Racial Differences in Consumption and Saving Behavior: New Survey Evidence and Quantitative Theory of Status Signaling

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Abstract

The racial wealth gap is large. An explanation for the persistence of this gap is that people spend their resources differently. Estimating the marginal propensity to consume (MPC) by race is crucial in understanding the wealth gap. I draw on survey data I collected to estimate MPCs by race. MPCs are considerably higher among black than white respondents, even after adjusting for characteristics such as age, education, and income. In the Consumer Expenditure Survey, black households consume a higher share of visible goods out of overall consumption to signal status than white households. However, black consumers have more of a need to signal status to compensate for perceptions of them having lower incomes. To match these facts, I introduce status compensation motives into a standard life-cycle model and show that this mechanism can account for 36% of the racial difference in MPCs. Models that include racial heterogeneity in earnings volatility, unemployment shocks, and expenses, but exclude status motives, do not match the data showing that black people's spending on visible goods increases with wealth. I use my model to show how understanding status spending motives can be used to address the racial wealth gap by estimating the size of a new policy to eliminate racial differences in wealth.

JEL classification: D15, E21, G51, J15
Keywords: marginal propensity to consume, race, status, life-cycle model

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1 Introduction

In the US, a black household has on average about 16% of the wealth of a white household. One explanation for this difference in wealth accumulation is that people make different spending decisions. Over a century ago, Du Bois (1899), Duesenberry (1949), and Friedman (1957) found important differences in the average propensity to consume of black and white households. The persistence of the racial wealth gap has led researchers to estimate the interaction of wealth with the marginal propensity to consume (MPC). The wealth gap can inform how households respond to fiscal transfers since households with high MPCs tend to be more constrained and have low wealth. However, estimates of racial differences in consumption focus on changes in earnings and few mechanisms have been tested to explain these racial differences in spending. Exploring links between the drivers of MPCs and wealth accumulation for different racial groups is crucial to understanding racial differences in consumption and wealth.

This paper estimates racial differences in MPCs from newly collected survey data and proposes a theory of status compensation to explain a large part of the spending gap. In order to study racial differences in consumer behavior, I designed a survey and collected it in September 2023. In the survey, I asked individuals how they would spend a hypothetical \$500. The reported average MPC out of this unexpected transfer is 59% for black and 38% for white respondents. These are the first empirical estimates of MPCs out of transfer shocks by race in the literature. I find that 72% of the racial difference in MPCs is unexplained even after empirically controlling for respondent characteristics such as age, education, income, and household composition. There is a lack of existing data linking wealth and MPCs. I therefore develop a quantitative model to test how the black-white wealth gap and its drivers influence the unexplained racial differences in MPCs.

I empirically and theoretically show that racial differences in MPCs are not fully explained by mechanisms such as income, financial uncertainty, and higher expenses. Empirical estimates show that earnings volatility is higher for black than white individuals. Standard life-cycle models predict that greater earnings volatility leads to higher precautionary savings and lower consumption out of transfer income (Aguiar et al. 2024). This mechanism thus works in the opposite direction of the racial gaps in reported MPCs.

Status compensation is a mechanism that explains part of the racial differences in MPCs. In the Consumer Expenditure Survey (CE), the share of visible expenditures out of total expenditures is 25% higher for black than white households. As in Charles et al. (2009), black households spend more on visibles to signal economic status and compensate for perceptions of them having lower incomes. I introduce status compensation in a life-cycle model, adapting the framework in Charles et al. (2009). This paper is the first, to my knowledge, to incorporate racial differences in status signaling within a life-cycle model to study MPCs. Status spending raises overall consumption and limits wealth accumulation. The average MPC in the model thus increases to closely match the survey data.

The status compensation mechanism is introduced into the model's utility function. Individuals gain utility from two types of goods: visible goods and non-visible goods. Visible goods have luxury properties, so that status spending is a luxury (Roussanov 2010). Status is signaled through the consumption of visible goods relative to one's own racial group's average consumption. Individuals that are associated with a low-consumption group compensate with proportionally more spending on visibles. When individuals have wealth, they especially want to differentiate themselves from their group to signal higher status (Roussanov 2010). I estimate that black individuals have a greater need to signal status because they are associated with a lower average consumption. Wealthy black individuals have additional status compensation motives due to biased societal perceptions of their incomes. Perceptions of the average consumption of black individuals are below the real average. In my model, biased perceptions are reflected by a parameter in the status term that widens the racial gap in consumption further than the average.

The estimated model shows that the status compensation mechanism explains a large part of the racial differences in MPCs. I parameterize and calibrate the model to match racial differences in median earnings, earnings volatility, average propensity to consume, and wealth in the data. Status compensation explains 36% of the empirically unexplained racial difference in MPCs. This mechanism provides an explanation consistent with data for part of the racial difference in wealth that determines consumption behavior.

The baseline model is compared to alternatives to show that a model with status compensation matches consumption behaviors in the data more closely than other models. Alternative models exclude the status mechanism and match wealth and consumption targets through racial heterogeneity in the discount factor, rates of return, unemployment shocks, and expenses. These alternative mechanisms do not match the data that black household spending on visible goods increases with wealth. They also miss racial differences in consumption elasticities with respect to negative versus positive income shocks.

I estimate several fiscal policy experiments using the status compensation model. When accounting for status spending, larger transfer sizes reduce the average MPC and transfers induce smaller changes in consumption than a negative income shock of the same size. Models using alternative mechanisms to explain racial differences in MPCs miss these standard features of MPCs and transfer sizes. I also examine whether certain policies address racial differences in wealth. My analysis shows that the existing Social Security system redistributes wealth from black to white individuals. Modeling status motives in addition to separate spending on visible and non-visible goods allows me to calculate the size of transfers that eliminate the racial wealth gap, financed via a tax on visible goods. White individuals would pay 80% of the collected tax revenue. This policy has large welfare gains for black individuals and relatively small welfare losses for white individuals. It also supports spending on non-visible goods.

1.1 Related literature

This paper relates to the literature estimating racial differences in consumption responses to income shocks. Ganong et al. (2020) and Patterson (2023) find that MPCs out of labor income shocks are higher for black than white individuals. I contribute to the ongoing literature on racial differences in MPCs by focusing on those out of transfers in particular. While these studies estimate racial differences in MPCs out of a loss in labor income due to unemployment, measuring differences out of transfers are important to account for asymmetries in consumption responses and to directly inform government transfer policies (Jappelli and Pistaferri 2010). MPCs by race out of transitory transfers have not yet been estimated. The available US data on MPCs out of transfers, such as from Fuster et al. (2021), has too small of a minority sample for conclusive analysis. New survey data are thus needed. My survey over-samples minority respondents to ensure the sample of minorities is statistically representative. I collect MPCs out of a transitory transfer shock and find they are higher for black than white individuals.

My survey also contributes new estimates to the empirical literature on MPCs. MPC estimates range widely, even when distinguishing between permanent or transitory shocks, estimation methods, or consumption horizons (Jappelli and Pistaferri 2010; Havranek and Sokolova 2020; Crawley and Theloudis 2024). Crawley and Kuchler (2023) write a literature review citing MPC estimates ranging from 5% to 90%. There is also contrasting empirical evidence on whether MPCs and income have a negative relationship (Jappelli and Pistaferri 2014; Ganong et al. 2020; Albuquerque and Green 2022). The MPCs from my survey are consistent with the upper range of MPC estimates and fall with higher household income.

The literature has proposed several theories for racial differences in wealth and MPCs. Black individuals have higher labor market risk, which can influence precautionary savings and consumption behaviors (Ganong et al. 2020; Carr and Hardy 2022; Derenoncourt et al. 2023). However, Aguiar et al. (2024) uses a quantitative model to show that absent preference heterogeneity, higher volatility of income leads to more precautionary savings and a lower MPC. Higher earnings risk thus cannot explain the higher MPC of black households. Racial differences in income, renting, education, household composition, rates of return, and life expectancy have also been argued to shape racial gaps in wealth and MPCs (Park et al. 2019; Puig 2022; Aliprantis et al. 2022; Giorgi et al. 2022; Boerma and Karabarbounis 2023; Nakajima 2023; Patterson 2023; Derenoncourt et al. 2024).[1] My empirical analysis shows that income, renting, education, and household composition do not explain a large part of racial differences in MPCs. This is consistent with Hamilton and Darity Jr. (2017) who argue that education is not a large determinant of the racial wealth gap. I also find that models with many of these mechanisms do not accurately capture visible good spending across the wealth distribution.

The literature studying MPCs in heterogeneous agent models usually generate high MPCs while targeting wealth moments (Kaplan and Violante 2022). Households with relatively lower wealth have higher MPCs on average. This relationship matches the racial differences in the data.[2] However, quantitative models often achieve their wealth targets with heterogeneity in the discount factor (Aguiar et al. 2024; Carroll et al. 2017; Epper et al. 2020; Fuster et al. 2021; Fagereng et al. 2021). A lower discount factor, interpreted as impatience, leads consumers to spend more and thus be more constrained and have a higher MPC. Li-Grining (2007) and Sektnan et al. (2010) find no systematic racial or ethnic differences in impatience. Thus, another explanation is needed to explain the racial differences in MPCs.

An extensive economics literature theoretically motivates signaling status through the 'destruction of assets' or consumption (Veblen 1899; Cole et al. 1995; Wisman 2009). Du Bois (1899) discussed that signaling wealth was important for black families to compensate for racist perceptions of black 'inferiority'. In contrast, Duesenberry (1949) argued that

[1]For example, Park et al. (2019) find that black households are more likely to have dependents and unemployed members. Transfers are therefore more likely to be split among more people in black households, leading to higher average MPCs. Puig (2022) shows that racial gaps in renter and mortgagor rates affect differences in consumption responses to interest rate shocks.

[2]See Derenoncourt et al. (2024) for the literature documenting the racial wealth gap.

status spending was more important for white than black households since he considered that individuals mainly compared themselves to others within their own racial group. [3] Charles et al. (2009) use the 1986-2002 CE to estimate that black households consume a higher share of visible goods than white households. They build a theoretical framework, founded in empirical results, in which black individuals have more of a need to signal status due to being associated with a lower income distribution. This paper extends the empirical analysis in Charles et al. (2009) to 2019 and finds consistent results. I also contribute to this literature by merging the racial theory in Charles et al. (2009) with the life-cycle signaling model in Roussanov (2010). My life-cycle model is novel in using status signaling to study MPCs by race. Models without status compensation motives do not match visible goods consumption dynamics found in the data.

My model also builds on research examining the Social Security system and explores alternative policies that can eliminate the racial wealth gap and adjust status spending motives. It relates to literature on Social Security's re-distributional effects and the impact of lifespan inequality on reform (Krueger and Kubler 2006; Hong and Rios-Rull 2007; İmrohoroğlu and Kitao 2012; Borella et al. 2023; Jones and Li 2023; Choukhmane et al. 2024). Consistent with critiques by Feldstein (2005), the model captures regressive features of the current Social Security system. This paper also analyzes policies targeting wealth inequality such as universal Baby Bonds and transfer payments to black Americans (Zewde 2019; Darity Jr and Mullen 2020; Aliprantis et al. 2022; Boerma and Karabarbounis 2023; Derenoncourt et al. 2024).[4] Frank (1985) argues that taxes can alleviate distortions in spending due to status signaling. My model allows for the analysis of the implications of a tax on visible goods and proposes this straightforward policy to fund government transfers.

2 Data and empirical motivation

The main data source for this paper is a survey that I collected. The survey has data on MPCs as well as other respondent characteristics. I supplement my analysis with existing data from US surveys that are routinely used in the literature. Empirical moments from these data sources are used to parameterize and calibrate the life-cycle model.

2.1 Survey overview

I collected a survey of 602 US consumers in September 2023.[5] The survey was hosted on Prolific, an online platform that connects researchers to individuals that are compensated to take surveys. Prolific thoroughly vets respondents to ensure they are survey-takers who genuinely complete the full survey and do not answer randomly or rush through the questions. Prolific also allows researchers to reject respondents if they fail to submit certain answers or fail certain checks. This quality-check process led me to use all responses that I collected

[3] Duesenberry (1949) considered the segregation of racial groups in his analysis of spending in the 1930s. Thus, white individuals compared themselves to a relatively wealthier peer group who gave more importance to status signaling.

[4] See Darity Jr and Mullen (2020) for a comprehensive survey of the literature on reparations policies.

[5] Funding for this survey covered a sample size of 600 respondents. An extra two respondents were surveyed due to sampling error at the time of collection.

in my analysis. The survey took respondents an average of 10 minutes to complete and I compensated survey-takers the equivalent of $15/hour, which is slightly higher than Prolific's minimum recommended compensation.

I over-sample minority respondents by surveying an equal number of black and white individuals.[6] This ensures that the sample of black respondents is statistically representative. I construct survey weights by race, gender, and income and use them in overall sample regressions to make the estimates more representative of the US population.

The survey sample matches many demographic breakdowns in the US. See Table 1 for summary statistics from the survey sample compared to the US population. The sample I collected closely matches the US population by race in terms of income, home-ownership, marriage, and household composition. White respondents have higher incomes and are more likely to be mortgagors and be married. In contrast, black respondents are more likely to be unemployed, renters, and have more children in the household. Most of my survey sample has a college degree and is in the labor force, which are higher rates than the US population.[7]

Table 1: Summary statistics: survey vs US data

	Survey			US Data		
Group	White	Black	Total	White	Black	Total
Age	39.08	39.42	38.99 (11.73)	43.0	35.4	39.0
College degree	0.58	0.51	0.57 (0.50)	0.39	0.25	0.36
Labor force participation	0.85	0.90	0.86 (0.35)	0.62	0.64	0.64
Unemployed	0.04	0.10	0.06 (0.23)	0.03	0.08	0.04
Income <$30,000	0.11	0.24	0.20 (0.40)	0.17	0.31	0.19
Income >$75,000	0.54	0.32	0.49 (0.50)	0.53	0.34	0.50
Mortgagor	0.49	0.24	0.42 (0.49)	0.44	0.32	0.43
Owner	0.15	0.17	0.15 (0.36)	0.26	0.14	0.24
Renter	0.33	0.54	0.39 (0.49)	0.30	0.54	0.33
Married	0.66	0.40	0.59 (0.49)	0.52	0.30	0.48
Household size	2.88	3.13	2.89 (2.58)	2.49	2.45	2.51
Number of adults	2.17	2.38	2.18 (1.12)	1.96	1.83	1.96
Number of children	0.71	0.75	0.71 (1.85)	0.53	0.62	0.55

Note: This table displays means, except for medians for age, and standard deviation in parentheses. Survey means by race are unweighted, totals are weighted. US data on age, education, employment, income, and marital status are from the 2022 American Community Survey while data on housing tenure is from the 2019 Consumer Expenditure Survey and data on household composition is from the 2023 Current Population Survey.

