

Long-Term Care Needs and Savings in Retirement

Jesús Bueren*

March 4, 2021

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, endogenous LTC expenses, and differences in access to informal care provision. I find that the model is able to reproduce both large spending propensities when individuals are in most need while being consistent with strong bequest motives. The model highlights the importance of informal care in protecting future bequests but finds little evidence of exchange motivated bequests. Counterfactual simulations show that both bequest and LTC needs are important drivers of savings for the old.

Keywords: Savings, Retirement, Long-Term Care, Health.

JEL classification: E21, I14, J14, C51

European University Institute.* **e-mail:jesus.bueren@eui.eu

1 Introduction

Contrary to the predictions of a standard life-cycle model (Huggett, 1996), many elderly dissave slowly during retirement. Identifying the reasons why the simple model fails is crucial for the design of policies related to health care, Social Security, and insurance markets for the old. 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, drive 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, endogenous LTC expenses, and access to informal care in structural models. First, I find that both LTC expenses and mortality rates increase sharply as health deteriorates, thus limiting the time persistence of expensive care. 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. 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, additionally buy formal care at a market price. Then, LTC is produced by combining both formal and informal care through a CES production function. The marginal utility of LTC is also allowed to differ depending on the level of LTC need. Finally, the willingness to bestow is allowed to vary across family types to capture potential exchange motivated bequest to informal caregivers.

I use HRS data on savings, hours of formal care consumption, and reported probabilities to leave bequests 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 and strong bequest motives for the rich. For example, the share of resources that an individual with \$100K in assets and little informal care support would leave as a bequest in the year before her certain death moves from 54%, 52%, 47%, to 9% 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.

In order to identify differences in the provision of informal care, I study the individual characteristics that are predictive of being recipient of informal care. Having children (especially a daughter) and being African American are strong predictors of future available informal care if in need of LTC. Based on these characteristics, I then categorize individuals as being in *close* and

distant families. In order to estimate differences in the willingness to bestow across family types, I require the model to match the self-reported probability of leaving bequests for each family type. In comparison to differences across healthy and impaired individuals, the model estimates that the differences in willingness to bestow are small and statistically non-significant. In spite of this, the model highlights the role of informal care at protecting bequests in case an individual requires LTC. For example, the share of resources that an impaired individual with \$100K in assets would leave as a bequest in the year before her certain death moves from 57% to 10% if receiving and not receiving LTC support from children, respectively.

Counterfactual simulations reveal how differently single retired individuals would dissave given an initial wealth endowment at age 70 and allow to identify the relative importance of bequests and LTC needs. In a world without LTC needs (bequest motives) the median wealth holdings at the age of 85 would be 36% (21%) lower than in the benchmark model. Nevertheless, 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 22% (30%) 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 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 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 dataset 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 Strategic Survey Questions (SSQ) and find LTC to be the main driver of savings while bequest motives play a relatively minor role. In my paper, I show that LTC expenses vary importantly across levels of LTC needs. Indeed, I find that 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.

Dobrescu (2015) estimates a model for a set of European countries in which individuals can produce care by combining formal and informal care. She assumes that the provision of informal care is a function of bequathable wealth implying a one to one mapping between access to informal care and willingness to bestow. In contrast, I estimate that in spite of large differences in the access to informal care, individuals differ little in their willingness to bestow across family types.

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, İmrohoroglu and Zhao (2018) find that the deterioration of informal care provision due to the one-child policy can 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. In contrast, 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 and in line with my results, Mukherjee (2020) uses variation in Social Security benefits and finds little support for exchange motivated transfers.

The rest of the paper is organized as follows. In Section 2, 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 3. In Section 4, I present counterfactual experiments to quantify the forces affecting the saving behavior. Section 5 concludes.

2 Heterogeneous Long-Term Care Needs, Provision of Care from Families, and Formal Care Choices

In this section, I first describe how I identify heterogeneity in LTC needs using the HRS. Next, I document determinants of the provision of informal care from family members when individuals are in need of care. Finally, I explain how individuals complement the provision of care provided by relatives using formal care.

2.1 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 indi-

vidual'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 estimate a modified version of the model in Amengual, Bueren, and Crego (2017). Following Amengual et al. (2017), I 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

I assume that the main source of heterogeneity in I-ADLs² in the population is represented by a finite number of possible health groups that are not observed by the econometrician. Each individual i at time t belongs to one health group $h_{i,t}$. Health groups differ in the probability of reporting a difficulty with each I-ADL. Given her group g , the probability of facing difficulties with the k 'th I-ADL (out of 12 I-ADLs), say $x_{i,k,t} = 1$ is $\mu_{k,g}$. Under the assumption that I-ADLs are independently distributed conditional on health status, the joint distribution of $\mathbf{x}_{i,t} = (x_{1,i,t}, \dots, x_{12,i,t})$ is characterized by:

$$p(\mathbf{x}_{i,t} | \mu_g) = \prod_{k=1}^{12} \mu_{k,g}^{x_{k,i,t}} (1 - \mu_{k,g})^{1-x_{k,i,t}} \quad (1)$$

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

¹ADLs: 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).

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

periods during which she is observed. Non-asset income includes Social Security benefits, defined pensions benefits and annuities.

