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

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Abstract

The textbook permanent-income hypothesis predicts that the level of consumption is proportional to the level of permanent income, while, in the data, the elasticity of consumption to permanent income appears to be far below one. In this paper, I provide evidence for a novel theory for this consumption under-response to permanent income based on *consumption commitments* – hard-to-adjust consumption choices that resemble long-term commitments. Empirically, I document four main new facts that support the theory: (a) the consumption elasticity to permanent income is larger for younger households, (b) it depends on past income trajectories, and (c) it becomes larger after households adjust their commitments; furthermore, I show that (d) those households that have "under-responded" to their income growth skew spending away from hard-to-adjust goods (notably shelter). These facts are evidence in favor of household "lock-in" to past consumption choices. Quantitatively, I show that consumption commitments are necessary for life-cycle models to account for all the documented facts.

Keywords: Permanent Income, Life-cycle Consumption, Lumpy Adjustments

JEL - Classification: D15, D31, D52, E21

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1 Introduction

The textbook permanent-income hypothesis, the benchmark theory for understanding consumption decisions, implies a much tighter connection between permanent income and consumption than observed in the data. First, it predicts that households must fully absorb permanent income shocks into their consumptions, while, in both aggregate and microdata, consumption appears to be excessively smooth, i.e., it reacts too little to permanent income shocks to be consistent with the theory (Campbell and Deaton, 1989; Blundell, Pistaferri, and Preston, 2008). Second, it predicts that the level of consumption is proportional to the level of permanent income, while, in the data, the elasticity of consumption to permanent income appears to be far below one (Dynan, Skinner, and Zeldes, 2004; Straub, 2019).

In this paper, I provide empirical and quantitative evidence for a novel explanation for the consumption under-response to permanent income based on what Chetty and Szeidl (2007) termed *consumption commitments* – hard-to-adjust consumption choices that resemble long-term commitments.[1] My empirical contribution is to document four novel facts that support the importance of consumption commitments. In particular, I document how the consumption elasticity to permanent income, an across-household moment that I use as my measure of consumption's response, behaves over the life-cycle, depends on past income trajectories, and becomes larger after households adjust their commitments. Furthermore, I show that those households that have "under-responded" to their income growth skew spending away from hard-to-adjust goods (notably shelter). My quantitative contribution is to show that consumption commitments are necessary for life-cycle models to account for all the documented facts. I also explore the model's welfare and aggregate implications.

Empirically, I use data from the Panel Survey of Income Dynamics (PSID) to document four main new facts that demonstrate the importance of consumption commitments for understanding the under-response puzzle. I first document that younger households respond more to permanent income than older households, with an estimated elasticity of 0.9 and 0.6, respectively. If commitments are made gradually over the life-cycle, that suggests that younger households should have fewer commitments and, consequently, their consumption responds more to permanent income. On the other hand, models that rely on young households being more risk-averse and saving to

[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), portfolio choices (Chetty, Sándor, and Szeidl, 2017), and adjustment of durables during recessions (Berger and Vavra, 2015).

consume when old are inconsistent with this evidence.

Second, I document path-dependency in household responses to permanent income. More precisely, I compare households with the same permanent income today but with different permanent income trajectories – one that recently experienced permanent income growth and another that experienced permanent income growth earlier in their life cycle. Across households with the same permanent income, households that experienced 10% permanent income growth in the past 10 years have 3% lower current consumption than households with no permanent income growth during the same period.

Third, I document that the path-dependency in household responses to permanent income also shows up in their allocation of expenditure across goods categories. Again, I compare households with the same permanent income today but with different permanent income trajectories. Holding current expenditure constant, high past expenditure growth in the last 10 years is associated with a higher share of easy-to-adjust goods consumption (nondurables, such as food) and less hard-to-adjust goods consumption (i.e., consumption commitments). This pattern is especially marked for shelter consumption (housing flow for homeowners and rent for renters).

Consumption commitments rationalize these observed path-dependencies. Young households choose an expenditure path, committing to some hard-to-adjust goods, given their current expectations of future income. However, after the realization of uncertainty and because of consumption commitments' costly adjustment, most households partially adjust their consumption bundle by changing only their consumption of easy-to-adjust goods. As documented in the data, after increases in permanent income, households have, on average, lower overall consumption and relatively larger shares of easy-to-adjust goods.

As my last fact in favor of the consumption commitment mechanism, I document that households who adjust their consumption commitments exhibit little or no dependence on past variables in their consumption response to permanent income or allocation of expenditure across goods categories. For this exercise, I use past moving decisions as a proxy for adjustments. This choice reflects a focus on shelter consumption as it is the principal hard-to-adjust good in the data; shelter accounts for a significant share of a typical household's consumption bundle and has substantial transaction costs.

Some of my empirical results rely on having a time-varying measure of permanent income at the household level. Permanent income is defined as current assets plus the discounted future expected path of income; so, crucially for the empirical exercise, I construct a measure of permanent income in the PSID using reported net worth and forecasting each household's future income profile. This exercise builds on Carroll (1994), who also constructs a measure of expected lifetime income to examine consumption behavior.[2]

To address the question of why this characterization matters, I propose a quantitative model consistent with the documented microdata evidence. It consists of a life-cycle consumption model (Deaton, 1991; Carroll, 1997; Gourinchas and Parker, 2002) that incorporates two consumption goods, one of which exhibits a non-convex adjustment cost in its level (Chetty and Szeidl, 2007; Berger and Vavra, 2015). I allow for other mechanisms that are potentially important in generating savings that increase with income, such as late-in-life luxury consumption (Straub, 2019) and elastic bequest motives (De Nardi, 2004). I calibrate the model by explicitly targeting commonly used moments in the literature, as well as incorporating two of my empirical: the average consumption response to permanent income and the average path-dependency in the consumption response to permanent income.

With non-convex adjustment costs, some households 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 optimal, which works as a utility wedge. The mechanism works through diminishing returns to specific goods relative to a near-constant return to marginal saving, which is given by the bequest motive. Consequently, households substitute present consumption for future consumption and future bequest.

The model can account for the novel facts on consumption's response to permanent income documented in the empirical section. By measuring permanent income in the model as I do in the data to ensure consistency, I evaluate the model by its ability to replicate observed untargeted moments following regression of simulated data. I treat all other documented empirical facts that were not targeted in the calibration as untargeted moments. The model captures most of them well, highlighting the importance of consumption commitments in understanding consumption's response to permanent income.

With a model broadly consistent with the micro-data evidence on household behavior, I perform two counterfactual exercises. First, by shutting off consumption commitments, I show that they are necessary to account for all the target moments. However, lumpy adjustment alone is not enough to explain all key facts, meaning preference-based explanations are also quantita-

[2]Two concerns with my permanent income measure are: i) error in reported income and ii) that households have superior information than the econometrician to forecast future income. To address concerns about measurement error, I first take advantage of the panel structure and use reported income in adjacent surveys and industry dummies as instruments. Second, using the reported asset path and a measure of active savings, I show that the under-consumed income goes into asset accumulation. These results should help alleviate concerns about measurement error and reaffirm the quality of the PSID data. To address concerns about households' superior information, I show that current consumption, which embodies most of the information available for households, has low power in forecasting future income forecast errors. This result should alleviate concerns about the quantitative importance of households' superior information.

tively important. Consumption commitments generate stronger responses to permanent income for younger households and consumption responses and expenditure allocations that depend on lagged variables, while preferences are essential to generate the degree of consumption's under-response.

Second, I analyze the impact of an exogenous increase in the cross-household variance of permanent income. In particular, I compute the impact of an increase in permanent income inequality on wealth and consumption inequality. I show that this increase in the variance of permanent income leads to a larger welfare loss if households face consumption commitments. Moreover, I compute the impact of an increase in permanent income inequality on wealth and consumption inequality. Consumption tracks income inequality in the model, consistent with the conclusions of Attanasio, Hurst, and Pistaferri (2014) and Aguiar and Bils (2015). Because the relationship between consumption and permanent income is stable in the model, consumption and permanent income inequalities increase by the same proportion, even though their levels differ.

Related Literature My paper primarily relates to three strands of the literature. First, it adds to the vast empirical literature that tests the permanent income hypothesis (PIH). Starting with Friedman (1957), this literature focuses on consumption responses to transitory or permanent income changes. PIH predictions have been tested using aggregate time series (Hall, 1978; Flavin, 1981; Campbell and Deaton, 1989) and microdata (Hall and Mishkin, 1982; Altonji and Siow, 1987; Shea, 1995). I first contribute by showing that the aggregate bundle masks substantial heterogeneity among disaggregated consumption categories and demonstrate how this heterogeneity can help distinguish between various consumption theories. Bils and Klenow (1998) and Aguiar and Hurst (2013) also examine disaggregated consumption in different contexts. Second, I use recent data from the PSID with novel detail on household expenditure, an improvement relative to older studies that rely on proxy or imputed consumption measures. Other studies using these recent PSID releases include Blundell, Pistaferri, and Saporta-Eksten (2016) and Arellano, Blundell, and Bonhomme (2017).

Second, I add to the body of work comparing the consumption response to permanent income in simulated models and the data. Kaplan and Violante (2010) find that the pass-through of permanent income shocks to consumption is close to 0.78 in a simulated consumption model, while Blundell et al. (2008) find a pass-through of 0.64 using PSID data. Closely related to my work, Straub (2019) defines permanent income as an individual-specific fixed productivity term in the log labor income process. By assuming that agents know this fixed component and that it is riskless, he estimates a consumption elasticity to this permanent fixed productivity of 0.7 and shows that canonical models would have an elasticity of 1. This evidence motivates the addition of non-homothetic preferences to the model as a way to capture backloaded consumption, such as health expenditures and intervivo transfers.

Third, I add to the literature that studies the implications of adjustment costs on household behavior. Chetty and Szeidl (2007) study implications for individual risk preferences. Berger and Vavra (2015) and Chetty and Szeidl (2016) study the implications for aggregate consumption dynamics. Kaplan and Violante (2014) use a model in which households can hold two assets, one of which is subject to adjustment costs, to study consumption responses to fiscal stimulus. I contribute to this literature by showing that lumpy goods adjustment is a key mechanism behind the consumption under-response to permanent income. I also contribute to the broad literature on housing consumption dynamics (Yang, 2009) and their aggregate implications (Hurst and Stafford, 2004; Berger, Guerrieri, Lorenzoni, and Vavra, 2018; Beraja, Fuster, Hurst, and Vavra, 2019).

Roadmap. Section 4 presents a standard incomplete markets life cycle model nesting lumpy goods adjustment and other mechanisms proposed by the literature to explain consumption's under-response to permanent income. Section 5 describes the calibration procedure and how I measure permanent income in the data and model. Section 3 estimates consumption's response to permanent income in the data and model. A significant part of the section explores how the model performs with respect to non-target moments. Section 7 examines the model's aggregate implications. Finally, Section 8 concludes. The appendix contains additional empirical and quantitative results.

2 Measuring Consumption Responses to Permanent Income Over

My empirical exercise documents novel facts that highlight the role of consumption commitments in shaping how consumption responds to permanent income. In this section, I first describe the Panel Study of Income Dynamics (PSID), the dataset used throughout this paper. Second, I define permanent income and explain its measurement in the data. Then, I explain how I recover the consumption elasticity to permanent income, my measure of consumption responses to permanent income.

2.1 PSID data

I use data from the 1999 to 2019 waves of the PSID, the longest-running household panel survey in the US. The panel nature of the data and the broad measures of consumption, income, and wealth collected in these years allow for analyses of household paths of consumption, income, and wealth over time.[3] My sample consists of all households whose heads are between 25 and 80 years old, but I use only working-age heads in most regressions.

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

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

First, my empirical measure of assets is reported net worth (assets net of debt).[4] Second, I construct a discounted future expected income profile for each household. I estimate an expected path of income for each household and express it in present value terms using a constant interest rate, $R = 1.05$, and age-specific survival probabilities.[5] In equation (1), the discount term is expressed as $\psi(age_i(t), age_i(s))/R^{s-t}$, where $age_i(\cdot)$ returns the age of household i as a function of the time period, $\psi(a_1, a_2)$ returns the probability of an individual aged a_1 surviving until age a_2, and $\widehat{Y}_{i,s}^{t}$ is the expected income for household i at time s using the information set available at t.

The crucial step in my measurement exercise is to estimate an expected path of income for each household, which requires a set of assumptions. First, I assume that past income and certain demographic characteristics describe the information set and that the household and the econometrician have the same information set. Second, I assume that the formation of expectations is approximated by a linear autoregressive process. Finally, I estimate all equations by OLS, which implies that I am using a "linear least squares forecast."[6]

[3] The PSID was conducted annually until 1996 and biennially since 1997. I use data from the 1980 - 2019 PSID waves to estimate the income process used to compute expected income. For waves before 1999, I use only odd survey years for consistency.

[4] Net worth is the sum of net illiquid and net liquid wealth. Following Kaplan, Violante, and Weidner (2014) and Aguiar, Bils, and Boar (2020), liquid assets are the sum of checking and savings (checking or savings accounts, money market funds, certificates of deposit, government bonds, and treasury bills) and stocks (shares of stock in publicly-held corporations, stock mutual funds, and investment trusts). Liquid debt is all debt other than mortgages (credit card charges, student loans, medical or legal bills, or loans from relatives). Net liquid wealth is liquid assets minus liquid debt. Net illiquid wealth is the sum of the household's home equity (home value minus mortgages), the value of other real estate assets (net of debt), the value of any business or farm assets (net of debts), the value of any vehicles (net of debt), and IRA and other pension holdings. In a robustness exercise, I follow Cooper, Dynan, and Rhodenhiser (2019) and use the pension data available in the PSID to create a more comprehensive measure of wealth, which includes employer-provided defined-contribution (DC) retirement accounts.

[5] My results are robust to different values of R. Death probabilities are from the US Life Tables from the National Vital Statistics System.

[6] More formally, let $g(\mathbf{Y}_{i,t-1}, \mathbf{X}_{i,t})$ be the function that approximates the expectation formation process and

As a benchmark, I use a first-order autoregressive process to construct the expected income path for each household. Since the PSID runs biannually after 1999, I use income at $t-2$ to forecast future income. I also use a cubic in age, dummies for educational attainment, marital status, census region, and occupation groups. That is,

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

in which $\ln\widehat{Y}^t_{i,t+2}$ is expected log income in period $t+2$ using the information set in t. In the long run, income converges to the sample means determined by demographic characteristics, $\mathbf{X}_{i,\tau}$. This idea resembles Carroll (1994), which constructs expected future income using average income for households with similar education and occupation. However, the autoregressive structure adds dynamics to the measure, since a lower-than-average income will slowly converge to its long-run level. To forecast income in periods after $t+2$, I iterate the previous equation forward and linearly interpolate income in even years.[7]

When constructing permanent income for period t, I estimate the forecast process restricting the estimation sample to observations collected before year t. This restriction ensures that no future information is used to forecast income. In detail, I use a rolling sample of 16 years, meaning that I use income data from the 16 years prior to t to estimate the income process. The parameters in equation (2) are denoted by θ^t, where the t-subscript is the last year in the sub-sample (i.e., the year that indexes the information set).

I use household after-tax labor income as my main measure of income, which is the sum of household labor earnings and government transfers minus payroll taxes. Household labor earnings are the sum of the head and their 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 are the sum of any head and their partner's (if any) government transfer income from AFDC, supplemental security income, other welfare payments, unemployment benefits, worker's compensation, and social security benefits. My measure of payroll taxes comes from the NBER's TAXSIM. For robustness, I also construct a broader alternative measure

assume that it is the same for every household. $g(\cdot)$ is a function of $\mathbf{Y}_{i,t-1}$, a vector of past income realizations, and $\mathbf{X}_{i,t}$, a vector of demographic characteristics. I restrict $g(\cdot)$ to linear autoregressive processes, which are the best linear approximation (under quadratic loss) to the conditional mean $E(Y_t|\mathbf{Y}_{i,t-1},\mathbf{X}_{i,t})$.

[7]For a significant fraction of households, social security wealth is their main source of income when retired. I assume households retire at age 65 and their social security income is 45% of their last preretirement income forecast. This replacement rate is consistent with the simulations of Diamond and Gruber (1999), who also note that the US social security system discourages additional work after 65 years old. For households who are retired or disabled, transfers and benefits are the main income source, so I still use the estimated income process to forecast their transfer path.

of income by adding asset income. [8]

My forecast exercise is vulnerable to measurement error in income data. In particular, since I forecast income for many periods ahead and sum it to construct the discounted future expected income profile, any measurement error will accumulate and potentially imply a noisy permanent income measure. Even though my measure is unbiased under classical measurement error, it still biases estimated coefficients downward in any regression analysis. In Appendix A, I show that standard instrumental variable techniques also apply to the permanent income measure, and I instrument the log of permanent income with lagged income and industry dummies. Measurement errors in assets are harder to address, so I rely on the same set of instruments used to deal with errors in income.[9]

I address other possible concerns with my measure of permanent income. I present the results i) using different measures of income and assets, ii) using higher-order autoregressive processes, and ii) allowing the parameters of the autoregressive process to vary by occupation or industry. The latter deals with the possibility that the persistence parameter differs by occupation. Lastly, I show in Appendix B that my measure is meaningful and captures household expectations by testing whether the forecast errors are unforecastable using the other variables available in the household's information set.

2.3 Estimating Consumption's Response to Permanent Income

I use the consumption elasticity to permanent income as my measure of consumption responses. In particular, I am interested in how much consumption increases across the permanent income distribution. Recently, Straub (2019) and Abbott and Gallipoli (2019) documented that the relationship between these variables is concave, while most consumption models predict a linear relationship. My empirical exercise provides novel evidence on the role of consumption commitments in generating the observed relationship between consumption and permanent income.

