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

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Abstract

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

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

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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 fully absorb permanent income shocks into their consumption, 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 with respect to permanent income appears to be far below one (Dynan, Skinner, and Zeldes, 2004; Straub, 2019). I refer to this latter puzzle as the under-consumption puzzle.

In this paper, I provide empirical and quantitative evidence for a novel explanation of this 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 to measure 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 contributions are twofold: I show that consumption commitments are necessary for life-cycle models to account for all the documented facts, and I show that this characterization has implications for aggregate distributions.

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 in 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. Commitments rationalize this pattern because they are made gradually over the life cycle, implying that younger households have fewer commitments and, consequently, their consumption should re-

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

spond more to permanent income. This evidence also implies that any model that relies on young households saving to consume when old is inconsistent with this evidence, as it would predict an elasticity that increases with age.

Second, I document path dependence in household responses to permanent income. More precisely, I compare households with the same permanent income today but that experienced different permanent income trajectories – one that experienced permanent income growth recently and one that experienced it earlier in their life cycle. Comparing 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 path dependence in household responses to permanent income also shows up in their expenditure allocation across categories of goods. Again, I compare households with the same permanent income today but that experienced different trajectories 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 based on their current expectations of future income. However, after the realization of uncertainty and due to 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, households with recent permanent income growth have, on average, lower overall consumption and a relatively larger share of easy-to-adjust goods than what their current permanent income would predict.

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 in expenditure allocation across categories of goods. Moreover, these households respond more to their permanent income. In this exercise, I use past moving decisions as a proxy for consumption commitment 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.

The finding that, after consumption commitment adjustments, the documented path dependencies decrease significantly or disappear in the data suggests that the under-consumption puzzle is closely tied to the frictions associated with adjusting commitments. Alternative explanations for path dependencies, such as habit formation, do not produce similar patterns. In the appendix, I address concerns that households move to obtain permanent income increases. In particular, all my findings remain robust when restricting the sample to households that report increasing housing consumption as their reason for moving.[2]

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; therefore, crucially for my empirical exercises, 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.

Estimating households' future income profiles raises two concerns with my permanent income measure: i) households possessing superior information relative to the econometrician in forecasting future income and ii) mismeasurement in reported income and consumption. To mitigate concerns about households' superior information, I take advantage of the panel structure and test the bias and forecastability of income forecast errors. Importantly, I conduct all tests using out-of-sample forecasts. I show that short-period income forecast errors are unbiased, but there is a small bias in longer-period forecasts. Moreover, I show that current consumption, which arguably embodies most of the information available to households, has low power in forecasting future income forecast errors. This result should alleviate concerns about the quantitative importance of households' superior information.

Regarding measurement error, I conduct three exercises. First, I again take advantage of the panel structure and use reported income in adjacent surveys and industry dummies as instruments. Second, I construct an implied net worth measure based on reported income and expenditure and compare it with the actual net worth reported by households in the survey.[3] The asset paths implied by both measures are consistent. Third, I use a measure of active savings and show that the under-consumption puzzle and path dependencies also show up on the asset side as over-savings. These results should help alleviate concerns about measurement errors and reaffirm the

[2] The focus on shelter consumption raises the question of how renters and homeowners respond differently. In the appendix, I test and document that there are no differences in path dependencies between current homeowners and current renters. However, I show that households who were renters before the realization of permanent income growth respond more strongly than those who were homeowners. These results emphasize the importance of the life cycle and suggest that the timing of the homeownership decision plays a crucial role in shaping households' responses to permanent income.

[3] Active savings measures the net flow of money into and out of different asset classes, excluding capital gains or changes in asset valuation. Arguably, this measure better reflects households' conscious decisions about how much to save from their income. To construct active savings, I clean the survey questions available in the PSID Wealth Module. Hurst, Luoh, and Stafford (1998) also use these questions.

quality of the PSID data.

To address the question of why this characterization matters, I propose a quantitative model in line 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 proportional, non-convex adjustment cost in its level (Chetty and Szeidl, 2007; Berger and Vavra, 2015). I allow for other potentially important mechanisms for generating savings that increase with income, such as late-in-life luxury consumption (Straub, 2019) and bequest motives (De Nardi, 2004). I calibrate the model by explicitly targeting commonly used moments in the literature and some of my empirical findings. In particular, I target the life-cycle behavior of the consumption response to permanent income and its path dependencies.

The model works because some households partially adjust their consumption bundle in response to permanent income increases due to the non-convex adjustment costs. For those households, the diminishing returns to consumption are exacerbated by the possibility of only increasing consumption of adjustable goods, while the marginal return to savings is near-constant. This near-constant return comes from the possibility of consuming in the future when the allocation is potentially less distorted and from the bequest motive, which is calibrated to be elastic. Consequently, these households substitute present consumption for future consumption and future bequests and exhibit path dependence in their allocations. For households that fully adjust their consumption, expenditure allocation is not distorted and does not depend on past permanent income levels. Their saving behavior is mainly driven by the model's other mechanisms that generate increasing savings in income: the late-in-life luxury consumption and the bequest motive.

The model can account for the novel facts on consumption's response to permanent income documented in the empirical section. I assess the model's performance by examining its ability to replicate both calibration-targeted and untargeted moments. In particular, I measure permanent income in the model as I do in the data to ensure consistency, and I compute the facts on consumption's response by running regressions on simulated data. The model successfully replicates most empirical patterns, highlighting the importance of all elements in the model, including consumption commitments, in understanding consumption's response to permanent income.

After showing that the model is broadly consistent with the micro-data evidence on household behavior, I perform two counterfactual exercises. First, I show that consumption commitments are necessary to account for the target moments. I do this by individually shutting off commitments and the other mechanisms in the model. Consumption commitments are important for generating stronger consumption responses for younger households and responses that depend on lagged variables. In contrast, the other mechanisms are essential for generating the level of consumption's under-response.

Second, I analyze the model's ability to generate realistic wealth and consumption inequality. Conditional on the calibrated income process, I ask how much consumption and wealth inequality the model can generate by computing Gini indices. The income process is calibrated in a first step outside the model and is consistent with the behavior of earnings in microdata. The model generates aggregate inequality comparable to what is observed in the data. In particular, by individually shutting off the model's mechanisms, I show that commitments are important in generating realistic consumption inequality. In contrast, a model with only non-homothetic preferences, such as late-in-life luxury consumption, cannot generate a realistic consumption distribution. In contrast, a model with only non-homothetic preferences, such as late-in-life luxury consumption, cannot generate a realistic consumption distribution. In this model, households accumulate assets to finance consumption when old. However, as older households consume these assets, the model predicts contractual dispersion in consumption.

In sum, this paper demonstrates that consumption commitments play a fundamental role in shaping household responses to permanent income, leading to systematic deviations from the predictions of the textbook permanent-income hypothesis. Commitments shape consumption, savings, and expenditure allocation across goods and have important implications for the distribution of consumption and wealth. In particular, commitments' role in shaping life-cycle consumption behavior is central to these findings. By documenting novel empirical facts and developing a quantitative framework that accounts for these mechanisms, this paper contributes to broader debates on consumption smoothing, wealth accumulation, and the transmission of economic shocks.

Roadmap. Section 2 details the methodology for measuring permanent income and consumption's responses in the data. Section 3 presents the novel empirical facts on consumption's response to permanent income. Section 4 presents a standard incomplete markets life-cycle model that incorporates consumption commitments and other mechanisms proposed in the literature to explain the consumption's under-response. Section 5 describes the calibration procedure. Section 6 quantifies consumption's response within the model and evaluates its performance. Section 7 assesses the model's aggregate implications. Finally, Section 8 concludes. The appendix provides additional empirical and quantitative results.

Related Literature. My paper contributes to two strands of literature: one on how consumption responds to income, particularly its response to the permanent component of income, and another on the implications of adjustment costs for household behavior, particularly the implications of consumption commitments and housing consumption.

The extensive literature on consumption responses to permanent income can be traced back nearly 80 years. Friedman and Kuznets (1945) introduced the concepts of transitory and permanent income components. Reid (1952) then emphasized the importance of the permanent income component in understanding income-expenditure patterns. Ultimately, Friedman (1957) formalized the permanent-income hypothesis (PIH). Since then, the PIH has been widely tested across various settings and datasets. For example, it has been examined using aggregate time series data, such as in Hall (1978), Flavin (1981), and Campbell and Deaton (1989), as well as using microdata, such as in Hall and Mishkin (1982), Altonji and Siow (1987), and Zeldes (1989). For comprehensive reviews of this literature, see Jappelli and Pistaferri (2010), Jappelli and Pistaferri (2017), Havranek and Sokolova (2020) and Sokolova (2023).

More specifically, this paper contributes to the recent literature comparing consumption responses in quantitative life-cycle models to those observed in the data. Early examples include Hubbard, Skinner, and Zeldes (1995), Carroll (1997), and Gourinchas and Parker (2002). I extend this work by documenting novel empirical facts and identifying the key mechanisms that the quantitative models must incorporate to match these patterns. Empirically, I provide a comprehensive analysis of household consumption responses, showing how the under-consumption puzzle varies by age and income trajectory, how it shows up in asset accumulation and expenditure composition, and how it differs between households that have adjusted their consumption commitments and those that have not. All these facts are novel to the literature. Quantitatively, I demonstrate that life-cycle models must incorporate consumption commitments to reconcile theory with the full empirical findings.

Specifically, regarding consumption responses to permanent income, a general finding in the literature is that consumption responds more to permanent income in models than in the data. For example, Kaplan and Violante (2010) find a pass-through of permanent income shocks to consumption larger than that Blundell et al. (2008) estimated using PSID data. Closely related to my work, Straub (2019) defines permanent income as an individual-specific fixed term in a log labor income process, estimates a consumption elasticity with respect to this component using PSID data, and shows that canonical macroeconomic models cannot quantitatively generate this elasticity at a magnitude comparable to the data. This evidence motivates his addition of non-homothetic preferences to a model as a way to capture backloaded consumption, such as health expenditures and inter-vivo transfers. In this paper, I refer to what Straub calls non-homothetic preferences as late-in-life luxury consumption.

Empirically, I differ from Straub's approach by defining permanent income in a manner more consistent with the broader literature and by constructing a measure that captures the evolution of expectations over the life cycle rather than relying on a fixed component. In my approach, I recover his baseline result and go further by documenting additional facts. Quantitatively, I incorporate Straub's late-in-life luxury consumption and consumption commitments into a quantitative model and assess their relative importance. I show that consumption commitments are crucial for generating the life-cycle pattern of the consumption response and its dependence on past permanent income. In contrast, late-in-life luxury consumption and bequest motives primarily account for the overall level of consumption's under-response. By explicitly quantifying the contribution of each mechanism, this paper confirms previous findings in the literature and expands our understanding of why consumption under-responds to permanent income.

My paper also relates to the broader literature on the implications of adjustment costs for a set of goods on household behavior. The seminal work in this literature is Grossman and Laroque (1990), which analyze consumption and asset pricing in a continuous time model with a single durable good and a smooth diffusion process for wealth. Other works have studied the implications of adjustment costs for individual risk preferences (Chetty and Szeidl, 2007), housing choices of couples (Shore and Sinai, 2010), aggregate consumption dynamics (Berger and Vavra, 2015; Chetty and Szeidl, 2016), life-cycle dynamics (Yang, 2009), wage rigidities (Postlewaite, Samuelson, and Silverman, 2008), and asset pricing (Flavin and Nakagawa, 2008). Others have analyzed the implications of adjustment costs on the asset side, such as the implications of mortgage refinancing for monetary policy (Beraja, Fuster, Hurst, and Vavra, 2019) and those of liquid assets for fiscal policy (Kaplan and Violante, 2014). I contribute to this literature by empirically and quantitatively documenting that lumpy goods adjustment is a key mechanism behind the consumption under-response to permanent income.

My model combines elements from existing models in a new way that has not been previously done and is essential to answering my question. For example, Kaplan and Violante (2014) use a model in which households can hold two assets, one subject to adjustment costs, to study consumption responses to fiscal stimulus. However, there is no distinction in the intra-period allocation of expenditure because they assume a frictionless rental market that allows households always to obtain the optimal intra-period allocation. Berger and Vavra (2015) use a model with two goods, one subject to adjustment costs, to study sluggish macro responses during recessions. However, unlike my model, they do not analyze consumption over the life cycle or quantify the implication of commitments to responses to permanent income.

2 Measuring Consumption Responses to Permanent Income

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

2.1 PSID data

Throughout this paper, I use data from the Panel Study of Income Dynamics (PSID), in particular, its 1999 to 2019 waves. The panel nature of the PSID and the broad measures of consumption, income, and wealth collected in these years allow for analyses of how households' consumption, income, and wealth evolve and interact over time. My sample consists of all households whose heads are between 25 and 65 years old. Throughout the paper, I highlight whenever I use a sample with a different age range and explain the reasons for doing so.[4]

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

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

I measure assets using reported net worth[5] and construct a discounted future expected income profile for each household. The expected income path is expressed in present value terms using a constant interest rate, $R = 1.05$, and age-specific survival probabilities.[6] In equation (1), the discount factor is $\psi(age_i(t), age_i(s))/R^{s-t}$, where $\psi(a_1, a_2)$ represents the probability of an individual of age a_1 surviving until age a_2 and $age_i(t)$ returns the age of household i as a function of the time period t. Finally, $\widehat{Y}_{i,s}^{t}$ is the expected income for household i at time s using the information set available at t.

The crucial step in my measurement exercise is estimating an expected income path for each household. First, I assume that past income and certain demographic characteristics describe the

[4]The PSID was conducted annually until 1996 and biennially since 1997. I use data from the 1997 - 2019 PSID waves in most exercises. However, I use data from the 1980 - 2019 PSID waves when estimating the forecast equation used to compute expected income. I use only odd survey years for PSID waves before 1999 to maintain consistency across years.

[5]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 include checking and savings accounts and stocks. Liquid debt includes all debt other than mortgages. Net liquid wealth is liquid assets minus liquid debt. Net illiquid wealth includes the household's home equity (home value minus mortgages), the net value of other assets, 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. Appendix A provides detailed descriptions of how the variables were constructed.

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

information set and that the household and the econometrician share it. Second, I assume that a linear autoregressive process approximates the expectations-formation process. Finally, I estimate all equations using OLS, which implies that I am using a "linear least squares forecast." I discuss challenges with this approach at the end of this subsection.[7]

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

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

in which $\ln \widehat{Y}^t_{i,t+2}$ is the expected log income in period $t+2$ using the information set in t. I iterate the previous equation to forecast income beyond period $t+2$ and linearly interpolate income in even years.[8]

I estimate the autoregressive process using a rolling sample of observations collected over the 16 years before t. This restriction ensures that my permanent income measure only captures information available to the household when the forecast is made and that no future information is used in the forecast. Thus, to estimate permanent income for 1997, I estimate the income process using data from 1981 to 1997 and iterate it forward to construct the future income path. To estimate permanent income for 1999, I roll the sample, re-estimate the process, and iterate it again, and so on. The t-subscript in the parameters of equation (2) denotes the last year in the estimation sample (i.e., the year that indexes the information set).

In the long run, income converges to the sample means determined by the cubic polynomial in age and by dummies for educational attainment, marital status, census region, and occupation groups. These variables are all included in $\mathbf{X}_{i,t}$. This approach is similar to Carroll (1994), who measures expected future income using average income among older households with similar education and occupation. In particular, the autoregressive structure in my approach introduces

[7]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) of the conditional mean $E(Y_t|\mathbf{Y}_{i,t-1}, \mathbf{X}_{i,t})$.

[8]When forecasting the income path, I need to make an assumption about how much a household expects to receive from retirement and Social Security income. This is particularly important because Social Security and retirement wealth constitute the main sources of resources 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 U.S. Social Security system discourages additional work after age 65.

dynamics by ensuring that future income does not adjust instantaneously to the long-run mean and instead allows it to evolve gradually over time. My approach explicitly captures the persistence of income shocks and their slow adjustment.

I use household after-tax labor income as my measure of income, which consists of labor earnings and government transfers, net of payroll taxes. Labor earnings consist of the head and partner's (if any) total labor income, including the labor component of income from any unincorporated business and excluding business and farm income. Government transfers consist of any head and partner's government transfer income from AFDC, Supplemental Security Income, Social Security benefits, unemployment benefits, workers' compensation, and other welfare payments. Payroll taxes come from the NBER's TAXSIM. For robustness, I construct a broader measure that includes asset income and discuss how the results change in Appendix D.1.[9]

I address various concerns with my forecast exercise. First, I use instrumental variables to deal with measurement error in income data. In particular, since I forecast income for many periods ahead and sum it to construct permanent income, any measurement error will accumulate and potentially imply a noisy measure. A downward-biased estimate could explain a lower consumption response. In Appendix B, I show that, under the assumption of classical measurement error, the true 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. Therefore, in my analysis, I instrument for the log of permanent income with lagged income and industry dummies. Measurement errors in assets are harder to address, and I rely on the same set of instruments used to deal with errors in income.[10]

Another possible concern is households possessing superior information relative to the econometrician when forecasting future income. To mitigate these concerns, I take advantage of the panel structure, construct out-of-sample forecast errors, and test their bias and forecastability in Appendix C. Short-term errors are unbiased, but longer-term ones have a small bias. Moreover, I show that current consumption, which arguably embodies most of the information available to households and is a good proxy for capturing households' information set, has low power in fore-

[9]Asset income consists of the head and partner's business income, farm income, dividends, interest, rents, trust funds, and royalties. I follow Aguiar et al. (2020) and add 6% of the respondent's assessed home value to their total income to account for the implicit rent on their house. Again, I compute taxes using the NBER's TAXSIM (payroll, federal, and state income taxes). I treat business/farm labor and asset income as wages/salary for TAXSIM purposes, following Kimberlin, Kim, and Shaefer (2014). Allocating 100% to labor income is less arbitrary than the PSID's current approach, which splits business/farm income equally between labor and asset income if the head or partner reports working any number of hours in their business/farm. Both allocations differ from how the IRS taxes individual business/farm income.

[10]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. They consider measurement issues: (i) wealth having some imputed component or (ii) a change in the interview respondent (e.g., the head in some wave and the spouse in another).

casting future income forecast errors. This result should alleviate concerns about the quantitative importance of households' superior information.

Finally, I address any additional concerns about my measure of permanent income with a series of robustness exercises. I consider (i) constructing the income path using a broader income measure that includes 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. The latter deals with the possibility that the persistence parameter differs by occupation. Appendix D.1 discusses how these robustness exercises impact the results.

2.3 Specifying Consumption's Response to Permanent Income

I use the consumption elasticity with respect to permanent income as my measure of consumption responses. Most macro models predict a linear relationship, while empirical studies find a concave relationship, with elasticity estimates around 0.7 (Straub, 2019; Abbott and Gallipoli, 2019). My empirical analysis provides novel evidence on this role of consumption commitments in generating this concave relationship in the data.

I estimate the consumption elasticity with respect to permanent income by projecting the logarithm of consumption on the logarithm of permanent income. This exercise uses cross-sectional 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 in the PSID since 1999. Following Kaplan et al. (2014), Blundell, Pistaferri, and Saporta-Eksten (2016), and Aguiar et al. (2020), my consumption measure includes expenditures on food, health, childcare, education, insurance, transportation, vehicle repair, vehicle service flow, utilities, and shelter. Spending on shelter reflects rent payments for renters and implicit rent for homeowners, which I set to 6% of the respondent's house value, following Aguiar et al. (2020). I set the vehicle service flow to 10% of the respondent's vehicle net worth. I consider other expenditure measures for robustness in Appendix B.[11]

[11]My base expenditure measure relative to total after-tax income averages 58.3 percent for the whole sample. For

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.

I estimate path dependence in consumption's response by modifying regression (3) to include past permanent income growth as an explanatory variable. With this specification, I test whether households with different permanent income trajectories differ in their consumption levels, conditional on having the same permanent income level today. This analysis also uses cross-sectional variation to identify the relationship between consumption, permanent income, and permanent income trajectory. In particular, I estimate

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

$\Delta \log \widehat{\mathrm{PI}}_{i,t}$ is the 10-year permanent income growth. $\boldsymbol{Z}_{i,t-10}$ 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 shape consumption behavior, then past permanent income growth should be negatively associated with current consumption. To illustrate, consider two households with the same permanent income today but with different income trajectories over the past decade. For both to have the same permanent income today, one must have had a lower permanent income in the past. Because commitments are made gradually and are costly to adjust, the household with lower past income would have made fewer commitments. Following a permanent income increase, it can adjust its consumption only through flexible, easy-to-change goods while committed expenditures remain fixed. As a result, its expenditure allocation deviates from the optimal consumption basket, leading to lower overall consumption than that of a household with the same permanent income and more distortions in expenditure allocation. Thus, higher past permanent income growth indicates lower commitment levels and a worse expenditure allocation.

Building on this idea, I test whether expenditure allocation across goods' categories also displays path dependency by estimating demand systems. Similar to my previous specification, I compare the expenditure allocations of households with the same total expenditure level today but with different expenditure trajectories. In particular, based on the almost ideal demand system

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.

(AIDS) of Deaton and Muellbauer (1980), I estimate

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

i indexes household, j indexes expenditure component, and t indexes time. $\log X_{it}$ is log expenditure. $\Delta \log X_{it}$ is past expenditure growth from period $t-10$ to period t $\mathbf{Z}_{it}$ are demographic controls. w_{ijt} is the expenditure share of component j. 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).

I construct the expenditure shares using the detailed goods' categories available in the PSID after 2005. Moreover, since total expenditure appears on the right as a control and in the denominator on the left, this specification is vulnerable to measurement error. Following the literature, 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 used demographic characteristics, the sample has 18,213 observations corresponding to 5,724 households. I use the CPI to express all monetary values in 2017 US dollars. Appendix A presents some sample descriptions. I present robustness exercises by looking at different samples in Appendix D.1.

