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INCIDENTAL BEQUESTS:
BEQUEST MOTIVES AND THE CHOICE TO SELF-INSURE LATE-LIFE RISKS

Lee M. Lockwood

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ABSTRACT

Despite facing significant uncertainty about their lifespans and health care costs, most retirees do not buy annuities or long-term care insurance. In this paper, I find that retirees' saving and insurance choices are highly inconsistent with standard life cycle models in which people care only about their own consumption but match well models in which bequests are luxury goods. Bequest motives tend to reduce the value of insurance by reducing the opportunity cost of precautionary saving. The results suggest that bequest motives significantly increase saving and significantly decrease purchases of long-term care insurance and annuities.

Lee M. Lockwood
Department of Economics
University of Virginia
Monroe Hall, Room 237
248 McCormick Rd
Charlottesville, VA 22903
and NBER
lockwood@nber.org

1 Introduction

Retirees face significant uncertainty about how long they will live and how much money they will spend coping with bad health. Among 65-year-olds in the U.S., for example, about one in five will die before age 75 while another one in five will live to at least age 90 (Bell and Miller, 2005). Over half of 50-year-olds will live in a nursing home before they die (Hurd, Michaud and Rohwedder, 2013), and nursing home stays, which in countries such as the U.S. and U.K. are not covered by universal social insurance programs, cost an average of about \$84,000 per year (MetLife Mature Market Institute, 2010). Although these risks could quickly exhaust the wealth of even relatively wealthy retirees, few people choose to insure them. In the U.S., only about five percent of retirees buy life annuities to convert their wealth into a lifelong income stream and only about ten percent buy long-term care insurance to cover the costs of nursing homes and other long-term care.

In this paper, I propose and test a new explanation for why many retirees self-insure: bequest motives. Bequest motives are often thought to increase the demand for products that insure bequests, such as long-term care insurance. But many types of bequest motives—including the type that appears to be widespread among U.S. retirees, in which bequests are luxury goods—decrease the demand for insurance against late-life risks. Bequest motives can decrease the demand for insurance by reducing the opportunity cost of precautionary saving. Without long-term care insurance, people who wish to avoid relying on Medicaid or their families must set aside substantial wealth in case they will require costly care. This greatly limits how much they can consume. Such limits on consumption are much more costly to people without bequest motives, who would like to consume all of their wealth, than they are to people with bequest motives, who value the prospect of leaving wealth to their heirs. For people with bequest motives, self-insurance has a major advantage that is absent for people without bequest motives: Only people with bequest motives value the large bequests that arise incidentally from self-insuring late-life risks.

I estimate several versions of a life cycle model of retirement to answer two main questions. First, can a standard life cycle model match retirees' saving and long-term care insurance choices? Second, can the model match the data without a bequest motive? I solve the problem of separately identifying precautionary and bequest motives by analyzing long-term care insurance decisions together with saving and by comparing the insurance and saving decisions of retirees with different levels of wealth. Both of these identification strategies produce the same conclusion: Standard models with bequest motives match retirees' behavior well while models without bequest motives miss badly.

I use the Method of Simulated Moments to estimate bequest and precautionary motives in

a model that nests as special cases models with a wide range of bequest motives, including no bequest motive. This enables me to perform statistical tests of the restrictions implicit in nested versions of the model. At the core of the model are rich approximations of U.S. social insurance programs and of the medical spending and lifespan risks facing single retirees. The estimation is based on the saving and long-term care insurance choices of single retirees in the Health and Retirement Study, a panel study of people over the age of 50.

Without bequest motives, the model is highly inconsistent with three major features of the data and is strongly rejected by over-identification tests of the model's fit. One feature is low long-term care insurance ownership rates, especially among the wealthy. Models without bequest motives tend to over-predict both the level of long-term care insurance coverage and its elasticity with respect to wealth. A second feature of the data that the model without bequest motives cannot match is the pattern of saving across the wealth distribution. In the model without bequest motives, middle-class retirees save too much relative to both richer and poorer retirees. Middle-class retirees tend to be the ones most affected by the precautionary motive since they are neither so rich as to be well-protected from costly medical needs nor so poor as to be well-insured by means-tested social insurance programs.

The third major feature of the data that the model without bequest motives cannot match is the combination, among middle-class and richer retirees, of low long-term care insurance coverage and slow drawdown of wealth. Previous research has established that standard life cycle models without bequest motives can match the low rates of long-term care insurance coverage among middle-class retirees (Brown and Finkelstein, 2008; Friedberg et al., 2014) and, separately, the slow drawdown of wealth among middle-class retirees (e.g., Palumbo, 1999; De Nardi, French and Jones, 2010; Ameriks et al., 2011). I find, however, that models without bequest motives cannot match both of these patterns simultaneously. To match the saving decisions of middle-class retirees, the model without bequest motives requires a strong precautionary motive: retirees must be highly risk averse or highly averse to relying on means-tested social insurance programs. But to match the long-term care insurance decisions of middle-class retirees, the model without bequest motives requires that people have a weak precautionary motive. As a result, models without bequest motives that match the long-term care insurance coverage of middle class retirees predict far too little saving and models that match the saving of middle-class retirees predict far too much long-term care insurance coverage.

With bequest motives, by contrast, the model matches retirees' saving over the life cycle and throughout the wealth distribution, and it matches the limited demand for long-term

care insurance, including by the rich. The estimated bequest motive, in which bequests are luxury goods, increases the saving of richer retirees relative to poorer ones and encourages people to self-insure their late-life risks. Although buying long-term care insurance would allow people to consume more of their wealth by reducing their need to engage in precautionary saving, my estimates indicate that most retirees are not willing to pay available insurance prices in order to increase their consumption at the expense of leaving smaller bequests. Buying long-term care insurance would also protect bequests from the risk of being depleted by costly care episodes, but my estimates—as well as other evidence such as the high wealth elasticity of bequests (Auten and Joulfaian, 1996; Hurd and Smith, 2002)—indicate that most retirees are not sufficiently risk-averse over bequests to justify buying available long-term care insurance contracts. For most people, the benefits of buying long-term care insurance are outweighed by the costs, which are comprised of the loads on these contracts (which in the U.S. average 18 percent of premiums [Brown and Finkelstein (2007)]) and the reduced eligibility for means-tested social insurance (Pauly, 1990; Brown and Finkelstein, 2008).¹

My results suggest that bequest motives are central for understanding retirees' saving and insurance decisions. This finding is important because much of the literature on saving and insurance decisions relegates bequest motives to a secondary role or ignores them altogether. One fact that has been cited as evidence against bequest motives is the low rate of long-term care insurance coverage, since (non-strategic) bequest motives are generally thought to increase the demand for long-term care insurance.² My results suggest instead that low rates of long-term care insurance coverage, especially among retirees in the top half of the wealth distribution and especially in combination with the slow drawdown of wealth, are more likely to be evidence in favor of bequest motives. Bequest motives, which primarily affect relatively wealthy retirees, naturally complement Medicaid (Pauly, 1990; Brown and Finkelstein, 2008) and other factors that reduce rates of long-term care insurance coverage primarily among people with little wealth to help explain the low rates

¹An insurance policy with an 18 percent load pays 82 cents of benefits per dollar of premiums on average.

²The view that (non-strategic) bequest motives should increase the demand for long-term care insurance is based on two observations made by Pauly (1990): Bequest motives make spending down wealth to qualify for means-tested programs such as Medicaid less attractive, and long-term care insurance insures bequests. Strategic bequest motives, on the other hand, which refer to situations in which people exchange bequests for services from their heirs, have been proposed as an explanation for why some people do not buy long-term care insurance (Bernheim, Shleifer and Summers, 1985; Pauly, 1990; Zweifel and Struwe, 1996).

of insurance coverage throughout the wealth distribution.^{3,4} The estimated bequest motive also makes the model consistent with the low ownership rate of life annuities observed empirically, despite not targeting this fact.

What is likely a more important reason for the relegation of bequest motives to a secondary role is that standard life cycle models without bequest motives can (separately) match the saving and long-term care insurance decisions of non-rich retirees. A standard finding in the large literature that analyzes saving during retirement (e.g., Hubbard, Skinner and Zeldes, 1995; Palumbo, 1999; De Nardi, French and Jones, 2010; Ameriks et al., 2011; Kopecky and Koreshkova, 2014) is that, given the significant medical spending risk faced by retirees, even models without bequest motives can match well the slow drawdown of wealth by middle-class retirees. Although this finding is sometimes interpreted as evidence against the importance of bequest motives, it actually just reflects the difficulty—due to the uncertainty facing retirees and the nature of non-contingent wealth—of interpreting retirees’ saving. My strategies for separately identifying precautionary and bequest motives—analyzing long-term care insurance decisions together with saving and comparing the insurance and saving decisions of retirees with different levels of wealth—complement those of three recent papers that use additional information beyond saving to obtain sharper identification of preference parameters. Ameriks et al. (2011) analyze saving together with survey questions about people’s state-contingent plans (see also Ameriks et al., 2015). De Nardi, French and Jones (2016) analyze saving together with Medicaid reciprocity rates. Koijen, Nieuwerburgh and Yogo (2016) analyze holdings of life insurance, annuities, and long-term care insurance. All three conclude that bequest motives play an important role in retirees’ choices.

³Many of the explanations for why few retirees buy long-term care insurance are, like Medicaid, most applicable to people who save little wealth into old age. These include failing to plan for the future or planning to rely on informal care (Pauly, 1990; Zweifel and Struwe, 1996). (See Brown and Finkelstein (2009) for a review.) People with more wealth are more likely to have planned for their retirement (Lusardi and Mitchell, 2007) and are less likely to use informal care (Kemper, 1992; Ettner, 1994). Yet it is difficult to find any group of retirees, even among the rich, in which the long-term care insurance ownership rate exceeds 30 percent.

⁴The role of bequest motives in reducing the demand for long-term care insurance is related to Davidoff’s suggestion that housing wealth can substitute for long-term care insurance (Davidoff, 2009, 2010). Davidoff observes that people who consume their housing wealth if and only if they require long-term care—a strategy that appears to be widespread empirically—are partially insured by their housing wealth. Bequest motives can help explain why people might consume their housing wealth only in high-cost states and not in other states as well. As a result, bequest motives can also help explain the limited market for reverse mortgages, which is puzzling in the context of models without bequest motives.

2 Long-Term Care Risk and Long-Term Care Insurance

This section summarizes the key features of long-term care risk and the market for long-term care insurance in the U.S. These facts guide my choices about the specification of the model and the set of facts with which to estimate and test the model. The model attempts to approximate in detail the key features of long-term care risk and the long-term care insurance market. For dimensions on which the approximation is less good and on which some slippage between the model and reality cannot be avoided, I test the robustness of the conclusions to plausible alternative assumptions and discuss any likely bias in the results. For overviews of long-term care risk and long-term care insurance, see Brown and Finkelstein (2011) and Davidoff (2013). For an overview of the role of the means-tested Medicaid program, see De Nardi et al. (2012).

2.1 Long-Term Care Risk

Long-term care risk is the greatest financial risk facing the elderly. Unlike acute medical care, much of which is covered by the universal Medicare program, long-term care is mostly not covered by Medicare or private health insurance contracts. Recent work (e.g., Hurd, Michaud and Rohwedder, 2013; Friedberg et al., 2014) indicates that the lifetime risk of requiring costly care is in many ways even greater than previously thought. Between 53 and 59 percent of 50-year-olds will live in a nursing home before they die, and among those who do the average length of stay is about one year (Hurd, Michaud and Rohwedder, 2013). With an average price in 2010 of a year in a private room in a nursing home of about \$84,000 (MetLife Mature Market Institute, 2010), a long stay in a nursing home can easily exhaust the wealth of most retirees, including those in the upper half of the wealth distribution. As a result, the means-tested Medicaid program covers at least some of the expenses of 70 percent of the nursing home population (Kaiser Commission on Medicaid and the Uninsured, 2013).

Patterns of long-term care usage are not uniform throughout the population. They vary by a variety of personal, household, and family characteristics. Appendix Table A1, described in more detail in Appendix Section A.1.1, presents the results of several descriptive regressions of long-term care usage. Being single, having no children, and having more income are all positively correlated with the use of formal care. These patterns are consistent with married people, people with children, and lower-income people relying more heavily on informal care. The positive correlation of income and formal care use is

consistent with quasi-experimental evidence that formal care is a normal good (e.g., Goda, Golberstein and Grabowski, 2011; Tsai, 2015). That single people and higher-income people tend to use more formal care and less informal care suggests that a single-agent model that does not explicitly include family dynamics or informal care may provide a reasonable approximation to the tradeoffs facing single retirees in the upper part of the wealth distribution—precisely the people most likely to buy long-term care insurance. Of course, an important cost of focusing on single people is that, because of the importance of informal care among couples, the choices of the retired single people that I investigate likely differ in important ways from those of members of couples.

2.2 Long-Term Care Insurance

Despite the significant risk that people face from long-term care, only about ten percent of people 65 and older own long-term care insurance. Under a typical contract, the insured individual pays premiums each period in which she does not require long-term care and receives benefits in qualifying periods in which she does require long-term care.⁵ Within this common structure, there is substantial heterogeneity in coverage levels, from relatively little coverage (e.g., contracts that do not cover home care or that limit daily benefits to an amount far below the daily cost of nursing homes) to comprehensive coverage of long-term care costs. The type of contract most often chosen is not very comprehensive.⁶ The modal maximum daily benefit limit is \$100 (about 70 percent of the average daily cost of nursing home care), and typical elimination periods (essentially deductibles, as only stays longer than this period are covered) range from 30 to 100 days. The premium for a typical policy purchased at age 65 is about \$1,200 per year.

Underwriting is an important part of the long-term care insurance purchasing process. People who are deemed high risk are charged higher prices or rejected altogether (i.e., not offered insurance at any price). Hendren (2013) shows how such rejections can arise in equilibrium due to adverse selection. Estimates suggest that among 65-year-olds, between 12 and 23 percent would be rejected from purchasing long-term care insurance if they tried (Murtaugh et al., 1997). Would-be rejections increase rapidly with age. Murtaugh et al.

⁵Information in this section about long-term care insurance contracts and the people who buy them comes from a survey of buyers in the individual (non-group) market conducted by LifePlans Inc. in 2000 (see HIAA, 2000).

⁶It is important to note that in the case of long-term care, full *consumption* insurance does not require full coverage of long-term care costs. Full consumption insurance can be achieved with less-than-full coverage of long-term care costs, since long-term care often comes bundled together with a significant amount of non-care consumption, such as room and board for residents of nursing homes and assisted living facilities. As a result, residents' greater care-related costs are partially offset by their lower non-care costs of living, since they no longer have to provide for their own room and board outside of what they pay for the nursing home.

(1997) estimate that between 20 and 31 percent of 75-year-olds would be rejected if they tried to buy long-term care insurance, and underwriting guidelines used by an insurance broker for many of the largest long-term care insurance companies advise rejecting anyone over the age of 80 regardless of their health status (Hendren, 2013). This provides a “reclassification risk” motive for buying long-term care insurance relatively early in life, before experiencing health problems that might increase premiums or lead to rejection. Empirically, people most often purchase long-term care insurance in their early 60s (America’s Health Insurance Plans, 2007), and the average age of buyers in the individual (non-group) market is 67.

This process of underwriting and rejections appears to greatly limit the extent of adverse selection within the set of people who can purchase long-term care insurance. Finkelstein and McGarry (2006) find that on average people with long-term care insurance do not use long-term care services more than people without long-term care insurance, though Finkelstein, McGarry and Sufi (2005) find evidence of dynamic adverse selection, in which people whose health improves relative to the average health of people in their pool are more likely to drop their long-term care insurance coverage. Finkelstein, McGarry and Sufi (2005) also present evidence consistent with moral hazard not being a large factor in determining long-term care use. This conclusion is reinforced by Grabowski and Gruber’s (2007) finding that nursing home use is not responsive to Medicaid reimbursement rates.

Some long-term care insurance policy holders let their policies lapse before receiving benefits—that is, they stop paying premiums and thereby lose their claims to future benefits. Estimates suggest that each year around five percent of policies lapse (Society of Actuaries, 2011). The prevalence of lapsation is somewhat surprising given that premiums are front-loaded, perhaps in an effort to limit dynamic adverse selection (Hendel and Lizzeri, 2003), and that there are safeguards against unintentional lapsation (Kaiser Family Foundation, 2003). The effect of the possibility of lapsation on the demand for long-term care insurance depends on what drives lapsation. To the extent that lapsation is driven by privately-optimal behavior (e.g., dropping coverage in response to improvements in one’s health relative to the average health of the insurance pool or in response to binding liquidity constraints), then the option to lapse is valuable and increases the demand for long-term care insurance (holding premiums fixed). But to the extent that lapsation is driven by mistakes, then the “risk” of lapsation might reduce the demand for long-term care insurance. Given the significant front-loading of premiums in long-term care insurance contracts, the option to lapse is unlikely to be very valuable, while the risk of lapsing mistakenly, if large enough, could significantly reduce the value of long-term care insurance. Given the lack of consensus about the determinants of lapsation (e.g., Finkelstein, McGarry and Sufi, 2005; Konetzka and Luo, 2011), I exclude lapsation from

the baseline model. But given the potential importance of mistaken lapsation in reducing the value of long-term care insurance, I test the robustness of the key conclusions to varying degrees of lapsation risk.

There is significant heterogeneity in long-term care insurance ownership rates by personal and household characteristics. Descriptive regressions, reported in Appendix Table A1 and described in more detail in Appendix Section A.1.1, show that long-term care insurance ownership is strongly related to wealth; ownership rates are close to zero in the bottom half of the wealth distribution and greater at the top. Yet even in the top wealth quartile, the ownership rate is just 17 percent. Controlling for wealth, ownership rates are similar between single and married people and between people with and without children. One explanation for the lack of a strong relationship between family structure and long-term care insurance ownership is that, as discussed above, informal care from children appears to be an inferior good (Tsai, 2015). To the extent that informal care from children is an inferior good, richer people are less likely to have their demand for long-term care insurance affected by whether they have children and their children’s characteristics. For poorer people, the presence of Medicaid suggests that few would buy long-term care insurance even if they did not plan to use informal care (Brown and Finkelstein, 2008).

3 Model

The model follows closely those in Brown and Finkelstein (2008) and De Nardi, French and Jones (2010) in their analyses of the demand for long-term care insurance and saving, respectively. A single retiree decides whether to buy long-term care insurance at the beginning of retirement and how much to consume each period. Each period is one year.

Preferences.— The individual maximizes expected discounted utility from consumption and bequests,

$$EU_t = u(c_t) + E_t \left\{ \sum_{a=t+1}^{T+1} \beta^{a-t} \left(\prod_{s=t}^{a-1} (1 - \delta_s) \right) [(1 - \delta_a)u(c_a) + \delta_a v(b_a)] \right\},$$

subject to the constraints detailed below. t is the individual’s current age. T is the maximum possible age. β discounts future utility from consumption and bequests. δ_s is the (stochastic) probability that an $(s - 1)$ -year-old will die before age s . Utility from consumption is constant relative risk aversion,

$$u(c) = \frac{c^{1-\sigma} - 1}{1 - \sigma}.$$

Utility from bequests is

$$v(b) = \left(\frac{\phi}{1-\phi} \right)^\sigma \frac{\left(\frac{\phi}{1-\phi} c_b + b \right)^{1-\sigma}}{1-\sigma} \text{ if } \phi \in (0, 1),$$

$v(b) = c_b^{-\sigma} b$ if $\phi = 1$, and $v(b) = 0$ if $\phi = 0$. This is a re-parameterized version of a commonly-used functional form (e.g., De Nardi, 2004; De Nardi, French and Jones, 2010; Ameriks et al., 2011), which nests as special cases nearly all of the functional forms used in the literature, including linear (e.g., Hurd, 1989; Kopczuk and Lupton, 2007) and constant relative risk aversion (e.g., Friedman and Warshawsky, 1990). This parameterization has good numerical properties and easy-to-interpret parameters. $c_b \geq 0$ is the threshold consumption level below which, under conditions of perfect certainty or with full, fair insurance, people do not leave bequests: $v'(0) = c_b^{-\sigma} = u'(c_b)$. Smaller values of c_b mean the bequest motive “kicks in” at a lower rate of consumption. If $c_b = 0$, preferences over consumption and bequests are homothetic and people are equally risk-averse over consumption and bequests. If $c_b > 0$, bequests are luxury goods and people are less risk-averse over bequests than over consumption. $\phi \in [0, 1)$ is the marginal propensity to bequeath in a one-period problem of allocating wealth between consumption and an immediate bequest for people rich enough to consume at least c_b .⁷ Larger values of ϕ mean that people leave a larger share of the wealth left over after buying c_b worth of consumption as bequests. As ϕ approaches one, the bequest motive approaches a linear bequest motive with a constant marginal utility of bequests equal to $c_b^{-\sigma}$.

Health and medical spending risks.— The individual faces uncertainty about how long he or she will live and how much acute medical care and long-term care he or she will require. At any time, the individual is in one of five health states: healthy (*he*), requiring home health care (*hhc*), requiring assisted living facility care (*alf*), requiring nursing home care (*nh*), or dead (*d*). The “healthy” state is healthy in the sense that the individual does not have chronic health problems that compel him or her to receive long-term care. But someone in this state may require acute medical care to deal with acute health problems. Acute medical care costs and future health depend probabilistically on current health (h), age (t), sex (s), and income quintile (q), $m_t \sim F_m(m; h_t, t, s, q)$ and $Pr(h_{t+1} = h' | h_t, t, s, q)$.

