Health-Dependent Preferences, Consumption, and Insurance

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Abstract

How does health affect one's preferences and ability to self-insure? How does it impact one's valuation of government insurance? I build a life-cycle model in which health affects not only survival, earnings, and medical expenses but also, and importantly, the marginal utility of consumption. While there is previous evidence showing that the effect of health on preferences is important, the literature has not reached a consensus on either its size or its direction. I calibrate my model using data on health, consumption, and income from the Panel Study of Income Dynamics. I find that bad health reduces the marginal utility of (non-medical) consumption and that this effect lowers savings over the life cycle and decreases consumption in old age. I also show that a model without health-dependent preferences does not replicate the degree of self-insurance against health shocks observed in the data. Finally, I find that health-dependent preferences reduce the household valuation of means-tested government insurance programs in the United States.

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1 Introduction

Health affects many key economic outcomes, including how long people live, how much they earn, and how large their medical expenses are. It may also affect how much people enjoy consumption. While there is plenty of evidence and consensus on the size and direction of the first set of effects, there is less evidence and no consensus on the second effect of health, that on one's marginal utility of (non-medical) consumption. My goal is to understand how health affects households' preferences, consumption, savings, ability to self-insure, and their valuation of means-tested government programs in a quantitative framework in which both sets of health-related effects are present.

Standard optimality conditions predict that households keep the marginal utility of consumption constant across states of the world. Smoothing the marginal utility from consumption is equivalent to smoothing consumption only when health does not affect preferences (and there are no other preference shocks). However, previous literature raises the possibility that the marginal utility from consumption when sick might be different from that when healthy. In this case, optimal consumption is no longer constant because health fluctuates. This, in turn, might change household consumption and saving behavior over the life cycle, the effectiveness of self-insurance, and the value of government support across health states.

I use data from the Panel Study of Income Dynamics (PSID) to measure (bad) health using the frailty index (following Hosseini, Kopecky, and Zhao (2022)). Frailty combines information from a wide array of health indicators—such as diseases, difficulties with activities of daily living (ADL), and harmful lifestyle habits. In particular, it is defined as the sum of all the adverse health events at each age as a fraction of the total possible ones.

I build and calibrate a life-cycle model of consumption and savings in which households, starting at age 25, face uncertainty about their health, medical expenses, and longevity. During their working period, households face earnings uncertainty. I allow for both persistent and transitory health and earnings shocks. After the working stage, households retire and receive Social Security benefits.

Importantly, health affects survival, earnings, out-of-pocket medical expenses, and the marginal utility of consumption. In my model, as in De Nardi, French, and Jones (2010) and Keane, Capatina, and Maruyama (2020), medical expenses are exogenous and affect one's resources. Households optimally choose how much to consume and save, given realistic levels of uncertainty and government insurance. In particular, the government provides means-tested transfers that bridge the gap between households' available resources and a minimum consumption level.

I also use the PSID data to calibrate my model's parameters in two steps. First, I estimate all components that do not require using my model. These include, among others, the processes for earnings and health. Second, I calibrate the government-provided consumption floor and the effect of health on marginal utility by matching the consumption response to transitory earnings and transitory health shocks. The model matches its targets well and also fits the life-cycle profile of consumption despite not being required to match it by construction.

The main idea of my identification strategy is that consumption fluctuations are informative about the means-tested government consumption floor and the effect of health on the marginal utility of consumption. Starting from the identification of the consumption floor, when a transitory earnings shock hits, it affects current resources. Because a higher consumption floor reduces the fraction of people whose consumption fluctuates in response to a transitory earnings shock, the average consumption response to a transitory earnings shock identifies the consumption floor. Turning to the identification of the effects of a transitory health shock on the marginal utility of consumption, it is worth pointing out that this kind of shock has two main effects. First, it affects current resources by impacting current income and medical expenses. Second, it affects the marginal utility of consumption directly. Hence, when a transitory health shock hits, consumption reacts because of the change in resources (resource channel) and the change in the marginal utility of consumption (marginal utility channel). My model explicitly acknowledges the effects of health on resources. If there were no effects on marginal utility, the effects of a health shock on consumption would be, for a given resource effect size, the same as those of an earnings shock. This is because the effect of a change in resources on consumption is the same regardless of whether the change is driven by earnings or health. Once the resource channel is identified, the marginal utility channel is identified residually from the consumption response to a transitory health shock. A third, much smaller effect of a transitory health shock is that it has a negligible impact on life expectancy, which might thus affect the consumption response. However, because my model explicitly accounts for this effect, it is "netted out" of the consumption response to a transitory health shock. This ensures the validity of my identification strategy. Blundell, Borella, Commault, and De Nardi (2022) formalize a discussion of these effects.

Persistent earnings and health shocks have additional effects compared to their transitory counterparts. A persistent earnings shock also affects the distribution of future earnings. A persistent health shock has even richer effects because it impacts future health and, thus, life expectancy, future medical expenses, and future earnings. While my model, as long as it captures the main features of the data, is designed to capture these effects, the typical estimation of the consumption response to persistent shocks from the data is based on more stringent assumptions than those for transitory shocks. In particular, identifying the consumption response to transitory shocks only requires that the laws of motion of the underlying processes are well specified and that consumption is independent of future shocks. In contrast, identifying the consumption response to persistent shocks requires assuming that log consumption evolves as a random walk. This assumption has been shown to be violated (both in the data and in life-cycle models with precautionary savings) by Carroll (1997) and Commault (2022). Moreover, it typically assumes permanent rather than persistent shocks, or at least that the persistence of the shocks is known in advance (See Kaplan and

Violante (2010) on this point). For these reasons, I check my model's implications for the consumption response to persistent shocks, but I do not use it for identification purposes.

I provide four main sets of findings. The first one is that, for consumption fluctuations to be consistent with transitory earnings and health shocks, poor health has to reduce the marginal utility of consumption. This result is consistent with, among others, De Nardi, French, and Jones (2010) and Finkelstein, Luttmer, and Notowidigdo (2013). My calibrated effect of health on preferences implies that, for a household with median frailty, the onset of two additional chronic conditions (which corresponds to about a one standard deviation increase in frailty) results in a decrease of 5.5% in the marginal utility of consumption. My identification also implies a calibrated value for the consumption floor consistent with those found or used in previous work. In particular, the consumption floor is \$3,561 per-year-per-capita, which is within the standard range in the literature of \$3,000-\$7,000.

Using my calibrated model, I generate three more sets of important findings. The second set concerns the effects of health-dependent preferences on consumption and savings. Analyzing this is important because most studies on the determinants of savings ignore the effects of bad health on preferences. I show that this force affects optimal consumption and savings over the life cycle. By comparing the predictions of my baseline model with those from a model in which health does not affect the marginal utility of consumption, I show that, for instance, households in their eighties would consume 4% more if health did not affect their marginal utility of consumption. This is because health worsens over the life cycle and the marginal utility of consumption is lower in worse health. As households desire to consume less when in worse health and health deteriorates with age, savings are also lower. For instance, households in their eighties would save 13% more if health did not affect their marginal utility of consumption.

Third, I evaluate the effects of health-dependent preferences on self-insurance. This is interesting because a large amount of literature compares changes in income and consumption to infer self-insurance (a seminal paper is Blundell, Pistaferri, and Preston (2008)). Most of this literature (except for Blundell, Borella, Commault, and De Nardi (2022), which focuses on the post-age 65 periods and does not calibrate a structural model) ignores the effects of health shocks on both income and preferences. I show that a model without health-dependent preferences does not match the degree of self-insurance against health shocks observed in the data as well as my baseline model does. For instance, the consumption response to a transitory health shock predicted by a model without health-dependent preferences is 20% smaller than what I estimate from the data.

Fourth, I study how health-dependent preferences affect households' valuation of means-tested government insurance. This matters because, as far as I know, this is the first study to quantify this effect in a quantitative structural model. I show that health-dependent preferences reduce the household valuation of government insurance. For instance, the compensation associated with a 30% cut in government insurance is $17,851 with health-dependent preferences and $18,162 without. Intuitively, when a bad health shock hits, the marginal utility of consumption is lower with health-dependent preferences and households need a lower consumption floor. I also show that government insurance is very valuable for poor households. For instance, households in the bottom 5% of the earnings distribution have to be compensated with about $66,000 when means-tested government programs are cut in half. This number is almost three times larger than the average compensation for the whole population and eight times larger than the average compensation for households in the top 5% of the earnings distribution. I also find that government insurance is more valuable for sicker households. For example, the welfare effect of a 30% reduction in means-tested government insurance programs is 7% larger for households in the top 5% of the frailty distribution than for those in the bottom 5%.

The remainder of the paper is organized as follows. Section 2 presents the relationship with the literature and my contributions. Section 3 describes my quantitative model. Section 4 illustrates the data and how I measure health. Section 5 discusses my empirical strategy and presents my calibration results. Section 6 shows the effects of health-dependent preferences on consumption and savings. Section 7 analyzes the effects of health-dependent preferences on self-insurance against health shocks. Section 8 discusses the welfare effects of reforming means-tested government insurance. Section 9 concludes.

