Long-Term Care Needs and Savings in Retirement

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Abstract

Contrary to predictions of standard life cycle models, individuals dissave slowly during retirement. I investigate the role of long-term care (LTC) needs in the saving decisions of the elderly. For this purpose, I develop and estimate a model for retired single individuals with heterogeneous LTC needs and endogenous LTC expenses. I find that the model is able to reproduce both large spending propensities when individuals are in most need and is consistent with strong bequest motives at the top of the wealth distribution. Counterfactual simulations show that both bequest and LTC needs are important drivers of savings for the old.

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Contrary to the predictions of a standard life-cycle model (Huggett, 1996), many elderly dissave slowly during retirement. Identifying the the reasons why the simple model fails is crucial for the design of policies related to health care, Social Security, and insurance markets. In the US, the risk of needing long-term care (LTC) is likely a very important driver of savings because it is insured to a lesser extent than medical expenses and it is expensive when paid out-of-pocket. This paper analyzes to what extent LTC needs, defined as assistance to perform basic tasks of everyday life, drives the savings decision of individuals late in life.

To address this goal, it is crucial to separate LTC needs from actual LTC expenditure choices taken by individuals. For this purpose, using the Health and Retirement Study (HRS), I document that LTC needs can be parsimoniously represented by four latent health states labeled as: healthy, physically frail, mentally frail, and impaired. The four health states summarize the information contained in 12 variables reporting difficulties with Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs). Healthy individuals do not need help with daily self-care activities. In contrast, physically and mentally frail individuals are in need of assistance with activities related to mobility and cognition, respectively. Finally, impaired individuals are in need of assistance with both physical and cognitive tasks. The estimated transition probabilities uncover sizeable differences in expected LTC needs across gender and income groups; in particular, women and the poor face significantly larger average duration of their LTC needs.

Based on the previous health classification, I present new empirical evidence highlighting the importance of modeling heterogeneity in LTC needs and endogenous LTC expenses in structural models. First, I find that both LTC expenses and mortality rates increase sharply as health deteriorates. In particular, healthy individuals aged 70+ do not have LTC needs and face a 7% probability of dying in a 2-year window. Physically and mentally frail individual use an average of 24 minutes and 1.5 hours of formal care per day respectively, while chances of dying are around 15% for both groups. At the extreme, an impaired individual consumes on average 4.6 hours of formal care per day and dies with a 50% probability over a two-year window. Second, I document that the observed LTC expenses reflect choices and hence cannot be taken at face value to measure need. In fact, conditional on health, richer individuals spend significantly more on formal care. An impaired individual in the top quintile of the permanent income distribution consumes three hours more of formal care per day than an impaired individual in the bottom quintile. And third, the data reveal that relatives also affect the consumption of formal care. Conditional on health, individuals who do not have access to informal care from relatives consume 2.5 times more formal care than those who have strong informal care support.

Motivated by these facts, I develop and estimate a model of single retired individuals allowing for heterogeneity in both LTC needs and family types, as well as in gender, permanent income, medical shocks, and wealth. Agents in the model derive utility from regular consumption, LTC and leaving bequests. Family types differ in the hours of informal care provided by children when the old is in need of LTC. Families provide informal care for free but agents can, on top, decide to buy formal care at a market price. The marginal utility of consuming LTC is allowed to differ depending on the level of LTC need. Finally, agents have the option to access a government means-tested program that provides a consumption floor and LTC services if necessary.

I use HRS data on savings and reported hours of formal care consumption to estimate the parameters in the model with the method of simulated moments. The estimated model is able to match the pattern of targeted features in the data as well as other important non-targeted dimensions. The estimated preference parameters imply increasing marginal propensities of care consumption as LTC needs become more acute as well as strong bequest motives for the rich. For example, the share of resources that an individual with $200K in assets would leave as a bequest in the year before her certain death moves from 72%, 70%, 56%, to 23% if healthy, physically frail, mentally frail and impaired, respectively. Therefore, the marginal propensity to spend when in need of LTC varies greatly across states of care.

Counterfactual simulations reveal how differently single retired individuals would dissave given an initial wealth endowment at age 70 and allows me to identify the relative importance of bequests and LTC needs. Results show that LTC needs are a crucial driver of savings of the old and quantitatively more important than bequests. In a world without LTC needs (bequest motives) the median wealth holdings at the age of 85 would be 36% (13%) lower than in the benchmark model. Since care consumption is estimated as a necessity while bequests are estimated as luxury, the relative importance of bequests increases as we move along the wealth distribution. In a world without LTC needs (bequest motives) the top 75th percentile of wealth holdings at the age 85 would be 26% (21%) lower.

My paper builds on earlier work by Kotlikoff et al. (1989) who underline the importance of health expenditures for understanding the lack of dissaving of the elderly. In contrast, Hubbard, Skinner, and Zeldes (1994) and Palumbo (1999) find such expenses to have a small effect. Using more recent data, De Nardi, French, and Jones (2010) for the US and Dobrescu (2015) for Europe find health-related expenses to be crucial drivers of savings. My results are consistent with theirs in the sense that health expenditures (medical plus LTC) are an important driver of savings. In addition, my model allows me to identify the independent contribution of medical and LTC expenses. My estimates show that medical expenses excluding LTC expenses have negligible effects on savings which is key for addressing effective policies aiming at increasing the welfare of the old.

Closely related to my paper, Lockwood (2018) develops a model with exogenous LTC expenses and finds that strong bequest motives can rationalize the low take-up of LTC insurance. However, by assuming exogeneity in LTC expenses, his model underestimates the sensitivity of the LTC needs on the savings behavior of the wealthiest. By making LTC expenses endogenous and by requiring the model to match consumption of formal care for different levels of the permanent income distribution, I find that LTC needs play quantitatively a bigger role as determinant of the savings behavior of the rich.

In contrast to Lockwood (2018), Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2020) estimate a much smaller intensity of the willing to bestow. Using a novel data with strategic survey questions, the authors document that when faced with hypothetical scenarios between leaving a bequest or consuming when in need of LTC, individuals report a large propensity to spend when in need of LTC. They estimate health transition probabilities using the HRS and define being in LTC need as an individual with one or more difficulties with ADLs. Then, they estimate their model to match answers to the SSQ and find LTC to be the main driver of savings while bequest motives playing a relatively minor role. In my paper, I show that LTC expenses vary importantly across levels of LTC needs. Indeed, I find that the impaired individuals, who represent only one fourth of individuals reporting difficulties with one or more ADLs in the HRS, hold marginal propensities to consume versus bequeath that are in line with the SSQs in Ameriks et al. (2020). However, in my model, both the low likelihood of becoming impaired coupled with large mortality rates limit the risk of LTC needs when impaired. Thus, in order to match asset holdings of the rich in the data, I estimate a stronger bequest motive.

Moreover, my paper is related to two studies that include LTC expenses in a general equilibrium framework. First, Kopecky and Koreshkova (2014) estimate the independent contribution of medical and nursing home expenses on aggregate wealth without considering intentional bequests. They find that savings for out-of-pocket health expenses account for 13.5 percent of the aggregate wealth, half of which is due to nursing home expenses. Second, İmrohoroğlu and Zhao (2018) find that the deterioration of informal care provision due to the one-child policy can to account for around half of the increase in the saving rate in China between 1980 and 2010.

My paper is also connected to the literature analyzing the provision of informal care from relatives both theoretically and empirically. On the theory side, I disentangle regular consumption and LTC expenditure choices taking family care as given. As opposed, a recent strand of the literature analyzes family care arrangements as the outcome of a bargaining process between an elderly parent and her adult child fixing LTC expenses exogenous across arrangements (Barczyk and Kredler 2018; Fahle 2015; Ko 2017; Mommaerts 2015). By abstracting from the children's problem, I am able to add heterogeneity in LTC transitions across income levels and gender, a persistent shock to medical expenses, and to allow agents to adjust LTC spending. On the empirical side, there is a lack of consensus on how future bequests affect the provision of informal care. On the one hand, Brown (2006) and Groneck (2016) find that end-of-life transfers tend to favor both current and expected caregivers. On the other hand, Mukherjee (2020) using variation in Social Security benefits finds little support for exchange motivated transfers.

The rest of the paper is organized as follows. In Section 1, I explain how I identify different levels of LTC needs from the data and document new facts on LTC expenditure choices. Then, I propose a model that is able to accommodate these facts in Section 2. In Section 3, I present counterfactual experiments to quantify the forces affecting the saving behavior. Section 4 concludes.

1 Heterogeneous Long-Term Care Needs and Formal Care Choices

In this section, I first describe how I identify heterogeneity in LTC needs using the HRS. Next, I explain the different formal care expenditure choices that individuals make to deal with these needs.

1.1 Heterogeneous Needs

The HRS is a longitudinal survey nationally representative of Americans above age 50 conducted by the University of Michigan. It contains a wide array of health variables analyzing the individual's desire for consumption of LTC services. Given its panel structure, the HRS is ideal for analyzing different levels of LTC needs and their dynamics over time which crucially affect individuals' saving and consumption decision.

