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

Paulo Lins*

University of Rochester

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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 estimated elasticities 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 saving to consume when old are

[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).

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 who experienced 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 today, 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 who experienced different paths to their permanent income. 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.

Finally, 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 findings: 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 the different mechanisms in the model, I show that consumption commitments are necessary to account for the target moments. However, lumpy adjustment alone is not enough to explain all key facts, meaning that the bequest

[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.

motive and late-in-life luxury consumption are also quantitatively important. Consumption commitments generate stronger responses to permanent income for younger households and consumption responses and expenditure allocations that depend on lagged variables, while the other mechanisms 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. 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 2 describes how I measure permanent income and consumption's responses in the data. Section 3 presents the novel facts on consumption's response to permanent income. Section 4 presents a standard incomplete markets life cycle model nesting consumption commitments and other mechanisms the literature proposes to explain consumption's under-response. Section 5 describes the calibration procedure. Section 6 estimates consumption's response in the model and 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

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 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 65 years old. Throughout the paper, I highlight whenever a

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

sample with a different age range is used and explain the reasons for doing so.

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

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

My empirical measure of assets is reported net worth (assets net of debt).[4] Secondly, I construct a discounted future expected income profile for each household. I express the expected path of income 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 $\widehat{Y}^t_{i,s}$ 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]

As a benchmark, I use a first-order autoregressive process to construct the expected income

[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 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 $E(Y_t|\mathbf{Y}_{i,t-1}, \mathbf{X}_{i,t})$.

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), who 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]

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 of income by adding asset income.[8]

[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).

When forecasting the income path, I need to take a stand on how much a household expects to receive from social security income. This is particularly important since social security wealth is the main source of income for a significant fraction of retired households. I assume that households retire at age 65 and that their social security income is 45% of their last pre-retirement 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.

[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.

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. In Appendix A, I show that, under the assumption of classical measurement error, the "non-noisy" permanent income measure is also uncorrelated with the measurement errors. Any variable correlated with the former but not with the latter can be used as an instrument. In the empirical analysis, I instrument for 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) constructing the income path using a broader income measure that includes labor earnings, government transfers, and asset income, ii) using a more comprehensive measure of wealth, which includes employer-provided defined-contribution retirement accounts, iii) using higher-order autoregressive processes, and iv) 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 test in Appendix B whether the income forecast errors are unforecastable using the other variables available in the household's information set. I show that current consumption, which should embody the information available for households, has low power in forecasting future income forecast errors. This exercise should alleviate concerns about the quantitative importance of households having superior information than the econometrician to forecast future income.

2.3 Specifying Consumption's Response to Permanent Income

As my measure of consumption responses, I use the consumption elasticity to permanent income. This moment measures how much consumption increases across the permanent income distribution. While most consumption models predict a linear relationship, recently Straub (2019) and Abbott and Gallipoli (2019) documented that the relationship between these variables is concave in the data. My empirical exercise provides novel evidence on the role of consumption commitments in generating the observed relationship between consumption and permanent income.

My first exercise will project the logarithm of consumption on the logarithm of permanent income to recover the consumption elasticity to permanent income. This analysis uses cross-

[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).

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.

As my measure of consumption, I use expenditure in all categories available since 1999. Following Kaplan et al. (2014) and Blundell et al. (2016), my consumption measure 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. I set the service flow of owning a vehicle 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 income trajectory. In particular, I estimate

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

[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$_t$).

$\widehat{\text{PI}}_{i,t-10}$ is the 10-year lagged estimated 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.

In equation (4), if commitments are important, past permanent income should increase current consumption. 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] Because commitments are arguably made gradually over the life cycle, the household with lower permanent income 10 years ago has fewer commitments. This household only partially adjusts its consumption bundle via easy-to-adjust goods after the permanent income growth, and, as a result, its allocation of expenditure across consumption categories is not optimal. Its consumption should be lower than that of a household with the same permanent income level but with less distortion in its expenditure allocation. A high permanent income growth captures the idea that the consumption basket is worst allocated because some commitments were made in the past when the household had a different permanent income level.

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).

To construct the expenditure shares, I use the detailed expenditure data available in the PSID after 2005 to see a broad picture of households' intra-period allocations. However, since total expenditure appears on the right as a control and in the denominator on the left, this specification

[12] The household with no permanent income growth has the same permanent income in both periods, while the one with positive (negative) growth has permanent income larger (smaller) than lagged permanent income.

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.

3.1 Consumption Responses to Permanent Income

I first estimate equation (3) to recover the consumption response to permanent income for working-age households. The results are reported in Table 1, where each column differs in estimation method and/or the set of instruments. In the first column, I report the OLS estimate without controlling for education dummies. For each 1% increase in constructed permanent income, household consumption increases by about 0.6%. This value 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 0.7. Straub also theoretically shows that most models with homothetic preferences predict an elasticity close to 1. Since permanent income is a generated regressor, I report bootstrap estimates of the standard errors in the tables. The elasticity of 0.6 is precisely estimated with a standard error of 0.01.

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 second column shows that, incorporating instruments, the consumption elasticity with respect to permanent income remains approximately 0.6. The F statistic is sufficiently high to defuse any concerns about weak instruments.

Table 1: Expenditure Response to Permanent Income

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

Note: This table reports the estimated consumption elasticity to permanent income. Column 1 uses ordinary least squares, while columns 2 and 3 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. Column 3 also includes dummy variables for education groups as a control variable. In column 2, the excluded instruments are lagged income and dummy variables for industry groups and education groups, while in column 3 the excluded instruments are lagged income and dummy variables for industry groups. All variables are weighted by sampling weights, and standard errors are calculated using a bootstrap with 100 replications. The foot table reports the number of observations and the Kleibergen-Paap F statistic.

Another possible concern is whether higher permanent income is associated with higher levels of patience, which could explain the estimated consumption elasticity to permanent income. For that reason, in the third column, I control for education dummies. Since college-educated workers have systematically higher savings rates, possibly reflecting preference heterogeneity in the patience level (Dynan et al., 2004), education dummies are commonly used to capture heterogeneity in the discount factor. Interestingly, 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.

I use column 3 of Table 1 as my baseline specification since it deals with both concerns, measurement error and discount factor heterogeneity. So, results should be interpreted as variations within educational groups. In Section 6, I calibrate the model to match this estimate.

Table 2 presents a new fact: the elasticity of consumption with respect to permanent income decreases with age. 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. 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. Indeed, looking at the case of housing as an example of consumption commitments, younger households have lower homeownership rates and housing is a lower part of their asset portfolio. On the other hand, models that rely on young households being more risk-averse and saving to consume when old are inconsistent with this evidence.

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.

