Health-Dependent Preferences, Consumption, and Insurance

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October 8, 2022

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Abstract

I study the effect of health on preferences and the implications of this effect on self and government insurance. To do so, I build a life-cycle model in which health affects survival, earnings, medical expenditures, and the marginal utility of non-medical consumption. I then calibrate the model using data from the Panel Study of Income Dynamics in the United States. I find that bad health reduces the marginal utility of non-medical consumption. To shed light on the implications of health-dependent preferences on self-insurance, I examine the differences in life-cycle consumption and savings when health does and does not influence marginal utility. My results suggest that health-dependent preferences lower savings over the whole life cycle and decrease consumption in old age. Finally, I study the welfare effects of reforming means-tested government insurance in the United States. I find that health-dependent preferences reduce the household valuation of government insurance programs.

*Department of Economics, University of Minnesota. I would like to thank my advisor, Mariacristina De Nardi, for her invaluable guidance and support. I would also like to thank Alessandra Fogli, Jeremy Lise, and Jo Mullins for their advice and suggestions, as well as Filip Babalievsky, Lidia Cruces, Dhananjay Ghei, Martin Garcia, and all the participants of the Macro-Micro workshop at the University of Minnesota.

1 Introduction

Health affects many outcomes in a person's life. For example, it affects how long they will live and how much they can work. While the effects of health on outcomes like mortality and labor supply have been studied extensively, the literature has given less attention to the fact that health may affect how much people enjoy consumption. This means, for example, that consuming when sick may be more or less enjoyable – i.e., give a higher or lower utility – than when healthy. The available results in the literature are ambiguous on the magnitude and direction of this effect. To help resolve this ambiguity and shed light on the impact of health on preferences, I build and calibrate a life-cycle model in which health affects survival, earnings, medical expenditures, and the marginal utility of consumption. I then use my calibrated model to analyze the quantitative effects of health-dependent preferences on self and government insurance.

Standard optimality conditions predict that households smooth marginal utility across states of the world. In the absence of preference shocks – so if health does not affect preferences – smoothing marginal utility leads to smoothing consumption. However, when health affects preferences, this is not true anymore. In particular, it may be the case that optimal consumption when sick is different than optimal consumption when healthy. This observation has consequences for both self and government insurance. If health affects preferences, it will affect the optimal choice of savings and people's ability to self-insure via savings. Moreover, the change in optimal consumption across states of the world has consequences on how much people value government insurance and on the optimal design of insurance programs for the sick.

To study the effect of health-dependent preferences on the value of social insurance programs, I build a structural life-cycle model of consumption and savings for households between 25 and 89. In my model, households face health risk over the whole life cycle, and health affects survival, working-age earnings, medical expenditures, and the marginal utility of consumption. The government provides social insurance through means-tested transfers, which bridge the gap between a minimum level of acceptable consumption (i.e., a consumption floor) and a household's resources.

I calibrate my model to the United States using data from the Panel Study of Income Dynamics (PSID.) I show that the consumption response to a transitory health shock identifies the effect of health on preferences. I find that this effect is negative, and thus poor health significantly lowers the marginal utility of non-medical consumption. This result contributes to reducing the ambiguity in the literature on health-dependent preferences.

Using my calibrated model, I provide the first quantitative assessment of the effects of health-dependent preferences on self and government insurance. I find that health-dependent preferences increase consumption at older ages, reduce consumption when young, and increase savings at all ages. I also find that health-dependent preferences reduce the value household place on means-tested government insurance, which is more valuable for poorer and sicker households.

The remainder of the paper is organized as follows. Section 2 describes the relationship with the literature and presents my contributions. Section 3 describes my quantitative model. Section 4 illustrates the data and my health measure. Section 5 discusses my empirical strategy and presents my calibration results. Section 6 shows the effects of health-dependent preferences on self-insurance. Section 7 discusses the welfare effects of reforming means-tested government insurance. Section 8 concludes.

2 Relationship to the literature and contributions

My paper relates to three branches of the literature and contributes to each. First, my paper is related to the literature on **health-dependent preferences** There is no consensus on the magnitude and direction of the effect of health on preferences. Two approaches have emerged in this literature. On the one hand, some papers take a structural-life-cycle-model approach. Among these, Lillard and Weiss (1997) find a positive effect of health on preferences, meaning marginal utility increases with deteriorating health. In contrast, De Nardi, French, and Jones (2010) and Hong, Pijoan-Mas, and Ríos-Rull (2015) find evidence of a negative effect, so marginal utility decreases as health worsens. On the other hand, some papers take a purely empirical approach. Among these, Viscusi and Evans (1990) and Finkelstein, Luttmer, and Notowidigdo (2013) find evidence of a negative effect of health on preferences, while Evans and Viscusi (1991) find that there is no effect at all.[1] My paper provides new estimation and identification results for the effect of health on preferences. In particular, I take a structural approach and estimate the effect of health on preferences through the Method of Simulated Moments.

Second, my paper relates to the literature on **structural life-cycle models with health risk.** Seminal contributions in this literature are Palumbo (1999), French (2005), and De Nardi, French, and Jones (2010). This literature is growing fast and includes, among others, Scholz and Seshadri (2011), Kopecky and Koreshkova (2014), Capatina (2015), De Nardi, French, and Jones (2016), De Nardi, Pashchenko, and Porapakkarm (2017), and recent contributions by Dal Bianco (2019), Hosseini, Kopecky, and Zhao (2020), Keane, Capatina, and Maruyama (2020), and Salvati (2020). Despite some notable exceptions, for example, De Nardi, Pashchenko, and Porapakkarm (2017) and Hosseini, Kopecky, and Zhao (2020), most papers in this literature focus on the effects of health uncertainty on the elderly. I, instead, focus on the whole life cycle, thus acknowledging the importance of health shocks even when young. I contribute to this literature by studying the effect of health risk on the marginal utility of consumption and by analyzing the welfare effects of health-dependent preferences.

Third, my paper relates to the literature on **insurance against health shocks.** Two relevant papers in this literature are Braun, Kopecky, and Koreshkova (2016) and Blundell, Borella, Commault, and De Nardi (2022). Braun, Kopecky, and Koreshkova (2016) build a structural model of the whole life-cycle to study the role of means-tested social insurance programs - such as Medicaid and Supplemental Security Income - for medical expenses, longevity, and poverty risk. Blundell, Borella, Commault, and De Nardi (2022) use a structural model for the elderly to show that the response of consumption to transitory health shocks depends on the shock's effect on resources and marginal utility, with the marginal utility channel being the strongest driver. I contribute to this literature by studying the whole life cycle, rather than only the elderly like Blundell, Borella, Commault, and De Nardi (2022), and considering health risk at all ages, rather than only for the elderly like Braun, Kopecky, and Koreshkova (2016).

[1] Appendix A reviews the literature on health-dependent preferences in more depth.

3 Model

In this section, I outline a partial equilibrium life cycle model in which health affects the marginal utility of consumption, survival, earnings, and medical expenditures.

3.1 Environment

Households enter the model at age 25, retire exogenously at 63, and die with certainty by the time they are 89. Households are subject to health, earnings, and survival risk until retirement, after which earnings risk is resolved. To be consistent with biennial PSID data, each period in my model corresponds to two years.

I assume that asset markets are incomplete. Households enter the model with zero assets and can only invest in a risk-free asset with a constant rate of return. There are no annuity markets to insure against mortality risk, and I assume accidental bequests are lost to the economy.

3.2 Preferences and Health State Dependence

Each period, utility depends on health status and consumption of non-durable and non-medical goods. The period flow utility of consumption is:

$$u(c_t, h_t) = \delta(h_t)\frac{c_t^{1-\gamma}}{1-\gamma}, \tag{3.1}$$

where c_t is consumption; h_t is health status; γ is the coefficient of relative risk aversion; and $\delta(h_t)$ measures the effect of health on marginal utility. Following Palumbo (1999) and De Nardi, French, and Jones (2010), I model the effect of health on marginal utility as:

$$\delta(h_t) = 1 + \delta h_t, \tag{3.2}$$

where δ is a parameter to be estimated. This formulation implies that when δ is equal to 0, health status does not affect utility.

3.3 Health Status

Health status is measured by the frailty index.[2]. In each period, frailty can be either zero or positive. A value of zero signals perfect health, while a positive value denotes some unhealthiness. In particular, frailty can be at most 1, and the closer it is to 1, the more unhealthy a household is.

I assume that if frailty is zero in period t, there is a transition probability that captures how likely frailty is to remain at zero in period $t+1$ or to increase to a positive value. I also assume that if frailty is positive in period t, it cannot go back to zero in period $t+1$.[3] When frailty is positive, I follow Hosseini, Kopecky, and Zhao (2022) and assume it evolves according to the following process:

$$\log(h_t) = \kappa_t + \pi_t^h + \varepsilon_t^h, \tag{3.3}$$

$$\pi_t^h = \rho_h \pi_{t-1}^h + \eta_t^h, \tag{3.4}$$

$$\varepsilon_t^h \sim \mathbb{N}(0, \sigma^2_{\varepsilon^h}), \tag{3.5}$$

$$\eta_t^h \sim \mathbb{N}(0, \sigma^2_{\eta^h}), \tag{3.6}$$

$$\pi_0^h \sim \mathbb{N}(0, \sigma^2_{\pi_0^h}), \tag{3.7}$$

where κ_t is a deterministic component that depends on age; π_t is a persistent component, and ε_t is a transitory component. Following Hosseini, Kopecky, and Zhao (2022), I assume that, when $h_t = 0$, $\pi_t = 0$ as well.