In order to classify individual health status, I follow Amengual, Bueren, and Crego (2017). The authors exploit information contained in 12 dummy variables that characterize individual's reported difficulty with ADLs and IADLs. Each variable is equal to 1 if the individual reports difficulty and 0 otherwise. ADLs were proposed by Katz, Ford, Moskowitz, Jackson, and Jaffe (1963) as a measure of patient's independence with basic personal tasks of everyday life such as being able to get in or out of bed. IADLs, in contrast, consist of activities more closely related to cognition. Examples of the latter include the ability to use a phone or controlling her medication. Thus, both ADLs and IADLs are related to the individual's LTC needs.[1]

Amengual et al. (2017) assume that the main source of heterogeneity in I-ADLs[2] in the population is represented by a finite number of possible health groups that are not observed by the econometrician. They consider that each individual belongs to one health group and that health groups differ in the probability of reporting a difficulty with each I-ADL. Therefore, individuals within the same health group have the same probabilities of experiencing problems with any I-ADL but these probabilities might vary if individuals belong to a different group.

On top, dynamics, i.e the probability of moving from one health group to another, and survival rates, are jointly estimated conditioning on individual's cubic in age, gender, gender interacted with age, a quadratic in permanent income decile, and the permanent income decile interacted with age. Permanent income is computed as the individual's average non-asset income over all periods during which she is observed. Non-asset income includes Social Security benefits, defined pensions benefits and annuities.

Amengual et al. (2017) estimate their econometric model by pooling single and married individuals. For the purpose of my study, I re-estimate the model restricting the sample to single individuals in the HRS from 1996 to 2014[3] and

[1] ADLs: Some difficulty with dressing (DRESS), using the toilet (TOILET), bathing (BATH), getting in or out of bed (BED), to walk across a room (WALK) and eating (EAT). IADLs: Some difficulty with preparing a hot meal (MEALS), shopping for groceries (SHOP), managing money (MONEY), taking medications (MEDS), using a phone (PHONE), and using a map (MAP).

[2] I use I-ADLs to refer to both ADLs and IADLs

[3] There was a change in the HRS in the number of adls asked prior to 1996, thus I drop observa-

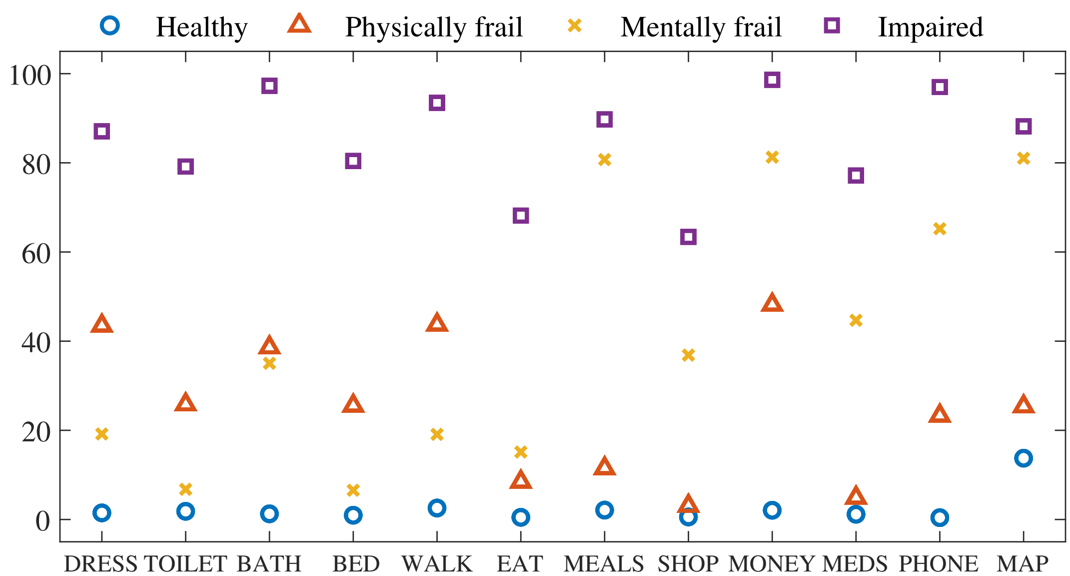


FIGURE 1. PROBABILITY OF REPORTING DIFFICULTY WITH ANY I-ADL BY HEALTH GROUP

aged 70 or older. The estimation of the econometric model shows that variation in LTC needs can be parsimoniously represented by four clearly different health states of need: the healthy, the physcally frail, the mentally frail, and the impaired[4]. The healthy are those individuals whose probability of declaring problems with I-ADLs is close to 0 for every I-ADL and thus do not require LTC. The physically frail have problems with physical activities while the mentally frail have problems mainly with activities related with cognition. Finally, the impaired show problems with both cognitive and physical activities.

However, in order to characterize the risk of LTC needs, one must take into account not only the severity of the different levels of need but also their dynamics. The left panel of figure 2 shows the estimated two-year mortality rates for women in the median of the permanent income distribution. The figure shows that survival

tions from earlier waves

[4]The reader is referred to the original paper for details on the estimation procedure

probabilities sharply decrease as individual's health status deteriorates. The differences are salient even after conditioning on being in need of LTC: for example a woman who is impaired faces a mortality rates which is twice as large as a women who is mentally frail. Differences in mortality rates and transitions across health states characterize the duration that individuals expect to live in different levels of LTC need. Table 1 summarizes the expected duration in each health status at age 70 for the top and bottom PI deciles across gender. The first column sums the expected duration in all possible health states which is equal to the life expectancy at age 70. The table shows dramatic differences in health dynamics across permanent income groups. An individual in the top of the permanent income distribution expects to live around 5 years longer than an individual in the bottom. Moreover, richer individuals live healthier lives with a shorter expected duration in need of LTC. The right panel of figure 2 compares the share of impaired women conditional on being alive for the top (thick line) and the bottom PI decile. The share of impaired individuals in the top permanent income decile at the age of 80 is around 50% of those in the bottom permanent income decile.

All in all, I have shown that first, LTC needs can be parsimoniously represented by four different health groups. Second, the estimated transition probabilities imply that as health deteriorates, mortality rates sharply increase. Finally, there is a strong health income gradient with poorer individuals facing larger expected LTC needs in spite of living shorter lives.

1.2 Choices

In order to understand how LTC needs affect savings of the old, I analyze how the consumption of formal care varies across levels of need. For this purpose, I make

Table 1. Expected duration of each health state at age 70 across permanent income deciles and sex

Permanent income	Total	=	Healthy	+	Physically frail	+	Mentally frail	+	Impaired
					Men				
Bottom	7.9		4.6		1.7		0.6		1.0
Top	12.8		10.4		1.3		0.5		0.6
					Women				
Bottom	11.3		5.9		2.6		1.3		1.5
Top	16.5		12.3		2.0		1.0		1.2

Source: HRS 1998-2014. Single and retired individuals in the sample. The second column sums the expected duration in all possible health states which is equal to the life expectancy at age 70.

use of the HRS helpers files that contain information on help provided with I-ADLs. This module of the HRS includes information on hours of care provided as well as on the identity of the helpers. I classify informal care received as care provided by relatives (mainly children) or friends and formal care as care provided by a paid helper, a professional or an employee of an institution.

Table 2 shows average formal care hours consumed across health status and permanent income quintiles [5]. As the table shows, individuals adjust their formal care consumption in two ways. First, as health deteriorates, individuals consume more care. While the average consumption on formal care is 24 minutes per day for the physically frail, it rises to 4.3 hours of care per day for the impaired. At 18$ per hour of care[6], formal care can constitute a significant financial burden for the old.

[5]I treat reported formal care hours for individuals in nursing homes as missing since they tend to under-report the amount of care received. Indeed, 80% of the institutionalized individuals report zero formal care. Formal care hours consumed for impaired individuals in the top of the permanent income distribution drops to 4.9 hours of care when considering nursing home residents.

[6]Source: LongTermCare.gov. Lockwood (2018) finds relatively small differences in the price of care across permanent income groups.

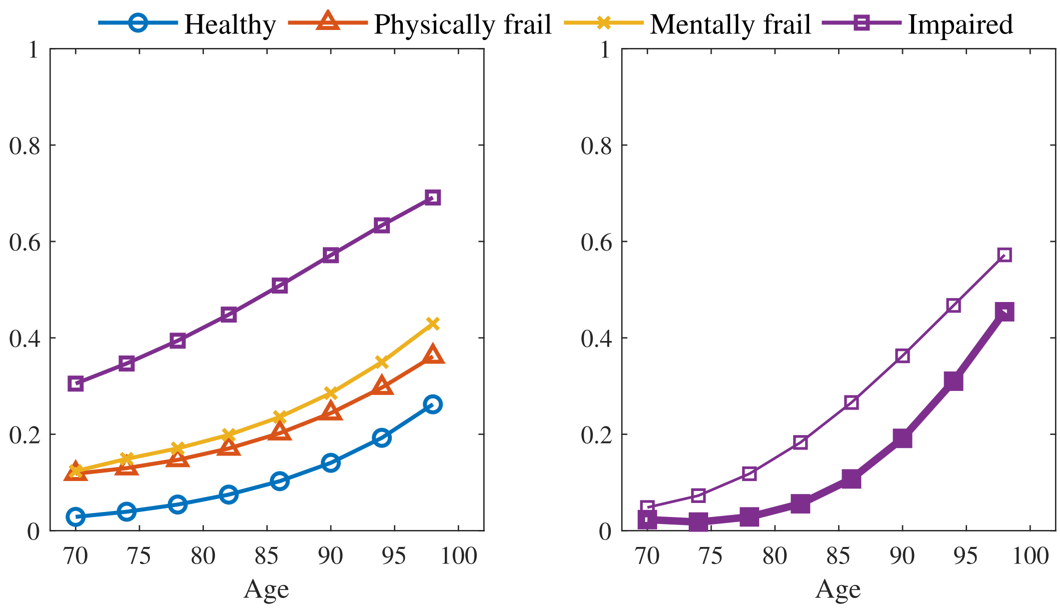


FIGURE 2. TWO-YEAR MORTALITY RATES ACROSS HEALTH GROUPS FOR WOMEN (LEFT PANEL) AND SHARE OF ALIVE INDIVIDUAL IMPAIRED FOR TOP (THICK LINE) AND BOTTOM (THIN LINE) DECILE OF PERMANENT INCOME DISTRIBUTION (RIGHT PANEL)

Nevertheless, as shown in the previous section, the persistence of large LTC needs is limited by high mortality rates.