In Appendix C, 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 C1 shows that my results are robust to allowing the parameters of the autoregressive process to vary by occupation or industry and using higher-order autoregressive processes. Second, I used an expenditure measure that includes all categories available since 1999. Table C2 shows that my results are robust when using a broader measure with the categories included in the 2005 wave. Lastly, I used the PSID definition of net worth to construct the measure of permanent income. Table C3 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 path dependency in household responses to permanent income. I document this by estimating equation (4), which contrasts households who have the same permanent income today but differ in their permanent income trajectories in the past 10 years.[13]

Table 3 presents estimates based on the specifications that allow current consumption to

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

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. 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.[14] So, a household with no permanent income growth, or, in other words, who already knew its permanent income level 10 years earlier, consumes more than another with positive growth.

Consumption commitments can generate this dependence on past permanent income. Young households choose an expenditure path, committing to some hard-to-adjust goods, given their current expectations of future income. Those households with past commitments must respond to increases in permanent income by increasing adjustable goods (e.g., nondurable goods) 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. 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, consumption 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

I have documented new facts about consumption's response to permanent income, which highlight a potential role for consumption commitments in understanding the consumption underresponse puzzle. In this subsection, I show that the estimated consumption elasticity translates for observed asset accumulation. This addresses concerns that my previous results were due to

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

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
$\log(\mathrm{PI}_t)$	0.62	0.86	0.63	0.49
	(0.03)	(0.06)	(0.05)	(0.04)
$\log(\mathrm{PI}_{t-10})$	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.

the mismeasurement of expenditures. 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 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 manifested in accumulation of household assets, then 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 synthetic net worth closely comove, highlighting the quality of the PSID data for longitudinal analysis. In the figure, median reported net worth is the solid blue line and median synthetic net worth is the solid red line. Both series change in tandem at similar levels, with the exception of synthetic net worth missing some of the dynamics around the 2008 financial crisis. A possible explanation is that the capital gains measure I am using, see note 15, 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 (dashed blue line) and mean synthetic net worth (dashed red line) are also closely linked.

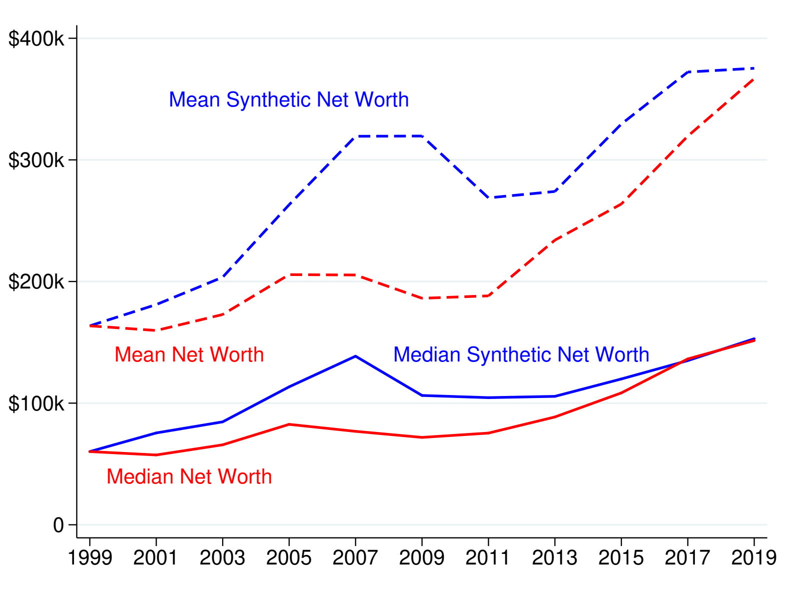
Figure 2 replicates the previous analysis but divides the sample into two groups: Panel 2a plots those households that experienced positive permanent income growth over 20 years and Panel 2b plots those that did not. Median reported net worth is again the solid blue line and median synthetic net worth the solid 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

[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 $C_t/0.67$.

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.

reliable in measuring lifecycle household behavior.

Active Savings

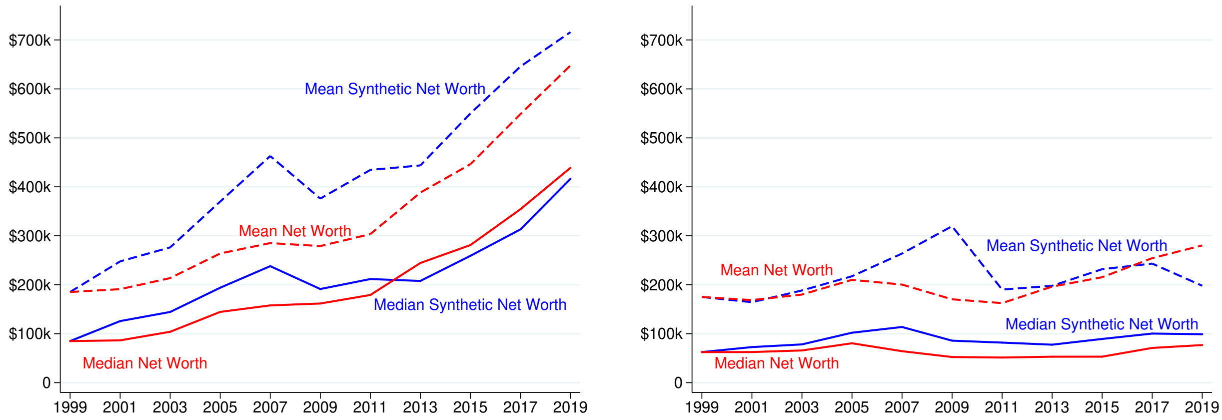
In the previous subsection, I documented path dependency in consumption responses to permanent income. I now investigate whether these path dependencies also show up in a measure of household savings. In particular, I investigate how active saving rates project onto the current and lagged permanent income 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 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

[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.

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.

income in the spirit of the previous analysis in Table 3. 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, consistent with the previously documented results. 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.

3.4 Expenditure Components

In this subsection, I show that expenditure allocation across categories also depends on current and past variables. Again, using dependence on past variables as a proxy for the importance of consumption commitments, I show that households with rapid past expenditure growth consume more easy-to-adjust goods and fewer hard-to-adjust goods (i.e., consumption commitments). I document this new fact by estimating demand systems to capture how past income growth is as-

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)
$\log(\text{PI}_{t-10})$			-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.

sociated with expenditure allocation across different goods, conditional on a given level of total expenditures – equation (5). I focus on the demand system for nondurable and shelter expenditures, arguably an easy-to-adjust and a hard-to-adjust good. Shelter expenditure is the most important consumption commitment in the data, 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 allow the expenditure share of a good to depend on the log of total expenditure to control for possible non-homothetic preferences, i.e., goods' Engel curves that differ from unit. These curves trace out total expenditures on a good against permanent income, and, without controlling for them, the estimates of permanent income trajectory on bundle allocation would also capture Engel elasticities. For a more straightforward interpretation, the coefficient on the log of total expenditure is expressed already as Engel elasticity in brackets in the first row of Table 5. Columns 1 and 3 imply an Engel elasticity of 0.8 for nondurable expenditures, indicating that nondurable goods are a necessity and their expenditure increases by 0.8% for each 1% increase in total expenditure. Columns 2 and 4 imply an Engel elasticity of 1.1 for shelter expenditures, suggesting that shelter is a luxury good and its expenditure increases by 1.1% for each 1% increase in total expenditure.

