Health State Dependence and the Value of Social Insurance

Nicolo Russo*

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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.

*Department of Economics, University of Minnesota.

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.

Health state dependence measures the effect of health on the marginal utility of non-medical consumption. Numerous studies have demonstrated its existence, but its magnitude and direction remain ambiguous.[1] Health state dependence matters many economic choices: portfolio choices (Edwards (2010);) the purchase of life and health insurance products (Koijen, Van Nieuwerburgh, and Yogo (2016);) and the optimal level of savings (Finkelstein, Luttmer, and Notowidigdo (2013).) However, it is unclear how health state dependence affects 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 state dependence 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.** Seminal

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

contributions in this literature are Palumbo (1999), French (2005), and De Nardi et al. (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-state dependence.

Second, my paper connects to the literature on **health state dependence.** There is no consensus on the magnitude and direction of health state dependence. Two approaches have emerged in this literature. On the one hand, some papers take a structural approach. Among these, Lillard and Weiss (1997) find positive health state dependence, 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 negative health state dependence, 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 negative health state dependence, while Evans and Viscusi (1991) find that there is no health state dependence at all.[2] I contribute to this literature by taking a structural approach and providing new estimates and identification results for health state dependence.

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, longevity, and poverty risk. Blundell, Borella, Commault, and De Nardi (2020) use a struc-

[2]Section 2 reviews the literature on health state dependence in more depth.

tural 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 State Dependence in the literature

Finkelstein, Luttmer, and Notowidigdo (2009) define health state dependence as the effect of health on non-medical consumption. The literature on health state dependence 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 health state dependence and attempted to quantify its magnitude and direction, they have obtained different - sometimes opposite - results. In particular, positive health state dependence arises when marginal utility increases with worsening health. Negative health state dependence, in turn, results in marginal utility declining as health deteriorates.

2.1 The empirical literature on health state dependence

There are numerous empirical studies on health state dependence. 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 negative state dependence: marginal utility for the unhealthy is between 17 and 23 percent lower than marginal utility for the healthy. Sloan, Kip Viscusi, Chesson, Conover, and Whetten-Goldstein (1998) find evidence of more considerable negative health state dependence, 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 health state dependence.

A second branch of the empirical literature on health state dependence focuses on reported well-being as a proxy for utility. Finkelstein, Luttmer, and Notowidigdo (2013) construct a sample of elderly Americans and estimate health state dependence using changes in subjective well-being.[3] They find evidence of negative health state dependence. 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 their health state dependence.[4] They find evidence of positive health state dependence. 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 on health state dependence 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 health state dependence at younger ages and negative health state dependence 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 health state dependence. In particular, she finds positive health state dependence for intermediate health states but no health state dependence for more minor and more severe health states.

[3] 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.

[4] They 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 health state dependence using portfolio choices. Edwards (2008) uses a sample of older American households and studies their portfolio compositions to conclude they exhibit positive health state dependence.

2.2 The structural literature on health state dependence

A few papers have used structural consumption models to estimate health state dependence. 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 positive health state dependence. 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 health state dependence using the Euler equation for consumption. They estimate negative health state dependence at 65 and positive at older ages.

Numerous papers embed health state dependence in their structural models to answer various questions. A few papers consider health state dependence 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 positive health state dependence. De Donder and Leroux (2021) study the demand for long-term care insurance when health affects preferences. They assume negative health state dependence so that consumption and good health are complements.

Another set of papers embeds health state dependence 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 negative - but not significant - health state dependence. 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 negative health state dependence. 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 positive health state dependence.

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 65, and die with certainty by the time they are 90. Households are subject to health, earnings, and survival risk until retirement, after which earnings risk is resolved.

I assume that asset markets are incomplete. Households enter the model with zero assets and can only invest in a risk-free asset, which has 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 on consumption of non-durable and non-medical goods. The period flow utility of consumption is:

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

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

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

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

3.3 Health Status

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

When health is positive, I follow Hosseini, Kopecky, and Zhao (2022) and assume it evolves according to the following process:

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

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

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

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

where κ_t is a deterministic component which depends on age; π_t is the persistent component of health; and ε_t is the transitory component of health. I assume that, when $h_t = 0$, $\pi_t = 0$ as well.

