

Late-in-Life Risks and the Under-Insurance Puzzle

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Abstract

Individuals face significant late-in-life risks, including potential long-term care (LTC) needs. Yet they hold little corresponding insurance (LTCI). We investigate the degree to which a fundamental lack of interest, poor product features, and possible behavioral factors determine low LTCI holdings. We estimate a rich set of individual-level preferences and use a life-cycle model to find that ideal insurance would be far more widely held than are products in the market. We find that flaws in existing products provide only a partial explanation for this under-insurance puzzle, with analogous findings for the gap between estimated and actual annuity holdings. Our results derive from “strategic survey questions” that identify preferences as well as stated demand questions.

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1 Introduction

Long-term care is expensive and the need for it pervasive. As documented by Brown and Finkelstein (2011), aggregate long-term care expenditure accounted for 8.5 percent of total health expenditure and 1.2 percent of GDP in 2004. One in three 65 year old Americans will eventually enter a care facility, and the average private room in a nursing home costs \$84,000, with well-located and high quality care potentially costing far more (Genworth (2013)). Hence it is striking that only 10 percent of elderly Americans hold long-term care insurance (LTCI) and that these policies account for only 4 percent of aggregate LTC expenditure.

There is substantial uncertainty about the determinants of low observed LTCI holdings, with some combination of fundamental lack of interest, poor product features, and possible behavioral factors likely being key contributors. We study the motives generating late-in-life insurance demand in the newly-created Vanguard Research Initiative (VRI) panel. For every (single) panel member, we estimate a rich set of preferences and use a state-of-the-art life-cycle model to predict demand for insurance products, including interest in a perfect form of LTCI. Our estimates imply that more than 60 percent of panel members would purchase such insurance, three times the number that actually hold LTCI. The estimated intensive-margin demands are also high. While the VRI is relatively wealthy, we find that the gap between estimated demand and actual holdings is present across the wealth and income distribution, survives in more representative subsamples, and is robust to reasonable loads. We conclude that there is a significant “LTCI puzzle”, in the form of a gap between actual holdings and estimated holdings in reasonably calibrated models.

To what extent does the LTCI puzzle result from the yawning chasm between the ideal LTCI product that we model and those available in the market? We model “Activities of Daily Living” insurance (ADLI), an Arrow security that delivers wealth precisely when individuals have difficulties with ADLs and may therefore need care. ADLI is not subject to default risk, premium risk, inflation risk, or the uncertain and potentially adversarial claims process based on expense reimbursement that characterizes existing products. To assess the extent to which features of available LTCI as opposed to idealized ADLI explains the puzzle, we posed stated demand questions in the VRI.¹ We find that a significant proportion of those who do not hold LTCI but are predicted to have positive demand also have positive stated demand for ADLI. Hence imperfections in the products on offer do indeed limit interest. This suggests that development of improved products would be of great private value. Since provision of government provided care is placing ever-increasing pressure on public finances (Brown and Finkelstein (2008, 2011)), this also suggests potential for great public value in the provision of higher quality private LTCI.

While providing a partial explanation, it does not appear that product imperfections are enough to fully explain the LTCI puzzle either in a qualitative or a quantitative sense. Even the ideal product would seem to be of lower interest than our model implies. We also find the annuity puzzle in our sample (see Yaari (1965), Modigliani (1986), Brown (2007)), with modeled demand far in excess of holdings. There is also a gap between modeled and stated demand, larger even than was the case for LTCI. Hence under insurance of late-in-life risks appears to be broad-based.

Our analysis rests critically on custom-designed survey instruments. Particularly central are “strategic survey questions” (SSQs) that are purposefully designed to elicit key preference parameters. Given their centrality, we dedicate significant effort to verifying the quality of these SSQs. As part of a broader process

¹ We craft these questions as much as possible to meet criteria of reasonableness, as in Beshears, Choi, Laibson, and Madrian (2008).

of quality control, we posed a series of comprehension tests before allowing respondents to answer these questions. These were generally very well answered. As a result of this and other tests of reason, we have confidence that they were answered with deliberation and honest purpose. Moreover the responses that rationalize the LTCI puzzle are highly reasonable. Most panel members indicated a desire to spend on private LTC to achieve high quality care even at the expense of leaving a smaller bequest. Hence standard preference based explanations for low LTCI holdings appear first order inconsistent with survey responses. Reliance on government provision of long-term care via Medicaid is not seen as an attractive alternative to private provision (as discussed by Pauly (1990) and similar to Hubbard, Skinner, and Zeldes (1994)), and bequest motives do not overwhelm precautionary motives (Lockwood (2014) and Koijen, Van Nieuwerburgh, and Yogo (2015)).

A key feature that makes SSQs of value in model estimation is that they are quantitative rather than qualitative. In this sense, there are analogies with the quantitative questions about beliefs pioneered by Juster (1966) and Manski (1990). The quantitative nature of our survey instrument liberates one further analytic step, which is to analyze the gap between estimated and stated demand. We identify variables that predict this gap in the quantity of insurance demanded related to the structure of the model, survey comprehension, and private information about health.

Following a brief literature review, Section 2 provides an overview of our model. Section 3 introduces the VRI and the key data items on which our analysis rests. Section 4 provides evidence on the credibility of survey responses. Section 5 produces our individual-level parameter estimates. Section 6 derives model-based estimates of demand for ADLI, while Section 7 presents the stated ADLI demand. Section 8 confirms the findings for annuities, and Section 9 concludes.

1.1 Relation to the Literature

Long-term Care and Long-term Care Insurance. As noted in Brown and Finkelstein (2011), the need for long-term care is one of the largest uninsured risks facing the elderly and understanding the reasons for such high exposure to this risk is a first-order issue in improving household welfare and the economic and health security of elderly Americans. It is well understood that there could be supply-side limitations on the provision of LTCI. Cutler (1996) discusses the difficulties of insuring inter-temporal risk, Finkelstein and McGarry (2006), Brown and Finkelstein (2007), and Hendren (2013) document evidence of adverse selection, and Koijen and Yogo (2015) discusses the interaction of financial frictions and statutory regulation that affect the profitability of insurance offerings. The literature has also pointed out that there may also be significant demand-side reasons explaining the low holdings of LTCI. Demand might be limited due to crowding out from government provided care (Pauly (1990); Brown and Finkelstein (2008)) and means tested programs can have effects on both low wealth and affluent households (Braun, Kopecky, and Koreshkova (2015)). The perceived value of this publicly provided care is certainly a determinant of the demand for private LTCI. Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011) estimated preferences reflecting a sizable degree of public care aversion. Furthermore, Hackmann (2015) documents that the low reimbursement rates of Medicaid actually contributes to lower quality and less attentive care in nursing homes. Thus, there is ample reason to believe that people may have a precautionary saving motive driven by the desire to purchase high quality convenient care. We complement this body of work by developing measures of the counterfactual demand for high quality private insurance in a model with heterogeneous preferences and government provided care—isolating the

supply from the demand-side contributions to the low observed LTCI holding.

Health-state Utility. Since demand for LTCI depends crucially on the desire to have wealth in the state of the world when help is needed with ADLs, we are intimately connected to the literature that estimates health-state dependent utility functions. Although health-state dependent utility is not a new concept—around since at least Arrow (1974)—this feature is increasingly being incorporated into quantitative evaluations of household decision-making. Our approach uses stated preference survey methods, which complements previous research using other techniques, such as the health and consumption dynamics approach of Lillard and Weiss (1997), health and utility proxy dynamics approach of Finkelstein, Luttmer, and Notowidigdo (2013), and the compensating differentials approach of Viscusi and Evans (1990) and Evans and Viscusi (1991) (see Finkelstein, Luttmer, and Notowidigdo (2009) for an overview). Estimates vary on whether poor health increases or decreases the marginal utility of consumption. Even so, there is a limit to the applicability of previous measures using a general poor-health state, since estimates may be highly contextual and LTC is a distinct health state associated with different care, maladies, and behavior. Similar to our findings, new work by Hong, Pijoan-Mas, and Rios-Rull (2013) uses panel data and Euler equations to estimate that lower health gives higher marginal utility at older ages. Most closely related to our approach is Brown, Goda, and McGarry (2013), who use a related survey methodology to document the degree to which there exists health-state dependent utility and find evidence of state dependence and significant heterogeneity in preferences. Furthermore, the demand for LTCI is driven not just by preferences in the ADL state of the world, but also by preferences in all possible health states. Thus, our work is also closely related to the literature estimating risk aversion and bequest utility parameters.

Structured Surveys Survey measurement of model preference parameters was initiated by Barsky, Juster, Kimball, and Shapiro (1997) who estimated risk tolerance using stated preferences over lotteries. The methodology was refined in Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011) who developed strategic survey questions (SSQs). These specify choice scenarios engineered to aid in estimation of a life-cycle model in which the ability to identify parameters using available behavioral data is very limited. For these questions, as for the expectations questions before them, one must establish credibility using rich additional measurements. A particular innovation in this paper is the extensive process for designing SSQs, including rich yet simple detailing of the scenarios and explicit tests of subject comprehension (see Section 3.2 below).

This work forms part of a growing body of work that incorporates answers to theoretically-inspired survey questions in estimating structural models of important life-cycle choices. The pioneering work on expectations measurement due to Juster (1966) and Manski (1990) is designed with just such estimation possibilities in mind and, following their lead, such data has been gathered by the Health and Retirement Study in many domains (as discussed in Attanasio (2015)). van der Klaauw and Wolpin (2008) make explicit use of HRS data on retirement and longevity expectations in estimating a structural model of the link between social security and the retirement and saving behavior of low-income households. Wiswall and Zafar (2015) implement a specific information intervention and combine it with belief measurement to separate informational from preference-based determinants of college major choice. As the importance of measuring expectations has been increasingly realized, so the fundamental reasonableness of numerical answers has been confirmed (Manski (2004)) and further improvements have been made in the design process (Delavande and Rohwedder (2008)).

While different in structure from measurement of expectations and preferences, our approach is spiritually akin to the work of Paweenawat and Townsend (2012) on measurement of household and village financial accounts and of Attanasio, Cunha, and Jervis (2015) and Attanasio and Cattan (2015) in the estimation of human capital production functions. In both cases, as in ours, a complete theoretical framework was developed to guide the design of survey questions.