[8] Asset income is the sum of the head and their partner's (if any) business income, farm income, dividends, interest, rents, trust funds, and royalties. I follow Aguiar et al. (2020) and add 6 percent of the respondent's assessed home value to their total income to account for the implicit rent on their home. Again, I compute taxes using the NBER's TAXSIM (payroll and federal and state income taxes).

In the PSID, when the head or their partner reports working any positive number of hours in their business/farm, the earned income is arbitrarily divided into labor and asset income (half for each). The IRS does not follow this process for taxing individual business/farm income. Following Kimberlin, Kim, and Shaefer (2014), both business/farm labor and asset income are treated as wages/salary for TAXSIM purposes and not as property income.

[9] Using logit models, Pfeffer and Griffin (2015) ask which variables forecast extreme fluctuations in measured wealth in the PSID. They find that demographic variables account for a greater share of the variation. Moreover, "measurement issues" have small predictive power. With measurement issues, they refer to 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).

My first exercise is to project the logarithm of consumption on the logarithm of permanent income to recover the consumption elasticity to permanent income in the data. This analysis uses cross-section variation to identify the relationship between the levels of these variables. In particular, I estimate:

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

$\log c_{i,t}$ is the log of consumption for household i at time t. $\widehat{\mathrm{PI}}_{i,t}$ is the estimated measure of permanent income. $\boldsymbol{Z}_{i,t}$ is a vector of demographic controls that includes a cubic in age, fixed effects by year, and dummies for education groups, marital status, census regions, and family size. $\epsilon_{i,t}$ is an error term capturing both idiosyncratic taste shocks and consumption measurement errors.

I use total expenditure as my measure of consumption. Following Kaplan et al. (2014) and Blundell et al. (2016), total expenditure includes expenditures on food (food at home, food away from home, and delivered food), utilities (gas for home, electricity, water and sewer, and other utilities), transportation (gasoline, parking, public transportation, taxi, and other transportation expenditures), health (doctors, hospitals, prescription drugs, and health insurance), childcare, education, insurance (auto insurance and home insurance), service flow that owning a vehicle provides and vehicle repair, and shelter expenditures. Spending on shelter reflects rent payments for renters and implicit rent for homeowners, which I set to 6% of the respondent's house value. The service flow of a vehicle reflects service flow, and I set it to 10% of the respondent's vehicle net worth. I consider other expenditure measures for robustness.[10]

My measurement of consumption's response relies on the assumption that idiosyncratic taste shocks or consumption measurement errors 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 under the assumption that the cycle impacts all households similarly.

For my second exercise, I modify regression (3) to include past permanent income as an explanatory variable. With this specification, I test if household responses to permanent income are path-dependent by comparing households with the same permanent income today but with different permanent income trajectories in the past 10 years.[11] This analysis also uses cross-section variation to identify the relationship between consumption, permanent income, and permanent

[10] My base expenditure measure relative to total after-tax income averages 58.3 percent for the whole sample. For a broader measure with the categories included in the 2005 wave, this average is 76.2 percent. Aguiar et al. (2020) compute the same averages and find 58.3 and 73.2 percent, respectively.

[11] To make the dependence of permanent income trajectories explicitly, observe that β_1 log(PI$_t$) + β_2 log(PI$_{t-10}$) is equivalent to (β_1+β_2) log(PI$_t$) - β_2 Δ log(PI$_t$).

income trajectory. In particular, I estimate

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

$\widehat{\mathrm{PI}}_{i,t-10}$ is the 10-year lagged estimated measure of permanent income. $\boldsymbol{Z}_{i,t-10}$ is a vector of lagged demographic controls that includes dummies for marital status, census regions, and family size. $\epsilon_{i,t}$ is an error term capturing both idiosyncratic taste shocks and consumption measurement errors.

For illustrative proposes, consider two households with the same permanent income level today, but one has experienced permanent income growth in the past decade, while the other has experienced no growth during the same period.[12] It is reasonable to argue that the household with a lower permanent income level 10 years ago chose a lower level of commitment in the past. Because consumption commitments are costly to adjust, this household might only partially adjust its consumption bundle via easy-to-adjust goods after the permanent income growth. As a result, its allocation of expenditure across consumption categories is not optimal, which works as a utility wedge (or a tax on current consumption). This household will substitute present consumption for future consumption and future bequest. In equation (4), past permanent income growth should decrease current consumption if commitments are important.

For my third novel fact, I test if expenditure allocation across categories also depends on current and past variables. I document this new fact by estimating demand systems to capture how past income growth is associated with expenditure allocation across different goods, conditional on a given level of total expenditures. In particular, based on the almost ideal demand system (AIDS) of Deaton and Muellbauer (1980), I estimate

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

in which i indexes household, j indexes expenditure component, t indexes time, $\log X_{it}$ is log expenditure, $\mathbf{Z}_{it}$ are demographic controls, and w_{ijt} is the expenditure share of component j. I allow past expenditure growth from period $t-s$ to period t, $\Delta \log X_{it}$, to enter the specification. In the AIDS specification, the log of each component price index and the overall price index are usually used as controls. I use year fixed effects to capture all relative price effects. If consumption commitments are important, I expect that, conditional on the same current expenditure level, households with rapid past expenditure growth consume more easy-to-adjust goods and fewer hard-to-adjust goods (i.e., consumption commitments).

[12] In other words, a household learned about its permanent income level in the past decade while the other already knew it (learned before the past decade).

To construct the expenditure shares, I use the detailed expenditure data available in the PSID after 2005 since it gives a broad picture of household intra-period allocation. However, since total expenditure appears on the right as a control and in the denominator on the left, this specification is vulnerable to measurement error. I deal with this measurement issue by instrumenting total expenditure with a cubic polynomial of log income and lagged log income. I assume that income shocks and the error term in the AIDS specification are not correlated.

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 of the demographic characteristics used, 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 C.1 presents some sample descriptions.

3 Responses to Permanent Income in the Data

In this section, I present several novel facts on consumption's response to permanent income. The empirical evidence indicates the importance of consumption commitments in understanding consumption's response to permanent income. Since permanent income is a generated regressor, I report bootstrap estimates of the standard errors.

3.1 Consumption Responses to Permanent Income

I first estimate the consumption response to permanent income for working-age households. I do this by estimating equation (3). Each column of Table 1 differs in estimation method and/or the set of instruments. In the first column, I report the OLS estimate. For each 1% increase in constructed permanent income, household consumption increases by 0.6%. In the second column, I control for education since college-educated workers have systematically higher savings rates (Dynan et al., 2004), possibly reflecting preference heterogeneity. The estimated responses to permanent income do not vary much between educational groups in the OLS estimates.

A possible concern is that measurement error in permanent income measure biases my estimates downward. To deal with this concern, I instrument the log of permanent income with lagged income and industry dummies, as discussed in Appendix A. The third column shows that, incorporating instruments, the consumption elasticity with respect to permanent income is still quite different from in benchmark models, as the estimate remains approximately 0.6. Interest-

Table 1: Expenditure Response to Permanent Income

	OLS		IV	
	(1)	(2)	(3)	(4)
	log(expenditure)	log(expenditure)	log(expenditure)	log(expenditure)
log(PI)	0.57	0.59	0.61	0.79
	(0.01)	(0.02)	(0.01)	(0.02)
Educ Dummies		Y		Y
KP-F test			1,676.7	616.3
Observations	54,970	54,970	54,970	54,970

Note: This table reports the estimated consumption elasticity to permanent income. Columns 1 and 2 use ordinary least squares, while Columns 3 and 4 use instrumental variables. 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, and year fixed effect. Columns 2 and 4 also include dummy variables for education groups as a control variable. In column 3, the excluded instruments are lagged income and dummy variables for industry groups and education groups, while in column 4 the excluded instruments are lagged income and dummy variables for industry groups. 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.

ingly, when controlling for education in the second stage, the consumption elasticity with respect to permanent income increases to almost 0.8. This result highlights how correcting measurement error is important and the different savings behavior across educational groups. The F statistic is sufficiently high to defuse any concerns about weak instruments.

The estimated consumption elasticity to permanent income could be seen as indicative that higher permanent income is associated with higher levels of patience. Because of that, I use column 4 of Table 1 as my baseline specification since differences in education dummies are commonly used to capture heterogeneity in the discount factor. So, most results should be interpreted as variations within educational groups. In Section 6, I calibrate the model to match this estimate. Moreover, the value that I recover is in line with previous findings in the literature, with Straub (2019) and Abbott and Gallipoli (2019) documenting a consumption elasticity with respect to permanent income of around 0.70. Straub also theoretically shows that most models with homothetic preferences predict an elasticity close to 1.

Table 2 presents a new fact: the elasticity of consumption with respect to permanent income decreases with age. I focus on the specification corrected for measurement error and with education dummies. For households between 25 and 45 years old, the estimated elasticity is close to 0.9, as seen in the second and third columns. However, for households between 45 and 65 years old, the estimated elasticity is smaller and decreases with age, falling as low as 0.64, as seen in the fourth and fifth columns.

Consumption commitments can rationalize a consumption elasticity that decreases with age.

Table 2: Consumption Response 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	823.6	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 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.

Since commitments are made gradually throughout the life cycle, it is reasonable to argue that older households have more commitments on average. Indeed, looking at the case of housing as an example of consumption commitments, older households have higher homeownership rates and housing is a larger part of their asset portfolio. Therefore, their consumption is more detached from their permanent income level because they are more "locked" into past consumption commitments.

I perform several robustness checks on my results. First, I have assumed an AR(1) process when forecasting the expected income path to compute the permanent income measure. Table B1 of Appendix C shows that my results are robust to different forecast specifications. Second, I used an expenditure measure that includes all categories available since 1999 and in which shelter expenditure is defined as rent payments for renters and implicit rent for homeowners. Table B2 of Appendix C shows that my results are robust when using other consumption measures. Lastly, I used the PSID definition of net worth to construct the measure of permanent income. Table B3 of Appendix C shows that my results are robust to using two different measures of wealth. The first follows Cooper et al. (2019) and uses the information on defined contribution (DC) pension accounts available in the "pension module" of the PSID to create a more comprehensive measure of wealth. The second controls for the increase in permanent income driven by asset valuation by creating a wealth measure at constant prices.

3.2 Consumption Responses to Current and Past Permanent Income

My second novel fact is the dependence of consumption not only on the current level of permanent income but also on past permanent income. I document this by modifying regression

(3) to include lagged permanent income as an explanatory variable. This regression captures the insight of Chetty and Szeidl (2016) that consumption commitments at the household level resemble consumption habits in regression analysis; therefore, the importance of permanent income trajectories to understand current consumption is evidence that commitments are important.[13]

Table 3 presents estimates based on the specifications that allow current consumption to depend on permanent income and 10-year lagged permanent income. Again, I focus on the specification corrected for measurement error and with education dummies. Column 1 shows that, for working-age households, current and past permanent income are positively associated with current consumption, with an estimated coefficient of 0.62 and 0.33, respectively. This result implies that households with the same permanent income but with different permanent incomes in the past have different consumption levels today.

This specification's result can be seeing as comparing households with the same permanent income today but with different permanent income trajectories in the past 10 years.[14] Households that experienced a 10% permanent income growth in the past have 3% lower consumption today than households with no permanent income growth during the same period. So, a household with no permanent income growth, or, in other words, who already knew its permanent income level in the past, consumes more than another with positive growth.

Consumption commitments generate this dependence on past permanent income. In the sample, some households have made commitments and so their permanent income trajectory influences their current consumption choices. Because of these "locked in" households, lagged permanent income is significant in the regression analysis. Moreover, consumption commitments rationalize why past permanent income growth depresses current consumption. Households with past commitments must respond to increases in permanent income by increasing adjustable goods (e.g., food) or savings. This adjustment happening only for some goods increases the curvature of the utility function (Chetty and Szeidl, 2007), making consumption today less desirable, which explains the depressed consumption. In the next subsections, I show that, consistent with the consumption commitment mechanism, past permanent income growth increases savings and the share of nondurable goods in the consumption basket.

The remaining columns of Table 3 show the path dependence results by age. These results are consistent with those in column 1, indicating that current consumption is associated with current and past permanent income in all age groups. The strength of the association between current consumption and past permanent income increases slightly with age. For example, con-

[13]Further on, I will present new findings that convincingly argue against consumption habits being the driving force behind this result.

[14]To make the dependence of permanent income trajectories explicitly, observe that 0.62 $\log(\text{PI}_t)$ + 0.33 $\log(\text{PI}_{t-10})$ is equivalent to 0.95 $\log(\text{PI}_t)$ - 0.33 $\Delta \log(\text{PI}_t)$.

Table 3: Path Dependence on Consumption Response by Age Group

	(1) All Sample	(2) 35<age<45	(3) 45<age<55	(4) 55<age<65
$\log(\text{PI}_t)$	0.62	0.86	0.63	0.49
	(0.03)	(0.06)	(0.05)	(0.04)
$\log(\text{PI}_{t-10})$	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.

sumption responses to current permanent income are stronger for households aged between 35 and 45 years, while consumption responses to past permanent income are stronger for households aged between 55 and 65 years. This suggests that older households have more commitments on average, reflecting commitments being made gradually throughout the life cycle.

3.3 Asset Accumulation

So far, I have documented new facts about consumption's response to permanent income, which highlights the importance of consumption commitments in understanding the consumption under-response puzzle. In this subsection, I show that, as predicted by the commitment mechanism, the reduced consumption increases asset accumulation. This rules out concerns that my previous results were due to the mismeasurement of expenditure or permanent income. In section 3.6, I show that part of these accumulated assets goes to leaving bequests and helping children through intervivo transfers.

Constructing Net Worth from Expenditure and Income

In the first exercise, I use the budget constraints as an accounting identity to construct implied net worth given reported income and expenditure and compare this constructed measure with the actual net worth reported by households. In other words, I check if households that consistently report less expenditure also report more net worth. The budget constraint ties together income, expenditure, and assets: households must be saving if they are not consuming. If this is not the case, the quality of the PSID data should be questioned.

For a household at period t, the budget constraint is

$$C_t + A_{t+1} = (1 + r_t)A_t + Y_t \ .$$

The left-hand side is total expenditure - consumption plus next-period assets - and the right-hand side is cash on hand - last-period assets and returns plus income. The budget constraint can be rewritten as

$$A_{t+1} - A_t = Y_t - C_t + r_t A_t \ ,$$

where the left-hand side is the change in assets and the right-hand side is savings. Summing over T-periods yields

$$A_T - A_0 = \sum_{t=j}^{T} (Y_j - C_j) + \sum_{t=j}^{T} r_j A_j \ . \tag{6}$$

The increase in net worth between period t and period T is equal to the sum of each period's savings and returns on assets. I use this equation to construct synthetic net worth.[15]

Figure 1 shows how reported net worth and constructed net worth closely comove, highlighting the quality of the PSID data for longitudinal analysis. In the figure, median reported net worth is the dashed blue line and median synthetic net worth is the dashed red line. Both series change in tandem at similar levels, with the exception of synthetic net worth missing some of the net worth dynamics around the 2008 financial crisis. A possible explanation is that the capital gains measure I am using is not capturing the top of the wealth distribution. For example, Fagereng, Holm, Moll, and Natvik (2021) documents that wealthier Norwegian households earn higher rates of return on capital. Mean reported net worth (solid blue line) and mean synthetic

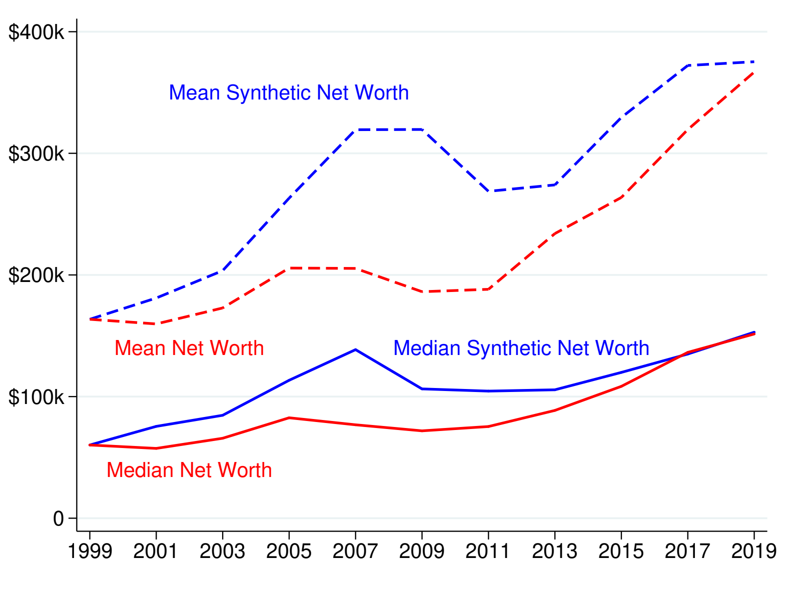
[15] I measure Y_t and C_t using total income and out-of-pocket expenditures. Total income includes household asset income, such as business income, farm income, dividends, interest, rents, trust funds, and royalties. Out-of-pocket expenditures measure shelter and vehicle expenditures by actual payments, such as mortgage and lease payments, not using implicit rent as I do in other exercises.

In equation (6), A_t is an aggregate measure that captures different asset classes. I compute capital returns for each asset class. I aggregate home equity, other real estate net assets, and farm and business net worth into a broad measure of capital and assume that their return is given by the CPI-deflated price change of the S&P Case-Shiller U.S. National Home Price Index. The stock return is the CPI-deflated change of the Wilshire 5000 Price Index, which already excludes dividend distributions. The return on Individual Retirement Accounts (IRAs) is assumed to be a constant 5% annually. Vehicles are assumed to depreciate by 15% annually. The return on checking or savings accounts is taken as the Fed funds rate. I assume "other debt" has a 10% annual interest rate. Finally, I assume that all savings go into home equity. My results do not change when savings are directed into private pension accounts.