[6]The sample is composed of 302 black and 300 white respondents.

[7]Higher rates of college-educated respondents are typical in surveys collected online. See Binder (2020).

2.2 MPC question

I elicit MPCs by asking respondents to allocate an unexpected transfer of $500 between several categories as follows:

Consider a hypothetical situation where you unexpectedly receive $500 today. Indicate how you would split this $500 in the below categories. The total amount should be $500.

Groceries	*$* _____
Clothing	*$* _____
Transportation	*$* _____
Personal care, recreation, and entertainment	*$* _____
Education and medical expenses	*$* _____
Housing and large items	*$* _____
Savings	*$* _____
Debt (such as on student loans or credit cards)	*$* _____
Total	***$500***

The wording of the question used to elicit MPCs can impact how respondents report their consumption behavior. My question is most similar to the question asked in Jappelli and Pistaferri (2014).[8] The wording of the MPC question in this paper allows respondents to directly report the quantity of the transfer they would spend, similar to Colarieti et al. (2024), which facilitates the calculation and interpretation of the average sample MPC.

The mean MPC for the overall sample is 48%, consistent with Jappelli and Pistaferri (2014).[9] Figure 1 shows that the collected MPCs are consistent with the literature both in their distribution and in their relationship with household income. Similar to Jappelli and Pistaferri (2014), approximately 22% of the sample would not spend the $500 and MPCs fall with higher income.[10] Jappelli and Pistaferri (2014) collect MPCs that are more concentrated around 0, 0.5, and 1 than my survey due to their question asking respondents to report percentages of the transfer spent. Naturally, individuals' answers are frequently 0, 50, and 100 percent. In contrast, my survey asks individuals to allocate dollar amounts, and thus there is more variation in responses although some concentrate around amounts that are factors of 10.

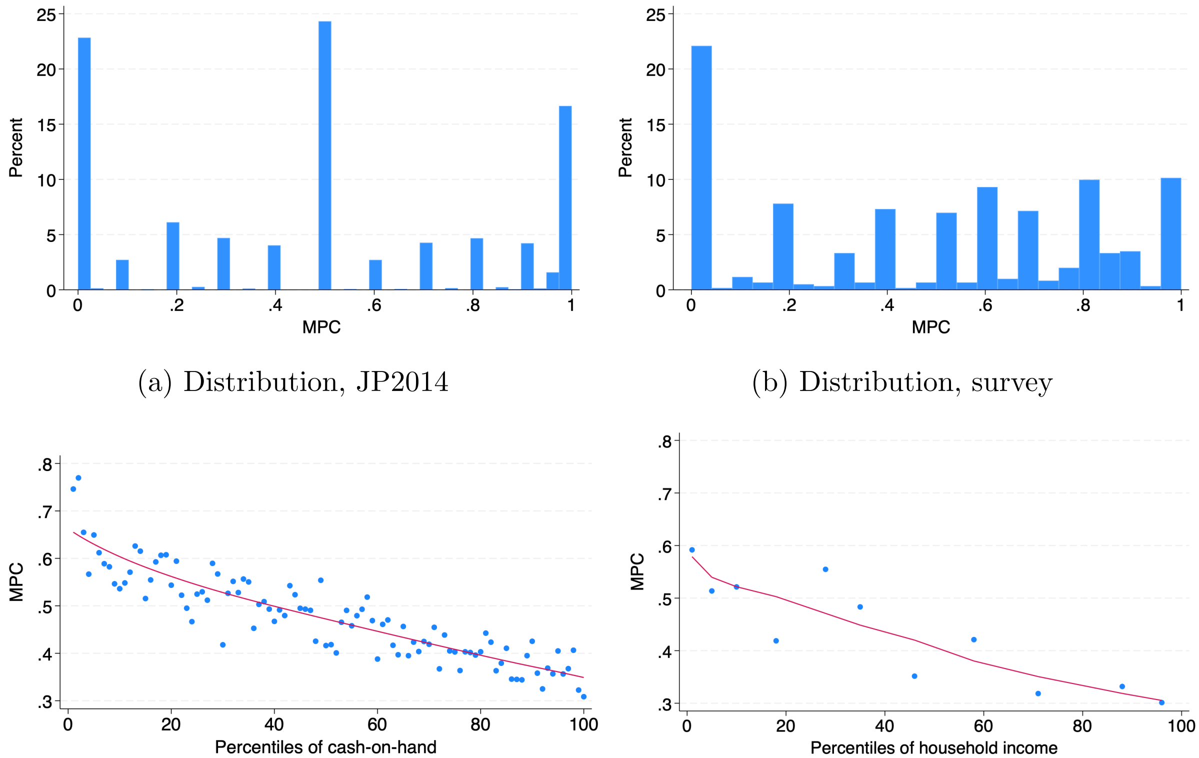
I find important racial differences in MPCs: the average MPC is 59% for black while 38% for white respondents. These values are consistent with the average MPC estimates in Patterson (2023) of about 85% for black and 45% for white workers. My finding that MPCs are on average 55% higher for black than white individuals is also in line with estimates

[8] In contrast, Fuster et al. (2021) first ask respondents whether or not they would change their spending in response to a transfer and later ask for the specific amount. A large proportion of their respondents report that they would not change their spending, which results in a sample MPC that is among the lowest in the literature.

[9] The MPC is the proportion of $500 not allocated to savings or debt. Jappelli and Pistaferri (2014) estimate an average MPC of 48%.

[10] Since wealth is not collected in my survey, I do not have a measure of cash-on-hand similar to Jappelli and Pistaferri (2014). I construct a measure of cash-on-hand by using the 1997-2021 Panel Study of Income Dynamics (PSID) to infer respondent wealth from household income, age, and race. I find a negative relationship between MPCs and cash-on-hand similar to Jappelli and Pistaferri (2014) (see Appendix A).

Figure 1: Comparison of MPC measure between literature and survey



(a) Distribution, JP2014

(b) Distribution, survey

(c) MPC & finances, JP2014

(d) MPC & finances, survey

Note: This figure shows the distribution of MPCs in the sample (a-b) and the relationship between MPCs and percentile of cash-on-hand (c) or income percentile (d). Sub-figures a and c are from Jappelli and Pistaferri (2014) (labeled JP2014) while b and d are from my survey.

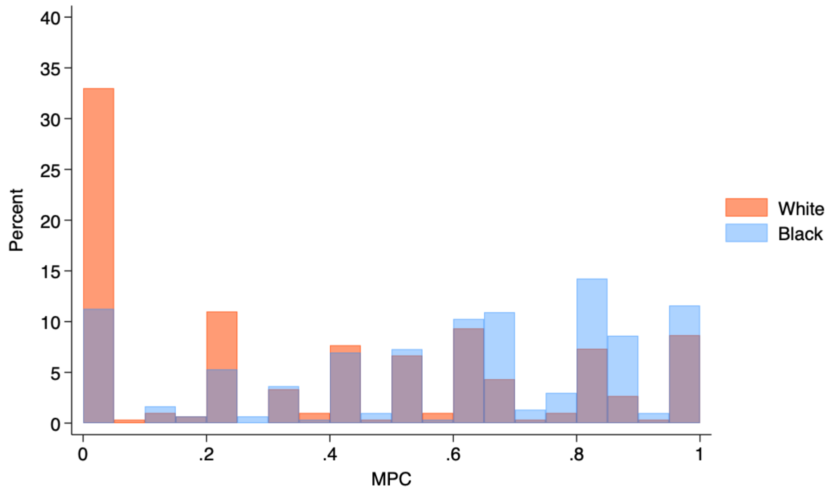
of 50% from Ganong et al. (2020) and 45% from Nakajima (2023).[11] The distributions of MPCs collected by race of the respondent are shown in Figure 2. The black respondent MPC distribution is relatively flat, with the same percentage of respondents (11.3%) indicating they would spend none or all of the transfer. Most black respondents (68.5%) indicate spending half or more of the $500. In contrast, the white respondent MPC distribution is more concentrated at lower MPC values. About a third of white respondents indicate not spending the transfer, 41.7% would spend half or more, and 8.7% would spend the full $500.

2.3 MPC decomposition

I next use my survey data to investigate the main drivers of racial differences in MPCs and test several theories from section 1.1. The decomposition is calculated from an OLS regression of MPCs on respondent characteristics. The OLS estimate of the racial gap in

[11]The value 55% is the difference in average MPC between black and white respondents in the survey.

Figure 2: MPC distribution by race



Note: This figure shows the distribution of MPCs in the sample by race of the respondent (white in orange, black in blue).

MPCs conditional on other respondent characteristics is consistent with a nonparametric estimation of the same data.[12]

Table 2 shows how much the black-white difference in average MPC, of 21 percentage points (pp), is explained by racial differences in respondent characteristics that theory suggests are important. I estimate that differences in income between black and white households explain only 1.58 pp of the 21 pp gap. Differences in being a renter versus a mortgagor or homeowner explain 1.87pp and differences in having a college degree explain 0.86pp. The total number of household members and children are also statistically significant drivers of racial differences in MPC. However, racial differences in household composition only explain about 1 pp of the MPC gap.

In Table 2, over 15pp of the 21pp gap are attributed to the race dummy in the regression even after controlling for other factors. Thus, 72% of the black-white difference in MPCs is unexplained by other respondent characteristics such as age, education, income, and household composition. It is not probable that almost all racial differences in MPCs are solely due the race of the respondent. Instead, it is likely that racial differences in consumption behaviors are shaped by factors that are not captured in the survey data.

2.4 Wealth and status compensation mechanisms

In this section, I explore mechanisms that could explain the 15pp racial difference in MPCs found in Table 2. These mechanisms are motivated with data from standard representative US surveys since they are not measured in my survey. In the next sections, I build a life-cycle model to test how these mechanisms influence the racial MPC gap.

The first mechanism is the racial wealth gap. Theory and the quantitative modeling

[12]See Appendix B for the OLS regression coefficients and Appendix C for the nonparametric estimation.

Table 2: Explaining MPC racial gap through other racial gaps

	Percentage Points
Household income	1.58*
Renter	1.87**
College degree	0.86**
Number of household members	1.37***
Number of children	−0.25***
Race: Black	15.27***
Age	0.02
Age squared	−0.03
Sex: Female	0.01
Employment	−0.04
Marriage	0.43

Note: This table presents how much racial gaps in respondent characteristics explain the average MPC racial gap between black and white respondents. Estimates are from an OLS regression using sampling weights. *** p<0.01, ** p<0.05, * p<0.1.

literature in section 1.1 show that groups with lower wealth will have higher MPCs on average. The black to white mean liquid wealth ratio is 0.16 in the 2022 Survey of Consumer Finances (SCF). These large racial differences in wealth imply racial differences in MPCs in the same direction as in the survey.

Spending behavior is also likely influenced by motives to show wealth. When wealth is unobserved by others, individuals who have wealth often signal their status to others through their purchases of goods that are visible to others (Cole et al. 1995). In the 2022 wave of the General Social Survey (GSS), respondents more often rate black people as a group as poor or below average, while white people as a group as rich or above average.[13] Black households compensate for these biases in ascribed economic position by signaling their status more than white households (Charles et al. 2009). Individuals that signal their status through consumption have fewer resources left over to save and accumulate wealth. Status signaling could therefore inform racial differences in MPCs when signaling motives differ by race.

I extend Charles et al. (2009) using CE data from 1980-2019 to capture any recent changes in spending during the last two decades. I follow their classification of visible goods as clothing, jewelry, personal care, and vehicles.[14] Given that consumption theory states that expenditures should be influenced by permanent income (Friedman 1957; Charles et al. 2009), I would want to estimate the following regression:

[13]See Appendix D for a breakdown of categories by race.

[14]This classification of visible goods is consistent with alternative classifications excluding less-visible clothing items or including home goods and furniture, recreational activities, cigarettes and alcohol, or food outside the home. See Appendix E for a discussion.

$$log(visible_i) = \alpha_0 + \alpha_1 Black_i + \zeta log(PermanentIncome)_i + \theta X_i + \xi_i, \tag{1}$$

where *Black* is a dummy indicating whether the household head is black, *PermanentIncome* is the permanent income of the household, and X is a vector of controls. The control variables are a quadratic polynomial of age of the household head, three dummies for the education of the household head, log household liquid wealth, a dummy for positive liquid wealth, effective family size following the OECD equivalence scale, year dummies, and indicators for whether the household head is male, employed, single, urban, Census region, and state.

The specification in equation 1 must be adjusted because permanent income is difficult to measure in the CE.[15] The Permanent Income Hypothesis states that total expenditures are a good proxy for permanent income (Friedman 1957). The CE has high quality measures of total household expenditures. However, introducing total expenditures in equation 1 leads to several problems: total expenditures are endogenous to visible expenditures and measurement error in total and visible expenditures are likely related. To address these problems, I follow Charles et al. (2009) and estimate:

$$log(visible_i) = \alpha_0 + \alpha_1 Black_i + \zeta log(TotalExpenditure)_i + \theta X_i + \xi_i, \tag{2}$$

where the log of total expenditure is instrumented by a vector of current and permanent income controls. This vector includes the log of current income and a cubic in income. The regression has a valid instrument that is relevant and passes a test of overidentifying restrictions.[16] The instrument is strong as it is correlated with the endogenous variable, the F-statistic from the first stage regression is very large (>100), and the t-statistic on the instrument in the second stage regression is 12. The Sargan (1958) test verifies that the instruments are uncorrelated with the error term. This specification has real household measures CE family sample weights.[17]

Consistent with Charles et al. (2009), Table 3 shows that black households spend 25% more on visibles than white households, but that this racial difference is mostly erased when controlling for the mean income of the household's racial group.[18] The lower the own group income, the higher the share of visible good expenditure. Since average income is lower for black than white individuals, a larger share of spending is on visible goods in black than white households.

The fact that the need to signal status is stronger among black than white individuals can be motivated by several scenarios. Freeman et al. (2011) run a survey in which respondents are shown black and white images of a janitor and businessman and then asked to indicate the race of the employee. People more often indicated the race of the employee as black when shown the janitor and white when shown the businessman. This study shows that people do associate racial groups with certain income distributions and occupations. Racial discrimination can also directly impact the economic positions that are ascribed to individuals. Bertrand and Mullainathan (2006) find that black individuals are often hired less than

[15] See Charles et al. (2009) for a detailed explanation of CE shortcomings for income measures.

[16] See Appendix E for estimates of the validity of this instrument.

[17] Estimates are consistent with no sampling weights or with clustering standard errors at the state level to account for the time serial correlation in visible spending across states.

[18] Charles et al. (2009) estimate visible goods spending is 26% higher among black than white households.