2 Relationship to the literature and contributions

My paper relates to three strands of the literature and contributes to each. First, my paper relates to the literature on **health-dependent preferences**, which yields no consensus on the magnitude and direction of the effect of health on preferences. Two approaches have emerged in this literature. The first one is empirical. Among the empirical studies, Evans and Viscusi (1991) finds no evidence of an effect of health on preferences. Finkelstein, Luttmer, and Notowidigdo (2013) shows that bad health reduces the marginal utility of non-medical consumption. Kools and Knoef (2019) indicates that bad health raises the marginal utility of consumption. The second approach uses structural life-cycle models. These papers model the effect of health on the marginal utility of consumption and estimate or calibrate this effect in the context of their structural models. Among these, Lillard and Weiss (1997) and Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2020) find that marginal utility increases with deteriorating health. In contrast, De Nardi, French, and Jones (2010) finds that marginal utility decreases as health worsens.[1] I contribute to this literature by providing a new way to identify the effect of health on preferences. I also provide

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

the first quantitative assessment of the consequences of health-dependent preferences on self-insurance and government insurance.[2]

Second, my paper relates to the literature on **consumption insurance**. Notable papers in this literature are Cochrane (1991), Attanasio and Davis (1996), Blundell, Pistaferri, and Preston (2008), Kaplan and Violante (2010), Blundell, Pistaferri, and Saporta-Eksten (2016a), Blundell, Pistaferri, and Saporta-Eksten (2018), Wu and Krueger (2018), Commault (2022), and Blundell, Borella, Commault, and De Nardi (2022). Numerous studies in this literature—including Blundell, Pistaferri, and Preston (2008)—focus only on income risk over the working age. More recently, Blundell, Borella, Commault, and De Nardi (2022) considers income and health risks but focuses on the elderly and does not estimate a structural model. I contribute to this literature by constructing and calibrating a life-cycle model that includes both earnings and health risks and does so for the whole life cycle.

Third, 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), Braun, Kopecky, and Koreshkova (2016), De Nardi, French, and Jones (2016), De Nardi, Pashchenko, and Porapakkarm (2017), and recent contributions by Hosseini, Kopecky, and Zhao (2020), Keane, Capatina, and Maruyama (2020), Salvati (2020), Bolt (2021), Dal Bianco (2022), and Dal Bianco and Moro (2022). I contribute to this literature by studying the effect of health on preferences and its consequences on welfare.

[2] Finkelstein, Luttmer, and Notowidigdo (2013) uses a stylized two-period model to evaluate the consequences of health-dependent preferences on savings for retirement but do not evaluate the welfare effects of health-dependent preferences. I use a richer model and evaluate the consequences of health-dependent preferences on insurance.

3 Model

Households enter the model at age 25, retire exogenously at 63, and die with certainty by the time they are 89. They are subject to health, earnings, and survival risk until retirement, after which earnings risk is resolved. I use biennial data from the PSID because it contains information on consumption, health, and income. The PSID samples households every other year. To be consistent with this data structure, each period in my model lasts two years.

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 accidental bequests are lost to the economy.

3.1 Health-Dependent Preferences

In each period, utility depends on the consumption of non-durable and non-medical goods, c_t, and frailty, f_t. The period flow utility of consumption is:

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

The parameter γ is the coefficient of relative risk aversion, and $\delta(f_t)$ 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:

$$\delta(f_t) = 1 + \delta f_t. \tag{3.2}$$

Hence, δ is the parameter capturing the effect of health on the marginal utility of consumption; when δ is equal to 0, health does not affect utility.

3.2 Frailty

Frailty can take values between zero and one. The larger frailty is, the worse a household's health is. If a household's frailty is zero in period t, there is a positive probability that it becomes positive in the next period. I also assume that if frailty is positive in period t, it cannot go back to zero in period $t+1$.[3] Once frailty is positive, I follow Hosseini, Kopecky, and Zhao (2022) and assume that it evolves according to the following process:

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

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

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

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

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

where κ_t is a deterministic component that depends on age; π_t is a persistent component, and ε_t is a transitory component. I assume that the shocks ε_t^f and η_t^f are mutually and serially uncorrelated. Following Hosseini, Kopecky, and Zhao (2022), I also assume that, when $f_t = 0$, $\pi_t^f = 0$.

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

3.3 Earnings

Households face earnings risk during their working period. Earnings depend on age, frailty, and a persistent and transitory component as follows

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

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

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

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

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

where $\kappa_t(f_t)$ denotes a deterministic function of age and frailty, π_t^y is a persistent component, and ε_t^y is a transitory component. I assume that the shocks ε_t^y and η_t^y are mutually and serially uncorrelated.

3.4 Medical Expenses and Death

Until death, households incur out-of-pocket medical expenses and face survival probabilities. I model the evolution of out-of-pocket medical expenses as follows,

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

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

where $g(t, f_t)$ denotes a deterministic function of age and frailty and ξ_t denotes an i.i.d. shock. Medical expenses occur also for households in perfect health (i.e., zero frailty). They capture, for instance, preventative care, such as routine physicals and examinations. Households face an age-and-frailty-specific survival probability, $s_{f,t}$, up to the maximum age of 89.

3.5 Government

The government imposes taxes on income, provides Social Security benefits to retirees, and provides a means-tested transfer to needy households. I model taxes on total income as in Bénabou (2002) and Heathcote, Storesletten, and Violante (2017). This tax function allows for negative tax rates (and thus incorporates the Earned Income Tax Credit (EITC)) and is given by:

$$T(y_t) = y_t - (1-\lambda)y_t^{1-\tau}. \tag{3.15}$$

where y_t 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]

The government provides Social Security benefits after retirement. To reduce computational costs, I follow De Nardi, Fella, and Paz-Pardo (2019) and approximate Social Security benefits as a function of the last realization of earnings:

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

Government-provided means-tested transfers ensure that a household's available resources are sufficient to reach a minimum consumption floor, $\underline{c}$:

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

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

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.

3.6 Timing

Working-age households start each period with a stock of assets and draw realizations of the stochastic process for frailty, earnings, and medical expenses, and then make consumption and 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 expenses and then make consumption and saving decisions.

3.7 Recursive Formulation

There are two value functions, one for each stage of life.

3.7.1 The Value Function for Workers

The vector of state variables X_t for workers includes: age, t; assets, a_t; the medical expenses shock, ξ_t; the persistent earnings component, π_t^y; the transitory earnings component, ε_t^y; the persistent frailty component, π_t^f; and the transitory frailty component, ε_t^f. Workers maximize the objective function:

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

subject to the intertemporal budget constraint,

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

and Equations (3.3)-(3.7), (3.8)-(3.12), (3.13)-(3.14), (3.17), and a no borrowing constraint in every period, $a_t \geq 0$.

3.7.2 The Value Function for Retirees

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

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

subject to the intertemporal budget constraint,

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

and Equations (3.3)-(3.7), (3.13)-(3.14), (3.16), (3.18), and a no borrowing constraint in every period, $a_t \geq 0$.

4 Data

The PSID is a longitudinal survey representative of the U.S. population, conducted annually since 1968 and biennially since 1997. Starting in 2003, the PSID collected detailed health information. Moreover, beginning in 2005, the PSID covered almost all of the consumption categories considered in the Consumer Expenditure Survey (CEX). Hence, I use each biennial wave of the PSID between 2005 and 2019 because, during this sample period, the dataset contains detailed information on health and medical conditions, labor and non-asset income, wealth, and consumption. 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.

I measure non-medical consumption from the PSID as the sum of household expenses 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 expenses, and consumption into real quantities using the Consumer Price Index for Urban Consumers (CPI-U) and 2018 as my base year. Appendix D presents some facts on my key variables of interest.

4.1 Measuring (Bad) Health

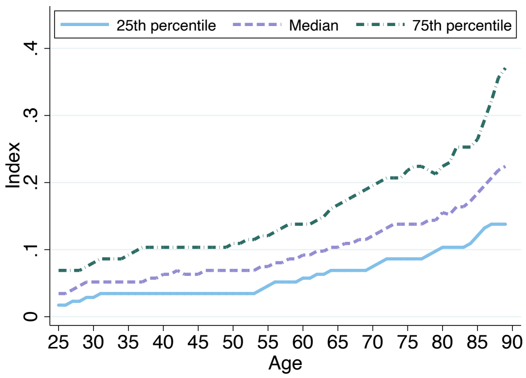
The frailty index captures the idea that, as people age, they become increasingly burdened by adverse health events (such as chronic diseases or temporary ailments) which I refer to as deficits. As such, the frailty index is an objective measure of bad health. It has been used extensively in the medical and gerontology literature, and it has been shown to be an excellent predictor of health, mortality, medical expenses, and the probability of becoming a disability insurance recipient (See, among others, Hosseini, Kopecky, and Zhao (2022) and Nygaard (2021)).