Long-term care costs depend deterministically on those same characteristics,

$$ltc_t = ltc(h_t, t, s, q).$$

Public care aversion and the precautionary motive.— Residents of nursing homes and assisted living facilities receive a certain amount of consumption from their long-term care,

⁷With these utility functions, the optimal bequest by someone maximizing $U = \max\{u(c) + v(b)\}$ subject to $c + b = w$ is $b^*(w) = \max\{0, \phi(w - c_b)\}$.

$c_m(h_t \in \{alf, nh\}, Pub_t) > 0$. This reflects the fact that residents of nursing homes and assisted living facilities receive some non-medical goods and services, such as food and housing, bundled with their long-term care. People who are healthy or who are receiving home health care, on the other hand, do not receive any consumption from any care that they receive, $c_m(h_t \in \{he, hhc\}) = 0$. The consumption value of facility-based care potentially depends on whether the care is paid for at least partially by the government: $c_{pub} \equiv c_m(h_t \in \{alf, nh\}, Pub_t = 1)$ may differ from $c_{priv} \equiv c_m(h_t \in \{alf, nh\}, Pub_t = 0)$. Institutional care that is at least partially financed by the government may be less desirable than privately-financed care for several reasons. For example, it may be costly to apply for government support, there may be stigma attached to receiving government support, or recipients of government support may stay in lower-quality nursing homes. These or other factors would give people an additional reason to save or buy insurance beyond a desire to smooth their marginal utility over time and across states. I follow Ameriks et al. (2011) in calling the extent to which people prefer privately-financed care to publicly-financed care “public care aversion”: $PCA \equiv [u(c_{priv}) - u(c_{pub})]$. Public care aversion is a key determinant of the precautionary motive to save and the demand for long-term care insurance.

Long-term care insurance.— Individuals who are eligible to purchase long-term care insurance (based on their health and age) make a once-and-for-all decision about whether to buy long-term care insurance at the beginning of retirement. People who buy long-term care insurance pay premiums when they are healthy ($h_t = he$) in exchange for receiving benefits when they require long-term care ($h_t \in \{hhc, alf, nh\}$). Net long-term care insurance benefits received (net of premiums paid) are $ltci_t(h_t, t; ltc_i)$, where $ltci$ (without a subscript) is an indicator of whether the individual owns long-term care insurance, $ltci \in \{0, 1\}$.

Timing, budget sets, and social insurance.— The individual enters the period with wealth $w_t \geq 0$. The individual receives non-asset income y , realizes acute medical care costs m_t and long-term care costs ltc_t , and pays or receives any net long-term care insurance benefits due under her contract, $ltci_t$. Then the individual receives any social insurance transfers for which she qualifies and decides how much to consume. Finally, the rate of return on savings, r_t , and mortality are realized. Individuals who die transfer any remaining wealth to their heirs as a bequest. People cannot die in debt or, equivalently, leave negative bequests. Together with mortality risk, this amounts to a no-borrowing constraint.

Net wealth before government transfers is

$$\hat{x}_t = w_t + y - m_t - ltc_t + ltci_t.$$

This is the financial state variable of the model.⁸ Net wealth before transfers may be negative, as medical needs may exceed the value of assets, income, and net insurance transfers.

Social insurance programs ensure that people can enjoy at least a minimum standard of living after paying for any medical care by putting a floor under net wealth.⁹ Net wealth after transfers is

$$x_t = \max\{\hat{x}_t, \bar{x}(h_t, ltc_i_t)\}. \quad (1)$$

The individual therefore relies on social insurance if and only if her net wealth before transfers is below the relevant floor,

$$Pub_t = \mathbf{1}(\hat{x}_t < \bar{x}(h_t, ltc_i_t)). \quad (2)$$

The level of the floor depends on whether the individual is in a care-giving facility, since long-term care from care-giving facilities comes bundled with some non-medical consumption. The level of the floor also depends on the individual's net long-term care insurance benefit, since social insurance programs will not pay people's long-term care insurance premiums:

$$\bar{x}(h_t, ltc_i_t) = \begin{cases} \bar{x}_{comm} + \min\{0, ltc_i_t\}, & \text{if } h \in \{he, hhc\}; \\ \bar{x}_{facil}, & \text{if } h \in \{alf, nh\}. \end{cases}$$

Consumption, saving, returns, and next-period assets.— Utility-producing consumption, c_t , is the sum of consumption spending, \hat{c}_t , and the consumption value of long-term care services received, if any, $c_m(h_t, Pub_t)$,

$$c_t = \hat{c}_t + c_m(h_t, Pub_t).$$

Consumption spending is limited by the individual's net wealth after government transfers, $\hat{c}_t \in [0, x_t]$. Assets earn a real, after-tax rate of return of r_t , which is drawn from a distribution that depends on the individual's income quintile, $r_t \sim F_r(r; q)$. Next-period wealth is

$$w_{t+1} = (1 + r_t)(x_t - \hat{c}_t) \geq 0.$$

⁸The reason to use wealth before rather than after transfers as the state variable is that only wealth before transfers encodes whether the individual relies on social insurance. The individual's reliance on social insurance can affect utility through its effect on the consumption value of facility-based long-term care.

⁹This "wealth floor" is similar to a consumption floor. The difference is that under a consumption floor individuals must consume the full amount of the floor, whereas under a wealth floor people can consume less than the floor and so save some of the transfers they receive. The wealth floor seems a better approximation to U.S. means-tested programs, though this difference should have little effect on any of the key results.

Thus, conditional on living, next-period net wealth before transfers is

$$\hat{x}_{t+1} = (1 + r_t)(x_t - \hat{c}_t) + y - m_{t+1} - ltc_{t+1} + ltc_{t+1}. \quad (3)$$

Solution method and value functions.— Given a set of parameter values, I solve the model numerically by backward induction from the maximum age, T . As long-term care insurance is purchased once-and-for-all, long-term care insurance ownership, $ltci \in \{0, 1\}$, is a fixed characteristic in every period other than the purchasing period, in which it is a control variable. The other fixed individual characteristics are sex (s) and retirement income (y). The time-varying state variables are age (t), health (h_t), and net wealth before government transfers (\hat{x}_t). The individual dies by age $T + 1$ with probability one, and leaves any remaining wealth as a bequest. For younger ages, I discretize wealth into a fine grid and use piecewise cubic hermite interpolation to evaluate the value function between grid points. For each sex-income-long-term care insurance group and at each age-health-wealth node, I solve for optimal consumption. The problem can be written recursively in terms of the value function as

$$V_t(\hat{x}_t, h_t; s, y, ltc_i) = \max_{\hat{c}_t \in [0, x_t]} \left\{ u[\hat{c}_t + c_m(h_t, Pub_t)] + \beta Pr(h_{t+1} = d | h_t, t; s, y) E_t[v(b_{t+1})] \right. \\ \left. + \beta Pr(h_{t+1} \neq d | h_t, t; s, y) E_t[V_{t+1}(\hat{x}_{t+1}, h_{t+1}; s, y, ltc_i)] \right\}$$

subject to equations 1, 2, 3, and

$$b_{t+1} = (1 + r_t)(x_t - \hat{c}_t).$$

If eligible, the individual makes a once-and-for-all choice about whether to buy long-term care insurance at age l . The individual buys insurance if and only if

$V_l(\hat{x}_l, h_l; s, y, ltc_i = 1) > V_l(\hat{x}_l, h_l; s, y, ltc_i = 0)$. Details about the numerical solution procedure and its accuracy are available in Appendix Section A.2.

4 The Method of Simulated Moments and the Key Parameters in the Estimation

The Method of Simulated Moments (MSM) extends Minimum Distance Estimation to situations in which the model is too complex to admit closed-form analytical solutions.¹⁰

¹⁰See Pakes and Pollard (1989), McFadden (1989), and Duffie and Singleton (1993) for the development of the MSM and Gourinchas and Parker (2002) for its application to the life cycle model.

MSM estimations of life cycle models typically proceed in two stages (e.g., Gourinchas and Parker, 2002; Cagetti, 2003). In the first stage, all of the parameters that can be identified without using the model are estimated or calibrated. In the second stage, the remaining parameters are estimated using the MSM, taking as given the first-stage parameter estimates.

The second stage of the estimation attempts to recover the values of the key preference parameters: the strength and curvature of bequest motives, ϕ and c_b ; the consumption value of publicly-financed nursing care, c_{pub} ; the discount factor, β ; the coefficient of relative risk aversion, σ ; and the net wealth floor for people living in the community, \bar{x}_{comm} . The parameter estimates, $\hat{\theta} \equiv (\hat{\phi}, \hat{c}_b, \hat{c}_{pub}, \hat{\beta}, \hat{\sigma}, \hat{x}_{comm})$, minimize the distance between the simulated wealth and long-term care insurance moments and their empirical counterparts, as evaluated by a classical minimum distance-type criterion function. Appendix Section A.3 contains details about the asymptotic distribution of the parameter estimates and over-identification tests of the model's fit.

5 Data and Parameterization

5.1 Data and Sample Selection Procedure

The main dataset I use is the Health and Retirement Study (HRS), a longitudinal survey of a representative sample of the U.S. population over 50 years old. The HRS surveys more than 22,000 Americans every two years. It is a rich dataset with especially detailed information about health and wealth. Households are initially drawn from the non-institutionalized population, which excludes people living in nursing homes, but members of sampled households who later move into nursing homes remain in the sample. I use data from six waves, which occur in even-numbered years from 1998–2008. Individuals in my sample are therefore covered for up to ten years. I restrict the analysis to single retirees who are at least 65 years old in 1998 and who do not miss any of the 1998–2008 interviews while they are alive. The resulting sample contains 3,386 individuals. Where possible, I use the RAND version of the variables.¹¹

¹¹I restrict to retirees by dropping individuals who earn more than \$3,000 dollars in any wave 1998–2008. I exclude waves that occur before 1998 due to sample size issues and problems with certain key variables. The first two waves of the HRS cohort (1992 and 1994) contain individuals who are too young. The first wave of the AHEAD cohort (1993) has inaccurate data on wealth (Rohwedder, Haider and Hurd, 2006) and long-term care insurance (Brown and Finkelstein, 2007). The second wave of the AHEAD cohort (1995) and the third wave of the HRS cohort (1996) have inaccurate wealth data due to problems with information about secondary residences (RAND Codebook). I exclude waves after 2008 because the sample becomes quite small due to mortality. (Almost two-thirds of the individuals in the sample died before the 2008

	Everyone 65+	Single retirees 65+
Female	0.58	0.78
Age	74.4	77.5
Wealth	\$419,086	\$238,643
Income	\$33,891	\$18,360
Own LTCI	0.10	0.09
Own annuity	0.06	0.06
Have children	0.91	0.85
Widowed	0.33	0.79
Never married	0.03	0.07
Importance of leaving a bequest		
Very	0.22	0.24
Somewhat	0.46	0.43
Not	0.32	0.32
Sample size	20,072	3,386

Table 1: Summary statistics of the sample of people aged 65 and older in the HRS and the subset of those who are single retirees (my sample). The statistics reported are means and are weighted by HRS respondent-level weights. The measure of wealth is at the household level and includes all non-annuity wealth and excludes annuitized wealth (e.g., the expected present value of future Social Security benefits). The measure of income is annual. The annuity ownership rate corresponds to annuities whose income stream continues as long as the individual lives. The values of all variables other than the importance of leaving a bequest come from the 1998 wave. The question about the importance of leaving a bequest was asked only in the 1992 wave, which primarily sampled cohorts younger than those in my sample. Among my sample of single retirees, less than nine percent answered this question.

Table 1 presents summary statistics from the HRS. The first column corresponds to the population of people aged 65 and older in the U.S., and the second column corresponds to the population of single retirees aged 65 and older, my sample. The population of single retirees is older, more female, and poorer than the overall elderly population. Only about ten percent of each group owns long-term care insurance and only about six percent owns life annuities. The vast majority of both samples have children; even among the sample of single retirees, 85 percent have children. Slightly more than two-thirds of the people in each group (and more than half of people without children) report that it is somewhat or very important to leave an inheritance to their heirs.¹²

In order to develop a rich model of the long-term care risk facing different individuals, I supplement the information in the HRS with data from the National Long-Term Care

wave.) I convert all dollar variables to constant 2010 dollars using the Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W), the price index that the Social Security Administration uses to adjust Social Security benefits.

¹²This question was asked only in the first wave of the HRS (in 1992), at which time most members of my sample were not yet part of the HRS. As a result, less than nine percent of my sample answered this question.

Survey (NLTC). The NLTC is a longitudinal survey of Americans 65 and older that contains detailed information about health and health-related expenditures. Two key features of the NLTC make it a useful supplement to the extensive information available in the HRS. First, the NLTC has a much larger number of people using long-term care services. Second, the NLTC includes a measure of the price of care (which is the input required for the model), whereas the HRS has only measures of spending on care. This is a crucial difference given that Medicaid pays for at least part of the care of a majority of residents of nursing homes.

5.2 First-Stage Parameter Values

Table 2 presents the baseline values of the first-stage parameters and the sources from which these values are adopted or estimated. These values are chosen to approximate the situation facing single retirees in the U.S. I adopt some of the values of the first-stage parameters from other sources and estimate the others. Later, I test the robustness of the results to many changes in the values of these parameters. All dollar values are expressed in 2010 dollars.

Health and lifespan risk.— The (Markov) transition probabilities across health states are based on a model estimated by Friedberg et al. (2014), which itself is based on a widely-used actuarial model developed by James Robinson (see Robinson, 2002; Brown and Finkelstein, 2004). I use Friedberg et al.’s (2014) model for women for both the men and the women in my sample because it better approximates the long-term care risk facing single individuals, who receive much less informal care than the average man in the full population. I adjust the model to match De Nardi, French and Jones’s (2010) estimates of life expectancy conditional on reaching age 70 for different sex and income groups. Women live longer than men, and richer retirees live longer than poorer ones. The life expectancy of 65-year-old women ranges from 16.1 in the bottom income quintile to 20.8 in the top, whereas the life expectancy of 65-year-old men ranges from 9.8 in the bottom income quintile to 14.2 in the top. The expected number of years spent in a nursing home is 0.84 for women and 1.06 for men. Health tends to be quite persistent, though the strength of the persistence depends on health and age. Among 65-year-old women in the third income quintile, 98 percent who are healthy will remain healthy at age 66, 24 percent who require home care will continue to require home care at age 66, but just one percent of those living in a nursing home will continue to do so at age 66 (42 percent will become healthy and 7 percent will die). Details of the model of health and lifespan risk are in Appendix Section A.1.2.¹³

¹³Appendix Table A2 summarizes my adjustments to Friedberg et al.’s (2014) model to match De Nardi,

Parameter	Source	Value in source	Value in this paper
Health states and transition probabilities: h_t , $Pr(h_{t+1} = h' h_t, t; s, y)$	Friedberg et al. (2014), De Nardi, French and Jones (2010), author's calculations	h_t : healthy (<i>he</i>), home health care (<i>hhc</i>), assisted living facility (<i>alf</i>), nursing home (<i>nh</i>), dead (<i>d</i>). $Pr(h_{t+1} = h' h_t, t; s, y)$: Friedberg et al. model for females	Adjust health transitions to match life expectancies by sex and income quintile in De Nardi, French and Jones (2010) (see Appendix A.1.2); maximum age (T) is 104
Long-term care costs: $ltc(h_t, t, s, q)$	MetLife Mature Market Institute (2002a,b), Friedberg et al. (2014), author's calculations	U.S. averages in 2002: $ltc(nh) = \$52,195$, $ltc(alf) = \$26,280$, $ltc_i(hhc, t) = \$37 * Q_s(t) + \$18 * Q_u(t)$, where $Q_s(t)$, $Q_u(t)$ from Friedberg et al. model ^a	Scale averages based on heterogeneity in NLTCs. Inflate values to reflect growth in spending, timing of care use. See Appendix A.1.3.
Acute medical care costs: $m_t \sim F_m(m; h_t, t, s, q)$	Author's estimates	$m_t \sim \log N(\mu(h_t, t, s, q), \sigma(h_t, t, s, q)^2)$	Inflate values in source to reflect growth in spending, timing of care use. See Appendix A.1.4.
Long-term care insurance: $ltc_i(h_t, t; ltc_i)$	Brown and Finkelstein (2007): Typical contract, average load on policies held for life ^b	Pay premiums when healthy, receive benefits up to \$36,500 when require LTC (\$100/day benefit cap); 18% load	Inflate value in source to 2010 dollars: maximum benefit = \$44,350. Test robustness
Consumption value of privately-financed institutional care: c_{priv}	Author's judgment ^c	$c_{priv} = \$20,000$	Same as source, test robustness
Anticipated returns: $r \sim F_r(r; q)$	Author's estimates	$r \sim N(\mu_r(q), \sigma_r(q)^2)$	Same as source. See Appendix A.4.

Table 2: Baseline values of first-stage parameters. Notes:

(a) Q_s and Q_u are annual hours of skilled and unskilled home care, respectively. In the model, Medicare covers 35 percent of home health care spending (Robinson, 2002; Brown and Finkelstein, 2008), 25 percent of nursing home spending (Friedberg et al., 2014), and 0 percent of assisted living facilities.

(b) In calculating long-term care insurance premiums, future benefits and premiums are discounted at the risk-free interest rate, assumed to be 2 percent per year. The 18 percent load means that on average people receive 82 cents worth of benefits for each \$1 of premiums paid.

(c) As discussed in the text, the main effect of using different values of c_{priv} is to shift the estimated value of c_{pub} to maintain the same utility advantage, if any, of privately-financed care, $PCA = u(c_{priv}) - u(c_{pub})$. The results are robust to a wide range of values of c_{priv} .

Long-term care costs.— Long-term care costs, $ltc(h_t, t, s, q)$, are a deterministic function of the individual's health, age, sex, and income quintile. I start with the average prices of

French and Jones's (2010) estimates of life expectancy conditional on reaching age 70 for different sex and income groups, and Appendix Table A3 reports detailed statistics on the original and adjusted models. The major advantage of basing the model of long-term care risk on observed patterns of utilization as opposed to spending is that it captures the care paid for by all sources, not just the care paid for out-of-pocket by households. This is important because Medicaid assists 70 percent of nursing home residents and even higher shares of poorer retirees (Kaiser Commission on Medicaid and the Uninsured, 2013).

different long-term care services in the U.S. in 2002 (MetLife Mature Market Institute, 2002*a,b*), $ltc_{2002}(h)$. I estimate scaling factors for these population-average prices for different groups defined by age, sex, and income quintile using individual-level regressions in the NLTCs, $ltc_{2002}(h_t, t, s, q)$. (The results are in Appendix Table A4 and additional details are in Appendix Section A.1.3.) Finally, I inflate these values to reflect the growth in the relative price of long-term care services from the middle of the sample period, 2002, to roughly the average time at which members of the sample will use long-term care services, 2008. Historically, the relative price of long-term care has grown roughly in line with wages, or about 1.5 percent per year in real terms (see Brown and Finkelstein, 2008, and the sources cited therein). For a female in the middle income quintile, the cost of a year of home care ranges from about \$5,000 at age 65 to about \$34,000 at age 105, the cost of a year in an assisted-living facility is about \$33,000 (roughly constant in age), and the cost of year in a nursing home is about \$50,000 (also roughly constant in age).

Long-term care insurance.— The baseline long-term care insurance contract, $ltci_t(h_t, t; ltc_i)$, is a simplified version of a typical contract. In exchange for paying annual premiums when healthy ($h = he$), people with insurance have their long-term care costs covered up to a maximum of \$44,350 in years in which they are sick ($h \in \{hhc, alf, nh\}$). This corresponds to a maximum daily benefit of \$100 in 2002 expressed in 2010 dollars.¹⁴ Premiums exceed expected discounted benefits by 18 percent, the average load on long-term care insurance policies held for life in the U.S. (Brown and Finkelstein, 2007).¹⁵ Only people in good health can purchase long-term care insurance. This reflects the widespread rejections of unhealthy applicants during the underwriting process (Hendren, 2013).

Acute medical care costs.— Acute medical care costs are log-normally distributed, with type-specific means and variances, $m_t \sim \log N(\mu_m(h_t, t, s, q), \sigma_m^2(h_t, t, s, q))$. The log-normal distribution provides a fairly close approximation to the observed distribution of medical spending in the HRS. I estimate the type-specific means and variances using regressions of log medical spending and its square; see Appendix Table A5. I limit the sample for these regressions to the person-waves in which the individual is not receiving long-term care, had at least \$100,000 in combined non-housing wealth and annual income in the previous wave, and, to take logs, has strictly positive medical spending. As in the case of long-term care, I scale up the means and standard deviations of the acute medical care distributions to capture the rapid growth over time in spending on acute medical care, which grew by

¹⁴Results are robust to instead using a (less-popular) comprehensive long-term care insurance contract. At the baseline estimates, the model matches the greater popularity of less comprehensive long-term care insurance contracts.

¹⁵Brown and Finkelstein (2007) find that men face significantly higher loads on long-term care insurance than women, mainly because married men receive much more care from their spouses—and thus less benefit-eligible formal care—than married women do. Among single retirees, however, spousal care is not an issue and men and women likely face more similar loads.

about 4.2 percent per year in real terms between 1975 and 2005 (Orszag, 2007). I use the distribution of spending by retirees with significant holdings of liquid wealth to minimize the bias introduced by the fact that Medicaid pays for much of the care received by people with little wealth. Further details are in Appendix Section A.1.4. To solve the model, I approximate the distribution of acute medical care costs using Gaussian quadrature.

