The Hidden Interaction Between Household Consumption and Advance Information about Future Income

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Abstract

We study how advance information about future labour income affects current household consumption. Using data from the Panel Study of Income Dynamics, we find that working households adjust their current consumption in anticipation of future persistent income changes. Their positive consumption response indirectly confirms households' undocumented access to advance information. We construct a consumption-saving model and use it to map observed consumption response patterns into the unobserved probability of receiving future information ahead of time. Our estimation results suggest this probability has a baseline value and increases with current persistent income. Moreover, the consumption response to advance information is asymmetric and depends on the type of income change expected. We find that households with access to advance information are better self-insured against persistent income shocks than those without such information. Their consumption responses to persistent shocks are dynamic, with about 70% of the total adjustment occurring in the period when the information is first received. Finally, we show that the conventional covariance-based estimators of consumption insurance exhibit sizeable biases when advance information is ignored.

1 Introduction

The existence of advance information affects our understanding of the insurability of truly unanticipated income fluctuations. Traditionally, observed consumption changes are interpreted as primarily reflecting contemporaneous income changes, therefore serving as a measure of consumption "insurability" to income shocks. This interpretation has lead to a rich literature studying how well individuals can insure their consumptions given available resources. Many studies find that households are moderately insured against persistent changes in their income and are very well insured against transitory shocks (Blundell, Pistaferri, and Preston (2008)).

These results on consumption insurance rely on a key assumption that households have no advance information about future income change, which indirectly restricts consumption behaviours. This powerful assumption enables a covariance-based identification strategy and the subsequent linkage between structural models and empirical data. Empirical examination of this assumption is challenging due to the lack of direct measurements of information from the household's perspective. Subjective expectation data can provide some insights into household's income expectations at the time of survey but due to its limited availability, the evidence on advance information affecting consumption choices remains ambiguous (Kaufmann and Pistaferri (2009)). Tests based on auto-covariances generally have low statistical power and are susceptible to measurement errors in survey data (Blundell, Pistaferri, and Saporta-Eksten (2016)). Thus, Identifying the existence of advance information would require a different approach.

We address the challenge of missing measures on household information sets through an indirect approach. If advance information about future income changes enter a rational household's information set, economic theory suggests that risk-averse households will use such information about the future to improve inter-temporal consumption smoothing. Thus, consumption choices today can be viewed as dynamic outcomes influenced by both current and future incomes. A positive statistical relationship between current consumption and future income fluctuations provides evidence of household's endogenous use of short-term foresight in their decision-making, and naturally implies to their possession of such advance information.

The basis of our empirical approach is an empirical consumption function that includes current and future income components as control variables, along with other observed household characteristics. We show that this empirical consumption function can be non-parametrically identified and estimated using a nonlinear panel framework based on Arellano, Blundell, and Bonhomme (2017). Using a long panel of household consumption and labour incomes from Panel Study of Income Dynamics, we find that current consumption responds to short-term future persistent income changes in anticipation, and the response patterns display heterogeneity across several household characteristics. This supports the existence of advance information in the U.S. context during our sampling period. An interesting feature of consumption responses to advance information is the importance of unobserved income components in driving the heterogeneity in the magnitude. This helps resolve a common puzzle found in studies using subjective expectation data, which often no observed characteristics can be used to explain the ability of forming accurate income expectations.

Translating observed consumption responses into the underlying probability of receiving advance information requires a structural model. We construct an infinite-horizon, consumption-saving model with the possibility of receiving advance information to understanding the consequence of omitting this key factor. In our model, households' access to advance information is temporary and dynamic. The arrival of information is governed by an i.i.d information shock with shock probability is allowed to correlate with current persistent income, as suggested by our empirical findings. Our model and results contribute to the existing literature in three ways. *First*, we provide estimates of the probability of receiving advance information given the structure of our model. We find that households with higher persistent income are more likely to receive advance information than those with lower persistent incomes. *Second*, we show that households with access to advance information have a greater ability to self-insure against persistent income shocks, as evidenced by pass-through regressions. This effect is driven by the implicit selection arising from the positive correlation between the probability of receiving information and current persistent income levels. *Finally*, we demonstrate that the covariance-based consumption insurance estimator proposed by Blundell et al. (2008) produces inaccurate estimates in the presence of advance information. The insurance coefficient for persistent shocks is understated by up to 25%, while the degree of insurance against transitory shocks is mildly overstated by around 5%. Both biases stem from the restriction on the dynamics of consumption responses to income shocks imposed by the "no advance information" assumption.

Our findings are based on the extensive application of a general nonlinear income process.

The canonical permanent-transitory income process used in existing work assumes the income persistence is valued at one and applies for all household, irrespective of their current income states or histories. We find this form of income dynamics is hard to reconcile with the U.S. data. More importantly, the use of canonical income dynamics imposes a subtle rigidity: households must view the arrival of permanent shocks as having an unambiguous, one-to-one effects on their "permanent income". In contrast, the nonlinear income dynamics is very flexible and allows for heterogeneity in income persistence, enabling households to correctly interpret the effects of persistent shocks on their long-term incomes given their current states.

This study directly relates to existing literature on advance information. Many earlier studies tested the existence of advance information using household panel data. Blundell et al. (2008) and Blundell et al. (2016) are two influential examples where they performed covariance-based tests on PSID data. Guvenen and Smith (2014) examine long-term foresight on after-tax income and show that workers can learn about their future income growth when they first enter the labour market. Interest in advance information has grown in recent years: Stoltenberg and Singh (2020) highlight the interactive role of advance information with various insurance market structures. Pedroni, Singh, and Stoltenberg (2022) shows that current consumption growth is significantly and positively correlated with future income growth rate when current income growth is properly controlled for. Pistaferri (2001) and Kaufmann and Pistaferri (2009) use subjective expectation data from Italy and find supporting evidence of advance information in consumption growth with limited explanatory power. There are also on-going efforts on collecting and constructing a larger and longer subjective expectation panel in Denmark, namely the *Copenhagen Life Panel* of Caplin, Gregory, Lee, Leth-Petersen, and Sæverud (2023) which are not currently available for public use. This study also relates to recent advancements in modelling and estimating complex income processes. Recent progress including approximating the distribution of income shocks using mixtures of non-Guassian distributions (Guvenen, Ozkan, and Madera (2024), Guvenen, Karahan, Ozkan, and Song (2021)), as well as allowing for history-dependent, quantile-specific persistence of shocks (Arellano, Blundell, Bonhomme, and Light (2023)).

We organize this paper as follows. Section 2 presents the empirical framework used to indirectly test the existence of advance information based on a nonlinear method and panel data, with Section 2.6 reporting the empirical results. Section 3 introduced our infinite-horizon consumption-saving model with details on parameterization, solution and estimation. Consumption behaviours under advance information are characterized in Section 3.4. Section 3.5 investigates the differences in the degree of consumption insurance between households with or without advance information. The origin and extent of biases found in existing consumption insurance estimators are illustrated in Section 3.6. Section 4 discusses policy implications. Section 5 concludes.

2 Empirical evidences on advance information

Due to the lack of observable measures on anticipated future income from household's perspective, finding supporting evidences for advance information is a challenging first step. We take an indirect approach by examining whether current household consumption responds in anticipation to future persistent labour income shocks prior to its realization. Household consumption is modelled as a non-parametric function of assets and latent income components, such that a statistically significant consumption response would indicate the presence of advance information in households' information set. We discuss in detail the design of the empirical consumption function and steps taken to ensure reliable estimation in the presence of unobserved income components.

2.1 Empirical consumption function

We start by modelling household consumption choices as a function of future labour income components to understand the influence of advance information. The theoretical background is a life-cycle model in which each household acts as a single agent making consumption and saving decisions. Markets are incomplete with one-period, risk-free bonds as the saving option. We assume there is no aggregate uncertainty so that all uncertainty is idiosyncratic. Household labour income is modelled as sum of two orthogonal components: a persistent component that displays serial correlation over time, and a transitory component with only contemporaneous effects. In a standard setting, a household's period-t information set would contain only current assets and current income components as future information is assumed away. We extend this by including one-period-ahead persistent income in households' information sets to account for the potential presence of advance information. This form of advance information can be considered as a "short-term foresight" (Kaplan and Violante (2010)), which differs from long-term foresight regarding future income growth, such as heterogeneous income profiles (Guvenen and Smith (2014)).

Given our setup, households' optimal consumption decision in period t is a function of all state variables contained in their information set:

$$C_{i,t} = G_t(A_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \eta_{i,t+1}) \tag{1}$$

where $A_{i,t}$ is current asset, $\eta_{i,t}$ is the current persistent income component, $\varepsilon_{i,t}$) is the current transitory income components. The key variable of interest is $\eta_{i,t+1}$, the one-period-ahead persistent income component representing the influence of advance information to consumption decisions. $G_t(.)$ is a nonlinear function capturing the complex interactions among between its arguments. Clearly, household consumption is the outcome of a dynamic model with time-varying covariates that evolve according to their respective processes. The inclusion of current persistent income $\eta_{i,t}$ as a control variable in the consumption function is necessary for two reasons. First, consumption adjustments in response to $\eta_{i,t}$ at the time of shock realization measures the degree of self-insurance against income shocks, an object of policy interest. Second, current persistent income $\eta_{i,t}$ is used to control for the effect of income expectation on household consumption decisions, such that consumption response to $\eta_{i,t+1}$ correctly reflects knowledge of future income beyond the content of rational expectation. We provide additional remarks in later part of this section.

Consumption dynamics are heavily influenced by the nature of income risks. We model the observed household labour income $Y_{i.t}$ using the following structure:

$$Y_{i,t} = \kappa_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $\kappa_{i,t}$ is the deterministic part of labour income that can be explained by observed household characteristics (such as age, education, family size, etc.). The remaining part of labour income is stochastic and modelled as a sum of a persistent and a transitory income component. The persistent income component $\eta_{i,t}$ is modelled to follow a first-order general Markov process:

$$\eta_{i,t} = \rho_t(\eta_{i,t-1}, u_{i,t})\eta_{i,t-1} + u_{i,t} \tag{3}$$

where ρ_t denotes income persistence and $u_{i,t}$ denotes the persistent income shock. In this income model, $\rho_{i,t}$ is a nonlinear function of previous persistent income $\eta_{i,t-1}$ and current persistent shock $u_{i,t}$, which can take up values between zero and one. This implies that we can effectively nest both the stationary first-order autoregressive case and the unit-root case using a single function. The introduction of nonlinear persistence is crucial as there are growing evidences suggest that income shocks can affect income persistence through nonlinear interactions (Arellano et al. (2017)) and these interactions is an important mechanism explaining empirical consumption inequality patterns (De Nardi, Fella, and Paz-Pardo (2020)). From the households' perspective, they would internalize the fact that income persistence is nonlinear and dynamic, such that the same piece of advance information could provide different implications to their future incomes given the stage of their life-cycle and the history of income events. The transitory income component $\varepsilon_{i,t}$ is assumed to be independent and identically distributed ($i.i.d.$), follows a stationary distribution and displays no persistence over time.

Average consumption responses to advance information are represented using derivative effects. Given the nonlinear consumption function G_t, a small change in household's future persistent income is associated with an adjustment in their current consumption by an average amount of:

$$\mathbb{E}\left[\frac{\partial C_{i,t}}{\partial \eta_{i,t+1}}\right] = \mathbb{E}\left[\frac{\partial G_t(A_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \eta_{i,t+1})}{\partial \eta_{i,t+1}}\right] \tag{4}$$

where the average is taken between individual households with different values of control variables. Testing for the statistical significance of average consumption response can be regarded as a test on a hypothesis where advance information is affecting households' consumption decisions. This conjecture is based on the prediction of macroeconomic theory: rational and risk-averse households observing short-term foresight will incorporate this advance information in their decision making, due to welfare improvements from a better consumption smoothing and a more accurate perception about future income risks. In the meantime, our flexible specification of consumption function allows the average consumption response to be heterogeneous as the derivative effect itself is a function of family assets and income components.[1] We are interested in estimating and documenting the different magnitudes and patterns of consumption response to future persistent income driven by different observed and unobserved household characteristics.

[1] In the simplest case where consumption function is linear, this derivative effect reduces to a single regression coefficient associated to $\eta_{i,t+1}$, making the average response identical among all households.

In our empirical model, households' rational expectation about their future labour income is not considered as advance information. We define advance information as knowledges about future persistent income that are not included in one's income expectation by default. For example, a rational household would form the income expectation about next period's persistent income using its information set as $\mathbb{E}_t[\eta_{i,t+1}] = \mathbb{E}[\eta_{i,t+1}|\eta_{i,t}]$, where the first-order Markov property rules out the relevance of persistent income from earlier periods. Hence, our definition of advance information concerns prior knowledge of the difference $\eta_{i,t+1} - \mathbb{E}_t[\eta_{i,t+1}]$ in period t, reflecting early observation of future persistent income shock before its realization.

It is possible to consider an alternative way to structure our empirical consumption function with distinction between income expectation and advance information. Replacing the one-period-ahead persistent income $\eta_{i,t+1}$ with the following differences $\eta_{i,t+1} - \mathbb{E}_t[\eta_{i,t+1}]$, the alternative consumption function is:

$$C_{i,t} = \tilde{G}_t(A_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \eta_{i,t+1} - f_t(\eta_{i,t})) \tag{5}$$

where $\tilde{G}_t$ is a nonlinear function similar to G_t with a different set of variables as arguments, and $f_t(\eta_{i,t})$ represents the conditional expectation of $\eta_{i,t+1}$ at period t. Estimating this alternative consumption model $\tilde{G}_t$ would require complete specification on the conditional expectation function $f_t(.)$. Instead of applying extra structural assumptions on $f_t(.)$, our empirical consumption function G_t delivers quantitatively equivalent results by implicitly controlling for income expectation through the usage of $\eta_{i,t}$ as an argument in the consumption function alongside $\eta_{i,t+1}$. This approach avoids applying direct transformation on the income components and is analogue to the control function approach in linear regressions.[2]

2.2 Quantile representation and finite-dimensional approximation

In practice, we work with natural logarithm transformed variables and approximate the non-parametric consumption function using orthogonal polynomials. We start by transforming income, consumption and family asset into natural logarithms and remove the deterministic components by

[2]In theory, we can regard the difference $\eta_{i,t+1} - \mathbb{E}_t[\eta_{i,t+1}] = \check{f}_t(\eta_{i,t}, \eta_{i,t+1})$, such that our empirical consumption function should instead be $C_{i,t} = \check{G}_t(A_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \check{f}_t(\eta_{i,t}, \eta_{i,t+1}))$ with single-index restriction. Since non-parametric identification of G_t is feasible, applying the semi-parametric form $\check{G}_t$ may be restrictive.

separately regressing them on a vector of observed household characteristics and time indicators. Residuals from these regressions are our measures of income, consumption and assets, denoted using lower-case letters $\{y_{i,t}, c_{i,t}, a_{i,t}\}$ respectively. The empirical consumption function then takes residual log income and log assets as arguments:

$$c_{i,t} = g_t(a_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \eta_{i,t+1}, v_{i,t}) \tag{6}$$

where $v_{i,t}$ is an exogenous consumption shifter representing the part of consumption unexplained by our model. We assume that $v_{i,t}$ is independent and identically distributed and is orthogonal to other variables. We adapt a conditional quantile representation (Arellano et al. (2017)) for g_t where heterogeneities in consumption choices are captured through quantile-specific coefficients:

$$c_{i,t} = Q^c(\text{age}_{i,t}, a_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \eta_{i,t+1}, \tau),\ \tau \sim \mathcal{U}(0,1) \tag{7}$$

where the exogenous consumption shifter v_{it} is normalized without loss of generality to follow a standard uniform distribution. The conditional quantile function of consumption is set to be age-dependent rather than time-dependent, with the intention to better reflect life-cycle perspectives in household expenditure. The adaptation of quantile representation places restrictions on the form of heterogeneity in g_t and restricts the dimension of consumption shifter.