Life-cycle Models and Saving Motives. The determinants of LTCI demand are similar to the forces driving late in life saving behavior. Thus, our work is closely related to the literature that uses life-cycle models to study the dynamics of savings in old age. Many recent models that explain the observed slow spend down of wealth in later life allow for both bequest motives and precautionary motives associated with high late in life health and long-term care (LTC) expenses. Laitner, Silverman, and Stolyarov (2014) and Barczyk and Kredler (2015) provide analytically tractable models that cleanly highlight the impact of different motives on saving decisions. Late in life health risks induce precautionary savings much like income risk does for workers (e.g., Zeldes (1989), Carroll (1997)). Despite early work by Hubbard, Skinner, and Zeldes (1994) and Palumbo (1999) suggesting that health expenses contribute only slightly to late in life saving, more recent studies find such expenses to be of greater importance. For example, Gourinchas and Parker (2002) provide a decomposition that identifies the role of precautionary saving in wealth accumulation. Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011), Kopecky and Koreshkova (2014), and Lockwood (2014) all model LTC expenses explicitly and De Nardi, French, and Jones (2010) and Koijen, Van Nieuwerburgh, and Yogo (2015) allow for a health expense risk that includes LTC, with all finding that health expenses introduce a significant precautionary saving motive. In previous work, Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015) also examined long-term care risk. In contrast to the environment studied in this paper, that paper studies saving dynamics using a model with homogeneous preferences while this one estimates how preferences differ individual-by-individual and focuses on the demand for insurance.

Bequests have also long been accepted as an important saving motive, with Kotlikoff and Summers (1981) and Hurd (1989) modeling and estimating their contributions to wealth accumulation. The bequest motive itself reflects a variety of intergenerational linkages, from joy of giving (Abel and Warshawsky (1988)) to strategic bequest motives (Bernheim, Shleifer, and Summers (1985)). A workhorse in modern quantitative models, De Nardi (2004) introduced a flexible end of life bequest functional form, and estimated a luxury bequest motive for individuals with large resources. Since both precautionary and bequest saving motives could drive observed saving behavior, in our paper, we allow for flexible functional forms for bequest and health-related utility functions, and use SSQs to estimate preferences and see how they contribute to insurance demand.

In broad terms, our paper shares a key goal with Laibson, Repetto, and Tobacman (2007), De Nardi, French, and Jones (2010), French and Jones (2011), Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011), and Lockwood (2014), of estimating preferences of structural life-cycle models to understand the determinants of household financial behavior. Given our focus on studying the demand for insurance, we are closely related in method and purpose to Hong and Rios-Rull (2007), Hong and Rios-Rull (2012), Lockwood (2012), and Koijen, Van Nieuwerburgh, and Yogo (2015) who all use life-cycle models with a rich specification of preferences to estimate demand for insurance products.

2 The Model

This section presents the consumer choice model and model for insurance demand as first presented in Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015). The model considers consumers who are heterogeneous over wealth, income age-profile, age, gender, health status, and preferences. We outline below the key features of this model and provide the complete consumer decision problem in Appendix A. Individuals health status can either be good health, poor health, needs help with the “activities of daily living” (ADLs), or dead. Needing help with ADLs is defined as needing significant help with activities such as eating, dressing, bathing, walking across a room, and getting in or out of bed, and is commonly regarded as provoking need for long-term care. Health status evolves according to a Markov process conditional on age, gender, and prior health status. Individuals start at age 55 and live to be at most 108 years old. Each period individuals choose ordinary consumption, savings, expenditure when in need of help with ADLs, and whether to use government care. The model groups people into five income groups with deterministic age-income profiles.² Each individual has a perfectly foreseen deterministic income sequence and receives a risk free rate of return of $(1 + r)$ on his savings. The risk free return is calibrated to a baseline 1 percent, although Section 6.5 shows that results are robust to allowing for a 3 percent rate. The only uncertainty an individual has is over health/death.

When in good or poor health, consumers value consumption according to standard CRRA preferences with parameter σ :

$$\frac{c^{1-\sigma}}{1-\sigma}.$$

Utility associated with expenditure level e_{ADL} when in need of help with ADLs is

$$(\theta_{ADL})^{-\sigma} \frac{(e_{ADL} + \kappa_{ADL})^{1-\sigma}}{1-\sigma}.$$

Capturing the fact that private LTC provision is expensive, there is a minimum level of expenditure needed to obtain private LTC, i.e., $e_{ADL} \geq \chi_{ADL}$. Finally upon death, the individual receives no income and pays all mandatory health costs. Any remaining wealth is left as a bequest, b , which is valued with warm glow utility

$$(\theta_{beq})^{-\sigma} \frac{(b + \kappa_{beq})^{1-\sigma}}{1-\sigma}.$$

Both ADL state and bequest utility are governed by two key parameters: θ and κ . θ affects the marginal utility of an additional dollar spent and κ controls the degree to which the expenditure is a luxury or a necessity. Increases in θ increase the marginal utility of a unit of expenditure, while increases in κ indicate that expenditure is more of a luxury. Negative κ can be interpreted as the expenditure being a necessity.

The consumer has the option to use a means-tested government provided care program. The cost of using government care is that a consumer forfeits all wealth.³ If the consumer chooses to use government care when

²The model abstracts from labor supply decisions, including retirement. These labor market decisions are taken into account through the exogenous income profiles.

³This aligns with public welfare only being accessible to individuals with sufficiently low financial resources.

not in the ADL health state, the government provides a consumption floor, $c = \omega_G$. A person who needs help with ADLs has access to government-provided care that is loosely based on the institutions of Medicaid. If an individual needs help with ADLs and uses government care, the government provides $e_{ADL} = \psi_G$. The value ψ_G parameterizes the consumer's value of public care, since that parameter essentially determines the utility of an individual who needs help with ADLs and chooses to use government care. There is no borrowing, and the retiree cannot leave a negative bequest.

3 The VRI and the Strategic Survey Questions

3.1 The Sample

This paper draws on the newly developed Vanguard Research Initiative (VRI). Respondents are Vanguard clients aged 55 and older who agreed to participate in up to three surveys. The sample has been stratified across two of Vanguard's major lines of business—individual accounts and retirement accounts through employers. The survey protocol involves a number of elements to maintain participant engagement: periodic updates; an electronically delivered “Dillman letter” (email) prior to each survey; an email with the survey link; and up to three reminders.

Since the surveys involve innovative measurement, not only research economists and research psychologists, but also survey experts at Vanguard and IPSOS contributed critically to their design, as further detailed below. The resulting design involves testing and improving questions with cognitive interviews carried out at the Survey Research Center at the University of Michigan.⁴ In addition, a set of initial respondents is designated as the pilot sample. A pilot version of each survey is fielded to this sample to test all aspects of the design. The pilot includes a scripted electronic real-time chat with a subset of respondents using a pop-up interview with questions similar to those used in the cognitive interviews. The survey that the production sample receives reflects findings from the cognitive interviews, pilot survey responses, and the online chats from the pilot.

Currently, the VRI consists of three completed surveys (for links to all three surveys see http://ebp-projects.isr.umich.edu/VRI/survey_overview.html). VRI survey 1 introduces novel methods for measuring household portfolios of assets and debts (see Ameriks, Caplin, Lee, Shapiro, and Tonetti (2014) for detailed analysis). The pilot was conducted in June 2013, followed in August 2013 by the production sample. Because surveys are conducted via the Internet, respondents must possess a valid email address, and have logged onto Vanguard's website within the last six months. Additionally, we required a total account balance of at least \$10,000. Respondents received an incentive for participation in each survey in the form of a sweepstakes for prizes such as an iPad, as well as a monetary payment for completing all three surveys. Respondents also indicated a willingness to participate to aid and participate in a scientific endeavor.

We make essential use in this paper not only of the data from Survey 1, but also from Surveys 2 and 3. Survey 2 has at its center the key SSQs and stated preference questions. It was piloted in October 2013 with the production version in January 2014. Survey 3 gathers information on family structure as well as family transfers. The pilot was conducted in May 2014 and the production version in August 2014. The sample that

⁴In these interviews, respondents are shown Internet survey instruments and given in-person interviews to assess their comprehension: see Section 4 for further details.

we analyze in this paper consists of single respondents who completed all three surveys and provided answers to all necessary survey questions. Knowing ahead of time that singles would be better suited for research that does not directly model family interaction, singles were over-sampled when constructing the VRI. The sampling procedure and comparison of the VRI to the broader U.S. population is detailed in Ameriks, Caplin, Lee, Shapiro, and Tonetti (2014). Here it is shown that the VRI sample is wealthier, more educated, more married, and healthier than the U.S. population through comparison to the Health and Retirement Study (HRS). However the employer-based VRI panel members have wealth and demographic profiles that align reasonably with the correspondingly conditioned HRS. Summary statistics are included in Table 1.

		Wealth						
		<u>N</u>	<u>Mean</u>	<u>10p</u>	<u>25p</u>	<u>50p</u>	<u>75p</u>	<u>90p</u>
Full Sample		1087	745,274	115,000	271,720	543,191	1,012,263	1,587,400
Employer Only		162	557,026	52,473	168,150	392,926	836,400	1,161,000
		Demographics						
		<u>Education</u>		<u>Health</u>			<u>Gender</u>	
		<u>< College</u>	<u>≥ College</u>	Poor or <u>Fair</u>	Very Good or <u>Good</u>	<u>Excellent</u>	<u>Male</u>	<u>Female</u>
Full Sample		25.7%	74.3%	5.2%	22.5%	72.2%	44.3 %	55.7%
Employer Only		37.7%	62.3%	4.3%	29.0%	66.7%	54.9%	45.1%

Table 1: **Sample Characteristics:** This table presents the wealth distribution and demographic characteristics of the sample used in this paper. Individuals in this sample completed all three surveys and answered all survey questions needed to produce all required estimates. In addition, this table presents details from two subsamples: those who do not own any private LTCI and the employer subsample. The employer subsample satisfies all of the above requirements and also entered Vanguard through an employer sponsored plan.

3.2 Strategic Survey Questions

Strategic Survey Questions place respondents in hypothetical choice scenarios that are significantly more detailed than those in standard stated preference questions. Since SSQs require respondents to comprehend and imagine complex scenarios, their design involved rich interaction with early respondents who were subjected to cognitive interviews and various respondents to the pilot who were themselves subjected to interviews structured by the psychologists on the research team. On their advice, we broke questions up and presented them in four parts to ease comprehension. We illustrate this four part process in the context of a particular SSQ (SSQ 3) related to the tradeoff between expenditure when in need of help with ADLs and leaving a bequest, starting with the introduction of the subject of interest and the scenario itself. To reinforce the definition of needing help with ADLs, respondents were given a comprehension test on the definition prior to this SSQ. Furthermore, we make the definition available in a hover button whenever *ADL appears.

