# Long-Term Care Needs and Savings in Retirement

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**Abstract**

In this paper, I investigate to what extent heterogeneity in both long-term care (LTC) needs and informal care support affects the savings decisions of the old. For this purpose, I develop and estimate a model of retired single individuals where agents are exposed to physical and/or cognitive health deterioration that triggers demand for LTC. To cope with LTC, agents differ in the amount of informal care provided by relatives and can purchase formal care at a market price to supplement this. I find that (i) LTC is relatively more important than bequest motives in explaining the lack of dissaving of individuals with limited access to informal care, (ii) concurrent cognitive and physical limitations account for most of the precautionary savings related to LTC, and (iii) Abstracting from informal care provision from relatives overestimates the welfare gains from expansions in government-provided means-tested care programs.

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# 1 Introduction

The uncertainty about the need for long-term care (LTC) during retirement and its associated cost constitutes a major financial risk faced by the old. However, not everyone is equally exposed to this. Some individuals rely on their families to partially offset the financial burden entailed by LTC expenses. Moreover, not all states of LTC entail the same level of need. As health deteriorates, cognitive and/or physical impairment require an increasing dependence on both formal (either in the form of a caregiver or nursing homes) and informal care. In this paper I first investigate how these two margins of heterogeneity (informal care access and level of LTC need) affect the savings decisions of the old. Then, I study the importance of taking into account the provision of informal care from relatives for evaluating the welfare implications of expansions in government provided LTC programs.

For this purpose, I start by documenting three novel facts about the heterogeneity in LTC needs and access to informal care in the data. First, 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. 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. While these two groups do not show large differences in mortality rates, mentally frail individuals consume more formal care if they live in the community and face a larger probability of living in a nursing home. Impaired individuals are in need of assistance with both physical and cognitive tasks and are the ones consuming the most formal care and facing larger chances of moving into nursing homes. High mortality rates for impaired individuals reduce the risk of being in acute need of care for long periods of time, thus limiting the financial risk implied by LTC.

Second, I document that formal LTC expenses in the community reflect choices and hence cannot be taken at face value to measure needs. In fact, conditional on health, richer individuals spend significantly more on formal care when the patient lives outside a nursing home. An impaired individual in the top quintile of the permanent income distribution consumes three hours more of formal care at home per day than an impaired individual in the bottom quintile.

Finally, the data reveals that the provision of informal care from relatives affects the consumption of formal care when in need of LTC. Conditional on health and living in the community, individuals who have limited access to informal care consume 2.5 times more formal care than those who have strong informal care support. Moreover, the probability of nursing home entry is around 30% higher for those with limited access to informal care. Therefore, differences in access to informal care imply a differential exposure to LTC risk.

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 expenses, nursing home entry, 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 and drive the probability of nursing home entry. 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. When individuals enter in a nursing home, they lose most of the informal care support and need to pay for a fixed quantity of formal care. The willingness to bestow is modeled using a warm-glow utility function. In order to capture potential differences in the willingness to bestow, I allow the marginal utility of bequest to vary across family types. Finally, agents have the option to access a government means-tested program that provides a consumption floor and LTC services if necessary.

In order to characterize family types in the model, I investigate socio-economic and demographic characteristics that predict informal care support in the data. Having children (especially a daughter), being African American, and a low education level are strong predictors of future access to informal care if in need of LTC. Based on these characteristics, I find that around one-third of individuals receive high informal care support from relatives if in need of LTC and outside a nursing home. I label them as *close* families. On the other hand, two-thirds of individuals are classified as belonging to *distant* families and receive little informal care support. In order to estimate potential differences in the willingness to bestow across family types, I require the model to match the self-reported probability of leaving bequests and Medicaid recipiency rates for each family type. The model estimates that the willingness to bestow varies little across family types.

I construct counterfactual simulations to identify the relative importance of LTC needs and bequest motives across family types. I find that LTC needs are relatively more important than bequests as drivers of savings for individuals in *distant families*. In a world without LTC needs, the median of wealth holdings at the age of 85 would be 45% lower than in the benchmark model for individuals in distant families. As we move along the wealth distribution, the importance of bequests increases. At the $75^{th}$ percentile of the wealth distribution of individuals in distant families, the importance of bequest and LTC is quantitatively comparable. On the other hand, *close* families are much better insured against LTC needs. The slow dissaving of rich individuals in *close* families is almost exclusively explained by bequest motives.

Next, I use the model economy to quantify what fraction of the precautionary savings related to LTC can be attributed to physical difficulties, mental difficulties or both. At the age of 85, 80% of the precautionary savings related to LTC can be attributed to concurrent physical and cognitive deterioration. Physical care and mental care needs separately play a quantitative small role on savings.

Finally, I assess the importance of taking into account the provision of informal care from relatives for understanding the savings decision of the old. For this purpose, I estimate a model omitting informal care provision and matching the same set of moments averaged across family types. I find that a model omitting the provision of informal care would underestimate the importance of LTC as a driver of savings for individuals in distant families but would overestimate it for individuals in close families. Furthermore, I show that considering informal care is important for public policy as a model without informal care would overestimate the welfare gains of individuals in close families from expansions in government-provided LTC means-tested programs.

My paper is related to the literature that analyzes the interaction between savings and the provision of informal care during retirement. Barczyk and Kredler (2018) and Barczyk, Fahle, and Kredler (2019) develop a theoretical framework where provision of informal care is ex-ante available to everyone but arises endogenously from a bargaining process between parents and their offspring. In their work, the old have an incentive to accumulate wealth to induce their children to provide informal care and thus informal care is ex-post heterogeneous. In my paper instead, I focus on ex-ante heterogeneity based on a set of time-invariant children characteristics that predict provision of care when parents are in need of LTC. While Barczyk and Kredler (2018) also document the presence of ex-ante heterogeneity, they do not incorporate it into their model. Moreover, in contrast to Barczyk and Kredler (2018) where bequests are exchange motivated, in this paper, I model the bequest motives as a warm glow for several reasons. First, this formulation is convenient as it simplifies computations by avoiding modeling strategic interactions between parents and children. Second, it can be very flexible and thus I can allow the parameters of the bequest function to vary across family types. Finally, previous work has found substantial heterogeneity in the bequest motives depending on individual characteristics (Kopczuk and Lupton 2007; Laitner and Juster 1996). Thus, the literature has not reached a consensus on how to best model bequests.

Lockwood (2018) develops a model with exogenous LTC expenses and finds that strong bequest motives can rationalize the low take-up of LTC insurance. By both endogenizing LTC expenses and requiring the model to match consumption of formal care for different levels of the permanent income distribution and family types, I find that LTC needs play a larger role quantitatively as a determinant of the savings behavior of individuals in *distant families* but are of comparable magnitude for individuals in close families.

In contrast to Lockwood (2018), Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2020) estimate a much smaller intensity of the willingness 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. In my paper, I study which particular LTC needs drive savings the most. I find that while physically frail individuals hold marginal propensities to consume close to the healthy ones, impaired individuals, who represent one fourth of individuals in need of LTC, hold marginal propensities to consume versus bequeath that are in line with Ameriks et al. (2020).

Dobrescu (2015) estimates a model for a set of European countries in which individuals can produce care using a combination of formal and informal care. The author assumes that the provision of informal care is exchange motivated by making it a function of bequeathable wealth and ruling out altruistic bequests. In order to match the fact that individuals in southern Europe are more likely to receive informal care in spite of holding lower wealth, the author allows for an elasticity of care to wealth which is larger for children in southern Europe. Through the lens of my model, differences across European countries could potentially be rationalized by variation in socio-economic and demographic factors that drive the share of *close* and *distant families* (e.g. education of parents and children, ethnicity, divorce) as well as cultural differences in family arrangements.

In the empirical literature, 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) finds little support for exchange motivated transfers using variation in Social Security benefits. My parameter estimates imply that the intensity of the bequest motive does not significantly vary across family types in spite of the large differences in the provision of informal care and the fact that individuals in close families tend to accumulate lower savings during their working life. These facts point towards a stronger role for altruistic bequest motives even if in my setting I cannot explicitly separate them from exchange motivated transfers.

From the policy point of view, previous literature has quantified the welfare consequence of changes in the current structure of US government insurance through means-tested programs. Kopecky and Koreshkova (2014) find large welfare gains from increases in the generosity of transfers to nursing homes residents. De Nardi, French, and Jones (2016) find that expansions of Medicaid would be valued at less than its cost. Barczyk and Kredler (2018) find welfare gains from subsidies to formal care. In this paper I show that in order to analyze the welfare benefits of expansions of means-tested LTC programs it is important to take into account heterogeneity in the provision of informal care. First, I find that for individuals in close families, the cost of expanding the generosity of formal care in means-tested programs outweighs welfare gains. Second, I show that abstracting from the provision of informal care would over-estimate the welfare gains from increases in the generosity of LTC means-tested programs.

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 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 importantly 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 (2021). Following Amengual et al. (2021), I exploit information contained in 12 dummy variables that characterize individual's reported difficulty with Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (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 the 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 (see Atkinson et al. 2005; Ng, Niti, Chiam, and Kua 2006). Examples of the latter include the ability to use a phone or control 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-ADLs[2] in the population is represented

[1] ADLs: Some difficulty with dressing (DRESS), using the toilet (TOILET), bathing (BATH), getting in or out of bed (BED), walking 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

by a finite number of possible health groups that are not observed by the econometrician. Each individual $i$ at 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 $y_{i,k,t} = 1$ is $\mu_{k_g}$. Under the assumption that I-ADLs are independently distributed conditional on health status, the joint distribution of $\boldsymbol{y}_{i,t} = (y_{1,i,t}, \dots, y_{12,i,t})$ is characterized by:

$$p(\boldsymbol{y}_{i,t}|\mu_g) = \prod_{k=1}^{12} \mu_{k,g}^{y_{k,i,t}} (1 - \mu_{k,g})^{1-y_{k,i,t}} \tag{1}$$

In addition, 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.