The second row of Table 5 shows the impact of past expenditure growth on the allocation of expenditure between different consumption categories. Given the same expenditure today, a

Table 5: Consumption Category Shares

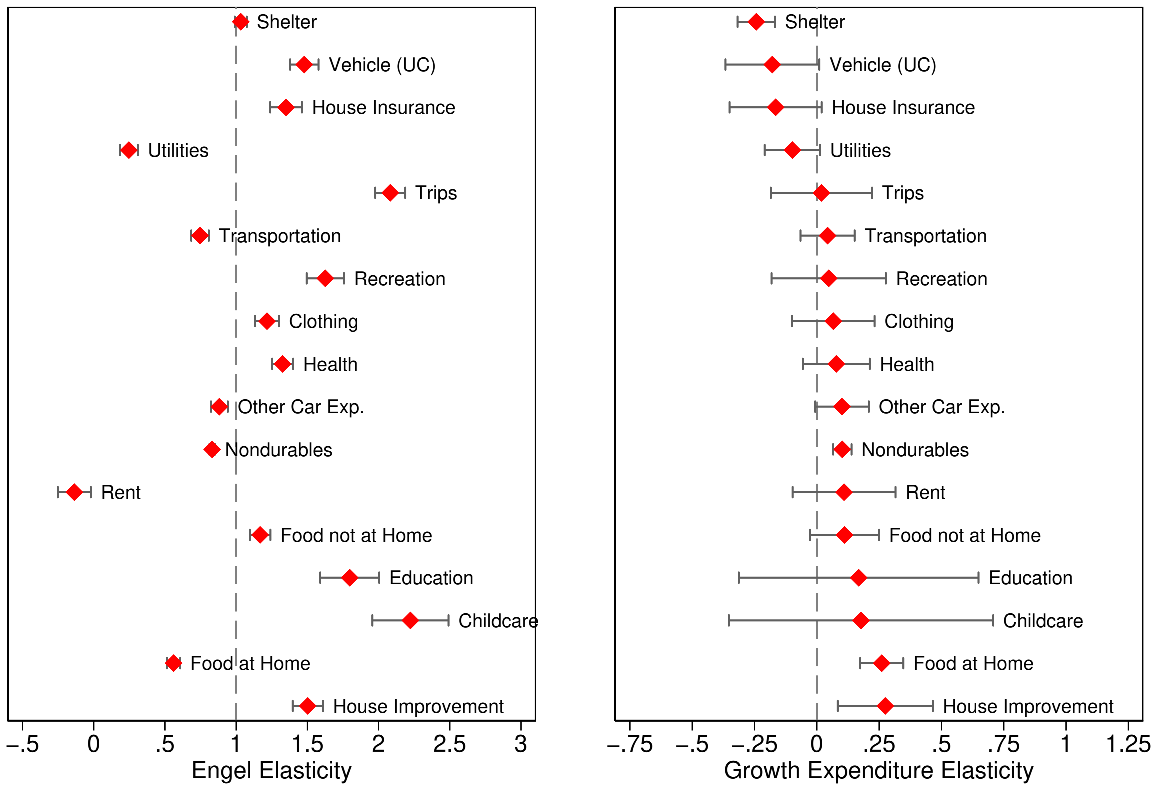
	(1) Nondurable Share	(2) Shelter Share	(3) Nondurable Share	(4) Shelter Share
log(exp)	-10.20	2.37	-9.98	3.21
	(0.60)	(0.69)	(0.81)	(0.86)
	[0.80]	[1.09]	[0.81]	[1.12]
Δ log(exp)			5.66	-8.01
			(1.52)	(1.64)
			[0.11]	[-0.31]
Educ Dummies	Y	Y	Y	Y
KP-F test	294.0	294.0	17.1	17.1
Observations	26,046	26,046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

household with faster expenditure growth consumes less shelter and more nondurables. Again, for a more straightforward interpretation, I will focus on the coefficient displayed in brackets, which represents the association between total expenditure growth and the log expenditure on a particular category. 10% growth in total expenditure decreases shelter expenditure by 0.3% and increases nondurable spending by 0.1%. Consistent with the commitment explanation, households respond to increases in permanent income, proxied here by the expenditure growth, 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 their strength as a consumption commitment. For shelter, and, at the margin of statistical significance, vehicle, house insurance, and utility 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. On the other hand, past growth skews the basket towards nondurables, food at home, and house improvement expenditures. These goods are broader than nondurable goods, including, for example, house improvement expenditures, which are usually 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.

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.

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.[17] If consumption commitments are important in the data, the consumption

[17] 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.

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.[18]

Column 1 of Table 6 shows that consumption responds less to lagged permanent income for households who recently moved. For households that did not move, 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 estimated elasticities of 0.61 and 0.22 for current and 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.

Column 2 of Table 6 shows, consistent with column 1, that savings rates 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 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 mechanism predicts. The first and second columns show the nondurable and shelter consumptions of households that did not move load significantly on lagged expenditure growth, with estimated coefficients of 12.4 and -19.4 for the growth rate, respectively. For households that recently moved, nondurable and shelter consumptions load almost exclusively on current expenditure. The estimated coefficients for the growth rate, 3.5 and -4.5 for nondurable and shelter consumptions, respectively, are economically small and less than 30 percent of the ones estimated for households that did not move recently.

[18]The different response to permanent income of renters and owners stresses the importance of the life cycle. Consumption commitments are accumulated over the life cycle, so, arguably, differences in the timing of the buying-a-house decision influence households' responses to permanent income. Households that were renters 10 years ago respond more to permanent income than those that were owners, while households that are renters and owners today have similar responses to permanent income.

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.

3.6 Additional Results

I perform several additional empirical tests that I briefly discuss here, with more detailed discussions in the appendices.

Quality of the Expected Income Growth Measure: When constructing my permanent income measure, I assume that household information sets are captured by lagged income, occupation, age, and demographic characteristics. However, the literature has found that, in general, 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 show in Appendix B that, while current consumption predicts future forecast error, it has low forecasting power, suggesting that households' superior information is quantitatively unimportant for my results.

Bequest and Intervivo Transfers, and Charitable Givings: The underconsumption puzzle implies that rich households save more. A commonly assumed force in many consumption models

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.

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.

In Appendix C.6, I propose a second test to determine the importance of the bequest motive in the data. The idea of the exercise is that if young households have information about their parents' permanent income level, and the bequest motive is important, 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. I interpret children responding to their parents' permanent income as evidence that they expect to receive money from their parents. However, I do not find evidence that locked-in parents transfer more money to their children.

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.7, 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.