3 Responses to Permanent Income in the Data

In this section, I present several novel facts on consumption's response to permanent income that indicate the role of consumption commitments in understanding consumption's response to permanent income.

3.1 Consumption Responses to Permanent Income

I first establish that the average consumption response to permanent income is approximately 0.8 in my preferred estimate, which is lower than 1.0. An elasticity of 1.0 is an important benchmark, as Straub (2019) shows theoretically that most models with homothetic preferences predict a value close to 1.0. Later in my quantitative section, I also show that a model with homothetic preferences and without consumption commitments also predicts an elasticity of 1.0. Moreover, my estimates are consistent with previous findings (Straub, 2019; Abbott and Gallipoli, 2019), which document an elasticity of around 0.7. This consistency, despite differences in my measurement of permanent income, provides support for further empirical documentation.

To establish this average elasticity, I estimate equation (3) and report the results in Table 1. In the first column, I report the OLS estimate without controlling for education dummies. I recover an elasticity of 0.6, meaning that, for each 1% increase in constructed permanent income, household consumption increases by about 0.6%. Since permanent income is a generated regressor, I report bootstrap estimates of the standard errors in the table. The elasticity of 0.6 is precisely estimated with a standard error of 0.01.

Because my measure of permanent income is constructed using income measure in a survey setting, measurement error is a concern. It would bias my estimates downward, which could explain why I recover an elasticity lower than 1.0. To address this concern, I instrument the log of permanent income with lagged income and industry dummies, as discussed in Appendix B. Table 1, Column 2 shows that, when incorporating instruments, the consumption elasticity to permanent income remains approximately 0.6. The F statistic is sufficiently high to defuse any concerns about weak instruments.

Another possible concern is whether higher permanent income is associated with higher levels of patience, which could explain the estimated elasticity. To address this concern, in Table 1, Column 3, I control for education dummies. Those dummies are commonly used to capture heterogeneity in the discount factor since college-educated workers have systematically higher savings rates, possibly reflecting preference heterogeneity in the patience level (Dynan et al., 2004). Interestingly, after controlling for education in the second stage, the estimated consumption elasticity to permanent income rises to nearly 0.8. I use this specification as my baseline since it addresses both measurement error and discount factor heterogeneity. The results should be interpreted as variations within educational groups.

My first novel fact is that the elasticity of consumption with respect to permanent income declines with age. I document this pattern by estimating equation (3) across different subsamples and presenting the results in Table 2. For households aged 25 to 45, the estimated elasticity is

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.

approximately 0.9, as shown in the second and third columns. However, it declines for households aged 45 to 65, reaching an elasticity as low as 0.64 in the fifth column. These estimates are precisely estimated, and the F-statistics are sufficiently high to mitigate concerns about weak instruments.

This fact helps distinguish between possible explanations for the under-consumption puzzle. In particular, a valid explanation must account for the higher responsiveness of young households to permanent income and the lower responsiveness of older households.[12] Any model that predicts young households primarily saving for future consumption is inconsistent with this fact because, in that case, their consumption response would be weaker, not stronger.

Consumption commitments are a plausible explanation for this pattern. Households accumulate these commitments over time—such as purchasing a home and signing long-term contracts—which reduces their flexibility in adjusting consumption. Young households, having made fewer such commitments, are more likely to adjust their expenditures in response to permanent income. Older households, however, have already made big commitments and are less likely to adjust them, being less responsive to current levels of permanent income. As a result, the elasticity of consumption with respect to permanent income declines with age.

In Appendix D.1, I consider several robustness exercises that (i) allow the autoregressive process parameters to vary by occupation, (ii) incorporate higher-order autoregressive processes,

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

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	823.7	423.9	359.2	152.7
Observations	54,970	14,770	17,556	15,704	11,475

Note: This table reports the estimated consumption elasticity to permanent income for 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.

(iii) use broader income measures that include asset income, (iv) employ more comprehensive wealth measures, including employer-provided defined-contribution retirement accounts, and (v) impose additional restrictions on the sample selection. Under some exercises, the average elasticity to permanent income changes, but the fact that the elasticity declines with age, which is novel in the literature, is robust across all specifications.

3.2 Consumption Responses to Current and Past Permanent Income

My second novel fact documents that household responses to permanent income depend on their past income trajectories. I document this fact by estimating equation (4), which contrasts households with the same permanent income today but who differ in their past permanent income growth. Again, I focus on the specification corrected for measurement error and with education dummies, and I use 10-year permanent income growth.

Table 3, Column 1 shows that, for working-age households, consumption is positively associated with current permanent income levels and negatively associated with past permanent income growth, with an estimated coefficient of 0.95 and -0.33, respectively. This suggests that households with no permanent income growth–those who knew their permanent income level 10 years ago–consume more than those with positive growth. In other words, today's consumption depends not only on current permanent income but also on past levels. A 10% permanent income growth is associated with a 3% lower consumption today.

The remaining columns of Table 3 show the path-dependency 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 35 and 45 years, while consumption responses to past permanent income are stronger for households aged 55 and 65 years. This suggests that older households have more commitments on average, reflecting commitments being made gradually throughout the life cycle.

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

In the following subsections, I show that past permanent income growth increases savings and the share of easy-to-adjust goods in the consumption basket. I also present evidence against the path dependency being driven by consumption habits by comparing the responses of households that have adjusted and those that have not adjusted their commitments.

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
$\log(PI_t)$	0.95	1.11	0.98	0.84
	(0.03)	(0.07)	(0.05)	(0.04)
Δ log(PI)	-0.33	-0.25	-0.35	-0.35
	(0.04)	(0.09)	(0.06)	(0.06)
Educ Dummies	Y	Y	Y	Y
KP-F test	130.4	67.7	69.1	56.5
Observations	15,180	4,322	5,900	6,054

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

3.3 Asset Accumulation

So far, I have documented novel facts about households' consumption response to permanent income. Because income is under-consumed, it must show up somewhere and cannot just disappear. So, in this subsection, I confirm that under-consumption implies over-accumulation of assets. This addresses concerns that my previous results were due to the mismeasurement of expenditure.

Constructing Net Worth from Expenditure and Income

In the first exercise, I check if households that consistently report expenditures lower than income also report having more assets. If this is not the case, then the quality of the PSID data should be questioned. In particular, I use the budget constraint to construct a new measure of net worth based on reported income and expenditure and compare this constructed measure with the actual net worth reported by households.

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

$$A_T - A_0 = \sum_{j=0}^{T}(Y_j - C_j) + \sum_{j=0}^{T} r_j A_j \ . \tag{6}$$

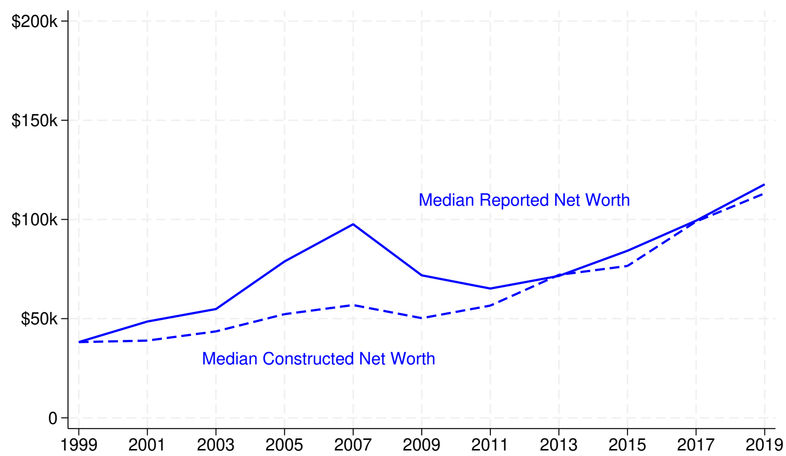
The increase in net worth between period 0 and period T equals the sum of each period's savings and returns on assets. I use this equation to construct the alternative measure of net worth. Details, including sample restrictions and capital returns, are presented in the footnote.[13]

[13] 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.

Figure 1 shows how the reported net worth and the alternative net worth closely co-move, highlighting the quality of the PSID data for longitudinal analysis. In the figure, the median reported net worth is the solid blue line, and the median alternative net worth is the dashed blue line. Both series change in tandem at similar levels, with the exception of alternative 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.

Figure 1: Asset Path Implied by Expenditure and Income



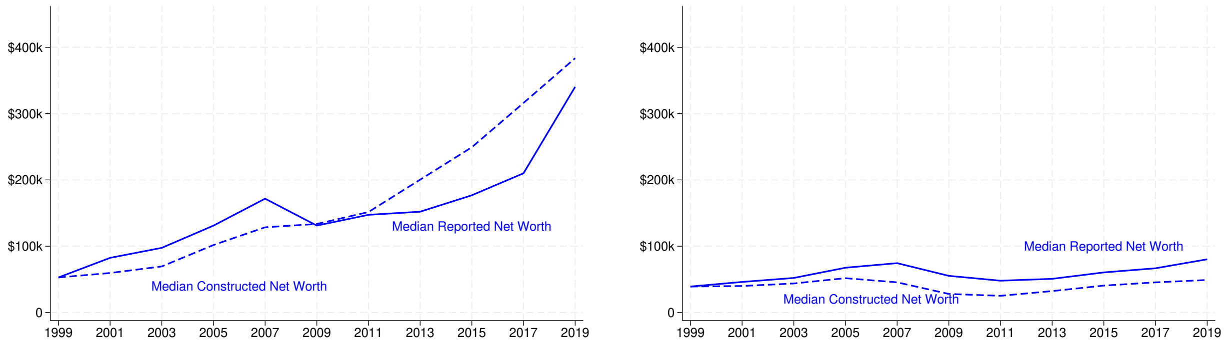
Note: This figure depicts the path of reported net worth and constructed net worth measures of households in the PSID. Reported net worth refers to the net worth that respondents report when answering the questions in the PSID. Constructed net worth refers to the net worth constructed using respondents' reported income and expenditures. In total, I follow 1,262 households. More details on the construction are given in the main text. The median reported net worth is the solid blue line, and the median constructed net worth is the dashed blue line. Mean profiles are present in Appendix D.2.

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. The median reported net worth is again the solid blue line, and the median alternative net worth is the dashed blue line. First, it is immediately noticeable from both panels that both series are closely linked together. The consistency between the reported asset path and the one inferred from the reported expenditure and income verifies that the data collected is accurate and reliable in measuring life-cycle household behavior. Second, both groups begin at similar starting points, but households that experienced permanent income

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 70% 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 $C_t/0.70$.

growth accumulated more wealth than those that did not, consistent with the results on consumption responses.

Figure 2: Asset Path Implied by Expenditure and Income



(a) Positive PI growth

(b) Negative PI growth

Note: This figure depicts the path of reported net worth and constructed net worth measures of households in the PSID. I divide the sample into households that experienced positive permanent income growth over 20 years and those that did not. Reported net worth refers to the net worth that respondents report when answering the questions in the PSID. Constructed net worth refers to the net worth constructed using respondents' reported income and expenditures. In total, I follow 483 households, with 607 negative growth and with 359 positive growth. The difference between the previous figure sample is that I restrict the selection to those for whom I observe permanent income both when I start following them and 20 years later. More details on the construction are given in the main text. The median reported net worth is the solid blue line, and the median constructed net worth is the dashed blue line. Mean profiles are present in Appendix D.2.

Active Savings

In the second asset exercise, I now investigate whether the documented path dependencies in consumption also show up in a measure of household savings. In particular, I investigate how a measure of active saving rates projects onto current permanent income and past permanent income growth.

I construct active savings by cleaning a set of questions available in the PSID Wealth Module and defining the active savings rate by dividing total active savings by labor income. This set of questions hasn't been explored in detail in the literature, except in a few papers, such as Hurst et al. (1998). 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.[14]

In Table 4, Columns 1 and 2 show the results with only current permanent income, while

[14] 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.

Column 3 includes current permanent income and its past growth. 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 permanent income growth is positive and significant, with a value of 0.17. This result implies that households with the same permanent income today but who experienced different permanent income trajectories have different savings responses. In particular, households that experienced permanent income growth save more, supporting the patterns observed in the consumption results. Since the active saving measure is constructed from a completely different set of questions than the expenditure measure, it is reassuring that the results from both analyses are consistent.

Table 4: Savings Response to Permanent Income

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

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

3.4 Expenditure Components

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

I document this novel fact by estimating equation (5), which captures how past income growth is associated with expenditure allocation across different goods, conditional on a given level of total expenditures. I focus on the demand system for nondurable and shelter expenditures, arguably an easy-to-adjust and a hard-to-adjust good. Shelter expenditure is the most important consumption commitment in the data 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.

The first row of Table 5 shows the coefficient on log expenditure, and, for a more straightforward interpretation, I focus on the coefficient expressed as Engel elasticity (the value in brackets). Engel curves trace out total expenditures on a good against permanent income, and, without controlling for them, the estimates of permanent income trajectory on bundle allocation would also capture the expenditure increase on luxury goods and decrease on inferior goods. Columns 1 and 3 imply an Engel elasticity of 0.8 for nondurable expenditures, indicating that nondurable goods are a necessity and that 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 that their expenditure increases by 1.1% for each 1% increase in total expenditure.

The second row of Table 5 shows the coefficient on past expenditure growth, and I focus on the coefficient inside the brackets, which represents the association between log 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%. Thus, given the same expenditure today, which captures Engel curves, households respond to increases in permanent income, proxied here by the expenditure growth, by increasing adjustable goods (e.g., nondurables). These results are strong evidence in favor of the consumption commitment mechanism.

The pattern in which path dependency depends on goods' adjustability also holds in more disaggregated consumption categories. The right panel of Figure 3 sorts 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, past growth skews the basket away from them. hese goods extend beyond durable goods, including housing, vehicles, and some servicesOn the other hand, past growth skews the basket toward nondurables, food at home, and home improvement expenditures. These goods extend beyond nondurable goods, including, for example, home improvement expenditures, which are usually considered durables. Importantly, the categories' Engel elasticities – left panel – do not follow the same pattern as the growth rate elasticities, meaning that households increasing expenditure on luxury goods is not driving the results.

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

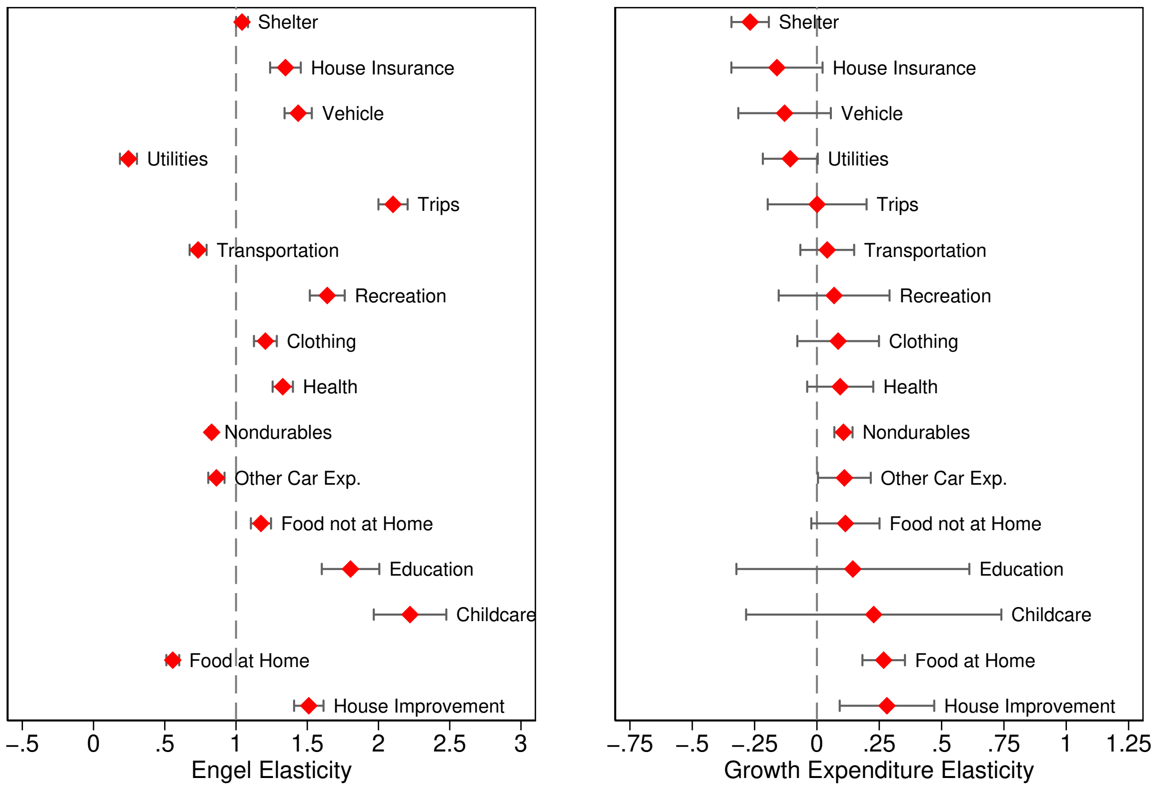
Note: This table reports the estimated AIDS demand system. All columns use instrumental variables, with the excluded instruments being cubic polynomials in log income and dummy variables for industry groups. In the specification with 10-year expenditure growth, cubic polynomials in lagged log income 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.

3.5 Consumption Resets

My fourth novel fact compares the behavior of households that recently adjusted the quantity of their hard-to-adjust goods to those that did not. I classify households that moved at least once within the prior decade as households that adjusted their bundle. This focus on shelter expenditure reflects its role as an important commitment in the data. I find that the consumption responses and expenditure allocation of these households that recently adjusted their commitments respond more strongly to permanent income and depend at most weakly on lagged variables. Because the consumption commitment mechanism relies on adjustment friction to generate depressed consumption and path dependencies, the fact that households that adjusted do not display these patterns is strong evidence in favor of my mechanism.

Table 6, Column 1 shows that, for households that did not move recently, their consumption response loads significantly more on past permanent income growth, with estimated elasticities of 0.35 for current levels and 0.45 for past growth. For those households that moved, their consumption response loads more on current permanent income, with estimated elasticities of 0.61 for current levels and 0.22 for past growth. 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 growth.

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.

Turning to saving behavior, Table 6, Column 2 shows that, for households that have not moved, the saving rate responds to current permanent income and past growth, with an estimated semi-elasticity of 0.40 for current levels and -0.36 for past growth. However, for households that moved, the saving rate depends almost exclusively on current permanent income, with estimated semi-elasticities of 0.15 for current levels and -0.03 for past growth. Again, the saving rate results are consistent with the consumption results, even though savings and expenditures are constructed from completely different questions. These results serve as important checks on the consistency of the results and further support the commitment mechanism.

Finally, Table 7, Columns 1 and 2 show that for households that did not move recently, their nondurable and shelter expenditures load significantly on past expenditure growth, with esti-

Table 6: Heterogeneous Effects: Household Moves

	(1) log(expenditure)	(2) Savings Rate
log(PI)	0.95	0.02
	(0.04)	(0.04)
Δ log(PI)	-0.53	0.34
	(0.09)	(0.11)
Moved $\times$ log(PI)	0.01	0.06
	(0.03)	(0.04)
Moved $\times$ Δ log(PI)	0.30	-0.30
	(0.14)	(0.16)
Educ Dummies	Y	Y
KP-F test	15.9	24.2
Observations	14,613	14,613

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.

mated coefficients of 12.4 and -19.4 for the growth rate, respectively. However, for households that have recently moved, their nondurable and shelter expenditures depend almost exclusively on current expenditure, and their coefficient on past expenditure growth is economically small, with estimated coefficients of 3.5 and -4.5 for the growth rate, respectively. Again, the fact that the expenditure allocation for households that adjust their basket depends more on current expenditure and less on past growth is consistent with the consumption commitment mechanism.

Overall, the evidence in Tables 6 and 7 supports the consumption commitment mechanism. Young households choose a level of commitments given their current expectations of future income. After experiencing permanent income growth, some households decide not to adjust their commitments and must respond by either increasing adjustable-goods spending or savings. Because commitments were decided in the past, their responses depend on past permanent income. Other households decide to adjust their commitments, and their responses depend on their current permanent income. The evidence in Tables 6 and 7 challenges behavioral-habit explanations since these would not generate path dependency that changes with past moving decisions.

Table 7: Heterogeneous Effects: Household Moves

	(1) Nondurable Share	(2) Shelter Share
log(exp)	-11.64	4.72
	(1.03)	(1.15)
	[0.77]	[1.18]
Δ log(exp)	12.27	-19.63
	(2.45)	(2.92)
	[0.24]	[-0.75]
Moved $\times$ log(exp)	2.86	-2.82
	(1.01)	(1.15)
	[0.06]	[-0.11]
Moved $\times$ Δ log(exp)	-9.33	16.07
	(2.61)	(3.11)
	[-0.18]	[0.62]
Educ Dummies	Y	Y
KP-F test	8.0	8.0
Observations	9,950	9,950

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.

In Appendix D.3, I show that renters' response to consumption and savings also displays path dependencies, but their response to expenditure allocation does not. This result contrasts with the economic intuition that renters should not depend on past variables since adjusting their consumption is arguably less costly. In Appendix D.4, I show that the probability of moving increases in the absolute value of the permanent income change. I also discuss concerns regarding reverse causality, where the decision to move may drive permanent income growth rather than being a response to it.

3.6 Additional Results

In the next section, I present a quantitative life-cycle model with consumption commitments to assess whether commitments are necessary to explain the documented empirical facts and to examine their implications for wealth and consumption inequality. However, before proceeding, I conduct several additional empirical tests to ensure the robustness of my results. I briefly discuss these below and leave a more detailed analysis for the appendices.

Quality of the Expected Income Measure: In Appendix C, I address the concern that households possess superior information than the econometrician and that this might impact my permanent income measure. In particular, the concern is if the superior information leads to systematic underprediction of permanent income for low-income households and overprediction for high-income households, potentially driving my empirical results. To assess this concern, I construct out-of-sample forecast errors and test their bias and forecastability. A good forecast should produce errors that are unbiased and uncorrelated with any additional variable measured at the time of forecasting.