To construct the frailty index for the households in my sample, I follow Searle, Mitnitski, Gahbauer, Gill, and Rockwood (2008) and include the following:

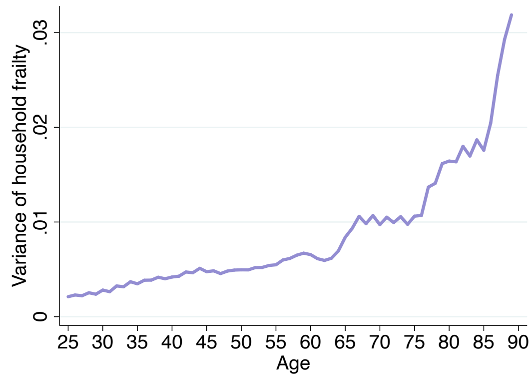
- Difficulties with activities of daily living (ADL) and instrumental ADL (IADL) such as difficulty dressing, bathing, and walking.
- Diagnosed diseases, such as diabetes, cancer, and arthritis.
- Cognitive impairments and mental health measures, such as memory loss and psychological problems.
- Lifestyle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

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

I construct a household's frailty as the average frailty index of each member. It has a mean of 0.09 and a median of 0.07. The left panel of Figure 1 reports the distribution of household frailty by age and shows that the median, 25th, and 75th percentiles increase with age. The right panel of Figure 1 reports the variance of frailty by age and shows that this increases with age and is particularly high after age 75.



(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 statistic is smoothed using a 3-year moving average. PSID, 2005-2019.

Figure 2 displays the fraction of households with positive frailty by age and shows that health risk is present at all ages. In particular, it indicates that almost 80% of 25-year-old households have positive frailty and that this share increases rapidly with age. To understand why frailty is so prevalent, even at younger ages, Table 1 displays the three most common deficits for household heads at selected ages. Smoking and obesity are the most common deficits for younger people, while high blood pressure and arthritis are the most common for older people.[5]

[5]These numbers are consistent with statistics from the Centers for Disease Control and Prevention (CDC). In particular, the CDC documents that, in 2020, 14.1% of people aged 25 to 44 smoked cigarettes (Centers for Disease Control and Prevention (2022b)), while about 40% of people aged 20 to 39 were obese (Centers for Disease Control and Prevention (2022a)). Moreover, the CDC reports that, in 2018, 74.5% of people over 60 had high blood pressure (Centers for Disease Control and Prevention (2020)), while, between 2013 and 2015, about 50% of people over 65 had arthritis (Centers for Disease Control and Prevention (2021)).

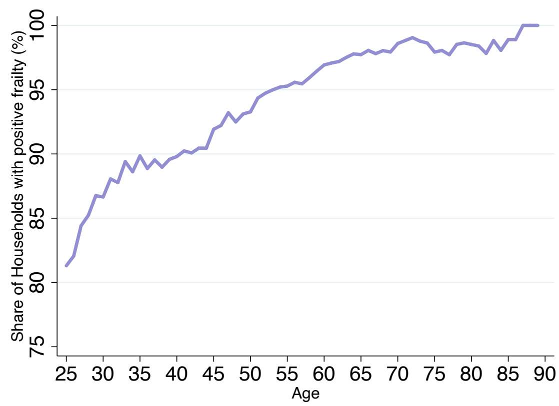


Figure 2: Share of households with positive frailty by age. The share is smoothed using a 3-year moving average. PSID, 2005-2019.

Age	Top 3 Deficits
25	Smoke, Obese, Asthma
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 1: Top 3 deficits for household heads for selected ages. PSID, waves 2005-2019.

5 Calibration

I use a two-step strategy similar to that of Gourinchas and Parker (2002) and De Nardi, French, and Jones (2010). In the first step, I estimate the parameters that I can cleanly identify outside my model. For example, I estimate the frailty process from the PSID and fix the discount factor and risk aversion to values commonly used in the literature.

In the second step, I calibrate the consumption floor, $\underline{c}$, and the effect of health on preferences, δ, to match the consumption response to transitory earnings and health shocks.

5.1 First-Step Calibration and Estimation

Frailty Process I model the probability that the household's frailty remains at zero at each age using a probit model as in Hosseini, Kopecky, and Zhao (2022):

$$\text{Prob}(f_t = 0|X_t) = \Phi(X_t'\alpha). \tag{5.1}$$

where Φ is the c.d.f. of a standard normal distribution and X_t is a set of regressors. Here, X_t contains family size, education level, cohort effects, and a second-order polynomial in household age. Table A-3 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 education.

The probability that a household has zero frailty, conditional on having zero frailty during the previous is:

$$\text{Prob}(f_t = 0|f_{t-1} = 0) = \frac{\text{Prob}(f_t = 0|X_t)}{\text{Prob}(f_{t-1} = 0|X_{t-1})} = \frac{\Phi(X_t'\alpha)}{\Phi(X_{t-1}'\alpha)}. \tag{5.2}$$

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

I estimate the deterministic component of the evolution of frailty once it becomes positive (κ_t in Equation (3.3)) by regressing log-frailty for those with positive frailty on family size, education level, cohort effects, and a second-order polynomial in age. Then, I use the residuals from this regression to estimate the autoregressive coefficient, ρ_f, the variance of the transitory shock, $\sigma^2_{\varepsilon^f}$, the variance of the shock to the persistent component, $\sigma^2_{\eta^f}$, and the variance of the initial persistent component, $\sigma^2_{\pi_0^f}$. I identify them using the variances and covariances of the residuals and estimate them using equally weighted minimum distance (Appendix E.1 discusses the identification restrictions and estimation details). Table A-4 in Appendix E.1 reports my 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 age-and-frailty-specific two-year survival probabilities for household heads. To do so, I run a logistic regression of a binary indicator of survival using frailty in the previous period, education, family size, cohort effects, and a second-order polynomial in age as covariates. Table A-5 in Appendix E.2 reports the estimation results. Age and frailty reduce the probability of surviving to the next period.

I then compute the average survival probabilities by age and confirm the finding in French (2005) that the PSID overestimates survival probabilities. Hence, I adjust them so that my estimated average survival probabilities match those reported by the Social Security Administration in the life tables for 2019.

Earnings Process Earnings include labor earnings, the labor part of business income, and farm income. When married, household earnings are the sum of each spouse's earnings. I estimate the earnings process for households between the ages of 25 and 61, reporting positive labor earnings. I estimate the deterministic function

$\kappa_t(f)$ in Equation (3.8) by regressing the logarithm of earnings on frailty, family size, education level, cohort effects, and a second-order polynomial in age. The left panel Table A-6 in Appendix E.3 displays my estimation results and shows that age, family size, and education positively affect earnings, while frailty hurts them.

Using the residuals from this regression, I estimate the autoregression coefficient ρ_y, the variance of the transitory shock, $\sigma^2_{\varepsilon^y}$, the variance of the shock to the persistent component, $\sigma^2_{\eta^y}$, and the variance of the initial persistent component, $\sigma^2_{\pi^y_0}$, by equally weighted minimum distance. Appendix E.1 presents details on the identification and estimation. The right panel of Table A-6 in Appendix E.3 shows the estimated variances of the earnings shocks.

Out-Of-Pocket Medical Expenses Medical expenses are the sum of what households spend out-of-pocket for hospital and nursing home stays, doctor visits, prescription drugs, and insurance premia. I replace values of medical expenses equal to zero with \$100. I estimate the deterministic function $g(t, f_t)$ in Equation (3.13) by regressing the logarithm of medical expenses on frailty, family size, education level, cohort effects, and a second-order polynomial in household age. Column (1) in Table A-7 in Appendix E.4 reports the estimation results for this regression. They show that medical expenses increase with age, frailty, family size, and education.

To estimate the variance of the i.i.d. shock, σ^2_ξ, I regress the squared residuals from the regression above on the same covariates. Column (2) of Table A-7 in Appendix E.4 reports these 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 2 summarizes my first-step parameters, including those that I set to commonly adopted values in the literature. I use the parameters of the tax function estimated 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). 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 as in 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).

Parameter	**Value**	**Description**	**Source**
		Preference Parameters	
β	0.9756	Annual Discount factor	Gourinchas and Parker (2002)
γ	2	Risk Aversion	Guvenen and Smith (2014)
		Frailty Process	
κ_t	see text	Deterministic component	PSID
ρ_f	0.93	Autoregressive coefficient	PSID
$\sigma^2_{\varepsilon^f}$	0.02	Variance of transitory shock	PSID
$\sigma^2_{\eta^f}$	0.06	Variance of persistent shock	PSID
$\sigma^2_{\pi^f_0}$	0.36	Variance of initial persistent component	PSID
		Earnings Process	
$\kappa_t(f_t)$	see text	Deterministic function of age and frailty	PSID
ρ_y	0.90	Autoregressive coefficient	PSID
$\sigma^2_{\varepsilon^y}$	0.09	Variance of transitory shock	PSID
$\sigma^2_{\eta^y}$	0.10	Variance of persistent shock	PSID
$\sigma^2_{\pi^y_0}$	0.79	Variance of initial persistent component	PSID
		Medical Expenses and Death	
$g(f_t, t)$	see text	Deterministic function of age and frailty	PSID
σ^2_{ξ}	0.04	Variance of shock to medical expenses	PSID
$s_{f,t}$	see text	Age-and-frailty-specific survival probabilities	PSID
		Government and Interest Rate	
λ	2	Average level of income taxation	Borella, De Nardi, Pak, Russo, and Yang (2021)
τ	0.07	Progressivity of the income tax system	Borella, De Nardi, Pak, Russo, and Yang (2021)
r	0.02	Interest rate	Paz-Pardo (2022)

Table 2: First-Step Parameters

5.2 Second-Step Calibration

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

Measuring Self-Insurance. I follow a long-standing tradition in the consumption insurance literature and measure self-insurance with pass-through coefficients.[6] As described in the seminal contribution of Blundell, Pistaferri, and Preston (2008), the pass-through coefficient of an idiosyncratic shock x_t is the ratio of the covariance between log-consumption growth and the shock and the variance of the shock:

$$\phi^x = \frac{\text{cov}(\Delta \log c_t, x_t)}{\text{var}(x_t)}, \tag{5.3}$$

Pass-through coefficients capture the share of the variance of a shock that translates into consumption growth. If households had access to full insurance against idiosyncratic shocks (as would be the case if markets were complete) the pass-through coefficients would be zero. If there were no insurance, the pass-through coefficients would be one, as consumption would react one-to-one to idiosyncratic shocks. As shown by Blundell, Pistaferri, and Preston (2008) and Blundell, Borella, Commault, and De Nardi (2022), households in the United States only have access to partial insurance against income and health shocks, which results in pass-through coefficients between zero and one.

