Consumption's Response to Permanent Income: The Role of Consumption Commitments

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Abstract

The permanent-income hypothesis predicts consumption is proportional to permanent income, yet empirical elasticities are far below one. I provide evidence that this under-response reflects consumption commitments—hard-to-adjust goods that lock households into past choices. Four facts support this mechanism: consumption elasticity (i) declines with age, (ii) depends negatively on past permanent income growth, (iii) exhibits path-dependent expenditure composition toward easy-to-adjust goods, and (iv) all path dependences disappear among households that recently adjusted commitments. I use a quantitative life-cycle model to show that commitments are necessary to generate the age decline and history dependence. However, commitments are not sufficient to explain the average under-response; bequest motives and late-in-life luxury consumption are also quantitatively important. The calibrated model matches both micro consumption responses and aggregate wealth inequality.

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1 Introduction

Most macroeconomic models predict that consumption should be proportional to permanent income. This proportionality result holds from Friedman's permanent-income hypothesis to modern quantitative frameworks based on standard income-fluctuation problems. However, empirical evidence consistently shows that consumption is far from proportional to permanent income: the elasticity of consumption with respect to permanent income is around 0.7, rather than one as the proportionality result predicts (Dynan, Skinner, and Zeldes, 2004; Blundell, Pistaferri, and Preston, 2008; Straub, 2019). This consumption under-response has important macroeconomic implications for trends such as falling real interest rates and rising wealth inequality (Straub, 2019; Mian, Straub, and Sufi, 2021), as well as for optimal capital and labor income taxation (Gaillard, Wangner, Hellwig, and Werquin, 2023; Morrison, 2024).

In this paper, I use life-cycle patterns in consumption to distinguish among competing mechanisms that generate deviations from proportionality to permanent income. My empirical results support the theory of consumption commitments of Chetty and Szeidl Chetty and Szeidl (2007, 2016): hard-to-adjust consumption choices that resemble long-term commitments.[1] However, I show that commitments alone are not sufficient to account for all facts. Using a quantitative life-cycle model, I find that three mechanisms are quantitatively necessary to reproduce the empirical patterns: consumption commitments, bequest motives, and late-in-life luxury consumption. I also show that, while each mechanism can individually generate the average consumption elasticity to permanent income, they have different implications for aggregate savings because each has distinct life-cycle patterns.

The key insight is that consumption commitments generate two testable predictions that vary systematically over the life cycle. First, young consumers have fewer accumulated commitments, so their consumption responds more to permanent income than that of older households. This implies that consumption elasticity should decline with age. Second, because commitments are costly to adjust, part of the current consumption bundle was determined by past permanent-income rather than current permanent income. This generates path dependence: controlling for

[1]For example, adjusting the level of housing consumption involves large transaction and moving costs, while adjusting certain services, such as some utilities and insurance, involves penalties for early contract termination. These infrequently adjusted goods involving consumption commitments pervade household consumption baskets and comprise more than 50% of a typical household's expenditure. Consumption commitments have been shown to be important in understanding several decisions in the microdata, such as risk behavior (Chetty and Szeidl, 2007), housing choices of couples (Shore and Sinai, 2010), portfolio choices (Chetty, Sándor, and Szeidl, 2017), and adjustment of durables during recessions (Berger and Vavra, 2015).

current permanent income, households with higher past permanent income should have more commitments and consume more today.

As mentioned, alternative preference-based explanations can also generate consumption under-response to permanent income, but with different life-cycle implications. With late-in-life luxury consumption (Straub, 2019) or strong bequest motives De Nardi, French, and Jones (2016), households save today to consume or bequeath in the future. In particular, late-in-life luxury predicts that consumption elasticity increases with age; the opposite pattern from consumption commitments. Habit formation can generate path dependence through a different channel: households smooth consumption growth rather than levels. High permanent income in the past leads to high past consumption, and habits preserve this consumption path, predicting higher consumption today. However, habits have implications that differ from those of consumption commitments, as I discuss later.

Using data from the Panel Study of Income Dynamics (PSID), I document four novel facts about how consumption responds to permanent income over the life cycle. First, the elasticity of consumption with respect to permanent income declines dramatically with age, from 0.9 for households aged 25-45 to 0.6 for those aged 45-65. Second, consumption responses exhibit strong path dependence. Comparing households with identical current permanent income, those who experienced 10% permanent income growth over the past decade consume 3% less than those with no permanent income growth.

The third and fourth facts provided additional evidence in favor of consumption commitments and help to distinguish them from habit formation. Third, path dependence extends to the composition of expenditures across goods. Holding current expenditure constant, households with high past expenditure growth consume a larger share of easy-to-adjust goods (such as food) and a smaller share of hard-to-adjust goods (particularly shelter). Fourth, path dependence largely disappears among households that have adjusted their consumption commitments. Focusing exclusively on shelter consumption and using past moves as a proxy for adjustment, I find that movers show little dependence on past variables and respond more strongly to current permanent income than non-movers. Habit formation has no implications for the composition of expenditures across goods, nor for whether path dependence disappears after households adjust their commitments.

To quantify the importance of consumption commitments relative to other mechanisms, I calibrate a life-cycle consumption model that incorporates two consumption goods, one subject to proportional, non-convex adjustment costs (Chetty and Szeidl, 2007; Berger and Vavra, 2015). The model also includes bequest motives (De Nardi, 2004), late-in-life luxury consumption (Straub, 2019), and borrowing constraints. I calibrate the model to match key moments from my empirical analysis and conduct counterfactual exercises to assess the contribution of each mechanism.

The model with all three components successfully reproduces the empirical patterns. The mechanism works as follows: for households that do not adjust their commitments, the adjustment occurs in only one good, which exacerbates diminishing returns to consumption, while strong bequest motives generate near-constant marginal returns to savings, inducing substitution toward future consumption and bequests. Path dependence arises because part of the consumption bundle was determined in the past based on past income expectations. In contrast, households that fully adjust face no distortion in expenditure allocation, and their consumption depends only on current permanent income.

Counterfactual exercises reveal that all three mechanisms are necessary. A model with strong late-in-life luxury consumption but without commitments generates counterfactual predictions: consumption elasticity increases over the life cycle, and no path dependence. Conversely, a model with only commitments predicts that young households over-accumulate commitments and old households under-consume due to adjustment costs, with an overall elasticity above one. Only the model combining all mechanisms reproduces both the life-cycle patterns and the overall under-response in consumption observed in the data.

In the final set of exercises, I evaluate the implications of commitments and other mechanisms for the distribution of consumption and wealth by computing Gini coefficients. A model with strong late-in-life luxury consumption but without commitments predicts excessive consumption dispersion, as young households accumulate assets and old households rapidly decumulate them to finance late-life consumption. Conversely, a model with only consumption commitments slightly overpredicts consumption and wealth inequality, as young households over-accumulate commitments and old households under-consume their assets due to high adjustment costs. The model with all three mechanisms generates consumption and wealth inequality levels consistent with the data, suggesting that consumption and wealth inequality arise not only from heterogeneity in saving behavior but also from heterogeneity in consumption flexibility that compounds over the life cycle.

Related Literature

My first major contribution is to the literature on how consumption responds to permanent income. I document several new facts that provide a comprehensive picture of how consumption responds to permanent income, varies over the life cycle, and depends on income history, and I show that consumption commitments are a necessary mechanism to jointly explain these patterns.

A key difference relative to most empirical work is how I measure permanent income. Rather than relying on instrumental-variable strategies that proxy permanent income with lagged or future income and other characteristics (e.g. Dynan et al., 2004; Straub, 2019), I construct a measure of permanent income directly from observables, defined as current net worth plus the discounted value of expected future income. This definition is closer to the permanent-income hypothesis, which emphasizes lifetime resources, and it is particularly important for older and richer households, whose resources are dominated by assets. The approach is related to Carroll (1994), who project future income on observables, and to Abbott and Gallipoli (2019), who nonparametrically estimate permanent income using a risk-adjusted lifetime budget constraint. Relative to these studies, I allow for a richer autoregressive income process and deliberately avoid using consumption to forecast income, since I later project consumption on the constructed measure. I address concerns about differences in information sets between the econometrician and households and about mismeasurement in income and consumption in the empirical section, where I show that my results are robust to forecast-error tests and alternative measurement choices.

A second contribution is to the literature on adjustment costs and consumption commitments in household behavior. Adjustment frictions have been widely used to study risk-taking (Chetty and Szeidl, 2007), housing choices (Shore and Sinai, 2010), aggregate consumption dynamics (Berger and Vavra, 2015; Chetty and Szeidl, 2016), life-cycle behavior (Yang, 2009), and the interaction of illiquid assets with monetary and fiscal policy (Kaplan and Violante, 2014). I contribute by showing, empirically and quantitatively, that lumpy adjustment of commitment goods is a key mechanism behind the under-response of consumption to permanent income. Empirically, I bring together new life-cycle and history-dependent facts on consumption, assets, and expenditure composition; quantitatively, I discipline a life-cycle model and use it to quantify the role of commitments relative to other forces that generate savings that increase with permanent income, such as bequest motives and late-in-life luxury consumption.

The idea that consumption commitments can help explain under-responsiveness to permanent income was first developed theoretically by Chetty and Szeidl (2016), who show that, under certain conditions, a model in which some goods are costly to adjust is observationally equivalent to a representative-agent model with habit formation. Their analysis is primarily theoretical, with illustrative calibrations. I provide empirical evidence in favor of this theory by using rich micro-data to discipline a life-cycle model with consumption commitments, documenting moments that identify the strength of adjustment frictions and showing which facts a model with commitments alone can and cannot match. This allows me to assess the quantitative importance of consumption commitments and to separate their role from other mechanisms.

Finally, my paper is related to work that introduces non-homothetic preferences into quantitative heterogeneous-agent models to generate consumption under-response. Straub (2019) studies consumption responses to permanent income in a model with late-in-life luxury consumption. I allow Straub's late-in-life luxury motive into my life-cycle framework and use my new micro facts to disentangle its role. I find that late-in-life luxury consumption and bequests primarily determine the overall level of under-response, while commitments are crucial for generating other facts. My quantitative results also connect with Gaillard et al. (2023), who show that standard heterogeneous-agent models struggle to match the tails of income, consumption, and wealth distributions, and argue for wealth-dependent preferences and scale-dependent returns to assets. I instead focus on Gini measures of consumption and wealth inequality. Interestingly, in my calibration, the coefficient on their wealth utility function is similar to the one I endogenously calibrate for my bequest motive.

2 Measuring Consumption Responses to Permanent Income

To study the role of consumption commitments in shaping how consumption responds to permanent income, I first define permanent income and explain its measurement in the data. I then describe how I estimate the consumption elasticity to permanent income, which serves as my measure of consumption responses.

2.1 PSID data

I use data from the Panel Study of Income Dynamics (PSID), specifically the 1999–2019 waves. The panel structure and the broad measures of consumption, income, and wealth collected in these years allow me to track how households' consumption, income, and wealth evolve over time. The baseline sample consists of all households whose heads are between 25 and 65 years old.[2]

2.2 Measuring Permanent Income

Permanent income is defined as the sum of current household assets plus its discounted future expected income profile. I mimic this definition when constructing permanent income in the data.

For household i at time t, permanent income is

$$\widehat{\text{PI}}_{i,t} = \text{net worth}_{i,t} + \sum_{s=t}^{age_i(s)=100} \frac{\Psi\Big(age_i(t), age_i(s)\Big)}{R^{s-t}} \widehat{Y}_{i,s}^{t} \ . \tag{1}$$

Net worth is measured using PSID wealth data and is the sum of net liquid and net illiquid wealth.[3] and construct a discounted future expected income profile for each household. The expected income path is expressed in present value terms using a constant interest rate, $R = 1.05$, and age-specific survival probabilities.[4] Here $age_i(t)$ denotes the age of household i at time t, $\Psi(a_1, a_2)$ represents the probability of an individual of age a_1 surviving until age a_2, and $\widehat{Y}_{i,s}^{t}$ is the expected income of household i at time s based on information available at t.

The crucial step in my measurement exercise is estimating an expected income path for each household. I assume that the information set is described by past income and observable demographics and that the household and the econometrician share this information. I approximate the expectation-formation process by a linear autoregressive specification estimated by OLS, so that the forecast is the best linear predictor given this information set. I discuss challenges with this approach at the end of this subsection.

As a benchmark, I use a first-order autoregressive process. Since the PSID is biennial after

[2]The PSID was conducted annually until 1996 and biennially thereafter. I use data from the 1997–2019 waves in most exercises. When estimating the income-forecasting equation used to construct expected income, I use data from the 1980–2019 waves and restrict pre-1999 waves to odd survey years for consistency.

[3]Following Kaplan, Violante, and Weidner (2014) and Aguiar, Bils, and Boar (2020), liquid assets include checking and savings accounts and stocks; liquid debt includes all non-mortgage debt. Net liquid wealth is liquid assets minus liquid debt. Net illiquid wealth includes home equity, the net value of other real and financial assets, and IRA and other pension holdings. In a robustness exercise, I also use a broader wealth measure that includes employer-provided defined-contribution retirement accounts (Cooper, Dynan, and Rhodenhiser, 2019). Appendix A describes variable construction in detail.

[4]Results are robust to different values of R. Survival probabilities come from U.S. Life Tables from the National Vital Statistics System.

1999, I use income at $t-2$ to forecast income at t:

$$\begin{aligned}\mathbb{E}[\ln Y_{i,t+2} \mid I_t] &= \mathbb{E}[\ln Y_{i,t+2} \mid \ln Y_{i,t}, \mathbf{X}_{i,t}] \\ \ln \widehat{Y}^t_{i,t+2} &= \widehat{\theta}^t_0 + \widehat{\rho}^t_1 \ln Y_{i,t} + \widehat{\Gamma}^t \mathbf{X}_{i,t}\,,\end{aligned} \tag{2}$$

where $\mathbf{X}_{i,t}$ includes a cubic in age and dummies for educational attainment, marital status, census region, and occupation. I iterate (2) forward to obtain income forecasts $t+2$ and beyond and linearly interpolate for missing even years. [5] I use household after-tax labor income as my measure of income, which consists of labor earnings and government transfers, net of payroll taxes.[6]

I estimate the forecasting equation using a rolling sample of observations collected over the 16 years before t. This restriction ensures that my measure captures only information available at time t, and that no future information is used. For example, to compute permanent income in 1997, I estimate (2) using data from 1981–1997 and then iterate the process forward; for 1999, I roll the window and re-estimate using 1983–1999. The t-subscript in the parameters of equation (2) denotes the last year in the estimation sample (i.e., the year that indexes the information set). In the long run, income converges to age–education–marital–region–occupation-specific means implied by $\mathbf{X}_{i,t}$, in the spirit of Carroll (1994). However, the autoregressive structure introduces persistence so that convergence is gradual rather than instantaneous.

I address various concerns with my forecast exercise. First, I use instrumental variables to deal with measurement error in income data. Since I use survey data and sum forecast income over many periods, any measurement error will accumulate and potentially yield a noisy measure. A downward-biased estimate could explain a lower consumption response. Therefore, I instrument for the log of permanent income with lagged income and industry dummies. Appendix B lays out the conditions under which these instruments are valid.[7]

[5]When forecasting the income path, I assume that households retire at age 65 and receive Social Security income equal to 45% of their last pre-retirement forecasted income. This is particularly important because Social Security and retirement wealth are the main resources for many retired households. The replacement rate is consistent with the simulations of Diamond and Gruber (1999), who also note that the U.S. Social Security system discourages additional work after age 65.

[6]Labor earnings consist of the head and partner's (if any) total labor income, including the labor component of income from any unincorporated business and excluding business and farm income. Government transfers include any income from AFDC, Supplemental Security Income, Social Security benefits, unemployment benefits, workers' compensation, and other welfare payments. Payroll taxes come from the NBER's TAXSIM. For robustness, I construct a broader measure that includes asset income and discuss how the results change in Appendix E.

[7]Measurement errors in assets are harder to address, so I rely on the same set of instruments used to address errors in income. Pfeffer and Griffin (2015) analyze wealth measurement error in the PSID and find that demographic variables account for a greater share of extreme fluctuations in measured wealth. "Measurement issues," on the other hand, have small predictive power. They consider measurement issues: (i) wealth having some imputed component or (ii) a change in the interview respondent (e.g., the head in some wave and the spouse in another).

A second concern is that households may possess information about their future income that is not captured by the econometrician's information set. To mitigate these concerns, I take advantage of the panel structure, construct out-of-sample forecast errors, and test their bias and forecastability in Appendix C. Short-term errors are unbiased, but longer-term ones have a slight bias. Moreover, I show that current consumption, which arguably captures most of the information available to households and serves as a good proxy for households' information set, has low power to forecast future forecast errors.

Finally, Appendix E reports robustness checks using broader income and wealth measures and alternative income processes (higher-order autoregressive specifications and occupation-specific parameters). It also discusses a procedure that uses out-of-sample forecast errors to adjust permanent income for systematic misforecasting at the household level. This exercise helps assess how sensitive the results are to including a household-specific term that shifts the entire predicted income path.

2.3 Specifying Consumption's Response to Permanent Income

I summarize consumption responses by the elasticity of consumption with respect to permanent income. Most models imply a linear relationship between log consumption and log permanent income, while empirical work finds a concave relationship with elasticities around 0.7 (Straub, 2019; Abbott and Gallipoli, 2019). My empirical analysis provides new evidence on the role of consumption commitments in shaping the life-cycle and history dependence of consumption responses.