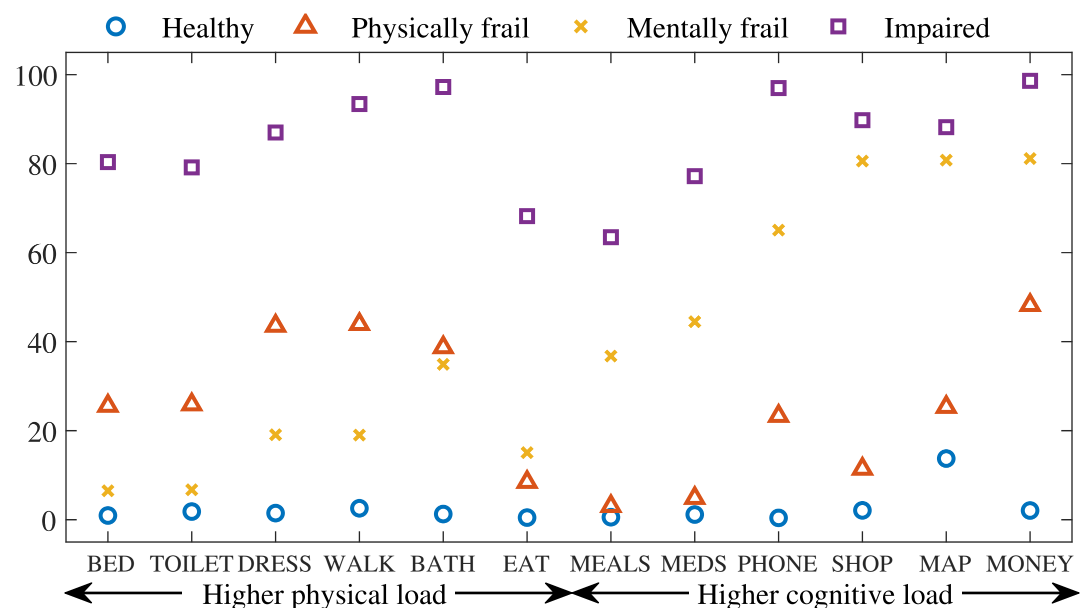



FIGURE 1. PROBABILITY OF REPORTING DIFFICULTY WITH ANY I-ADL BY HEALTH GROUP

I estimate the model including all single individuals in the HRS from 1996 to 2014[3] and who

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

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.

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 persistence. For this purpose, 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 reveals that survival probabilities sharply decrease as individual's health status deteriorates. The differences are salient across the different levels of LTC need: for example, a woman who is impaired faces a mortality rate twice as large as a woman who is mentally frail. Differences in mortality rates and transitions across health states characterize the time spent 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 up the expected duration in all possible health states which is equal to the life expectancy at age 70. The table shows large 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 shorter expected spells (both in years 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

[4]The 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 up the expected duration in all possible health states which is equal to the life expectancy at age 70.

individuals facing larger expected LTC needs in spite of living shorter lives.

## 2.2 Determinants of Informal Care Provision and Formal Care Consumption Choices

One important advantage of using the HRS is that, in addition to describing individuals' LTC needs, it also contains detailed information on care provided to non-institutionalized individuals. I make use of the HRS helpers files that contain information on help provided with I-ADLs for individuals living outside a nursing home. This module of the HRS includes information on hours of care provided as well as on the identity of the helpers. In order to characterize how individuals cope with LTC needs when they still are at home, I classify informal care as care provided by relatives or friends and formal care as care provided by a paid helper.

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 and living outside a nursing home. *Distant families* are those whose reported informal care hours are below the top

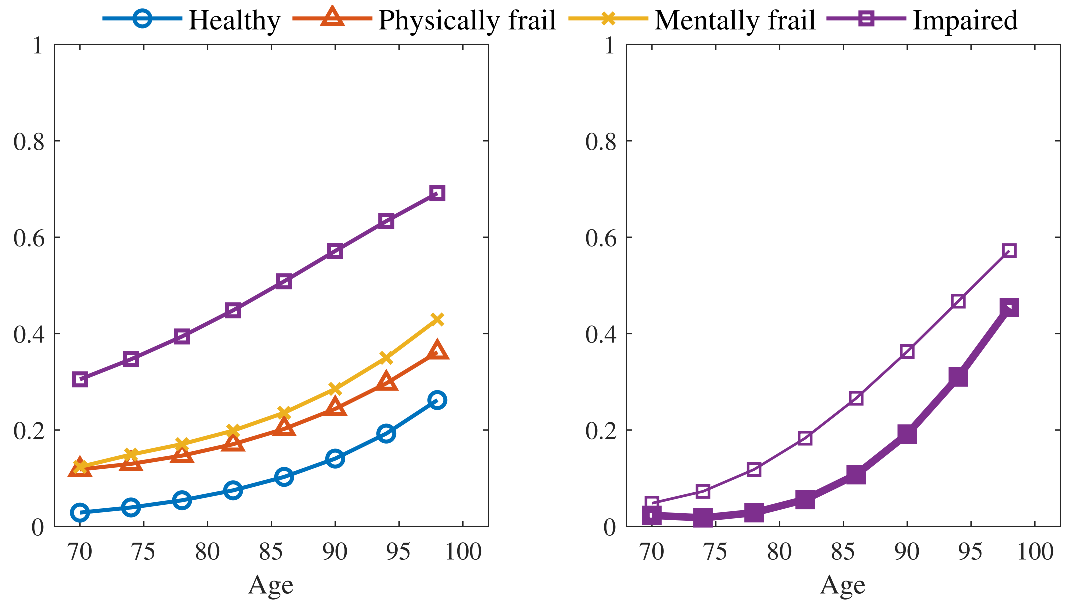



FIGURE 2. TWO-YEAR MORTALITY RATES ACROSS HEALTH GROUPS FOR WOMEN (LEFT PANEL) AND SHARE OF ALIVE INDIVIDUAL IMPAIRED FOR TOP (THICK LINE) AND BOTTOM (THIN LINE) DECILE OF PERMANENT INCOME DISTRIBUTION (RIGHT PANEL)

tercile. Individuals belonging to *close families* receive much stronger support; they receive 3.6, 8.9, and 13.6 hours of care per day from their relatives when physically frail, mentally frail, and impaired, respectively. Individuals in *distant families*, on the other hand, receive on average 35 minutes of care per day with little difference across levels of need conditional on living outside a nursing home. The proposed family classification correlates well with having children living nearby. Conditional on having children, the fraction of children within close (distant) families cohabiting is 59% (18%), living within 10 miles is 32% (52%), and living more than 10 miles away is 9% (29%).

To study which individuals are more likely to receive informal care outside a nursing home, 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 no clear correlation between permanent income and the provision of informal care as none of the coefficients on quintile dummies are significantly different from each other. Second, the table shows that having children and especially a daughter increases the chances of receiving strong informal care support by 10 and 11 percentage points (p.p.), respectively. Moreover, African Americans who never married and high-school dropouts are also more likely to belong to a *close* family than are Caucasians, divorced and more

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$^2 \times 10^{-4}$ | College (kid) |
|---|---|---|---|---|---|
| 0.05 | 0.10 | 0.11 | 0.02 | -1.17 | -0.06 |
| (0.01) | (0.03) | (0.02) | (0.01) | (5.75) | (0.02) |

| 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.

educated individuals, respectively. Finally, the pseudo r-square of the logistic regression is 5%, showing the difficulty of predicting the provision of informal care in the overall population based on the observable characteristics.

Next, 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 LTC needs and permanent income quintiles for individuals living outside of the nursing homes.[5] As the table shows, individuals outside of nursing homes adjust their formal care consumption in two ways. First, as health deteriorates, individuals consume more care. While the average consumption of 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 care[6], formal care can constitute a significant financial burden for

[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: Mean hourly wage for health aide in BLS. Lockwood (2018) finds relatively small differences in the price of care across permanent income groups.

the old. Nevertheless, as shown in the previous section, the persistence of long spells as impaired is limited by high mortality rates. Second, conditional on needs and living outside of a nursing home, 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 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.

Finally, Table 4 shows average formal care and informal care hours per day across family types for individuals outside of nursing homes. To characterize the LTC risk associated with nursing home stays, the table also includes the probability of nursing home entry and exit across family types. The table shows large differences in LTC risk across family types. While an impaired individual outside of a nursing home in a *close* family receives 13.6 hours of informal care when in need of LTC, an individual who is in *a distant* family barely receives any care. Moreover, the table shows that individuals with access to informal care consume less formal care consumption when not living in a nursing home. 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. The last two columns in Table 4 show that conditional on being impaired, individuals in *close* families have 11.5 p.p. lower probability of nursing home entry. Moreover, the probability of moving out of the institution is more prevalent among *close* families. Even though nursing home stays are very persistent through time, conditional on surviving, the probability that an institutionalized impaired individual moves back to the community is 2.0 p.p. higher for individuals in *close* families.

In summary, I document that the provision and the amount of informal care provided by children greatly varies across individuals but that there exists a number of characteristics that are helpful as predictors of its future recipiency. Moreover, the data shows that more informal care support reduces both the consumption of formal care when individuals are in the community and also the chance of long stays in nursing homes.

TABLE 3. FORMAL CARE HOURS PER DAY ACROSS PERMANENT INCOME QUINTILES

| Health | Permanent income quintile | | |
|---|---|---|---|
| status | 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, INFORMAL CARE HOURS PER DAY AND NURSING HOME ENTRY PROBABILITY ACROSS FAMILY TYPES

| Family | Health | Informal Care | Formal Care | NH entry | NH exit |
|---|---|---|---|---|---|
| Types | Status | Hours per day | Hours per day | Pr (%) | Pr (%) |
| *Distant* | Physically frail | 0.0 | 0.5 | 5.0 | 21.9 |
| *Distant* | Mentally frail | 0.6 | 1.8 | 13.3 | 15.7 |
| *Distant* | Impaired | 0.6 | 6.8 | 37.3 | 4.8 |
| *Close* | Physically frail | 3.6 | 0.5 | 4.3 | 24.6 |
| *Close* | Mentally frail | 8.9 | 0.7 | 11.0 | 13.5 |
| *Close* | Impaired | 13.6 | 2.4 | 25.8 | 6.8 |

*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 informal care access that can reproduce the main features of the data: (i) as health deteriorates, need for and use of formal care increases for individuals outside nursing homes, (ii) richer individuals consume more formal care hours, and (iii) individuals with higher access to informal care are exposed to lower LTC risk through lower average consumption of formal care conditional on living outside a nursing home and lower chances of long nursing home stays.

The model closely follows De Nardi, French, and Jones (2010) and Dobrescu (2015) but 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 regard to their family type, which differs in the amount of informal care provided. Individuals in the community decide on formal care consumption and take the informal care provided by their families as given. Moreover, individuals face heterogeneous nursing home entry risks depending on their family type. Individuals in a nursing home are required to spend a fixed amount of care services but are able to adjust their non-care consumption. Finally, I allow the marginal utility of leaving the bequest to depend on the family type, thus capturing potential compensations for the care provided from relatives or from differences in the altruistic willingness to bestow.

*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: $a \in \{70, 72, ..., 110\}$. Individuals derive utility from regular consumption and care. Care is produced by combining informal and formal care through a CES production function where $\tau$ is the share parameter attributed to formal care and $\omega$ 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 ($F$), their health, and nursing home status ($nh = 0 \vee 1$). Following the empirical section, there are two types of families in the model: *distant* ($F = 1$) and *close* ($F = 2$).