Estimating pass-through coefficients from the data is challenging because shocks are not observable. For example, the PSID records information on earnings and frailty but not on earnings and frailty shocks. Therefore, I use moments on observable consumption, earnings, and frailty to estimate the pass-through coefficients.

I apply a similar strategy to that used by Kaplan and Violante (2010) to identify the pass-through coefficients of transitory earnings and frailty shocks (Appendix I describes the details for the pass-through coefficients of persistent shocks.) First, I define the quasi difference of log earnings as $\tilde{\Delta} \log y_t = \log y_t - \rho_y \log y_{t-1}$ and the quasi difference of log frailty as $\tilde{\Delta} \log f_t = \log f_t - \rho_f \log f_{t-1}$. Notice that I have

[6] A few notable papers using pass-through coefficients to measure consumption insurance are Blundell, Pistaferri, and Preston (2008), Kaplan and Violante (2010), Blundell, Pistaferri, and Saporta-Eksten (2016b), Blundell, Pistaferri, and Saporta-Eksten (2018), Wu and Krueger (2018), and Blundell, Borella, Commault, and De Nardi (2022)

estimated ρ_y and ρ_f in Section 5.1. Second, using the processes for earnings and frailty and assuming that shocks are mutually uncorrelated, one can show that

$$\begin{aligned}
\text{cov}(\Delta \log c_t, \tilde{\Delta} \log y_{t+1}) &= -\rho_y \text{cov}(\Delta \log c_t, \varepsilon_t^y), \\
\text{cov}(\tilde{\Delta} \log y_t, \tilde{\Delta} \log y_{t+1}) &= -\rho_y \text{var}(\varepsilon_t^y), \\
\text{cov}(\Delta \log c_t, \tilde{\Delta} \log f_{t+1}) &= -\rho_f \text{cov}(\Delta \log c_t, \varepsilon_t^f), \\
\text{cov}(\tilde{\Delta} \log f_t, \tilde{\Delta} \log f_{t+1}) &= -\rho_f \text{var}(\varepsilon_t^f),
\end{aligned}$$

Therefore, the pass-through coefficients to transitory shocks are identified as:

$$\phi_\varepsilon^y = \frac{\text{cov}(\Delta \log c_t, \varepsilon_t^y)}{\text{var}(\varepsilon_t^y)} = \frac{\text{cov}(\Delta \log c_t, \tilde{\Delta} \log y_{t+1})}{\text{cov}(\tilde{\Delta} \log y_t, \tilde{\Delta} \log y_{t+1})}, \tag{5.4}$$

$$\phi_\varepsilon^f = \frac{\text{cov}(\Delta \log c_t, \varepsilon_t^f)}{\text{var}(\varepsilon_t^f)} = \frac{\text{cov}(\Delta \log c_t, \tilde{\Delta} \log f_{t+1})}{\text{cov}(\tilde{\Delta} \log f_t, \tilde{\Delta} \log f_{t+1})}, \tag{5.5}$$

I estimate the pass-through coefficients of transitory shocks using Equation (5.4) and Equation (5.5). Appendix F provides details on the estimation procedure.

Calibration Procedure. I calibrate the consumption floor, $\underline{c}$, and the effect of bad health on preferences, δ. To solve and simulate the model, I follow Gourinchas and Parker (2002) and French (2005) and fix the cohort to the middle one in the data, fix family size to the average family size, and fix the education level to high school graduate. I keep these values constant over the life cycle, as in French (2005).

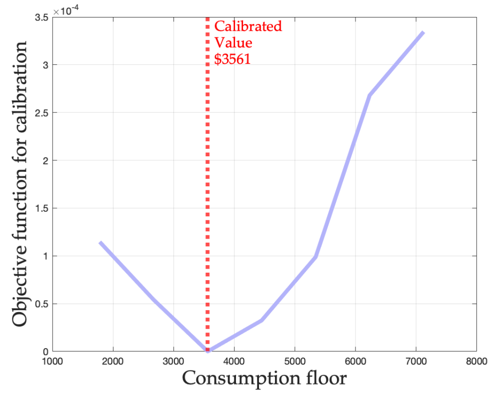
The calibration procedure is as follows. First, given an initial guess for the two parameters to be calibrated, I solve the life-cycle model and obtain optimal decision rules for consumption and savings. Second, I use the optimal decision rules to simulate the life-cycle choices of households. Third,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

Identification. In a non-linear model like mine, all parameters potentially affect all moments. In the Introduction, I provide some intuition on what moments in the data help identify my parameters of interest. Appendix G provides more details and shows the identification argument for the effect of health on preferences using the structure of the model.

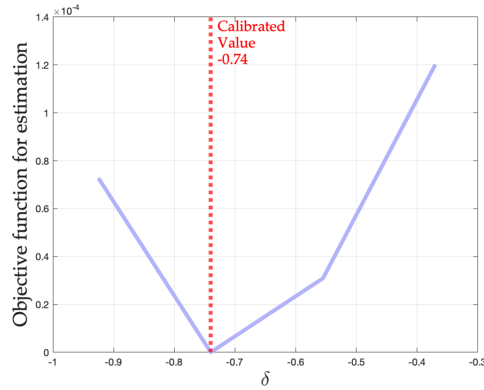
In this section, I show how my objective function varies with the two parameters I calibrate. Figure 3 displays my objective function as a function of δ and $\underline{c}$. It shows that, quantitatively, the qualitative intuition that I have discussed in the Introduction holds. In particular, Panel (a) shows the evolution of the objective function when I fix δ at my calibrated value and vary the consumption floor. The function achieves a minimum at my calibrated value of the consumption floor. Similarly, Panel (b) displays my objective function when I set the consumption floor at my calibrated value and vary δ. In this case, too, the objective function is minimized at my calibrated value for $\underline{c}$. Finally, Panel (c) shows a surface plot of my objective function when both $\underline{c}$ and δ are allowed to vary. This figure shows that my objective function is minimized at my calibrated values.

Calibration Results. The second column of Table 3 reports the pass-through coefficients to transitory earnings and health shocks that I estimate from the PSID. The third column shows the corresponding coefficients in my simulated data and the fifth column shows the values of my calibrated parameters.

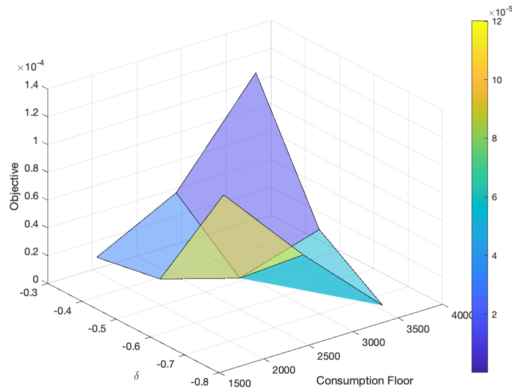
The first row of Table 3 shows that the pass-through coefficient of a transitory earnings shock, ϕ^y_ε, is 0.175. This means that a 10% increase in earnings due to a transitory shock leads to a rise in consumption of 1.75%. This finding is in line with the results of Blundell, Pistaferri, and Preston (2008) and Blundell, Borella,



(a) Objective function fixing δ and varying $\underline{c}$



(b) Objective function fixing $\underline{c}$ and varying δ



(c) Objective function varying $\underline{c}$ and δ

Figure 3: Objective function for calibration as a function of $\underline{c}$ and δ.