Following Arellano et al. (2023), we approximate the non-parametric consumption function using tensor products of lower-order Hermite polynomials:

$$Q^c(\text{age}_{i,t}, a_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \eta_{i,t+1}, \tau) = \sum_{k=0}^{K} b_k^c(\tau)\phi_k(a_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \eta_{i,t+1}, \text{age}_{i,t}) \tag{8}$$

where $b_k^c(\tau)$ are quantile-specific model coefficients associated to ϕ_k, the tensor products of Hermite polynomial of order k in asset, income components and age. The average consumption response to future persistent income is given by the partial derivative of conditional quantile function Q^c with respect to η_{t+1}, averaged over current assets, income components and age. We proceed in a similar manner to model other variables using quantile representations. The process for persistent income component is specified as:

$$\eta_{i,t} = Q^{\eta}(\eta_{i,t-1}, \tau) = \sum_{k=0}^{K} a_k^{\eta}(\tau)\phi_k(\eta_{i,t-1}, \text{age}_{i,t}) \tag{9}$$

where $\alpha_k^{\eta}(\tau)$ are quantile-specific coefficients and the persistent shock $u_{i,t}$ is normalized to follow a standard uniform distribution. This specification accommodate the nonlinear income persistence which varies depending on the value of previous persistent income, the rank of current persistent income, and age. In this setting, the exact magnitude of persistent income shock is less meaningful since only its relative magnitude (i.e. rank) directly influences income persistence. The transitory income components is modelled using an age-dependent quantile function:

$$\varepsilon_{i,t} = Q^{\varepsilon}(\text{age}_{i,t}, \tau) = \sum_{k=0}^{K} a_k^{\varepsilon}(\tau)\phi_k(\text{age}_{i,t}) \tag{10}$$

such that the extent of age-dependence $a_k^{\varepsilon}(\tau)$ can vary with the magnitude of transitory shocks. Asset accumulation is modelled as "predetermined" to satisfy identification requirements:

$$a_{i,t+1} = Q^{a}(a_{i,t}, c_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \text{age}_{i,t}, \tau) = \sum_{k=0}^{K} b_k^{a}(\tau)\phi_k(a_{i,t}, c_{i,t}, \eta_{i,t}, \varepsilon_{i,t}, \text{age}_{i,t}) \tag{11}$$

The standard asset rule implied by the binding budget constraint $a_{t+1} = (1+r)a_t + \eta_t + \varepsilon_t - c_t$ is a special case when Q^a is linear and age-independent. Linearity in asset accumulation is not enforced in identification or estimation.

Initial conditions for assets and income components are modelled separately using additional control variables. Initial asset is specified as a quantile function of age (when entering the sample), the level of education and birth cohort:

$$a_{i,1} = Q_{a_1}(\text{age}_{i,1}, \text{educ}_{i,1}, \text{cohort}_{i,1}, \tau) = \sum_{k=0}^{K} b_k^{a_1}(\tau)\phi_k(\text{age}_{i,1}, \text{educ}_{i,1}, \text{cohort}_{i,1}) \tag{12}$$

Since initial assets are likely strongly tied to past income histories which lie outside the sampling window, we adopt a similar setup for initial persistent income component:

$$\eta_{i,1} = Q_{\eta_1}(\text{age}_{i,1}, \text{educ}_{i,1}, \text{cohort}_{i,1}, \tau) = \sum_{k=0}^{K} a_k^{\eta_1}(\tau)\phi_k(\text{age}_{i,1}, \text{educ}_{i,1}, \text{cohort}_{i,1}) \tag{13}$$

Therefore, there are two sets of model coefficients need to be identified and estimated: $\{a_k^{\eta}, a_k^{\eta_1}, a_k^{\varepsilon}\}$ are related to the nonlinear income process, and $\{b_k^c, b_k^a, b_k^{a_1}\}$ are related to consumption and asset functions.

Conditioning. Series estimation based on orthogonal polynomials requires proper conditioning to ensure good numerical performance (Hansen (2022)). Hermite polynomials used in the empirical specification has a weighting function with its support as the standard normal density on $(-\infty, \infty)$. Therefore, we rescale all residual log-transformed variables (income, consumption, asset) and age to have mean zero and variance one. This normalization is performed prior to the construction of polynomials.

2.3 Identification of income and consumption functions

The non-parametric identification of average consumption response to advance information can be established when panel data on income, consumption and asset are available. We assume that income transition is independent to consumption and saving choices, such that income process is exogenous from household's perspective. This procedure involves multiple steps: we begin by identifying the income process using income data alone, then proceed to identify the consumption model and derivative effects using the joint data. Using income and consumption panel data jointly to study consumption dynamics is gaining popularity due to increased availability of panel data and improvements on panel estimation techniques.

Identification of the income process builds on existing works on panel measurement error model. Net of the deterministic component κ, observed labour income Y can be viewed as a mis-measured version of the true persistent component η with an additive *i.i.d.* measurement error ε. With repeated measurements and the first-order Markov assumption, the joint distribution of persistent and transitory income can be identified non-parametrically as shown in Arellano et al. (2017). The introduction of advance information does not affect the identification of income process, since it does not alter the way income transitions occur over time.

Identification of average consumption response relies on proper identification of joint distribution of consumption, income components and assets. Let $f(.)$ be the generic notation for conditional probability density function and let $z_i^t = \{z_{i,1}, z_{i,2}, \dots, z_{i,t}\}$ denoting a sequence of variables from time 1 to time t. Our goal is to first identify the conditional distribution of consumption $f(c_t|a_t, y_t, \eta_t, \eta_{t+1})$ given household panel data on $\{c, a, y\}$ and latent income components (η, ε). The identification of conditional quantile of consumption and its response follows. We impose the following assumptions for identifying the consumption function:

Assumption 1. *For all $t \geq 1$,*

(i) independence of current and future income shocks: $u_{i,t+s}$ and $\varepsilon_{i,t+s}$ are independent of a_i^t, η_i^{t-1} and y_i^{t-1} for all $s \geq 0$; the initial condition $\varepsilon_{i,1}$ is independent of $a_{i,1}$ and $\eta_{i,1}$ [3];

(ii) asset accumulation is first-order Markov: $a_{i,t+1}$ is independent of $(a_i^{t-1}, c_i^{t-1}, y_i^{t-1}, \eta_i^{t-1})$ conditional on $(a_{i,t}, c_{i,t}, y_{i,t}, \eta_{i,t})$ [4];

(iii) independence of consumption shifter: $\nu_{i,t}$ is independent of $\eta_{i,1}$, $(u_{i,s}, \varepsilon_{i,s})$ for all s, $\nu_{i,s}$ for all $s \neq t$ and a_i^t;

The argument proceeds sequentially and start with first period assets:

$$f(a_1|y) = \int f(a_1|\eta_1, y_1) f(\eta_1|y)\, d\eta_1 = \int f(a_1|\eta_1) f(\eta_1|y)\, d\eta_1 \tag{14}$$

where we have applied assumption (i) that conditional on η_1, $f(a_1|\eta_1, y)$ coincides with $f(a_1|\eta_1)$ as future income shocks do not affect initial asset choices. The above integral can be viewed as an expectation:

$$f(a_1|y) = \mathbb{E}[f(a_1|\eta_{i,1})|y_i = y] \tag{15}$$

where the expectation is taken over the density of $\eta_{i,1}$ given the sequence y_i, for a fixed a_1. Provided the distribution of $(\eta_{i,1}|y_i)$ (which is identified from the income data) is complete, the density

[3] We implicitly allow $\eta_{i,1}$ to be arbitrarily dependent with $a_{i,1}$, as current assets may correlated with past income shocks that weren't available in the observed panel data.

[4] Note that different income components are allowed to affect assets differently. This model also holds when the interest rate r_t is time-varying and known to households.

$f(a_1|\eta_1)$ is identified. Applying assumption (i), the following joint density is also identified:

$$f(a_1, \eta_1|y) = f(a_1|\eta_1, y)f(\eta_1|y) = f(a_1|\eta_1)f(\eta_1|y) \tag{16}$$

Consequently, the joint distribution of persistent income components from period 1 and 2 can be identified given (16) and the Markov structure:

$$f(\eta_1, \eta_2|a_1, y) = f(\eta_2|a_1, \eta_1, y)f(\eta_1|a_1, y) = f(\eta_2|\eta_1)\frac{f(a_1, \eta_1|y)}{f(a_1|y)} \tag{17}$$

under completeness in $(y_{i,2}, \ldots, y_{i,T})$ of the distribution of $(\eta_{i,1}, \eta_{i,2}|y_i)$. Moving on to period 1 consumption and apply assumption (iii):

$$f(c_1|a_1, y) = \iint f(c_1|a_1, \eta_1, \eta_2, y_1)f(\eta_1, \eta_2|a_1, y)\, d\eta_1\, d\eta_2 \tag{18}$$

the conditional density of period 1 consumption $f(c_1|a_1, \eta_1, \eta_2, y_1)$ and the joint density

$$f(c_1, \eta_1, \eta_2|a_1, y) = f(c_1|a_1, \eta_1, \eta_2, y_1)f(\eta_1, \eta_2|a_1, y) \tag{19}$$

are both identified given (17), provided the distribution of $(\eta_{i,1}, \eta_{i,2}|a_{i,1}, y_i)$ is complete in $(y_{i,2}, \ldots, y_{i,T})$. The identification of consumption function for $t = 1$ follows, as $g_1(.)$ is the conditional quantile function of c_1, given a_1, η_1, η_2 and ε_1.

Now consider the asset from period 2. Apply assumption (i) and (iii):

$$f(a_2|c_1, a_1, y) = \iint f(a_2|c_1, a_1, \eta_1, \eta_2, y_1)\frac{f(c_1, \eta_1, \eta_2|a_1, y)}{f(c_1|a_1, y)}\, d\eta_1\, d\eta_2 \tag{20}$$

It follows that the density $f(a_2|c_1, a_1, \eta_1, \eta_2, y_1)$ can be identified, provided that the distribution of $(\eta_{i,1}, \eta_{i,2}|c_{i,1}, a_{i,1}, y_i)$ is complete in $(y_{i,2}, \ldots, y_{i,T})$. The joint density of a_2, η_1 and η_2:

$$f(a_2, \eta_1, \eta_2|c_1, a_1, y) = f(a_2|c_1, a_1, \eta_1, \eta_2, y_1)\frac{f(c_1, \eta_1, \eta_2|a_1, y)}{f(c_1|a_1, y)} \tag{21}$$

can also be identified given (19). Moving on to the period 2 consumption:

$$f(c_2|a_2, c_1, a_1, y) = \iint f(c_2|a_2, \eta_2, \eta_3, y_2) f(\eta_2, \eta_3|a_2, c_1, a_1, y)\, d\eta_2\, d\eta_3 \tag{22}$$

we can see that the identification of period 2 conditional density for consumption $f(c_2|.)$ depends on the identification of $f(\eta_2, \eta_3|.)$. Applying assumption (i) and the Markov property of persistent income components, we have:

$$f(\eta_2, \eta_3|a_2, c_1, a_1, y) = f(\eta_3|\eta_2) f(\eta_2|a_2, c_1, a_1, y) \tag{23}$$

As shown in Arellano et al. (2017), we can apply Bayes' rule to get:

$$f(\eta_2|a_2, c_1, a_1, y) = \int \frac{f(y|\eta_2, \eta_1, y_1) f(\eta_1, \eta_2|a_2, c_1, a_1, y_1)}{f(y|a_2, c_1, a_1, y_1)}\, d\eta_1 \tag{24}$$

Since we already identified $f(\eta_1, \eta_2|a_2, c_1, a_1, y_1)$ using (21), it follows that (24) and (23) can be identified accordingly. Since the Markov transition $f(\eta_3|\eta_2)$ is already identified using income data alone, the conditional density $f(c_2|a_2, \eta_2, \eta_3, y_2)$ is identified, provided that the distribution of $(\eta_{i,2}, \eta_{i,3}|a_{i,2}, c_{i,1}, a_{i,1}, y_i)$ is complete in $(c_{i,1}, a_{i,1}, y_{i,1}, y_{i,4}, \ldots, y_{i,T})$. Identification of the period 2 consumption model follows directly as it is the conditional quantile function of c_2 given a_2, η_2, η_3 and ε_2. By induction and repeatedly apply the assumptions for period 3 and onward, the joint density of income components, consumption and assets are identified, provided that the distributions of $(\eta_{i,t}, \eta_{i,t+1}|c_i^t, a_i^t, y_i)$ and $(\eta_{i,t}, \eta_{i,t+1}|c_i^{t-1}, a_i^t, y_i)$ are complete in $(c_i^{t-1}, a_i^{t-1}, y_i^{t-1}, y_{i,t+1}, \ldots, y_{i,T})$ for all $t \geq 1$.

The average consumption responses calculated as derivatives of consumption function can be identified regardless of the dimension of consumption shifter. Arellano et al. (2023) showed that the consumption function itself is identified up to a nonlinear transformation of a scaler shifter under monotonicity assumption. This is very intuitive as the conditions coincides exactly with the case of conditional quantile regression.

2.4 Estimation algorithm

Non-parametric estimation of income and consumption quantile functions with latent variables require iterative methods. We extend the iterative estimation algorithm designed by Arellano et al. (2023) where a statistical sampling method is implemented alongside non-parametric quantile regressions to provide candidate imputation values for unobserved control variables based on data likelihoods.

We use a finite-dimensional vector θ to index model coefficients related to the income components (a_k^{η}, $a_k^{\eta_1}$ and a_k^{ε}) and use another vector μ to index remaining model coefficients (b_k^c, b_k^a, $b_k^{a_1}$). Income-related coefficients are estimated first and we estimate the consumption function taking estimated income process as given. Coefficient restrictions implied by the income model is:

$$\bar{\theta} = \arg\min_{\theta} \mathbb{E}\left[\int R(y_i, \eta|\theta) f(\eta|y_i^{T_i}, \text{age}_i^{T_i}; \bar{\theta})\ d\eta\right]$$

where R is the quantile loss function, $\bar{\theta}$ is the set of true coefficients and $f(.)$ is the posterior density of unobserved persistent component η given household income data. Criterion function inside the expectation can be minimized using the following stochastic EM algorithm:

0. **(initialization)** starting with a parameter vector $\hat{\theta}^{(s)}$, $s \geq 0$

1. **(stochastic E-step)** For every household i, draw M parallel copies of sequences of persistent income components $\eta_i^{(m)} = (\eta_{i,t_i}^{(m)}, \dots, \eta_{i,T_i}^{(m)})$ from the posterior distribution $f_i(\eta_i^{T_i}|y_i^{T_i}, \text{age}_i^{T_i}; \hat{\theta}^{(s)})$, where $m = 1, \dots, M$ is the index for parallel draws, and T_i denotes data availability for household i given unbalanced panel

2. **(M-step)** Compute a new estimate $\hat{\theta}^{(s+1)}$ given M parallel draws of $\eta_i^{(m)}$ by minimizing:

$$\hat{\theta}^{(s+1)} = \arg\min_{\theta} \sum_{m=1}^{M} \sum_{i=1}^{N} R(y_i, \eta_i^{(m)}; \theta)$$

   where R is the quantile loss function calculated using draws from the stochastic E-step

We iterate between the above two steps for large number of times until the convergence of coefficient series $\hat{\theta}^{(s)}$. The identical algorithm is used in estimating consumption model. The posterior density in stochastic E-step and the criterion function in M-step are adjusted accordingly to match the consumption function specification.