Table 3: Estimates of visible goods expenditure by race

	Log share visible expenditure	
	(1)	(2)
Black coefficient	0.25***	0.09
	(0.01)	(0.09)
Log of mean own racial group income		-0.40*
		(0.21)
Observations	186515	186515
R-squared	0.14	0.14
Controls	Yes	Yes

Note: This table shows estimates of a regression of the log share of visible expenditure out of total expenditure on a race dummy and other controls. Column (1) follows the specification in equation 2. Column (2) is the same specification as column (1) but also includes a control for log of mean own group income by race. Data is from the Consumer Expenditure Survey 1980-2019. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

white individuals solely due to racial associations of applicant names. It is thus plausible that black individuals have a stronger motive to visibly signal their status to compensate for stereotypes of them having lower incomes than white individuals.

3 Model

I build a life-cycle model to test the mechanisms I hypothesize influence group differences in MPCs further than those outlined in Table 2. Racial differences in earnings, wealth, and status compensation are incorporated into the model. I envision households composed of one individual and will compare the model output to household data in per capita terms. Henceforth, I refer to these households as individuals.

3.1 Simple model with status

I first present a two-period model of one consumption good without income risk for intuition into the status compensation mechanism. In this model, income and wealth are unobserved by others, while consumption is observed. People use their consumption, or 'burned wealth', to show others their economic position or status (Cole et al. 1995). Agents thus receive utility not only from the goods they consume, but also from their status. The individual maximizes consumption subject to budget constraints and status as below:

$$\max_{c_1,c_2} \quad log(c_1) + \beta log(c_2) + s_1$$

$$\text{subject to} \quad c_1 = a_1 + y_1, \;\; c_2 = y_2 + (1+r)a_1, \;\; s_1 = \eta\left(\frac{c_1}{\bar{c}_1}\right),$$

where c is consumption, y is exogenous income, a is wealth, s is status, η is the importance of status, and $\bar{c}$ is average consumption. I abstract from types of goods and income risk in this simple model, but incorporate these features in the full model in the next section.

Status is represented as individuals' share of average consumption in the population.[19] Higher average consumption lowers an individual's relative status if they do not change their individual consumption. This definition of status implies that the importance of status rises with higher consumption, since $U_{s_1 c_1} > 0$. Thus, individuals that have higher wealth and are able to consume more will want to increase their consumption for higher utility from their derived status. This behavior can be characterized as 'Getting ahead of the Joneses', rather than 'Keeping up with the Joneses' that would imply that excess consumption lowers status.[20]

Maximizing the above problem leads to an Euler equation that simplifies to:

$$(c_1)^{-1}(1+s_1) = \beta(1+r)(c_2)^{-1} \tag{3}$$

From the left side of equation 3, it is clear that higher status, or lower aggregate consumption, raises the marginal utility of consumption if individual consumption is held constant ($U_{c_1 s_1} > 0, U_{c_1 \bar{c}_1} < 0$). Some people have higher relative status but also have higher marginal utility of consumption. This effect causes these people to want to continue spending rather than follow the aggregate trend (Roussanov 2010). However, in a 'Keeping up with the Joneses' model, individuals would not have a motive to spend more since they would be satisfied with their now higher status relative to the aggregate.

The status compensation term also directly changes the model MPC ($\frac{\partial c_1}{\partial y_1}$). The MPC from this model compares to the MPC from a model without the status term (s_1) in the utility function as follows:

$$MPC_{s_1} = \frac{1+s_1}{1+\beta+s_1} > \frac{1}{1+\beta} = MPC_{ns} \quad ,$$

where MPC_{s_1} is the MPC of this simple model with status, and MPC_{ns} is the model without status. Introducing the status compensation mechanism should thus theoretically raise the average MPC in the model.

In equilibrium, this model implies that others' beliefs of status and economic position are correctly derived from consumption. Also, that spending is increasing in wealth and income (Cole et al. 1995).[21]

3.2 Life-cycle model

I next extend the theory presented in the simple model to a life-cycle model to test mechanisms that could explain the racial differences in MPCs collected in my survey.[22] This model differs from a standard life-cycle model in that I model consumption of two types of goods -

[19]The status mechanism is assumed to be linear in consumption for simplicity. Derivations in Appendix H show that the model dynamics hold for other utility functions with curvature in the status term.

[20]See Roussanov (2010) for an in-depth discussion and derivation of these two types of models.

[21]These predictions are standard of signaling models (Ireland 1994; Cole et al. 1995; Charles et al. 2009).

[22]This life-cycle model collapses to the simple model in section 3.1 if $T = 2$, all goods are visible, $\psi = 1$ so that consumption is logged in utility, $\phi^g = 1$, and the labor income process is exogenous.

non-visibles and visibles - and introduce the status mechanism discussed in section 3.1. The individual problem has a continuum of agents who maximize utility according to:

$$\max_{cn_t, cv_t, a_{t+1}} \quad E\sum_{t=1}^{T^g} \beta^{t-1,g} \left\{ \frac{cn_t^{1-\gamma}}{1-\gamma} + \frac{cv_t^{1-\psi}}{1-\psi} + \eta(\bar{c}_t^g)^{1-\psi} \left(\frac{cv_t}{\phi^g \bar{c}_t^g} \right) \right\} \tag{4}$$

$$\text{subject to} \quad cn_t + cv_t + a_{t+1} = w\ell_t^g + (1+r)a_t, \;\; a_0 \geq 0, \;\; a_{t+1} \geq 0, \;\; \gamma > \psi,$$

where cn and cv are consumption of non-visible and visible goods, respectively, and total consumption is split between the two types of goods. Average total consumption, $\bar{c}$, differs by racial group, $g \in \{B, W\}$, and is weighted by ϕ. The parameter ϕ differs by racial group to capture the heterogeneity in how others perceive the average consumption of black versus white individuals. The third term in the utility function thus represents the status compensation motive, which is derived from an individual's spending on visible goods relative to their own racial group's average total consumption.[23] I set $\gamma > \psi$ so that visible goods are luxuries compared to non-visible goods.[24] Other variables include t as an index for age, β for the discount factor, a for assets, w for median earnings, ℓ for labor earnings, and r for the interest rate.[25]

Individuals work and receive labor income for the first $t < T_R$ periods of their life as follows:

$$\begin{gathered} log(\ell_t^g) = m_t^g + z_t^g, \\ z_t^g = \rho_z^g z_{t-1}^g + \zeta_t^g, \;\; \zeta_t^g \sim N(0, \sigma_\zeta^g) \end{gathered} \tag{5}$$

The income process consists of a deterministic age profile component, m_t, and an idiosyncratic stochastic component, z_t with persistence ρ_z and innovation variance σ_ζ. The income process varies by race of the individual. After retirement age, $t \geq T_R$, individuals receive deterministic retirement benefits as follows:

$$log(\ell_t^g) = m_t^g + \lambda^g log(\ell_{TR-1}^g),$$

where λ is the replacement ratio of labor income in retirement. In retirement, individuals thus receive a fraction of their income from their last year of work.

The model is solved separately for each racial group. I estimate the average MPC out of total consumption following Kaplan and Violante (2022):

$$MPC^g = \frac{c^g(a + x^g, w^g\ell^g) - c^g(a, w^g\ell^g)}{x^g},$$

[23]Total consumption (of both types of goods) represents a consumer's overall wealth in this model since consumption is observed and wealth is unobserved by others. The reference group consumption in the status term is total consumption to represent the relative wealth of that group. Many in the economics literature derive status as a function of total consumption. Ireland (1994), a seminal paper, writes a status signaling model with visible and non-visible goods in which status is a function of others' views of their overall consumption.

[24]It is common to model the consumption of these two types of goods with non-homothetic preferences. Aït-Sahalia et al. (2004) estimate that households are more risk averse with respect to the consumption of basic than luxury goods. Charles et al. (2009) estimate that visible goods have luxury properties.

[25]See Appendix I for numerical details on how the model is solved.

where x is the model equivalent of \$500. This specification allows for a direct comparison between the MPCs that the model estimates and those I collected in the survey.

The Euler equations for non-visible goods simplify to:

$$cn_t^{-\gamma} \geq \beta^g(1+r)E\left[cn_{t+1}^{-\gamma}\right] \text{ if } a_{t+1}=0$$
$$cn_t^{-\gamma} = \beta^g(1+r)E\left[cn_{t+1}^{-\gamma}\right] \text{ if } a_{t+1}>0$$

and for visible goods simplify to:

$$cv_t^{-\psi} + \frac{\eta}{\phi^g}(\bar{c}_t^g)^{-\psi} \geq \beta^g(1+r)E\left[cv_{t+1}^{-\psi} + \frac{\eta}{\phi^g}(\bar{c}_{t+1}^g)^{-\psi}\right] \text{ if } a_{t+1}=0 \tag{6}$$

$$cv_t^{-\psi} + \frac{\eta}{\phi^g}(\bar{c}_t^g)^{-\psi} = \beta^g(1+r)E\left[cv_{t+1}^{-\psi} + \frac{\eta}{\phi^g}(\bar{c}_{t+1}^g)^{-\psi}\right] \text{ if } a_{t+1}>0$$

The intuition behind the status mechanism in this model follows the motivation described in the two-period model. Equation 6 shows the positive marginal utility of cv_t that rises with higher wealth. It is also apparent that as group consumption rises, status falls: $U_{\bar{c}_t^g} = -\frac{\psi\eta}{\phi^g}(\bar{c}_t^g)^{-\psi-1}cv_t < 0$. The motive of 'Getting ahead of the Joneses' also arises in this model, as lower group consumption raises status and induces individuals to continue spending on visibles to show status: $U_{cv_t\bar{c}_t^g} = -\frac{\psi\eta}{\phi^g}(\bar{c}_t^g)^{-\psi-1} < 0$.

4 Quantitative results

I estimate the life-cycle model and demonstrate that the status compensation mechanism explains a significant part of the racial differences in MPCs found in the survey. The model is estimated at an annual frequency to match the annual MPCs I collected.[26] I first present the parameters that are assigned and calibrated in the model. I then display the model output of MPC for each racial group and compare other model moments to the data.

4.1 Parameter inputs

Table 4 displays the parameters that are assigned in the model. Individuals are born at age 25 and retire at age 65. Agents live until age 80 if they are white and age 77 if black, following the Center for Disease Control (CDC) estimates of average life expectancy in 2023. Therefore, age 1 in the model is age 25 in the data, while $T_R = 40$, $T^W = 55$, and $T^B = 52$. I solve the model in partial equilibrium with an annual interest rate of 1% following Kaplan and Violante (2022). I also set the risk aversion parameter of non-visible goods, γ, equal to 1 for log preferences as is standard in the literature.[27]

I use the PSID to estimate differences in total household income for black and white individuals. I follow Krueger et al. (2016) to clean the PSID sample, excluding heads of

[26] I interpret my survey MPCs as being cumulative over a year since they are consistent with the yearly estimates in Colarieti et al. (2024). Jappelli and Pistaferri (2014) do not specify a spending period in their question, similar to my survey, and also model their MPC estimates at an annual frequency.

[27] The main results are consistent for other values of γ ($\gamma > \psi$) when the model is recalibrated. A higher risk aversion parameter for non-visible goods slightly increases the share of visible goods consumption.

Table 4: Assigned parameters

	Description	Value White	Value Black	Source
T_R	Retirement age	40	40	*Standard*
T	Lifespan	55	52	CDC (2023)
r	Interest rate	0.01	0.01	Kaplan and Violante (2022)
γ	Non-visibles risk aversion	1	1	Kaplan and Violante (2022)
w	Earnings	1	1	
λ	Income share replaced in retirement	0.74	0.82	PSID 1997-2021
m_t	Age profile of income	Figure K.1		PSID 1970-1997
ρ_z	Productivity shock persistence	0.984	0.962	PSID 1970-1997
σ_ζ	Productivity shock volatility	0.011	0.025	PSID 1970-1997
x	Model \$500	0.0067	0.0046	Equivalent of average income
η	Status utility weight	1	1	Roussanov (2010); Table 3
ϕ^W	Fraction of consumption	1	–	*Normalized*
D_0	Distribution of wealth age 25	Figure K.2		PSID 1999-2021
$\frac{cv_T}{c_T}$	Share visibles in last period	0.07	0.06	CE 1980-2019

Note: This table displays parameters that are assigned. Parameters at annual frequency.

households younger than age 25 and older than 60, unemployed, and with wages less than half of the minimum wage in that year or \$1,000. The earnings parameter, w, is set to 1 since working-age earnings dynamics are fully captured by the income process parameters. I use the PSID to compare after-tax real money income of white and black households five years pre- and post-retirement using family sample weights.[28] I find that the average replacement of income in retirement years is higher for black than white individuals.

The income age profile, m_t, and the persistent component, z_t, are estimated separately for each race group; see Appendix J for details. I first regress the log of per capita real disposable income on age, education, and year dummies. I use a Heckman-selection estimator with an inverse mills ratio to account for selection into employment. I then remove the age and education profiles of income from the residuals of the previously described regression. The persistent component in equation 5 is estimated on these adjusted residuals using a Minimum Distance Estimator following Daruich and Fernandez (2024).

The age profiles of black and white earners differ mainly in their level rather than in their shape. I normalize the average age profile of the white earner to 1, while the average of the black earner is 0.7 (see Figure K.1).[29] I also find racial differences in the persistence and volatility of income. Shocks are persistent, especially for white individuals, while shocks are

[28] Sample weights in the PSID were constructed starting in 1997. Estimates of the replacement ratio are consistent with not using sample weights.

[29] This racial difference in average income is consistent with PSID data 1968-2021 and recent estimates in Heathcote et al. (2023).

more volatile for black individuals, consistent with Carr and Hardy (2022).

I calculate the model equivalent of a \$500 transfer relative to annual income in the data. Guzman and Kollar (2023) estimate that US median annual income was \$74,580 in 2022. The transfer is thus equivalent to $0.0067 = 500/74,580$ for white individuals since average income is normalized to 1 in the model. I account for the racial difference in average income to calculate the transfer for black individuals. The model equivalent of the \$500 transfer is thus 30% larger in the model of white than black individuals.

The status utility weight is set to 1 following the estimation in Roussanov (2010) and my finding of no racial difference in the importance of status in Table 3. I also normalize ϕ^W to 1 so that the average total consumption of white households is fully transmitted to others.

The last inputs of the model are the distribution of wealth at the beginning of life and the share of visible consumption at the end of life.[30] The distribution of liquid wealth of household heads age 25 by racial group is calculated from the PSID. Wealth data in the PSID is cleaned following Kaplan and Violante (2022) and begins in 1999 since that is when data on wealth started being collected in each survey wave. At age 25, white households on average have more wealth than black households. The share of consumption on visible goods at the end of life is estimated using the same CE data as in Table 3. This consumption share is slightly higher on average for white than black households.

4.2 Calibration

Table 5 shows the parameters that are calibrated to match certain targeted moments from the data. The model closely matches all four targeted moments.