Finally, I restrict the sample to households observed in all PSID waves for 20 years. I approximate $(Y_t - C_t) + (Y_{t+1} - C_{t+1}) \approx 2 \times (Y_t - C_t)$ since the PSID is a biannual survey. The consumption categories present in every PSID wave since 1999 capture about 67% of expenditure surveyed in the Consumer Expenditure Survey (C.E.) and the U.S. National Income and Product Accounts (NIPA) (Andreski, Li, Samancioglu, and Schoeni, 2014). Consequently, I scale up consumption as $C_t/0.67$.

net worth (solid red line) are even more closely linked.

Figure 1: Asset Path Implied by Expenditure and Income



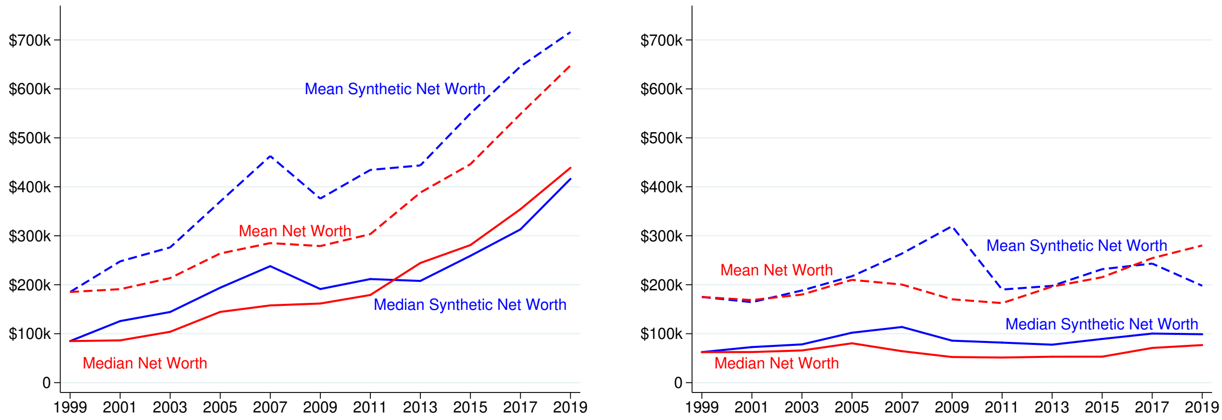
Note: This figure depicts the path of the reported net worth and synthetic net worth for households in the PSID. Reported net worth refers to the net worth respondents report when answering the questions in the PSID. Synthetic net worth refers to the net worth constructed using respondents' reported income and expenditure. Details on the construction are given in the text of subsection 4.2. Median (mean) reported net worth is the solid (dashed) blue line and mean (median) synthetic net worth is the dashed (solid) red line.

Figure 2 replicates the previous analysis but divides the sample into two groups: Panel 2a plots those households that experienced positive permanent income growth over 20 years and Panel 2b plots those that did not. Median reported net worth is again the dashed blue line and median synthetic net worth the dashed red line. First, it is immediately noticeable from both panels that both series are closely linked together. Second, both groups begin from similar starting points, but households that experienced permanent income growth accumulated more wealth than those that did not, consistent with the consumption responses. The same conclusion holds when looking at the mean instead of the median. The consistency between the reported asset path and the one inferred from the expenditure and income reported verifies that the data collected is accurate and reliable in measuring lifecycle household behavior.

Active Savings

Building on the previous subsection, I now investigate active saving rates project onto the current and lagged permanent income measures. Active savings measures the flow of money in and out of different assets, excluding any capital gains or changes in asset valuation. Arguably, this measure better reflects households' conscious decisions about how much to save from their current income. In contrast, savings measures that include capital gains reflect changes in asset values beyond

Figure 2: Asset Path Implied by Expenditure and Income



(a) Positive PI growth

(b) Negative PI growth

Note: This figure depicts the path of the reported net worth and synthetic net worth for households in the PSID, dividing 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 respondents report when answering the questions in the PSID. Synthetic net worth refers to the net worth constructed using respondents' reported income and expenditure. Details on the construction are given in the text of subsection 4.2. Median (mean) reported net worth is the solid (dashed) blue line and mean (median) synthetic net worth is the dashed (solid) red line.

household control. To construct active savings, I clean the questions available in the PSID Wealth Module following Hurst, Luoh, and Stafford (1998).[16] I define the active savings rate by dividing total active savings by labor income.

In Table 4, I present the results of regressing the savings rate on current and past permanent income in the spirit of the previous analysis in Table 6. The first and second columns show the results with only current permanent income, while the third has current and lagged permanent income. The coefficient of current permanent income is positive and significant in all three models, meaning that high-permanent-income households save a larger fraction of their income. Looking at the third column, the coefficient of lagged permanent income is negative and significant, with a value of -0.17. This result implies that households with the same permanent income today but with different permanent incomes in the past have different savings responses. Households that experienced faster permanent income growth save more, which is consistent with the previously documented results. This result also reaffirms the quality of the PSID data. Since the active saving measure is constructed from a completely different set of questions than the expenditure measure, it is reassuring that both analyses show consistent results.

[16]Following Hurst et al. (1998), active savings is the sum of i) net inflows into the stock market, ii) change in vehicle equity, iii) net change in transaction account balances, iv) net inflows to business, v) net inflows to annuities, vi) home improvements, and vii) net inflows into real estate other than main home minus increases in uncollateralized debt. Only changes in home equity classified as home improvements are included in active savings.

Table 4: Savings Response to Permanent Income

	(1) Savings Rate	(2) Savings Rate	(3) Savings Rate
log(PI)	0.19	0.16	0.24
	(0.02)	(0.03)	(0.04)
$\log(\mathrm{PI}_{t-10})$			-0.17
			(0.05)
Educ Dummies	Y	Y	Y
KP-F test	709.6	380.6	153.9
Observations	48,852	14,402	14,402

Note: This table reports the estimated savings rate elasticity to permanent income. All columns use instrumental variables, with the excluded instruments being log expenditure and dummy variables for industry groups. In the specification with lagged permanent income, lagged log expenditure 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 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.

3.4 Expenditure Components

In this subsection, I show that expenditure allocation across categories also depends on current and past variables. Again, developing the insight of Chetty and Szeidl (2016) and using dependence on past variables as a proxy for the importance of consumption commitments, I show that, conditional on the same current expenditure level, households with rapid past expenditure growth consume more easy-to-adjust goods and fewer hard-to-adjust goods (i.e., consumption commitments). The broad picture remains that consumption, savings, and expenditure composition depend on current and past variables, consistent with my commitment mechanism. I document this new fact by estimating demand systems to capture how past income growth is associated with expenditure allocation across different goods, conditional on a given level of total expenditures – equation (5).

Table 5 shows estimates of 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, since it has a large share in the consumption bundle and carries significant adjustment costs, such as moving costs, brokerage fees, search time, and nonpecuniary costs. I focus on Engel elasticities, which are displayed in brackets, for a more straightforward interpretation. The first rows of columns 1 and 3 imply an Engel elasticity of 0.8 for nondurable expenditure, which implies that nondurable goods are a necessity and expenditure on such increases by 0.8% for each 1% increase in total expenditure. Columns 2 and 4 imply an

Engel elasticity of 1.1 for shelter expenditure, which implies that shelter is a luxury good and its expenditure increases by 1.1% for each 1% increase in total expenditure.

Table 5: 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 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.

The second row of Table 5 shows the impact of past expenditure growth on the allocation of expenditure between different consumption categories. Conditional on the same expenditure today, a household with faster expenditure growth consumes less shelter and more nondurables. For example, 10% growth in total expenditure decreases shelter expenditure by 0.3% and increases nondurable spending by 0.1%. Consistent with my model, households with commitments must respond to increases in permanent income by increasing adjustable goods (e.g., nondurables).

Figure 3 presents the allocation of expenditure for more disaggregated consumption categories. In the right panel, I sort the categories by their demand system coefficient on the expenditure growth rate, which I interpret as a proxy for the degree of consumption commitment. Shelter, and, at the margin of statistical significance, vehicle, home insurance, utility, and out-of-pocket (health) expenditure, are categories reduced by past growth. Conversely, past growth skews the basket towards nondurables, car insurance, health insurance, food at home, and home improvement expenditures. Interestingly, the categories' Engel elasticities – left panel – do not follow the same pattern as the growth rate elasticities, meaning that households increasing expenditure on luxury goods is not driving the results.[17]

[17]Commitments are a different good characteristic and justify its definition. Commitments goods are broader than

Figure 3 presents the allocation of expenditure for more disaggregated consumption categories. In the right panel, I sort the categories by their demand system coefficient on the expenditure growth rate, which I interpret as a proxy for their strength as a consumption commitment. For shelter, and, at the margin of statistical significance, vehicle, house insurance, utilities, and out-of-pocket (health) expenditures are categories for which past growth skews the basket away from them. These goods are broader than durable goods, including housing and vehicles, but also services and taxes. On the other hand, past growth skews the basket towards nondurables, car insurance, health insurance, food at home, and house improvement expenditures. These goods are broader than nondurable goods, including, for example, house improvement expenditures, which are considered durables. Interestingly, the categories' engle elasticities – left panel – do not follow the same pattern as the growth rate elasticities, meaning that households increasing expenditure on luxury goods is not driving the results.

3.5 Consumption Resets

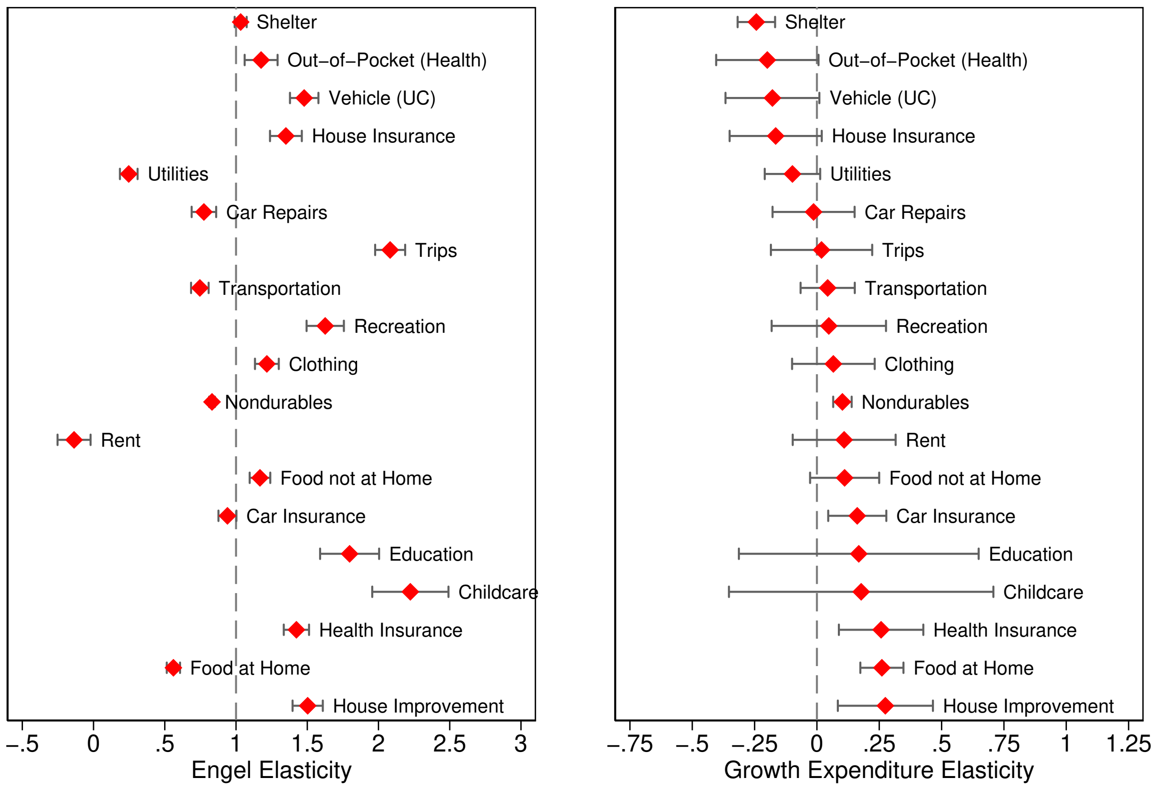
My mechanism relies on adjustment frictions on some goods. As empirical support for this, I compare the behavior of households who recently adjusted the quantity of their hard-to-adjust goods to those that did not. Since shelter expenditure is an important consumption commitment in the data, I classify households that moved at least once within the prior decade as households that adjusted their bundle.[18] If consumption commitments are important in the data, the consumption responses and expenditure allocation of these households should depend at most weakly on lagged variables. In Appendix C.4, I discuss the consumption response of renters, as adjusting their consumption is arguably less costly.

Column 1 of Table 6 shows that consumption responds less to lagged permanent income for households which recently moved. For households that did not move in the past, consumption loads significantly more on past permanent income, with an estimated elasticity of 0.35 for current permanent income and 0.45 for lagged. For those households that moved, the consumption response loads more on current permanent income with an estimated elasticity of 0.61 and 0.22 for lagged permanent income. These results are consistent with the commitment mechanism: consumption for households that adjust their basket depends more on current permanent income and less on past decisions.

just durable goods such as housing and vehicles, but also include some services (utilities and house insurance). On the other hand, Non-commitments goods are broader than nondurable goods, including, for example, house improvement expenditures, which are considered durables.

[18] In Appendix C.3, I show that the probability of moving increases in the absolute value of the permanent income change. This implies that the permanent income measure forecasts moving behavior, with larger permanent income changes being associated with a higher moving probability of households, as standard lumpy adjustment models predict.

Figure 3: Consumption Categories



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.

In a mirror image of the previous result, column 2 of Table 6 shows that savings rates also respond less to past permanent income for households who recently moved. For households that have not moved, the savings rate has an estimated semi-elasticity of 0.40 with respect to permanent current permanent income and -0.36 for lagged, meaning that such households accumulate assets following permanent income growth. However, for households that moved the saving rate loads almost exclusively on current permanent income, with an estimated semi-elasticity of 0.15 for current and -0.03 for lagged. Again, these results align with the consumption commitment mechanism.

In Table 7, I use the same proxy for adjustment to show that the expenditure allocation of households that recently moved does not depend on history, as the consumption commitment

Table 6: Heterogeneous Effects: Household Moves

	(1) log(expenditure)	(2) Savings Rate
log(PI)	0.35	0.40
	(0.07)	(0.09)
$\log(\text{PI}_{t-10})$	0.45	-0.36
	(0.09)	(0.10)
Moved $\times$ log(PI)	0.26	-0.25
	(0.12)	(0.12)
Moved $\times$ $\log(\text{PI}_{t-10})$	-0.23	0.33
	(0.14)	(0.14)
Educ Dummies	Y	Y
KP-F test	15.8	23.6
Observations	14,531	14,402

Note: This table reports the estimated consumption and savings rate elasticity to permanent income and 10-year lagged permanent income for movers and no movers. Movers are defined as households that moved at least once within the prior decade. 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 excluded instruments in the second column are 2-year and 12-year lagged expenditure 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.

mechanism predicts. The first column shows the nondurable consumption of households that did not move loads significantly on lagged expenditure, with an estimated coefficient of -13.4 for log expenditure and 12.4 for the growth rate. However, for households that recently moved, nondurable consumption loads more on current expenditure, with an estimated coefficient of -10.4 for log expenditure and 3.5 for the growth rate. As expected, the estimated coefficients for shelter consumption have opposite signs than those estimated for nondurable consumption.

3.6 Additional Results

I perform several additional empirical tests that I briefly discuss here, postponing a more detailed discussion to the appendices.

Quality of the Expected Income Growth Measure: When constructing my permanent income measure, I assumed that household information sets could be captured by lagged income, occupation, age, and demographic characteristics. However, the literature has found that, in gen-

Table 7: Heterogeneous Effects: Household Moves

	(1) Nondurable Share	(2) Shelter Share
log(exp)	-13.40	6.26
	(0.92)	(0.97)
Δ log(exp)	12.43	-19.38
	(2.58)	(2.87)
Moved $\times$ log(exp)	3.32	-3.34
	(1.03)	(1.12)
Moved $\times$ Δ log(exp)	-8.91	14.83
	(2.73)	(3.10)
Educ Dummies	Y	Y
KP-F test	7.7	7.7
Observations	10,163	10,167

Note: This table reports the estimated AIDS demand system for movers and no movers. Movers are defined as households that moved at least once within the prior decade. All columns use instrumental variables. The excluded instruments are 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 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.

eral, households have superior information than the econometrician. If true here, some of the estimated permanent income growth could have been known of by households and incorporated into their current consumption choices. To address this concern, I present evidence in Appendix B that while households have superior information it is not a major issue. In particular, I show that current consumption predicts future forecast error but has low forecasting power, suggesting that households' superior information is quantitatively unimportant.

Bequest and Intervivo Transfers: The underconsumption puzzle implies that rich households save a lot. A commonly assumed force in many consumption models is strong preferences for larger bequests (e.g., De Nardi, 2004) or insuring heirs through intervivo transfers (e.g., Boar, 2021). I examine the presence of these forces in the PSID in Appendix C.5. The probabilities of leaving bequests and helping children, and the bequeathed and transferred amounts, are positively associated with permanent income. However, there are not enough observations to test the dependence on past permanent income.