3.4 Working Age Earnings

Households face earnings risk during their working age. Labor earnings depend on age, health status, and a persistent and transitory component. I assume that log earnings evolve

[2] I present details on the frailty index as a measure of health in Section 4.1

[3] This is consistent with my data. In my PSID sample, less than one percent of households are transitioning from positive to zero frailty.

according to the following process:

$$\log y_t(h) = \kappa_t(h) + \pi_t^y + \varepsilon_t^y, \tag{3.8}$$

$$\pi_t^y = \rho_y \pi_{t-1}^y + \eta_t^y, \tag{3.9}$$

$$\varepsilon_t^y \sim \mathbb{N}(0, \sigma_{\varepsilon^y}^2), \tag{3.10}$$

$$\eta_t^y \sim \mathbb{N}(0, \sigma_{\eta^y}^2), \tag{3.11}$$

$$\pi_0^y \sim \mathbb{N}(0, \sigma_{\pi_0^y}^2), \tag{3.12}$$

where $\kappa_t(h)$ denotes the deterministic component of earnings, π_t^y is a persistent component, and ε_t^y is a transitory component.

3.5 Medical Expenditures and Death

In each period until death, households incur out-of-pocket medical expenditures and face survival probabilities. I only consider medical expenditures that are not covered by health insurance and I do not model health insurance itself. Consistently with De Nardi, French, and Jones (2010) and Keane, Capatina, and Maruyama (2020), medical expenditures are exogenous and modeled as cost shocks. I model log-medical expenditures as follows:

$$\log m_t(h) = g(t, h) + \xi_t, \tag{3.13}$$

$$\xi_t \sim \mathbb{N}(0, \sigma_\xi^2), \tag{3.14}$$

where $g(t, h)$ denotes a deterministic function of age and health status and ξ_t denotes an i.i.d. shock. Medical expenditures are present even for households with perfect health to capture preventative care, such as routine physicals and examinations.

Households face an age-health-specific survival probability up to the maximum age of 89. I denote survival probabilities by $s_{h,t}$.

3.6 Government

The government imposes taxes on income, provides Social Security benefits to retirees, and supplies a means-tested transfer.

Income taxes paid are a function of total income. I follow Bénabou (2002), Heathcote, Storesletten, and Violante (2017), and Borella, De Nardi, Pak, Russo, and Yang (2021), and adopt a log-linear tax function which allows for negative tax rates, and thus incorporates the Earned Income Tax Credit (EITC.) In particular, income taxes are given by:

$$T(y) = y - (1-\lambda)y^{1-\tau}, \tag{3.15}$$

where y denotes the level of total income, λ captures the average level of taxation in the economy, and τ denotes the degree of progressivity of the income tax system. [4]

I assume that the only source of income after retirement is government-provided Social Security benefits. In reality, Social Security benefits depend on workers' earnings histories. Modeling earnings histories requires adding a continuous state variable. To reduce computational costs, I follow De Nardi, Fella, and Paz-Pardo (2019) and assume that Social Security benefits are a function of the last realization of labor earnings. So Social Security benefits are given by:

$$ss_t = ss(y_{T^{ret}-1}), \tag{3.16}$$

The government provides a means-tested transfer to guarantee a minimum level of consumption, $\underline{c}$. In particular, means-tested transfers ensure that a household's available resources are enough to meet a minimum consumption floor. The transfer is computed as:

$$b_t = \max\{0, \underline{c} + m_t(h) - [a_t + y^n(ra_t + y_t(h), \tau)]\}, \qquad \text{if } t < T^{ret}, \tag{3.17}$$

$$b_t = \max\{0, \underline{c} + m_t(h) - [a_t + ss^n(ra_t + ss_t, \tau)]\}, \qquad \text{if } t \geq T^{ret}, \tag{3.18}$$

where b_t denotes the transfer; $y^n(\cdot)$ denotes net income during the working age; and $ss^n(\cdot)$ indicates net income during the retirement period.

[4] See Borella, De Nardi, Pak, Russo, and Yang (2021) for a detailed description of this tax function and the interpretation of its parameters.

3.7 Timing

The timing is as follows. Working-age households start each period with a stock of assets and draw realizations of the stochastic process of frailty, earnings, and medical expenditures. Then, they make consumption-saving decisions. Retired households start each period with a stock of assets and Social Security benefits that remain constant until they die. They draw realizations of the stochastic processes of frailty and medical expenditures and then make consumption-saving decisions.

3.8 Recursive Formulation

I compute two value functions, one for each stage of life.

3.8.1 The Value Function for Workers

The vector of state variables X_t for workers is composed of: age t, assets a_t, the shock to medical expenditures ξ_t, the persistent component of earnings π_t^y, the transitory component of earnings ε_t^y, the persistent component of health π_t^h, and the transitory component of health ε_t^h. Workers maximize the objective function:

$$V(X_t) = \max_{c_t, a_{t+1}} \left\{ \delta(h_t) \frac{c_t^{1-\gamma}}{1-\gamma} + \beta s_{h,t} \mathbb{E}_t[V(X_{t+1})] \right\}, \tag{3.19}$$

Subject to the intertemporal budget constraint:

$$a_{t+1} = a_t + y^n(ra_t + y_t(h), \tau) - m_t(h) + b_t - c_t, \tag{3.20}$$

And Equations 3.3-3.7, 3.8-3.12, 3.13-3.14, 3.17, and a no borrowing constraint in every period, $a_t > 0$.

3.8.2 The Value Function for Retirees

The vector of state variables X_t for retirees comprises: age t, assets a_t, the shock to medical expenditures ξ_t, Social Security benefits ss_t, the persistent component of health π_t^h, and the transitory component of health ε_t^h. Retirees maximize the objective function:

$$V(X_t) = \max_{a_{t+1}} \left\{ \delta(h_t) \frac{c_t^{1-\gamma}}{1-\gamma} + \beta s_{h,t} \mathbb{E}_t[V(X_{t+1})] \right\}, \tag{3.21}$$

Subject to the intertemporal budget constraint

$$a_{t+1} = a_t + ss^n(ra_t + ss_t, \tau) - m_t(h) + b_t - c_t, \tag{3.22}$$

And Equations 3.3-3.7, 3.13-3.14, 3.16, 3.18, and a no borrowing constraint in every period, $a_t > 0$.

Households' Social Security benefits are a state variable because they depend on the last realization of labor earnings. The terminal value function is set to zero, as households do not derive utility from bequests.

4 Data

I use data from the Panel Survey of Income Dynamics (PSID), a longitudinal survey of a representative sample of the U.S. population. The University of Michigan runs the PSID. The PSID has been conducted annually since 1968 and biennially since 1997. I use each biennial wave between 2005 and 2019. During my sample period, the PSID contains detailed information on health status and medical conditions, labor and non-asset income, wealth, and consumption. I conduct a household-level analysis and use every wave of the PSID between 2005 and 2019. To be consistent with my model, I consider households whose head is between 25 and 89 years old. Appendix B provides details about my data and sample selection.

My measure of health is the frailty index. Section 4.1 describes the frailty index in detail. I construct a household's frailty index as the average of each member's frailty index. Working-age earnings for workers include labor earnings, the labor part of business income, and farm income. When married, household earnings are the sum of each spouse's earnings. Medical expenditures are the sum of what households spend out-of-pocket for hospital and nursing home stays, doctor visits, prescription drugs, and insurance premia. Non-medical consumption is the sum of household expenditures on food at and away from home, utilities, phone bills, internet bills, transportation(excluding car loans, lease payments, and down payments,) trips and vacations, entertainment and recreation, donations to charity, and clothing. I convert nominal earnings, medical expenditures, and consumption into real quantities using the Consumer Price Index for Urban Consumers (CPI-U) and 2018 as my base year. Finally, I identify a household's education level with that of the household's head. I consider three possible education levels: less than high school, high school graduate, and college graduate. Appendix D presents some facts on my key variables of interest.

4.1 Measuring health

I measure health status on a continuous scale using the frailty index. The frailty index captures the idea that, as people age, they become increasingly exposed to adverse health events - such as chronic diseases or temporary ailments - which I refer to as deficits. The frailty index is the ratio of the number of deficits a person currently has to the total number of deficits considered. By construction, the frailty index ranges between zero for perfectly healthy people and one for completely unhealthy people.

The frailty index is an objective measure of health. It has been used extensively in the medical and gerontology literature, which has shown it to be an excellent predictor of health and mortality.[5] Hosseini, Kopecky, and Zhao (2022) and Nygaard (2021) pioneered its use in economics. To construct the frailty index for the households in my sample, I follow the guidelines in Searle, Mitnitski, Gahbauer, Gill, and Rockwood (2008) and use the same categories of deficits in Hosseini, Kopecky, and Zhao (2022). In particular, I include:

- Difficulties with activities of daily living (ADL) and instrumental ADL (IADL,) such as difficulty dressing, bathing, and walking.
- Diagnosed diseases, such as diabetes, cancer, and arthritis.
- Cognitive impairments and mental health measures, such as memory loss and psychological problems.

[5] See Hosseini, Kopecky, and Zhao (2022) for a review of the medical literature using the frailty index.

- Lifestyle habits, such as smoking and excessive alcohol consumption.

In total, I consider 29 deficits to construct the frailty index. Each deficit can take a value of either zero or one, based on whether the individual currently has a specific deficit or not. Table A-2 in Appendix C reports the complete list of deficits I use.

My frailty index does not include any measure of subjective health, such as self-reported health status. I do so to keep my frailty index objective. Hosseini, Kopecky, and Zhao (2022) consider a version of the frailty index that includes self-reported health status and conclude that it conveys the same information about the dynamics of health over the life cycle as the completely objective index.

I construct a household's frailty as the average frailty index of each member. Table 1 summarizes the distribution of the household frailty index in my sample. The household frailty index has a mean of 0.09 and a median of 0.07.[6] Figure 1 shows the distribution of household frailty by age. This figure shows that median - as well as the 25th and 75th percentiles - frailty increases with age. It also shows that the variance of frailty increases with age and is particularly high after age 75. Table A-3 in Appendix C displays the three most common deficits for household heads at selected ages. For younger people, smoking and obesity are the most common deficits, while, for older people, high blood pressure and arthritis are the leading causes of frailty.