The stochastic E-step is based on Sequential Monte Carlo (thereafter SMC, also known as sequential importance resampling) which is a statistical sampling technique. SMC is used when the posterior distribution has no known form or is very difficult to directly sample from. To illustrate this technique can provide reliable imputations for latent income variables, for now consider the income model and assume a likelihood function is available. Details on obtaining a closed-form likelihood function are provided in later part of this section. Our target is to produce valid draws from the posterior distribution of η given income data for each household i using SMC:

$$\eta^{T-1} \sim f(\eta_0, \ldots, \eta_{T-1} | y_0, \ldots, y_{T-1})$$

This is done sequentially. At $t = 0$, we initialize S particles (i.e. draws) as $\eta_0^{(s)}$[5] from a proposal distribution $\pi \sim \mathcal{N}(\mu_0, \sigma_0^2)$ and (μ_0, σ_0^2) are estimated from data. An adaptive resampling step is then applied to these particles: if the effective sample size is below a certain threshold (such that they looks as if they are drawn from the true posterior), we store existing particles for later use. Otherwise, we re-sample from existing particles with replacement using resampling weights w_0 calculated as $w_0^{(s)} \propto \frac{f(\eta_0^{(s)}|y_0)}{\pi(\eta_0^{(s)})}$, where π denotes the normal density function with mean and variance equal (μ_0, σ_0^2). The posterior f is approximated using sample likelihood. This resampling step corrects biases induced by the sampling procedure, as η_0's were drawn from the importance distribution $\pi(.)$ rather than the true posterior $f(.)$. In subsequent periods until $T-1$, new particles are generated from a normal proposal distribution $\pi \sim \mathcal{N}(\mu_t, \sigma_t^2)$, where (μ_t, σ_t^2) are estimated using data and previously generated particles. Adaptive re-sampling follows with resampling weights defined recursively as $w_t^{(s)} \propto \frac{f(\eta_{t+r}^{(s)}|y_{t+r}, \eta_{t+r-1}^{(s)})}{\pi(\eta_{t+r}^{(s)}|\eta_{t+r-1}^{(s)})} w_{t-1}^{(s)}$. Note that previously generated particles are not directly used as the starting point for subsequent periods. They only affect subsequent particles through two channels: (i) statistical properties of the proposal distribution (μ and σ^2) and (ii) recursive construction of resampling weights (i.e. $w_t \propto w_{t-1}$). The second channel is a key feature of SMC method. At the end, we have a sequence of persistent income for each household that approximately distributes as the true posterior density. They will be used in the M-step to update

[5] The s super-script indicates that η are generated in the s iteration. The previously mentioned m super-script indexing parallel draws still applies but are omitted here.

model parameters.

The SMC procedure for consumption model differs from the income model as advance information complicates the time aspects. For household i, our goal is to generate a sequence of η from the following posterior distribution given joint data:

$$\eta^{T-1} \sim f(\eta_0, \ldots, \eta_{T-1} | y^{T-1}, c^{T-2}, a^{T-1}, \text{age}^{T-1})$$

where $y^{T-1} = (y_0, y_1, \ldots, y_{T-1})$ denotes a sequence of variable y's from period 0 to period $T-1$. At $t = 0$, we aim to approximate a target distribution $f(\eta_0 | y_0, \text{age}_0)$. We initialize S particles of $\eta_0^{(s)}$ from a proposal distribution $\pi(\eta_0^{(s)}) \sim \mathcal{N}(\mu_0, \sigma_0^2)$ and resample with replacement using resampling weights: $w_0^{(s)} \propto \frac{f(\eta_0^{(s)} | y_0, \text{age}_0)}{\pi(\eta_0^{(s)})}$. This gives S particles approximately distributed as $f(\eta_0^{(s)} | y_0, \text{age}_0)$. At $t = 1$, we initialize a set of S particles of $\eta_1^{(s)}$ from a proposal distribution $\pi(\eta_1^{(s)} | \eta_0^{(s)}) \sim \mathcal{N}(\mu_1, \sigma_1^2)$ and resampled with replacement based on weights $w_1^{(s)} \propto \frac{f(\eta_1^{(s)} | y^1, c^0, a^1, \eta_0^{(s)})}{\pi(\eta_1^{(s)} | \eta_0^{(s)})} w_0^{(s)}$ and this gives S particles approximately distributed as $f(\eta_1^{(s)}, \eta_0^{(s)} | y^1, c^0, a^1)$. Using Bayes' rule, we approximate $t = 1$ conditional posterior as $f(\eta_1 | y^1, c^0, a^1, \eta_0) \propto f(y_1, c_0, a_1 | \eta_1, \eta_0) f(\eta_1 | \eta_0)$, using sample likelihood of $\{y_1, c_0, a_1\}$ given $\{\eta_0, \eta_1\}$ and the sample likelihood of η_1 given η_0 from the income model.[6] We repeat this sampling procedure for every subsequent periods $t \leq T - 1$. For example, we aim to approximate the following target distribution in period t: $f(\eta_t, \ldots, \eta_0 | y^t, c^{t-1}, a^t)$. We initialize S particles from a proposal distribution $\pi(\eta_t^{(s)} | \eta_{t-1}^{(s)}) \sim \mathcal{N}(\mu_t, \sigma_t^2)$, then resample with replacement based on weights $w_t^{(s)} \propto \frac{f(\eta_t^{(s)} | y^t, c^{t-1}, a^t, \eta_{t-1}^{(s)})}{\pi(\eta_t^{(s)} | \eta_{t-1}^{(s)})} w_{t-1}^{(s)}$. This yields S particles approximately distributed as the target posterior. At the end of SMC step, we have a sequence of valid draws of η-components, $\{\eta_{i,t_i}^{(s)}, \ldots, \eta_{i,T_i}^{(s)}\}$, for every household. In practice, this SMC method can be parallelized across households to accelerate the stochastic E-step, while alternative methods (such as Random Walk Metropolis-Hastings) do not support this feature.

The operation of the SMC technique in the stochastic E-step requires a likelihood function constructed from conditional density functions. We exploit the fact that conditional quantile function is the inverse function of conditional distribution function (c.d.f.), provided the c.d.f. is absolutely continuous and strictly monotonic. Consequently, the conditional density function can be calculated as the first derivative of the inverse of quantile function, evaluated at corresponding percentile

[6] These likelihood-based approximations are used empirically to construct the resampling weights as illustrated.

τ.[7] To ensure that the inverse of quantile function always exists, the dependencies between quantile coefficients (e.g. $a_k^\eta(\tau)$) and quantile locations τ are assumed to be piecewise linear in τ. The existing implementations of interpolating spline will produce multiple sets of quantile coefficients that are discrete in τ, therefore do not guarantee the existence of Q^{-1}. This additional piecewise linear assumption ensures Q^{-1} always exists and can be regarded as a finite-dimensional approximation to the true infinite-dimensional process (Wei and Carroll (2009)). Given the above specifications, the sample likelihood function has a closed-form and does not require numerical inversion of $Q(.)$ since $Q'(.)$ is a constant within each grid.

The M-step takes advantage of the quantile income and consumption functions. The minimization of criterion function R is equivalent to performing a conditional quantile function for each parallel draws of $\eta^{(m)}$ and averaging over them. Since θ and μ are parameter vectors, we perform conditional quantile regressions separately for each set of coefficients of interest. Each element in θ and μ is a collection of polynomial coefficients modelled as piecewise-polynomial interpolating splines on a grid $[\tau_1, \tau_2]$, $[\tau_2, \tau_3]$, ..., $[\tau_{L-1}, \tau_L]$ contained in the unit interval.[8] In simpler terms, we perform non-parametric quantile regressions at L quantile locations, and regression coefficients for income and consumption model will vary based on actual value of L. The rest of empirical setup largely follows Arellano et al. (2017), including tail parameter restrictions.

2.5 Data

Our panel dataset is constructed from a subset of households interviewed in the Panel Study of Income Dynamics (PSID). We use data from 2005 to 2021 (covering nine biannual PSID waves) as these waves provide consistent measurements on consumption categories, labour income and wealth. Beginning in 2005, PSID expands its coverage of household consumption items to include multiple types of food spendings, healthcare, transportation, home utility, clothing and recreational expenses. These updates make post-2005 PSID consumption coverages comparable to the Consumer Expenditure Survey (CEX) (Li, Schoeni, Danziger, and Charles (2010), Andreski, Li, Samancioglu, and Schoeni (2014)). Combined with information on household demographics, income and wealth,

[7] Under generic notations, we have: $f(x|y) = F'(x|y) = \left[Q^{-1}\right]'(x|y) = \frac{1}{Q'\left[Q^{-1}(x|y)\right]}$.

[8] For example, the function a_k^η is empirically implemented as $a_{\ell,k}^\eta \equiv a_k^\eta(\tau_\ell)$ with $1 \leq \ell \leq L$. These polynomial coefficients are designed to vary within each of the L grids, thus forming an interpolating spline.

Table 1: PSID Family Demographics, 2005-2021

	(1) 2005	(2) 2007	(3) 2009	(4) 2011	(5) 2013	(6) 2015	(7) 2017	(8) 2019	(9) 2021
HEAD									
Age	40.78	41.75	42.86	44.02	45.00	45.55	46.00	46.76	47.34
Years of education	14.30	14.26	14.27	14.28	14.28	14.30	14.34	14.45	14.54
Weeks employed	47.21	47.37	46.56	45.30	45.39	46.05	46.19	46.78	46.09
% in labour force	96.35%	95.55%	94.80%	91.86%	89.06%	90.52%	90.90%	90.37%	93.29%
% currently employed	94.70%	94.07%	89.70%	88.74%	86.22%	89.41%	88.12%	89.17%	91.08%
SPOUSE									
Age	39.32	40.26	41.32	42.46	43.46	44.10	44.58	45.36	45.95
Years of education	14.53	14.50	14.53	14.56	14.55	14.59	14.67	14.77	14.95
Weeks employed	37.75	37.18	38.12	36.27	36.57	37.64	37.48	38.77	37.53
% in labour force	73.03%	66.70%	69.72%	59.66%	63.22%	60.69%	62.00%	63.37%	69.24%
% currently employed	71.38%	64.89%	67.18%	57.75%	61.10%	59.57%	60.93%	62.57%	67.58%
Number of kids	1.28	1.23	1.21	1.17	1.14	1.16	1.23	1.27	1.26
% use SNAP	1.53%	1.68%	2.55%	3.30%	3.54%	3.07%	1.44%	1.07%	3.43%
Observations	849	1011	1097	1181	1270	1076	901	748	583

Note: sample mean displayed as coefficients.

Table 2: PSID Expenditure Categories, 2005-2021

	(1) 2005	(2) 2007	(3) 2009	(4) 2011	(5) 2013	(6) 2015	(7) 2017	(8) 2019	(9) 2021
NON-DURABLES									
Food (incl. food stamps)	8,764.88	8,791.13	8,468.86	8,676.86	8,880.51	9,253.36	10,003.17	10,128.91	10,575.90
Clothing & gasoline	4,883.92	5,175.00	4,147.98	4,994.90	4,754.45	4,245.72	3,630.17	3,868.89	3,405.03
Food share	24.14%	24.04%	24.41%	24.88%	24.49%	24.51%	26.62%	26.09%	29.11%
SERVICES									
Utilities and telecom.	4,827.46	5,069.38	5,513.50	5,433.80	5,451.39	5,572.90	5,441.41	5,624.16	5,568.50
Medical expenses	3,245.68	3,440.92	3,652.63	3,713.94	4,967.38	5,488.33	5,205.79	5,462.37	5,349.37
Trips and recreations	3,639.30	3,906.48	3,866.83	3,521.84	3,503.49	3,777.89	3,691.50	4,088.66	2,614.86
Education	2,612.85	2,583.39	2,645.92	2,438.83	2,854.05	3,065.42	2,659.15	2,700.64	2,881.50
Transportations	2,318.58	2,174.55	1,918.87	1,922.27	1,862.78	1,966.69	1,966.10	2,012.43	1,893.04
Childcare	919.26	961.69	982.89	951.92	961.53	978.48	901.59	956.22	692.42
Observations	849	1011	1097	1181	1270	1076	901	748	583

Note: sample mean displayed as coefficients.

PSID satisfies the identification requirements of our quantile model.

We selected households that meet both participation and model-specific requirements. The participation requirement sets a minimum of three continuous waves in which a household must be appear. This helps reduce inconsistencies in self-reported measures and filters out household with low willingness to participate in the survey. We do not restrict the specific wave in which a household enters or exits the sample, as long as participation occurs within the sampling window.

Table 3: PSID Income and Family Wealth, 2005-2021

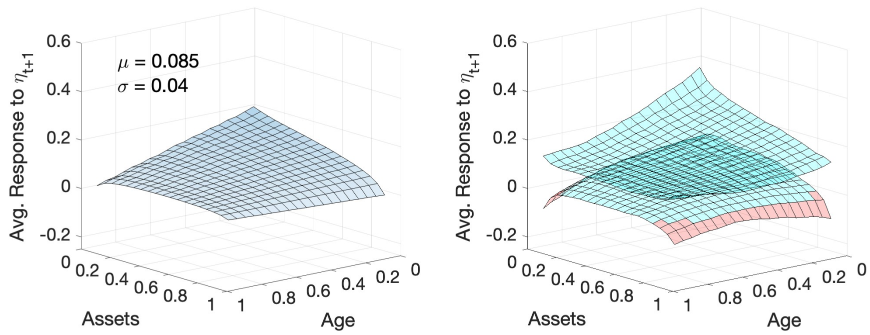
	(1) 2005	(2) 2007	(3) 2009	(4) 2011	(5) 2013	(6) 2015	(7) 2017	(8) 2019	(9) 2021
HEAD									
Labour income	68,670.43	71,235.13	73,385.36	66,239.50	70,009.25	69,336.98	73,768.34	73,378.10	78,578.94
Wage per working week	1,460.64	1,504.93	1,569.12	1,471.75	1,550.20	1,514.42	1,605.64	1,587.58	1,713.72
SPOUSE									
Labour income	30,116.80	30,001.34	32,161.01	30,022.04	30,893.43	31,493.14	32,193.52	34,350.80	36,795.00
Wage per working week	785.59	845.95	847.07	821.46	839.47	830.25	852.93	903.18	972.77
FAMILY WEALTH									
Home equity	134,157.00	145,148.55	111,548.49	98,125.70	98,779.71	109,551.36	120,122.60	138,555.02	177,923.43
Wealth (excl. home equity)	192,315.85	220,033.01	248,388.60	228,434.75	224,367.40	272,008.23	296,807.34	297,135.22	407,082.30
Wealth	326,472.86	365,181.56	359,937.09	326,560.45	323,147.10	381,559.59	416,929.94	435,690.24	585,005.73
Observations	849	1011	1097	1181	1270	1076	901	748	583

Note: sample mean displayed as coefficients.

Conditional on meeting this requirement, we retain only households with complete information on key demographics (age, state of residence, eduction, etc.) and economic variables. We restrict the ages of reference persons (also referred to as "household heads" in PSID terminology) and their spouses to between 25 and 60, reflecting our focus on labour incomes. No further restrictions are placed on state of residence, family size or marital status. We focus on non-durables and service consumption categories, including food, clothing, gasoline, utility and telecommunication, healthcare, trips and recreations, education, transportation and childcare. These items account for more than 75% of total household expenditures recorded in the PSID. Our measure of family asset includes business assets, cash, bonds, stocks and vehicles, net of debts (student, medical, etc.). This definition is intended to capture the relatively liquid component of family wealth.