Moment	Data	Model	Parameter	Value
ϕ_ε^y	0.175	0.175	Consumption floor, $\underline{c}$	\$3,561
ϕ_ε^f	-0.087	-0.087	Effect of bad health on preferences, δ	-0.74

Table 3: Targeted moments, model fit, and parameter values

Commault, and De Nardi (2022). My model exactly matches the pass-through of a transitory earning shock and predicts a consumption floor of \$3,561, which is well within the standard range in the literature of \$3,000-\$7,000.[7]

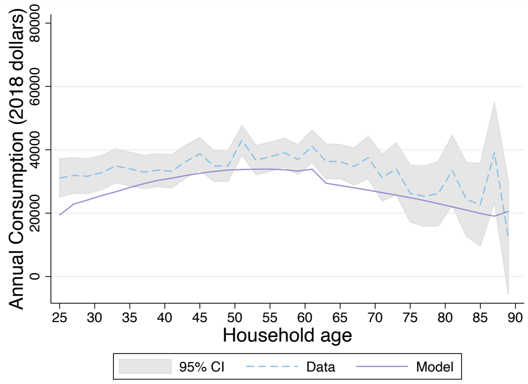
[7] Here, I report the annual consumption floor per capita. My model is biennial, and I solve it by fixing the family size to the average one. Thus, to obtain the biennial consumption floor implied

The second row of Table 3 shows that the pass-through coefficient of a transitory frailty shock, ϕ_{ε}^{f}, is -0.087. This means that a 10% increase in frailty due to a transitory shock leads to a 0.9% decrease in consumption. My model replicates the pass-through of transitory frailty shocks exactly and implies a calibrated value of δ of -0.74. The fact that δ is negative means that the marginal utility of 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), Koijen, Van Nieuwerburgh, and Yogo (2016), and Blundell, Borella, Commault, and De Nardi (2022). The magnitude of δ implies that, for a household with median frailty, the onset of two additional chronic conditions (which corresponds to about a one standard deviation increase in frailty) results in a decrease of 5.5% in the marginal utility of consumption.

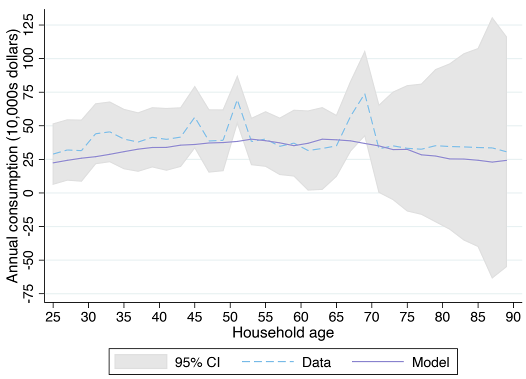
Untargeted Moments. To validate my model, I compare its implied consumption evolution to the one estimated from the PSID. First, I compare the average annual consumption for the whole population. Second, I analyze consumption for households in the top and bottom 5% of the frailty distribution to evaluate my model performance for the most unhealthy and healthy households.

To compute the life-cycle profile of consumption from the data, I follow French (2005). I first 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 and compute the predicted values from the regression and a 95% confidence interval. To calculate average consumption from the model-simulated data, I divide biennial consumption by two and then regress it on age dummies. I then repeat this process, in the data and the model, for households in the top and bottom 5% of the frailty distribution by age.

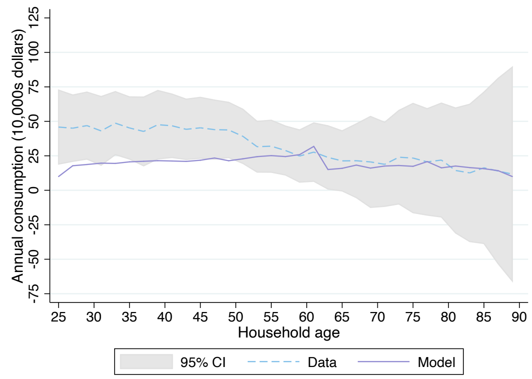
by my model, one needs to multiply the annual per capita value first by two and then by 2.6, the average family size in my sample.



(a) Annual Consumption over the life-cycle



(b) Bottom 5% of frailty distribution



(c) Top 5% of frailty distribution

Figure 4: Life cycle profile of annual consumption. Panel (a) reports the whole population's average annual consumption over the life cycle. Panel (b) reports the profile for households in the bottom 5% of the frailty distribution. Panel (c) reports the analogous figure for households in the top 5% of the frailty distribution.

Panel (a) of Figure 4 shows the life-cycle profile of consumption for the whole population. My model matches the trends of consumption well. It slightly underpredicts consumption between the ages of 25 and 35 and between 60 and 70 but is within the 95% confidence interval at all other ages.

Panel (b) of Figure 4 shows average annual consumption for relatively healthy households. These households are in the bottom 5% of the frailty distribution by age. My model does an excellent job of matching annual consumption for these households. The model-simulated consumption is almost always within the 95% confidence interval and is very close in levels to the data, especially after age 45.

Panel (c) of Figure 4 shows the average annual consumption for relatively unhealthy households. These households are in the top 5% of the frailty distribution by age. My model matches annual consumption after age 60 remarkably well. However, despite the model-predicted consumption being at the border of the 95% confidence interval, the model underpredicts annual consumption at younger ages.

Next, I compare the pass-through coefficients against persistent earnings and frailty shocks in the model and the data. As I argued in the Introduction, identifying the pass-through coefficients requires stringent assumptions on consumption, which are violated in the observed and the model-generated data. However, I compare the estimates in the data and the ones from the model to evaluate my model's performance, even though they are biased measures of the true degree of self-insurance against persistent shocks. Table 4 reports the results of this comparison and shows that my model generates results that are qualitatively similar to those in the data.[8] In particular, a persistent positive earnings shock generates a consumption increase both in the data and in the model, while a persistent frailty shock causes a consumption drop. In terms of size, Table 4 shows that my model generates a pass-through of persistent earnings shocks that is larger than that in the data. Conversely, it implies a pass-through of persistent health shocks that is lower (in absolute value) than what is observed in the data. The bias in the model-generated pass-through coefficient to persistent shocks could be due to the identification strategy issues leading to biased estimates both in the model and in the data. Moreover, the bias in the pass-through to a persistent frailty shock could also be due to misspecification of the long-term effects of bad health, such as its effects on survival.

[8] Appendix I provides more details on estimating the pass-through coefficients of persistent shocks and the assumptions needed for identification.

	Data	Model
ϕ^y_η	0.240***	0.338***
	(0.03)	(0.003)
N	6,437	511,996
ϕ^h_η	-0.062**	-0.030***
	(0.02)	(0.003)
N	7,751	878,161

Table 4: Pass-through coefficients of persistent earnings (ϕ^y_η) and frailty (ϕ^f_η) shocks.

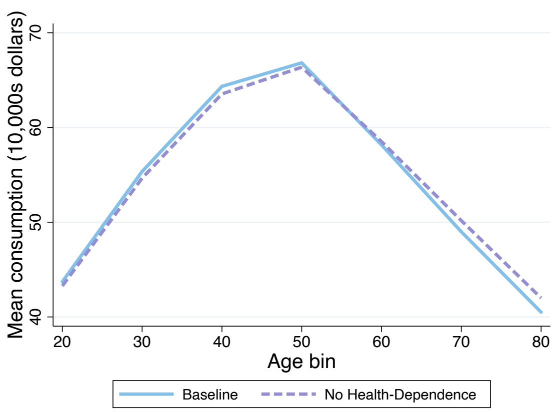
6 Health-Dependent Preferences, Consumption, and Savings

In this section, I use my calibrated model to assess the quantitative effects of health-dependent preferences on consumption and savings. The literature has largely ignored this effect. For example, Scholz, Seshadri, and Khitatrakun (2006) investigates the adequacy of retirement savings in the United States and allows for medical expense risk but does not consider the possibility that health-driven fluctuations in marginal utility may be a driver of consumption and savings patterns.

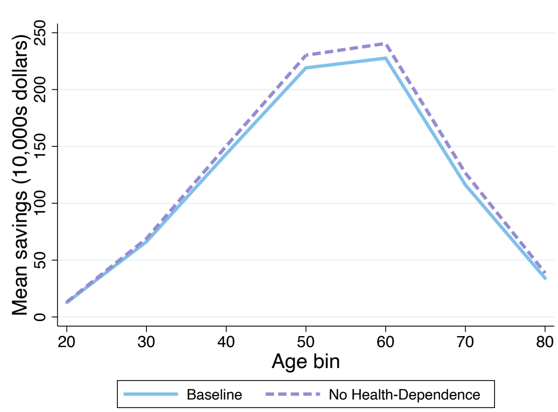
To fill this gap in the literature, I solve the model using the baseline calibration and setting $\delta = 0$, thereby removing the relationship between health and marginal utility. I then simulate the life cycle of 50,000 households and compare their consumption and savings over the life cycle with those from my baseline calibration.

Health-dependent preferences affect optimal consumption and savings over the life cycle. Figure 5 plots the life-cycle profile of average consumption and savings by 10-year age bins. Panel (a) shows that average consumption is higher without health-dependent preferences is lower before 50 but higher at older ages. For example, without health-dependent preferences, households consume about 1% less in their twenties but almost 4% more in their eighties. Panel (b) shows that average savings are higher at every age without health-dependent preferences. In particular, the increase in savings ranges from 3% when households are in their twenties to 13% in their eighties. These results show that health-dependent preferences should be carefully considered when studying the patterns and determinants of savings.

