

Health-Dependent Preferences and the Value of Social Insurance

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Abstract

This paper studies the welfare effects of reforming social insurance programs in the United States when health affects the marginal utility of consumption. I build a life cycle model of consumption and savings in which health affects survival, earnings, and preferences. I estimate the model using data on the United States from the Panel Study of Income Dynamics and the Method of Simulated Moments. I use the estimated model to assess the welfare effects of removing or reforming social insurance programs such as Medicaid and Supplemental Security Income.

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1 Introduction

Bad health affects many aspects of people’s lives. It determines how long they will live, how much they earn, how much they can consume, and how much they enjoy consumption. While it is understood that governments should provide insurance against the change in resources caused by bad health, it is unclear what they should do in response to health-driven changes in preferences. I build and estimate a life-cycle model in which health affects survival, resources, and preferences. Using the estimated model, I analyze the welfare effects of reforming social insurance programs in the United States when health affects the marginal utility of consumption.

Numerous studies have shown an effect of health on the marginal utility of non-medical consumption, but its magnitude and direction remain ambiguous.¹ The effect of health on preferences matters for many economic choices: portfolio choices (Edwards (2010);) the purchase of life and health insurance products (Kojen, Van Nieuwerburgh, and Yogo (2016);) and the optimal level of savings (Finkelstein, Luttmer, and Notowidigdo (2013).) However, it is unclear how health-dependent preferences affect the value of government-provided social insurance programs. Suppose bad health reduces the marginal utility of consumption. In that case, it might not be optimal for governments to provide additional insurance to smooth consumption across health states because optimal consumption when sick is different than when healthy.

To shed light on the effect of health-dependent preferences on the value of insurance programs in the United States, I build and estimate a partial equilibrium life-cycle model of consumption and saving. I focus on households between 25 and 90 years of age and allow health to affect survival probabilities, earnings, and the marginal utility of consumption. I estimate the model using the Panel Study of Income Dynamics and the Method of Simulated Moments. I use the estimated model to assess the welfare effects of removing or reforming social insurance programs.

My paper connects to three branches of the literature and contributes to each. First, it relates to the literature on **structural life-cycle models with health risk**. Sem-

¹See Section 2 for a review of the approaches and results to estimating the effect of health on preferences.

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

Second, my paper connects to the literature on **health-dependent preferences**. There is no consensus on the magnitude and direction of the effect of health on preferences. Two approaches have emerged in this literature. On the one hand, some papers take a structural approach. Among these, [Lillard and Weiss \(1997\)](#) find a positive effect of health on preferences, meaning marginal utility increases with deteriorating health. In contrast, [De Nardi, French, and Jones \(2010\)](#) and [Hong, Pijoan-Mas, and Ríos-Rull \(2015\)](#) find evidence of a negative effect, so marginal utility decreases as health worsens. On the other hand, some papers take an empirical approach. Among these, [Viscusi and Evans \(1990\)](#) and [Finkelstein, Luttmer, and Notowidigdo \(2013\)](#) find evidence of a negative effect of health on preferences, while [Evans and Viscusi \(1991\)](#) find that there is no effect at all.² I contribute to this literature by taking a structural approach and providing new estimates and identification results for the effect of health on preferences.

Third, my paper relates to the literature on **insurance against health shocks**. Two important papers in this literature are [Braun, Kopecky, and Koreshkova \(2016\)](#) and [Blundell, Borella, Commault, and De Nardi \(2020\)](#). [Braun, Kopecky, and Koreshkova \(2016\)](#) build a structural model of the whole life-cycle to study the role of means-tested social insurance programs - such as Medicaid and Supplemental Security Income - for medical expenses,

²Section 2 reviews the literature on health-dependent preferences in more depth.

longevity, and poverty risk. [Blundell, Borella, Commault, and De Nardi \(2020\)](#) use a structural model for the elderly to show that the response of consumption to transitory health shocks depends on the shock's effect on resources and marginal utility, with the marginal utility channel being the strongest driver. I contribute to this literature by studying the whole life cycle, rather than only the elderly like [Blundell, Borella, Commault, and De Nardi \(2020\)](#), and considering health risk at all ages, rather than only for the elderly like [Braun, Kopecky, and Koreshkova \(2016\)](#).

The remainder of the paper is organized as follows. Section 2 reviews the literature on health state dependence. Section 3 describes my quantitative model. Section 4 describes the data and my measure of health. Section 5 discusses my empirical strategy. Section 6 presents the estimation results for the exogenous processes. Section 8 illustrates the results for the estimated parameters. Section 9 discusses policy experiments and the value of social insurance programs. Section 10 concludes.

