Health-Dependent Preferences, Consumption, and Insurance

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Abstract

I study the effect of bad health on preferences and the implications of this effect on self and government insurance. To do so, I build a life-cycle model in which bad health affects survival, earnings, medical expenditures, and the marginal utility of non-medical consumption. I then calibrate the model using data from the Panel Study of Income Dynamics in the United States. I find that bad health reduces the marginal utility of non-medical consumption. To shed light on the implications of health-dependent preferences on self-insurance, I examine the differences in life-cycle consumption and savings when bad health does and does not influence marginal utility. My results suggest that health-dependent preferences lower savings over the whole life cycle and decrease consumption in old age. I also show that a model without health-dependent preferences does not replicate the degree of self-insurance against bad health shocks observed in the data. Finally, I study the welfare effects of reforming means-tested government insurance in the United States. I find that health-dependent preferences reduce the household valuation of government insurance programs.

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1 Introduction

A person's health affects many outcomes in their life. For example, bad health influences how long they will live and how much they can work. Moreover, bad health may also affect how much people enjoy consumption. Thus, consuming when sick may be more or less enjoyable–i.e., give a higher or lower utility–than when healthy. The available results in the literature are ambiguous about the magnitude and direction of this effect. Moreover, there is little evidence on how this effect affects household consumption and saving behavior. I seek to fill this gap.

My goal is to understand how bad health affects preferences and to study the consequences of this effect on self and government insurance. Standard optimality conditions predict that households keep the marginal utility of consumption constant across states of the world. If bad health does not affect preferences–and if there are no further preference shocks–smoothing marginal utility leads to smoothing consumption. In turn, when preferences depend on bad health, this equality fails. In particular, it may be the case that optimal consumption when sick is different than optimal consumption when healthy. Therefore, the relationship between bad health and preferences has significant implications for insurance. If optimal consumption is lower when ill, people do not need to save as much as if they had to smooth consumption across health states. Moreover, health-dependent preferences may affect the value people place on government-provided insurance programs.[1]

To shed light on the effect of bad health on preferences and quantify its consequences for insurance, I build and calibrate a life-cycle model of consumption and savings. In my model, bad health affects survival, labor earnings, out-of-pocket medical expenditures, and the marginal utility of non-medical consumption.[2] Households

[1] Brown and Finkelstein (2009) notice that health-dependent preferences may affect the optimal demand for Long Term Care insurance. Though interesting, I abstract from private insurance.

[2] I follow standard practice in the literature–see, for example, Finkelstein, Luttmer, and Notowidigdo (2013) and Gyrd-Hansen (2017)–and allow bad health to affect only the preferences for non-medical consumption. Medical consumption enters my model as out-of-pocket medical expenditures.

face uncertainty about their earnings, health, medical expenses, and longevity. They can counteract this uncertainty with their savings and government insurance. In particular, the government provides means-tested transfers that bridge the gap between households' available resources and a minimum consumption level (known as a consumption floor.) After stochastic shocks are realized, households choose how much to consume and save.

Using the Panel Study of Income Dynamics (PSID) and a novel health measure, I show that health risk is present at all ages. I measure bad health using the frailty index, following Nygaard (2021) and Hosseini, Kopecky, and Zhao (2022). The frailty index combines information from a wide array of health indicators–such as diseases, difficulties with Activities of Daily Living (ADL), and habits–into a unitary measure. In particular, frailty is the sum of all the adverse health events a person has incurred, and a larger value of frailty denotes poorer health. In my PSID sample, I show that almost 80 percent of 25-year-olds already have positive frailty, so some degree of unhealthiness.

After carefully describing the dynamics of frailty, I 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 labor earnings and health process. Second, I calibrate the effect of bad health on marginal utility and the consumption floor by matching the consumption response to transitory bad health and earnings shocks. My model excellently matches its targets and generates results consistent with previous literature. Moreover, my model fits the life-cycle profile of consumption fairly well, despite not being required to match it.

My calibration results suggest that poor health reduces the marginal utility of consumption. This results is consistent with, among others, De Nardi, French, and Jones (2010) and Finkelstein, Luttmer, and Notowidigdo (2013). I also find a value of the consumption floor which is well within the established bounds in the literature.

Using my calibrated model, I analyze the effects of health-dependent preferences on self-insurance. Most studies of the patterns and determinants of savings have ignored the effect of bad health on preferences. I show that they significantly affect optimal consumption and savings over the life cycle. In particular, I compare the predictions of my baseline model with those of a model in which bad health does not affect the marginal utility of consumption. Because health worsens over the life cycle, consumption is lower with health-dependent preferences at older ages. I also find that savings are always lower when bad health affects marginal utility. I then show that a model without health-dependent preferences cannot match the degree of self-insurance against bad health shocks observed in the data as well as my baseline model.

After evaluating the effects of health-dependent preferences on self-insurance, I analyze their impact on the household valuation of government insurance. Having an accurate measure of the welfare effects of changing government insurance is crucial when designing policy reforms. I compute the welfare effects of reforming means-tested government insurance programs–such as Medicaid and Supplemental Security Income–which are captured by the consumption floor in my model. I compare the results between my baseline calibration and one in which bad health does not affect marginal utility. I show that health-dependent preferences reduce the household valuation of government insurance. I also find that government insurance is more valuable for poorer and sicker households.

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

2 Relationship to the literature and contributions

My paper relates to three strands of the literature and contributes to each. First, my paper relates to the literature on **health-dependent preferences**. There is no consensus on the magnitude and direction of the effect of bad health on preferences. Two approaches have emerged in this literature. On the one hand, some papers take an empirical approach. Among these, Evans and Viscusi (1991) finds no evidence of an effect of bad 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. On the other hand, some papers take a structural-life-cycle-model approach. These papers model the effect of bad 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) find evidence of a negative effect, so marginal utility decreases as health worsens.[3] I contribute to this literature by providing a new way to identify the effect of bad health on preferences. I also provide the first quantitative assessment of the consequences of health-dependent preferences on self and government insurance.[4]

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

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

[4] Finkelstein, Luttmer, and Notowidigdo (2013) use 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.