4 A Life-Cycle Model with Lumpy Goods Adjustment

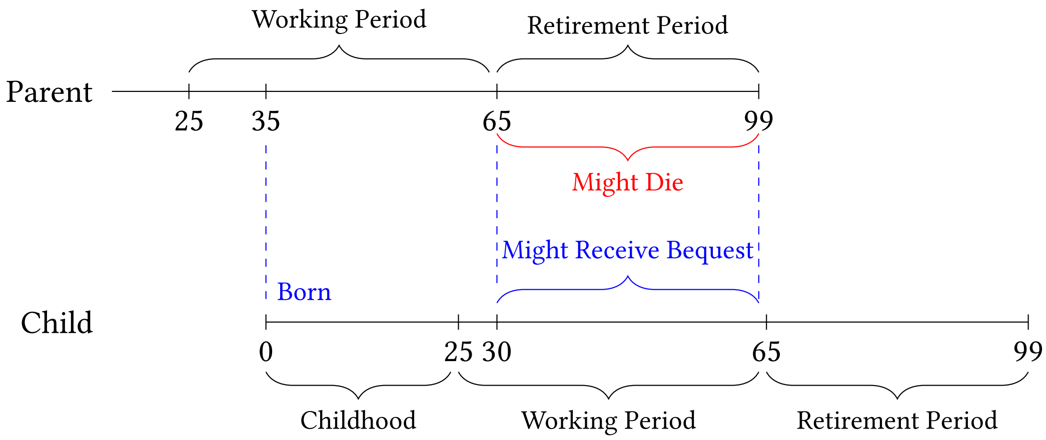
In this section, I extend a canonical incomplete markets model (Deaton, 1991; Carroll, 1997; Gourinchas and Parker, 2002) incorporating two consumption goods, one of which is hard-to-adjust. The hard-to-adjust good, which can be interpreted as housing or durables, provides a utility flow from its stock, 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 mechanisms used to explain consumption's under-response, such as luxury late-in-life consumption (Straub, 2019) and bequest motives (De Nardi, 2004). Lastly, to quantify the implications for wealth distribution, the model is cast in an overlapping generations structure.

4.1 Environment

Demographics: I consider a continuum of households in an overlapping generations structure. Each period corresponds to one year and j indexes 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 model age $j = 74$ (biological age 99). 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. The commitments flow reflects, $c^h = \zeta h$, where ζ is the return (in utility terms) on the commitment stock h, or rented quantity for renters. Both commodities are aggregated by a CES function,

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

ω determines the weight of commitments flow in the aggregator function, and $1/(1-\gamma)$ is the elasticity of substitution.

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 bequest motives as in De Nardi (2004).

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

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

where $\sigma_j^c > 0$ is an age-dependent elasticity. As in Straub (2019), the coefficient of risk aversion in the utility function follows a simple exponential decay, $\sigma^c_{j+1}/\sigma^c_j = \sigma^{c,slope}$ during one's working life, and is flat after that. The model is parameterized so that σ^c_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 commitment 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:

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

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

Assets: Households invest in liquid risk-free bonds and illiquid commitment stock, which can be interpreted as housing 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 commitment 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 commitments when adjusting their 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 commitment stock: $a > -\theta h$. In other words, households can borrow using their commitments as collateral.

In the quantitative analysis, I calibrate two versions of the model: i) a version with consumption commitments and without luxury late-in-life consumption, and ii) a version with luxury late-in-life consumption and without consumption commitments. Those cases correspond to $\kappa \neq 0$ and $\sigma^{c,slope} = 0$ and to $\kappa = 0$ and $\sigma^{c,slope} \neq 0$. I am currently working on calibrating a version of the model where both forces are present.

Rental Market: Households that decide not to be owners can enjoy commitments by buying it in a rental market. Renters can buy any positive amount of commitment flow subject to paying a mark-up λ over its 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 owners or renters, not both. This ensures that distortions in the intra-period expenditure allocation cannot be undone by buying additional commitment flow in the rental market.[19]

[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

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

4.2 Recursive Formulation

Let s denote the vector of state variables for a household, $s = \Big\{j, a, h_{-1}, \bar{z}, \alpha, \epsilon, \bar{z}^p\Big\}$. These variables indicate, respectively, age (j), bonds carried over from the previous period (a), past commitment stock (h_{-1}), and labor productivity components ($\bar{z}, \alpha, \epsilon$). The last 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 commitment size (possibly returning to rent). Specifically, households solve the discrete choice maximization problem

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

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 solves the following problem:

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

s.t.

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

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

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

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

When a household dies, they pass on a lump-sum bequest. This bequest, b, enters the child

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 $\text{pen}(\bar{z}) = 0.60 \times w \times exp(b_1 40 + b_2 40^2 + \bar{z})$. The value of 60% follows Diamond and Gruber (1999).

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 the child household expects to receive. Second, it helps differentiate between households 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 with the same commitment stock and solves the following problem:

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

where z evolves according to a conditional c.d.f. Γ^z, the bequest belief 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 adjustment is optimal, the household solves the following problem:

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

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

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 most consumption models, the optimal choices of savings and consumption are approximately proportional to permanent income, which implies that consumption has an elasticity of 1 with respect to permanent income. 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. The model's mechanism works through diminishing returns to specific goods relative to a near-constant return to marginal saving, which is given by the bequest motive. Households substitute present consumption for future consumption and future bequest. This breaks the tight connection between permanent income and consumption in my model.

The key implication is that the permanent income trajectory influences current consumption choices, especially for households locked into past consumption choices. This path dependence gives rise to four key implications, which I tested in the empirical section. First, younger households respond more to permanent income than older households. Second, for households with the same level of permanent income, the elasticity of consumption to permanent income is lower for those who recently experienced permanent income growth. Third, those households with faster-growing permanent income allocate a higher share of their expenditure to easy-to-adjust goods. Fourth, history matters less for households that recently adjusted their consumption bundle. In the next section, I explain how I calibrate the model to match this evidence.

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 in the calibration. Second, I describe other moments used 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 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) which adds 10-year lagged PI to the regression above in the model-generated data. 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 moments describing the consumption's response to permanent income, I calibrate the model 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

[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).

model-simulated and PSID moments. Tables 8 and 10 present the model parameters, discussed below, 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 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. Conditional on the income process parameters described in the last paragraph, the calibrated parameters match the correlation between parental and child income ranks in the model with the estimates of Chetty, Hendren, Kline, and Saez (2014).

Commitment parameters. I calibrate certain parameters governing the commitment structure to values found in the housing 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 value implies that expenditures on repairs and improvements fully delay depreciation. I set the maximum loan-to-value (LTV) ratio to 0.8 reflecting Greenwald (2018) and Boar, Gorea, and Midrigan (2022). Lastly, I set the utility flow of owning commitments to 4%. I follow the literature and use the equivalent expenditure (or implicit rent) that owning a house provides. My value for implicit rent is a slightly lower rent-to-value ratio than Katz (2017) estimated for a $400,000 house.[23]

[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

Preference parameters. Lastly, I calibrate some preference parameters exogenously. I set the risk aversion coefficient in bequest utility, σ^b, to 0.2 and the exponential decay of the consumption CRRA utility coefficient, $\sigma^{c,slope}$, to 1. Those choices imply that the bequest motive is a luxury, while late-in-life consumption is not. When the utility function is iso-elastic and additively separable, the income elasticity is approximately proportional to the inverse of the coefficient of risk aversion. Houthakker (1960) shows it in a static setup, while Straub (2019) applies it to an intertemporal context. Because the bequest motive has a lower coefficient than consumption utility, it is a luxury in my model. Also, because the latter is constant across ages, late-in-life consumption is not. Finally, I calibrate the scale term in the utility function, o, to 0.2, in line with the value used by Straub (2019), and I set the Stone–Geary parameter in the bequest function, ϕ_2, to 0.