3.4 Working Age Earnings

Households face earnings risk during their working age. Labor earnings depend on health and other demographics and on a permanent and a transitory component. I follow a 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:

$$\log y_t(h) = \kappa_t(h) + \pi_t^y + \varepsilon_t^y, \tag{3.7}$$

$$\pi_t^y = \pi_{t-1}^y + \eta_t^y, \tag{3.8}$$

$$\varepsilon_t^y \sim \mathbb{N}(0, \sigma^2_{\varepsilon^y}), \tag{3.9}$$

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

where $\kappa_t(h)$ denotes the deterministic component of earnings, which depends on age, health status, marital status, and birth cohort;[5] π_t^y is the permanent component of earnings; and ε_t^y is the transitory component of earnings.

3.5 Medical Expenditures and Death

In each period until death, households incur out-of-pocket medical expenditures and face survival probabilities.

I only consider medical expenditures that are not covered by health insurance and I do not model health insurance itself. Consistently with De Nardi, French, and Jones (2010) and Keane, Capatina, and Maruyama (2020), medical expenditures are exogenous and modeled as cost shocks. I model log-medical expenditures as follows:

$$\log m_t(h) = g(t,h) + \xi_t, \tag{3.11}$$

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

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 a 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

[5] Because I do not model marital status and birth cohort explicitly, when solving the model, I use the average marital status by age and the average cohort effect I compute in my sample.

the Earned Income Tax Credit (EITC.) In particular, income taxes are given by:

$$T(y) = y - (1 - \lambda)y^{1-\tau}, \tag{3.13}$$

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.

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

$$b_t = \max\{0, \underline{c} + m_t(h) - [a_t + y^n(ra_t + y_t(h), \tau)]\}, \qquad \text{if } t < T^{ret}, \tag{3.14}$$

$$b_t = \max\{0, \underline{c} + m_t(h) - [a_t + ss^n(ra_t + ss_t, \tau)]\}, \qquad \text{if } t \geq T^{ret}, \tag{3.15}$$

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.

3.7 Recursive Formulation

I compute four value functions for the following stages of life and realizations of health status.

3.7.1 The Value Function for Workers with Positive Health

The value function of a worker with positive health status depends on 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:

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

$$V(X_t) = \max_{c_t, a_{t+1}} \left\{ \delta(h_t) \frac{c_t^{1-\gamma}}{1-\gamma} + \beta s_{h,t} \mathbb{E}_t[V(X_{t+1})] \right\}, \tag{3.16}$$

$$\text{sub. to } a_{t+1} = a_t + y^n(ra_t + y_t(h), \tau) - m_t(h) + b_t - c_t, \tag{3.17}$$

$$\log m_t(h) = g(t,h) + \xi_t, \quad \xi_t \sim N(0, \sigma_\xi^2), \tag{3.18}$$

$$\log(h_t) = \kappa_t + \pi_t^h + \varepsilon_t^h, \tag{3.19}$$

$$\pi_t^h = \rho \pi_{t-1}^h + \eta_t^h, \tag{3.20}$$

$$\log y_t(h) = \kappa_t(h) + \pi_t^y + \varepsilon_t^y, \tag{3.21}$$

$$\pi_t^y = \pi_{t-1}^y + \eta_t^y, \tag{3.22}$$

$$b_t = \max\{0, \underline{c} + m_t(h) - [a_t + y^n(ra_t + y_t, \tau)]\}, \tag{3.23}$$

$$a_t \geq 0, \tag{3.24}$$

$$\eta_t^h \sim N(0, \sigma_{\eta h}^2), \quad \varepsilon_t^h \sim N(0, \sigma_{\varepsilon h}^2), \tag{3.25}$$

$$\eta_t^y \sim N(0, \sigma_{\eta y}^2), \quad \varepsilon_t^y \sim N(0, \sigma_{\varepsilon y}^2), \tag{3.26}$$

where the vector of state variables is:

$$X_t = \{t, a_t, \xi_t, \pi_t^y, \varepsilon_t^y, \pi_t^h, \varepsilon_t^h\}, \tag{3.27}$$