2 Health-Dependent Preferences in the Literature

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

2.1 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 \(1990\)](#) find evidence of a negative effect of health on preferences: marginal utility for the unhealthy is between 17 and 23 percent lower than the marginal utility for the healthy. [Sloan, Kip Viscusi, Chesson, Conover, and Whetten-Goldstein \(1998\)](#) find evidence of a more considerable negative effect of health on preferences, with marginal utility in bad health being just 8 percent of the one in good health. [Evans and Viscusi \(1991\)](#), on the other hand, find no evidence of an effect of health on preferences.

A second branch of the empirical literature on the effect of health on preferences focuses on reported well-being as a proxy for utility. [Finkelstein, Luttmer, and Notowidigdo \(2013\)](#) construct a sample of elderly Americans and estimate the effect of health on preferences using changes in subjective well-being.³ They find evidence of a negative effect of 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 \(2019\)](#) focus on a sample of elderly Europeans and use changes in material well-being to estimate the effect of health on preferences.⁴ They find evidence of a positive effect of health on preferences. In particular, the marginal utility of consumption increases as the number of activities of daily living a person struggles with increases.

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

³They 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.

⁴They measure material well-being by observing the answer to the question “How difficult is it for you to make ends meet?”

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

2.2 The structural literature on health-dependent preferences

A few papers have used structural consumption models to estimate the effect of health on preferences. [Lillard and Weiss \(1997\)](#) develop a life-cycle model to study the impact of health and survival risk on retirees' consumption and savings decisions. Their results point to a positive effect of health on preferences. In particular, consumption when sick is fifty-five percent higher than when healthy. [Hong, Pijoan-Mas, and Rios-Rull \(2015\)](#) use a life cycle model with endogenous health and estimate the effect of health on preferences using the Euler equation for consumption. They estimate a negative effect at 65 and a positive one at older ages.

Numerous papers embed the effect of health on preferences in their structural models to answer various questions. A few papers consider this effect but do not estimate it. [Low and Pistaferri \(2015\)](#) build a life cycle model to evaluate the welfare effects of changing the Disability Insurance program in the United States. Their model allows disability to influence marginal utility and assumes a positive effect of health on preferences. [De Donder and Leroux \(2021\)](#) study the demand for long-term care insurance when health affects preferences. They assume a negative effect of health on preferences so that consumption and good health are complements.

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

help identify the effect of health on preferences and estimate a positive effect of health on preferences.

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. I will estimate my model to assess the magnitude and direction of health state dependence, and I will use the estimated model to conduct policy experiments.

3.1 Environment

Households enter the model at age 25, retire exogenously at 62, and die with certainty by the time they are 89. Households are subject to health, earnings, and survival risk until retirement, after which earnings risk is resolved. To be consistent with biennial PSID data, each period in my model corresponds to two years.

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

3.2 Preferences and Health State Dependence

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

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

where c_t is consumption; h_t is health status; γ is the coefficient of relative risk aversion; and $\delta(h_t)$ measures health state dependence. Following [Palumbo \(1999\)](#) and [De Nardi, French,](#)

and Jones (2010), I model health state dependence as:

$$\delta(h_t) = 1 + \delta h_t, \quad (3.2)$$

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

3.3 Health Status

Health status is measured by the frailty index. I present details on the frailty index as a measure of health in Section 4.1. 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.

If frailty is zero in period t , it remains at zero with positive probability and transitions to a positive value with one minus this probability. If frailty is positive, it cannot go back to zero.⁵ When frailty is positive, I follow Hosseini, Kopecky, and Zhao (2022) and assume it evolves according to the following process:

$$\log(h_t) = \kappa_t + \pi_t^h + \varepsilon_t^h, \quad (3.3)$$

$$\pi_t^h = \rho \pi_{t-1}^h + \eta_t^h, \quad (3.4)$$

$$\varepsilon_t^h \sim \mathbb{N}(0, \sigma_{\varepsilon^h}^2), \quad (3.5)$$

$$\eta_t^h \sim \mathbb{N}(0, \sigma_{\eta^h}^2), \quad (3.6)$$

$$\pi_0^h \sim \mathbb{N}(0, \sigma_{\pi_0^h}^2), \quad (3.7)$$

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

⁵This is consistent with my data. In my PSID sample, less than one percent of households are transitioning from positive to zero frailty.

3.4 Working Age Earnings

Households face earnings risk during their working age. Labor earnings depend on age, health status, and a permanent and transitory component. I follow standard practice in the earnings dynamics literature - see, for example, [Blundell, Pistaferri, and Preston \(2008\)](#) and [Blundell, Borella, Commault, and De Nardi \(2020\)](#) - and assume that log earnings evolve according to the following permanent-transitory process:

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

$$\pi_t^y = \pi_{t-1}^y + \eta_t^y, \quad (3.9)$$

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

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

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

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

3.5 Medical Expenditures and Death

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

$$\log m_t(h) = g(t, h) + \xi_t, \quad (3.13)$$

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

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

Survival probabilities in each period depend on age and health status.