Second, conditional on needs, richer individuals consume more care. This finding suggests that LTC expenses cannot be taken at face value to measure risk. For example, when impaired, an individuals in the top decile of the permanent income distribution consumes 3 hours more of formal care per day than an individual in the bottom decile.

Next, I document how access to informal care can alleviate individual's care needs. To do so and in order to summarize the large heterogeneity in the provision of informal care observed in the data, I group all individuals into three equally likely family types according to their provision of informal care as observed in the data: *close families*, *distant families*, and *on your own*. *Close families* are those

TABLE 2. FORMAL CARE HOURS PER DAY ACROSS PERMANENT INCOME QUINTILES

Health status	Permanent income quintile Bottom	Middle	Top
Physically frail	0.5	0.4	0.6
Mentally frail	1.1	1.4	1.7
Impaired	2.9	4.1	5.9

Source: HRS 1998-2014, single and retired individuals aged over 70. Reported hours of formal care from non-institutionalized individuals.

whose reported informal care hours lie in the top tercile of the informal care hours conditional on health status. *Distant families* are those whose reported informal care hours lie in the middle tercile while *on your own* individuals lie in the bottom tercile of the informal care hour distribution.

Table 3 shows average formal care and informal care hours per day across family types. When impaired, while an individual in a *close family* receives 13.6 hours of informal care when in need of LTC, an individual who is *on his own*, barely receives any care. Moreover, the table shows that individuals with access to informal care greatly reduce their formal care consumption. For example, an *on your own* individual consumes around 7.3 hours of formal care per day when impaired while an individual in a *close family* consumes 2.4 hours per day.

In summary, I document that individuals greatly adjust their consumption of formal care depending on three characteristics: state of need, financial resources, and access to informal care from relatives. I now develop a structural model that is able to replicate these facts.

TABLE 3. FORMAL AND INFORMAL CARE HOURS PER DAY ACROSS FAMILY TYPES

Family Types	Health Status	Informal Care Hours per day	Formal Care Hours per day
On your own	Physically frail	0.0	0.5
On your own	Mentally frail	0.1	2.2
On your own	Impaired	0.0	7.3
Distant	Physically frail	0.2	0.4
Distant	Mentally frail	1.1	1.4
Distant	Impaired	1.1	6.3
Close	Physically frail	3.6	0.5
Close	Mentally frail	9.0	0.7
Close	Impaired	13.6	2.4

Source: HRS 1998-2014, single and retired individuals aged over 70. Reported hours of formal care from non-institutionalized individuals.

2 The Model

Motivated by the previous section, I build a structural model that includes heterogeneity in LTC needs and that can reproduce the main features of the data: (i) as health deteriorates, individuals increase their consumption of formal care, (ii) richer individuals consume more care hours, and (iii) individuals with higher access to informal care, consume less formal care.

The model closely follows De Nardi et al. (2010) but at the same time incorporates three important elements to disentangle LTC choices from LTC needs. First, in order to capture the correlation between frailty and survival probabilities, LTC needs are heterogeneous. Second, agents in the model suffer health shocks that affect individuals' marginal utility of care consumption allowing individuals to adjust care consumption based on their available financial resources. Third, there are two types of care: formal care bought at a market price and informal care provided by families for free. Agents are ex-ante heterogeneous with regards to their family type, which differs in the amount of care provided. Individuals decide on formal care consumption taking the informal care provided by their families as given. Agents start their life at age $a = 70$ and live at most 110 years old. In order to match HRS data, every period lasts for two years of time: $a \in \{70, 72, ..., 110\}$.

Preferences.— Individuals derive utility from regular consumption and care hours. The marginal utility of consuming care hours is allowed to vary depending on health status. Health status h can take five values: healthy ($h = 1$), physically frail ($h = 2$), mentally frail ($h = 3$), impaired ($h = 4$) and dead ($h = 5$). Furthermore, individuals in need of LTC ($1 < h < 5$), receive informal care hours (l_{ic}) depending on their family type (F) and their health status. Following the empirical section, there are three types of families in the model: *on your own* ($F = 0$), *distant* ($F = 1$) and *close* $F = 2$.

Each period their utility flow is given by,

$$u(c, l_{fc}, l_{ic}; h, F) = \frac{c^{1-\sigma}}{1-\sigma} + \exp(\alpha(h)) \frac{\Big[l_{fc} + l_{ic}(h, F)\Big]^{1-\nu}}{1-\nu} \tag{1}$$

where, c is regular consumption expressed in dollar values, l_{fc} is hours of care spent in formal care and l_{ic} the informal care provided by relatives. α is the LTC needs shifter, which affects the marginal utility of consuming care hours. σ and ν are the risk aversion parameters of regular consumption and total care hours, respectively. I normalize $\alpha(h = 1) = 0$ so that healthy individuals do not derive utility from consuming care.

When the person dies, individuals derive utility from leaving bequest according to:

$$\phi(k) = \exp(\lambda)\frac{(k+\delta)^{1-\sigma}}{1-\sigma}, \tag{2}$$

where k denotes savings from the previous period, δ captures the extent to which bequests is a luxury good or a necessity and λ captures the intensity of the bequest motive.

Medical expenses uncertainty.— Individuals face uncertainty in out-of-pocket medical expenses (m). I follow French and Jones (2004) and model log health costs as the sum of a white noise process and a persistent AR(1).[7] The mean of log medical expenses and the variance of the shock is a function of health status, age, sex, and permanent income.

$$\ln m_{i,t} = m(h, a, s, PI) + \gamma(h, a, s, PI)\psi_{i,t} \tag{3}$$

$$\psi_{i,t} = \xi_{i,t} + \zeta_{i,t},\ \zeta_{i,t} \sim N(0, \sigma_\zeta^2) \tag{4}$$

$$\xi_{i,t} = \rho\xi_{i,t-1} + \epsilon_{i,t},\ \epsilon_{i,t} \sim N(0, \sigma_\epsilon^2) \tag{5}$$

Government insurance.— Agents have the option of using a means-tested government program. In case an individual decides to use the government program, consumer's wealth is set to zero [8] and the government provides a utility floor. The government implements the utility floor by transferring the minimum resources possible $\underline{x}(h)$ such that an individual not receiving any informal care, achieves the floor. I define $G = 1$ if the consumer chooses to use the program and $G = 0$, otherwise.

[7] In the model, medical expenses are considered as shocks. Moreover, I do not allow care consumption to affect future LTC needs. A different approach, based on Grossman (1972), is to consider health related expenses as investment (Ozkan 2017; Yogo 2016). However, many studies in the empirical literature have found such effects to be small: Brook et al. (1983), Fisher et al. (2003) or Finkelstein and McKnight (2008).

[8] In reality, Medicaid has an asset disregard threshold whose modal value across states is $\$2,000$. For simplicity, I set this threshold to zero.

Government transfers are then given by:

$$\max\{0, \underline{c}(h) + p_{fc}\underline{l}(h) + m - b - (1+r)k\}, \tag{6}$$

where p_{fc} denotes the market price of an hour of formal care and $\underline{c}(h)$ and $\underline{l}(h)$ denote the level of consumption and care hours, respectively provided by the government. I assume that the government optimally splits $\underline{c}(h)$ and $\underline{l}(h)$ given $\underline{x}(h)$ to maximize the agent's utility.