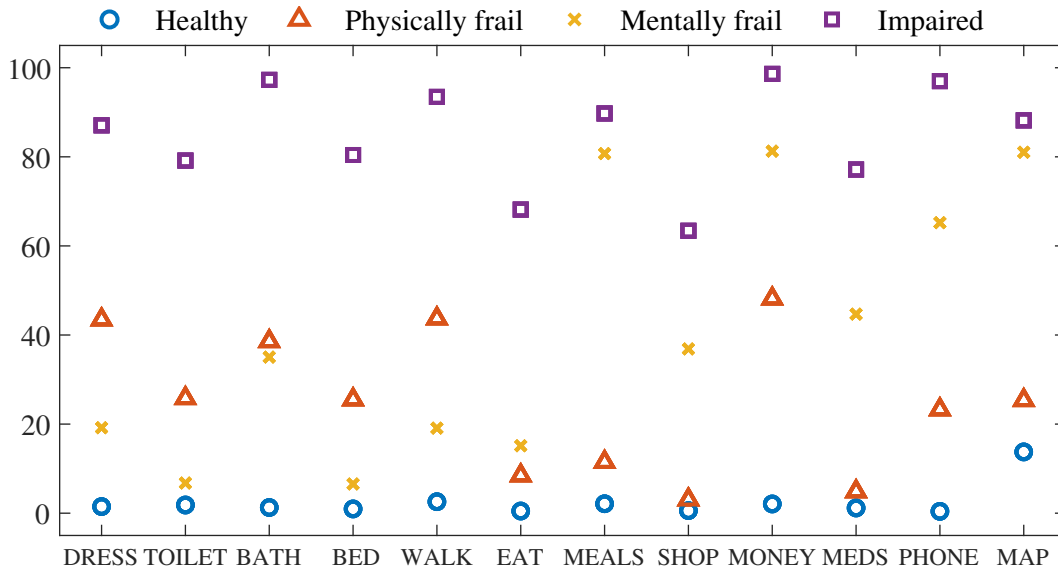


FIGURE 1. PROBABILITY OF REPORTING DIFFICULTY WITH ANY I-ADL BY HEALTH GROUP

I estimate the model including all single individuals in the HRS from 1996 to 2014³ and who are 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 physically frail, the mentally frail, and the impaired.⁴ Figure 1 displays the probability of reporting each I-ADL for each group ($\mu_{k,g}$). The healthy are 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 to 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 probabilities sharply decrease as individual's health status deteriorates. The differences are salient even after conditioning on being in need of LTC: for

³There was a change in the HRS in the number of adls asked prior to 1996, thus I drop observations from earlier waves

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

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.

example a woman who is impaired faces a mortality rate which is twice as large as a woman 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 state 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 (both in absolute and as a fraction of their remaining life expectancy) 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.

To conclude, 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.

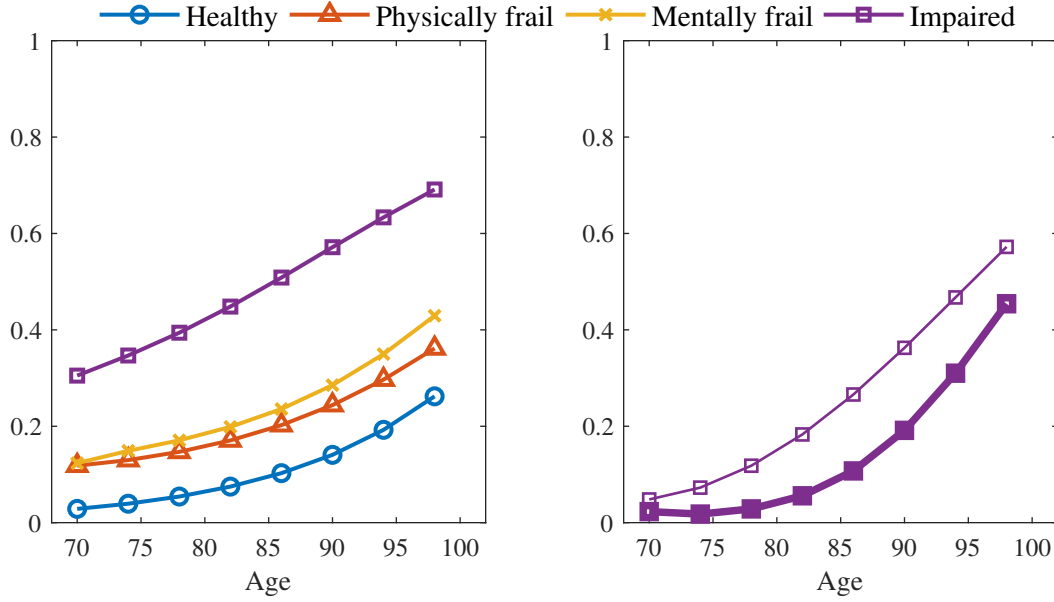


FIGURE 2. TWO-YEAR MORTALITY RATES ACROSS HEALTH GROUPS FOR WOMEN (LEFT PANEL) AND SHARE OF ALIVE INDIVIDUAL IMPAIRED FOR TOP (THICK LINE) AND BOTTOM (THIN LINE) DECILE OF PERMANENT INCOME DISTRIBUTION (RIGHT PANEL)

2.2 Determinants of Informal Care Provision and Formal Care Consumption Choices

Two thirds of individuals in the HRS, report receiving care from relatives (mainly children) when in need (physically frail, mentally frail or impaired). Thus, not taking into account the provision of care from family members would overestimate the risk of long-term care. In this section, I document which individual characteristics are informative of the provision of informal care and then how consumption of formal care varies by level of need, permanent income and provision of care from relatives.

For this purpose, I make 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 or friends and formal care as care provided by a paid helper, a professional or an employee of an institution.

In order to summarize the large heterogeneity in the provision of informal care observed in the data, I group all individuals into two “family types” according to their provision of informal care:

close families and *distant families*. *Close families* are those whose reported informal care hours lie in the top tercile of the informal care hour distribution conditional on health status. *Distant families* are those whose reported informal care hours are below the top tercile. Individuals belonging to *close families* receive a much stronger support as they receive 3.6, 8.9, and 13.6 hours of care per day from their relatives when physically frail, mentally frail, and impaired. Individuals in *distant families*, on the other hand, receive on average 35 mins of care per day with little differences across levels of need.