(2022). Numerous studies in this literature–including Blundell, Pistaferri, and Preston (2008)–focus only on income risk over the working age. 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 considers 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), 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 bad health on preferences and its consequences on welfare.

3 Model

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

3.1 Environment

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

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

Following Nygaard (2021) and Hosseini, Kopecky, and Zhao (2022), I measure bad health using the frailty index, which captures the accumulated sum of all adverse health events a household has incurred.[5]

3.2 Health-Dependent Preferences

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

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

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

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

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

3.3 Frailty

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

I assume that if frailty is zero in period t, there is a transition probability that captures how likely frailty is to remain at zero in period $t+1$ or to increase to a

[5]Section 4.1 provides more details on frailty.

positive value. I also assume that if frailty is positive in period t, it cannot go back to zero in period $t+1$.[6] When frailty is positive, I follow Hosseini, Kopecky, and Zhao (2022) and assume 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. Following Hosseini, Kopecky, and Zhao (2022), I assume that, when $f_t = 0$, $\pi_t^f = 0$ as well.

3.4 Working Age Earnings

Households face earnings risk during their working age. Labor earnings depend on age, frailty, and a persistent and transitory component. I assume that log earnings evolve according to the following process:

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

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

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

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

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

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

where $\kappa_t(f)$ denotes a deterministic function of age and frailty, π_t^y is a persistent component, and ε_t^y is a transitory component.

3.5 Medical Expenditures and Death

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

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

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

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

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

3.6 Government

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

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

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

where y denotes the level of total income, λ captures the average level of taxation in the economy, and τ denotes the degree of progressivity of the income tax system.[7]

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

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

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

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

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

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.

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

3.7 Timing

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

3.8 Recursive Formulation

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

3.8.1 The Value Function for Workers

The vector of state variables X_t for workers is composed of: age t, assets a_t, the shock to medical expenditures ξ_t, the persistent component of earnings π_t^y, the transitory component of earnings ε_t^y, the persistent component of frailty π_t^f, and the transitory component of frailty 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:

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

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

3.8.2 The Value Function for Retirees

The vector of state variables X_t for retirees comprises: age t, assets a_t, the shock to medical expenditures ξ_t, Social Security benefits ss_t, the persistent component of frailty π_t^f, and the transitory component of frailty 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

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

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

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

4 Data

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

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

4.1 Measuring Bad Health

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

The frailty index is an objective measure of bad health. It has been used extensively in the medical and gerontology literature, which has shown it to be an excellent predictor of health and mortality.[8] Hosseini, Kopecky, and Zhao (2022) and Nygaard (2021) pioneered its use in economics and have demonstrated it to be an excellent

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

predictor of medical expenditures and the probability of becoming a disability insurance recipient. To construct the frailty index for the households in my sample, I follow the guidelines in Searle, Mitnitski, Gahbauer, Gill, and Rockwood (2008). In particular, I 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 deficits to construct the frailty index. Each deficit can take a value of either zero or one, based on whether the individual currently has a specific deficit or not. Table A-2 in Appendix C reports the complete list of deficits I use.[9]

I construct a household's frailty as the average frailty index of each member. Table 1 summarizes the distribution of the household frailty index in my sample. The household frailty index has a mean of 0.09 and a median of 0.07.[10] Figure 1 shows the distribution of household frailty by age. This figure shows that median - as well as the 25th and 75th percentiles - frailty increases with age. It also shows that the variance of frailty increases with age and is particularly high after age 75.

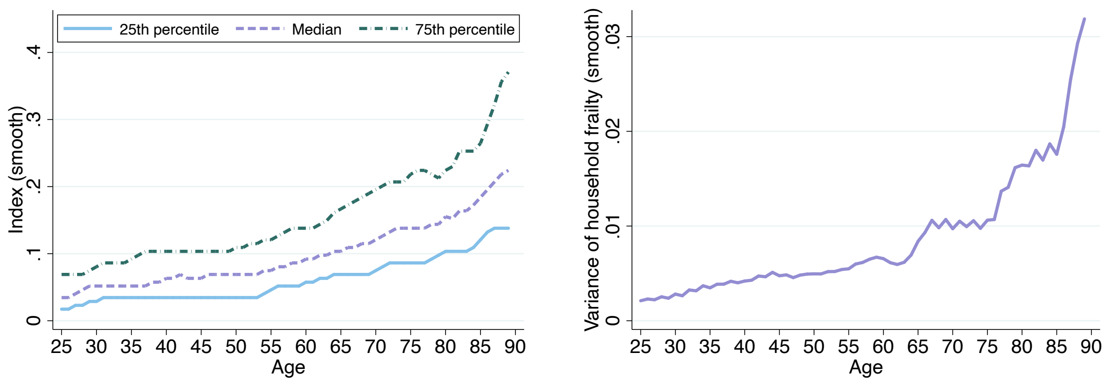
Figure 2 shows that health risk is present at all ages. In particular, it shows that almost 80 percent of 25-year-old households have positive frailty and that this share

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

[10]These results are in line with Hosseini, Kopecky, and Zhao (2022), who construct a frailty index using 28 deficits from the PSID (they use the same deficits I use, but do not include excessive alcohol consumption). They use a sample of household heads and spouses aged 25 and older and report a mean of 0.11 and a median of 0.07.