Social insurance and public care aversion.— To qualify for public coverage of nursing care, people must exhaust all of their assets, $\bar{x}_{facil} = \$0$. This is a rough approximation to the stringent asset and income tests imposed by many state Medicaid programs. Using small positive values (e.g., \$2,000, the modal asset eligibility requirement in 1999) has little effect on the results while slightly complicating the exposition and solution of the model, since it means that in some rare cases individuals would have a choice about whether to take up benefits. (This choice can be non-trivial due to the possibility of public care aversion.) The income floor for people living in the community, \bar{x}_{comm} , is estimated in the second stage. In principle, this parameter could be calibrated based on the statutory payments of means-tested programs.¹⁶ But estimating this parameter allows for the possibility that hassle or stigma costs of claiming benefits, lack of awareness about benefits, or other factors might lead people to behave as if they view transfers from income-floor programs differently from their statutory amount, which would affect the strength of the precautionary motive to save and the demand for long-term care insurance.

The baseline value of the non-care consumption provided by privately-financed care facilities is $c_{priv} = \$20,000$. The consumption value of publicly-financed care facilities, c_{pub} , is estimated in the second stage. The lower is c_{pub} relative to c_{priv} , the greater is “public care aversion,” and so the greater is the incentive to save or buy insurance in order to avoid relying on publicly-financed care in the future. The main effect of using different values of c_{priv} is to change the value of c_{pub} that maps into a given level of public care aversion, $PCA = u(c_{priv}) - u(c_{pub})$. So to a first approximation, the choice of any particular value of c_{priv} is inconsequential; changing the value of c_{priv} mainly just shifts the estimated value of c_{pub} in order to maintain the level of public care aversion implied by retirees’ saving and insurance choices. But a secondary effect of using different values of c_{priv} is to change the value of resources in bad-health states, which affects precautionary motives to save and buy insurance. This is the way in which the chosen c_{priv} value can have substantive effects. The results are robust to a wide range of alternative values of c_{priv} .

Anticipated returns on wealth.— Individuals view the annual, real, after-tax rates of return

¹⁶A natural benchmark is the federal Supplemental Security Income (SSI) benefit. For single elderly people in 2002, this benefit was about \$7,950 in 2010 dollars. (This figure comes from inflating the SSI benefit in 2002, the middle of the sample period, of \$545 per month (Social Security Administration, 2003) to 2010 dollars.)

on wealth as arising from independent draws from a normal distribution whose mean and variance depend on the individual’s income quintile. (As discussed below, the return that a particular retiree actually earns each year in the simulations is based on his or her portfolio allocation and the realized returns on different assets in that year.) I estimate the means and variances of these distributions using data on historical asset returns and the average portfolio compositions of the different income quintiles of my sample. Retirees’ portfolios, though not without risk, are roughly an order of magnitude less volatile than the stock market. Over the past 51 years (1960–2010), the standard deviation of the rate of return based on the average portfolio shares of my sample of single retirees was about 3.3 percent. Appendix Table A6 reports summary statistics. Additional details are in Appendix Section A.4.

5.3 Second-Stage Moments: Wealth and Long-Term Care Insurance

Empirical wealth moments.— The wealth moments track the evolution of wealth over time as members of the sample age. The measure of wealth is total non-annuity wealth, including housing.¹⁷ I split the sample into six 5-year birth cohorts. The age ranges of these cohorts in 1998 are 65–69, 70–74, 75–79, 80–84, 85–89, and 90–94. For each cohort and in each wave *after* 1998—2000, 2002, 2004, 2006, and 2008—in which there are at least 100 surviving members of the cohort, I calculate the share of people with zero wealth and the 50th and 75th percentiles of the wealth distribution. Thus there are potentially 90 wealth moments: three moments for each of five waves for each of six cohorts. Discarding the cohort-waves with fewer than 100 surviving members eliminates the 2008 observations of five of the six cohorts, which leaves 75 wealth moments. (The results are not sensitive to whether these moments are excluded.) Each cohort’s wealth moments trace the evolution over time of the distribution of wealth of its surviving members. Later waves contain fewer people due to deaths. Of the 3,386 individuals in the sample in 1998, 1,183 (34.9 percent) were still alive in the last wave in 2008. Averaging the moments across cohorts and waves (from 2000–2008), the average share of people with zero wealth was 13.8 percent, the average 50th percentile (median) wealth level was about \$72,400, and the average 75th

¹⁷In reality, different types of wealth have different properties, including liquidity and how they are treated by means-tested programs. Housing wealth is an important case. It is a major component of household wealth, it is likely to be less liquid than most other components of wealth, and it is sometimes exempted from the asset tests of means-tested programs. I follow much of the literature in lumping it together with other types of wealth. Doing so seems like a reasonable approximation in this case, since reverse mortgages and other products have increased the liquidity of housing wealth, and since the modal state Medicaid program did not exempt the housing wealth of single elderly people from asset testing during the sample time period. I have tested the robustness of the results to excluding housing wealth entirely and found that the quantitative results are relatively unaffected and the qualitative conclusions are highly robust.

percentile wealth level was about \$272,700.¹⁸

Empirical long-term care insurance moments.— The empirical long-term care insurance moments are the ownership rates of each of the four quartiles of the wealth distribution among the subset of the sample who were 70–79 years old in 1998, weighted by their 1998 HRS individual sample weights. These ownership rates are 1.2, 2.6, 6.3, and 12.5 percent (increasing across wealth quartiles), for an overall average of 5.6 percent. As discussed in Section 2.2, wealth is one of the strongest predictors of long-term care insurance ownership in the HRS.

These calculations count an individual as owning long-term care insurance if he or she owns a long-term care insurance policy that covers both nursing home care and home care in at least half of the waves in which information on his or her long-term care insurance is available.¹⁹ Policies that cover both nursing homes and home health care are the most popular type empirically (Brown and Finkelstein, 2007) and are the type I use in the model. Averaging an individual’s reported ownership over time likely provides a better measure of his or her “lifetime” ownership than point-in-time estimates because of measurement error and policy lapsation.²⁰ The subset of the sample who were 70–79 years old in 1998 completed their prime buying years, ages 65–69 (Brown and Finkelstein, 2007), immediately before the sample period, 1998–2008.

5.4 Simulation Procedure and Estimation

For each candidate parameter vector θ , I solve the model separately for men and women, different income groups, and people with and without long-term care insurance. I use the resulting value functions and optimal choice rules to simulate the wealth path and long-term care insurance ownership status of each individual in the simulation sample, which is described below. I use the resulting simulated data to calculate the simulated moments, using the same procedure as that used to calculate the empirical moments from the actual data. Finally, I evaluate the goodness of fit of the simulated moments at this particular set of parameter values θ to the empirical moments using a classical minimum

¹⁸For many cohort-waves, the 25th percentile of the wealth distribution is zero or close to it. This prevents me from using the 25th percentiles as target moments, since percentile-based moments require that the distribution not have mass points near the moments. Moreover, the share of people with zero wealth is interesting in its own right, as people with no wealth must rely on means-tested programs in response to even small shocks.

¹⁹Missing data prevent me from determining the ownership status of 11 individuals. I exclude these individuals from the calculation of the empirical long-term care insurance moments. When simulating the wealth paths of these individuals, I assume that they do not own long-term care insurance.

²⁰For this group, the point-in-time ownership rate (5.7 percent) is only slightly higher than the “lifetime” ownership rate (5.6 percent).

distance-type objective function. Details of the simulation procedure are available in Appendix Section A.5.

To create the simulation sample, I draw with replacement 10,000 individuals from the sample of single retirees in the HRS. To ensure that the resulting population is representative of the population of single retirees in the U.S., the probability that individual i in the sample of single retirees is chosen on any draw is proportional to i 's 1998 person-level weight, $\frac{weight_i}{\sum_{j=1}^{3,386} weight_j}$. For each individual in the simulation sample, the simulation uses: three fixed individual characteristics (sex, average retirement income, and long-term care insurance ownership status), three initial state variables (age, health, and wealth in 1998), health status in 1999–2008, and portfolio shares in 1998–2006.²¹

The simulation uses each individual's health status in 1999–2008 to ensure that individuals contribute to the same wealth moments in the simulation as in the data—individuals who die in 2001 in the data also die in 2001 in the simulation. This protects against bias from the model of health transitions not matching perfectly the true risk facing retirees. The simulation uses each individual's portfolio shares in 1998–2008 together with Baker, Doctor and French's (2007) estimates of the annual returns on various assets to construct person-year-specific realized rates of return on wealth, $r_{i,t}$. This ensures that neither heterogeneity in realized returns over time and across people nor differences between anticipated and realized returns are incorrectly attributed to differences in saving behavior. This is important given the large differences in retirees' portfolios across the wealth distribution and the unusually—and probably unexpectedly—high returns during the sample period. Details are available in Appendix Section A.4.

Estimation.— The baseline estimation of $\theta \equiv (\phi, c_b, c_{pub}, \beta, \sigma, \bar{x}_{comm})$ is based on 79 moment conditions: four long-term care insurance moments and 75 wealth moments. The baseline weighting matrix is the inverse of the estimated variance-covariance matrix of the second-stage moment conditions, $W = \hat{\Omega}_g^{-1}$. The more precisely a particular moment is estimated, and the less correlated it is with other moments in the estimation, the greater the weight it receives in the estimation. As a result, the long-term care insurance moments receive non-negligible weight in the estimation, despite being far outnumbered by wealth

²¹Each individual's average (real) retirement income equals the simple average between 1998 and 2008 of his or her non-asset income less the cash value of means-tested government transfers received, such as Supplemental Security Income and food stamps. Means-tested transfers are excluded from income because these transfers arise endogenously in the model. Health status in the year of interview j is nursing home if the individual is living in a nursing home when interview j occurs, home health care if the individual is not living in a nursing home when interview j occurs and reports using home care anytime in the two years preceding interview j , dead if the individual is dead when interview j would otherwise occur, and healthy otherwise. I simulate health status between interview years using the model health transition probabilities and Bayes' rule.

moments.²² Following Pischke (1995), I check the robustness of the results to using the inverse of the diagonal of the estimated variance-covariance matrix of the second-stage moment conditions as the weighting matrix, $W_{robust} = [diag(\hat{\Omega}_g)]^{-1}$. By ignoring the correlation between different moments, this alternative weighting matrix tends to put more weight on the wealth moments. Any differences between the results based on these different weighting matrices can therefore help reveal the relative influence of the wealth and long-term care insurance moments on the parameter estimates.

6 Results

6.1 The Baseline Model Matches Retirees' Choices

The first column of Table 3 presents the results of the baseline estimation. The estimates of the bequest motive parameters indicate important bequest motives in which bequests are luxury goods. The estimates imply that people are only moderately risk-averse over bequests and, equivalently, that among people rich enough to leave bequests, the marginal propensity to bequeath out of wealth is fairly high. The estimated bequest motive falls somewhere in the middle of those estimated in the literature. It is broadly similar to those estimated by Kopczuk and Lupton (2007), De Nardi, French and Jones (2016), and Ameriks et al. (2015) and that calibrated by De Nardi (2004). It is weaker than that estimated by Ameriks et al. (2011), and it is stronger than those estimated by Hurd (1989) and De Nardi, French and Jones (2010).²³ One key message of this paper is that even relatively modest bequest motives have a large effect on (privately-)optimal purchases of insurance against late-life risks.

The estimates of the other parameters, with one exception, take standard values. The exception is the discount factor, which is estimated to be unusually low, $\hat{\beta} = 0.84$, indicating strong impatience. If β is calibrated to a more standard value, like 0.975, as in

²²The objective-function penalty for a 5-percentage point deviation from the empirical long-term care insurance moments (i.e., for simulated ownership rates that are five percentage points greater than their empirical counterparts) is roughly equal to the objective-function penalty for a ten percent deviation from all of the median wealth moments (i.e., for simulated median wealth moments that are 1.1 times their empirical counterparts), an eight percent deviation from all of the 75th percentile wealth moments, or a 14 percent deviation from all of the “share with zero wealth” moments.

²³Many of the comparisons across bequest motives are ambiguous, since often estimates in which bequests are less of a luxury good (smaller c_b in my parameterization) have smaller marginal propensities to bequeath (smaller ϕ in my parameterization) in a simple one-period problem of splitting wealth between consumption and bequests. When this is the case, it is not possible to unambiguously rank the bequest motives; those bequest motives with smaller c_b and ϕ values will tend to have a greater impact on poorer retirees, whereas those with greater c_b and ϕ values will tend to have a greater impact on richer retirees.

	Baseline		$\beta = 0.975$	
		No bequest		No bequest
	Baseline model (1)	motive ($\phi = 0$) (2)	Baseline model (3)	motive ($\phi = 0$) (4)
Parameter estimates, $\hat{\theta}$				
$\hat{\phi}$: bequest motive	0.96 (0.01)	0 -	0.95 (0.01)	0 -
\hat{c}_b : bequest motive (\$1,000s)	17.1 (1.4)	0 -	24.8 (1.0)	0 -
\hat{c}_{pub} : public care (\$1,000s) ($c_{priv} = \$20,000$)	19.1 (4.0)	19.7 (1.0)	6.2 (0.5)	20.0 (0.9)
\hat{x}_{comm} : wealth floor in community (\$1,000s)	3.0 (0.1)	5.2 (0.2)	1.8 (0.2)	5.3 (0.2)
$\hat{\beta}$: discount factor (annual)	0.84 (0.02)	0.95 (0.02)	0.975 -	0.975 -
$\hat{\sigma}$: risk aversion	4.5 (0.1)	5.0 (0.3)	2.0 (0.02)	4.6 (0.2)
Goodness-of-fit				
χ^2 stat	97.3	185.6	107.9	187.9
p-value of model	0.03	2.4e-11	0.01	1.9e-11
p-value of no-bequest motive restriction	<2.3e-16	-	<2.3e-16	-
Simulated LTCI (%) (Empirical LTCI = 5.6%)	4.3	15.3	6.2	15.0

Table 3: Estimation results. Columns one and two are based on the baseline assumptions. Columns three and four calibrate β to 0.975. The second and fourth columns come from estimating the nested version of the model without a bequest motive ($\phi = 0$). Standard errors are in parentheses.

column 3, the estimated bequest motive, simulated moments, and fit all change little relative to the baseline estimation, but the estimates of the non-bequest motive parameters change significantly. The estimate of the coefficient of relative risk aversion falls from 4.5 to 2.0, and the estimates of the consumption values of the means-tested programs fall from $\hat{c}_{pub} = \$19,100$ to $\$6,200$ and from $\hat{x}_{comm} = \$3,000$ to $\$1,800$.

As discussed in detail in Appendix Section A.6, retirees' saving and long-term care insurance choices are much more informative about bequest motives than about the other parameters.²⁴ Many changes in the first-stage parameter values and second-stage moments

²⁴Appendix Figures A1 and A2 plot several versions of the objective function based on different combinations of moments and as a function of different pairs of parameters. The baseline objective function increases rapidly as the bequest motive parameters move away from their estimated values and more slowly as most of the other parameters move away from their estimated values. The wealth moments alone, the long-term care insurance and median wealth moments together, and, especially, the full set of long-term care insurance and wealth moments are all much more consistent with models in which bequests are valuable luxury goods than with other configurations, including those with no bequest motive.

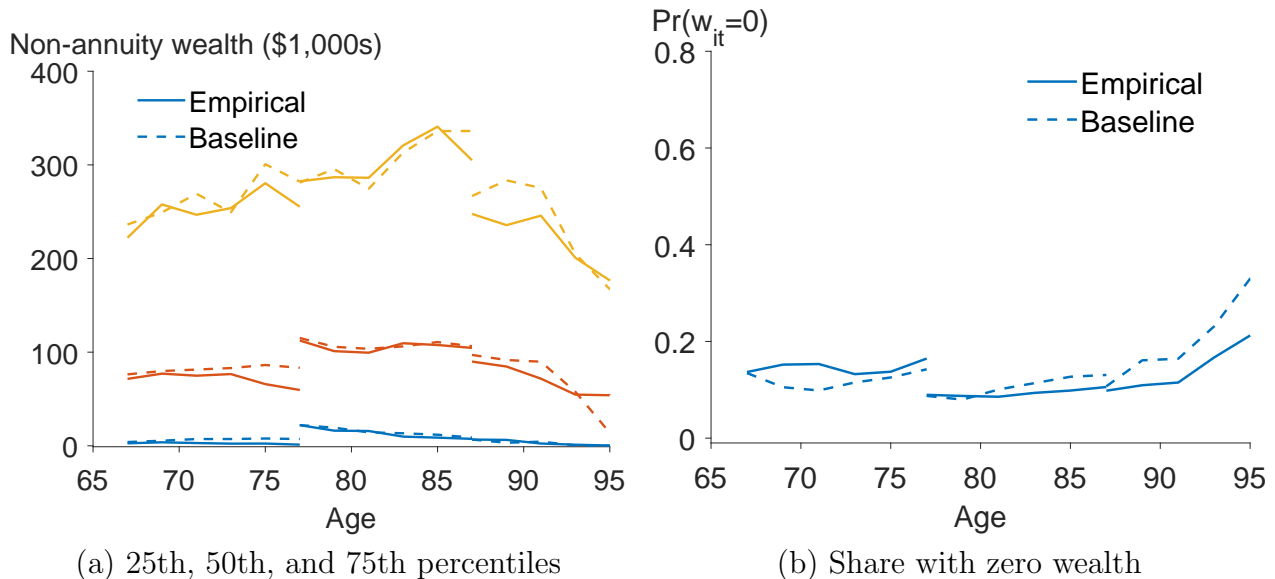


Figure 1: Empirical wealth moments (solid lines) and simulated wealth moments (dashed lines) for odd-numbered cohorts. (Even-numbered cohorts, excluded to avoid overlapping lines, are shown in Appendix Figure A3.) Panel (a) shows the 25th, 50th, and 75th percentiles of wealth; the 25th percentiles are not targeted by the estimation. Panel (b) shows the share with zero wealth. The x -axis shows the average age of surviving members of the cohort. The empirical and simulated wealth moments do not coincide in 1998 (the left-most points of each set of curves) due to sampling error from drawing a finite sample for the simulation.

have non-negligible effects on the estimates of the discount factor, the coefficient of relative risk aversion, and the consumption values of means-tested programs. These parameters are not pinned down very sharply because they have similar effects on saving and long-term care insurance. A given change in each of these parameters pushes saving and long-term care insurance in the same direction, so changes in one or more of these parameters can often be roughly offset by changes in others, and different combinations of values of these parameters can have similar implications for retirees' saving and long-term care insurance choices. Bequest motives, by contrast, affect saving and long-term care insurance in a way that is qualitatively different from those of the other parameters, increasing saving but *reducing* long-term care insurance. Retirees' choices are highly informative about bequest motives because bequest motives play a key role in allowing the model to match the broad patterns that many retirees hold much of their wealth well into retirement yet do not buy long-term care insurance.

Figure 1 plots the empirical and simulated wealth moments of the odd-numbered cohorts. (The results for even-numbered cohorts, shown in Appendix Figure A3, look similar.) The model reproduces the main patterns in the wealth data and therefore in consumption and saving decisions. Figure 2 shows the empirical and simulated long-term care insurance moments (the ownership rates by wealth quartile) as well as the overall ownership rates. The baseline model over-predicts ownership in the second wealth quartile and

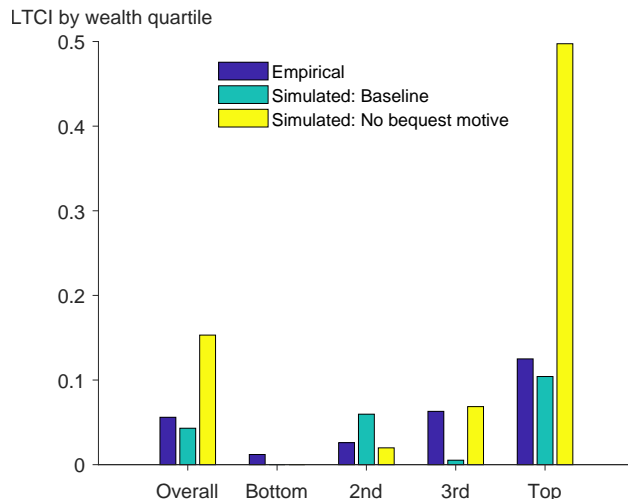


Figure 2: Simulated and empirical long-term care insurance ownership rates, overall and by wealth quartile. The simulated ownership rates are based on two sets of preferences: estimates from the baseline model and estimates from the model without bequest motives.

under-predicts ownership in the third wealth quartile, but it matches the major patterns that long-term care insurance ownership is low throughout the wealth distribution and greatest at the top of the wealth distribution. Appendix Table A7 reports statistics on the fit of various versions of the model to each set of moments. The baseline model matches most of the moments quite closely. On average, it understates the long-term care insurance moments by 1.4 percentage points and the median wealth moments by \$2,700, and it overstates the 75th percentile wealth moments by \$7,300. It does less well matching the “share with zero wealth” moments, overstating them by 4.3 percentage points on average. As discussed in Appendix Section A.6, this likely reflects certain mismatches between the concept of wealth in the model and what is measured in the data. The results are robust to addressing these mismatches, which matter most at the bottom of the wealth distribution, in a variety of ways, including using alternative measures of wealth and excluding the low-wealth moments. The baseline model also performs well on various validation tests. Appendix Figure A4 shows, for example, that the simulated bequest distribution matches closely its empirical counterpart.