I estimate the elasticity by projecting log consumption on log permanent income:

$$\log c_{i,t} = \beta_0 + \beta_1 \log \widehat{\mathrm{PI}}_{i,t} + \Gamma \boldsymbol{Z}_{i,t} + \epsilon_{i,t} \ . \tag{3}$$

Here $\log c_{i,t}$ is log consumption for household i at time t, $\widehat{\mathrm{PI}}_{i,t}$ is the permanent income measure in (1), and $\boldsymbol{Z}_{i,t}$ is a vector of demographic controls including a cubic in age, year fixed effects, and dummies for education, marital status, census region, and family size. The error term $\epsilon_{i,t}$ captures idiosyncratic taste shocks and measurement error in consumption. My consumption measure aggregates all expenditure categories available in the PSID since 1999, following Kaplan et al. (2014), Blundell, Pistaferri, and Saporta-Eksten (2016), and Aguiar et al. (2020).[8]

[8] The consumption measure includes expenditures on food, health, childcare, education, insurance, transportation, vehicle repair, vehicle service flow, utilities, and shelter. Shelter spending is rent for renters and an implicit rent of

My measurement of consumption's response relies on the assumption that idiosyncratic taste shocks or measurement errors in consumption are orthogonal to the permanent income measure, conditional on demographic controls and time-fixed effects. Demographic variables capture some correlations related to preference heterogeneity, in line with Attanasio and Weber (1995). The time-fixed effects control for business cycles, assuming that cycles affect all households similarly.

To study path dependence, I augment (3) with past permanent-income growth:

$$\log c_{i,t} = \beta_0 + \beta_1 \log \widehat{\mathrm{PI}}_{i,t} + \beta_2 \Delta \log \widehat{\mathrm{PI}}_{i,t} + \Gamma_1 \boldsymbol{Z}_{i,t} + \Gamma_2 \boldsymbol{Z}_{i,t-10} + \epsilon_{i,t} \, , \tag{4}$$

where $\Delta \log \widehat{\mathrm{PI}}_{i,t}$ denotes 10-year permanent-income growth and $\boldsymbol{Z}_{i,t-10}$ includes lagged demographic controls (marital status, census region, and family size). This specification compares households with the same current permanent income but different income histories. If consumption commitments matter, higher past permanent-income growth should be associated with lower current consumption: households that expected lower life-time resources in the past accumulated fewer commitments, so following a permanent-income increase they adjust mainly along flexible goods, leaving committed expenditures largely unchanged. This implies an expenditure allocation skewed toward easy-to-adjust goods and a lower overall consumption level.

Building on this idea, I test whether expenditure allocation across goods' categories also displays path dependence by estimating demand systems. Conditional on current total expenditure, I compare the budget shares of households with different expenditure histories. Based on the almost ideal demand system (AIDS) of Deaton and Muellbauer (1980), I estimate

$$w_{jit} = \alpha_{jt} + \alpha_j \log X_{it} + \beta_j \Delta \log X_{it} + \Gamma_j \mathbf{Z}_{it} + u_{jit} \, . \tag{5}$$

where w_{jit} is the expenditure share of good j, X_{it} is total expenditure, $\Delta \log X_{it}$ is 10-year expenditure growth, and $\mathbf{Z}_{it}$ contains demographic controls. Year fixed effects absorb relative price movements. If commitments are important, households with fast past expenditure growth should devote a larger share of their budget to easy-to-adjust goods and a smaller share to hard-to-adjust goods, conditional on current expenditure.[9]

6% of reported house value for homeowners (Aguiar et al., 2020). Vehicle service flow is set to 10% of reported vehicle net worth. Appendix E reports robustness to alternative expenditure definitions.

[9] I construct expenditure shares using the detailed categories available in the PSID after 2005. Because total expenditure appears both on the right-hand side and in the denominator of w_{jit}, measurement error in X_{it} can bias the estimates. Following the literature, I instrument total expenditure with a cubic polynomial in log income and education dummies, assuming that income shocks are uncorrelated with the demand-system error u_{jit}.

Sample selection: For each wave, I drop observations with total income below $2,000.00 or above the 99th percentile and total expenditure below the 1st or above the 99th percentile to minimize the bias caused by outliers and measurement error. Considering only observations without missing information for any used demographic characteristics, the sample has 18,213 observations corresponding to 5,724 households. I use the CPI to express all monetary values in 2017 US dollars. Appendix A provides further sample statistics, and Appendix E reports robustness to alternative sample definitions.

3 Responses to Permanent Income in the Data

In this section, I present the four facts on consumption's response to permanent income. These facts suggest an important role of consumption commitments in understanding these consumption responses. I first estimate the average elasticity and its age profile, then show path dependence in levels and in expenditure composition, and finally compare households that recently adjusted their commitments to those that did not.

3.1 Consumption Responses to Permanent Income

I begin by estimating equation (3) for the full sample of households with heads aged 25–65. The first column of Table 1 reports my preferred estimate of the elasticity of consumption with respect to permanent income, which is approximately 0.8. This value is well below the benchmark of 1.0 implied by models with homothetic preferences.[10] My finding of 0.8 aligns closely with previous empirical work, which documents elasticities around 0.7 (Straub, 2019; Abbott and Gallipoli, 2019).

I present my preferred specification here and relegate alternative specifications and robustness checks to Appendix E. Two choices deserve discussion. First, because permanent income is constructed from survey data, measurement error is a concern. I address this by instrumenting log permanent income with lagged income and industry dummies. Second, because higher permanent income may be correlated with greater patience, which could drive the estimated elasticity, I include education dummies. These dummies capture heterogeneity in discount factors, as college-educated workers exhibit systematically higher savings rates that likely reflect differences in patience (Dynan et al., 2004). Consequently, my results should be interpreted as within-

[10] Straub (2019) shows that most models with homothetic preferences predict an elasticity close to 1.0. This result also holds in a special case of the life-cycle model presented in the quantitative section.

education-group variation.

My first fact is that the elasticity of consumption with respect to permanent income declines with age. Columns 2–5 of Table 1 estimate equation (3) separately by age group. For households aged 25–45, the elasticity is close to 0.9, while for households aged 55–65 it falls to about 0.64. All coefficients are precisely estimated, and first-stage F statistics are sufficiently large to mitigate concerns about weak instruments.

This fact helps distinguish between possible explanations for the under-consumption puzzle. A valid explanation must account for the strong responsiveness of young households to permanent income and the weaker responsiveness of older households. Models that predict young households primarily save for future consumption are inconsistent with this pattern, as they would imply weaker, not stronger, consumption responses for the young. By contrast, consumption commitments produce a declining profile: as households age, they accumulate hard-to-adjust commitments, which progressively reduce the flexibility of consumption to track permanent income.[11]

Table 1: Consumption Response–Full Sample and by Age Group

	(1) All Sample	(2) 25<age<35	(3) 35<age<45	(4) 45<age<55	(5) 55<age<65
log(PI)	0.79	0.86	0.89	0.75	0.64
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
Educ Dummies	Y	Y	Y	Y	Y
KP-F test	616.3	823.7	423.9	359.2	152.7
Observations	54,970	14,770	17,556	15,704	11,475

Note: This table reports the estimated consumption elasticity to permanent income for the full sample and for different age groups. All columns use instrumental variables, with the excluded instruments being lagged income and dummy variables for industry groups. Besides the log of constructed measure of permanent income, the other controls are cubic polynomial in age, dummy variables for marital status, family size, census region, education groups, and year fixed effect. All variables are weighted by sampling weights, and the standard errors are calculated using a bootstrap with 100 replications. The foot table reports the number of observations and the Kleibergen-Paap F statistic.

3.2 Consumption Responses to Current and Past Permanent Income

My second fact documents that consumption depends not only on current permanent income but also on its past trajectory. I document this path dependence by estimating equation (4), which

[11]In particular, the lower responsiveness of older households to permanent income relates to the retirement-saving puzzle, which highlights that many retirees–especially those with high lifetime earnings–do not withdraw their savings as fast as standard life-cycle models predict. Unlike most studies in this literature, my analysis focuses on working-age households rather than retirees.

compares households with the same permanent income today but different 10-year permanent-income growth. I again use the IV specification with education dummies.

Table 2, Column 1 shows that, for working-age households, consumption is positively associated with current permanent income levels and negatively associated with past permanent income growth, with an estimated coefficient of 0.95 and -0.33, respectively. A 10% permanent income increase is associated with a 3% lower consumption today. This suggests that households with no permanent income growth–those who knew their permanent income level 10 years ago–consume more than those with positive growth.

The remaining columns of Table 2 present the path-dependence results by age group. In all age groups, consumption loads on both current permanent income and permanent income growth. The strength of the association between current consumption decreases with age, while that with past permanent income growth increases slightly with age. Older households, therefore, display stronger path dependence, consistent with having accumulated more commitments over time.

This fact reframes the under-consumption puzzle, emphasizing that it is more pronounced among households that have experienced permanent income growth. Consumption commitments rationalize this pattern. Young households choose an expenditure path and a level of commitments given their current expectations of lifetime resources. After experiencing permanent income growth, those households with past commitments must respond to increases in permanent income by either increasing spending on adjustable goods (e.g., nondurable goods) or savings. This partial adjustment makes consumption today less desirable, which explains the depressed consumption.

3.3 Expenditure Components

My third novel fact documents that these differences in behavior that depend on past permanent income trajectories also appear in their expenditure allocation across different goods categories. Importantly, I find that the sign of these path dependencies differs based on goods' adjustability, which is an important finding in favor of the consumption commitment mechanism. Households with fast past expenditure growth consume more easy-to-adjust goods and fewer hard-to-adjust goods (i.e., consumption commitments).

I document this novel fact by estimating equation (5), which captures how past income

Table 2: Path Dependence on Consumption Response by Age Group

	(1) All Sample	(2) 35<age<45	(3) 45<age<55	(4) 55<age<65
$\log(\text{PI}_t)$	0.95	1.11	0.98	0.84
	(0.03)	(0.07)	(0.05)	(0.04)
Δ log(PI)	-0.33	-0.25	-0.35	-0.35
	(0.04)	(0.09)	(0.06)	(0.06)
Educ Dummies	Y	Y	Y	Y
KP-F test	130.4	67.7	69.1	56.5
Observations	15,180	4,322	5,900	6,054

Note: This table reports the estimated consumption elasticity to permanent income and 10-year lagged permanent income for different age groups. All columns use instrumental variables. The excluded instruments in the first column are 2-year and 12-year lagged income and dummy variables for current and 10-year lagged industry groups. The control variables are cubic polynomials in age, year fixed effects, dummy variables for marital status, family size, census region, and education groups. The dummies enter in current and 10-year lagged values. All variables in the regression are weighted by sampling weights, and standard errors are estimated using a bootstrap method with 100 replications. The foot table reports the number of observations and the Kleibergen-Paap F statistic.

growth is associated with expenditure allocation across different goods, conditional on a given level of total expenditures. I focus on the demand system for nondurable and shelter expenditures, arguably an easy-to-adjust and a hard-to-adjust good. Shelter expenditure is the most important consumption commitment in the data, as it accounts for a large share of the consumption bundle and entails significant adjustment costs, such as moving costs, brokerage fees, search time, and nonpecuniary costs.

The first row of Table 3 shows the coefficient on log expenditure, and, for a more straightforward interpretation, I focus on the coefficient expressed as Engel elasticity (the value in brackets). Engel curves trace out total expenditures on a good against permanent income, and, without controlling for them, the estimates of permanent income trajectory on bundle allocation would also capture the expenditure increase on luxury goods and decrease on inferior goods. Columns 1 and 3 imply an Engel elasticity of 0.8 for nondurable expenditures, indicating that nondurable goods are a necessity. Columns 2 and 4 imply an Engel elasticity of 1.1 for shelter expenditures, indicating that shelter is a luxury good.

The second row shows the coefficient on past expenditure growth, and I focus on the coefficient in brackets, which represents the association between log expenditure growth and log expenditure for a particular category. 10% increase in total expenditure decreases shelter expenditure by 0.3% and increases nondurable spending by 0.1%. Thus, given the same expenditure

Table 3: Consumption Category Shares

	(1) Nondurable Share	(2) Shelter Share	(3) Nondurable Share	(4) Shelter Share
log(exp)	-10.20	2.37	-9.98	3.21
	(0.60)	(0.69)	(0.81)	(0.86)
	[0.80]	[1.09]	[0.81]	[1.12]
Δ log(exp)			5.66	-8.01
			(1.52)	(1.64)
			[0.11]	[-0.31]
Educ Dummies	Y	Y	Y	Y
KP-F test	294.0	294.0	17.1	17.1
Observations	26,046	26,046	9,950	9,950

Note: This table reports the estimated AIDS demand system. All columns use instrumental variables, with the excluded instruments being cubic polynomials in log income and dummy variables for industry groups. In the specification with 10-year expenditure growth, cubic polynomials in lagged log income and dummy variables for lagged industry groups are also used as the excluded instruments. The other controls are cubic polynomial in age, dummy variables for marital status, family size, census region, education groups, and year fixed effect. In the specification with lagged permanent income, the lagged controls are also used. All variables in the regression are weighted by sampling weights, and standard errors are clusted at the household level. The foot table reports the number of observations and the Kleibergen-Paap F statistic.

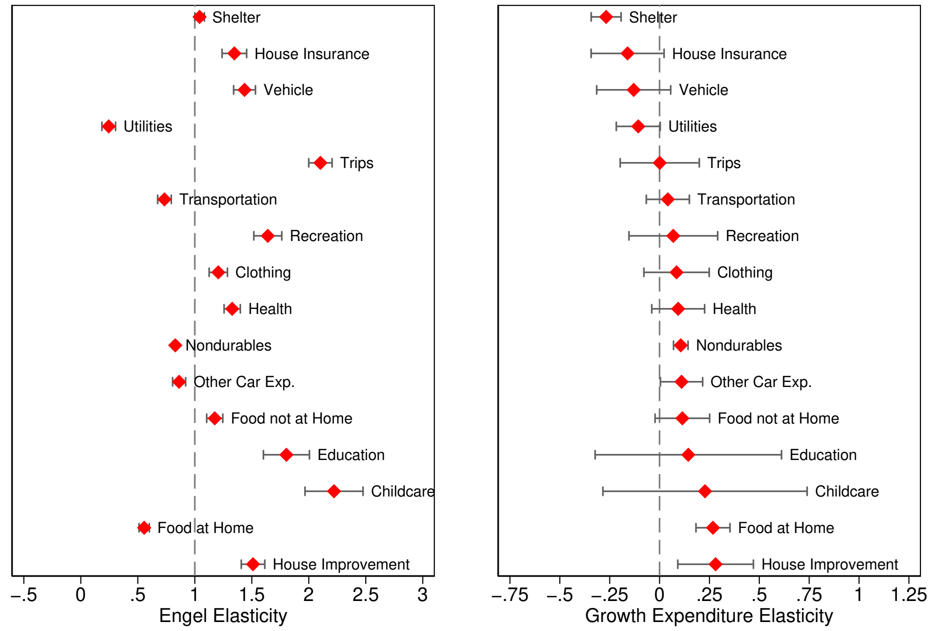
today, households respond to increases in permanent income, proxied here by the expenditure growth, by increasing adjustable goods (e.g., nondurables). This is exactly the pattern implied by consumption commitments: when permanent income rises, most of the adjustment happens in flexible expenditure.

Figure 1 extends this analysis to a richer set of expenditure categories. The right panel orders categories by the coefficient on expenditure growth, which I interpret as a measure of how strongly a category behaves as a commitment good. For shelter, and, at the margin of statistical significance, for vehicles, home insurance, and utilities, past growth shifts the basket away from these categories. By contrast, past growth shifts the basket toward nondurables, food at home, and home improvement. Importantly, the left panel shows that Engel elasticities do not line up with these growth coefficients: the composition effects are not simply driven by higher spending on luxury goods.

3.4 Consumption Resets

My fourth fact compares households that recently adjusted their commitments to those that did not. I focus on shelter expenditure because it is the most important commitment in the data, and

Figure 1: Consumption Categories



Note: Note: This figure depicts the estimated coefficients for log expenditure (left panel) and expenditure growth (right panel) for different AIDS demand systems. Each row is a different expenditure category, in which the demand system is estimated using instrumental variables, with the excluded instruments being cubic polynomials in log income and lagged log income and dummy variables for industry groups and lagged industry groups. The other controls are cubic polynomial in age, dummy variables for marital status, family size, census region, education groups, and year fixed effect, all dummies in current and lagged values. All variables are weighted by sampling weights, and the standard errors are clustered at the household level. The foot table reports the number of observations and the Kleibergen-Paap F statistic.

I classify households that moved at least once in the prior decade as having fully adjusted their bundle. I find that, for movers, both consumption levels and expenditure composition depend much more on current permanent income and total expenditure and much less on past growth. Because the consumption-commitment mechanism relies on adjustment frictions to generate depressed and history-dependent consumption, the absence of such patterns among movers is strong evidence in its favor.