We are now going to ask about a different situation where you are older and definitely need long-term care. In this situation, you are asked to make tradeoffs between spending on your long-term care and leaving a bequest. This scenario is hypothetical and does not reflect a choice you are likely ever to face.

Suppose you are 85 years old, live alone, rent your home, and pay all your own bills. You know with certainty that you will live for only 12 more months and that you will need help with *ADLs for the entire 12 months.

You have **\$100,000** that you need to split into Plan E and Plan F.

- Plan E is reserved for your spending. From Plan E, you will need to pay all of your expenses, including long-term care and any other wants, needs, and discretionary purchases.
- Plan F is an irrevocable bequest.

Immediately after the scenario is presented, respondents are provided with a summary of the rules that govern their choice. This recaps the previous screen but is presented in a bulleted, easy to read format. In addition, some features that were hinted at in the first screen, e.g., that there is no public care option and that determination of which plan pays out is made by an impartial third party, are stated explicitly. To further reinforce details of the scenario and obtain a quantitative measure of understanding, we ask the respondents to answer a sequence of comprehension questions. For all SSQ questions, these comprehension questions are introduced with:

Again for research purposes, it is important to verify your understanding. We will now ask you a series of questions (each question no more than 2 times). At the end we will give you the correct information for any questions which you haven't answered correctly just to make sure that everything is clear.

When answering these questions the respondents do not have access to the screens describing the scenario, but have a chance to review the information before retrying any missed questions a second time. If they fail to answer questions correctly a second time, they are presented with the correct answers. The questions asked for this and the other SSQs verified the understanding of the ADL state, what the exact tradeoffs in that question were, which plan allocated resources to which state, what restrictions there are on the use of funds, and the nature of the claims process. Because respondents who make errors review the scenario between their first and second attempt, they get to reinforce those aspects they failed to understand the first time through before reporting their demand.

Having measured and reinforced understanding, we asked respondents to split their wealth between the two plans after again presenting them with the original scenario and including a link in the top right corner to the full scenario. The actual division of money involved a custom-designed interface that presents the trade off as clearly as possible. Specifically, we use an interactive slider that presents the payoffs in different states of the world. This payoff changes as the slider is moved, allowing respondents to observe how their choice is impacted by moving the slider. Text is included instructing the respondent how to allocate money by moving the slider, as well as what their allocation implies about resources available for different uses. The exact presentation can be seen in Figure 1.

When the slider first appears, it does not have an allocation selected. It is only when respondents themselves click on the slider that any allocation is shown. To further dampen possible anchoring and status quo bias, we ask respondents to move the slider at least once, which helps also to clarify the connection to the chosen allocation.

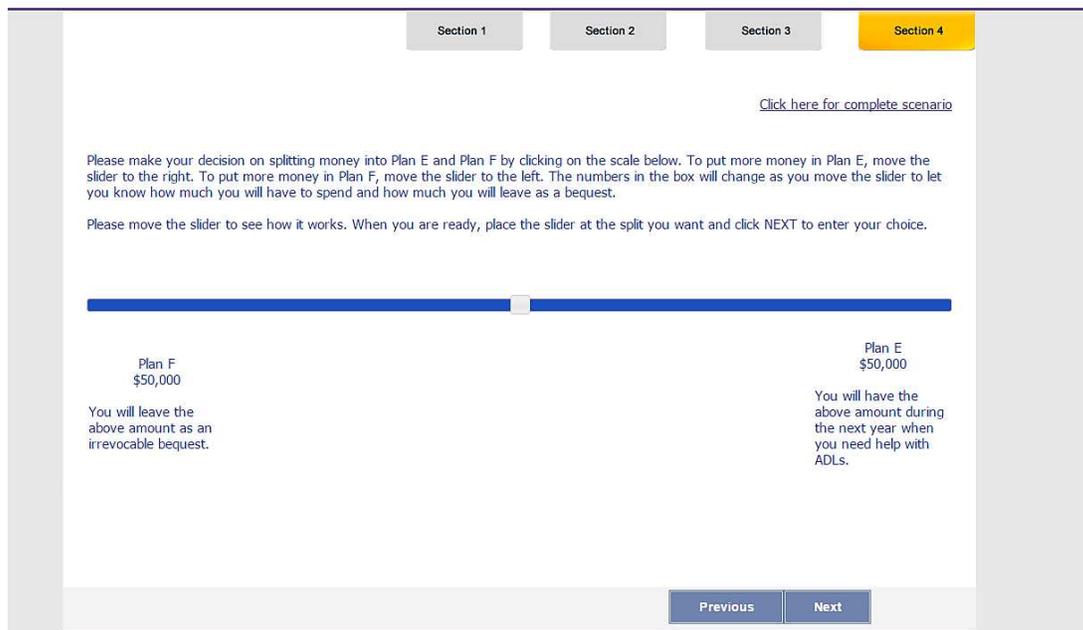


Figure 1: **SSQ Response Slider.**

Having spent such a long time setting up the scenario and aiding comprehension, we stayed within the scenario and asked respondents to make new choices with different scenario parameters. In the above question, answers were gathered not only concerning division of \$100,000, but also of \$150,000 and \$200,000.

In addition to this SSQ, we posed three other SSQs. SSQ 1 asks about willingness to take a risky bet over income, using an analogous survey question and identification strategy to those developed in Barsky, Juster, Kimball, and Shapiro (1997) and Kimball, Sahm, and Shapiro (2008). SSQ 2 asks individuals facing uncertain future health to allocate wealth to states when healthy and in need of help with ADLs. SSQ 4 asks individuals how much wealth they would need to have in order to purchase private LTC instead of using government provided care. A brief summary of these SSQs and their variants is presented in Table 2. The same strategy of providing a long educational process followed by investigation of detailed scenarios was followed for all SSQs. In Appendix B.1 we present the the text for each SSQ, including all rules and a full list of comprehension questions. The results of these comprehension tests are summarized in the next section.

3.3 Family Transfers, Expectations, and Insurance Holdings Data

In the analysis that follows we make use of many data items in addition to those identified above. Specifically, from Survey 2 we use data on expectations of longevity and on future need for help with ADLs. We also use data indicative of prior insurance holdings, in particular LTCI. From Survey 3 we use data on family transfers as well as whether the respondent has children. We also use answers to a categorical question concerning the perceived quality of public long term care relative to a typical private nursing home, as well as beliefs about the cost of a year of care in a typical private nursing home in their community.

	Question	Motives	Scenario Parameters	Preference Parameters
SSQ 1	Lottery over spending	Ordinary consumption	(a) $W = \$100K$ (b) $W = \$50K$	σ
SSQ 2	Allocation between ordinary and ADL states	Ordinary consumption and ADL expenditure	(a) $W = \$100K, \pi = 0.75$ (b) $W = \$100K, \pi = 0.50$ (c) $W = \$50K, \pi = 0.75$	$\sigma, \theta_{ADL}, \kappa_{ADL}$
SSQ 3	Allocation between ADL and bequest states	ADL expenditure and bequest	(a) $W = \$100K$ (b) $W = \$150K$ (c) $W = \$200K$	$\sigma, \theta_{ADL}, \kappa_{ADL}$ $\theta_{beq}, \kappa_{beq}$
SSQ 4	Indifference between public and private LTC	ADL expenditure and bequest	(a) Public Care Available	$\sigma, \theta_{ADL}, \kappa_{ADL}$ $\theta_{beq}, \kappa_{beq}, \psi_G$

Table 2: **Link between parameters and SSQs:** Here we provide a bit more information on each SSQ. The first column briefly summarizes the tradeoffs, while the second lists the relevant motives. The third column lists how question parameters were changed for different variations of each SSQ. The fourth column lists the parameters that determine optimal responses in the model. More information, including the text for all questions, is provided in the Online Appendix: SSQs.

4 Credibility of SSQ Responses

Three forms of evidence are used to assess the credibility of the responses. First, we present results of key comprehension tests. Second, we report responses to the questions designed directly to assess how well the respondents felt they had understood and internalized the SSQs. Finally, we analyze the internal coherence of responses and their relationship to important correlates.

4.1 Comprehension tests

As indicated above, we included direct comprehension tests that respondents attempted at most twice. In the case of SSQ 3, there were 6 such questions in total. More than 50 percent of respondents answered all questions correctly on their first attempt, with nearly 75 percent doing so after their second attempt, and more than 90 percent making one or fewer errors after the second attempt. Analogous tests were presented for each set of SSQs, with performance presented in Table 3. In practice, comprehension may be even higher than the table indicates, since important aspects of the scenario are reiterated when respondents make their final decisions, which occurs after the tests have been completed.

4.2 Respondent Feedback and SSQ Design

The SSQ design process incorporates several forms of feedback that provided us with opportunities to improve the survey prior to fielding to the production sample. In addition to survey design feedback obtained as a result of cognitive interviews, we also gathered feedback from scripted “iModerate” pop-up interviews with a

	<u>SSQ 1</u>	<u>SSQ 2</u>	<u>SSQ 3</u>	<u>SSQ 4</u>
Number of questions	6	9	3	2
All correct, 1 st try	46.3%	18.6%	55.4%	77.3%
All correct, 2 nd try	75.1%	55.5%	81.9%	94.1%
≤ 1 wrong, 2 nd try	93.4%	80.8%	96.2%	99.5%

Table 3: **Specific SSQ Comprehension Questions:** When introducing each survey instrument, we asked a series of test questions that examined respondents knowledge of and reinforced details of each scenario. Statistics on the number of correct responses are presented in the above table.

Overall, how clear were the tradeoffs that the hypothetical scenarios asked you to consider?		Overall, how well were you able to place yourself in the hypothetical scenarios and answer these questions?		How much thought had you given to the issues that the hypothetical scenarios highlighted before taking the survey?	
<u>Response</u>	<u>Percent</u>	<u>Response</u>	<u>Percent</u>	<u>Response</u>	<u>Percent</u>
Very Clear	51.8	Very Well	23.1	A lot of thought	29.5
Somewhat Clear	39.7	Moderately Well	60.5	A little thought	52.1
Somewhat Unclear	7.4	Not very well	14.2	No thought	18.4
Very Unclear	1.1	Not very well at all	2.2		

Table 4: **General SSQ Comprehension Questions:** Each respondent was asked each of the three questions presented above. This table provides the distribution of responses.

subset of the pilot sample. The iModerate chats provide feedback in free response form on issues that may trouble respondents. In addition to asking respondents for their overall reactions to the survey, we posed specific questions about each SSQ, with broadly encouraging and informative results.