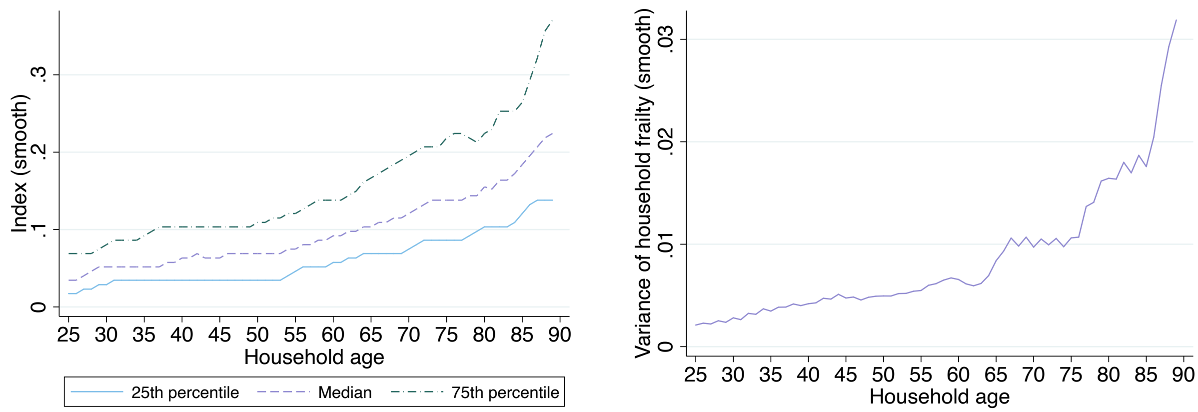
Mean	10th pct	25th pct	50th pct	75th pct	99th pct
0.09	0.02	0.03	0.07	0.12	0.40

Table 1: Distribution of household frailty index. Statistics computed for PSID households with head aged between 25 and 91, interviewed between 2005 and 2019 wave.

5 Estimation

To estimate the model, I use a two-step estimation strategy similar to the one of Gourinchas and Parker (2002) and De Nardi, French, and Jones (2010). In the first step, I estimate or

[6]These results are in line with Hosseini, Kopecky, and Zhao (2022), who construct a frailty index using 28 deficits from the PSID. They use a sample of household heads and spouses aged 25 and older and report a mean of 0.11 and a median of 0.07.



(a) Percentiles by age

(b) Variance by age

Figure 1: Distribution of household frailty by age: 25th, 50th, 75th percentiles (left) and variance (right.) Each statistics is smoothed using a 3-year moving average. PSID, 2005-2019.

calibrate the parameters I can cleanly identify outside my model. In this step, for example, I estimate the health process from the PSID and fix the discount factor, β, and risk aversion, γ, to values from the literature.

In the second step, I calibrate the health state dependence parameter, δ, and the consumption floor, $\underline{c}$, taking the parameters estimated in the first step as given, to match the consumption response to transitory earnings and health shocks.

5.1 First-Step

This section describes the parameters and processes I estimate or calibrate without using my model.

Health Process I divide the process for health into two parts. First, I model the probability of having perfect health at every age. Second, I specify a stochastic model for the non-perfect health dynamics.

In my sample, almost 25 percent of households have perfect health - that is, zero frailty - at age 25. The share of households with zero frailty declines gradually with age. To capture this data feature, I follow Hosseini, Kopecky, and Zhao (2022) and allow for a positive mass of households with zero frailty at age 25. Each period, households with zero frailty either maintain perfect health - with a certain positive probability - or transition to positive frailty - with one minus that probability. I assume that once a household's frailty becomes positive, it cannot return to zero. Thus, I assume that positive frailty is an absorbing state.

Let h_{it} denote the frailty of household i at age t. I model the probability that the household's frailty is zero at each age using a probit model:

$$Prob(h_{it} = 0|X_{it}) = \Phi(X'_{it}\alpha), \tag{5.1}$$

where Φ is the c.d.f. of a standard normal distribution and X_{it} is a set of regressors. In particular, X_{it} contains a second-order polynomial in household age, family size, the head's education level, and cohort effects. Table A-4 in Appendix E.1 reports the probit regression results. On average, the probability of having zero frailty decreases with age and family size and increases with the head's education level.

The probability a household has zero frailty, conditional on having zero frailty the period before, is:

$$Prob(h_{it} = 0|h_{i,t-1} = 0) = \frac{Prob(h_{it} = 0|X_{it})}{Prob(h_{i,t-1} = 0|X_{i,t-1})} = \frac{\Phi(X'_{it}\alpha)}{\Phi(X'_{i,t-1}\alpha)}, \tag{5.2}$$

Thus, the probability a household has zero frailty is: given by Equation (5.1) at age 25; given by Equation (5.2) at ages older than 25 and if frailty is zero in the previous period; zero otherwise. Figure A-3 in Appendix E.1 displays the share of households with zero frailty in the data and the model.

I then define a persistent-transitory process for log-non-zero frailty. I estimate the deterministic component of the process in Equation (3.3) by regressing log-frailty on a second-order polynomial in age, family size, and the head's education level.

I then use the residuals from the regression for the deterministic component to estimate the parameters of the persistent and transitory components. I need to estimate the autoregressive coefficient, ρ, the variance of the transitory shock, $\sigma^2_{\varepsilon,h}$, the variance of the shock to the persistent component, $\sigma^2_{\eta,h}$, and the variance of the first persistent component, $\sigma^2_{\pi^h_0}$. I identify them using the variances and covariances of the residuals and estimate them using standard minimum distance techniques. See Appendix E.1 for the identification restrictions and estimation details. Table A-5 in Appendix E.1 reports the estimation results. The results show that frailty is increasing in age and persistent, confirming the findings of Hosseini, Kopecky, and Zhao (2022).

Survival Probabilities I estimate two-year survival probabilities for household heads. I run a logistic regression of a binary indicator for whether the head is alive or not using a second-order polynomial in age, frailty in the previous period, head's education, and family size as covariates. Table A-6 in Appendix E.2 reports the estimation results. Age and frailty harm the probability of surviving to the next period.

I then compute the average survival probabilities by age and confirm the finding of French (2005) that the PSID overestimates survival probabilities. Therefore, I calculate an adjustment factor as the ratio of the estimated average survival probabilities and those reported by the Social Security Administration life tables for 2019.[7] I then correct my estimates by multiplying the estimated survival probabilities by the adjustment factor.

Earnings Process To be consistent with my model, I estimate the working-age earnings process for households between 25 and 61 years old who report positive labor earnings. I estimate the deterministic component in Equation (3.8) by regressing the logarithm of earnings on a second-order polynomial in age, frailty, family size, the head's education level, and cohort effects. The left panel Table A-7 in Appendix E.3 shows the estimation results and that age, family size, and education positively affect earnings, while frailty hurts them.

Using the residuals from the regression above, I estimate by minimum distance the autoregression coefficient ρ_y, the variance of the transitory shock, $\sigma^2_{\varepsilon,y}$, the variance of the shock to the persistent component, $\sigma^2_{\varepsilon,h}$, and the variance of the first persistent component, $\sigma^2_{\pi_0^y}$. Appendix E.1 presents details on the identification and estimation. The right panel of Table A-7 in Appendix E.3 shows the estimated variances of the earnings shocks.

[7] Available at https://www.ssa.gov/oact/STATS/table4c6.html

Out-Of-Pocket Medical Expenditures I estimate the deterministic component of medical expenditures by regressing their logarithm[8] on a second-order polynomial in household age, frailty, family size, head's education, and cohort effects. Column (1) in Table A-8 in Appendix E.4 displays the estimation results for this regression. These results show that medical expenditures increase with age, frailty, family size, and education.

Then, to estimate the variance of the i.i.d. shock, I regress the squared residuals from the regression above on the same covariates. Column (2) of Table A-8 in Appendix E.4 reports the estimation results. I then compute the predicted values from this regression and their variance, which provides the estimate for the variance of the i.i.d. shock.

Fixed Parameters Table A-9 in Appendix E.5 summarizes the parameters I set to common values in the literature. I use the parameters of the tax function reported by Borella, De Nardi, Pak, Russo, and Yang (2021) for 2017 (their last available data point.) I set the interest rate to two percent following Paz-Pardo (2022). Then, I set the coefficient of relative risk aversion to two, as in Guvenen and Smith (2014) and Fella, Frache, and Koeniger (2020). Finally, I set the annual discount factor to 0.9756 following Low and Pistaferri (2015), which uses the central value of the estimates of Gourinchas and Parker (2002) and Cagetti (2003). I square the annual value to obtain the biennial discount factor, as in Kydland and Prescott (1982).

5.2 Second-Step

I calibrate the consumption floor and the effect of health on the marginal utility of consumption to match the degree of self-insurance against transitory health and income shocks in the data. This section illustrates my identification strategy, describes my measures of self-insurance, and presents the results for my estimated parameters.

Identification In a non-linear model like mine, all parameters potentially affect all moments. In this section, I provide some intuition on what moments in the data help identify my parameters of interest.

[8] I replace values of medical expenditures equal to zero with one hundred dollars.

I identify the consumption floor, $\underline{c}$, by matching the consumption response – or degree of self-insurance – to a transitory income shock. An income shock affects the resources available for consumption. The more insurance the government provides (i.e., the higher the consumption floor), the less household consumption should respond to an income shock. Conversely, the lower the consumption floor, the more consumption should respond to an income shock. Therefore, matching the consumption response to a transitory income shock is informative about the magnitude of the consumption floor.

I identify the effect of health on preferences, δ, by matching the consumption response to a transitory health shock. A health shock affects consumption through two channels: available resources and preferences. My model explicitly considers how health affects each of these channels. Therefore, the consumption response to a transitory health shock is informative about the effect of health on preferences.

Measuring Self-Insurance I measure self-insurance using pass-through coefficients. The pass-through coefficient of an idiosyncratic shock x_{it} is the ratio of the covariance between log-consumption growth and the shock and the variance of the shock. Formally:

$$\phi^x = \frac{\text{cov}(\Delta \log c_{it}, x_{it})}{\text{var}(x_{it})}, \tag{5.3}$$

Since shocks are not observable in the data, I need to use moments on observable consumption, earnings, and frailty to estimate the pass-through coefficients. In particular, I need to find functions g_t^x:

$$\begin{aligned} \text{cov}(\Delta \log c_{it}, x_{it}) &= \text{cov}(\Delta c_{it}, g_t^x(\boldsymbol{v}_i)), \\ \text{var}(x_{it}) &= \text{cov}(\Delta v_{it}, g_t^x(\boldsymbol{v}_i)), \end{aligned}$$

Where v denotes either earnings or frailty and $\boldsymbol{v}_i$ denotes the vector of earnings or frailty realizations for household i.