3.7.2 The Value Function for Workers with Zero Health

The value function of a worker with health status equal to zero depends on age t, assets a_t, the shock to medical expenditures ξ_t, the permanent component of earnings π_t^y, and the transitory component of earnings ε_t^y:

$$V(X_t) = \max_{c_t, a_{t+1}} \left\{ \frac{c_t^{1-\gamma}}{1-\gamma} + \beta s_{h,t} \mathbb{E}_t[V(X_{t+1})] \right\}, \tag{3.28}$$

$$\text{sub. to } a_{t+1} = a_t + y^n(ra_t + y_t(h), \tau) - m_t(h) + b_t - c_t, \tag{3.29}$$

$$\log m_t(h) = g(t,h) + \xi_t, \quad \xi_t \sim N(0, \sigma_\xi^2), \tag{3.30}$$

$$\log y_t(h) = \kappa_t(h) + \pi_t^y + \varepsilon_t^y, \tag{3.31}$$

$$\pi_t^y = \pi_{t-1}^y + \eta_t^y, \tag{3.32}$$

$$b_t = \max\{0, \underline{c} + m_t(h) - [a_t + y^n(ra_t + y_t, \tau)]\}, \tag{3.33}$$

$$a_t \geq 0, \tag{3.34}$$

$$\eta_t^y \sim N(0, \sigma_{\eta y}^2), \quad \varepsilon_t^y \sim N(0, \sigma_{\varepsilon y}^2), \tag{3.35}$$

where the vector of state variables is:

$$X_t = \{t, a_t, \xi_t, \pi_t^y, \varepsilon_t^y\}, \tag{3.36}$$

3.7.3 The Value Function for Retirees with Positive Health

The value function of a worker with positive health status depends on 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:

$$V(X_t) = \max_{a_{t+1}} \left\{ \delta(h_t) \frac{c_t^{1-\gamma}}{1-\gamma} + \beta s_{h,t} \mathbb{E}_t[V(X_{t+1})] \right\}, \tag{3.37}$$

$$\text{sub. to } a_{t+1} = a_t + ss^n(ra_t + ss_t, \tau) - m_t(h) + b_t - c_t, \tag{3.38}$$

$$\log m_t(h) = g(t,h) + \xi_t, \quad \xi_t \sim N(0, \sigma_\xi^2), \tag{3.39}$$

$$\log(h_t) = \kappa_t + \pi_t^h + \varepsilon_t^h, \tag{3.40}$$

$$\pi_t^h = \pi_{t-1}^h + \eta_t^h, \tag{3.41}$$

$$ss_t = ss(y_{T^{ret}-1}), \tag{3.42}$$

$$b_t = \max\{0, \underline{c} + m_t(h) - [a_t + ss^n(ra_t + ss_t, \tau)]\}, \tag{3.43}$$

$$a_t \geq 0, \tag{3.44}$$

$$\eta_t^h \sim N(0, \sigma_{\eta h}^2), \quad \varepsilon_t^h \sim N(0, \sigma_{\varepsilon h}^2), \tag{3.45}$$

where vector of state variables is:

$$X_t = \{t, a_t, \xi_t, ss_t, \pi_t^h, \varepsilon_t^h\} \tag{3.46}$$

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.

3.7.4 The Value Function of Retirees with Zero Health

The value function of a worker with positive health status depends on age t, assets a_t, the shock to medical expenditures ξ_t, and Social Security benefits ss_t:

$$V(X_t) = \max_{a_{t+1}} \left\{ \frac{c_t^{1-\gamma}}{1-\gamma} + \beta s_{h,t} \mathbb{E}_t [V(X_{t+1})] \right\}, \tag{3.47}$$

$$\text{sub. to } a_{t+1} = a_t + ss^n(ra_t + ss_t, \tau) - m_t(h) + b_t - c_t, \tag{3.48}$$

$$\log m_t(h) = g(t,h) + \xi_t, \quad \xi_t \sim N(0, \sigma_\xi^2), \tag{3.49}$$

$$ss_t = ss(y_{T^{ret}-1}), \tag{3.50}$$

$$b_t = \max\{0, \underline{c} + m_t(h) - [a_t + ss^n(ra_t + ss_t, \tau)]\}, \tag{3.51}$$

$$a_t \geq 0, \tag{3.52}$$

$$\tag{3.53}$$

where vector of state variables is:

$$X_t = \{t, a_t, \xi_t, ss_t\} \tag{3.54}$$

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 perform minimal sample selection and conduct household-level analysis. I keep both married and single households in my sample.[7] To be consistent with my model, I only consider households whose head is between 25 and 90 years old. My final sample consists of 45,595 observations divided into 10,024 households.

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

[7]Following Borella, De Nardi, and Yang (2018), I label "married" both legally married couples and unmarried but cohabiting ones.

earnings for workers include labor earnings, the labor part of business income, and farm income. Household earnings are the average of each member'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.