For each period their utility flow is given by,

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

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

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

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

where $k$ denotes savings from the previous period, $\delta$ captures the extent to which bequests is a luxury good or a necessity and $\lambda$ 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 medical 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.

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

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

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

[7] In the model, medical and nursing home 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).

*Nursing homes.—* Individuals in the model face uncertain entry and exit into a nursing homes state. Following the empirical section, nursing home transition probabilities exogenously vary by LTC need and family type. All individuals in a nursing home ($nh = 1$) are required to pay a fixed number of hours of formal care $l_{nh}$ but are able to adjust consumption value $c$ (room, board, and amenities). Moreover, in order to capture the inability of family members to provide care when the elderly face extreme LTC needs (e.g. advanced states of dementia), I assume that individuals in a close family who move into a nursing home receive the same informal care support as individuals in *distant* families outside nursing homes (40 minutes per day).

*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]. For individuals living outside of a nursing home ($nh = 0$), the government provides a utility floor by transferring the minimum resources possible $\underline{x}(h)$ such that an individual in a *distant* family, achieves the floor. I differentiate $G = 1$ if the consumer chooses to use the program and $G = 0$ otherwise. I assume that the government optimally splits $\underline{c}(h)$ and $\underline{l}(h)$ given $\underline{x}(h)$ to maximize the agent's utility. For individuals in nursing homes, the government pays for a fixed level of formal care hours $l_{nh}$ and provides the same consumption floor as individuals outside of the nursing home conditional on health. Thus, government transfers are given by:

$$\max\{0, \underline{c}(h) + p_{fc}\underline{l}(h) + m - b - (1+r)k\} \text{ if } nh = 0,$$
$$\max\{0, \underline{c}(h) + p_{fc}l_{nh} + m - b - (1+r)k\} \text{ if } nh = 1,$$

where $p_{fc}$ denotes the market price of an hour of formal care and $b$ is the level of permanent income of the individual.

*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. $\beta$ represents

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

the discount factor. The value function is represented by:

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

subject to

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

$$
G = 1 \Leftrightarrow \begin{cases} c = \underline{c}(h) \\ l_{fc} = \underline{l}(h) \text{ if } nh = 0 \\ l_{fc} = l_{nh} \text{ if } nh = 1 \end{cases} \tag{10}
$$

## 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 outside 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 fix the discount factor to 0.95 and 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 and nursing home transition probabilities.*— The health expenditure model is estimated using HRS data from 1996-2014. Details on the estimation procedure can be found in Appendix D. When estimating medical expenditures, I exclude individuals living in nursing homes or benefiting from 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. I compute nursing home transition probabilities from the data across LTC needs and family types. Nursing home transition probabilities are reported in Table 4.

*Hours of care provided by the family.*— Individuals in *distant* and *close* families receive the average value of the two bottom terciles and the top tercile of the informal care hours distribution, respectively. Therefore two-thirds of individuals in the sample are assumed to belong to a *distant* family while the reminder one-third is assumed to belong to a *close* family.

*Price of formal and nursing home care.*— I set the hourly price of formal care to $12 per hour[9]. To calibrate the level of care needed at a nursing home, I follow Barczyk and Kredler (2018). Using nursing-home expenditure data, the authors estimate the annual cost of basic services to be $21,640.

#### 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 $\geq 85$, 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

[9]According to the BLS the mean hourly wage for health aide in 2019 was $11.6

groups $\times$ 8 waves $\times$ 4 groups).

*Formal care moments.*— The empirical care moments are defined as the 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 $(a, s, k, b, h, \zeta, \xi, nh, F)$. $(a, s, k, b)$ are drawn from the data distribution when individuals are first observed. $\zeta$ and $\xi$ are Monte Carlo draws from discretized versions of the estimated shock processes.

*Sampling family types.*— In order to simulate savings decisions, individuals in the data need to be assigned a family type. There are two issues to consider. First, 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 logistic regression from the empirical section. In the simulation, I sample the family type from the predicted probabilities for all individuals whose family type I do not observe.

Second, 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 I sample the family type based on the frequency observed in the data. For example, if an individual is observed in two waves and in one wave she is classified in a close family but for the other wave she is classified in a distant family; this individual has a 50% chance of belonging to either family type.

*Sampling health state.*— 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]

*Measurement error in the simulation in moment conditions.*— Given that family and health status are latent, moment conditions are estimated with measurement error. In order to take this measurement error in the simulation into account, I sample a latent type which drives the individual policy functions in the simulation and a measured type to construct moment conditions. Given the uncertainty related to the type, the measured and the latent type may not coincide.

*Estimation procedure.*— Given a guess for my parameter vector $\theta$, I solve the model using discrete value function iteration. This yields a set of policy functions 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 conditions in order to include at least 40 observations. Thus, the final estimation of $\theta$ is based on 161 moment conditions. The weighting matrix (**W**) used in the estimation is the optimal variance-covariance matrix of the moment conditions, meaning that more precisely estimated data moments receive greater weight in the estimation.

## 3.3 Estimated Parameter values

Column 1 of Table 5 shows the estimated preference parameters. The estimate for $\sigma$, the coefficient of risk aversion for regular consumption, is 2.90. De Nardi et al. (2016) estimate $\sigma = 2.83$ while

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

Ameriks et al. (2020) estimate $\sigma = 5.6$. My estimate of $\nu$, the coefficient of risk aversion for care hours, is 4.55. In addition, the estimated care multipliers across different health states imply that, as expected, an 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 spend a smaller share of total consumption on formal care than do 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 $2\%$, $17\%$, and $53\%$ when physically frail, mentally frail and impaired, respectively.

Formal and informal care are estimated to be substitutes, although the precision of the estimated parameter is low. I cannot reject the null of a Cobb-Douglas production function. The share parameter attributed to formal care is 0.59. 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. In the model, the lack of substitutability in states of care is exogenously partially captured when individuals in *close families* enter in a nursing home as they lose most of the provision of informal care and must therefore rely on formal care.

The transfer needed to achieve the utility floor when healthy corresponds to $5,310 per year ($10,620 per two years) which is on the upper side of 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 $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 literature[11]:

[11] To 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

| | Model w/ Informal Care (1) | Model w/o Informal Care (2) |
|---|---|---|
| Risk Aversion | | |
| $\sigma$: Consumption | 2.90 | 2.96 |
| | (0.63) | (0.58) |
| $\nu$: Care hours | 4.55 | 4.56 |
| | (0.17) | (0.34) |
| LTC | | |
| $\alpha(h=2)$: Physically frail | 7.64 | 7.63 |
| | (6.76) | (5.07) |
| $\alpha(h=3)$: Mentally frail | 16.51 | 16.43 |
| | (0.68) | (2.36) |
| $\alpha(h=4)$: Impaired | 20.30 | 20.98 |
| | (2.49) | (2.08) |
| $\tau$: Share formal care | 0.59 | - |
| | (0.17) | |
| $\omega$: substitution formal/informal care | 0.06 | - |
| | (2.16) | |
| Bequest | | |
| $\delta$: curvature | 1,704 | 1,646 |
| | (65.57) | (77.72) |
| $\lambda(F$=*Distant*): marginal utility | 8.49 | 8.40 |
| | (3.14) | (1.77) |
| $\lambda(F$=*Close*): marginal utility | 8.69 | 8.40 |
| | (2.23) | (1.77) |
| Maximum transfer to achieve utility floor $\times 10^3$ | | |
| $\underline{x}$*(h=1)*: Healthy | 10.62 | 11.03 |
| | (0.82) | (2.20) |
| Moment Conditions | 161 | 149 |

*Notes*: Standard errors are reported in parentheses.

$$\max_{c,l_{fc},k} \frac{c^{1-\sigma}}{1-\sigma} + \exp(\alpha(h))\frac{\left[\left(\tau l_{fc}^{\omega} + (1-\tau)l_{ic}(h,F)^{\omega}\right)^{1/\omega}\right]^{1-\nu}}{1-\nu} + \exp(\lambda)\frac{(k+\delta)^{1-\sigma}}{1-\sigma} \tag{12}$$
$$s.t.\ W = c + k + l_{fc}p_{fc}$$

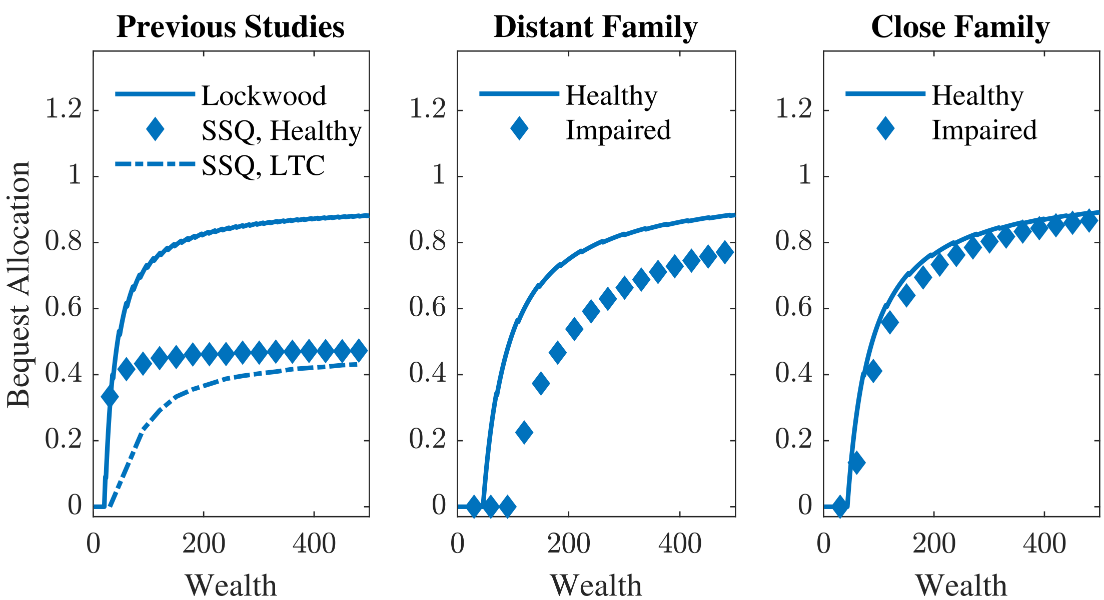
Figure 3 plots the ratio of wealth bestowed to total ressources before death ($k/W$). The left panel displays results from previous literature. There are large differences in the strength of the bequest motives estimated by Ameriks et al. (2020) when healthy (SSQ, healthy), in need of LTC (SSQ, LTC), and by 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 estimated by Ameriks et al. (2020). The center and right panel of Figure 3 display the results implied by my model across family types when healthy and impaired. When healthy, differences in willingness to bestow are small across family types and line up with the estimates in Lockwood (2018). When individuals in *distant families* become impaired, the share devoted to bequeath falls and the wealth level at which bequest motives become active increases. Given that bequest motives are estimated to be a luxury while LTC is a necessity, the difference in shares devoted to bequest across health states decreases as financial ressources increase. The right panel shows that in *close families*, being in LTC implies small changes in the propensity to bestow.