The observed consumption and savings patterns are consistent with the deterioration of health over the life cycle. Households are more unhealthy at older ages; therefore, their marginal utility of consumption is higher at that stage of life without health-dependent preferences than in the baseline case. Consequently, their optimal consumption is higher than in the baseline case because consumption is more "enjoyable." To sustain higher consumption at older ages, households must save more and give up consumption when young.[9]



(a) Average consumption by age



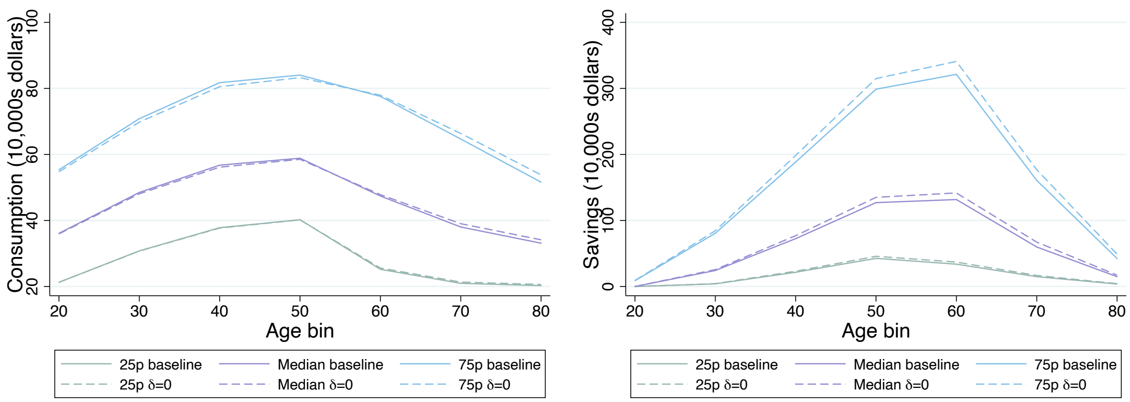
(b) Average savings by age

Figure 5: 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

The patterns described above apply across the consumption and savings distributions. Figure 6 displays the 25th, 50th, and 75th percentiles of consumption and savings by 10-year age bins with and without health-dependent preferences. Panel (a) shows that households consume more without health-dependent preferences at older ages and less at younger ones. In particular, all households consume less without

[9]Using a stylized two-period model, Finkelstein, Luttmer, and Notowidigdo (2013) shows that an adverse effect of bad health on the marginal utility of non-medical consumption reduces the optimal level of savings for retirement, which is consistent with what I find.

health-dependent preferences until their fifties and more after that. The difference in consumption is increasing along the distribution: in their eighties, households consume 1.6, 3.1, and 4.3 percent more without health-dependent preferences if they are in the 25th, 50th, and 75th percentile of consumption, respectively. 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 at all ages. For example, households in their thirties save 7.6, 5.6, and 4.6 percent more without health-dependent preferences if they are in the savings distribution's 25th, 50th, and 75th percentile, respectively.



(a) Percentiles of consumption by age

(b) Percentiles of savings by age

Figure 6: 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.

7 Health-Dependent Preferences and Self-Insurance

I now use my calibrated model to quantify the effect of health-dependent preferences on households' ability to self-insure against health shocks. To do so, I compute the pass-through coefficients of transitory and persistent health shocks in my baseline model and compare them with those from a model in which health does not affect the marginal utility of consumption. To the best of my knowledge, with the exception of Blundell, Borella, Commault, and De Nardi (2022), no paper has considered the effect of health-dependent preferences on self-insurance against health shocks.

Table 5 reports the pass-through coefficient of transitory frailty shocks in my PSID sample, baseline model, and a model without health-dependent preferences. Its first row shows that the model without health-dependent preferences predicts that a 10% increase in frailty generated by a transitory shock results in a 0.7% decrease in consumption. This change is 20% smaller than what is observed in the data and predicted by my baseline model. The second row of Table 5 shows that the counterfactual model also predicts a smaller consumption response to persistent frailty shocks (measured by the pass-through coefficient ϕ_η^f) than the one indicated by my baseline model. These results suggest that a model without health-dependent preferences predicts a smaller consumption response—thus a higher degree of self-insurance—to bad health shocks. This result is consistent with savings being higher in the counterfactual model but inconsistent with what I measure from the PSID.

Moment	Data	Baseline $\delta = -0.74$	No health-dependent preferences $\delta = 0$
ϕ_ε^f	-0.087	-0.087	-0.069
ϕ_η^f	-0.062	-0.030	-0.021

Table 5: Pass-through coefficients to transitory (first row) and persistent (second row) frailty shocks in the baseline calibration, $\delta = -0.74$, and counterfactual experiment in which $\delta = 0$.

8 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. Obtaining an accurate measure of the value that households place on these programs is crucial to evaluate potential reforms. Moreover, because MTGI includes programs targeted to the poor and unhealthy—such as Medicaid and Supplemental Security Income—it is interesting to see how health-dependent preferences influence the household valuation of such programs.

I compute the welfare changes associated with MTGI reforms using the compensating variation. In particular, I follow De Nardi, French, and Jones (2016) and McGee (2021) and define the compensating variation as the immediate payment after the reform that would make households as well off as before the reform. 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. As argued in McGee (2021), the compensating variation is an ex-ante measure that incorporates the mechanical and behavioral responses to a reform.

Group	Average Earnings	Average Frailty	30% reduction in $\underline{c}$ Baseline $\delta = -0.74$	No HDP $\delta = 0$	50% reduction in $\underline{c}$ Baseline $\delta = -0.74$	No HDP $\delta = 0$
All 25-year-olds	56,110	0.05	17,851	18,162	23,841	24,292
Bottom 5% earnings	5,457	0.08	51,773	52,113	65,754	66,156
Top 5% earnings	266,132	0.04	7,232	8,264	8,093	8,817
Bottom 5% frailty	67,443	0.00	17,023	17,300	22,811	23,146
Top 5% frailty	31,278	0.19	18,169	18,458	24,250	24,657

Table 6: Household valuation of MTGI reform. Columns 4 and 5 report the compensating variation associated with a 30% reduction in the consumption floor, while columns 6 and 7 display the compensating variation associated with a 50% reduction in the consumption floor. For each reform, I report the compensating variation in the baseline calibration, $\delta = -0.74$, and without health-dependent preferences, $\delta = 0$.

Health-dependent preferences affect the household valuation of MTGI. Table 6 shows the compensating variation associated with two reforms: one that reduces the consumption floor by 30% compared to my baseline value (columns 4 and 5) and one that reduces it by 50% (columns 6 and 7).[10] Table 6 provides several interesting insights. First, households place a higher value on government insurance without health-dependent preferences across groups and reforms. For instance, the first row of Table 6 shows that for all 25-year-olds (who earn $56,110 on average and have a frailty index of 0.05) the compensating variations associated with a 30% and 50% reduction in the consumption floor are about 2% higher without health-dependent preferences.

Second, government insurance is more valuable for low earners. In the second and third rows of Table 6, I compare households in the bottom and top 5% of the earnings distribution and show that, for both reforms, the welfare effects are larger for low earners, who are, on average, also more unhealthy. For instance, the compensating variation associated with a 50% reduction in the consumption floor is about eight times larger for households in the bottom 5% of the earnings distribution. Across the earnings distribution, the household valuation of government insurance is larger without health-dependent preferences.

Third, government insurance is more valuable for sicker households. In the fourth and fifth rows of Table 6, I compare relatively healthy households (i.e., in the bottom 5% of the frailty distribution) with rather unhealthy ones (i.e., in the top 5% of the frailty distribution.) My results show that sicker households (that, on average, also earn less than healthier ones) value government insurance more than healthier ones. For example, the compensating variation associated with a 30% reduction in the consumption floor is about 7% larger for households in the top five percent of the frailty distribution. The value of government insurance is higher without health-dependent preferences in all cases.

[10] The baseline consumption floor is $3,561 per-year-per-capita.

9 Conclusions

I study the effect of bad health on preferences and the consequences of this effect on consumption, savings, self-insurance, and household valuation of government insurance. I do so by building a life-cycle model in which health affects survival, earnings, medical expenditures, and the marginal utility of consumption. I then calibrate the model using the PSID and use it for quantitative analysis.

I find that poor health reduces the marginal utility of consumption and that health-dependent preferences reduce old-age consumption and lower savings over the whole life cycle. I also show that a model without health-dependent preferences cannot replicate the degree of self-insurance against bad health shocks observed in the data as well as my baseline model can. In particular, a model without health-dependent preferences underestimates the consumption response to bad health shocks compared to the data and my baseline model.

Finally, I show that health-dependent preferences affect the household valuation of means-tested government insurance programs such as Medicaid and Supplemental Security Income. In particular, I show that households value these programs more when bad health does not affect preferences. My results indicate that it would be interesting to study the optimal design of taxes and transfers when bad health lowers the marginal utility of consumption.

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APPENDICES FOR ONLINE PUBLICATION

A The Literature on Health-Dependent Preferences

Finkelstein, Luttmer, and Notowidigdo (2009) defines 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-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 contributions

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 that 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 that the marginal utility for the unhealthy is between 17 and 23 percent lower than the marginal utility for the healthy. Evans and Viscusi (1991), instead, finds no evidence of an effect of bad health on preferences. Sloan, Kip Viscusi, Chesson, Conover, and Whetten-Goldstein (1998) finds that marginal utility in bad health is just 8 percent of the one in good health.

A second branch of this literature 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.[11] They find evidence of a negative effect of bad health 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) focuses on a sample of elderly Europeans and uses changes in material well-being to estimate the effect of health on preferences.[12] They find evidence of a positive effect of bad 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 preferences. Brown, Goda, and McGarry (2016) uses the American Life Panel (ALP) to study the differences in the value of marginal consumption in healthy and disabled states. They find little 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 bad 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 that bad health has a positive effect on marginal utility.