First, I show that longer-term ones exhibit a small bias, while short-term forecast errors are unbiased. Second, I show that current consumption–arguably a proxy for households' information set–has limited power in predicting future income forecast errors. Although households do possess some superior information, its magnitude is small and does not significantly distort my forecast measures. An instrumental variable analysis further suggests that measurement error in income forecasts, rather than households' private information, is a more relevant factor affecting forecast accuracy. Overall, household information does not pose a major concern for my results.

Alternative Measurement Choices: In the main analysis, I make choices about income, expenditure, net worth, and sample construction. For robustness, I present the results with several other choices and discuss how the results change in Appendix D.1. My results are sensitive to how permanent income is constructed and the expenditure measure. First, with some alternative permanent income measures, the average consumption response is closer to 1 in some specifications, but the path dependency is robust across all specifications. Second, consumption responses are lower when expenditures are constructed with fewer items, such as nondurable goods, and higher when including broader expenditure categories. The wealth measures or the sample criteria do not seem to impact the measured elasticity.

Results by Ownership Status: In Appendix D.3, I test whether homeowners and renters have different responses to permanent income, which is an important check on the mechanisms since housing is the most relevant consumption commitment in the data. I examine two cases: (1) whether households who were renters before the permanent income growth have a stronger response to permanent income and (2) whether those who became renters after the income growth have a stronger response.

With respect to the consumption responses to permanent income, there is little evidence that households that differ in their current homeownership status differ in their responses, while those that differ in their past homeownership status have a stronger response. With respect to expenditure allocation, renters always have less path dependency, regardless of how the timing of ownership is measured. Therefore, the data suggests that prior homeownership influences how households adjust their consumption.

Changes in the Permanent Income Predicts Moving Decisions: In Appendix D.4, I show that the likelihood of households having recently moved increases with the absolute growth of permanent income. Therefore, larger deviations in permanent income are systematically linked to higher probabilities of housing adjustment. This is consistent with standard lumpy adjustment models, which predict adjustment after the gap between current and desired housing consumptions crosses certain theoretical bounds.

Results by Reason for Moving Decisions: I classify households that moved at least once within the prior decade as those that adjusted their bundle. A potential concern with this analysis is that permanent income growth and moves are measured over the same 10-year interval, raising the possibility of reverse causality–where moving itself affects income growth rather than the other way around. I address this concern in appendix D.5 by leveraging respondents' self-reported reasons for moving in the PSID. Respondents provide reasons for their moves, among those (i) purposive, productive reasons, such as taking another job or finishing school, and (ii) purposive, consumptive reasons, such as expanding or downsizing housing, and other house-related or neighborhood-related motives. To mitigate endogeneity concerns, I exclude households that moved for productive reasons and focus on those who moved primarily for consumptive reasons. The consumption responses remain nearly unchanged to the baseline, supporting the interpretation that households move primarily to adjust their housing consumption levels rather than to increase permanent income.

Financial Factors: Borrowing constraints are important for understanding consumption behavior, especially responses to transitory income changes. I construct indicators to identify whether households are constrained or hand-to-mouth (H2M), following the definitions of Zeldes (1989) and Kaplan et al. (2014). I perform three tests in Appendix D.6. (i) I introduce dummies for H2M households based on net worth and liquidity definitions, (ii) I drop all H2M households from the sample, and (iii) I restrict the sample to households with positive home equity, removing those with negative housing wealth. The estimated consumption responses to permanent income are stable in all exercises.

Income Risk: Income risk affects consumption by influencing precautionary saving behavior. This saving behavior could generate the under-consumption puzzle if high-permanent-income households have riskier income and, therefore, larger savings. Young workers tend to be more liquidity-constrained and have higher expected future income growth; therefore, precautionary saving should be stronger for them. The fact that we see pronounced under-consumption among older households suggests that uncertainty is not an important driver of this puzzle. However, I test how income risk influences consumption responses to permanent income in Appendix D.7.

Controlling for an income risk measure does not alter my baseline results. In more detail, I create a measure of income risk following Boar (2021). I use the income forecasts computed in Appendix C and construct out-of-sample forecast errors. Permanent income uncertainty is computed in two steps. First, I compute the present value of these forecast errors (4, 6, 8, and 10 periods ahead). Second, I compute the standard deviation of these errors within occupation-industry groups. Income risk is assigned to each household based on their occupation-industry group.

Placebo Tests: In Subsection 3.5, I document that households that have recently adjusted their commitments respond more strongly to permanent income and depend only weakly on lagged variables. I classify households that moved at least once within the prior decade as households that adjusted their bundle. In Appendix D.8, I conduct placebo tests to confirm that adjustment decisions alter households' responses. Moves made before the past decade, 14 to 16 years ago, have no impact on the estimated path dependence, while moves in the future, 4 to 6 years ahead, show up as stronger path dependence. Households that are expected to move in the future and have experienced faster permanent income growth in the past are the ones that have lower consumption today. These results are consistent with my findings, especially in light of the evidence showing that past permanent income growth predicts future moves.

Wealth Transfers: Bequests, Inter Vivos Transfers, and Donations: A commonly assumed force to generate large savings for rich households is strong preferences for larger bequests (e.g., De Nardi, 2004) or for insuring heirs through inter vivos transfers (e.g., Boar, 2021). The quantitative model incorporates bequest motives. Therefore, in Appendix D.9, I examine their presence in the PSID and their interaction with the permanent income path.

I identify bequests using three different methods: (i) assets reported by households near death or lump-sum transfers reported by their children, (ii) inter vivos transfers and donations reported by households or their children, (iii) children's consumption responses to their parents' permanent income. I find that the likelihood of leaving bequests and helping children, as well as the bequeathed and transferred amounts, are positively associated with permanent income. However, none of the methods for identifying bequests provides a sufficient number of observations to examine their dependence on past permanent income.

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 overlaping-generations structure.

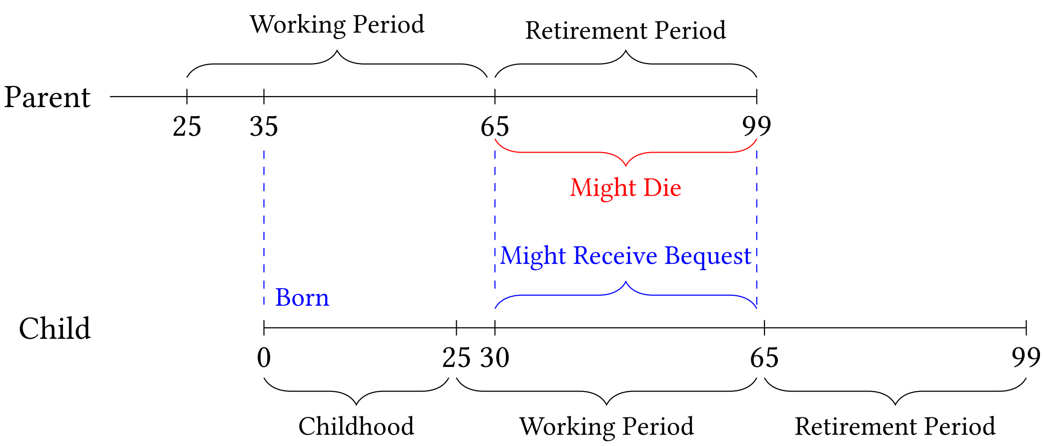
4.1 Environment

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.

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.

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, denoted as nondurable consumption, c^n. The second one comprises hard-to-adjust goods, denoted as commitments consumption, c^h. Commitment consumption and stock are related by $c^h = \zeta h$, where ζ is the return

Figure 4: Overlapping Generations Structure



(in utility terms) on the commitment stock h. Both commodities are aggregated using a CES function,

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

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

The empirical results from the previous section imply that household savings rates increase in expected lifetime income, which contradicts the predictions of standard homothetic life-cycle models. Others, such as Dynan et al. (2004) and Straub (2019), have also identified this result in the data. Important motives for this saving behavior are intergenerational transfers (such as bequests and inter-vivo transfers) and other expenses later in life (such as health expenditures). I capture these motives by incorporating luxury late-in-life consumption, following 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, where $\sigma_{j+1}^c/\sigma_j^c = \sigma_{slope}^c$ during one's working life, and it is flat after retirement. The model is parameterized so that σ_j^c 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 that can be used to retain aggregate scale invariance.

Preferences over bequests are given by

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

in which a is a risk-free bond. This functional form depends on two parameters: ϕ is a weight parameter, while σ^b governs the degree of luxury associated with the bequest motive. In particular, 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_ϵ^2 and σ_ξ^2, respectively. Total labor income is calculated as the product of the market wage per efficiency unit of labor (denoted as w) and the exponential of the productivity term: $w \times \exp(z_{i,j})$. 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 $\sigma^2_{\bar{\varepsilon}}$.

Assets: Households invest in liquid risk-free bonds and illiquid commitment stock, which can be interpreted as a housing stock. The risk-free bonds carry a constant risk-free rate r. Commitments provide a utility flow represented by ζ and depreciate at a 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 an 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.

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.[15]

4.2 Recursive Formulation

Let s denote the vector of state variables for a household, $s = \left\{j, a, h_{-1}, \bar{z}, \alpha, \epsilon, \bar{z}^p\right\}$. These variables indicate, respectively, age (j), bonds carried over from the previous period (a), past 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 household's first decision is whether to adjust the commitment stock. Specifically, households solve the discrete choice maximization problem

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

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

[15]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).

income shocks, but before they make the consumption decision.

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

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

$$\begin{aligned}
&\text{s.t.}\\
&h = (1-\delta(1-\chi))h_{-1}\\
&c^n + a' = \text{pen}(\bar{z}) + we^z + (1+r)a - \delta\chi h_{-1}\\
&c^n > 0, \quad a \geq -\theta h\\
&\bar{z}^{p'} = \begin{cases} \bar{z}^p & \text{with prob } (1-\psi_{j+35}) \\ 0 & \text{with prob } \psi_{j+35} \end{cases}
\end{aligned}$$

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

When a household dies, they pass on a lump-sum bequest. This bequest, b, enters the child household's state vector as an increase in next-period assets. Therefore, child households need to form a belief about the distribution of bequest sizes, which is assumed to be a function of their age and their parents' fixed productivity. So the last state variable ($\bar{z}^p$) has two purposes, as in De Nardi (2004). First, when it takes on a positive value, it represents the fixed productivity of the parent household and is used to calculate the probability distribution of bequests that 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 adjustment is optimal, the household solves the following problem:

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

$$\begin{aligned}
&\text{s.t.}\\
&h = (1-\kappa)(1-\delta)h_{-1} + x\\
&c^n + a' + x = \text{pen}(\bar{z}) + we^z + (1+r)a\\
&c^n > 0, \quad h > 0, \quad a \geq -\theta h\\
&\bar{z}^{p'} = \begin{cases} \bar{z}^p & \text{with prob } (1-\psi_{j+35}) \\ 0 & \text{with prob } \psi_{j+35} \end{cases}
\end{aligned}$$

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 $s' = \left\{ j+1, a'+b', h, \bar{z}, \alpha', \epsilon', \bar{z}^p \right\}$. 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

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

The key implication is that the permanent income trajectory influences current consumption choices, especially for households locked into past commitment 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 calibrate the model using PSID data. I explicitly target commonly used moments in the literature and some of my empirical findings. For that purpose, I first explain the 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

$$\mathrm{PI}_{i,j} = a_{i,j} + h_{i,j-1} + \mathbb{E}_{i,j}\left[\sum_{s=j}^{74} \frac{y_{i,j}}{R^{s-j}}\right] ,$$

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 term is computed using the same method proposed in the empirical section. First, the income path is estimated using a linear autoregressive process. Second, the discount rate combines a constant interest rate and survival probabilities.[16]

I calibrate the model by matching its consumption responses to the ones estimated from the PSID data. First, 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). Specifically, I estimate:

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

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

Second, I estimate regression (4), which adds past permanent income growth to the regression above. I estimate this equation for two different age groups, 40-50 and 50-60, which provide four moments. The coefficient on past permanent income growth 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 from the PSID data. I follow a two-step calibration procedure.

First, I externally set some parameters, including those that describe the income process.

[16] 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).

Then, I endogenously calibrate the remaining parameters, conditional on the parameters in the first step. I do this by matching the model-simulated and PSID moments. Tables 8 and 9 present the model parameters, while Table 10 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 the time when households begin their working life, have a child, retire, and reach their maximum lifespan. The mortality risk that households face when retired is calibrated using data from the 2011 US Life Tables from the National Vital Statistics System. 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. In particular, I calibrate seven parameters to match twenty-seven moments. Those moments are divided into six groups: (i) cumulative income growth measured over different ages, (ii) variance of log income over different ages, (iii) autocovariance of log income for two age intervals, (iv) income growth volatility over a 2-year horizon, (v) income inequality, and (vi) forecast errors over different horizons. Unlike the previous literature, I include many moments that capture how predictable income is. I describe the details in Appendix F, where I also discuss an alternative calibration based on Aguiar and Hurst (2013).

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).[17] I set the maintenance cost to 0.8 – the value estimated by Berger and Vavra (2015). This value implies that expenditures on repairs and improvements partially 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 slightly higher than the

[17] 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.

rent-to-value ratio that Katz (2017) estimated for a $400,000 house.[18]

Preference parameters. Lastly, I calibrate some preference parameters exogenously. I set the risk aversion coefficient in the consumption utility for retired households, σ_j^c for $j \geq R$, to 1.1 following Straub (2019). When the utility function is isoelastic and additively separable, the income elasticity is approximately proportional to the inverse of the risk aversion coefficient. Houthakker (1960) demonstrates it in a static setup, while Straub (2019) applies it to an intertemporal context. Because the σ_j^c for $j < R$ is parameterized so that this coefficient decreases creases with age, later-in-life consumption is a luxury, and higher-income households have a back-loaded consumption profile. Finally, I calibrate the scale term in the utility function, o, to 0.2, in line with the value used by Straub (2019).

Endogenously Set Parameters

I endogenously calibrate the remaining seven parameters to match data moments. Table 9 lists the endogenous parameters.

The discount factor β, 0.84, implies a moderately impatient household, a crucial factor for accurately capturing wealth dynamics in incomplete-market models (Carroll, 1997, 2001; Gourinchas and Parker, 2002). The coefficient of relative risk aversion in the utility function follows a simple exponential decay, $\sigma_{j+1}^c/\sigma_j^c = \sigma_{slope}^c$. I endogenously calibrate σ_0^c to 4.09 while I externally calibrate σ_j^c for $j \geq R$ to 1.1 following Straub (2019). Therefore, $\sigma^c slope$ is also pinned down. My calibration process recovers a mild preference for late-in-life consumption, especially when compared with $\sigma_0^c = 11$ in Straub (2019)'s calibration.

The function that describes the preference for bequest has two parameters: (i) the curvature of the function, captured by σ^b, is calibrated to 0.57, and (ii) the weight in total utility assigned to bequest ϕ is calibrated to 4.72. Because the bequest motive has a lower curvature coefficient than consumption utility, it is a luxury in my model. My approach to model luxury bequest contrasts with De Nardi (2004) and Straub (2019), who model it with a Stone-Geary preference.

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

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

Table 8: Externally Set Parameters

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

The parameters $\{\omega, \gamma, \kappa\}$ are crucial in determining the following 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, and iii) the ratio of average housing wealth to average total wealth. The parameters $\{\beta, o, \sigma_0^c, \phi\}$ play a crucial role in generating other specific moments: iv) the ratio of average wealth to average income, v) bequests relative to GDP, vi-viii) consumption's response to permanent income across different age groups, ix-xii) consumption's response to current permanent income and permanent income growth across different age groups. Note 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 10 compares data and model moments, showing that the calibration closely matches consumption's response to permanent income across age groups. The model slightly overesti-

Table 9: Endogenously Set Parameters

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

mates responses for younger cohorts (30-50) and underestimates them for older cohorts (50-60). For permanent income growth, it produces slightly lower responses, particularly for ages 40-50. The model also captures key housing and wealth moments well, closely matching the moving rate of homeowners (10% vs. 12%) and the housing wealth-to-total wealth ratio (0.49 vs. 0.47). However, it underpredicts the shelter expenditure ratio (10% vs. 25%) and slightly underestimates the wealth-to-income ratio (5.45 vs. 6.12). The bequest-to-GDP ratio is well-matched at 0.11 vs. 0.10.

Table 10: Calibrated Moments

Description	Data	Model
Moving rate of owners (past 2 years)	0.12	0.13
Ratio Shelter to Total Expenditure	0.25	0.14
Ratio Housing Wealth to Total Wealth	0.47	0.54
Ratio Total Wealth to Income	5.92	6.88
Bequest flow over GDP	0.10	0.10
Cs response to PI age 30-40	0.92	1.05
Cs response to PI age 40-50	0.84	0.87
Cs response to PI age 50-60	0.72	0.70
Cs response to PI age 40-50	1.09	0.59
to Δ PI age 40-50	-0.39	0.30
Cs response to PI age 50-60	0.84	0.48
to Δ PI age 50-60	-0.21	0.24

6 The Role of Consumption Commitments in Consumption Responses

In this section, I assess the model's ability to account for the novel facts documented in Section 3 and evaluate the contribution of each mechanism. To isolate the role of specific mechanisms, I individually shut down some features, such as luxury late-in-life consumption and consumption commitments, and recalibrate β to keep the baseline wealth-income ratio. Each calibration is assessed based on its ability to replicate both targeted and untargeted moments following regressions on simulated data. The targeted moments correspond to six facts on consumption responses to permanent income, while untargeted moments include all other facts documented in Section 3. The baseline model successfully captures most untargeted moments, highlighting the importance of consumption commitments in understanding response to permanent income. However, other mechanisms also play a significant role.

6.1 Consumption Responses to Permanent Income

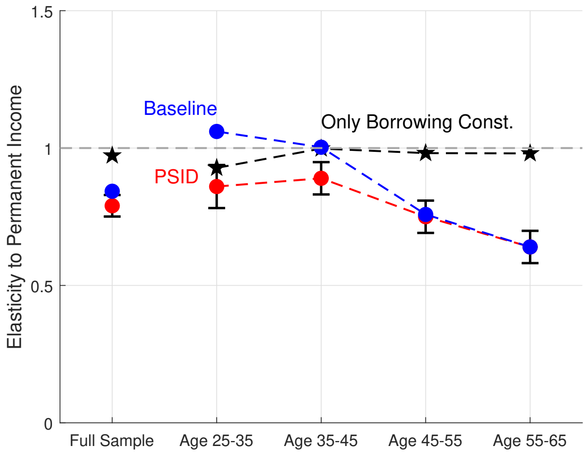
I first evaluate the model's ability to generate life-cycle dynamics in the consumption elasticity to permanent income. In particular, I assess the model's ability to account for a stronger consumption elasticity among young households and an elasticity that decreases with age–i.e., the results in Table 2. Figure 5, Panel A displays the PSID (the red dots), together with the baseline calibration (the blue dots) and a homothetic calibration (the black stars). The first dots are the average consumption responses for the sample of all working-age households, an untargeted moment in the calibration. The other dots are life-cycle elasticities, which are target moments in the calibration. Details on the homothetic calibration and other counterfactuals are provided in Appendix F.

The baseline model generates the average consumption responses and a decreasing response profile, as seen in the data, although it slightly overpredicts the elasticity for consumers aged 25-35 and 35-45 years old. Moreover, the model with only homothetic preferences generates a consumption response of approximately 1.0 throughout the life cycle, failing to capture either the average response or the decreasing profile of consumption elasticity. Therefore, when calibrated to capture homothetic preferences and without consumption commitments, the quantitative model also predicts an elasticity of 1.0, which is consistent with the findings of Straub (2019).

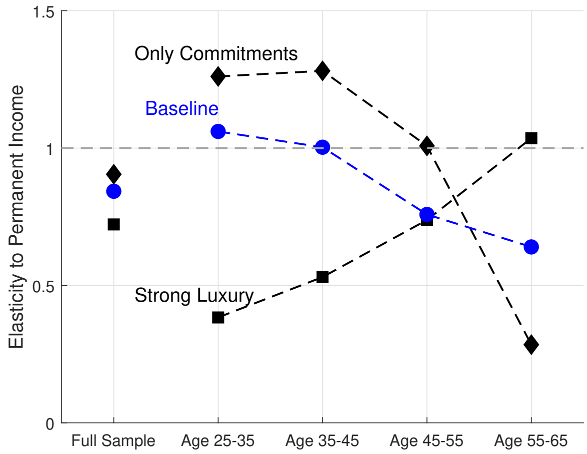
I proceed by evaluating the contribution of consumption commitments and luxury late-in-life consumption in generating the consumption responses observed in the PSID data. In particular, to assess the contributions of the luxury late-in-life consumption mechanism, I shut down consumption commitments ($\kappa = 0$) and calibrate the preference parameters as in Straub (2019): $\sigma_0^c = 11$ and $\sigma^b = 2.5$. To assess the contributions of the consumption commitments mechanism, I shut down the luxury late-in-life mechanism ($\sigma_0^c = \sigma_R^c = 2.5$). The former results are plotted as black squares and the latter as black diamonds in Figure 5, Panel B.

The model with commitments generates a consumption response profile that decreases with age, as seen in the data. However, it significantly overpredicts the elasticity among young households and underpredicts the elasticity among older households. The model with strong luxury late-in-life consumption cannot generate the observed dynamics in the data and predicts a counterfactual pattern in which the consumption response increases with age. It also significantly underpredicts the elasticity among young households and overpredicts the elasticity among older households. Interestingly, the baseline model seems to be an "average" of both mechanisms, where the commitment mechanism is key to generating the decreasing response profile. Additionally, it is reasonable to assume that the baseline calibration also misses the elasticity among young households because this calibration probably requires a strong consumption commitment mechanism to match other moments.