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

Table 1: Distribution of household frailty index. Statistics computed for PSID households with heads aged between 25 and 89 interviewed between 2005 and 2019 wave.



(a) Percentiles by age

(b) Variance by age

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

increases rapidly with age. To understand why frailty is so prevalent, even at younger ages, Table A-3 in Appendix C 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 ones for older people.

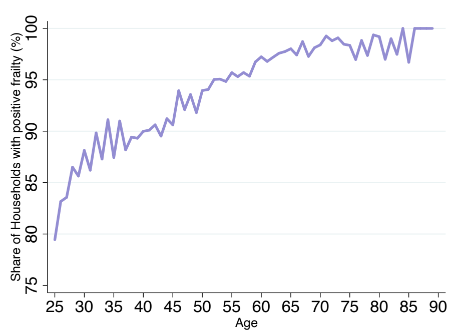


Figure 2: Share of households with positive frailty by age. PSID, 2005-2019.

5 Calibration

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

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

5.1 First-Step

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

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

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

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

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

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

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

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

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

I then define a persistent-transitory process for log non-zero frailty. I estimate the deterministic component of the process in Equation (3.3) by regressing log-frailty on family size, the head's education level, cohort effects, and a second-order polynomial in age. Then, I use the residuals from the regression for the deterministic component to estimate the parameters of the persistent and transitory components. I need to estimate the autoregressive coefficient, ρ_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 first persistent component, $\sigma^2_{\pi^f_0}$. I identify them using the variances and covariances of the residuals and estimate them using equally-weighted minimum distance. See Appendix E.1 for the identification restrictions and estimation details. Table A-5 in Appendix E.1 reports the estimation results. The results show that frailty is increasing in age and persistent, confirming the findings of Hosseini, Kopecky, and Zhao (2022).

Survival Probabilities I estimate age-and-frailty-specific two-year survival probabilities. 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-6 in Appendix E.2 reports the estimation results. Age and frailty harm the probability of surviving to the next period.

I then compute the average survival probabilities by age and confirm the finding of French (2005) that the PSID overestimates survival probabilities. Therefore, I calculate an adjustment factor as the ratio of the estimated average survival probabilities and those reported by the Social Security Administration life tables for 2019.[11] I then correct my estimates by multiplying the estimated survival probabilities by the adjustment factor.

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

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

Out-Of-Pocket Medical Expenditures I estimate the deterministic function $g(t, f)$ in Equation (3.13) by regressing the logarithm of medical expenditures on

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

frailty, family size, head's education, cohort effects, and a second-order polynomial in household age.[12] Column (1) in Table A-8 in Appendix E.4 displays the estimation results for this regression. These results show that medical expenditures increase with age, frailty, family size, and education.

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

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

5.2 Second-Step

I calibrate the consumption floor and the effect of 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, illustrates my identification strategy, and presents the results for my calibrated parameters.

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

Measuring Self-Insurance. I follow a long-standing tradition in the consumption insurance literature and measure self-insurance with pass-through coefficients.[13] As described in the seminal contribution of Blundell, Pistaferri, and Preston (2008), the pass-through coefficient of an idiosyncratic shock x_{it} is the ratio of the covariance between log-consumption growth and the shock and the variance of the shock. Formally:

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

An interpretation popularized by Kaplan and Violante (2010) is that 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 need to use moments on observable consumption, earnings, and frailty to estimate the pass-through coefficients. In particular, I need to find functions g_t^x:

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

[13] 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)

Where v denotes either earnings or frailty and $\boldsymbol{v}_i$ denotes the vector of earnings or frailty realizations for household i. I apply a similar strategy to Kaplan and Violante (2010) to construct the g_t^x functions and identify the pass-through coefficients of transitory earnings and frailty shocks.[14] First, I define the quasi difference of log earnings as $\tilde{\Delta} \log y_{it} = \log y_{it} - \rho_y \log y_{it-1}$ and the quasi difference of log frailty as $\tilde{\Delta} \log f_{it} = \log f_{it} - \rho_f \log f_{it-1}$. Notice I have estimated ρ_y and ρ_f in Section 5.1. Second, I set:

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

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

Using the processes for earnings and frailty and assuming that shocks are mutually uncorrelated, one can show that

$$\begin{aligned}
\text{cov}(\Delta \log c_{it}, \tilde{\Delta} \log y_{i,t+1}) &= -\rho_y \text{cov}(\Delta \log c_{it}, \varepsilon_{it}^y), \\
\text{cov}(\Delta \log y_{it}, \tilde{\Delta} \log y_{i,t+1}) &= -\rho_y \text{var}(\varepsilon_{it}^y), \\
\text{cov}(\Delta \log c_{it}, \tilde{\Delta} \log f_{i,t+1}) &= -\rho_f \text{cov}(\Delta \log f_{it}, \varepsilon_{it}^f), \\
\text{cov}(\Delta \log f_{it}, \tilde{\Delta} \log f_{i,t+1}) &= -\rho_f \text{var}(\varepsilon_{it}^f),
\end{aligned}$$

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

$$\phi_{\varepsilon}^y = \frac{\text{cov}(\Delta \log c_{it}, \varepsilon_{it}^y)}{\text{var}(\varepsilon_{it}^y)} = \frac{\text{cov}(\Delta \log c_{it}, \tilde{\Delta} \log y_{i,t+1})}{\text{cov}(\Delta \log y_{it}, \tilde{\Delta} \log y_{i,t+1})}, \tag{5.6}$$

$$\phi_{\varepsilon}^f = \frac{\text{cov}(\Delta \log c_{it}, \varepsilon_{it}^f)}{\text{var}(\varepsilon_{it}^f)} = \frac{\text{cov}(\Delta \log c_{it}, \tilde{\Delta} \log f_{i,t+1})}{\text{cov}(\Delta \log f_{it}, \tilde{\Delta} \log f_{i,t+1})}, \tag{5.7}$$

I estimate the pass-through coefficients of transitory shocks using Equation (5.6) and Equation (5.7). Appendix F provides details on the estimation procedure.