To summarize the heterogeneous responses in a compact way, I estimate a specification that interacts permanent income and its growth with a mover dummy. Equation 6 reports the estimated response of log consumption to current permanent income, its 10-year growth, and their interactions with the mover indicator. For households that did not move, consumption loads strongly on past permanent-income growth (coefficient -0.53), while for movers the dependence on past growth is substantially attenuated (the interaction coefficient is 0.30). The loadings on current permanent income are similar across groups. Thus, for movers, consumption depends primarily on current permanent income, whereas for non-movers it depends heavily on past permanent-income growth as well.[12]

$$\begin{aligned}\log(c_{it}) &= \underset{(0.04)}{0.95}\log(PI_{it}) - \underset{(0.09)}{0.53}\Delta\log(PI_{it}) + \underset{(0.03)}{0.01}(Moved_{it}\times\log(PI_{it})) \\ &+ \underset{(0.14)}{0.30}(Moved_{it}\times\Delta\log(PI_{it})) + X_{it}'\gamma\end{aligned} \tag{6}$$

An analogous pattern appears in expenditure composition. Equation 7 reports estimates of an AIDS system for nondurable and shelter expenditure shares that interacts log expenditure and its growth with the mover indicator. For households that did not move, past expenditure growth has large and opposite effects on the two categories: the coefficients on growth are 12.27 for nondurables and -19.63 for shelter. For movers, the corresponding interaction terms largely offset these effects (-9.33 and 16.07, respectively), so that the total effects of past growth become much smaller (approximately 3 for nondurables and -4 for shelter). This implies that movers' expenditure shares are driven primarily by current expenditure levels rather than by past expenditure growth, consistent with the consumption commitments mechanism.[13]

$$\begin{aligned}w_{it}^{nd} &= -\underset{(1.03)}{11.64}\log(exp_{it}) + \underset{(2.45)}{12.27}\Delta\log(exp_{it}) + \underset{(1.01)}{2.86}(Moved_{it}\times\log(exp_{it})) \\ &- \underset{(2.61)}{9.33}(Moved_{it}\times\Delta\log(exp_{it})) + X_{it}'\gamma \\ w_{it}^{sh} &= \underset{(1.15)}{4.72}\log(exp_{it}) - \underset{(2.92)}{19.63}\Delta\log(exp_{it}) - \underset{(1.15)}{2.82}(Moved_{it}\times\log(exp_{it})) \\ &+ \underset{(3.11)}{16.07}(Moved_{it}\times\Delta\log(exp_{it})) + X_{it}'\gamma\end{aligned} \tag{7}$$

Taken together, these results show that path dependence in levels and in composition is concentrated among households that have not recently adjusted their commitments. For movers, responses are much closer to the benchmark in which consumption and expenditure shares depend only on current permanent income and total expenditure. This pattern is a distinctive prediction

[12]Standard errors in parentheses. IV estimates with 2-year and 12-year lagged income and industry dummies as excluded instruments. Controls include cubic polynomials in age, year fixed effects, and dummies for marital status, family size, census region, and education (current and lagged). $N = 14,613$, KP F-stat$= 15.9$.

[13]Standard errors in parentheses. IV estimates of AIDS demand system with cubic polynomials in log income (current and lagged) and industry dummies as excluded instruments. Controls include cubic polynomials in age, dummies for marital status, family size, census region, education, and year fixed effects (current and lagged). $N = 9,950$, KP F-stat$= 8.0$.

of the consumption-commitments mechanism: once households pay the adjustment costs and reset their bundle, the role of past permanent income largely disappears. Habit-formation models, by contrast, would not predict that the relevance of past permanent income fades simply because a household moved.

3.5 Additional Results

Before proceeding, I briefly discuss several additional empirical tests to ensure the robustness of my results below and leave a more detailed analysis for the appendices.

Quality of the Expected Income Measure. In Appendix C, I address the concern that households possess superior information relative to my income forecasts and that this information leads to systematic underprediction for low-income households and overprediction for high-income ones. To assess this, I construct out-of-sample forecast errors and test whether they are unbiased and uncorrelated with variables measured at the time of forecasting. Overall, I find that households possess some superior information, but its magnitude is small and does not significantly distort my forecast measures.

Asset Accumulation Results. Because under-consumed income must accumulate somewhere, I verify that consumption patterns translate into corresponding asset accumulation in Appendix D. First, I construct an alternative net worth measure using the budget constraint and reported income and expenditure. This constructed measure closely tracks reported net worth over 20 years, confirming that the PSID measures of income, expenditure, and wealth are consistent. I find that households experiencing positive growth accumulated substantially more wealth despite similar starting points. Second, I examine active savings–flow measures excluding capital gains that better capture conscious saving decisions. Households with identical current permanent income but different past trajectories save differently. These results, derived from independent survey questions, corroborate the consumption findings and rule out concerns about expenditure mismeasurement.

Financial Factors. Borrowing constraints are important for understanding consumption behavior, especially responses to transitory income shocks. I construct indicators to identify whether households are constrained or hand-to-mouth (H2M), following the definitions of Zeldes (1989) and Kaplan et al. (2014). I perform three tests in Appendix F. (i) I introduce dummies for H2M households based on net worth and liquidity definitions, (ii) I drop all H2M households from the sample, and (iii) I restrict the sample to households with positive home equity, removing those with negative housing wealth. The estimated consumption responses to permanent income are stable in all exercises, suggesting that borrowing constraints are not the main driver of the under-response or the life-cycle patterns I document.

Income Risk. Income risk affects consumption by influencing precautionary saving behavior. This saving behavior could generate the under-consumption puzzle if high-permanent-income households have riskier income and, therefore, larger savings. Young workers tend to be more liquidity-constrained and have higher expected future income growth; therefore, precautionary saving should be stronger for them. The fact that we observe pronounced under-consumption among older households suggests that uncertainty is not a major driver of this puzzle. To formalize this point, I create a measure of permanent-income risk following Boar (2021) and confirm that income risk does not alter my baseline results in Appendix Appendix F, indicating that precautionary saving is not the main force behind the under-response or its age profile.

Alternative Measurement Choices. In the main analysis, I make choices about income, expenditure, net worth, and sample construction. For robustness, I present results with several other choices and discuss how they change in Appendix E. It also discusses a procedure that uses out-of-sample forecast errors to adjust permanent income for systematic misforecasting at the household level. Overall, the average level of under-response is quantitatively sensitive to how permanent income is constructed and to the expenditure measure, but two core patterns–the decline of the elasticity with age and the negative dependence on past permanent-income growth–are robust across all specifications.

Other Results. I report several additional robustness exercises in Appendix Appendix F. First, I compare homeowners and renters and show that the main consumption and composition responses are not driven by current tenure status but by past homeownership. Second, I exclude households that report moving for job reasons and find similar results, alleviating concerns about reverse causality from income growth to moves. Third, I show that the likelihood of moving–either recently or in the near future–rises with the absolute change in permanent income, as in standard lumpy adjustment models. Fourth, placebo timing tests confirm that moves in the distant past do not matter, while future moves are predicted by the same households that currently display strong path dependence. Finally, I examine bequests and inter vivos transfers in the PSID, but sample sizes are too small to reliably study their dependence on past permanent-income growth.

4 A Life-Cycle Model with Lumpy Goods Adjustment

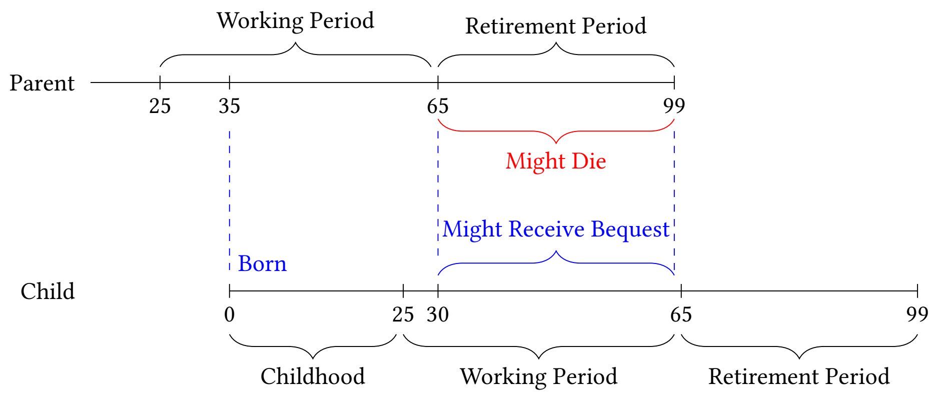
In this section, I extend a canonical incomplete markets model (Deaton, 1991; Carroll, 1997; Gourinchas and Parker, 2002) by introducing two consumption goods, one of which is hard to adjust. The hard-to-adjust good, which can be interpreted as housing or durables, delivers a flow of services from a stock but is subject to a non-convex adjustment cost when its stock is changed (Chetty and Szeidl, 2007; Berger and Vavra, 2015). Households insure idiosyncratic labor-income risk using the stock of hard-to-adjust goods and a single risk-free bond subject to a borrowing constraint. The model also accommodates other mechanisms used to explain consumption's under-response, such as luxury late-in-life consumption (Straub, 2019) and bequest motives (De Nardi, 2004). Lastly, to quantify the implications for wealth distribution, the model is cast in an overlapping-generations structure.

4.1 Environment

Demographics: I consider a continuum of households in an overlapping-generations structure. Each period corresponds to one year, and j indexes model age. Households enter the labor market at age $j = 0$ (biological age 25) and retire at model age $R = 40$ (biological age 65). Once retired, households face a probability ψ_j of dying between age j and $j + 1$ and die with certainty at model age $J = 74$ (biological age 99). Households start their working lives with zero assets.

Figure 2 displays the generational structure of the model. Each household has a child household at parent age $j = 10$ (parent biological age 35, child age 0). Thus, the child enters the labor market when the parent is age $j = 35$ and retires after the parent's death. Parents and children are linked by bequests and intergenerational transmission of skill, as detailed below. Because parents face a positive mortality risk in retirement, children might receive a bequest between age $j = 5$ (biological age 30) and age $j = 39$ (biological age 64). The timing is chosen so that at most two generations overlap and bequests flow only from parents to children; there is no population growth.

Figure 2: Overlapping Generations Structure



Preferences: Households have standard time-separable preferences with discount factor β and period utility defined over an aggregated consumption bundle composed of two commodities. The first commodity, c^n, represents easy-to-adjust goods (nondurables). The second, c^h, represents hard-to-adjust goods (commitments). Commitment consumption and stock are related by $c^h = \zeta h$, where ζ is the flow of services (in utility terms) per unit of commitment stock h. The two commodities are aggregated through a CES function,

$$c = g(c^h, c^n) = \Big(\omega(c^h)^\gamma + (1-\omega)(c^n)^\gamma\Big)^{\frac{1}{\gamma}},$$

where ω governs the weight of commitments in the aggregator and $1/(1-\gamma)$ is the elasticity of substitution between c^n and c^h.

The empirical results in Section 3 show that saving rates rise with permanent income, contrary to the predictions of standard life-cycle models with homothetic preferences. To allow the model to match this under-response of consumption, I incorporate two additional mechanisms beyond consumption commitments. First, I introduce preferences over bequests to capture intergenerational motives (bequests and inter vivos transfers), as in De Nardi (2004). Second, following Straub (2019), I allow for luxury late-in-life consumption to capture expenditures that are concentrated at older ages and among richer households, such as health spending, college payments for children, and charitable giving.

Period utility for a household of age j is given by

$$u_j(c) = \frac{(c/o)^{1-\sigma_j^c} - 1}{1-\sigma_j^c},$$

where $\sigma_j^c > 0$ is an age-dependent coefficient of relative risk aversion, and $o > 0$ is a normalization parameter that preserves aggregate scale invariance. As in Straub (2019), σ_j^c declines with age during working life according to a simple exponential schedule $sigma_{j+1}^c/\sigma_j^c = \sigma_{\text{slope}}^c$, and is held constant in retirement. This parameterization predicts a back-loaded consumption profile for higher-income households. Equivalently, it implies a higher elasticity of consumption with respect to income at older ages and provides a parsimonious way to capture late-in-life expenditures such as college tuition, charitable giving, or costly medical treatments.

Preferences over bequests are given by

$$\mathcal{B}(a,h) = \frac{\phi}{1-\sigma^b}\left(\frac{a+h}{o}\right)^{1-\sigma^b},$$

where a is the position in a risk-free bond, ϕ is a scale parameter, σ^b governs the curvature of the bequest motive, and $o > 0$ is again a normalization parameter. A lower σ^b makes bequests more of a luxury good. I assume that commitment stock and bonds are perfect substitutes in the bequest function, so households are indifferent between leaving either asset to their children. Estate taxes are borne by the child household and therefore do not distort parents' decisions.

Idiosyncratic Earnings: Households face idiosyncratic labor-productivity risk. The labor productivity process is a combination of a Markov process and a deterministic component. To clarify the notation, I use i for time-invariant, individual-specific productivity components, j for components common to all households, and both i and j for time-varying, individual-specific components. In particular, for household i at age j, the productivity process is

$$\begin{aligned} z_{i,j} &= b_1 j + b_2 j^2 + \bar{z}_i + \alpha_{i,j} + \epsilon_{i,j} \\ \alpha_{i,j} &= \rho\alpha_{i,j-1} + \xi_{i,j}\ , \end{aligned} \tag{8}$$

where b_1 and b_2 define the age-specific deterministic component, $\bar{z}_i$ is individual fixed productivity, $\alpha_{i,j}$ is a persistent component of productivity that follows an AR(1) process, and $\epsilon_{i,j}$ is a transitory productivity component. The shocks $\epsilon_{i,j}$ and $\xi_{i,j}$ are independent and identically distributed (i.i.d.) across households i and ages j, each following a normal distribution with variances σ_ϵ^2 and σ_ξ^2, respectively. Total labor income is calculated as the product of the market wage per efficiency unit of labor (denoted as w) and the exponential of the productivity term: $w \times \exp(z_{i,j})$. Labor income in the model is interpreted as income net of taxes and transfers, matching the after-tax concept used in the PSID sample.

Finally, the fixed productivity draw $\bar{z}_i$ is correlated across generations. Specifically, for household i, $\bar{z}_i$ follows the equation:

$$\bar{z}_i = \bar{\rho}\bar{z}_i^p + \bar{\varepsilon}_i \ .$$

Here, $\bar{z}_i^p$ represents the fixed productivity of household i's parent, $\bar{\rho}$ is a persistence parameter, and $\bar{\varepsilon}_i$ is a shock that follows a normal distribution with a variance of $\sigma_{\bar{\varepsilon}}^2$.

Assets: Households can save in liquid risk-free bonds and in an illiquid commitment stock, which can be interpreted as a housing stock. The risk-free bonds carry a constant risk-free rate r. Commitments provide a utility flow ζ per unit and depreciate at a rate δ per period. To adjust their commitment stock, households must incur non-convex costs, reflecting, for example, brokerage fees or moving costs in the housing consumption case (Grossman and Laroque, 1990; Berger and Vavra, 2015). These costs are modeled as a proportional cost, meaning that households lose a fraction of their stock as a transaction cost. Formally, the adjustment cost function is

$$\mathcal{A}(h) = \begin{cases} 0 & \text{doesn't adjust} \\ \kappa h & \text{does adjust} \end{cases} .$$

I also allow for a "required maintenance" parameter χ, which captures the fraction of depreciation that must be offset each period to keep the commitment stock operational. Economically, χ represents repairs and maintenance expenditures needed to maintain the flow of services from commitments. Finally, households face a collateral constraint that links borrowing to the commitment stock: $a' > -\theta h$. In other words, commitment stock can be used as collateral up to a multiple θ.

Retirement: After retired, households live off their financial wealth a, commitment stock h, and social security benefits pen$(\bar{z})$, which is a function of fixed-income productivity.[14]

[14] Labor income in the model is already net of taxes and transfers, so taxes financing retirement benefits are implicit. In the quantitative analysis, the model is solved for partial equilibrium and pen$(\bar{z}) = 0.60 \times w \times exp(b_1 40 + b_2 40^2 + \bar{z})$. The value of 60% follows Diamond and Gruber (1999), and 40 is the number of working periods.

4.2 Recursive Formulation

Let s denote the vector of state variables for a household, $s = \Big\{j, a, h_{-1}, \bar{z}, \alpha, \epsilon, \bar{z}^p\Big\}$. These variables indicate, respectively, age (j), bonds carried over from the previous period (a), past commitment stock (h_{-1}), and labor productivity components ($\bar{z}, \alpha, \epsilon$). The last state variable $\bar{z}^p$ has two roles, as in De Nardi (2004). First, it determines beliefs about the distribution of future bequests. Second, once a household has received a bequest, $\bar{z}^p$ is set to zero, so it also distinguishes between households that have and have not yet inherited.

The household's first decision is whether to adjust the commitment stock. They solve the discrete choice maximization problem

$$V(s) = \max\Big\{V^{adj}(s), V^{noadj}(s)\Big\},$$

where $V^{adj}(s)$ and $V^{noadj}(s)$ are the value functions conditional on adjusting and not adjusting. These commitment decisions take place at the beginning of the period, after households receive income shocks, but before they make the consumption decision.

When no-adjustment is optimal, the household stays with the same commitment stock and solves the following problem:

$$V^{noadj}(s) = \max_{c^n, a'} u_j\Big(g(\zeta h, c^n)\Big) + (1-\psi_j)\,\beta\,\mathbb{E}\Big\{V(s')\Big|s\Big\} + \psi_j\,\beta\,\mathcal{B}\Big(a', h\Big)$$

s.t.

$$h = (1-\delta(1-\chi))h_{-1}$$

$$c^n + a' = \text{pen}(\bar{z}) + w\exp(z) + (1+r)a - \delta\chi h_{-1}$$

$$c^n > 0, \quad a' \geq -\theta h$$

$$\bar{z}^{p\prime} = \begin{cases} \bar{z}^p & \text{with prob } (1-\psi_{j+35}) \\ 0 & \text{with prob } \psi_{j+35} \end{cases}$$

where z' evolves according to the conditional distribution $\Gamma^z(\cdot \mid z)$ implied by (8). Next-period state vector is $s' = \{j{+}1,\ a'{+}b',\ h,\ \bar{z},\ \alpha',\ \epsilon',\ \bar{z}^{p\prime}\}$. Households that do not adjust the commitment stock must pay maintenance $\delta\chi h_{-1}$ to consume its services; those that adjust do not need to pay this cost.

A fraction ψ_j of households dies between ages j and $j+1$, in which case they generate bequest utility $\mathcal{B}(a', h)$ and pass on a lump-sum bequest to their child; the remaining fraction $1-\psi_j$ survives and continues with value $V(s')$. The evolution of $\bar{z}^p$ reflects the parent's survival. If the parent is still alive when the child is age j, the parent has age $j+35$. The distribution of bequests b' is given by the conditional c.d.f. $\Gamma^{j,\bar{z}^p}(b)$, which gives the c.d.f. of bequests from a parent of fixed productivity $\bar{z}^p$ to a child of age j. Importantly, beliefs about bequests coincide with the actual distribution of bequests implied by parents' decisions in equilibrium.