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



(a) Model vs. Data



(b) Mechanisms' Contributions

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

6.2 Consumption Responses to Current and Past Permanent Income

Next, I evaluate the model's ability to generate path dependence in the consumption elasticity to permanent income—i.e., the results in Table 3. Figure 6, Panels A and C display the PSID (the red dots), the baseline calibration (the blue dots), and a homothetic calibration (the black stars). Figure 6, Panels B and D display the contributions of the luxury late-in-life consumption mechanism (the black squares) and the consumption commitments mechanism (the black diamonds). The upper panels show the response to current permanent income, and the bottom panels show the response to permanent income growth.

The baseline calibration yields consumption responses to current and past permanent income growth consistent with the PSID data. It also yields path dependencies for the different age groups, but it underpredicts the path dependence for younger households. These life-cycle dynamics of the consumption responses to the current permanent income level and past permanent income growth are targeted moments in the calibration. When comparing a model with homothetic preferences to the data, one can see that it cannot generate a similar pattern, predicting again an elasticity of current consumption close to 1 and a path dependence close to 0. Therefore, some friction is needed to generate these path dependencies.

The panels on the right-hand side of Figure 6 show the contribution of different mechanisms to generating path dependence. Interestingly, neither the commitment nor luxury late-in-life mechanisms can generate realistic path dependencies. Both mechanisms predict a positive dependence on permanent income growth, meaning those with positive income growth consume more when they are old. Commitments generate this pattern because households want to minimize the number of times they buy big commitments, so they overspend on those and, therefore, have low adjustable goods and a suboptimal expenditure locaiton. Therefore, like the luxury late-in-life mechanisms, it predicts that households with permanent income growth will consume more.

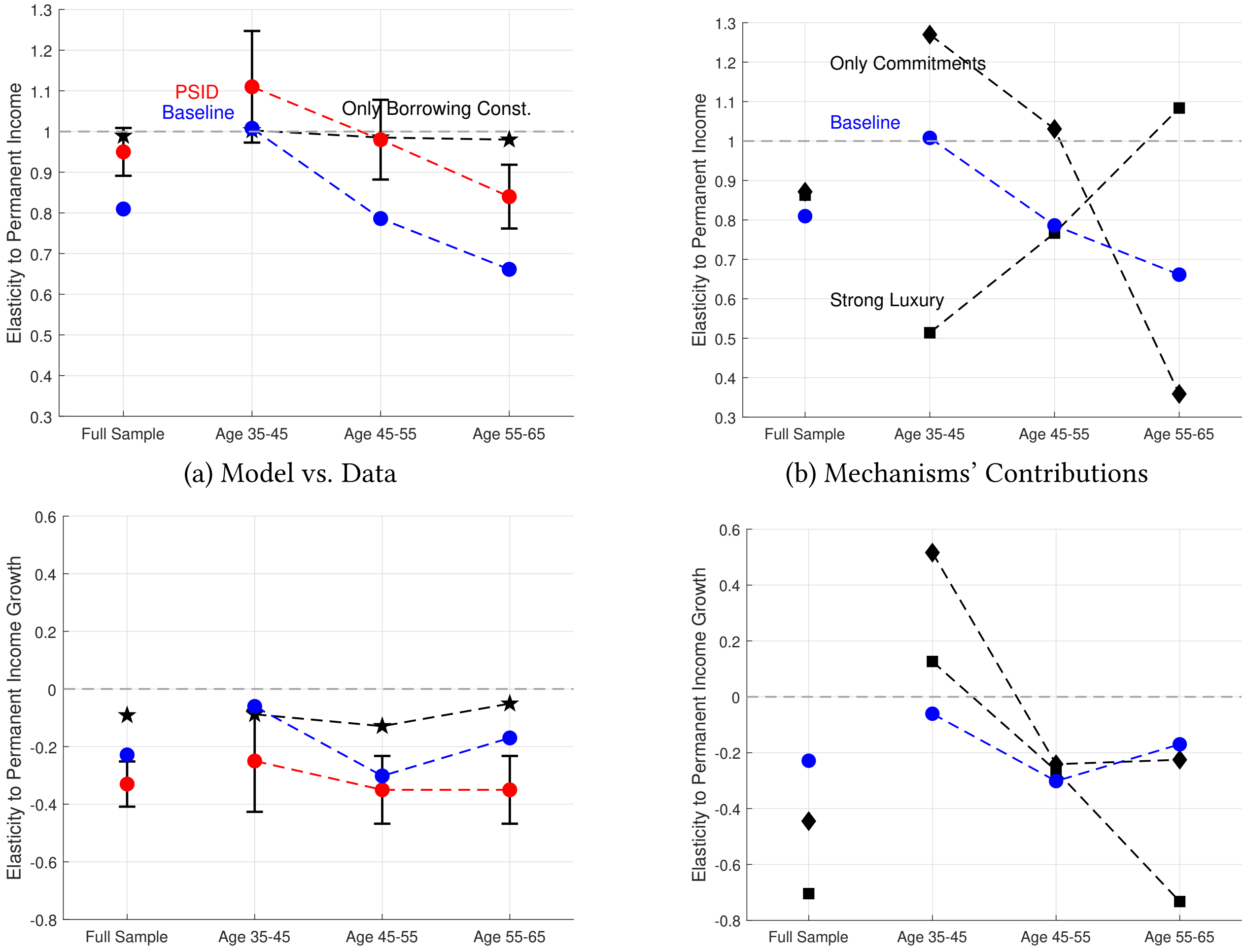
6.3 Savings

I also evaluate the model's ability to generate path dependence in savings rates. Recall that in Table 4, I project a measure of active saving rates onto current permanent income and past permanent income growth. Expenditure and active saving measures are constructed from different questions, so the consistency of the results is an important test of the robustness of the empirical facts.

Figure 7, Panel A displays the PSID (the red dots), the baseline calibration (the blue dots), and a homothetic calibration (the black stars). The baseline and the homothetic calibrations yield savings responses to current and past permanent income growth stronger than those in the PSID data. These facts were not targeted in the calibration.

Figure 7, Panel B displays the contributions of the luxury late-in-life consumption mechanism (the black squares) and the consumption commitments mechanism (the black diamonds). Alone, the commitment mechanism or the luxury late-in-life mechanism can generate realistic savings in response to current permanent income. Interestingly, as in the path dependence in expenditure, the combination of both mechanisms generates the baseline calibration: both are individually lower than the baseline. Moreover, the commitment and luxury late-in-life mechanisms cannot generate realistic savings in response to past permanent income growth. The former decreases the response to past permanent income growth, while the latter increases it.

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



(a) Model vs. Data (b) Mechanisms' Contributions

(c) Model vs. Data (d) Mechanisms' Contributions

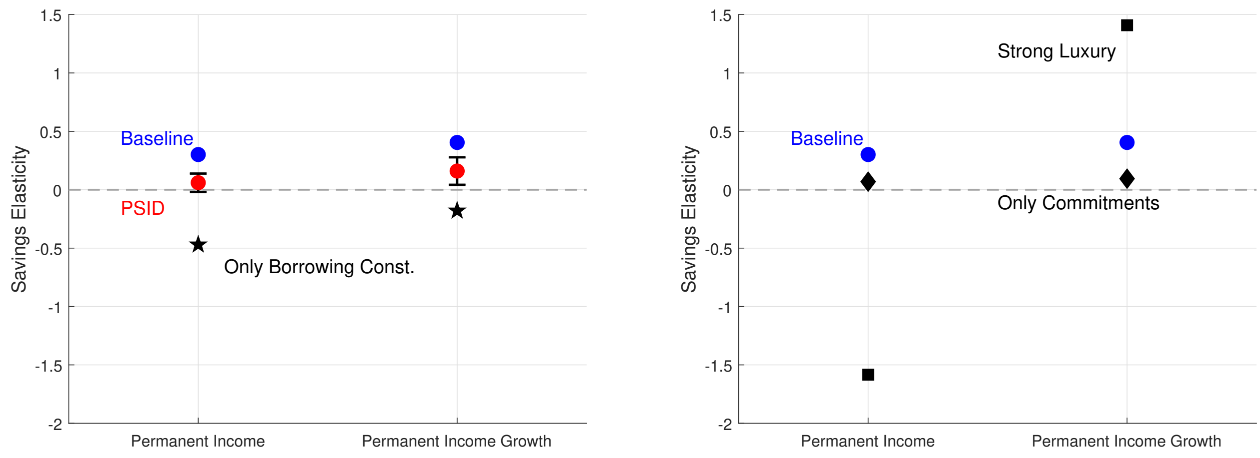
Note: In the figure, black triangles, black diamonds, and black squares represent the models with homothetic preferences, late-in-life luxury consumption, and consumption commitments, respectively, while blue and red dots denote the baseline calibration and PSID data, respectively.

6.4 Expenditure Components

I further evaluate the model's ability to capture the observed patterns in goods category shares and their elasticity to current expenditure and past expenditure growth. Again, I compare the model's predictions to the PSID data, as documented in Table 5, and decompose the contributions of different mechanisms. None of these moments were targeted in the calibration.

The upper panels of Figure 8 present Engel curves for nondurable and housing consumption. First, because the model aggregates goods with a CES structure, consumption categories are homothetic and have elasticities of approximately 1. Therefore, the homothetic model (black stars) generates unitary Engel elasticities for both goods. On the other hand, the PSID data (red dots)

Figure 7: Savings' Responses to Permanent Income – Data and Model



(a) Model vs. Data

(b) Mechanisms' Contributions

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

indicate a lower Engel elasticity that is significantly below 1 for nondurable goods and above 1 for housing consumption. The baseline model improves upon the homothetic model and closely matches housing Engel elasticities but still slightly overestimates nondurable elasticities.

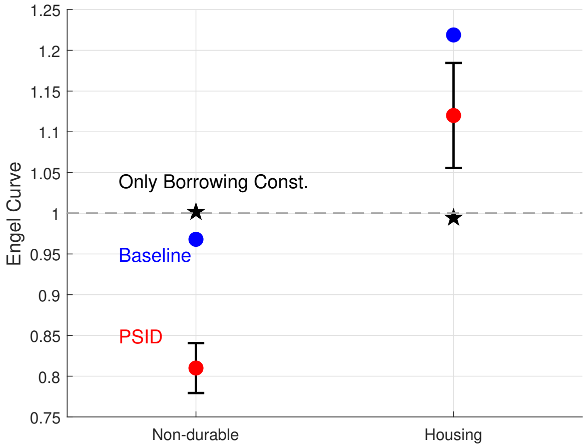
The right panel isolates the contribution of individual mechanisms. Again, it is a combination of the commitment and late-in-life consumption mechanisms that improve the ability of the baseline model to reproduce the evidence on Engel curves. Individually, the commitment mechanism (black squares) lowers the Engel curve for housing and increases it for nondurables. Strong luxury effects (black diamonds) have the same effect.

The lower panels of Figure 8 examine the elasticity of expenditure to lagged consumption. The PSID data reveal a negative elasticity for housing, a feature that the baseline model captures but that the homothetic model entirely misses. The right panel decomposes the contribution of different mechanisms, showing that neither commitments nor luxury mechanisms alone can generate the observed patterns.

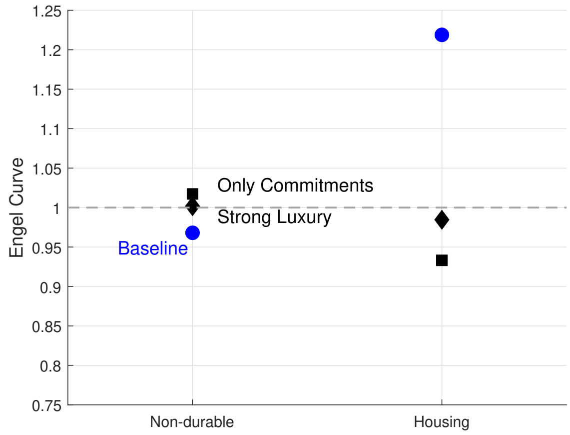
6.5 Consumption Resets

Finally, I assess the baseline model's ability to reproduce the differences between movers and stayers documented in Tables 6 and 7. Since these empirical facts were not explicitly targeted in the calibration, this result serves as an important validation of the role of commitments in shaping consumption dynamics. Figure 9 presents these findings by comparing the baseline model

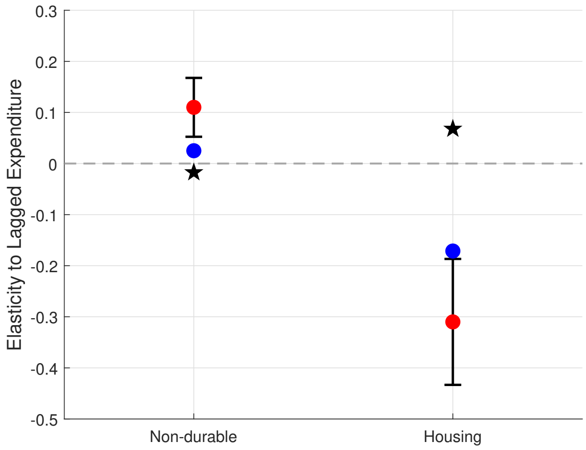
Figure 8: Consumption Category Shares – Data and Model



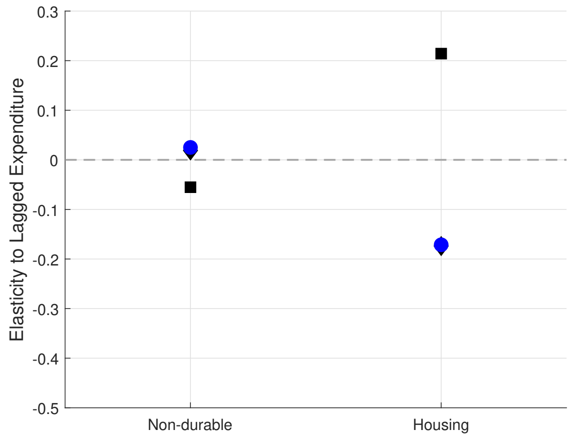
(a) Model vs. Data



(b) Mechanisms' Contributions



(c) Model vs. Data



(d) Mechanisms' Contributions

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

calibration (blue dots) with the PSID data (red dots).

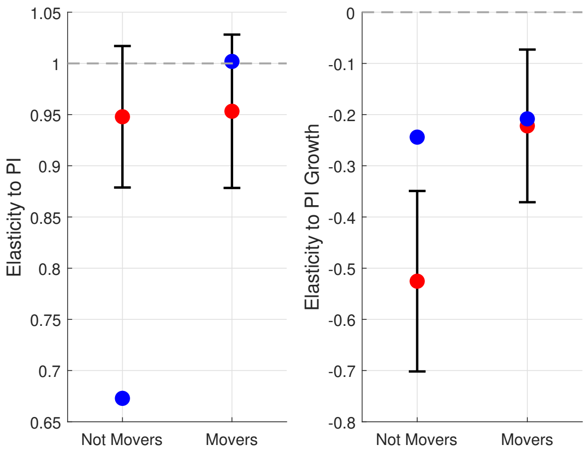
Panel (a) shows that in both the model and the data, movers exhibit a strong consumption response to current permanent income (left sub-panel) but a near-zero response to permanent-income growth (right sub-panel). The model captures the broad pattern in the data, although it slightly overpredicts the response for non-movers and underpredicts it for movers.

Panel (b) shows the savings rate responses. The model successfully generates a stronger savings response to current permanent income among movers (left sub-panel) and a muted response to lagged permanent income (right sub-panel). However, the model somewhat overpredicts the savings response for non-movers relative to the data.

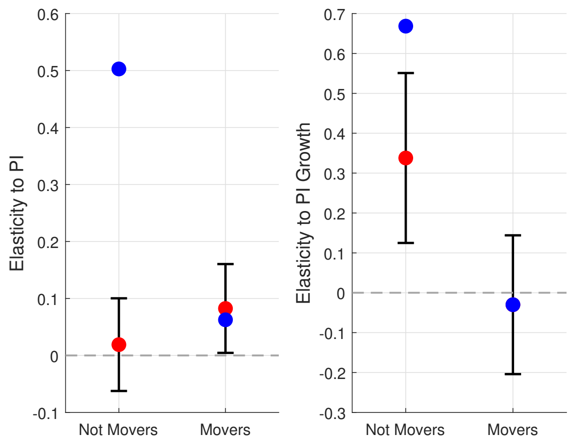
Finally, panel (c) shows consumption category shares. The model broadly captures movers' expenditure allocation patterns, particularly the high elasticity to expenditure growth (left sub-panel). However, in the right sub-panel, the model overstates the negative elasticity to permanent-income growth for movers, suggesting that it may overemphasize the role of commitments in driving expenditure rigidity.

Overall, while the baseline model aligns well with the key patterns observed in the PSID data and reinforces the importance of consumption commitments in shaping consumption responses to permanent income.

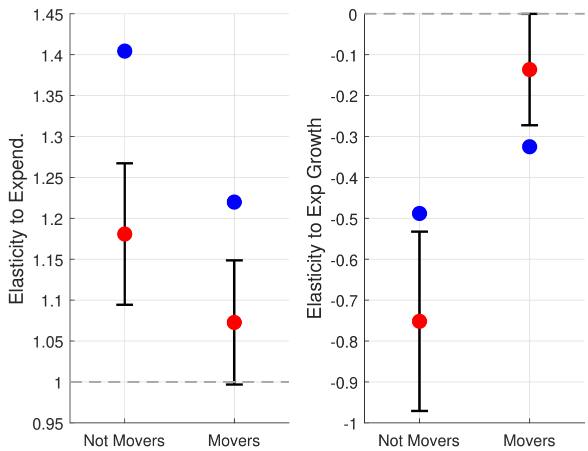
Figure 9: Responses for Movers and Not Movers – Data and Model



(a) Consumption's Responses



(b) Savings' Responses



(c) Shelter Shares

7 Aggregate Implications

In the previous section, I verified that the quantitative model with the baseline calibration accurately replicates the micro-level evidence on consumption responses to permanent income. This last section explores the model's aggregate capacity to generate realistic consumption and wealth distributions.

Table 11 shows the Gini indices for income, consumption, and wealth for the PSID, the baseline model, the homothetic model, the strong luxury late-in-life consumption model, and the consumption commitment model, sequentially in each of its rows. In particular, these four calibrations of the model are: (i) the baseline version, (ii) a version with strong luxury late-in-life consumption ($\sigma_0^c = 11$ and $\sigma^b = 2.5$) and without consumption commitments ($\kappa = 0$), (iii) a version with consumption commitments and without the luxury late-in-life mechanism ($\sigma_0^c = \sigma_R^c = 2.5$), and (iv) a homothetic model. The income process is externally calibrated to match observed earnings dynamics in microdata, and in all versions, β is recalibrated to maintain a constant wealth-income ratio.

The baseline model performs best, closely aligning with key empirical patterns: it preserves the ranking Income Gini > Consumption Gini and generates substantial wealth inequality (0.84, close to 0.82 in the data). The consumption Gini (0.36) is slightly higher than in the data (0.32) but remains within a reasonable range.

The homothetic model fails to generate sufficient wealth inequality, producing a wealth Gini of 0.78, significantly lower than the 0.82 observed in the data. While it captures income and consumption inequality well (0.47 and 0.38, respectively), it lacks the mechanisms necessary to produce realistic wealth dispersion. This is a known problem among this class of models.[19]

The luxury late-in-life model overstates consumption inequality (0.52 vs. 0.32 in the data). In this calibration, households accumulate assets to finance consumption when they are old. However, as older households consume these assets, the model predicts excessive dispersion in consumption. The luxury late-in-life model matches wealth inequality (0.87 vs. 0.82 in the data), indicating that this mechanism alone leads to strong wealth concentration but at the cost of unrealistic consumption inequality.

The commitments model also generates high wealth inequality (0.88), even exceeding the data, but slightly worsens the fit for consumption inequality (0.40 vs. 0.32 in the data). This suggests that commitments alone increase wealth inequality while slightly overstating consumption dispersion.

[19]The PSID is broadly representative of the 5th to 95th percentiles of the U.S. population, missing the extreme tails, particularly the upper tail, where the highest levels of wealth concentration are observed. My mechanism should be understood within the sample frame that I have data for. In particular, my model misses the role of asset pricing, even though there is both model and data evidence stressing that asset prices play an important role in generating wealth distributions and explaining their current trends. For example, 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 both the dynamics and the observed wealth inequality in the data.

The comparison with the PSID data shows that the baseline model performs best, capturing key data features while maintaining reasonable consumption and wealth inequality. Only the luxury late-in-life and the commitment mechanisms produce high levels of wealth inequality but overstate consumption inequality. In sum, these results highlight that consumption commitments are key to explaining consumption dynamics, as Section 4 has shown, but they are also important in replicating inequality patterns among aggregates.

Table 11: Distributional Implications

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

8 Conclusion

In this paper, I provide empirical and quantitative evidence for a novel explanation of why consumption under-responds to permanent income. Empirically, I document four main novel facts supporting the importance of consumption commitments using PSID data. Quantitatively, I calibrate a life-cycle model consistent with the documented microdata evidence. Consumption commitments are necessary to account for the life-cycle pattern of the consumption under-response, with other mechanisms contributing to the magnitude of the consumption under-response. Lastly, I explore the model's implications for aggregate consumption and wealth inequalities.

Several avenues for future research emerge from this analysis. First, while this paper focuses on the implications of commitments for life-cycle consumption, further work could explore how households anticipate and plan for consumption commitments. Second, my findings suggest that policies that reduce adjustment costs—such as mortgage refinancing assistance or rental market flexibility—may have heterogeneous effects across the life cycle, generating differential responses by age group and by permanent income that could be explored empirically. Finally, it would be valuable to examine how these policies—or other interventions such as fiscal transfers and tax policy—alter macroeconomic predictions when consumption commitments are explicitly incorporated into structural models. For instance, standard macroeconomic models may overestimate or underestimate policy effectiveness if they ignore commitments.