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.[8] Hosseini, Kopecky, and Zhao (2022) and Nygaard (2021) pioneered its use in economics. To construct the frailty index for the households in my sample, I follow the guidelines in Searle, Mitnitski, Gahbauer, Gill, and Rockwood (2008) and use the same categories of deficits in Hosseini, Kopecky, and Zhao (2022). In particular, I include:

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

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

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

In total, I consider 29 deficits to construct the frailty index. Each deficit can take a value of either zero or one, based on whether the individual currently has a specific deficit or not. Table 2 in Appendix A 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.[9] 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 3 in Appendix A displays the three most common deficits for household heads at selected ages. For younger people, smoking and obesity are the most common deficits, while, for older people, high blood pressure and arthritis are the leading causes of frailty.

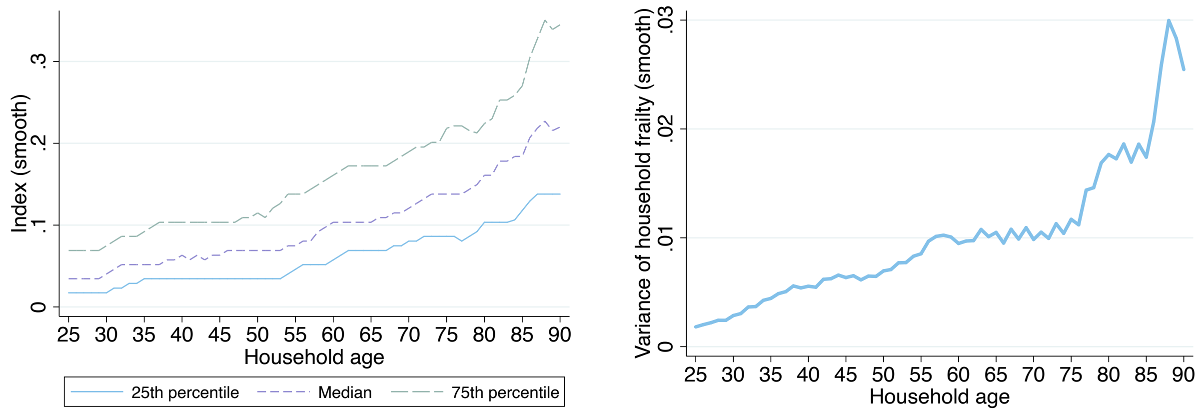
Mean	10th pct	25th pct	50th pct	75th pct	99th pct
0.09	0.02	0.03	0.07	0.12	0.45

Table 1: Distribution of household frailty index. Statistics computed for PSID households with head aged between 25 and 90, interviewed between 2005 and 2019 wave.

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

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



(a) Percentiles by age

(b) Variance by age

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

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

In the second step, I 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 health state dependence 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.

Health state dependence influences self-insurance against health shocks because of the effects of health on consumption. Health affects consumption through two channels: available resources and marginal utility. Indeed, after a health shock, households have fewer resources for consumption - due to higher medical expenditures - and enjoy consuming differently. Thus, the degree of self-insurance against health shocks helps identify health state dependence.

The consumption floor affects self-insurance against earnings shocks because households must supplement government insurance with savings to protect themselves from earnings shocks. If the government provided full insurance against earnings shocks, households would not need to save to respond to such a shock. If government insurance is incomplete, households must adjust consumption and self-insure to deal with earnings shocks. Thus, the degree of self-insurance against earnings shocks helps identify the consumption floor.

6 First-Step Estimation Results

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

6.1 Health Process

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

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

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

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

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, marital status, and cohort effects. Table 4 in Appendix B.1reports the probit regression results. On average, the probability of having zero frailty decreases with age and is lower for married households than for single ones.

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

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

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 2 in Appendix B.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. In particular, I assume that the log of the frailty index is the sum of a deterministic component, κ, a persistent component, π^h, and a transitory component, ε^h. In particular, the process for log-non-zero frailty is:

$$\begin{aligned} \log(h_{it}) &= \kappa_{it} + \pi_{it}^h + \varepsilon_{it}^h, \\ \pi_{it}^h &= \rho \pi_{it-1}^h + \eta_{it}^h, \\ \eta_{it}^h &\sim N(0, \sigma_{\eta,h}^2), \quad \varepsilon_{it}^h \sim N(0, \sigma_{\varepsilon,h}^2), \end{aligned} \tag{6.3}$$

I estimate the deterministic component by regressing log-frailty on a fourth-order polynomial in household age.