[14] Appendix I describes the details for the pass-through coefficients of persistent shocks.

I focus on the pass-through coefficients of transitory shocks for identification because they are less susceptible to misspecification issues, and their identification does not require stringent assumptions. In particular, as noted in Commault (2022) and Blundell, Borella, Commault, and De Nardi (2022), the identification of the pass-through coefficients of 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 turn, identifying the pass-through coefficients of persistent shocks requires much more stringent assumptions on consumption. In particular, the identification strategy from Blundell, Pistaferri, and Preston (2008) requires assuming that log consumption evolves as a random walk. Commault (2022) shows that the random walk assumption is violated in survey data. Moreover, Carroll (1997) and Commault (2022) show analytically that the assumption is violated in a life-cycle model with precautionary savings like mine.

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

I identify the consumption floor, $\underline{c}$, by matching the consumption response–measured by the pass-through coefficient–to a transitory earnings shock. The intuition is that if the consumption floor is high, more households will consume at the floor level, and there will be fewer consumption fluctuations. Thus, the pass-through coefficient to a transitory earnings shock will be small. On the other hand, if the consumption floor is low, fewer households will consume at the floor level, and there will be more consumption fluctuations. Therefore, the pass-through coefficient to a transitory earnings shock would be large.

Then, I identify the effect of frailty on preferences, δ, by matching the pass-through coefficient to a transitory frailty shock. A transitory frailty shock affects non-medical consumption because it affects available resources (the resource channel) and the marginal utility of consumption (the marginal utility channel).[15] The effect of a resource change on consumption is the same, regardless of whether the change is due to an earnings or frailty shock. Therefore, this effect is captured by the pass-through coefficient to a transitory earnings shock, ϕ_{ε}^{y}. The impact of a change in resources, together with the response of medical expenditures to a transitory frailty shock (known because I estimate medical expenditures from the PSID and feed them into the model), identifies the pass-through coefficient that would occur if only the resource channel were at play. Then, the marginal utility channel is identified residually from the pass-through to a transitory frailty shock and the one that would occur if only the resource channel were at play.

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

The calibration procedure is as follows. First, given an initial guess for the two parameters to be estimated, I solve the life-cycle model and obtain optimal decision rules for consumption and savings. Second, I use the optimal decision rules to simulate the life-cycle choices of households. Third, I compute the pass-through coefficients for transitory earnings and health shocks using the simulated data. Fourth, I compute 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 yields the minimum distance between the model and the data. Appendix H provides more details on the model solution and simulation.

[15] A transitory frailty shock also affects the survival probability. I abstract from this in this discussion for simplicity and because the effect is small since households fully recover from a transitory frailty shock within two years. Appendix G provides more details and shows the identification argument using the structure of the model.

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

Moment	Data	Model	Parameter	Value
ϕ_ε^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 2: Targeted moments, model fit, and parameter values

The first row of Table 2 shows that an increase in earnings leads to a rise in consumption. In particular, in my PSID sample, the pass-through coefficient of a transitory earnings shock is 0.175. Therefore, a 10 percent increase in earnings due to a transitory shock leads to a rise in consumption of 1.75 percent. This finding is in line with the results of Blundell, Pistaferri, and Preston (2008) and Blundell, Borella, Commault, and De Nardi (2022), which also show that an increase in income caused by a transitory shock leads to a rise in consumption. My model successfully matches the pass-through of a transitory earning shock, which predicts a consumption floor of \$3,561. The calibrated consumption floor is well within the standard range in the literature of \$3,000-\$7,000.[16]

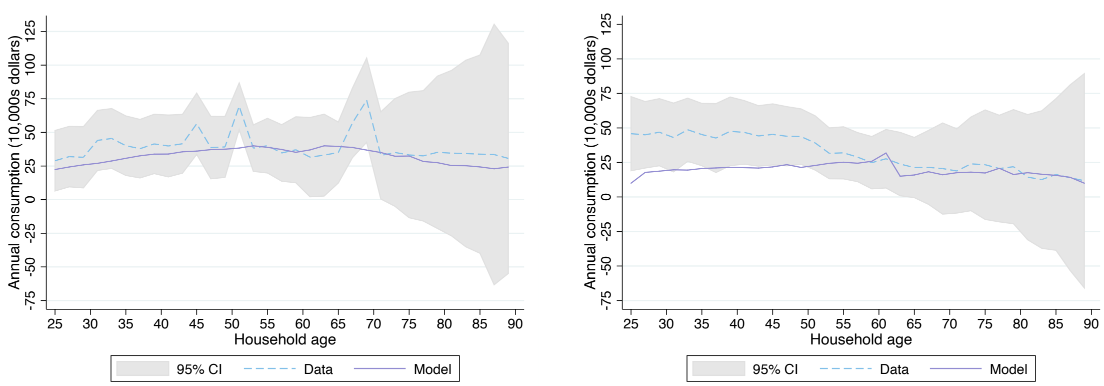
The second row of Table 2 shows that higher frailty–so worse health–leads to a consumption drop. In particular, in my PSID sample, a 10 percent increase in frailty due to a transitory shock leads to a 0.9 percent decrease in consumption. This result is consistent with Blundell, Borella, Commault, and De Nardi (2022), which shows that an adverse health shock causes a decrease in consumption. My model excellently replicates the pass-through of transitory frailty shocks and implies a calibrated value of δ of -0.74. The negative value of δ suggests an adverse effect

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

of bad health on preferences. In particular, it indicates that the marginal utility of non-medical consumption decreases as health worsens. This finding is in line with the results of, among others, De Nardi, French, and Jones (2010), Finkelstein, Luttmer, and Notowidigdo (2013), and Koijen, Van Nieuwerburgh, and Yogo (2016).