I follow Commault (2022) and Blundell, Borella, Commault, and De Nardi (2022) and focus on transitory shocks. I do so because identifying the pass-through coefficients of transitory shocks only requires that the law of motions of the underlying processes are well specified. In turn, identifying the pass-through coefficients of persistent shocks requires stringent assumptions on the evolution of log-consumption growth. These assumptions are likely to be violated in a life-cycle model like mine.[9]

I apply a similar strategy to Kaplan and Violante (2010) to identify the pass-through coefficients of transitory earnings and health shocks. First, I define the quasi difference of log earnings as $\tilde{\Delta} \log y_{it} = \log y_{it} - \rho_y \log y_{it-1}$ and the quasi difference of log frailty as $\tilde{\Delta} \log h_{it} = \log h_{it} - \rho_h \log h_{it-1}$. Notice I have estimated ρ_y and ρ_h in Section 5.1. Second, I set:

$$g_t^{\varepsilon}(\boldsymbol{y}_i) = \tilde{\Delta} y_{i,t+1}, \tag{5.4}$$

$$g_t^{\varepsilon}(\boldsymbol{h}_i) = \tilde{\Delta} h_{i,t+1}, \tag{5.5}$$

Using Equation (5.3)-(5.5), I can estimate the pass-through coefficients of earnings and health shocks using moments on consumption, earnings, and frailty. The pass-through coefficients are defined for "detrended" consumption, earnings, and frailty. That is consumption, earnings, and frailty net of demographics. I detrend log earnings and frailty when I estimate their processes in Section 5.1 by regressing them on a second-order polynomial in age, family size, the head's education level, and cohort effects. The results are presented in Appendix E.3 and Appendix E.1. Then, I detrend log consumption by regressing it on the same covariates. Table A-10 in Appendix F.1 reports the regression results. Log-consumption increases with age, family size, and education. To estimate the pass-through coefficients, I use the residuals from these three regressions to measure detrended consumption, earnings, and frailty. Appendix F.2 describes how I estimate the pass-through coefficients and presents the estimated values in my PSID sample.

Method of simulated moments estimation I calibrate the effect of health on preferences (δ) and the consumption floor ($\underline{c}$) using the Method of Simulated Moments (MSM.) To solve and simulate the model, I follow Gourinchas and Parker (2002) and French (2005)

[9] Blundell, Pistaferri, and Preston (2008), for example, impose that log-consumption growth evolves as a random walk. Carroll (1997) and Commault (2020) show analytically that log consumption does not evolve as a random walk in a life-cycle model with precautionary savings like mine.

and fix the cohort to the middle one in my PSID sample, family size to the average family size, and the education level to high school.

The MSM procedure is as follows. First, given an initial "guess" for the two parameters to be estimated, I solve the life-cycle model and obtain optimal decision rules for consumption and savings. Second, I use the optimal decision rules to simulate the life-cycle choices of households. Third, using the simulated data, I compute the pass-through coefficients for transitory earnings and health shocks. Fourth, I compute the squared difference between the pass-through in the model and the data. Finally, using the Nelder-Mead algorithm, I search for the combination of δ and $\underline{c}$ that yields the minimum distance between the model and the data. Appendix G provides more details on the model solution and simulation.

Calibration Results Table 2 displays the pass-through coefficients I target, their values in the data and the simulated model, and the values of the calibrated parameters.

Moment	Data	Model	Parameter	Value
ϕ_{ε_h}	-0.087	-0.087	Effect of health on preferences, δ	-0.74
ϕ_{ε_y}	0.175	0.175	Consumption floor, $\underline{c}$	\$3,561

Table 2: Targeted moments, model fit, and parameter estimates

Table 2 shows that my model successfully matches the pass-through coefficients for transitory health and earnings shocks. The estimated value of δ, -0.74, suggests an adverse effect of health on preferences. In particular, it indicates that good health and non-medical consumption are complements, so the marginal utility of non-medical consumption decreases as health worsens. This finding is in line with the results of, among others, De Nardi, French, and Jones (2010), Finkelstein, Luttmer, and Notowidigdo (2013), and Koijen, Van Nieuwerburgh, and Yogo (2016). The estimated consumption floor of \$3,561 lies within the standard range in the literature of \$3,000 to \$7,000.[10]

[10]Here, I report the annual consumption floor per capita. My model is biennial, and I solve it by fixing the family size to the average one in my PSID sample. Thus, to obtain the biennial consumption floor implied by my model, one needs to multiply the annual per capita value first by two and then by 2.6, the average family size in my sample.

Untargeted Moments To validate my model, I compare my model's life-cycle profile of annual consumption and the data. To estimate the life-cycle consumption profile in the PSID, I follow French (2005) and regress annual household consumption on family size, education level, and cohort and age dummies. I then fix family size, education level, and cohort to the same values I use to solve the model. To compute the life-cycle consumption profile in the model, I first divide biennial consumption by two and then regress it on age dummies. Figure 2 shows that my model matches the consumption trend over the life cycle. My model underestimates the overall level of consumption, but after age 85, my model's predicted consumption lies within the 95 percent confidence interval of the estimates from the data.

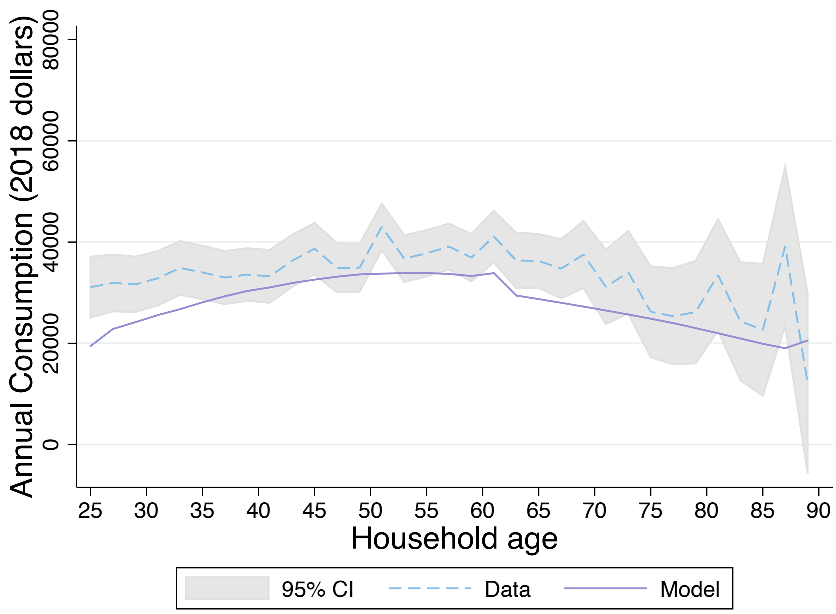


Figure 2: Life-cycle profile of annual consumption in the data and model. The gray shaded area denotes the 95% confidence interval for the data profile.

Then, I compare the pass-through coefficients against persistent earnings and health shocks in the model and the data.[11] Table 3 shows that my model overestimates the response of consumption to persistent earnings and health shocks. However, as Appendix H discusses, identifying the pass-through coefficients of persistent shocks relies on the assumption that log consumption evolves as a random walk. As argued in Carroll (1997) and Commault

[11]Appendix H provides more details on estimating the pass-through coefficients of persistent shocks.

(2022), this assumption is violated in a life-cycle model with precautionary savings like mine. Therefore, the difference between the model-generated coefficients and their data counterparts is expected.

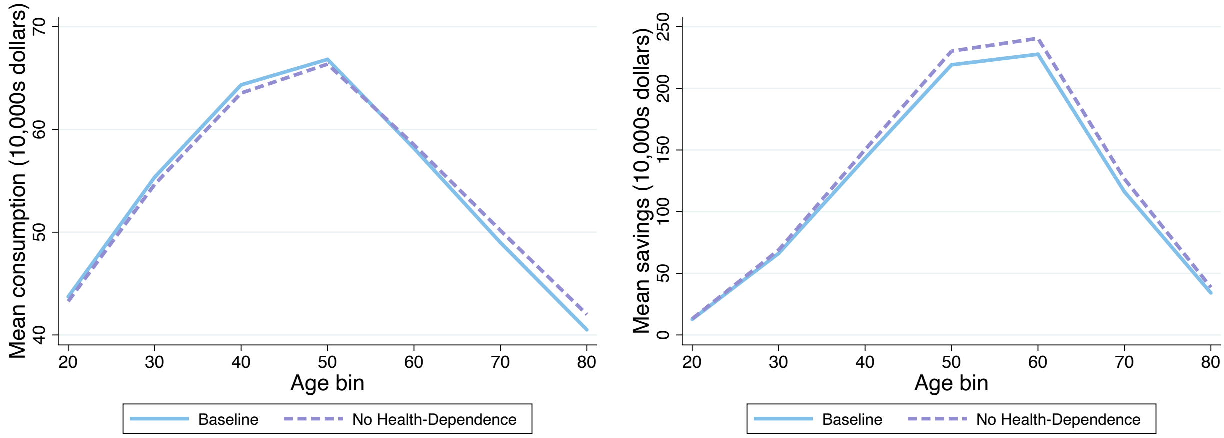
	Data			Model		
	25-61	63-89	25-89	25-61	63-89	25-89
ϕ^y_η	0.235***	-	-	0.378***	-	-
	0.03			0.004		
N	7,191			61,200		
ϕ^h_η	-0.077 **	-0.078	-0.077***	-0.046***	0.03***	-0.01***
	0.03	0.06	0.02	0.004	0.001	0.003
N	6,900	1,712	8,612	50,662	45,604	96,266

Table 3: Pass-through coefficients of persistent earnings (ϕ^y_η) and health (ϕ^h_η) shocks. I present results for three age groups: 25-61 (working period,) 63-89 (retirement period,) and 25-89 (whole life cycle.) Earnings shocks are present only during the working period, 25-61.