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, $\sigma_{\pi_{25}^h}^2$. I identify them using the variances and covariances of the residuals and estimate them using standard minimum distance techniques. See Appendix B.1 for the identification restrictions and estimation details. Table 5 in Appendix B.1 reports the estimation results. The results show that frailty is increasing in age and is highly persistent, confirming the findings of

Hosseini, Kopecky, and Zhao (2022). The estimated process for non-zero frailty and the estimated probabilities of zero frailty replicate the dynamics of average frailty and its standard deviation. See Figure 3 in Appendix B.1.

6.2 Survival Probabilities

I estimate two-year survival probabilities for household heads since I equate a household's age to the age of its head. I run a logistic regression of a binary indicator for whether the head is alive or not using a fourth-order polynomial in age and frailty in the previous period as covariates. Table 6 in Appendix B.2 reports the estimation results. Age and frailty have a negative effect on 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.[10] I then correct my estimates by multiplying the estimated survival probabilities by the adjustment factor. Figure 4 in Appendix B.2 displays the corrected average two-year survival probabilities by age, which, by construction, coincide with the ones reported by the life tables.

6.3 Earnings Process

I estimate the working-age earnings process for households between 25 and 64 years old. I first deflate nominal earnings using the CPI-U with 2018 as the base year. Then, I drop the households with zero earnings.[11] I trim the sample and drop the bottom 0.5th and top 99.5th percentiles of earnings by age. Finally, I take the logarithm of the trimmed real earnings and proceed with the estimation.

I estimate the deterministic component, $\kappa(t, h)$, by regressing the logarithm of earnings on a fourth-order polynomial in age, health status, marital status, and cohort effects. The left panel Table 7 in Appendix B.3 shows the estimation results. Age positively affects earnings, which are higher for married couples than for singles.

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

[11] These are about 7% of the sample of 25 to 64-year-old households.

Using the residuals from the regression above, I identify the variances of the earnings shocks using covariance restrictions, as in Meghir and Pistaferri (2004) and Blundell, Pistaferri, and Preston (2008). Appendix B.1 presents details on the identification. The right panel of Table 7 in Appendix B.3 shows the estimated variances of the earnings shocks and Figure 5 in Appendix B.3 show the fit of my estimated earnings process. My estimated process fits the mean of log earnings remarkably well but does not accurately replicate their standard deviation. This imperfect fit is due to the permanent component's random walk specification and is a well-known fact in the earnings dynamics literature - see, for example, De Nardi et al. (2019). One can obtain a better fit of the standard deviation of log earnings by adopting a non-linear process for earnings, such as the one in Arellano, Blundell, and Bonhomme (2017).

6.4 Out-Of-Pocket Medical Expenditures

I perform minimal cleaning and selection before estimating the process for medical expenditures. I deflate nominal out-of-pocket expenses using the CPI-U and 2018 as the base year. Then, I trim the dataset by dropping the bottom 0.5th and top 99.5th percentiles by age, and I replace zero medical expenditures with a predetermined value of \$250.[12] I then take the logarithm of real medical expenditures and estimate their process following the procedure outlined in Borella, De Nardi, and Yang (2022).

I estimate the deterministic component of medical expenditures by regressing their log on a second-order polynomial in household age, frailty, marital status, family size, and cohort effects.[13] Column (1) in Table 8 in Appendix B.4 displays the estimation results for this regression. These results show that medical expenditures increase with age and frailty and are higher for couples than for singles.

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 8 in Appendix B.4 reports the estimation results. I then compute the predicted values from this regression and their

[12]The fraction of my sample with zero medical expenditures is ten percent.

[13]The PSID records medical expenditures at the household level as the sum of the expenses of each member. Therefore, we must control for family size.

variance, which provides the estimate for the variance of the i.i.d. shock. This is $\hat{\sigma}_\xi = 0.016$. Finally, I construct estimated average medical expenditures by age by adding half of the variance $\hat{\sigma}_\xi$ to the average in logs before exponentiating. Figure 6 in Appendix B.4 shows that my estimated process fits the data very well until age 80.

