	YES	YES	YES
Age sq	YES	YES	YES	YES	YES	YES
Female dummy	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Edu dummies			YES	YES		
Wealth					YES	YES
Constant	YES	YES	YES	YES	YES	YES
Test diff in coeff	0.0985		0.4547		0.1234	
N	61281	33967	61281	33967	61281	33967

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Double/debiased lasso estimation results. Data for the years 1999-2017. Dependent variable is log of total family income (LTFA)

Finally, since the effects of a health shock on consumption may go in different directions (i.e. an increase in out-of-pocket health expenditure and a decrease in all the other expenditure cathegories), in Table 6 we analyze the impact of a health shock on out of pocket annual expenditure for health (health premium excluded). From this Table, it emerges that expenditure of the whites increases on average 100USD more than that of the Blacks following a health shock. This difference is statistically significant in all the estimations reported in Table 6. Hence, we find indication that health expenditure of the Whites increases more than that of the Blacks after a health shock, this may be part of the explanation why total consumption of the Blacks falls more than that of the Whites.

Impact of the shock on health expenditure (out-of-pocket)

	(1) Whites	(2) Blacks	(3) Whites	(4) Blacks	(5) Whites	(6) Blacks
Shock	196.6***	99.20***	215.4***	107.9***	217.0***	117.3***
	(11.71)	(7.01)	(12.54)	(7.48)	(12.53)	(7.98)
Age	YES	YES	YES	YES	YES	YES
Age sq	YES	YES	YES	YES	YES	YES
Female dummy	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Edu dummies			YES	YES		
Wealth					YES	YES
Constant	YES	YES	YES	YES	YES	YES
Test diff in coeff	0.0001		0.0000		0.0000	
N	61281	33967	61281	33967	61281	33967

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Double/debiased lasso estimation results. Data for the years 1999-2017. Dependent variable is out-of-pocket annual expenditures for health (e.g. doctor visits and drugs)

6 Concluding Remarks

It is well known, and confirmed in the current paper, that Blacks and Whites differ substantially in their amount of savings and wealth, it is however novel that the gap in savings then results into lower ability to insure against (transitory) income shocks. The lack of insurance in the face of such shocks, e.g. health shocks, makes Blacks more vulnerable and in fact more prone to downfalls in the consumption distribution.

Our application of the Commault [2022] model shows, indeed, that the degree of (two-year) pass through from a transitory income shock and log consumption is equal to 0.29 for the Whites and 0.35 for the Blacks. As a consequence of their lower degree of insurance against income shocks, Blacks suffer more and longer for a health shock, as we document by applying a double/debiased lasso estimation procedure. Their drop in consumption following such a shock is around 65% higher than that experimented by Whites.

On this basis, policy actions to improve access to insurance and financial markets could be promoted by the policy-maker.

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Appendices

Appendix A Data

A.1 Sample Selection

As explained in Section 2, to create our dataset we append together all waves from 1999-2017. 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 individuals with the richest and most consistent set of observables overtime. We thus create a consistent race indicator for all households. The PSID asks heads to identify their race in every wave. For all heads, we assign race as the mode value of race from all reported years. We only keep households identifying themselves as Black or as White in the current paper. Our full sample, using all waves of data for our period of interest, 1999-2017, includes 153,592 individual-year observations.

A.2 Variables

A.2.1 Education

Over time, the PSID has altered how it collects educational data. From 1968 until 1990, households reported educational attainments; afterwards education is collected in terms of years. To create a consistent education status, we assign households to the four categories used by Attanasio and Pistaferri [2014]: 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 in every wave in the period 1999-2017. We generate our education variable for each individual as their maximum education status attained.

A.2.2 Consumption

Starting in 1999, the PSID asks respondents the amount spent over different categories of goods, always at the household level. The expenditure categories for which we have information are the following: food at home, food out, food stamps (if used), rent, home insurance, electricity, heating, water, other utilities, car insurance, car repairs, gas, parking, bus, train, cab, other transportation, cost of school, cost of childcare, health insurance, expenditures on hospitals, doctors, and drugs.