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:

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

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. ⁶

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:

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

The government provides a means-tested transfer to guarantee a minimum level of consumption, \underline{c} . The transfer is computed as:

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

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

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

⁶See [Borella, De Nardi, Pak, Russo, and Yang \(2021\)](#) for a detailed description of this tax function and the interpretation of its parameters.

indicates net income during the retirement period.

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 permanent component of earnings π_t^y , the transitory component of earnings ε_t^y , the persistent component of health π_t^h , and the transitory component of health ε_t^h . Workers maximize the objective function:

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

Subject to the intertemporal budget constraint:

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

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

3.8.2 The Value Function for Retirees

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

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

Subject to the intertemporal budget constraint

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

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

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

4 Data

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

My measure of health is the frailty index. Section 4.1 describes the frailty index in detail. I construct a household's frailty index as the average of each member's frailty index.

Working-age earnings for workers include labor earnings, the labor part of business income, and farm income. When married, household earnings are the sum of each spouse’s earnings. Medical expenditures are the sum of what households spend out-of-pocket for hospital and nursing home stays, doctor visits, prescription drugs, and insurance premia. Non-medical consumption is the sum of household expenditures on food at and away from home, utilities, phone bills, internet bills, transportation(excluding car loans, lease payments, and down payments,) trips and vacations, entertainment and recreation, donations to charity, and clothing. I 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. 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 C presents some facts on my key variables of interest.

4.1 Measuring health

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

The frailty index is an objective measure of health. It has been used extensively in the medical and gerontology literature, which has shown it to be an excellent predictor of health and mortality.⁷ Hosseini, Kopeccky, and Zhao (2022) and Nygaard (2021) pioneered its use in economics. To construct the frailty index for the households in my sample, I follow

⁷See Hosseini, Kopeccky, and Zhao (2022) for a review of the medical literature using the frailty index.

the guidelines in [Searle, Mitnitski, Gahbauer, Gill, and Rockwood \(2008\)](#) and use the same categories of deficits in [Hosseini, Kopecky, and Zhao \(2022\)](#). In particular, I include:

- Difficulties with activities of daily living (ADL) and instrumental ADL (IADL,) such as difficulty dressing, bathing, and walking.
- Diagnosed diseases, such as diabetes, cancer, and arthritis.
- Cognitive impairments and mental health measures, such as memory loss and psychological problems.
- 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 5 in Appendix B reports the complete list of deficits I use.

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

I construct a household’s frailty as the average frailty index of each member. Table 1 summarizes the distribution of the household frailty index in my sample. The household frailty index has a mean of 0.09 and a median of 0.07.⁸ Figure 1 shows the distribution of household frailty by age. This figure shows that median - as well as the 25th and 75th percentiles - frailty increases with age. It also shows that the variance of frailty increases with age and is particularly high after age 75. Table 6 in Appendix B displays the three most common deficits for household heads at selected ages. For younger people, smoking and obesity are the most common deficits, while, for older people, high blood pressure and arthritis are the leading causes of frailty.

⁸These results are in line with [Hosseini, Kopecky, and Zhao \(2022\)](#), who construct a frailty index using 28 deficits from the PSID. They use a sample of household heads and spouses aged 25 and older and report a mean of 0.11 and a median of 0.07.

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

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

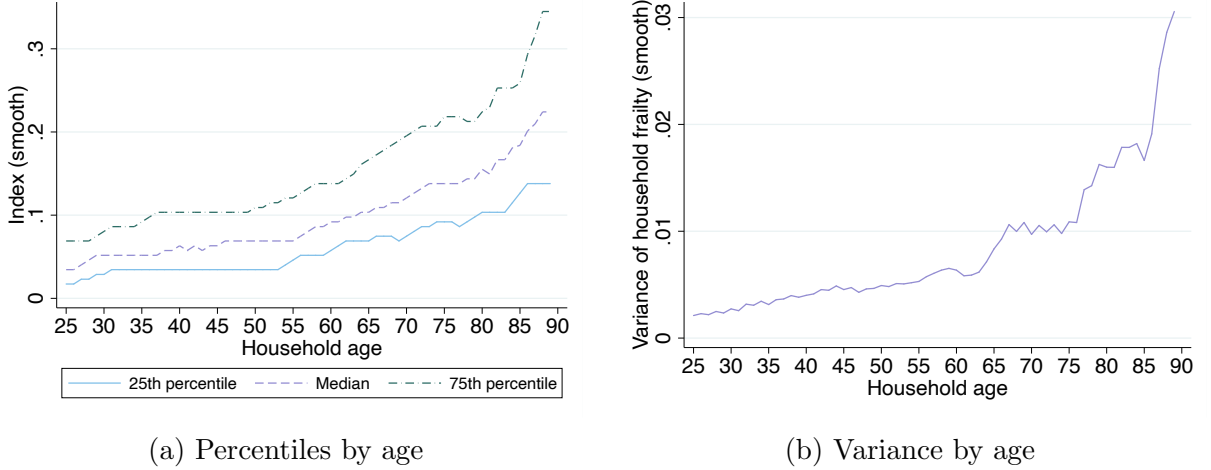


Figure 1: Distribution of household frailty by age: 25th, 50th, 75th percentiles (left) and variance (right.) Each statistics is smoothed using a 3-year moving average. PSID, 2005-2019.