Untargeted Moments. To validate my model, I compare its implied life-cycle consumption profile with the one estimated from the PSID. In particular, I compute household consumption profiles in the bottom and top 5 percent of the frailty distribution by age.

To compute consumption profiles from the PSID, I follow French (2005). I first divide households into percentiles of frailty by age. Then, I select those in the bottom and top 5 percentiles and regress annual household consumption on family size, education level, and cohort and age dummies. I then fix family size, education level, and cohort to the same values I use to solve the model and compute the predicted values from the regression and a 95 percent confidence interval. To calculate consumption profiles from the model-simulated data, I divide biennial consumption by two and then regress it on age dummies.



(a) Bottom 5% of frailty distribution

(b) Top 5% of frailty distribution

Figure 3: Life cycle profile of annual consumption. Panel (a) reports the profile for households in the bottom 5% of the frailty distribution in the model and in the data. Panel (b) reports the analogous figure for households in the top 5% of the frailty distribution.

Panel (a) of Figure 3 shows the life-cycle profile of annual consumption for relatively healthy households.[17] These households are in the bottom 5 percent of the frailty distribution by age. My model does an excellent job of matching annual consumption from the PSID. 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 (b) of Figure 3 shows the life-cycle profile of annual consumption for relatively unhealthy households. These households are in the top 5 percent of the frailty distribution by age. My model matches annual consumption after age 60 remarkably well. However, despite the model-predicted profile being at the border of the 95 percent confidence interval, the model underpredicts annual consumption at younger ages.

Then, I compare the pass-through coefficients against persistent earnings and frailty shocks in the model and the data.[18] As argued in Section 5.2, identifying the pass-through coefficients requires stringent assumptions on consumption, which are violated in the data and the model. 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 3 shows that my model generates qualitative results similar to what is observed in the data. In particular, a persistent positive earnings shock increases consumption in the data and the model, while a persistent frailty shock reduces it. Turning to the quantitative results, the first row of Table 3 shows that my model overestimates the consumption response to a persistent earnings shock. The second row of Table 3 shows that my model generates a pass-through coefficient of persistent frailty shocks that lies just outside one standard deviation from the point estimate from the data. The bias in the model-generated pass-through coefficient to persistent shocks could

[17]The 95% confidence interval expands at older ages as a consequence of the small number of observations for older people in the PSID.

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

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.

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

6 Health-Dependent Preferences and Self-Insurance

In this section, I use my calibrated model to assess the quantitative effects of health-dependent preferences on self-insurance. Because bad health affects the marginal utility of consumption, it will affect the optimal choice of consumption and savings. Therefore, it will affect households' ability to self-insure against bad health shocks.

The literature studying savings over the life cycle has largely ignored the effect of health-dependent preferences. 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. Moreover, except for Blundell, Borella, Commault, and De Nardi (2022), no paper has considered the effect of health-dependent preferences on the consumption response to bad health shocks.

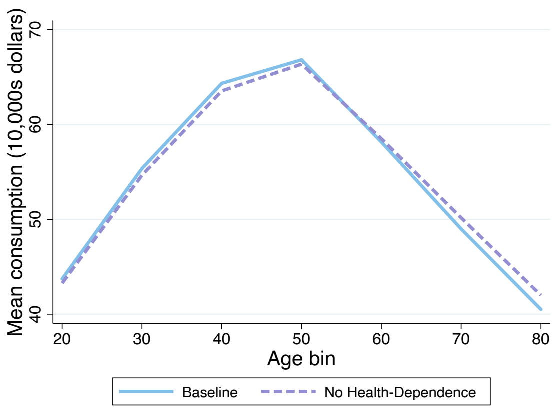
I fill these gaps in the literature by quantifying the effects of health-dependent preferences on consumption, savings, and the consumption response to bad health shocks. To do so, I solve the model using the baseline calibration and setting $\delta = 0$, thereby removing the relationship between bad health and marginal utility. I then simulate the life cycle of 50,000 households and compare their consumption, savings, and pass-through coefficients to transitory and persistent frailty shocks.

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

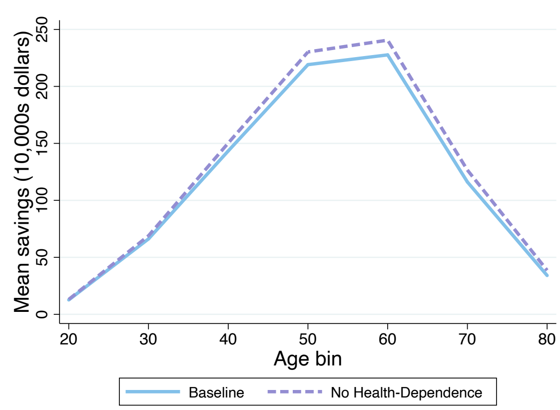
The observed consumption and savings patterns are consistent with the deterioration of health over the life cycle. Households are more unhealthy at older ages; therefore, their marginal utility of non-medical consumption is much higher when $\delta = 0$ than in the baseline case. Consequently, their optimal consumption is higher than in the baseline case because consumption is more "enjoyable." To sustain higher consumption at older ages, households must save more and give up consumption when young.[19]

Figure 5 shows that the patterns described above apply across the consumption and savings distributions. In particular, Figure 5 displays the 25th, 50th, and 75th percentiles of consumption and savings by 10-year age bins with and without health-

[19]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.