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 consumed at home. This value includes the cost of food delivered, but excludes alcohol, cigarette expenditure and 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 from 1994, so we 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.

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. 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 large 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 yearly rent equivalent by taking 6% of this house-value (Dougherty et al. [1982]). 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 1993-2017. In all waves, rent values can be either positive or 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.

A.3 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 for the current year, 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.

We consider families to be households where the identity of the head and the wife remain the same. 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.

One more final consideration is that when values in the PSID are topcoded, we keep the topcoded values. This applies to very few observations.

Variable	Mean	Std. Dev.	Min.	Max.
		1999		
TFA	18034.166	20292.438	0	442666.688
actualcons	5986.952	3901.901	0	119611.391
N		12500		
		2001		
TFA	19189.136	21892.72	0	550718.75
actualcons	6463.723	4388.664	91.786	49180.75
N		11716		
		2003		
TFA	18624.48	24043.646	0	1170284.5
actualcons	6504.675	4324.173	0	64184.227
N		11019		
		2005		
TFA	19494.563	63952.397	0	2816656.25
actualcons	6424.593	4286.441	0	102475.07
N		10981		
		2007		
TFA	18796.915	23173.652	0	605274.313
actualcons	6571.044	4673.152	0	92787.836
N		10016		
		2009		
TFA	19669.109	26718.896	0	1338246.5
actualcons	6262.046	4740.977	0	119139.188
N		9181		
		2011		
TFA	18165.633	22331.199	0	632876.625
actualcons	6239.923	4566.454	0	101653.117
N		8041		
		2013		
TFA	18970.978	30863.878	0	1001752.938
actualcons	6236.947	4129.054	0	45655.512
N		7064		
		2015		
TFA	19881.72	21854.351	0	724659.813
actualcons	6513.549	4325.748	0	63662.863
N		5930		
		2017		
TFA	19996.422	21505.025	0	422695.906
actualcons	6319.437	3989.289	0	56872.887
N		5231		

Table A.1: Summary statistics for Whites

Variable	Mean	Std. Dev.	Min.	Max.
		1999		
TFA	8701.844	7724.233	0	178739.734
actualcons	3741.464	2995.214	0	67871.938
N		8342		
		2001		
TFA	9822.130	10121.061	0	158814.75
actualcons	4194.044	3149.597	0	32322.271
N		7898		
		2003		
TFA	9195.946	7916.405	0	82923.273
actualcons	4271.134	3972.678	0	73323.266
N		7575		
		2005		
TFA	9560.468	9576.31	0	172469.484
actualcons	4361.005	3170.128	0	35436.867
N		7207		
		2007		
TFA	9410.23	8465.74	0	112421.305
actualcons	4503.911	3264.382	0	37360.477
N		6659		
		2009		
TFA	10476.44	9723.115	0	105669.18
actualcons	4355.833	3119.395	0	34086.176
N		6066		
		2011		
TFA	9669.542	9308.157	0	84470.727
actualcons	4388.644	3326.487	0	39137.273
N		5480		
		2013		
TFA	9709.758	9395.634	0	107313.633
actualcons	4436.818	3301.408	0	53169.184
N		4865		
		2015		
TFA	10621.632	10570.812	0	112127.578
actualcons	4617.021	3109.535	0	33648.969
N		4183		
		2017		
TFA	11368.417	10558.515	0	144210.766
actualcons	4762.87	3196.46	0	35045.852
N		3638		

Table A.2: Summary statistics for Blacks

A.4 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 mainly from the SEO subsample.