5 Estimation Strategy

To estimate the model, I use a two-step estimation strategy similar to the one of [Gourinchas and Parker \(2002\)](#) and [De Nardi, French, and Jones \(2010\)](#). In the first step, I estimate or calibrate the parameters I can cleanly identify outside my model. In this step, for example, I estimate the health process from the PSID and fix the discount factor, β , and risk aversion, γ , to values from the literature.

In the second step, I estimate the health state dependence parameter, δ , and the consumption floor, \underline{c} , with the method of simulated moments (MSM), taking the parameters estimated in the first step as given. In particular, I find the combination of parameters that yields the simulated results closest - as measured by a GMM criterion function - to the ones in the data.

In the second step, I estimate the effect of health on preferences and the consumption floor by matching the degree of self-insurance against health and earnings shocks in the

model and the data. In particular, I match the pass-through coefficients against health and income shocks. These coefficients measure the fraction of the variance of a shock translated into consumption growth and thus measure the “exposure” of household consumption to a shock. Section 7 provides more details on the pass-through coefficients.

6 First-Step Estimation Results

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

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

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

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

$$Prob(h_{it} = 0|X_{it}) = \Phi(X'_{it}\alpha), \quad (6.1)$$

where Φ is the c.d.f. of a standard normal distribution and X_{it} is a set of regressors. In particular, X_{it} contains a second-order polynomial in household age, family size, the head’s education level, and cohort effects. Table 7 in Appendix D.1 reports the probit regression results. On average, the probability of having zero frailty decreases with age and family size and increases with the head’s education level.

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

before, is:

$$Prob(h_{it} = 0|h_{i,t-1} = 0) = \frac{Prob(h_{it} = 0|X_{it})}{Prob(h_{i,t-1} = 0|X_{i,t-1})} = \frac{\Phi(X'_{it}\alpha)}{\Phi(X'_{i,t-1}\alpha)}, \quad (6.2)$$

Thus, the probability a household has zero frailty is: given by Equation (6.1) at age 25; given by Equation (6.2) at ages older than 25 and if frailty is zero in the previous period; zero otherwise. Figure 4 in Appendix D.1 displays the share of households with zero frailty in the data and the model.

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

I then use the residuals from the regression for the deterministic component to estimate the parameters of the persistent and transitory components. I need to estimate the autoregressive coefficient, ρ , the variance of the transitory shock, $\sigma_{\varepsilon,h}^2$, the variance of the shock to the persistent component, $\sigma_{\eta,h}^2$, and the variance of the first persistent component, $\sigma_{\pi_0}^2$. I identify them using the variances and covariances of the residuals and estimate them using standard minimum distance techniques. See Appendix D.1 for the identification restrictions and estimation details. Table 8 in Appendix D.1 reports the estimation results. The results show that frailty is increasing in age and persistent, confirming the findings of Hosseini, Kopecky, and Zhao (2022).

Survival Probabilities I estimate two-year survival probabilities for household heads. I run a logistic regression of a binary indicator for whether the head is alive or not using a second-order polynomial in age, frailty in the previous period, head's education, and family size as covariates. Table 9 in Appendix D.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 2019.⁹ I then correct my estimates by multiplying the estimated survival probabilities by the adjustment factor.

Earnings Process To be consistent with my model, I estimate the working-age earnings process for households between 25 and 61 years old who report positive labor earnings. I estimate the deterministic component in Equation (3.8) by regressing the logarithm of earnings on a second-order polynomial in age, frailty, family size, the head’s education level, and cohort effects. The left panel Table 10 in Appendix D.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 identify the variances of the earnings shocks using covariance restrictions log-income growth, as in Meghir and Pistaferri (2004) and Blundell, Pistaferri, and Preston (2008). Appendix D.1 presents details on the identification. The right panel of Table 10 in Appendix D.3 shows the estimated variances of the earnings shocks.

Out-Of-Pocket Medical Expenditures I estimate the deterministic component of medical expenditures by regressing their logarithm¹⁰ on a second-order polynomial in household age, frailty, family size, head’s education, and cohort effects. Column (1) in Table 11 in Appendix D.4 displays the estimation results for this regression. These results show that medical expenditures increase with age, frailty, family size, and education.