Table 5: Calibrated parameters

	Parameter	Value	Target	Data	Model
β^W	Discount factor, white	0.9846	Wealth/income, white	0.50	0.50
β^B	Discount factor, black	0.9838	Wealth/income, black	0.15	0.15
ψ	Visibles risk aversion	0.53	Share of visibles, white	0.10	0.10
ϕ^B	Consumption fraction, black	0.18	Black to white visibles share	0.24	0.24

Note: This table presents calibrated parameters to empirical targeted moments. Parameters are in annual frequency. Wealth is liquid wealth, sourced from the 2022 SCF. The last empirical target is the percent difference in share of visible goods expenditure between black and white individuals after controlling for income, wealth, and other characteristics.

I calibrate the discount factor of white and black individuals to target the mean liquid wealth to income ratio of each racial group. I focus on liquid wealth as the best measure of wealth to study MPCs since it directly informs the cash-on-hand available to spend and accounts for most of the variation in MPCs (Kaplan and Violante 2022).[31] I use the 2022

[30] See Appendix K for details.

[31] Parameterization of the model according to liquid wealth is also relevant for considerations of housing equity. Housing is a large source of wealth for households, especially for black households who hold a larger

SCF to estimate the ratios of liquid wealth to total income. The wealth-to-income ratio estimated for white individuals is similar to the overall population wealth-to-income ratio found by Kaplan and Violante (2022), while that of black individuals is considerably smaller.

The average share of consumption on visible goods for white individuals is 10% in the CE data. I calibrate the risk aversion of visible goods to match this moment, with the same value for both racial groups.

The last empirical target is the percent difference in share of visible goods expenditure between black and white individuals after controlling for observable characteristics. I estimate the empirical target following equation 2 with observables that can be controlled for in the model to ensure a direct comparison between the data and the model.[32] In the model, I simulate a population of individuals and run the same regression as in the CE data.[33]

I set ϕ^B to target the black-to-white difference in share of visibles, since this parameter largely influences the need for status consumption versus accumulating wealth for black individuals. This parameter can represent how others perceive the economic positions of racial groups. The fact that $\phi^B < \phi^W$ follows from GSS respondents rating black people as pertaining to a much lower end of the income distribution than white people.

4.3 Results of model with status compensation

I present the model results of the MPC and several additional patterns in the data that the model encompasses. The model is consistent with the data on the share of visible consumption, wealth, and hand-to-mouth status. There are also similar patterns in the data and model on total consumption by cash-on-hand. I next decompose the model to show the contribution of the status compensation mechanism versus racial differences in the discount factor and income.

4.3.1 MPC

The model results of average MPCs and other moments are shown in Table 6. The model estimates a mean MPC of 42.67% for white individuals and 57.09% for black individuals. These magnitudes are close to the gap in MPCs attributed to race and income from the survey, although slightly higher for both groups. The variance of MPCs from the model is also consistent with the survey data, although it is higher for both racial groups.

share of their wealth in housing equity than white households. My model abstracts from housing costs and decisions to rent versus own for similar reasons as Ashman and Neumuller (2020). My focus in this paper is in explaining racial differences in MPCs. Housing equity could affect consumption in restricting how much cash-on-hand a household has to spend. My model's focus on liquid wealth thus allows for an abstraction from housing, as total net wealth includes housing equity. In Appendix L, I incorporate housing expenses into my model and find consistent estimates with my baseline model.

[32] This exercise is the same as in Table 3 Column 1, excluding controls that are not available in the model. I regress the ratio of expenditure of visible versus all goods on a race dummy and controls of log total expenditure, a quadratic polynomial of age, log household liquid wealth, and a dummy for positive wealth. The log of total expenditure is instrumented by a vector of current and permanent income controls, as in equation 2. This specification has a strong instrument. When estimating the empirical moment, household measures are real and I use CE family sample weights.

[33] I simulate 10,000 households per age and racial group.

Table 6: Results of MPC moments

MPC (%)	Data	Model
Mean, white	37.71	42.67
Mean, black	54.83	57.09
Variance, white	11.87	19.34
Variance, black	9.11	19.58

Note: This table shows results of the MPC mean and variance in the model compared to the survey data. 'Mean MPC, black' is the sum of 'Mean MPC, white' and gaps attributed to race and household income in Table 2.

The distribution of MPCs generated from the model follows those collected in the survey. The model mirrors the survey data in that more white individuals have MPCs close to zero: 33% versus 46% are in the bottom decile of MPCs in the data and model, respectively. Also, in that black individuals have relatively higher MPCs: 35% versus 50% are in the top quintile of MPCs in the data and model, respectively. The model also produces values within the entire range of MPCs, similar to the data.

4.3.2 Other moments

Table 7 shows how the model matches several other non-targeted moments in the data. Using CE data from section 2.4, I estimate that the share of spending on visible versus non-visible goods increases in wealth for black individuals.[34] The slope of the share of spending over wealth is 0.005. The model matches this moment exactly. In both the data and model, the share of visible goods spending does not clearly differ by wealth for white individuals.

Black individuals have considerably lower wealth than white individuals in the data and model. The median wealth to income ratio is over three times higher for white than black households in the SCF, similar to in the model. I estimate that the black-to-white mean liquid wealth ratio is 0.16, consistent with estimates in Boerma and Karabarbounis (2023) and Derenoncourt et al. (2024). The model generates a ratio of 0.21.

I additionally estimate the share of individuals that are hand-to-mouth (HTM). The HTM have net wealth lower than half of their monthly income. This share is calculated from the 2021 PSID, omitting the top 5% of the wealth distribution as in Kaplan and Violante (2022). The model generates more white HTM individuals, 46%, compared to 30% in the data. But, it closely matches the 70% share of black individuals in the data.

[34] I estimate the relationship between the share of visible spending and wealth in OLS regressions using the same CE data as in Table 3 and sampling weights. I run the regressions separately for white and black households, regressing the share of visible versus non-visible goods consumption on percentiles of household per capita real wealth.

Table 7: Results of other moments

Moment	Data	Model
Visibles/non-visibles by wealth, white	<0.001 (<0.001)	0.001
Visibles/non-visibles by wealth, black	0.005 (0.001)	0.005
Median wealth to income ratio, white	0.13 (0.024)	0.22
Median wealth to income ratio, black	0.04 (0.015)	0.00
Black to white wealth ratio	0.16	0.21
Share HTM, white	0.30 (0.01)	0.46
Share HTM, black	0.70 (0.01)	0.67

Note: This table shows results of other moments. Standard errors in parentheses. Wealth is liquid wealth, sourced from the 2022 SCF. Share of hand-to-mouth (HTM) estimated from the 2021 PSID.

4.3.3 Consumption by cash-on-hand

I assess the ability of the model to match spending on status in the data. Status spending is per capita visible goods consumption relative to the average total consumption of the individual's own race. This ratio follows the specification of status in equation 4. The share of status spending is higher for black than white individuals at middle and higher levels of cash-on-hand, as shown in Figure 3 (a). I also plot the relationship between status spending and cash-on-hand from the model's decision rules. The model is similar to the data in the magnitudes of the shares of status spending. However, the shares in the model are slightly higher (lower) than the data for black (white) individuals.

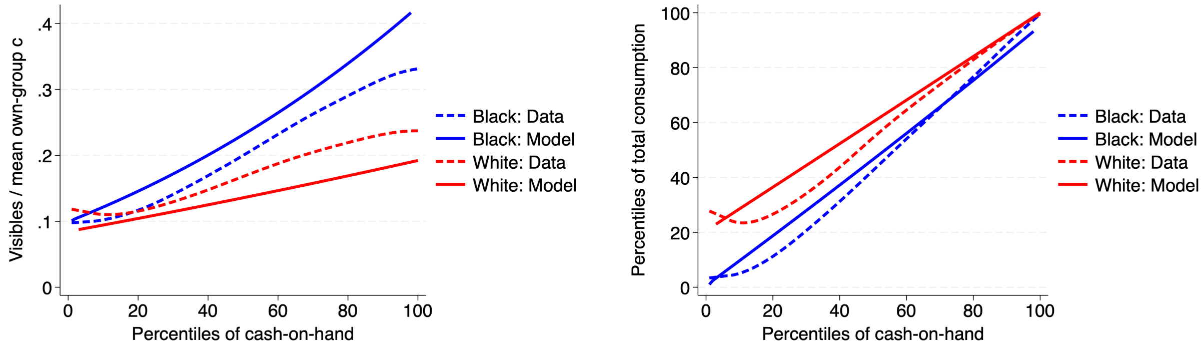
I reconstruct the measures of consumption across the income distribution in Du Bois (1899), Duesenberry (1949), and Friedman (1957) with more recent data and compare them to the output of my model.[35] I use CE data to plot percentiles of average total consumption by cash-on-hand for black and white households. Measures of real per capita household consumption are constructed using the OECD equivalence scale. Figure 3 (b) shows that total consumption increases in wealth and is higher for white than black individuals for most levels of cash-on-hand, consistent with Du Bois (1899) and Friedman (1957). The consumption of black and white individuals converges at upper levels of wealth, which matches the model. These results additionally mirror my survey in that black respondents have higher savings rates on average than white respondents.[36]

It is possible to reconcile the higher savings ratio and MPC of black versus white individuals by considering financial constraints. In the model, black individuals have large precautionary savings motives due to higher earnings uncertainty, however, a higher proportion are hand-to-mouth due to lower average earnings and a higher need for status compensation.

[35] Du Bois (1899) surveyed black families in Philadelphia and reported higher expenditures among wealthy than poor households. Duesenberry (1949) and Friedman (1957) found that household consumption was higher among white than black households at all levels of income in the mid-1930s.

[36] See Appendix F for more details. Colarieti et al. (2024) also find that individuals that are strongly constrained and have high income risk have a high desire to save more.

Figure 3: Other empirical consumption moments matched by model



(a) Status spending (b) Average propensity to consume

Note: This figure compares status and total consumption patterns in the data and model. Sub-figure (a) displays per capita visible goods consumption relative to average total consumption of own race group by cash-on-hand. Sub-figure (b) shows per capita total consumption by cash-on-hand. Dashed lines show CE data with lowess smoothing and solid lines show model values for individuals at the average income shock at age 50. Values for black individuals are in blue and for white individuals in red.

These mechanisms lead black individuals to spend more out of an unexpected transfer and overall consume less out of their income and liquid wealth.

4.3.4 Decomposing model mechanisms

I next decompose the model to analyze the contribution of each mechanism to the results. In separate estimations, I omit the status compensation mechanism, racial heterogeneity in the discount factor, and racial differences in income. I report average MPCs as well as wealth and consumption behaviors.

Table 8 shows how the model performs without the status compensation mechanism and racial heterogeneity in the discount factor. Comparing the baseline model (1) and the model without status (2), the status compensation mechanism explains 36% of the MPC racial gap.[37] This measure includes the direct effects of status compensation on individuals as well as the indirect effects of the interaction of status with other mechanisms. Without the status motive, both racial groups have lower MPCs and higher wealth. However, model (2) shows that the impacts are larger for black individuals since they have more needs for status compensation spending.

I remove racial differences in the discount factor by setting the β of black individuals equal to that of white individuals. Model (3) in Table 8 shows that the MPC of black individuals falls and wealth rises. In this model, racial differences in earnings volatility drive a larger part of the spending decision and black individuals save more to insure against

[37]See Appendix M for a detailed decomposition of the status mechanism in the model. The component of this mechanism that drives racial differences in MPCs is the average racial group consumption ($\bar{c}^g$), which explains over 28% of the MPC racial gap.

Table 8: Model decomposition of MPC

	Data	(1) Model Baseline	(2) Model No status	(3) Model No status, β
Mean MPC (%), white	37.71	42.67	42.58	42.58
Mean MPC (%), black	54.83	57.09	51.78	49.92
Black to white wealth ratio	0.16	0.21	0.31	0.36
Black to white share of visible goods	0.24	0.24	-0.17	-0.17
Visibles/non-visibles by wealth, black	0.005	0.005	<0.001	<0.001
Status term	-	Yes	No	No
β^g	-	Yes	Yes	No

Note: This table shows several outputs of alternative models by race. Model (1) is the baseline model shown in Table 6. Model (2) is the baseline model without the status term ($\eta = 0$) and Model (3) also omits heterogeneity in the discount factor ($\beta^B = \beta^W = 0.9846$). Models (2)-(3) are not recalibrated to match targeted moments.

future uncertainty. This explains why the racial difference in average MPCs is now greatly reduced.

Models (2) and (3) in Table 8 are not recalibrated to match empirical moments in Table 5. Without status and discounting motives, black individuals also spend less on visible goods. In these alternative models, the share of visible goods spending is higher for white than black individuals after controlling for income, total consumption, age, and wealth. Additionally, the share of visible goods spending is slightly higher for black individuals that are poor than wealthy. This contradicts the data showing that status spending is more important for wealthy black individuals.

I also calculate the part of the racial difference in MPCs that is attributed to racial differences in income in the model. This is directly comparable to the estimate of 1.58 pp in Table 2. The parameters that represent racial differences in income are the working-age wage, w, the age profile of income, m_t, and the replacement rate of income in retirement, λ. Table 9 shows that racial differences in income explain less than half of the racial differences in MPCs both in the data and model. Racial differences in income explain a larger portion of the MPC gap in the model (45.21%) than in the data (9.23%).

4.4 Alternative mechanisms

I explore several other mechanisms proposed in the literature that could explain the racial differences in MPCs in the model. I test the performance of the model without the status term and instead with racial heterogeneity in the discount factor, rates of return, unemployment shocks, and household expenses. Each alternative model is recalibrated to targets in

Table 9: Gap in MPCs attributed to income in data and model

	Data	Model
Percentage points	1.58	6.52
Percent of gap	9.23	45.21

Note: This table shows the part of the racial difference in MPCs that is attributed to racial differences in income. The Data column shows estimates from Table 2. The Model column displays the results of the model with no racial differences in w, m_t, and λ.

Table 5.[38] Although the alternative models produce MPCs that are on average higher for black than white individuals, they miss other important consumption moments. No alternative model can match the data showing that black individuals' share of spending on visible goods increases with wealth. The baseline model with the status compensation mechanism is thus the most acute in matching the data on consumption behaviors across the wealth distribution by racial group.

The first mechanism I study is differences in the discount factor. Without racial differences in the discount factor, a lower β would raise the model MPC equally for both racial groups. Heterogeneity in β by race, such as a lower β in the model of black individuals, can produce the consumption and wealth dynamics found in the data without the status mechanism. Although there are studies estimating that people differ in their levels of impatience, there is no evidence that impatience is higher among black consumers as a group versus white consumers. Racial heterogeneity in β can thus mechanically produce MPC estimates in line with the data, but does not hold as a mechanism that explains differences in consumer behaviors by race.

Racial differences in rates of return is a mechanism that has been proposed in the literature explaining the racial wealth gap. The interest rate on savings has been estimated to be lower for black than white individuals on average due to differences in composition of wealth (Nakajima 2023; Derenoncourt et al. 2024). This rate gap can generate part of the racial differences in wealth in quantitative models, as individuals who have lower rates of return save less.[39] In my model, I find that racial differences in rates of return of less than 1 pp can produce average MPCs in line with the data.