Compared to Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2016), I find a stronger bequest motive. One important difference that could explain this is the fact that I allow for heterogeneous LTC needs in my framework. As in Ameriks et al. (2016), impaired individuals in my model report large propensities to consume. However, given that the impaired status is relatively short lived due to high mortality rates, my model requires a stronger bequest motive in order to match the savings profiles of the elderly rich.

## 3.4 Model Fit

The upper panels of Figure 4, Figure 5, and Table 6 report the model fit for the targeted moments in the data. In general, the model is able to quantitatively replicate the key features of the data. In

FIGURE 3. BEQUEST ALLOCATION ACROSS STUDIES

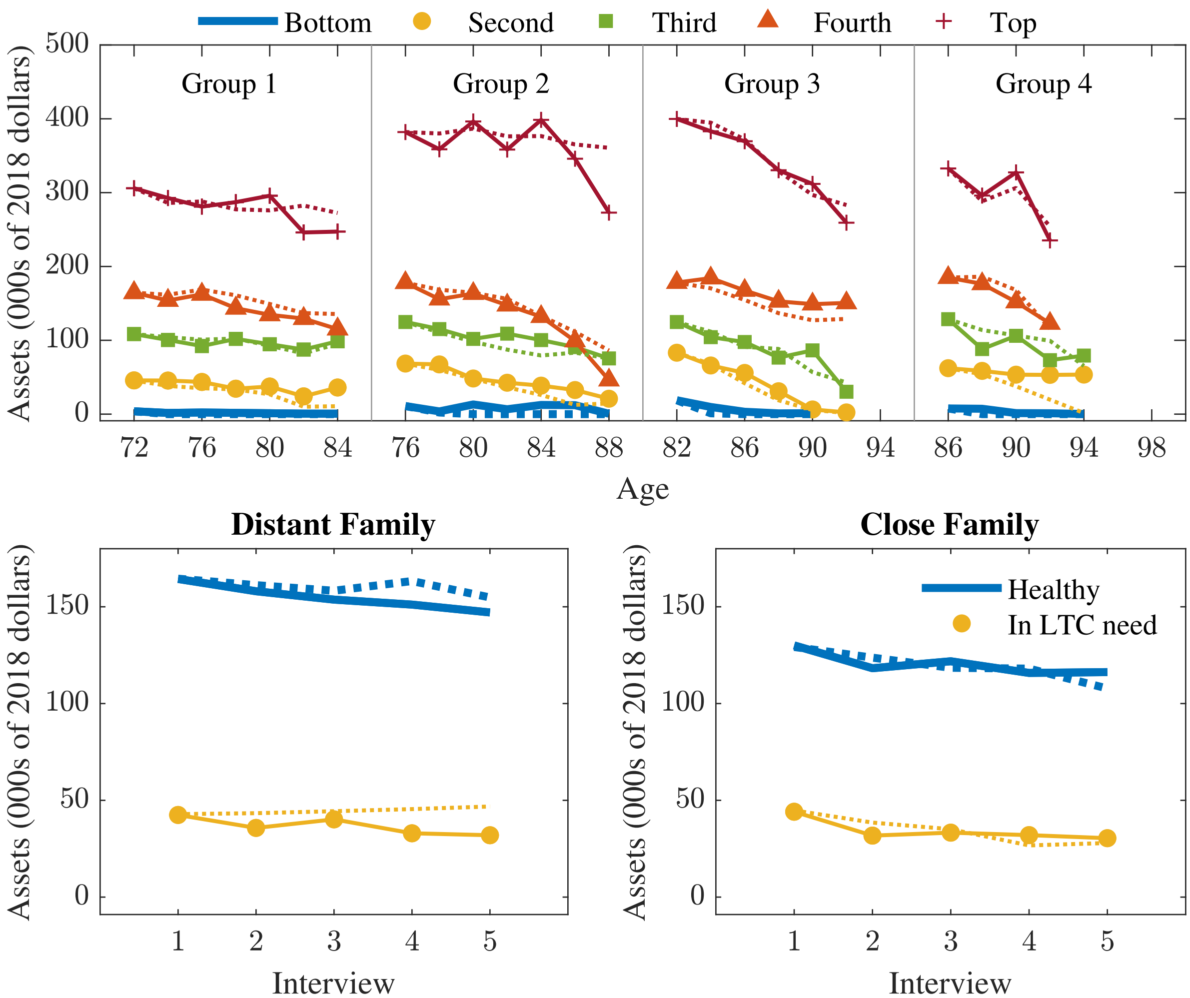



*Notes*: Ameriks et al. (2020): SSQ; Lockwood (2018): Lockwood.

the upper panel of Figure 4 we see that the model can generate the lack of dissaving of the elderly rich. Table 6 reveals that the model captures the increasing consumption of formal care as health deteriorates, the size of the income gradient of formal care consumption, and the role played by families, which reduces the amount of formal care hours consumed. Moreover, the model is able to account for the differences in the probability of leaving a positive bequest across levels of the permanent income distribution as displayed in the top panel of Figure 5. Finally, the bottom panel of Figure 5 shows that while healthy individuals in *close* families are more likely to be in Medicaid than individuals in *distant* families, the reverse is true when individuals are impaired according to the data and the model.

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 and health states with the data. Given that there are relatively few individuals in LTC, I pool individuals across ages and compute median wealth by interview number, family and health status. The lower panel in Figure 4 shows that the model is able to match the larger differences in median wealth holdings between healthy and non-healthy individuals in *distant families*, even if these are not explicitly targeted in the estimation.

FIGURE 4. MODEL FIT: MEDIAN ASSETS BY PERMANENT INCOME (UPPER PANEL), BY FAMILY TYPE AND HEALTH STATUS (LOWER PANEL)



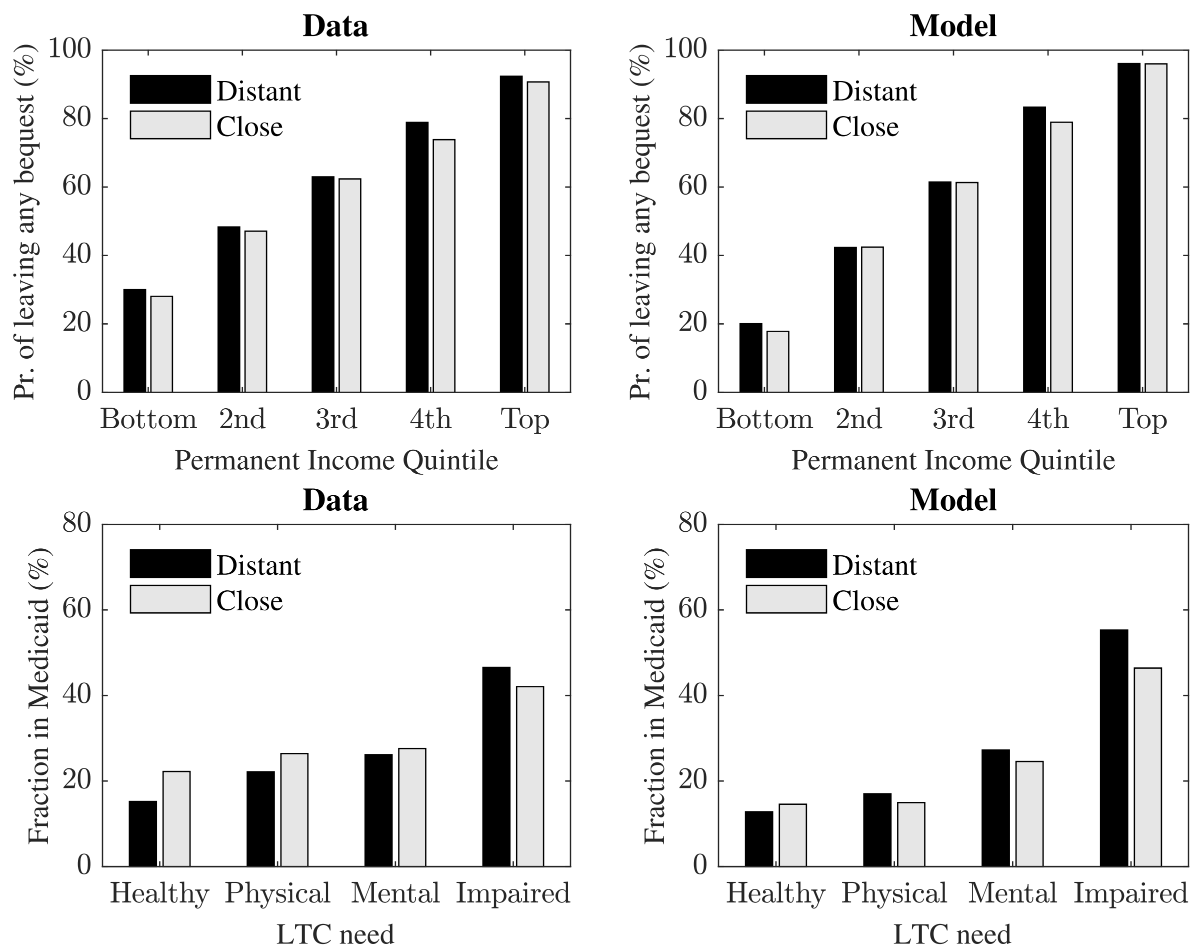

*Notes*: Retired single individuals in the HRS 1998-2014. Figure compares data (solid) and simulated (dotted) moments. In the upper panel individuals in groups 1 to 4 were age 70/74, 75/79, 80/84 and 85+ at first interview, respectively. Moments in the lower panel are untargetted in the estimation procedure.

TABLE 6. MODEL FIT: FORMAL CARE HOURS

| | Permanent Income | | | Family Type | |
|---|---|---|---|---|---|
| LTC Need | Bottom | Middle | Top | Distant | Close |
| Physically Frail | 0.5 | 0.4 | 0.6 | 0.5 | 0.5 |
| | [0.2] | [0.3] | [0.7] | [0.5] | [0.1] |
| Mentally Frail | 1.1 | 1.5 | 1.7 | 1.8 | 0.7 |
| | [0.7] | [1.4] | [2.2] | [1.7] | [0.6] |
| Impaired | 3.0 | 4.1 | 5.9 | 6.8 | 2.4 |
| | [2.5] | [3.0] | [5.9] | [4.8] | [2.0] |

*Notes*: Numbers in brackets are model moments. HRS 1998-2014, single and retired individuals aged over 70. Reported hours of formal care from non-institutionalized individuals in the data and model.