Additionally, a subset of the iModerate questions were posed to the full production sample at the end of the survey. As shown in Table 4, nearly 90 percent of respondents found the tradeoffs either very clear or somewhat clear. Furthermore, more than 80 percent indicated that they were able to place themselves in the hypothetical scenario either moderately or very well. There is also a significant and interesting difference, with evidence that it was harder to place oneself in the scenario when answering than it was to comprehend the question. This is consistent with our prior, and is suggestive of how seriously respondents took their charge. Finally, more than 80 percent had given the underlying issues at least a little thought before taking the survey.

In broad terms, concerns about hypothetical survey questions can be grouped in to respondents either not understanding the scenario and questions or respondents not reporting answers that coincide with what their actions would be if the situation was realized. The specific comprehension questions are designed to measure respondent understanding of the scenario and tradeoffs. In our sample, comprehension is very high, alleviating concern about a lack of understanding the scenario. The general comprehension questions are

	SSQ 1a	SSQ 1b	SSQ 2a	SSQ 2b	SSQ 2c	SSQ 3a	SSQ 3b	SSQ 3c	SSQ 4a
SSQ 1a	1.00								
SSQ 1b	0.44	1.00							
SSQ 2a	-0.01	0.04	1.00						
SSQ 2b	-0.04	-0.01	0.61	1.00					
SSQ 2c	-0.08	0.07	0.55	0.56	1.00				
SSQ 3a	-0.01	-0.08	-0.11	-0.04	-0.11	1.00			
SSQ 3b	-0.06	-0.08	0.04	0.04	0.023	0.78	1.00		
SSQ 3c	-0.08	-0.08	0.07	0.08	0.07	0.63	0.86	1.00	
SSQ 4a	-0.03	-0.00	0.04	0.06	0.04	-0.11	-0.10	-0.08	1.00

Table 5: **Correlation Matrix of SSQ responses:** The correlation matrix for the SSQ responses are presented above. Of key interest are the bolded correlations between SSQs of the same type.

designed to measure the ability of respondents to answer from the perspective of the hypothetical. Although more suggestive than quantitative, these indicate a clear understanding of the tradeoffs, and an ability to think hypothetically, even though they acknowledge that thinking as if in the hypothetical is more challenging than understanding the scenario. Furthermore, even if the actions are not those that respondents would actually take if the scenarios are realized, these are their current views of their preferences, which are driving their forward-looking behavior today.

Patterns of slider movement provide additional evidence of deliberation in the survey responses. Given our use of a slider technology, there may be a concern with possible anchoring effects if individuals settled immediately for their first chosen allocation. An analysis of click patterns shows that most respondents followed our suggestion and moved the slider before finalizing their choice. Regressions show that initial clicks have little predictive power for final answers, further suggestive of deliberation.

4.3 Coherence

As Manski (2004) stresses, one necessary criterion for judging responses as meaningful is internal coherence. One indication of internal coherence derives from analyzing the pattern of correlations in survey responses. SSQ 1, SSQ 2, and SSQ 3 were each asked to all correspondents with a few variants using the same scenario with different scenario parameters. Internal coherence would require a strong positive correlation in responses for each individual within each scenario across scenario parameterizations. Just such a pattern is present in the diagonal blocks of the correlation matrix presented in Table 5. However there is no reason to expect such a strong correlation across SSQs aimed at very different motivations: this relative lack of correlation is again evident.

A second indication of coherence derives from exploring how individuals trade off leaving money as a bequest and having wealth when in the ADL state for different wealth levels. In SSQ 3, all respondents were asked to divide up not only \$100,000, but also \$150,000 and \$200,000. The distributions of responses to these different SSQ variants indicate systematic patterns in responses. Most respondents allocate almost all of their wealth to the ADL state when wealth is \$100,000, about two-thirds to the ADL state when wealth

	<u>SSQ 3a</u>	<u>SSQ 3b</u>	<u>SSQ 3c</u>
<i>Average ADL Cost</i>	.03	.05**	.07**
	(.02)	(.02)	(.03)
<i>Prob. Family Cares for ADLs</i>	-56.33	-90.82*	-135.51**
	(40.86)	(47.95)	(60.41)
<i>Above Median Transfers</i>	-4,858.13**	-9,401.06***	-11,331.22***
	(2,307.98)	(2,697.35)	(3,391.45)
<i>Opinion of Public ADL Facility</i>	-2,423.81*	80.29	1,466.69
	(1,358.17)	(1,586.00)	(1,991.96)

Table 6: **External Validation of SSQs 3:** This table presents the results from a Tobit regression of SSQ 3 responses on demographic variables and the listed covariates. For ease of exposition we only present covariates of interest in the main text, but include the fully specified regression results in Appendix Table B.3.

is \$150,000, but only about half when wealth is \$200,000, as illustrated in Figure 2.

In addition to being internally coherent, another measure of validity comes from checking whether individual responses to SSQs are predicted by behaviors or characteristics outside the model in expected ways. To identify relevant patterns, we regress responses to the SSQs on related economic and demographic variables. In SSQ 3 that we have been detailing, the allocation to the ADL state is recorded as the response. Hence higher responses should indicate a higher preference for wealth in the ADL state relative to an end of life bequest. Regressions of these responses on standard demographic variables and other variables of particular relevance are presented in Table 6.

Note that having transferred wealth to children is a strong predictor of allocating less money to the ADL state, as might be expected based on likely differences in bequest motives. The expectation of receiving care from a family member is also associated with lower allocations to the ADL state, while individuals who believe ADL costs are higher allocate more to the ADL state. Note that we observe little predictive power for state variables such as wealth, age, health. This may be because these variables were specified to be common to all respondents in the SSQ scenario. Appendix B.1 documents that fundamental internal and external consistency conditions hold for the other three SSQs as well.

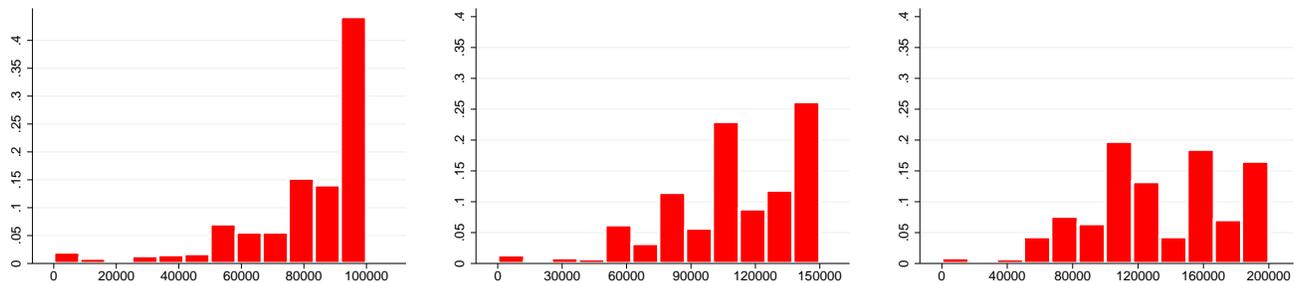


Figure 2: **SSQ 3 Response Distributions:** We ask SSQ 3, the SSQ presented in the section above, for wealth values of \$100,000, \$150,000, and \$200,000. The response distributions are presented above in this order.

5 Estimating Preferences

5.1 Estimation Strategy

This section presents estimates of individual preference parameters from SSQ data. The identification strategy relies upon assuming functional forms that characterize each individuals' utility from SSQ responses. There are 9 different variations of 4 SSQs. In our model of SSQ responses, measured SSQ response is determined by the relevant utility functions and individual parameter sets Θ_i . For each individual we assume a response process that permits a likelihood function, and then use the 9 SSQ variations to estimate via MLE the parameter set that generated each individual's response set (denoted $\hat{Z}_i = [\hat{z}_k]_{k=1}^9$). Table 2 summarizes the SSQs and the relevant parameters and motives for each.

In this paper, identification is achieved via multiple responses to SSQ variants at different scenario parametrizations. This is in contrast to Barsky, Juster, Kimball, and Shapiro (1997) and Kimball, Sahn, and Shapiro (2008), which use multiple responses to the same question across waves, although we share the same additive normal error structure. There are two main differences in the approaches of this paper and Barsky, Juster, Kimball, and Shapiro (1997) or Kimball, Sahn, and Shapiro (2008). First, these previous studies assume a lognormal population distribution of preference parameters to accommodate the discrete cutoffs that are built into the design of the HRS questions. Having continuous responses allows us to treat the population distribution of preference parameters non-parametrically. Second, this study estimates multiple preference parameters for each individual, whereas these previous studies focus on estimating the risk aversion parameter for each individual. Finally, the effect of measurement error on subsequent analysis using the estimated parameter sets is accounted for differently, as will be detailed later.

To derive the likelihood function, denote the response to the k^{th} SSQ as $z_k(\Theta)$ and assume each individual's response is reported with normally distributed response errors. That is, let observed responses be expressed as

$$\hat{z}(\Theta_i) = z_k(\Theta_i) + \hat{\epsilon}_{k,i}, \quad (1)$$

where $\epsilon_{k,i} \sim \mathbb{N}(0, \sigma_{k,i}^2)$ and $\hat{\epsilon}_{k,i}$ denotes the realization of individual i 's response error to SSQ variant k . For the six preference parameters to be identified at an individual level from 9 questions, the error distribution must be a function of no more than three free parameters. This is satisfied by specifying $\sigma_{k,i}^2$ to be a function of a question specific and an individual specific component. Specifically, we assume that the standard deviation of the response error to question k is linear in the maximum feasible response W_k and individual scaling factor $\bar{\sigma}_i$, so that $\sigma_{k,i} = \bar{\sigma}_i \times W_k$. The idiosyncratic component accounts for differences in the precision with which individuals report answers. The question specific component takes into account the different scales of the nine SSQ variations and thus normalizes the error standard deviation according to the feasible response size. Note that W_k is naturally defined in each question by the budget constraint, except in SSQ 4. In SSQ 4, W_k is set to the 95th percentile of the survey responses, resulting in \$500,000 as the maximum response in the cleaned data.