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 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) bequests relative to GDP, iii) consumption's response to permanent income, iv) and v) consumption's response to permanent income and lagged permanent income. 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 compares data and model moments. The calibration matches consumption's responses to current permanent income and 10-year lagged permanent income, though producing a smaller coefficient for the latter. The model also does reasonably well in matching other commitment moments, including the likelihood of owners moving, the homeownership rate, the ratio of shelter expenditure to total expenditure, and the ratio of housing wealth to total wealth. Lastly, the model matches the bequest-to-income ratio in the data, but overpredicts the wealth-to-income ratio.

Table 10 lists the endogenous parameters. The discount factor, 0.92, and the coefficient of relative risk aversion, 1.25, fall within the range of values commonly used in the literature. The discount rate implies a moderately impatient household, a crucial factor for accurately capturing wealth dynamics in incomplete market models (Carroll, 2001). The risk aversion coefficient implies a consumption preference that is more elastic than the traditional $\sigma_c = 2$ but less elastic

(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	PSID
b_2	Quadratic trend	-0.0007	
$\sigma_{\bar{z}}$	Fixed-effect variance	0.17	
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)
	Commitments		
ζ	Commitment utility flow	0.04	Katz (2017)
δ	Commitment depreciation	0.03	BEA
χ	Maintenance cost	1.00	Berger and Vavra (2015)
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	-

than logarithmic utilities. The weight assigned to housing in the CES goods aggregator, $\omega = 0.27$, is slightly larger than 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 mainly determined by the likelihood of owners moving house and is in line with other papers in the literature, such as Berger and Vavra (2015). 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.

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: 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

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 match 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 untarget 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 are in Appendix D.

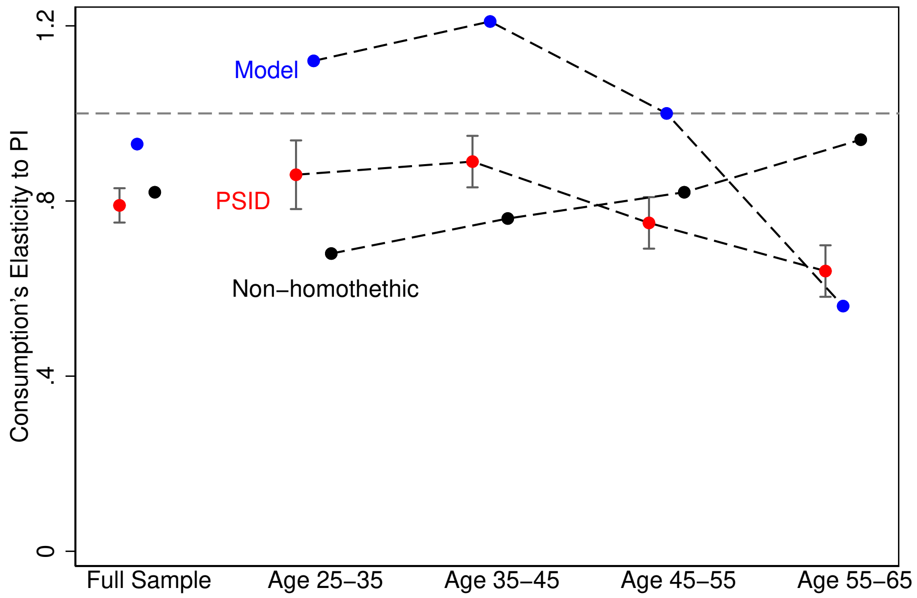
6.1 Consumption Responses to Permanent Income

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. For households between 45 and 65 years old, I estimate an elasticity smaller and decreasing with age, falling as low as 0.6. 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 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.

Why can 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 (Figure 11, Appendix D). Therefore, their consumption is more detached from their permanent income level because they are more "locked" into past consumption commitments.

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



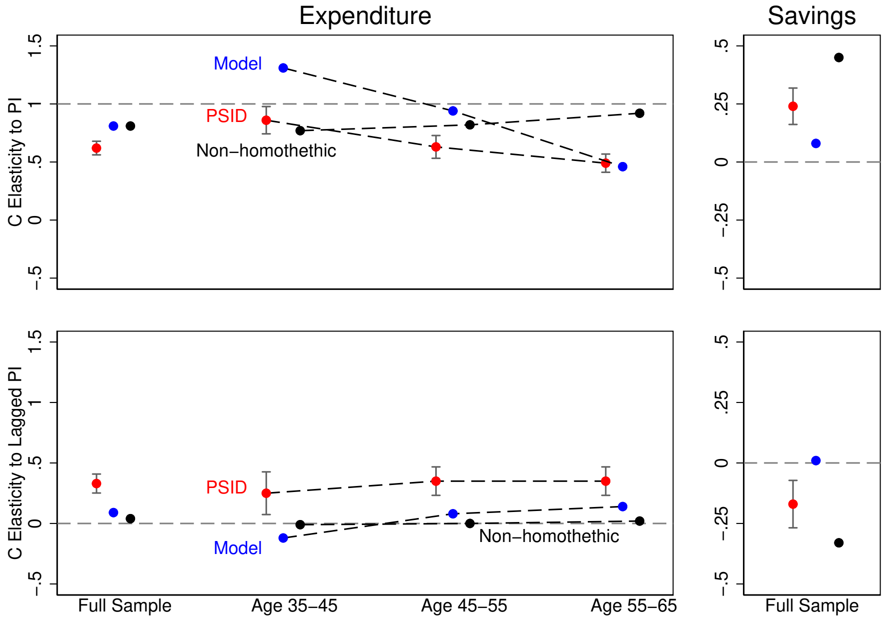
6.2 Consumption Responses to Current and Past Permanent Income

Other facts the model with consumption commitments can generate are consumption and savings responses to current and lagged permanent income, as documented in Tables 3 and 4. Consumption responses are displayed in the left panel of Figure 6, while savings responses are presented in the right panel.

In the left panel of 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 correspond to 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. However, despite some 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).

On the right panel of Figure 6, 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.