Then, to estimate the variance of the i.i.d. shock, I regress the squared residuals from the regression above on the same covariates. Column (2) of Table 11 in Appendix D.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 12 in Appendix D.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 annual interest rate to 4 percent and the risk aversion to 2 following De Nardi, Fella, and

⁹Available at <https://www.ssa.gov/oact/STATS/table4c6.html>

¹⁰I replace values of medical expenditures equal to zero with one hundred dollars.

Paz-Pardo (2019). Finally, I set the annual discount factor to 0.9756 using the central value of the estimates of Gourinchas and Parker (2002).

7 Self Insurance

7.1 Pass-through coefficients

The pass-through coefficient of an idiosyncratic shock x_{it} is the ratio of the covariance between log-consumption growth and the shock and the variance of the shock. Formally:

$$\phi^x = \frac{\text{cov}(\Delta \log c_{it}, x_{it})}{\text{var}(x_{it})}, \quad (7.1)$$

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

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

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

I use the identification conditions of Blundell, Pistaferri, and Preston (2008) to estimate the pass-through coefficients of earnings shocks. In particular, for permanent earnings shocks, I set $g_t^\eta(\mathbf{y}_i) = \Delta \log y_{t-1} + \Delta \log y_t + \Delta \log y_{t+1}$ so that the pass-through coefficient is:

$$\phi_t^{\eta_{it}} = \frac{\text{cov}(\Delta \log c_{it}, \eta_{it}^y)}{\text{var}(\eta_{it}^y)} = \frac{\text{cov}(\Delta \log c_{it}, \Delta \log y_{i,t-1} + \Delta \log y_{i,t} + \Delta \log y_{i,t+1})}{\text{cov}(\Delta \log y_{it}, \Delta \log y_{i,t-1} + \Delta \log y_{it} + \Delta \log y_{i,t+1})} \quad (7.2)$$

For transitory earnings shocks, I set $g_t^\varepsilon(\mathbf{y}_i) = -\Delta \log y_{t+1}$ so that the pass-through coefficient is:

$$\phi_t^{\varepsilon_{it}} = \frac{\text{cov}(\Delta \log c_{it}, \varepsilon_{it}^y)}{\text{var}(\varepsilon_{it}^y)} = \frac{\text{cov}(\Delta \log c_{it}, -\Delta \log y_{i,t+1})}{\text{cov}(\Delta \log y_{it}, -\Delta \log y_{i,t+1})} \quad (7.3)$$

Then, I apply a similar strategy to Kaplan and Violante (2010) to estimate the pass-

through coefficients of persistent and transitory health shocks. First, I define the quasi difference of log frailty as $\tilde{\Delta} \log h_{it} = \log h_{it} - \rho \log h_{it-1}$. Notice I have estimated ρ in Section 6. Then, for persistent health shocks, I set $g_t^\eta(\mathbf{h}_i) = \rho^2 \tilde{\Delta} \log h_{i,t-1} + \rho \tilde{\Delta} \log h_{it} + \tilde{\Delta} \log h_{i,t+1}$ and identify the pass-through coefficient as:

$$\phi_t^{\eta^h} = \frac{\text{cov}(\Delta \log c_{it}, \eta_{it}^h)}{\text{var}(\eta_{it}^h)} = \frac{\text{cov}(\Delta \log c_{it}, \rho^2 \tilde{\Delta} \log h_{i,t-1} + \rho \tilde{\Delta} \log h_{it} + \tilde{\Delta} \log h_{i,t+1})}{\text{cov}(\tilde{\Delta} \log h_{it}, \rho^2 \tilde{\Delta} \log h_{i,t-1} + \rho \tilde{\Delta} \log h_{it} + \tilde{\Delta} \log h_{i,t+1})} \quad (7.4)$$

For transitory shocks, I set $g_t^\varepsilon(\mathbf{h}_i) = \tilde{\Delta} h_{i,t+1}$ and identify the pass-through coefficient as:

$$\phi_t^{\varepsilon^h} = \frac{\text{cov}(\Delta \log c_{it}, \varepsilon_{it}^h)}{\text{var}(\varepsilon_{it}^h)} = \frac{\text{cov}(\Delta \log c_{it}, \tilde{\Delta} h_{i,t+1})}{\text{cov}(\tilde{\Delta} h_{it}, \tilde{\Delta} h_{i,t+1})} \quad (7.5)$$

7.2 Estimation of pass-through coefficients

The pass-through coefficients in Equation (7.2)-Equation (7.5) are defined for “detrended” consumption, earnings, and frailty. That is consumption, earnings, and frailty net of demographics. I detrend log earnings and frailty when I estimate their processes in Section 6 by regressing them on a second-order polynomial in age, family size, the head’s education level, and cohort effects. The results are presented in Appendix D.3 and Appendix D.1. Then, I detrend log-consumption by regressing it on the same covariates. Table 2 reports the regression results. Log-consumption increases with age, family size, and education. To estimate the pass-through coefficients, I use the residuals from these three regressions to measure detrended consumption, earnings, and frailty.