6.2 The Model Without Bequest Motives is Strongly Rejected

The second column of Table 3 shows results from estimating the model without bequest motives, i.e., under the restriction that $\phi = 0$. The model without bequest motives fits the data poorly, and the restriction of no bequest motive is rejected at the one percent confidence level. The same is true when β is calibrated to 0.975, shown in the fourth column. The strong statistical rejections of versions of the model without bequest motives

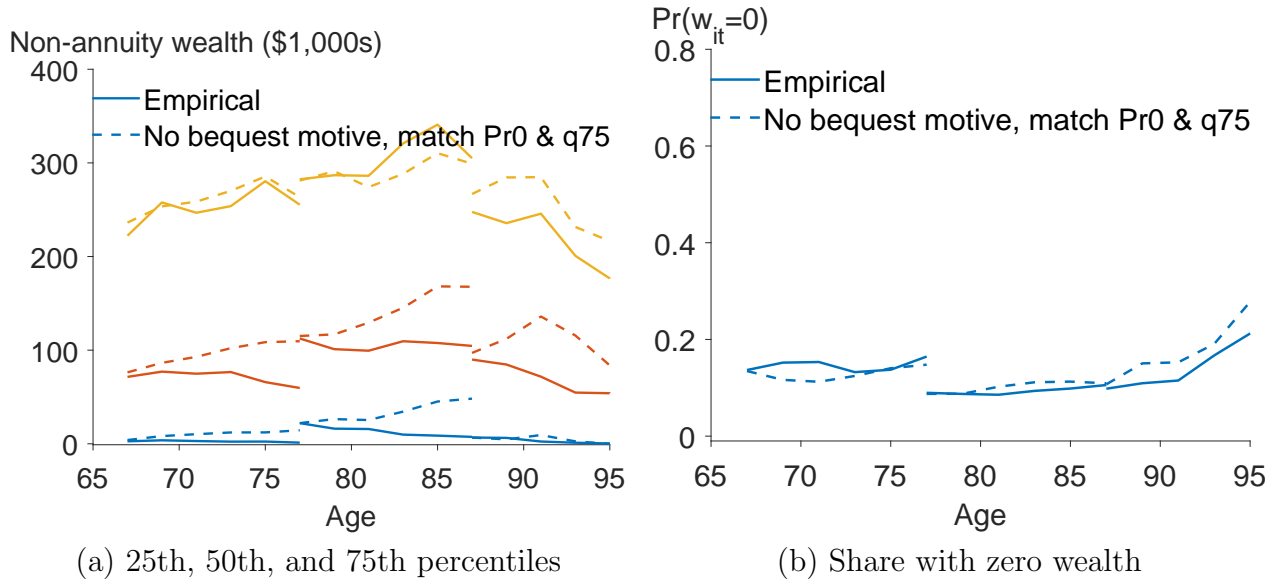


Figure 3: Empirical wealth moments (solid lines) and simulated wealth moments from the model without bequest motives estimated to match the shares with zero wealth and the 75th percentile wealth moments (and not the median wealth moments or long-term care insurance) (dashed lines). Panel (a) shows the 25th, 50th, and 75th percentiles of wealth. Panel (b) shows the share with zero wealth. The x-axis shows the average age of surviving members of the cohort.

are driven by their large prediction errors on every set of moments. Appendix Table A7 shows that the model without bequest motives fits every set of moments less well than the model with bequest motives, sometimes substantially. It understates the 75th percentile wealth moments, for example, by \$55,100 on average.

Three major patterns in the data are responsible for the strong rejection of the model without bequest motives. First are the low rates of long-term care insurance ownership, both overall and, especially, among retirees in the top quartile of the wealth distribution. The model without bequest motives predicts too much long-term care insurance ownership overall (15.3 percent vs. 5.6 percent observed) and, especially, among retirees in the top wealth quartile (49.7 percent vs. 12.5 percent observed).

The second major pattern in the data responsible for the strong rejection of the model without bequest motives is the pattern of saving across the wealth distribution. Retirees in the middle of the wealth distribution save too little relative to both richer and poorer retirees to be matched by versions of the model without bequest motives. Although the model without bequest motives can match well the saving of retirees at particular points in the wealth distribution, the restriction of no bequest motives is strongly rejected when the model is estimated with broader sets of wealth moments.²⁵ Figure 3 shows the wealth

²⁵In estimations based on the wealth moments (and not long-term care insurance), reported in Table 5, the restriction of no bequest motive is strongly rejected ($p \ll 0.01$). But in estimations based on only the median wealth moments, the model matches the data about as well without a bequest motive as with one. This

moments when the model without bequest motives is estimated to match the shares of people with zero wealth and the 75th wealth percentiles. The model matches these targeted moments quite well but predicts too much saving around the median; on average the simulated medians exceed the empirical medians by about \$29,600, 41 percent percent of the average median. (For comparison, the simulated medians based on the baseline estimates understate the empirical medians by \$2,700 on average; see Appendix Table A7.) Middle-class retirees are particularly sensitive to precautionary concerns because they have too much wealth to be well-insured by means-tested programs yet too little wealth to pay for especially costly health problems. In the data, retirees around the middle of the wealth distribution save too little relative to both richer and poorer retirees for life cycle models in which saving is driven primarily by medical spending and lifespan risk to match the pattern of saving.²⁶

The third and most important pattern in the data responsible for the strong rejection of the model without bequest motives is the combination among middle-class and richer retirees of the slow rate at which they draw down their wealth and the low rates at which they own long-term care insurance. For these retirees, the model without bequest motives predicts far too much long-term care insurance ownership relative to saving. For example, if the model without bequest motives is estimated to match the median wealth moments, the predicted long-term care insurance ownership rate is 40.1 percent, about seven times the empirical ownership rate. Long-term care insurance ownership is too low—both absolutely and, especially, relative to saving—to be consistent with the model without bequest motives.

Within the context of the standard life cycle model, retirees' saving and long-term care insurance choices indicate that important bequest motives are widespread. As Section 6.4 and Appendix Section A.6 show in more detail, retirees' saving and long-term care insurance choices are much more consistent with models in which bequests are valuable luxury goods than with other versions of the model, including those with no bequest motive. Non-poor retirees buy too little long-term care insurance—both absolutely and, especially, relative to how much they save—and retirees in the middle of the wealth distribution save too little relative to both richer and poorer retirees to be explained by

is a manifestation of the identification problem that arises when analyzing the saving decisions of retirees at a particular point in the wealth distribution (Dynan, Skinner and Zeldes, 2002). The saving of retirees at a particular point in the wealth distribution is consistent with a wide range of combinations of bequest motives and precautionary motives, so long as the combined motive is strong enough to match the slow rates of wealth drawdown observed empirically.

²⁶Although the significant heterogeneity in wealth at retirement is almost surely driven to some extent by heterogeneity in preferences, wealth heterogeneity arises naturally in life-cycle models with homogeneous preferences. Scholz, Seshadri and Khitatrakun (2006), for example, find that a life cycle model with homogeneous preferences can account for over 80 percent of the variation in retirement wealth.

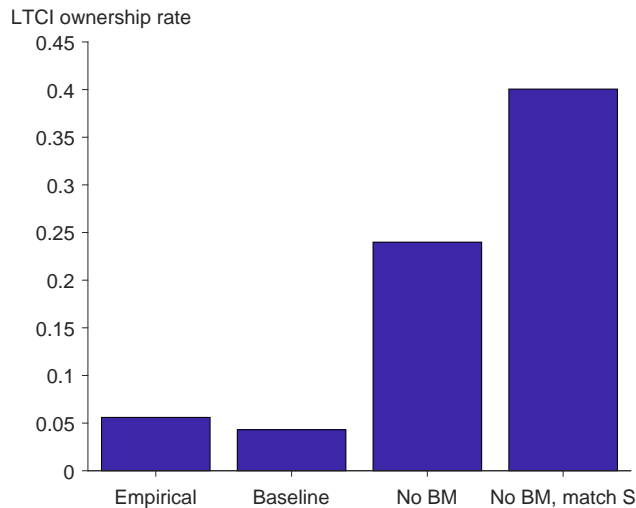


Figure 4: Simulated and empirical long-term care insurance ownership rates. The simulated ownership rates are based on three sets of preferences: the baseline estimates, the baseline estimates except with the bequest motive turned off (“No BM”), and estimates from the model without bequest motives fitted to the median wealth moments (“No BM, match S”).

versions of the model without important bequest motives.

6.3 Bequest Motives Encourage Retirees to Self-Insure

Figure 4 shows simulated and empirical long-term care insurance ownership rates. The three simulated ownership rates correspond to three different sets of preferences: the baseline estimates, the baseline estimates except with the bequest motive turned off, and the estimates from fitting a model without a bequest motive to the median wealth moments.

One way to judge the effect of the bequest motive on the demand for long-term care insurance is to turn off the bequest motive while holding fixed the other preference parameters. This experiment gives the model’s forecast of the effect on long-term care insurance coverage of 100 percent estate (and gift) taxes, if such taxes were levied successfully. Figure 4 reveals the results of such an experiment in the second and third bars. These reveal that the bequest motive decreases the long-term care insurance ownership rate from 24.0 percent to 4.3 percent.

One major disadvantage of this counterfactual of shutting down the bequest motive is that it conflates the effects of two separate factors that affect the value of long-term care insurance: the value that people place on bequests and the “implicit tax” on private insurance from means-tested programs like Medicaid (Brown and Finkelstein, 2008). The implicit tax from Medicaid is much greater in the model in which the bequest motive is

turned off since in this case individuals spend down their wealth much more rapidly and thus qualify for greater transfers from Medicaid. An alternative counterfactual that controls (albeit imperfectly) for the implicit tax from Medicaid to produce a cleaner measure of the effect of bequest motives on the value of insurance involves comparing predicted long-term care insurance ownership in the baseline model to insurance ownership in a model without bequest motives that matches retirees' saving. Figure 4 reveals the results of such an experiment in the second and fourth bars. This comparison suggests that among similar-saving retirees, the bequest motive significantly reduces the demand for insurance. Long-term care insurance coverage is over nine times greater in the model without bequest motives than in the baseline model (40.0 percent vs. 4.3 percent). Among people who draw down their wealth at similar rates, long-term care insurance is much less attractive to someone with the estimated bequest motive than to someone without a bequest motive.²⁷

To clarify why the estimated bequest motive reduces the demand for long-term care insurance, Table 4 shows, for a healthy 67-year-old female with a \$20,000 income stream and \$200,000 of non-annuity wealth (placing her around the 75th percentile of the wealth distribution), expected consumption and bequests without long-term care insurance, the effect of buying long-term care insurance on expected consumption and bequests, and the willingness to pay for access to long-term care insurance (after which premiums must still be paid). With the baseline preferences, the individual is better off not buying long-term care insurance at available prices: The individual would have to be paid about \$7,400 to be induced to buy (and hold for life) the typical long-term care insurance contract. Although the individual values the consumption and bequest insurance that long-term care insurance provides, she does not value this insurance enough to justify paying the loads on available contracts (which reduce her willingness to pay for long-term care insurance by about \$5,500) and losing access to means-tested benefits in some states of the world. Together, the loads on the typical contract and the loss of means-tested benefits from buying insurance mean that by self-insuring, the individual can on average enjoy about \$15,700 more consumption and bequests than she could by buying insurance. These considerations

²⁷These results highlight the difficulty of interpreting comparisons of long-term care insurance ownership rates across groups with different values of proxies for bequest motives. There are at least two major issues. First, both bequests and long-term care insurance appear to be luxury goods. For this reason, the model predicts a *positive* relationship between desired bequests and long-term care insurance coverage, despite predicting that bequest motives reduce long-term care insurance coverage relative to the case of similar-saving people without bequest motives. Second, with heterogeneity in risk aversion over bequests, bequest motives might increase the demand for insurance among people who are especially risk averse over bequests while reducing it for others. Consistent with this, survey evidence suggests that the desire to insure bequests contributes to some people's purchasing decisions (LifePlans, 2004). These considerations might explain why comparisons of long-term care insurance ownership rates across groups with different values of proxies for bequest motives sometimes yield inconsistent results. For example, Sloan and Norton (1997) find no significant relationship between long-term care insurance ownership and reported preferences for leaving bequests, while Brown, Goda and McGarry (2011) find a positive relationship.

	Baseline preferences		Baseline preferences but turn off bequest motive		No bequest motive, match saving	
	No LTCI	Effect	No LTCI	Effect	No LTCI	Effect
		of LTCI		of LTCI		of LTCI
Expected consumption (\$)	333,621	-7,113	347,787	-6,871	276,336	+58,294
Expected bequest (\$)	51,598	-8,562	40,357	-12,147	103,557	-68,810
Willingness to pay for long-term care insurance (\$)						
Average load (18%)	-7,396	-	9,225	-	97,718	-
Actuarially fair	-1,872	-	19,238	-	107,325	-

Table 4: Long-term care insurance demand and simulated outcomes with and without long-term care insurance. Expected discounted consumption, expected discounted bequests, and the willingness to pay for access to long-term care insurance (after which premiums must still be paid) are simulated for a healthy 67-year-old female near the 75th percentile of the wealth distribution ($N = \$200,000$, $y = \$20,000$) with one of three sets of preferences: the baseline estimates, the baseline estimates but with the bequest motive turned off, and the estimates from a model without bequest motives fitted to the share-zero and 75th-percentile wealth moments (which matches well the 75th percentile moments). The first column in each pair shows the values of the outcomes for someone without long-term care insurance. The second column in each pair shows the effect of buying long-term care insurance on these outcomes.

are similar for the individual with the baseline preferences except with the bequest motive turned off, although this individual does not value bequest insurance and instead wants to increase consumption at the expense of bequests. This individual prefers buying available long-term care insurance to self-insuring and would be willing to pay up to about \$9,200 for access to a typical contract.

An individual without bequest motives whose saving is consistent with observed wealth profiles, by contrast, is much better off buying available long-term care insurance. Such an individual would be willing to pay up to about \$97,700 for access to a typical contract—almost half of her initial non-annuity wealth. Long-term care insurance is so valuable in this case because, by reducing the individual’s need to engage in precautionary saving, it allows her to enjoy a much higher rate of consumption. Without insurance, the individual’s strong desire to avoid running out of wealth forces her to consume much less—and leave much larger bequests on average—than the individual would otherwise like. The individual leaves bequests of about \$103,600 on average without insurance—over half of her initial wealth—despite not valuing bequests at all. Buying long-term care insurance allows the individual to convert much of these bequests into greater consumption; she consumes about \$58,300 more on average with insurance than without it, despite the loads on insurance and the foregone Medicaid benefits.

Among retirees who do not wish to rely on social insurance or their families, a key

determinant of how much they should value long-term care insurance is the value they place on the bequests that arise incidentally from self-insuring their long-term care risk. People who value the prospect of leaving wealth to their heirs but are not very risk-averse over how much they leave—a preference that is consistent with altruism and that appears to be widespread—are in many cases better off not buying available long-term care insurance. The wealth they hold into old age serves the dual purpose of paying for costly care episodes in some states and of augmenting bequests in others. For them, the benefits of buying long-term care insurance—of being able to choose a more desirable mix of consumption and bequests, of insuring their consumption and bequests, and of avoiding public care—are outweighed by the costs: insurance loads and reduced social insurance transfers.²⁸

6.4 The Results are Robust to Many Alternative Assumptions

Table 5 presents results from estimating the model with different “first-stage” parameter values and estimating moments. The estimations based on different first-stage parameter values include: increasing long-term care costs by 50 percent, strengthening the relationship between health spending and income, and assuming residents of nursing homes and assisted living facilities cannot buy additional consumption beyond what they receive from their care (to reflect the many limitations they may face in buying and enjoying additional consumption).²⁹ The specifications with different estimating moments or weights include: using the robust weighting matrix; using only the wealth moments (no long-term care insurance); estimating the model based on the baseline wealth moments and a single, overall long-term care insurance ownership rate of 15 percent (over 2.5 times the observed ownership rate); and estimating the model based on the baseline long-term care insurance moments and only the median wealth moments (excluding the shares with zero wealth and the 75th percentile wealth moments). The estimates of some of the non-bequest motive parameters vary significantly across specifications. This reflects the challenge, discussed briefly in Section 6.1 and extensively in Appendix Section A.6, of pinning down the values of the parameters that affect saving and long-term care insurance choices similarly. The

²⁸To understand saving decisions, it can be useful to think of bequest motives as effectively extending an individual’s lifespan. To understand insurance decisions, however, this analogy is much less useful. The reason that bequest motives are central for decisions about how much to insure against late-life risks is that they smooth the marginal utility of wealth across states. Bequest motives disproportionately increase the marginal utility of wealth in short-lifespan, low-medical spending states—exactly those states that would otherwise have especially low marginal utility levels. The low marginal utility levels of these states without bequest motives explain the high valuation in models without bequest motives of insurance products like long-term care insurance and annuities that shift wealth out of these states and into others.

²⁹An important caveat of these exercises is that many of the contemplated changes in the environment facing retirees would be expected to affect people’s wealth at retirement, not just their behavior after retirement.

	Different first-stage parameter values				Different estimating moments or weights			
	Baseline model (1)	50% greater LTC costs (2)	Stronger health spending-income relationship (3)	No consump in nursing facilities (4)	Wealth only (no LTCI) (5)	Exclude 0 wealth 75th ptiles (6)	Robust weighting matrix (7)	Target LTCI ownership rate = 15% (8)
Parameter estimates, θ								
$\hat{\phi}$: bequest motive	0.96 (0.01)	0.95 (0.01)	0.95 (0.01)	0.95 (0.01)	0.99 (0.01)	0.93 (0.01)	0.95 (0.01)	0.95 (0.01)
\hat{c}_b : bequest motive (\$1,000s)	17.1 (1.4)	12.5 (0.6)	20.0 (1.4)	20.6 (1.6)	30.0 (2.6)	20.0 (1.5)	15.0 (1.5)	18.9 (1.3)
\hat{c}_{pub} : public care (\$1,000s) ($c_{priv} = \$20,000$)	19.1 (4.0)	10.2 (1.7)	16.5 (2.3)	12.6 (1.6)	11.4 (1.2)	4.0 (0.4)	12.9 (2.6)	16.5 (2.4)
\hat{a}_{comm} : wealth floor in community (\$1,000s)	3.0 (0.1)	2.3 (0.1)	3.0 (0.1)	2.8 (0.1)	3.2 (0.1)	1.1 (1.1)	5.2 (0.2)	3.2 (0.1)
$\hat{\beta}$: discount factor (annual)	0.84 (0.02)	0.82 (0.02)	0.92 (0.01)	0.91 (0.02)	0.90 (0.02)	0.93 (0.01)	0.80 (0.02)	0.87 (0.02)
$\hat{\sigma}$: risk aversion	4.5 (0.1)	3.5 (0.05)	4.0 (0.1)	4.0 (0.05)	4.8 (0.1)	2.0 (0.04)	6.1 (0.1)	5.0 (0.1)
Goodness-of-fit								
χ^2 stat	97.3	111.3	96.4	99.8	89.8	21.5	114.4	93.1
p-value of model	0.03	2.6e-3	0.03	0.02	0.05	0.55	1.4e-3	0.03
p-value of no-bequest motive restriction	<2.3e-16	<2.3e-16	<2.3e-16	8.3e-10	9.2e-7	2.2e-11	<2.3e-16	9.2e-8
Simulated LTCI (%)	4.3	5.9	5.0	2.9	17.5	7.6	5.9	13.9
(Empirical LTCI = 5.6%)								

Table 5: Robustness of results to different first-stage parameter values and estimating moments. The first column reproduces the baseline estimates. The next set of columns shows results based on different values of first-stage parameters. The final set of columns shows results based on estimating the model based on different sets of moments or weights. The second column shows results based on a model with 50 percent greater long-term care costs. The third column shows results based on a model with a much stronger positive relationship between income and health spending (both acute and long-term care) than is observed empirically. I scale the health spending faced by someone in income quintile q by 1.15^{q-3} . Health spending in the middle income quintile is unchanged, health spending among lower-income people is decreased, and health spending among higher-income people is increased. The fourth column shows results based on a model that does not allow residents of nursing homes and assisted living facilities to buy consumption over and above the consumption they receive from their long-term care. This is meant to reflect the many limitations they may face in buying and enjoying additional consumption. The fifth column shows results from estimating the model based on only the wealth moments (no long-term care insurance). The sixth column shows results from estimating the model based on the baseline long-term care insurance moments and only the median wealth moments (excluding the shares with zero wealth and the 75th percentile wealth moments). The seventh column shows results from estimating the model based on the “robust” weighting matrix, the inverse of the diagonal of the estimated variance-covariance matrix of the second-stage moment conditions (Pischke, 1995). The eighth and final column shows results from estimating the model based on the baseline wealth moments and a single, overall long-term care insurance ownership rate of 15 percent (about three times the observed ownership rate). Standard errors are in parentheses.

bequest motive estimates, by contrast, are fairly similar across specifications, and the key conclusion—that retirees’ decisions favor models with important bequest motives—is extremely robust. In every specification, the model without bequest motives is highly inconsistent with some of the main features of the data and can be rejected at the one percent confidence level.