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A Data Construction and Sample Description

Expenditures I construct total expenditures using all available categories since 1999. I follow closely the definition of Kaplan et al. (2014), Blundell et al. (2016), and Aguiar et al. (2020). My measure includes expenditures on food (including 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, taxis, and other transportation expenses), medical expenses (doctors, hospitals, prescription drugs, and health insurance), childcare, education, insurance (auto and home insurance), vehicle repairs, service flow from vehicle ownership, and shelter expenditures. Spending on shelter reflects rent payments for renters and implicit rent for homeowners. Since the PSID only began collecting data on implicit rent in the 2017 wave, I impute it as 6 percent of the respondent's house value. I set 10 percent of the respondents' vehicle net worth as vehicle service expenditures reflect flow.

To assess robustness, I consider alternative measures of expenditures. First, I construct nondurable expenditures by excluding vehicle and shelter expenses, except for insurance and vehicle repairs, as these categories represent service expenditures and are relatively flexible. Second, I define a broad expenditure measure incorporating additional categories in the 2005 wave, including home repairs, home furnishings, clothing, vacations, recreation, telecommunications, and donations. Third, I construct an alternative expenditure measure in which shelter expenditures include all housing-related expenses (rent, mortgage payments, and property taxes), and vehicle expenditures comprise all outflows associated with vehicle ownership (down payments, lease payments, loan payments, and other vehicle-related costs).

Since the 2019 wave, the PSID has provided two aggregated consumption variables. Both sum all subcategories into total household consumption, differing only in their treatment of shelter expenditures. The first variable, Total Consumption, defines shelter expenditures as the sum of rent for renters and implicit rent for homeowners. The second variable, Total Expenditure, defines shelter expenditures as the sum of rent for renters, mortgage payments, and property taxes. My baseline measure aligns with Total Consumption except in the treatment of vehicle expenditures. I explore Total Expenditure as a robustness check.

Table A1 reports that the average expenditure as a percentage of the average total after-tax income is 58.5 percent. For the broad expenditure measure including the categories available since 2005, this ratio rises to 74.6 percent. Aguiar et al. (2020) reports comparable figures of 58.3 percent and 73.2 percent, respectively.[20]

Earnings I construct two measures of household income. First, household after-tax labor income is defined as the sum of household labor earnings plus government transfers, net of payroll taxes. Household labor earnings include the total labor income of the household head and partner (if any), excluding busi-

[20] The broad expenditure measure with additional categories is only available from 2005 onward. Applying the same ratio of averages but computing the income average for the sample starting in 2005, this ratio rises to 76.2 percent.

ness and farm income but incorporating the labor component of income from any unincorporated business. Government transfers consist of any transfer income the head or partner receives from AFDC, Supplemental Security Income, other welfare programs, unemployment benefits, workers' compensation, or Social Security benefits. Payroll taxes are estimated using the NBER's TAXSIM model.

For robustness, I construct a broader income measure that includes asset income and examine how the results change. Asset income includes any income the head or partner receives from businesses, farms, dividends, interest, rents, trust funds, and royalties. When shelter expenditures consist of rent for renters and implicit rent for homeowners, I follow Aguiar et al. (2020) and include implicit rent as 6 percent of the respondent's assessed home value as a source of income. When shelter expenditures are rent for renters, and mortgage payments and property taxes for homeowners, I exclude implicit rent from income. Taxes (payroll, federal, and state income taxes) are again estimated using the NBER's TAXSIM model.

In the PSID, when the household head or partner works any hours in their business or farm, the reported earned income is arbitrarily divided equally into labor and asset income. However, the IRS does not use this approach when taxing business or farm income. Following Kimberlin et al. (2014), I classify both business and farm labor and asset income as wages and salaries for TAXSIM purposes, rather than treating them as property income. This method also differs from how the IRS taxes individual business/farm income.

Wealth Following Kaplan et al. (2014) and Aguiar et al. (2020), I define liquid assets as the sum of checking and savings accounts (including money market funds, certificates of deposit, government bonds, and Treasury bills) and stocks (including publicly traded stocks, stock mutual funds, and investment trusts). Liquid debt includes all non-mortgage debts, such as credit card balances, student loans, medical or legal bills, and loans from relatives. Net liquid wealth is then calculated as liquid assets minus liquid debt.

Net illiquid wealth comprises the household's home equity (home value net of mortgage debt), plus the net value of other real estate holdings, businesses, farms, vehicles, and retirement accounts such as IRAs and other pensions. Net worth is the sum of net illiquid and net liquid wealth.

For robustness, I follow Cooper et al. (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.

Sample Description Table A1 shows statistics for households across quartiles of the wealth distribution, emphasizing key demographic characteristics, housing and mobility patterns, and wealth, income, and expenditure measures. The first panel shows that wealthier households tend to be older, with males as household heads, more educated, and more likely to be married. Homeownership rates rise sharply across wealth quartiles, from 20% in the lowest quartile to 95% in the highest. Meanwhile, household mobility is inversely related to wealth; higher-wealth households are less likely to have moved in the past two years.

The second and third panels focus on mean and median household wealth. Households in the bottom quartile have negative average home equity and net worth, indicating significant debt, whereas those in the top quartile accumulate substantial wealth. This concentration of wealth is also reflected in permanent income. Median values reveal wealth accumulation is highly skewed, with lower-wealth households having little to no assets while the top quartile holds the vast majority of wealth.

The fourth panel examines household income and expenditures. Both labor and transfer income and total income increase with wealth, though the gap is more pronounced in total income, reflecting higher capital income among wealthier households. Expenditures follow a similar pattern, with total spending rising across quartiles, though slower than income, suggesting higher savings rates among wealthier households. Shelter expenditures are significantly higher for the top quartile, reflecting higher housing consumption and homeownership-related expenses. The comparison of expenditure measures across different categorical definitions (1999 and 2005) shows a consistent pattern.

Table A1: Sample Description

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

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

B Measurement Error in Income

One concern in my empirical exercise is the possibility of measurement error in my permanent income measure since I use income data to construct it, and a well-known problem with survey data is that income tends to be measured with error. For my exercise, a downward-biased estimate due to measurement error in permanent income could explain a lower consumption response. I use instrumental variables to deal with this issue. I explain the rationale for using instrumental variables in this appendix.

Recall that the crucial step in my measurement exercise of permanent income is estimating an expected income path for each household. This step relies on the assumptions that past income and certain demographic characteristics define the information set and that a linear autoregressive process approximates the expectations formation process. I use a noisy income measure to forecast income for many periods ahead and sum those forecasts to construct permanent income. Any measurement error accumulates and potentially implies a noisy permanent income measure.

To be able to use instrumental variables, I make two additional assumptions: that the measurement error is (i) classical and (ii) sufficiently small. 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 the logarithm of variables using lowercase letters, e.g., $x_{i,t} = \log(X_{i,t})$. I assume that the unobservables – actual income $y^*_{i,t}$ and measurement error $v_{i,t}$ – are mutually independent, with variances σ^2_* and σ^2_v, respectively.

To simplify the notation, I drop the i subscript. Let once-lagged income be a sufficient statistic for the household's information set, such that the expectation error is unforecastable. The best linear forecast for y_{t+1} is

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

where, again, v_t is the 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 impacts my permanent income measure, consider the AR(1) case and index the base year of the information set as 0, such that $\widehat{Y}_1$ is the forecast one year ahead, $\widehat{Y}_2$ is the forecast two years ahead, and so on. Then, 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

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

In the second line, I used the approximation $\exp(\rho^j v_0) \approx 1 + \rho^j v_0$. This is approximately true if $\rho^j v_0$ is sufficiently small. Observe that the measurement error is multiplied by ρ^j, which means that this term approaches zero for large j. Lastly, $f(y_0^*)$ is a general function of y_0^* and $\widehat{\mathrm{PI}}_t^*$ is the "non-noisy" measure of permanent income. Any regression that uses the permanent income measure constructed with noisy income data, Y_t, as an explanatory variable will suffer from 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.

Because of the assumption 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. In other words, 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. I use reported income in adjacent surveys, specifically the one-year lagged y_{-1}, and industry dummies as instruments. Measurement errors in assets are harder to address, and I rely on the same set of instruments used to deal with errors in income.[21]

The result I derived in this appendix is for the measure of permanent income in levels, but taking its

[21] 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. They consider measurement issues: (i) wealth having some imputed component or (ii) a change in the interview respondent (e.g., the head in some wave and the spouse in another).

logarithm 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 true under the assumption that v_0 is sufficiently small. 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 $(1/R)^j$, this is likely true in the data.

C Quality of the Expected Income Measure

To document some empirical results, I construct a permanent income measure at the household level. For this, I estimate each household's expected income path by assuming a forecast process and an information set. A possible concern is households possessing superior information relative to the econometrician when forecasting future income. In particular, a concern is whether I systematically underpredict permanent income for low-income households or overpredict permanent income for high-income households, which would explain my empirical results.

To address this concern, I provide evidence that households possessing superior information are not a major issue in this Appendix. I take advantage of the panel structure and construct out-of-sample forecast errors to test their bias and forecastability. In particular, this allows me to test for systematic biases in my forecasting approach. Good forecasts should lead to forecast errors that are unforecastable based on information available at the time the forecast was made (Diebold, 2017).

Short-term errors are unbiased, but longer-term ones have a small bias. Moreover, I show that current consumption, which arguably embodies most of the information available to households and is a good proxy for capturing households' information set, has low power in forecasting future income forecast errors. Households have superior information than the econometrician, but its magnitude appears small and not economically significant.

My analysis focuses on forecast errors, $\epsilon^t_{i,t+h}$, defined as:

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

I define the forecast error as the difference between the realized value, $yi, t+h$, and its forecast, $\hat{y}^t_{i,t+h}$. Here, $\hat{y}i, t+h^t$ is the h-step-ahead forecast of the variable yi, t, made at time t using the information available at that period. The superscript t in $\hat{y}i, t+h^t$ denotes the time when the forecast is made, while the subscript $t+h$ indicates the period for which the forecast is generated. The income measure is after-tax labor income.

Test 1: I inspect the mean and variance of the h-step-ahead forecast. I pool all observations for all households together and compute descriptive statistics. Table C1 has three panels that show the statistics for the realized income, $y_{i,t+h}$, its forecast, $\hat{y}^t_{i,t+h}$, and the forecast error, $\epsilon^t_{i,t+h}$.

Column 1 shows that the realized value is systematically larger than its forecast, implying positive forecast errors. The average forecast error ranges from 0.01 to 0.02, which is clearly small. Thus, the forecast exercise, which is done out-of-sample, shows that a significant part of the unconditional variation in income is forecastable with a limited information set. Column 2 shows that there is also a large dispersion in the forecast errors, with their standard deviations increasing as the forecast horizon extends. Optimal forecast errors should exhibit non-decreasing variances as the forecast horizon extends and should ultimately converge to the unconditional variance of the process (Diebold, 2017). Column 3 shows that the number of observations decreases as the forecast horizon increases because households drop out of the sample for different reasons.

Table C1: h-Step-Ahead Forecast Errors

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

Note: This table presents summary statistics of realized income, $y_{i,t+h}$, its forecast, $\hat{y}^t_{i,t+h}$, and forecast error, $\epsilon^t_{i,t+h}$. The income measure is after-tax labor income. h denotes the different forecast horizons.

Test 2: I check whether other variables that capture households' available information can forecast the forecast errors. This exercise tests if there is a systematic bias in the forecast exercise and assesses the importance of households' superior information set. In particular, a biased forecast is not a problem if the errors are not systematically correlated with permanent income. The constant would capture them in my projections, and the slope coefficient is my object of interest. The problem arises if the errors are negatively correlated with consumption. In this case, I am over-predicting permanent income for low-consumption households and under-predicting permanent income for high-consumption ones, thus underestimating the slope coefficient.

First, I test whether higher forecasts predict higher realized incomes by estimating the equation for five different forecast horizons:

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

Realized income is $y_{i,t+h}$, the income forecast is $\hat{y}^t_{i,t+h}$, and the residual is u_t. The necessary condition for forecast orthogonality is $(\alpha_0, \alpha_1) = (0, 1)$, which implies that forecast errors are unbiased.

Table C2 presents estimation results across different forecast horizons. The estimated coefficient α_1 on the forecasted income is close to 1 across all horizons, ranging from 0.90 at the ten-period horizon to 1.01 at the two-period horizon. These estimates suggest that forecasts predict realized income, although the coefficient slightly declines at longer horizons, indicating a potential attenuation effect. Standard errors are small, confirming statistical precision. The intercept term is not uniformly zero, suggesting some bias in forecasts, especially at longer horizons. The R^2 values decline from 0.6352 at the two-period horizon to 0.3443 at the ten-period horizon, implying that forecasted income explains a large share of realized income variation, although this share decreases as the horizon lengthens. The results indicate that income forecasts contain substantial predictive power but may not be unbiased, particularly at longer horizons.

Table C2: Income Growth Forecast Equation

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

Note: This table presents the results from regressions of realized income on income forecasts at different forecast horizons (h = 2, 4, 6, 8, 10). The coefficient on forecasted income remains close to one, suggesting strong predictive power, but declines slightly at longer horizons. The constant term varies across specifications, indicating potential bias in forecasts. The R^2 values decrease as the forecast horizon increases. Standard errors are computed using Bootstrap and reported in parentheses.

Second, I test whether higher forecasts are sufficient to predict higher realized incomes by estimating the following equation for five different forecast horizons:

$$y_{i,t+h} = \alpha_0 + \alpha_1 \hat{y}^t_{i,t+h} + \alpha_2 c_{i,t} + u_t \ .$$

Realized income is $y_{i,t+h}$, the income forecast is $\hat{y}^t_{i,t+h}$, the logarithm of consumption is $c_{i,t}$, and the residual is u_t. The necessary condition for forecast orthogonality is $(\alpha_0, \alpha_1, \alpha_2) = (0, 1, 0)$, which implies that the forecast captures all available information. In particular, all variables on the right-hand side are measured at period t. So, if α_2 is different from zero, it means that there is information useful to predict future income.

Current consumption arguably embodies most of the information available to households and is a good proxy for capturing households' information set. According to the Permanent Income Hypothesis, households should always align their consumption with their perceived permanent income. Therefore, if households possess a superior information set, then among two households with the same measured expected income but different consumption levels, the one with higher consumption should also have higher future income realizations. This would translate to a positive α_2.

Table C3 shows that the coefficient on the income forecast, α_1, is significantly less than one across all forecast horizons, declining from 0.88 at the two-period horizon to 0.62 at the ten-period horizon. This systematic deviation suggests that forecasts tend to overpredict income growth. To see why $\alpha_1 < 1$ indicates overprediction, consider that if forecasts fully incorporated all available information, α_1 would equal 1, meaning that a one-unit increase in the income forecast would translate into an identical one-unit increase in realized income. Since α_1 is consistently below 1, realized income systematically falls short of its forecasted value, leading to forecast errors characterized by excessive optimism. This pattern could also result from attenuation bias, which occurs due to measurement error in reported income.

The coefficient on log consumption, α_2, is positive and statistically significant at all forecast horizons. Moreover, its magnitude increases with the forecast horizon, rising from 0.22 at the two-period horizon to 0.47 at the ten-period horizon. This pattern suggests that consumption contains predictive information about future income that is not fully captured by the income forecast. In other words, households with higher current consumption tend to experience higher future income realizations, conditional on their expected income.

A comparison of R^2 values with those in the previous table confirms a consistent decline in explanatory power as the forecast horizon increases. More importantly, the increase in R^2 from adding consumption is modest, suggesting that the income forecast already incorporates most of the predictive information relevant for future income.

Table C3: Income Growth Forecast Equation

	$y^t_{i,t+2}$	$y^t_{i,t+4}$	$y^t_{i,t+6}$	$y^t_{i,t+8}$	$y^t_{i,t+10}$
$\hat{y}^t_{i,t+j}$	0.88	0.78	0.69	0.64	0.62
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
$\log(c_{i,t})$	0.22	0.34	0.42	0.46	0.47
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-0.89	-1.07	-1.03	-0.82	-0.69
	(0.08)	(0.12)	(0.15)	(0.18)	(0.22)
N	43586	35110	27885	21804	16589
R^2	0.6454	0.5356	0.4768	0.4265	0.3949

Note: This table presents the results from regressions of realized income on income forecasts and consumption at different forecast horizons. The coefficient on forecasted income is significantly less than one and declines with the forecast horizon, suggesting that forecasts overpredict future income growth. The coefficient on log consumption is positive and statistically significant, indicating that consumption contains predictive information about future income. Standard errors are computed using Bootstrap and reported in parentheses.

Table C4 presents the results from estimating the income growth forecast equation using instrumental variables to address attenuation bias caused by measurement error in forecasted income (see discussion in Appendix B. Compared to Table C3, the coefficient on forecasted income, α_1, increases and is now slightly above one across all horizons. This suggests that the OLS estimates in Table C3 were biased downward due to measurement error in income forecasts. Correcting for measurement errors is key to my exercise.

The coefficient on log consumption, α_2, decreases substantially across all forecast horizons, indicating that consumption has less predictive power for future income after accounting for measurement error. This suggests that the predictive power of consumption in Table C3 was partly due to its correlation with the non-noisy income forecasts rather than its ability to reveal superior information about future income.

After instrumenting, the model appears to underpredict future income, with realized income systematically above its forecasted value and leading to negative forecast errors. This implies that the IV approach leads to an overprediction of permanent income for low-consumption households and an underprediction for high-consumption households, resulting in an overestimated consumption elasticity to permanent income. This pattern suggests that the bias from measurement error in IV estimates works against the hypothesis that consumption under-responds to permanent income.

Although consumption still has some predictive power, the relatively small coefficient values, combined with the similarity in R^2 in Table C2 and C3, suggest that its role in forecasting income is not quantitatively important. This indicates that while households may have a superior information set, their advantage in forecasting income is limited in magnitude.

Table C4: Income Growth Forecast Equation

	$y^t_{i,t+2}$	$y^t_{i,t+4}$	$y^t_{i,t+6}$	$y^t_{i,t+8}$	$y^t_{i,t+10}$
$\hat{y}^t_{i,t+j}$	1.12	1.15	1.16	1.16	1.17
	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)
$\log(c_{i,t})$	0.01	0.05	0.09	0.11	0.10
	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)
Constant	-1.37	-2.12	-2.62	-2.80	-2.88
	(0.08)	(0.14)	(0.19)	(0.24)	(0.29)
N	43586	35110	27885	21804	16589
R^2	0.6280	0.4998	0.4207	0.3564	0.3178

Note: This table presents the results from regressions of realized income on income forecasts and consumption at different forecast horizons, using an instrumental variables (IV) approach to correct measurement error in income forecasts. The instruments used for income forecasts are lagged income and industry dummies. Standard errors are computed using Bootstrap and reported in parentheses.

D Additional Tables and Figures

Contents

D.1 Alternative Measurement Choices

In the main analysis, I have to make choices about income, expenditure, net worth, and sample construction. For robustness, I present the results with several other choices and discuss how the results change. I focus on a particular set of results: (i) Table 1, Column 1: the average consumption response estimated by OLS; (ii) Table 1, Column 3: the average consumption response estimated by IV; (iii) Table 2, Column 2: the consumption response of young households; (iv) Table 2, Column 5: the consumption response of old households; and (v) Table 3, Column 1, Rows 1 and 2: the average consumption response and its path dependence.

My results are sensitive to how permanent income is constructed and the expenditure measure. First, with some alternative permanent income measures, the average consumption response is closer to 1 in some specifications, but the path dependency is robust across all specifications. Second, consumption responses are lower when expenditures are constructed with fewer items, such as nondurable goods, and higher when including broader expenditure categories. The wealth measures or the sample criteria do not seem to impact the measured elasticity.

Alternative Permanent Income Measures

In Table D1, I present the results with other measures of permanent income. Recall that I assume an AR(1) process when forecasting the expected path of labor to construct the permanent income measure. I show how the results change when: (i) allowing the parameters of the autoregressive process to vary by occupation, (ii) allowing the parameters of the autoregressive process to vary by industry, (iii) using total income instead of labor income, and (iv) using higher-order autoregressive processes.

Table D1 shows the elasticity estimates across these alternative measures. Column 1 reports elasticity estimates consistently below 1, suggesting an under-response of consumption to permanent income across all definitions. Column 2 reports higher IV estimates and shows how correcting for measurement error leads to larger estimates, consistent with an attention bias in OLS estimates. The IV approach addresses attenuation bias originating from classical measurement error. Columns 3 and 4 report a declining elasticity with age across most specifications, though some specifications exhibit a flatter profile at later ages. In particular, when using industry- or occupation-specific permanent income, the elasticity remains relatively flat or even slightly increases. Columns 5 and 6 report evidence of path dependence across all specifications. The role of past income in determining current consumption responses is robust.

Alternative Expenditure Measures

In Table D2, I present results with other expenditure measures. My original results use the categories available since 1999. I show how the results change when (i) using direct expenditure to measure shelter

Table D1: Different Measures of Permanent Income

	Table 1 Column 1	Table 1 Column 3	Table 2 Column 2	Table 2 Column 5	Table 3 Row 1	Table 3 Row 2
PI based on AR(1)	0.57	0.79	0.86	0.64	0.95	-0.33
	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
PI w/ ind-specific AR(1)	0.58	0.93	0.77	0.87	1.08	-0.18
	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
PI w/ occ-specific AR(1)	0.57	0.97	0.86	0.87	1.07	-0.18
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.06)
PI w/ total income AR(1)	0.60	0.98	1.08	0.81	1.08	-0.34
	(0.01)	(0.02)	(0.04)	(0.02)	(0.03)	(0.05)
PI based on AR(2)	0.55	0.69	0.75	0.58	0.82	-0.32
	(0.01)	(0.01)	(0.04)	(0.02)	(0.03)	(0.04)

Note: See text for details.

expenditure instead of imputing flow services, (ii) incorporating broader expenditure categories available after 2005, (iii) combining both adjustments, (iv) considering only nondurable expenditure, (v) including donations and charitable giving, and (vi) including donations, charitable giving, and money transfers to individuals outside the household.[22]

Table D2 reports results using other consumption measures. The results are consistent across all specifications. However, consumption responses are lower when expenditures are constructed with fewer items, as in the definition of nondurables. Elasticity estimates increase when including broader expenditure categories, such as donations, charitable giving, and money transfers to individuals outside the household. This makes sense since these goods are luxury goods, whereas nondurable goods are inferior goods. Therefore, it is important to account for broad consumption measures when analyzing consumption responses, as income levels determine these responses through Engel curves that are not unitary.