A.2 The structural-model literature

A few papers have used structural models of consumption to estimate the effect of health on preferences. Lillard and Weiss (1997) develops a life-cycle model to study

[11] They measure subjective well-being by using the response to the question "Much of the time during the past week, I was happy. (Would you say yes or no?)." as a proxy for utility.

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

the impact of health and survival risk on retirees' consumption and savings decisions. Their results point to a positive effect of bad health on preferences. In particular, consumption when sick is fifty-five percent higher than when healthy. Rust and Phelan (1997) studies the effects of Social Security and Medicare on the labor supply of older American workers. They find a positive effect of bad health on preferences, so sick people have a higher marginal utility of consumption than healthy ones. Hong, Pijoan-Mas, and Rios-Rull (2015) uses a life cycle model with endogenous health to estimate the effect of bad health on preferences using the Euler equation for consumption. They estimate a negative effect at age 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 of them consider this effect but do not estimate it. Low and Pistaferri (2015) builds 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 bad health on preferences. De Donder and Leroux (2021) studies the demand for long-term care insurance when health affects preferences. They assume a negative effect of bad health on preferences. Jung and Tran (2022) studies 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) builds a structural model of savings for elderly American households to study the effect of medical expenses on savings. They estimate a negative—but not significant—effect of bad health on preferences. Koijen, Van Nieuwerburgh, and Yogo (2016) develops 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 bad health on preferences. Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2020) builds 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 bad 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.

The PSID has been recording 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, it collected only information on food consumption. Starting in 1999, it 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.

Johnson, McGonagle, Freedman, and Sastry (2018) provides 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. 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 expenses, and wealth. Thus, in my sample, I only keep household heads, to whom I link information on the spouse when one is present.

Then, I restrict my attention to the core sample of the PSID.[13] 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 expenses, 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.

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

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

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.

Institute on Alcohol Abuse and Alcoholism[14] 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.

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

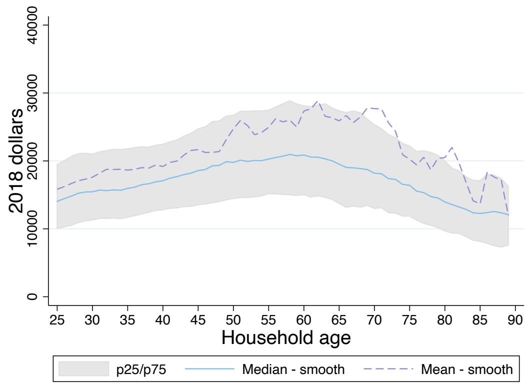
[14]Available at https://www.niaaa.nih.gov/alcohol-health/overview-alcohol-consumption/moderate-binge-drinking

D Facts about my key variables of interest

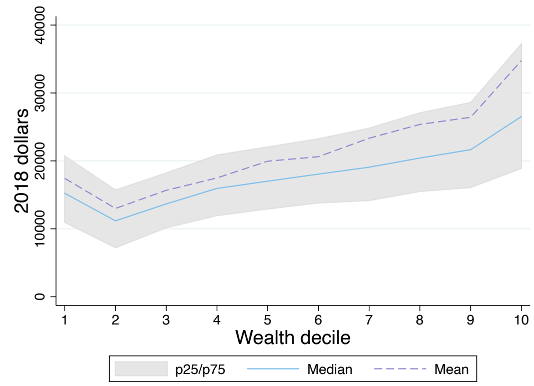
In this section, I report facts for my key variables of interest. For ease of exposition, consumption and wealth are equivalized (I equivalize household consumption and wealth by dividing them by the square root of family size). Here, I measure a household's total wealth as the sum of all assets minus 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.

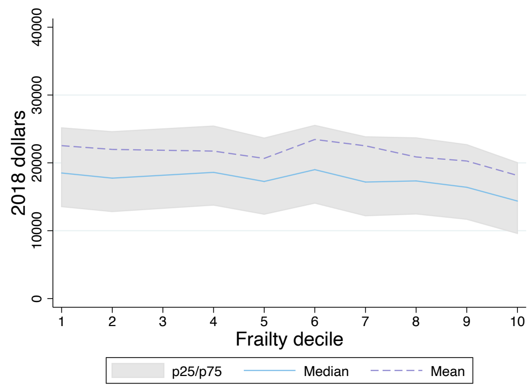
Figure A-2 shows the mean and the 25th, 50th, and 75th percentiles of equivalized wealth by age (Panel (a)) and frailty decile (Panel (b).) Panel (a) shows that average wealth increases until 65 and slightly decreases after then. Panel (b) shows that wealth is roughly stable across frailty deciles.



(a) By age

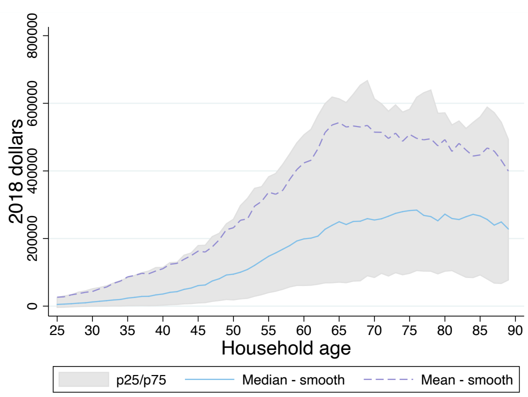


(b) By wealth decile

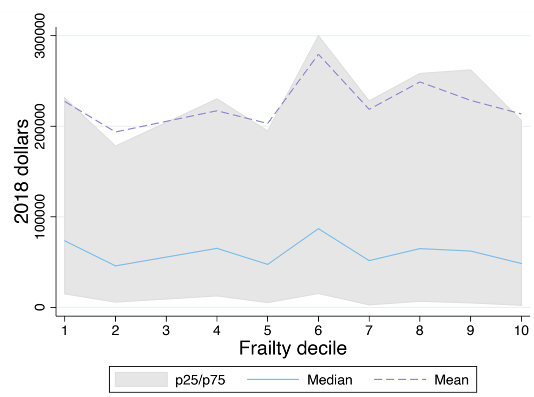


(c) By frailty decile

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 Frailty Process

Table A-3 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-3: 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 $\tilde{f}_{it} = \log f_{it} - \kappa_{it}$.

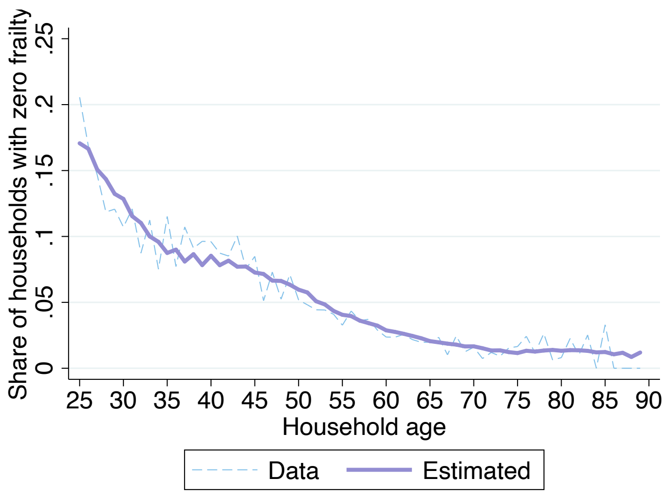


Figure A-3: Share of households with zero frailty in the data (dashed blue line) and predicted by probit regression (solid purple line.)

Then, the identification conditions I use are:

$$\begin{aligned}
\mathrm{var}(\tilde{f}_{i,25}) &= \sigma^2_{\pi_0^f} + \sigma^2_{\varepsilon^f} \\
\mathrm{var}(\tilde{f}_{it}) &= \frac{\sigma^2_{\eta^f}}{1-\rho_f^2} + \sigma^2_{\varepsilon,f} \\
\mathrm{cov}(\tilde{f}_{it}, \tilde{f}_{i,t-1}) &= \rho_f^{(j-k)} \frac{\sigma^2_{\eta^f}}{1-\rho_f^2}, \quad \text{for } j > k, \quad j,k = 1,\ldots,8
\end{aligned}$$

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 frailty process using equally-weighted minimum distance techniques. Table A-4 reports the estimation results for the deterministic and stochastic components of frailty.

E.2 Survival Probabilities

Table A-5 reports the estimation results for the logistic regression of a survival indicator for household heads.

	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_f	0.93
$\sigma^2_{\varepsilon^f}$	0.02
$\sigma^2_{\eta^f}$	0.06
$\sigma^2_{\pi_0^f}$	0.36

Table A-4: Estimation results for non-zero frailty process. Deterministic component (left) and parameters of the stochastic components (right.) The dependent variable for the deterministic component is log non-zero frailty. The parameters of the stochastic component are estimated by equally-weighted minimum distance. PSID waves 2005-2019.