Donations: Another possible reason for why consumption does not track permanent income is that some expenditures of rich households are not being measured. In Appendix C.6, I use new and unexplored information on philanthropic giving available in the PSID since 2001. Current permanent income is positively associated with the likelihood of reporting donation expenditure and with the amount donated. However, there is no evidence that households with faster permanent income growth donate more.

Parent-Child Pairs: The bequest motive plays an important role in my calibration. In Appendix C.7, I examine whether this force is also present in the data. The idea of the exercise is that if child households have information about their parents' permanent income level and the bequest motive is important in the data, the child's consumption should respond to their parents' permanent income. The data shows a positive correlation between the children's expenditure and their parents' current and lagged permanent income. Children respond to their parents' permanent income, which I interpret as evidence that they expected to recive money from their parents. However, I do not find evidence that locked-in parents transfer more money to their children.

4 A Life-Cycle Model with Lumpy Goods Adjustment

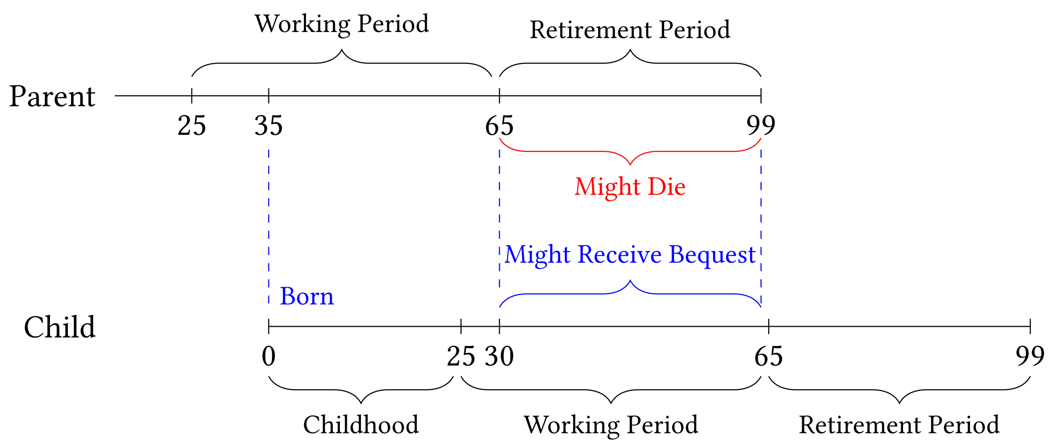
In this section, I extend a canonical incomplete markets model (Deaton, 1991; Carroll, 1997; Gourinchas and Parker, 2002) incorporating two consumption goods, one of which is hard-to-adjust. The hard-to-adjust good, which can be interpreted as housing or durables, provides a utility flow from its stock,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

4.1 Environment

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

Figure 4 displays the generational structure of the model. Households have a child-household at age $j = 10$ (biological age 35), which implies that the child enters the labor market when the parent is age $j = 35$ (biological age 60) and retires when the parent has already passed away at a hypothetical age $j = 75$ (biological age 100). Parents and children are connected by bequests and intergenerational transmission of skill, to be detailed later. Since parents face a positive mortality risk during retirement, children might receive a bequest between age $j = 5$ (biological age 30) and age $j = 39$ (biological age 64). This timing ensures that only two generations are alive simultaneously in the model and that no bequests are transferred directly from grandparents to grandchildren. There is no population growth in the model.

Figure 4: Overlapping Generations Structure



Preferences Households have standard time-separable preferences characterized by a discount factor, β, and period utility defined over an aggregated consumption bundle composed of two commodities. The first commodity comprises easy-to-adjust goods, and I denote it as non-durable consumption, c^n. The second one comprises hard-to-adjust goods, and I will denote it as commitments consumption, c^h. It is commitments flow for owners, $c^h = \zeta h$, where ζ is the return (in utility terms) on the commitments stock h, or rented quantity for renters. Both commodities are aggregated by a CES function,

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

where ω is the share parameter that determines the weight of commitments flow in the aggregator function, and $1/(1-\gamma)$ is the elasticity of substitution. An aspect in which my model differs from the one of Kaplan and Violante (2014) is that distortions in the allocation of expenditure across different consumption categories play an important role in my mechanism, while they assume a frictionless rental market for hard-to-adjust goods, which implies that total expenditure is optimally allocated across categories.

Dynan et al. (2004), Straub (2019), and others have identified in the data that household savings rates increase in expected lifetime income, which contradicts the predictions of standard homothetic life-cycle models. Important motives for this saving behavior are intergenerational transfers (such as bequests and intervivo transfers) and other expenses later in life (such as health expenditures). I capture these different motives using luxury late-in-life consumption as in Straub (2019) and elastic bequest motives as in De Nardi (2004).

In particular, I assume that period utility for a household at age j is given by

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

where $\sigma_j > 0$ is an age-dependent elasticity. As in Straub (2019), the coefficient of risk aversion in the utility function follows a simple exponential decay, $\sigma_{j+1}/\sigma_j = \sigma_{slope}$ during one's working life, and is flat after that. The model is parameterized so that σ_j decreases as the household ages, resulting in a high income elasticity of consumption when old. In other words, these preferences imply a back-loaded consumption profile for higher-income households and are a tractable way of capturing their later-in-life expenses, such as payments for college education, charitable giving, or expensive medical treatments. $o > 0$ is a normalization parameter which can be used to retain aggregate scale invariance.

Preferences over bequests are given by

$$\mathcal{B}(a,h) = \frac{\phi_1}{1-\sigma}\left(\frac{\phi_2 + a + h}{o}\right)^{1-\sigma_b} \,,$$

in which a is a risk-free bond. The assumed functional form has three parameters: ϕ_1 is a weight parameter, while σ_b and ϕ_2 govern the degree of luxury associated with the bequest motive. In particular, a positive and large ϕ_2 or a small σ_b implies that bequests behave as a luxury good. I assume that commitments stock and bonds are perfect substitutes in the bequest function, implying that households are indifferent between leaving either to their children. Estate taxes are paid by the child-household, so they do not distort parents' decisions. Again, $o > 0$ is a normalization parameter.

Idiosyncratic Earnings Households are subject to idiosyncratic labor income risk. The labor productivity process is a combination of a Markov process and a deterministic component. To clarify the notation, I use subscript 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

$$
\begin{aligned}
z_{i,j} &= b_1 j + b_2 j^2 + \bar{z}_i + \alpha_{i,j} + \epsilon_{i,j} \\
\alpha_{i,j} &= \rho \alpha_{i,j-1} + \xi_{i,j} \ ,
\end{aligned}
\tag{7}
$$

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^2_ϵ and σ^2_ξ, 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: $w \times \exp(z_{i,j})$. It is important to note that labor income in the model corresponds to income after accounting for taxes and transfers. This concept is also applied when working with the PSID sample, ensuring consistency in the treatment of labor income.

Finally, the fixed productivity draw depends on the fixed productivity of the parent household. Specifically, for household i, $\bar{z}_i$ follows the equation:

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

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

Assets Households invest in liquid risk-free bonds and illiquid commitments stock. The risk-free bonds carry a constant risk-free rate r. Commitments provide a utility flow represented by ζ and depreciate at rate δ per period. To adjust their commitments stock, households must incur non-convex costs, reflecting, for example, expenses such as 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 the value of their housing when adjusting their housing stock. The adjustment cost function is specified as follows:

$$
\mathcal{A}(h, h_{-1}) = \begin{cases} 0 & \text{doesn't adjust} \\ \kappa h_{-1} & \text{does adjust} \end{cases} .
$$

Commitments owners incur a "required maintenance" parameter, χ, which accounts for the repairs and maintenance needed to continue enjoying unchanged commitments flows. Additionally, households face a borrowing constraint that depends on their commitments stock: $a > -\theta h$. In other words, households can borrow using their commitments as collateral.

When households own a house, they incur a "required maintenance" parameter, , which accounts for maintenance needed to continue enjoying housing flows, such as repairing a broken furnace or reforming the electrical circuit system. Additionally, households face a borrowing constraint that depends on their housing stock: . In other words, households can borrow using their house as collateral. They start their working lives with zero assets and a minimum quantity of housing.

Rental Market Households that decide not to be owners can enjoy housing consumption by buying it in a rental market. Renters can buy any positive amount of housing consumption subject to paying a mark-up λ over the housing price. In this case, they will consume c^h bought in the rental market at a cost of λc^h. I assume that households have to be either owners or renters, meaning that it is not possible to own a house and then rent another one.[19]

Retirement Once retired, households live off their financial wealth a, housing wealth h, and social security benefits pen$(\bar{z})$, which is a function of fixed-income productivity.[20]

4.2 Recursive Formulation

Let s denote the vector of state variables for a household, $s = \left\{j, a, h_{-1}, \bar{z}, \alpha, \epsilon, \bar{z}^p\right\}$. These variables indicate, respectively, age (j), bonds carried over from the previous period (a), past commitments stock (h_{-1}), and labor productivity components ($\bar{z}, \alpha, \epsilon$). The last variable ($\bar{z}^p$) has two purposes, to be detailed later.

The first household decision is commitments: to own or to rent, and if a prior owner, whether to adjust commitments size. Specifically, households solve the discrete choice maximization problem

$$V(s) = \max \left\{V^{rent}(s), V^{adj}(s), V^{noadj}(s)\right\},$$

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

In the case where renting is optimal, the household chooses not to own commitments and

[19]The rental problem can be solved in two stages. In the first stage, I solve for total expenditures and liquid asset savings. In the second stage, I solve the within-period problem of allocating total spending on nondurables and rental housing services, conditional on the optimal total expenditure and liquid assets.

[20]Labor income in the model corresponds to income after accounting for taxes and transfers, so the implicit assumption is that these taxes will cover the retirement benefits. In practice, 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).

solves the following problem:

$$V^{rent}(s) = \max_{c^h, c^n, a'} u_j\Big(g(c^h, c^n)\Big) + (1-\psi_j)\,\beta\,\mathcal{B}\Big(a', 0\Big) + \psi_j\,\beta\,\mathbb{E}\Big\{V(s')\Big|s\Big\}$$

$$\text{s.t.}$$

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

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

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

where z evolves according to a conditional c.d.f. Γ^z and the next-period state vector is $s' = \Big\{j+1, a'+b', 0, \bar{z}, \alpha', \epsilon', \bar{z}^{p'}\Big\}$.

When a household dies, they pass on a lump-sum bequest. This bequest, b, enters the child household's state vector as an increase in next period assets. Therefore, child households need to form a belief about the distribution of bequest sizes, which is assumed to be a function of their age and their parents' fixed productivity. So the last state variable ($\bar{z}^p$) has two purposes, as in De Nardi (2004). First, when it takes on a positive value, it represents the fixed productivity of the parent household and is used to calculate the probability distribution of bequests that a household expects to receive. Second, it helps differentiate between agents who have already inherited (for whom $\bar{z}^{p'}$ is set to 0) and those who have not (for whom $\bar{z}^{p'}$ is strictly positive). The bequest belief has conditional c.d.f $\Gamma^{j,\bar{z}^p}$.

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

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

$$\text{s.t.}$$

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

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

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

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

where z evolves according to a conditional c.d.f. Γ^z, b has conditional c.d.f $\Gamma^{j,\bar{z}^{p'}}$, and the next-period state vector is $s' = \Big\{j+1, a'+b', h_{-1}(1-\delta(1-\chi)), \bar{z}, \alpha', \epsilon', \bar{z}^{p'}\Big\}$.

Lastly, when housing adjustment is optimal, the household picks a new commitment stock and solves the following problem

$$
\begin{aligned}
V^{adj}(s) = \max_{c^n,h,a'}\ & u_j\Big(g(\zeta h, c^n)\Big) + (1-\psi_j)\,\beta\,\mathcal{B}\Big(a', h\Big) + \psi_j\,\beta\,\mathbb{E}\Big\{V(s')\Big|s\Big\} \\
\text{s.t.}\ & \\
& h = (1-\kappa)(1-\delta)h_{-1} + x \\
& c^n + a' + x = \text{pen}(\bar{z}) + we^z + (1+r)a \\
& c^n > 0, \quad h > 0, \quad a \geq -\theta h \\
& \bar{z}^{p\prime} = \begin{cases} \bar{z}^p & \text{with prob } (1-\psi_{j+35}) \\ 0 & \text{with prob } \psi_{j+35} \end{cases}
\end{aligned}
$$

where z evolves according to a conditional c.d.f. Γ^z, b has conditional c.d.f $\Gamma^{j,\bar{z}^{p\prime}}$, and the next-period state vector is $s' = \Big\{j+1, a'+b', h, \bar{z}, \alpha', \epsilon', \bar{z}^p\Big\}$.

I solve the model for the partial equilibrium with $w = 1$ and $r = 0.03$. The child's bequest expectation has to be consistent with the actual bequest that parents leave, so I iterate the bequest belief until convergence. Appendix E describes the computational algorithm used to solve the problem.

4.3 Mechanism

In the optimization problem, households choose savings and consumption to maximize their lifetime utility given their assets (a and h) and their expected income path. In most consumption model, the optimal choices of savings and consumption are approximately linear in permanent income, which is the sum of total assets and the present value of future income. This implies that consumption has an elasticity of 1 with respect to permanent income, and any increase in permanent income leads to a proportional increase in consumption.

However, 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 optimal, which works as a utility wedge (or a tax on current consumption). Consequently, households will substitute present consumption for future consumption and future bequest. This substitution allows households to mitigate the inefficiencies caused by suboptimal expenditure allocation by consuming more when the bundle is closer to optimal or by leaving larger bequests. Households that experience a decrease in permanent income should overconsume and reduce savings, as cutting back on easy-to-adjust goods would just create more inefficiencies.

The key implication is that, for households locked into past consumption choices, the history of permanent income influences current consumption choices. In the emprical section, I used PSID data to measure how current consumption depends on current and past permanent income. I calibrate the model to match this evidence. This path dependence arises due to imperfect substitutability between expenditure categories and lumpy adjustment in response to changes in permanent income. This path dependence gives rise to three key implications. First, for households with the same level of permanent income, the elasticity of consumption to permanent income is lower for those whose permanent income has grown faster. Second, households with faster-growing permanent income allocate a higher share of their expenditure to easy-to-adjust goods. Third, history matters less for households that recently adjusted their consumption bundle.

5 Calibration

I use data from the PSID to calibrate the model. First, I explain permanent income measurement in the model and how I use it to calibrate the model. Second, I describe other moments used in the calibration and the chosen parameters.

5.1 Calibrating Consumption's Response to Permanent Income

Permanent income is defined as the sum of current household assets plus its discounted future expected income profile. As in Subsection 2.2, I mimic this definition when constructing permanent income in the model. In particular, for household i of age j, it is

$$\mathrm{PI}_{i,j} = a_{i,j} + h_{i,j-1} + \mathbb{E}_{i,j}\left[\sum_{s=j}^{99} \frac{y_{i,j}}{R^{s-j}}\right] ,$$

where $a_{i,j}$ are bonds carried from the previous period, $h_{i,j-1}$ is commitments owned last period, $y_{i,j} = we^{z_{i,j}}$ is labor income, and $R = 1 + r$ is the risk-free rate. The expectation is computed using the same method proposed in the empirical section.[21]

I calibrate the model by matching its consumption response to the one estimated from the PSID data. I estimate the model's elasticity of consumption to permanent income by regression, as in Subsection 2.3. For that, I simulate the 5,000 individuals and measure consumption's response

[21] As robustness, I also explore constructing the expectation using all available information for the household (i.e., the components of labor productivity and the survival probabilities).

in the model by implementing an analogous regression to (3). In particular, I estimate:

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

$\log c_{i,j}$ 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.

As an additional moment in the calibration, I also estimate regression (4) in the model-generated data. This regression captures the insight of Chetty and Szeidl (2016) that household-level consumption commitments resemble consumption habits; therefore, if commitments are important, past permanent income growth should matter for current consumption. I match the estimated coefficients for both current and 10-year lagged permanent income using model-generated data with those estimated using the PSID data. The coefficient on lagged permanent income helps identify the strength of consumption commitments.

5.2 Other Moments and Calibrated Parameters

In addition to consumption's response to permanent income, I calibrate the model parameters to match other moments of the PSID data. I follow a two-step calibration procedure.

First, I externally set some parameters: those that describe the income process and certain ones commonly calibrated in the literature. In the second step, I endogenously calibrate the remaining parameters, conditional on the parameters in the first step. I do this by matching the model-simulated and PSID moments. Tables 8 and 10 present the model parameters, while Table 9 presents the data moments and their corresponding counterparts in the model.

Externally Set Parameters

Demographics and Initial Distributions. All demographic parameters in the model are set externally. In particular, I set when households begin their working life, have a child, retire, and their maximum lifespan. The mortality risk that households face when retired is calibrated with data from US Life Tables from the National Vital Statistics System for 2011. I set the initial asset positions to zero.

Income Process. I set the parameters governing the income process parameters to reproduce key moments of the distribution of household after-tax labor in the PSID sample. First, I estimate a second-order polynomial in age to extract the common life-cycle earnings profile, b_1 and b_2. Second, I estimate the persistence parameters and the standard deviations of the transitory and persistent shocks by matching data moments of income variation and income growth. The individual fixed productivity is set to reproduce the dispersion of average earnings between ages 23 and 27. Using the average decreases the importance of measurement error. Appendix D has more detail on the computational process.

Lastly, I calibrate the parameters characterizing the intergenerational transmission of skill. This calibration procedure should be seen as, conditional on the income process parameters described in the last paragraph, which parameters of the intergenerational transmission of skill process match the correlation between parental and child income ranks measured in the literature (Chetty, Hendren, Kline, and Saez, 2014).