Solution method.— To save on state variables, I redefine the problem in terms of cash in hand, x:

$$x = (1+r)k + b(s, PI) - m. \tag{7}$$

Given a set of parameter values, I can solve the model numerically by backward induction starting at age $a = 110$. We can write the model in recursive form in terms of cash in hand. β represents the discount factor. The value function is given by:

$$\begin{aligned} V_a(x, h, \zeta, s, PI, F) = \max_{c, l_{fc}, G} \Big\{ & u(c, l_{fc}; h, F) \\ & + \beta \pi_{h' \neq 5, h, a, s, PI} E_t[V_{a+2}(x', h', \zeta', s, PI, F)] \\ & + \beta \pi_{h'=5, h, a, s, PI} \phi(k') \Big\} \end{aligned} \tag{8}$$

subject to

$$x' = (1-G)\Big[(1+r)(x - c - p_{fc}.l_{fc}) - m'\Big] \tag{9}$$

$$G = 1 \Leftrightarrow \begin{cases} c = \underline{c}(h) \\ l_{fc} = \underline{l}(h) \end{cases} \tag{10}$$

2.1 Estimation

I estimate the model using a two steps Method of Simulated Moments (MSM) estimator following Gourinchas and Parker (2002) and Cagetti (2003). In the first step, I estimate all the parameters that can be identified out of the model. In the second stage, I estimate the remaining parameters using the model and taking first-step parameters as given.

First stage parameters include non-asset income levels, health transitions, hours of care received in each type of family, and medical expenses. In the second stage, I estimate the set of parameters $\theta = (\sigma, \nu, \delta, \underline{u}, \alpha(h), \lambda)$ that minimize the distance between simulated wealth and formal care hours moments with their empirical counterparts.

2.1.1 First Stage Parameters

Permanent income.— To compute permanent income, I consider individual non-asset income in each wave. Non-asset income is the sum of Social Security benefits, defined benefit pension benefits, and annuities. I do not include means-tested government transfers such as Supplemental Security Income or food stamps because agents in the model have access to social insurance. Next, I, define permanent income for each individual as average non-asset income across all waves in which she is observed. Finally, I split the distribution into deciles of the permanent income distribution. Each individual in the simulation receives the median non-asset income by gender of her permanent income decile.

Medical expenses.— The health expenditure model is estimated using HRS data 1996-2014. Details on the estimation procedure can be found in Appendix D. When estimating medical expenditures, I drop individuals living in nursing homes or in Medicaid since LTC expenditures and government transfers are modeled explicitly. I jointly estimate the mean and variance of log-medical expenditures. The mean is modeled conditional on age, age squared, sex, PI ranking dummies, health dummies and PI interacted with health.

Hours of care provided by the family.— Following the empirical section, I assume that there exist three family types: *on your own*, *distant* and *close*. Individuals in the *on your own*, *distant* and *close* category receive the average value of the bottom, middle, and top tercile of the informal care hours distribution, respectively.

Discount factor and price of formal care.— I set the discount parameter to 0.95 and hourly price of formal care to 18$ per hour. [9]

2.1.2 Second Stage Moments

Empirical wealth moments.— Wealth moments track the evolution of wealth as members of the sample age. I group individuals depending on age at first interview. Individuals belonging to groups 1 to 4 were interviewed for the first time when they were aged 70-74, 75-79, 80-84, and ≥ 85 respectively. For each group and permanent income quintile, I compute the median wealth as individuals age. Thus, there are potentially 160 targeted wealth moments (5 permanent income groups $\times$ 8 waves $\times$ 4 groups).

Formal care moments.— The empirical care moments are average formal care hours across permanent income groups, family types and health status, leaving a total of 24 formal care moments (5 Permanent income groups $\times$ 3 LTC need status + 3 family types $\times$ 3 LTC need status).

[9] see Lockwood (2018) price of unskilled formal care

2.2 Simulation Procedure

I simulate a large number of artificial individuals. Each of these individuals is endowed with a value of the state vector $(a, s, k, b, h, \zeta, \xi, F)$. (a, s, k, b) are drawn from the data distribution when individuals are first observed. ζ and ξ are Monte Carlo draws from discretized versions of the estimated shock processes.

Sampling family types.— Individuals in the model need to be given a family type before the start of the simulation. However, family types are observed only for a fraction of the total sample because in the HRS, only individuals reporting difficulties with I-ADLs answer questions related to the provision of informal care hours. Therefore, I impute the family type for individuals who never report difficulties with I-ADLs. For this purpose, I run an ordered logit model on the family type against individual time invariant covariates for the sample of individuals for whom I observe the family type.[10] Based on the order logit estimated coefficients, I compute predicted probabilities for the remaining individuals in the sample. In the simulation, I bootstrap the family type for all individuals whose family type I do not observe.

Moreover, due to differences in reported care hours across waves, an individual might be classified as *on your own* in one wave but as *distant* in a different wave. For these individuals I consider the family type as latent and sample the family type based on the frequency a given family type was observed in the data.

Sampling health status.— Following De Nardi et al. (2010), the simulation uses each individual's survival history in 2000-2014 to ensure that individuals contribute to the same wealth moments in the simulation as in the data. Furthermore, given

[10]The included covariates are: gender, permanent income decile, number of children, race, religion, marital status (widowed, divorced or ever single), education, children education, has a daughter.

the latent nature of the health classification, I use the Kim smoother proposed by Kim (1994).[11]

Procedure.— Given a guess for my parameter vector θ, I solve the model using discrete value function iteration. This yields a set of policy function which allows me to simulate the savings decision and consumption of formal care hours for each artificial individual. The optimal choice of $\hat{\theta}$ is the solution to the criterion function:

$$\hat{\theta} = \arg\min_{\theta}(\mathbf{m}_{\text{data}} - \mathbf{m}_{\text{sim}}(\theta))\mathbf{W}(\mathbf{m}_{\text{data}} - \mathbf{m}_{\text{sim}}(\theta))' \tag{11}$$

I restrict moment condition with at least 40 observations. Thus the final estimation of θ is based on 146 moment conditions. The weighting matrix (**W**) used in the estimation is the optimal variance-covariance matrix of the moment conditions, meaning, more precisely estimated data moments receive greater weight in the estimation.

2.3 Identification

In this section I informally discuss how targeted moment conditions allow me to identify parameters in the model. The model can generate a slow asset decumulation of the elderly rich through different channels: high risk aversion, low consumption floors, high bequest motives or large marginal utilities from consuming care.

Risk aversion in consumption is identified by the curvature of wealth trajectories across age. As individuals age and the level of uncertainty is reduced, risk aversion lowers the willingness to accumulate precautionary savings affecting the

[11] Appendix C derives the smoother equations) in order to ensure that the simulated health draws have the same persistence as the estimated health process

concavity of wealth trajectories with age. Bequests and government insurance both generate differences in the dissaving pattern across the permanent income distribution. Identification of one from the other arises from exploiting variation across age. Early in retirement, mortality rates are still low and differences in the savings behavior are mainly driven by the generosity of government insurance. As individuals age, the chances of dying increases and thus the willingness to bequeath can be pinned down. Finally, the parameters driving the marginal utility and risk aversion of care can be identified by matching formal care hours. More precisely, from the intra-temporal first order conditions, I get the optimal ratio of formal care hours to regular consumption.

$$\frac{l_{fc}}{c} = \mu(h) p_{fc}^{-1/\nu} c^{\sigma/\nu - 1},$$

therefore, the risk aversion in care hours can then be determined by the income gradient in formal care hours consumed. In case care was regarded as luxury, hours of care would be a convex function with respect to regular consumption. The marginal utility of care can be identified from average care hours consumed across health states. I achieve additional identification of the parameters governing the marginal utility of care and bequests by requiring the model to match formal care hours for different levels of informal care provision across families.

2.4 Estimated Parameter values

Table 4 shows the estimated preference parameters. The estimate for σ, the coefficient of risk aversion for regular consumption, is 2.49. De Nardi, French, and Jones (2016) estimate $\sigma = 2.83$ while Ameriks et al. (2020) estimate $\sigma = 5.6$. My estimate of ν, the coefficient of risk aversion for care hours, is 2.8. On top, the estimated care multipliers across different health states imply that, as expected,

TABLE 4. ESTIMATED PREFERENCE PARAMETERS

Risk Aversion		
σ: Consumption	2.49	(0.15)
ν: Care hours	2.84	(0.12)
LTC Needs		
$\alpha(h=2)$: Physically frail	1.06	(2.91)
$\alpha(h=3)$: Mentally frail	8.14	(1.08)
$\alpha(h=4)$: Impaired	11.79	(1.24)
Bequest		
δ: curvature	5,818.92	(1,595.09)
λ: marginal utility	10.05	(0.99)
Maximum transfer to achieve utility floor $\times 10^3$		
$\underline{x}(h=1)$: Healthy	6.25	(0.59)

Notes: Standard errors are reported in parentheses and clustered at the individual level.

individual's marginal utility of consuming care increases with deteriorating health conditions. Risk aversion and care multipliers estimates imply that care is an inferior good with richer individuals spending a slightly lower share of total consumption on formal care than the relatively poor. This share, however, increases as health deteriorates. For example, the share devoted to formal care for an individual spending $\$20,000$ on total consumption and no access to informal care will be 6.5%, 47%, and 78% when physically frail, mentally frail and impaired, respectively.

The transfer needed to achieve the utility floor when healthy corresponds to $6,025 per two years which lies within range of the previous estimates. For example, De Nardi et al. (2010) estimate it to be $2,663 per year and Lockwood (2018) estimate at $19,000 per year.