The robustness of the results is driven by three main factors. First, multiple major patterns point to the same conclusion in that they are highly inconsistent with the model without bequest motives and matched well by the model with bequest motives. These are the three patterns discussed already: the low rates of long-term care insurance ownership, overall and especially among retirees at the top of the wealth distribution; the pattern of saving across the wealth distribution; and, most important, the combination among middle-class and richer retirees of the slow rate at which they draw down their wealth and the low rates at which they own long-term care insurance.

The second factor driving the robustness of the conclusion that the model requires a bequest motive to match retirees’ choices is that the bequest motive has a unique effect on saving and long-term care insurance choices, increasing saving while reducing long-term care insurance purchases. The other θ and χ parameters and many alternative modeling assumptions all tend to affect saving and long-term care insurance in the same direction. As a result, changes in these other parameters or assumptions that would help the model without bequest motives match the slow rates at which retirees draw down their wealth would hurt that model’s ability to match the low rates of long-term care insurance ownership and vice-versa. For example, retirees might think that Medicare covers more long-term care expenses than it does, they might underestimate the cost or risk of requiring long-term care, or they might be more myopic than is allowed for by the model of exponential discounting. Each of these factors would improve the ability of the model without bequest motives to match the low rates of long-term care insurance ownership. But at the same time, each of these factors would hurt the ability of the model without bequest motives to match the slow drawdown of wealth. This helps explain why the estimated bequest motive is relatively stable across a wide range of specifications despite the often large changes in the assumptions and other parameter values.

The third factor driving the robustness of the conclusion that the model requires a bequest motive to match retirees’ choices is the large magnitude of the mismatch between the predictions of the model without bequest motives and the combination of saving and long-term care insurance decisions among middle-class and richer retirees. There are a variety of ways to measure the size of this mismatch, including some that have been discussed already, such as statistical and economic measures of the goodness of fit of

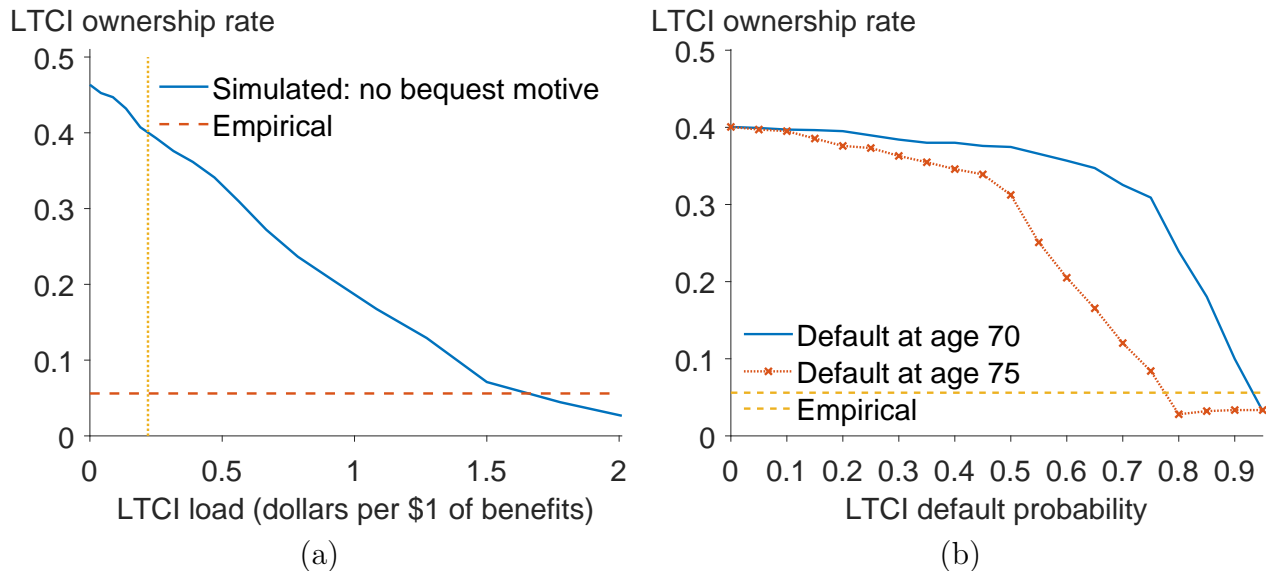


Figure 5: Long-term care insurance ownership rate in the model without bequest motives fitted to the median wealth moments.

Panel (a): Long-term care insurance ownership rate as a function of the load. The load is measured in dollars of load per dollar of benefits. Actuarially fair insurance corresponds to a load of zero. The vertical dotted line shows the average load on contracts in the U.S. market, about 22 cents per dollar of benefits (which corresponds to the 18 percent load as a share of premiums found by Brown and Finkelstein (2007)).

Panel (b): Long-term care insurance ownership rate as a function of the default probability. Default means that the contract vanishes at the specified age.

alternative versions of the model to various empirical patterns. This section presents the results of alternative measures that answer the question: How much less attractive would long-term care insurance have to be in order for the model without bequest motives to match retirees' saving and long-term care insurance decisions?

The two panels of Figure 5 show two possible answers to this question. Panel (a) shows, in the model without bequest motives fitted to the median wealth moments, the simulated long-term care insurance ownership rate as a function of the load on the contract. As already reported, at the average load in the U.S. predicted ownership in this model is 40.1 percent—about seven times the empirical ownership rate. Panel (a) shows that in order to match both saving and long-term care insurance, the model without bequest motives requires extremely high loads on long-term care insurance, far greater than those observed in the U.S. market. Whereas the average load on long-term care insurance contracts in the U.S. requires people to pay about 22 cents worth of loads per dollar of benefits (corresponding to an 18 percent load as a share of premiums, $\frac{\$0.22}{\$1.22} = 0.18$), the model without bequest motives requires a load of \$1.67 per dollar of benefits—over seven times the market average.

Panel (b) shows, in the same model without bequest motives fitted to the median wealth

moments, the simulated long-term care insurance ownership rate as a function of the probability that the insurance contract vanishes at some point in the future. The risk that the contract vanishes is meant to capture in a simple way the possibility that the insurer defaults on its obligations to the insured or the possibility that the individual, for one reason or another, allows his or her contract to lapse and thus loses coverage thereafter. The results show that in order to simultaneously match retirees’ saving and long-term care insurance decisions, the model without bequest motives requires extremely high probabilities of long-term care insurance vanishing at about the worst possible time.³⁰ Only extremely high probabilities of default (over 75 percent) at the worst time can allow the model without bequest motives to simultaneously match retirees’ saving and long-term care insurance choices.

These results suggest that default risk and other un-modeled potential disadvantages of long-term care insurance are unlikely to overturn the result that the model without bequest motives is inconsistent with retirees’ behavior. Middle-class (and richer) retirees buy far too little long-term care insurance relative to how much they save to be consistent with the model without bequest motives. Additional information about the extent to which different features of the data are informative about the key parameters of the model is discussed in detail in Appendix Section A.6.

6.5 Implications of the Results

Bequest motives increase saving significantly.— Figure 6 shows, for three different simulations, the simulated evolution of the median and 75th percentile of the distributions of wealth and consumption spending for a balanced panel of retirees in the first cohort (aged 65–69 in 1998).³¹ Bequest motives significantly slow the rate at which retirees’ draw down their wealth: Wealth declines more slowly in the baseline model (solid lines) than in

³⁰These simulations are based on two ages at which long-term care insurance potentially vanishes, 70 and 75. Because of the front-loading of premiums in long-term care insurance contracts, these ages are the worst ones (among all “round” ages between 65 and 95 ending in fives or zeros) for long-term care insurance to vanish. Healthy 65-year-olds tend to remain healthy for several years, during which time they would pay premiums, before becoming sick and collecting benefits. The worst time for a contract to vanish is immediately after the “premiums phase” and before the “benefits phase.”

³¹Constructing these figures involves three main steps. First I clone each member of the first cohort ten times to increase the sample size. Then I simulate each clone’s subsequent health realizations over the next 23 years (at which time the average age of the cohort is 90), and simulate the wealth and consumption spending paths of only those clones who live at least 23 years. Finally, I calculate the median and 75th percentile of the simulated wealth and consumption spending distributions in each of those years and plot them against the average age of the cohort on the x -axis. The figures therefore show the evolution of the wealth and consumption spending distributions as the cohort ages of only those cloned members of the first cohort who survive at least 23 years. This balanced-panel construction avoids the bias that can result from selective mortality.

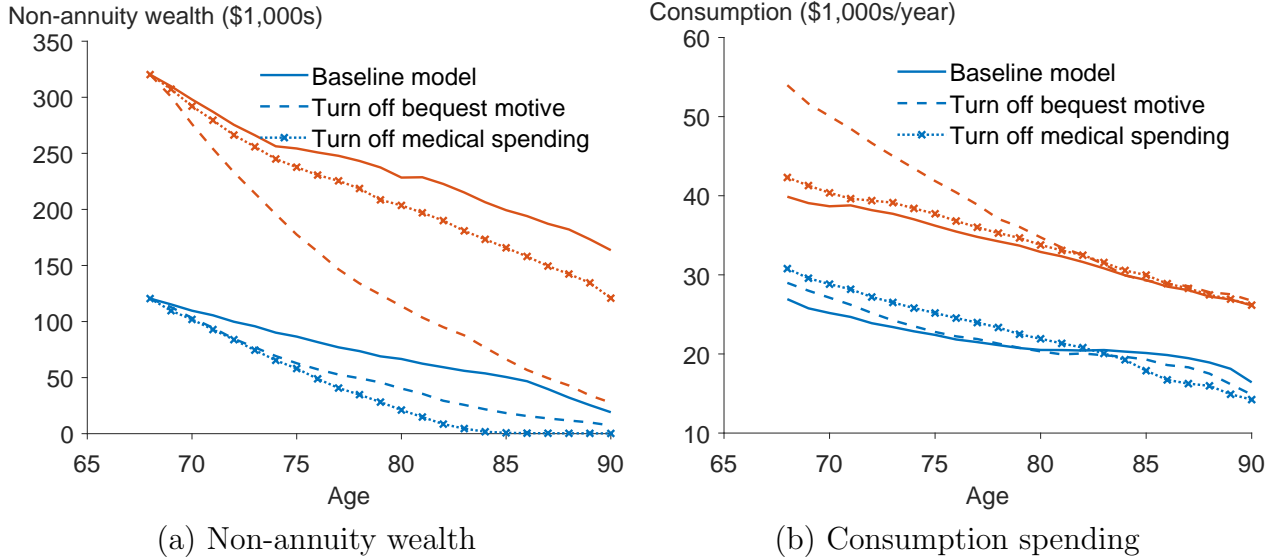


Figure 6: Simulated evolution of the median and 75th percentile of the distributions of non-annuity wealth and consumption spending among members of the first cohort (aged 65–69 in 1998) who remain alive for at least 23 years into their simulated future (at which time their average age is 90). The solid lines track wealth and consumption spending in the baseline model. The dashed lines track wealth and consumption spending if the bequest motive is turned off. The dotted lines with x markers track wealth and consumption spending if medical spending, including spending on both acute and long-term care, is shut down. Specifically, the decision rules come from a model without any long-term care or acute medical care costs ($ltc(h,t) = m_t = 0 \forall h,t$), but the simulation of wealth and consumption spending profiles includes medical costs. Differences in wealth and consumption spending therefore reflect only differences in behavior and not differences in realized medical expenses. Individuals in the simulation are assigned their reported (empirical) long-term care insurance ownership status.

the model without bequest motives (dashed lines). The bequest motive-induced slowing of the drawdown of wealth leads to significantly greater wealth holdings among the oldest retirees and significantly larger bequests. Consistent with intuition, bequest motives have a similar effect on consumption paths as a reduction in the rate of time preference. Without bequest motives, consumption decreases rapidly at older ages, as individuals seek to consume their wealth before dying. With the estimated bequest motive, consumption declines more gradually with age. Compared to bequest motives, medical care costs (including both long-term care and acute medical care) have a smaller effect on the 75th percentiles and a greater effect on the medians.

Bequest motives significantly reduce purchases of annuities.— Figure 7 shows simulated purchases of an annuity that pays \$5,000 of (real) income per year for life and has a ten percent load, a typical load in the U.S. private market (Brown, 2007). The estimated bequest motive significantly reduces the demand for annuities. The simulated ownership rate is 6.1 percent in the baseline model, close to the empirical estimate of 7.1 percent. Without bequest motives, the model predicts much greater purchases of annuities than is

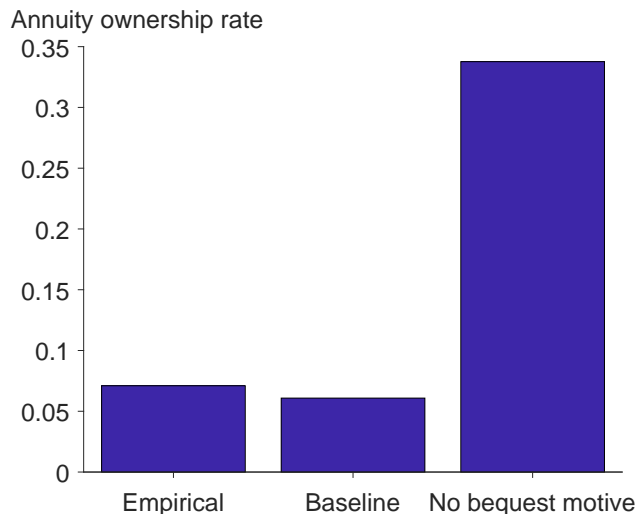


Figure 7: Empirical and simulated ownership rates of life annuities. The empirical annuity ownership rate corresponds to the fraction of single retirees aged 70–79 in 1998 who in the 1998 wave report owning an annuity that lasts for life, weighted by HRS respondent weights. The simulated annuity ownership rates are based on an annuity that pays the annuitant \$5,000 of real income each year for life and has a ten percent load, typical of the U.S. private market (Brown, 2007). “Baseline” is the simulated ownership rate under the baseline estimates. “No bequest motive” is the simulated ownership rate in the model without a bequest motive estimated to match the median wealth moments.

observed. The model without bequest motives estimated to match the median wealth moments predicts an ownership rate of 33.8 percent, over 60 percent of those who can afford the premium. These results are consistent with Lockwood’s (2012) conclusion that relatively modest bequest motives can significantly reduce the demand for available annuities.

Bequest motives increase the scope for and effectiveness of policies to encourage private long-term care insurance coverage. — Several U.S. states have implemented policies designed to increase private insurance coverage, presumably with the goal of reducing spending by means-tested programs. There are at least two reasons why the role of bequest motives in reducing private long-term care insurance coverage could be of interest to policymakers who wish to increase private insurance coverage. First, as Brown and Finkelstein (2008) show, to the extent that means-tested programs like Medicaid explain the low rates of private insurance coverage, the potential for premium subsidies to expand coverage are extremely limited, since the “net load” on insurance, inclusive of public benefits foregone, remains large even if policies such as premium subsidies reduce the “gross load” on private contracts. But bequest motives, by increasing saving, reduce Medicaid’s implicit tax on long-term care insurance and increase the own-price elasticity of demand for long-term care insurance. Comparison of the first two bars in Figure 8 shows the predicted effect of a premium subsidy that reduces the after-tax price of insurance

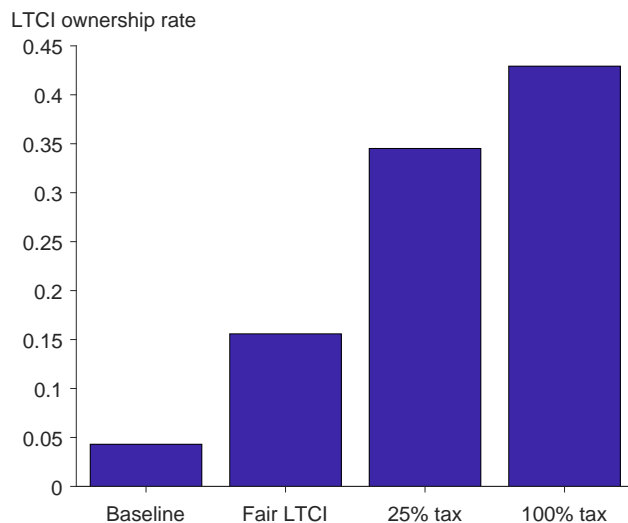


Figure 8: Simulated long-term care insurance ownership rates under two types of policies. The first bar shows the ownership rate in the baseline model. The second bar shows the ownership rate under a long-term care insurance subsidy that makes the subsidy-inclusive price actuarially fair. The remaining bars show ownership rates under long-term care insurance-contingent estate and gift taxes, under which only people *without* long-term care insurance pay taxes on their gifts and estates (people with long-term care insurance pay no transfer tax).

exactly enough to make the policy actuarially fair. This subsidy more than triples predicted coverage, from 4.3 percent to 15.6 percent.³²

The second reason that the role of bequest motives in reducing private long-term care insurance coverage could be of interest to policymakers who wish to increase private insurance coverage is that it admits new possibilities for the types of policies that could encourage private coverage. One such policy is a long-term care insurance-contingent estate and gift tax, under which only people *without* long-term care insurance must pay taxes on their gifts and bequests; buying (qualifying) long-term care insurance allows one to escape transfer taxation. As Figure 8 shows, an insurance-contingent transfer tax of 25 percent increases predicted insurance ownership to 34.5 percent, more than double that under the premium subsidy. Such a policy potentially helps correct the externality that, because of Medicaid, taxpayers at large benefit from the decision of any individual to buy insurance.

³²Although the subsidy has a noticeable effect on private insurance coverage, Medicaid still severely limits the market for private insurance, as even with actuarially fair insurance only about one in every six single retirees is predicted to buy insurance. Moreover, and consistent with Goda's (2011) empirical findings, the subsidies increase coverage primarily among rich retirees. The subsidies are therefore unlikely to pay for themselves by reducing Medicaid expenditures, since the rich rely less heavily on Medicaid even without insurance.

7 Conclusion

Rather than buy insurance against some of the main risks they face, many retirees self-insure by holding much of their wealth into old age. Although the choice of many retirees to self-insure is often viewed as evidence against the importance of bequest motives since it exposes bequests to significant risk, I find that the choice to self-insure constitutes evidence in favor of bequest motives. Bequest motives reduce the demand for insurance by reducing the opportunity cost of precautionary saving; setting aside wealth to pay for possible future contingencies is much more costly for people without bequest motives who would otherwise like to consume all of their wealth.

The evidence in favor of bequest motives is perhaps surprisingly strong given that models without bequest motives can roughly match either the saving or long-term care insurance decisions of middle-class retirees and given the elusive nature of bequest motives in which bequests are luxury goods. By their nature, such bequest motives tend to have a marginal rather than a decisive impact on most decisions: Few choices involve a clear tradeoff between bequests and other goods.³³ Despite this, several patterns in the data are much more consistent with a standard life cycle model with bequest motives than with a model without bequest motives.

Although the elusive nature of bequest motives necessarily makes the conclusion that bequest motives play an important role in retirees' behavior more tentative than the conclusion that standard models without bequest motives cannot match retirees' behavior, a variety of evidence supports the idea that bequest motives—or preferences like altruism that might lead people to value bequests—are widespread. This evidence includes the prevalence and size of inter-household transfers during life (e.g., Gale and Scholz, 1994), survey responses about the importance of leaving bequests (e.g., Ameriks et al., 2011), and annuity guarantee choices (Laitner and Juster, 1996). In light of this evidence and my results, bequest motives are a high priority for future research.

My results suggest that the term *accidental bequests*, which is used to describe bequests that arise as a byproduct of precautionary saving against uninsured risks, may be misleading in its connotation that such bequests are neither intended nor valued. Although

³³The elusive nature of bequest motives helps explain why bequest motives have been the subject of a prolonged debate in economics (e.g., Kotlikoff and Summers, 1981; Modigliani, 1988). Even life insurance decisions, perhaps the main decision that involves a clear tradeoff between bequests and other goods, would only register much stronger bequest motives (at least among retirees) than those estimated in this paper. Due to the actuarial unfairness in life insurance, only retirees who wish to leave more than their entire non-annuity wealth as a bequest should consider buying life insurance to augment their bequest (Bernheim, 1991). With the preferences that I estimate, by contrast, many retirees would leave *no* bequest if fair insurance were available. These results are consistent with Brown's (2001) conclusion that few retirees buy life insurance to increase their bequests.

self-insurance tends to produce bequests that are both larger on average and more variable than those that would occur under full insurance, my results suggest that the value people place on these *incidental bequests* plays a key role in their decisions of how much risk to bear in the first place. Even individuals who would leave small bequests or even no bequest if perfect insurance were available, may—because of the value they place on bequests—choose far less insurance coverage than they would if insurance markets were perfect (Lockwood, 2012). If bequests were accidental in the sense that people did not value bequests, realized bequests would likely be much smaller, both because people would save less and, even more important for the non-rich, because people would buy more insurance.

My results highlight the importance of accounting for bequest motives in evaluating policies that affect people’s exposure to late-life risks. The decision about how to model bequest motives can have first-order consequences for estimates of the welfare and other impacts of changes to insurance-related policies such as Social Security, Medicare, and Medicaid. Policies that affect the behavior of retirees, owners of much of the world’s non-human wealth, are likely to have significant effects on the economy, especially through their effects on the budgets of means-tested social insurance programs and on the size, distribution, and risk of bequests received by future generations. My results suggest that taxes on saving and inter-household transfers are likely to affect bequests by affecting retirees’ decisions about their insurance coverage as well as their saving. The induced changes in insurance coverage can change not only the magnitude but even the direction of policies’ effects on bequests.