Appendix B Additional descriptive statistics on health shocks

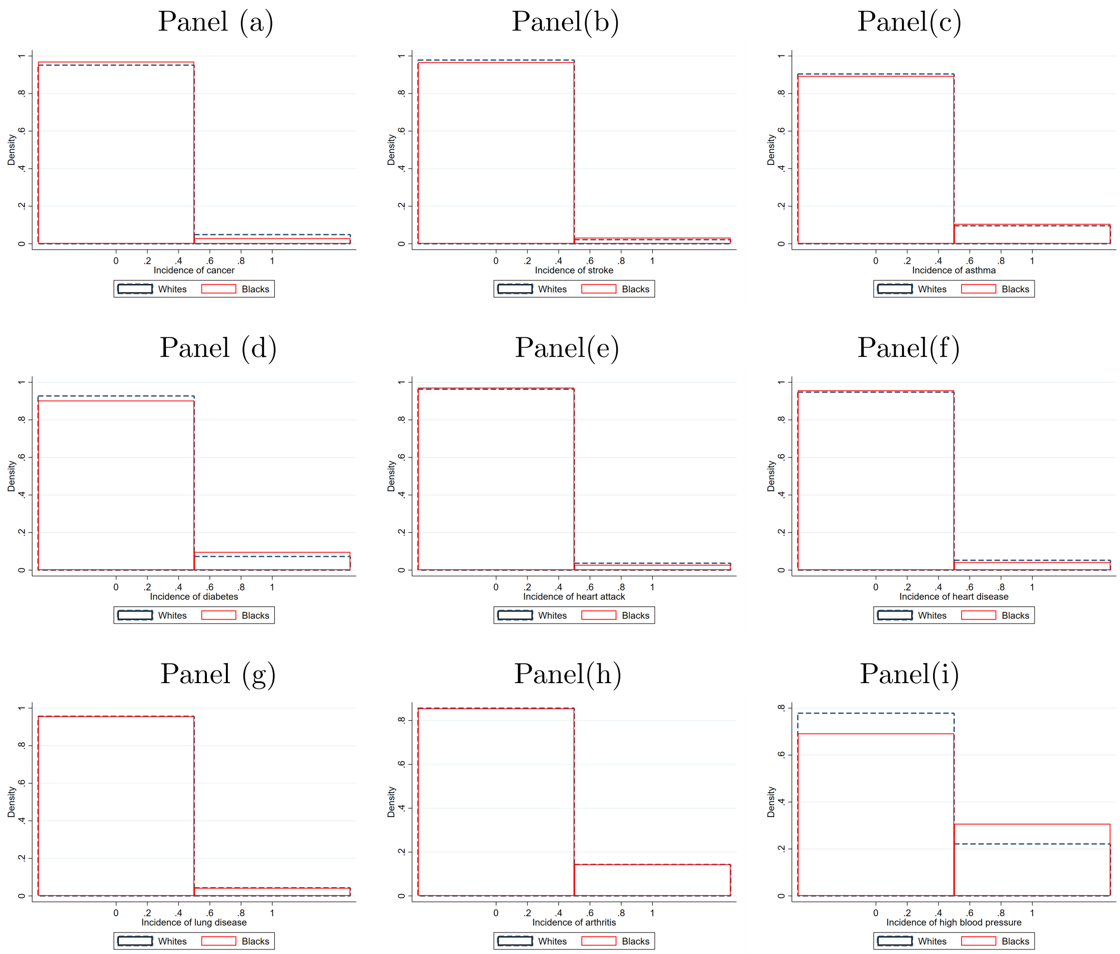

Figure B.1: Descriptive statistics: exposure to different health shocks for Black and White individuals. Data for the period 1999-2017. Panel (a) cancer, Panel (b) stroke, Panel (c) asthma, Panel (d) diabetes, Panel (e) heart attack, Panel (f) heart disease, Panel (g) lung disease, Panel (h) arthritis, Panel (i) high blood pressure.