FIGURE 5. MODEL FIT: SELF-REPORTED PROBABILITY OF LEAVING POSITIVE BEQUESTS AND MEDICAID RECIPIENCY RATES ACROSS FAMILY TYPES



## 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 bequests from precautionary savings associated with LTC. For this purpose, I illustrate how these moments are affected when I shift the marginal utility of care and bequest.

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 bequests and LTC move these targeted moments in same direction and similar magnitude thus do not providing valuable identification. Increases in bequest motives will induce individuals to deccumulate resources more slowly as they age, shifting the probability of leaving positive bequests. Nevertheless, it is unclear how changes in the bequest motive affect consumption of formal care: on the one hand, increases in bequest motives induce individuals to become more frugal. Therefore, when in need of LTC a wealth effect might influence individuals to consume more formal care. On the other hand, larger willingness to bestow will also result in a larger desire to protect accumulated savings, even if in need of LTC. The dark bars in Figure 6 show how formal care consumption changes in response to an increase in the marginal utility of leaving bequests. The upper panel shows that an increase in the willingness to bequeath results in lower consumption of care.

Second, increases in the marginal utility of care when impaired will increase precautionary savings related to care but the effect on the probability of leaving bequests is unclear. On the one hand, larger 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 6 show how formal care consumption and the probability of leaving a positive bequest change in response to an increase in the marginal utility of care when impaired. The light grey bars in Figure 6 show that the probability of leaving bequests decreases.

Finally, even if increases in the marginal utility of leaving bequests and the marginal utility of being in need of LTC move formal care consumption and probabilities of leaving bequests in opposite directions, it could be that these changes are proportional to each other and thus not suitable for identification of each independent mechanism. However, Figure 6 also shows that changes in these parameters vary across individual characteristics. The upper panel of Figure 6 shows that a change in the marginal utility of care results in a stronger increase in formal care for individuals in distant families. This result highlights that differences in consumption of formal care hours across family types are a source of identification for the marginal utility of care. Moreover, the lower left panel of Figure 6 shows that the shift in LTC needs generates a U-shaped pattern in changes in the probability of leaving bequests. Middle permanent income individuals in distant families are the ones who most react while there is less action at the top and bottom of the distribution by comparison. Changes in bequests, on the other hand, are increasing with the level of permanent income. This result suggests that the gradient in the probability of leaving bequests helps disentangle the two.

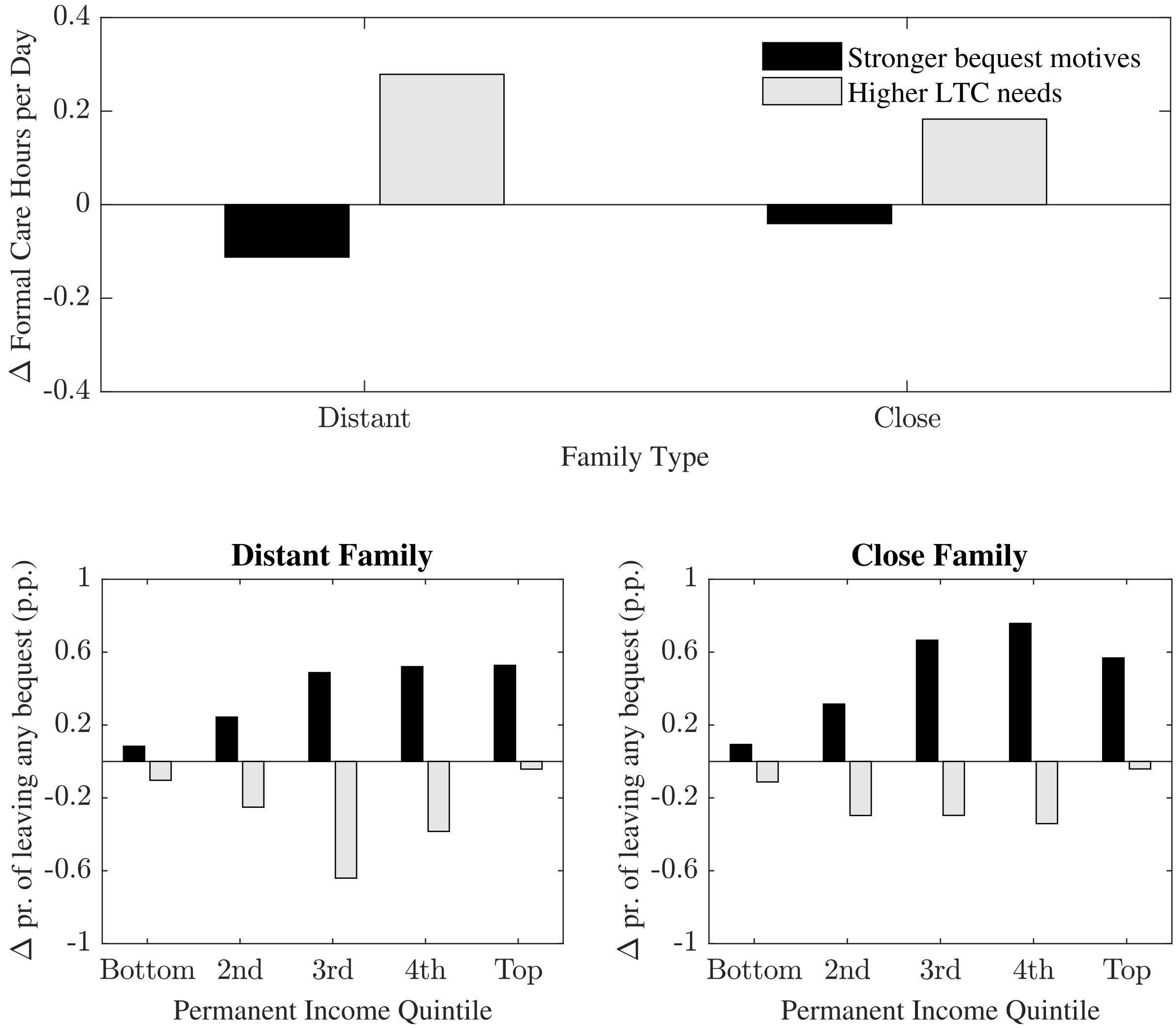
Thus, although it is not possible to provide a formal proof that the parameters are identified, this section discusses how formal care moments and the probability of leaving bequests provide identification in a neighborhood of the estimated parameter values.

# 4 Results

In order to identify key drivers of savings during retirement, I use the model to run a set of counterfactual experiments. For this purpose, I fix the estimated parameters at their benchmark values and display the evolution of assets for individuals who were aged 70-74 at their first interview (Group 1). Then, I change one feature of the model at a time, solve and simulate the model, and compare the resulting asset accumulation profile to the asset profile generated by the baseline model. To focus on underlying changes in saving, I display the asset distribution for individuals who live until age 90.

First, I determine the importance of LTC needs comparing the simulation of the benchmark model to a simulation of the model where the utility derived from LTC is set to zero ($\mu(h) = 0 \ \forall \ h$). To determine the importance of bequests, I repeat the previous exercise, this time setting the utility of leaving bequest to zero.

FIGURE 6. CHANGES IN FORMAL CARE CONSUMPTION AND PROBABILITY OF LEAVING BEQUEST.




*Notes*: Figure shows changes from the benchmark model in formal care consumption measured in hours of care and changes in the probability of leaving positive bequests measured in percentage points from a 5% and 1% increase in the marginal utility of leaving bequests and care consumption when impaired, respectively.

Figure 7 reports the wealth distribution in the benchmark model and in the no bequest and no LTC counterfactuals. The left panel shows that around the median level of savings, LTC is quantitatively more important than bequests as a driver of savings for individuals in distant families. As we move along the wealth distribution, bequest motives become increasingly more important. At the 75th percentile of the asset distribution the quantitative importance of LTC and bequest on the savings decisions of the old coincide. The right panel of Figure 7 shows that the savings decisions of individuals in *close families* are quantitatively more affected by bequest motives at the 75th percentile and less affected by LTC needs. In a world without LTC the 75th percentile of the wealth distribution of individuals in *distant families* would be 26% (10%) lower relative to the benchmark economy.

Second, I run a set of experiments to identify which LTC needs most affect the savings decisions of the old. For this purpose, I simulate a set of counterfactuals by fixing the utility derived from LTC to zero ($\mu(h) = 0$) in each state of need, separately. Then, I compare the simulations to the benchmark model and to the previous counterfactual where the marginal utility of consuming care was equal to zero for all LTC states. Figure 8 shows mean assets across age and families for the benchmark model and for each counterfactual. The figure shows that in the absence of all LTC needs, mean assets would be 13% lower at age 85. Furthermore, 80% of the increase in spending is driven exclusively by the need of care for the impaired state. In contrast, physical and cognitive limitations have a quantitatively smaller effect on the savings decisions of the old.

Finally, I zero in on the importance of taking into account informal care provisions for LTC implied savings and its consequences for public policy evaluation. For this purpose, I first estimate a model where the utility flow exclusively depends on formal care:

$$u(c, l_{fc}; h) = \frac{c^{1-\sigma}}{1-\sigma} + \exp(\alpha(h))\frac{l_{fc}^{1-\nu}}{1-\nu}.$$

In this model, individuals in distant and close families are identical and nursing home entry rates are set to the population average. The model is estimated by targeting the same set of moment conditions as in Section 3 but in this case, averages are taken across family types. One important distinction is therefore, that for individuals in close and distant families, I am targeting the average formal care consumption. Appendix G shows that a model abstracting from heterogeneity in access to informal care is able to match key features of the data well. Column 2 of Table 5 shows the estimated parameters for the model abstracting from the provision of informal care.

Next, I compute how savings would differ in the absence of LTC needs when taking into account the provision of informal care. Comparing the right and left panel of Figure 9 shows that taking into account the provision of informal care plays a quantitatively minor role. The benchmark simulation for both models and their corresponding counterfactuals without LTC look very similar. As such, a model that takes into account informal care and a model that doesn't can match aggregate savings equally well. However, this result arises from two offsetting effects: individuals in close families are saving more for LTC in a model abstracting from informal care while individuals in distant families are saving less. To show this, I compute the precautionary savings related to LTC as the difference in mean savings between the benchmark and the no LTC simulation for the model with and without long-term care but also across individuals in different family types in the two model specifications. The left panel of Figure 10, shows that individuals in distant families in a model with informal care save around 15% more for LTC than in a model which abstracts from LTC. This result arises because, in the new specification I am targeting the average formal care hours unconditional on family type, thus individuals in distant families in a model abstracting from informal care consume fewer hours of formal care than in the data. Indeed and as the right panel shows, the opposite is true for individuals in close families. Individuals in close families save more for LTC in a model that abstracts from informal care. Analogously, given that in the new specification I am targeting the average formal care hours unconditional on family type, individuals in close families in a model abstracting from informal care consume more hours of formal care than in the data. These two opposing effects offset each other and thus the average effect of LTC needs on savings remains unchanged between the models with and without informal care.