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A Appendix

A.1 Health Uncertainty: Mortality, Long-Term Care, and Acute Medical Care Risks

This section reports the results of descriptive regressions about long-term care and long-term care insurance and describes the key elements of the model of health risks. I test the robustness of the results to a variety of changes to these risks in Section 6.4.

A.1.1 Long-Term Care and Long-Term Care Insurance: Descriptive Regressions

Table A1 reports results from descriptive regressions of long-term care usage and long-term care insurance ownership on key demographic and economic variables. These regressions are based on a sample of people 65 and older in the 1998 wave of the Health and Retirement Study. The regressions of long-term care usage further restrict the sample to people who report difficulties with at least two activities of daily living (ADLs). The table shows the estimated marginal effects from probit regressions.

Use of formal care is much greater among people with more ADL limitations, is slightly greater among single people and people without children, and is perhaps slightly greater among people with greater income, though the income results are statistically insignificant and the point estimates are non-monotonic in income quartile. Long-term care insurance ownership is strongly increasing in wealth but is otherwise not well predicted by the other demographic variables, including whether someone is single and whether he or she has children.

A.1.2 Health Transitions

An individual's future health depends probabilistically on the individual's current age and health status as well as on the individual's sex (s) and (permanent) income (y), $Pr(h_{t+1} = h' | h_t, t; s, y)$. I base the model of health transitions on a model developed by Friedberg et al. (2014). This model makes a number of important improvements on the widely-used Robinson model of long-term care requirements (Robinson, 2002), including using updated data and more robust procedures.

I make three adjustments to the Friedberg et al. (2014) model in order to cater it to my application. First, I convert the monthly health transitions calculated by Friedberg et al. (2014) into annual transitions. This choice is driven both by computation time considerations and by data limitations, since the Health and Retirement Study and many other datasets measure medical spending and other variables at lower frequencies (e.g.,

every year or every second year). Second, I use the estimated transition matrices for women as the baseline transition matrices for both the single men and the single women in my sample. The care usage patterns of women likely provide a closer approximation to the usage patterns of single people, whether male or female, because women receive a much smaller share of their long-term care from their spouses than men do. Women receive less informal care from their spouses because their spouses (predominantly men) tend to get sick and die at earlier ages than they do. As a result, a smaller share of women’s care episodes occur when their husbands are alive and well enough to provide them with informal care. Of course, the care use patterns of women in the general population—including married women—suffers from this same problem and so tends to understate the care needs of singles, but the bias is less severe than it is for men.

The third set of adjustments I make is to adjust the Friedberg et al. (2014) transition probabilities to match De Nardi, French and Jones’s (2010) estimates of life expectancy conditional on reaching age 70 for different sex and income groups. A t -year-old in sex-income quintile group (s, q) faces the Friedberg et al. (2014) transition probabilities of a $(t + \Delta(s, q))$ -year-old female, where $\Delta(s, q)$ is chosen to minimize the difference between predicted life expectancy at age 70 and De Nardi, French and Jones’s (2010) estimates of life expectancy at age 70.

Table A2 shows the age adjustments, $\Delta(s, q)$, and the resulting life expectancies of each group. The differences in life expectancies at age 70 across sex and income groups are substantial: Women live more than five years longer than men in the same income quintile, and men and women in the top income quintile live almost four years longer than their counterparts in the bottom quintile. Each group’s adjusted life expectancy is within 0.3 years of De Nardi, French and Jones’s (2010) estimate. It is important that the model of health risk be consistent with this substantial heterogeneity in life expectancy, since life expectancy can have an important impact on saving and insurance decisions (De Nardi, French and Jones, 2009).

Table A3 presents statistics related to the unconditional and conditional probabilities of being in different health states in the original and adjusted Friedberg et al. (2014) models. The adjusted model preserves the essential character of the original model in terms of the key determinants of saving and insurance decisions: the expected share of remaining life spent in different health states. The key difference is that males spend a greater share of their remaining lives in nursing homes under the adjusted model than under the original model. This is due to the much greater supply of informal care to married than to single men and is why I base the model of health transitions for single males on the Friedberg et al. (2014) model for females. The other main differences have to do with time aggregation. Using yearly rather than monthly transitions reduces the probability of ever experiencing a nursing home stay and of leaving a nursing home alive, since yearly transitions rule out the possibility of stays of less than one year in duration. Although it would be desirable to base the model of health transitions on a model specifically estimated to match the heterogeneous experiences of single men and women with different levels of income, such a model is not available, and, as discussed in Section 6.4, the conclusions are robust to many alternative assumptions and are unlikely to be affected by plausible changes in the model of health risk.

A.1.3 Long-term Care Prices

The cost of the individual's long-term care is a deterministic function of the individual's health, age, sex, and income quintile, $ltc(h_t, t, s, q)$. Part of this heterogeneity could reflect differences in the prices that people face for the same care, due, for example, to differences in prices across different locations. Other sources of heterogeneity could include unmeasured and un-modeled differences in the quantity or quality of the long-term care services consumed by different groups, conditional on their health status. For example, higher-income people might purchase higher-quality (and so costlier) long-term care.

To estimate $ltc(h_t, t, s, q)$, I combine two sources of data. The first is data from a MetLife survey about long-term care prices (MetLife Mature Market Institute, 2002*a,b*). This reports average prices for different long-term care services, including stays in nursing homes and assisted living facilities and skilled and unskilled home care. According to this survey, average prices in 2002 were \$52,195 per year in a nursing home, \$26,280 per year in an assisted living facility, \$18 per hour for unskilled home care, and \$37 per hour for skilled home care.

The second source of data is the National Long-Term Care Survey (NLTC). This is a longitudinal survey of Americans age 65 and older with detailed information about health and health-related expenditures, including information about the prices of any long-term care services that surveyed individuals consume. I use the NLTC data to estimate the following regression:

$$\frac{p_i}{\bar{p}} = \alpha + \beta \text{female}_i + \gamma \text{age}_i + \sum_{q=2}^5 \delta_q \text{income quintile } q_i + \varepsilon_i,$$

where p_i is the price per month of care in i 's nursing facility, \bar{p} is the average price per month of care in facilities, and female_i and $\text{income quintile } q_i$ are indicators for whether i is a female and in income quintile q , respectively. I use the predicted values from this regression to scale the average prices of each long-term care service (nursing homes, assisted living facilities, skilled home care, and unskilled home care).³⁴

A summary of the results is presented in Table A4. Females pay slightly higher prices than males (about 6 percent) and higher-income people pay slightly higher prices than lower-income people (the top income quintile pays about 12 percent more than the bottom). Conditional on the type of care being used, age has little effect on long-term care prices (the coefficient estimate is a precise zero). The biggest source of heterogeneity is between people in the bottom income quintile and everyone else; the prices that people in the bottom income quintile pay are between 1.6 and 11.5 percent lower than the prices paid by people in higher income quintiles. But a striking feature of the results is how little heterogeneity there appears to be on average across different sex, age, and income groups. None of the individual coefficients is significant at conventional confidence levels, and the covariates taken as a whole are not significant either.

³⁴Data considerations lead me to estimate a single scaling factor to apply to all types of long-term care rather than estimating different scaling factors for different types of care. These considerations are the difficulty of distinguishing between nursing homes and assisted living facilities and the difficulty of estimating hourly prices of skilled and unskilled home care in the data.

A.1.4 Acute Medical Care Spending

The cost of an individual’s acute medical care is log-normally distributed with the mean and variance depending on the individual’s health, age, sex, and income quintile, $m_t \sim \log N(\mu_m(h_t, t, s, q), \sigma_m^2(h_t, t, s, q))$. That the mean and variance are allowed to depend on health, age, sex, and income quintile allows for rich heterogeneity in the spending risk facing different people.

I estimate the mean and variance of different groups’ spending on acute medical care in two steps, using data from the HRS. First, I decompose total out-of-pocket spending (the variable in the RAND release of the HRS) into separate acute and long-term care components. To do this, I use disaggregated data on out-of-pocket spending by service type in 2006. For each health status (healthy, home care, and nursing home), I estimate the share of total out-of-pocket spending that is due to acute medical care (as opposed to long-term care). The sample is everyone age 65 and older whose combined previous-wave non-housing wealth and annual income is at least \$100,000. I convert observed total out-of-pocket spending to acute out-of-pocket spending by multiplying observed total out-of-pocket spending by the estimated shares of spending on acute care for each health status. The estimates imply that among healthy people, about 97 percent of total out-of-pocket spending is due to spending on acute medical care. Among people who require home care, this share is 72 percent. Among people who require nursing home care, this share is just 11 percent.

I restrict the sample to person-waves in which the individual’s combined previous-wave non-housing wealth and annual income is at least \$100,000 in order to reduce the bias from censoring by Medicaid, charities, and uncompensated care. These factors tend to limit an individual’s out-of-pocket medical spending to his or her net wealth or liquid assets, which means that including low-net-worth individuals in the sample would bias downward the estimate of the risk people face.³⁵

Second, I estimate the means and variances of the acute medical spending distributions by running two versions of the following regression:

$$m_{it} = \alpha + \beta \text{female}_i + \gamma \text{age}_{it} + \sum_{h \in \{hc, nh\}} \phi_h \text{health } h_{it} + \sum_{q=2}^5 \delta_q \text{income quintile } q_i + \varepsilon_{it},$$

where health is either healthy (omitted), home care, or nursing home and the remaining variables are as defined in Section A.1.3. In one version of this regression, the dependent variable is the log of out-of-pocket acute medical spending. In the other, the dependent variable is the square of the log of out-of-pocket acute medical spending. In both cases, person-waves with zero spending, which comprise less than five percent of the sample, are dropped in order to take logs. Together, these regressions and the identity $Var(X) = E(X^2) - (E(X))^2$ identify the mean and variance of the distribution of acute

³⁵The proper input to the life cycle model is total medical spending net of care paid for by Medicare, not just out-of-pocket spending by the individual. The key difference between these two objects is care paid for by Medicaid, charities, and uncompensated care. The extent to which care that is not covered by Medicare is paid for by the individual rather than by Medicaid and other means-tested programs is an endogenous outcome of the model that depends in an important way on people’s preferences.

medical spending facing these groups. The sample is the subset of my main sample of single retirees 65 and older whose combined previous-wave non-housing wealth and annual income is at least \$100,000, in order to avoid the censoring issue discussed above.

Table A5 presents the results. The results are mostly as expected. On average people in worse health spend more than people in better health, women spend more than men, and older people spend more than younger people. Higher-income people are estimated to spend somewhat less than lower-income people, though none of the coefficients on the income quintile indicators are statistically significant.

The results of the main estimation are robust to large changes in the model of acute medical spending risk, including scaling mean spending up or down by 50 percent. This is because acute medical spending is the type of risk for which saving or buying long-term care insurance are not very effective. The vast majority of people spend little out-of-pocket on acute medical care, given Medicare's relatively comprehensive coverage and holdings of supplementary Medigap policies on top of that. Although people might wish to send extra resources to those rare states of the world in which out-of-pocket acute medical spending is very high, saving and buying long-term care insurance do not target these states well, so the exact model of acute medical spending risk has relatively little effect on predicted behavior.

A.2 Numerical Solution Procedure: Details and Accuracy

I solve the model numerically using value function iteration. The method proceeds by backward induction, beginning from the maximum possible age T . Because the individual dies by age $T + 1$ with probability one and leaves any remaining wealth as a bequest, the age- T value function can be found easily. To solve for the value function at younger ages, I discretize wealth into a fine grid and use piecewise cubic hermite interpolation to evaluate the value function between grid points. For each sex-income-long-term care insurance group and at each age-health-wealth node, I solve for optimal consumption.

The solution produced by such a method is necessarily an approximation, and its accuracy depends on a number of factors, including the wealth grid. The existence of means-tested programs poses a special challenge, since they cause the value function to be non-concave, which in turn means that the individual's first-order condition for optimal consumption is necessary but not sufficient for an optimum. The effects of means-tested programs on the value function are especially pronounced in the regions of the function in which wealth is relatively small. For this reason, I ensure that the wealth grid is especially fine at small values of wealth by combining (i) a grid that is equally-spaced in logs from the maximum of \$1,000 and the Medicaid wealth threshold (which in the baseline specification is \$0) to \$6 million with (ii) a grid that is equally-spaced in levels from -\$1,000 to the maximum of \$1,000 and the Medicaid wealth threshold. The resulting grid has 196 distinct values.

I turn now to tests of the accuracy of the numerical solution. The tests are based on the Euler equation, the fundamental condition for intertemporal optimization. The first-order

condition for optimal consumption spending is

$$u'(c_t) = \beta \left\{ Pr(h_{t+1} = d|h_t, t; s, y) E_t[(1 + r_t)v'(b_{t+1})] \right. \\ \left. + Pr(h_{t+1} \neq d|h_t, t; s, y) E_t \left[(1 + r_t) \frac{\partial V_{t+1}(\hat{x}_{t+1}, h_{t+1}; s, y, ltc_i)}{\partial \hat{x}_{t+1}} \right] \right\}.$$

This equation is a necessary but not sufficient condition for optimal consumption spending away from corners, $c \in (c_m(h, Pub), c_m(h, Pub) + x)$. The condition about consumption not being at a corner involves one more element than the usual case because of the consumption value of long-term care, $c_m(h_t, Pub_t)$. The usual corner solution is when borrowing constraints bind, i.e., when the marginal utility of consumption today when borrowing as much as possible exceeds the expected discounted marginal utility of resources tomorrow. The consumption value of facility-based care creates another type of corner solution. In certain circumstances, people in facilities might wish they could save some of the consumption that is bundled together with their long-term care, which is not possible. In states of the world in which this is true, the Euler equation does not hold, since the marginal utility of consumption today (when consuming only the goods and services bundled together with long-term care) is strictly less than the expected discounted marginal utility of resources next period. States of the world in which consumption is at a corner are excluded from Euler equation-based tests of numerical solution accuracy.

The marginal increase in future utility from a marginal increase in \hat{x}_{t+1} is

$$\frac{\partial V_{t+1}(\hat{x}_{t+1}, h_{t+1}; s, y, ltc_i)}{\partial \hat{x}_{t+1}} = \begin{cases} 0, & \text{if } \hat{x}_{t+1} < \bar{x}(h_{t+1}, ltc_i); \\ u'(c_{t+1}), & \text{if } \hat{x}_{t+1} \geq \bar{x}(h_{t+1}, ltc_i) \text{ and } \hat{c}_{t+1} > 0; \\ \Delta \geq u'(c_{t+1}), & \text{otherwise.} \end{cases}$$

The marginal increase in future utility is zero if $\hat{x}_{t+1} < \bar{x}(h_{t+1}, ltc_i)$, since any savings simply reduce transfers from means-tested programs one-for-one. The marginal increase in future utility is $u'(c_{t+1})$ if $\hat{x}_{t+1} \geq \bar{x}(h_{t+1}, ltc_i)$ and $\hat{c}_{t+1} > 0$, by the Envelope theorem. The marginal increase in future utility is

$$\Delta \equiv \beta \left\{ Pr(h_{t+2} = d|h_{t+1}, t; s, y) E_{t+1}[(1 + r_{t+1})v'(b_{t+2})] \right. \\ \left. + Pr(h_{t+2} \neq d|h_{t+1}, t; s, y) E_{t+1} \left[(1 + r_{t+1}) \frac{\partial V_{t+2}(\hat{x}_{t+2}, h_{t+2}; s, y, ltc_i)}{\partial \hat{x}_{t+2}} \right] \right\} \geq u'(c_{t+1})$$

if $\hat{x}_{t+1} \geq \bar{x}(h_{t+1}, ltc_i)$ and $\hat{c}_{t+1} = 0$. Δ could be less than $u'(c_{t+1})$ due to borrowing constraints; the individual might wish she could borrow in period $t + 1$. Or Δ could exceed $u'(c_{t+1})$ due to the consumption value of facility-based care; the individual might wish she could sell some of the consumption that comes bundled with her care. If next-period consumption spending is strictly positive, $\hat{c}_{t+1} > 0$, the right-hand side of the first-order condition can be calculated using the optimal consumption function to calculate $u'(c_{t+1})$. This is the idea behind the Euler equation test.

The Euler equation test measures the closeness of the approximate (numerical) solution to the exact solution that satisfies the Euler equation. I follow Judd (1992) and Fella (2014)

in calculating Euler equation errors in units of current consumption:

$$EE(s) = \left| 1 - \frac{c^*(s)}{\bar{c}(s)} \right|,$$

where s is the state vector, $c^*(s)$ is the analytical solution of the Euler equation (the exact consumption level at which the marginal utility of consumption equals the expected discounted marginal utility of resources in the next period), and $\bar{c}(s)$ is the (approximate) optimal consumption rule delivered by the numerical solution algorithm. I calculate Euler equation errors for each member of the simulation sample in each year of the sample period in which he or she is alive and not at a corner.

The results suggest that the numerical solution method is performing well. The average and maximum error among everyone in the sample are 0.001 (-6.7 in natural log units) and 0.039 (-3.3 log units), respectively. The average and maximum error among people within five years of the maximum age, at which point errors have accumulated, are 0.002 (-6.5 log units) and 0.004 (-5.5 log units), respectively. These compare favorably with the results reported by Fella (2014) in tests of his endogenous grid method against value function iteration.

A.3 Asymptotic Distribution of the MSM Estimator and Over-identification Tests of the Model's Fit

Pakes and Pollard (1989) and Duffie and Singleton (1993) show that the MSM estimator, $\hat{\theta}$, is consistent and asymptotically normally distributed under regularity conditions satisfied here. The variance-covariance matrix of $\hat{\theta}$ is

$$\Omega_{\theta} = (G'_{\theta} W G_{\theta})^{-1} G'_{\theta} W \left[\Omega_g + \frac{N_d}{N_s} \Omega_g + G_{\chi} \Omega_{\chi} G'_{\chi} \right] W G_{\theta} (G'_{\theta} W G_{\theta})^{-1},$$

where G_{θ} and G_{χ} are the gradient matrices of the moment conditions with respect to θ and χ , Ω_g is the variance-covariance matrix of the second-stage moment conditions, Ω_{χ} is the variance-covariance matrix of the first-stage parameter estimates, and N_d and N_s are the empirical sample size and the simulation sample size, respectively. I approximate the derivatives in the gradient matrices numerically. The square roots of the diagonal entries of Ω_{θ} are the standard errors of the second-stage parameter estimates, $\hat{\theta}$.

The number of second-stage moment conditions exceeds the number of second-stage parameters, so over-identification tests of the model are possible. If the model is correct, the (scalar) statistic

$$\hat{\varphi}(\hat{\theta}, \chi_0)' R^{-1} \hat{\varphi}(\hat{\theta}, \chi_0)$$

converges in distribution to a chi-squared random variable with degrees of freedom equal to the number of second-stage moments less the number of second-stage parameters. In this formula, $\hat{\varphi}(\hat{\theta}; \chi_0)$ is the vector of moment conditions and

$$R = P \left(\frac{\Omega_g}{N_d} + \frac{\Omega_g}{N_s} + G_{\chi} \Omega_{\chi} G'_{\chi} \right) P,$$

where $P = I - G_\theta(G'_\theta W G_\theta)^{-1} G'_\theta W$, except if $W = \Omega_g^{-1}$, in which case $R = \left(\frac{\Omega_g}{N_d} + \frac{\Omega_g}{N_s} + G_\chi \Omega_\chi G'_\chi \right)$. I use this matrix for all of the results in the paper.

I estimate Ω_g and W from the data. Because I adopt many of the first-stage parameter values from other sources rather than estimating them, I treat χ as if it were known with certainty, $G_\chi = 0$. Excluding the correction for the uncertainty in the first-stage parameters tends to make the second-stage parameter estimates appear more precise than they actually are and the fit of the model (as measured by the chi-squared test statistic) appear worse than it actually is. To estimate G_θ , I follow the procedure for analyzing moment conditions of non-smooth functions (Pakes and Pollard, 1989; Newey and McFadden, 1994; Powell, 1994), since the functions inside the moment conditions $\varphi(\theta; \chi)$ are non-differentiable at certain points. This involves estimating the derivatives of the simulated moments with respect to the parameters θ . The procedure approximates the change in the share of people with wealth no larger than a threshold level by assuming that the density of the wealth distribution is constant within a small neighborhood of that threshold.

A.4 Anticipated and Realized Rates of Return on Wealth

Table A6 lists the historical returns data that I use to estimate the anticipated and realized rates of returns on retirees' portfolios. I follow Baker, Doctor and French (2007) and French and Benson (2011) in terms of data sources and assumptions.³⁶ Using data from the HRS, I classify retirees' assets into the six categories shown in the table as well as a residual "Other" category (which includes vehicles, for example) that I assume earns 0 percent real, after-tax returns. Following Baker, Doctor and French (2007), I assume that Individual Retirement Account (IRA) assets are allocated 60 percent to stocks and 40 percent to bonds and that the rate of return on business assets is a weighted average of the returns on housing and stocks, with an 85 percent weight on housing.