To partially mitigate measurement errors, we exclude families with reported wages below half of state minimum wage (or federal minimum wage if no state-level minimum wage laws). We also drop families reporting extreme changes in income, wealth or unreasonable large transfers. Extreme changes in consumption items are much rarer, except for certain durable expenditures such as home repairs and furnishes, which are excluded from our consumption measure.

Table 1 reports summary statistics for household demographics. Most individuals included in the sample have at least high school education, are employed and own their homes. Average family sizes is relatively small with fewer than two children. Table 2 reports family expenditures. Spending on most service related items is relatively stable over time, while food and medical expense rise noticeably across waves. We find a 20.7% increase in average food spendings and a 65% increase in average medical expenses over our sampling period, partially due to our sample is aging. The



(a) Response profile (b) Bootstrap confidence bands

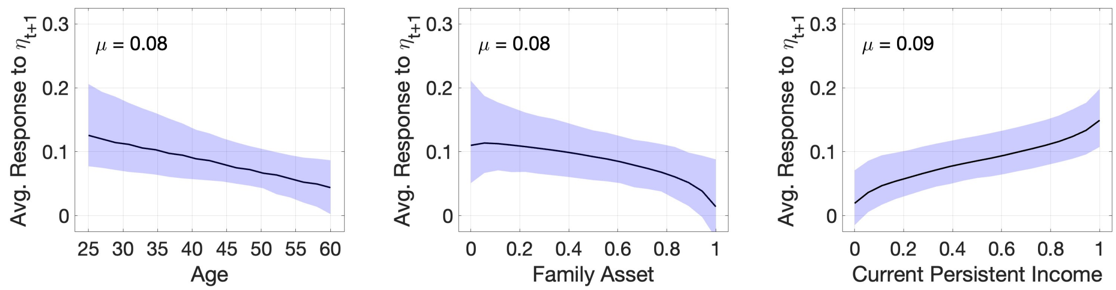
Figure 1: Average consumption response to future persistent income component

Covid-19 effects are visible in the 2021 wave, with sharp decreases in recreational and childcare expenses. On average, household expenditures across all PSID consumption categories are around \$40,000 per year, with the food consistently accounting for more than 24% and increasing steadily over time. Table 3 reports labour income and family wealth. Average labour income rose from \$68,670 for household heads and \$30,116 for spouses in 2005 to \$78,578 and \$36,795 in 2021, respectively. Wage growth is the main driver of this increase, as there are no clear trends in working times. Family wealth also increase steadily, with most of the growth attributable to assets other than home equity. Overall, our PSID sample is relatively stable and homogeneous with good coverage on the U.S. working population.

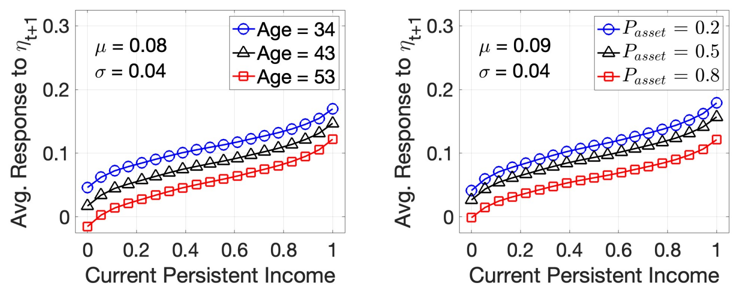
2.6 Empirical results

We present results from consumption function estimation based on iterative method using PSID data. Our analysis focus on the average consumption response to future persistent income and explores heterogeneities in response patterns. We also provide results on household income dynamics and illustrate how nonlinearities in income persistence can affect our understanding of advance information.

Figure 1 shows the average consumption response to one-period-ahead persistent income as a function of household head's age and family assets. This response is computed as the partial derivative of consumption c_t with respect to η_{t+1}, averaged over other dimensions of the consumption function. We find that many households adjust their consumption in anticipation to future persistent income changes, with an average response coefficient estimated at 0.085. See panel (a).



(a) Primary: age groups (b) Primary: asset levels (c) Primary: persistent income



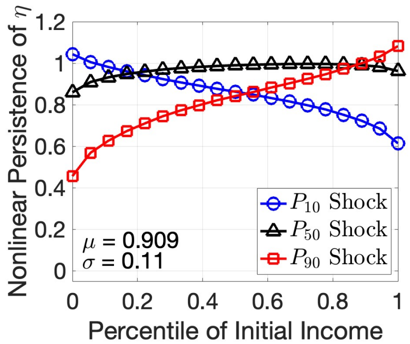
(d) Secondary: age groups (e) Secondary: asset levels

Figure 2: Primary and secondary heterogeneity in average response

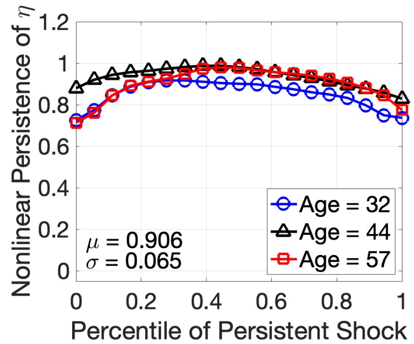
This value can be interpret as an elasticity: a 1 percentage change in future persistent income is associated with a 0.085 percentage change in log consumption today, on average. The response is strongest among young households with lower level of assets, with average response coefficients estimated between 0.15 to 0.2, roughly two times larger than the sample average. The response declines monotonically as households age or accumulate more assets, since their consumption becomes less dependent on current income. Panel (b) reports the 95% non-parametric bootstrap confidence bands for the average response profile in panel (a), with colour coding indicating statistical significance: cyan colour indicates the confidence bands are valued above zero and red colour indicates the confidence bands overlap with zero. We find our consumption response to advance information is relatively precisely estimated given limited observations available. Moreover, there is statistically significant evidence supporting our hypothesis that households have access to information about future income changes that are not observed by economists through survey data. Utilization of such information appears across most age groups and asset levels, except among households with the highest asset level or older working households with minimal savings. Insignificance in these boundary may partly reflect smaller sample size for these sub-groups in the PSID data.

Figure 2 explores heterogeneity in consumption responses to future information across observed and unobserved household characteristics. We refer to these results displayed in panel (a) through (c) as primary heterogeneities, since they are linked to specific household characteristics. Panel (a) plots the response coefficients by age group, showing that advance responses decline with the age of household head. In particular, household heads aged 25 have an estimated response coefficient of about 0.12, nearly double that of response for household heads aged 55. A similar monotonic pattern emerges for family assets (panel (b)): high asset levels dampen response to future income changes, and households with abundant liquid wealth show little sensitivity. Although heterogeneities in age and assets are modest (as confidence bands overlaps), substantial differences emerge across persistent income levels. Panel (c) shows that response coefficients rise with the current level of persistent income. Households experiencing adverse persistent income events (at 20th percentile or lower of the shock distribution) respond significantly less than those enjoying favourable (at 75th percentile or higher) persistent income shocks. This stark contrast suggests that current persistent income is likely, a key determinant of both the ability to act on future information and the ability to receive it. The secondary heterogeneity between households with similar level of current persistent income is subtle. Panel (d) and (e) in Figure 2 shows that small heterogeneities in age and assets remain even after controlling for latent persistent income. Panel (d) suggests the impact of age on consumption response to advance information is roughly constant: the gaps in average response coefficients across age groups are similar at each level of persistent income. A similar pattern holds for assets in panel (e), although the effects are larger for higher asset levels.

At the same time, household labour income exhibits nonlinear and dynamic persistence. These two features of income influence how households interpret current and future income changes. Figure 3 illustrates our estimates of income persistence and its variation with age, shock size and income history. We find that income persistence is no longer equal to one across all households (panel (a)). More extreme persistent income shocks are associated with stronger history-dependence, such that income persistence is generally much lower than unity. This property implies that households receiving the same piece of information about tomorrow may interpret it differently depending on their current income state. For example, a very positive signal will be regarded as a long-lasting income innovation by households with high current persistent income, but would alternatively being treated as a temporary fluctuation by households at lower end of persistent income distribution. Without the assumption of "permanent", persistent income shocks exert varying degree of influ-



(a) By percentile of shocks



(b) By ages

Figure 3: Average persistence of persistent income components

ence on household's permanent income, which in turn induces variation in consumption responses. Meanwhile, variation in income persistence across age groups is empirically small (panel (b)).

A potential factor explaining differences in household responses to advance information is household-level unobserved effects. If the ability to observe future information is permanent for some households only, then including a "fixed-effect" type of control in the consumption function would help explain the behavioural differences between households. We therefore estimate a consumption function with household-level, time-invariant effects following the approach of Arellano et al. (2023). The household-specific unobserved effect is modelled as a a function of education, birth year and long-term average income, in the style of correlated random effects. This alternative consumption function is estimated on the identical PSID sample. We find that including household effects does not explain the heterogeneities in consumption response in a statistically meaningful way, and we conclude that the ability to observe advance information is likely dynamic. See the appendix for more details.

3 Consumption choices under advance information

We set up a partial-equilibrium consumption model to study the implications of advance information for households' consumption and saving behaviours. In this model, early access to information about future income changes is driven by an *information shock*, and the probability of receiving advance information is dynamic across periods. We subsequently recover the probability of receiving such shocks for households experiencing different income episodes and highlight the role of nonlinear income persistence in shaping households' interpretation of this informations.

3.1 Model setup and household's problem

Specifically, we consider an infinite-horizon consumption-saving model with advance information. Households are risk-averse and act as a single agent when making consumption decisions. Their degree of risk aversion is governed by parameter σ and they discount future utilities using discount factor β. Each household receives labour income y_t every period, modeled as the sum of a persistent component η_t and a transitory component ε_t:

$$
\begin{aligned}
y_t &= \eta_t + \varepsilon_t \\
\eta_t &= \rho_t(\eta_{t-1}, u_t)\eta_{t-1} + u_t
\end{aligned}
$$

The flexible process for η_t allows income persistence to change dynamically depending on the shocks received and the associated income history. Households are rational and fully understand the nature of income dynamics. All risks take the form of idiosyncratic income shocks, and we assume there is no aggregate uncertainty in the economy. Markets are incomplete and households can save using one-period risk-free bonds at a fixed annual interest rate of r. They may borrow up to a pre-specified borrowing limit.

The advance information feature takes the form of short-term foresight about one-period-ahead persistent income η_{t+1} only. This is introduced through an *i.i.d.* information shock realized at the beginning of each period alongside persistent and transitory income shocks[9]. The effect of this information shock is limited to the current period. We model the shock probability P_{AI} to be dependent on household's current persistent income as motivated by the empirical evidence. The arrival of information shock adds η_{t+1} to household's information set in period t. In this model, observing future income *component* η_{t+1} is equivalent to observing future income *shock* u_{t+1}, since households fully understand income dynamics and can infer u_{t+1} from η_{t+1}. Households do not have access to advance information about future transitory shock or longer-term shocks.

[9] A possible alternative on introducing advance information is regarding future persistent shock as a sum of two orthogonal components $u_{t+1} = u^s_{t+1} + u^{AI}_{t+1}$ and allow all households to observe the u^{AI}_{t+1} part ahead of time. See Kaplan and Violante (2010). We find this setup require additional assumptions on how u^s_{t+1} versus u^{AI}_{t+1} affect the nonlinear persistence of η_t, as well as the assumption on access to advance information by all households may be restrictive.

This distinguishes our setting from models of heterogeneous income profiles (Guvenen and Smith (2014)) where households know their future income growth when they first enter the labour market.

The realizations of information shock and income shock occur at the beginning of each period. Given these realizations, there are two types of households in the economy: "uninformed" households and "informed" households. Uninformed households do not receive an information shock in the current period and therefore do not have η_{t+1} in their information set. Their optimization problem is expressed using the Bellman equation:

$$
\begin{aligned}
V_{AI=0}(a,\eta,\varepsilon) = \max_{\{c,a'\}} \; & u(c) + \beta\mathbb{E}[P_{AI}(\eta') * V_{AI=1}(a',\eta',\varepsilon',\eta'') + (1-P_{AI}(\eta')) * V_{AI=0}(a',\eta',\varepsilon')] \\
s.t. \quad & c + a' \leq (1+r)a + \eta + \varepsilon \\
& \eta' = \rho(\eta, u')\eta + u', \varepsilon \sim iid \\
& a' \geq \underline{a}
\end{aligned}
$$

where $\{a, \eta, \varepsilon\}$ are state variables denoting current asset, persistent income and transitory income respectively. Uninformed households face probability $P_{AI}(\eta')$ of receiving advance information and becoming "informed" in the next period. Their conditional expectation for future value functions are formed based on their current information set, and they must predict the probability of becoming "informed" in the future. Informed households, by contrast, are those that receive an information shock in the current period and are therefore informed about their future persistent income η'. Their recursive optimization problem can be similarly characterized with the Bellman equation:

$$
\begin{aligned}
V)AI = 1(a,\eta,\varepsilon,\eta') = \max_{\{c,a'\}} \; & u(c) + \beta\mathbb{E}[P_{AI}(\eta') * V_{AI=1}(a',\eta',\varepsilon',\eta'') + (1-P_{AI}(\eta')) * V_{AI=0}(a',\eta',\varepsilon')|\eta'] \\
s.t. \quad & c + a' \leq (1+r)a + \eta + \varepsilon \\
& \eta' = \rho(\eta, u')\eta + u', \varepsilon \sim iid \\
& a' \geq \underline{a}
\end{aligned}
$$

The informational advantage of observing η' allows informed households to know exactly their probability of remaining informed in the next period. Therefore, they can form conditional expectations more accurately than their uninformed counterparts. Their optimization problem can be rearranged into:

$$V_{AI=1}(a,\eta,\varepsilon,\eta') = \max_{c,a'} \; u(c) + P_{AI}(\eta')\beta\mathbb{E}[V_{AI=1}(a',\eta',\varepsilon',\eta'')|\eta'] + (1-P_{AI}(\eta'))\beta\mathbb{E}[V_{AI=0}(a',\eta',\varepsilon')|\eta']$$

where the same set of constraints apply. In this case, the shock probability P_{AI} is taken outside the conditional expectation to reflect the utilization of information. In this model, informed households have early opportunities to adjust their consumption in anticipation of future income changes that have not been ealized. Importantly, the arrival and possession of advance information does not affect the amount of income currently available. Informed households may use their saving or borrowing capability to finance consumption adjustments within the current period. In general, they cannot borrow against future information beyond their existing borrowing constraints.

3.2 Parameterization, discretization and model solution

We parameterize the model following existing studies on consumption insurance, with the exception of parameters related to the information shock. Preferences are specified as a natural logarithm utility function with $\sigma = 1$. The annual risk-free interest rate is set to $r = 0.03$, as in Kaplan and Violante (2010) who also study consumption insurances in a Bewley-style partial equilibrium model. The discount factor is set to $\beta = 0.959$ by matching a wealth-to-income ratio of 3 in the simulated data, following De Nardi et al. (2020). The borrowing constraint is set to $\underline{a} = 0$, as we focus on the consumption dynamics of households with non-negative assets. We provide more details on the approach used to recover the information shock parameters in later in this section.

The flexible nonlinear income process is based on our empirical results and is discretized into a finite-state Markov chain using the simulation-based method of De Nardi et al. (2020). We begin by simulating a large panel of income components (η, ε) using the estimated quantile income model. Simulated persistent income components are ordered by size and grouped into N^P bins. The median value of each bin is assigned as the value of the corresponding discretized persistent income state. The transition matrix for persistent income components is then computed from the observed frequencies of transitions between income bins. This provides a natural way to allow for state-dependent income persistence. Transitory income components are discretized similarly into N^T bins. Transition probabilities between any two transitory income states are set to $1/N^T$ given model setup. In practice, we set $N^P = 18$ for persistent income and $N^T = 8$ for transitory income.