Table 3 shows my estimated pass-through coefficients.

Log household consumption	
Age	0.0386*** (0.00226)
Age ²	-0.000422*** (0.0000224)
Family size	0.160*** (0.00226)
Head's education	0.255*** (0.00477)
Constant	8.557*** (0.0606)
Cohort effects	Yes
Observations	30327
R^2	0.271
Standard errors in parentheses	
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$	

Table 2: Estimation results for consumption detrending

	All 25-61	Low wealth	High wealth
ϕ_y^η	0.375*** 0.03	0.341*** 0.06	0.389*** 0.04
ϕ_y^ε	-0.073* 0.04	0.026 0.09	-0.102 0.04
N	7693	1464	6229
	All 25-89	Low wealth	High wealth
ϕ_h^η	-0.061*** 0.013	-0.090*** 0.027	-0.054*** 0.015
ϕ_h^ε	-0.096* 0.05	-.284* 0.15	-0.063 0.06
N	8800	1438	7362

Table 3: Pass-through coefficients

These sections are currently work in progress

8 Second-Step Estimation Results

9 Computing the Value of Social Insurance

10 Conclusions

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Appendix

A PSID data and Sample Selection

A.1 Sample Selection

Table 4 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.¹¹ Then, I restrict my attention to the core sample of the PSID.¹² 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.) Then, following [Blundell, Borella, Commault, and De Nardi \(2020\)](#), I drop the top and bottom 1 percent of the change in log consumption, income, and medical expenditures. I repeat the same for the change in the level of wealth. The final sample consists of 30,327 observations.

B Frailty Index

Table 5 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, Kopeccky, and Zhao \(2022\)](#), I add alcohol

¹¹The 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, I only need to keep track of household heads to conduct my household-level analysis.

¹²As 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 \(2016\)](#), 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	3,665	30,327

Table 4: Sample Selection, PSID waves 2005 - 2019.

consumption as a deficit. I follow the definition of the National Institute on Alcohol Abuse and Alcoholism¹³ 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 6 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.

C 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.¹⁴

¹³Available at <https://www.niaaa.nih.gov/alcohol-health/overview-alcohol-consumption/moderate-binge-drinking>

¹⁴I equalize household consumption and wealth by dividing them by the square root of family size.

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

Table 5: 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 6: Top 3 deficits for household heads for selected ages. PSID, waves 2005-2019.