When adjustment is optimal, the household solves the following problem:

$$V^{adj}(s) = \max_{c^n, x, a'} \; u_j\Big(g(\zeta h, c^n)\Big) + (1-\psi_j)\,\beta\,\mathbb{E}\Big\{V(s')\Big|s\Big\} + \psi_j\,\beta\,\mathcal{B}\Big(a', h\Big)$$

s.t.

$$h = (1-\kappa)(1-\delta)h_{-1} + x$$

$$c^n + a' + x = \text{pen}(\bar{z}) + w\exp(z) + (1+r)a$$

$$c^n > 0, \quad h > 0, \quad a' \geq -\theta h$$

$$\bar{z}^{p'} = \begin{cases} \bar{z}^p & \text{with prob } (1-\psi_{j+35}) \\ 0 & \text{with prob } \psi_{j+35} \end{cases}$$

where z' evolves according to Γ^z, the bequest belief follows $\Gamma^{j,\bar{z}^{p'}}$, and the next-period state vector is $s' = \Big\{j+1, a'+b', h, \bar{z}, \alpha', \epsilon', \bar{z}^{p'}\Big\}$. x is the net investment in commitments. h_{-1} denotes the pre-depreciation stock carried forward from the previous period. The adjustment cost κ is levied on the post-depreciation stock $(1-\delta)h_{-1}$.

I solve the model in partial equilibrium, fixing $w = 1$ and $r = 0.03$. The distribution of bequests implied by parents' optimal policies must be consistent with the beliefs of children. Explicitly, given a guess $\Gamma^{j,\bar{z}^p}$, I solve the household problem, simulate the stationary cross-sectional distribution, and recover the implied distribution of bequests by $(j, \bar{z}^p)$. I then update $\Gamma^{j,\bar{z}^p}$ and iterate until convergence. Appendix G describes the computational algorithm in detail.

Throughout the paper, I mentioned that consumption commitments break the tight connection between permanent income and consumption in my model. Now, formally, in the model with non-convex adjustment costs, households can only partially adjust their consumption bundle in response to an increase in permanent income. As a result, the allocation of expenditure across consumption categories is not the same as the frictionless optimum. The commitment mechanism works through diminishing returns to specific goods relative to a near-constant return to marginal saving, which is given by the bequest motive. Households substitute present consumption for future consumption and future bequests.

5 Calibration

I calibrate the model using PSID data, targeting both standard moments in the literature and the empirical facts documented in Section 3. For that purpose, I begin by defining permanent income in the model and explaining how I recover the model-implied elasticities. I then describe the other moments used in the calibration and how they discipline the parameter choices. Finally, I summarize the fit of the calibrated model.

5.1 Calibrating Consumption's Response to Permanent Income

Permanent income is defined as the sum of current household net worth and the discounted value of expected future income. As in Subsection 2.2, I mimic this definition in the model. For household i of age j,

$$\widehat{\mathrm{PI}}_{i,j} = a_{i,j} + h_{i,j-1} + \sum_{s=j}^{J} \left(\prod_{\tau=j}^{s-1} \psi_\tau \right) \frac{\hat{y}_{i,s}}{R^{s-j}} \ ,$$

where $a_{i,j}$ are bonds carried from the previous period, $h_{i,j-1}$ are commitments owned last period, $\hat{y}_{i,s}$ is expected labor income, ψ_τ is the survival probability at age τ, $R = 1+r$ is the risk-free rate, and $J = 74$ is the maximum age. In the model, the total net worth is the sum of commitments and the risk-free bond. The discount rate combines a constant interest rate and survival probabilities. Lastly, the expected future income is computed using the same method proposed in the empirical section. [15]

I calibrate the model by matching its consumption responses to the ones estimated from the PSID data. For that, I simulate 5,000 households, create a panel, estimate the model's permanent income $\widehat{\mathrm{PI}}_{i,j}$, and measure the model's consumption response by implementing an analogous regression to (3). Specifically, I estimate:

$$\log c_{i,j} = \beta_0 + \beta_1 \log \widehat{\mathrm{PI}}_{i,j} + \Gamma \boldsymbol{Z}_{i,j} + \epsilon_{i,j} \ .$$

[15] As a robustness check, I also consider constructing the expectation using the full set of state variables $(\bar{z}_i, \alpha_{i,j})$ and the survival probabilities directly, rather than relying on the reduced-form forecast. I compare both measures in Appendix H.

$\log c_{i,j}$ is the log of consumption for household i at age j. $\widehat{\mathrm{PI}}_{i,j}$ is the estimated measure of permanent income. $\boldsymbol{Z}_{i,j}$ is a cubic polynomial in age. I estimate this equation for three different age groups: 30-40, 40-50, and 50-60, yielding three target moments.

I also estimate the analogue of the path-dependence regression (4) in the simulated data. I estimate this equation for two different age groups, 40-50 and 50-60. The coefficient on past permanent income growth helps identify the strength of consumption commitments, yielding four additional moments.

5.2 Other Moments and Calibrated Parameters

Beyond the consumption–permanent-income moments, I target housing, wealth, and bequest moments from the PSID and related data. The calibration proceeds in two steps. First, I set a subset of parameters externally. Second, conditional on those choices, I calibrate the remaining parameters endogenously to match model-simulated moments to their empirical counterparts via a method of simulated moments. Tables 4 and 5 summarize the parameter values, while Table 6 reports the targeted data moments and their model counterparts.

5.2.1 Externally Set Parameters

Demographics and Initial Distributions. Demographic parameters are set to match the life-cycle structure described in Section 4. Households enter the labor market at age 25, have a child at age 35, retire at 65, and die with certainty at 99. Retirement mortality risks $\{\psi_j\}$ are calibrated using the 2011 US Life Tables from the National Vital Statistics System. Households enter the labor market with zero assets and zero commitment stock.

Income Process. The income process parameters are chosen to reproduce key features of the distribution of after-tax labor income in the PSID. I calibrate seven parameters to match twenty-seven moments, grouped into: (i) cumulative income growth over different ages, (ii) the variance of log income across ages, (iii) the autocovariance of log income for two age intervals, (iv) the volatility of 2-year income growth, (v) income inequality measures, and (vi) forecast errors at several horizons. Relative to the previous literature, I place particular emphasis on moments capturing the predictability of income, since my results rely on this predictability to construct permanent income. Guvenen and Smith (2014) make a similar point. Appendix H provides further details and discusses an alternative calibration based on Aguiar and Hurst (2013).

The parameters governing the intergenerational transmission of fixed productivity are calibrated to match the empirical correlation between parental and child income ranks documented in Chetty, Hendren, Kline, and Saez (2014).

Commitment parameters. Some commitment parameters are calibrated based on the housing literature. I set the depreciation rate of commitments to 3%, in line with BEA estimates for residential capital (Fraumeni, 1997). The maintenance parameter is set to $\chi = 0.8$, as in Berger and Vavra (2015), implying that 80% of depreciation requires out-of-pocket maintenance expenditures, while only 20% materializes as decay of the stock. The maximum loan-to-value ratio is set to 0.8, consistent with Greenwald (2018) and Boar, Gorea, and Midrigan (2022). The utility flow from commitments is set to $\zeta = 0.06$, consistent with the implicit-rent approach to owner-occupied housing that I used to construct the PSID sample. My value is slightly higher than the rent-to-value ratio estimated by Katz (2017) for a $400,000 house.

Preference parameters. Two preference parameters are set externally. First, I set the risk aversion coefficient in the consumption utility for retired households, σ^c_j for $j \geq R$, to 1.1, following Straub (2019). In isoelastic, additively separable preferences, the income elasticity is approximately proportional to the inverse of the risk aversion coefficient; see Houthakker (1960) and Straub (2019). For working-age households, σ^c_j follows an exponential decay path pinned down by the endogenously calibrated σ^c_0 together with the externally set σ^c_R, so that risk aversion declines with age and late-in-life consumption behaves as a luxury good. Second, I set the scale parameter in the utility function, $o = 0.2$, also in line with Straub (2019).

5.2.2 Endogenously Set Parameters

The remaining seven parameters are calibrated endogenously to match some targeted moments. Table 5 lists these parameters and their calibrated values.

The discount factor $\beta = 0.84$ implies moderately impatient households at an annual frequency. Because households face strong precautionary motives and a bequest motive, matching the wealth–income ratio requires a relatively low annual discount factor. The coefficient of relative risk aversion at labor market entry $\sigma^c_0 = 4.09$ implies a moderate preference for back-loaded consumption compared with Straub (2019), who set $\sigma^c_0 = 11$. Nevertheless, this declining risk aversion is essential for reproducing the observed level of consumption responses. Given σ^c_0 and σ^c_R, the σ^c_{slope} is mechanically pinned down.

Table 4: Externally Set Parameters

Parameters	Description	Value	Source
	Demographics and Initial Asset Positions		
$\{\psi_j\}$	Survival probability		CDC, 2011
a_0	Initial Asset	0.00	
h_0	Initial Housing	0.00	
	Labor Market Entry	25	
	Childbearing	35	
R	Retirement age	65	
J	Certain Death age	99	
	Income Process		
b_1	Linear trend	0.07	PSID
b_2	Quadratic trend	-0.002	
$\sigma_{\bar{z}}$	Fixed-effect variance	0.69	
σ_ϵ	Transitory variance	0.32	
σ_ξ	Persistent variance	0.02	
ρ	Persistence parameter	0.27	
$\bar{\rho}$	Pers. of intergen. skill transmission	0.40	Chetty et al. (2014)
	Commitments		
δ	Commitment depreciation	0.03	BEA
ζ	Commitment utility flow	0.06	Katz (2017)
θ	Collateral parameter (LTV)	0.80	Greenwald (2018)
χ	Maintenance cost	0.80	Berger and Vavra (2015)
	Preferences		
σ^c_R	CRRA for consumption when retired	1.10	Straub (2019)
o	Scale term in utility function	0.20	

The bequest utility function has two parameters. The curvature parameter $\sigma^b = 0.57$ governs how luxurious bequests are, and the weight parameter $\phi = 4.72$ controls their importance in lifetime utility. Because $\sigma^b < \sigma^c_j$ for all ages, bequests behave as a luxury good in the model. This way of generating luxury bequests differs from the Stone–Geary specifications used by De Nardi (2004) and Straub (2019). The calibrated curvature is close to the estimates in Gaillard et al. (2023) for their wealth-in-utility preferences. This similarity suggests that their "wealth in utility" term may be capturing forces akin to bequest motives in my model.

The weight assigned to housing in the CES goods aggregator, $\omega = 0.20$, is slightly lower than the ratio of shelter expenditure to total expenditure. The CES preference parameter implies an elasticity of substitution $1/(1-\gamma)$ of 0.79, implying that housing and nondurable consumption are complements. Lastly, the adjustment cost is $\kappa = 0.4$. This value is considerably higher than what has been found in the literature, such as by Berger and Vavra (2015).

Table 5: Endogenously Set Parameters

Parameters	**Description**	**Value**
β	Discount factor	0.84
σ_0^c	CRRA for consumption	4.09
σ^b	CRRA for bequest	0.57
ϕ	Bequest preference (weight)	4.72
ω	Consumption aggregator	0.20
γ	Goods Elasticity of Substitution	-0.26
κ	Adjustment cost	0.40

The parameters $\{\omega, \gamma, \kappa\}$ are particularly important for matching three housing-related moments: (i) the share of owners who have moved at least once in the past two years, (ii) the ratio of average shelter expenditure to average total expenditure, and (iii) the ratio of average housing wealth to average total wealth. The parameters $\{\beta, o, \sigma_0^c, \phi\}$ mainly discipline: (iv) the ratio of average wealth to average income, (v) bequests relative to aggregate income, (vi–viii) the elasticity of consumption with respect to permanent income across age groups, and (ix–xii) the response of consumption to current permanent income and past permanent income growth. Several moments, especially the consumption–permanent-income elasticities, load on more than one parameter, so there is no one-to-one mapping between individual parameters and specific moments.

Table 6 compares data and model moments. The calibration closely matches the consumption response to permanent income across age groups: the model slightly overstates the elasticity for ages 30–40 and slightly understates it for ages 50–60, while matching the overall decline with age. For path dependence, the model generates negative coefficients on past permanent income growth that are somewhat smaller in magnitude, especially for ages 40–50, but preserve the qualitative pattern documented in the data.

The model also reproduces key housing and wealth moments. It closely matches the homeowners' moving rate, the housing wealth-to-total wealth ratio, and the bequest-to-income ratio. It underpredicts the shelter expenditure share; matching the stock of housing wealth seems more important than the flow of shelter expenditure. Lastly, the model slightly overstates the wealth-to-income ratio.

Table 6: Calibrated Moments

Description	Data	Model
Moving rate of owners (past 2 years)	0.12	0.13
Ratio of shelter to total expenditure	0.25	0.14
Ratio of housing wealth to total wealth	0.47	0.54
Ratio of total wealth to income	5.92	6.88
Ratio of bequests to income	0.10	0.10
Consumption response to PI, age 30–40	0.92	1.05
Consumption response to PI, age 40–50	0.84	0.87
Consumption response to PI, age 50–60	0.72	0.70
Response to PI, age 40–50 (path-dependence spec)	1.09	0.89
to ΔPI, age 40–50 (path-dependence spec)	-0.39	-0.30
Response to PI, age 50–60 (path-dependence spec)	0.84	0.72
to ΔPI, age 50–60 (path-dependence spec)	-0.21	-0.24

6 The Role of Consumption Commitments in Consumption Responses

In this section, I assess the model's ability to account for the empirical facts documented in Section 3 and quantify the contributions of different mechanisms. To isolate each mechanism's role, I shut it down one at a time and recalibrate the discount factor β to keep the aggregate wealth-income ratio at its baseline level. Each calibration is evaluated by running the same regressions on simulated panels as in the data and comparing both targeted and untargeted moments. The targeted moments are the six facts on consumption responses to permanent income; the untargeted moments are the remaining empirical patterns in Section 3. The counterfactual analysis highlights the central role of consumption commitments in shaping consumption responses to permanent income, and also points to an important role for late-in-life luxury consumption and bequest motives.

Details on these alternative calibrations, the implied values of β, and the resulting endogenous moments are provided in Appendix I.

6.1 Consumption Responses to Permanent Income

I begin by evaluating the model's ability to generate the life-cycle pattern in the elasticity of consumption to permanent income, namely a high elasticity for young households and a decline with age–the pattern documented in Table 1. Figure 3, Panel (a) plots the PSID estimates (red dots), the baseline calibration (blue dots), and a homothetic benchmark with borrowing constraints but no non-homothetic mechanisms (no luxury late-in-life consumption, no bequest luxury) and no commitments (black stars). The leftmost points report the average consumption response for all working-age households (an untargeted moment); the remaining points report life-cycle elasticities for narrower age bins (targeted moments).

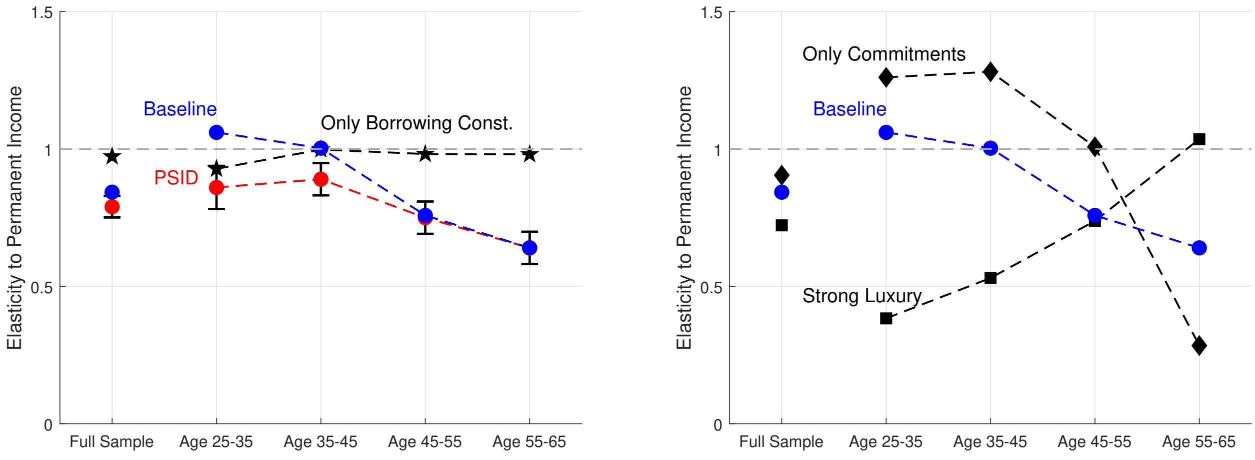
The baseline model reproduces both the average elasticity and the declining profile with age observed in the data, although it somewhat overstates the elasticity for households aged 25-35 and 35-45. By contrast, the homothetic benchmark with only borrowing constraints delivers an elasticity of approximately 1.0 at all ages and thus fails to match either the average response or the declining profile.

Next, I decompose the contributions of consumption commitments and luxury late-in-life consumption. Panel (b) of Figure 3 shows two additional counterfactuals. In the first, I shut down consumption commitments by setting $\kappa = 0$ and calibrate preferences as in Straub (2019), with $\sigma_0^c = 11$ and $\sigma^b = 2.5$; this "luxury-only" calibration is plotted with black squares. In the second, I shut down luxury late-in-life consumption by imposing $\sigma_0^c = \sigma_R^c = 2.5$ and keep commitments active; this "commitments-only" calibration is plotted with black diamonds. In both cases, β is recalibrated to match the baseline wealth–income ratio.