Strength of the bequest motive and willingness to bequeath.— Following Ameriks et al. (2020), I compare the intensity of the bequest motive implied by my estimated preference parameter to those estimated in lead papers. For this purpose, I solve the following maximization problem for different parameter values from the literature[12]:

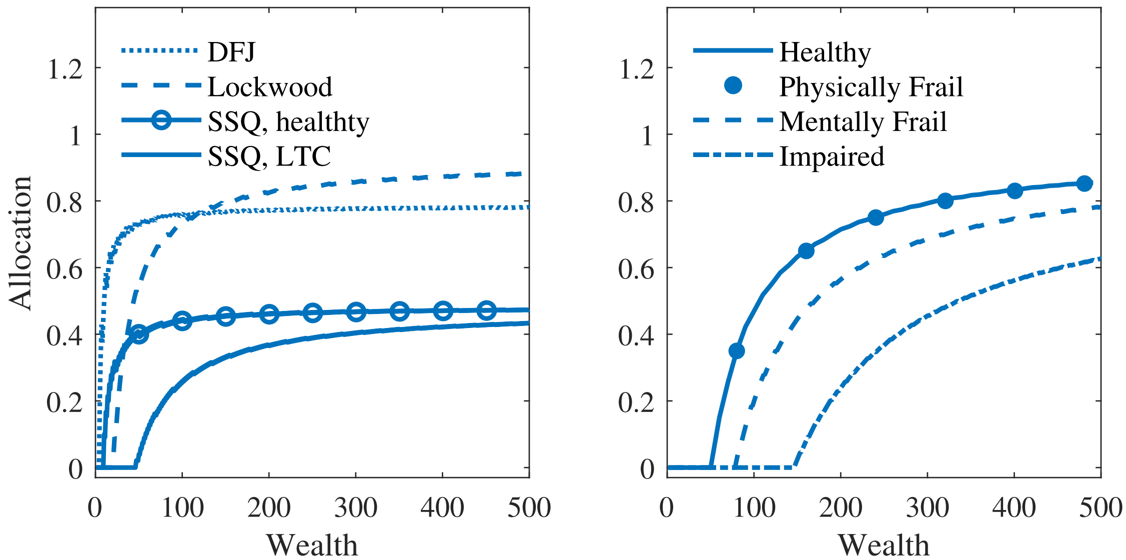
$$\max_{c,l_{fc},k} \frac{c^{1-\sigma}}{1-\sigma} + \exp(\alpha(h))\frac{l_{fc}^{1-\nu}}{1-\nu} + \exp(\lambda)\frac{(k+\delta)^{1-\sigma}}{1-\sigma} \tag{12}$$
$$s.t.\; W = c + k + l_{fc}p_{fc}$$

The left panel shows large differences in the strength of the bequest motives estimated for Ameriks et al. (2020) when healthy (SSQ, healthy) and when in need of LTC (SSQ, LTC) and Lockwood (2018) (Lockwood) and De Nardi et al. (2010) (DFJ). For individuals holding more than \$200K in assets De Nardi et al. (2010) and Lockwood (2018) estimate a bequest motive which is around twice as large than the one estimated by Ameriks et al. (2020). Moreover, differences in the bequest allocation across health status are relatively modest in Ameriks et al. (2020) beyond \$200K.

The right panel of figure 3 shows that the strength of my estimated preference parameters for healthy individuals line-up well with those estimated by De Nardi et al. (2010) and by Lockwood (2018) for relatively rich individuals. Nevertheless, for the relatively poor, the bequest motives is activated at a larger value. A reason for the discrepancy is that I target the wealth trajectories of all single retired individuals in the HRS and not only those interviewed from 1996 onward. Therefore, I am including individuals from later refreshment samples who were more exposed to the Great Recession. On the other hand, the share of resources allocated to bequests when impaired in my model is similar to that of Ameriks et al. (2020) when

[12] To make my estimates comparable to the previous literature that use annual models, I multiply the consumption part of equation (12) by 0.5

FIGURE 3. BEQUEST ALLOCATION ACROSS STUDIES



Notes: De Nardi et al. (2010): DFJ; Ameriks et al. (2020): SSQ; Lockwood (2018): Lockwood (left panel) vs proposed model for individuals without access to informal care (right panel).

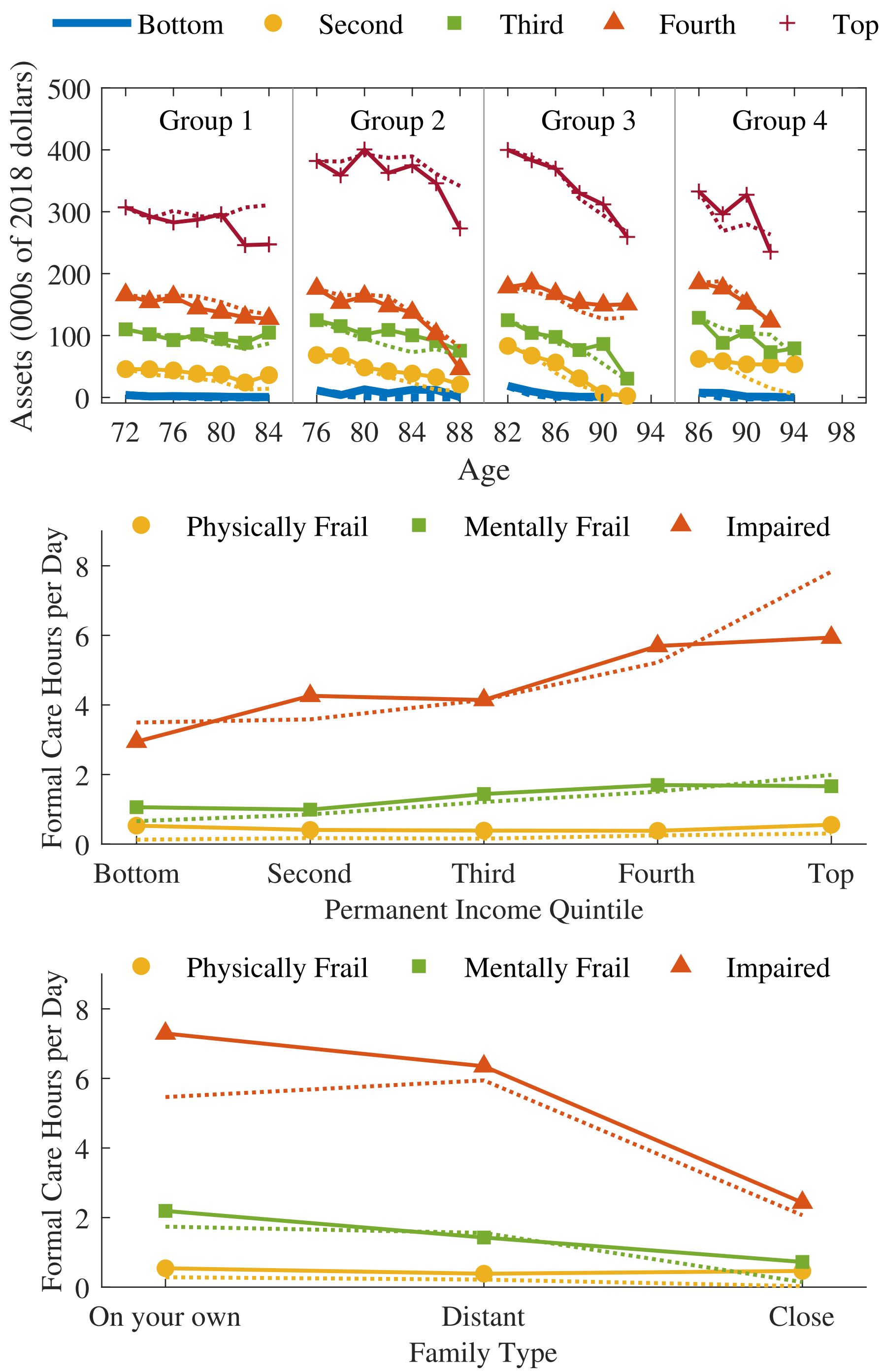
individuals are in need of LTC. Thus, my model matches well the lab data on LTC spending that is used in Ameriks et al. (2020).

2.5 Model Fit

Figure 4 reports the model fit for the targeted wealth moments. In general, the model is able to quantitatively replicate the key features of the data. Figure 4 shows that the model can generate the lack of disssaving of the elderly rich, the increasing consumption of formal care as health deteriorates, and the size of the income gradient of formal care consumption. Besides, figure 4 shows that the model captures well the role played by families at reducing the amount of formal care hours bought.