6.5 Calibrated Parameters

Table 9 in Appendix B.5 summarizes the parameters I calibrate 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 Paz-Pardo (2019). Finally, I set the discount factor to 0.9756 using the central value of the estimates of Gourinchas and Parker (2002).

These sections are currently work in progress

7 Second-Step Estimation Results

8 Computing the Value of Social Insurance

9 Conclusions

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Appendix

A Frailty Index

Table 2 presents the complete list of deficits I use to construct the frailty index in my sample. I use 29 deficits in total. Compared to Hosseini, Kopecky, and Zhao (2022), I add alcohol consumption as a deficit. I follow the definition of the National Institute on Alcohol Abuse and Alcoholism[14] and assign a value of one to the excessive drinking deficit if: the respondent drinks every day or several times a week and, when they drink, they have more than four drinks for a man and more than three drinks for a woman.

Table 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.

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

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

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

B First-Step Estimation

B.1 Health Process

Table 4 displays the estimation results for the probit regression for the probability of having zero frailty at each age. Figure 2 displays the share of households with zero frailty in the data and in the model.

	Household has zero frailty
Age	-0.0463***
	(0.00809)
Age^2	0.0000533
	(0.0000904)
Marital Status	-0.264***
	(0.0193)
Cohort effects	Yes
Observations	40545
Pseudo R^2	0.0767

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

Table 4: Estimation results from zero frailty probit regression. The dependent variable is a dummy equal to 1 when the households has zero frailty. The marital status variable takes value one for married and zero for single households.

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

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

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

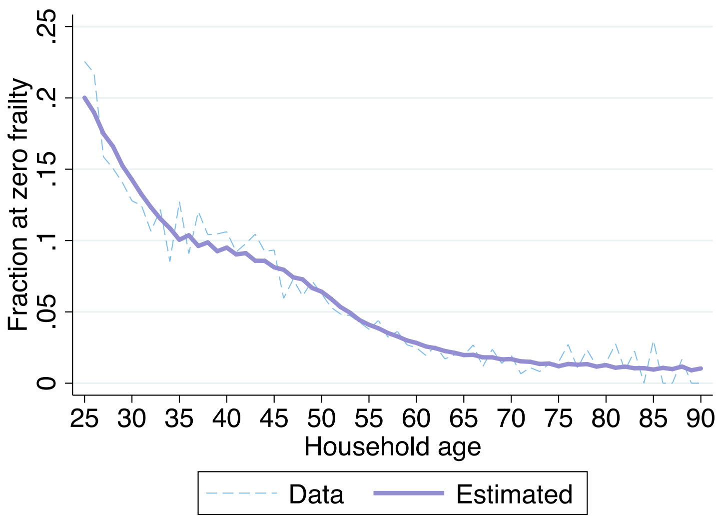


Figure 2: Share of households with zero frailty in the data (dashed blue line) and predicted by probit regression (solid purple line.)

it - together with the identification conditions above - to estimate the parameters of the stochastic part of the health process by minimum distance. Table 5 reports the estimation results for the deterministic and stochastic components of frailty.

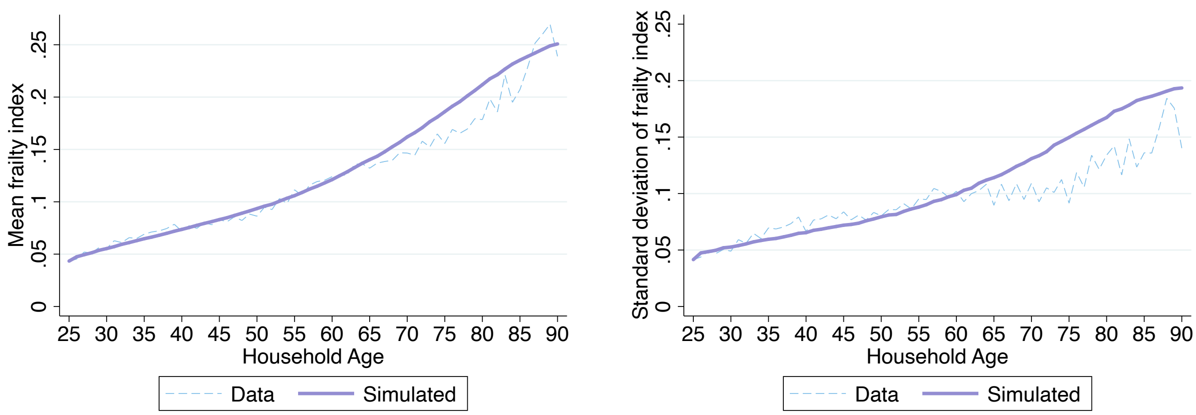
	Log frailty
Age	0.106***
	(0.0314)
Age^2	-0.00290***
	(0.000940)
Age^3	0.0000394***
	(0.0000120)
Age^4	-0.000000183***
	(5.48e-08)
Constant	-4.441***
	(0.376)
Observations	37387
R^2	0.162