In order to study which individuals are more likely to receive informal care, I run a logistic model on the family type against individual covariates. Table 2 shows the marginal effect of the covariates used. First, the table shows that there is not a clear correlation between permanent income and the provision of informal care as none of the coefficients on quintiles dummies are significantly different from each other. Second, the table shows that having children and especially a daughter increase the chances of receiving strong informal care support by 10 and 11 percentage points, respectively. Moreover, African americans, never married and high-school dropout are also more likely to belong to a *close* family than Caucasians, divorced and more educated individuals, respectively. Finally, the pseudo r-square of the logistic regression is 5%, showing the difficulty to predict the provision of informal care in the overall population by the observed characteristics.

Now, I document how formal care consumption changes with the level of need, permanent income, and across family types. Table 3 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 12\$ per hour of care⁶, formal care can constitute a significant financial burden for the old. 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

⁵I 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.

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

TABLE 2. MARGINAL EFFECTS ON THE PROBABILITY OF BELONGING TO A *Close Family*

Permanent income quintile					
Second	Middle		Fourth	Top	
-0.00	0.02		-0.02	-0.02	
(0.01)	(0.02)		(0.02)	(0.02)	
Female	Any Child	Daughter	N. Children	N. Children ² $\times 10^{-4}$	
0.05	0.10	0.11	0.02	-1.17	
(0.01)	(0.03)	(0.02)	(0.01)	(5.75)	
Race		Marital Status		Education	
African Am.	Other	Widowed	Never married	HS	College
0.12	0.05	0.06	0.10	-0.06	-0.08
(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.01)

Source: HRS 1998-2014. Standard errors in parentheses. Single and retired individuals in the sample. Omitted categories: Bottom permanent income quintile, male, no children, Caucasian, Divorced, highschool dropout. N=9,234.

at face value to measure risk. For example, when impaired, an individual 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.

Table 4 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 individual in a *distant family* consumes around 6.8 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 the provision of informal care is highly heterogeneous across individuals but that there exists a number of characteristics that are helpful as predictors of future reciprocity of informal care. Moreover, 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 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	1.5	1.7
Impaired	3.0	4.1	5.9

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

TABLE 4. FORMAL AND INFORMAL CARE HOURS PER DAY ACROSS FAMILY TYPES

Family Types	Health Status	Informal Care	Formal Care
		Hours per day	Hours per day
<i>Distant</i>	Physically frail	0.0	0.5
<i>Distant</i>	Mentally frail	0.6	1.8
<i>Distant</i>	Impaired	0.6	6.8
<i>Close</i>	Physically frail	3.6	0.5
<i>Close</i>	Mentally frail	8.9	0.7
<i>Close</i>	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.

3 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) and Dobrescu (2015) 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 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. Finally, I allow the marginal utility of leaving bequest to depend on the family type, thus allowing for possible compensations for the care provided.

Timing and Preferences.— 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: $a \in \{70, 72, \dots, 110\}$. Individuals derive utility from regular consumption and care. Care is produced by combining informal and formal care through a CES production function where τ is the share parameter attributed to formal care and ω the substitution parameter. 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. $\alpha(h)$ captures differences in the marginal utility of care across health states. Following the empirical section, there are two types of families in the model: *distant* ($F = 1$) and *close* ($F = 2$).

Each period their utility flow is given by,

$$u(c, l_{fc}, l_{ic}; h, F) = \frac{c^{1-\sigma}}{1-\sigma} + \exp(\alpha(h)) \frac{\left[\left(\tau \cdot l_{fc}^\omega + (1-\tau) \cdot l_{ic}^\omega(h, F) \right)^{1/\omega} \right]^{1-\nu}}{1-\nu} \quad (2)$$

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:

$$\phi(k) = \exp(\lambda(F)) \frac{(k + \delta)^{1-\sigma}}{1 - \sigma}, \quad (3)$$

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 which might vary across family types.

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.

$$\ln m_{i,t} = m(h, a, s, PI) + \gamma(h, a, s, PI)\psi_{i,t} \quad (4)$$

$$\psi_{i,t} = \xi_{i,t} + \zeta_{i,t}, \quad \zeta_{i,t} \sim N(0, \sigma_\zeta^2) \quad (5)$$

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

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 zero⁸ 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 $G = 0$,

⁷In 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).

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

otherwise. Government transfers are then given by:

$$\max\{0, \underline{c}(h) + p_{fc}\underline{l}(h) + m - b - (1 + r)k\}, \quad (7)$$

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 and b is the level of permanent income of the individual. 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 :

$$x = (1 + r)k + b(s, PI) - m. \quad (8)$$

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:

$$\begin{aligned} V_a(x, h, \zeta, s, PI, F) = \max_{c, l_{fc}, G} \bigg\{ & u(c, l_{fc}; h, F) \\ & + \beta \pi_{h' \neq 5, h, a, s, PI} E_t[V_{a+2}(x', h', \zeta', s, PI, F)] \\ & + \beta \pi_{h' = 5, h, a, s, PI} \phi(k') \bigg\} \end{aligned} \quad (9)$$

subject to

$$x' = (1 - G) \left[(1 + r)(x - c - p_{fc}l_{fc}) - m' \right] \quad (10)$$

$$G = 1 \Leftrightarrow \begin{cases} c = \underline{c}(h) \\ l_{fc} = \underline{l}(h) \end{cases} \quad (11)$$

3.1 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 $\theta = (\sigma, \nu, \delta, \underline{u}, \alpha(h), \lambda(F), \tau, \omega)$ that minimize the distance between simulated wealth and formal care hours moments with their empirical counterparts.