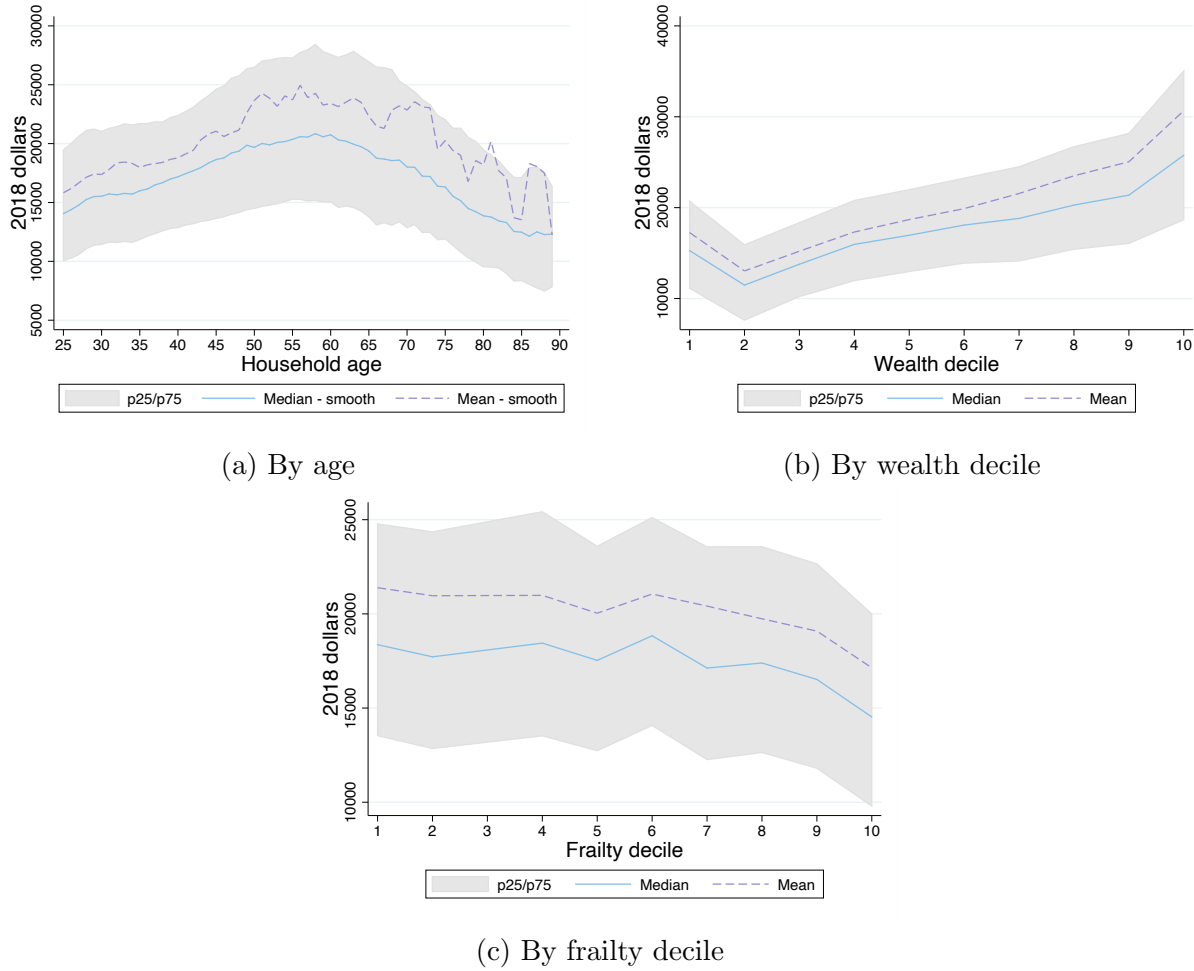
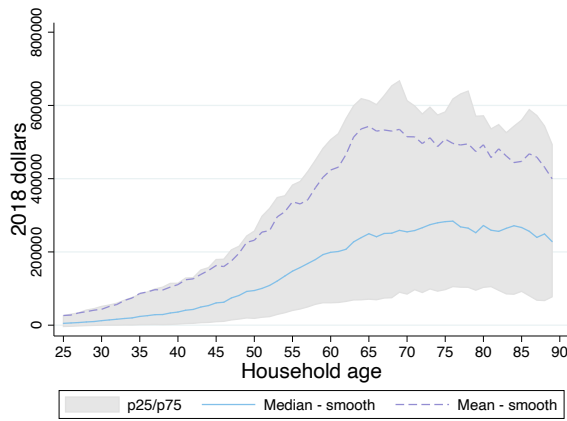
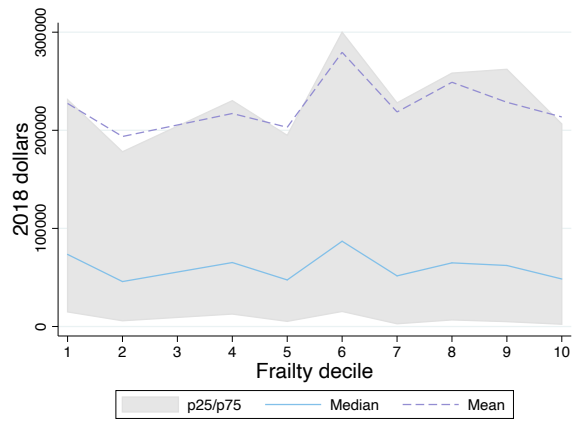


Figure 2: Equivalized consumption by age, wealth deciles, and frailty deciles. Equivalized consumption by age is smoothed using a three-year moving average.



(a) By age



(b) By frailty decile

Figure 3: Equivalized wealth by age and frailty deciles. Equivalized wealth by age is smoothed using a three-year moving average.

D First-Step Estimation

D.1 Health Process

Table 7 displays the estimation results for the probit regression for the probability of having zero frailty at each age. Figure 4 displays the share of households with zero frailty in the data and in the model.

Household has zero frailty	
Age	-0.0565*** (0.00994)
Age ²	0.000119 (0.000110)
Family size	-0.0407*** (0.00862)
Head's education	0.438*** (0.0200)
Constant	0.829*** (0.245)
Cohort effects	Yes
Observations	30300
Pseudo R^2	0.100

Standard errors in parentheses

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

Table 7: Estimation results from zero frailty probit regression. The dependent variable is a dummy equal to 1 when the households has zero frailty.

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

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

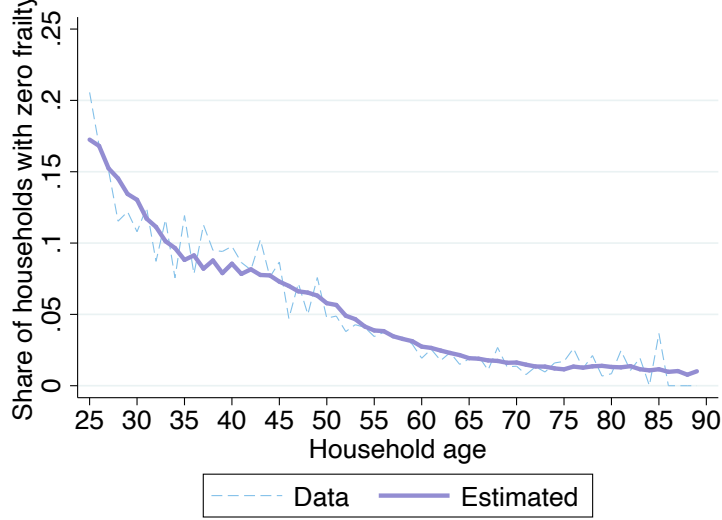


Figure 4: Share of households with zero frailty in the data (dashed blue line) and predicted by probit regression (solid purple line.)