Given the discretized income states, we solve the model using value function iteration over a large grid of asset values. We find that a very large number of asset grids are required to capture the subtle differences in saving choices between uninformed and informed households. To keep computational time and memory requirements manageable, we implement asset grids using the "coarse-fine" strategy. We initialize assets on 200 exponentially-spaced "coarse" grids between the borrowing limit and the maximum asset value. In each iterative optimization step, we expand the asset space between two adjacent coarse asset grids with 20 additional "fine" grid points and use interpolation to evaluate the expected value at each fine grids. The optimal saving decision for each income-asset state is determined using both types of grids, while only a fixed number of saving choices are recorded to conserve memory. The consumption policy function is then computed from saving policy function and budget constraint.

3.3 Estimating information shock probabilities

We specify the information shock probability as a linear function:

$$P_{AI}(\eta) = \alpha_{AI} + \beta_{AI} Q(\eta)$$

where α_{AI} represents the baseline probability that applies universally to all households regardless of their current income state and β_{AI} captures the probability gain associated with higher levels of persistent income. $Q(\eta)$ represents the quantile rank of η, so that households with high (or low) level of persistent income would have a large (or small) quantile rank. In this setup, only the relative magnitude of persistent income would affect the shock probability.

The shock probability parameters are estimated using indirect inference. We match the consumption responses to future information from simulated data with empirical patterns found in the PSID. Given the relatively simple structure of our model, a fully non-parametric quantile regressions is no longer appropriate as an auxiliary model. Instead, we use linear regression with interaction terms as the auxiliary model:

$$c_{i,t} = \gamma_1 a_{i,t} + \gamma_2 \eta_{i,t} + \gamma_3 \varepsilon_{i,t} + \gamma_4 \eta_{i,t+1} + \gamma_5 (\eta_{i,t} \times \eta_{i,t+1}) + \gamma_6 (a_{i,t} \times \eta_{i,t})$$

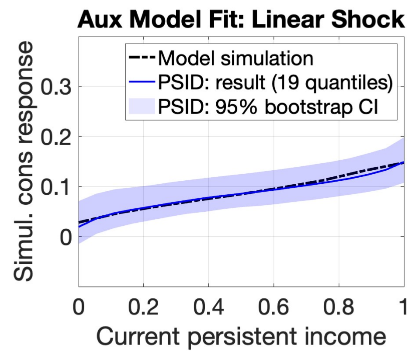


Figure 4: Simulated and empirical consumption response

which effectively captures the primary heterogeneity in consumption response. The coefficient γ_4 represents the baseline, average consumption response to advance information, while γ_5 allows the magnitude of response to vary with current persistent income. Current assets and income components are included as additional controls, broadly mirroring the specifications of our empirical consumption function. The auxiliary regression is estimated on a synthetic household panel with 50000 households [10]. We evaluate the implied consumption response from the auxiliary model $\phi^{AUX} = \gamma_4 + \gamma_5 \eta_t$ at 9 selected quantiles of persistent income η_t. Thus, ϕ^{AUX} represents the heterogeneous consumption responses in the simulated sample and they are compared to the empirical consumption responses ϕ^{PSID} estimated at the identical set of 9 quantile locations. The indirect inference algorithm is based on matching these two response profiles:

$$\{\alpha_{AI}^*, \beta_{AI}^*\} = \arg\min_{(\alpha_{AI}, \beta_{AI})} (\phi^{PSID} - \phi^{AUX})^\top (\phi^{PSID} - \phi^{AUX})$$

where ϕ^{PSID} and ϕ^{AUX} are column vectors. Inference on the shock parameters is performed via Delta method. To account for variations in ϕ^{AUX} due to randomness in the synthetic panel, we perform a large number of replications in the simulation step and use the mean response to calculate sum of squared deviations. The parameter space is set up to ensure coverage on all feasible intercept-slope combinations, subject to the restriction that the implied probabilities are between zero and one.

Our consumption model can match the empirical findings well. Figure 4 compares the consumption responses from simulated data (dot-dashed line) and PSID data (solid line with shaded

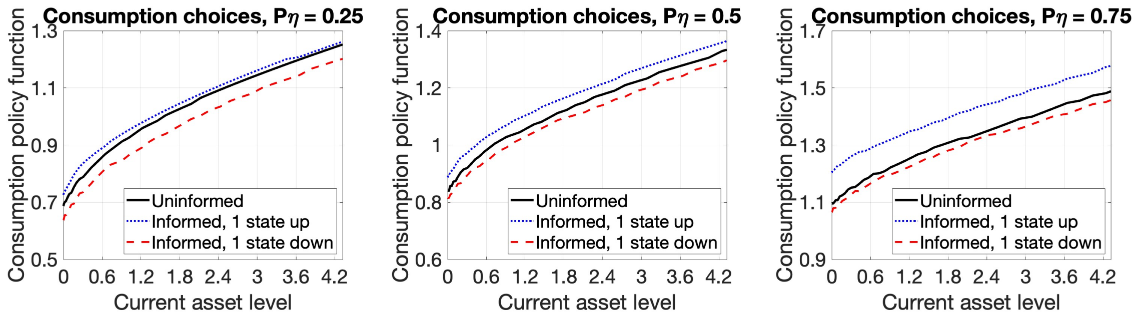
[10]We have tested and confirmed that increasing the size and/or length of simulated panel data do not affect the quantitative outcome of auxiliary model.

Table 4: Normalized probability by type of information received

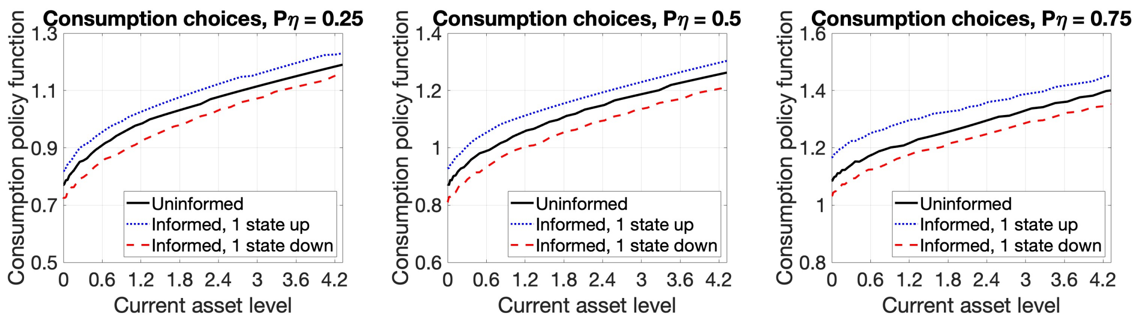
Information type	$Q_\eta = 0.25$	$Q_\eta = 0.5$	$Q_\eta = 0.75$
$\eta_{t+1} > \eta_t$			
1 state only	20.78%	20.87%	19.52%
2 states+	16.90%	9.62%	3.01%
$\eta_{t+1} < \eta_t$			
1 state only	16.90%	19.18%	18.84%
2 states+	8.91%	13.65%	12.45%
$\eta_{t+1} = \eta_t$			
no change	39.42%	36.68%	46.18%

95% confidence bands). Both the shape and the magnitude aligned well. We estimate the intercept coefficient as $\alpha_{AI} = 0.321$ (SE=0.133) and the slope coefficient as $\beta_{AI} = 0.117$ (SE=0.037). These shock parameters suggest that households have an average of 32% chance to become informed in each period, regardless of their current income state. At the same time, being at the top of the persistent income distribution provides some benefits: households at the 90th percentile are 28% more likely to receive advance information than those at the 10th percentile, given identical set of other state variables.

Although the probability of observing future income changes seems sizeable, the content of advance information varies substantially with current incomes. By combining transition probabilities with the information shock probability, we can characterize the types of signals embedded in the information. Table 4 reports the normalized probability of different types of future income change conditional on being informed today. Each column lists five possibilities: a small downward or upward changes (limited to one persistent income state), a large downward or upward change (two states or more) or no change. On average, households receive short-term foresight of no change or only small changes in persistent income more than 75% of the time. By contrast, the probability of receiving signals about large persistent income changes varies substantially. For example, low persistent income households ($Q_\eta = 0.25$) are 5.6 times more likely to learn about an upward income change ($\eta_{t+1} > \eta_t$) than high persistent income households ($Q_\eta = 0.75$). This difference in the content of advance information direct shapes how households adjust their consumption in response.



(a) Nonlinear income: $P_\eta = 0.25$ (b) Nonlinear income: $P_\eta = 0.5$ (c) Nonlinear income: $P_\eta = 0.75$



(d) AR(1) income: $P_\eta = 0.25$ (e) AR(1) income: $P_\eta = 0.5$ (f) AR(1) income: $P_\eta = 0.75$

Figure 5: Consumption policy function under different income process

3.4 Consumption behaviours under advance information

We document consumption behaviours of uninformed and informed household in Figure 5. In this model, an uninformed household behaves much like households in a model without advance information: consumption choices increase with current income and assets. Households with low level of assets would experience a period of lower consumption as they build up savings to buffer future income shocks. The only distinction is that uninformed households still account for the probability of becoming informed in future periods–a factor absent in models without advance information. Informed households share broadly similar consumption patterns with their uninformed counterparts, but the exact level of consumption depends on the nature of future income changes. Given identical assets and transitory income, an informed household anticipating a future upward income change consumes more than an uninformed household, while one anticipating a downward change consumes less.

Top panels in Figure 5 shows that household consumption exhibits asymmetric response to advance information received. This is evident from the different sized gaps between the consumption of uninformed households and that of informed households who receive information of opposite signs. Low persistent income households (panel (a)) respond more strongly to a future downward income changes stronger than to an upward future income change of similar magnitude. By contrast, high persistent income households (panel (c)) react more strongly to future upward changes. At the median persistent income level (panel (b)), responses are roughly symmetric. This asymmetry arises from the nonlinear persistence of the income process. Under nonlinear persistence, a downward income change is highly persistent for households with low persistent income but less so for those with high persistent income, whereas an upward change is very persistent only for households with high persistent income. As a results, consumption respond more strongly to persistent income shocks with longer-lasting effects (i.e. higher persistence) than to those with shorter-lived effects (i.e. lower persistence).

Bottom panels in Figure 5 illustrates the contrast using a consumption model based on AR(1) income process. In that case, consumption response to advance information are symmetric across all levels of persistent income levels since income persistence is fixed. The introduction of nonlinear persistence is therefore essential for correctly capturing households' interpretation to future information. Assuming unit root implicitly forces all persistent income shocks to have permanent effects, leading households to respond strongly and symmetrically to these future shocks. This common assumption may be overly restrictive and bias estimates of shock probabilities: small consumption responses might be incorrectly attributed to a low probability of receiving information, rather than to the dynamic nature of income persistence.

3.5 Consumption insurance to income risk under advance information

We are interested in assessing the degree of consumption insurability against income shocks when advance information is present. Informed households have an early opportunity to adjust their consumption based on knowledge of future income, which gives them a greater ability to smooth consumption than uninformed households. This behavioural difference suggests that the pass-through of persistent income shocks to consumption is dynamic for many informed households, while the pass-through of income shocks remains static for uninformed households. We evaluate the extent of consumption insurance based on the cumulative pass-through of income shocks:

$$\Delta^2 c_t \equiv c_t - c_{t-2} = (1 - \psi^P)\nu_t + (1 - \psi^T)\varepsilon_t + \xi_t$$

where ν_t denotes period t persistent income shocks and ε_t denote period t transitory income shocks. Additional control variables are unnecessary because income shocks are *i.i.d.* and independent to other state variables. The regression coefficients $\phi^P = 1 - \psi^P$ and $\phi^T = 1 - \psi^T$ can be interpret as pass-through coefficients. They measure the cumulative effects of income shocks on household consumption spanning two adjacent periods. A low pass-through coefficient implies that only a small fraction of an income shock is transmitted to consumption, meaning household expenditure is less affected. Equivalently, we can apply the inverse relationship between shock pass-through and degree of self-insurance, and treat ψ^P and ψ^T as consumption insurance coefficients to persistent and transitory income shocks respectively. Higher insurance means that consumption is less volatile and utility is higher due to better consumption smoothing. Our setup shares similarities to the partial insurance coefficients defined in Blundell et al. (2008), distinguished by the details that we use the second difference of consumption instead of the first difference to capture the dynamic aspect of shock pass-through.

Given model setup that persistent and transitory income shocks are independent to each other. Therefore, it is equivalent to estimating two separate univariate regressions, each with a single type of income shock as the independent variable. We can express the insurance coefficients in terms of shock variances and the covariance between income shocks and consumption changes. For transitory income shocks, we have:

$$\psi^T = 1 - \frac{Cov(\Delta^2 c_t, \varepsilon_t)}{Var(\varepsilon_t)} = 1 - \frac{Cov(\Delta c_t + \Delta c_{t-1}, \varepsilon_t)}{Var(\varepsilon_t)} = 1 - \frac{Cov(\Delta c_t, \varepsilon_t)}{Var(\varepsilon_t)}$$

where we applied the condition that the advance information is only relevant to the persistent income shocks. Therefore, long difference and short difference of consumption deliver identical results. For persistent income shocks, we show that:

$$\psi^P = 1 - \frac{Cov(\Delta^2 c_t, \nu_t)}{Var(\nu_t)} = 1 - \frac{Cov(\Delta c_t + \Delta c_{t-1}, \nu_t)}{Var(\nu_t)} = 1 - \Bigg[\underbrace{\frac{Cov(\Delta c_t, \nu_t)}{Var(\nu_t)}}_{\substack{\text{contemporaneous} \\ \text{response}}} + \underbrace{\frac{Cov(\Delta c_{t-1}, \nu_t)}{Var(\nu_t)}}_{\substack{\text{anticipatory} \\ \text{response}}} \Bigg]$$

where the extent consumption insurance depends on both the size of pass-through when persistent shocks are realized (at period t) and whether the advance information is involved (at period $t-1$). We use a more compact notation to characterize the relationship between consumption insurance and shock pass-through:

$$\begin{aligned} \psi^T &= 1 - \phi^T \\ \psi^P &= 1 - \phi^P = 1 - [\phi^P_{\text{anticipatory}} + \phi^P_{\text{contemporaneous}}] \end{aligned}$$

where $\phi^P_{\text{anticipatory}} \equiv \frac{Cov(\Delta c_{t-1}, \nu_t)}{Var(\nu_t)}$ is the fraction of cumulative consumption change occurred in period $t-1$ due to the arrival of advance information. $\phi^P_{\text{anticipatory}}$ is expected to be zero (or very close to zero in simulations) for uninformed households, while this anticipatory response will be non-zero for informed households. $\phi^P_{\text{contemporaneous}} \equiv \frac{Cov(\Delta c_t, \nu_t)}{Var(\nu_t)}$ is the remaining consumption adjustments in period t upon the actual realization of persistent shock ν_t in period t. The relative magnitude between $\phi^P_{\text{anticipatory}}$ and $\phi^P_{\text{contemporaneous}}$ provides details on the extent of dynamic consumption smoothing in anticipation to future shocks.

To implement this estimation and decomposition exercise based on our consumption model, we use the simulated household panel data containing income components and consumption choices. Given that our model employs discretized persistent income states, we define the persistent shock as $\nu_t \equiv \eta_t - \mathbb{E}_{t-1}[\eta_t]$ and set transitory shocks equal to the transitory income components. We classify households as informed if they received advance information in period $t-1$, thus knowing their persistent income shock ν_t prior to its realization. For comparison, uninformed households are those who did not receive advance information in period $t-1$. Pass-through coefficients are estimated separately for both types of households and reported in Table 5.