3.1.1 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 two family types: *distant* and *close*. Individuals in *distant* and *close* category receive the average value of the two bottom terciles and the 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 \$12 per hour ⁹.

⁹According to the BLS the mean hourly wage for health aide in 2019 was \$12.71

3.1.2 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 21 formal care moments (5 Permanent income groups \times 3 LTC need status + 2 family types \times 3 LTC need status).

Likelihood of leaving bequests.— In order to disentangle the effect of LTC expenses and formal care on savings, I exploit information in the HRS on self-reported probability of leaving large bequests. Given that the probabilities of being in need of care and formal care consumption are known, the self-reported probabilities on leaving large inheritance help disentangle accidental from intentional motives. I thus target the average probability of leaving bequests across family types with a total of 10 moment conditions.

3.2 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 use the predicted probabilities from the

logit from the empirical section. 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 in a *close* family in one wave but in a *distant* one 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 the latent nature of the health classification, I use the Kim smoother proposed by Kim (1994).¹⁰

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:

$$\hat{\theta} = \arg \min_{\theta} (\mathbf{m}_{\text{data}} - \mathbf{m}_{\text{sim}}(\theta))' \mathbf{W} (\mathbf{m}_{\text{data}} - \mathbf{m}_{\text{sim}}(\theta)) \quad (12)$$

I restrict moment condition to have at least 40 observations. Thus the final estimation of θ is based on 153 moment conditions. The weighting matrix (\mathbf{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.

3.3 Estimated Parameter values

Table 5 shows the estimated preference parameters. The estimate for σ , the coefficient of risk aversion for regular consumption, is 2.23. 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 5.84. On top, the estimated care multipliers across different health states imply that,

¹⁰Appendix C derives the smoother equations) in order to ensure that the simulated health draws have the same persistence as the estimated health process

as expected, 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 smaller 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 1%, 4%, and 66% when physically frail, mentally frail and impaired, respectively.

Formal and informal care are estimated to be complements although the precision of the estimated parameter is low. I cannot reject the null of both of a Cobb-Douglas production function. The share parameter attributed to formal care is 0.57. There is currently no consensus on whether informal and formal care are complementary or substitute goods in the micro literature. Langa, Chernew, Kabeto, and Katz (2001) and Liu, Manton, and Aragon (2000) find them to be complements. Van Houtven and Norton (2004) and Bonsang (2009) using instrumental variable estimation find them to be substitutes however they find that this substitution effect tends to disappear as the level of disability of the elderly person increases.

The transfer needed to achieve the utility floor when healthy corresponds to \$5,440 per two years which close to the 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 \$3,000 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 literature¹¹:

$$\max_{c, l_{fc}, k} \frac{c^{1-\sigma}}{1-\sigma} + \exp(\alpha(h)) \frac{l_{fc}^{1-\nu}}{1-\nu} + \exp(\lambda) \frac{(k+\delta)^{1-\sigma}}{1-\sigma} \quad (13)$$

$$s.t. \ W = c + k + l_{fc}p_{fc}$$

Figure 3 plots the ratio of wealth bestowed to total resources before death (k/W). The left

¹¹To make my estimates comparable to the previous literature that use annual models, I multiply the utility from regular consumption and care by $2^{-\sigma}$ and $2^{-\nu}$, respectively.

TABLE 5. ESTIMATED PREFERENCE PARAMETERS

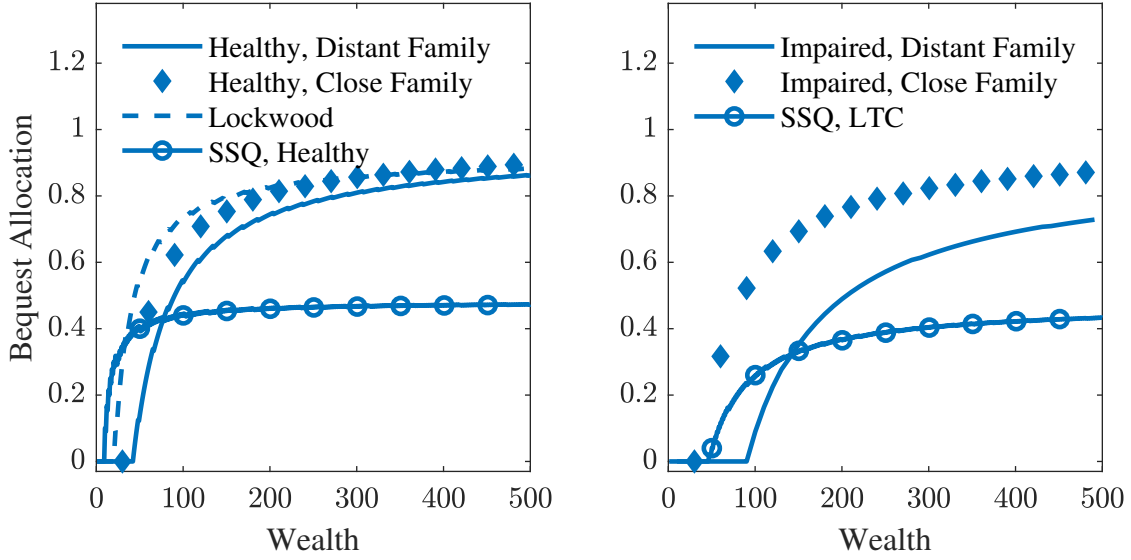
Risk Aversion		
σ : Consumption	2.23	(0.43)
ν : Care hours	5.20	(0.23)
LTC		
$\alpha(h = 2)$: Physically frail	13.34	(2.20)
$\alpha(h = 3)$: Mentally frail	23.39	(1.46)
$\alpha(h = 4)$: Impaired	28.01	(0.93)
τ : Share formal care	0.57	(0.18)
ω : substitution formal/informal care	-0.39	(0.74)
Bequest		
δ : curvature	684.80	(15.22)
$\lambda(F=Distant)$: marginal utility	4.67	(1.44)
$\lambda(F=Close)$: marginal utility	5.31	(1.58)
Maximum transfer to achieve utility floor $\times 10^3$		
$\underline{x}(h=1)$: Healthy	5.44	(1.69)