(a) Average consumption by age

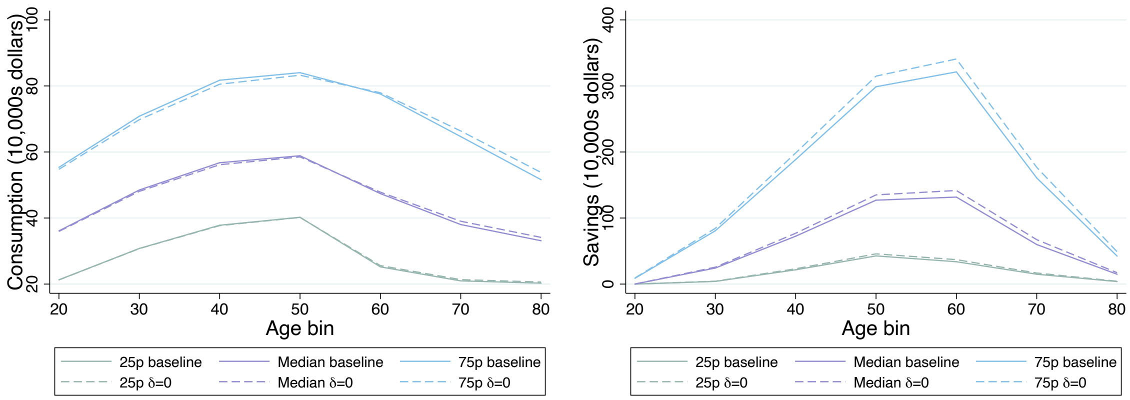


(b) Average savings by age

Figure 4: 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

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 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 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 more without health-dependent preferences if they are in the savings distribution's 25th, 50th, and 75th percentile, respectively.

Table 4 shows that a model without health-dependent preferences cannot match the consumption response to bad health shocks in the data and underestimates the response to such shocks. The first row of Table 4 shows that my baseline calibration matches the pass-through coefficient to a transitory frailty shock, ϕ^f_ε, much better than one without health-dependent preferences. In particular, the model without health-dependent preferences predicts that a 10% increase in frailty generated by a



(a) Percentiles of consumption by age

(b) Percentiles of savings by age

Figure 5: 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.

transitory shock results in a 0.7 percent decrease in consumption. This decrease is 20 percent smaller than what is observed in the data and predicted by my baseline model. The second row of Table 4 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 4: 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 $\delta = 0$.

7 Health-Dependent Preferences and Government Insurance

In this section, I analyze the welfare effects of reforming means-tested government insurance (MTGI) with and without health-dependent preferences. Obtaining an accurate measure of the value 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, so indifferent to it. I compute the compensating variation at age 25 (the initial age in my model and simulations) and define it as $\chi_{25}(a_{25}, \xi_{25}, \pi^y_{25}, \varepsilon^y_{25}, \pi^h_{25}, \varepsilon^h_{25})$ solving:

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

Where $V_{25}(\cdot)$ is the age 25 value function for a given set of state variables. As argued in McGee (2021), the compensating variation is an ex-ante measure that incorporates the mechanical and behavioral responses to a reform.

Table 5 reveals that health-dependent preferences significantly affect the household valuation of MTGI. I show 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).[20] Table 5 provides several interesting insights. First, households place a higher value on government insurance without health-dependent preferences across groups and reforms.

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

Group	Average Earnings	Average Frailty	30% reduction in $\underline{c}$ Baseline $\delta = -0.74$	30% reduction in $\underline{c}$ No HDP $\delta = 0$	50% reduction in $\underline{c}$ Baseline $\delta = -0.74$	50% reduction in $\underline{c}$ 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 5: 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, $\delta = 0$.

For instance, the first row of Table 5 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, the second and third rows of Table 5 show that government insurance is more valuable for low-earners. I compare households in the bottom and top five percent 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 percent reduction in the consumption floor is about eight times larger for households in the bottom five percent of the earnings distribution. Across the earnings distribution, the household valuation of government insurance is larger without health-dependent preferences.

Third, the fourth and fifth rows of Table 5 show that government insurance is more valuable for sicker households. I compare relatively healthy households (i.e., in the bottom five percent of the frailty distribution) with rather unhealthy ones (i.e., in the top five percent of the frailty distribution.) My results suggest 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 seven percent 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.

8 Conclusions

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

I identify the effect of bad health on preferences using the consumption response to transitory bad health shocks. I show that poor health reduces the marginal utility of non-medical consumption. My identification and calibration results help reduce the ambiguity in the literature about the size and direction of the effect of bad health on preferences.

Using my calibrated model, I perform the–to the best of my knowledge–first quantitative analysis of the effects of health-dependent preferences on self-insurance. Health-dependent preferences reduce old-age consumption and lower savings over the whole life cycle. I 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. Moreover, a model without health-dependent preferences underestimates the consumption response to bad health shocks compared to the data and my baseline model.

I also find that health-dependent preferences significantly affect the household valuation of means-tested government insurance programs such as Medicaid and Supplemental Security Income. In particular, I show that households always value these programs more when bad health does not affect preferences. Moreover, my results suggest that government insurance is more valuable for poorer and sicker households.

In this paper, I assessed the magnitude and consequences of the effect of bad health on preferences. The next step is to study the optimal design of taxes and transfers when bad health lowers the marginal utility of non-medical consumption. The normative literature has mostly ignored health-dependent preferences, but these will affect the benevolent planner's optimal allocation of consumption. Future research will focus on the normative consequences of health-dependent preferences.

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APPENDICES FOR ONLINE PUBLICATION

A Health-Dependent Preferences in the Literature

Finkelstein, Luttmer, and Notowidigdo (2009) defines the effect of bad health on preferences as the effect of bad 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 bad health on preferences and attempted to quantify its magnitude and direction, they have obtained different - sometimes opposite - results.