I also test how other racial differences in the labor market could influence consumption behaviors. Black individuals are much more likely to experience a period of no labor earnings, such as from being unemployed or out of the labor force due to labor market frictions or incarceration. A simple way to test this in my model is to change the income shock estimated in equation 5 so that the lowest shock is zero earnings. This ensures some probability that

[38] See Appendix Table N.1 for the results of these tests.

[39] Ganong et al. (2020), Giorgi et al. (2022), and Nakajima (2023) calibrate their models with rates of return on savings that are lower for black than white households by 3-6pp monthly, 3pp annually, and 3pp quarterly, respectively.

individuals have no labor income in a given period. I parameterize transitions in and out of employment using data on job loss and finding transitions by race from Cajner et al. (2017) at a yearly frequency.[40] These earnings shocks lead to considerably lower wealth levels and higher MPCs. When the model is recalibrated to match wealth moments, the average MPC of each racial group is over 10pp higher than in the data. The share of visible goods consumption of black individuals is also higher than in the data.

I lastly test whether higher expenses of black individuals contribute to their higher MPCs in this model framework. The model is neutral in the exact type of expense; it could be utility bills, bank fees, repairs from natural disasters, or familial financial support. Du Bois (1899) published data that black households pay higher household expenses and rent. Black individuals are also 7.1pp more likely to pay bank overdraft fees and 1.8 pp more likely to be affected by natural disasters than white individuals.[41] Chiteji and Hamilton (2002) find that necessary financial transfers from middle-class black households to poorer extended family members weaken their ability to accumulate wealth, thus contributing to the persistent black-white wealth gap.[42] I model these expenses as a tax on income that only exists on black individuals in the model. The expense tax reduces wealth, but also lowers average MPCs due to strong precautionary savings motives. The mean MPC of black individuals is therefore lower with this added expense than in the baseline model.

Overall, the baseline model with status compensation matches the racial differences in MPCs, wealth, and visible consumption from the data closer than the other explored models. The mechanism of status compensation is also consistent with the data and empirical estimates in the literature.

5 Policy implications

In this section, I use the baseline model to evaluate how government interventions affect consumption behavior and wealth redistribution across racial groups. I begin by comparing average MPCs out of different sizes of income shocks. I then estimate the re-distributional effects of the current Social Security system through a policy experiment on benefit timing. Finally, I explore several policies that can address racial differences in wealth through targeted government investment or transfers.

5.1 Transfer sign and size

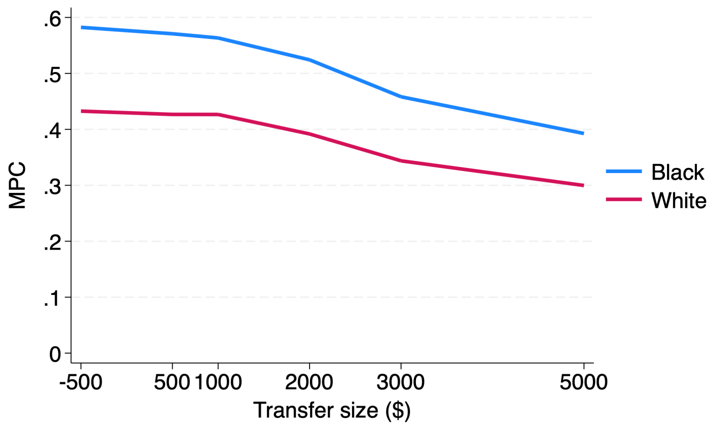
I first estimate the model with a negative \$500 income shock. Figure 4 shows that individuals change their consumption slightly more in response to a loss rather than gain in income. The asymmetry in response by sign of the shock is more pronounced for black individuals, with a 2pp higher average MPC out of a negative shock. The average MPC of white individuals rises by 1pp out of a negative shock.

[40]See Appendix Table N.2 for job loss and finding values by race.

[41]Estimates from the 2021-2023 Survey of Household Economics and Decisionmaking. See details in Appendix G.

[42]In my survey, black respondents are more likely to indicate they will borrow from family or friends when they have a negative income shock. This is consistent with the data collected in the Survey of Household Economics and Decisionmaking.

Figure 4: MPC out of different transfers



Note: This figure shows mean MPCs out of different transfers by racial group (black in blue, white in red) for the baseline model.

Average MPCs fall with transfers that are larger than $500, consistent with findings in Colarieti et al. (2024) and others.[43] However, MPCs remain relatively high at 39% for black individuals and 30% for white individuals with the largest transfer size of $5000. Fiscal policy in the form of government transfers to individuals can thus be effective at influencing spending behavior with reasonable transfer sizes.

I conduct this same experiment with the alternative models described in section 4.4. The model with the unemployment shock produces a different relationship of MPCs out of negative and positive income shocks. The mean MPC out of a negative income shock is 50% and 30% lower than from a positive income shock for black and white individuals, respectively. This follows from the large precautionary savings motives that exist when households have a probability of unemployment. Individuals are induced to save for the future and thus have even lower MPCs when they lose part of their income. This result is not consistent with the literature that shows individuals tend to be more affected by negative than positive shocks. The baseline model with status compensation matches this data moment more closely.

5.2 Social Security policy

There is ongoing policy debate regarding the reform of the US Social Security system. Although this discussion has persisted for decades, it has gained renewed urgency due to the projected depletion of Social Security's primary trust fund by 2033 (Social Security Administration 2025). An early prominent critique of the system by Feldstein (2005) argued that Social Security operates as a regressive policy, redistributing wealth toward higher-income households. Recent policy proposals aim to address concerns of program solvency and in-

[43]Figure 4 is also consistent with estimates of spending out of Covid-19 stimulus payments in the US. Coibion et al. (2020) and Karger and Rajan (2020) estimate MPCs of 40% and 46%, respectively, out of stimulus checks with an average size of $1,200.

equity.[44]

In this section, I evaluate the distributional implications of the current Social Security system using my rich model that incorporates racial heterogeneity. I estimate that the system generates net wealth transfers from black to white individuals. Details of the model, including calibration and implementation of the Social Security policy, are provided in Appendix O.

Model calibration implies that a 9% income tax is sufficient to finance the total annual Social Security benefit payments of approximately $1.13 trillion.[45] The Social Security benefit formula is progressive in structure, providing a higher replacement rate for low-income earners. However, after accounting for demographic differences in population size and life expectancy, I estimate that $6.5 billion is transferred annually from black to white individuals. This redistribution arises primarily from differences in longevity, with white individuals receiving benefits over a longer period on average.

The timing of Social Security benefit disbursement affects welfare outcomes. I explore an alternative policy design in which a portion of Social Security benefits is front-loaded in the form of publicly funded child trust accounts, known as Baby Bonds. Economist Darrick Hamilton first proposed Baby Bonds as a policy that would provide greater financial security for young adults (Markoff et al. 2024).[46] Baby Bonds accounts are similar to a Social Security program of government investment in children and are proposed to be financed via government taxes. These Bonds would be allocated on the basis of parental wealth to provide the largest funding to children from low-wealth households.

I simulate the introduction Baby Bonds into the Social Security framework within the model and compare outcomes across policy regimes. In my model, the Baby Bonds program is parameterized to match estimates of a total bill of $80 billion from Hamilton et al. (2015). The average Baby Bond allocation at the beginning of the lifecycle is $21,428 for white individuals and $23,981 for black individuals.[47] I then compute the net present value (NPV) of the system under the two policy regimes. First, I evaluate the current US system in which benefits are distributed evenly throughout retirement. Second, I consider a modified system in which the fraction of benefits represented by Baby Bonds is distributed as a lump sum at the onset of retirement. Baby Bonds appreciate at a rate of 2% annually, following Hamilton et al. (2015), until disbursement in retirement.[48]

Table 10 presents the present value of Social Security taxes, benefits, and Baby Bonds for white and Black individuals under two different timing scenarios for Bond disbursement. The present value of taxes is substantially higher for white than black individuals, reflecting higher average lifetime earnings. White individuals also have a higher present value of benefits, which is driven by their longer life expectancy. In contrast, black individuals have a relatively higher present value of Baby Bonds due to their higher average receipt.

[44]Recent reforms include the benefit tax deductions under the 2025 One Big Beautiful Bill Act. Several bipartisan reform proposals have also been introduced in Congress, but none have yet been enacted.

[45]This calibration aligns closely with the OASI payroll tax rate of 10.6% and reported Social Security expenditures of $1.2 trillion in 2022.

[46]Baby Bonds have been implemented at the state level in several jurisdictions since 2021 and were introduced at the federal level through the American Opportunity Accounts Act.

[47]This corresponds to a Baby Bonds bill of $84 billion, funded via a 0.7% income tax.

[48]At age 65, the accumulated value of the bonds is $47,314 for white individuals and $52,951 for black individuals.

Table 10: Estimates of value ($) by timing of benefits

	White	Black
Present value SS income tax	-258,570	-177,410
Present value SS benefit	183,210	112,530
Present value Baby Bonds		
(1) Distributed evenly in retirement	29,668	33,690
(2) Distributed in first year of retirement	31,778	35,564
System net present value		
(1) Distributed evenly in retirement	-45,697	-31,189
(2) Distributed in first year of retirement	-43,586	-29,314
Change in net present value	2,111	1,875

Note: This table displays the present value of the Social Security (SS) tax and benefit in dollar amounts. The SS benefit row excludes Baby Bonds, which are calculated in separate rows based on the timing of their distribution. The net present value adds the present value of the SS tax, SS benefit, and Bonds. The last row is the absolute value difference in net present value between experiments (1) and (2).

Redesigning the timing of Social Security benefits with early-life transfers like Baby Bonds can increase the NPV of the system. The NPV of the Social Security system is negative for all individuals, reflecting that taxes paid exceed benefits received. However, shifting the timing of the portion of benefits modeled as Baby Bonds to the first year of retirement increases the NPV by approximately $2,000 for all individuals. This is driven by the higher present value of the bonds when received earlier in the lifecycle.[49] These results highlight the potential welfare gains from redesigning benefit timing through programs such as Baby Bonds.

In light of these findings from the Social Security model, I next evaluate alternative policy proposals aimed at narrowing wealth inequality between racial groups. These proposals are designed to address structural inequalities embedded within the current system through broader asset-building interventions and targeted transfers. The following section presents estimates of their potential impact on wealth inequality.

5.3 Policies to mitigate the racial wealth gap

Several policies have been proposed to mitigate racial differences in wealth in the US. These include publicly funded child trust accounts and direct transfer payments to black individuals. I explore the implications of these various policies within my model in partial equilibrium. My model's separation of non-visible and visible goods allows for the estimation of policies that target visible good spending. Accounting for status compensation motives

[49]This experiment compares the value of receiving a non-interest-bearing asset to one that earns a positive rate of return. Unsurprisingly, the asset with a positive return yields greater value due to its capacity to grow over time. The model currently overlooks the fact that Social Security is a policy of insurance against longevity risk.

leads the model to match consumption behaviors in the data. These motives also enable the testing of policy experiments to close the wealth gap. Without status compensation, policies designed to target visible good spending affect consumption of both types of goods in similar ways. Overall, models that account for status motives can help tailor policies to be welfare-improving.

5.3.1 Baby Bonds

I use my model to test the implications of a Baby Bonds policy that equalizes the racial wealth gap at the beginning of life. This experiment represents the design of Baby Bonds accounts to be accessible to children once they become adults for, "asset-enhancing endeavors, such as purchasing a home, starting a new business, or financing a debt-free college education" (Hamilton and Darity Jr. 2017). In the model, I change the initial distribution of wealth of black individuals so that their model-simulated wealth at age 25 is the same as that of white individuals. All else the same, black individuals accumulate slightly more wealth on average, but in the long run have the same wealth as without Baby Bonds at age 55. Table 11 shows that the black-white wealth ratio is 0.129 in the model with the status compensation mechanism.

Table 11: Decomposition of black to white wealth ratio at age 55

	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model
Wealth ratio	0.129	0.564	0.559	0.709	0.814
Removed heterogeneity:					
Income (w, m_t, λ)	No	Yes	Yes	Yes	Yes
Productivity process (ρ, σ_ς)	No	No	Yes	Yes	Yes
Discount factor (β)	No	No	No	Yes	Yes
Life expectancy (T)	No	No	No	No	Yes

Note: This table displays the black to white wealth ratio at age 55 in models with equalized initial wealth by race. Column (1) shows the baseline model, while columns (2)-(5) remove racial heterogeneity by setting parameters of black individuals to match those of white individuals.

However, Baby Bonds support the elimination of the black-white wealth gap in the long run if racial differences in income level and volatility, consumption discounting, and life expectancy converge. In Table 11, the wealth gap at age 55 becomes 0.814 when racial heterogeneity in these factors is removed. Government transfers can thus be a long run solution to racial wealth inequality if other racial disparities are also eliminated, consistent with Aliprantis et al. (2022), Boerma and Karabarbounis (2023), and Derenoncourt et al.

(2024).[50]

Table 11 also displays a decomposition of the racial wealth gap by each component of racial heterogeneity. The elimination of racial differences in income level raise wealth among black individuals and the wealth gap to 0.564. This represents 63% of the change in the wealth ratio in the model with convergence in all components. In contrast, the wealth ratio slightly falls if racial heterogeneity in the stochastic income process is also removed. Racial differences in income level and volatility work as opposing forces for wealth accumulation. The wealth ratio also rises when differences in consumption discounting are removed. The contributions of income and discounting heterogeneity are sizable, consistent with Boerma and Karabarbounis (2023) and Derenoncourt et al. (2024). Initial wealth transfers can thus reduce the racial wealth gap in the long term alongside complementary policies that address racial disparities in income, consumption, and health.

The implications of Baby Bonds are different in a model without the status compensation mechanism.[51] In this model, the elimination of racial differences in initial wealth and other previously mentioned factors leads to slightly higher wealth for black than white individuals in the long run. Compared to the model with status compensation, this model attributes more of the change in the wealth gap to racial differences in the discount factor and less to differences in the income level. Including the status compensation mechanism in the model is therefore important to avoid under-predicting the contribution of income convergence to the elimination of the wealth gap. Status compensation is a mechanism that is consistent with consumption data and is different from discount factor heterogeneity. The model without the status mechanism is also inconsistent with data as it estimates a higher consumption of visible goods for white than black individuals and a lower share of visible spending for wealthy individuals. It is thus important to study the effects of Baby Bonds with the model of status compensation spending to more accurately capture consumption behaviors.

5.3.2 Direct transfers: funding and welfare implications

Reparations payments have been implemented by governments throughout the world to acknowledge and provide recompense for injustices (Darity Jr and Mullen 2020). Various reparations policies have been proposed by US officials to, "redress the enslavement of Black people and the long history of state-sanctioned exploitation and extrapolation of the labor, assets and personhood of Black people and communities" (Markoff et al. 2024).