Anticipated returns on wealth in the model.— Individual i in income quintile q believes that she draws an (annual) rate of return on any saving she might have from the following distribution: $r_i \sim N(\mu_r(q), \sigma_r(q)^2)$, where $\mu_r(q)$ and $\sigma_r(q)$ are estimated based on (i) the average portfolio shares of individuals in income quintile q in the data and (ii) historical data on the realized rates of return on different types of assets. For each income quintile, I estimate the average shares of their portfolios held in the asset classes listed in Table A6. Then, using annual rate-of-return data for each asset class from 1960–2010, I estimate the mean and variance of the distribution of annual rates of return for each income quintile based on their portfolio shares. The resulting means and variances are similar if I instead estimate them based on returns during the time period immediately preceding the sample period (1960–1997), rather than including data through the sample period.

Realized returns on wealth in the simulation, $r_{i,t} = \sum_j \alpha_{i,j,t} r_{j,t}$.— Retiree i 's realized rate of return in year t is the weighted average of the realized rates of returns on different assets j in year t ($r_{j,t}$), weighted by i 's portfolio shares in that year ($\alpha_{i,j,t}$). The portfolio shares of

³⁶The main exception is that I use a different rate-of-return series for bonds because Baker, Doctor and French's (2007) series does not extend to 2008, the end of my sample period. I am grateful to Eric French for providing me with the historical returns data.

retirees with zero or negative net wealth are set equal to the median shares among people with between \$5,000 and \$15,000 of net worth. I assume that individuals' portfolio shares are the same in years between interviews as they were in the previous year.

Allowing for differences between anticipated and realized returns and estimating person-wave-specific rates of return protect against two potential sources of bias. One potential source of bias is that the sample period, 1998–2008, was characterized by unusually high rates of return on many assets. The average real return earned by a portfolio that matches the asset allocations of retirees around the middle of the wealth distribution was about 6 percent per year over the period, compared to about 4 percent in the three-and-a-half decades leading up to the sample period. Failing to account for the unusually, and probably unexpectedly, high rates of return could bias the results; the naive estimation would attribute wealth outcomes as arising solely from purposeful saving behavior whereas unusual capital gains or losses may have been important as well (Baker, Doctor and French, 2007). The other source of bias that this procedure protects against is that retirees' portfolios vary systematically across the wealth distribution. Retirees in the middle of the wealth distribution, for example, hold more of their wealth in housing than richer and poorer retirees, and the average return on housing wealth was especially high (7.9 percent per year) over the sample period. Ignoring the differences in retirees' portfolios could bias the results by leading the estimation to wrongly attribute differences in wealth as arising solely from differences in saving behavior whereas differences in realized returns may have been important as well.

A.5 Simulation Procedure

Simulated wealth moments.— The simulated wealth moments are analogous to their empirical counterparts. Given a vector of parameter values, θ , I solve the model to find optimal consumption spending, $\hat{c}_t(\hat{w}_t, h_t, t; s, y, ltc_i; \theta)$. I use these decision rules together with each individual's fixed characteristics, initial state, subsequent health path, and year-specific rates of return on wealth to simulate each individual's wealth as long as they live between 1999–2008. Given the simulated wealth profiles of each individual in the simulation sample, I use the same procedure to calculate the simulated wealth moments from the simulated data as I use to calculate the empirical wealth moments from the actual data.

Simulated long-term care insurance moments.— The simulated long-term care insurance moments are the long-term care insurance ownership rates by wealth quartile among the subset of the simulation sample who were 65–69 years old in 1998. Only people in good health in 1998 are allowed to buy long-term care insurance in the simulation. This is meant to capture the fact that people in bad health are prevented from buying long-term care insurance—their applications are rejected by insurers (Murtaugh et al., 1997; Hendren, 2013). Given a vector of parameter values, θ , I solve the model to find the value functions, $V_t(\hat{x}_t, h_t; s, y, ltc_i; \theta)$. Simulated long-term care insurance ownership by individual i is one if both (i) i is healthy in 1998 and (ii) i would be better off buying long-term care insurance

given his or her state variables; it is zero otherwise:

$$lrci_i^s = \mathbb{1}(h_{i,t_i} = he) \times \mathbb{1} [V_{t_i}(\hat{x}_{i,t_i}, h_{i,t_i}; s, y, lrci = 1; \theta) > V_{t_i}(\hat{x}_{i,t_i}, h_{i,t_i}; s, y, lrci = 0; \theta)].$$

The simulated aggregate long-term care insurance ownership rates are the averages of the individual ownership indicators among individuals in each wealth quartile. Simulated long-term care insurance ownership depends on θ through the value functions' dependence on θ .

Because long-term care insurance premiums depend on the age at which long-term care insurance is purchased, and because the model must be solved separately for each long-term care insurance premium schedule, I simulate the demand for long-term care insurance only among healthy 65–69-year-olds and treat them for this purpose as if they were all 67 years old, the average age at which people buy long-term care insurance (Brown and Finkelstein, 2007). Everyone who can buy long-term care insurance therefore faces the same load (proportional markup over actuarial cost); there is no adverse selection in the model once insurance rejections are accounted for.³⁷ The assumption that people face a one-time decision about whether to buy long-term care insurance—which I make to economize on computation time—is a rough approximation to the fact that people most often purchase long-term care insurance in their 60s (America's Health Insurance Plans, 2007), with an average purchasing age of 67 (Brown and Finkelstein, 2007).

A.6 Roles of Different Features of the Data in Determining the Parameter Estimates

This section discusses the extent to which different features of the data are informative about the key parameters of the model and the sensitivity of the parameter estimates to changes in the first-stage parameter values and second-stage moments.

A.6.1 Bequest Motives, (ϕ, c_b)

Retirees' saving and long-term care insurance choices, when interpreted in standard life cycle models, are highly informative about bequest motives. As reported in Tables 3 and 5, across a wide range of first-stage parameter values and second-stage estimating moments, the estimates imply that bequests are a luxury good, that bequest motives significantly increase saving and decrease holdings of long-term care insurance and annuities, and that versions of the model without bequest motives are highly inconsistent with retirees' choices. The estimated bequest motive is pinned down relatively sharply and is not very sensitive to changes in the first-stage parameter values and second-stage moments. Across

³⁷In practice, insurance companies limit adverse selection by denying coverage to people with certain health conditions (Murtaugh et al., 1997; Hendren, 2013) and by front-loading premiums to minimize policy lapsation by people who remain healthy (Hendel and Lizzeri, 2003). In long-term care, Finkelstein and McGarry (2006) find that average long-term care usage is roughly equal for the insured and uninsured population, though Finkelstein, McGarry and Sufi (2005) find that people who become healthier than average are more likely than others to drop their coverage.

the wide range of specifications in Tables 3 and 5, \hat{c}_b is always between \$12,500 and \$30,000 and usually between \$15,000 and \$20,000, $\hat{\phi}$ is always between 0.93 and 0.99 and usually between 0.95 and 0.96, and the restriction implicit in nested versions of the model without bequest motives is always strongly rejected (in all cases $p \ll 0.01$).

Figure A1 plots four versions of the classical minimum distance objective as a function of the bequest motive parameters, ϕ and c_b , holding fixed the other parameters at their baseline estimates. Each of the four objective functions is based on a different set of moment conditions: the baseline set of wealth and long-term care insurance moments, only the wealth moments, only the long-term care insurance and median wealth moments, and only the median wealth moments. With the exception of the objective function based on the median wealth moments alone, the objective functions are well behaved and imply that the underlying data are highly informative about the bequest motive. The objective functions all feature a single, small “valley” in the same location, centered on the estimate, the “hills” around which increase steeply as ϕ and c_b move away from their estimated values in any direction. These imply that the wealth moments alone, the long-term care insurance and median wealth moments together, and, especially, the full set of long-term care insurance and wealth moments are all much more consistent with models in which bequests are valuable luxury goods than with other configurations, including those with no bequest motive.

The median wealth moments alone, by contrast, are relatively uninformative about the bequest motive parameters: Many combinations of ϕ and c_b are similarly consistent with these moments. This illustrates the lack of power in the saving choices of retirees at a particular point in the wealth distribution to discriminate between different underlying preferences. But as the other figures show, taking into account a broader set of patterns—the saving of retirees with different levels of wealth or retirees’ saving and long-term care insurance choices together—is a powerful way to discriminate between different underlying preferences. Both broader sets of patterns are highly inconsistent with versions of the model without bequest motives but are matched well by the model with bequest motives.

A.6.2 Non-Bequest Motive Parameters, $(c_{pub}, \bar{x}_{comm}, \beta, \sigma)$

Retirees’ saving and long-term care insurance choices are less informative about the other, non-bequest motive parameters. As reported in Tables 3 and 5, many changes in the first-stage parameter values and second-stage moments have non-negligible effects on the estimates of the discount factor, the coefficient of relative risk aversion, and the consumption values of means-tested programs. Across the specifications reported in Tables 3 and 5, for example, $\hat{\beta}$ varies from 0.80 to 0.95, $\hat{\sigma}$ from 2.0 to 6.1, \hat{c}_{pub} from \$4,000 to \$19,100, and \hat{x}_{comm} from \$1,100 to \$5,200.

Figure A2 plots the baseline objective function as a function of different combinations of parameters, holding fixed the other parameters at their baseline estimates. The objective function is well behaved, but in many cases it is not very informative about the non-bequest motive parameters. Panel (a) shows that a wide range of β and \bar{x}_{comm} values are similarly consistent with retirees’ saving and long-term care insurance choices. Panel

(b) compares the extent to which β and c_b are pinned down by the estimation. β is extremely poorly pinned down, as values of β from 0.75 to 0.95 are similarly consistent with the data. c_b is much more tightly pinned down, between about \$13,000 and \$23,000, despite its range being increased by interaction effects with β given β 's large range. Panel (c) shows that β is also much less well pinned down than σ . Panel (d) shows that c_{pub} is poorly pinned down as well, as values between about \$10,000 and \$20,000 are similarly consistent with retirees' saving and long-term care insurance choices as a whole.

A.6.3 Why Bequest Motives are Pinned Down More Sharply than the Other Parameters

Retirees' saving and long-term care insurance choices are highly informative about bequest motives and less informative about the other parameters because bequest motives affect saving and long-term care insurance choices in a way unlike those of any of the other second-stage parameters (or, indeed, any of a large set of plausible changes one might make to the model, including, for example, if people over- or underestimate health spending risk or life expectancy), whereas the other parameters tend to affect saving and long-term care insurance choices in ways that are similar to one another.

All of the non-bequest motive parameters affect saving and long-term care insurance in the same direction. Saving and long-term care insurance are monotonically increasing in β and σ and monotonically decreasing in c_{pub} and \bar{x}_{comm} . As a result, a change in one or more of these parameters can be roughly offset by changes in others, so many different combinations of values of these parameters have similar implications for retirees' saving and long-term care insurance choices. The result is that the estimates of these parameters are not pinned down very sharply; they are sensitive to changes in the first-stage parameter values and the relative weights of different second-stage moments in the estimation. In other words, retirees' saving and long-term care insurance choices are relatively uninformative about the non-bequest motive parameters because these parameters all have similar effects on saving and long-term care insurance.³⁸

Bequest motives in which bequests are a luxury good, by contrast, tend to increase saving but reduce long-term care insurance by reducing the opportunity cost of precautionary saving. That is why retirees' saving and long-term care insurance choices are highly informative about bequest motives; bequest motives play a key role in allowing the model to match observed behavior in which many retirees hold much of their wealth well into retirement yet do not buy annuities or long-term care insurance. This is also why the bequest motives are pinned down well even though the other parameters are not.

³⁸Most of the difficulty lies in pinning down the values of these parameters jointly, not individually given values of the others. The standard errors on the estimates of these parameters, with the partial exception of c_{pub} , tend to be small. Across specifications, σ tends to be negatively related to β and positively related to c_{pub} and \bar{x}_{comm} , presumably because the effects of a given increase in σ can be roughly offset by a decrease in β or an increase in c_{pub} or \bar{x}_{comm} .

A.6.4 Why $\hat{\beta}$ Tends to be Low

While most of the parameter estimates take standard or plausible-seeming values, the estimates of the discount factor, β , tend to be unusually low. Across a wide range of specifications, $\hat{\beta}$ ranges from values around 0.95, a typical value in the literature, down to values as low as 0.80, which implies strong impatience. The large range indicates that β is not well pinned down by this evidence, so it would be premature to conclude that retirees' saving and long-term care insurance choices are strongly indicative of a low discount factor. But the estimates of β tend to be lower than is often the case in this literature, with a central tendency around 0.9, so it is useful to discuss why this might be.³⁹

With many estimating moments and parameters, determining the relative roles of different features of the data in driving a particular parameter estimate is not straightforward; all of the parameter estimates are determined jointly by all of the moments. But a variety of tests suggest that the low values of β arise from the difficulty of matching the wealth holdings of the poor, especially in combination with the low rates of long-term care insurance ownership throughout the wealth distribution.

The model has trouble matching the wealth holdings of poor people. In the data, many people report holding small-but-positive amounts of wealth and fewer report holding zero wealth. Among my sample of single retirees, for example, of the roughly 27 percent of person-waves in which wealth is no greater than \$10,000, about 56 percent have strictly positive wealth. In the model, with plausible-seeming parameter values fewer people hold small-but-positive amounts of wealth and more hold zero wealth. When $\theta = (c_{pub} = \$20,000, \phi = 0.95, c_b = \$20,000, \sigma = 3, \beta = 0.97, \bar{x}_{comm} = \$7,000)$, for example, the model matches well the long-term care insurance moments, the median and 75th percentile wealth moments, and even the (low and not targeted) 25th percentiles of wealth, but it over-predicts the “probability of zero wealth” moments by an average of almost 16 percentage points, 29.4 percent vs. 13.8 percent.

By increasing the strength of precautionary motives to save (i.e., increasing σ and decreasing c_{pub} and \bar{x}_{comm}), the model can better match the probability of zero wealth. But, absent other adjustments, this comes at the expense of dramatically over-predicting saving higher in the wealth distribution and long-term care insurance holdings. When θ is the baseline estimate except with $\beta = 0.97$, for example, the model matches pretty well the “probability wealth equals zero” moments (overstating them by 3.0 percentage points on average) but over-predicts the long-term care insurance moments by 8.5 percentage points on average, the median wealth moments by about \$16,100 on average, and the 75th percentile wealth moments by about \$46,400 on average.

Reducing β helps the model reduce the extent to which it over-predicts saving higher in the wealth distribution and long-term care insurance ownership, while only slightly worsening its over-prediction of the probabilities of zero wealth. When θ is the baseline estimate, the model matches each set of moments pretty well. It under-predicts the long-term care insurance moments by 1.4 percentage points and the median wealth moments by \$2,700 on

³⁹The strength of the baseline estimation's “preference” for a low value of β is moderate, much less than its preference for bequest motives but not a matter of indifference either. The p -value of the restriction that $\beta = 0.95$ is 0.015, that $\beta = 0.925$ is 0.06, and that $\beta = 0.90$ is 0.48.

average, and it over-predicts the 75th percentile wealth moments by \$7,300 and the zero-wealth moments by 4.3 percentage points on average.

To summarize, the estimations tend to favor a relatively low β because that tends to be the least-costly way (in terms of the objective-function penalty) to reduce the over-predictions of saving higher up in the wealth distribution and long-term care insurance ownership that result from their efforts to match the prevalence of small-but-positive wealth levels among the poor.

All of the key conclusions are highly robust to calibrating β to more standard values.

A.6.5 Why it is “Hard” for the Model to Match the Very Bottom of the Wealth Distribution

The proximate reason the model has trouble matching the prevalence of small-but-positive wealth holdings with reasonable parameter values is that holding small amounts of wealth means forgoing consumption today in exchange for small expected future benefits. The expected future benefits are low mainly because of health spending shocks, which, given the presence of means-tested programs, effectively function as stochastic wealth taxes. The ultimate reason the model has trouble matching the prevalence of small-but-positive wealth holdings with reasonable parameter values is that there is a mismatch between the concept of wealth in the model and available measures in the data.⁴⁰

The model does not include many of the real-world motives to hold at least small amounts of wealth, many of which arise from the desire to economize on transactions costs. For example, in reality most people who regularly consume “car services” own their own car rather than renting car services on a flow basis. There is no analogous motive for holding wealth in the model. Moreover, there is a mismatch in the timing of when wealth is measured. In the model, wealth is measured “between periods,” immediately after the income and spending from one period are realized and immediately before the income and spending from the next period occur. In the data, by contrast, wealth is measured whenever the individual happens to be surveyed, which is unlikely to coincide perfectly with the analog—to the extent there even is one—of the beginning- or end-of-period timing in the model. Someone who lives “hand-to-mouth,” exhausting her resources by the time the next income payment arrives, will typically have a small but positive amount of wealth when she is surveyed by the HRS, despite not saving anything from the perspective of the model.

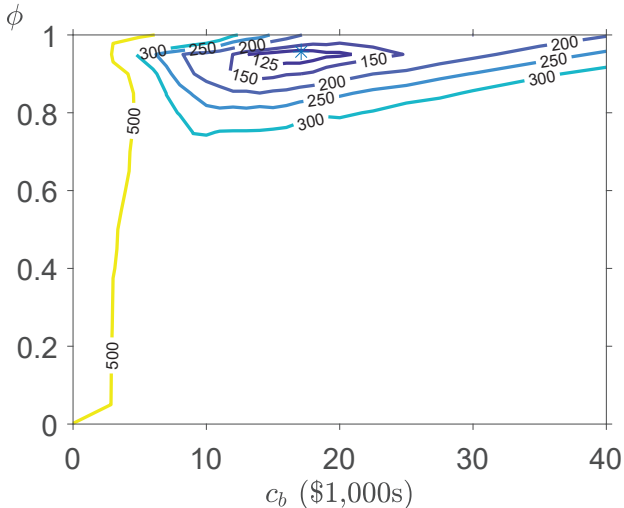
These mismatches cause the estimations to “stretch”—i.e., adjust the values of some of the parameters away from the more standard values that they would otherwise prefer—to try to reduce the predicted share of people with zero wealth to come into closer alignment with the low share in the data. Reducing β enables it to do so without missing the other target moments too badly, especially long-term care insurance holdings.

All of the key conclusions are highly robust to a wide range of changes in the assumptions

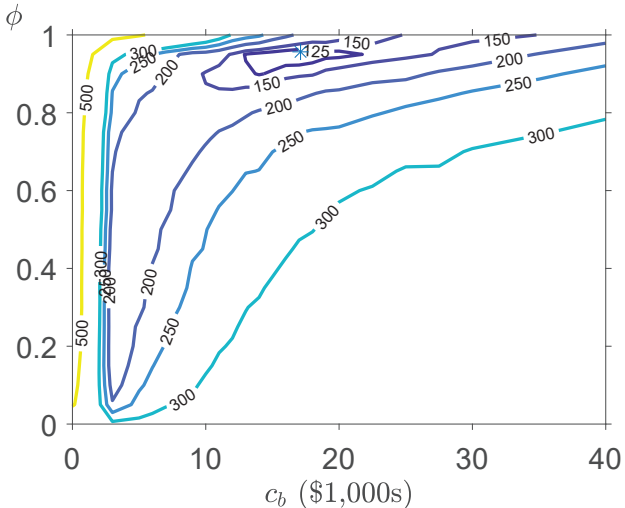
⁴⁰This mismatch is present for other models in this literature as well, but it becomes important mainly when low wealth levels are targeted, which is rarely done.

and target moments that at least partially address this mismatch, including using different measures of wealth (e.g., excluding the value of cash and vehicles or housing) and dropping the zero-wealth moments.