Notes: Standard errors are reported in parentheses.

panel shows large differences in the strength of the bequest motives estimated for Ameriks et al. (2020) when healthy (SSQ, healthy) and Lockwood (2018) (Lockwood). For individuals holding more than \$200K in assets Lockwood (2018) estimates a bequest motive which is around twice as large than the one estimated by Ameriks et al. (2020). My estimates of bequest when individuals are healthy imply a larger point at which bequest motives are active but then line up well with the estimates by Lockwood (2018). There are small differences in willingness to bestow across family types.

The right panel of figure 3 shows that when individuals become impaired the willingness to bestow decreases importantly for individuals in distant families as they need to pay for their care but it is only slightly affected for individuals in close families. The strength of my estimated preference parameters for impaired individuals are close to Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2016) in the range of their targeted moments conditions i.e. between \$100K and \$200K. One important difference that could explain the result is the fact that in my framework I allow for heterogeneous LTC needs. Impaired individuals in my model do report the large propensities to consume found in Ameriks et al. (2016). However, given that the impaired status is relatively shortly lived due to high mortality rates, my model requires a strong bequest motive of the rich in

FIGURE 3. BEQUEST ALLOCATION ACROSS STUDIES



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

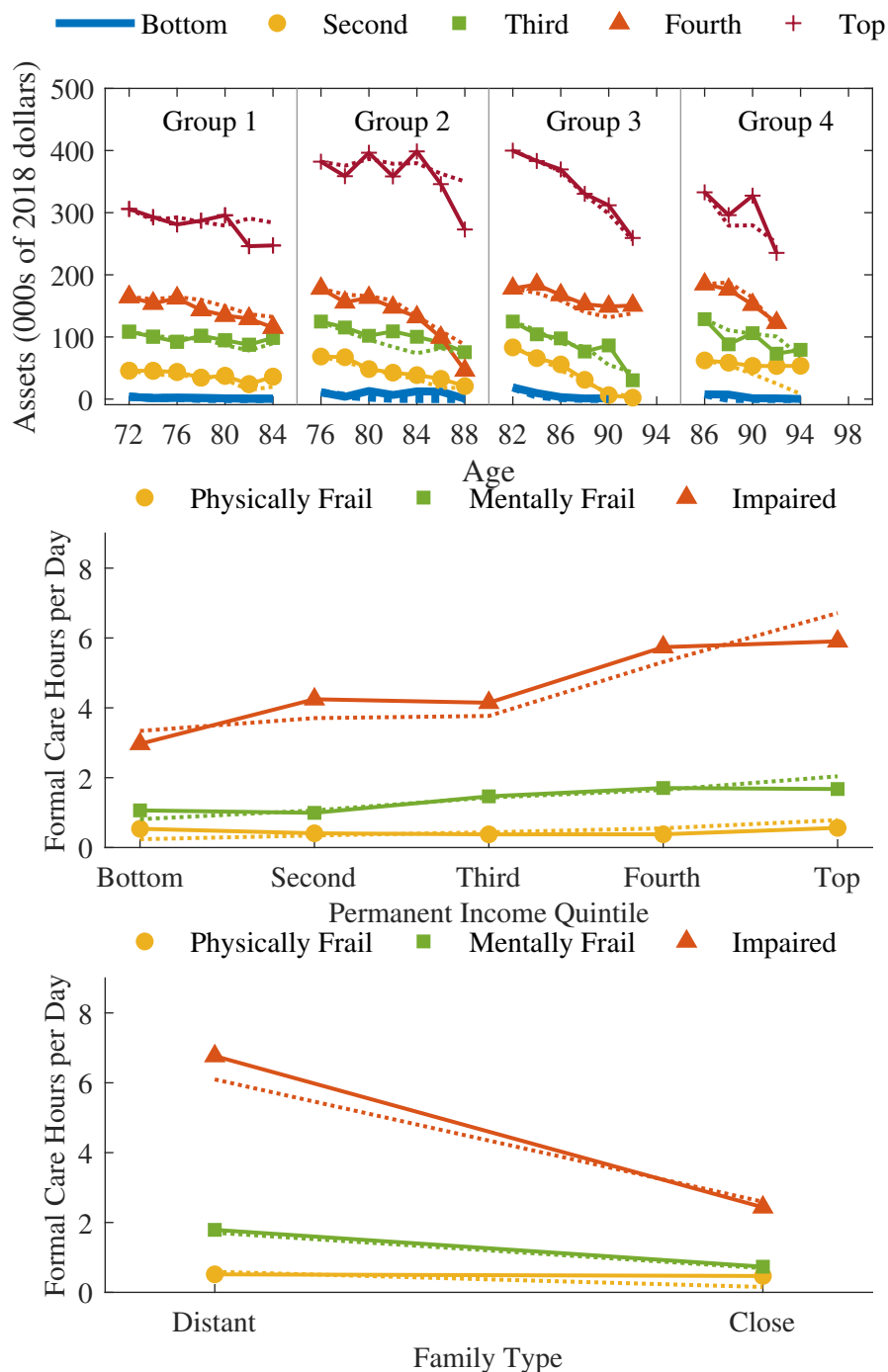
order to match the savings profiles of the elderly rich.