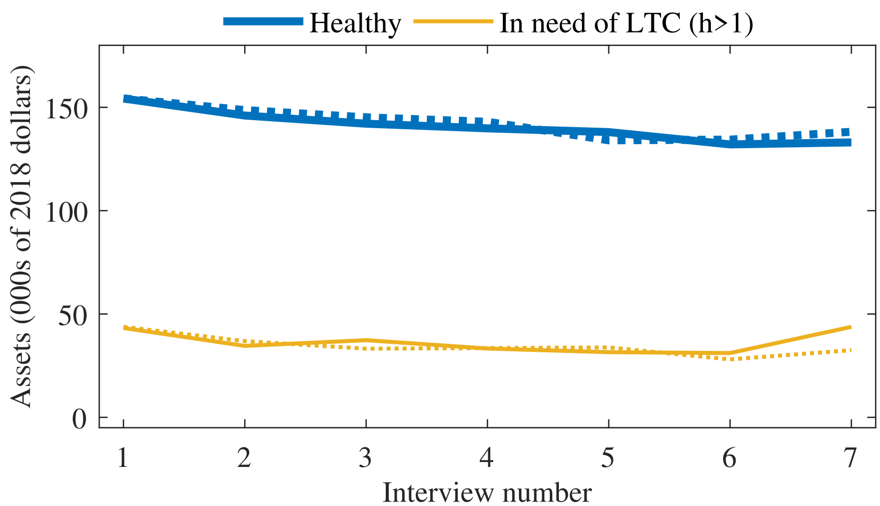
In favor of parsimony the model does not allow the marginal utility of regular

Figure 4. Model Fit: Median Assets (Upper Panel), Average Formal Care Hours Across Permanent income Quintile (Middle Panel), and Average Formal Care Hours Across Family Types (Lower Panel)



Notes: Figure compares data (solid) and simulated (dotted) moments. Retired single individuals in the HRS 1998-2014. In the upper panel individuals in groups 1 to 4 were age 70/74, 75/79, 80/84 and 85+ at first interview, respectively

FIGURE 5. INFORMAL VALIDATION: MEDIAN WEALTH ACROSS HEALTH STATES



Notes: Figure compares data (solid) and simulated (dotted) statistics. Retired single individuals in the HRS 1998-2014.

consumption to vary with health. In case, the marginal utility of regular consumption felt sharply as health deteriorated my model would be overestimating decumulation of assets when in need of LTC.[13] In order to informally validate the model along this dimension, I check the implied differences in median wealth across individuals in different health status. For this purpose, I group individuals depending on whether they are in need of LTC and track their median level of wealth across interviews. Figure 5 shows that the model is able to track the median wealth of individuals across health states even if these are not explicitly targeted in the estimation.

[13]There is no consensus in the literature on how worsening health affects consumption. While Evans and Viscusi (1991) find no effect of health changes on consumption, Finkelstein, Luttmer, and Notowidigdo (2013) and Blundell, Borella, Commault, and De Nardi (2020) find significant declines in the marginal utility of consumption as health deteriorates.

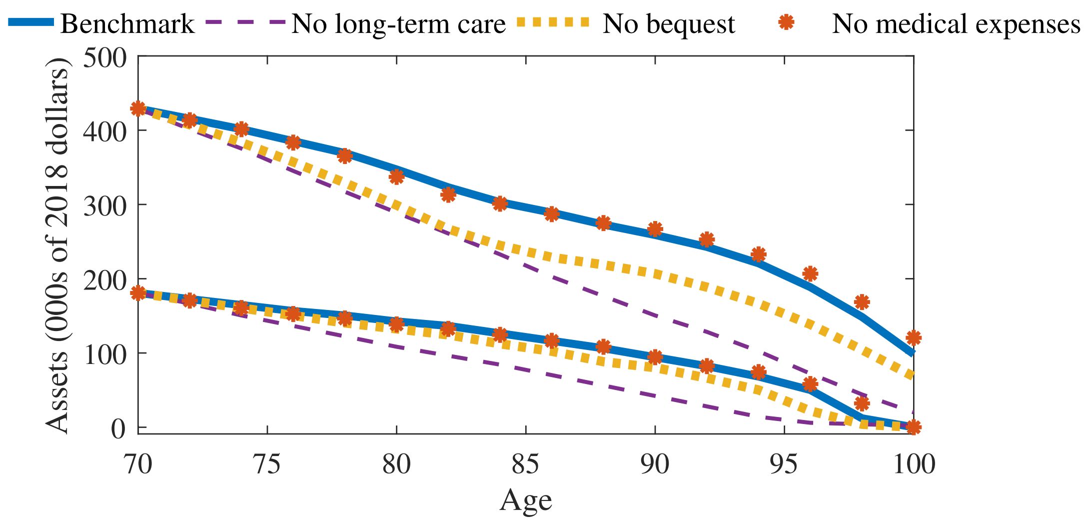
3 Results

In order to identify the key drivers of savings of the elderly, I use the model to run a set of counterfactual scenarios. For this purpose, I fix the estimated parameters at their benchmark values and change one feature of the model at a time. I then compute the optimal savings decisions, simulate the model, and compare the resulting asset accumulation profile to the asset profile generated by the baseline model. I display the median assets for individuals who were aged 70-74 at their first interview (Group 1). To focus on underlying changes in saving, I display the asset distribution for individuals who live until age 100.

I run three counterfactual simulations. First, to determine the importance of LTC needs, I simulate the model by setting the utility derived from LTC to zero ($\mu(.) = 0$). This could be seen as if families were providing enough informal care so that LTC would not distort the savings decisions of the old. Second, to determine the importance of bequests, I set the utility of leaving bequest to zero. Finally, in order to identify the role of medical expenses, I shut down medical expenses. This could be seen as if Medicare covered 100% of medical expenses.

Figure 6 plots the median and the 75th percentile of wealth holdings in the benchmark model and in the three counterfactual scenarios. It shows that between age 70 and age 85, LTC and bequests motives are the main reasons why the elderly rich don't dissave at a faster pace. Quantitatively, in the absence of LTC (bequest), the top 75th percentile of the wealth distribution at age 85 is 26% (21%) lower than in the benchmark. Besides, figure 6 shows that medical expenses are negligible for explaining the lack of asset deccumulation during old age. As such, the results imply that Medicare and Medicaid provide a large level of insurance against medical expenses excluding LTC.

FIGURE 6. COUNTERFACTUAL DISSAVING: 75TH PERCENTILE AND MEDIAN ASSETS.



Notes: Figure shows median assets and the 75th percentile for the simulated benchmark and the counterfactual without long-term-care, and no medical expenses for individuals aged 70/74 at first interview.

Besides, the relative importance of bequests and LTC varies along the wealth distribution. As we move towards the lower end of the wealth distribution, the importance of LTC increases given that the model estimates care as a necessity while bequests as luxury. In the absence of LTC (bequest), median wealth at age 85 is 36% (13%) lower than in the benchmark model.

4 Conclusions

In this paper, I develop and estimate a model of savings for retired single individuals with heterogeneous LTC needs and where LTC expenses are endogenous. It is important to do so because, first, by including heterogeneous LTC needs I can capture large spending propensity of the most frail individuals that we observe in the data. However, as the mortality rate for individuals in most need is very high, the expected duration that individuals expect to live in most need is limited thus lowering the savings motives for long-term care. Hence, a strong bequest motive is necessary to match the savings trajectories of individuals in the top of the wealth distribution. Second, by allowing endogenous LTC expenditures helps disentangle LTC risks from LTC expenditure choices. I find LTC to be a necessity therefore affecting the most the savings decisions of poorer individuals. All in all, my model is able to reconcile the discrepancies in the literature on the relative importance of LTC and bequests for the savings behavior of the old.

References

Amengual, D., Bueren, J., & Crego, J. (2017). Endogenous health groups and heterogeneous dynamics of the elderly. *Working Paper*.

Ameriks, J., Briggs, J., Caplin, A., Shapiro, M. D., & Tonetti, C. (2020). Long-term-care utility and late-in-life saving. *Journal of Political Economy*, *128*(6), 2375–2451.

Barczyk, D., & Kredler, M. (2018). Evaluating long-term-care policy options, taking the family seriously. *The Review of Economic Studies*, *85*(2), 766–809.

Blundell, R., Borella, M., Commault, J., & De Nardi, M. (2020). *Why does consumption fluctuate in old age and how should the government insure it?* (Tech. Rep.). National Bureau of Economic Research.

Brook, R. H., Ware Jr, J. E., Rogers, W. H., Keeler, E. B., Davies, A. R., Donald, C. A., ... Newhouse, J. P. (1983). Does free care improve adults' health? results from a randomized controlled trial. *New England Journal of Medicine*, *309*(23), 1426–1434.

Brown, M. (2006). Informal care and the division of end-of-life transfers. *Journal of Human Resources*, *41*(1), 191–219.

Cagetti, M. (2003). Wealth accumulation over the life cycle and precautionary savings. *Journal of Business & Economic Statistics*, *21*(3), 339–353.

De Nardi, M., French, E., & Jones, J. B. (2010). Why do the elderly save? the role of medical expenses. *Journal of Political Economy*, *118*(1), 39-75.

De Nardi, M., French, E., & Jones, J. B. (2016). Medicaid insurance in old age. *The American Economic Review*, *106*(11), 3480–3520.

Dobrescu, L. I. (2015). To love or to pay savings and health care in older age. *Journal of Human Resources*, *50*(1), 254–299.

Evans, W. N., & Viscusi, W. K. (1991). Estimation of state-dependent utility functions using survey data. *The Review of Economics and Statistics*, 94–104.

Fahle, S. (2015). Harnessing the potential of family caregivers: A solution to the u.s. long-term care crisis? *Working Paper*.

Finkelstein, A., Luttmer, E. F., & Notowidigdo, M. J. (2013). What good is wealth without health? the effect of health on the marginal utility of consumption. *Journal of the European Economic Association*, *11*(suppl_1), 221–258.