The commitments-only model generates a consumption response profile that declines with age, as in the data, but it substantially overpredicts the elasticity for young households and underpredicts it for older households. The luxury-only model fails by producing a counterfactual profile in which the elasticity increases with age, while simultaneously underpredicting the elasticity for young households and overpredicting it for older ones. The baseline calibration can be interpreted as combining these forces: commitments are essential to generate a downward-sloping age profile, while a moderate luxury motive helps temper the response at older ages. The remaining gap for young households is likely due to the relatively strong commitment frictions needed to match the path-dependence moments and housing/wealth moments.

In the commitments calibration, I keep the bequest-curvature parameter σ^b at its baseline

Figure 3: Consumption's Responses to Permanent Income – Data and Model



(a) Model vs. Data

(b) Mechanisms' Contributions

Note: In the figure, black stars, black diamonds, and black squares represent the models with homothetic preferences, consumption commitments, and late-in-life luxury consumption, respectively, while blue and red dots denote the baseline calibration and PSID data, respectively.

value. To obtain an average elasticity of consumption to permanent income below one, the model also needs diminishing returns to specific goods relative to a nearly constant marginal return to saving. In my setup, the former is generated by the complementarity between commitments and nondurables in the CES aggregator, while the latter is generated by the luxury bequest motive (low σ^b), which keeps the marginal value of additional saving high even at elevated wealth levels.

6.2 Consumption Responses to Current and Past Permanent Income

I now turn to the model's ability to generate path dependence in consumption responses, as in Table 2. Figure 4 plots the PSID estimates (red dots), the baseline calibration (blue dots), the homothetic benchmark (black stars), and the two mechanism-specific counterfactuals (black diamonds and black squares). The top panels display the elasticity with respect to current permanent income; the bottom panels display the elasticity with respect to 10-year permanent income growth.

The baseline calibration yields responses to past permanent income growth and life-cycle patterns that are qualitatively in line with the PSID estimates. It matches the magnitude of path dependence for older households reasonably well, but it understates it for younger households. These moments are targeted in the calibration. In contrast, the homothetic benchmark again fails to generate any path dependence: it yields an elasticity to current permanent income close to one and an elasticity to permanent income growth close to zero at all ages.

The panels on the right-hand side of Figure 4 show that neither the commitments-only nor the luxury-only model can, on its own, generate realistic path dependence. Both predict a positive dependence on permanent income growth–households with faster past growth consume more today–which is the opposite of what I find in the PSID. Intuitively, when only commitments are present, households with strong expected income growth upgrade their stock of hard-to-adjust goods aggressively early in life to smooth consumption over the lifecycle. Later on, the high flow of services from these commitments raises the marginal utility of nondurable consumption through complementarity, leading to higher rather than lower consumption today. A strong luxury motive alone generates a similar positive coefficient. Households with faster past permanent income growth initially depressed consumption to save for future consumption, thereby accumulating more wealth over time. This accumulated wealth in the past translates into higher consumption. Negative path dependence emerges only when both features interact, trapping households between accumulated commitments and aspirations for future luxuries.

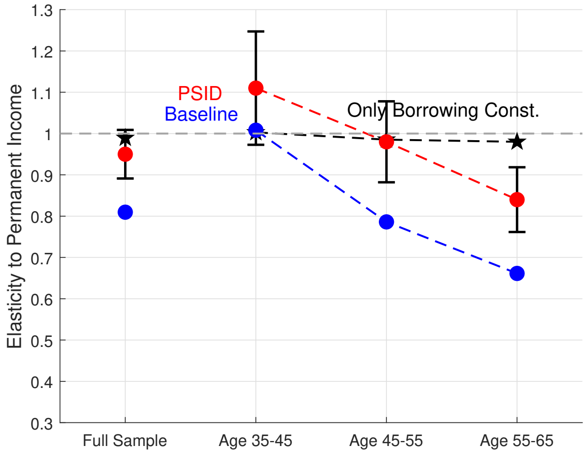
6.3 Expenditure Components

I next assess the model's performance in capturing the behavior of expenditure shares across categories and their elasticities with respect to current total expenditure and past expenditure growth, as in Table 3 and Figure 1. None of these moments is included in the calibration, so they serve as an additional, untargeted test of the model.

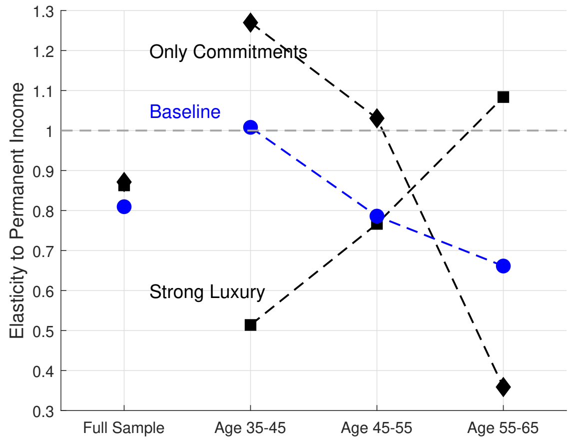
The top panels of Figure 5 report the estimated Engel elasticities for nondurable and housing expenditures. Because goods are aggregated using CES preferences, category expenditures are homothetic and have Engel elasticities close to one. Indeed, the homothetic model (black stars) generates approximately unitary Engel elasticities for both nondurables and housing. By contrast, the PSID data (red dots) show that nondurables have an Engel elasticity significantly below one, while housing has an elasticity above one. The baseline model (blue dots) closely matches the high Engel elasticity for housing but still slightly overpredicts the elasticity for nondurables.

The right-hand top panel decomposes the contributions of individual mechanisms. Both the commitments-only model (black diamonds) and the luxury-only model (black squares) move the Engel curves in the right direction relative to the homothetic benchmark: they tend to lower the elasticity for nondurables and raise it for housing. However, neither mechanism alone is sufficient to match the observed magnitudes. The baseline calibration, which combines both mechanisms with borrowing constraints, delivers the best overall fit.

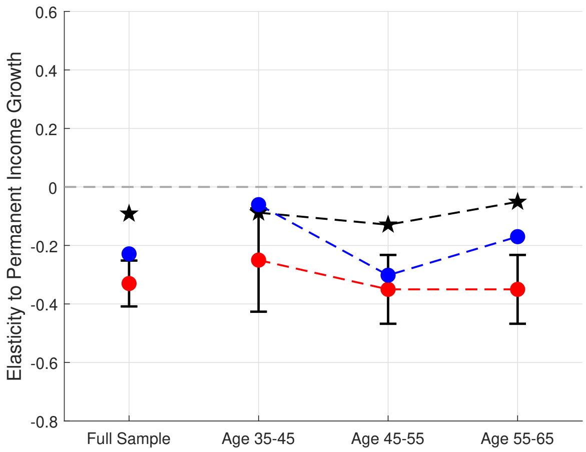
Figure 4: Consumption's Responses to Current and Past Permanent Income – Data and Model



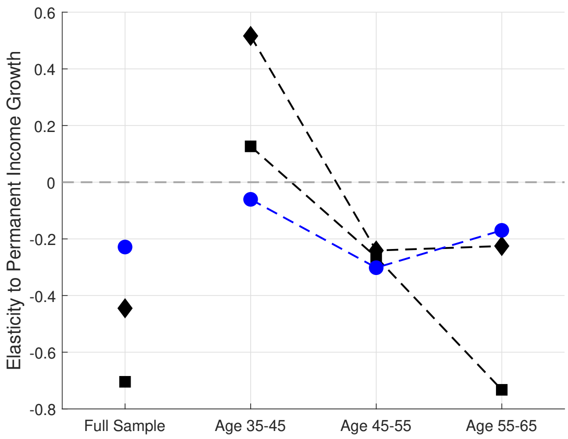
(a) Model vs. Data



(b) Mechanisms' Contributions



(c) Model vs. Data

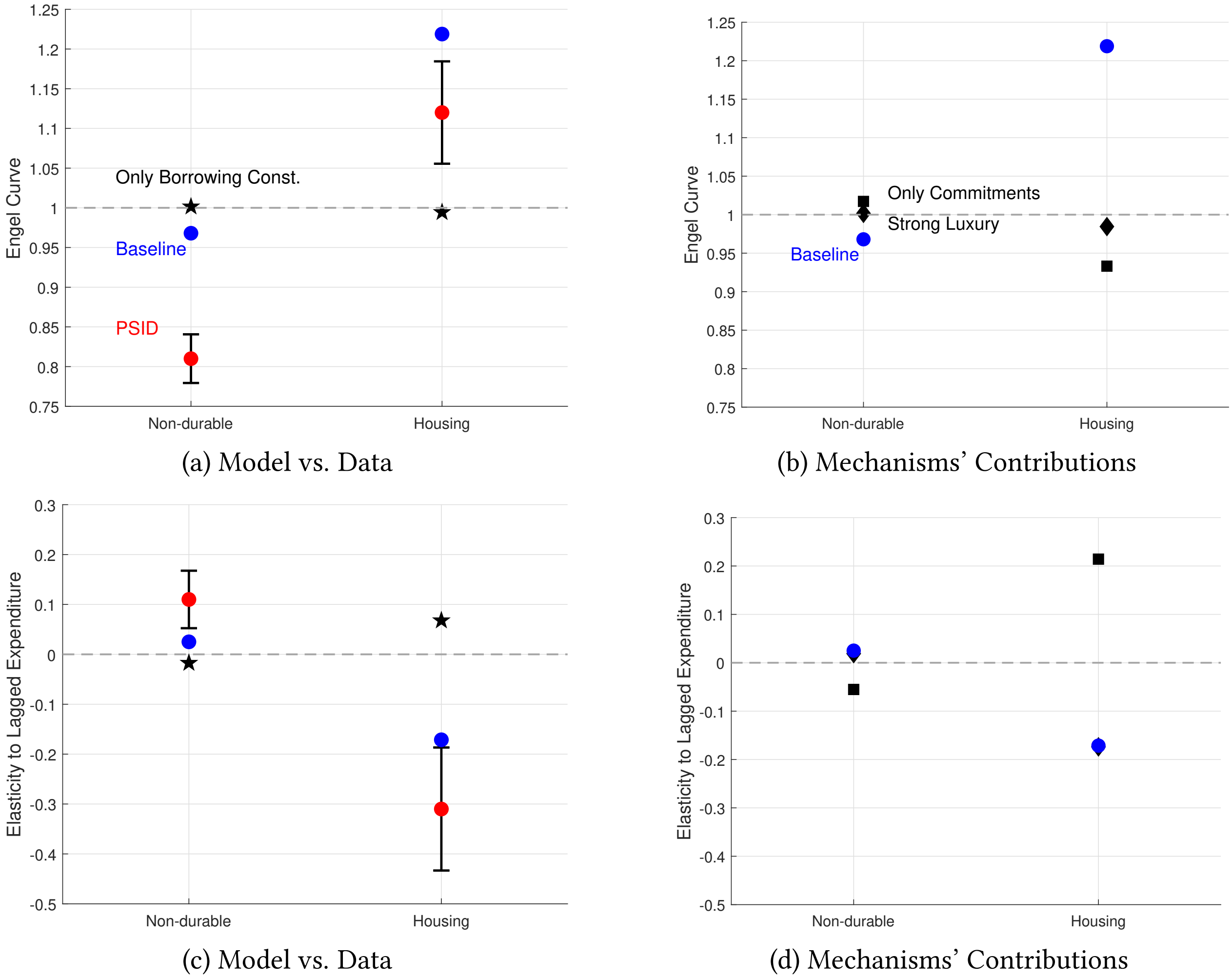


(d) Mechanisms' Contributions

Note: In the figure, black stars, black diamonds, and black squares represent the models with homothetic preferences, consumption commitments, and late-in-life luxury consumption, respectively, while blue and red dots denote the baseline calibration and PSID data, respectively.

The bottom panels of Figure 5 examine the elasticity of category expenditures to past total expenditure growth. The PSID data exhibit a negative elasticity for housing: households with faster past growth in total expenditure allocate a smaller share to housing today and a larger share to nondurables, consistent with the consumption-commitment mechanism documented in Section 3. The baseline model qualitatively replicates the negative response of housing shares to past expenditure growth, though it does not fully match the magnitude. The homothetic benchmark completely misses this pattern. The bottom right panel shows that neither commitments nor luxury effects alone can reproduce the sign and magnitude of the elasticities; again, the interaction of mechanisms is key.

Figure 5: Consumption Category Shares – Data and Model



Note: In the figure, black stars, black diamonds, and black squares represent the models with homothetic preferences, consumption commitments, and late-in-life luxury consumption, respectively, while blue and red dots denote the baseline calibration and PSID data, respectively.

6.4 Consumption Resets

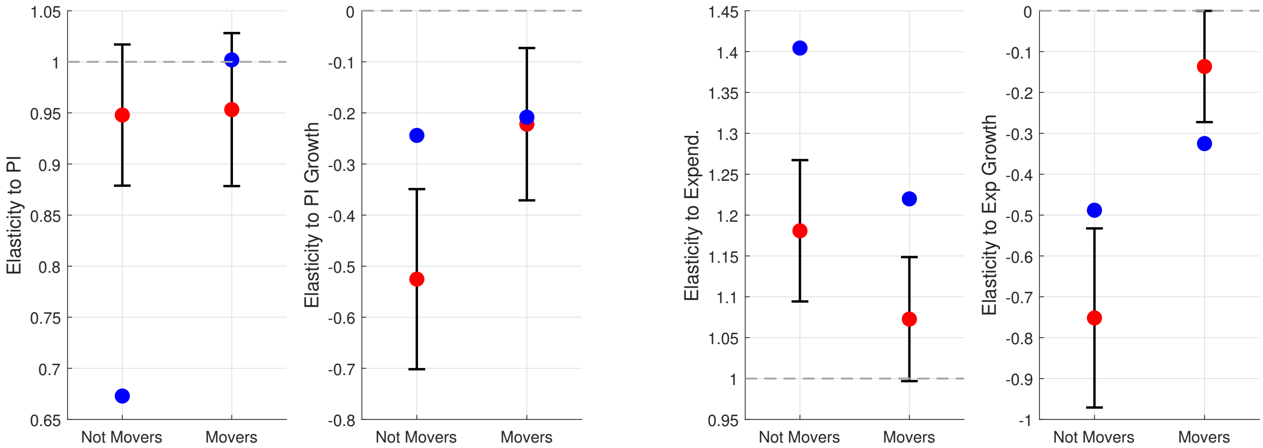
Finally, I assess how well the baseline model reproduces the differences between movers and non-movers documented in Tables 6 and 7. These facts were not directly targeted in the calibration, so they provide an additional out-of-sample validation of the role of commitments.

Figure 6, Panel (a) shows that, in both the model and the data, movers display a strong response of consumption to current permanent income and a weaker response to past permanent income growth. The baseline model captures this qualitative pattern and matches the difference between movers and non-movers reasonably well, although it slightly understates the dependence on past permanent income growth for non-movers.

Panel (b) reports the responses of shelter expenditure shares. The model successfully reproduces the higher sensitivity of movers' shelter shares to current expenditure and the weaker dependence on past expenditure growth, consistent with the idea that movers are actively re-optimizing their consumption bundle. For non-movers, the model generates the negative response of shelter shares to past growth, indicating that it captures the rigidity induced by commitments for households who do not move.

Overall, the baseline model aligns well with the key patterns observed in the PSID data. It reproduces the stronger dependence of non-movers' behavior on past permanent income and expenditure growth, and the greater sensitivity of movers' behavior to current conditions. These results further reinforce the importance of consumption commitments in shaping consumption dynamics and in generating the under-response of consumption to permanent income documented in Section 3.

Figure 6: Responses for Movers and Non-Movers – Data and Model



(a) Consumption's Responses (b) Shelter Shares

7 Aggregate Implications

The previous sections showed that the baseline calibration match the micro-level evidence on consumption responses to permanent income and to its past trajectory. I now ask whether the same mechanisms that help the model fit these responses also generate realistic cross-sectional inequality in income, consumption, and wealth.

Table 7 reports Gini indices and the aggregate wealth–income ratio in the PSID and in four model calibrations. The income process is held fixed across all calibrations and is externally disciplined by PSID earnings dynamics. In each model variant, I recalibrate the discount factor β to keep the aggregate wealth–income ratio at its baseline level, so differences in inequality are driven by preference and commitment mechanisms rather than by changes in average wealth.

The first row reproduces the PSID moments. Income is more unequal than consumption, and wealth is substantially more concentrated than either, with income Gini of 0.44, consumption Gini of 0.32, and wealth Gini of 0.82. The implied wealth–income ratio is 5.92. These numbers should be interpreted relative to the PSID sample frame, which is broadly representative of the 5th–95th percentiles but under-represents the extreme upper tail where wealth concentration is highest.[16]

The baseline model reproduces these broad patterns well. It preserves the ranking Income Gini $>$ Consumption Gini and generates a wealth Gini of 0.84, close to the PSID value of 0.82, together with a wealth–income ratio of 6.88. Consumption inequality is slightly higher than in the data (0.36 vs. 0.32), but the model remains within a reasonable range while delivering the desired wealth concentration.[17]

The remaining rows in Table 7 show that generating realistic cross-sectional inequalities is not automatic. In the homothetic benchmark with only borrowing constraints, the model reproduces the income and consumption Gini coefficients and is calibrated to the same aggregate wealth–income ratio. However, it generates too little wealth inequality (wealth Gini of 0.78 vs. 0.82 in the PSID). This is a familiar limitation of incomplete-markets models with homothetic preferences: they struggle to generate sufficient wealth dispersion.