3.4 Model Fit

Figure 4 and 5 report 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 dissaving 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. On top figure 5 shows that the model is able to reproduce the increase in reported the probability of leaving a positive bequest at different levels of the permanent income distribution.

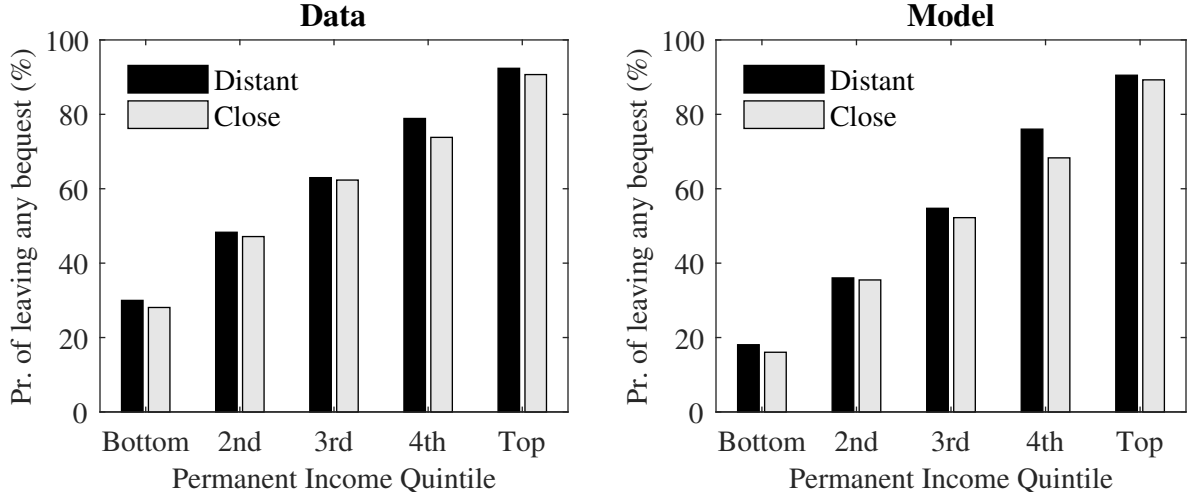
In order to informally validate the model, I assess its accuracy at matching a set of untargeted moments. For this purpose I confront the model predicted dissaving profiles across family types with the data. I focus on the 75th percentile because bequest motives are most relevant for asset-rich individuals. Hence, given the small differences in the estimated willingness to bestow across

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. MODEL FIT: SELF-REPORTED PROBABILITY OF LEAVING POSITIVE BEQUESTS ACROSS FAMILY TYPES



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.

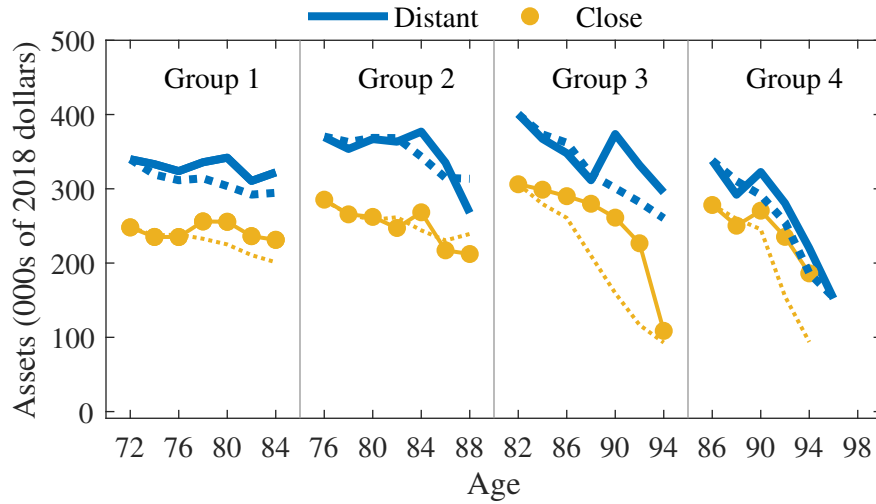
families, discrepancies between model and data are most likely to arise in the upper part of the wealth distribution. Figure 6 shows that the model is able to track the the top 75th percentile of the wealth distribution of individuals across family types even if these are not explicitly targeted in the estimation.

3.5 Identification of Bequest from Long-Term Care Parameters

In this section, I discuss how hours of care when impaired and the self-reported probability of leaving bequests allow me to separate savings for intentional bequest from precautionary savings associated to LTC. For this purpose, I illustrate how these moments adjust when I shift the marginal utility of care and bequest, one at a time.

Ex-ante it is hard to say whether hours of care and the probability of leaving bequest contain valuable information for identifying the parameters in the model. More precisely, it could be that both increases in bequest and LTC move these targeted moments in the same direction thus not providing identification. First, increases in bequest motives will induce individuals to deaccumulate resources more slowly as they age, driving an increase in their probability of leaving positive