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



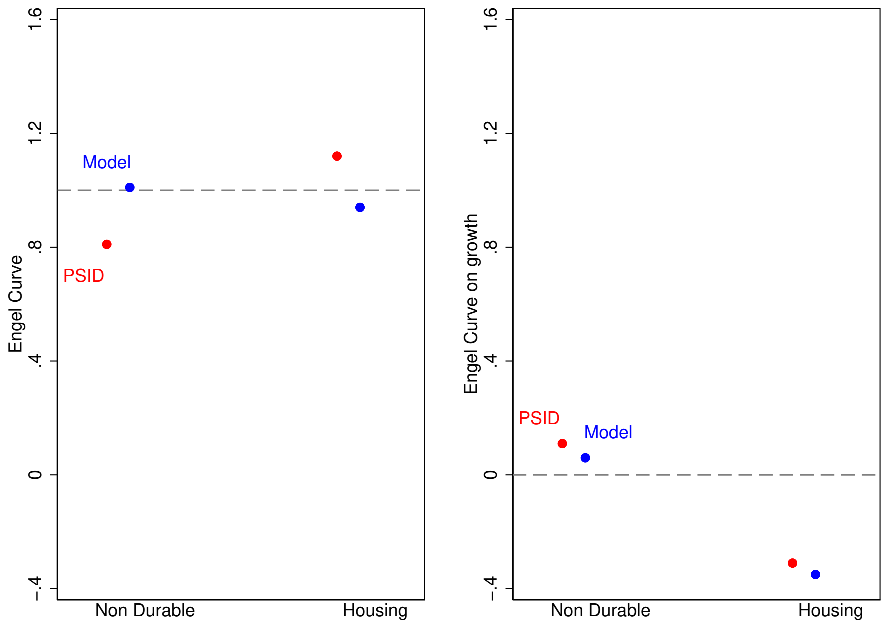
6.3 Expenditure Components

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, differently from the behavior in the data, shelter expenditure is not a luxury, and neither is nondurable spending a necessity. This is because the model aggregates goods with a CES structure, thus having elasticities of approximately 1. All those moments were not targeted in the calibration.

6.4 Consumption Resets

Lastly, the model with consumption commitments generates all the differences between movers and stayers 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 recently 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.

Figure 7: Consumption Category Shares – Data and Model



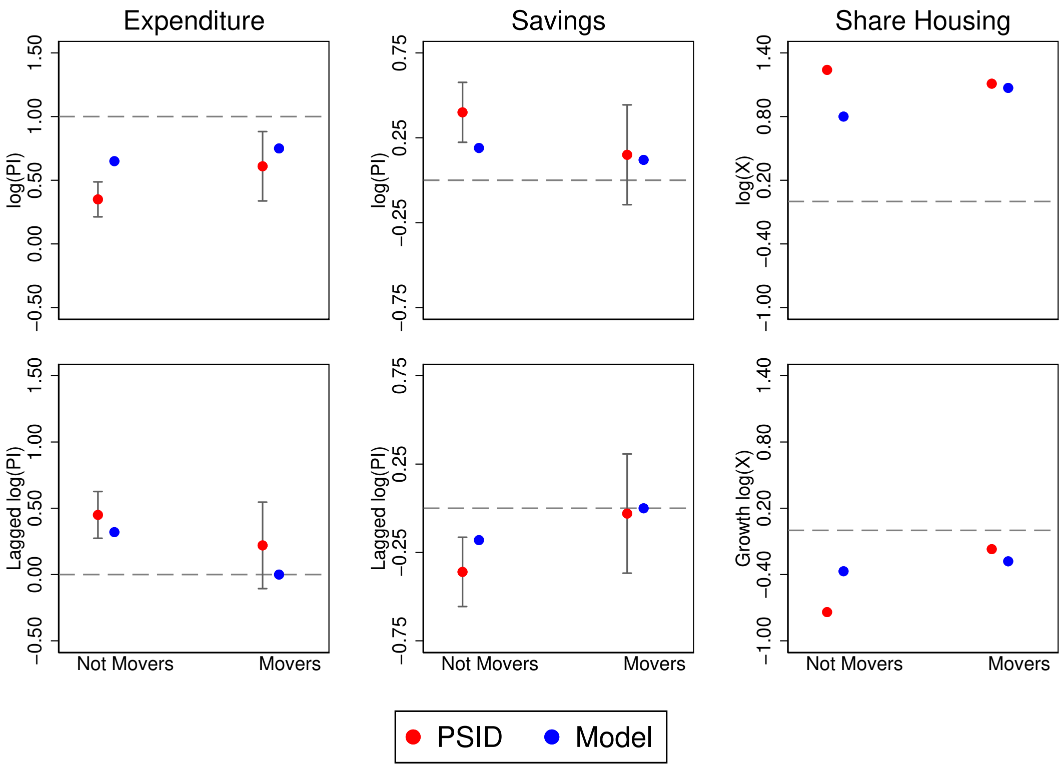
7 Aggregated Implications

In the previous section, I verified that my model accurately replicates the micro-level evidence on consumption responses to permanent income. In this last section, I explore its aggregate implications. First, I delve into the model's capacity to generate realistic consumption and wealth distributions. Second, I examine the aggregate consequences of an increase in permanent income inequality.

First, I compute Gini inequality indices for the PSID data and three versions of the model: i) one with consumption commitments, one with luxury late-in-life consumption, and another with neither mechanism. I refer to this last version as the homothetic model. The Gini indices for income, consumption, and wealth in the PSID are shown in the first row of Table 11. The second row shows the indices for the homothetic model, the fifth row shows the indices for the model with luxury late-in-life consumption, and the eighth row shows the indices for the model with consumption commitments.

Of the three model versions, the model with consumption commitments does the best job of generating realistic wealth distributions. It generates Gini indices for consumption and wealth inequality of 0.30 and 0.80, which are close to the ones observed in the data, 0.31 and 0.77, respectively. The model with luxury late-in-life consumption overstates consumption inequality by 12 percent while generating a wealth inequality relatively close to the data. Lastly, the homothetic

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



model produces realistic consumption inequality but understates wealth inequality by 17 percent.

Second, I investigate the aggregate implications of an increase in permanent income inequality. I do this by comparing the steady states at 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.

I perform this counterfactual exercise, again, in a model with only consumption commitments, in one with only luxury late-in-life consumption, and in one with neither mechanism. As illustrated in Table 11, the commitment model exhibits lower increases in consumption and wealth inequalities, with the Gini indices for consumption and wealth increasing by 7.4% and 2.2%, respectively. Consumption inequality increases by 8.2% in the homothetic model and the luxury late-in-life consumption model. On the other hand, wealth inequality increases by 2.7% in the homothetic model and by 2.2% in the luxury late-in-life consumption model.

These findings align with the ongoing debate in the literature on the relationship between

Table 11: Distributional Implications

	Income Gini	Consum. Gini	Wealth Gini	Wealth-Income
PSID	0.40	0.31	0.77	4.39
Homothethic				
Benchmark	0.36	0.30	0.62	5.12
$\nearrow$ PI inequality	0.39	0.33	0.64	5.46
	7.2%	8.2%	2.7%	6.7%
Luxury late-in-life				
Benchmark	0.36	0.35	0.73	5.44
$\nearrow$ PI inequality	0.39	0.38	0.75	6.08
	7.2%	8.2%	2.2%	11.8%
Commitments				
Benchmark	0.36	0.30	0.80	5.17
$\nearrow$ PI inequality	0.39	0.32	0.82	6.02
	7.2%	7.4%	2.2%	16.4%

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 Attanasio et al. (2014) and 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. 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.