We find that informed households are better insured than uninformed households. The consumption insurance coefficient for uninformed households is estimated as $\psi^P_{AI=0} = 1 - \phi^P_{AI=0} =$

Table 5: Cumulative income shocks pass-through by household types

	Persistent shocks			Transitory shocks
	ϕ^P	$\phi^P_{\text{anticipatory}}$	$\phi^P_{\text{contemporaneous}}$	ϕ^T
Uninformed ($AI = 0$) at $t-1$	0.4131	0.0079	0.4052	0.1358
Informed ($AI = 1$) at $t-1$	0.3521	0.2437	0.1084	0.1295
Sample: informed at $t-1$				
& uninformed at $t-2$	0.3557	0.2459	0.1098	-
& informed at $t-2$	0.3456	0.2411	0.1045	-
Sample: informed at $t-1$				
& uninformed at t	0.3480	0.2446	0.1034	-
& informed at t	0.3599	0.2428	0.1171	-

0.5869, whereas for informed households it is $\psi^P_{AI=1} = 1 - \phi^P_{AI=1} = 0.6479$. For transitory income shocks, the difference in the degree of insurance between them are small. We find an insurance coefficient of $\psi^T_{AI=1} = 1 - \phi^T_{AI=1} = 0.8705$ for informed households and $\psi^T_{AI=0} = 1 - \phi^T_{AI=0} = 0.8642$ for uninformed households. The results from uninformed households reflect the consumption insurance to truly unanticipated income shocks, which is often a primary object of policy interest.[11] The superior self-insurance ability of informed households against persistent income shocks is driven by their higher persistent income and greater asset accumulation compared to uninformed households. This reflects an implicit selection effect arising from the positive correlation between information shock probability and persistent income levels. We confirm this by comparing selected percentiles (P10, P25, P50, P75, P90) of the asset distribution: informed households consistently hold more assets than uninformed households on average.

Meanwhile, the dynamic consumption response to income shocks is substantial among informed households. We find that about 70% of the cumulative response occurs in the period when the shock is first observed (the anticipatory response), while the remaining 30% occurs upon the actual realization of the shock (the contemporaneous response). This “incomplete” anticipatory response is consistent with the fact that persistent income shocks are not necessarily permanent when nonlinear persistence is present. The contemporaneous response among informed households is relatively small, with a magnitude about 25% of the cumulative response by uninformed households. Since persistent income shocks are no longer news to informed households, their consumption response at

[11] It is worth noting that uninformed households in our model are not equivalent to households in a model without advance information. The former still consider the possibility of becoming informed in the future and may adjust their savings accordingly, while this motive is entirely absent in the later case.

the time of shock realization partly reflects the degree of constraint they faced in the earlier period when advance information was first received. Importantly, this 70%-30% split between anticipatory and contemporaneous effects does not depend on households' past history of informedness or their current information status. In the same table, we repeat the decomposition exercise for households informed at $t-1$ with different information histories in the previous period (at $t-2$) and find negligible differences in the relative size of responses. Similar results hold when grouping households by their current information status (at t). Therefore, the dynamic pattern of consumption response to anticipated persistent income changes is consistent across informed households, regardless of their past or current information status.

3.6 Comparison to covariance-based consumption insurance estimators

Without a structural consumption model, it is infeasible to distinguish between informed and uninformed households, as well as estimating insurance coefficients directly from empirical data without observing the income shocks. Blundell et al. (2008) proposed a pair of covariance-based estimators for identifying both insurance coefficients:

$$\psi^P_{BPP} \equiv 1 - \phi^P_{BPP} = 1 - \frac{Cov(\Delta c_t, \Delta^3 y_{t+1})}{Cov(\Delta y_t, \Delta^3 y_{t+1})}$$
$$\psi^T_{BPP} \equiv 1 - \phi^T_{BPP} = 1 - \frac{Cov(\Delta c_t, \Delta y_{t+1})}{Cov(\Delta y_t, \Delta y_{y+1})}$$

These consumption insurance estimators are proven valid as long as the following assumptions hold:

(i) income process is permanent-transitory with persistence equals to one

(ii) households do not adjust current consumption c_t in response to income shocks from previous periods, specifically ν_{t-1} and ε_{t-2}

(iii) households have no access to advance information regarding future persistent shock ν_{t+1} and future transitory shock ε_{t+1}

In short, these assumptions ensure that current consumption changes respond to contemporaneous income shocks only. While straightforward, this approach would require an inaccurate assumption of no advance information about future persistent incomes, such that it leads to biased estimates of insurance coefficients for both type of income shocks. The source of biases can be illustrated using covariance relationships. For transitory shocks ε_t:

$$Cov(\Delta c_t, \Delta y_{t+1}) = Cov(\Delta c_t, \nu_{t+1}) + Cov(\Delta c_t, \varepsilon_{t+1}) - Cov(\Delta c_t, \varepsilon_t)$$

Imposing all three assumptions would result in BPP-identified shock covariance term:

$$Cov^{BPP}(\Delta c_t, \varepsilon_t) = -Cov(\Delta c_t, \Delta y_{t+1})$$

Given the presence of advance information, the third assumption needs to be modified in order to accommodate that some households can observe their future persistent shock ν_{t+1} in period t. Under the updated assumptions:

$$Cov^{BPP}(\Delta c_t, \varepsilon_t) = -Cov(\Delta c_t, \Delta y_{t+1}) = Cov(\Delta c_t, \varepsilon_t) - Cov(\Delta c_t, \nu_{t+1}) < Cov(\Delta c_t, \varepsilon_t)$$

where we have applied the fact that the presence of advance information would cause consumption change today to positively correlate with future persistent income shocks. Given the identified shock variance, BPP insurance coefficient for transitory shock is upward biased:

$$\psi^T_{BPP} = 1 - \frac{Cov^{BPP}(\Delta c_t, \varepsilon_t)}{Var(\varepsilon_t)} > 1 - \frac{Cov(\Delta c_t, \varepsilon_t)}{Var(\varepsilon_t)} = \tilde{\psi}^T$$

The insurance coefficient for persistent shocks is also biased when advance information is not properly accounted for in the covariance structure. Given the specification of income process, the covariance between current consumption change (Δc_t) and a three-period income change ($\Delta^3 y_{t+1}$) reflect the joint impacts of past and future income shocks:

$$Cov(\Delta c_t, \Delta^3 y_{t+1}) = Cov(\Delta c_t, \nu_t) + Cov(\Delta c_t, \nu_{t-1}) - Cov(\Delta c_t, \varepsilon_{t-2}) + Cov(\Delta c_t, \nu_{t+1}) + Cov(\Delta c_t, \varepsilon_{t+1})$$

Under the three identifying assumptions, BPP-identified shock covariance term is:

$$Cov^{BPP}(\Delta c_t, \nu_t) = Cov(\Delta c_t, \Delta^3 y_{t+1})$$

Given the presence of advance information about future persistent income shocks, the covariance between current consumption change and one-period-ahead persistent income shocks are positive:

$$Cov^{BPP}(\Delta c_t, \nu_t) = Cov(\Delta c_t, \Delta^3 y_{t+1}) = Cov(\Delta c_t, \nu_t) + Cov(\Delta c_t, \nu_{t+1}) > Cov(\Delta c_t, \nu_t)$$

The differences between BPP-identified covariance and the true shock covariance suggest that BPP insurance coefficient for persistent shock is downward biased:

$$\psi^P_{BPP} = 1 - \frac{Cov^{BPP}(\Delta c_t, \nu_t)}{Var(\nu_t)} < 1 - \frac{Cov(\Delta c_t, \nu_t)}{Var(\nu_t)} = \tilde{\psi}^P$$

Note that the BPP coefficient for persistent shocks only accounts for consumption changes occurred in period t (instead of two-period consumption changes), which only reflect the contemporaneous part of cumulative consumption response. The extent of downward bias in consumption insurance to persistent shocks is further amplified by the "non-permanence" of persistent shocks and the presence of borrowing constraints. These additional factors and their influences are discussed extensively in Kaplan and Violante (2010).

To quantify the extent of biases in the existing method, we estimate both the true consumption insurance coefficients (via pass-through regressions) and the BPP insurance coefficients using simulated household panel data that mimic the realistic structure of empirical datasets. Since existing datasets (such as PSID) do not allow us to distinguish between informed and uninformed household, we conduct this exercise on the entire sample. The results are reported in Table 6.

We find that the magnitudes of these biases are substantial, and their directions are consistent with theoretical predictions. The true insurance coefficient for persistent income shocks is 25% larger than the covariance-based BPP estimate. This suggests that properly accounting for the presence of advance information is crucial for avoiding an understatement of average consumption insurance against persistent shocks. Ignoring the existence of informed households, whose consumption changes in anticipation of future income shocks, leads to a mistakenly attribution of part of the consumption-income co-movement entirely to shocks, rather than to a combination of truly unanticipated shocks and advance information. The biases on transitory shocks are much smaller. The true insurance coefficient for transitory shock is 5.5% smaller than the BPP estimate, placing

Table 6: BPP-style consumption insurance coefficients

	persistent ψ^P	transitory ψ^T
BPP covariance-based ψ_{BPP}	0.5637	0.9187
True regression-based $\tilde{\psi}$	0.7077	0.8684

it further away from unity. This implies that the existing conclusion of U.S. households enjoying near-complete insurance against transitory income shocks may not hold. Many households must balance now their limited resources between responding to realized income shock and adjusting to new information about the future persistent income changes.

Our findings emphasize the importance of utilizing consumption data in both levels and changes, as they each contain complementary information relevant for identifying different economic mechanisms. In our model, consumption levels reveals the presence and extent of advance information, while consumption changes reflect the degree of consumption insurance to income shocks, conditional on the identification of advance information.

4 Discussions

Our findings motivate a new type of government-sponsored employment insurance policy that better aligns the timing of income assistance with the welfare changes arising from consumption fluctuations. The existing design of employment/unemployment insurance determines the eligibility primarily around the time of job termination and income loss. This decision is based on two considerations. First, income loss events generally align well in time with consumption declines, as a worker's budget constraint becomes tighter or binding upon job loss. Hence, income loss is regarded as a sufficient condition for consumption reduction and a reliable indicator of welfare deterioration. Second, deferring the claim of UI/EI benefits until after income loss is a low-cost mechanism to prevent double-compensation, since workers continue to receive regular pay until their contract officially ends.

Our empirical and structural modelling results suggest that the timing of welfare loss, in form of consumption decrease, may not align in time with actual income loss. Risk-averse workers who are aware of foreseeable job losses tend to increase their savings and reduce consumption as soon as advance information about future termination becomes available, as predicted by our model. Consequently, these workers experience declines in welfare before their actual job termination date, suggesting that the EI/UI benefits may indeed arriving "too late". Although we abstract away from aggregate economic conditions in this paper, it is reasonable to expect the magnitude of anticipatory saving and consumption adjustments would increase as aggregate uncertainty rises. Consider again the case in which workers are anticipating a job loss. If job searching (either on the job prior to termination or after job loss) is difficult, workers will save more to account for the higher expected duration of unemployment and the greater uncertainty of restoring their previous income levels. This implies larger welfare losses under the current EI/UI eligibility framework, as households may face substantial consumption reduction before any income assistance is received.

We believe these welfare losses can be at least partially mitigated by allowing early access to existing income assistance programs. We recognize, however, that implementing early access to UI/EI benefits faces two main challenges.First, verifying the authenticity and inevitability of future job termination, as well as other additional program requirements (such as evidence of job search), is time-consuming, time-sensitive and case-specific. Second, determining the appropriate amount and duration of early income assistance is complex and may interfere with the incentive structure embedded in current UI/EI design. Despite these challenges, existing legislations such as the Worker Adjustment and Retraining Notification (WARN) Act in the U.S. and the Canada Labour Code provides verifiable sources of advance information about future job losses, since firms are legally required to issue notices weeks or months before termination. Designing and evaluating incentive-compatible, proactive income assistance programs that target anticipated job losses is an interesting and important future research direction, particularly as the aggregate uncertainty continues to rise in the U.S. and Canadian labour markets.

5 Conclusions

We study the interaction between current household consumption and future persistent income changes. Using a nonlinear panel method on PSID data, we estimated an empirical consumption function in which future persistent income component is included as a control variable to capture the potential roles played by advance information. We find that household consumption responds in anticipation to future persistent income component with a positive and statistically significant average response coefficient, suggesting the existence of advance information in the U.S. context. Moreover, consumption response to advance information exhibits strong heterogeneity between households with different levels of current persistent income.

Through the structure of our consumption-saving model with information, we find there exists a moderate probability of receiving short-term foresight about future persistent income. Given the arrival of information, household's consumption responses are influenced by the nonlinearities in the income process, as households with different levels of current persistent income may interpret the long-term impacts of same piece of information differently.

Our results suggest that informed households in the U.S. are better self-insured to persistent income shocks than their uninformed counterparts, which is largely driven by the implicit selection effects since informed households have higher persistent income and more accumulated assets on average. In the meantime, informed households adjust their consumption dynamically in anticipation of future income changes. We find that about 70% of the cumulative consumption adjustments to persistent income shocks occur in the period when advance information about persistent shocks first becomes available.

Ignoring the presence of advance information leads to inaccurate assumptions and biased results. We find that existing estimator of consumption insurance to persistent income shocks is subject to a sizeable downward bias. Using synthetic panel data simulated from our consumption-saving model, we show that the covariance-based estimator proposed by Blundell et al. (2008) would understate the extent of consumption insurance by approximately 25% relative to the true value, since the identifying assumption of "no advance information" does not applied universally to all U.S. households.

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A Model Identification

A.1 Completeness conditions

We briefly illustrate the concept of "completeness" that is extensively applied in the model identification. See Newey and Powell (2003) and Horowitz (2011) for formal introductions.

A basic NPIV model takes the form:

$$Y = m(X) + e \tag{A.1}$$

$$\mathbb{E}[e|Z] = 0 \tag{A.2}$$

where Y, X, Z are real valued. Specifically, X is an endogenous variable and Z is an instrumental variable. A series estimator approximates the function $m(X)$ with $m_K(x) = X_k(x)^\top \beta_K$ and the series structural equation is:

$$Y = X_K^\top(X)\beta_K + e_K \tag{A.3}$$

If a polynomial basis is used, then $X_K(X) = (1, X, \dots, X^{K-1})$.

Since X is endogenous, the vector X_K is also endogenous. Therefore, we need at least K instruments. A non-parametric reduced-form equation for X can be specified as:

$$X = g(Z) + u \tag{A.4}$$

$$\mathbb{E}[u|Z] = 0 \tag{A.5}$$

Similar to above, $g(z)$(which is a generic notation for the function $g(.)$) can be approximated by series expansion:

$$g(z) \simeq g_L(z) = Z_L(z)^\top \gamma_L \tag{A.6}$$

where $Z_L(z)$ is an $L \times 1$ vector of basis transformations and γ_L is an $L \times 1$ coefficient vector. If a polynomial basis is used, then $Z_L(z) = (1, z, \dots, z^{L-1}$.

Suppose $L \geq K$, we can use $Z_L = Z_L(Z)$ as an instrument for X_K. One could apply the 2SLS estimator for β_K and get $\hat{\beta}_{K,L}$. Indeed, the reduced-form system suggests that we are actually estimating a "separate" reduced-form equation for each of the X_k, with $Z_L(z)$ as the regressors. When $L = K$, the reduced-form coefficient matrix Γ (from regressing X_K on Z_L) is lower-triangular and full rank. This means that the reduced-form equation can be identified for any choices of $K = L$. Consequently, a sufficient condition for strong identification of β_K is a strong reduced-form relation between X and Z. Notice that the identification of β_K (referred to as the "pseudo-true coefficient") does not imply the identification of the structural function $m(X)$.