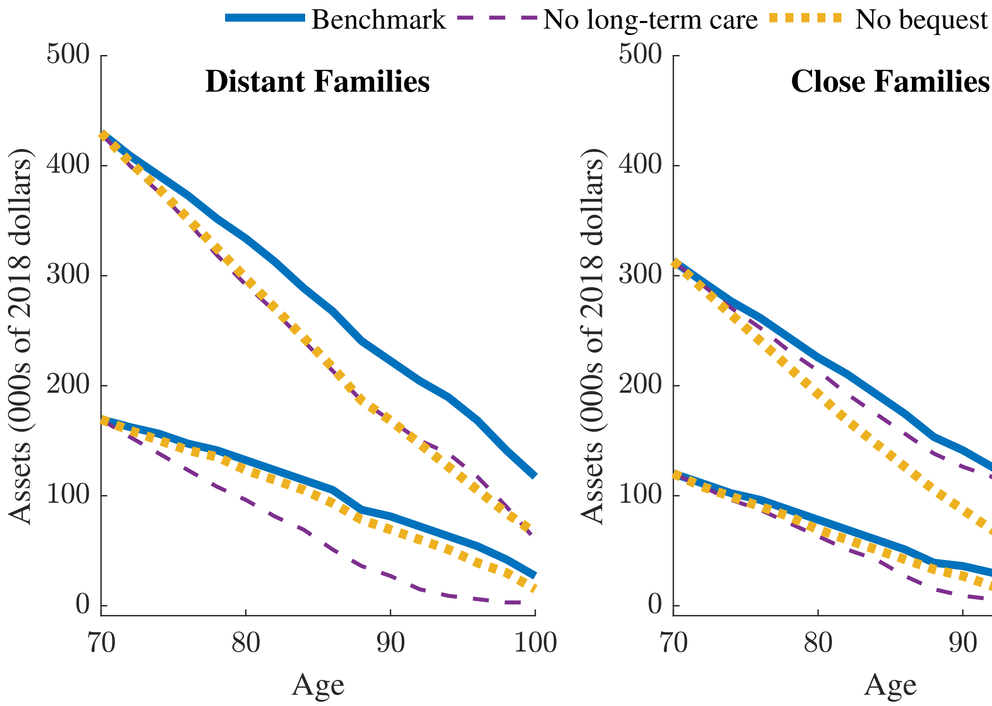
I now turn to assess the importance of informal care provision for public policy. For this purpose, I compare the costs and welfare gains across model specifications of a 20% increase in the provision of formal care hours for individuals outside of nursing homes who rely on government means-tested programs. I measure the increase in costs as the present discounted increase in government transfers at the time that the policy is introduced. To measure welfare gains, I compute equivalent variations: the asset transfer that would leave the retiree before the reform as well off as after the policy introduction.

Table 7 shows that both the present discounted value of transfers and its increase after the policy reform change little across model specifications. However, the table shows that a model without informal care would overestimate the welfare gains of the policy intervention by a factor of two. While the difference in welfare gains across model specifications for individuals in distant families is \$20 (\$2,630 versus \$2,610), the difference in welfare gains for individuals in close families is \$2,560. These large differences arise because in close families, relatives are already providing considerable support and therefore any extra formal care support provides little extra utility. Panel B shows that abstracting from care provided by relatives would overestimate the welfare gains from this policy for individuals in close families. All in all, column (4) shows that in both models the welfare gains outweigh the cost but the ratio of the two is 50% larger in the model abstracting from informal care. Moreover, in a model including heterogeneity in informal care provision the extra cost outweighs the welfare gains for individuals in close families while it does not do so in a model without informal care.

# 5 Conclusions

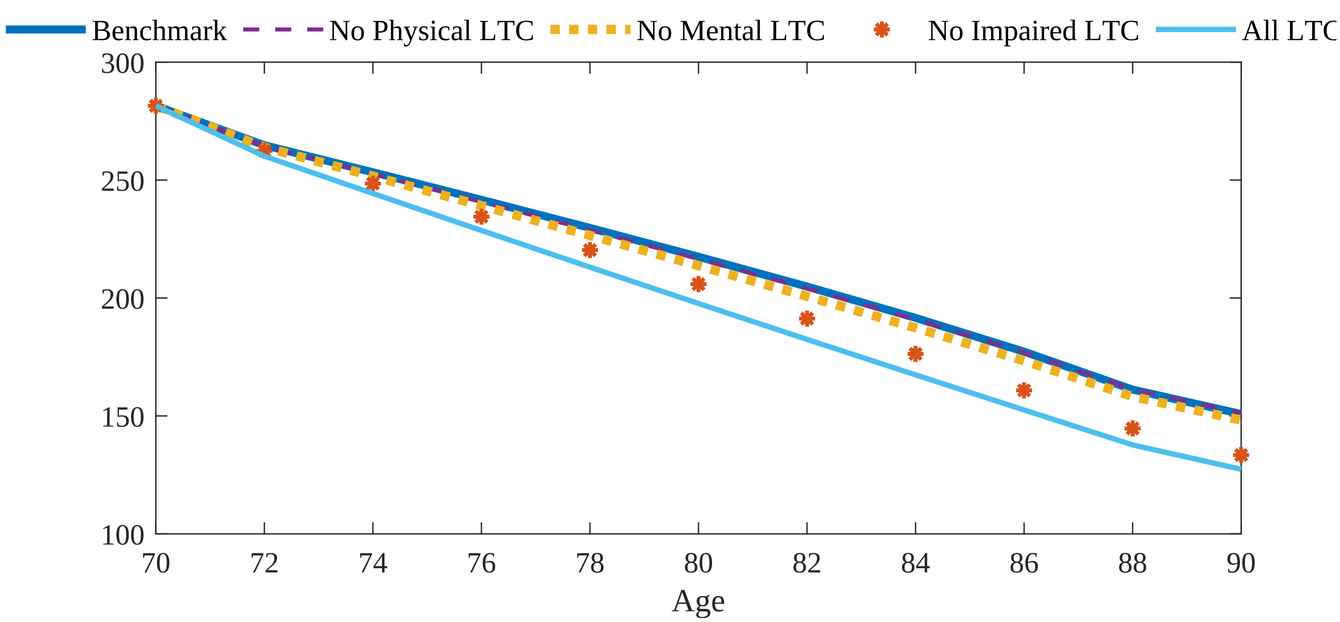
In this paper, I show that differences in access to informal care across individuals are important for understanding the lack of dissaving of the old and for analyzing the welfare implications of changes in the provision of LTC by government means-tested programs. Counterfactual simulations show that first, the savings decisions of individuals with limited access to informal care are mainly driven by LTC needs while strong bequest motives are necessary in order to match the wealth trajectory of rich individuals with large access to informal care. Second, the model shows that health states with concomitant physical and cognitive limitations account for the largest fraction of precautionary savings related to LTC. Finally, the paper shows that ignoring the availability of informal care over-predicts the welfare gains associated with expansions in means-tested public LTC programs.

FIGURE 7. COUNTERFACTUAL DISSAVING: 75TH PERCENTILE AND MEDIAN ASSETS.



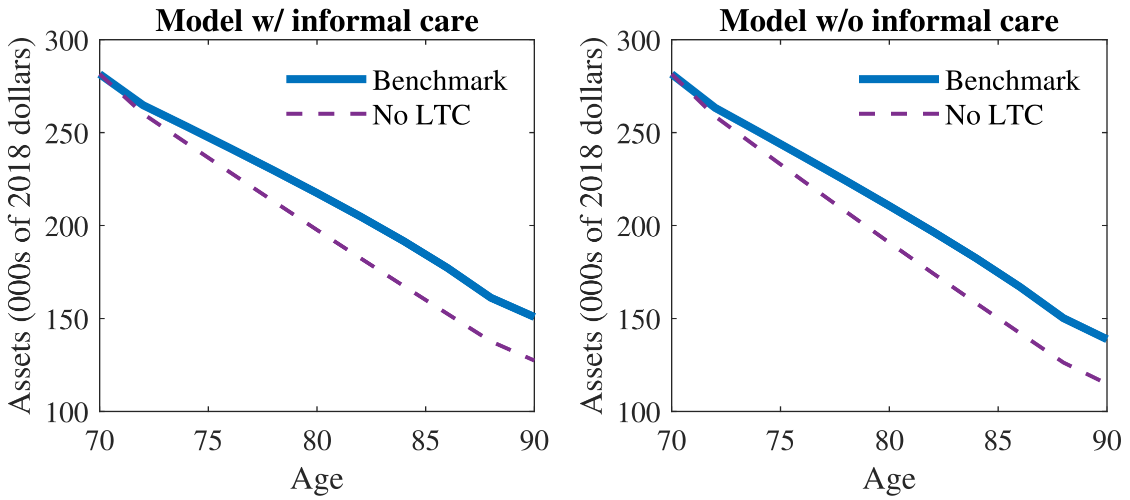

*Notes*: Figure shows median assets and the 75th percentile for the simulated benchmark and the counterfactual without long-term-care, and no bequest motives for individuals aged 70/74 at first interview.

FIGURE 8. COUNTERFACTUAL DISSAVING: HETEROGENOUS LTC NEEDS



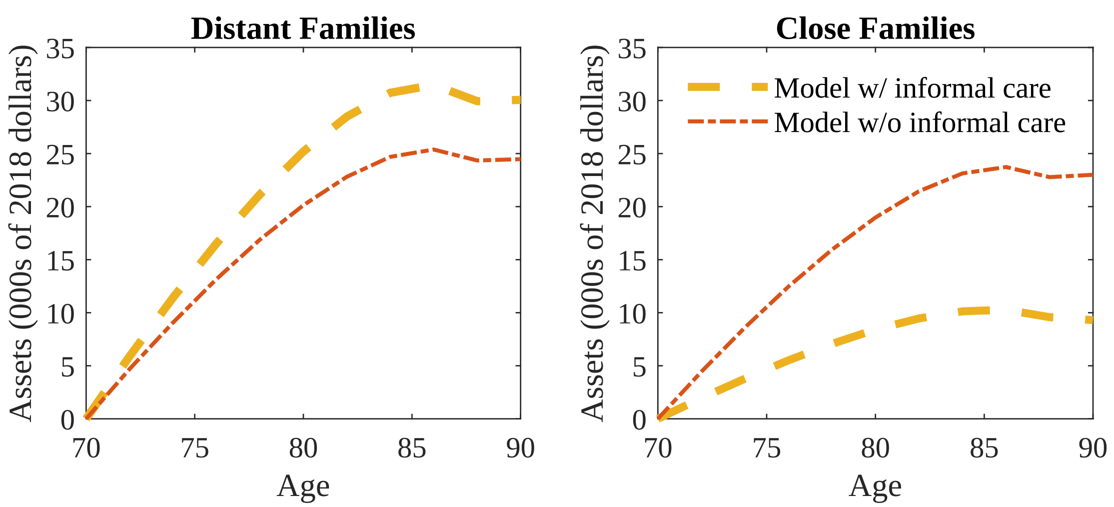

*Notes*: Figure shows mean assets for the simulated benchmark and the counterfactual without physical, mental and impaired LTC needs separately for individuals aged 70/74 at first interview.