[22]In particular, (i) I define shelter expenditure as the sum of all housing expenditures (rent, mortgage payments, and property taxes) and vehicle expenditure as the sum of down payments, lease payments, loan payments, and additional vehicle costs; (ii) I construct broad expenditures using more categories included in the 2005 wave (home repairs, home furnishings, clothing, vacations, recreation, and telecommunications); and (iii) I construct nondurable expenditures, excluding all spending on vehicles and shelter except insurance and vehicle repair. These last two are service expenditures and are easy to adjust.

Table D2: Different Measures of Expenditure

	Table 1 Column 1	Table 1 Column 3	Table 2 Column 2	Table 2 Column 4	Table 3 Row 1	Table 3 Row 2
Expenditure, 1999 Cat.	0.59	0.79	0.86	0.64	0.95	-0.33
	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
Expenditure, Alt. Shelter	0.54	0.87	0.94	0.72	0.98	-0.25
	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
Expenditure, 2005 Cat.	0.62	0.86	0.92	0.73	1.01	-0.33
	(0.01)	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)
Expenditure, 2005 Cat.	0.58	0.93	0.99	0.80	1.05	-0.27
& Alt. Shelter	(0.01)	(0.02)	(0.05)	(0.03)	(0.04)	(0.05)
Expenditure, Nondurables	0.48	0.73	0.83	0.57	0.81	-0.17
	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
Expenditure, 2005 Cat.	0.64	0.89	0.93	0.75	1.04	-0.33
& Donations	(0.01)	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)
Expenditure, 2005 Cat.	0.69	0.98	1.02	0.83	1.11	-0.34
& Donations and More	(0.01)	(0.02)	(0.05)	(0.03)	(0.04)	(0.04)

Note: See text for details.

Alternative Wealth Measures

Table D3 presents the results using different permanent income measures constructed with two wealth measures. In particular, I use (i) the reported Net Worth available in the PSID and (ii) the reported Net Worth plus Retirement Accounts. For the latter, I follow Cooper et al. (2019) and use the pension data available in the PSID to create a more comprehensive measure of wealth. The table suggests that the different choices do not impact the measured elasticity.

Table D3: Different Measures of Asset

	Table 1 Column 1	Table 1 Column 3	Table 2 Column 2	Table 2 Column 4	Table 3 Row 1	Table 3 Row 2
PSID Net Worth	0.59	0.79	0.86	0.64	0.95	-0.33
	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
Net Worth + Ret. Accounts	0.58	0.76	0.86	0.61	0.91	-0.31
	(0.01)	(0.02)	(0.04)	(0.02)	(0.03)	(0.04)

Note: See text for details.

Alternative Sample Selection

Table D4 presents the results using different sample criteria. In particular, I (i) transform all variables to an adult equivalent scale, (ii) transform all variables to a per-earner term, (iii) exclude supplementary tables, and (iv) focus on households that never changed their marital status. The table suggests that the different choices do not impact the measured elasticity.

Table D4: Alternative Sample Selection

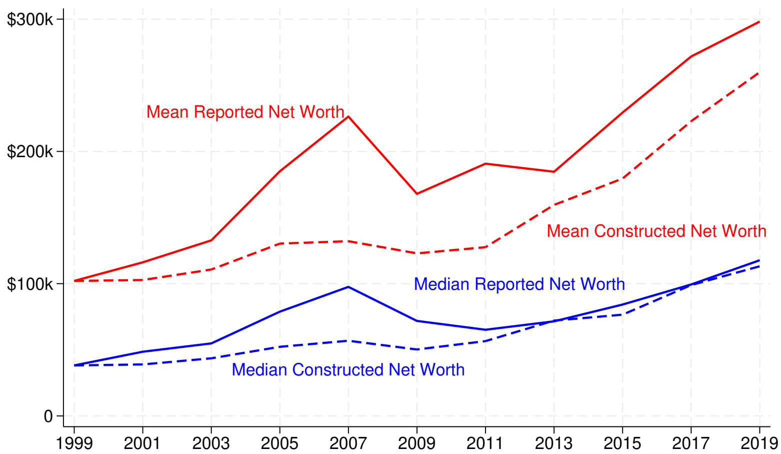
	Table 1 Column 1	Table 1 Column 3	Table 2 Column 2	Table 2 Column 4	Table 3 Row 1	Table 3 Row 2
Adult Equivalence Adjusted	0.57	0.72	0.78	0.59	0.89	-0.31
	(0.01)	(0.02)	(0.04)	(0.02)	(0.03)	(0.04)
Marital Status Adjusted	0.59	0.78	0.83	0.63	0.96	-0.34
	(0.01)	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
No Supplement Samples	0.57	0.74	0.81	0.58	0.97	-0.33
	(0.01)	(0.01)	(0.03)	(0.02)	(0.04)	(0.05)
No Martial Status Change	0.58	0.74	0.80	0.61	0.98	-0.34
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.05)

Note: See text for details.

D.2 Additional Wealth Paths

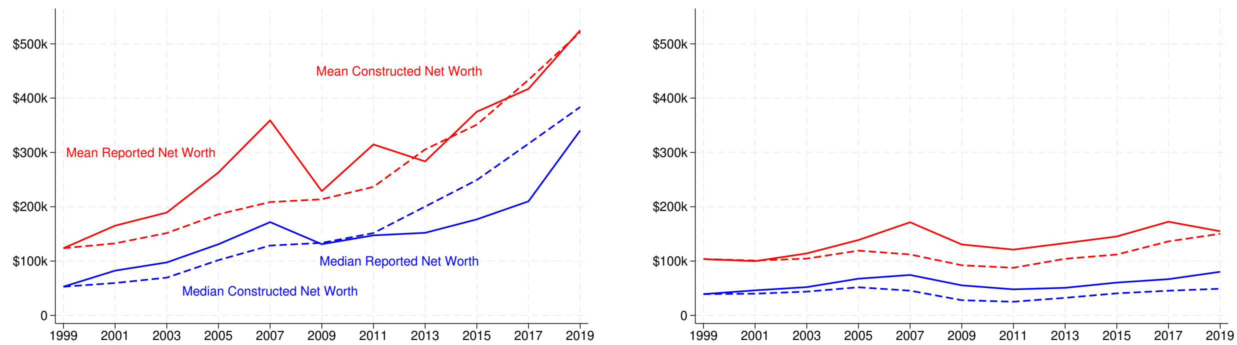
Recall that Figure 1 shows how the median reported net worth and the median alternative net worth closely co-move, highlighting the quality of the PSID data for longitudinal analysis. Figure 2 replicates the previous analysis but splits the sample into two groups: Panel 2a plots those households that experienced positive permanent income growth over a 20-year period, and Panel 2b plots those that did not. The same pattern emerges for the mean profiles, displayed in the solid and dashed red lines. Again, all series change in tandem at similar levels, except for some of the dynamics around the 2008 financial crisis. The disparity around 2008 is larger for the mean, implying that I am probably missing large capital gains from the crisis.

Figure D1: Asset Path Implied by Expenditure and Income



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

Figure D2: Asset Path Implied by Expenditure and Income



(a) Positive PI growth

(b) Negative PI growth

Note: This figure depicts the path of reported net worth and constructed net worth measures of households in the PSID. I divide the sample into households that experienced positive permanent income growth over 20 years and those that did not. Reported net worth refers to the net worth that respondents report when answering the questions in the PSID. Constructed net worth refers to the net worth constructed using respondents' reported income and expenditures. In total, I follow 483 households, with 607 negative growth and with 359 positive growth. The difference between the previous figure sample is that I restrict the selection to those for whom I observe permanent income both when I start following them and 20 years later. More details on the construction are given in the main text. The median reported net worth is the solid blue line, and the median constructed net worth is the dashed blue line. The mean reported net worth is the solid red line, and the mean constructed net worth is the dashed red line.

D.3 Results by Ownership

My main claim in this paper is that consumption commitments are important to understand how consumption responds to permanent income. Therefore, I test whether homeowners and renters have different responses to permanent income, which is an important check on the mechanisms since housing is the most relevant consumption commitment for most households. The economic intuition is that renters' responses should not depend on past permanent income growth since they face arguably smaller adjustment costs than homeowners.

Table D5 shows the comparison between renters and homeowners in their consumption and savings responses to permanent income. I compare households that are renters and homeowners at current period t, as well as those that differ in their past status at period t-10. In particular, these comparisons shed light on whether households who were renters before the permanent income growth respond more, those who are renters after the income growth respond more, or if both exhibit stronger responses.

Table D5, Column 1 shows that the consumption response to permanent income growth is stronger for homeowners than for renters, with an estimated coefficient of 0.17 Own $\times$ log(PI). However, this difference is not statistically significant. Similarly, Table D5, Column 2 shows that the savings rate response to permanent income growth is slightly higher for homeowners than for renters, but again, the coefficient of is not significant.

Path dependency is more evident when considering past homeownership status. Table D5, Column 3 shows that the interaction term $\text{Own}_{t-10} \times$ log(PI) is negative, suggesting that households who were homeowners in the past exhibit a weaker response to permanent income growth than those who were renters. This supports the idea that past housing commitments create long-term frictions that reduce the adjustment of consumption, even years after the initial commitment. Although the difference is not statistically significant, the economic magnitude suggests that prior homeownership may have persistent effects on how households adjust their consumption. Table D5, Column 4 shows that past homeownership status has little impact on savings rate responses to permanent income growth, with an estimated coefficient near zero.

Table D5: Heterogeneous Effects: Homeownership Status

	(1) log(expenditure)	(2) Savings Rate	(3) log(expenditure)	(4) Savings Rate
log(PI)	1.00	0.14	0.93	0.04
	(0.05)	(0.05)	(0.05)	(0.05)
Δ log(PI)	-0.47	0.07	-0.12	0.16
	(0.10)	(0.09)	(0.11)	(0.11)
Own $\times$ log(PI)	-0.10	-0.06		
	(0.04)	(0.05)		
Own $\times$ Δ log(PI)	0.17	0.09		
	(0.13)	(0.11)		
Own_{t-10} $\times$ log(PI)			-0.03	0.02
			(0.05)	(0.05)
Own_{t-10} $\times$ Δ log(PI)			-0.28	-0.00
			(0.14)	(0.13)
Educ Dummies	Y	Y	Y	Y
KP-F test	19.8	43.3	20.2	30.9
Observations	14,241	14,241	14,190	14,190

Note: This table examines homeownership's role in shaping consumption responses to permanent income changes. It shows that past and current homeowners exhibit weaker consumption responses to permanent income growth than renters.

Table D6 compares renters and homeowners in their expenditure allocation. Column 1 shows that households that own a home allocate more of their expenditure to nondurable goods following past expenditure growth. The coefficient on Own $\times$ Δ log(exp) is positive, suggesting that homeowners shift their consumption baskets toward nondurables after experiencing income growth. This aligns with the idea that consumption commitments make it harder for homeowners to adjust their shelter expenditures, leading them to adjust their nondurable spending instead. Column 2 presents results for shelter expenditure, which follow the opposite pattern.

Past homeownership status also plays a role in shaping expenditure allocation. Column 3 shows that households that were homeowners in the past allocate significantly more to nondurables following expenditure growth, reinforcing again the idea that past commitments shape spending patterns. Column 4 presents results for shelter expenditure, which follow the opposite pattern.

Table D6: Heterogeneous Effects: Homeownership Status

	(1) Nondurable Share	(2) Shelter Share	(3) Nondurable Share	(4) Shelter Share
log(exp)	-2.70	-2.94	-4.52	-1.13
	(1.08)	(1.27)	(1.17)	(1.40)
Δ log(exp)	1.67	-3.75	-0.35	-3.78
	(1.56)	(1.77)	(2.10)	(2.36)
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)		
Own_{t-10} $\times$ log(exp)			-11.55	9.38
			(1.24)	(1.41)
Own_{t-10} $\times$ Δ log(exp)			10.91	-10.91
			(2.51)	(2.71)
Educ Dummies	Y	Y	Y	Y
KP-F test	9.5	9.6	10.1	10.6
Observations	9,757	9,759	9,688	9,696

Note: This table examines homeownership's role in shaping expenditure allocation. It shows that past and current homeowners exhibit expenditure shares skewed towards nondurables and away from shelter.

D.4 Changes in the Permanent Income Predicts Moving Decisions

In my results, I compare the behavior of households that recently adjusted the quantity of their hard-to-adjust goods to those that did not. I classify households that moved at least once within the prior decade as households that adjusted their bundle. In this appendix, I show that the likelihood of households having recently moved increases with the absolute growth of permanent income. This is consistent with standard lumpy adjustment models, which predict adjustment after the gap between current and desired housing consumptions crosses certain theoretical bounds.

Table D7 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. Specifically, in Column 1, a one-unit increase in the absolute log change in permanent income is associated with a 22.8 percentage point increase in the probability of moving, with a standard error of 1.9 percentage points. This effect remains significant in Column 2, which adds an interaction of absolute income changes with homeownership dummies. 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 homeownership is near zero and statistically insignificant, suggesting that homeowners and renters exhibit similar sensitivity to income changes in their moving decisions.

A potential concern with this analysis is that permanent income growth and moves are measured over the same 10-year interval, raising the possibility of reverse causality–where moving itself affects income growth rather than the other way around. To address this issue, Table D7, Columns 3 and 4 examine households' self-reported likelihood of moving in the future. The results remain qualitatively similar, with absolute permanent income growth continuing to be positively associated with the probability of expecting to move. However, the magnitude of the effect is smaller than in the retrospective case. Additionally, homeownership continues to be strongly negatively associated with expected mobility, reinforcing the role of housing-related adjustment costs in explaining household decisions.

Figure D3 provides a graphical representation of the relationship documented in Table D7. It illustrates the likelihood of households having moved at least once in the past 10 years as a function of past absolute growth of permanent income. To construct this figure, past permanent income growth is partitioned into equal-sized bins, and for each bin, the mean probability of having moved is computed. The scatter points represent these mean probabilities, while the red line shows the fitted linear relationship.

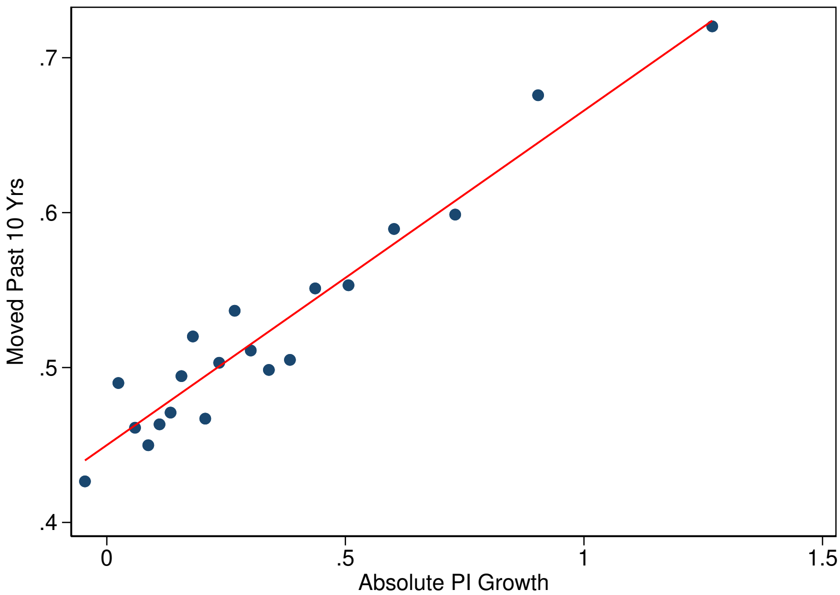
The figure confirms the strong positive association between the absolute growth of permanent income and the probability of moving. Moreover, the relatively tight clustering of points around the fitted line reinforces the robustness of this relationship and suggests that a linear approximation is good for this relationship. Furthermore, the trend suggests that larger deviations in permanent income are systematically linked to higher probabilities of housing adjustment.

Table D7: Probability of Housing Adjustment

	(1) Moved Past 10 Yrs	(2) Moved Past 10 Yrs	(3) Might Move	(4) Might Move
$\lvert\log(\mathrm{PI}/\mathrm{PI}_{t-10})\rvert$	0.228	0.183	0.096	0.022
	(0.019)	(0.027)	(0.016)	(0.030)
Own $\times$ $\lvert\log(\mathrm{PI}/\mathrm{PI}_{t-10})\rvert$		0.002		0.048
		(0.036)		(0.036)
Own		-0.334		-0.346
		(0.026)		(0.023)
N	14653	14653	14653	14653

Note: The table presents estimates from linear probability models. The dependent variables are whether a household moved in the past ten years and whether the household reports a likelihood of moving in the future. Permanent income growth is measured as the absolute log difference in permanent income over a ten-year interval. All regressions control for age, family size, marital status, education group, region, and year-fixed effects. Regressions are weighted using sample weights. Standard errors are bootstrapped.

Figure D3: Probability of Moving



Note: The figure provides a binned scatter plot visualizing the relationship between absolute permanent income growth and the probability of having moved in the past ten years. I use 20 equally sized bins. I control for age, family size, marital status, education group, region, and year-fixed effects. A fitted linear regression line is shown in red.

D.5 Results by Reason for Moving Decisions

In my results, I compare the behavior of households that recently adjusted the quantity of their hard-to-adjust goods to those that did not. I classify households that moved at least once within the prior decade as those that adjusted their bundle. A potential concern with this analysis is that permanent income growth and moves are measured over the same 10-year interval, raising the possibility of reverse causality–where moving itself affects income growth rather than the other way around. In this appendix, I address this concern by leveraging respondents' self-reported reasons for moving in the PSID.

PSID respondents provide reasons for their moves, which can be categorized as follows: (i) purposive, productive reasons, such as taking another job or finishing school, (ii) moving closer to work, (iii) purposive, consumptive reasons, such as expanding or downsizing housing, other house-related motives, or neighborhood-related changes, (iv) involuntary reasons, and (v) ambiguous, mixed, or other reasons. To mitigate endogeneity concerns, I exclude households that moved for productive reasons and focus on those who moved primarily for consumptive adjustments.

Tables D8 and D9 explore how consumption and expenditure allocation respond to permanent income for all movers and for those moving explicitly for consumptive reasons. Table D8 shows that the elasticity of log expenditures to permanent income remains nearly unchanged between the two samples, suggesting that the decision to move is not systematically driving permanent income growth. Table D9 shows that movers who relocate for consumptive motives exhibit similar patterns in their expenditure allocation. Overall, these results support the interpretation that households move primarily to adjust their durable consumption levels rather than to increase permanent income.

Table D8: Heterogeneous Effects: Consumption Adjustments and Moving Decisions

	(1) log(expenditure)	(2) log(expenditure)
log(PI)	0.96	0.95
	(0.03)	(0.03)
Δ log(PI)	-0.56	-0.50
	(0.09)	(0.09)
Moved $\times$ log(PI)	0.00	
	(0.03)	
Moved $\times$ log(PI_{t-10})	0.35	
	(0.14)	
Moved for consump. $\times$ log(PI)		0.03
		(0.03)
Moved for consump. $\times$ Δ log(PI)		0.24
		(0.14)
Educ Dummies	Y	Y
KP-F test	16.8	15.5
Observations	15,180	14,361

Note: This table examines reported reasons for past moves in shaping consumption responses to permanent income changes. It shows that consumption-related moves exhibit the same consumption responses to all moves.

Table D9: Heterogeneous Effects: Expenditure Allocation and Moving Decisions

	(1) Nondurable Share	(2) Nondurable Share
log(exp)	-13.03	-13.14
	(0.91)	(0.92)
Δ log(exp)	12.54	12.86
	(2.45)	(2.48)
Moved $\times$ log(exp)	2.97	
	(1.03)	
Moved $\times$ Δ log(exp)	-9.10	
	(2.61)	
Moved for consumption $\times$ log(exp)		3.63
		(1.07)
Moved for consumption $\times$ Δ log(exp)		-8.77
		(2.71)
Educ Dummies	Y	Y
KP-F test	7.8	7.8
Observations	10,025	9,323

Note: This table examines reported reasons for past moves in shaping consumption responses to permanent income changes. It shows that consumption-related moves exhibit the same consumption responses to all moves.

D.6 Financial Factors

Borrowing constraints are important to understanding consumption behavior, especially responses to transitory income changes. I construct two indicators to identify whether households are constrained or hand-to-mouth (H2M). The first follows Zeldes (1989)' definition, classifying households as H2M if their net worth is less than two months of income. The second follows Kaplan et al. (2014)'s definition, identifying households as H2M if they have positive but low liquid wealth relative to their weekly income or negative liquid wealth exceeding a certain fraction of their income. These classifications capture different aspects of financial constraints–the former approach focuses on overall net worth, while the latter emphasizes liquidity.

Table D10 presents results testing how constrained households change the estimated consumption responses to permanent income. Column 1 reports the baseline regression for comparison. In Column 2, I introduce dummies for H2M households based on net worth and liquidity definitions. The estimated elasticities remain unchanged, indicating that borrowing constraints do not fundamentally alter the relationship between consumption and permanent income. The coefficients on the H2M dummies are positive and significant, suggesting that constrained households consume more, conditional on their measured permanent income. This aligns with the theoretical results.