Identifying the structural equation $m(X)$ is considerably more challenging. Recall the basic NPIV model and apply a conditional expectation operator $\mathbb{E}[.|Z = z]$:

$$\mathbb{E}[Y|Z = z] = \mathbb{E}[m(X)|Z = z] \tag{A.7}$$

This equation can be rewritten as:

$$\mu(z) = \int m(x)f(x|z)\,dx \tag{A.8}$$

where $\mu(z)$ is the CEF of Y given $Z = z$ and $f(x|z)$ is the conditional density of X given Z. These two functions are identified from the joint distribution of (Y, X, Z). This means that the unknown structural function $m(x)$ is the solution to the above integral equation. A key concern is the uniqueness of the solution $m(x)$ and having a strongly identified reduced-form relation will not able to solve this problem. This is known as the ill-posed inverse problem: the solution $m(x)$ is not necessarily a continuous function of $\mu(z)$.

Thus, identification of $m(x)$ requires restricting the class of allowable functions $f(x|z)$. Formally, the function $m(x)$ is identified if it is the unique solution to the integral function above. Equivalently, $m(x)$ is not identified if we can replace $m(x)$ with $m(x) + \delta(x)$ for some non-trivial function $\delta(x)$ and the solution does not change. This situation occurs when

$$\int \delta(x)f(x|z)\,dx = 0, \forall z \tag{A.9}$$

It's straightforward to see that $m(x)$ can be identified if and only if the above equation holds with a trivial function $\delta(x) = 0, \forall z$. Newey and Powell (2003) defined this fundamental condition as "completeness": $m(x)$ is identified if and only if the completeness condition holds. Note that completeness is a property of the reduced-form conditional density and is unaffected by the structural equation $m(x)$. An analogue statement in linear IV problems would be that the identification is a property of the reduced-form equation (between x and z), rather than the structural relationship (between y and x). One cannot possibly achieve identification by claiming to restrict the functional form of $\delta(.)$, as it is indeed an object outside our NPIV model.

In this project, the assumption of completeness is applied to ensure the integral equation(s) involving the quantile model of interest has a unique solution.

B Estimation

We use a variant of the stochastic EM algorithm following Arellano et al. (2023). In the stochastic E-step, we use Sequential Monte Carlo sampling method to generate efficient"particles" for latent η-components that are approximately distributed as their target posteriors. In the M-step, we estimate and update quantile model parameters via quantile regression. This algorithm is designed to iterate between these two steps for a large number of times until the sequences of estimated parameters converge.

B.1 Likelihood functions

We specify the quantile-dependence of model coefficients as a piecewise-linear function in $[\tau_1, \tau_L]$. This means that for any given $\tau \in [\tau_1, \tau_L]$ and for any k, the function $a^{\eta}_{k,\tau}$ can be computed as:

$$a^{\eta}_{k,\tau} = \left[a^{\eta}_{k,\ell} + \frac{a^{\eta}_{k,\ell+1} - a^{\eta}_{k,\ell}}{\tau_{\ell+1} - \tau_l} (\tau - \tau_\ell) \right] \mathbf{1}\{\tau_\ell \leq \tau < \tau_{\ell+1}\}, \forall \ell = \{1, 2, \ldots, L\} \tag{B.10}$$

Whereas for percentiles in $[0, \tau_1]$ and $[\tau_L, 1]$, a^{η}_k with $k \geq 1$ are set to be constant and a^{η}_0 subject to the previously specified Laplace model. Likelihood function is available in closed-form given quantile process above. Use (θ, μ) to denote income and consumption model coefficients respectively.

Income model. The likelihood function for income model is:

$$f(y_i^{T-1}, \eta_i^{T-1}; \theta, \mu) = \prod_{t=0}^{T-1} f(y_{it}|\eta_{i,t}; \theta) \prod_{t=1}^{T-1} f(\eta_{i,t}|\eta_{i,t-1}; \theta) f(\eta_{i,1}; \theta) \tag{B.11}$$

Consumption model. Similarly, the full likelihood function for consumption model is:

$$\begin{aligned} f(y_i^{T-1}, c_i^{T-2}, a_i^{T-1}, \eta_i^{T-1}; \theta, \mu) = & \prod_{t=0}^{T-1} f(y_{i,t}|\eta_{i,t}; \theta) \prod_{t=1}^{T-1} f(\eta_{i,t}|\eta_{i,t-1}; \theta) f(\eta_{i,1}; \theta) \\ & \times \prod_{t=0}^{T-2} f(c_{i,t}|a_{i,t}, \eta_{i,t}, y_{i,t}, \eta_{i,t+1}; \mu) \\ & \times \prod_{t=0}^{T-1} f(a_{i,t}|a_{i,t-1}, y_{i,t-1}, c_{i,t-1}, \eta_{i,t-1}; \mu) f(a_{i,1}|\eta_{i,1}; \mu) \end{aligned} \tag{B.12}$$

In the baseline model, asset is modelled as a function of lagged assets, consumption and income. The corresponding likelihood function for baseline consumption model is:

$$\begin{aligned} f(y_i^{T-1}, c_i^{T-2}, a_i^{T-1}, \eta_i^{T-1}; \theta, \mu) = & \prod_{t=0}^{T-1} f(y_{i,t}|\eta_{i,t}; \theta) \prod_{t=1}^{T-1} f(\eta_{i,t}|\eta_{i,t-1}; \theta) f(\eta_{i,1}; \theta) \\ & \times \prod_{t=0}^{T-2} f(c_{i,t}|a_{i,t}, \eta_{i,t}, y_{i,t}, \eta_{i,t+1}; \mu) \\ & \times \prod_{t=0}^{T-1} f(a_{i,t}|a_{i,t-1}, y_{i,t-1}, c_{i,t-1}; \mu) f(a_{i,1}|y_{i,1}; \mu) \end{aligned} \tag{B.13}$$

B.2 M-step

Use (θ, μ) to denote income and consumption model coefficients respectively. The following compact notation represents model restrictions relevant to the income model:

$$\bar{\theta} = \arg\max_{\theta} \mathbb{E}\left[\int R(y_i, \eta; \theta) f_i(\eta; \bar{\theta})\, d\eta\right] \tag{B.14}$$

where R is our income model of interest, $\bar{\theta}$ is the true value of θ and $f_i(.; \bar{\theta})$ is the household-specific posterior density given income data. We let $f_i(.; \bar{\theta}) = f(.|y_t^T, \texttt{age}_i^T; \bar{\theta})$ in practice.

Two types of model restrictions applies here. The first type is directly implied by the nature of quantile regressions. Let $\rho_\tau(u) = u(\tau - \mathbf{1}\{u \leq 0\})$ denotes the "check" function of quantile regression. Given that income model is fully-specified, the posterior density f_i is a known function of $\bar{\theta}$. For all $\ell \in \{1, \ldots, L\}$, income model coefficients are by definition:

$$(\bar{a}_{0\ell}^Q, \ldots, \bar{a}_{K\ell}^Q) = \arg\max_{\{\bar{a}_{0\ell}^Q, \ldots, \bar{a}_{K\ell}^Q\}} \sum_{t=2}^{T} \mathbb{E}\left[\int \rho_{\tau_\ell}\left(\eta_{i,t} - \sum_{k=0}^{K} a_{k\ell}^Q \varphi_k(\eta_{i,t-1}, \texttt{age}_{i,t})\right) \times f_i(\eta_i^T; \bar{\theta})\, d\eta_i^T\right] \tag{B.15}$$

where $\bar{a}_{k\ell}^{Q}$ denotes true value of income model coefficients at a given quantile τ_ℓ, and the expectation is taken with respect to the distribution of observed income and age. As mentioned in Arellano et al. (2017), the objective function described above is both smooth (due to the presence of integral) and convex (due to the "check" function). Restrictions for other model coefficients are analogue to above expression.

The second type is tail parameter restrictions. We follow Arellano et al. (2023) and specify the intercept coefficients a_0^Q on $(0, \tau_1]$ and $[\tau_{L-1}, 1)$ using a parametric, Laplace model. Similar tail parameter restrictions apply to consumption model as well.

C Numerical setups

Numerical setups are based extensively on Arellano et al. (2023) given similarities in the source of data and variables of interest.

C.1 Quantile functions

We select $L = 11$ as the number of quantile locations used in the algorithm. We specify the order of Hermite polynomials used in the main estimation as following to ensure a good fit.Income model:

- For η_1: $K_{\texttt{age}_1} = 2$, $K_{\texttt{educ}_1} = 1$, $K_{\texttt{cohort}_1} = 1$;
- For η_t with $t > 1$: $K_{\eta_{t-1}} = 2$, $K_{\texttt{age}_t} = 2$;
- For ε_t: $K_{\texttt{age}_t} = 2$;

Consumption model:

- $K_{\texttt{asset}_t} = 2$, $K_{\eta_{t+1}} = 2$, $K_{\eta_t} = 1$, $K_{\varepsilon_t} = 1$, $K_{\texttt{age}_t} = 1$;

Asset model in baseline case:

- For a_1: $K_{\texttt{age}_1} = 1$, $K_{y_1} = 1$, $K_{\texttt{educ}_1} = 1$, $K_{\texttt{cohort}_1} = 1$;
- For a_t with $t > 1$: $K_{\texttt{asset}_{t-1}} = 2$, $K_{y_{t-1}} = 1$, $K_{c_{t-1}} = 1$, $K_{\texttt{age}_t} = 1$;

The order of Hermite polynomials will also adjust in different sub-samples, such as the dual-earner sample. For more details on model complexity, see Appendix C.4.

C.2 Stochastic E-step: proposal distributions

We use the following proposal distributions in the stochastic E-step as suggested by Arellano et al. (2023). Consider the income model as an example. In the first period 0, the proposal distribution π for household i is:

$$\begin{aligned}
&\eta_{i,0} \sim \mathcal{N}(\mu_0, \sigma_0^2) \\
&\mu_0 = \left(1 - \frac{\sigma_{\eta_0}^2}{\sigma_{\eta_0}^2 + \sigma_\varepsilon^2}\right) \sum_{k=0}^{K} \beta_k^{\eta_0} \varphi_k(\texttt{age}_{i,0}, \texttt{educ}_{i,0}, \texttt{cohort}_{i,0}) \\
&\sigma_0^2 = \frac{c}{\frac{1}{\sigma_{\eta_0}^2} + \frac{1}{\sigma_\varepsilon^2}}
\end{aligned}$$

where $\beta_k^{\eta_0}$ and σ_0^2's are parameters to be estimated by running OLS counterparts to the M-step quantile regressions using latent components from the previous iteration. $c = 2$ is a constant.

For subsequent periods until $T-1$, the proposal distribution is:

$$\begin{aligned}
&\eta_{i,t}|\eta_{i,t-1} \sim \mathcal{N}(\tilde{\mu}_{i,t}, \tilde{\sigma}_t^2) \\
&\tilde{\mu}_{i,t} = \left(1 - \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\varepsilon^2}\right) \sum_{k=0}^{K} \beta_k^{\eta_t} \varphi_k(\eta_{i,t-1}, \texttt{age}_{i,t}) + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\varepsilon^2} y_{i,t} \\
&\tilde{\sigma}_t^2 = \frac{c}{\frac{1}{\sigma_\eta^2} + \frac{1}{\sigma_\varepsilon^2}}
\end{aligned}$$

where $\beta_k^{\eta_t}$ and $\tilde{\sigma}_t^2$'s are parameters to be estimated by running OLS counterparts to the M-step quantile regressions using latent components from the previous iteration. $c = 2$ is a constant. We proceed similarly to construct proposal distributions for the consumption model.

C.3 Miscellaneous specifications

The maximum number of iterations in the stochastic EM algorithm is set at 5000. In every iteration, we set the number of "particles" to be generated as $S_i = 50T_i$ and set the threshold effective sample size for resampling as $S_i/2$.

C.4 Specification selection

Income model. We investigated many different nonlinear persistence profiles implied by changes in income model specification. There are two possible directions in terms of changing specifications: we can either change the order of polynomials used in initial income model (i.e. income model in the very first period when a household first appears in the data), or change the order of polynomials used in the "main" income model (i.e. income model for all subsequent periods).

We tested a large number of possible combinations in approximating the income model. In summary, we noticed that a higher-order approximation provides a better fit in the middle section of the income history distribution. At the same time, it leaves moderate-sized decreases in estimated persistence at the upper tail of the income history distribution for the lowest income shocks. A higher-order approximation also produces a more concave-shaped nonlinear persistence profiles. Meanwhile, a lower-order of approximation gives a more linear persistence profile and a lower estimated mean persistence in the full sample. In practice, we select the order of polynomials used in approximating income quantile functions based on the following criterions. A suitable income model specification:

- captures the nonlinear nature of income persistence well
- does not over-fit or under-fit the data to a significant extent
- gives comparable estimates to existing results on income persistence

For exact income model specifications used in our estimation, see Appendix C.

Consumption model. Similar to the previous section, the order of Hermite polynomials used in approximating consumption quantile functions follows similar selection criterions. A suitable consumption model specification:

- delivers consistent consumption response patterns across similar samples
- does not over-fit or under-fit the data to a significant extent
- generates a response profile with sufficient level of monotonicity along key dimensions

Apart from above criterions, we also monitor the numerical performance of the stochastic EM algorithm when testing various specifications. Overall, most specifications performed well. We change the order of Hermite polynomials for the dual-earner sub-sample employed in this project. This is a common practice in series regressions where model complexity depends on sample size (see Hansen (2022)). For exact model specifications used in the main estimation, see Appendix C.

D Additional description of PSID Data

D.1 Income, consumption and wealth variables in the PSID

The PSID data collection scheme has changed significantly in 1999 and 2005. In 1999, more consumption data become available while the coverage for income and wealth related variables remain unchanged. A further change in 2005 expanded consumption categories such that it has comparable coverage as in the CEX. The only missing categories are alcohol and tobacco related expenses. We present a detailed documentation in variable availability in this section of appendix.

D.1.1 Itemized consumption categories

	1999-2005	Post-2005
Food stamp	✓	✓
Food, at home	✓	✓
Food, dine out	✓	✓
Food, delivered	✓	✓
Mortgage	✓	✓✓
Rent	✓	✓
Property tax	✓	✓
Home insurance	✓	✓
Utilities	✓	✓
Heat subsidy	✓	✓
Telecommunications		✓
Vehicle, loan	✓	✓✓
Vehicle, downpayment	✓	✓✓
Vehicle, lease	✓	✓✓
Vehicle, insurance	✓	✓
Vehicle, other costs	✓	✓
Vehicle, repair	✓	✓
Gasoline	✓	✓
Parking	✓	✓
Bus and train	✓	✓
Taxicab	✓	✓
Transportation, other	✓	✓
Education	✓	✓✓
Childcare	✓	✓
Medical instances	✓	✓
Doctor visits	✓	✓
Prescription	✓	✓
Health insurance	✓	✓
Home, repairs		✓
Home, furnishes		✓
Clothing		✓
Trips		✓
Other recreations		✓

Note: ✓✓ indicates multiple interview of identical question.