FIGURE 6. INFORMAL VALIDATION: TOP 75th WEALTH PERCENTILE ACROSS FAMILY TYPES



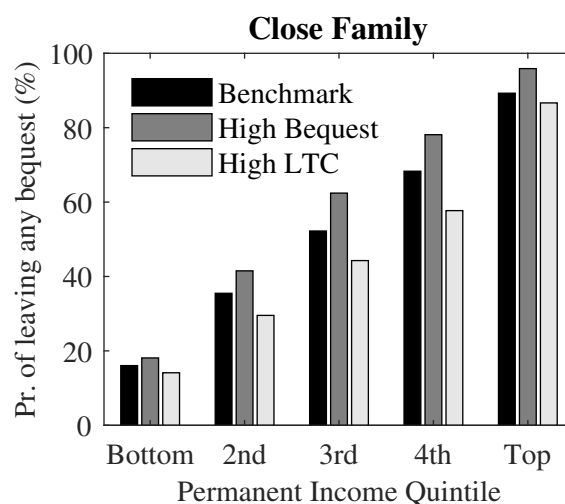
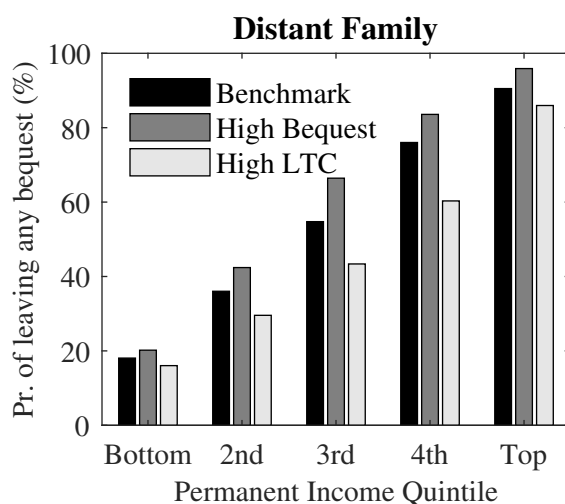
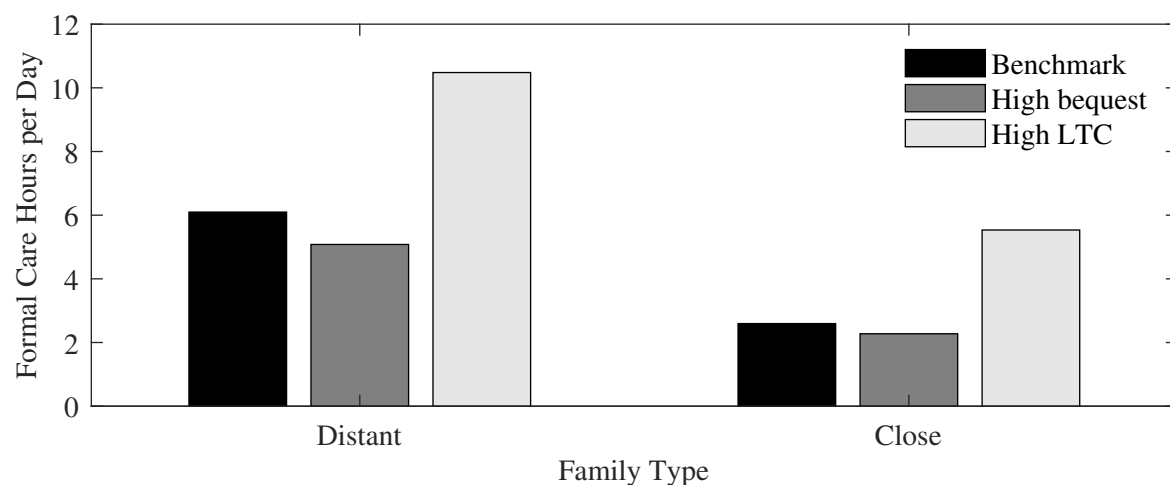
Notes: Figure compares data (solid) and simulated (dotted) statistics. Retired single individuals in the HRS 1998-2014.

bequests. Nevertheless, it is unclear how changes in the bequest motive will drive changes in consumption of formal care: on the one hand, increases in bequest motives will result in higher wealth levels when in need of LTC thus pushing up consumption of formal care. On the other hand, larger willingness to bestow will also result in larger desire for protecting the accumulated savings. The dark grey bars in figure 7 show that the former effect dominates and increases in willingness to bequeath result in lower consumption of care when in need.

Second, increases in the marginal utility when impaired will increase precautionary savings related to care but the effect on the probability of leaving bequests is unclear. On the one hand, more precautionary savings increase the likelihood of accidental positive bequest. On the other hand, in case the probability of becoming impaired is sufficiently high, individuals will anticipate a decrease in the probability of leaving bequest due to larger spending when in need of LTC. The light grey bars in figure 7 show that the later effect dominates and that the probability of leaving bequests decreases.

All in all, this exercise shows that increases in the bequest motive and a larger marginal utility of LTC drive formal hours of care and the probability of leaving a bequest in opposite directions, allowing for identification in the model.

FIGURE 7. CHANGE IN FORMAL CARE CONSUMPTION WHEN IMPAIRED AND PROBABILITY OF LEAVING BEQUEST FROM INCREASES IN WILLINGNESS TO BESTOW AND THE MARGINAL UTILITY OF CARE.