FIGURE 9. COUNTERFACTUAL DISSAVING: THE ROLE OF LTC IN A MODEL WITH AND WITHOUT INFORMAL CARE.




*Notes*: Figure shows mean assets for the simulated benchmark and the counterfactual without long-term care for individuals aged between 70 and 74 at first interview. Left panel: model with informal care. Right panel: model without informal care.

FIGURE 10. PRECAUTIONARY SAVINGS RELATED TO LTC IN A MODEL WITH AND WITHOUT INFORMAL CARE.




*Notes*: Figure shows the difference in mean assets between the benchmark model and a counterfactual without LTC needs in the original model (model with informal care) and in a model abstracting from informal care (model without informal care) for individuals aged 70/74 at first interview.

TABLE 7. THE WELFARE GAINS OF EXPANDING FORMAL CARE IN MEANS-TESTED PROGRAMS BY 20%: MODEL WITH AND WITHOUT INFORMAL CARE

**Panel A: Model with informal care**

| Family Type | PDV of transfers<br>(1) | $\Delta$ Transfers<br>(2) | Welfare Gains<br>(3) | Ratio<br>(4) |
|---|---|---|---|---|
| Distant | 11,800 | 900 | 2,630 | 2.9 |
| Close | 13,500 | 800 | 370 | 0.5 |
| All individuals | 12,400 | 850 | 1,900 | 2.2 |

**Panel B: Model without informal care**

| Family Type | PDV of transfers<br>(1) | $\Delta$ Transfers<br>(2) | Welfare Gains<br>(3) | Ratio<br>(4) |
|---|---|---|---|---|
| Distant | 10,900 | 750 | 2,610 | 3.5 |
| Close | 13,500 | 990 | 2,930 | 3.0 |
| All individuals | 11,800 | 800 | 2,700 | 3.3 |

*Notes*: Column 1 represents the present discounted value of government transfers before the reform. Column 2 is the increase in government transfers after the reform. Column 3 is the dollar amount needed to ensure that an individual before the reform is as well off as after the reform. Column (4) is the ratio of (3)/(2).

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# 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. (2021) 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-ADL[12], say $y_{i,k,t} = 1$, is $\iota_{k,g}$. Under the assumption that I-ADLs are independently distributed conditional on the health status, the joint distribution of $\mathbf{y}_{i,t} = (y_{1,i,t}, y_{2,i,t}, \dots, y_{K,i,t})'$ is characterized by

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

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

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

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

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

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

In practice, I set the number of latent health groups $H = 4$[13]. 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 minor 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.

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

# 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 %).

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 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 $\theta = \left(\beta, \gamma, \sigma_\epsilon^2, \sigma_\zeta^2, \rho\right)$. Given the normality assumptions, I use the Kalman filter to evaluate the likelihood function. I then maximize numerically the likelihood function with respect to the parameters.

# Appendix E Simulating The Model

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

1. Set the preference parameters for the simulation: $\theta^g$
2. Compute optimal policies using structural model for $\theta^g$.
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 condition and the 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 $\theta_0$ is the value of $\theta$ 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:

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

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:

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

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, Probability of Leaving Positive Bequests, and Medicaid Recipiency Rats

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

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

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

$$\mathbb{E}\Bigg[\Big(G_{it}(\theta) - \bar{G}_{H,F}\Big) \times \mathbb{1}_{\{h_i=H \wedge f_i=F \wedge \text{interviewed at t}\}}\Bigg] = 0, \tag{10}$$

$$\mathbb{E}\Bigg[\Big(Pr_{it}(\text{Bequest} > 0)(\theta) - Pr_Q(\text{Bequest} > 0)\Big) \times \mathbb{1}_{q_i=Q \wedge \text{interviewed at t}\}}\Bigg] = 0, \tag{11}$$

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

### 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 $\Omega$ 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:

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

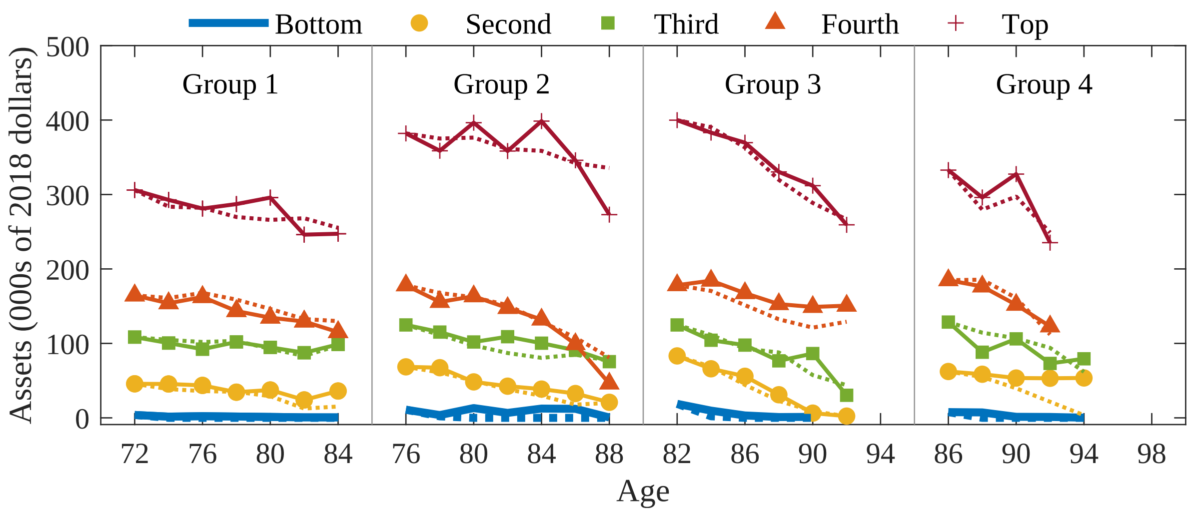
It follows that the rows of the D matrix associated to asset moments is obtained by applying Leipniz rule for differentiation to the previous equation:

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

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.

# Appendix G Model abstracting from informal care provision

FIGURE G1. MODEL FIT: MEDIAN ASSETS BY PERMANENT INCOME (UPPER PANEL) AND HEALTH STATUS (LOWER PANEL)




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

TABLE G2. MODEL FIT: FORMAL CARE HOURS

| | Permanent Income | | | Average |
|---|---|---|---|---|
| LTC Need | Bottom | Middle | Top | |
| Physically Frail | 0.5 | 0.4 | 0.6 | 0.5 |
| | [0.2] | [0.3] | [0.4] | [0.3] |
| Mentally Frail | 1.1 | 1.5 | 1.7 | 1.3 |
| | [0.8] | [1.5] | [2.0] | [1.3] |
| Impaired | 3.0 | 4.1 | 5.9 | 4.1 |
| | [2.2] | [3.3] | [5.5] | [3.1] |

*Notes*: Numbers in brackets are model moments. HRS 1998-2014, single and retired individuals aged over 70. Reported hours of formal care from non-institutionalized individuals in the data and model.

# Appendix H Robustness Check

Table 6 shows that the model underestimates the average consumption of formal care when individuals are impaired. In this Appendix H, I estimate the model increasing the weight given to formal care consumption when individuals are impaired in distant and close families. Counterfactual simulations show that the results from the paper become even more salient.

TABLE H3. ESTIMATED PREFERENCE PARAMETERS. MORE WEIGHT TO FORMAL CARE HOURS WHEN IMPAIRED

| | | |
|---|---|---|
| Risk Aversion | | |
| $\sigma$: Consumption | 2.92 | (0.66 ) |
| $\nu$: Care hours | 4.54 | (0.34) |
| LTC | | |
| $\alpha(h=2)$: Physically frail | 7.64 | (7.62) |
| $\alpha(h=3)$: Mentally frail | 16.54 | (3.49) |
| $\alpha(h=4)$: Impaired | 20.72 | (1.67) |
| $\tau$: Share formal care | 0.55 | (0.25) |
| $\omega$: substitution formal/informal care | 0.06 | (1.91) |
| Bequest | | |
| $\delta$: curvature | 1,741.48 | (75.29) |
| $\lambda(F$=*Distant*): marginal utility | 6.85 | (5.77) |
| $\lambda(F$=*Close*): marginal utility | 9.39 | (3.49) |
| Maximum transfer to achieve utility floor $\times 10^3$ | | |
| $\underline{x}$*(h=1)*: Healthy | 10.97 | (1.08) |

*Notes*: Standard errors are reported in parentheses.

TABLE H4. MODEL FIT: FORMAL CARE HOURS. MORE WEIGHT TO FORMAL CARE HOURS WHEN IMPAIRED

| | Permanent Income | | | Family Type | |
|---|---|---|---|---|---|
| LTC Need | Bottom | Middle | Top | Distant | Close |
| Physically Frail | 0.5 | 0.4 | 0.6 | 0.5 | 0.5 |
| | [0.2] | [0.3] | [0.9] | [0.6] | [0.1] |
| Mentally Frail | 1.1 | 1.5 | 1.7 | 1.8 | 0.7 |
| | [0.8] | [1.6] | [2.5] | [2.0] | [0.6] |
| Impaired | 3.0 | 4.1 | 5.9 | 6.8 | 2.4 |
| | [3.5] | [3.7] | [7.4] | [6.4] | [2.5] |

*Notes*: Numbers in brackets are model moments. HRS 1998-2014, single and retired individuals aged over 70. Reported hours of formal care from non-institutionalized individuals in the data and model.