	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-5: 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, earnings net of the deterministic function $\kappa(t, h)$. Then, the identification conditions I use are:

$$\begin{aligned}
\text{var}(\tilde{y}_{i,25}) &= \sigma^2_{\pi^y_0} + \sigma^2_{\varepsilon^y} \\
\text{var}(\tilde{y}_{it}) &= \frac{\sigma^2_{\eta^y}}{1-\rho^2_y} + \sigma^2_{\varepsilon^y} \\
\text{cov}(\tilde{y}_{it}, \tilde{y}_{i,t-1}) &= \rho_y^{(j-k)} \frac{\sigma^2_{\eta^y}}{1-\rho^2_y}, \quad \text{for } j > k, \quad j, k = 1, \dots, 8
\end{aligned}$$

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 frailty 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 earnings process using equally-weighted minimum distance techniques. Table A-6 presents the estimation results for the deterministic and stochastic components of log earnings.

E.4 Out-of-pocket medical expenses

Table A-7 reports the estimation results for the process for medical expenses. The variance of the i.i.d. shock to medical expenses is $\sigma^2_\xi = 0.039$

	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
$\sigma^2_{\pi^y_0}$	0.79

Table A-6: 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.

	Log medical expenses	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-7: Estimation results for medical expenses. 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.

F Estimation of Pass-Through Coefficients

Detrending I estimate pass-through coefficients for frailty and earnings by calculating the moments described in Section 5.2 for detrended (i.e., net of deterministic components) 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-4 presents the estimation results. Similarly, I detrend log earnings when I estimate their deterministic component. The estimation results are in Table A-6. Finally, I detrend log consumption by regressing it on the head's education level, family size, cohort effects, and a second-order polynomial in age. Table A-8 reports the results of this regression. I estimate pass-through coefficients using the residuals from these regressions.

	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-8: Estimation results for consumption detrending. PSID waves 2005-2019.

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

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

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}^{f} denotes the pass-through coefficient for transitory frailty 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:

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

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-9 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 frailty 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^f_ε	-0.087*
	0.08		0.05
N	11419	N	13692

Table A-9: Pass-through coefficients for transitory shocks in PSID sample.

G Details on the Identification of δ

In this section, I formalize the intuition for the identification of the effect of bad health on preferences. I follow Blundell, Borella, Commault, and De Nardi (2022), who use a similar argument but a different methodology.

The policy function for consumption is informative about the total effects of frailty shocks on consumption but is silent about the channels at play. In particular, the consumption policy function for workers in my model is:

$$c_t = c_t(a_t, \xi_t, \pi^y_t, \varepsilon^y_t, \pi^f_t, \varepsilon^f_t), \tag{A1}$$

To analyze the channels at play, start with the Euler equation:

$$u_c(c_t, f_t) \geq s_{f,t} R \mathbb{E}[u_c(c_{t+1}, f_{t+1})], \tag{A2}$$

where $u(c_t, f_t) = (1 + \delta f_t)\frac{c_t^{1-\gamma}}{1-\gamma}$, $u_c(\cdot)$ denotes the derivative of $u(c_t, f_t)$ with respect to its first argument, and $R = \beta(1 + r)$. Then, using Equation (A1), the intertemporal budget constraint, and the laws of motion for π^y_t and π^f_t, rewrite the Euler equation as:

$$
\begin{aligned}
&u_c(c_t, f_t) \geq \\
&s_{f,t} R \\
&\mathbb{E}[u_c(c_{t+1}(a_t + y^n(ra_t + y_t(f), \tau) + b_t - m_t(f) - c_t, \xi_{t+1}, \\
&\rho_y \pi_t^y + \eta_{t+1}^y, \varepsilon_{t+1}^y, \rho_f \pi_t^f + \eta_{t+1}^f, \varepsilon_{t+1}^f), \rho_f \pi_t^f + \eta_{t+1}^f + \varepsilon_{t+1}^f)]
\end{aligned}
\tag{A3}
$$

Equation (A3) relates current consumption c_t to the current state variables. It highlights the following channels at play:

1. Current frailty affects the marginal utility of current consumption–in purple,
2. Current frailty affects the survival probability–in green,
3. Assets, earnings, medical expenses, and government transfers affect the available resources after choosing current consumption. Available resources affect the next period's consumption and thus the value of current consumption that equalizes current and expected marginal utility–in blue,
4. The current persistent components of earnings and frailty affect the value of earnings and frailty in the next period and thus consumption in the next period–in orange

This optimality condition implicitly defines consumption as a function of these four channels. Thus, write log consumption as:

$$
\begin{aligned}
\log(c_t) = f(&\underbrace{f_t}_{MU_c \text{ channel}}, \underbrace{f_t}_{\text{Survival channel}}, \\
&\underbrace{a_t + y^n(ra_t + y_t(f), \tau) + b_t - m_t(f)}_{\text{Resource channel}}, \underbrace{\pi_t^y, \pi_t^f}_{\text{Future distributions channel}}),
\end{aligned}
\tag{A4}
$$

Using Equation (A4), I analyze the consumption response to a transitory frailty shock. Because a transitory frailty shock does not affect the future distribution of frailty, it affects consumption only through the first three channels. Then, because people fully recover from a transitory shock within two years, I abstract from the effect of a transitory frailty shock on survival probabilities.[15] Thus, a transitory frailty shock affects consumption only through the marginal utility and resource channels.

The effect of a change in resources on consumption is the same regardless of whether the change is due to frailty or an earnings shock. As Blundell, Borella, Commault, and De Nardi (2022) notice, the effect on consumption (holding constant the ability to derive marginal utility from it) is the same whether people have to pay \$1,000 medical bill or earn \$1,000 less. Therefore, the effect of a change in resources is captured by the consumption response to a transitory earnings shock, which I measure with the pass-through coefficient ϕ_{ε}^{y}. This effect and the impact of a transitory frailty shock on medical expenses (which is known because I estimate medical expenses from the PSID and feed them into the model) give the hypothetical consumption response to a transitory frailty shock that would occur if only the resource channel were at play. Then, the effect of frailty on the marginal utility of consumption is identified residually from the overall pass-through coefficient to a transitory frailty shock and the one that would occur if only the resource channel were at play.

H Computational Details

Solution. The problem I describe in Section 3.7 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 expenses, the persistent and transitory components of frailty, and the persistent and transitory components of earnings. During the retirement years (ages 63 to 89,) the household's state variables

[15] Although the effect of transitory frailty shocks on survival is small, it may still cause fluctuations in consumption. I abstract from this for simplicity, but this effect is well-disciplined by the model.

include age, assets, the shock to medical expenses, and the persistent and transitory components of frailty. 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 frailty and earnings and the shock to medical expenses using Markov chains. In particular, I discretize and approximate the AR(1) processes for π^y and π^f and the normally distributed shocks ξ, ε^y, and ε^f using grids with 5 points each.[16] 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 50,000 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 expenses using their laws of motion. Finally, based on the realizations 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.

I Pass-through Coefficients of Persistent Shocks

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

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

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

Following Kaplan and Violante (2010), I identify these pass-through coefficients using the following covariance restrictions:[17]

$$\begin{aligned}
\operatorname{cov}(\Delta \log c, \eta_t^y) &= \frac{1}{\rho_y}\operatorname{cov}(\Delta \log c, \rho_y^2 \tilde{\Delta} \log y_{t-1} + \rho_y \tilde{\Delta} \log y_t + \tilde{\Delta} \log y_{t+1}),\\
\operatorname{var}(\eta^y) &= \frac{1}{\rho_y}\operatorname{cov}(\tilde{\Delta} \log y_t, \rho_y^2 \tilde{\Delta} \log y_{t-1} + \rho_y \tilde{\Delta} \log y_t + \tilde{\Delta} \log y_{t+1}),\\
\operatorname{cov}(\Delta \log c, \eta_f^h) &= \frac{1}{\rho_f}\operatorname{cov}(\Delta \log c, \rho_f^2 \tilde{\Delta} \log f_{t-1} + \rho_f \tilde{\Delta} \log f_t + \tilde{\Delta} \log f_{t+1}),\\
\operatorname{var}(\eta^f) &= \frac{1}{\rho_f}\operatorname{cov}(\tilde{\Delta} \log f_t, \rho_f^2 \tilde{\Delta} \log f_{t-1} + \rho_f \tilde{\Delta} \log f_t + \tilde{\Delta} \log f_{t+1}),
\end{aligned}$$

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

Estimating the pass-through coefficients of persistent shocks is similar to what I describe for transitory shocks in Appendix F. 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 and the following estimating restrictions:

$$\begin{aligned}
&\mathbb{E}[\Delta \log c \cdot (\rho_y^2 \tilde{\Delta} \log y_{t-1} + \rho_y \tilde{\Delta} \log y_t + \tilde{\Delta} \log y_{t+1}) - \phi_\eta^y \tilde{\Delta} \log y_t \cdot (\rho_y^2 \tilde{\Delta} \log y_{t-1} + \rho_y \tilde{\Delta} \log y_t + \tilde{\Delta} \log y_{t+1})] = 0,\\
&\mathbb{E}[\Delta \log c \cdot (\rho_f^2 \tilde{\Delta} \log f_{t-1} + \rho_f \tilde{\Delta} \log f_t + \tilde{\Delta} \log f_{t+1}) - \phi_\eta^f \tilde{\Delta} \log f_t \cdot (\rho_f^2 \tilde{\Delta} \log f_{t-1} + \rho_f \tilde{\Delta} \log f_t + \tilde{\Delta} \log f_{t+1})] = 0,
\end{aligned}$$

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