4 Results

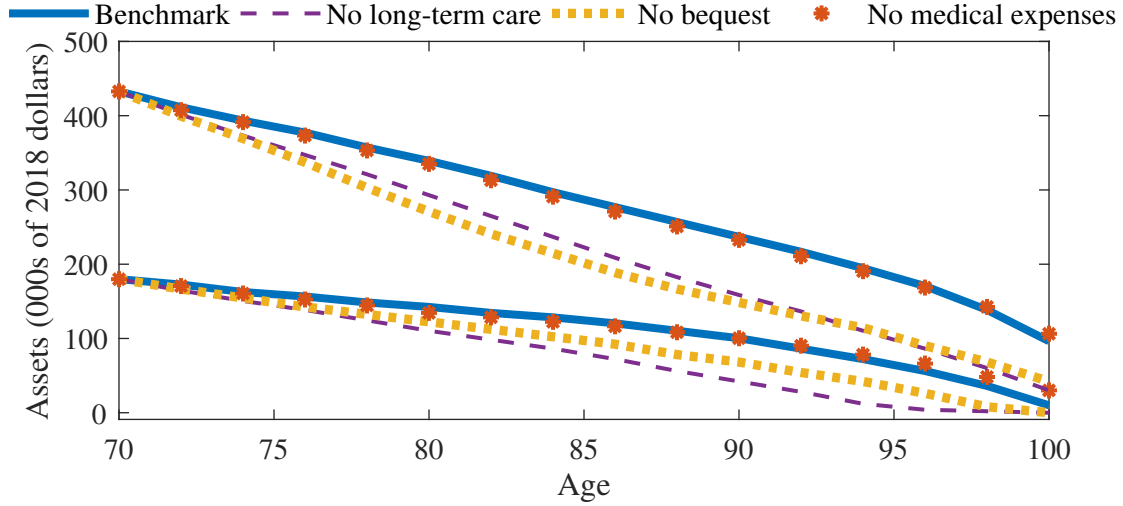
In order to identify the key drivers of savings of the elderly, I use the model to run a set of counterfactual scenarios. For this purpose, I fix the estimated parameters at their benchmark values and change one feature of the model at a time. I then compute the optimal savings decisions, simulate the 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 8 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 8 shows that medical expenses are negligible for explaining the lack of asset deaccumulation during old age. As such, the results imply that Medicare and Medicaid provide a large level of insurance against medical expenses excluding LTC.

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.

FIGURE 8. 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.

5 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 live in the frail state 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 to 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.

Acknowledgements: For helpful suggestions, I thank Dante Amengual, Annika Bacher, Russell Cooper, Julio A. Crego, Maria Cristina De Nardi, Raquel Fonseca, Philipp Grübener, Tullio Jappelli, Matthias Kredler, Nezih Guner, Pierre-Carl Michaud, and Josep Pijoan-Mas. I have also benefited from feedback provided by seminar participants at the III European Workshop on Household Finance, Banca d'Italia, Cemfi, École Polytechnique, European University Institute, Nova, Stockholm University, UQAM, Universitat Autònoma de Barcelona, and Université de Montréal. Errors and omissions are exclusively my own responsibility.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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. (2016). *The long-term-care insurance puzzle: Modeling and measurement* (Tech. Rep.). National Bureau of Economic Research.
- 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.
- Bonsang, E. (2009). Does informal care from children to their elderly parents substitute for formal care in europe? *Journal of health economics*, 28(1), 143–154.
- 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.
- Fahle, S. (2015). Harnessing the potential of family caregivers: A solution to the u.s. long-term care crisis? *Working Paper*.
- 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.
- İmrohoroglu, 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.

- Langa, K. M., Chernew, M. E., Kabeto, M. U., & Katz, S. J. (2001). The explosion in paid home health care in the 1990s: who received the additional services? *Medical care*, 147–157.
- Liu, K., Manton, K. G., & Aragon, C. (2000). Changes in home care use by disabled elderly persons: 1982–1994. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 55(4), S245–S253.
- 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.
- Van Houtven, C. H., & Norton, E. C. (2004). Informal care and health care use of older adults. *Journal of health economics*, 23(6), 1159–1180.
- 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 $i = 1, \dots, N$ followed for $t_i = 1, \dots, T^i$ 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-ADL¹², 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 $\mathbf{x}_{i,t} = (x_{1,i,t}, x_{2,i,t}, \dots, x_{K,i,t})'$ is characterized by

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

where $\iota_g = (\iota_{1,g}, \iota_{2,g}, \dots, \iota_{K,g})'$. 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

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

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 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 $f_{g,c}(a, s, Q)$:

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

¹²Along the paper I use I-ADLs to denote the set of both ADLs and IADLs

TABLE B1. FRACTION OF INDIVIDUALS BY HEALTH STATUS ACROSS PERMANENT INCOME QUANTILES 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.

In practice, I set the number of latent health groups $H = 4$ ¹³. Estimation of the econometric model delivers two sets of parameters: $[\hat{\beta}, \hat{\epsilon}]$. $\hat{\epsilon}$ 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.

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 %).

¹³For details on the estimation procedure and how we select the optimal number of health groups, the reader is referred to the original paper.

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 $\hat{\beta}$ and $\hat{\mu}$. 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:

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

Appendix D Medical Expenditures: Estimation

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

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

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

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 assigned to the health group with the largest probability. The parameter vector to be estimated is $\theta = (\beta, \gamma, \sigma_\epsilon^2, \sigma_\zeta^2, \rho)$. 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.
 - (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 reciprocity rates and formal care hours.

and the statistics generated by the model.

Asset Moments

For each calendar year $t \in \{1998, \dots, 2014\}$, 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:

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

where $a_{P,Q,t}^{0.5}$ 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:

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

with sample analog,

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

Formal Care hours and Probability of Leaving Positive Bequests

For all single retired individuals observed in the HRS, I simulate formal care hours decisions and probability of leaving positive bequests.

Moment conditions for hours of formal care and probability of leaving positive bequests by permanent income quintiles

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

$$\mathbb{E} \left[\left(Pr_{it}(\text{Bequest} > 0)(\theta) - Pr_Q(\text{Bequest} > 0) \right) \times \mathbb{I}_{\{q_i=Q \wedge \text{interviewed at } t\}} \right] = 0, \quad (10)$$

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

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 both consistent and asymptotically normally distributed:

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

where V is given by,

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

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:

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

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

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

In practice, I find $f(a_{P,Q,t}^{0.5}(\theta) | P \wedge Q \wedge t)$, 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 $\frac{\partial a_{P,Q,t}^{0.5}(\theta)}{\partial \theta}$ using numerical derivatives.