FIGURE G2. MODEL FIT: SELF-REPORTED PROBABILITY OF LEAVING POSITIVE BEQUESTS AND MEDICAID RECIPIENCY RATES ACROSS FAMILY TYPES

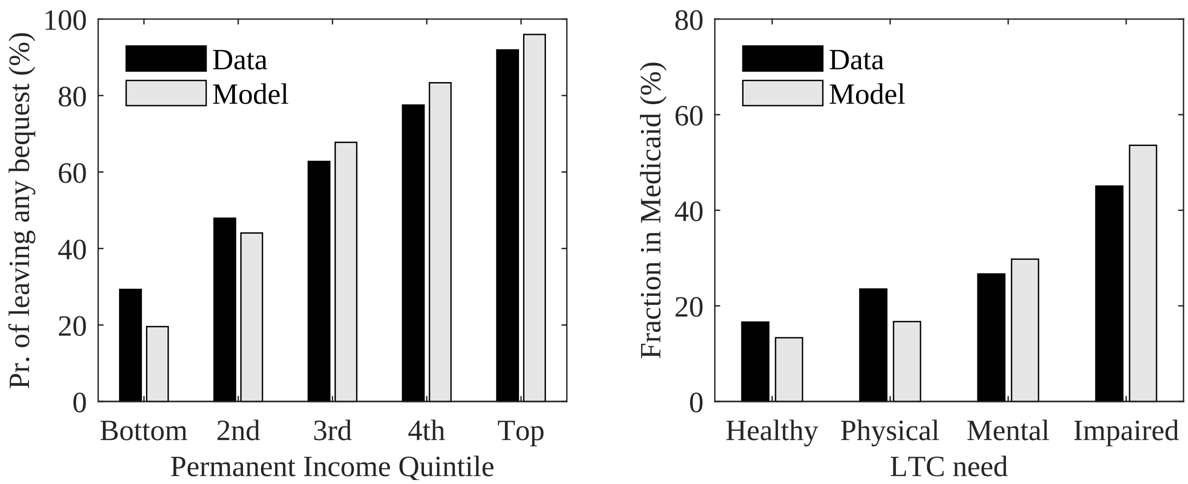
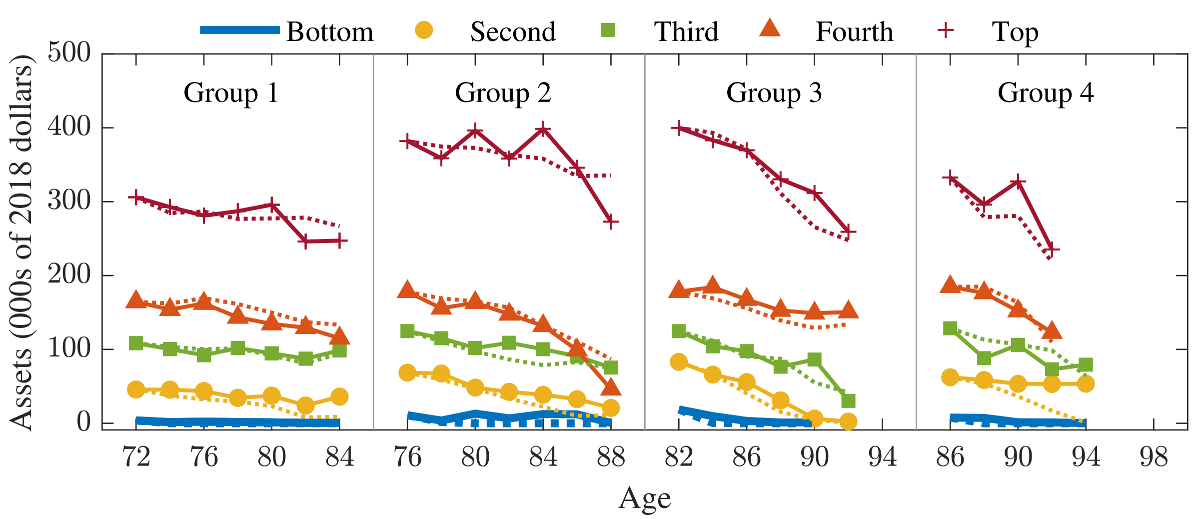



FIGURE H3. MODEL FIT: MEDIAN ASSETS BY PERMANENT INCOME (UPPER PANEL) AND HEALTH STATUS (LOWER PANEL). MORE WEIGHT TO FORMAL CARE HOURS WHEN IMPAIRED




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

FIGURE H4. MODEL FIT: SELF-REPORTED PROBABILITY OF LEAVING POSITIVE BEQUESTS AND MEDICAID RECIPIENCY RATES ACROSS FAMILY TYPES. MORE WEIGHT TO FORMAL CARE HOURS WHEN IMPAIRED

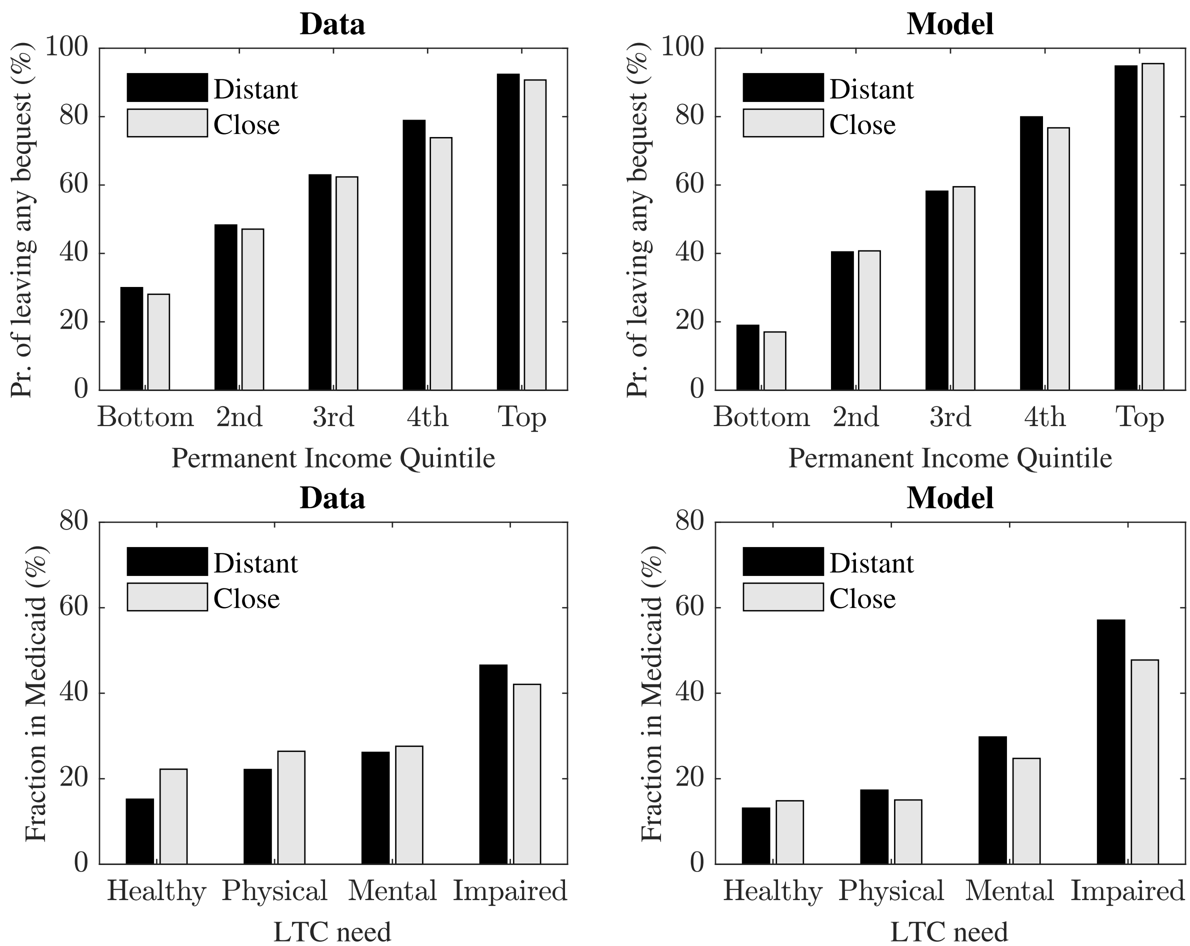
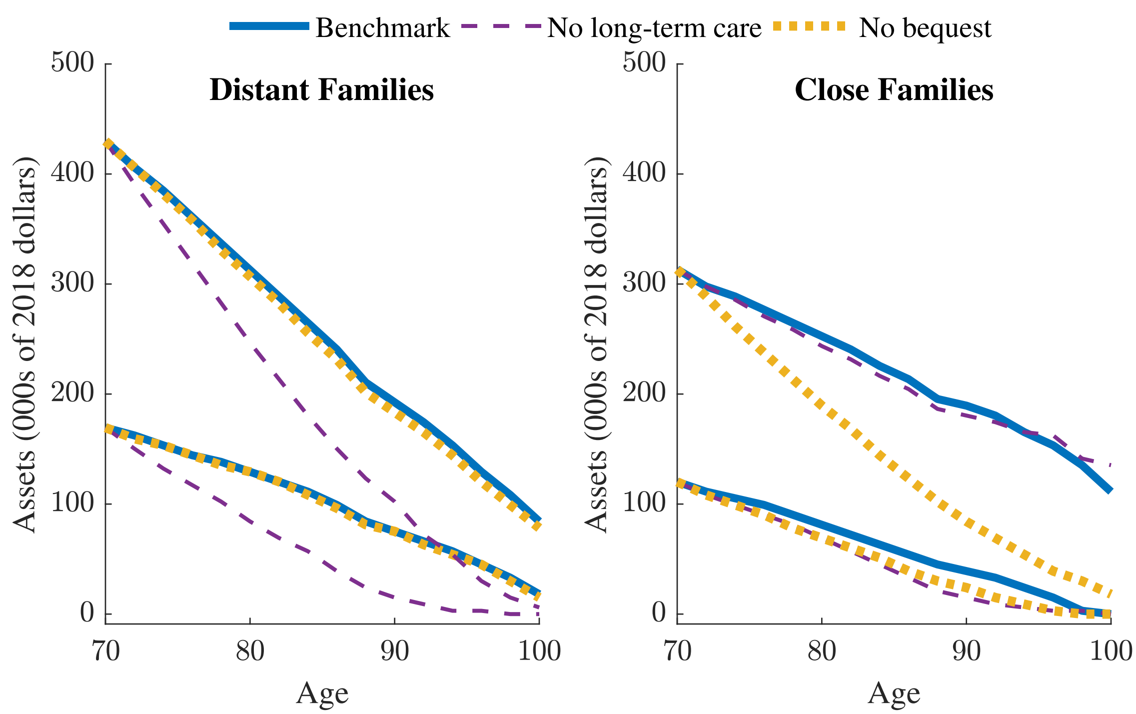


FIGURE H5. COUNTERFACTUAL DISSAVING: 75TH PERCENTILE AND MEDIAN ASSETS. MORE WEIGHT TO FORMAL CARE HOURS WHEN IMPAIRED




*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.