This specification yields the following closed form expression for the likelihood of observing a response to each question as a function of $[\Theta_i, \bar{\sigma}_i]$:

$$\mathcal{L}_k(\Theta_i, \bar{\sigma}_i | \hat{z}_{k,i}) = \begin{cases} F_{\sigma_{k,i}^2}(-z_k(\Theta_i)) & \text{if } \hat{z}_{k,i} = 0 \\ f_{\sigma_{k,i}^2}(\hat{z}_{k,i} - z_k(\Theta_i)) & \text{if } 0 < \hat{z}_{k,i} < W_k \\ 1 - F_{\sigma_{k,i}^2}(W_k - z_k(\Theta_i)) & \text{if } \hat{z}_{k,i} = W_k. \end{cases} \quad (2)$$

The boundary cases take into account error truncation due to the budget constraint, and $F_{\sigma_{k,i}^2}$ and $f_{\sigma_{k,i}^2}$ denote the mean-zero normal cdf and pdf with variances $\sigma_{k,i}^2$. We assume independence of survey response errors, yielding a multiplicatively separable likelihood function for the full response set \hat{Z}_i

$$\mathcal{L}(\Theta_i, \bar{\sigma}_i | \hat{Z}_i) = \prod_{k=1}^9 \mathcal{L}_k(\Theta_i, \bar{\sigma}_i | \hat{z}_{k,i}). \quad (3)$$

We use MLE to estimate individual parameter sets, such that

$$[\hat{\Theta}_i, \hat{\sigma}_i] = \arg \max \mathcal{L}(\Theta_i, \bar{\sigma}_i | \hat{Z}_i).$$

This provides a consistent estimate of each parameter set estimate with the standard asymptotic distribution for all respondents with no more than one response on the boundary of the response distribution. All subsequent analysis is restricted to respondents that satisfy this condition.

Derivation of the FOC's necessary to calculate \mathcal{L}_k for each SSQ k is presented in Online Appendix: Modeling. Below we sketch the identification argument for SSQ 3. As shown in Table 2, σ , θ_{ADL} , and κ_{ADL} determine responses to SSQs 1 and 2, and identification of these parameters rests largely on these questions. SSQ 3 primarily affects identification of θ_{beq} and κ_{beq} . The text of SSQ 3 asks individuals to choose allocations that map to the solution of the following optimization problem:

$$\begin{aligned} \max_{z_3^1, z_3^2} & (\theta_{ADL})^{-\sigma} \frac{(z_3^1 + \kappa_{ADL})^{1-\sigma}}{1-\sigma} + (\theta_{beq})^{-\sigma} \frac{(z_3^2 + \kappa_{beq})^{1-\sigma}}{1-\sigma} \\ \text{s.t.} & z_3^1 + z_3^2 \leq W \\ & z_3^1 \geq 0; z_3^2 \geq 0. \end{aligned} \quad (4)$$

The optimal allocation rule is given by

$$z_3^1 = \begin{cases} 0 & \text{if } (\theta_{beq} (W + \kappa_{beq}))^{-\sigma} - (\theta_{ADL} \kappa_{ADL})^{-\sigma} > 0 \\ W & \text{if } (\theta_{ADL} (W + \kappa_{ADL}))^{-\sigma} - (\theta_{beq} \kappa_{beq})^{-\sigma} > 0 \\ \frac{\theta_{beq}(W + \kappa_{beq}) - \theta_{ADL} \kappa_{ADL}}{\left(\frac{\theta_{ADL} + \theta_{beq}}{\theta_{ADL}}\right)} & \text{otherwise} \end{cases} \quad (5)$$

Conditional on σ , θ_{ADL} , and κ_{ADL} , the interior response is linear in wealth, and thus θ_{beq} and κ_{beq} are identified by two interior responses at different wealth levels. Because SSQ 3 is fielded for variants at three different wealth levels and these parameters also impact the response to SSQ 4, the system is overidentified. Identification of other parameters from the remaining SSQs follow a similar argument. These responses,

identify all relevant structural model parameters.⁵

5.2 Estimated Preference Parameters

Table 7 presents the 10th/25th/50th/75th/90th percentiles of the marginal distributions for the estimated population parameter distribution and compares to the estimates in Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015). Given the difference in estimation procedures and that the presented marginals do not account for correlation between parameters, there is no clean mapping of parameters across studies.⁶ Comparison with the bottom row does, however, show consistency in qualitative patterns. Furthermore, previous estimates with homogeneous preferences are contained between the 25th – 75th percentiles of the estimated parameter distribution. The median marginal estimates suggest a relative risk aversion parameter $\sigma = 4.52$, ADL expenditure as a necessity ($\kappa_{ADL} < 0$) with high marginal valuations ($\theta_{ADL} < 1$), bequests as a significant luxury ($\kappa_{beq} > 0$) with a high marginal valuation ($\theta_{beq} < 1$), and a public long-term care dollar equivalent of \$60,000 (ψ_G). This median estimate of the dollar equivalent of public long-term care corresponds to an equivalent utility level of an expenditure of \$40,700 in a model without state dependent preferences.⁷

The parameter sets are reasonably well identified. The individual component of the response error ($\bar{\sigma}$) is estimated to be between 0 and 0.2 for over 95 percent of our population. This implies that when individuals have \$100,000 to allocate, the standard deviation of response error is between 0 and \$20,000 for 95 percent of our population, with a median value of \$8,000. Furthermore, Table 7 presents median estimated standard errors for each of the preference parameters. These are perhaps surprisingly small given that we are identifying all parameters from only 9 questions. The precision of the estimates reflects that the design of the SSQ survey instruments ensures identification.

Section 4 showed that SSQ responses are predicted by covariates that may reflect higher bequest and care motives. Unsurprisingly, these differences in answer patterns cause meaningful variation in parameter estimates. For example, individuals with children are estimated to have stronger bequest motives and individuals that report higher subjective opinions of the quality of public care are estimated to assign a higher monetary equivalent to the public care option.

6 The Long-term Care Insurance Puzzle

6.1 ADLI Risk

To highlight potential interest in LTCI, Figure 3 presents the distribution of the number of years spent needing help with ADLs for healthy men and women at various ages. The figures have several striking features. First, although most individuals will need help with ADLs at some point in their life, approximately 45 percent of males and 35 percent of women will not need any help with ADLs while alive. Second, there is substantial risk of spending extended time in need of help with ADLs. For men, approximately 25 percent will spend three or more years, 17 percent will spend four or more years, and 13 percent will spend five or more years

⁵The parameters ω_G and β are not identified by any of the SSQs, and thus are calibrated to standard values from the literature.

⁶Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015) estimates a single population parameter set and matches both SSQ and wealth moments.

⁷To calculate this expenditure equivalent in a model without the health state utility function, we find the expenditure level $\bar{\psi}$ that would equate utility across the two specifications: $\frac{\bar{\psi}^{1-\sigma}}{1-\sigma} = (\theta_{ADL})^{-\sigma} \frac{(\psi_G + \kappa_{ADL})^{1-\sigma}}{1-\sigma}$.

Marginal Distribution of Parameters

	σ	θ_{ADL}	κ_{ADL}	θ_{beq}	κ_{beq}	ψ_G
10%	2.04	.27	-82.44	.16	3.23	19.97
25%	3.02	.43	-50.65	.28	11.70	39.75
50%	4.52	.86	-9.45	.55	125.72	59.99
75%	6.74	2.26	46.23	2.26	362.64	99.87
90%	10.11	6.45	148.81	7.72	781.45	178.34
Median Standard Errors	.13	.38	10.71	.82	18.44	.35
Ameriks, et.al 2015	5.85	1.57	-45.65	0.59	7.88	85.11

Correlations of Parameters

	σ	θ_{ADL}	κ_{ADL}	θ_{beq}	κ_{beq}	ψ_G
σ	1.00					
θ_{ADL}	-.18	1.00				
κ_{ADL}	-.10	-.06	1.00			
θ_{beq}	-.19	.52	-.07	1.00		
κ_{beq}	-.14	.01	.30	-.06	1.00	
ψ_G	.07	-.01	-.28	.00	-.12	1.00

Table 7: **Estimated Parameter Distributions:** The marginal distributions of each parameter are presented in the top panel table above. Note that each column is the marginal distribution of the specified parameter, and there is no relationship between parameters in rows. The next line of the top panel presents the median standard error for each parameter, and the final line presents the parameters estimated from a similar model with homogeneous preferences. The bottom panel presents the correlation of estimates for each parameter.

needing help with ADLs. For women this risk is even larger, as approximately 40 percent will spend three or more years, 30 percent will spend four or more years, and 24 percent will spend five or more years needing help with ADLs. This suggests there is substantial room for private insurance if not crowded out by social insurance.

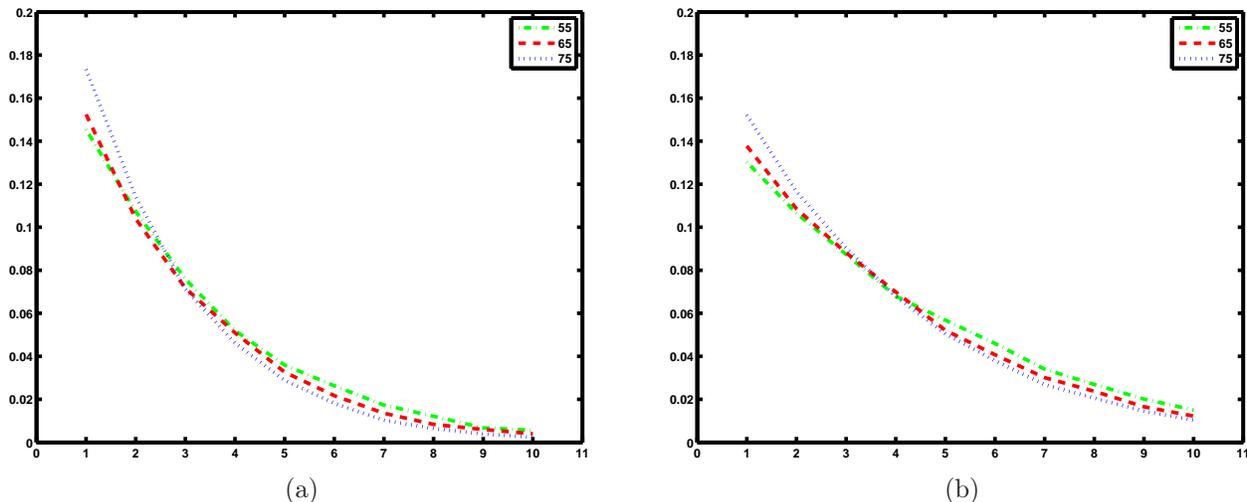


Figure 3: **Years Needing Help With ADLs:** Panel (a) presents the distribution of the number years needing help with ADLs for a 55, 65, and 75 year old male in good health. Panel (b) presents the corresponding figure for females.