To further test robustness, Column 3 drops all H2M households from the sample. The estimated elasticity of log consumption to permanent income remains stable at 0.94, and the response of consumption growth to changes in permanent income is -0.35, similar to the baseline specification. This finding suggests that financially constrained households are not driving the main results. Finally, Column 4 restricts the sample to households with positive home equity, removing those with negative housing wealth. Again, the estimated consumption elasticities remain almost identical to the baseline. This finding suggests that housing equity constraints do not drive the main findings.

Overall, these results demonstrate that the estimated consumption responses to permanent income are stable across different household financial conditions, reinforcing the reliability of the baseline estimates.

Table D10: Financial Factors and Consumption Responses

	(1) All Sample	(2) All Sample	(3) No H2M	(4) Positive Home Equity
$\log(\mathrm{PI}_t)$	0.95	0.96	0.94	0.96
	(0.03)	(0.03)	(0.04)	(0.03)
Δ log(PI)	-0.34	-0.36	-0.35	-0.33
	(0.04)	(0.04)	(0.05)	(0.04)
Net worth H2M		0.08		
		(0.01)		
Liquidity H2M		0.06		
		(0.02)		
Educ Dummies	Y	Y	Y	Y
KP-F test	130.6	128.8	66.5	126.5
Observations	15,022	15,022	9,446	14,693

Note: This table examines consumption responses to permanent income for different samples. See text for details.

D.7 Income Risk

Theoretically, income risk affects consumption by influencing precautionary saving behavior. This saving behavior could generate the under-consumption puzzle if high-permanent-income households have riskier income and, therefore, larger savings. Young workers tend to be more liquidity-constrained and have higher expected future income growth; therefore, precautionary saving should be stronger for them. The fact that we see pronounced under-consumption among older households suggests that uncertainty is not an important driver of this puzzle. However, I test how income risk influences consumption responses to permanent income in Table D11.

To measure income risk, I follow Boar (2021). I use the income forecasts computed in Appendix C and construct out-of-sample forecast errors, which I interpret as the unforeseen component of income. Permanent income uncertainty is computed in two steps. First, I compute the present value of these forecast errors (4, 6, 8, and 10 periods ahead), discounted at an annual interest rate of 5%. Second, I compute the standard deviation of these errors within occupation-industry groups. Lastly, I assign an income risk measure to each household based on their occupation-industry group.

Table D11, Column 1 presents the OLS estimate of log expenditures on income risk. The coefficient on income risk is negative (-0.07) with a standard error of 0.04. This result is consistent with theoretical predictions: higher income risk reduces consumption as individuals increase precautionary savings. However, the magnitude of the effect is relatively small, suggesting that while precautionary motives are present, they do not primarily drive consumption behavior.

Column 2 introduces log permanent income as a control variable. The coefficient on income risk turns positive and remains statistically significant. The positive coefficient may reflect an alternative channel where income risk is correlated with expected earnings growth. The coefficient on log permanent income is larger than the one in the baseline specification. However, under-consumption is still present. Column 3 extends the specification by adding past permanent income growth. The coefficient on income risk remains positive. Importantly, path dependence on past permanent income growth remains in the data. Table D11, Column 4 adds the 10-year lagged income risk measure. The coefficient on this income risk is essentially zero.

Table D11: Income Risk and Consumption Responses

	(1) OLS: log(exp)	(2) IV: log(exp)	(3) IV: log(exp)	(4) IV: log(exp)
Income Risk$_t$	-0.07	0.44	0.37	0.37
	(0.04)	(0.03)	(0.05)	(0.05)
Income Risk$_{t-10}$				-0.00
				(0.05)
log(PI)		0.86	0.98	0.98
		(0.02)	(0.03)	(0.03)
Δ log(PI)			-0.28	-0.28
			(0.04)	(0.05)
Educ Dummies	Y	Y	Y	Y
KP-F test		503.2	123.4	99.5
Observations	54,970	54,970	15,180	15,180

Note: This table examines consumption responses to permanent income for different samples. See text for details.

D.8 Placebo

In Subsection 3.5, I document that the consumption responses and expenditure allocation of these households that have recently adjusted their commitments respond more strongly to permanent income and depend at most weakly on lagged variables. I classify households that moved at least once within the prior decade as households that adjusted their bundle. I conduct placebo tests to confirm that past moving decisions alter households' responses in TablesD12 and D13.

TablesD12, Column 2 is my baseline result, where I use a dummy variable that equals one if a household moved at least once in the past decade. It shows that past moving decisions lower path dependence on permanent income growth. TablesD12, Column 1 uses a dummy variable that equals one for households that moved at least once before the past decade, 14 to 16 years ago. It shows no sign of path dependence, suggesting the robustness of my interpretation. Because permanent income growth has been computed over the past decade, households' responses to it should not be influenced by moves made before the growth was realized. TablesD12, Column 4 uses a dummy variable that equals one if a household will move in the future, 4 to 6 years ahead. It shows the opposite sign of path dependence, meaning that households that will move in the future and have had faster permanent income growth in the past are the ones that have lower consumption today. Again, these results are consistent with my findings, especially in light of the results showing that past permanent income growth predicts future moves. Those households probably have a suboptimal consumption allocation.

Tables D12, Column 3 uses a dummy variable that equals one if a household moved at least once in the past two years. It shows no path dependence. A possible explanation is that the comparison group of this specification is not the correct one. The households that did not move in the past two years include those that did not move at all in the past ten years and those that moved at least once in the last decade but not in the past two years. The former households should display strong path dependence, while the latter should display weak path dependence.

Table D13 shows the results for expenditure allocation. Again, Column 1 uses a dummy variable that equals one for households that moved at least once before the past decade, 14 to 16 years ago. Column 3 uses a dummy variable that equals one if a household moved at least once in the past two years. It shows no path dependence. Column 4 uses a dummy variable that equals one if a household will move in the future, 4 to 6 years ahead. The results align with my mechanism, with moves before the past decade having no path dependence and moves within the past decade having path dependence consistent with adjustment costs. Column 4 shows that future moves also lower path dependence. The small number of observations raises some caveats with this specification.

Table D12: Placebo

	(1) log(expenditure)	(2) log(expenditure)	(3) log(expenditure)	(4) log(expenditure)
log(PI)	0.93	0.96	0.94	1.00
	(0.03)	(0.03)	(0.03)	(0.04)
Δ log(PI)	-0.34	-0.56	-0.34	-0.28
	(0.06)	(0.09)	(0.05)	(0.06)
Moved 14-16 yrs ago × log(PI)	0.04			
	(0.03)			
Moved 14-16 yrs ago × Δ log(PI)	-0.02			
	(0.10)			
Moved 2-10 yrs ago × log(PI)		0.00		
		(0.03)		
Moved 2-10 yrs ago × Δ log(PI)		0.35		
		(0.14)		
Moved 2 yrs ago × log(PI)			0.07	
			(0.04)	
Moved 2 yrs ago × Δ log(PI)			0.03	
			(0.13)	
Will move in 4-6 yrs × log(PI)				0.17
				(0.04)
Will move in 4-6 yrs × Δ log(PI)				-0.55
				(0.15)
Educ Dummies	Y	Y	Y	Y
KP-F test	19.3	16.8	19.6	10.6
Observations	13,193	15,180	15,177	8,880

Note: See text for details.

Table D13: Placebo

	(1) Nondurable Share	(2) Nondurable Share	(3) Nondurable Share	(4) Nondurable Share
log(exp)	-11.38	-11.92	-10.82	-13.18
	(1.02)	(1.04)	(0.87)	(1.43)
Δ log(exp)	5.47	11.88	6.38	10.08
	(2.49)	(2.56)	(1.73)	(3.09)
Moved 14-16 yrs ago $\times$ log(exp)	1.09			
	(1.01)			
Moved 14-16 yrs ago $\times$ Δ log(exp)	1.17			
	(2.58)			
Moved 2-10 yrs ago $\times$ log(exp)		3.02		
		(1.03)		
Moved 2-10 yrs ago $\times$ Δ log(exp)		-8.91		
		(2.71)		
Moved 2 yrs ago $\times$ log(exp)			2.67	
			(1.09)	
Moved 2 yrs ago $\times$ Δ log(exp)			-4.58	
			(2.03)	
Will move in 4-6 yrs $\times$ log(exp)				4.60
				(1.91)
Will move in 4-6 yrs $\times$ Δ log(exp)				-8.69
				(3.90)
Educ Dummies	Y	Y	Y	Y
KP-F test	9.0	7.9	13.8	4.7
Observations	7,586	10,056	9,718	2,855

Note: See text for details.

D.9 Identifying Bequest in the data

A commonly assumed force to generate large savings for rich households is strong preferences for larger bequests (e.g., De Nardi, 2004) or for insuring heirs through inter vivos transfers (e.g., Boar, 2021). The quantitative model incorporates bequest motives. Therefore, in this appendix, I examine their presence in the PSID and their interaction with the permanent income path.

I identify bequests using three different methods: (i) assets reported by households near death or private transfers reported by their children, (ii) inter vivos transfers and donations reported by households or their children, (iii) children's consumption responses to their parents' permanent income. In general, I find that the likelihood of leaving bequests and helping children, as well as the bequeathed and transferred amounts, are positively associated with permanent income. However, none of the methods for identifying bequests provides sufficient observations to examine their dependence on past permanent income.

Reported Assets by Parents or Reported Transfers by Children

My first method to identify bequests leverages the generational structure of the PSID. In particular, the PSID allows the identification of new households that originated from another household. These are called split-off families: either an individual or a group of individuals that relocated from a family to form a new, economically independent family unit. I measure bequests by the inheritance split-off families report receiving or by the total assets households report holding before death.

To perform this analysis, I create a crosswalk linking parents' household IDs to their children's household IDs. In the PSID, a household is identified by its head's ID. Due to historical conventions, the head is generally the husband when present. Thus, if a daughter marries and forms a new household within the PSID, the husband will typically be designated as the household head. Therefore, cross-checking IDs is necessary to ensure the correct linkage of all split-off families with their originating parent household. I use the family identification files and the family relationship mapping system to do this. I also construct a crosswalk linking each individual to their recorded death year, which is available in the PSID's individual files.

After constructing the necessary linkages, I measure bequests by aggregating any inheritances reported by a split-off family within three years of a parent's death. I consider both the father and mother's passing and aggregate reported inheritances if multiple split-off families are associated with the same parents. To capture bequests, I rely on two survey questions: one on private transfers and another on large gifts or inheritances. The first asks about large private transfers, with households specifying the portion attributed to inheritance. The second directly asks about gifts or inheritances exceeding \$10,000.

I then create two variables: a binary indicator to determine whether the household left a bequest and the log of any bequest amount. I regress these two variables on current and past permanent income measured on the last data observation before the parent household's death.

Table D14 presents the results of projecting bequests onto current permanent income and past permanent income growth. Column 1 shows that the probability of leaving a bequest increases with permanent income, aligning with my modeling assumption of luxury bequests. Column 3 indicates that the bequeathed amount also rises with permanent income. Columns 2 and 4 reveal that while current permanent income is positively associated with both the probability of leaving a bequest and the bequeathed amount, past permanent income growth exhibits a negative relationship. However, these estimates are based on a relatively small number of observations.

Table D14: Bequest

	(1) wrt bequest	(2) wrt bequest	(3) log(bequest)	(4) log(bequest)
log(PI)	0.142	0.341	0.842	0.507
	(0.033)	(0.080)	(0.139)	(0.426)
Δ log(PI)		-0.269		-0.048
		(0.086)		(0.448)
N	489	181	144	49

Note: This table presents regression estimates of bequest incidence and log bequest amounts on permanent income and past permanent income growth. The dependent variable in Columns (1) and (2) is an indicator of whether a positive bequest was reported, while it is the log of the bequest amount in Columns (3) and (4). Control variables include age, marital status, family size, and education group. All regressions use analytical weights and bootstrap standard errors. The sample is restricted to observations within a 3-year window around the parent's year of death.

Another method to measure bequests is to look at household asset levels just before the recorded death year, precisely at a maximum of five years before passing. Again, I create two variables and project them onto current and past permanent income. The first variable is a binary indicator for whether the household passed away with positive assets, and the second is the log of those assets (if positive).

Table D15, Column 1 shows that the probability of passing with positive assets increases with permanent income, and Column 3 shows that assets at death are also positively associated with permanent income. Column 2 shows that past permanent income growth is negatively associated with dying with positive assets, and Column 4 shows a close to zero effect of past permanent income growth on assets at death. However, the number of observations is low, especially in the last specification.

Table D15: Assets at Death

	(1) Wtr Net Worth > 0	(2) Wtr Net Worth > 0	(3) log(net worth)	(4) log(net worth)
log(PI)	0.124	0.179	2.307	2.634
	(0.021)	(0.042)	(0.118)	(0.172)
Δ log(PI)		0.037		-0.190
		(0.044)		(0.162)
Educ Dummies	Y	Y	Y	Y
Observations	658	304	572	263

Note: This table presents regression estimates of net-worth incidence and log net-worth amounts on permanent income and past permanent income growth. The dependent variable in Columns (1) and (2) is an indicator of whether a household passed with positive net-worth, while it is the log of the net-worth amount in Columns (3) and (4). Control variables include age, marital status, family size, and education group. All regressions use analytical weights and bootstrap standard errors. The sample is restricted to observations within a 3-year window around the parent's year of death.

Inter Vivos Transfers and Donations

My second method for identifying bequests leverages inter vivos transfers and donations reported by households or their children. The measure of inter vivos transfers is constructed using a question recording any support given to anyone outside the household, including child support, alimony, and money given to parents. I focus on child support, even though the results are the same for a broader measure. The measure of bequests is constructed using an unexplored philanthropic supplement available in the PSID since 2001 that asks about donations to different causes. I aggregate all of them into a single donation expenditure measure.

I estimate demand systems as before, using the share in these expenditures as the dependent variable and the logarithm of expenditure and expenditure growth as explanatory variables. I follow the same logic as when estimating the demand systems in the main text, and I use a cubic in income as an instrument to deal with measurement errors. I show the results for three samples: (i) all observations, (ii) a sample of households that reported a child in the survey, and (iii) a sample of households that reported having a child younger than 18 years old in the household.

All columns show the same pattern: transferring money to people outside the household and donations are luxury expenditures, with Engel curves well above 1. However, there is no evidence that households with faster permanent income growth donate or help their children more.

Bequest: Parent-Child Pairs

My third method to identify bequests also leverages the generational structure of the PSID. In particular, I evaluate how children's consumption responds to their parents' permanent income, where both children

Table D16: Donations and Inter Vivo Transfers

	All Sample		Reported Child		Reported Child Less 18 yrs	
	(1) Donation Sh.	(2) Help Others Sh.	(3) Donation Sh.	(4) Help Others Sh.	(5) Donation Sh.	(6) Help Others Sh.
log(exp)	0.016	0.010	0.017	0.013	0.009	0.003
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
	[1.74]	[1.91]	[1.82]	[2.11]	[1.48]	[1.45]
Δ log(exp)	0.003	0.004	0.001	0.001	0.016	-0.002
	(0.004)	(0.006)	(0.004)	(0.007)	(0.007)	(0.004)
	[0.16]	[0.39]	[0.04]	[0.10]	[0.81]	[-0.30]
Educ Dummies	Y	Y	Y	Y	Y	Y
KP-F test	20.5	20.5	22.1	22.1	16.2	16.2
Observations	10,515	10,515	8,795	8,795	4,194	4,194

Note: See text for details.

and parents are measured at the same period. Children's consumption should respond to their parents' permanent income if they have information about their parents' permanent income level and if bequest motives are important. Therefore, I interpret any children's response to their parents' permanent income as evidence that they expect to receive bequests in the future.

To construct the sample, I first merge split-off households with their parent households. I carefully track all possible merges since, as mentioned, when a daughter of an original household marries and forms a new household, her husband will typically be designated as the household head. As a second step, I then project split-off expenditure on their permanent income, parents' permanent income, and parents' permanent income growth.

Table D17 shows a positive correlation between split-off expenditure and parents' current permanent income. Overall, children respond to their parents' permanent income. However, I do not find evidence that locked-in parents, proxied by permanent income growth, transfer more money to their children.

Table D17: Child-Parent Pairs

	(1) Child's expend.	(2) Child's expend.	(3) Child's expend.
Child's log(PI)	0.689	0.803	0.795
	(0.029)	(0.040)	(0.041)
Dad's log(PI)	0.113	0.199	0.215
	(0.015)	(0.027)	(0.036)
Dad's Δ log(PI)	-0.045	-0.065	-0.087
	(0.015)	(0.035)	(0.070)
Moved $\times$ Dad's log(PI)			0.022
			(0.037)
Moved $\times$ Dad's Δ log(PI)			-0.093
			(0.130)
Educ Dummies		Y	Y
KP-F test		63.9	7.5
Observations	7,839	7,839	7,839

Note: This table reports regression estimates analyzing the relationship between a child's total expenditure and parental permanent income. The dependent variable in all columns is the child's log total expenditure. The key independent variables include the child's log permanent income, the father's log permanent income, and the father's permanent income growth. Column (1) presents OLS estimates, while Columns (2) and (3) use instrumental variables (IV), where the instruments are lagged income measures and industry indicators. All regressions control for parental and child demographic characteristics, including age (linear, quadratic, and cubic terms), marital status, family size, region, and education group fixed effects.

E Computational Appendix

In this section, I describe the algorithm used to solve the model. First, I briefly describe the model. Second, I describe the algorithm used. Third, I explain the optimization routines.

E.1 Brief Model Description

Households are described by the vector of state variables s, $s = \left\{j, a, h_{-1}, \bar{z}, \alpha, \epsilon, \bar{z}^p\right\}$. These variables indicate, respectively, age (j), bonds carried over from the previous period (a), past commitment stock (h_{-1}), and labor productivity components ($\bar{z}, \alpha, \epsilon$). The last variable ($\bar{z}^p$) has two purposes. 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 that 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 household's first decision is whether to adjust the commitment stock. Specifically, households solve the discrete choice maximization problem

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

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

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. Also, given the timing of lifetime events (see Figure 4), a child may inherit bequests at a random age between 30 and 64. The timing of lifetime events excludes the possibility that a child receives bequests from their grandparents.

E.2 Grids and Interpolation

Because households face a borrowing constraint, I do not use equidistant grid points. Instead, I let the distance between grid points grow as they move further away from zero (see Fehr and Kindermann (2018)). Also, to deal with the collateral constraint, a state-dependent borrowing constraint, I express the liquid savings grid as excess savings beyond the constraint. This way, the property that there are more grid points near the constraint still holds. Lastly, I use linear interpolation between grid points, which has an intuition that helps compute the expected value function. In particular, I assume that the household mass at the left point of the grid is equal to the interpolation weight, and the complementary fraction is at the right grid point.

E.3 Optimal Decision Rules

I use optimization routines to find the best choice given a set of states. In particular, I use the Brent method to find the optimal liquid assets in the non-adjusting problem and the Powell method to find the optimal liquid assets and commitments in the adjusting problem. However, because the problem features non-convex adjustment costs, the optimization routine could find local maxima, not global ones. Thus, I examine the value function at all kinks in the budget set, which are known and easily computed, and I also start the optimization routine with five different starting points for the one-dimensional problem and twenty-five points for the two-dimensional problem. The optimal point is found by comparing the value function at all possible solutions.

E.4 Algorithm Description

The algorithm solves for household decisions and the population distribution given an initial guess of the bequest distribution. I solve the model recursively from the last period of life to the first. In an outer loop, it iterates over the bequest distribution until convergence.

- *Set 0, Initialization*: I begin by loading the necessary input data (parameters, data moments, mortality matrix, etc.), initializing grids and empty matrices, and drawing random numbers for the simulation. I set the initial bequest distribution to a predetermined value.

- *Step 1, Solve the Household Problem*: First, I compute the optimal decision in both states–adjusting commitments and not adjusting them. For each state, I solve for nondurable expenditure, risk-free assets, and, if adjusting, commitment stock. Second, I determine the optimal adjustment decision.

- *Step 2, Update Population and Bequest Distributions*: I start by computing the distribution of households across states. To do this, I redistribute households across the state space by interpolating their asset and commitment positions and reallocating them to adjacent grid points. I also account for the shock-transition probabilities. Next, I use the population distribution to update the bequest distribution.

- *Step 3, Check for Convergence*: I evaluate the difference between the new and old bequest distributions. If convergence is achieved, I proceed to Step 4. Otherwise, I update the bequest distribution and return to Step 1.

- *Step 4, Simulate Household Behavior*: I simulate 5,000 households using the computed optimal decisions. I then compute the moments and perform regressions on the simulated data.

F Calibration Appendix

F.1 Income Profile Calibration

I calibrate the income process using an interactive procedure that selects the parameters to match model and empirical moments. In particular, I calibrate seven parameters to match twenty-seven moments. Those moments are divided into big groups: (i) cumulative income growth measured over different ages, (ii) variance of log income over different ages, (iii) autocovariance of log income for two age intervals, (iv) income growth volatility over a 2-year horizon, (v) income inequality, and (vi) forecast errors over different horizons.

Differently from the previous literature, I focus on moments that capture an important fact in my model: the predictability of income. I compute forecast errors similarly to what I do in my empirical exercise. I forecast income regressing log income on a polynomial in age, dummies for fixed effects, and a two-year lag of log income. The fixed effects enter as categorical dummies and capture observable heterogeneity, analogous to how education, occupation, and other demographic characteristics are used in empirical estimations. I use a two-year lag to mimic the biennial structure of the PSID, and I linearly interpolate income for odd years. I use forecast errors for 2, 4, 6, and 8 periods ahead to compute the moments used in the calibration.