8 Conclusion

In this paper, I provide empirical and quantitative evidence for a novel explanation for the consumption under-response to permanent income. I document four main novel facts that support the importance of *consumption commitments*, hard-to-adjust consumption choices that resemble long-term commitments, and explore their quantitative implications by employing a calibrated

[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.

life-cycle consumption model.

Empirically, I first show that younger households exhibit a stronger response to permanent income than older ones. Commitments are made gradually over the life cycle, which implies that older households have accumulated more commitments on average and exhibit a greater detachment of consumption from permanent income. Second, I show that households' responses to permanent income depend on past income trajectories, with households whose permanent income grew more recently having lower total consumption on average. Third, I show that those households that have "under-responded" to their income growth skew spending away from hard-to-adjust goods (notably shelter) and toward easy-to-adjust goods. Lastly, I show that households who recently adjusted their hard-to-adjust goods consumption exhibit little or no dependence on past variables.

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. 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 bequest motives (De Nardi, 2004). The model successfully accounts for the novel documented facts on consumption's response to permanent income, even though most of these moments are not targeted in the calibration. Additionally, the model generates consumption and wealth inequalities that align with the ones observed in the PSID.

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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 under classical measurement error assumptions, lagged income is a good instrument to deal with measurement errors in permanent 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

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

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^*. The "non-noisy" measure of permanent income is $\widehat{\mathrm{PI}}_t^*$.

Any regression that uses as an explanatory variable the permanent income measure constructed with noisy income data, Y_t, will suffer attenuation bias since $\widehat{\mathrm{PI}}_t^*$ and $v_0 f(y_0^*)$ are positively correlated. In particular, this is the case when using OLS estimation to project the logarithm of consumption on the logarithm of permanent income. However, because of the assumption of classical measurement error, y_0^* is not correlated with either v_0 or $v_0 f(y_0^*)$. Therefore, any variable correlated with y_0^* but not with v_0 can be used as an instrument for permanent income. For example, y_{-1} is a good instrument, which is the one used in this paper.[25]

[25] First, note that the result that I derived in this appendix is for the measure of permanent income in levels, but taking the logarithm of it does not alter the conclusions. In particular, the log of permanent income is

$$
\log \widehat{\mathrm{PI}}_t = \log\left(\widehat{\mathrm{PI}}_t^* + v_0 f(y_0^*)\right) = \log \widehat{\mathrm{PI}}_t^* + \log\left(1 + \frac{v_0 f(y_0^*)}{\widehat{\mathrm{PI}}_t^*}\right) \approx \log \widehat{\mathrm{PI}}_t^* + v_0 g(y_0^*) \ .
$$

The last approximation holds if $v_0 f(y_0^*)/\widehat{\mathrm{PI}}_t^*$ is small, which is probably the case since both the numerator and the denominator are constructed from the path of $\widehat{Y}_j^*$, but the former is discounted by $(\rho/R)^j$ and the latter by $(1/R)^j$.
Second, note that, because of the assumption that of classical measurement error, $E[v_0 f(y_0^*)] = E[f(y_0^*)E[v_0|y_0^*]] = 0$, which implies that y_0^* and $v_0 f(y_0^*)$ are uncorrelated.

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 B1 and B2 show summary statistics for the forecast and percent errors for different time horizons. The first column of Table B1 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 B2 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 B1: 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 B2: 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

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

in which $p^t_{i,t+h}$ 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 B3, 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 B3: 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 B4, 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 B5. 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 B4: 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 B5: 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 C1: 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 C2 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 C2: 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 C3: 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 C4 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.

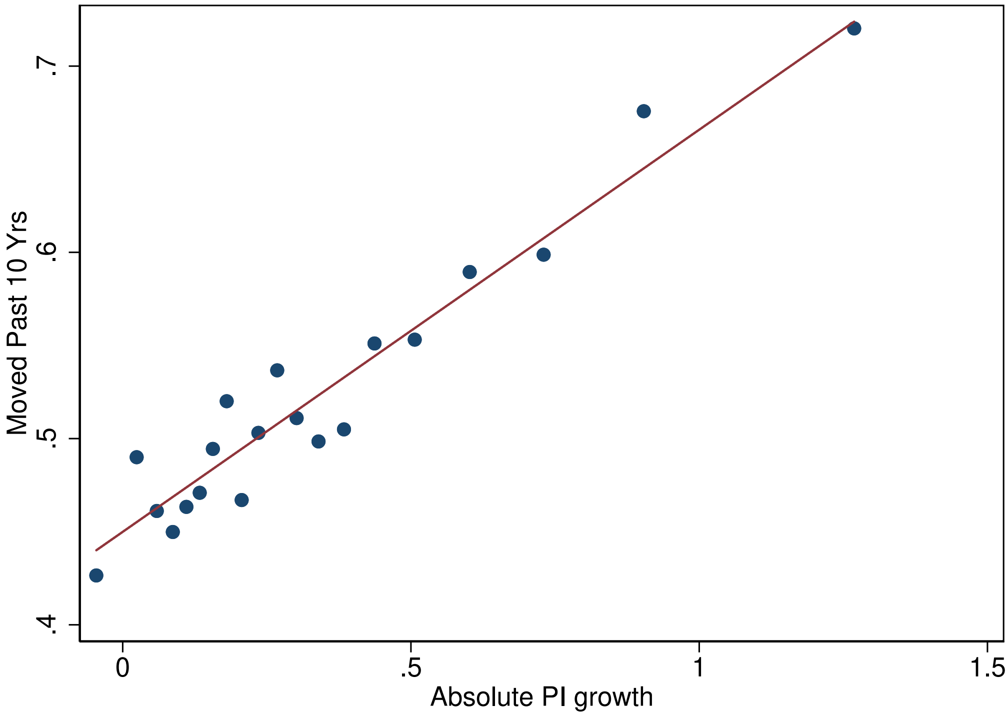
Table C4: Probability of Housing Adjustment

	(1) Moved Past 10 Yrs	(2) Moved Past 10 Yrs	(3) Might Move	(4) Might Move
$\lvert\log(\mathrm{PI}/\mathrm{PI}_{t-10})\rvert$	0.235	0.180	0.102	0.022
	(0.018)	(0.026)	(0.017)	(0.030)
Own $\times$ $\lvert\log(\mathrm{PI}/\mathrm{PI}_{t-10})\rvert$		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 C4, 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 C5 shows that renters and owners have similar responses to permanent income, both with respect to consumption and savings rates. Column 1 shows that 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 C5: 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 C6 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 C6: 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.