I first follow the procedure of Darity Jr and Mullen (2020) to calculate the size of the transfer to black individuals in 2022 to match my model parameters. The black population is about 14% of the total US population, but only holds 5% of US total household wealth (Sullivan et al. 2024). Total US household wealth was $148 trillion in 2022 (Reuters 2023). Fourteen percent of this total is $21 trillion, but black individuals only held $7 trillion in wealth. Eliminating this difference would require a reparation outlay of $14 trillion, for an average transfer of $311,000 per 45 million eligible black individuals.

[50] This literature finds that transfers are only a long run solution alongside the elimination of racial differences in income, capital gains and savings rates, and beliefs on risky returns (Aliprantis et al. 2022; Derenoncourt et al. 2024; Boerma and Karabarbounis 2023).

[51] I recalibrate a model without the status term in the utility function to match the first three moments in Table 5. See Appendix P for a decomposition of the racial wealth gap in this non-status model.

I use my model to estimate the implications of this size of transfer to black individuals and its financing. The effects of transfers are estimated alongside the convergence of racial differences in income, discounting, and life expectancy. I input an average lifetime transfer of $311,000 for black individuals in my model; see Appendix Q for model details. The model suggests that these transfers could be fully financed via a 10.6% tax on visible goods. Payments from white individuals collected in the form of taxes finance 80% of the total transfers to black individuals. This proposed tax on visible goods is a straightforward policy to collect the necessary revenue to finance direct transfers and address the racial wealth gap.[52]

The tax and transfer have opposing, but asymmetric, effects on consumption. In Table 12, I compare how the consumption of non-visible and visible goods changes as a result of this combined policy. Results are estimated for individuals age 25-30 to capture the full effects of payments over the life-cycle.[53] The tax on visible goods adds an additional cost of purchasing visible goods. Wealthy people have a larger tax contribution due to their larger share of visible goods spending. Table 12 shows that white people, which are taxed and do not receive a transfer, lower their consumption of visible goods by 0.29%. Consumption of non-visible goods is not significantly impacted. In contrast, individuals that receive payments increase their consumption. This change in consumption is higher for poorer compared to richer people.

Table 12: Mean change in consumption after tax and transfer policy (%, age 25-30)

	Goods	
	Non-visibles	Visibles
White	0.04	-0.29
	(0.04)	(0.04)
Black	7.66	5.92
	(0.01)	(0.02)

Note: This table shows the mean change in consumption for the simulated distribution of individuals between the equilibrium without the policy and the equilibrium with the policy. Standard deviation in parentheses.

Black people who experience both the tax and transfer increase their consumption. In Table 12, black individuals on average increase their consumption of non-visible goods by 7.66% and of visible goods by 5.92%. Spending on non-visible goods rises for all black individuals at a higher rate than spending on visible goods. The wealthiest black individuals decrease their consumption of visible goods due to their larger tax burden.

The tax and transfer policy creates large welfare gains for black individuals. In the stationary equilibrium without the policy, black people at the lowest quintile of cash-on-

[52]The US implemented a 10% federal tax on luxury goods in the US in the early 1990s. A similar tax policy could be reinstated and include all visible goods.

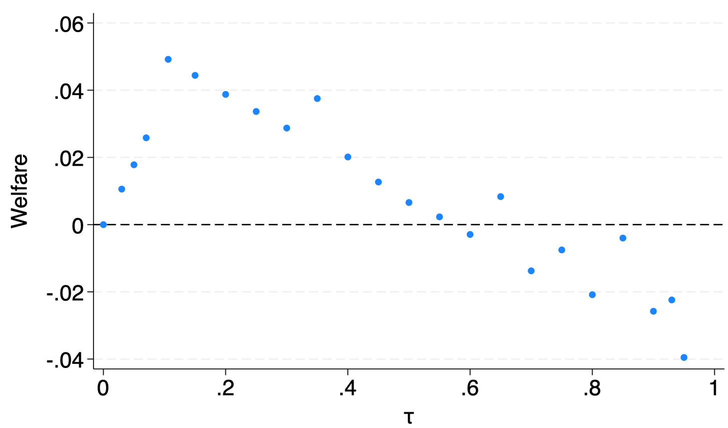
[53]See Appendix Table R.1 for results for all working-age individuals.

hand would need to spend over 10% more on non-visible goods to have the same welfare as in the equilibrium with the policy. The welfare gains from the policy fall with higher cash-on-hand, as wealthier individuals pay higher amounts of the visible goods tax.[54] In the simulated distribution, black individuals age 25-30 in the equilibrium without the policy would spend on average 32.3% more on non-visible goods to have the same welfare as in the equilibrium with the policy.[55]

White people have relatively small welfare losses from the policy. Their consumption of visible goods is taxed, which reduces welfare especially for individuals with higher cash-on-hand. However, white individuals age 25-30 would on average only spend 0.2% less on non-visible goods to have the same welfare as in the equilibrium with the policy reform.

Lifetime welfare for all people is maximized at with this level of tax. Figure 5 plots lifetime welfare for the entire population at different levels of tax τ. Lower taxes finance smaller transfers, which decrease welfare for black individuals. Higher taxes reduce welfare for all individuals since excess revenue collected by the government is assumed to not be spent on the transfers.

Figure 5: Overall lifetime welfare at different levels of tax τ



Note: This figure shows the lifetime welfare in certainty equivalence of non-visible goods for all individuals given the transfer and different tax rate. Overall welfare is calculated as the population weighted sum of mean welfare for the model distribution of black and white individuals.

This tax and transfer policy can thus support black people in purchasing non-visible goods, which are more likely to be necessities. This policy has large welfare benefits for black individuals without a large loss for white individuals. The racial wealth gap is also reduced since the tax lowers the wealth of white individuals while the transfer raises the

[54]See Appendix Figure R.1 for a graph of the change in welfare policy functions by cash-on-hand for individuals age 25-30.

[55]See Appendix Table R.2 for additional moments of this welfare calculation from the simulated distribution. Appendix Table R.2 also displays welfare moments from the simulated working-age population. The mean change in consumption for this population is higher for both racial groups since individuals that have fewer years to smooth the transfer are included in the mean.

wealth of black individuals. The racial wealth gap is slightly smaller under this policy than Baby Bonds, although both serve to greatly reduce the gap.

Omitting the status compensation mechanism from the model removes the ability to study transfer policy. The convergence of racial differences in earnings, consumption discounting, and life expectancy fully eliminates the wealth gap in a model without the status mechanism.[56] There is no room to test a policy that could close the wealth gap. Also, most of the narrowing of the wealth gap is attributed to racial differences in the discount factor, which does not hold in the data as discussed in previous sections. The status compensation mechanism models spending behavior in line with the data and allows for the estimation of a government transfer policy financed via taxes.

6 Conclusion

Racial differences in consumption-savings decisions influence the racial wealth gap. The main mechanisms proposed to explain racial differences in MPCs and wealth accumulation include labor market outcomes, education, and rates of return (Ganong et al. 2020; Patterson 2023; Nakajima 2023). Black individuals have greater earnings uncertainty and unemployment probability, which leads to them being more constrained. However, standard life-cycle models predict that greater income uncertainty leads to greater precautionary savings and lower MPCs (Aguiar et al. 2024).

This paper shows that status compensation is a mechanism that overcomes precautionary savings motives and explains 36% of the racial differences in MPCs unexplained in the data. All people with wealth gain from signaling their wealth with visible goods. However, some groups have a greater need to signal status due to being associated with lower incomes. The status motive is stronger for black than white individuals and leads black individuals to spend more on visible goods. This mechanism leads to higher MPCs among black individuals, which are consistent with the findings from data I collect in a new survey. I show that the racial difference in MPCs in the survey are largely unexplained by demographic characteristics such as age, education, income, and household composition. The life-cycle model I propose is useful in testing mechanisms that are unobserved in the data. I also estimate several policy implications of my model. A tax on visible goods could finance government transfers that support non-visible goods consumption and higher welfare for black households.

My model is a starting point for much future research. Future research should consider the general equilibrium effects of Baby Bonds, a tax on visible goods, and large transfers since these policies might alter consumption and labor market behavior. Welfare implications during the policy transition period would need to be calculated for the general equilibrium model. In an ideal world, we could estimate the effect of removing societal racial biases that

[56] I recalibrate a model without the status term in the utility function as in section 5.3.1. The wealth gap is eliminated due to these parameters being the main sources of racial differences in the model. I estimate the effects of the tax and transfer policy in this model. The tax on visible goods rises to 11.6% for the government budget constraint to be satisfied with the same size transfer as in the model with status motives. In this model, this tax reduces consumption of both types of goods at a similar rate. White individuals reduce their consumption of non-visibles most and the tax does not disincentivize visible spending. After the tax and transfer policy, black individuals increase their consumption similarly for both types of goods by 7.35%.

would eliminate the need for status compensation. However, it will likely take much time to change societal perceptions. It is also important to investigate the implications of status compensation for optimal policy. Status motives influence consumption behaviors, which affect the transmission of fiscal and monetary policies. Matching consumption behaviors and MPCs across the wealth distribution is thus important for models assessing policies.

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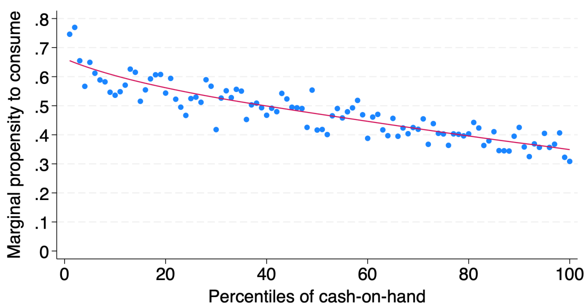
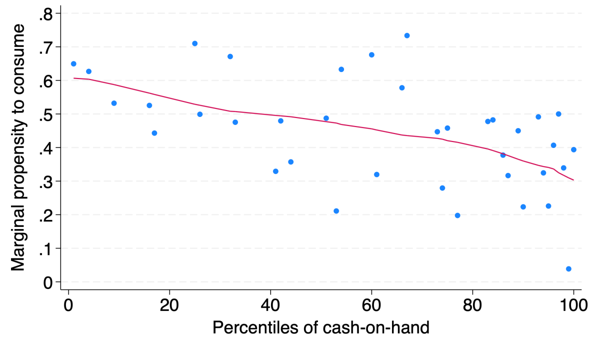
A Appendix: MPCs and cash-on-hand



(a) Jappelli and Pistaferri (2014)



(b) Survey

Note: This figure shows the relationship between MPCs and percentile of cash-on-hand from Jappelli and Pistaferri (2014) (a) and my survey (b). Cash-on-hand is earnings and wealth. I construct a measure of cash-on-hand from my survey by using the PSID 1997-2021 to infer respondent wealth from household income, age, and race.

B Appendix: Regression of survey MPC on respondent characteristics

	(1) MPC	(2) MPC
Female	-1.624	-2.079
	(3.685)	(2.679)
Black	15.268***	16.686***
	(2.956)	(2.809)
Age	0.063	-0.033
	(0.944)	(0.756)
Age squared	-0.001	0.000
	(0.011)	(0.009)
College degree	-8.787**	-4.955
	(4.002)	(3.009)
Employed	3.218	3.494
	(4.947)	(3.673)
Household income	-0.058*	-0.077***
	(0.035)	(0.028)
Renter	8.636**	6.319**
	(3.754)	(3.002)
Married	-1.641	2.448
	(3.836)	(3.112)
Number of household members	5.652***	4.296***
	(1.663)	(1.268)
Number of children	-7.064***	-5.247***
	(2.310)	(1.779)
Constant	34.059*	35.640**
	(19.991)	(16.039)
Observations	602	602
R-squared	0.145	0.144
Sampling weights	Yes	No

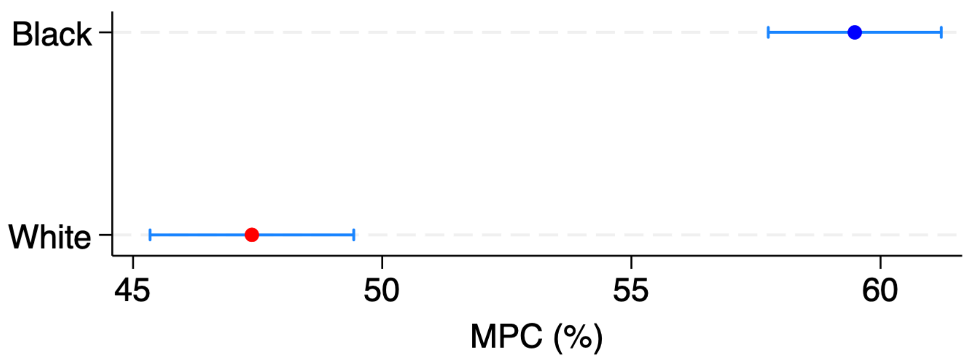
Note: This table displays OLS regression estimates with (1) and without (2) sampling weights. Household income is in $1,000 units. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C Appendix: Nonparametric estimation of racial difference in MPCs

As an alternative to an OLS regression, I conduct a nonparametric decomposition of the differences in MPCs between black and white respondents. I follow Barsky et al. (2002) and Firpo et al. (2018) in generating a weight that matches the sample of white respondents to that of black respondents. The samples are matched based on gender, age, college, employment, household income, renter status, marital status, number of household members, and number of children.

I then compare the weighted white population to the original black population to see whether racial differences in MPCs are due to observable characteristics or if some part is unexplained. Figure C.1 shows that the unexplained racial gap in MPCs is 12.1pp, as the mean MPC of black respondents is 59.5% and of the weighted white respondents is 47.4%. This is consistent with the unexplained gap estimated by OLS in Table 2.

Figure C.1: MPCs by race of respondent, nonparametric estimation



Note: This figure shows the estimates of mean MPCs of respondents from the survey. The mean MPC of black respondents is the original from the survey, while that of white respondents is estimated nonparametrically. The dots are the point estimates of the mean and the blue lines show the standard errors.

D Appendix: Where would you rate [Whites/Blacks] in general on this scale? 1=rich, ..., 7=poor

	Percent	
	Whites	Blacks
Rich (1-2)	17.87	2.32
Above average (1-3)	46.49	6.96
Average (4)	47.14	37.93
Below average (5-7)	6.37	55.10
Poor (6-7)	0.94	17.24

Note: This table shows the percent of respondents indicating each rating category using person post-stratification sampling weights from the 2022 General Social Survey. Columns 1 and 2 display ratings of whites and blacks, respectively. Sample includes 1178 observations. Consistent with Brown-Iannuzi et al. (2019).