The calibrated parameters include the variance and persistence of the fixed effect, the variance and persistence of persistent income shocks, the variance of transitory income shocks, and two parameters that determine the concavity of the deterministic income profile. Table Tables F1 and F2 and F3 show the income parameters and the moments.

Algorithm

I follow an iterative procedure for calibrating the income process:

- *Stage 0: Initialization* - I set the parameters governing the timing of life-cycle events and the dimensions of the income shock grids. I draw the shocks to be used in the simulation.
- *Step 1: Initialize Parameters* – I make an initial guess for the parameters governing the income process, including the persistence of the fixed-effect process.
- *Step 2: Simulate the Income Process* – I simulate income for parents and children. The parental fixed effect is sampled from a stationary distribution. The child's fixed effect is sampled from a distribution conditional on the parental fixed effect.
- *Step 3: Estimate the IGE* – I use the simulated income process to estimate a rank-rank regression and measure intergenerational income elasticity (IGE).

- *Step 4: Calibrate the IGE* – If the difference between the model-implied and empirical IGE exceeds the tolerance criteria, I update the persistence of the fixed effect and return to Step 3. I use the IGE estimate from Chetty et al. (2014) as a reference, 0.341. If the difference falls below the tolerance threshold, I proceed to Step 5.

- *Step 5: Compute Income Moments* – Given the calibrated IGE, I simulate income for the children and compute various income-related moments.

- *Step 6: Compare Model and Data Moments* – I compare the simulated moments to empirical data. If the distance exceeds the tolerance criteria, I return to Step 1 and update all parameter guesses. I repeat the process until the distance is minimized.

Income Process Results

Table F1 compares the model and data moments regarding moments on the income distribution. I compare the model and data regarding the forecastability of income below.

Overall, the process matches the moments regarding income distribution well, especially since it is overidentified. The first three rows indicate that cumulative income growth follows a concave pattern in the data and simulation, but the process overstates this concavity. In particular, the process matches the 10-year cumulative growth, overpredicts the 20-year growth, and underpredicts the 30-year growth. The next four rows indicate that the variance of log income increases over the life cycle, yet the process incorrectly predicts a concave pattern. Specifically, it underestimates the 1-year variance, matches the 20-year variance well, and underpredicts the 30-year variance. In contrast, it closely matches the overall variance of log income. The subsequent two rows report income autocovariance at two- and four-year intervals, where the process consistently predicts values nearly half of those observed in the data. The penultimate row shows that the process significantly overpredicts the standard deviation of income growth. Finally, the process predicts a marginally larger Gini inequality than that of the data.

In Table F2, I compare the model and data regarding income forecastability. The first panel shows the mean and standard deviation of the forecast errors for 2, 4, 6, and 8 years ahead. Both the mean and standard deviation were targeted in the calibration. The calibrated process predicts small and negative forecast errors, while they are small but positive in the data. The calibrated process predicts stable forecast errors across the forecast horizon, but they increase with the forecast horizon in the data. The second panel shows the constant and slope coefficient of the projection of ex-post income realization on the forecast. I target only the slope coefficient since the constant captures differences in the units of the income variable. The model matched the slope well. The third panel shows the constant and slope coefficient of an IV regression of ex-post income realization on the forecast, using lagged income and fixed-effects dummies as instruments. Again, I target only the slope coefficient. The model matched the slopes well.

Table F1: Income Moments: Model vs. Data

Moments	Model	Data
10-year income growth	1.623	1.621
20-year income growth	1.930	1.783
30-year income growth	1.550	1.713
Variance log income at 1-year	0.425	0.627
Variance log income at 10-year	0.666	0.712
Variance log income at 20-year	0.740	0.739
Variance log income at 30-year	0.643	0.833
Variance log income	0.650	0.683
Autocov log income (t, t-2)	0.450	0.863
Autocov log income (t, t-4)	0.448	0.782
Std dev log income growth (t, t-2)	0.643	0.186
Gini Inequality	0.466	0.420

Table F2: Income Forecastability: Model vs Data

Moments	Model		Data	
	Mean	Std	Mean	Std
2-period Ahead	-0.010	0.456	0.010	0.560
4-period Ahead	-0.009	0.458	0.020	0.650
6-period Ahead	-0.008	0.460	0.020	0.710
8-period Ahead	-0.008	0.460	0.020	0.750

Moments	Model		Data	
	Constant (n.t.)	Slope	Constant (n.t.)	Slope
2-period Ahead	-0.026	1.025	-0.060	1.010
4-period Ahead	-0.029	1.029	0.100	1.000
6-period Ahead	-0.031	1.034	0.480	0.960
8-period Ahead	-0.034	1.038	0.900	0.920

Moments	Model		Data	
	Constant (n.t.)	Slope	Constant (n.t.)	Slope
2-period Ahead	-0.042	1.003	-1.400	1.130
4-period Ahead	-0.021	1.290	-2.260	1.210
6-period Ahead	-0.030	1.279	-2.900	1.270
8-period Ahead	-0.032	1.290	-3.200	1.300

Note: n.t. refers to non-target moments

In Table F3, I show the calibrated parameters. The linear trend coefficient is estimated at 0.0764, indicating a positive but modest growth rate, while the quadratic trend coefficient is negative at -0.0020, suggesting a slight deceleration over time. The variance components reveal substantial heterogeneity, with the fixed-effect variance at 0.6674, far exceeding the transitory variance of 0.0391 and the persistent variance of 0.2584. This is important in my analysis since most of the heterogeneity in income is forecastable. The persistence parameter of 0.2090 suggests moderate autocorrelation in income shocks, while the intergenerational skill transmission parameter of 0.3984 reflects a stronger persistence across generations.

Table F3: Calibrated Income Parameters

Parameters	Description	Values
b_1	Linear trend	0.0764
b_2	Quadratic trend	-0.0020
$\sigma_{\bar{z}}$	Fixed-effect variance	0.6674
σ_ϵ	Transitory variance	0.0391
σ_ν	Persistent variance	0.2584
ρ	Persistence parameter	0.2090
$\rho_{inherit}$	Pers. of intergen. skill transmission	0.3984

Alternative Parameters

To understand how the target moments would change if the income process were calibrated with a high-income persistent parameter, I present how the income moments look using the parameters of Aguiar and Hurst (2013). This exercise aims to understand what a different calibration looks like and not criticize their paper, which uses different data, moments, and questions. They calibrate the same income process but differ in the moment target in the calibration. They use income data to estimate the common deterministic component of wages and the initial cross-sectional variance. They calibrate the remaining parameters of the distribution of income shocks and other model parameters using the consumption data.

The two sets of calibrated income parameters are significantly different. My calibration recovers greater heterogeneity in observable fixed effects and stronger yet less persistent income risk. In particular, the fixed-effect variance is larger in my calibration (0.6674 vs. 0.1660), indicating greater cross-sectional observable heterogeneity. The persistence of income shocks is drastically lower in my calibration (0.2090 vs. 0.9770) but has a higher variance (0.2584 vs. 0.0180). The stationary standard deviation of the stationary persistent process is higher in the alternative calibration. The linear and quadratic trends in income growth are steeper in my calibration, indicating stronger curvature in life-cycle income dynamics. Lastly, transitory income shocks and the persistence of intergenerational skill transmission are lower in my calibration.

Table F4: Calibrated Income Parameters, Aguiar and Hurst (2013)

Parameters	Description	Values
b_1	Linear trend	0.0300
b_2	Quadratic trend	-0.0007
$\sigma_{\bar{z}}$	Fixed-effect variance	0.1660
σ_ϵ	Transitory variance	0.1190
σ_ν	Persistent variance	0.0180
ρ	Persistence parameter	0.9770
$\rho_{inherit}$	Pers. of intergen. skill transmission	0.6642

Tables F5 and F6 show the moments implied by the alternative calibration. The alternative calibration predicts lower income variability than my calibration. However, it does not do better than my calibration for any moment. In particular, the alternative calibration predicts a slope coefficient that increases from 1 to 10 as the forecast horizon increases in the IV regression shown in the last panel of Table F6, while in the data, these numbers marginally increase from 1 to 1.3. My calibration better matches these moments.

Figures F1 and F2 show the implications of different calibrations. First, my baseline calibration implies more dispersed income, as seen in the comparison between groups. Second, my calibration implies that the labor component of permanent income is more predictable. In particular, I show this by estimating the labor component of permanent income in the simulated data and comparing it with the true permanent income, which is observed in the model.

Table F5: Income Moments: Model vs. Data, Aguiar and Hurst (2013)

Moments	Model	Data
10-year income growth	1.302	1.621
20-year income growth	1.478	1.783
30-year income growth	1.454	1.713
Variance log income at 1-year	0.154	0.627
Variance log income at 10-year	0.283	0.712
Variance log income at 20-year	0.350	0.739
Variance log income at 30-year	0.360	0.833
Variance log income	0.312	0.683
Autocov log income (t, t-2)	0.221	0.863
Autocov log income (t, t-4)	0.212	0.782
Std dev log income growth (t, t-2)	0.434	0.186
Gini Inequality	0.324	0.420

Table F6: Income Forecastability: Model vs Data, Aguiar and Hurst (2013)

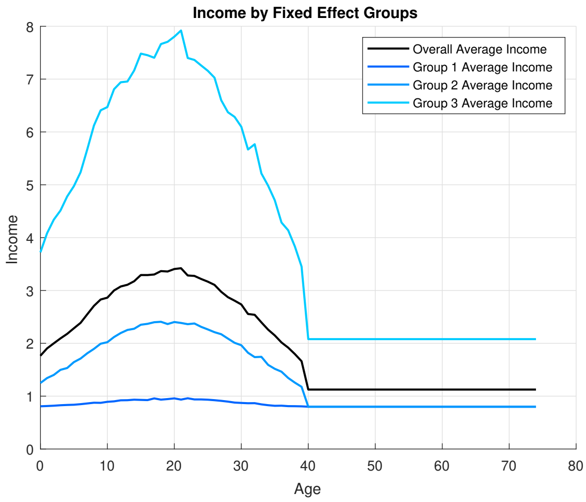
Moments	Model		Data	
	Mean	Std	Mean	Std
2-period Ahead	-0.000	0.388	0.010	0.560
4-period Ahead	0.000	0.418	0.020	0.650
6-period Ahead	0.000	0.449	0.020	0.710
8-period Ahead	0.000	0.470	0.020	0.750

Moments	Model		Data	
	Constant (n.t.)	Slope	Constant (n.t.)	Slope
2-period Ahead	-0.000	1.000	-0.060	1.010
4-period Ahead	-0.046	1.128	0.100	1.000
6-period Ahead	-0.048	1.132	0.480	0.960
8-period Ahead	-0.036	1.098	0.900	0.920

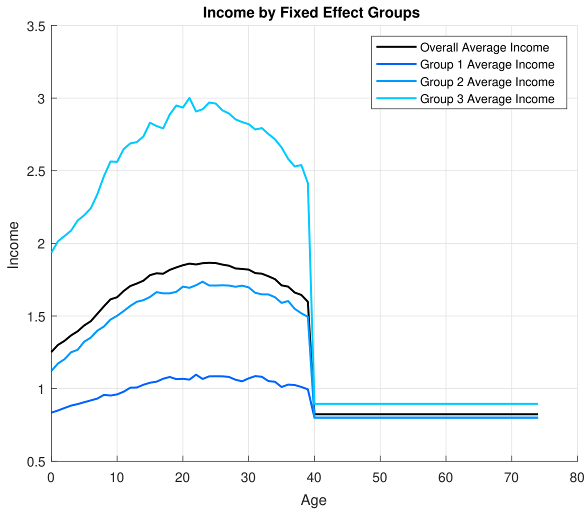
Moments	Model		Data	
	Constant (n.t.)	Slope	Constant (n.t.)	Slope
2-period Ahead	-0.000	1.014	-1.400	1.130
4-period Ahead	0.057	3.045	-2.260	1.210
6-period Ahead	0.106	5.754	-2.900	1.270
8-period Ahead	0.177	10.921	-3.200	1.300

Note: n.t. refers to non-target moments

Figure F1: Consumption's Responses to Permanent Income – Data and Model

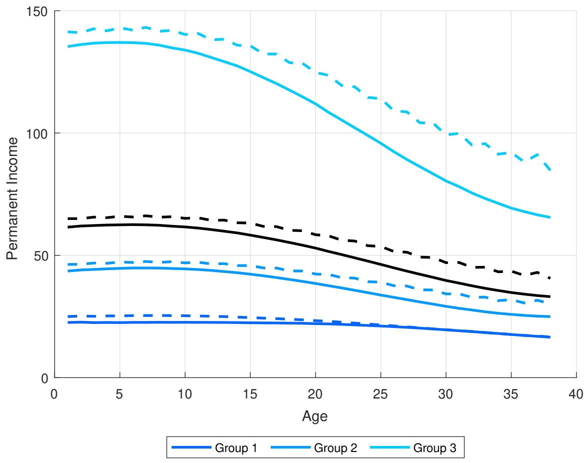


(a) Baseline Calibration

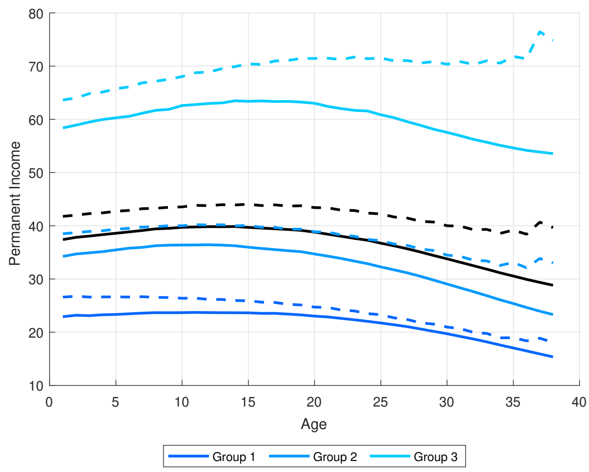


(b) Alternative Calibration

Figure F2: Estimated Permanent Income – Alternative Calibration



(a) Baseline Calibration



(b) Alternative Calibration

Note: In the figure, the dashed lines represent the estimated permanent income, while the solid lines represent permanent income. In the plot, it is only the labor component of permanent income, excluding assets.

F.2 Other Moments

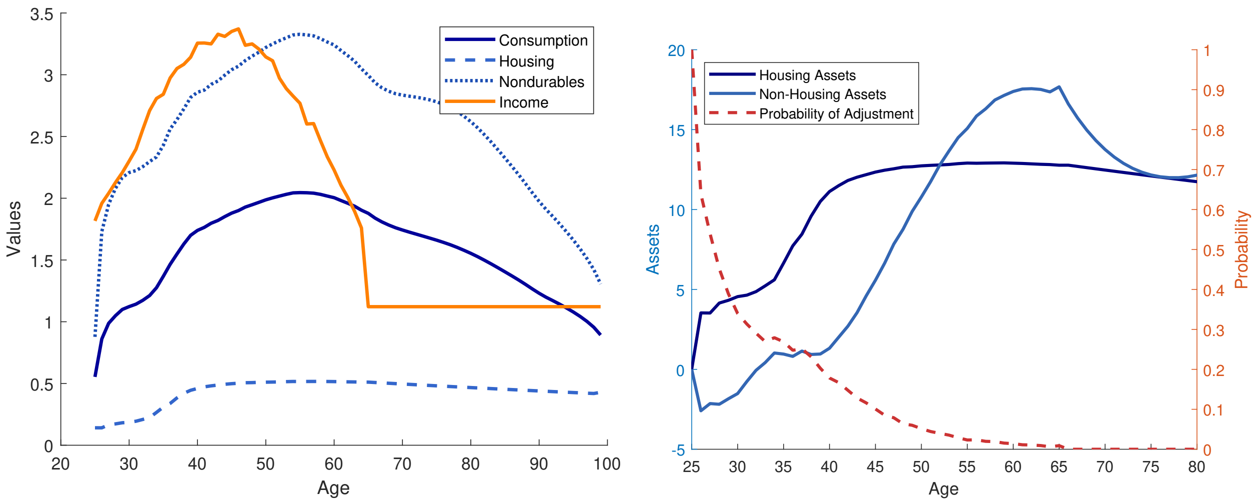
Life-Cycle Profiles

To complete the description of the quantitative results, I present other outcomes of the model that were not included in the main analysis. In particular, Figure F3 shows the average life-cycle profiles, and Figure F4 shows the leverage histograms.

Figure F3, Panel A, shows that the aggregate goods consumption profile is hump-shaped, peaking when households are around 50. Also, the consumption profile is smoother than income. The housing consumption profile is mostly flat throughout the life cycle, while nondurable consumption fluctuates more and tracks income more closely. Nondurable consumption declines sharply after its peak at 50, whereas housing consumption remains stable. Consequently, the importance of housing in the average household bundle increases over the life cycle. This pattern is also observed in the PSID data.

Figure F3, Panel B, shows the average asset profiles. Households first accumulate housing assets and hold negative liquid assets early in their life cycle. As households age, they first pay off their debts and then accumulate positive liquid assets. After retirement, households do not consume all their wealth; on the contrary, they consume some of their liquid assets while continuing to hold their housing. Panel B also shows a decrease in the average probability of moving over the life cycle. In the model, almost no household moves after retirement.

Figure F3: Mean Life-Cycle Profiles

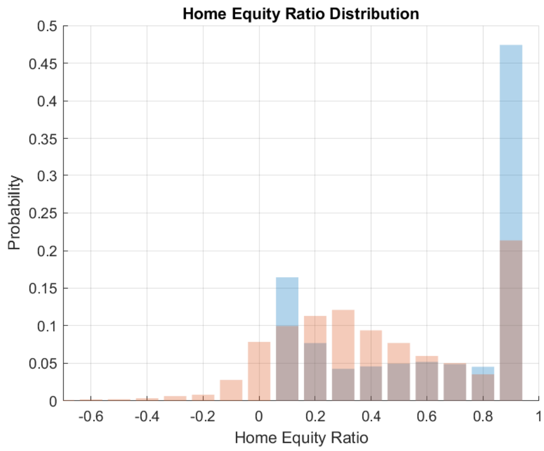


(a) Life Cycle

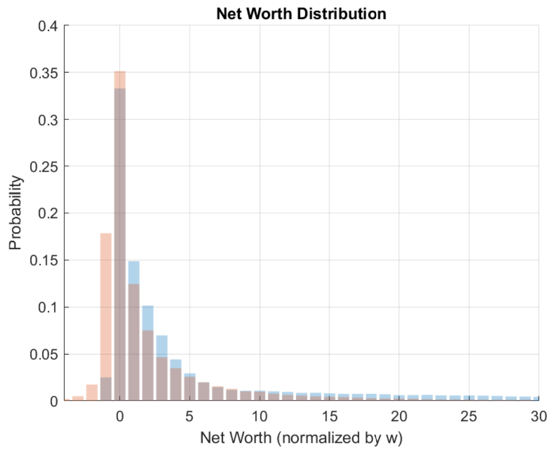
(b) Assets

Figure F4 shows the leverage histograms in the model. Panel A shows that households hold more positive home equity (shaded in blue) than in the data (shaded in red). Also, the data show households with negative home equity, which is not allowed in the model. Panel B shows that, even though the model has a simple financial structure, it captures leverage in the data relatively well. Again, the model does this even though negative leverage is not allowed. Also, because negative leverage is not allowed, the model overpredicts the distribution of households in the upper tails of the distribution.

Figure F4: Mean Life-Cycle Profiles



(a) Home Equity



(b) Net Worth

G Counterfactual Appendix

G.1 Alternative Calibration

To assess the ability of my quantitative model to account for the novel facts documented in Section 3 and to generate aggregate distributions, I perform counterfactual analyses in Sections 6 and 7. In particular, I individually shut down certain model features, such as luxury late-in-life consumption and consumption commitments, and recalibrate β to keep the baseline wealth-income ratio. I provide details on the homothetic calibration and other counterfactuals in this appendix.

Table G1 shows the different sets of parameters used in the counterfactual analyses. Column 1 repeats the baseline calibration, while Columns 2, 3, and 4 show the calibration of the model with only borrowing constraint, luxury-late-in-life consumption, and consumption commitments, respectively. Three parameters are kept constant in all calibrations: the bequest weight ϕ, the consumption aggregator ω, and the goods' elasticity of substitution γ. Five parameters change in the counterfactual calibrations, one of those the β, which is set to match wealth-to-income ratios.

- In the calibration with only borrowing constraints, I shut down consumption commitments $\kappa = 0$ and calibrate all preference parameters to the same number $\sigma_0^c = \sigma_R^c = \sigma^b = 2.5$.
- In the calibration with only luxury-late-in-life consumption, I shut down consumption commitments $\kappa = 0$ and calibrate the preference parameters $\sigma_0^c = 11$, $\sigma_R^c = 1.1$, and $\sigma^b = 2.5$ following Straub (2019).
- In the calibration with only consumption commitments, I keep consumption commitments $\kappa = 0.40$ and bequest preference $\sigma^b = 0.57$ and shut down luxury-late-in-life consumption $\sigma_0^c = \sigma_R^c = 2.5$.

Table G1: Parameters of the Counterfactual Analysis

Parameters	Description	Baseline	Borrowing Constraint	Luxury late-in-life	Commit.
β	Discount factor	0.84	0.97	0.78	0.74
$\sigma_{c,25}$	CRRA for consumption when young	4.09	2.50	11.00	2.50
$\sigma_{c,R}$	CRRA for consumption when retired	1.10	2.50	1.10	2.50
σ_b	CRRA for bequest	0.57	2.50	2.50	0.57
ϕ_1	Bequest preference (weight)	4.72	4.72	4.72	4.72
ω	Consumption aggregator	0.20	0.20	0.20	0.20
γ	Goods Elasticity of Substitution	-0.26	-0.26	-0.26	-0.26
κ	Adjustment cost	0.40	0.00	0.40	0.00

Table G1 shows the target moments used to calibrate in the counterfactual economies.

Table G2: Moments of the Counterfactual Analysis

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