The two "single-mechanism" calibrations help isolate the contribution of luxury late-in-life consumption and consumption commitments. In the calibration with strong luxury late-in-life motives but no commitments, wealth becomes very concentrated (wealth Gini of 0.87 vs. 0.82 in the PSID), but at the cost of counterfactually large dispersion in consumption (consumption Gini of 0.52 vs. 0.32 in the PSID). Households accumulate substantial assets to finance high late-life consumption; as they decumulate, the model produces excessive cross-sectional spread in

[16]The PSID does not fully capture the very top of the wealth distribution. My mechanism should therefore be understood as operating within the part of the distribution for which I observe reliable data. The model also abstracts from heterogeneity in asset returns. This margin appears empirically important for explaining the very top of the wealth distribution; see, for example, Benhabib and Bisin (2018), Kuhn, Schularick, and Steins (2020), Hubmer, Krusell, and Smith Jr (2021), and Xavier (2024).

[17]A related point is made by Gaillard et al. (2023), who show that quantitative heterogeneous-agent models struggle to jointly match the tails of the income, consumption, and wealth distributions. Their approach introduces non-homothetic preferences by allowing wealth to enter utility directly. Interestingly, the curvature parameter on the asset utility term in their specification is quantitatively similar to the curvature of my bequest motive.

consumption in old age.

In the calibration with commitments but without the luxury late-in-life mechanism, wealth is again highly concentrated (wealth Gini of 0.88 vs. 0.82 in the PSID), while consumption inequality rises modestly relative to the data (0.40 vs. 0.32 in the PSID). In this case, the non-convex adjustment costs and collateral channel associated with commitments strengthen the link between permanent income and wealth accumulation, but without the strong luxury late-life motive, they do not generate the same extreme dispersion in consumption.

Taken together, these experiments show that the full baseline model is needed to jointly match the micro and aggregate evidence. Borrowing constraints alone cannot generate enough wealth inequality; luxury late-in-life preferences alone generate too much consumption inequality; and commitments alone push wealth concentration beyond what is observed in the data. The baseline calibration, which combines consumption commitments with a moderate luxury motive and bequest preferences, delivers realistic wealth concentration while keeping consumption inequality close to the data. This suggests that the same forces that attenuate households' consumption responses to permanent income at the micro level are also important for understanding the joint distribution of income, consumption, and wealth in the cross-section.

Table 7: Distributional Implications

	Income Gini	Consum. Gini	Wealth Gini	Wealth-Income
PSID	0.44	0.32	0.82	5.92
Baseline	0.47	0.36	0.84	6.88
Only Borrowing Constraints	0.47	0.38	0.78	6.88
Only Luxury late-in-life	0.47	0.52	0.87	6.88
Only Commitments	0.47	0.40	0.88	6.88

8 Conclusion

In this paper, I provide empirical and quantitative evidence that consumption commitments help explain why consumption responds less than one-for-one to permanent income. Using PSID data, I show that consumption elasticities with respect to permanent income decline with age, depend on past income trajectories, differ across expenditure categories, and vary with recent housing adjustment. A life-cycle model with lumpy adjustment of a hard-to-adjust good can replicate these patterns. In the calibrated model, commitments are necessary to generate life-cycle decline and path dependence in consumption responses, while luxury late-in-life consumption and bequest motives are also quantitatively important. Taken together, the evidence suggests that consumption commitments are a key missing ingredient in standard models of household behavior.

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A Data Construction and Sample Description

This appendix describes the construction of key variables and the sample-selection criteria. Table 8 reports descriptive statistics for the final sample.

Consumption and expenditures. The baseline consumption measure sums all PSID expenditure categories consistently available since 1999 and closely follows Kaplan et al. (2014), Blundell et al. (2016), and Aguiar et al. (2020). It includes spending on food, utilities, transportation, medical expenses, childcare and education, insurance, vehicle repairs, and shelter. It captures consumption by incorporating service flows from housing and vehicle ownership. For homeowners, shelter is measured as implicit rent equal to 6 percent of the self-reported house value. For renters, shelter equals reported rent payments. For vehicle owners, vehicle services are imputed as 10 percent of vehicle net worth.

I also consider three alternative measures. First, nondurable consumption excludes shelter and vehicle service flows, while retaining insurance and vehicle repairs, which primarily reflect relatively flexible service expenditures. Second, I construct a broad measure that augments the baseline with additional spending categories available from the 2005 wave onward–home repairs, home furnishings, clothing, vacations, recreation, telecommunications, and donations. Third, I construct an expenditure (cash-flow) measure that replaces service flows with out-of-pocket housing and vehicle payments: housing includes rent, mortgage payments, and property taxes, and vehicle spending includes down payments, lease payments, loan payments, and other vehicle-related costs.

Table 8 shows that mean baseline expenditures correspond to 58.5 percent of mean total after-tax income. Under the broad measure (available since 2005), this ratio rises to 74.6 percent. These magnitudes are close to those reported by Aguiar et al. (2020) (58.3 percent and 73.2 percent, respectively).

Earnings. My baseline income measure is household after-tax labor income, defined as labor earnings of the household head and spouse/partner (if present) plus government transfers, net of payroll taxes. Labor earnings include wage and salary income and the labor component of income from unincorporated businesses, while excluding business and farm asset income. Transfers include AFDC, Supplemental Security Income, other welfare programs, unemployment benefits, workers' compensation, and Social Security benefits. Payroll taxes are imputed using the NBER TAXSIM model.

For robustness, I construct a broader after-tax income measure that adds asset income and nets out payroll taxes and federal and state income taxes. Asset income includes income from businesses and farms, dividends, interest, rents, trust funds, and royalties. Following Aguiar et al. (2020), I also include implicit rent (6 percent of assessed home value) as a component of income. All taxes are estimated using NBER TAXSIM.[18]

Wealth. My baseline wealth measure is household net worth, which aggregates both liquid and illiquid components. Net liquid wealth is defined as liquid assets minus liquid debt. Following Kaplan et al. (2014) and Aguiar et al. (2020), liquid assets include balances in checking and savings accounts–including money market funds, certificates of deposit, government bonds, and Treasury bills–as well as stocks–publicly traded stocks, stock mutual funds, and investment trusts. Liquid debt includes all non-mortgage liabilities, such as credit card balances, student loans, medical or legal bills, and loans from relatives. Net worth equals net liquid wealth plus net illiquid wealth. Net illiquid wealth consists of home equity (home value net of outstanding mortgage debt) and the net value of other real estate holdings, private businesses, farms, vehicles, and retirement assets such as IRAs and other pensions.

As a robustness check, I use the PSID pension modules to construct a more comprehensive wealth measure that incorporates employer-provided defined-contribution retirement accounts, following Cooper et al. (2019).

Sample Description. Table 8 reports summary statistics by wealth quartile. Wealthier households are older, more educated, and more likely to be married and to be homeowners. Wealth is highly skewed: the bottom quartile has a negative average net worth, while the top quartile holds most assets and has higher permanent income. Income and expenditures both increase with wealth, but expenditures rise more slowly, consistent with higher saving rates at the top.

[18] In the PSID, when the head or partner reports working any hours in a business or farm, the survey mechanically splits reported business/farm income into equal labor and asset components. For TAXSIM inputs, I follow Kimberlin, Kim, and Shaefer (2014) and classify both components as wages and salaries rather than property income.

Table 8: Sample Description

Networth Distribution Quartiles	Q1	Q2	Q3	Q4	Total
Demographics					
Age	40.04	41.71	44.96	50.49	45.02
Man	0.59	0.65	0.75	0.86	0.73
W/ College or more	0.26	0.19	0.28	0.51	0.33
Married	0.31	0.39	0.59	0.75	0.54
HH Size	2.24	2.38	2.65	2.65	2.50
House Ownership	0.21	0.34	0.82	0.94	0.64
Fraction HH Moved Last 2 Years	0.51	0.44	0.24	0.15	0.31
Wealth and Financial Variables (mean)					
Home Equity	-0.66	5.74	49.10	231.83	88.81
House Value	28.49	34.01	133.06	361.78	163.56
Networth	-26.89	13.82	83.79	881.23	305.29
Networth + DC accounts	-21.48	20.62	117.32	963.58	343.03
Permanent Income	599.07	616.81	885.01	1,608.28	1,030.47
Wealth and Financial Variables (median)					
Home Equity	0.00	0.00	44.71	166.87	21.27
House Value	0.00	0.00	118.61	285.08	91.23
Networth	-6.19	10.49	76.84	405.99	55.62
Networth + DC accounts	-4.17	12.54	89.08	465.25	67.13
Permanent Income	471.64	496.14	791.50	1,469.43	837.13
Income and Expenditures					
Labor and Transfers Income	37.51	39.94	61.50	92.35	61.62
Total Income	34.60	37.10	60.26	100.56	62.99
Total Expenditure (cat. 1999)	25.31	26.02	35.06	53.20	36.84
Total Expenditure (cat. 2005)	32.06	31.52	44.74	69.15	47.00
Shelter Expenditure	7.78	7.58	10.23	22.74	13.20

Note: This table reports summary statistics for households across quartiles of the wealth distribution. All demographic variables refer to the household head. All variables represent means except when otherwise noted. All monetary values are reported in thousands of dollars as of 2007 and deflated using the CPI.

B Measurement Error in Income

This appendix motivates the use of instrumental variables (IV) to address measurement error in permanent income (PI). Because PI is constructed by forecasting income over many periods from an initial survey income measure, noise in measured income can propagate into PI and attenuate OLS estimates of the consumption response.

Let observed log income be

$$y_t = y_t^* + v_t,$$

where y_t^* is true log income and v_t is classical measurement error: $E[v_t \mid y_t^*] = 0$ and v_t is independent of y_t^*.

To understand how measurement error enters PI, consider the AR(1) forecasting step in logs. Using information at date t, the j-period-ahead forecast is

$$\widehat{y}_{t+j} = \rho^j y_t = \rho^j (y_t^* + v_t).$$

In levels,

$$\widehat{Y}_{t+j} = \exp(\widehat{y}_{t+j}) = \underbrace{\exp(\rho^j y_t^*)}_{\widehat{Y}_{t+j}^*} \cdot \exp(\rho^j v_t).$$

Define the empirical PI measure as a discounted sum of forecasts,

$$\widehat{\mathrm{PI}}_t = \sum_{j=1}^{J} \frac{\widehat{Y}_{t+j}}{R^j} = \sum_{j=1}^{J} \frac{\widehat{Y}_{t+j}^* \exp(\rho^j v_t)}{R^j}.$$

Using the first-order approximation $\exp(\rho^j v_t) \approx 1 + \rho^j v_t$ (which is valid when $|\rho^j v_t|$ is small),

$$\widehat{\mathrm{PI}}_t \approx \underbrace{\sum_{j=1}^{J} \frac{\widehat{Y}_{t+j}^*}{R^j}}_{\widehat{\mathrm{PI}}_t^*} + v_t \underbrace{\sum_{j=1}^{J} \left(\frac{\rho}{R}\right)^j \widehat{Y}_{t+j}^*}_{f(y_t^*)}.$$

Thus, up to first order, $\widehat{\mathrm{PI}}_t = \widehat{\mathrm{PI}}_t^* + v_t f(y_t^*)$. Since $f(y_t^*)$ depends on y_t^*, the error component is correlated with the regressor, implying attenuation bias in OLS regressions of $\log C_t$ on $\log \widehat{\mathrm{PI}}_t$.

Under classical measurement error, y_t^* is uncorrelated with v_t. Hence, any instrument correlated with y_t^* but independent of v_t identifies the effect of PI on consumption. I use (i) income reported in adjacent surveys (e.g., y_{t-1}) and (ii) industry indicators as instruments. Lagged income is correlated with y_t^* through income persistence and is orthogonal to current measurement error if measurement error is not serially correlated across adjacent surveys. Industry indicators shift expected income profiles and are valid instruments if, conditional on controls, they affect consumption only through permanent income.[19]

The same logic applies to $\log \widehat{\text{PI}}_t$. A first-order expansion yields

$$\log \widehat{\text{PI}}_t = \log\Big(\widehat{\text{PI}}_t^* + v_t f(y_t^*)\Big) = \log \widehat{\text{PI}}_t^* + \log(1 + v_t g(y_t^*)) \approx \log \widehat{\text{PI}}_t^* + v_t\, g(y_t^*),$$

where $g(y_t^*) = f(y_t^*)/\widehat{\text{PI}}_t^*$. Because f discounts the measurement-error component by $(\rho/R)^j$ while $\widehat{\text{PI}}_t^*$ discounts levels by R^{-j}, the term $v_t g(y_t^*)$ is dominated by short-horizon forecasts and is typically small in magnitude; therefore the first-order (additive) approximation is a reasonable local approximation.

[19]Using PSID data, Pfeffer and Griffin (2015) study predictors of extreme changes in measured wealth and show that demographic variables account for a larger share of the variation than indicators of measurement issues. Their measurement-issue indicators include (i) whether wealth contains imputed components and (ii) changes in the interview respondent across waves (e.g., the head in one wave and the spouse in another). Thus, while measurement error may remain, measurement issues seem second-order to explaining permanent income growth.

C Quality of the Expected Income Measure

I construct household permanent income by forecasting an expected path of after-tax labor income using information observed at time t. A natural concern is that households may have additional information about future income that the econometrician does not observe. If so, the forecast-based PI measure could be systematically biased for some households (e.g., underpredicting PI for low-income households or overpredicting PI for high-income households). This appendix assesses forecast quality using out-of-sample forecast errors.

Let the h-step-ahead forecast error be

$$\epsilon_{i,t+h}^{t} \equiv y_{i,t+h} - \hat{y}_{i,t+h}^{t},$$

where $\hat{y}_{i,t+h}^{t}$ is the forecast formed at t using the econometrician's information set. All forecast errors are computed out of the estimation sample used to fit the forecasting model.

Test 1: Unconditional forecast errors. Table 9 summarizes realized income, forecasts, and forecast errors by horizon. Mean forecast errors are small (about 0.01–0.02), while dispersion increases with the horizon, as expected for multi-step forecasts (Diebold, 2017). The number of observations declines with h due to panel attrition.

Test 2: Calibration and information content. I first estimate Mincer-Zarnowitz calibration regressions for each horizon,

$$y_{i,t+h} = \alpha_0 + \alpha_1 \hat{y}_{i,t+h}^{t} + u_{i,t+h}.$$

A perfectly calibrated forecast satisfies $(\alpha_0, \alpha_1) = (0, 1)$. Table 10 shows that α_1 is close to one across horizons and that the forecasts explain a substantial share of realized income variation, although predictive power declines with h.

I then test whether variables observed at t proxying for households' information predict future income beyond the forecast. In particular, I estimate

$$y_{i,t+h} = \alpha_0 + \alpha_1 \hat{y}_{i,t+h}^{t} + \alpha_2 c_{i,t} + u_{i,t+h},$$

Table 9: h-Step-Ahead Forecast Errors

	Mean	Std. Dev.	Count
$y_{i,t+2}$	10.77	0.93	43773
$y_{i,t+4}$	10.79	0.94	35190
$y_{i,t+6}$	10.81	0.96	27904
$y_{i,t+8}$	10.82	0.96	21821
$y_{i,t+10}$	10.82	0.97	16601
$\hat{y}^t_{i,t+2}$	10.76	0.74	43773
$\hat{y}^t_{i,t+4}$	10.77	0.68	35190
$\hat{y}^t_{i,t+6}$	10.78	0.65	27904
$\hat{y}^t_{i,t+8}$	10.79	0.64	21821
$\hat{y}^t_{i,t+10}$	10.80	0.63	16601
$\epsilon^t_{i,t+2}$	0.01	0.56	43773
$\epsilon^t_{i,t+4}$	0.02	0.65	35190
$\epsilon^t_{i,t+6}$	0.02	0.71	27904
$\epsilon^t_{i,t+8}$	0.02	0.75	21821
$\epsilon^t_{i,t+10}$	0.02	0.78	16601

Table 10: Income Growth Forecast Equation

	$y^t_{i,t+2}$	$y^t_{i,t+4}$	$y^t_{i,t+6}$	$y^t_{i,t+8}$	$y^t_{i,t+10}$
$\hat{y}^t_{i,t+j}$	1.01	1.00	0.96	0.92	0.90
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Constant	-0.06	0.10	0.48	0.90	1.12
	(0.08)	(0.11)	(0.14)	(0.18)	(0.21)
N	43586	35110	27885	21804	16589
R^2	0.6352	0.5107	0.4353	0.3771	0.3443

where $c_{i,t}$ is log consumption at time t. Under forecast orthogonality, $\alpha_2 = 0$ (Diebold, 2017). Also, current consumption should embody household information under the PIH, so $\alpha_2 \geq 0$ would indicate superior household information about future income. Table 10 shows $\alpha_2 > 0$, implying that current consumption contains some incremental information about future income. However, the increase in fit from adding $c_{i,t}$ is modest, indicating that the forecast already captures most predictable variation in income.

Correcting attenuation in the forecast regressor. Because $\hat{y}^t_{i,t+h}$ is constructed from survey income, it may be measured with error (Appendix B), biasing α_1 toward zero and inflating the apparent role of consumption. Table 10 re-estimates the previous specification by IV, instrumenting the income forecast with lagged income and industry indicators. After instrumenting, α_1 increases (typically to around one) and α_2 declines substantially. Overall, households may possess some superior information, but its quantitative contribution to forecasting income appears limited, suggesting forecast-based PI bias cannot explain the under-consumption puzzle.[20]

[20]Consumption remains exogenous in this specification because households base decisions on their true expectations $\hat{y}^{t,*}_{i,t+h}$, not on survey measurement error $\eta_{i,t}$ where $\hat{y}^{t}_{i,t+h} = \hat{y}^{t,*}_{i,t+h} + \eta_{i,t}$. Under classical measurement error, $\eta_{i,t}$ is uncorrelated with the true forecast and future income realizations. Since consumption reflects the true forecast but not measurement error or future shocks, instrumenting only the mismeasured forecast yields consistent estimates of both α_1 and α_2.