E Appendix: Empirical estimation of racial difference in visible expenditure

I follow Charles et al. (2009) in categorizing visible goods in the CE as clothing, jewelry, personal care, and vehicles. Charles et al. (2009) classify visible goods items as those that are easily observed and are consumed more with higher income. This definition of visibles rules out other goods that consumers might easily observe such as alcohol and tobacco. They also exclude expenditures on food away from home from their category of visibles due to their finding that racial differences in consuming food away from home differ from those of other visible goods.

As robustness, I explore the implications of variations in how I classify visible goods in the CE. Heffetz (2018) proposes a new ranking of visible goods based on surveys of consumers in 2004 and 2014. This ranking makes a distinction between clothing items that are visible versus non-visible, and highlights other goods that are also visible such as home goods and furniture, recreational activities, cigarettes and alcohol, and food outside the home.

I construct alternative measures of visible goods in the CE using goods categories from Heffetz (2018). I first match the categories in Heffetz (2018) with the visibles classification in Charles et al. (2009). The direct translation of the visibles measure includes the following Heffetz (2018) categories: Clo (clothing and footwear excluding underwear, undergarments, and nightwear), Jwl (jewelry and watches), Car (purchase of new and used motor vehicles), and Brb (barbershops, beauty parlors, health clubs). Alternative measures include adding various Heffetz (2018) categories that are ranked as highly visible: (1) Cig (tobacco products) and AlH and AlO (alcohol in and out of the home); (2) Fur (home furnishings and household items); (3) Ot2 (TV, pets, sports, country clubs, movies, and concerts); or (4) FdO (food away from home, excluding alcohol).

I substitute each alternative measure of visible goods into equation 2 and estimate that black households spend between 10-30% more on visible expenditures than white households. This range is consistent with my preferred estimate in Table 3 Column 1. I also find that excluding non-visible clothing items such as underwear, undergarments, and nightwear from my preferred visible goods measure has no effect on the estimate of racial differences in visible expenditure.

I also test the validity of the instrument that I use in the estimation of racial differences in the share of visible goods expenditure. In equation 2, the log of total expenditure is instrumented by a vector of current and permanent income controls, following Charles et al. (2009). This vector includes the log of current income and a cubic in income.

The identifying assumption is that the instrument should be correlated with total expenditures, but not be directly correlated with the shares of expenditures on different consumption categories such as on visibles. The instrument vector supports both claims, as shown in Table E.1. The instrument vector is relevant in that it directly affects total expenditure. Income is positively correlated with expenditure. The facts that the F-statistic from the first stage regression and the t-statistic on the instrument in the second stage regression are large also support that this specification has a strong instrument. Table E.1 also shows that the instrument passes the Sargan (1958) test. Since this test has a statistically insignificant χ^2 estimate (p-value= 0.31), the instruments are uncorrelated with the error term and equation 2 is not misspecified.

Table E.1: Instrument validity

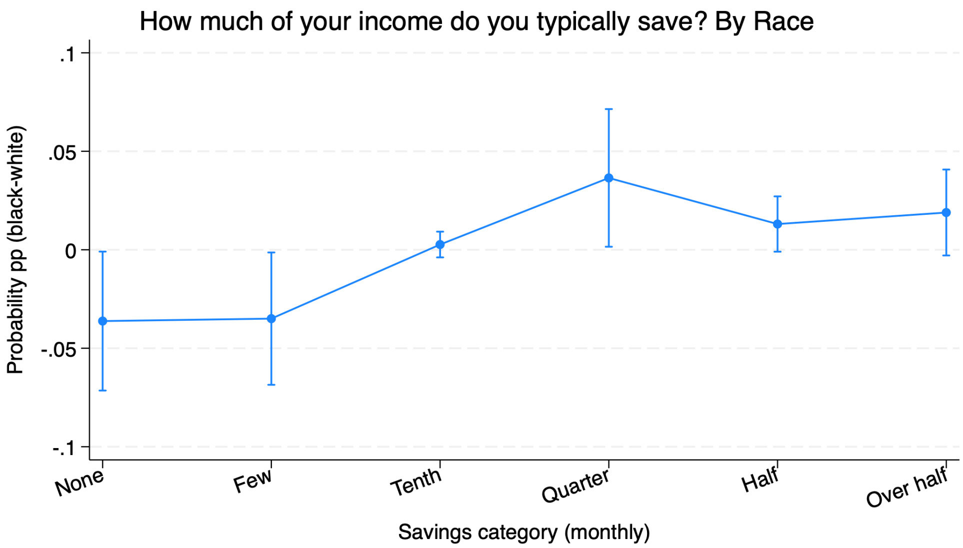
Test	Estimate
First stage	
F-statistic	990.86
Second stage	
$log(TotalExpenditure)$ t-statistic	12.54
Sargan (1958) test χ^2	1.04
Sargan (1958) test p-value	0.31
Observations	186515

Note: This table shows estimates of several tests for instrument validity in equation 2 in the regression shown in Table 3 Column 1.

F Appendix: Estimation of typical savings from survey

In the survey I ask respondents how much of their monthly income they save. I run an ordered logit regression of the category of savings quantity on respondent characteristics. Figure F.1 shows that black respondents are more likely to indicate they typically save a quarter or more of their income than white respondents when controlling for demographic characteristics. Table F.1 displays the all coefficient estimates from the logit regression.

Figure F.1: Estimate of black-white gap in typical savings rates



Note: This figure shows average marginal effects of the (black-white) Black dummy variable for each savings category in the ordered logit regression in Table F.1. Estimates use sampling weights.

Table F.1: Regression of category of amount of monthly income typically saved

	Amount saved category
Female	-0.338
	(0.224)
Black	0.465**
	(0.234)
Age	-0.093
	(0.064)
Age squared	0.001
	(0.001)
College degree	0.631**
	(0.293)
Employed	0.468
	(0.361)
Log household income	0.015***
	(0.002)
Owner	0.773*
	(0.402)
Married	-0.500*
	(0.277)
Number of household members	-0.164
	(0.115)
Number of children	-0.007
	(0.178)
Political affiliation: Independent	0.248
	(0.246)
Political affiliation: Republican	0.006
	(0.358)
Political affiliation: Other	1.225
	(0.880)
State FE	Yes
Observations	602
Pseudo R-squared	0.196

Note: This table shows coefficients of ordered logit regression of categories of typical monthly saving proportions on respondent characteristics. Regressions use sampling weights. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

G Appendix: Estimation of demographic differences in expenses

	(1) Overdraft fee	(2) Natural disaster
Female	0.033***	0.008*
	(0.005)	(0.004)
Black	0.071***	0.018***
	(0.008)	(0.006)
Age	-0.003***	-0.001***
	(0.000)	(0.000)
Education: High school or GED	-0.049***	-0.025**
	(0.014)	(0.011)
Education: Some college	-0.017	-0.001
	(0.014)	(0.011)
Education: Bachelor's degree or more	-0.060***	0.002
	(0.014)	(0.011)
Income: $10k-$24,999	0.032*	-0.039**
	(0.018)	(0.016)
Income: $25k-$49,999	0.022	-0.057***
	(0.017)	(0.016)
Income: $50k-$74,999	-0.007	-0.078***
	(0.017)	(0.016)
Income: $75k-$99,999	-0.047***	-0.085***
	(0.017)	(0.016)
Income: $100k-$149,999	-0.071***	-0.100***
	(0.016)	(0.016)
Income: $150k or more	-0.093***	-0.106***
	(0.017)	(0.016)
Observations	26,724	27,849
Controls	Yes	Yes
Type	AME Logit	AME Logit

Note: This table shows average marginal effect estimates of Logit regressions of the likelihood of being financially affected by a bank overdraft fee or a natural disaster in the past 12 months. Regressions include the dummy variables displayed in the table, a quadratic term for age, controls of state and year fixed effects, and population weights. Data are from the 2021-2023 SHED. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

H Appendix: Derivations of curvature of consumption in status term

The implications of the status compensation mechanism are not sensitive to the linearity of consumption. Linearity is assumed for simplicity in sections 3.1 and 3.2. I extend the simple model in section 3.1 to explore the implications of adding curvature in consumption to the status mechanism.

The first alternative model substitutes $log(c_1)$ for the linear c_1 component in the status term in the utility function. The curvature of consumption in status now follows the rest of the utility function. The individual problem becomes:

$$\max_{c_1,c_2} \quad log(c_1) + \beta log(c_2) + \eta \left(\frac{log(c_1)}{\bar{c}_1} \right)$$

$$\text{subject to} \quad c_1 = a_1 + y_1, \;\; c_2 = y_2 + (1+r)a_1,$$

where c is consumption, y is exogenous income, s is status, η is the importance of status, and $\bar{c}$ is average consumption. Maximizing the above problem and taking the first order conditions, the Euler equation is:

$$(c_1)^{-1}(1 + \frac{\eta}{\bar{c}_1}) = \beta(1+r)(c_2)^{-1} \tag{7}$$

The second alternative model generalizes the curvature in consumption in the utility function as follows:

$$\max_{c_1,c_2} \quad \frac{c_1^{1-\gamma}}{1-\gamma} + \beta \frac{c_2^{1-\gamma}}{1-\gamma} + \eta \left(\frac{c_1^{1-\gamma}}{(1-\gamma)\bar{c}_1} \right)$$

$$\text{subject to} \quad c_1 = a_1 + y_1, \;\; c_2 = y_2 + (1+r)a_1$$

Solving the above maximization problem, the Euler equation is:

$$(c_1)^{-\gamma}(1 + \frac{\eta}{\bar{c}_1}) = \beta(1+r)(c_2)^{-\gamma} \tag{8}$$

Both alternative models have the main properties of the simple model described in section 3.1. The property of 'Getting ahead of the Joneses' is shown in $U_{s_1 c_1} > 0$, which represents how the importance of status rises with higher consumption. Equations 7 and 8 show how lower average consumption raises the marginal utility of consumption if individual consumption is held constant, $U_{c_1 \bar{c}_1} < 0$, consistent with the simple model.

I Appendix: Model computation

The model is solved separately for each racial group in partial equilibrium with parameters at annual frequency. I solve the household maximization problem and then simulate a distribution of agents from the household decision rules.

I solve the model by backward induction using the endogenous grid point method (Carroll 2006). The grid of liquid assets has 200 points that are unequally spaced, with points more concentrated closer to the lowest grid point. I discretize the productivity process by the Tauchen (1986) method and use it to construct a Markov process with transitions between 7 income states, $\pi(\ell'|\ell) > 0$. The results are not sensitive to increasing the number of grids in assets or income states.

To solve for the decision rules, I input the share of consumption spent on visible goods in the last period of life. I use data from the Consumer Expenditure Survey to calculate this average share for households over age 70.

In the model with status compensation, I calculate average consumption ($\bar{c}$) from the consumption decision rules at every age by iterating through various values of $\bar{c}$ in the decision rules. The initial guess for $\bar{c}$ is set as the average total consumption of households in the model without the status term. I then iterate through solving the decision rules until $\bar{c}$ converges. The tolerance of convergence is when the median of $\bar{c}$ is within 0.001 of the previous guess.

I simulate the model distribution recursively starting at the beginning of life. The simulation follows the nonstochastic simulation algorithm of Young (2010). I input an initial distribution of wealth of households, which I measure from households age 25 in the PSID.

J Appendix: Income process estimation

I estimate the income process following the procedures of Krueger et al. (2016) and Daruich and Fernandez (2024), using PSID data and focusing on total household income, 1-year estimates, and separate groups by race.

The PSID data are cleaned as follows. Data are restricted to the SRC representative sample and to 1970-1997 to estimate the process on survey waves collected annually (Krueger et al. 2016). After focusing on households headed by a person of black or white race, age 25 to 60, employed, and with wages at least half of the minimum wage in that year or \$1,000, I am left with 6,601 individuals. This sample is split into 5,953 white and 648 black individuals. I also drop individuals with missing data, less than two observations of income, and those reporting extreme changes of annual income growth above 400% or reduction by 66% (Daruich and Fernandez 2024). The sample has 5,264 white and 559 black individuals.

I use this sample to estimate the age profile of income separately for each race group. The profile is estimated using a quadratic polynomial on age with college education and year fixed effects and selection into work:

$$log(\ell_{i,t}) = \beta_0 + \beta_1 Age_{i,t} + \beta_2 Age^2_{i,t} + \beta_3 X_{i,t} + \Gamma_{i,t} + u_{i,t}, \tag{9}$$

where $X_{i,t}$ is the Inverse Mills Ratio, $\Gamma_{i,t}$ is the fixed effect, and $u_{i,t}$ is the residual. The Inverse Mills Ratio is the control for selection into work from the Heckman-selection estimator. The Ratio is constructed by estimating the labor force participation equation separately for each race group, using college education and year-region (as defined by the Census) fixed effects following Daruich and Fernandez (2024). The estimates of the age profile of income are reported in Table J.1. The age profiles are clearly lower for black than white earners.

Table J.1: Income age profile

	(1) Black	(2) White
Age	0.0525***	0.0469***
	(0.0118)	(0.0045)
Age-squared	-0.00050***	-0.00045***
	(0.00014)	(0.00006)
Inverse Mills Ratio	0.808***	0.830***
	(0.288)	(0.151)
Constant	8.559***	9.077***
	(0.275)	(0.101)
Observations	4999	58039
R-squared	0.083	0.136
Num. of individuals	559	5264

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I then recover the residuals $u^g_{i,t}$ by removing the age and education profiles from equation 9. As in Daruich and Kozlowski (2020), I model the residual $u^g_{i,t}$ as the sum of two independent components:

$$u^g_{i,t} = z^g_{i,t} + \epsilon^g_{i,t},$$

where $z^g_{i,t}$ is the persistent shock assumed to have an AR(1) structure:

$$z^g_{i,t} = \rho^g_z z^g_{i,t-1} + \zeta^g_{i,t}, \;\; \zeta^g_{i,t} \sim N(0, \sigma^g_\zeta)$$

and $\epsilon^g_{i,t} \sim N(0, \sigma^g_\epsilon)$ is measurement error, which is considered to be noise in the model. I assume zero variance of the initial draw $z^g_{i,0}$. I estimate this separately for each race group using a Minimum Distance Estimator with moments as the covariances of income residuals at various lags for different age groups. Table J.2 displays the results.