D.2 Descriptive statistics: dual-earner sample

Table 7: PSID Family Demographics, Dual-earner Sample (2005-2021)

	(1) 2005	(2) 2007	(3) 2009	(4) 2011	(5) 2013	(6) 2015	(7) 2017	(8) 2019	(9) 2021
HEAD									
Age	40.94	41.79	42.71	43.93	44.92	45.42	45.96	46.66	47.39
	(7.79)	(8.16)	(8.65)	(8.99)	(9.53)	(9.06)	(8.53)	(7.99)	(7.39)
Years of education	14.42	14.39	14.39	14.39	14.41	14.41	14.47	14.57	14.66
	(2.34)	(2.37)	(2.39)	(2.37)	(2.36)	(2.37)	(2.31)	(2.21)	(2.19)
Weeks employed	48.03	48.37	47.91	47.14	47.10	48.02	48.08	48.28	47.36
	(5.25)	(3.87)	(5.42)	(6.57)	(7.53)	(5.06)	(5.46)	(5.60)	(8.21)
% in labour force	98.11%	98.29%	97.10%	94.97%	92.49%	93.66%	94.54%	94.86%	96.07%
% currently employed	96.98%	97.36%	93.36%	93.31%	90.23%	92.54%	92.15%	93.21%	94.01%
SPOUSE									
Age	39.49	40.41	41.27	42.49	43.48	44.16	44.69	45.33	46.13
	(8.00)	(8.38)	(8.88)	(9.21)	(9.68)	(9.34)	(8.80)	(8.20)	(7.67)
Years of education	14.79	14.81	14.79	14.83	14.84	14.89	14.94	15.04	15.18
	(2.17)	(2.18)	(2.20)	(2.19)	(2.17)	(2.14)	(2.11)	(2.10)	(2.04)
Weeks employed	45.64	44.93	46.51	45.80	46.51	47.01	47.44	48.09	46.35
	(8.74)	(8.62)	(7.16)	(7.90)	(7.70)	(7.19)	(6.46)	(5.87)	(9.51)
% in labour force	88.68%	80.43%	86.17%	75.77%	79.98%	76.90%	78.84%	79.84%	84.60%
% currently employed	87.55%	79.07%	83.82%	74.13%	78.78%	76.06%	77.82%	78.81%	83.33%
FAMILY									
Family size	3.45	3.44	3.39	3.36	3.32	3.38	3.40	3.45	3.48
	(1.12)	(1.13)	(1.16)	(1.21)	(1.23)	(1.19)	(1.20)	(1.20)	(1.18)
Number of kids	1.20	1.20	1.15	1.11	1.07	1.07	1.09	1.13	1.11
	(1.05)	(1.11)	(1.15)	(1.17)	(1.18)	(1.15)	(1.18)	(1.19)	(1.16)
% have newborn	13.21%	11.63%	11.48%	10.94%	7.51%	7.18%	5.97%	6.58%	3.39%
% use SNAP	0.75%	0.47%	0.97%	1.29%	1.43%	1.41%	1.19%	0.82%	2.60%
% as renter	5.09%	6.82%	7.75%	8.62%	8.70%	8.45%	7.34%	6.58%	5.73%
Observations	530	645	723	777	839	710	586	486	384

Note: sample mean displayed as coefficients; standard deviations in parentheses.

Table 8: PSID Expenditure Categories, Dual-earner Sample (2005-2021)

	(1) 2005	(2) 2007	(3) 2009	(4) 2011	(5) 2013	(6) 2015	(7) 2017	(8) 2019	(9) 2021
NON-DURABLES									
Food (incl. food stamps)	8,866.78	8,951.61	8,551.14	8,758.40	8,959.09	9,251.17	9,907.38	9,919.27	10,181.00
	(4,583.18)	(4,400.98)	(3,990.64)	(4,181.12)	(4,917.10)	(4,350.83)	(4,685.17)	(4,526.90)	(4,733.01)
Clothing & gasoline	5,034.71	5,438.31	4,380.28	5,176.45	4,927.76	4,314.55	3,732.65	3,910.32	3,479.24
	(3,420.19)	(4,906.62)	(3,590.07)	(3,603.91)	(3,363.97)	(3,450.40)	(2,470.35)	(2,677.42)	(2,389.08)
DURABLES									
Vehicles (excl. insurance)	8,929.04	8,515.23	7,882.89	6,868.57	6,530.76	6,833.88	6,683.24	7,015.03	6,119.89
	(9,141.46)	(8,994.29)	(8,181.74)	(7,805.94)	(7,037.29)	(6,255.20)	(6,264.27)	(6,596.82)	(6,218.07)
Home repairs and furnishes	4,285.52	5,817.29	5,290.65	3,837.76	3,483.83	3,766.48	4,234.91	4,125.75	4,456.85
	(6,601.82)	(22,002.35)	(19,074.76)	(6,928.11)	(6,855.07)	(6,411.39)	(9,026.52)	(10,496.64)	(10,994.09)
SERVICES									
Utilities and telecom.	4,864.29	5,080.46	5,517.10	5,489.19	5,541.24	5,664.06	5,547.88	5,729.13	5,533.24
	(1,871.41)	(1,772.68)	(3,634.65)	(2,149.86)	(2,266.86)	(2,171.34)	(1,926.64)	(2,123.31)	(2,078.25)
Medical expenses	3,284.90	3,455.01	3,640.76	3,667.24	4,929.64	5,495.17	5,161.81	5,503.97	5,342.61
	(3,249.67)	(3,319.07)	(3,494.37)	(3,656.78)	(4,266.52)	(7,640.20)	(4,216.25)	(4,683.93)	(4,501.10)
Trips and recreations	3,827.70	4,209.31	4,046.49	3,678.83	3,616.13	3,754.43	3,764.75	4,102.55	2,655.31
	(5,074.32)	(6,247.52)	(6,203.57)	(4,165.01)	(4,115.35)	(4,261.83)	(3,794.29)	(4,033.88)	(3,396.50)
Education	3,115.61	2,833.22	2,822.00	2,908.05	3,148.14	3,398.69	2,706.04	2,691.02	2,707.28
	(7,887.11)	(6,986.07)	(7,985.17)	(7,822.07)	(8,521.10)	(8,803.37)	(6,777.23)	(6,739.56)	(6,674.85)
Transportations	2,427.30	2,257.75	1,965.08	2,036.25	1,901.18	2,097.36	2,015.61	2,081.05	1,958.76
	(2,789.44)	(3,813.13)	(1,995.60)	(3,845.57)	(1,554.54)	(2,280.06)	(1,468.93)	(1,422.25)	(1,424.12)
Childcare	1,090.32	1,252.99	1,231.28	1,241.93	1,290.05	1,204.45	1,129.58	1,203.89	852.85
	(3,198.36)	(3,305.81)	(3,223.91)	(3,307.68)	(3,472.54)	(3,130.21)	(2,821.65)	(3,392.38)	(3,153.51)
Non-durables and services	32,541.88	33,491.68	32,168.97	32,975.61	34,330.33	35,203.71	33,993.41	35,151.29	32,738.68
	(17,684.15)	(17,622.37)	(17,653.44)	(17,742.09)	(17,731.22)	(18,132.63)	(14,845.24)	(16,000.36)	(14,672.81)
All PSID expenditures	41,440.65	41,993.88	40,037.02	39,824.90	40,843.99	42,013.77	40,648.95	42,156.24	38,830.17
	(22,303.17)	(21,520.01)	(20,754.42)	(20,896.24)	(20,255.80)	(20,055.42)	(17,101.39)	(18,643.93)	(17,110.47)
Food share	0.2316	0.2309	0.2339	0.2387	0.2336	0.2356	0.2557	0.2491	0.2788
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)
Observations	530	645	723	777	839	710	586	486	384

Note: sample mean displayed as coefficients; standard deviations in parentheses.

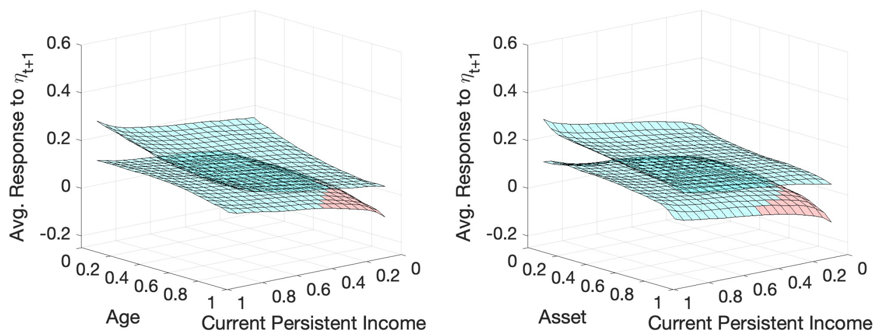
Table 9: PSID Income and Family Wealth, Dual-earner Sample (2005-2021)

	(1) 2005	(2) 2007	(3) 2009	(4) 2011	(5) 2013	(6) 2015	(7) 2017	(8) 2019	(9) 2021
HEAD									
Labour income	64,496.89	68,382.73	68,923.74	63,425.71	65,048.91	64,213.62	65,493.99	68,004.90	70,542.64
	(62.86)	(91.13)	(89.74)	(76.65)	(98.09)	(46.48)	(42.36)	(45.64)	(55.14)
Wage per working week	1,345.60	1,412.68	1,436.51	1,354.91	1,392.66	1,342.58	1,375.08	1,419.23	1,505.39
	(1,260.24)	(1,824.03)	(1,809.27)	(1,554.87)	(1,972.78)	(977.87)	(883.72)	(958.76)	(1,159.35)
SPOUSE									
Labour income	36,883.65	37,854.49	41,022.84	39,165.40	41,166.03	40,951.48	43,031.62	45,065.23	46,350.16
	(29.38)	(30.87)	(36.92)	(34.57)	(41.05)	(29.14)	(29.06)	(30.30)	(35.22)
Wage per working week	801.46	843.48	898.07	863.22	893.84	876.12	915.18	968.22	996.86
	(627.45)	(686.30)	(838.90)	(762.45)	(900.67)	(618.29)	(615.27)	(755.68)	(729.07)
FAMILY WEALTH									
Home equity	132,356.48	143,763.32	112,328.05	100,314.89	97,823.63	105,501.56	116,765.91	137,506.20	170,669.10
	(174,821.08)	(190,773.34)	(161,568.16)	(134,460.97)	(129,973.78)	(122,940.29)	(118,910.83)	(134,585.50)	(164,705.09)
Wealth (excl. home equity)	203,883.96	212,423.34	237,846.61	208,630.33	208,822.97	250,605.64	289,994.30	295,485.23	392,916.68
	(597,507.49)	(465,529.97)	(779,274.40)	(444,060.90)	(459,597.49)	(511,671.54)	(903,310.86)	(640,209.54)	(852,168.29)
Wealth	336,240.44	356,186.66	350,174.66	308,945.22	306,646.60	356,107.19	406,760.20	432,991.43	563,585.78
	(685,524.83)	(587,341.01)	(876,523.24)	(515,465.24)	(540,833.89)	(571,660.81)	(933,386.47)	(692,864.26)	(913,495.42)
Observations	530	645	723	777	839	710	586	486	384

Note: sample mean displayed as coefficients; standard deviations in parentheses.

E Additional empirical results

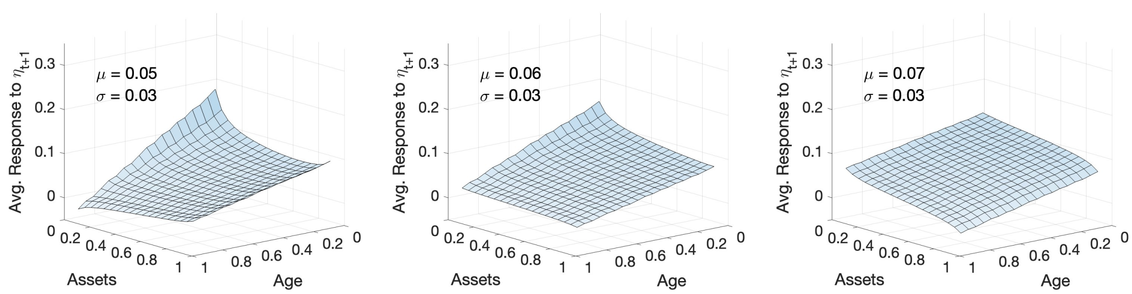
E.1 Additional bootstrap inference results



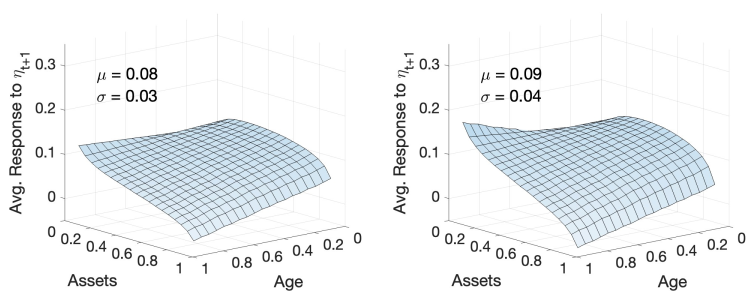
(a) By age and η_t (b) By asset and η_t

Figure E.1: Non-parametric bootstrapped 95% confidence band

E.2 Consumption response to future persistent income component, by time invariant unobserved household types



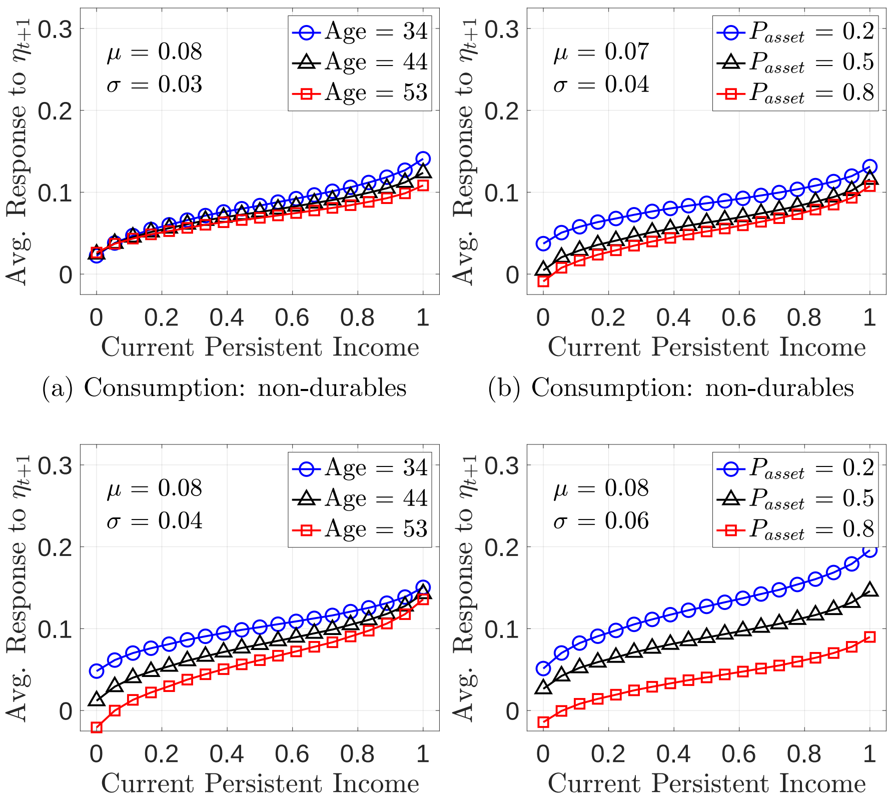
(a) Unobserved type $P = 0.1$ (b) Unobserved type $P = 0.25$ (c) Unobserved type $P = 0.5$



(d) Unobserved type $P = 0.75$ (e) Unobserved type $P = 0.9$

Figure E.2: Average response to future persistent income by unobserved household types

E.3 Consumption response to future persistent income component, alternative measures of consumption and asset



(a) Consumption: non-durables

(b) Consumption: non-durables

(c) Consumption: services

(d) Consumption: services

Figure E.3: Average response to future persistent income by alternative consumption measures