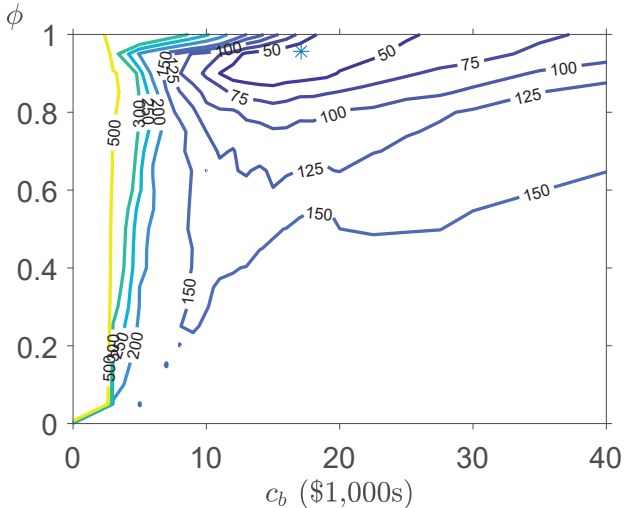
Appendix Figures and Tables



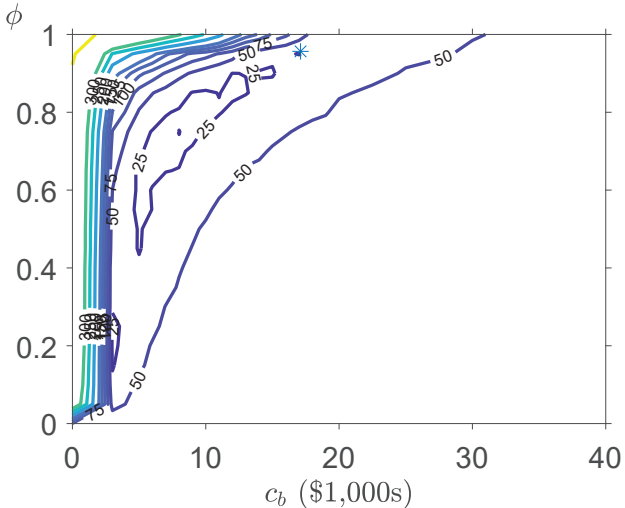
(a) Objective function: baseline



(b) Objective function: wealth only

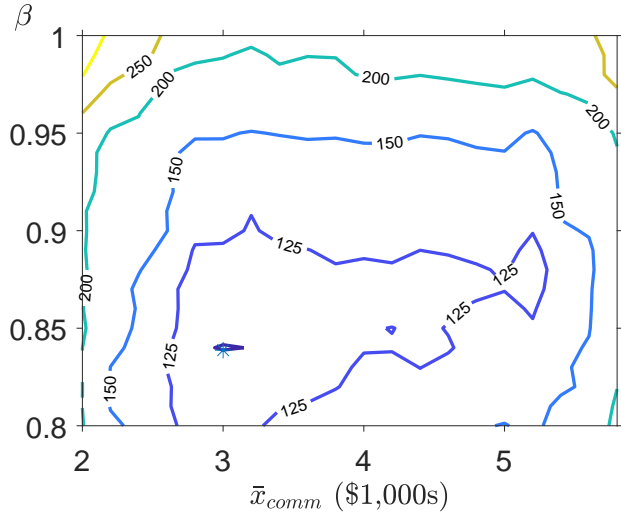


(c) Objective function: LTCI and median wealth

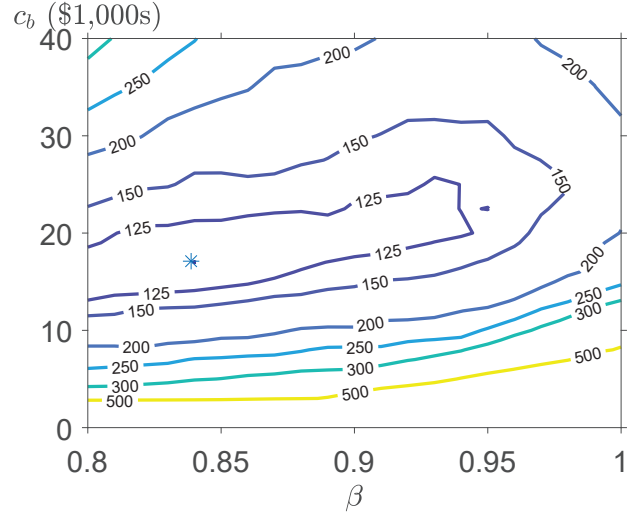


(d) Objective function: median wealth only

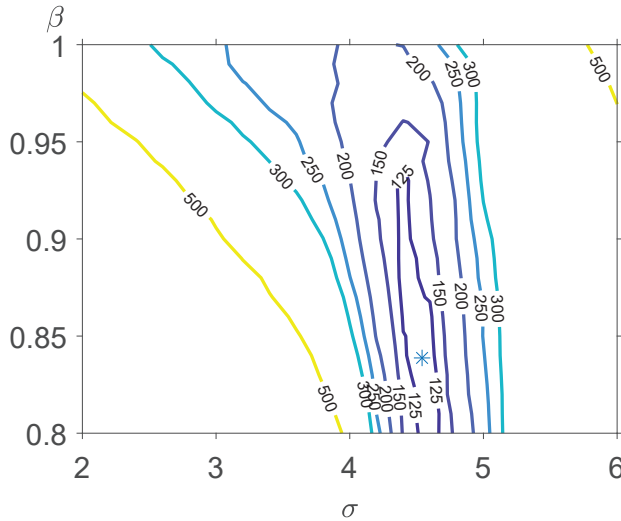
Figure A1: Contour plots of different versions of the objective function in (c_b, ϕ) -space with the other parameters held fixed at their baseline estimated values. Higher contours indicate greater mismatch between the simulated and empirical moments. The asterisks mark the baseline estimates. All plots use the same scale.



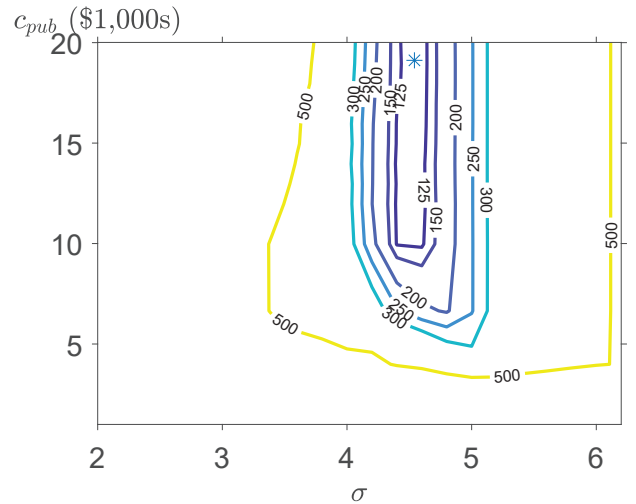
(a)



(b)

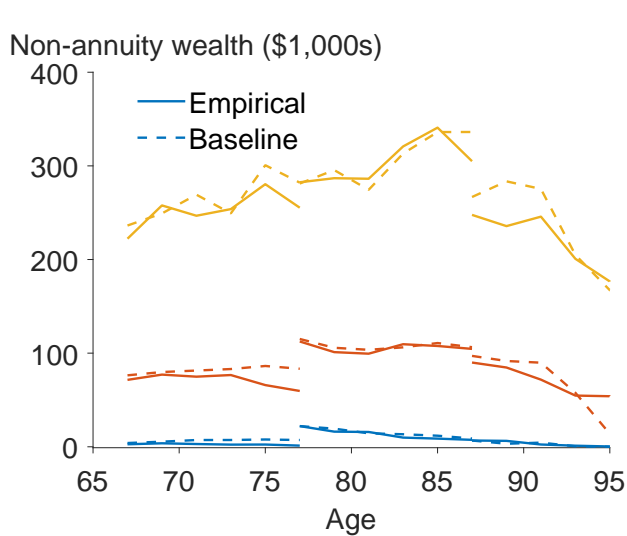


(c)

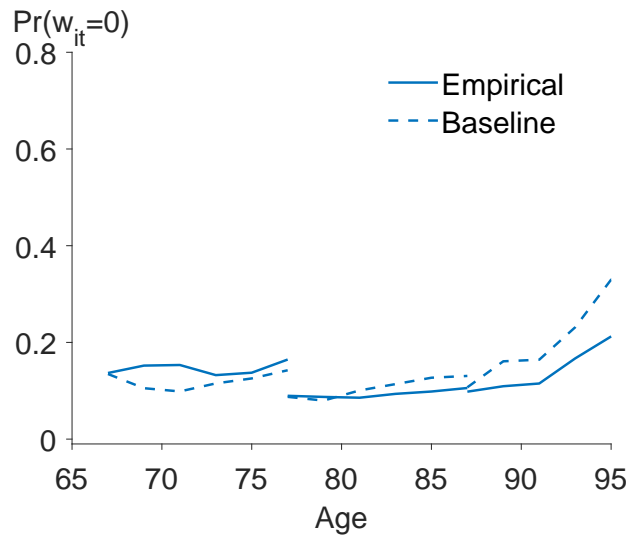


(d)

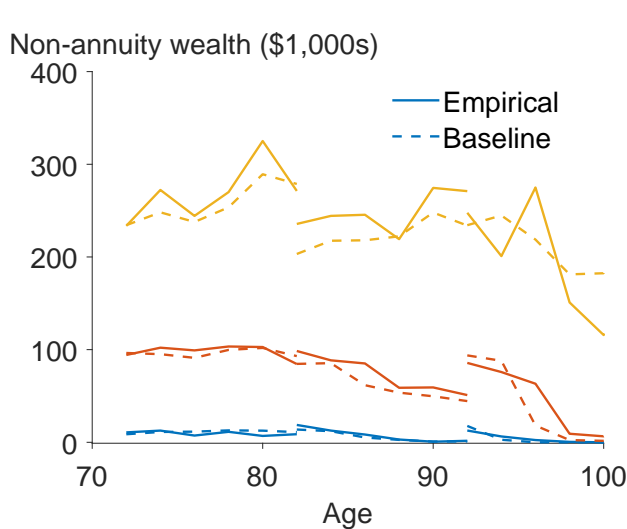
Figure A2: Contour plots of the baseline objective function as a function of different pairs of θ parameters with other parameters held fixed at their baseline estimated values. Higher contours indicate greater mismatch between the simulated and empirical moments. The asterisks mark the baseline estimates. All plots use the same scale.



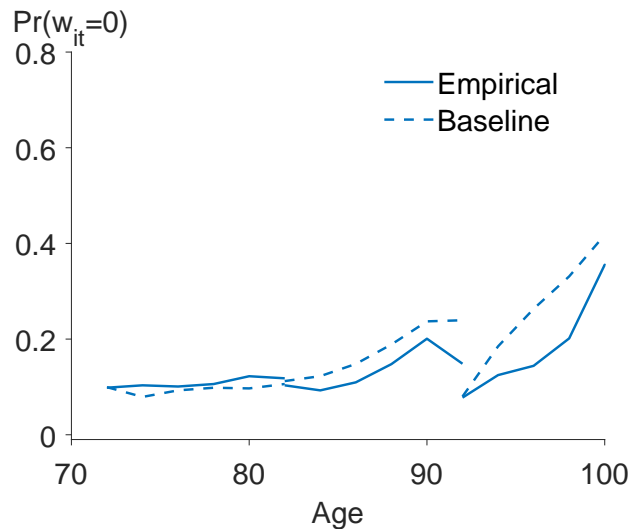
(a) Odd-numbered cohorts



(b) Odd-numbered cohorts



(c) Even-numbered cohorts



(d) Even-numbered cohorts

Figure A3: Empirical wealth moments (solid lines) and simulated wealth moments (dashed lines) for odd- and even-numbered cohorts under the baseline model. Panels (a) and (c) show the 25th, 50th, and 75th percentiles of the wealth distributions among surviving members of each cohort. The 25th percentiles are not included in the estimation. Panels (b) and (d) show the share with zero wealth among surviving members of each cohort. The x -axis shows the average age of surviving members of the cohort.

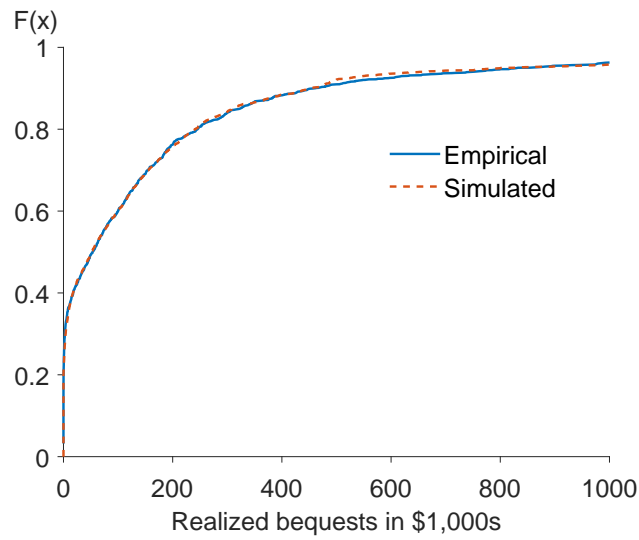


Figure A4: Cumulative distribution function of wealth in the last wave in which an individual is alive among individuals who die during the sample period. Wealth in the last period in which an individual is alive is a proxy for realized bequests that is better-measured than actual bequests (De Nardi, French and Jones, 2010, see, for example,). The simulated distribution is generated by the baseline model and parameter estimates.

	(1) Used formal home care since last interview	(2) Stayed in nursing home since last interview	(3) Owns long-term care insurance
Female=1	0.0494 (0.0333)	-0.0548* (0.0262)	0.0123* (0.00512)
Single=1	0.0263 (0.0402)	0.124*** (0.0299)	-0.0207*** (0.00564)
No kids=1	0.0310 (0.0448)	0.0905** (0.0336)	0.00535 (0.00973)
Age	0.0219 (0.0309)	0.0721** (0.0247)	-0.00438 (0.00711)
Age ²	-0.0000788 (0.000194)	-0.000360* (0.000151)	0.00000950 (0.0000468)
Number of ADLs (0-5)=3	0.0759* (0.0367)	0.0429 (0.0282)	
Number of ADLs (0-5)=4	0.187*** (0.0425)	0.107** (0.0327)	
Number of ADLs (0-5)=5	0.292*** (0.0431)	0.276*** (0.0321)	
Income quartile=2	0.0371 (0.0379)	0.0262 (0.0281)	
Income quartile=3	0.0618 (0.0475)	0.0127 (0.0375)	
Income quartile=4	0.0391 (0.0551)	0.0719 (0.0451)	
Wealth quartile=2			0.0124** (0.00464)
Wealth quartile=3			0.0482*** (0.00577)
Wealth quartile=4			0.137*** (0.00776)
Observations	1083	1360	10599
y _{mean}	0.422	0.283	0.0738
Sample restrictions	Age 65+ 2+ ADLs	Age 65+ 2+ ADLs	Age 65+

Marginal effects; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1: Marginal effects from probit regressions, i.e., the increase in the average predicted probability of the dependent variable being one if everyone in the sample had their value of the indicator variable in question increased from zero to one or their value of the continuous variable in question (age) increased by one unit. Columns 1, 2, and 3 report results from probit regressions of indicator variables for whether the individual used any (formal) home care since the last interview, whether the individual stayed in a nursing home since the last interview, and whether the individual owns long-term care insurance, respectively. All of the columns restrict the sample to people age 65 and older. Columns 1 and 2 further restrict the sample to people who report having problems with at least two activities of daily living. The difference in the number of observations between columns 1 and 2 reflect a difference in the number of missing values of the dependent variables. Age is measured in years. Wealth quartiles are calculated based on wealth values that are adjusted for whether the individual is part of a one- or two-person household according to the widely-used square root equivalence scale (e.g., OECD, 2011) (so an individual in a couple is assigned a wealth value equal to his or her household wealth divided by $\sqrt{2}$) before calculating quartiles). The qualitative results are not sensitive to plausible alternatives.

Income quintile	Healthy males			Healthy females		
	Age adjustment to FHSWL, Δ	Life expectancy at 70		Age adjustment to FHSWL, Δ	Life expectancy at 70	
		De Nardi et al. (2010)	Adjusted FHSWL		De Nardi et al. (2010)	Adjusted FHSWL
1	17	7.6	7.7	6	12.8	13.0
2	15	8.4	8.4	5	13.8	13.6
3	13	9.3	9.3	3	14.7	14.8
4	11	10.5	10.3	2	15.7	15.4
5	9	11.3	11.3	0	16.7	16.8

Table A2: Adjustments to the Friedberg et al. (2014) (FHSWL) model of health transitions for females to match the life expectancy differences across sex and income groups documented by De Nardi, French and Jones (2010).

	Life expect	Exp share of time from 65:				Prob ever in NH	Exp years in NH	Exp years in NH > 0	Prob leave NH alive	Prob leave NH ever NH
		He	HC	ALF	NH					
Males										
Original	16.8	0.95	0.02	0.01	0.02	0.43	0.39	0.90	0.35	0.82
Yearly transitions	17.3	0.95	0.02	0.01	0.02	0.20	0.38	1.92	0.11	0.56
By income quintile										
Bottom	9.8	0.81	0.03	0.04	0.12	0.45	1.19	2.65	0.22	0.48
Second	10.8	0.83	0.03	0.04	0.10	0.43	1.12	2.59	0.22	0.51
Third	11.9	0.84	0.04	0.03	0.09	0.41	1.05	2.56	0.22	0.53
Fourth	13.0	0.86	0.04	0.03	0.08	0.39	0.99	2.53	0.21	0.54
Top	14.2	0.87	0.04	0.03	0.07	0.37	0.94	2.52	0.21	0.55
Females										
Original	20.3	0.91	0.03	0.02	0.04	0.57	0.83	1.46	0.46	0.80
Yearly transitions	20.8	0.91	0.03	0.02	0.04	0.33	0.82	2.47	0.19	0.56
By income quintile										
Bottom	16.1	0.89	0.04	0.02	0.05	0.35	0.88	2.50	0.20	0.56
Second	16.8	0.89	0.04	0.02	0.05	0.35	0.86	2.49	0.19	0.56
Third	18.3	0.90	0.03	0.02	0.05	0.34	0.84	2.48	0.19	0.56
Fourth	19.1	0.90	0.03	0.02	0.04	0.34	0.83	2.48	0.19	0.56
Top	20.8	0.91	0.03	0.02	0.04	0.33	0.82	2.47	0.19	0.56

Table A3: Health transitions model statistics. “Original” corresponds to the Friedberg et al. (2014) (FHSWL) model of monthly health transitions. The other rows show simulated statistics from adjusted versions of the model. The adjustments are: switching from monthly to yearly transitions to economize on computation time and better match the frequency of the HRS data, using FHSWL’s female model for males in my sample to better reflect the long-term care risk facing single retirees, and adjusting the male and female models to match the heterogeneity in remaining life expectancy from age 70 documented by De Nardi, French and Jones (2010). The first column shows life expectancy at age 65. The next four columns show the expected shares of time from age 65 on spent healthy, receiving home care, living in assisted living facilities, and living in nursing homes, respectively. I am grateful to Wenliang Hou and Tony Webb for providing me with the transition matrices from Friedberg et al. (2014).

Relative price of nursing home care	
Female	0.0604 (0.0669)
Age	-0.0000976 (0.00369)
2nd income quintile	0.0783 (0.0799)
3rd income quintile	0.0164 (0.0782)
4th income quintile	0.0958 (0.0849)
Top income quintile	0.115 (0.0812)
<i>N</i>	536

Table A4: Regression of the relative price of nursing home care using data from the NLTCs. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)
	Log acute medical spending	Square of log acute medical spending
Age	0.00707 (0.00499)	0.0884 (0.0712)
Female	0.202** (0.0729)	3.158** (1.004)
Home care	0.331*** (0.0711)	4.905*** (1.024)
Nursing home	0.476*** (0.105)	6.970*** (1.513)
2nd income quintile	-0.0112 (0.159)	-0.115 (2.334)
3rd income quintile	-0.149 (0.148)	-2.237 (2.146)
4th income quintile	-0.141 (0.142)	-1.920 (2.070)
Top income quintile	-0.169 (0.140)	-2.186 (2.052)
<i>N</i>	3969	3969

Table A5: Acute medical spending regressions. The omitted dummy variables are “healthy” and “bottom income quintile.” The sample is the subset of my main sample (single retirees 65 and older) whose combined previous-wave non-housing wealth and annual income was at least \$100,000 and who have strictly positive spending (in order to take logs). Home care indicates whether the individual used home care since the last interview. Nursing home indicates whether the individual is living in a nursing home at the time of the interview. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Asset	Data source	Taxation	Return, 1998–2008 (%)		Portfolio share (%)
			Mean	Std. dev.	
Occupied housing	OFHEO, Baker et al. (2007)	0% on capital gains, 1%/yr property tax	7.9	3.2	54.8
Stocks	CRSP	0% on capital gains, 20% on div yield (assume 2% yield)	2.6	16.9	9.3
Bonds	AAA long bonds yield to maturity	20%	3.2	1.0	2.2
Liquid (CDs)	Treasury	20%	1.2	1.4	6.9
Unoccupied housing	OFHEO	0%	4.3	3.2	1.5
Debt	Baker et al. (2007)	20%	2.4	-	-16.9

Table A6: Data sources and assumptions underlying the calculations of the expected and realized rates of return on wealth. The mean returns are the geometric averages of annual real, after-tax returns. The portfolio shares are the average shares of net wealth held in each asset in 1998 by the sample of single retirees, weighted by HRS respondent-level weights. The assumption of zero taxation of capital gains comes from the assumption that a large share of retirees’ capital gains are not realized (by asset sales) during the sample period. Additional details about the data sources can be found in Baker, Doctor and French (2007).

	Average deviations, (simulated-empirical)			
	LTCI (p.p.)	Medians (\$1,000s)	75th ptils (\$1,000s)	Pr(w=0) (p.p.)
Baseline	-1.4	-2.7	7.3	4.3
No BM	9.1	-11.1	-55.1	6.3
No BM, medians	33.5	2.5	-50.1	2.0
No BM, 0s and p75s	44.0	29.6	-9.9	3.3
	Average absolute deviations, simulated-empirical			
	LTCI (p.p.)	Medians (\$1,000s)	75th ptils (\$1,000s)	Pr(w=0) (p.p.)
Baseline	2.7	10.9	27.5	5.9
No BM	9.9	15.4	62.7	6.8
No BM, medians	33.5	10.7	60.8	5.3
No BM, 0s and p75s	44.0	32.5	47.8	4.4

Table A7: Economic fit of different estimated models to each set of moment conditions. The estimations are the baseline estimation, the main estimation with no bequest motive (“No BM”), the estimation with no bequest motive based on the median wealth moments (“No BM, medians”), and the estimation with no bequest motive based on the “share with zero wealth” and 75th percentile wealth moments (“No BM, 0s and p75s”). The first set of rows shows the average excess of the simulated moments over the empirical moments of each type. The last set of rows shows the average absolute deviations of the simulated moments from the empirical moments of each type. Deviations from the long-term care insurance and probability-of-zero-wealth moments are in percentage points.