6 Health-Dependent Preferences and Self-Insurance

In this section, I use my calibrated model to assess the quantitative effects of health-dependent preferences on self-insurance. Because health affects the marginal utility of consumption, it will affect the optimal choice of consumption and savings. Therefore, it will affect households' ability to self-insure by saving. To quantify the effects of health-dependent preferences, I solve the model using the baseline calibration and setting $\delta = 0$, thereby removing the relationship between health and marginal utility. I then simulate the life cycle of 50,000 households and compare their consumption and savings.

Figure 3 shows the life-cycle profile of consumption and savings by 10-year age bins. Panel (a) shows that average consumption is higher without health-dependent preferences at older ages but lower before 50. Panel (b) shows that average savings are higher without health-dependent preferences at every age. These patterns are consistent with the deterioration of health over the life cycle. Households are more unhealthy at older ages; therefore, their marginal utility of non-medical consumption is much higher when $\delta = 0$ than in the baseline case. Consequently, their optimal consumption is higher than in the baseline case because consumption is more "enjoyable." Households must save more and give up consumption when young to sustain higher consumption at older ages.



(a) Average consumption by age

(b) Average savings by age

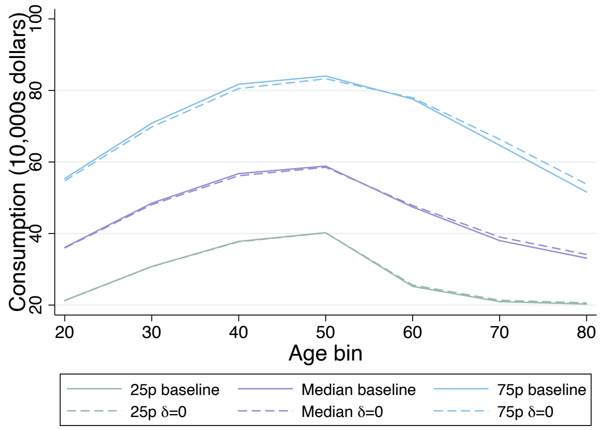
Figure 3: Panel (a) shows average consumption by 10-year age bin for the baseline calibration and the counterfactual experiment in which $\delta = 0$. Panel (b) shows the analogous figure for savings

Figure 4 shows the 25th, 50th, and 75th percentiles of consumption and savings by 10-year age bins in the baseline calibration and the counterfactual. Panel (a) shows that households consume more without health-dependent preferences at older ages and less at younger ages. In particular, households in the 25th percentile consume more without health-dependent preferences after age 50, while households in the 75th percentile of consumption do so after age 60. Panel (b) shows the 25th, 50th, and 75th percentiles of savings by age. This figure shows that all households save more without health-dependent preferences.

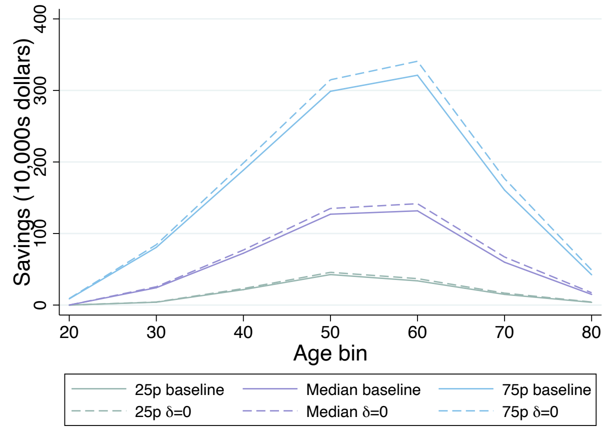
7 Health-Dependent Preferences and Government Insurance

In this section, I analyze the welfare effects of reforming means-tested government insurance (MTGI) with and without health-dependent preferences. In particular, I compute the welfare effects of setting the consumption floor to \$1 from my baseline calibrated value of \$3,561[12]

[12] I set the consumption floor to \$1 rather than 0 to avoid computational problems.



(a) Percentiles of consumption by age



(b) Percentiles of savings by age

Figure 4: Panel (a) shows the 25th, 50th, and 75th percentile of consumption by 10-year age bin for the baseline calibration and the counterfactual experiment in which $\delta = 0$. Panel (b) shows the analogous figure for savings.

Following De Nardi, French, and Jones (2016) and McGee (2021), I measure welfare changes using the compensating variation, defined as the immediate payment after the reform that would make households as well off as before the reform, so indifferent to it. I compute the compensating variation at age 25 (the initial age in my model and simulations) and define it as $\chi_{25}(a_{25}, \xi_{25}, \pi^y_{25}, \varepsilon^y_{25}, \pi^h_{25}, \varepsilon^h_{25})$ solving:

$$V_25(a_{25}, \xi_{25}, \pi^y_{25}, \varepsilon^y_{25}, \pi^h_{25}, \varepsilon^h_{25}|\text{Baseline}) = V_25(a_{25} + \chi_{25}, \xi_{25}, \pi^y_{25}, \varepsilon^y_{25}, \pi^h_{25}, \varepsilon^h_{25}|\text{Reform}),$$

Where $V_{25}(\cdot)$ is the age 25 value function for a given set of state variables for the case with the baseline consumption floor and the case with the consumption floor equal to one dollar. As noted in McGee (2021), the compensating variation is an ex-ante measure that incorporates the mechanical and behavioral responses to a reform. The compensating variation also yields the household valuation of MTGI; that is, the compensation households would require to be indifferent to having MTGI taken away.

Table 4 shows the effects of removing MTGI. When considering a specific group, I report the group average of the compensating variation. Columns 2 and 3 report the results for the baseline and no-health-dependent-preferences cases. Table 4 offers several interesting insights. First, the first row shows that, on average, households place a higher value on

MTGI when preferences do not depend on health. Second, lower-income households place a higher value on MTGI, and their valuation is always higher without health-dependent preferences. In particular, the compensating variation for households in the top tercile of income is less than half that of households in the first tercile. Third, unhealthier households give a higher value to MTGI, and their valuation is always higher without health-dependent preferences. The last row of Table 4 shows that, across values of δ, households in the top frailty tercile – that is, unhealthier households – value MTGI at about $1,000 more than households in the bottom tercile.

Group	Baseline $\delta = -0.74$	No health-dependent preferences $\delta = 0$
All 25 year-olds	37,312	39,194
First income tercile	55,504	58,390
Second income tercile	34,770	37,458
Third income tercile	21,663	21,734
First frailty tercile	36,949	38,846
Second frailty tercile	37,653	39,492
Third frailty tercile	37,918	39,809

Table 4: Household valuation of MTGI. Column 2 reports the compensating variation at 25 for households with the baseline value of δ. Column 3 reports the compensating variation for households with no health-dependent preferences, so with $\delta = 0$.

8 Conclusions

I study the effect of health on preferences and the consequences of this relationship on self and government insurance. I build a life-cycle model in which health affects survival, earnings, medical expenditures, and the marginal utility of non-medical consumption. I then calibrate the model to the United States using the PSID and use my calibrated model for quantitative analysis.

My first contribution is to reduce the ambiguity in the literature and provide a new estimate of the effect of health on preferences. I show that this effect is identified by the consumption response to a transitory health shock and find that poor health reduces the marginal utility of non-medical consumption.

My second contribution is to analyze the quantitative effects of health-dependent preferences on self and government insurance. To the best of my knowledge, I am the first to explore these effects quantitatively. I show that health-dependent preferences increase consumption at older ages while reducing consumption at younger ages and increasing savings over the whole life cycle. Then, I show that health-dependent preferences considerably affect households' valuation of government insurance. In particular, means-tested government insurance is more valuable without health-dependent preferences and for poorer and sicker households.

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APPENDICES FOR ONLINE PUBLICATION

A Health-Dependent Preferences in the Literature

Finkelstein, Luttmer, and Notowidigdo (2009) define the effect of health on preferences as the effect of health on the marginal utility of non-medical consumption. The literature on this topic has developed into two branches: an empirical and a structural-life-cycle-model one. This section summarizes some of the most notable studies in each branch, their approaches, and their results. While numerous papers have studied the effect of health on preferences and attempted to quantify its magnitude and direction, they have obtained different - sometimes opposite - results.

A.1 The empirical literature on health-dependent preferences

There are numerous empirical studies on the effect of health on preferences. One set of papers focuses on the change in utility associated with a health shock. In particular, Viscusi and Evans (1990), Evans and Viscusi (1991), and Sloan, Kip Viscusi, Chesson, Conover, and Whetten-Goldstein (1998) use the compensating wage differentials associated with job-related health risks; that is, the compensation workers would accept in exchange for being exposed to some job-related health risk. Despite taking a similar approach, these papers reach different conclusions. Viscusi and Evans (1990) finds evidence of a negative effect of health on preferences: marginal utility for the unhealthy is between 17 and 23 percent lower than the marginal utility for the healthy. Sloan, Kip Viscusi, Chesson, Conover, and Whetten-Goldstein (1998) finds evidence of a negative effect of health on preferences, with marginal utility in bad health being just 8 percent of the one in good health. Evans and Viscusi (1991) finds no evidence of an effect of health on preferences.

A second branch of the empirical literature on the effect of health on preferences focuses on reported well-being as a proxy for utility. Finkelstein, Luttmer, and Notowidigdo (2013) constructs a sample of elderly Americans and estimates the effect of health on preferences using changes in subjective well-being.[13] They find evidence of a negative effect of health

[13] They measure subjective well-being by using the response to the question "Much of the time during the

on preferences. In particular, they calculate that a one-standard-deviation increase in the number of chronic conditions results in an eleven percent decline in the marginal utility of consumption. Kools and Knoef (2019) focus on a sample of elderly Europeans and use changes in material well-being to estimate the effect of health on preferences.[14] They find evidence of a positive effect of health on preferences. In particular, the marginal utility of consumption increases as the number of activities of daily living a person struggles with increases.