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

Parameter	Value
ρ	0.965
$\sigma^2_{\varepsilon,h}$	0.170
$\sigma^2_{\eta,h}$	0.319
$\sigma^2_{\pi^h_{25}}$	0.441

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

Figure 3 displays the average household frailty and the standard deviation of household frailty in the data and the ones simulated using parameters from the estimated health process. To simulate the health process, I assign a health value at age 25 using the frailty distribution in the data. Then, I use the estimated probability of having zero frailty and the parameters for the non-zero frailty dynamics to simulate the evolution of frailty at older ages.



(a) Average frailty

(b) Standard deviation of frailty

Figure 3: Average household frailty and standard deviation in the data (dashed blue line) and predicted by estimated health process (solid purple line.) PSID, 2005-2019.

B.2 Survival Probabilities

Table 6 reports the estimation results for the logistic regression of a survival indicator. Figure 4 reports the average by age of the corrected estimated two-year survival probabilities.

B.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 detrended log earnings. In particular, I use the following:

$$cov(\tilde{y}_t, -\tilde{y}_{t+1}) = \sigma^2_{\varepsilon,y}$$

$$cov(\tilde{y}_t, \tilde{y}_{t-1} + \tilde{y}_t + \tilde{y}_{t+1}) = \sigma^2_{\eta,y}$$

$$var(\tilde{y}_{25}) - \sigma^2_{\varepsilon,y} = \sigma^2_{\pi^y_{25}}$$

	Alive indicator
Age	-1.682
	(1.037)
Age^2	0.0441
	(0.0274)
Age^3	-0.000511*
	(0.000311)
Age^4	0.00000215*
	(0.00000129)
Previous Period Frailty	-6.216***
	(0.432)
Constant	30.69**
	(14.22)
Observations	32042
Pseudo R^2	0.164

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

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

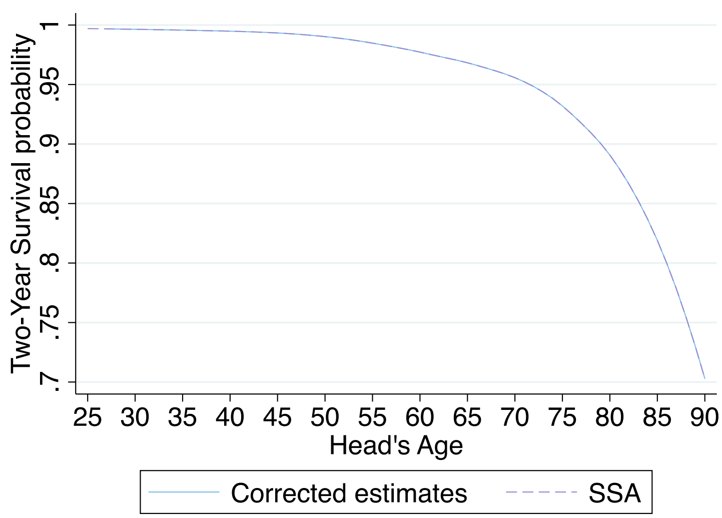


Figure 4: Average by age of the corrected two-year survival probabilities. They coincide with the ones reported by the life tables by construction. PSID waves 2005-2019.

Where period $t+1$ variables are one PSID wave - thus, two years - ahead of period t variables. Table 7 presents the estimation results for the deterministic and stochastic components of log earnings.

	Log earnings
Age	1.325***
	(0.139)
Age^2	-0.0455***
	(0.00499)
Age^3	0.000698***
	(0.0000772)
Age^4	-0.00000400***
	(0.000000437)
Marital status	0.120***
	(0.0106)
Cohort effects	Yes
Observations	32694
R^2	0.105

Standard errors in parentheses

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

Parameter	Value
$\sigma^2_{\varepsilon,y}$	0.318
$\sigma^2_{\eta,y}$	0.231
$\sigma^2_{\pi^y_{25}}$	0.805

Table 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 marital status variable takes a value of one for married and zero for single households. PSID waves 2005-2019.