6.2 Calculating Demand

Using the parameter estimates presented above and each individual’s specific state variables, we calculate the model-implied demand for insurance products. The model solves each individual’s decision problem conditional on age, gender, health, wealth, income, and preference parameter set. ADLI is modeled as a state contingent security that pays out whenever an individual is in the ADL health state ($s = 2$). When an individual purchases this product, they pay a lump sum of $\$ \tilde{y}_i \times p(X_i)$ at current age t to receive income \tilde{y}_i in each year that they need assistance with ADLs for the remainder of life. The demand is thus determined by preference over expected future consumption streams as determined by preference parameter set Θ_i , the set of state variables X_i , and the price $p(X_i)$ that individuals must pay to purchase an additional unit of state contingent income. The pricing function is determined so that the product is actuarially fair given an individual’s gender, age, health state, and access to a risk free outside asset promising 1 percent annual return. Actuarially fair is defined such that the insurer selling this product makes zero expected profit. Actuarially fair pricing requires the further assumption that health transitions are common amongst all agents. Formal expression of model implied demand and calculation of actuarially fair prices is included in Appendix A.

Finally, measurement error in parameters could bias the model implied demand estimates. To address this, we resample parameter sets from the distribution of estimates and calculate the demand for each parameter set. Taking the average of these demand measures thus integrates out error in demand measurement caused by parameter uncertainty and yields an unbiased estimate of demand. For the remainder of the paper, all reported demands reflect these bootstrapped estimates.

	σ	θ_{ADL}	κ_{ADL}	θ_{beq}	κ_{beq}	ψ_G
Don't Buy						
Mean	4.10	28.40	39.77	28.85	321.88	82.52
Median	3.60	1.16	10.12	.54	256.97	67.57
Buy						
Mean	5.68	3.47	-2.67	3.74	173.07	78.06
Median	4.96	.74	-14.68	.55	82.63	58.05

Table 8: **Parameter sets and ADLI purchase:** This table presents parameter sets for two groups: those with zero ADLI demand and those with positive ADLI demand.

6.3 Estimated ADLI Demand

We estimate 66 percent of respondents to have positive demand for ADLI. This indicates that most individuals assign a high valuation to wealth in the ADL state and, if offered suitable insurance products, would like to insure wealth in this state. While many have potential interest, there is a substantial minority for whom purchasing does not appear to make sense. It is therefore clear that different survey responses would have produced completely different estimates. Majority interest was not predestined, but rather a result of desires as inferred from the responses to SSQs.⁸

With regard to how preference parameters impact interest, Table 8 compares the mean and median parameter sets for individuals predicted to purchase versus not purchase ADLI. Most differences between the groups are as expected. ADLI purchasers are significantly more risk averse than non-purchasers. They also have a much stronger preference for expenditure when in the ADL state. Median κ_{ADL} of purchasers is negative yet positive for non-purchasers, so that they value ADL-state expenditure as more of a necessity. The median marginal utility multiplier θ_{ADL} of purchasers is 36 percent lower than that of non-purchasers, suggesting higher valuation of wealth on the margin in the ADL state. Purchasers also assign a lower valuation to a free government care option, as reflected in ψ_G . The comparison of bequest motives is less theoretically clear-cut. On one hand, bequest motives decrease desire to spend on ADLI by increasing the desire to hold on to bequeathable wealth. However, ADLI insures bequests against being depleted by large expenditures when in the ADL state. Table 1 suggests that the second motive is dominant, since purchasers have stronger bequest motives than non-purchasers, viewing it as substantially less of a luxury good (lower κ_{beq}).

For the entire sample, the annual predicted income purchase has mean \$42,274 and median \$22,016. For those individuals that the model estimates to have positive demand the corresponding mean is \$62,971 and median is \$49,684. Row 1 of Table 9 presents further summary statistics of the model predicted insurance purchases.

⁸Lockwood (2014) shows that a sufficiently strong bequest motive limits interest in either LTCI or annuities due to a preference for liquid wealth at the end of life, and Lockwood (2014) and Koijen, Van Nieuwerburgh, and Yogo (2015) both match observed insurance products holdings in their estimations. A key methodological difference with the current study is use of observed insurance holdings as a source of identification. While we are sympathetic to the idea that insurance holding patterns contain information about preference for wealth in these states, targeting low insurance holdings ensures that the model delivers a low preference for wealth in this state. Given the differences between modeled Arrow securities and products available in the market, we instead choose to identify preferences from SSQs and analyze their implications for predicted holdings.

6.4 The LTCI Puzzle

While the model predicts that 66 percent of the sample would want to purchase ADLI, only 22 percent own private LTCI. Moreover we do not know the extent to which this private ownership is due to deliberate purchase as opposed to being a job benefit, making this an upperbound on the fraction of individuals in the sample who have actively purchased private LTCI. The predicted demand for ADLI by those who do own private LTCI and those who do not are quite similar, at 71 and 65 percent, respectively.

Since the VRI is significantly wealthier than a representative U.S. sample, the lack of private LTCI ownership might be puzzling only for individuals with significant financial resources. Indeed, Pauly (1990) showed that publicly provided care can crowd out private LTCI purchase, suggesting that our sample might overstate the value of wealth in this state. To address this, Figure 4 compares actual LTCI ownership and model predicted ADLI ownership conditional on wealth and income quintiles. The smallest wealth quintile has median wealth of \$150,000 and the smallest income quintile has median age 65 annual income of \$35,000, not dissimilar to the broader U.S. population. Note that both observed holdings and model predictions of ADLI ownership are increasing in wealth and income. Note also that the difference between modeled and observed holdings is large and significant at all quintiles, confirming the robustness of the puzzle. We therefore conclude that there exists a puzzle regarding the lack of LTCI ownership: Observed insurance holdings among older wealth-holders are well below the levels suggested by the model.

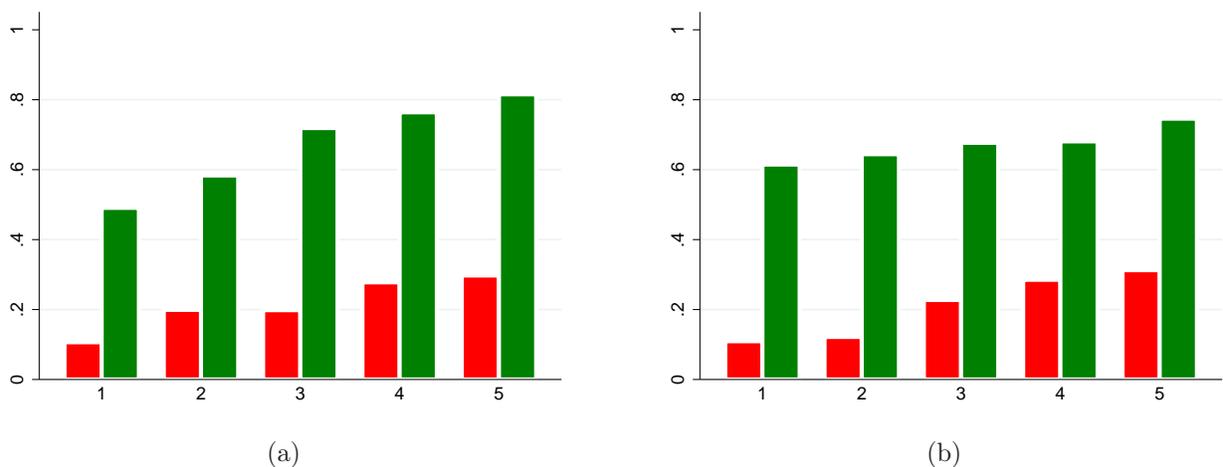


Figure 4: **Comparing Ownership Measures:** The above figures present various ownership measures of LTCI/ADLI by wealth and income quintiles. Panel a present measures of ADLI by wealth quintile, while Panel b presents measures of ADLI ownership by income quintile.

6.5 Robustness of the LTCI Puzzle

To document the robustness of the LTCI puzzle, we calculate ADLI demand for different model specifications and for different subsamples, always restricting the population to those who have zero private LTCI ownership. For the baseline specification, Table 9 displays that 66 percent of people who do not own any private LTCI are predicted to have positive ADLI demand.

The existence of the LTCI insurance puzzle is not sensitive to reasonable increases in the risk free interest rate on savings, which corresponds to higher loads on ADLI. To document this, we predict ADLI demand for

	<u>%>0</u>	<u>mean</u>	<u>p5</u>	<u>p10</u>	<u>p25</u>	<u>p50</u>	<u>p75</u>	<u>p90</u>	<u>p95</u>
Baseline	66	42,116	0	0	0	22,997	65,419	110,436	149,072
<u>Alt. Estimates</u>									
r = 3%	60	37,311	0	0	0	15,440	58,706	106,636	140,282
Wealth	84	91,381	0	0	75,803	88,758	110,805	160,386	192,111
<u>Subsamples</u>									
Employer	57	27,821	0	0	0	12,157	40,097	78,173	103,506
HRS Weighted	53	24,302	0	0	0	6,099	33,717	74,786	105,826

Table 9: **Robustness of ADLI Demand Patterns:** This table presents ADLI demands for various specifications and subsamples. Demand measures are for the subsample of the population that does not own any private LTCI.

the case in which consumers receive a risk free return of $r = 0.03$ on savings, while insurance products are still priced using $r = 0.01$. This exercise addresses two concerns. First, respondents might expect a higher return of wealth than the risk free rate, and so the baseline model might understate the saving motive. Second, this introduces a sizable positive load (equivalent to 18-35 percent on ADLI for males aged 55-85). Thus, if low observed insurance holdings are driven by high loads and low returns on investment, the model under this specification should predict substantially lower demand. As documented in Table 9, on the extensive margin, the fraction of the population with positive demand for ADLI drops from 66 percent to 60 percent. The intensive margin of demand, however, is somewhat more sensitive to this change in rates, with median modeled demand for ADLI reduced by 33 percent and mean modeled demand 11 percent lower.

To address concerns about robustness outside of the VRI sample we repeat the analysis on two different samples. First, we use a subsample of individuals restricted to be respondents with employer sponsored Vanguard plans. Second, we reweight the population using weights that match the HRS on wealth and demographic variables (see Ameriks, Caplin, Lee, Shapiro, and Tonetti (2014)). The employer subsample is less wealthy than the general population, as displayed in Table 1, and did not elect by themselves to become Vanguard clients. Thus, concerns of sample selection might be less severe amongst these individuals. As displayed in Table 9, we find that all qualitative results hold for this sample, with 57 percent of this population estimated to have positive demand for ADLI. Similarly, Table 9 shows that when reweighting to the HRS, even though the model predicts a lower 53 percent extensive margin and lower intensive margin demand for ADLI there is still a clear prediction of high interest in these products relative to observed holdings.