A third branch of the empirical literature focuses on strategic surveys to isolate the effect of health on marginal utility. Brown, Goda, and McGarry (2016) devise the American Life Panel (ALP) to study the differences in the value of marginal consumption in healthy and disabled states. They find limited evidence of an effect of health on preferences at younger ages and a negative effect at older ages. Gyrd-Hansen (2017) surveys a sample of Danish residents between the ages of 25 and 79 and finds evidence of a U-shaped effect of health on marginal utility. In particular, she finds a positive effect for intermediate health states but no effect for minor and more severe health states.

Finally, fewer papers attempt to estimate the effect of health on marginal utility using portfolio choices. Edwards (2008) uses a sample of older American households and studies their portfolio compositions to conclude there is a positive effect of health on marginal utility.

A.2 The structural-life-cyle-model literature on health-dependent preferences

A few papers have used structural consumption models to estimate the effect of health on preferences. Lillard and Weiss (1997) develop a life-cycle model to study the impact of health and survival risk on retirees' consumption and savings decisions. Their results point to a positive effect of health on preferences. In particular, consumption when sick is fifty-five percent higher than when healthy. Hong, Pijoan-Mas, and Rios-Rull (2015) use a life cycle model with endogenous health and estimate the effect of health on preferences using the

past week I was happy. (Would you say yes or no?)." as a proxy for utility.

[14] They measure material well-being by observing the answer to the question "How difficult is it for you to make ends meet?"

Euler equation for consumption. They estimate a negative effect at 65 and a positive one at older ages.

Numerous papers embed the effect of health on preferences in their structural models to answer various questions. A few papers consider this effect but do not estimate it. Low and Pistaferri (2015) build a life cycle model to evaluate the welfare effects of changing the Disability Insurance program in the United States. Their model allows disability to influence marginal utility and assumes a positive effect of health on preferences. De Donder and Leroux (2021) study the demand for long-term care insurance when health affects preferences. They assume a negative effect of health on preferences so that consumption and good health are complements. Jung and Tran (2022) study the effect of health risk on the optimal progressivity of the income tax system in the United States. In a robustness check, they allow health to affect preferences and assume a negative effect on the marginal utility of consumption.

Another set of papers embeds the effect of health on preferences into their structural models and estimates it. De Nardi, French, and Jones (2010) build a structural model of savings for elderly American households to study the effect of medical expenditures on savings. They estimate a negative - but not significant - effect of health on preferences. Koijen, Van Nieuwerburgh, and Yogo (2016) develop a life cycle model of insurance choice to study the optimal demand for life and health insurance. They focus on American men older than 51 and estimate a negative effect of health on preferences. Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2020) build a structural model in which health affects marginal utility to study savings patterns among the elderly. They develop strategic survey questions to help identify the effect of health on preferences and estimate a positive effect of health on preferences.

B PSID data and Sample Selection

B.1 The Panel Study of Income Dynamics

The Panel Study of Income Dynamics (PSID) is a longitudinal survey of US families conducted by the University of Michigan. It was an annual survey between its inception in 1968 and 1997 and has been biennial since then.

The original 1968 sample of the PSID contained a nationally representative sample of 2,930 households and a sample of 1,872 low-income families (the SEO subsample.) The PSID follows the original 1968 families and any family member who moves out of them. This feature of the survey allowed it to remain nationally representative over time.

The PSID has recorded rich information on family income and wealth dynamics since 1968. Throughout the years, it has added information on respondents' social, demographic, economic, and health characteristics. In particular, until 1997, the PSID recorded information only on food consumption. Starting in 1999, the PSID expanded its consumption measures, and, since 2005, it has covered almost all the consumption categories measured by the Consumption Expenditure Survey (CEX.) Moreover, in 2003, the PSID expanded its health-related questions and started recording information on specific medical conditions, ADLs, and IADLs.

See Johnson, McGonagle, Freedman, and Sastry (2018) for a detailed description of the PSID and its changes over the last fifty years.

B.2 Sample Selection

Table A-1 describes my sample selection. I use every biennial wave of the PSID between 2005 and 2019 and obtain an initial sample of 247,871 individual-wave observations. First, I focus on household heads.[15] Then, I restrict my attention to the core sample of the PSID.[16]

[15] The PSID records health variables only for household heads and their spouse. Thus I have to exclude all family members other than the two spouses from my sample. Then, household heads respond to questions about their own and their spouse's health and labor earnings and about total household consumption, medical expenditures, and wealth. Thus, in my sample, I only keep household heads, to whom I link information on the spouse when one is present.

[16] As discussed in Haider (2001) and Paz-Pardo (2022), the SRC subsample is a random sample, and therefore sample weights are not needed. This is standard practice in the literature. See, for example,

This leaves me with 42,788 observations. I remove households that appear only once in the survey. The resulting sample consists of 41,259 observations. To be consistent with my model, I focus on households whose head is between 25 and 89 years old. Then, I drop observations missing information on frailty, labor earnings, medical expenditures, wealth, family size, and head's education. The resulting sample contains 33,992 observations. After removing observations with missing information, I remove outliers. To do so, I first drop observations with consumption or labor earnings smaller than 50 dollars (in 2018 terms.) The final sample consists of 32,038 observations.

Sample Selection	Selected out	Selected in
Waves 2005 - 2019		247,871
Heads only	176,696	71,175
PSID core sample	28,387	42,788
Interview in subsequent year	1,529	41,259
Age between 25 and 89	2,580	38,679
Missing key variables	4,687	33,992
Remove outliers	1,954	32,038

Table A-1: Sample Selection, PSID waves 2005 - 2019.

C Frailty Index

Table A-2 presents the complete list of deficits I use to construct the frailty index in my sample. I use 29 deficits in total. Compared to Hosseini, Kopecky, and Zhao (2022), I add alcohol consumption as a deficit. I follow the definition of the National Institute on Alcohol Abuse and Alcoholism[17] and assign a value of one to the excessive drinking deficit if: the respondent drinks every day or several times a week and, when they drink, they have more than four drinks for a man and more than three drinks for a woman.

Table A-3 describes the top three deficits for household heads at selected ages. This table shows that, at ages younger than 45, smoking and obesity are the leading causes of frailty

Blundell, Pistaferri, and Preston (2008), Heathcote, Storesletten, and Violante (2014), Blundell, Pistaferri, and Saporta-Eksten (2016), and Arellano, Blundell, and Bonhomme (2017).

[17] Available at https://www.niaaa.nih.gov/alcohol-health/overview-alcohol-consumption/moderate-binge-drinking

in my sample. Starting at 55, high blood pressure and arthritis become the most common deficits for household heads.

Variable	Value
Some difficulty with ADL/IADLs:	
Eating	Yes=1, No=0
Dressing	Yes=1, No=0
Getting in/out of bed or chair	Yes=1, No=0
Using the toilet	Yes=1, No=0
Bathing/Showering	Yes=1, No=0
Walking	Yes=1, No=0
Using the telephone	Yes=1, No=0
Managing Money	Yes=1, No=0
Shopping for personal items	Yes=1, No=0
Preparing meals	Yes=1, No=0
Heavy housework	Yes=1, No=0
Light housework	Yes=1, No=0
Getting outside	Yes=1, No=0
Ever had one of the following conditions:	
High blood pressure	Yes=1, No=0
Diabetes	Yes=1, No=0
Cancer	Yes=1, No=0
Lung Disease	Yes=1, No=0
Heart Disease	Yes=1, No=0
Heart Attack	Yes=1, No=0
Stroke	Yes=1, No=0
Arthritis	Yes=1, No=0
Asthma	Yes=1, No=0
Loss of memory or mental ability	Yes=1, No=0
Psychological problems	Yes=1, No=0
Other serious chronic conditions	Yes=1, No=0
Other conditions:	
BMI $\geq$ 30	Yes=1, No=0
Has ever smoked	Yes=1, No=0
Smokes now	Yes=1, No=0
Drinking alcohol	Yes=1, No=0

Table A-2: Deficits used to construct the frailty index. For the “Ever had one of the following conditions” variables I make the following adjustment: If an individual reports one of these conditions, I assign a value of 1 to that deficit in every wave after the first report.

Age	Top 3 Deficits
25	Smoke, Obese, Ashtma
35	Obese, High Blood Pressure, Smoke
45	Obese, High blood pressure, Other chronic conditions
55	High blood pressure, Obese, Arthritis
65	High blood pressure, Arthritis, Other chronic conditions
75	High blood pressure, Arthritis, Other chronic conditions
85	High blood pressure, Arthritis, Other chronic conditions

Table A-3: Top 3 deficits for household heads for selected ages. PSID, waves 2005-2019.

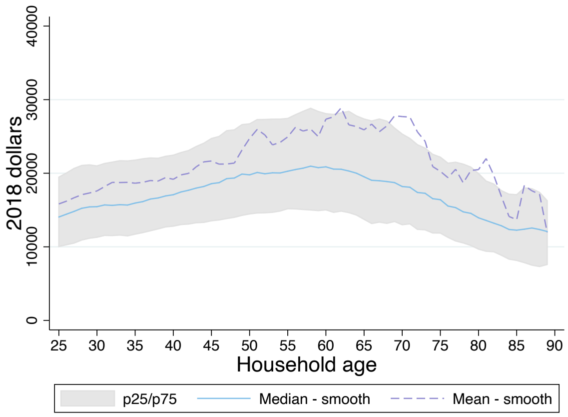
D Facts on my key variables of interest

In this section, I report facts for my key variables of interest. For ease of exposition, consumption and wealth are equivalized but not detrended.[18] Here, I measure a household's total wealth as the sum of all assets minus all liabilities. In particular, I define it as the sum of the equity in farms and businesses; transaction accounts (such as savings accounts, money market funds, certificates of deposits, government bonds, and treasury bills); equity in real estate, stock, vehicles, and IRAs; the value of home equity (calculated as home value minus remaining mortgage); net of total debt.