Housing parameters. . I calibrate certain parameters governing the housing structure to values found in the literature. I set the depreciation rate to 3%, which is the depreciation rate used by the BEA for residential capital Fraumeni (1997).[22] I set the maintenance cost to 1, a value slightly higher than the one estimated by Berger and Vavra (2015). This cost captures any expenditures on repairs and improvements that delay depreciation. I set the maximum maximum (LTV) to 0.8 reflecting Greenwald (2018) and Boar, Gorea, and Midrigan (2022). Lastly, I set the utility flow of owning a house to 4%. This parameter is difficult to identify in the data since it refers to the consumption utility flow of owning and living in a given house. I follow the literature and use the equivalent expenditure (or implicit rent) that owning a house provides. In particular, 4% implicit rent is a slightly lower rent-to-value ratio than Katz (2017) estimated for a $400,000 house.[23]

Preference parameters. Lastly, I calibrate some preference parameters exogenously. I set the exponential decay of the consumption CRRA utility coefficient, $\sigma^{c,slope}$, to 1, which implies late-in-life consumption is not a luxury. I calibrate the scale term in the utility function, o, to 0.2, in line with the value of 0.3 used by Straub (2019). I calibrate the risk aversion coefficient in bequest utility, σ^b, to 0.2, which means that the bequest decision is elastic and a luxury to the extent by which $\sigma^b > \sigma^c$. Finally, I set the Stone–Geary parameter in the bequest function, ϕ_2, to 0, which means that bequests are a luxury only due to the difference between σ^b and σ^c.

Endogenously Set Parameters

I now endogenously calibrate the remaining parameters – preferences, adjustment costs, and rental markup – in order to match certain data moments. The parameters $\{\omega, \gamma, \kappa, \lambda\}$ play a crucial role in generating certain moments: i) the proportion of owners who have moved at least

[22] I set the depreciation rate to the average depreciation rate of i) residential capital consisting of 1-to-4-unit structures with additions and alterations, and ii) residential capital consisting of 1-to-4-unit structures with major replacements.

[23] The BEA, when computing personal consumption expenditures (PCE), imputes implicit rent for owner-occupied housing by assuming it would rent for the same rate as rental units with similar market values. Information for this procedure comes from the Residential Finance Survey (RFS), which ceased in 2000. Katz (2017) updated the implicit rent schedule relative to housing market values for 2011. The BLS uses a similar approach, Owners' Equivalent Rent (OER), see Verbrugge (2012). The user-cost approach is also an option. Verbrugge (2008) and Garner and Verbrugge (2009) discuss the differences when estimating rents using user costs versus rental equivalence approaches.

Table 8: 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	Retirament age	65	-
T	Certain Death age	99	-
	Income Process		
b_1	Linear trend	0.03	
b_2	Quadratic trend	-0.0007	
$\sigma_{\bar{z}}$	Fixed-effect variance	0.17	PSID
σ_ϵ	Transitory variance	0.12	
σ_ν	Persistent variance	0.02	
ρ	Persistence parameter	0.98	
$\rho_{inherit}$	Pers. of intergen. skill transmission	0.74	Chetty et al. (2014)
	Housing		
ζ	Utility flow from housing	0.04	Katz (2017)
δ	Housing depreciation	0.03	BEA
χ	Maintenance cost	1.00	Berger & Vavra (2014)
θ	Collateral Parameter	0.85	Greenwald (2018)
	Preferences		
o	Scale term in utility function	0.20	Straub (2019)
σ^b	CRRA for bequest	0.20	-
$\sigma^{c,slope}$	Ratio of elasticities $\sigma^c_{j+1}/\sigma^c_j$	1.00	-
ϕ_2	Bequest preference (luxury)	0.00	-

once in the past two years, ii) the ratio of average shelter expenditure to average total expenditure, iii) the ratio of average housing wealth to average total wealth, and iv) the homeownership rate. The parameters $\{\beta, o, \sigma_c, \phi_1\}$ play a crucial role in generating other specific moments: i) the ratio of average wealth to average income, ii) the estimation of consumption's response to permanent income, as presented in Table 1, Column 4, iii) and iv) the estimation of consumption's response to permanent income and lagged permanent income, as presented in Table 3, Column 1, and vi) bequests relative to GDP. Observe that some moments, such as the responses to permanent income, are important for more than one parameter, since there is no 1-to-1 mapping between moments and parameters.

Table 9 presents the comparison between data and model moments. The calibration matches consumption's responses to current permanent income (Table 4, Column 4 and Table 7, Column 1) and 10-year lagged permanent income (Table 7, Column 1), though using a smaller coefficient. The model also does reasonably well in matching housing moments, including the likelihood of owners moving house, the homeownership rate, the ratio of shelter expenditure to total expenditure, and the ratio of housing wealth to total wealth. Lastly, the model overpredicts the wealth-to-income ratio but matches the bequest-to-income ratio in the data.

Table 9: Calibrated Moments

Description	**Data**	**Model**
Moving rate of owners (past 2 years)	0.14	0.14
Homeownership Rate	0.58	0.63
Ratio Shelter Expenditure to Total Expenditure	0.22	0.15
Ratio Housing Wealth to Total Wealth	0.64	0.58
Ratio Total Wealth to Income	4.39	5.18
Bequest flow over GDP	0.08	0.09
C's response to PI (Table 1, Column 4)	0.80	0.83
C's response to PI (Table 3, Column 1)	0.60	0.65
C's response to lagged PI (Table 3, Column 1)	0.30	0.18

Table 10 lists the endogenous parameters. The discount factor and the coefficient of relative risk aversion fall within the range of values commonly used in the literature. The choice of discount rate implies a moderately impatient household, a crucial factor for accurately capturing wealth dynamics in incomplete market models. The risk aversion coefficient implies a consumption preference that is more elastic than the traditional $\sigma_c = 2$ but less elastic than logarithmic utilities. The weight assigned to housing in the CES goods aggregator is determined by the ratio of shelter expenditure to total expenditure. The CES preference parameter implies an elasticity of substitution of 1.11, aligning with estimates in the literature (Piazzesi and Schneider, 2016). The adjustment cost of 10% is in line with other papers in the literature, such as Berger and Vavra (2015), and is mainly determined by the likelihood owners move house. The rental markup is mainly determined by the ownership rate. Finally, the bequest weight in the utility is most determined by the bequest flow to GDP.

6 The Role of Consumption Commitments in Consumption Responses

In this section, I analyze the model's ability to account for the novel facts on consumption's response to permanent income documented in Section 3. I evaluate the model by its ability to replicate observed untargeted moments following regression of simulated data. In particular, I march

Table 10: Endogenously Set Parameters

Parameters	Description	Value
	Demographics and Initial Asset Positions	
	Preferences	
β	Discount factor	0.92
σ_c	CRRA for consumption	1.25
ω	Consumption aggregator	0.27
γ	Goods elasticity of substitution	0.10
ϕ_1	Bequest preference (weight)	0.53
	Housing	
λ	Rent markup	2.00
κ	Adjustment cost	0.10

three moments related to the consumption response to permanent income in the calibration exercise: The average response to permanent income, as documented in Table 1, Column 4, and the average response to current and lagged permanent income, as documented in Table 3, Column 1. All other facts documented in Section 3 are treated as untargert moments. The model captures almost all such untargeted moments, highlighting the importance of consumption commitments in understanding consumption's response to permanent income.

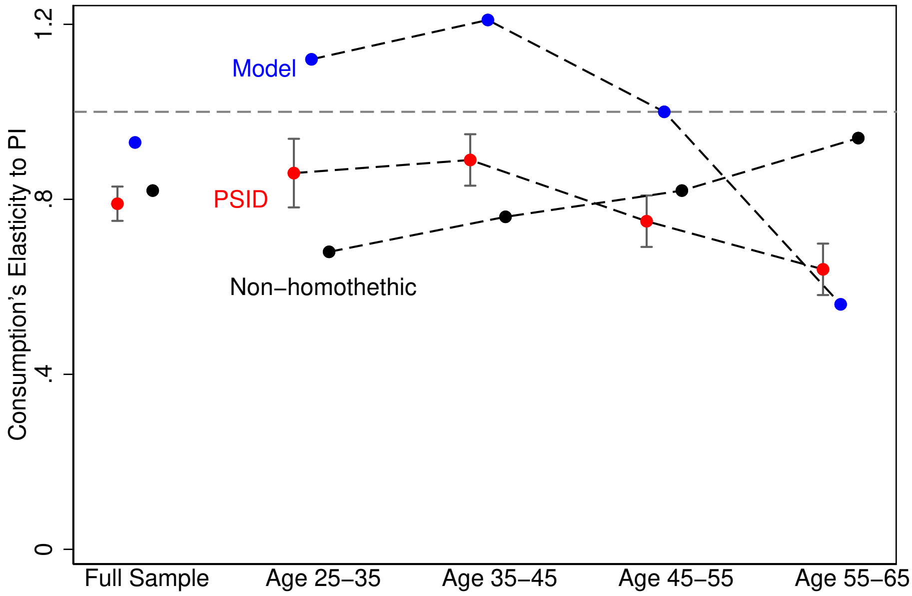
To contrast the model performance, I simulate a model with another mechanism proposed in the literature, luxury late-in-life consumption, but without the consumption commitment block. More details of this calibrated model is in Appendix D.

6.1 Consumption Responses to Permanent Income

The calibrated model with consumption commitments generates the lifecycle dynamics in the consumption elasticity. Recall that, in Table 2, I estimate a consumption elasticity to permanent income close to 0.9 for households between 25 and 45 years old, as seen in its second and third columns. However, for households between 45 and 65 years old, I estimate an elasticity smaller and decreasing with age, falling as low as 0.64, as seen in the fourth and fifth columns. These results are displayed using the red dots (named PSID data) in Figure 5. The first dots are the targeted moments, the average consumption responses for the sample of all working-age households. The other dots are non-targeted moments.

The model with commitments (blue dots) generates the hump-shaped profile of consumption response as seen in the data, although it misses the level and predicts a larger elasticity. On the

Figure 5: Consumption's Responses to Permanent Income – Data and Model



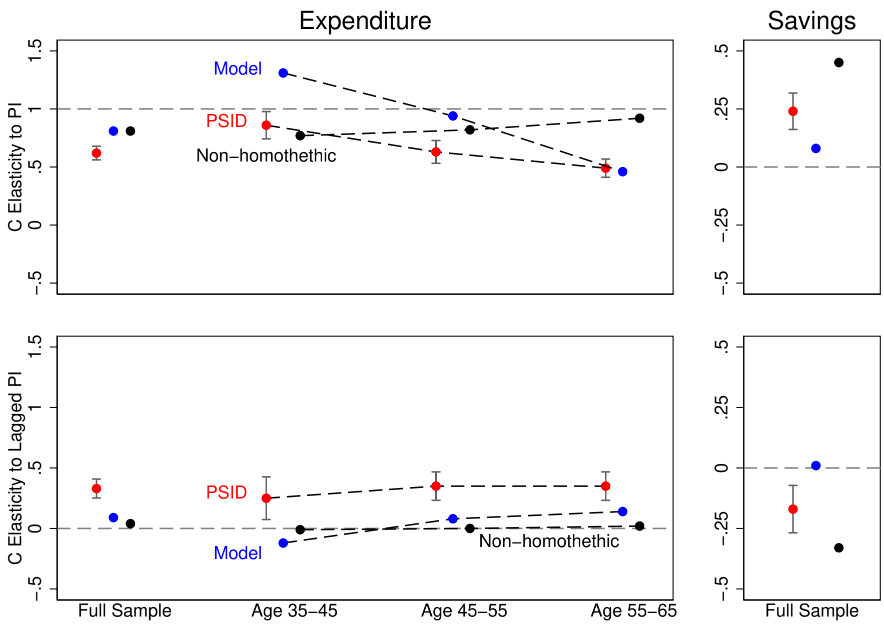
other hand, a model with only luxury late-in-life consumption (black dots) cannot generate the dynamics observed in the data and predicts a contrafactual pattern in which the consumption response increases with age.

Consumption commitments generate consumption elasticities that decrease with age. Since commitments are made gradually throughout the life cycle, older households have more commitments on average. Indeed, older households have higher commitment homeownership rates in the model, as seen in Figure 11 of Appendix D. Therefore, their consumption is more detached from their permanent income level because they are more "locked" into past consumption commitments.

6.2 Consumption Responses to Current and Past Permanent Income

Another fact that the model consumption with consumption commitments can generate is the responses to current and lagged permanent income, as documented in Table 3. In Figure 6, the first dots are the targeted moments, the consumption responses to current and lagged permanent income for working-age households. The other dots are non-targeted moments. The calibrated model – blue dots – generates some consumption path dependence, as in the data. On the other hand, a model with late-in-life luxury consumption – black dots – cannot generate a similar pattern. Despite the successes of the model with commitment, it still cannot generate a response to past permanent income as strong as in the PSID data – red dots.

Figure 6: Consumption's Responses to Permanent Income – Data and Model

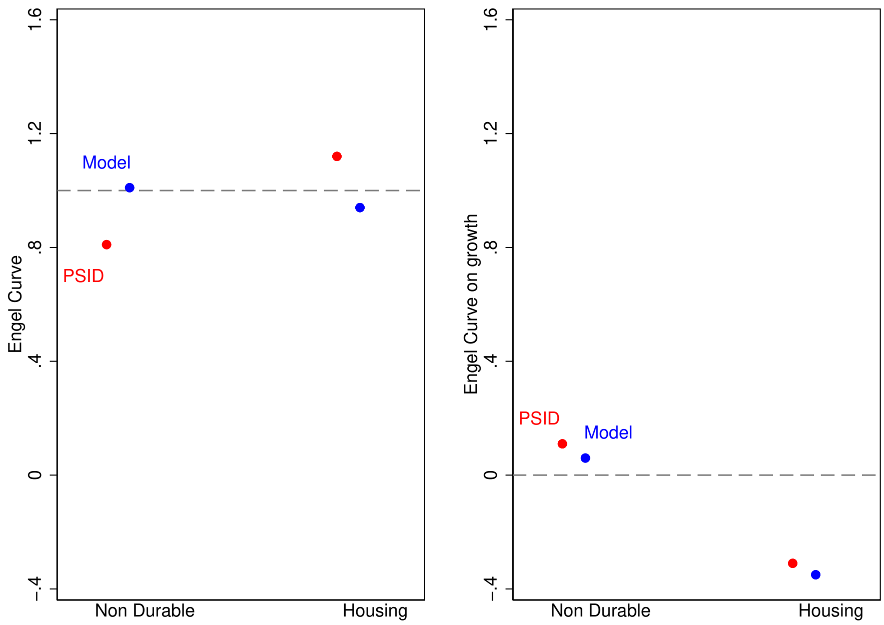


More over, the model with consumption commitments generates savings responses to current and lagged permanent income, as documented in Table 4. On the right panel of Figure 3, it is possible to see that the calibrated model – blue dots – generates less dependence on past variables than the model with late-in-life luxury consumption – black dots. In fact, the PSID data – red dots – seems to be a mixture of the two models.

6.3 Expenditure Components

The model with consumption commitments can also generate the skewed expenditure allocation of fast-permanent-income-growth households toward nondurable expenditure, as documented in Table 5. The right panel of Figure 7 shows that the model – blue dots – generates a positive expenditure growth elasticity for nondurables and a negative one for shelter, as seen in the PSID data – red dots. However, the left panel shows that the model does not replicate shelter as a luxury or nondurable spending as a necessity, as seen in the data. Since the model aggregates goods with a CES structure, the elasticities in the model are closer to 1.0 than in the data. All those moments were not targeted in the calibration.

Figure 7: Consumption Category Shares – Data and Model



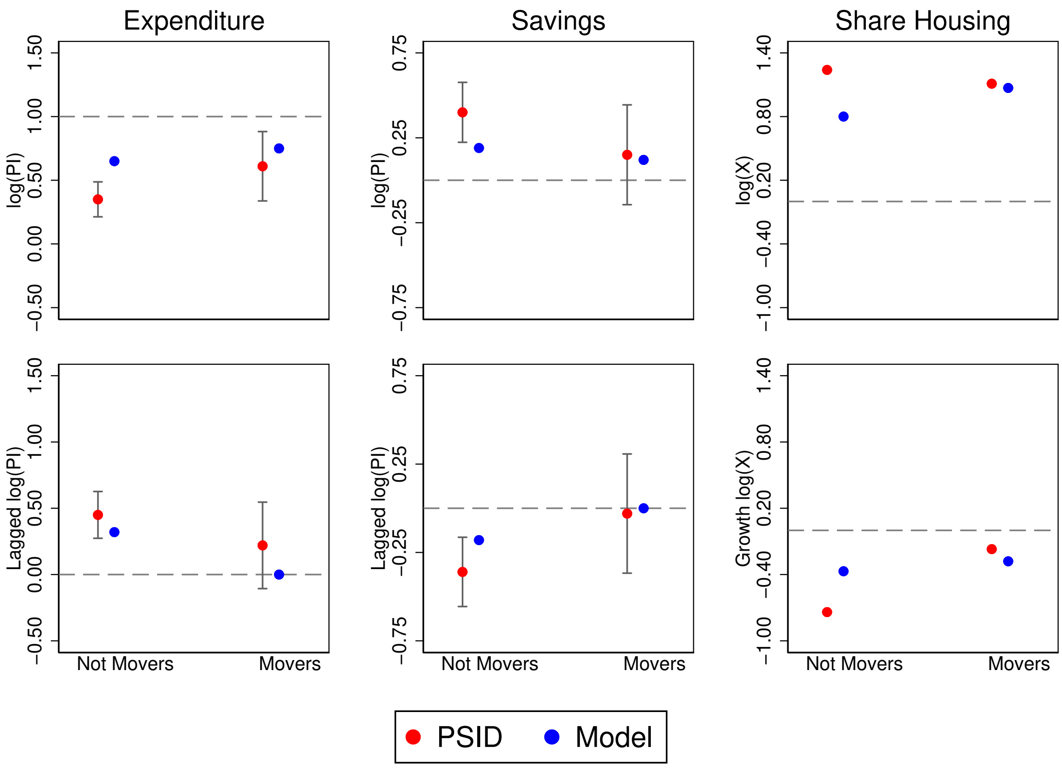
6.4 Consumption Resets

Lastly, the model with consumption commitments generates all the differences between movers and stayers documented in the data, as documented in Tables 6 and 7. Since none of these empirical facts were targeted in the calibration, the model's performance here is an important validation of the importance of commitments for consumption dynamics. The left panels in Figure 8 show that, for households that moved, the consumption response loads only on current permanent income. The middle panels show a similar picture for their savings rate. Lastly, the right panels show that the model also matches the expenditure allocation of these households.