Finally, since demand is driven in such large part by estimated preferences, we show that the puzzle remains even when estimating preference parameters using more traditional methods common in the literature that do not use SSQs. Table 9 presents ADLI demand in a model calculated using a parameter set from Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015) that was estimated using the same model but assuming homogeneous preferences and exclusively targeting cross-sectional moments of the wealth-age distribution (the 25th, 50th, and 75th percentiles of the wealth distribution by 3 year age bins). Under this parametrization the model predicts significantly higher ADLI demand, with 84 percent of the population having positive demand and quantity demanded much higher across the population.

Thus, the clear model prediction of high interest in ADLI—and the puzzle that emerges when comparing this prediction to observed holdings—is significant and robust to alternative pricing, alternative preference identification strategies, and in a number of subsamples.

7 Stated Demand for Insurance

7.1 The Survey Instrument

Note that ADLI is very different than LTCI available in the market place. Currently available LTCI products have many unattractive features: consumers face default risk, possible unilateral increases in future premia, high loads, and a potentially adversarial claims process that has strict and uncertain conditions on when holders can claim (see Cutler (1996), Hendren (2013), and Koijen and Yogo (2015) for reasons why this market may fail to provide high quality insurance products).

We are interested in assessing to what extent the LTCI puzzle derives from this gap in the quality of available LTCI products and modeled ADLI. In this section we use additional information from Survey 2, which included stated preference questions on the demand for improved insurance products. Our approach to stated demand is analogous to that of Beshears, Choi, Laibson, Madrian, and Zeldes (2012), who previously used stated preference questions with improved features of a product to study determinants of and how to increase annuity demand. For ADLI, an additional challenge in gathering this demand is that, by definition, it concerns a form of insurance that is not available in the market place. For that reason the demand questions were preceded by the definition of the ADL state, defined precisely in Section 2 as “needing significant help with activities such as eating, dressing, bathing, walking across a room, and getting in or out of bed.” Moreover, when gathering demand information, we explicitly ask respondents to “make choices in hypothetical financial scenarios.” In the specific case of ideal long-term care insurance, the product is presented in the following frame.

Please suppose that you are offered a hypothetical new form of insurance called ***ADL insurance** with the following features:

- You pay a one-time, nonrefundable lump sum to purchase this insurance.
- If you need help with activities of daily living (*ADLs), you will immediately receive a monthly cash benefit indexed for inflation.
- For each **\$10,000** you pay for this insurance, you will receive \$Y per month indexed for inflation in any month in which you need help with *ADLs
- The monthly cash benefit is set at the time of purchase and is not dependent on your actual expenses.
- There is **no restriction** on the use of the insurance benefits. You are free to use benefits in any way you wish: to pay for a nursing home; a nurse to help at home; for some other form of help; or in literally any other way you would like.
- An impartial third party who you trust will verify whether or not you need help with *ADLs immediately, impartially, and with complete accuracy.
- The insurance is priced fairly based on your gender, age, and current health.
- There is no risk that the insurance company will default or change the terms of the policy.

When gathering stated demand information, we price the product for each individual at the expected value of payouts conditional on age, gender, and current health based on the estimated health transition probabilities. This is reinforced by the qualitative statement that the pricing is actuarially fair. We price the product at monthly intervals because many nursing home stays and LTC provisions are short term. After all information is provided, demand is collected in two steps. We first ask respondents whether or not they would have any interest in purchasing ADLI were it available. If the answer is affirmative, we ask how large a monthly benefit they would purchase, while simultaneously reporting how much their purchase of any such benefit would cost up front. In the top right corner of the answer screen we present a link to a hover screen that presents the full specification of the product in case the respondent would like to review any features prior to reporting their demand.

While there are valid concerns whether stated preferences match normative preferences, Beshears, Choi, Laibson, and Madrian (2008) note that likelihood of significant disparities decreases when decisions require active choice, are simple, are familiar, are not influenced by third-party marketing, and limit intertemporal considerations. By forcing individuals to make an active choice we attempt to limit fall-back to the default option. Comprehension checks on the definition of ADLs, careful design of product presentation, use of hover screens to make forgotten information available, and an answer screen that dynamically highlights the trade-off to purchasing this product as the choice is made serve to reduce the complexity. In addition, the question makes it clear that the product is a one-time offer to reduce concerns surrounding intertemporal decisions, and because ADLI does not exist in practice concerns around third party marketing are minimal. Thus, these stated demand questions addressed the five factors that facilitate reporting of normative preference.

To analyze the coherence of the stated demands, we conduct a probit estimation of the purchase decision as a function of other survey measures. “Average ADLI Expense” is reported as the dollar amount a respondent would expect to pay in a typical nursing home, “Positive Opinion of Public LTC” is defined as having rated public LTC relative to typical private LTC as three or above on a one to five scale (with one being “much worse”, three being “about the same”, and five being “much better”), and $P(ADL\ state > 3\ year)$ is the reported subjective probability of needing help with the activities of daily living for three or more years at any point in the future. We present results of a probit regression of the decision to buy and a Tobit regression on the amount purchased. Stated interest correlates in a generally reasonable manner with demographic and economic characteristics, as well as other survey measures. Respondents who report higher probabilities of experiencing extended time in the ADL state are more likely to purchase ADLI. This suggests that the prices quoted to these individuals may be more than actuarially fair and that adverse selection affects ADLI purchases. There is also evidence that individuals who indicate a more favorable opinion of publicly provided LTC have less of a desire to purchase. Few demographic variables are significant, likely reflecting the survey practice of calculating actuarially fair pricing conditional on gender, age, and health status.

7.2 Stated Demand and the LTCI Puzzle

Twenty-nine percent of respondents reported that they would purchase a strictly positive amount of ADLI. Preexisting LTCI holdings may have caused individuals that would otherwise desire ADLI not to demand any more. When we include those individuals with prior LTCI coverage amongst those that would purchase ADLI, we find that 44 percent of respondent either already own LTCI or report positive demand in the survey. Thus, a unified extensive margin measure of stated demand suggests ownership one third smaller

	$\mathbb{I}_{ADLI>0}$	<u>Annual Income</u>
<i>Average ADL Cost</i>	0.00 (0.00)	0.03* (0.02)
<i>Prob. Family Cares for ADLs</i>	(0.00) (0.00)	0.70 (23.78)
<i>Above Median Transfers</i>	0.07 (0.11)	459.04 (1,403.37)
<i>Opinion of Public ADL Facility</i>	-0.13 (0.13)	-2,053.17 (1,571.91)
<i>Above Median Expect. of ADL state</i>	0.23** (0.10)	2,588.73** (1,285.42)

Table 10: **Validation of Surveyed ADL demand measurement:** This table presents how stated ADLI demand is predicted by covariates. Column 1 presents the results of a probit regression of the ADLI purchase decisions, and column 2 presents an OLS regression on the level of ADLI income demanded for those with positive demand. For ease of exposition we only present covariates of interest in the main text, but include the fully specified regression results in Appendix Table B.5.

than model predicted demand. These different measures of ownership are summarized in Figure 5. Hence, the low quality of existing LTCI products can contribute a considerable part to the LTCI puzzle, but it does not completely reconcile the difference.

Table 11 documents the distributions of stated and model predicted demands. Although median stated demand is zero, forty percent of respondents that report positive demand indicate a desire to purchase more than \$20,000, while the 95th percentile of the demand distribution is \$36,000. Furthermore, in comparing the distributions of demand presented in rows 1 and 2 of Table 11, we observe that the mean, median, and all percentiles of model estimated ADLI demand distributions are at least as large as the stated ADLI demand distribution. The gap is more pronounced on the intensive margin as seen in the distribution of differences in the third row of Table 11. The median demand difference is \$17,500 and mean difference is \$35,000, suggesting for most individuals that the model predicts significantly higher demand.

	<u>mean</u>	<u>p5</u>	<u>p10</u>	<u>p25</u>	<u>p50</u>	<u>p75</u>	<u>p90</u>	<u>p95</u>
Modeled	42,116	0	0	0	22,997	65,419	110,436	149,072
Stated	6,443	0	0	0	0	6,000	28,000	36,000
Difference	34,814	-17,763	-7,800	0	17,144	60,102	105,105	141,246

Table 11: **Distribution of Differences in ADLI Demand:** This table presents the distribution of each of the ADLI demand measures for those individuals that do not own LTCI. The top line presents the simulated demand distribution, and the middle line presents the surveyed demand distribution. The bottom line presents the distribution of the differences between the simulated and stated demand. Note that this is different from the difference of the distributions.

Lastly, the unified owned or stated demand measure is closer to the model predicted demand for lower wealth individuals. At the lowest wealth quintile, stated or owned demand is around 70 percent of the

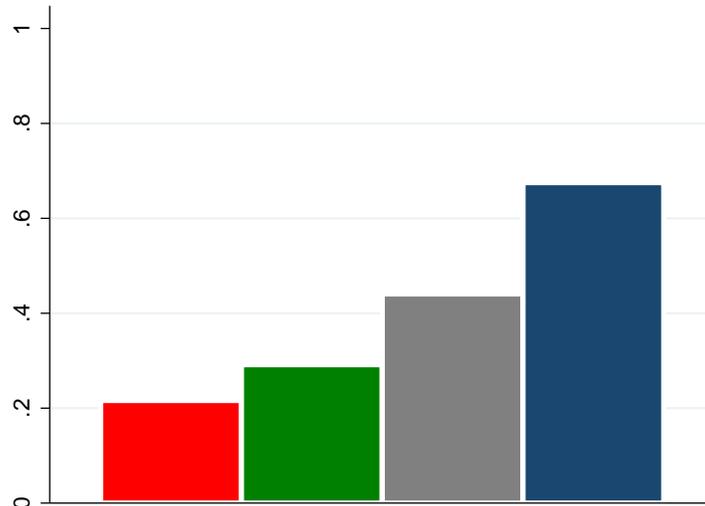


Figure 5: **Fraction of Population Owning LTCI:** This figure presents various measures of the fraction of the population with positive LTCI ownership. Column 1 is actual holdings of a private LTCI in the sample. Column 2 is stated ADLI demand. Column 3 is the union of private ownership and stated demand. Column 4 is model predicted ADLI demand.

model predicted fraction of the population with positive demand, perhaps reflecting crowding out from public insurance. At the second wealth quintile the owned or stated measure is over 80 percent of that predicted by the model, while at higher wealth quintiles owned or stated is between 50 to 60 percent of model predicted. Thus, for the lower wealth quintiles a large part of the puzzle can be explained by the low quality products available in the market, but for the higher wealth quintiles, there is likely another source significantly contributing to the LTCI puzzle.