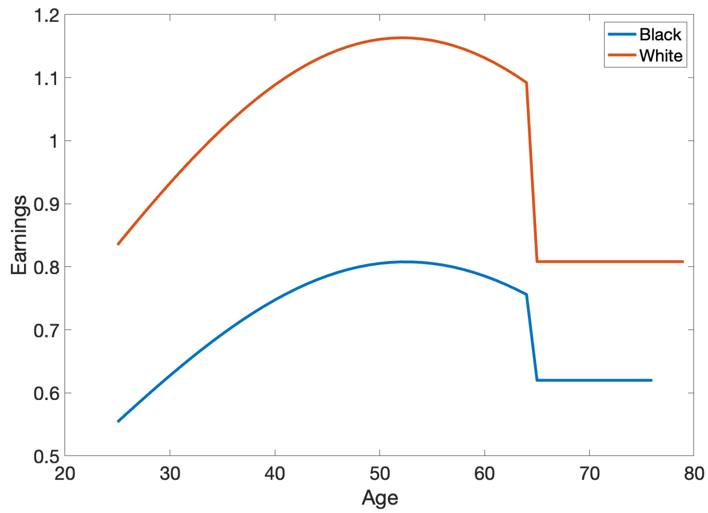
Table J.2: Income process

	(1) Black	(2) White
Persistence (ρ^g_z)	0.9621	0.9835
	(0.0005)	(0.0002)
Variance persistent shock (σ^g_ζ)	0.0248	0.0105
	(0.00024)	(0.00007)
Variance measurement error (σ^g_ℓ)	0.1283	0.1109
	(0.0007)	(0.0003)

Note: Bootstrap standard errors are reported in parentheses for ρ_z, σ_ζ, and σ_ℓ.

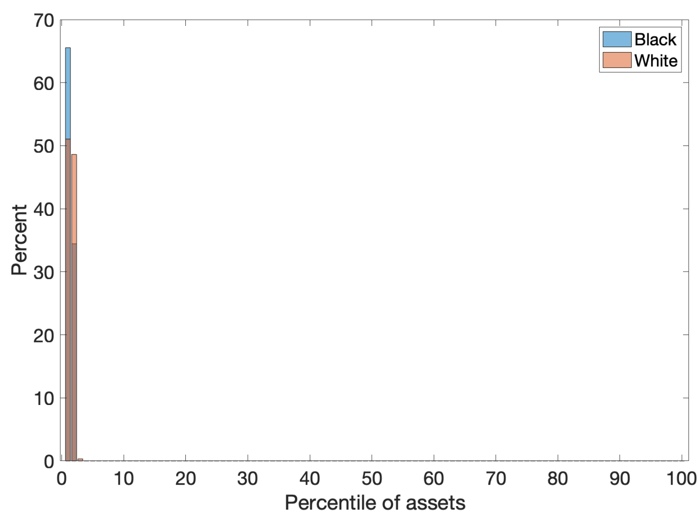
K Appendix: Life-cycle inputs

Figure K.1: Life-cycle earnings process



Note: This figure shows the life-cycle income process. The process for black individuals is in blue and white individuals is in red.

Figure K.2: Initial distribution of liquid wealth



Note: This figure shows the distribution of liquid wealth for household heads age 25 from the PSID 1999-2021. Household wealth is converted to per capita using the square root scale. The distribution for black households is in blue and white households is in red.

L Appendix: Model accounting for housing expenses

I explore the effect of housing expenses on MPCs by introducing parameter h in my model's household budget constraint:

$$\max_{cn_t, cv_t, a_{t+1}} \quad E \sum_{t=1}^{T^g} \beta^{t-1,g} \left\{ \frac{cn_t^{1-\gamma}}{1-\gamma} + \frac{cv_t^{1-\psi}}{1-\psi} + \eta(\bar{c}_t^g)^{1-\psi} \left(\frac{cv_t}{\phi^g \bar{c}_t^g} \right) \right\}$$

$$\text{subject to} \quad cn_t + cv_t + a_{t+1} = (1-h^g) w^g \ell_t^g + (1+r)a_t, \;\; a_0 \geq 0, \;\; a_{t+1} \geq 0, \;\; \gamma > \psi$$

The parameter h is the share of income allocated to housing expenses, parameterized using data from the 2022 SCF. I construct an measure of housing expenses that includes rent and owner's equivalent rent (OER). OER represents what a home-owning household would pay in rent if they were a renter. I calculate annual OER as 5% of a household's value of their owned house, following estimates of the aggregate rent-price ratio in Davis et al. (2008). Black households on average spend 37% of their income on these housing expenses, while white households spend 28%. The share of income spent on housing is on average higher for black than white households even within non-homeowners and homeowners.

The estimated MPCs from the alternative housing expense model are consistent with my baseline estimates. I re-calibrate the model to target moments in Table L.1. The model closely matches the targeted empirical moments. Table L.2 shows that introducing housing expenses minimally changes mean MPCs relative to the baseline model, by less than 1pp for both groups. Housing expenses also do not change the racial dynamics discussed in the analysis of the baseline model.

Table L.1: Calibrated parameters, housing expense model

	Parameter	Value	Target	Data	Model
β^W	Discount factor, white	0.9846	Wealth/income, white	0.50	0.50
β^B	Discount factor, black	0.9837	Wealth/income, black	0.15	0.15
ψ	Visibles risk aversion	0.53	Share of visibles, white	0.10	0.10
ϕ^B	Fraction of consumption, black	0.205	Black to white share of visibles	0.24	0.24

Note: This table presents calibrated parameters following Table 5.

Table L.2: MPC moments in baseline versus housing expense model

MPC (%)	Model Baseline	Model Housing expense
Mean, white	42.67	42.68
Mean, black	57.09	56.73
Variance, white	19.34	19.33
Variance, black	19.58	19.70

Note: This table shows the model MPC mean and variance.

M Appendix: Decomposing status compensation mechanism

	Data	(1) Model Baseline	(2) Model $\bar{c}_t^g = 1$	(3) Model $\bar{c}_t^g, \phi^g = 1$	(4) Model $\eta = 0$
Mean MPC (%), white	37.71	42.67	42.60	42.60	42.58
Mean MPC (%), black	54.83	57.09	52.89	52.18	51.78
MPC gap vs baseline (%)	-	-	-28.64	-33.56	-36.17
Black to white wealth ratio	0.16	0.21	0.30	0.31	0.31
Black to white share of visible goods	0.24	0.24	-0.19	-0.17	-0.17
Visibles/non-visibles by wealth, black	0.005	0.005	<0.001	<0.001	<0.001

Note: This table shows results for various model parameter specifications by race. Models (2)-(4) omit certain mechanisms and are not re-calibrated to match targeted moments. The third row shows the percent change in the MPC racial gap between each alternative model and the baseline model.

N Appendix: Alternative mechanisms to status compensation

Table N.1: Alternative models, re-calibrated

	Data	(1) Model Baseline	(2) Model No status β^g	(3) Model No status β, r^g	(4) Model No status Unemp.	(5) Model No status E^g
Mean MPC (%), white	37.71	42.67	43.90	44.00	39.78	43.90
Mean MPC (%), black	54.83	57.09	57.26	57.26	66.63	54.58
Vis./non-vis. by wealth, black	0.005	0.005	<0.001	<0.001	-0.002	<0.001
Status term	-	Yes	No	No	No	No
β^W	-	0.9846	0.9849	0.9825	0.9417	0.9849
β^B	-	0.9838	0.9825	0.9825	0.7875	0.9835
ψ^B	-	0.53	0.27	0.27	0.90	0.27
r^W	-	0.01	0.01	0.0125	0.01	0.01
r^B	-	0.01	0.01	0.01	0.01	0.01
$\ell(1)$	-	-	-	-	0	-
E^W	-	-	-	-	-	0.00
E^B	-	-	-	-	-	0.20

Note: This table shows results for various model parameter specifications by race. Models are re-calibrated to target the empirical targets of the baseline model. Model 'Unemp.' includes a labor shock of zero earnings, where $\ell(1)$ is the first shock in the labor endowment process and there are racial differences in transitions into positive earnings following Table N.2. 'Vis.' stands for visible goods. Parameter E is an expense modelled as a tax on income; earnings left for own consumption and savings are $w\ell(1-E)$.

Table N.2: Labor force transition probabilities by race (%)

	White	Black
Job Loss	1.11	2.02
Job Finding	28.45	19.21

Note: This table shows job loss (employment to unemployment) and job finding (unemployment to employment) probabilities of white and black individuals. The values are annual, converted from monthly frequency from Cajner et al. (2017).

O Appendix: Model of the Social Security system

I extend the baseline model in section 3.2 to include Social Security benefits that are financed via a tax on labor income. The household problem has a continuum of agents who maximize utility according to:

$$\max_{cn_t, cv_t, a_{t+1}} \quad E \sum_{t=1}^{T^g} \beta^{t-1,g} \left\{ \frac{cn_t^{1-\gamma}}{1-\gamma} + \frac{cv_t^{1-\psi}}{1-\psi} + \eta (\bar{c}_t^g)^{1-\psi} \left(\frac{cv_t}{\phi^g \bar{c}_t^g} \right) \right\}$$

$$\text{subject to} \quad cn_t + cv_t + a_{t+1} = w\ell_t^g + (1+r)a_t + b_t^g,$$

$$a_0 \geq 0, \;\; a_{t+1} \geq 0, \;\; \gamma > \psi,$$

$$b_t^g = \begin{cases} -w\ell_t^g \tau_{ss} & \text{if } t < T_R \\ ss_t^g & \text{if } t \geq T_R \end{cases}$$

where b_t^g represents the Social Security system. The system is modeled as a tax, τ_{ss}, on income during working age that is given as a benefit, ss, in retirement age. Other components of the household problem follow section 3.2.

Social Security benefits replace part of working age income according to the Social Security Administration Primary Insurance Amount (PIA) rule following İmrohoroğlu and Kitao (2012). The PIA rule calculates the benefit as a concave function of the average highest past 35 years of earnings, e. The Social Security system caps average past earnings e above at $147,000 in 2022. In 2022, the annualized PIA rule is as follows:

$$PIA = \begin{cases} 0.9 \times e & \text{if } e < \$12,288 \\ \$11,059 + 0.32 \times (e - \$12,288) & \text{if } \$12,288 \leq e < \$74,064 \\ \$30,828 + 0.15 \times (e - \$74,064) & \text{if } e \geq \$74,064 \end{cases}$$

The government taxes working age income and redistributes benefits starting at age 65. The government budget constraint in the steady state is:

$$\sum_t w\ell_t^g \tau_{ss} = \sum_t ss_t,$$

where total taxes collected in every period equal total Social Security benefits payments. I calibrate τ_{ss} to 0.0896 to satisfy the government budget constraint and finance the total Social Security bill of $1.13 trillion.

P Appendix: Non-status model decomposition of black to white wealth ratio at age 55

	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model
Wealth ratio	0.108	0.476	0.471	0.908	1.035
Removed heterogeneity:					
Income (w, m_t, λ)	No	Yes	Yes	Yes	Yes
Productivity process (ρ, σ_ζ)	No	No	Yes	Yes	Yes
Discount factor (β)	No	No	No	Yes	Yes
Life expectancy (T)	No	No	No	No	Yes

Note: This table displays the black to white wealth ratio at age 55 in models with equalized initial wealth by race. Column (1) is the model without the status term that is recalibrated as in Appendix Table N Column (2). In this table, columns (2)-(5) build on column (1) and remove racial heterogeneity by setting parameters of black individuals to match those of white individuals.

Q Appendix: Model of reparations financed via tax on visible goods

I extend the baseline model in section 3.2 to include reparations transfers to black households (TR^B) that are financed via a tax (τ) on visible goods. I am interested in estimating the long run effectiveness of such a policy, which would overlap with the elimination of other racial inequalities. I therefore remove some racial heterogeneity from the baseline model by replacing parameters of black individuals by those of white individuals. These parameters are the income level, productivity process, life expectancy, and discount factor.

The household problem has a continuum of agents who maximize utility according to:

$$\max_{cn_t, cv_t, a_{t+1}} \quad E \sum_{t=1}^{T} \beta^{t-1} \left\{ \frac{cn_t^{1-\gamma}}{1-\gamma} + \frac{cv_t^{1-\psi}}{1-\psi} + \eta(\bar{c}_t^g)^{1-\psi} \left(\frac{cv_t}{\phi^g \bar{c}_t^g} \right) \right\}$$

$$\text{subject to} \quad cn_t + cv_t(1+\tau) + a_{t+1} = w\ell_t + (1+r)a_t + TR_t^B,$$

$$a_0 \geq 0, \;\; a_{t+1} \geq 0, \;\; \gamma > \psi, \;\; TR_t^B = p_{TR}^B w \ell_t,$$

where transfers to black individuals are modeled as a proportion, p_{TR}^B, of income given to individuals in every period. Other components of the household problem follow section 3.2.

The government taxes all visible goods and redistributes them as reparations transfers to black households. The government budget constraint in the steady state is:

$$\sum_t \tau cv_t = \sum_t TR_t^B,$$

where total taxes collected in every period equal total transfer payments.

I calibrate p_{TR}^B to 0.0735 to match average lifetime transfers of \$311,000 per black individual. I also calibrate the tax on visible goods to 10.6% to satisfy the government budget constraint. The total reparations bill is \$14 trillion split by about 45 million black Americans.

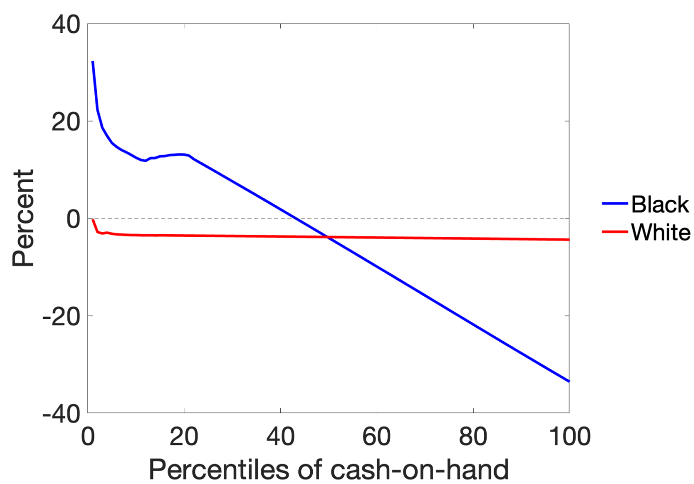
R Appendix: Results of tax and reparations policy

Table R.1: Mean change in consumption after tax and reparations policy (%, age 25-64)

	Goods	
	Non-visibles	Visibles
White	-0.44	-0.67
	(0.33)	(0.33)
Black	6.86	5.34
	(0.63)	(0.66)

Note: This table shows the mean change in consumption for the simulated distribution of individuals between the equilibrium without the policy and the equilibrium with the policy. Standard deviation in parentheses.

Figure R.1: Change in consumption after tax and reparations policy



Note: This figure shows the percent change in consumption of non-visible goods by cash-on-hand for individuals age 25-30 that would lead to equivalent welfare in the stationary equilibrium without the policy as in the equilibrium with the policy. Black individuals in blue and white individuals in red.

Table R.2: Moments from the welfare implications of the policy reform

Mean of non-visible consumption (%)	Black	White
Age 25-30	32.30	-0.19
	(0.22)	(0.12)
Age 25-64	56.34	-3.52
	(6.94)	(1.19)

Note: This table shows the mean consumption equivalence of non-visible goods for the simulated distribution of individuals in the equilibrium without the policy compared to the equilibrium with the policy. Standard deviation in parentheses.