Finkelstein, A., & McKnight, R. (2008). What did medicare do? the initial impact of medicare on mortality and out of pocket medical spending. *Journal of Public Economics*, *92*(7), 1644–1668.

Fisher, E. S., Wennberg, D. E., Stukel, T. A., Gottlieb, D. J., Lucas, F. L., & Pinder, E. L. (2003). The implications of regional variations in medicare spending. part 1: the content, quality, and accessibility of care. *Annals of Internal Medicine*, *138*(4), 273–287.

French, E., & Jones, J. B. (2004). On the distribution and dynamics of health care costs. *Journal of Applied Econometrics*, *19*(6), 705–721.

Gourinchas, P.-O., & Parker, J. A. (2002). Consumption over the life cycle. *Econometrica*, *70*(1), 47–89.

Groneck, M. (2016). Bequests and informal long-term care: Evidence from hrs exit interviews. *Journal of Human Resources*, *52*(2), 531–571.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political economy*, *80*(2), 223–255.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, *57*(2), 357–384.

Hubbard, R. G., Skinner, J., & Zeldes, S. P. (1994). The importance of precautionary motives in explaining individual and aggregate saving. In *Carnegie-*

rochester conference series on public policy (Vol. 40, pp. 59–125).

Huggett, M. (1996). Wealth distribution in life-cycle economies. *Journal of Monetary Economics*, *38*(3), 469–494.

İmrohoroğlu, A., & Zhao, K. (2018). The chinese saving rate: Long-term care risks, family insurance, and demographics. *Journal of Monetary Economics*, *96*, 33–52.

Katz, S., Ford, A. B., Moskowitz, R. W., Jackson, B. A., & Jaffe, M. W. (1963). Studies of illness in the aged: the index of adl: a standardized measure of biological and psychosocial function. *JAMA*, *185*(12), 914–919.

Kim, C.-J. (1994). Dynamic linear models with markov-switching. *Journal of Econometrics*, *60*(1-2), 1–22.

Ko, A. (2017). An equilibrium analysis of the long-term care insurance market. *Working Paper*.

Kopecky, K. A., & Koreshkova, T. (2014). The impact of medical and nursing home expenses on savings. *American Economic Journal: Macroeconomics*, *6*(3), 29-72.

Kotlikoff, L. J., et al. (1989). What determines savings? *MIT Press Books*, *1*.

Lockwood, L. M. (2018, September). Incidental bequests and the choice to self-insure late-life risks. *American Economic Review*, *108*(9), 2513-50.

Mommaerts, C. (2015). Long-term care insurance and the family. *Working Paper*.

Mukherjee, A. (2020). Intergenerational altruism and retirement transfers: Evidence from the social security notch. *Journal of Human Resources*, 0419–10140R3.

Ozkan, S. (2017). Preventive vs. curative medicine: A macroeconomic analysis of health care over the life cycle. *Working Paper*.

Palumbo, M. G. (1999). Uncertain medical expenses and precautionary saving near the end of the life cycle. *The Review of Economic Studies*, *66*(2), 395–421.

Yogo, M. (2016). Portfolio choice in retirement: Health risk and the demand for annuities, housing, and risky assets. *Journal of Monetary Economics*, *80*, 17–34.

Appendix A Latent Health Model

In this appendix I describe the econometric model used for estimating latent health states and transition probabilities. The model is a slight modification from the original one in Amengual et al. (2017) where transition probabilities differ across deciles of permanent income groups.

The HRS is an unbalanced panel of individuals $i = 1, \ldots, N$ followed for $t_i = 1, \ldots, T^i$ periods which correspond from ages a_1^i to age $a_{T_i}^i$. We consider that an individual i at time t belongs to a latent health group $h_{i,t}$ out of H possible ones. If the individual belonged to group g, the probability of reporting difficulties with the k' th I-ADL[14], say $x_{i,k,t} = 1$, is $\iota_{k,g}$. Under the assumption that I-ADLs are independently distributed conditional on the health status, the joint distribution of $\mathbf{x}_{i,t} = (x_{1,i,t}, x_{2,i,t}, \ldots, x_{K,i,t})'$ is characterized by

$$p(\mathbf{x}_{i,t}|\iota_g, h_{i,t} = g) = \prod_{k=1}^{K} \iota_{k,g}^{x_{k,i,t}} (1 - \iota_{k,g})^{1-x_{k,i,t}}, \tag{1}$$

where $\iota_g = (\iota_{1,g}, \iota_{2,g}, \ldots, \iota_{K,g})'$. We take into account health dynamics by explicitly modeling the transition probabilities across groups. In particular, an individual i at time t, with gender s and in PI decile Q who belongs to group g transits to group c with probability

$$\pi_{g,c}(a_{it}, s_i, Q_i) = \frac{\exp[f_{g,c}(a_{it}, s_i, Q_i)]}{1 + \sum_{c \in \mathcal{H}} \exp[f_{g,c}(a_{it}, s_i, Q_i)]} \tag{2}$$

where $\mathcal{H}$ is the set that contains the H health groups. The remaining possible event is that the individual dies, which is an observable state that occurs with

[14] Along the paper I use I-ADLs to denote the set of both ADLs and IADLs

probability

$$\pi_{g,D}(a_{it}, s_i, Q_i) = \frac{1}{1 + \sum_{c \in \mathcal{H}} \exp[f_{g,c}(a_{it}, s_i, Q_i)]}.$$

This specification allows health groups to own distinct dynamics as parameters differ according to the current health group. Moreover, to capture within-group heterogeneity, transition probabilities can depend on age, gender, permanent income ranking (I split PI distribution in deciles, $Q = 10$) and interaction terms through the function $f_{g,c}(a, s, Q)$:

$$\begin{aligned} f_{g,c}(a, s, Q) = &\beta_{1,g,c} + \beta_{2,g,c} a + \beta_{3,g,c} a^2 + \beta_{4,g,c} a^3 + \beta_{5,g,c} s + \beta_{6,g,c}(s \times a) + \beta_{7,g,c} Q \\ &+ \beta_{8,g,c} Q^2 + \beta_{9,g,c}(Q \times a) \end{aligned} \tag{3}$$

In practice, I set the number of latent health groups $H = 4$[15]. Estimation of the econometric model delivers two sets of parameters: $[\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\iota}}]$. $\hat{\boldsymbol{\iota}}$ shows that individuals are classified as physically frail, mentally frail, impaired or healthy, represent individuals' LTC needs suitably. Figure 1 shows the probability of reporting difficulty with I-ADLs in each LTC need group. The impaired have physical and cognitive limitations while the healthy have no or light difficulties with I-ADLs. In turn, the physically frail have limited mobility, while the mentally frail have difficulties with more cognitive tasks such as managing money.

[15] For details on the estimation procedure and how we select the optimal number of health groups, the reader is referred to the original paper.

TABLE B1. FRACTION OF INDIVIDUALS BY HEALTH STATUS ACROSS PERMANENT INCOME QUARTILES AND SEX

Category	Healthy	Physically Frail	Mentally Frail	Impaired	Age	Permanent Income	N
women	0.58	0.22	0.10	0.11	81.2	$16,000	26,939
men	0.64	0.20	0.07	0.09	80.3	$19,800	7,440
Bottom	0.45	0.26	0.13	0.16	81.1	$8,900	8,595
Second	0.55	0.23	0.11	0.11	81.4	$14,200	8,596
Third	0.65	0.20	0.07	0.08	81.1	$19,500	8,600
Top	0.71	0.16	0.06	0.07	80.0	$31,700	8,588
All	0.59	0.21	0.09	0.10	81.0	$16,700	34,379

Source: HRS 1998-2014, single and retired individuals aged over 70. PI is in dollars of 2018.

Appendix B Descriptive Statistics

Given the estimated parameter values and the latent nature of the health measure used, I compute the probability that each individual in the sample belongs to each health group. Table B1 presents descriptive statistics of the sample used. Women are relatively older, in worse health, and with a permanent income which is 20% lower than males. Poorer individuals have on average higher LTC needs in live with the estimated dynamics. For example, conditioning of permanent income, the fraction of impaired individuals is more than two times higher for the bottom quartile (16 %) than for the top (7 %).

Appendix C Smoothed Probabilities

In this appendix I explain the computation of smoothed probabilities. These are used for computing statistics by health status given our estimates of $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\mu}}$. The derivation is split in two parts: the filtered probabilities based on Hamilton (1989) and the smoothed probabilities based on Kim (1994).