D Asset Accumulation

So far, I have documented novel facts about households' consumption A central finding of the paper is that expenditures rise less than one-for-one with permanent income. By the household budget constraint, the "missing" spending must appear as higher asset accumulation. This appendix provides two complementary checks that support this interpretation and alleviate concerns that the main results are driven by expenditure mismeasurement.

Constructing net worth from income and expenditures. As a data-consistency check, I construct an alternative net-worth series implied by reported income and out-of-pocket expenditures and compare it to reported PSID net worth. If both net worth measures systematically differ, then the quality of the PSID data should be questioned, and mismeasurement of expenditure is likely a problem.

The budget constraint implies

$$A_T - A_0 = \sum_{t=0}^{T-1}(Y_t - C_t) + \sum_{t=0}^{T-1} r_t A_t. \tag{9}$$

I iterate (9) using reported income and expenditures, together with asset-class return assumptions described in the footnote.[21]

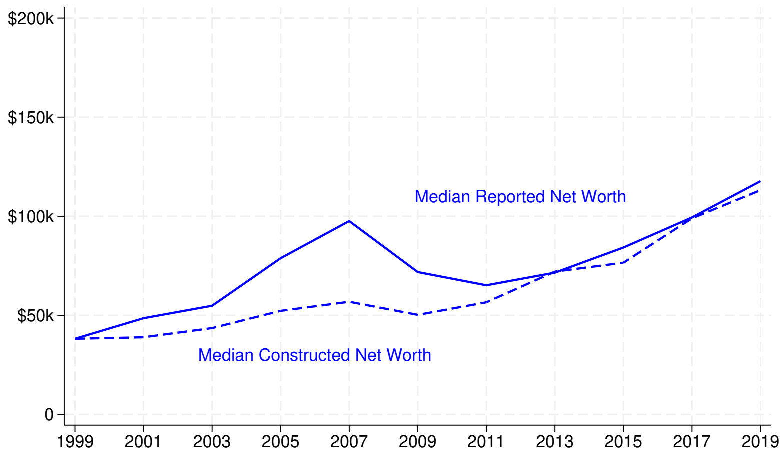
Figure 7 shows that the constructed series closely tracks reported net worth over time, supporting the internal consistency of reported income, expenditures, and wealth in the PSID. The main discrepancy occurs around the 2008 financial crisis, plausibly reflecting heterogeneity in realized returns at the top of the wealth distribution.

Figure 8 repeats the exercise by permanent-income growth over the 20-year window and yields two conclusions. First, it is immediately apparent from both panels that the series is closely

[21] I measure Y_t and C_t using total income and out-of-pocket expenditures. Total income includes asset income (business and farm income, dividends, interest, rents, trust funds, and royalties). Out-of-pocket expenditures measure housing and vehicles using actual payments (e.g., mortgage payments), rather than implicit rent. I assign returns by asset type: home equity/real estate/business/farm returns use the CPI-deflated change in the S&P Case-Shiller U.S. National Home Price Index; stock returns use the CPI-deflated change in the Wilshire 5000 Price Index (price component); IRA returns are set to 5% annually; vehicles depreciate at 15% annually; checking/savings earn the Fed funds rate; "other debt" accrues 10% annually. I assume net saving flows into home equity; results are similar if flows are directed to private pension accounts.

I restrict attention to households observed in all PSID waves for 20 years. Because the PSID is biennial, I approximate $(Y_t - C_t) + (Y_{t+1} - C_{t+1}) \approx 2(Y_t - C_t)$. Since the PSID categories available in every wave since 1999 cover about 70% of C.E./NIPA spending (Andreski, Li, Samancioglu, and Schoeni, 2014), I scale consumption by $C_t/0.70$.

Figure 7: Asset Path Implied by Expenditure and Income



Note: This figure depicts the path of reported net worth and constructed net worth measures of households in the PSID. Reported net worth refers to the net worth that respondents report when answering the questions in the PSID. Constructed net worth refers to the net worth constructed using respondents' reported income and expenditures. In total, I follow 1,262 households. More details on the construction are given in the main text. The median reported net worth is the solid blue line, and the median constructed net worth is the dashed blue line.

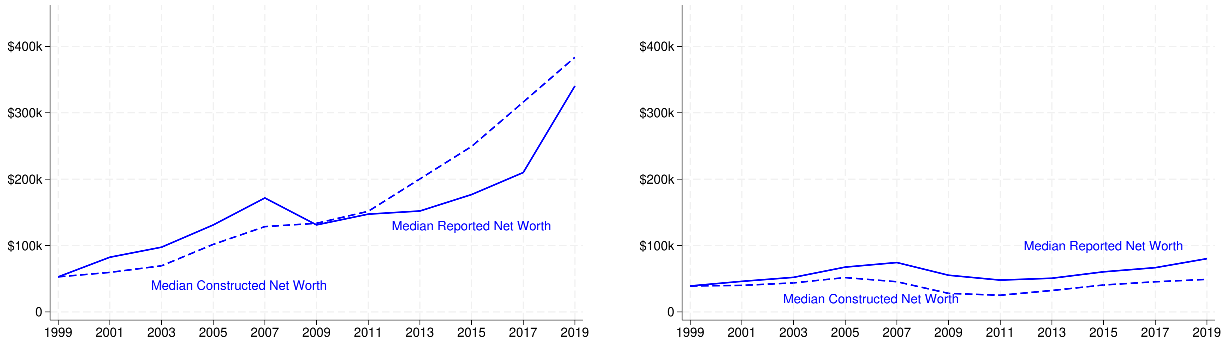
linked, confirming that the PSID is accurate and reliable in measuring life-cycle household behavior. Second, both groups begin at similar starting points, but households that experienced permanent income growth accumulated more wealth than those that did not, consistent with the results on consumption responses.

Active saving. I next ask whether the path-dependence patterns documented for consumption also appear in saving behavior. I construct a measure of active saving from PSID Wealth Module questions and define the active saving rate as active saving divided by labor income. Active saving is a flow measure that excludes capital gains and valuation changes, thereby capturing deliberate changes in asset positions.[22]

Table 11 reports IV estimates of the saving-rate elasticity to permanent income. The saving rate rises with current permanent income and is higher for households with stronger past permanent-income growth, even after controlling for current permanent income (Column 3). Because active saving is constructed from a distinct set of survey questions, these results reinforce the interpretation that the main findings reflect real behavior rather than expenditure mismea-

[22]Following Hurst, Luoh, and Stafford (1998), active saving is the sum of: (i) net inflows into stocks, (ii) changes in vehicle equity, (iii) net changes in transaction accounts, (iv) net inflows to business equity, (v) net inflows to annuities, (vi) home improvements, and (vii) net inflows into real estate other than the main home, minus increases in uncollateralized debt. Only home-equity changes classified as home improvements are included in active saving.

Figure 8: Asset Path Implied by Expenditure and Income



(a) Positive PI growth

(b) Negative PI growth

Note: This figure depicts the path of reported net worth and constructed net worth measures of households in the PSID. I divide the sample into households that experienced positive permanent income growth over 20 years and those that did not. Reported net worth refers to the net worth that respondents report when answering the questions in the PSID. Constructed net worth refers to the net worth constructed using respondents' reported income and expenditures. In total, I follow 1,090 households, with 607 negative growth and with 359 positive growth. The difference between the previous figure sample is that I restrict the selection to those for whom I observe permanent income both when I start following them and 20 years later. More details on the construction are given in the main text. The median reported net worth is the solid blue line, and the median constructed net worth is the dashed blue line.

surement or measurement error.

Table 11: Savings Response to Permanent Income

	(1) Savings Rate	(2) Savings Rate	(3) Savings Rate
log(PI)	0.18	0.15	0.06
	(0.02)	(0.03)	(0.04)
Δ log(PI)			0.16
			(0.06)
Educ Dummies	Y	Y	Y
KP-F test	723.6	385.6	153.6
Observations	49,585	14,613	14,613

Note: This table reports the estimated savings rate elasticity to permanent income using instrumental variables. The excluded instruments are log expenditure and industry dummies (or their lagged values in specifications with lagged permanent income). The saving rate is measured from active saving questions in the PSID, not constructed as $(Y - C)/Y$, eliminating mechanical correlation with the expenditure instrument. Results are robust to using lagged income and industry dummies as instruments instead. Controls include cubic polynomials in age, dummies for marital status, family size, census region, education, and year fixed effects (lagged controls included when using lagged permanent income). Standard errors are calculated using a bootstrap with 100 replications. All estimates use sampling weights. The foot of the table reports the number of observations and Kleibergen-Paap F statistic.

E Alternative Measurement Choices

This appendix reports robustness checks to choices in the construction of permanent income (PI), expenditures, wealth, and the estimation sample. To keep the presentation compact, I re-estimate a common set of headline coefficients from the main text: (i) the average elasticity from OLS (Table 1, Col. 1, but estimated by OLS), (ii) the average elasticity from IV (Table 1 Col. 1), (iii) the elasticity for young and old households (Table 2, Cols. 2 and 5), and (iv) the average elasticity and the path-dependence estimate (Table 2, Rows 1-2).

Two patterns emerge. First, the level of the average elasticity varies with PI and expenditure definitions and, in some cases, approaches 1, but the qualitative facts–life-cycle decline and path dependence–remain. Second, elasticities are smaller for narrower expenditure measures and larger for broader measures that include luxury categories. By contrast, alternative wealth measures and sample restrictions have little effect on the estimates.

Alternative Permanent Income Measures Table 12 varies the PI construction. The baseline uses an AR(1) forecasting rule for after-tax labor income. I then allow forecasting parameters to vary by industry or occupation, replace labor income with total income, and consider an AR(2). Lastly, I propose a procedure that uses out-of-sample forecast errors to adjust permanent income for systematic misforecasting at the household level.[23]

Across specifications, OLS elasticities remain below one, while IV elasticities are larger, consistent with attenuation from measurement error in PI. The life-cycle pattern generally persists, although allowing industry- or occupation-specific forecasting parameters tends to flatten the profile at older ages. Most importantly, the path-dependence estimate is stable: past income trajectories continue to predict current consumption responses conditional on current PI.

[23] As an additional robustness exercise (available upon request), I construct an alternative measure of permanent income that partially corrects for systematic misforecasting at the household level. In the baseline procedure, a household's income may be consistently mispredicted if the earnings profile includes individual-specific components. To capture this idea in a transparent way, I implement a two-step correction: (i) I generate out-of-sample income forecasts and compute realized forecast errors, and (ii) I augment the forecasting equation with each household's mean realized forecast error–a household-specific correction term that shifts the entire predicted path. This procedure is not mathematically equivalent to estimating the forecasting equation with household fixed effects, which would require a dynamic-panel estimator in the spirit of Arellano-Bond. Empirically, the two core patterns—the decline of the elasticity with age and the negative dependence on past permanent-income growth—are robust to this alternative permanent income measure, while the average level of the consumption elasticity is sensitive.

Table 12: Different Measures of Permanent Income

	Average elasticity		Life-cycle elasticity		Path dependence	
	OLS	IV	Young	Old	Level	PI growth
PI based on AR(1)	0.57	0.79	0.86	0.64	0.95	-0.33
	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
PI w/ ind-specific AR(1)	0.58	0.93	0.77	0.87	1.08	-0.18
	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
PI w/ occ-specific AR(1)	0.57	0.97	0.86	0.87	1.07	-0.18
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.06)
PI w/ total income AR(1)	0.60	0.98	1.08	0.81	1.08	-0.34
	(0.01)	(0.02)	(0.04)	(0.02)	(0.03)	(0.05)
PI based on AR(2)	0.55	0.69	0.75	0.58	0.82	-0.32
	(0.01)	(0.01)	(0.04)	(0.02)	(0.03)	(0.04)

Alternative Expenditure Measures Table 13 varies the expenditure definition. The baseline uses the categories available in all waves since 1999. I then (i) measure housing and vehicles using cash outlays rather than service flows; (ii) expand categories using items available since 2005; (iii) combine (i) and (ii); (iv) restrict spending to nondurables; (v) add donations; and (vi) add donations plus transfers outside the household.[24]

Elasticities are smaller under narrower definitions (e.g., nondurables) and larger under broader definitions that add high-Engel-elasticity categories (e.g., donations and transfers). Importantly, the life-cycle decline and path dependence remain.

Alternative Wealth Measures Table 14 compares results when conditioning on wealth measured as (i) PSID net worth and (ii) net worth augmented with employer-provided defined-contribution retirement accounts constructed from the pension modules following Cooper et al. (2019). The estimates are essentially unchanged.

Alternative Sample Selection Finally, Table 15 varies sample and scaling choices: adult-equivalence scaling, per-earner scaling, excluding supplementary samples, and restricting to households with stable marital status. None of these changes materially affects the elasticity estimates or the path-dependence results.

[24] Alternative shelter uses rent, mortgage payments, and property taxes; alternative vehicle spending includes down payments, lease and loan payments, and other vehicle costs. "2005 categories" add items such as home repairs, furnishings, clothing, vacations/recreation, and telecommunications. "Nondurables" excludes vehicles and shelter, except insurance and vehicle repairs.

Table 13: Different Measures of Expenditure

	Average elasticity		Life-cycle elasticity		Path dependence	
	OLS	IV	Young	Old	Level	PI growth
Expenditure, 1999 Cat.	0.59	0.79	0.86	0.64	0.95	-0.33
	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
Expenditure, Alt. Shelter	0.54	0.87	0.94	0.72	0.98	-0.25
	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
Expenditure, 2005 Cat.	0.62	0.86	0.92	0.73	1.01	-0.33
	(0.01)	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)
Expenditure, 2005 Cat.	0.58	0.93	0.99	0.80	1.05	-0.27
& Alt. Shelter	(0.01)	(0.02)	(0.05)	(0.03)	(0.04)	(0.05)
Expenditure, Nondurables	0.48	0.73	0.83	0.57	0.81	-0.17
	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
Expenditure, 2005 Cat.	0.64	0.89	0.93	0.75	1.04	-0.33
& Donations	(0.01)	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)
Expenditure, 2005 Cat.	0.69	0.98	1.02	0.83	1.11	-0.34
& Donations and More	(0.01)	(0.02)	(0.05)	(0.03)	(0.04)	(0.04)

Table 14: Different Measures of Asset

	Average elasticity		Life-cycle elasticity		Path dependence	
	OLS	IV	Young	Old	Level	PI growth
PSID Net Worth	0.59	0.79	0.86	0.64	0.95	-0.33
	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
Net Worth + Ret. Accounts	0.58	0.76	0.86	0.61	0.91	-0.31
	(0.01)	(0.02)	(0.04)	(0.02)	(0.03)	(0.04)

Table 15: Alternative Sample Selection

	Average elasticity		Life-cycle elasticity		Path dependence	
	OLS	IV	Young	Old	Level	PI growth
Adult Equivalence Adjusted	0.57	0.72	0.78	0.59	0.89	-0.31
	(0.01)	(0.02)	(0.04)	(0.02)	(0.03)	(0.04)
Marital Status Adjusted	0.59	0.78	0.83	0.63	0.96	-0.34
	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
No Supplement Samples	0.57	0.74	0.81	0.58	0.97	-0.33
	(0.01)	(0.01)	(0.03)	(0.02)	(0.04)	(0.05)
No Martial Status Change	0.58	0.74	0.80	0.61	0.98	-0.34
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.05)

F Additional Results

Availability of results. All tables and figures for the additional exercises summarized below are available upon request and can be provided by email.

Results by Ownership Status

A key implication of the commitment mechanism is that adjustment frictions generate path dependence in consumption. I therefore focus on shelter, the most important commitment for most households, and compare renters and homeowners. Homeowners typically face larger adjustment costs (moving, refinancing, transaction costs), whereas renters can adjust housing consumption more easily. If housing commitments are important, renters should exhibit weaker path dependence.

I estimate baseline consumption and saving responses by current and past (ten years earlier) homeownership status. Current status shows small, imprecisely estimated differences: homeowners show slightly weaker path dependence, but estimates lack statistical precision. Past ownership shows stronger patterns. Households that owned homes ten years earlier exhibit evident dependence of current consumption on permanent income growth–consistent with long-lived housing commitments constraining current adjustment. Commitment history matters more than current ownership.

Expenditure composition reinforces this interpretation. Homeowners adjust nondurable spending more following past expenditure growth, reflecting limited flexibility in shelter expenditures. Past ownership status predicts similar reallocation patterns. Overall, housing commitments generate persistent frictions that contribute to path dependence in consumption.

Permanent Income Changes and Housing Adjustment

The main empirical analysis compares households that recently moved (and thus adjusted their housing commitments) to those that did not. A necessary condition for this comparison to be valid is that moving decisions should be systematically related to the magnitude of permanent income changes. Standard lumpy adjustment models predict that households adjust their housing stock when the gap between desired and actual consumption crosses certain bounds, which should occur more frequently when income changes are larger. This subsection validates this prediction.

I estimate the likelihood of having moved at least once in the prior decade as a function of the absolute ten-year change in permanent income using linear probability models. A one-unit increase in the absolute log change in permanent income is associated with a 22.8 percentage point increase in the probability of moving (standard error: 1.9 percentage points). This relationship is monotone and well approximated by a linear trend, as shown by binned scatter plots. I also examine households' self-reported likelihood of moving in the future. Results remain qualitatively similar.

Income changes predict moving similarly for both renters and owners, suggesting that the underlying adjustment mechanism operates for both groups, even though the levels of adjustment differ. In particular, the sensitivity of moving to income changes is similar for renters and owners. However, owners have a substantially lower baseline probability of moving, consistent with higher adjustment costs.

Reasons for Moving and Reverse-Causality Concerns

A potential concern with the main analysis is that permanent income growth and moving are measured over the same ten-year horizon, raising the possibility of reverse causality. Specifically, moving itself might cause income growth rather than the other way around–for example, if households move for job opportunities that generate higher earnings.