7 Aggregated Implications

Using my model that accurately reflects the micro evidence on consumption responses to permanent income, I investigate the aggregate implications of an increase in permanent income inequality. I do this by comparing the steady states of the benchmark calibration and after an increase in the variance of persistent income shocks. I focus on increases in persistent income shocks since recent studies utilizing administrative income data have highlighted that the increasing variance in wages and earnings is primarily of a structural or persistent nature. In particular, studies by DeBacker, Heim, Panousi, Ramnath, and Vidangos (2013), Kopczuk, Saez, and Song (2010), and Guvenen, Kaplan, Song, and Weidner (2022) have emphasized this trend.

Figure 8: Responses for Movers and Not Movers – Data and Model



I perform this counterfactual exercise in the model with only consumption commitments and then with additional late-in-life luxury consumption. As illustrated in Table 11, the commitment model exhibits higher increases in consumption inequality and total wealth than the non-homothetic model. Specifically, for the commitment model, the Gini index for income increases by 10.5% and the Gini for consumption by 7.3%. In the case of the non-homothetic model, the Gini for income increases mechanically by the same 10.5%, but the consumption Gini increases by only 5.0%.

These findings align with the ongoing debate in the literature on the relationship between consumption and income inequality. While wealth and income inequality rose significantly after 1980, there is some debate about how much consumption inequality followed this trend.[24] For example, Krueger and Perri (2006) argue that consumption inequality rose considerably less than income inequality, while Aguiar and Bils (2015) argue that this is not the case once the data is corrected for measurement error in consumption. My results are consistent with the latter point of view, supporting the conclusions that changes in consumption inequality largely tracked the

[24]There is model and data evidence stressing that asset prices play an important role in shaping current trends in wealth distributions. Kuhn, Schularick, and Steins (2020) stress the importance of portfolio composition and asset prices for wealth dynamics in the data. Hubmer, Krusell, and Smith Jr (2021) and Benhabib and Bisin (2018) stress the importance of heterogeneous returns for Bewley models to match the dynamics and the observed wealth inequality in the data.

Table 11: Distributional Implications

	Income Gini	Consum. Gini	Wealth Gini	Wealth-Income
PSID	0.40	0.31	0.77	4.39
Commitments				
Benchmark	0.351	0.296	0.800	5.17
↗ PI inequality	0.388	0.318	0.818	6.02
	10.5%	7.3%	2.3%	16.5%
Non-homothethic				
Benchmark	0.351	0.362	0.734	5.44
↗ PI inequality	0.388	0.380	0.750	6.08
	10.5%	5.0%	2.2%	11.8%

change in income inequality.

8 Conclusion

In this paper, I investigate, both empirically and in a quantitative model, the role of consumption commitments in consumption responses to permanent income. In particular, I document three main novel facts that support the importance of consumption commitments and explore their quantitative implications by employing a calibrated life-cycle consumption model.

Empirically, I first show that younger households exhibit a stronger response to permanent income than older ones, reflecting commitments made gradually over the life cycle. This dynamic implies that older households, who have accumulated more commitments on average, exhibit a greater detachment of consumption from permanent income. Second, I show that households with faster past growth in income and expenditure consume less and their consumption baskets are skewed towards easy-to-adjust goods. Because consumption commitments are costly to adjust, most households only partially adjust their consumption bundle via easy-to-adjust goods, which lowers total consumption. Third, I show that households who recently adjusted their hard-to-adjust goods consumption by moving house exhibit little or no dependence on past variables, as predicted by the classic permanent income hypothesis.

Quantitatively, I propose a quantitative model consistent with the documented microdata evidence. It consists of a life-cycle consumption model that incorporates two consumption goods, one of which exhibits a non-convex adjustment cost in its level. I also allow for other mechanisms used to explain the savings rates of rich households, such as late-in-life luxury consumption

(Straub, 2019) and elastic bequest motives (De Nardi, 2004). I calibrate the model using moments computed from the PSID by explicitly targeting some of my empirical facts and other commonly used moments in the literature.

With nonconvex 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 optimal, which works as a utility wedge. The mechanism works through diminishing returns to specific goods relative to a near-constant return to marginal saving, which is given by the elastic bequest motive. Consequently, households substitute present consumption for future consumption, which allows them to mitigate the inefficiencies caused by suboptimal expenditure allocation.

The model is able to account for the novel facts on consumption's response to permanent income documented in the empirical section. In particular, I evaluate the model by its ability to replicate observed untargeted moments following regression of simulated data. It captures almost all such untargeted moments, highlighting the importance of consumption commitments in understanding consumption's response to permanent income.

Lastly, I investigate the aggregate performance of my model. The model can match consumption and wealth Gini inequality index as observed in the PSID. Moreover, I compute the impact of an increase in permanent income inequality on wealth and consumption inequality. Consumption tracks income inequality in the model, which is consistent with the conclusions of Aguiar and Bils (2015).

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A Measurement Error in Income

Since I am using survey data, using noisy income data to construct permanent income will also imply a noisy permanent income measure. In this appendix, I show that standard instrumental variable techniques deal with measurement errors in permanent income income.

Let $Y_{i,t}$ be the observed income for household i in period t, which is a noisy measure of its actual income, $Y^*_{i,t}$. The measurement error is log-additive, such that

$$\log Y_{i,t} = \log Y^*_{i,t} + v_{i,t}.$$

Denote logged variables using lowercase letters, e.g. $x_{i,t} = \log(X_{i,t})$. I assume that the unobservables, $y^*_{i,t}$ and $v_{i,t}$, are mutually independent with variances σ^2_* and σ^2_v.

To simplify the notation, I drop the i subscript. Let once-lagged income be a sufficient statistic for the household's information set, so the best linear forecast for y^*_{t+1} is

$$\widehat{y}_{t+1} = \rho y_t = \rho y^*_t + \rho v_t \ ,$$

where v_t is a measurement error. Clearly, $\widehat{y}_{t+1}$ is an unbiased forecast for y^*_{t+1} since $E(\widehat{y}_{t+1}) = \rho y^*_t$. The difference between y^*_{t+1} and $\widehat{y}_{t+1}$ is composed of the forecast error, $y^*_{t+1} - \rho y^*_t$, and the measurement error, ρv_t.

In my empirical application, I measure expected income using income forecasts from an autoregressive process. To see how measurement error will impact my permanent income measure, index the year of the information set as 0 such that $\widehat{Y}_1$ is the forecast 1 year ahead, $\widehat{Y}_2$ is the forecast 2 years ahead, and so on. Given my already-stated assumption,

$$\begin{aligned}
\widehat{Y}_1 &= \exp(\widehat{y}_1) = \exp(\rho y^*_0 + \rho v_0) = \exp(\rho y^*_0)\exp(\rho v_0) \\
\widehat{Y}_2 &= \exp(\widehat{y}_2) = \exp(\rho^2 y^*_0 + \rho^2 v_0) = \exp(\rho^2 y^*_0)\exp(\rho^2 v_0) \\
&\vdots \\
\widehat{Y}_j &= \exp(\widehat{y}_j) = \exp(\rho^j y^*_0 + \rho^j v_0) = \exp(\rho^j y^*_0)\exp(\rho^j v_0)
\end{aligned}$$

My empirical measure of permanent income is

$$\begin{aligned}
\widehat{\mathrm{PI}}_t = \sum_{j=1}^{J} \frac{\widehat{Y}_j}{R^j} &= \sum_{j=1}^{J} \frac{\exp(\rho^j y_0^*)\exp(\rho^j v_0)}{R^j} \\
&\approx \sum_{j=1}^{J} \frac{\exp(\rho^j y_0^*)}{R^j}(1+\rho^j v_0) \\
&= \sum_{j=1}^{J} \frac{\widehat{Y}_j^*}{R^j} + v_0 \sum_{j=1}^{J} \left(\frac{\rho^j}{R^j}\right)\exp(\rho^j y_0^*) \\
&= \sum_{j=1}^{J} \frac{\widehat{Y}_j^*}{R^j} + v_0 f(y_0^*) \,,
\end{aligned}$$

in which I used the approximation $\exp(\rho^j v_0) \approx 1 + \rho^j v_0$ in the second line. $f(y_0^*)$ is a general function of y_0^*.

Any regression that uses a permanent income measure constructed using Y_t as an explanatory variable will suffer attenuation bias. I deal with this problem using instrumental variables. Classical measurement error implies that $E[v_0 f(y_0^*)] = E[f(y_0^*)E[v_0|f(y_0^*)]] = 0$ and traditional instrumental variables can be used.[25] For example, y_{-1} is a good instrument, which is the one used in this paper.

[25] In the univariate case, the IV estimator is

$$\frac{\mathrm{Cov}(z,y)}{\mathrm{Cov}(z,x)} = \frac{\mathrm{Cov}(z,y^*)}{\mathrm{Cov}(z,x)} + \frac{\mathrm{Cov}(z,f(y^*)v)}{\mathrm{Cov}(z,x)} = \frac{\mathrm{Cov}(z,y^*)}{\mathrm{Cov}(z,x)} + \frac{E[zvf(y^*)]}{\mathrm{Cov}(z,x)} = \frac{\mathrm{Cov}(z,y^*)}{\mathrm{Cov}(z,x)}$$

B Quality of the Expected Income Growth Measure

Some of my empirical results are based on a constructed measure of permanent income at the household level. I define permanent income as the sum of current assets and the discounted future expected path of income. Crucially for the empirical exercise, I need to estimate each household's expected income path. I do this by assuming a forecast process and that household information is captured by lagged income, occupation, age, and demographic characteristics. In this Appendix, I provide evidence that, consistent with the literature, households have superior information than the econometrician, meaning that my assumed information set does not capture all the information that households have. However, I also show that this issue is not a major concern.

Good forecasts should lead to forecast errors that are unforecastable based on information available at the time the forecast was made (Diebold, 2017). So, to examine the accuracy of my forecast exercise, I construct the forecast errors, $\epsilon^t_{i,t+h}$,

$$\epsilon^t_{i,t+h} = y_{i,t+h} - y^t_{i,t+h} \ ,$$

and the percent errors, $p^t_{i,t+h}$,

$$p^t_{i,t+h} = 100 \times \frac{(y_{i,t+h} - y^t_{i,t+h})}{y_{i,t+h}} \ ,$$

where $y^t_{i,t+h}$ is the h-step-ahead forecast of variable $y_{i,t}$ using the information set available at t, and $y_{i,t+h}$ is the corresponding realization. The superscripts index the period of the information set. In the context of my analysis, $y_{i,t}$ is the log of after-tax labor income for household i in period t.

My first test is to check the mean and variance of the h-step-ahead forecast and percent errors. Since I am working with panel data, I pool all observations for all households together and compute statistics for the whole sample. The sample mean error (or forecast bias) is then defined as

$$\hat{\mu}_{e^t_{i,t+h}} = \sum_{i}^{N} \sum_{t \in \mathcal{T}_i} \epsilon^t_{i,t+h}$$

where the summation is over all observations of households i and over all households, N, and $\mathcal{T}_i = \{t | e^t_{i,t+h} \text{ is observed in t } \}$. The sample variance is defined similarly.

Tables 12 and 13 show summary statistics for the forecast and percent errors for different time horizons. The first column of Table 12 shows that the forecast is not unbiased, with an average forecast error ranging from -0.04 to -0.02. That is, I tend to slightly underestimate future income, which is the same as slightly overpredicting unexpected income growth. The first column of Table 13 shows that, on average, I underpredict income by 0.44 percentage points. The second columns of both tables show that there is also a large dispersion in the forecast and percent errors, with their standard deviations increasing as the forecast horizon extends. Optimal forecast errors have nondecreasing variances in the forecast horizon and converge to the unconditional variance of the process (Diebold, 2017). Finally, the number of observations decreases as the forecast horizon increases.

Table 12: h-Step-Ahead Forecast Errors

Forecast Errors	Mean	Std. Dev.	Count
$\epsilon_{i,t+2}$	-0.03	0.54	43273
$\epsilon_{i,t+4}$	-0.02	0.61	34710
$\epsilon_{i,t+6}$	-0.02	0.66	27506
$\epsilon_{i,t+8}$	-0.03	0.70	21471
$\epsilon_{i,t+10}$	-0.04	0.73	16278

Note: This table presents summary statistics of forecast errors ($\epsilon_{i,t+k}$) for a specific variable i at various forecast horizons, denoted by k. The statistics include the mean, standard deviation (Std. Dev.), and count of forecast errors over a specified time period.

Table 13: h-Step-Ahead Percent Errors

Percent Errors	Mean	Std. Dev.	Count
p_{t+2}	-0.44	5.36	43273
p_{t+4}	-0.45	6.05	34710
p_{t+6}	-0.53	6.57	27506
p_{t+8}	-0.62	6.97	21471
p_{t+10}	-0.74	7.21	16278

Note: This table presents summary statistics of percent errors ($p_{i,t+k}$) for a specific variable i at various forecast horizons, denoted by k. The statistics include the mean, standard deviation (Std. Dev.), and count of forecast errors over a specified time period.

My second test is to check if other variables available to the household forecast the forecast or percent errors. If the permanent income measure is biased downward for all households, it is not a problem since my parameter of interest is the consumption elasticity with respect to permanent income, which measures the strength of the consumption response across the permanent income distribution. In other words, the bias of the forecast is not a problem if it is not systematically correlated with permanent income.

I focus on the forecast power of the consumption-to-income ratio. According to the permanent income hypothesis, if households expect higher income in the future, they should consume more today. So, I test if, conditioning on current income, a larger consumption-to-income ratio predicts a larger percentage error. In particular, I test if households have a superior information set than the econometrician has by estimating

$$p_{i,t+h}^{t} = \alpha_0 + \alpha_1 \frac{c_{i,t}}{y_{i,t}} + \alpha_2 \log(y_{i,t}) + u_t$$

in which $p_{i,t+h}^{t}$ is the h-step-ahead percent error, $\frac{c_{i,t}}{y_{i,t}}$ is the consumption-to-income ratio, $\log(y_{i,t})$ is the log of labor income, and u_t is a residual. The necessary condition for forecast orthogonality is $(\alpha_0, \alpha_1, \alpha_2) = (0, 0, 0)$, which implies that percent errors are unforecastable. I focus on the percent errors instead of the forecast ones for ease of coefficient interpretation. I measure consumption using the categories available since 1999 in the PSID.

Looking across the columns of Table 14, a higher consumption-to-income ratio only predicts a larger 2-step-ahead percentage error, while the coefficient for all other horizons is statistically insignificant. The constant is negative and statistically significant, consistent with the result of Table 8 that the forecast is downward biased. Current income is important for predicting percent errors, suggesting that the persistent parameter in the forecast equation is small. Moreover, the estimated coefficient for income is economically small, indicating that increasing income by 1 log point increases the percent error by less than 2 percentage points. In sum, the overall picture is that this equation has little forecast power, which is summarized by a small R^2 of less than 4%. Households seem to have superior information than the econometrician, but without meaningful quantitative implications.

Table 14: Income Growth Forecast Equation

	$p^t_{i,t+2}$	$p^t_{i,t+4}$	$p^t_{i,t+6}$	$p^t_{i,t+8}$	$p^t_{i,t+10}$
$\frac{c_{i,t}}{y_{i,t}}$	0.29	0.18	0.11	0.02	0.17
	(0.09)	(0.10)	(0.13)	(0.15)	(0.15)
$\log(y_{i,t})$	0.81	1.27	1.62	1.68	1.82
	(0.07)	(0.09)	(0.12)	(0.14)	(0.16)
Constant	-9.38	-14.16	-17.82	-18.50	-20.19
	(0.80)	(1.07)	(1.36)	(1.64)	(1.84)
N	42024	33721	26754	20887	15849
R^2	0.0121	0.0256	0.0376	0.0381	0.0368

Note: The table presents the results of a test to assess whether the consumption-income ratio ($\frac{c_{i,t}}{y_{i,t}}$) forecasts the h-Step-Ahead Percentage Errors. The test evaluates the relationship between the consumption-income ratio and percentage errors at various time horizons ($t+2$ through $t+10$).

In Table 15, I modify the previous equation and check if the log of consumption or income can forecast percentage errors. The same picture as in Table 14 emerges: The log of consumption only predicts a larger 2-step-ahead percentage error, while the coefficient for all other horizons is negative, which is inconsistent with the permanent income hypothesis. Current income is also not important for predicting percent errors, with a 1 log point increase predicting less than a 2 percentage point increase in the percent error. The R^2 is negligible and is less than 4%.

Lastly, I check if the log of consumption predicts percentage errors. In this specification, the log of consumption is positively associated with positive percentage errors at all horizons, as shown in Table 16. However, the coefficient is economically small, with a 1 log point increase predicting less than a 1.5 percentage point increase in the percent error. The R^2 is negligible. This confirms that households seem to have superior information than the econometrician, but that the impact quantitatively small.