A.1 The empirical literature on health-dependent preferences

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

A second branch of the empirical literature on the effect of bad health on preferences focuses on reported well-being as a proxy for utility. Finkelstein, Luttmer, and Notowidigdo (2013) constructs a sample of elderly Americans and estimates the effect of bad health on preferences using changes in subjective well-being.[21] 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 use changes in material well-being to estimate the effect of bad health on preferences.[22] 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 bad health on preferences. Brown, Goda, and McGarry (2016) devises the American Life Panel (ALP) to study the differences in the value of marginal consumption in healthy and disabled states. They find limited evidence of an effect of bad 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 bad 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.

[21]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.

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

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

A few papers have used structural consumption models to estimate the effect of bad health on preferences. Lillard and Weiss (1997) develops a life-cycle model to study the impact of health and survival risk on retirees' consumption and savings decisions. Their results point to a positive effect of 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 65 and a positive one at older ages.

Numerous papers embed the effect of bad health on preferences in their structural models to answer various questions. A few papers consider this effect but do not estimate it. Low and Pistaferri (2015) 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 bad health affects preferences. They assume a negative effect of health on preferences so that consumption and good health are complements. 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 bad health to affect preferences and assume a negative effect on the marginal utility of consumption.

Another set of papers embeds the effect of bad 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 expenditures 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. This feature of the survey allowed it to remain nationally representative over time.

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

Moreover, in 2003, the PSID expanded its health-related questions and started recording information on specific medical conditions, ADLs, and IADLs.

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

B.2 Sample Selection

Table A-1 describes my sample selection. I use every biennial wave of the PSID between 2005 and 2019 and obtain an initial sample of 247,871 individual-wave observations. First, I focus on household heads.[23] Then, I restrict my attention to the core sample of the PSID.[24] This leaves me with 42,788 observations. I remove households that appear only once in the survey. The resulting sample consists of 41,259 observations. To be consistent with my model, I focus on households whose head is between 25 and 89 years old. Then, I drop observations missing information on frailty, labor earnings, medical expenditures, wealth, family size, and head's education. The resulting sample contains 33,992 observations. After removing observations with missing information, I remove outliers. To do so, I first drop observations with consumption or labor earnings smaller than 50 dollars (in 2018 terms.) The final sample consists of 32,038 observations.

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

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

[24]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.

(2022), I add alcohol consumption as a deficit. I follow the definition of the National Institute on Alcohol Abuse and Alcoholism[25] and assign a value of one to the excessive drinking deficit if: the respondent drinks every day or several times a week and, when they drink, they have more than four drinks for a man and more than three drinks for a woman.

Table A-3 describes the top three deficits for household heads at selected ages. This table shows that, at ages younger than 45, smoking and obesity are the leading causes of frailty in my sample. Starting at 55, high blood pressure and arthritis become the most common deficits for household heads.

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

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.

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

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

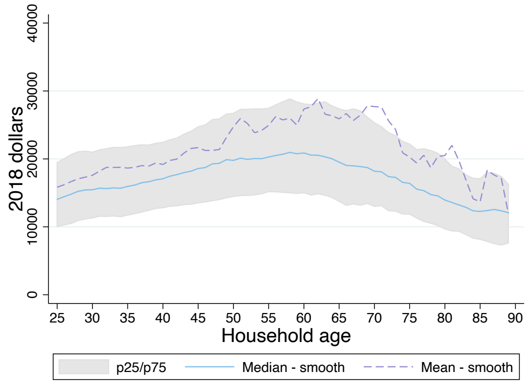
D Facts on my key variables of interest

In this section, I report facts for my key variables of interest. For ease of exposition, consumption and wealth are equivalized but not detrended.[26] 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.

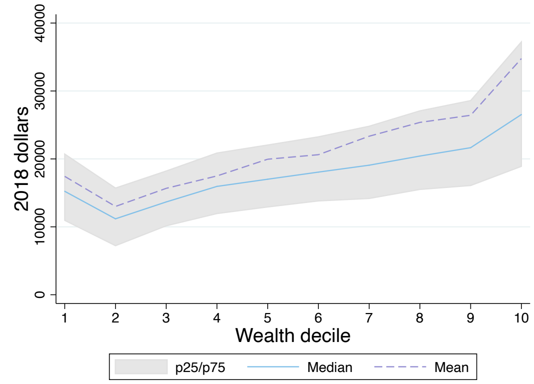
Figure A-1 displays the mean and the 25th, 50th, and 75th percentiles of equivalized consumption by age (Panel (a),) wealth decile (Panel (b),) and frailty decile (Panel (c).) Figure A-1 shows that consumption increases until 60 and declines after then, increases with wealth, and slightly decreases with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

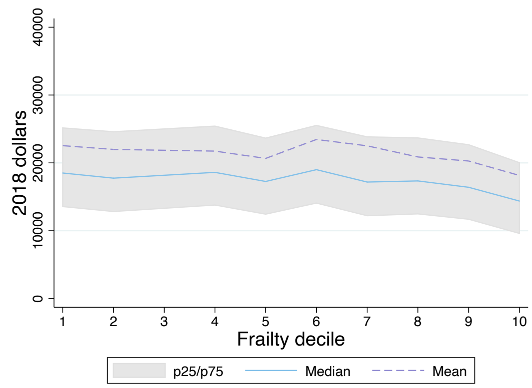
[26] I equivalize household consumption and wealth by dividing them by the square root of family size.