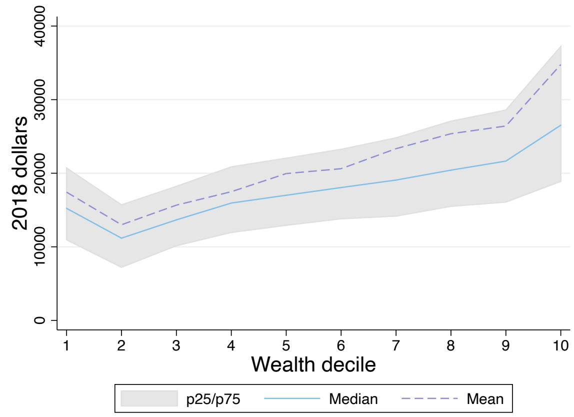
Figure A-1 displays the mean and the 25th, 50th, and 75th percentiles of equivalized consumption by age (Panel (a),) wealth decile (Panel (b),) and frailty decile (Panel (c).) Figure A-1 shows that consumption increases until 60 and declines after then, increases with wealth, and slightly decreases with frailty.

Figure A-2 shows the mean and the 25th, 50th, and 75th percentiles of equivalized wealth by age (Panel (a)) and frailty decile (Panel (b).) Panel (a) shows that average wealth increases until 65 and slightly decreases after then. Panel (b) shows that wealth is roughly stable across frailty deciles.

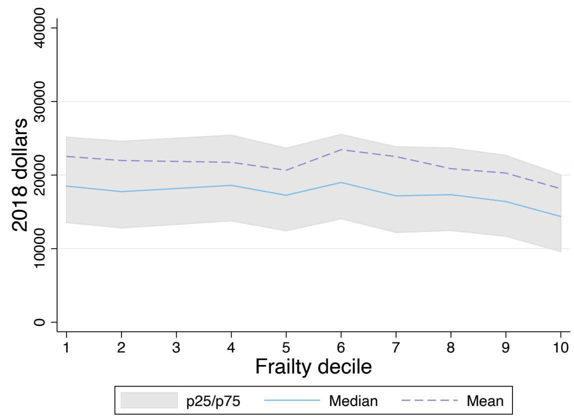
[18] I equivalize household consumption and wealth by dividing them by the square root of family size.



(a) By age

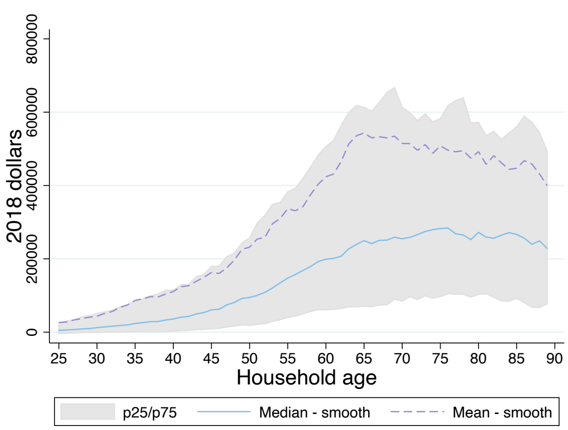


(b) By wealth decile

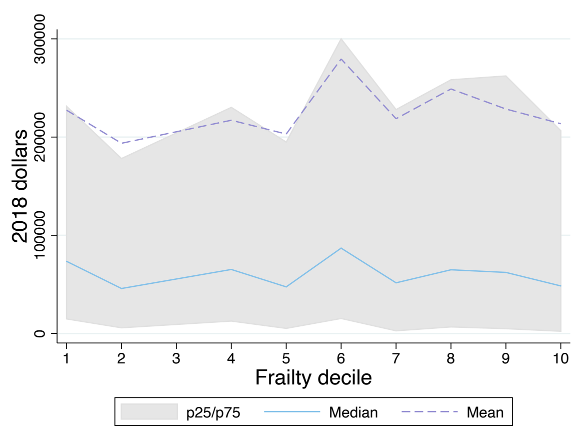


(c) By frailty decile

Figure A-1: Equivalized consumption by age, wealth deciles, and frailty deciles. Equivalized consumption by age is smoothed using a three-year moving average.



(a) By age



(b) By frailty decile

Figure A-2: Equivalized wealth by age and frailty deciles. Equivalized wealth by age is smoothed using a three-year moving average.

E First-Step Estimation

E.1 Health Process

Table A-4 displays the estimation results for the probit regression for the probability of having zero frailty at each age. Figure A-3 displays the share of households with zero frailty in the data and in the model.

	Household has zero frailty
Age	-0.0604***
	(0.00964)
Age^2	0.000172
	(0.000106)
Family size	-0.0374***
	(0.00838)
Head's education	0.451***
	(0.0195)
Constant	0.772***
	(0.238)
Cohort effects	Yes
Observations	32010
Pseudo R^2	0.0994

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-4: Estimation results from zero frailty probit regression. The dependent variable is a dummy equal to 1 when the households has zero frailty.

To identify the parameters of the stochastic process for non-zero frailty, I use the residuals from the regression for the deterministic component. Let $\tilde{h}_{it} = \log h_{it} - \kappa_{it}$. Then, the identification conditions I use are:

$$var(\tilde{h}_{i,25}) = \sigma^2_{\pi^h_{25}} + \sigma^2_{\varepsilon,h}$$
$$var(\tilde{h}_{it}) = \frac{\sigma^2_{\eta,h}}{1-\rho_h^2} + \sigma^2_{\varepsilon,h}$$
$$cov(\tilde{h}_{it}, \tilde{h}_{i,t-1}) = \rho_h^{(j-k)} \frac{\sigma^2_{\eta,h}}{1-\rho_h^2}, \quad \text{for } j > k, \quad j,k = 1,\ldots,8$$

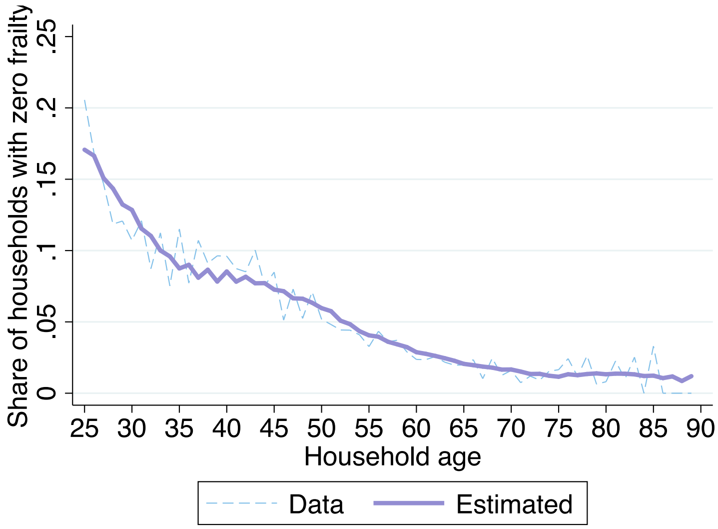


Figure A-3: Share of households with zero frailty in the data (dashed blue line) and predicted by probit regression (solid purple line.)

Where j and k denote one biennial wave of the PSID between 2005 and 2019 (8 waves in total.) I construct the variance-covariance matrix of the residuals from the data, and I use it - together with the identification conditions above - to estimate the parameters of the stochastic part of the health using equally-weighted minimum distance techniques. Table A-5 reports the estimation results for the deterministic and stochastic components of frailty.

	Log frailty
Age	0.0265***
	(0.00304)
Age^2	0.0000967***
	(0.0000296)
Family size	-0.0654***
	(0.00301)
Head's education	-0.243***
	(0.00633)
Constant	-4.119***
	(0.0819)
Cohort effects	Yes
Observations	29705
R^2	0.224

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Parameter	Value
ρ_h	0.93
$\sigma^2_{\varepsilon,h}$	0.02
$\sigma^2_{\eta,h}$	0.06
$\sigma^2_{\pi^h_{25}}$	0.36

Table A-5: Estimation results for non-zero health process. Deterministic component (left) and parameters of the stochastic components (right.) PSID waves 2005-2019.

E.2 Survival Probabilities

Table A-6 reports the estimation results for the logistic regression of a survival indicator.

	Alive indicator
Age	-0.0897
	(0.0908)
Age^2	0.000549
	(0.000714)
Previous Period Frailty	-6.623***
	(0.526)
Head's education	-0.107
	(0.144)
Family size	0.362***
	(0.103)
Cohort effects	Yes
Observations	26215
Pseudo R^2	0.172

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-6: Estimation results for logistic regression of survival indicator. PSID waves 2005-2019.

E.3 Earnings Process

Let $\tilde{y}_t$ denote "detrended" log-earnings, that is, $\log y_t - \kappa(t,h)$. Then, the identification conditions I use are:

$$
\begin{aligned}
var(\tilde{y}_{i,25}) &= \sigma^2_{\pi^y_{25}} + \sigma^2_{\varepsilon,y} \\
var(\tilde{y}_{it}) &= \frac{\sigma^2_{\eta,y}}{1-\rho_y^2} + \sigma^2_{\varepsilon,y} \\
cov(\tilde{y}_{it}, \tilde{y}_{i,t-1}) &= \rho_y^{(j-k)} \frac{\sigma^2_{\eta,y}}{1-\rho_y^2}, \quad \text{for } j > k, \quad j,k = 1,\dots,8
\end{aligned}
$$

Where j and k denote one biennial wave of the PSID between 2005 and 2019 (8 waves in total.) Similarly to what I have done for the health process, I construct the variance-covariance matrix of the residuals from the data, and I use it - together with the identification conditions above - to estimate the parameters of the stochastic part of the health using equally-weighted minimum distance techniques. Table A-7 presents the estimation results for the deterministic and stochastic components of log earnings.

	Log household earnings
Age	0.0900***
	(0.00636)
Age^2	-0.000808***
	(0.0000748)
Household frailty	-3.948***
	(0.0871)
Family size	0.119***
	(0.00393)
Head's education	0.450***
	(0.00905)
Constant	7.706***
	(0.121)
Cohort effects	Yes
Observations	25936
R^2	0.241

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Parameter	Value
ρ_y	0.90
$\sigma^2_{\varepsilon,y}$	0.09
$\sigma^2_{\eta,y}$	0.10
$\sigma^2_{\pi^y_{25}}$	0.79

Table A-7: Estimation results for earnings process. Deterministic component (left) and parameters of the stochastic components (right.) The dependent variable for the deterministic component is log earnings. The parameters of the stochastic component are estimated by equally-weighted minimum distance. PSID waves 2005-2019.