Table 15: Income Growth Forecast Equation

	$p^t_{i,t+2}$	$p^t_{i,t+4}$	$p^t_{i,t+6}$	$p^t_{i,t+8}$	$p^t_{i,t+10}$
$\log(c_{i,t})$	0.29	-0.04	-0.28	-0.42	-0.62
	(0.12)	(0.15)	(0.17)	(0.20)	(0.25)
$\log(y_{i,t})$	0.46	1.16	1.68	1.86	2.00
	(0.10)	(0.12)	(0.13)	(0.15)	(0.18)
Constant	-8.47	-12.39	-15.48	-16.10	-15.55
	(0.74)	(1.06)	(1.36)	(1.67)	(2.03)
N	42024	33721	26754	20887	15849
R^2	0.0100	0.0248	0.0377	0.0388	0.0379

Note: The table presents the results of a test to assess whether the log of consumption ($\log(c_{i,t})$) forecasts the h-Step-Ahead Percentage Errors. The test evaluates the relationship between the consumption-income ratio and percentage errors at various time horizons ($t + 2$ through $t + 10$).

Table 16: Income Growth Forecast Equation

	$p^t_{i,t+2}$	$p^t_{i,t+4}$	$p^t_{i,t+6}$	$p^t_{i,t+8}$	$p^t_{i,t+10}$
$\log(c_{i,t})$	0.72	1.02	1.25	1.26	1.17
	(0.07)	(0.11)	(0.14)	(0.16)	(0.20)
Constant	-7.89	-10.89	-13.22	-13.42	-12.58
	(0.76)	(1.11)	(1.44)	(1.72)	(2.06)
N	42024	33721	26754	20887	15849
R^2	0.0069	0.0103	0.0128	0.0115	0.0091

Note: The table presents the results of a test to assess whether the log of consumption ($\log(c_{i,t})$) forecasts the h-Step-Ahead Percentage Errors. The test evaluates the relationship between the consumption-income ratio and percentage errors at various time horizons ($t + 2$ through $t + 10$).

C Additional Tables and Figures

C.1 Sample Description

C.2 Alternative Definitions

Table B1: Different Measures of Permanent Income

	log(expenditure)
log(PI), AR(1) process	0.57
	(0.01)
log(PI), industry-specific AR(1)	0.58
	(0.01)
log(PI), occupation-specific AR(1)	0.56
	(0.01)
log(PI), AR(1) with total income	0.60
	(0.01)
log(PI), AR(2) process	0.55
	(0.02)

Note: This table presents OLS estimates of the consumption elasticity to permanent income for different measures of permanent income. Each row in the table corresponds to a different regression model. The sample size for the first four regressions is 53,327, while the sample size for the last regression is 39,427.

Column 1 of Table 4 shows that the estimated elasticity of consumption to permanent income is close to 0.6 absent controls for education. The explanatory variable is the constructed permanent income measure assuming an AR(1) process. The table shows the results for other PI measures. The first row assumes an AR(1) process. The second row assumes the AR(1) process is industry-specific. The third row assumes the AR(1) process is occupation-specific. The fourth row assumes an AR(1) process for total income instead of labor income. Finally, the fifth row assumes an AR(2) process. Overall, the table suggests that the elasticity of consumption to permanent income is close to 0.6, with a slight variation depending on the specific measure of PI used. The results are reported with their standard errors in parentheses.

Throughout the main text, I use the expenditure measure based on all PSID categories available since 1999 along with implicit rent as the measure of shelter consumption. Table B2 displays results using other measures of consumption. The first row shows the result when I use all categories available since 1999. The second row uses all categories available since 1999 but the alternative definition of shelter consumption. The third row uses all categories available since 2005. The fourth row uses all categories available since 2005 and the alternative definition of shelter consumption. Finally, the fifth row displays the result when considering only nondurable categories. The table suggests a slight variation in the estimated elasticity depending on the specific expenditure measure used, but overall the values are closely grouped.

The table above presents the estimated elasticity of consumption to permanent income using different measures of wealth to construct permanent income. The table presents three different measures of wealth: PSID Measured Net Worth, Net Worth plus Retirement Accounts, and Price-adjusted Net Worth. The first row uses the PSID definition of net worth, that is, total assets minus total debt. The second row follows

Table B2: Different Measures of Expenditure

	log(PI)
log(exp), categories available in 1999	0.57
	(0.01)
log(exp), categories available in 1999, alt. measure	0.53
	(0.01)
log(exp), categories available in 2005	0.62
	(0.01)
log(exp), categories available in 2005, alt. measure	0.58
	(0.01)
log(exp), nondurables categories	0.47
	(0.01)

This table presents OLS estimates of the consumption elasticity to permanent income using different expenditure measures. The sample size for the regressions using expenditure categories available since 1999 is 54,752, while the sample size for the regressions using expenditure categories available since 2005 is 42,323.

Table B3: Different Measures of Asset

	log(PI)
PSID Measuerd Net Worth	0.59
	(0.01)
Net Worth plus Retirement Accounts	0.58
	(0.01)
Price-adjusted Net Worth	-
	-

Note: This table presents OLS estimates of the consumption elasticity to permanent income using different asset measures. The sample size for all regressions is 55,320.

Cooper et al. (2019) and uses the pension data available in the PSID to create a more comprehensive measure of wealth. The third row tries to control for changes in permanent income driven by asset valuation. The table suggests that the different choices do not impact the measured elasticity

C.3 Changes in the Permanent Income Predicts Moving Decision

In this appendix, I show that households' probability of moving increases in the absolute value of permanent income changes. Larger permanent income changes are associated with more pronounced households' moving behavior, as standard lumpy adjustment models predict.

Table B4 presents the likelihood that households have moved at least once in the past 10 years as a function of past permanent income growth. The likelihood is estimated using linear probability models. Columns 1 and 2 show that the absolute growth of permanent income is positively associated with the likelihood of having moved in the past. For homeowners, the average probability of having moved is smaller, which is consistent with the intuition that it is easier for renters to move. Interestingly, the interaction between permanent income growth and an indicator of homeownership is not economically or statistically significant. Columns 3 and 4 report estimates of the likelihood of households reporting that they might move in the future as a function of past permanent income growth.

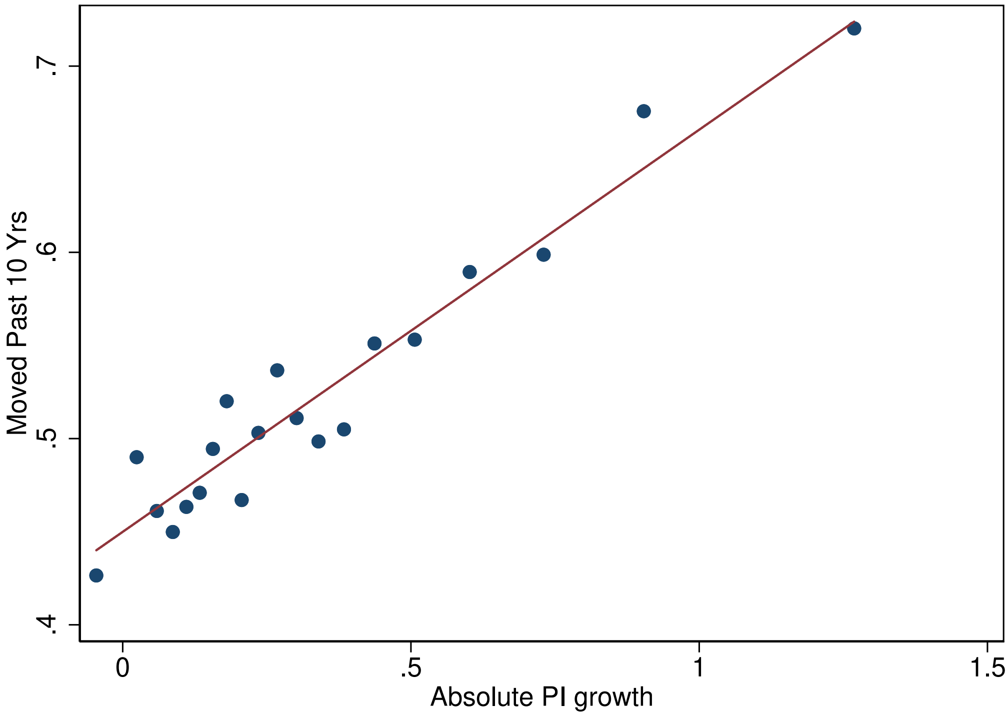
Table B4: Probability of Housing Adjustment

	(1) Moved Past 10 Yrs	(2) Moved Past 10 Yrs	(3) Might Move	(4) Might Move
$\lvert\log(\text{PI}/\text{PI}_{t-10})\rvert$	0.235	0.180	0.102	0.022
	(0.018)	(0.026)	(0.017)	(0.030)
Own $\times$ $\lvert\log(\text{PI}/\text{PI}_{t-10})\rvert$		0.007		0.048
		(0.035)		(0.036)
Own		-0.336		-0.346
		(0.026)		(0.023)
N	15421	14980	15075	14653

Note: To be added.

Figure 9 is the graphic representation of Table B4, and it presents the likelihood of households having moved at least once in the last 10 years as a function of past permanent income growth. Here past permanent income growth is partitioned into equal-sized bins, matched with the mean probability of having moved in the past within each bin, along with a linear OLS fit. The data shows the positive linear association between the absolute growth of permanent income and the likelihood of having moved in the past.

Figure 9: Probability of Moving



Note: To be added.

C.4 Results by Ownership

I showed that consumption commitments are important to understand how consumption responds to permanent income. Since shelter consumption is a key consumption commitment in the data, it is natural to expect that owners and renters have different responses to permanent income. In particular, renters' responses should not depend on past permanent income growth since they face arguably smaller adjustment costs.

Table B5 shows that renters and owners have similar responses to permanent income, both with respect to consumption and savings rates. Column 1 shows the consumption response of households that own a house loads less on past permanent income than the response of renters, with an estimated coefficient of -0.17, and the difference is not statistically significant. Similarly, column 2 shows that the saving rate response of owners loads more negatively on past permanent income, but again is not statistically significant. A possible explanation is that moving is also costly for renters, since it incurs the same packing, transportation, and search costs.

Table B5: Heterogeneous Effects: Homeownership Status

	(1) log(expenditure)	(2) Savings Rate
log(PI)	0.52	0.21
	(0.08)	(0.08)
$\log(\text{PI}_{t-10})$	0.49	-0.08
	(0.10)	(0.09)
Own $\times$ log(PI)	0.07	0.04
	(0.11)	(0.09)
Own $\times$ $\log(\text{PI}_{t-10})$	-0.17	-0.08
	(0.13)	(0.10)
Educ Dummies	Y	Y
KP-F test	20.4	43.0
Observations	14,164	14,046

Note: To be added.

Table B6 tests if owners show more dependence on past permanent income in their expenditure allocation. Column 1 shows that owners' consumption baskets are more skewed towards nondurable consumption after past expenditure growth – which in this specification proxies for permanent income growth. The results for shelter consumption follow the same logic, but with different signs. These results align with what the consumption commitment story predicts: owners are more locked in to past consumption choices than renters because their commitments are more costly to adjust; thus their consumption allocation skews more toward nondurables after growth in permanent income.

Table B6: Heterogeneous Effects: Homeownership Status

	(1) Nondurable Share	(2) Shelter Share
log(exp)	-2.70	-2.94
	(1.08)	(1.27)
Δ log(exp)	1.67	-3.75
	(1.56)	(1.77)
Own $\times$ log(exp)	-13.19	11.16
	(1.12)	(1.25)
Own $\times$ Δ log(exp)	5.05	-7.20
	(1.98)	(2.12)
Educ Dummies	Y	Y
KP-F test	9.5	9.6
Observations	9,757	9,759

Note: To be added.

Table B7: Heterogeneous Effects: Homeownership Status

	(1) log(expenditure)	(2) Savings Rate
log(PI)	0.78	0.24
	(0.07)	(0.08)
log(PI_{t-10})	0.16	-0.20
	(0.10)	(0.10)
Own_{t-10} $\times$ log(PI)	-0.28	0.01
	(0.10)	(0.09)
Own_{t-10} $\times$ log(PI_{t-10})	0.25	0.03
	(0.14)	(0.12)
Educ Dummies	Y	Y
KP-F test	20.9	30.7
Observations	14,072	13,985

Note: To be added.

Table B8: Heterogeneous Effects: Homeownership Status

	(1) Nondurable Share	(2) Shelter Share
log(exp)	-4.52	4.73
	(1.17)	(1.01)
Δ log(exp)	-0.35	-10.68
	(2.10)	(2.07)
$\text{Own}_{t-10} \times$ log(exp)	-11.55	-0.17
	(1.24)	(0.06)
$\text{Own}_{t-10} \times \Delta$ log(exp)	10.91	1.95
	(2.51)	(2.09)
Educ Dummies	Y	Y
KP-F test	10.1	11.6
Observations	9,688	9,425

Note: To be added.

C.5 Bequests and Intervivo Transfers in the PSID

A commonly assumed force in many consumption models is a desire to leave large bequests (e.g., De Nardi, 2004) or to insure heirs through intervivo transfers (e.g., Boar, 2021). I examine the presence of these forces in the PSID in this appendix.

I measure bequests in the PSID using two different methods. In the first, I measure bequests by the inheritance that split-off families report receiving.[26] In the second, I measure using the total assets that households hold at the time of their passing.

In the first method, I initially aggregate any inheritances reported by split-off families within a 3-year window around the death of one of their parents. This aggregation involves combining multiple inheritances received by a split-off family within the 3-year window and aggregating across multiple families if parents are associated with more than one split-off family. I then create two variables: a binary indicator to determine whether the household left a bequest and the log of any bequest amount. Lastly, I regress these two variables on current and past permanent income, based on the last observed data before the parent household's death.

Table B9 shows the results when projecting the bequest measures on current and past permanent income. Column 1 shows that the probability of leaving bequests increases with permanent income, consistent with my modeling assumptions of elastic bequests. Column 2 shows that the probability of leaving bequests is significant only for past permanent income. However, the number of observations is small, raising doubts about the test's strength. Column 3 shows that the bequeathed amount increases with permanent income. Column 4 shows that current or past permanent incomes are positively associated with the bequeathed amount, but the number of observations is very small, and no coefficient is significant.

Table B9: Bequest

	(1) $\mathbf{1}\{\text{bequest} > 0\}$	(2) $\mathbf{1}\{\text{bequest} > 0\}$	(3) log(bequest)	(4) log(bequest)
log(PI)	0.174	0.063	0.626	0.623
	(0.035)	(0.084)	(0.135)	(0.462)
$\log(\text{PI}_{t-10})$		0.240		0.209
		(0.094)		(0.472)
N	523	190	197	65

Note: To be added.

The second method for measuring bequests is to examine the amount of assets households held before passing. Since households are not surveyed postmortem, I focus on the last surveys conducted within a

[26]In the PSID, a split-off family refers to a distinct family entity – comprising either an individual or a collective group of individuals – that has relocated from the original or "main" family to form a new, economically independent family unit.

maximum of 6 years before the household's passing. First, I create two variables: a binary indicator to determine whether the household passed with positive assets and the log of any such assets. Second, I project these two variables on current and past permanent income.

Table B10 shows the results for the second measurement method. Column 1 shows that the probability of passing with positive assets increases with permanent income. Column 2 shows that, when allowing for past permanent income in the specification, both measures are positively associated with dying with positive assets but not significantly so. Column 3 shows that assets at death is also positively associated with permanent income. Column 4 shows that assets at death is positively associated with current permanent income and negatively with past permanent income. However, the number of observations is small and the coefficient associated with past permanent income is insignificant.

Table B10: Assets at Death

	(1) $\mathbf{1}\{\text{net worth} > 0\}$	(2) $\mathbf{1}\{\text{net worth} > 0\}$	(3) log(net worth)	(4) log(net worth)
log(PI)	0.100	0.093	2.164	2.502
	(0.041)	(0.064)	(0.271)	(0.360)
$\log(\text{PI}_{t-10})$		0.071		-0.121
		(0.089)		(0.410)
Educ Dummies	Y	Y	Y	Y
KP-F test	16.0	6.7	36.1	5.9
Observations	666	294	589	261

Note: To be added.

Another savings motive stressed in the literature is to insure heirs from economic shocks. I measure the strength of this channel by constructing a measure of intervivo transfers (money given to support heirs during the parent's lifetime). I use an expenditure question in the PSID that asks whether anything and if so how much was given to support anyone living outside the household, including child support, alimony, and money given to parents. I focus only on child support, even though the results are the same for a broader measure. Again, I construct two variables: a binary indicator of whether the household provided transfers and, if so, the log of the amount. Lastly, I regress these two variables on current and past permanent income.

Table B11 has two parts, one for all households and another only for households reporting at least one child. The coefficient of current permanent income is positively associated with a higher likelihood of child support transfers, but the coefficient for the lagged measure is not economically or statistically significant. On the other hand, the coefficient of current and lagged permanent income is positively associated with the log of the amount spent on child support. However, the sample size is small, which does not allow a meaningful conclusion. The results are the same if I merge households with their split-off families and analyze the reported private-transfer income children report receiving from people outside the household.

The evidence in Tables B9, B10 and B11 is that households with faster permanent income growth do not appear to leave more bequests or provide more transfers. However, it is worth noting that the sample

Table B11: Intervivo Transfers

	All Sample		Reported Child	
	(1)	(2)	(3)	(4)
	$\mathbf{1}\{\text{Help Child} > 0\}$	log(Help Child)	$\mathbf{1}\{\text{Help Child} > 0\}$	log(Help Child)
log(PI)	0.116	0.723	0.111	0.721
	(0.021)	(0.297)	(0.024)	(0.297)
$\log(\text{PI}_{t-10})$	-0.019	0.472	0.004	0.474
	(0.027)	(0.238)	(0.031)	(0.239)
Educ Dummies	Y	Y	Y	Y
KP-F test	131.0	13.2	124.1	13.2
Observations	15,421	542	13,064	538

Note: To be added.

size.