(a) By age

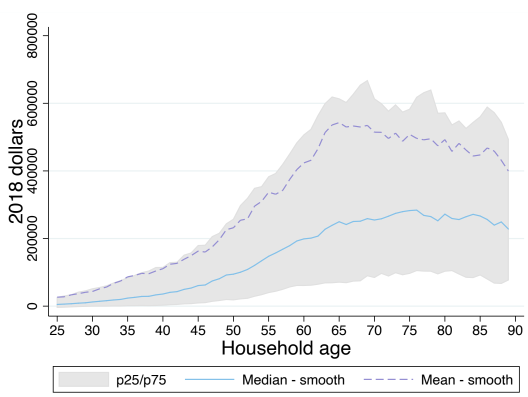


(b) By wealth decile

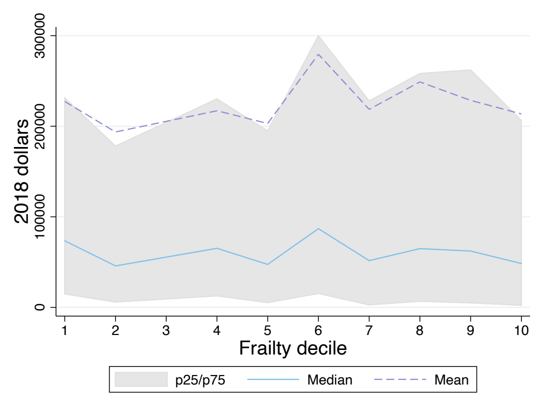


(c) By frailty decile

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



(a) By age



(b) By frailty decile

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

E First-Step Estimation

E.1 Frailty Process

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

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

Standard errors in parentheses

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

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

To identify the parameters of the stochastic process for non-zero frailty, I use the residuals from the regression for the deterministic component. Let $\tilde{f}_{it} = \log f_{it} - \kappa_{it}$.

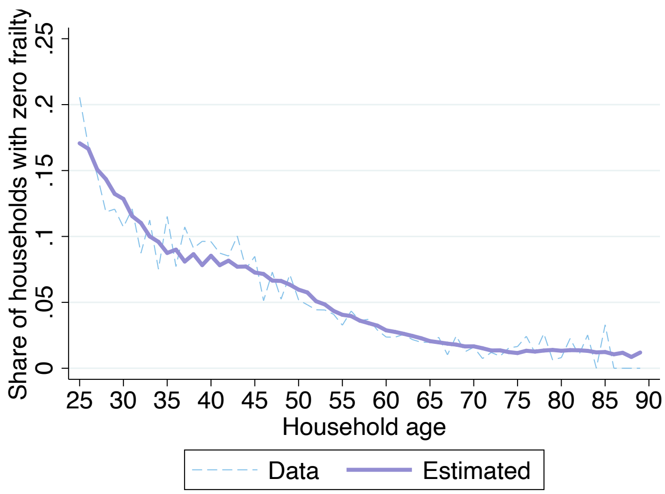


Figure A-3: Share of households with zero frailty in the data (dashed blue line) and predicted by probit regression (solid purple line.)

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-5 reports the estimation results for the deterministic and stochastic components of frailty.

E.2 Survival Probabilities

Table A-6 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-5: 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-6: Estimation results for logistic regression of survival indicator. PSID waves 2005-2019.

E.3 Earnings Process

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

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

Where j and k denote one biennial wave of the PSID between 2005 and 2019 (8 waves in total.) 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-7 presents the estimation results for the deterministic and stochastic components of log earnings.

E.4 Out-of-pocket medical expenditures

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

E.5 Fixed Parameters

Table A-9 summarizes the calibrated parameters.

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

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

Standard errors in parentheses

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

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

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

Table A-9: Calibrated Parameters.

F 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 log frailty, earnings, and consumption. As discussed in Commault (2022), the reason for using detrended values of such variables is to avoid mistaking as shocks–or as responses to shocks–the effect of demographic characteristics, such as age or family size. I detrend log-frailty when I estimate its deterministic component. Table A-5 presents the estimation results. Similarly, I detrend log earnings when I estimate their deterministic component. The estimation results are in Table A-7. Finally, I detrend log consumption by regressing it on the head's education level, family size, cohort effects, and a second-order polynomial in age. Table A-10 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-10: 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-11 reports pass-through coefficients I estimate from my PSID sample. I find a positive consumption response to a transitory earnings shock. In particular, a 10% increase in earnings caused by a transitory earnings shock results in an increase of 1.75% in consumption. I also find a negative response to a transitory 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_ε^y	0.175**	ϕ_ε^f	-0.087*
	0.08		0.05
N	11419	N	13692

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

G Identification Details

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:

$$c_t = c_t(a_t, \xi_t, \pi_t^y, \varepsilon_t^y, \pi_t^f, \varepsilon_t^f), \tag{A1}$$

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_t^y and π_t^f, 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 expenditures, 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.[27] 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^y_ε. This effect and the impact of a transitory frailty shock on medical expenditures (which is known because I estimate medical expenditures 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 3.8 has no analytical solution. Thus, I solve it numerically. I start from the final period of life (age 89) and proceed by backward iteration. I obtain policy functions for consumption and savings as functions of the household's state variables in each period. During the working years (ages 25 to 61,) the state variables are age, assets, the shock to medical expenditures, the persistent and transitory components of frailty, and the persistent and transitory

[27] 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 because I estimate survival probabilities from the PSID and feed them into the model.

components of earnings. During the retirement years (ages 63 to 89,) the household's state variables include age, assets, the shock to medical expenditures, and the persistent and transitory components of 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 expenditures 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.[28] I obtain the asset policy function by optimizing the household's objective function using Brent's method. I compute the household's expected utility by integrating the value function over the distributions of the stochastic state variables. Using the intertemporal budget constraint and the asset policy function, I obtain the consumption policy function.

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

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

[28] 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:[29]

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

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:

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

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