Filtered probabilities.— For computing the filtered probabilities, I need first to obtain

$$\begin{aligned} p(\mathbf{x}_{i,t+1}, h_{i,t+1}, h_{i,t}|\mathbf{x}_i^t) &= p(\mathbf{x}_{i,t+1}|\mathbf{x}_i^t, h_{i,t+1}, h_{i,t}) \cdot p(h_{i,t+1}|\mathbf{x}_i^t, h_{i,t}) \cdot p(h_{i,t}|\mathbf{x}_i^t) \\ &= p(\mathbf{x}_{i,t+1}|h_{i,t+1}) \cdot p(h_{i,t+1}|h_{i,t}) \cdot p(h_{i,t}|\mathbf{x}_i^t) \end{aligned}$$

where $p(\mathbf{x}_{i,t+1}|h_{i,t+1})$ is given by equation 1, $p(h_{i,t+1}|h_{i,t})$ is given equation 2 and $p(h_{i,t}|\mathbf{x}_i^t)$ is available by recursion. Then,

$$p(\mathbf{x}_{i,t+1}|\mathbf{x}_i^t) = \sum_{k,l} p(\mathbf{x}_{i,t+1}, h_{i,t+1} = k, h_{i,t} = l|\mathbf{x}_i^t)$$

I can thus compute the filtered probabilities as,

$$p(h_{i,t+1}|\mathbf{x}_i^{t+1}) = \frac{\sum_l p(\mathbf{x}_{i,t+1}, h_{i,t+1}, h_{i,t} = l|\mathbf{x}_i^t)}{p(\mathbf{x}_{i,t+1}|\mathbf{x}_i^t)}$$

Smoothed probabilities.— I observe,

$$\begin{aligned} p(h_{i,t+1}, h_{i,t}|\mathbf{x}_i^T) = p(h_{i,t+1}|\mathbf{x}_i^T) \cdot p(h_{i,t}|h_{i,t+1}, \mathbf{x}_i^T) &= p(h_{i,t+1}|\mathbf{x}_i^T) \cdot p(h_{i,t}|h_{i,t+1}, \mathbf{x}_{i,t}) \\ = p(h_{i,t+1}|\mathbf{x}_i^T) \cdot \frac{p(h_{i,t+1}|h_t) \cdot p(h_t|\mathbf{x}_{i,t})}{\sum_l p(h_{i,t+1}|h_{i,t} = l) \cdot p(h_{i,t} = l|\mathbf{x}_{i,t})} \end{aligned}$$

Therefore, if we sum over all values of $h_{i,t+1}$, I get my target, $p(h_{i,t}|\mathbf{x}_i^T)$.

Sample path for health states, given all the data.— I begin by drawing $h_{i,T}$

from the filtered $p(h_{i,T}|\mathbf{x}_i^T)$, I then draw using:

$$p(h_{i,T-1}|h_{i,T},\mathbf{x}_i^T) = \frac{p(h_{i,T}|h_{i,T-1}) \cdot p(h_{i,T-1}|\mathbf{x}_i^{T-1})}{\sum_l p(h_{i,T}|h_{i,T-1}=l) \cdot p(h_{i,T-1}=l|\mathbf{x}_i^{T-1})} \tag{4}$$

Appendix D Medical Expenditures: Estimation

Following French and Jones (2004), I estimate the following model:

$$\ln m_{it} = X_{it}'\beta + \sqrt{exp(X_{it}'\gamma)}(\xi_{it} + \zeta_{it}),\ \zeta_{it} \sim N(0,\sigma_\zeta^2) \tag{5}$$

$$\xi_{it} = \rho\xi_{it-1} + \epsilon_{it},\ \epsilon_{it} \sim N(0,\sigma_\epsilon^2) \tag{6}$$

X_{it} consists of a cuartic in age, sex, sex interacted with age, a quadratic in permanent income decile, permanent income decile interacted with a, health dummies, and health dummies interacted with income decile. In the estimation of the medical expenditure process I treat health as being observable. Each individual is asigned to the health group with the largest probability. The parameter vector to be estimated is $\theta = \left(\beta,\gamma,\sigma_\epsilon^2,\sigma_\zeta^2,\rho\right)$. I estimate all the parameters jointly using a state-space representation and the kalman filter.

Appendix E Simulating The Model

This section details step-by-step the simulation procedure:

1. Set the preference parameters for the simulation: θ^g
2. Compute optimal policies using structural model for θ^g.

3. Set a large number of simulations (S=1000)

4. For each single retired individual in the HRS (N=8439):

   (a) Sample a family type based on individual specific covariates (see corresponding Appendix)

   (b) I give each individual in the simulation health status, mortality history, and the initial level of wealth of the data.

   (c) Simulate her savings, medicaid, and hours of care decisions.

5. Construct moments for each simulation.

6. Compute the mean of each moment across simulations.

7. Compute the objective objective function using each moment conditions and weighting matrix.

8. Repeat steps 1 to 6 until the minimum objective function is located.

Appendix F Moment Conditions and Parameter Uncertainty

I follow the appendix in De Nardi et al. (2010) for deriving moment conditions. In the model, my estimates $\hat{\theta}$ of the "true" $M \times 1$ preferences parameters θ_0 is the value of θ that minimizes the relative distance between:

- the estimated life cycle profiles for assets.

- Medicaid recipiency rates and formal care hours.

and the statistics generated by the model.

Asset Moments

For each calendar year $t \in \{1998, \ldots, 2014\}$, I match the median assets for $Q = 5$ permanent income quintiles in $P = 4$ groups (groups 1 to 4 correspond to those aged $70-74, 75-79, 80-84, 85^{+}$ at first interview as single). In the simulation each individual in the first interview is given her initial wealth level. In addition, I require each group-income-age cell to have at least 30 observations to be included in the GMM criterion.

The conditional wealth moments are defined as:

$$\mathbb{E}\left[\mathbb{1}_{\{a_{it}<a^{0.5}_{P,Q,t}(\theta)\}} - 0.5 \mid p_i = P \, \wedge \, q_i = Q \, \wedge \, \text{interviewed at t}\right] = 0, \qquad (7)$$

where $a^{0.5}_{P,Q,t}$ denotes the model's implied median asset for group P, permanent income quintile Q in calendar year t and $i \in P, Q, t$ denotes that individual i belongs to P and Q and was observed at t. Following Chamberlain (1992), I write the unconditional moment condition as:

$$\mathbb{E}\left[\left(\mathbb{1}_{\{a_{it}<a^{0.5}_{P,Q,t}(\theta)\}} - 0.5\right) \times \mathbb{1}_{\{p_i=P\,\wedge\, q_i=Q\,\wedge\,\text{interviewed at t}\}}\right] = 0 \qquad (8)$$

with sample analog,

$$\frac{1}{N}\sum_{i=1}^{N}\left[\left(\mathbb{1}_{\{a_{it}<a^{0.5}_{P,Q,t}(\theta)\}} - 0.5\right) \times \mathbb{1}_{\{p_i=P\,\wedge\, q_i=Q\,\wedge\,\text{interviewed at t}\}}\right]$$

Formal Care hours

For all single retired individuals observed in the HRS, I simulate formal care hours decisions.

Hours of formal care by permanent income quintiles

$$\mathbb{E}\left[\left(l_{it}(\theta) - \bar{l}_{H,Q}\right) \times \mathbb{1}_{\{h_i=H \,\wedge\, q_i=Q \,\wedge\, \text{interviewed at t}\}}\right] = 0, \tag{9}$$

where $l_{it}(\theta)$ is the individual i decision on hours of care, $\bar{l}_{H,Q}$ is the expected hours of care for individuals with health H and permanent income Q.

Hours of formal care moments across family types are constructed as in the previous case.

Asymptotic Distribution

We have data on N independent individuals. Let $\hat{\varphi}(\theta)$ denote the sample analogue of the vector of moment conditions described above. We define,

$$\hat{\theta} = \arg\min_{\theta} \frac{N}{1+1/S}\hat{\varphi}(\theta)' W \hat{\varphi}(\theta)$$

The method of simulated moments estimator $\hat{\theta}$ is is both consistent and asymptotically normally distributed:

$$\sqrt{N}(\hat{\theta} - \theta_0) \sim N(0, V),$$

where V is given by,

$$V = (1 + 1/S)(D'WD)^{-1}D'W\Omega WD(D'WD)^{-1}$$

with Ω denoting the variance covariance matrix of the moment conditions. D is the Jacobian matrix of the moment conditions with respect to parameter values. To find the derivative of the asset moments with respect to each parameter, I re-write the moment condition as:

$$\frac{1}{N}\sum_{i=1}^{N}\left[\int_{-\infty}^{a^{0.5}_{P,Q,t}(\theta)} f(a_{it} \mid p_i = P \wedge q_i = Q \wedge \text{int. at t})da_{it} \times \mathbb{1}_{\{p_i=P \wedge q_i=Q \wedge \text{int. at t}\}}\right]$$

It follows that the rows of the D matrix associated to asset moments is obtained by applying Leipniz rule for differentiation to the previous equation:

$$\frac{1}{N}\sum_{i=1}^{N}\left[f(a^{0.5}_{P,Q,t}(\theta) \mid P \wedge Q \wedge t) \times \mathbb{1}_{\{p_i=P \wedge q_i=Q \wedge \text{int. at t}\}} \times \frac{\partial a^{0.5}_{P,Q,t}(\theta)}{\partial \theta}\right]$$

In practice, I find $f(a^{0.5}_{P,Q,t}(\theta) \mid P \wedge Q \wedge t)$, the conditional probability density function of assets evaluated at the model's median, by estimating a kernel density estimator on the sample data (I use a Epanechnikov approximation using Silverman (1986) bandwidth's decision rule with a sensitivity parameter equal to 0.5). I compute $\frac{\partial a^{0.5}_{P,Q,t}(\theta)}{\partial \theta}$ using numerical derivatives.