To address this concern, I leverage PSID respondents' self-reported reasons for moving. If moves are driven primarily by job or school opportunities (productive reasons), reverse causality is more plausible. However, if moves are driven primarily by housing or neighborhood considerations (consumptive reasons), the endogeneity concern is substantially reduced. The PSID categorizes moves as: (i) productive reasons (job/school), (ii) moving closer to work, (iii) consumptive reasons (housing/neighborhood changes), (iv) involuntary reasons, and (v) ambiguous reasons.

Restricting the sample to households moving for consumptive reasons, the estimated elasticity of log expenditures to permanent income remains nearly unchanged relative to the full sample of movers. Similarly, expenditure allocation patterns are preserved. These results support the interpretation that households move primarily to adjust durable consumption rather than in response to exogenous income opportunities.

Financial Constraints and Income Risk

Two alternative mechanisms could potentially explain the under-consumption puzzle and path dependence patterns without invoking consumption commitments. First, if high-permanent-income households are more likely to be liquidity constrained, they might under-consume relative to permanent income. Second, if high-permanent-income households face greater income uncertainty, precautionary saving motives could generate both under-consumption and persistent effects of past income on current consumption. This subsection tests both alternatives and finds they do not account for the main findings.

I check whether borrowing constraints drive the results using two standard hand-to-mouth (H2M) classifications: a net-worth-based definition (Zeldes, 1989) and a liquid-wealth-based definition (Kaplan et al., 2014). Dropping all H2M households yields nearly identical estimates, as does restricting to households with positive home equity. These results demonstrate that hand-to-mouth status does not explain the under-response or path dependence.

I also construct a measure of permanent-income uncertainty based on out-of-sample forecast errors (Boar, 2021): discounted present values of future forecast errors at multiple horizons, assigned using within occupation-industry dispersion. The precautionary saving hypothesis predicts that higher income risk should be associated with lower consumption and stronger dependence on lagged income. In a parsimonious specification, higher risk is associated with lower consumption. However, once permanent income and past permanent income growth are included, the risk coefficient becomes small and unstable, and lagged risk has little predictive content. Most importantly, the path-dependence pattern remains strong. While precautionary motives are present, they do not account for the main findings.

Placebo Tests for the Moving Indicator

The interpretation that movers have recently adjusted their consumption commitments relies on the timing of moves being aligned with the permanent income growth window. If the key mechanism is recent adjustment, then moves outside this window should not affect the estimated path dependence. This subsection validates this interpretation through placebo tests using alternative timing of moves.

My baseline specification uses a dummy for moves in the past decade (the same window over which permanent income growth is measured). First, using a dummy for moves 14-16 years earlier (before the permanent-income-growth window) shows no evidence of reduced path dependence, as expected. Second, a dummy for moves within the past two years shows no path dependence. However, the comparison group in this specification mixes households that never moved with those that moved earlier in the decade (but not recently), making interpretation ambiguous. Third, examining "future movers" (households reporting they will move 4-6 years ahead) provides an interesting test of the mechanism. These households exhibit the opposite sign of path dependence: those with faster past permanent income growth have lower current consumption. This is consistent with these households being temporarily away from their desired bundle–past income growth has not yet been accommodated through housing adjustment, so they remain "locked in" to their existing commitments. Expenditure allocation results follow similar patterns across these placebo specifications.

Bequests and Inter Vivos Transfers

My calibration requires strong bequest motives. Theory predicts locked-in households compensate for under-consumption by leaving larger bequests or making transfers. I test this using three approaches.

First, I match parents' assets near death with children's reported inheritances. Bequests increase with current permanent income (consistent with luxury bequest motives) but show no relation to past income growth. However, there is no evidence that locked-in households increase bequests. Importantly, sample sizes limit inference. Second, I examine support to non-household members and charitable donations using the demand equations. Both behave as luxury goods, but neither increases systematically with past income growth. Third, I test whether children's consumption responds to parents' permanent income contemporaneously. If bequest motives are strong and children are forward-looking, children should consume more when parents have a higher income. Children's spending does correlate with parents' current income, consistent with anticipated transfers. But children whose parents had faster past income growth do not consume more. Overall, bequests and transfers strongly relate to permanent income levels but not to path dependence.

G Computational Appendix

State Space, Grids, and Interpolation Households face borrowing and collateral constraints, so I use non-uniform grids with higher density near the constraint. To handle the state-dependent borrowing limit, I parameterize liquid assets as excess liquid wealth relative to the constraint, which keeps the grid stable across states. Value and policy functions are evaluated using linear interpolation on the grid.

Optimal Decision Rules At each age and state, I solve two problems: (i) a no-adjustment problem in which commitments are fixed and the household chooses liquid assets, and (ii) an adjustment problem in which the household chooses both liquid assets and the commitment stock. I use Brent's method for the one-dimensional no-adjustment problem and Powell's method for the two-dimensional adjustment problem. Because adjustment costs generate non-convexities, I guard against local maxima by evaluating the value function at all budget-set kink points and by using multiple starting values (five for the 1D problem and 5×5 for the 2D problem). The policy at each state is selected as the maximizer across all candidate solutions.

Algorithm I solve the model by backward induction and iterate on the bequest distribution in an outer loop:

1. *Initialization.* Load parameters, moments, mortality, and the shock process. Construct grids, initialize storage arrays, draw simulation shocks, and set an initial bequest distribution.
2. *Backward induction.* For $t = T, \ldots, 1$, solve the household problem at each grid point: compute value and policies under no-adjustment and adjustment, then choose whether to adjust by comparing the two values.
3. *Forward distribution update.* Given policies, update the cross-sectional distribution over states by moving probability mass across grid points using linear interpolation weights and applying shock-transition probabilities. Use implied terminal assets to update the bequest distribution.
4. *Convergence.* Repeat steps 2–3 until the bequest distribution converges (the distance between successive iterates is below a tolerance).

5. *Simulation.* Simulate 5,000 households using the converged policies and shock draws, compute moments, and run the same regressions as in the data.

H Income Profile Calibration

This appendix describes the calibration of the labor-income process. The goal is to match both life-cycle income dynamics (growth, dispersion, persistence, and inequality) and the predictability of income, which is central for constructing permanent income in the empirical analysis.

Calibration Procedure I use a nested iterative procedure:

1. *Initialization.* Fix demographic timing, shock-grid sizes, and simulation draws.
2. *Intergenerational persistence.* For a candidate transmission parameter, simulate parental and child fixed effects and estimate a rank–rank regression to obtain the model-implied intergenerational income elasticity (IGE). Update the transmission parameter until the model matches the empirical IGE (Chetty et al., 2014) within tolerance.
3. *Income-process calibration.* Conditional on the IGE match, simulate child incomes, compute the targeted moment vector, and update the remaining income-process parameters to minimize the distance between model and data moments.
4. *Convergence.* Iterate until the moment distance no longer improves.

Targets. I calibrate seven income-process parameters to match a set of moments calculated in the PSID. The moment set includes: (i) cumulative income growth over the life cycle; (ii) age profiles of the variance of log income; (iii) autocovariances of log income at two- and four-year horizons; (iv) volatility of two-year income growth; (v) cross-sectional inequality; and (vi) out-of-sample forecast errors at multiple horizons. Tables 17 and 18 report the fit.

Capturing the forecastability of income is essential for my exercise. Therefore, I construct income forecasts and forecast errors in the data analogously to the empirical procedure used to build permanent income. Specifically, I forecast log income using a flexible age profile, categorical fixed-effect dummies (to capture observable heterogeneity), and a two-year lag of log income to mirror the biennial PSID structure (with linear interpolation for odd years). I compute h-step-ahead forecast errors for $h \in \{2, 4, 6, 8\}$ and target their mean and dispersion, as well as calibration slopes from regression tests.

Parameters. The calibrated parameters include: the variance and persistence of the fixed-effect component, the variance and persistence of persistent shocks, the variance of transitory shocks, and two parameters governing the curvature of the deterministic life-cycle income profile. Table 16 reports the calibrated values.

Table 16: Calibrated Income Parameters

Parameters	Description	Baseline	Aguiar and Hurst (2013)
b_1	Linear trend	0.0764	0.0300
b_2	Quadratic trend	-0.0020	-0.0007
$\sigma_{\bar{z}}$	Fixed-effect variance	0.6674	0.1660
σ_{ϵ}	Transitory variance	0.0391	0.1190
σ_{ξ}	Persistent variance	0.2584	0.0180
ρ	Persistence parameter	0.2090	0.9770
$\bar{\rho}$	Pers. of intergen. skill transmission	0.3984	0.6642

Fit: Unconditional Moments Table 17 compares model and data moments for the income distribution. The process matches the overall level of dispersion and the concavity of life-cycle income growth reasonably well given overidentification, with three systematic deviations: it overstates the curvature of cumulative growth, understates short-horizon autocovariances, and overpredicts short-horizon income-growth volatility and inequality.

Table 17: Income Moments: Model vs. Data

	Baseline		Aguiar and Hurst (2013)	
Moments	Model	Data	Model	Data
10-year income growth	1.623	1.621	1.302	1.621
20-year income growth	1.930	1.783	1.478	1.783
30-year income growth	1.550	1.713	1.454	1.713
Variance log income at 1-year	0.425	0.627	0.154	0.627
Variance log income at 10-year	0.666	0.712	0.283	0.712
Variance log income at 20-year	0.740	0.739	0.350	0.739
Variance log income at 30-year	0.643	0.833	0.360	0.833
Variance log income	0.650	0.683	0.312	0.683
Autocov log income (t, t-2)	0.450	0.863	0.221	0.863
Autocov log income (t, t-4)	0.448	0.782	0.212	0.782
Std dev log income growth (t, t-2)	0.643	0.186	0.434	0.186
Gini Inequality	0.466	0.420	0.324	0.420

Fit: Income Forecastability Table 18 evaluates forecastability. The first panel reports the mean and dispersion of forecast errors; the second panel reports Mincer–Zarnowitz calibration slopes (realizations on forecasts); and the third panel repeats the calibration using IV to account for attenuation from measurement error in the forecast regressor. The calibrated process matches the calibration *slopes* well, which is the key requirement for generating a permanent-income measure with realistic predictability.

Table 18: Income Forecastability: Model vs Data

Moments	Data		Baseline Model		Aguiar and Hurst (2013)	
	Mean	Std	Mean	Std	Mean	Std
Panel A: Forecast Errors						
2-period Ahead	0.010	0.560	-0.010	0.456	-0.000	0.388
4-period Ahead	0.020	0.650	-0.009	0.458	0.000	0.418
6-period Ahead	0.020	0.710	-0.008	0.460	0.000	0.449
8-period Ahead	0.020	0.750	-0.008	0.460	0.000	0.470
	Const. (n.t.)	Slope	Const. (n.t.)	Slope	Const. (n.t.)	Slope
Panel B: OLS Regression						
2-period Ahead	-0.060	1.010	-0.026	1.025	-0.000	1.000
4-period Ahead	0.100	1.000	-0.029	1.029	-0.046	1.128
6-period Ahead	0.480	0.960	-0.031	1.034	-0.048	1.132
8-period Ahead	0.900	0.920	-0.034	1.038	-0.036	1.098
Panel C: IV Regression						
2-period Ahead	-1.400	1.130	-0.042	1.003	-0.000	1.014
4-period Ahead	-2.260	1.210	-0.021	1.290	0.057	3.045
6-period Ahead	-2.900	1.270	-0.030	1.279	0.106	5.754
8-period Ahead	-3.200	1.300	-0.032	1.290	0.177	10.921

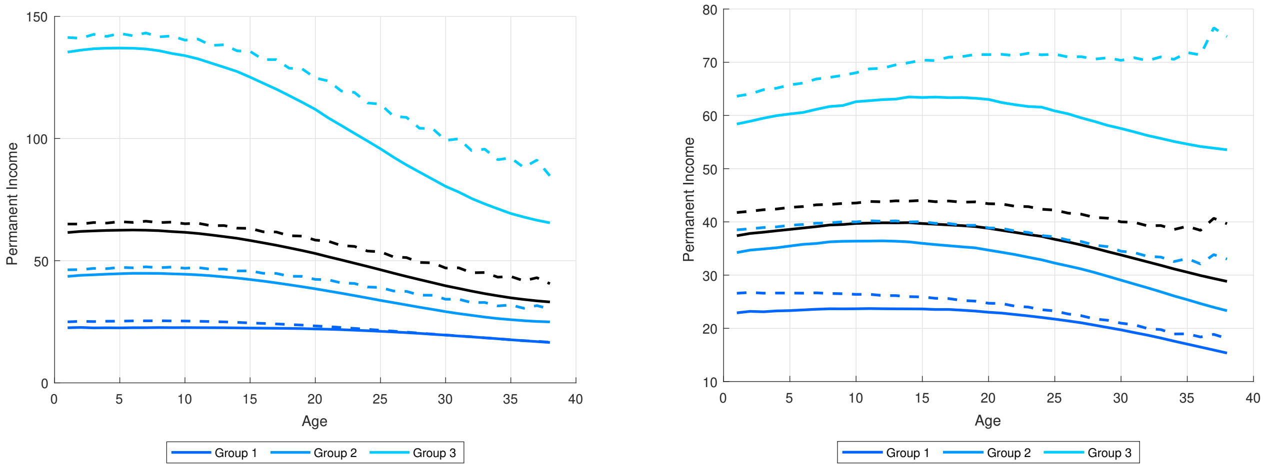
Note: n.t. refers to non-target moments. Panel A reports mean and standard deviation of forecast errors. Panel B reports constant and slope from OLS regression of realized income on forecasted income. Panel C reports constant and slope from IV regression of realized income on forecasted income and consumption.

Alternative Parameters As a sensitivity check, I report the moments implied by the income-process parameters used in Aguiar and Hurst (2013). This exercise is not meant as a critique; they use different data inputs and target moments. Table 16 reports the parameters from both calibrations.

Tables 17 and 18 compare the moments. Relative to my baseline, their calibration features substantially higher persistence and lower innovation variance, and much smaller fixed-effect heterogeneity. Importantly, this alternative calibration performs poorly on the forecastability moments that discipline my permanent-income construction, in particular producing implausibly large IV calibration slopes at long horizons.

Figure 9 illustrates the comparison between estimated permanent income using simulated data and true permanent income in the model. For the true permanent income, I construct the expectation using the full set of state variables $(\bar{z}_i, \alpha_{i,j})$ and the survival probabilities directly, rather than relying on the reduced-form forecast. The baseline calibration provides the best approximation.

Figure 9: Estimated Permanent Income vs. True Permanent Income



(a) Baseline Calibration

(b) Alternative Calibration

I Counterfactual Appendix

This appendix summarizes the counterfactual calibrations. In each counterfactual, I shut down one mechanism at a time (consumption commitments and/or luxury late-in-life consumption) and recalibrate the discount factor β so that the model matches the baseline wealth-to-income ratio.

Alternative Calibrations Table 19 reports the parameter sets used in the experiments. Three parameters are held fixed across all economies: the bequest weight ϕ_1, the consumption aggregator ω, and the intratemporal elasticity parameter γ. The remaining parameters vary across counterfactuals.

- *Borrowing constraint only.* Shut down commitments ($\kappa = 0$) and impose homothetic preferences by setting $\sigma_{c,25} = \sigma_{c,R} = \sigma_b = 2.5$.
- *Luxury late-in-life only.* Shut down commitments ($\kappa = 0$) and adopt the age-varying curvature values in Straub (2019): $\sigma_{c,25} = 11$, $\sigma_{c,R} = 1.1$, and $\sigma_b = 2.5$.
- *Commitments only.* Keep commitments active (baseline κ) and shut down luxury late-in-life curvature differences by setting $\sigma_{c,25} = \sigma_{c,R} = 2.5$, keeping the baseline σ_b.

Table 19: Parameters Used in the Counterfactual Analysis

Parameter	Description	Baseline	Borrowing constraint	Luxury late-in-life	Commit.
β	Discount factor	0.84	0.97	0.78	0.74
$\sigma_{c,25}$	CRRA (young)	4.09	2.50	11.00	2.50
$\sigma_{c,R}$	CRRA (retired)	1.10	2.50	1.10	2.50
σ_b	CRRA (bequest)	0.57	2.50	2.50	0.57
ϕ_1	Bequest weight	4.72	4.72	4.72	4.72
ω	Consumption aggregator	0.20	0.20	0.20	0.20
γ	Goods elasticity parameter	-0.26	-0.26	-0.26	-0.26
κ	Commitment adjustment cost	0.40	0.00	0.00	0.40

Targets Table 20 reports the data and the model-implied moments in each counterfactual economy. By construction, all economies match the same wealth-to-income ratio through the recalibration of β.

Table 20: Moments of the Counterfactual Analysis

Description	Data	Baseline	Borrowing Constraint	Luxury Late-in-life	Commit.
Moving rate of owners (past 2 years)	0.12	0.13	0.97	0.97	0.15
Ratio Shelter to Total Expenditure	0.25	0.14	0.20	0.20	0.11
Ratio Housing Wealth to Total Wealth	0.47	0.54	0.64	0.65	0.45
Ratio Total Wealth to Income	5.92	6.88	6.88	6.88	6.88
Bequest flow over GDP	0.10	0.10	0.07	0.03	0.17
Cs response to PI age 30-40	0.92	1.05	0.99	0.44	1.30
Cs response to PI age 40-50	0.84	0.87	0.99	0.63	1.19
Cs response to PI age 50-60	0.72	0.70	0.98	0.86	0.66
Cs response to PI age 40-50	1.09	0.89	0.99	0.64	1.19
to PI growth	-0.39	-0.30	-0.14	-0.06	-0.01
Cs response to PI age 50-60	0.84	0.72	0.98	0.91	0.73
to PI growth	-0.21	-0.24	-0.10	-0.45	-0.32