Figure 5 presents the average household log earnings and their standard deviation in the data and for the simulated earnings process. To simulate the earnings process, I use the simulated frailty process and the average marital status by age from the data.

B.4 Out-of-pocket medical expenditures

Table 8 reports the estimation results for the process for medical expenditures.

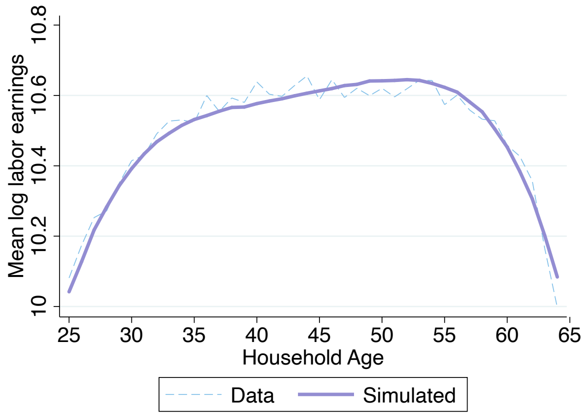
Figure 6 plots the average medical expenditures by age in the data and the estimated values.

	(1) Log Medical Expenditures	(2) Squared Residuals
Age	0.131***	-0.0672***
	(0.00537)	(0.0142)
Age^2	-0.00108***	0.000699***
	(0.0000535)	(0.000142)
Household frailty	-0.521***	2.592***
	(0.0866)	(0.229)
Marital status	0.979***	-0.502***
	(0.0172)	(0.0455)
Family size	-0.0280***	0.152***
	(0.00579)	(0.0153)
Cohort effects	Yes	Yes
Observations	40577	40577
R^2	0.141	0.00933

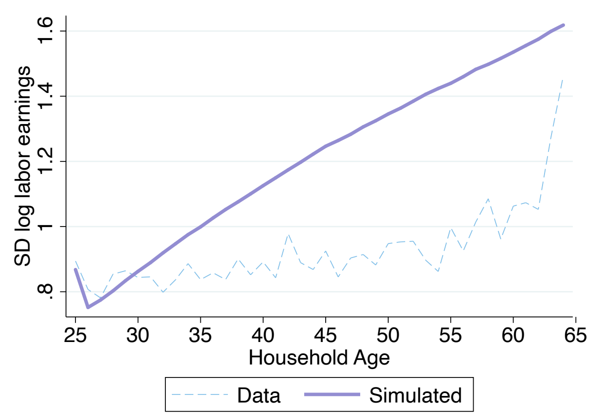
Standard errors in parentheses

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

Table 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.



(a) Average log earnings



(b) Standard deviation of log earnings

Figure 5: Average log earnings and standard deviation in the data (dashed blue line) and predicted by estimated earnings process (solid purple line.) PSID, 2005-2019.

B.5 Calibrated Parameters

Table 9 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 9: Calibrated Parameters.

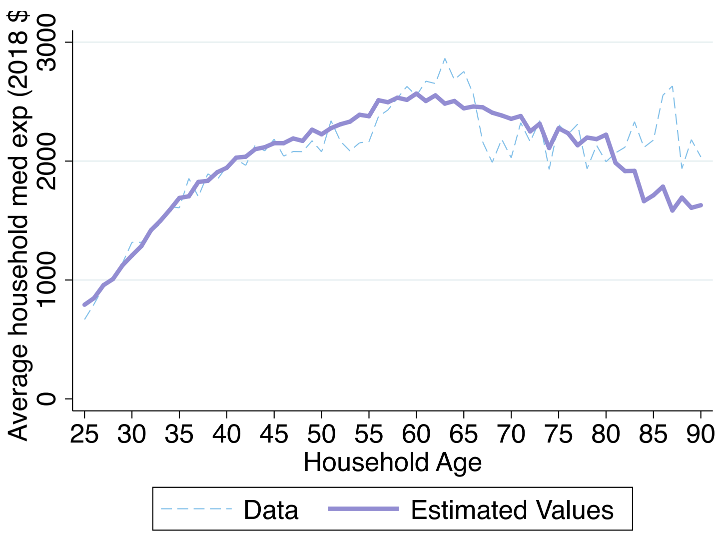


Figure 6: Caption