Importantly, many of my results stress the importance of understanding the life cycle to understand the households' responses to permanent income. In particular, consumption commitments are accumulated over the life cycle, with older households arguably having more commitments on average. So, I look at whether differences in the timing of the buying-a-house decision influence households' responses to permanent income. I look at differences between households that were homeowners 10 years ago versus households that were renters.

Table C7 shows that households that were renters 10 years ago respond more to permanent income. Column 1 shows that the consumption response of those households loads more on current permanent income than the response of households that were homeowners, with an estimated coefficient of 0.8 and 0.5, respectively. Contrarily, the path dependency is stronger for the latter than for the former, with an estimated coefficient of 0.16 and 0.41, respectively. Column 2 shows no evidence of differences between the two groups regarding savings rates' responses. The results for the allocation of expenditure, Table C8, align with what the consumption commitment story predicts as well.

Table C7: Heterogeneous Effects: Homeownership Status

	(1) log(expenditure)	(2) Savings Rate
log(PI)	0.78	0.24
	(0.07)	(0.08)
$\log(\mathrm{PI}_{t-10})$	0.16	-0.20
	(0.10)	(0.10)
$\mathrm{Own}_{t-10} \times \log(\mathrm{PI})$	-0.28	0.01
	(0.10)	(0.09)
$\mathrm{Own}_{t-10} \times \log(\mathrm{PI}_{t-10})$	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 C8: 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)
$\mathrm{Own}_{t-10} \times \log(\mathrm{exp})$	-11.55	-0.17
	(1.24)	(0.06)
$\mathrm{Own}_{t-10} \times \Delta \log(\mathrm{exp})$	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 C9 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 C9: Bequest

	(1)	(2)	(3)	(4)
	$\mathbf{1}\{\text{bequest} > 0\}$	$\mathbf{1}\{\text{bequest} > 0\}$	log(bequest)	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 C10 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 C10: 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 C11 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 C9, C10 and C11 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 C11: 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 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 C12 shows a positive correlation between split-off expenditure and parents' current and lagged permanent income. Overall, children respond to their parents' permanent income.

Table C12: 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.

C.7 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 C13 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 C13: Donations

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

Note: To be added.

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

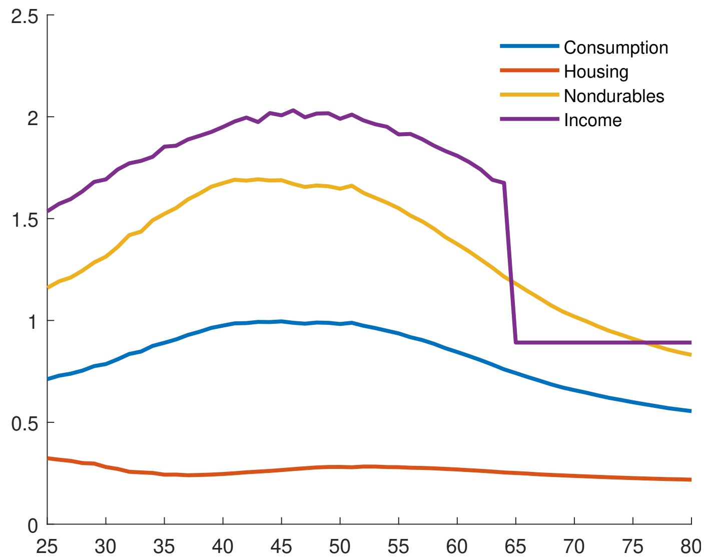
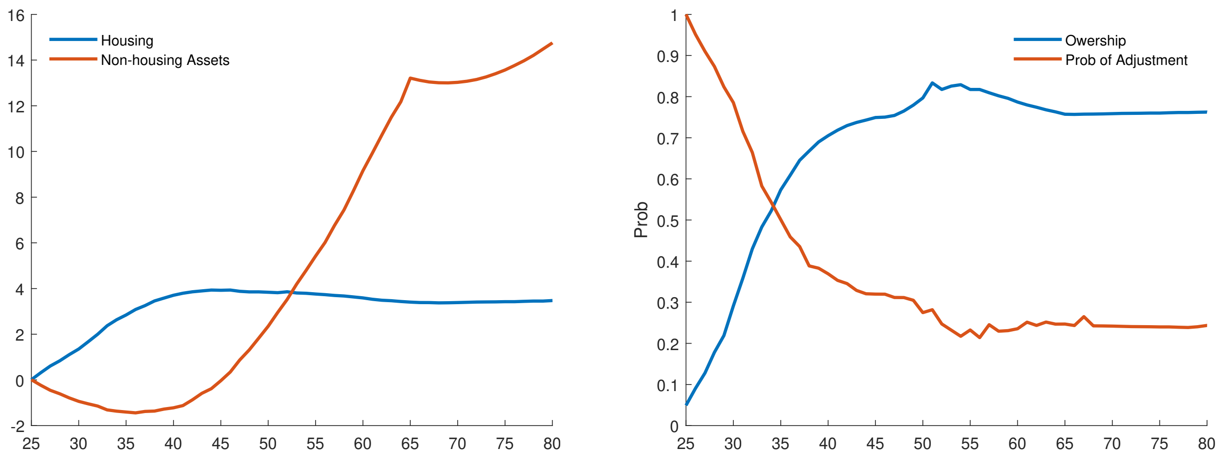


Figure 11 shows the average asset profiles in the model economy. Panel 11a shows that households first accumulate housing assets and hold negative liquid assets early in their life cycle. Throughout the life cycle households pay their debts and accumulate positive liquid assets. After retirement, households 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

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

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

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.

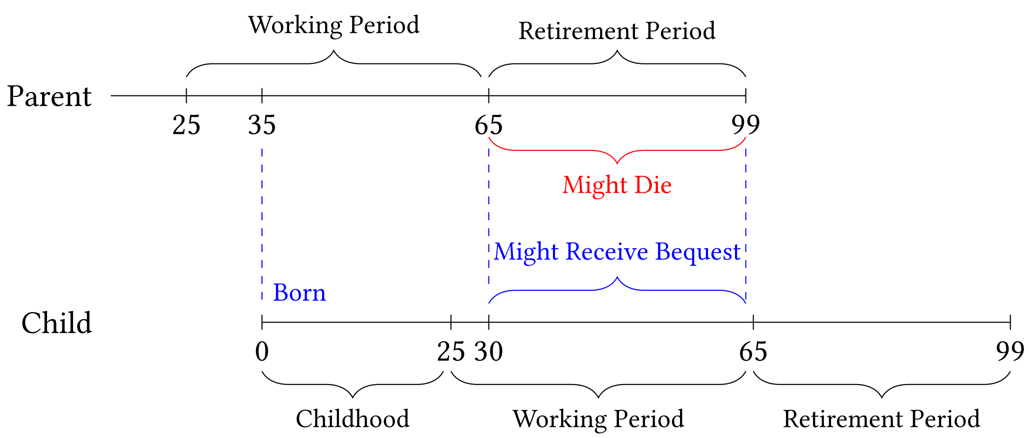


Figure 12: Overlapping Generations Structure

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

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

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.