C.6 Donations

Another possible reason for why consumption does not track permanent income is that some expenditures by rich households are unaccounted for. In this appendix, I look at the philanthropic donations of PSID households, a well-known luxury expenditure.

Since 2001, the PSID has collected data on philanthropic giving, becoming the only major panel survey in the US to collect data on such. I aggregate all available sub-donation categories and define an indicator for giving and a variable for log total giving.

Table B12 shows the association between total donation expenditure and current and lagged permanent income. Both measures are positively associated with the likelihood of reporting donation expenditure and with the amount donated. There is no evidence that households with faster permanent income growth donate more.

Table B12: Donations

	(1) Wrt. Donations	(2) log(Donations)
log(PI)	0.219	0.717
	(0.014)	(0.055)
log(PI_{t-10})	0.161	0.290
	(0.019)	(0.068)
N	15421	9257

Note: To be added.

C.7 Parent-Child Pairs

Because the bequest motive plays an important role in my calibration, in this appendix, I examine whether this force is present in the data by looking at the child's consumption. In particular, the idea of the exercise is that if child households have information about their parents' permanent income level and the bequest motive is important in the data, the child's consumption should respond to their parents' permanent income level.

I first merge split-off families with their parent households. This merge could be with the parent being head of a household or with the parent's spouse. Second, I project split-off expenditure on their current permanent income and their parents' current and past permanent income. Table B13 shows a positive correlation between split-off expenditure and parents' current and lagged permanent income. Overall, children respond to their parents' permanent income.

Table B13: Child-Parent Pairs

	(1) Child's log(exp)	(2) Child's log(exp)
Child's log(PI)	0.532	0.802
	(0.022)	(0.040)
Parent's log(PI)	0.072	0.141
	(0.026)	(0.029)
Parent's log(PI_{t-10})	0.047	0.051
	(0.031)	(0.036)
Educ Dummies		Y
KP-F test	69.7	63.0
Observations	7,846	7,846

Note: To be added.

This finding also implies that parents' permanent income growth is associated with less money transferred to their children, which is consistent with my results on intervivo transfers. In other words, mapping this coefficient to the "lock-in mechanism," locked-in parents are not transferring money to their children.

D Calibration Appendix

D.1 Life-Cycle Profiles

Figure 10 shows the average life-cycle profiles of different consumption types in the model economy. The aggregate good consumption profile is hump-shaped, peaking when households are around 50 years old. However, the aggregation masks heterogeneity between different goods. The housing consumption profile is flat through the life cycle, whereas nondurable consumption is more curved, dropping significantly after its peak around 50 years old, which implies that housing correspondingly gains importance in the average household bundle. This pattern is also observed in the PSID data.

Figure 10: Life Cycle

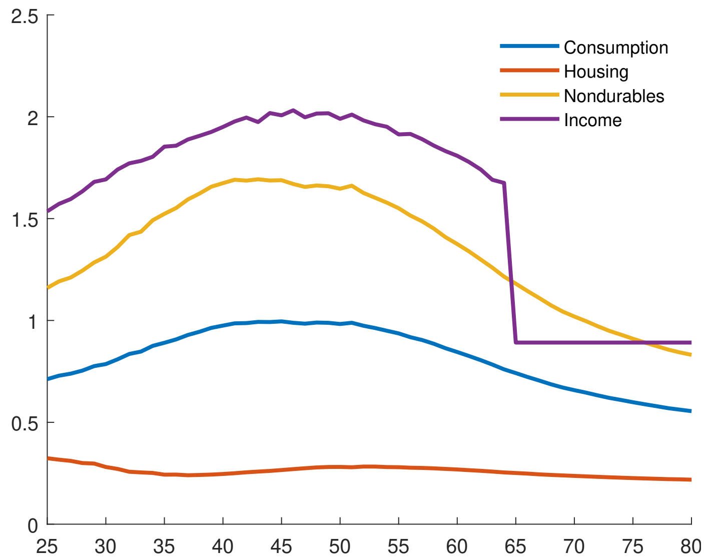
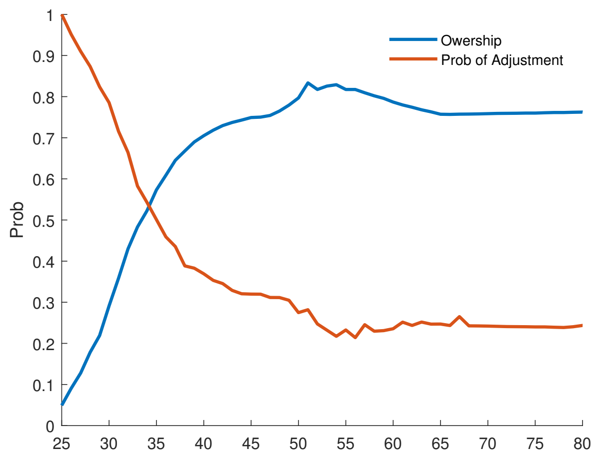


Figure 11 shows the average asset profiles in the model economy. Panel 11a shows that households first accumulate housing assets and hold negative liquid assets early in their life cycle. Throughout the life cycle households pay their debts and accumulate positive liquid assets. After retirement, households do not consume all their wealth; on the contrary, they continue to accumulate wealth, but at a slower pace. Housing assets remain constant during retirement after growing through the working years. Panel 11b shows that the ownership rate gradually increases during the life cycle, reaching a plateau when households are around 50 years old. The increase in ownership is followed by a decrease in the average probability of moving.

Figure 11: Mean Life-Cycle Profiles

(a) Assets



(b) Ownership

E Computational Appendix

In this section, I will explain how I solve the model. First, I provide a detailed description of the model. Second, I explain the algorithm used to find the optimal policy functions. Third, I provide details of the interpolation technique used.

E.1 Description of the Model

I use a recursive formulation of the problem. Let s denote the household's state variable vector: $s = \{j, a, h_{-1}, \bar{z}, \alpha, \epsilon, \bar{z}^p\}$, where j represents age, a denotes liquid assets, h_{-1} represents past housing decisions (commitment goods), $\bar{z}$ represents the fixed productivity, α represents the persistent income shock, ϵ represents the transitory income shock, and $\bar{z}^p$ represents the parent household's fixed productivity. For ease of notation, I denote $z \equiv (\bar{z}, \alpha, \epsilon)$.

The value function for a household with state s is

$$V(s) = \max\left\{V^{adj}(s), V^{noadj}(s)\right\}.$$

where $V^{adj}(s)$ and $V^{noadj}(s)$ are the value functions conditional on adjusting and not adjusting housing consumption, respectively. The adjustment decision is made at the beginning of the period, after receiving bequests and income shocks but before deciding on consumption and savings.

In the no-adjustment case, the household solves the following problem:

$$V^{noadj}(s) = \max_{n,a'} u_j\Big(g(h,n)\Big) + (1-\psi_j)\,\beta\,\mathcal{B}\Big(a',h\Big) + \psi_j\,\beta\,\mathbb{E}\Big\{V(s')\Big|s\Big\} \tag{8}$$

subject to

$$\begin{aligned} h &= (1-\delta(1-\chi))h_{-1} \\ n + a' &= pen(\bar{z}) + y(z) + (1+r)a - \delta\chi h_{-1} \\ \bar{z}^{p'} &= \begin{cases} \bar{z}^p & \text{with probability } (1-\psi_{j+35}) \\ 0 & \text{with probability } \psi_{j+35} \end{cases} \\ n > 0, &\quad a \geq -\theta h \end{aligned}$$

and where the next-period state vector is $s' = \Big\{j+1,\ a'+b',\ h_{-1}(1-\delta(1-\chi)),\ \bar{z},\ \alpha',\ \epsilon',\ \bar{z}^{p'}\Big\}$.

On the other hand, in the adjustment case, the household solves the following problem:

$$V^{adj}(s) = \max_{n,h,a'} u_j\Big(g(h,n)\Big) + (1-\psi_j)\,\beta\,\mathcal{B}\Big(a',h\Big) + \psi_j\,\beta\,\mathbb{E}\Big\{V(s')\Big|s\Big\} \tag{9}$$

subject to

$$
\begin{aligned}
h &= (1-\kappa)(1-\delta)h_{-1} + x \\
n + a' + x &= pen(\bar{z}) + y(z) + (1+r)a \\
\bar{z}^{p'} &= \begin{cases} \bar{z}^p & \text{with probability } (1-\psi_{j+35}) \\ 0 & \text{with probability } \psi_{j+35} \end{cases} \\
n > 0, &\quad a \geq -\theta h
\end{aligned}
$$

and where the next-period state vector is $s' = \left\{ j+1,\ a'+b',\ h,\ \bar{z},\ \alpha',\ \epsilon',\ \bar{z}^{p'} \right\}$.

The last variable in the state vector has two purposes, as in De Nardi (2004). First, when it takes on a positive value, it is used to calculate the probability distribution of bequests that a household expects to receive from a parent. Second, it helps differentiate between agents who have already inherited (for whom $\bar{z}^{p'}$ is set to 0) and those who have not (for whom $\bar{z}^{p'}$ is strictly positive).

Figure 12 depicts two parallel timelines, the first representing the parent and the second the child household. Both households start working at the age of 25 and retire with certainty at 65. I assume that households have uncertain lifespans, meaning they may pass away at any time between the ages of 65 and 99. The child is born when the parent is 35 years old and thus begins working when their parent is 60 years old and retires when their parents would be 100 years old. Given the timing of lifetime events, the child may inherit bequests at a random age between 30 and 64. Note that this structure does not allow for situations where the child receives a bequest from their grandparents.

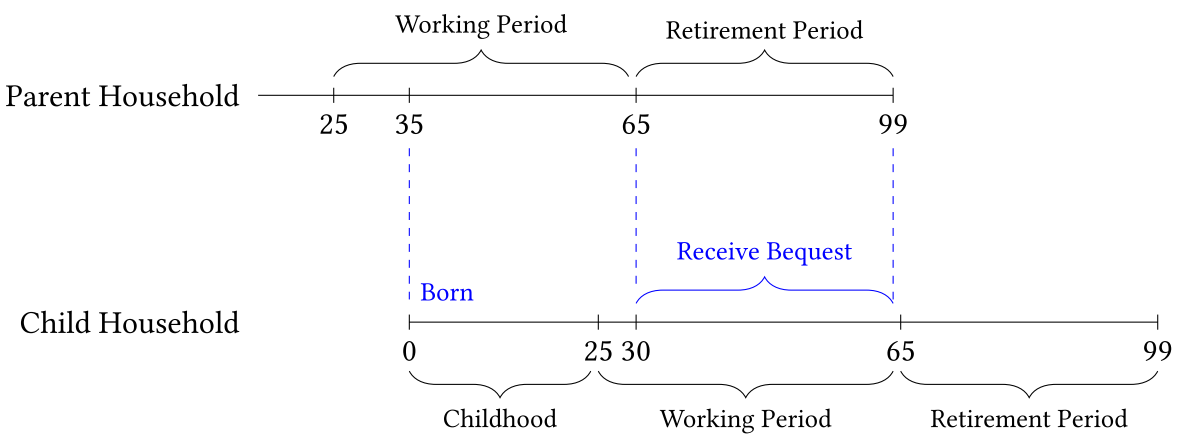


Figure 12: Overlapping Generations Structure

E.2 Optimal Decision Rules

I solve the method using first-order conditions. Since the problem features non-convex adjustment costs, first-order conditions are necessary but not sufficient. Thus, following the algorithm used by Kaplan and

Violante (2014), I examine all solutions to each set of first-order conditions, then determine the optimal solution by evaluating the value functions at each candidate solution. This includes considering all corner solutions and evaluating the value functions at these points. This search for the optimal solution is done at each point in the state space.

I solve the model recursively from the last period of life to the first. To do this, I follow Kaplan and Violante (2014) and define a new operator, $\widetilde{\max}\{\cdot,\cdot\}$, which chooses between two objects based on which of the corresponding value functions is higher. For example, $\widetilde{\max}\{n^{adj}, n^{noadj}\}$ selects nondurable expenditures n^{adj} when $V^{adj} > V^{noadj}$ at the specific point in the state space. I also compute partial derivatives of the value functions using envelope conditions, which are constructed recursively alongside the value function and policy functions. The value functions and the partial derivatives may not be continuous due to the discrete choices in the model. However, (i) if there is enough uncertainty in the problem, the jumps tend to be smoothed away, and (ii) there are a finite number of points of discontinuity.

Given the life-cycle structure of the problem, I describe the first-order conditions for the retirement and working periods separately.

E.2.1 Retirement-period

For a household in retirement, $R \leq j < J$, that decided not to adjust their housing consumption, its decision is determined by a standard Euler equation,

$$(1-\omega)c^{1-\sigma_j-\rho}n^{\rho-1} = (1-\psi_j)\,\beta\,\phi_1\Big(\phi_2 + a' + h\Big)^{-\sigma} + \psi_j\,\beta\,\widetilde{\max}\left\{\frac{\partial V^{adj\prime}}{\partial a'}, \frac{\partial V^{noadj\prime}}{\partial a'}\right\},$$

by the budget constraint defined in the previous subsection, and by $h = (1-\delta(1-\chi))h_{-1}$.

For a retired household, $R \leq j < J$, that decided to adjust their housing consumption, its decision is determined by the standard Euler equation for assets above, a portfolio problem that equates the marginal value of investing in assets and housing:

$$\begin{aligned}
(1-\omega)c^{1-\sigma_j-\rho}n^{\rho-1} &= (1-\psi_j)\,\beta\,\phi_1\Big(\phi_2 + a' + h\Big)^{-\sigma} + \psi_j\,\beta\,\widetilde{\max}\left\{\frac{\partial V^{adj\prime}}{\partial a'}, \frac{\partial V^{noadj\prime}}{\partial a'}\right\} \\
(1-\omega)c^{1-\sigma_j-\rho}n^{\rho-1} &= \omega\zeta c^{1-\sigma_j-\rho}(\zeta h)^{\rho-1} \\
&\quad + (1-\psi_j)\,\beta\,\phi_1\Big(\phi_2 + a' + h\Big)^{-\sigma} + \psi_j\,\beta\,\widetilde{\max}\left\{\frac{\partial V^{adj\prime}}{\partial h}, \frac{\partial V^{noadj\prime}}{\partial h}\right\}
\end{aligned}$$

and by the budget constraint defined in the previous subsection.

E.2.2 Working-period

A working household, $1 \leq j < R$, faces income uncertainty but no mortality risk. Thus, its optimal decision of not adjusting its housing satisfies

$$(1-\omega)c^{1-\sigma_j-\rho}n^{\rho-1} = \beta\mathbb{E}\left[\widetilde{\max}\left\{\frac{\partial V^{adj'}}{\partial a'}, \frac{\partial V^{noadj'}}{\partial a'}\right\}\Big| s\right]$$

and the budget constraint defined in the previous subsection. For a household that decided to adjust their housing consumption, its decisions satisfy

$$(1-\omega)c^{1-\sigma_j-\rho}n^{\rho-1} = \beta\mathbb{E}\left[\widetilde{\max}\left\{\frac{\partial V^{adj'}}{\partial a'}, \frac{\partial V^{noadj'}}{\partial a'}\right\}\Big| s\right]$$

$$(1-\omega)c^{1-\sigma_j-\rho}n^{\rho-1} = \omega\zeta c^{1-\sigma_j-\rho}(\zeta h)^{\rho-1} + \beta\mathbb{E}\left[\widetilde{\max}\left\{\frac{\partial V^{adj'}}{\partial h}, \frac{\partial V^{noadj'}}{\partial h}\right\}\Big| s\right]$$

and the budget constraint defined in the previous subsection.

E.2.3 Envelope Conditions

I compute partial derivatives of value functions using envelope conditions, which are constructed recursively alongside the value function and policy functions. The value functions and the partial derivatives may not be continuous due to the discrete choices in the model. However, (i) if there is enough uncertainty in the problem the jumps tend to be smoothed away, and (ii) there are a finite number of points of discontinuity.

The partial derivatives of the choice-specific value functions for the retirement period are

$$\begin{aligned}
\frac{\partial V^{noadj}}{\partial a} &= (1-\omega)(1+r)c^{1-\sigma_j-\rho}n^{\rho-1} \\
\frac{\partial V^{noadj}}{\partial h_{-1}} &= \omega\zeta\,(1-\delta(1-\chi))c^{1-\sigma_j-\rho}(\zeta h)^{\rho-1} - (1-\omega)\,\delta\chi\, c^{1-\sigma_j-\rho}n^{\rho-1} \\
&\quad + (1-\psi_j)(1-\delta(1-\chi))\,\beta\,\phi_1\Big(\phi_2 + a' + h\Big)^{-\sigma} \\
&\quad + \psi_j\,(1-\delta(1-\chi))\,\beta\,\widetilde{\max}\left\{\frac{\partial V^{adj'}}{\partial h}, \frac{\partial V^{noadj'}}{\partial h}\right\} \\
\frac{\partial V^{adj}}{\partial a} &= (1-\omega)(1+r)c^{1-\sigma_j-\rho}n^{\rho-1} \\
\frac{\partial V^{adj}}{\partial h_{-1}} &= (1-\omega)(1-\delta)(1-\chi)c^{1-\sigma_j-\rho}n^{\rho-1}
\end{aligned}$$

The partial derivatives for the working period are easily derived from the ones computed above.