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

D.2 Survival Probabilities

Table 9 reports the estimation results for the logistic regression of a survival indicator.

D.3 Earnings Process

Let \tilde{y}_t denote “detrended” log-earnings, that is, $\log y_t - \kappa(t, h)$. I identify the variances of the earnings shocks using covariance restrictions on the growth of detrended log earnings. In particular, I denote Δ as the first-difference operator and use the following restrictions:

$$\begin{aligned} cov(\Delta \tilde{y}_t, -\Delta \tilde{y}_{t+1}) &= \sigma_{\varepsilon, y}^2 \\ cov(\Delta \tilde{y}_t, \Delta \tilde{y}_{t-1} + \Delta \tilde{y}_t + \Delta \tilde{y}_{t+1}) &= \sigma_{\eta, y}^2 \end{aligned}$$

	Log frailty		
Age	0.0244*** (0.00310)		
Age ²	0.000118*** (0.0000303)	Parameter	Value
Family size	-0.0631*** (0.00309)	ρ	0.934
Head's education	-0.239*** (0.00651)	$\sigma_{\varepsilon,h}^2$	0.022
Constant	-4.106*** (0.0834)	$\sigma_{\eta,h}^2$	0.053
		$\sigma_{\pi_{25}^h}^2$	0.356
Cohort effects	Yes		
Observations	28100		
R^2	0.226		
Standard errors in parentheses			
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$			

Table 8: Estimation results for non-zero health process. Deterministic component (left) and parameters of the stochastic components (right.) 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 9: Estimation results for logistic regression of survival indicator. PSID waves 2005-2019.

Then, the variance of the first permanent component is identified from the variance of detrended earnings at 25 and the variance of the transitory shock:

$$\text{var}(\tilde{y}_{25}) - \sigma_{\varepsilon,y}^2 = \sigma_{\pi_{25}^y}^2$$

Period $t + 1$ variables are one PSID wave - thus, two years - ahead of period t variables. I estimate $\sigma_{\varepsilon,y}^2$ and $\sigma_{\eta,y}^2$ using GMM and the covariance restrictions above. Table 10 presents the estimation results for the deterministic and stochastic components of log earnings.

Log household earnings			
Age	0.0887*** (0.00612)		
Age ²	-0.000787*** (0.0000722)		
Household frailty	-3.570*** (0.0854)	Parameter	Value
Family size	0.113*** (0.00380)	$\sigma_{\varepsilon,y}^2$	0.049*** (0.004)
Head's education	0.436*** (0.00875)	$\sigma_{\eta,y}^2$	0.079*** (0.005)
Constant	7.756*** (0.116)	$\sigma_{\pi_{25}^y}^2$	0.826
Cohort effects	Yes	Observations	7693
Observations	24643		
R^2	0.243		

Standard errors in parentheses

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

Table 10: 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 GMM. PSID waves 2005-2019.

D.4 Out-of-pocket medical expenditures

Table 11 reports the estimation results for the process for medical expenditures. The variance of the i.i.d. shock to medical expenditures is $\sigma_{\xi}^2 = 0.043$

	Log medical expenditures	Squared Residuals
Age	0.152*** (0.00616)	-0.0868*** (0.0141)
Age ²	-0.00124*** (0.0000610)	0.000849*** (0.000140)
Household frailty	0.344*** (0.113)	2.265*** (0.259)
Family size	0.215*** (0.00616)	0.0637*** (0.0141)
Head's education	0.483*** (0.0132)	-0.628*** (0.0304)
Constant	2.382*** (0.165)	3.827*** (0.378)
Cohort effects	Yes	Yes
Observations	30327	30327
R^2	0.144	0.0306

Standard errors in parentheses

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

Table 11: 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.

D.5 Fixed Parameters

Table 12 summarizes the calibrated parameters.

Parameter	Description	Value	Source
$\lambda; \tau$	Tax function	2; 0.07	Borella, De Nardi, Pak, Russo, and Yang (2021)
r	Annual Interest rate	4%	De Nardi, Fella, and Paz-Pardo (2019)
β	Annual Discount factor	0.9756	Gourinchas and Parker (2002)
γ	Risk Aversion	2	De Nardi, Fella, and Paz-Pardo (2019)

Table 12: Calibrated Parameters.