E.4 Out-of-pocket medical expenditures

Table A-8 reports the estimation results for the process for medical expenditures. The variance of the i.i.d. shock to medical expenditures is $\sigma^2_\xi = 0.039$

E.5 Fixed Parameters

Table A-9 summarizes the calibrated parameters.

	Log medical expenditures	Squared Residuals
Age	0.149***	-0.0826***
	(0.00629)	(0.0171)
Age^2	-0.00122***	0.000852***
	(0.0000621)	(0.000169)
Household frailty	0.206*	2.423***
	(0.114)	(0.309)
Family size	0.226***	0.0375**
	(0.00626)	(0.0170)
Head's education	0.508***	-0.674***
	(0.0134)	(0.0365)
Constant	2.436***	3.955***
	(0.169)	(0.459)
Cohort effects	Yes	Yes
Observations	32038	32038
R^2	0.138	0.0204

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-8: Estimation results for medical expenditures. The first column is for the deterministic component. The second column is for the squared residuals from the regression in the first column. PSID waves 2005-2019.

Parameter	Description	Value
$\lambda; \tau$	Tax function	2; 0.07
r	Interest rate	0.02%
β	Discount factor	0.9756^2
γ	Risk Aversion	2

Table A-9: Calibrated Parameters.

F Second-Step Estimation

F.1 Detrending consumption

	Log household consumption
Age	0.0369***
	(0.00241)
Age^2	-0.000406***
	(0.0000237)
Family size	0.168***
	(0.00238)
Head's education	0.275***
	(0.00503)
Constant	8.541***
	(0.0645)
Cohort effects	Yes
Observations	32038
R^2	0.254

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-10: Estimation results for consumption detrending

F.2 Estimation of pass-through coefficients

Detrending I estimate pass-through coefficients for health and earnings by calculating the moments described in Section 5.2 for detrended log frailty, earnings, and consumption. As discussed in Commault (2022), the reason for using detrended values of such variables is to avoid mistaking as shocks – or as responses to shocks – the effect of demographic characteristics, such as age or family size. I detrend log-frailty when I estimate its deterministic component. Table A-5 presents the estimation results. Similarly, I detrend log earnings when I estimate their deterministic component. The estimation results are in Table A-7. Finally, I detrend log-consumption in Appendix F.1. I estimate pass-through coefficients using the residuals from these regressions.

Estimating restrictions I estimate the pass-through against health and earnings shocks using the following estimating restrictions:

$$\mathbb{E}\left[\Delta \log c_{it} \cdot \left(\tilde{\Delta} \log y_{i,t+1}\right) - \phi_{\varepsilon}^{y} \tilde{\Delta} \log y_{it} \left(\tilde{\Delta} \log y_{i,t+1}\right)\right] = 0,$$
$$\mathbb{E}\left[\Delta \log c_{it} \cdot \left(\tilde{\Delta} \log h_{i,t+1}\right) - \phi_{\varepsilon}^{h} \tilde{\Delta} \log h_{it} \left(\tilde{\Delta} \log h_{i,t+1}\right)\right] = 0,$$

Where $\tilde{\Delta}$ denotes the quasi-difference $\tilde{\Delta} x_{it} = x_{it} - \rho_x x_{i,t-1}$ for $x = y, h$, ϕ_{ε}^{y} denotes the pass-through coefficient for transitory earnings shocks, and ϕ_{ε}^{h} denotes the pass-through coefficient for transitory health shocks.

Estimation I follow Commault (2022) and estimate the pass-through coefficients using the estimating restrictions above and a generalized method of moments. I pool all years together and estimate variances and covariances for the whole sample. Let X_i be the set of variables involved, ϕ the vector of parameters, and $g(X_i, \phi)$ the vector of estimating restrictions. The parameter estimates are the values that minimize a norm of the sample analog of the moments:

$$\hat{\phi} = \underset{\phi_{\varepsilon}^{y}, \phi_{\varepsilon}^{h}}{\operatorname{argmin}} \left(\frac{1}{N} \sum_{n=1}^{N} g(X_n, \phi)\right)' \hat{W} \left(\frac{1}{N} \sum_{n=1}^{N} g(X_n, \phi)\right),$$

Where N is the number of household-year observations for which I observe the variables involved and $\hat{W}$ is a weighting matrix. I choose $\hat{W}$ so that the estimation of standard errors is robust to within-household correlations and heteroskedasticity.

Estimated values Table A-11 reports pass-through coefficients I estimate from my PSID sample. I find a positive consumption response to a transitory earnings shock. In particular, a 10% increase in earnings caused by a transitory earnings shock results in an increase of 1.75% in consumption. I also find a negative response to a transitory health shock. In this case, a 10% increase in frailty generates a 0.87% decrease in consumption. These results are in line with the findings of Blundell, Borella, Commault, and De Nardi (2022).

	All 25-61		All 25-89
ϕ^y_ε	0.175**	ϕ^h_ε	-0.087*
	0.08		0.05
N	11419	N	13692

Table A-11: Pass-through coefficients for transitory shocks in PSID sample.

G Computational Details

Solution. The problem I describe in Section 3.8 has no analytical solution. Thus, I solve it numerically. I start from the final period of life (age 89) and proceed by backward iteration. I obtain policy functions for consumption and savings as functions of the household's state variables in each period. During the working years (ages 25 to 61,) the state variables are age, assets, the shock to medical expenditures, the persistent and transitory components of health, and the persistent and transitory components of earnings. During the retirement years (ages 63 to 89,) the household's state variables include age, assets, the shock to medical expenditures, and the persistent and transitory components of health. I discretize the endogenous and continuous variable for assets using a grid with 20 points. Then, I use the method in Rouwenhorst (1995) to discretize and approximate the stochastic processes for the persistent and transitory components of health and earnings and the shock to medical expenditures using Markov chains. In particular, I discretize and approximate the AR(1) processes for ϕ^y and ϕ^h and the normally distributed shocks ξ, ε^y, and ε^h using grids with 5 points each.[19] I obtain the asset policy function by optimizing the household's objective function using Brent's method. I compute the household's expected utility by integrating the value function over the distributions of the stochastic state variables. Using the intertemporal budget constraint and the asset policy function, I obtain the consumption policy function.

Simulation. After obtaining the asset and consumption policy functions, I simulate the life-cycle of 10,000 households. I initialize the simulations by drawing from the data distribution of frailty and setting initial assets at zero. Then, I simulate the household's frailty, earnings, and medical expenditures using their laws of motion. Finally, based on the real-

[19] Kopecky and Suen (2010) shows that the Rouwenhorst method with five grid points is more accurate than the Tauchen (1986) method with twenty-five.

izations of the state variables in each period, I simulate optimal consumption and savings starting at 25 and moving forward until 89 by interpolating the policy functions.

H Pass-through Coefficients of Persistent Shocks

The pass-through coefficients of persistent earnings and health shocks are defined as:

$$\phi_\eta^y = \frac{\text{cov}(\Delta \log c, \eta_t^y)}{\text{var}(\eta^y)}, \quad \phi_\eta^h = \frac{\text{cov}(\Delta \log c, \eta_t^h)}{\text{var}(\eta^h)},$$

Following Kaplan and Violante (2010), I identify these pass-through coefficients using the following covariance restrictions:[20]

$$\begin{aligned}
\text{cov}(\Delta \log c, \eta_t^y) &= \frac{1}{\rho_y}\text{cov}(\Delta \log c, \rho_y^2 \tilde{\Delta} \log y_{t-1} + \rho_y \tilde{\Delta} \log y_t + \tilde{\Delta} \log y_{t+1}), \\
\text{var}(\eta^y) &= \frac{1}{\rho_y}\text{cov}(\tilde{\Delta} \log y_t, \rho_y^2 \tilde{\Delta} \log y_{t-1} + \rho_y \tilde{\Delta} \log y_t + \tilde{\Delta} \log y_{t+1}), \\
\text{cov}(\Delta \log c, \eta_t^h) &= \frac{1}{\rho_h}\text{cov}(\Delta \log c, \rho_h^2 \tilde{\Delta} \log h_{t-1} + \rho_h \tilde{\Delta} \log h_t + \tilde{\Delta} \log h_{t+1}), \\
\text{var}(\eta^h) &= \frac{1}{\rho_h}\text{cov}(\tilde{\Delta} \log h_t, \rho_h^2 \tilde{\Delta} \log h_{t-1} + \rho_h \tilde{\Delta} \log h_t + \tilde{\Delta} \log h_{t+1}),
\end{aligned}$$

Where $\tilde{\Delta}$ denotes the quasi-difference $\tilde{\Delta} x_{it} = x_{it} - \rho_x x_{i,t-1}$ for $x = y, h$.

Estimating the pass-through coefficients of persistent shocks is similar to what I describe for transitory shocks in Appendix F.2. In particular, I use detrended log frailty, earnings, and consumption. I then estimate the pass-through coefficients using the same GMM procedure outlined in Appendix F.2 and the following estimating restrictions:

$$\begin{aligned}
\mathbb{E}[\Delta \log c \cdot (\rho_y^2 \tilde{\Delta} \log y_{t-1} + \rho_y \tilde{\Delta} \log y_t + \tilde{\Delta} \log y_{t+1}) - \phi_\eta^y \tilde{\Delta} \log y_t \cdot (\rho_y^2 \tilde{\Delta} \log y_{t-1} + \rho_y \tilde{\Delta} \log y_t + \tilde{\Delta} \log y_{t+1})] = 0, \\
\mathbb{E}[\Delta \log c \cdot (\rho_h^2 \tilde{\Delta} \log h_{t-1} + \rho_h \tilde{\Delta} \log h_t + \tilde{\Delta} \log h_{t+1}) - \phi_\eta^h \tilde{\Delta} \log h_t \cdot (\rho_h^2 \tilde{\Delta} \log h_{t-1} + \rho_h \tilde{\Delta} \log h_t + \tilde{\Delta} \log h_{t+1})] = 0,
\end{aligned}$$

[20] These restrictions rely on the assumption that log consumption evolves as a random walk.