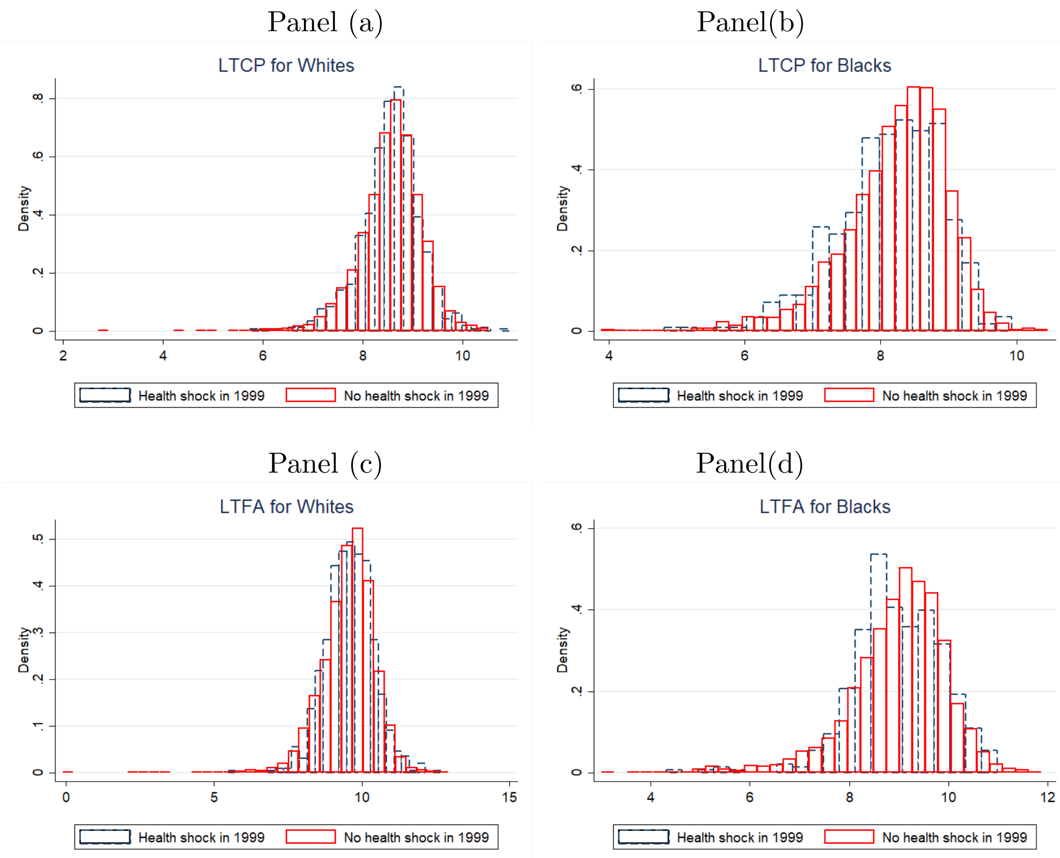

Figure B.2: Comparison of the distributions of log consumption (panels a and b) and log total family income (panels c and d) for those who experienced a health shock in the base year 1999 and for those who did not, among the whites (panels a and c) and among the blacks (panels b and d).

Appendix C Response to Income Shocks: The Bludelli, Pistaferri and Preston (2008) model

In this Section we adopt the framework developed by Blundell et al. [2008]. We disentangle the permanent and transitory income components 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:

$$\log Y_{i,t} = Z'_{i,t}\varphi_{i,t} + P_{i,t} + v_{i,t} \tag{10}$$

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 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:

$$P_{i,t} = P_{i,t-1} + \zeta_{i,t} \tag{11}$$

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:

$$\Delta c_{i,t} = \phi_{i,t}\zeta_{i,t} + \psi_{i,t}\varepsilon_{i,t} + \xi_{i,t} \tag{12}$$

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	t-stat of bootstrapped Wald test for equal coeffs
ϕ	0.7687***	0.7959***	-0.0615
	(0.0650)	(0.1182)	
ψ	0.1026***	0.1699***	-0.4024
	(0.0322)	(0.0550)	

Table B.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 B.1, it emerges that Blacks are less insured than the Whites, both with respect to transitory and to permanent shocks. 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. This finding is consistent with those by Ganong et al. [2020], who find that black households cut their consumption on average 50% more than white households in response to an unexpected temporary shock in income. A permanent shock has clearly a much larger 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	0.0395***	0.0509***
component	(0.0076)	(0.0161)
Var of transitory	0.0432***	0.0586***
component	(0.0055)	(0.0116)

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

Note that the similarity in income variances between Blacks and Whites is not merely a consequence of the model 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).