7.3 Predictors of the Estimated vs. Stated Demand Gap

In this section we analyze our model-bound and model-free demand measures to provide insight into possible reasons for their difference. Generally, there are two reason why the model and stated demand measures might not align. First, factors included in our demand measures might not be properly specified. Second, we might exclude considerations from our demand measures that should be taken into account. To identify whether such omitted considerations contribute to the difference between modeled and stated demands, we develop a general econometric method that identifies sources of model mis-specification both related to included state variables or preferences and omitted variables. Define an omitted variable as any variable that respondents may consider when forming demand that is not included in the model. Such omitted variables, denoted q , bias model estimates of demand from an individual’s true demand.

Defining the difference as

$$\eta_i = D_i - S_i \tag{6}$$

we decompose the difference into factors related to state variables, preferences, and omitted variables q . We do this by estimating the following equation, with details on the derivation of the estimation equation

included in Appendix C.⁹

$$\eta_i = \beta^x C_i^x + \beta^\Theta C_i^\Theta + \Gamma q_i + \epsilon_i \quad (7)$$

$$H_0 : \beta^\Theta = 0; \beta^x = 0; \Gamma = 0.$$

We allow the difference to be a nonlinear function of states and preferences, modeled non-parametrically by partitioning individuals into regions of the state and parameter space. Variables C are indicators of the partition element to which each individual belongs. For example, individuals of a similar age, gender, income, health, and wealth will be grouped into the same element of the partition C_i^x . Estimation of $\Gamma > 0$ indicates model mis-specification related to variable q that generates higher demand for insurance relative to stated, while $\Gamma < 0$ indicates model misspecification that generates lower demand for insurance.

Table 12 presents results from estimating Equation 7 for the full sample with q defined as a variety of variables related to omitted model elements, omitted motives that would be difficult to model, and potential behavioral biases. Results are similar, although less precise, when we restrict to the smaller subsample of non-owners of LTCI, as shown in Appendix Table C.1. For all variables considered (except college education and having a child), we define an indicator that is equal to one if the respondent's characteristic is above the median value of that characteristic for the sample. For example, $\mathbb{I}_{ADL\ help}$ is equal to one if the respondents subjective probability of needing help with the activities of daily living for at least one year is above the median respondent's. To address concerns of measurement error in the estimated parameters and demands included in this regression we follow Rubin (2004) and estimate this equation for multiple samples generated by resampling from the estimated parameter distribution. Reported coefficients and standard errors reflect this multiple imputation approach.

We find that the gap is smaller for those who have in the past made large inter-vivos transfers to a descendant. This is consistent with the idea that the warm-glow bequest specification that is the current workhorse in the quantitative literature since De Nardi (2004) is not a fully adequate summary of the bonds between generations. Model enrichment to capture other other family-related motives may be warranted.¹⁰ With regard to survey comprehension, the gap is smaller for those who performed better at the SSQ comprehension tests. This suggests that individuals whose responses better reflect their preferences have stated demands that better align with economic models (Beshears, Choi, Laibson, and Madrian (2008)). It is therefore plausible that demand in a working ADLI market would be somewhat higher than stated preferences indicate. Finally, the gap is smaller for those with adverse private information on the costs of care and likely length of care. This suggests that adverse selection may be significant problem, and that market provision of actuarially fair LTCI may be infeasible (Hendren (2013)). Variables such as real estate holdings, education, and the probability of receiving care from family, among others, do not significantly predict the difference.

⁹Note that the above specification ignores mis-specification caused by interaction of state variables and preferences. Attempts to control for these interaction effects through partial correlations of individual parameters and state variables do not significantly change any of the results presented in this paper, although estimates become less precise. Furthermore, we do not find significant evidence that omitted factors predict demand measures separately.

¹⁰See Barro (1974), Becker (1974), Bernheim, Shleifer, and Summers (1985), Barro and Becker (1988), Altonji, Hayashi, and Kotlikoff (1997), McGarry (1999), Light and McGarry (2003) for different treatments of intergenerational motives. Abel and Warshawsky (1988) provides discussion of different modeling approaches for rationalizing bequests.

	ADLI difference							
	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>	<u>7</u>	<u>8</u>
$\mathbb{I}_{Transfers}$	8,638*							9,703*
	(5,792)							(6,509)
\mathbb{I}_{child}		5,669						3,204
		(6,049)						(7,139)
$\mathbb{I}_{Real Estate}$			-2,424					-1,446
			(6,147)					(6,113)
$\mathbb{I}_{College}$				-4,482				-2439
				(5,979)				(6,152)
$\mathbb{I}_{Comp. Test}$					-7,208*			-8,037*
					(5,272)			(5,334)
$\mathbb{I}_{Family Care}$						-71		-2,614
						(5,442)		(5,791)
$\mathbb{I}_{ADL help}$							-8,568**	-8,805**
							(5,175)	(5,163)

Table 12: **Omitted Considerations, ADLI:** This table presents the Γ coefficient from estimation of equation 7. The coefficients on β^x and β^Θ are omitted, but in all estimations these coefficients are jointly significant at the 1% level. Standard Errors are included in parentheses.

	<u>mean</u>	<u>p5</u>	<u>p10</u>	<u>p25</u>	<u>p50</u>	<u>p75</u>	<u>p90</u>	<u>p95</u>
Modeled	45,925	1,579	4,985	13,734	32,476	63,515	100,592	129,637
Stated	7,388	0	0	0	0	0	10,000	20,000
Difference	42,555	0	2,430	12,093	29,400	61,349	99,881	126,215

Table 13: **Distribution of Differences in Annuity Demand:** This table presents the distribution of each of our annuity demand measures for those individuals that do not own a private annuity. The top line presents the simulated demand distribution, and the middle line presents the surveyed demand distribution. The bottom line presents the distribution of the differences between the simulated and stated demand.

8 Annuities and the Under-Insurance Puzzle

In this section we repeat the previous exercises for actuarially fair annuities. The annuity market is more developed than the market for LTCI products, and most individuals in our sample are familiar with them. Just as with ADLI, we use the model to calculate the implied annuity demands for the sample. Strikingly, all but four percent of respondents are estimated to purchase a strictly positive amount of an actuarially fair risk free annuity. Moreover, the expenditure on optimally chosen annuities is high, as shown graphically in Figure 6.

As Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015) show, precautionary motives related to long-term care can explain lack of interest in annuities in the presence of a 10 percent load, but only for those singles with wealth below \$400,000 and retirement income below about \$50,000. While this may cover the majority of the U.S. population, it does not cover the majority of the VRI sample. Respondents generally have high wealth as well as relatively high anticipated future income. They have enough resources to be able to self insure against an expensive LTC spell using retirement income and a purchased annuity. Given that their bequest motives are relatively low, it is optimal to annuitize the bulk of their wealth.

We also collect stated annuity demand measures, the distribution of which is presented in Table 13. The direct stated demand questions concerning actuarially fair annuities specify an annuity as paying a fixed amount of income annually for remaining life. There is a corresponding hover button whenever the word annuity appears. The hypothetical annuities for which demand is elicited are described as having no risk of default, being perfectly indexed for inflation, and as being fairly priced based on gender, age, and current health. In identifying respondent demand, it is specified that they pay a one-time, nonrefundable lump sum to purchase the annuity.

Despite being told explicitly that the offered annuity has no risk of default, is perfectly indexed for inflation, and is fairly priced, respondents reported little interest in this product. Only 23 percent of respondents indicated they would purchase any of this product. The lack of interest is also exhibited in a low-level of demand for the amount of annuity income. The 95th percentile of annuity demand is only \$20,000. However, a regression of this demand on demographic correlates yields two highly significant findings.¹¹ First, those with longer life expectancy are significantly more likely to have strictly positive demand than are those with lower life expectancy. As with ADLI, this points to possible adverse selection in the market for annuities. With respect to the extensive margin, among those who state a willingness to purchase, the quantity purchased

¹¹The results of this estimation are presented in Appendix B.2.

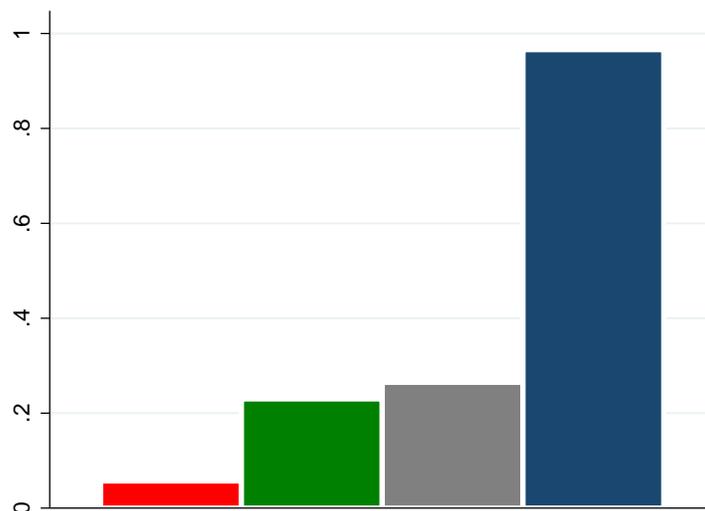


Figure 6: **Fraction of Population Owning Private Annuities:** This figure presents various measures of the fraction of the population with positive annuity ownership. Column 1 is actual holdings of a private annuities in the sample. Column 2 is stated demand. Column 3 is the union of private ownership and stated demand. Column 4 is model predicted demand.

increases strongly with wealth, as expected.

The distribution of stated annuity demand is dramatically different from model-predicted demand. Table 13 presents the demand distributions for both estimated and stated demands as well as the distribution of these differences. The table shows for actuarially fair annuities that the gap between what the model predicts individuals would demand and what individuals state they would purchase is massive. We observe that on average the model over-predicts annuity demand by more than \$44,000 with a median over-prediction of almost \$30,000. The model predicts most individuals should allocate most of their wealth to purchase a private annuity, while respondents state that they would generally only allocate a small share of wealth to such a purchase: almost all respondents stated demand at levels below 10 percent of wealth. This illustrates the annuity puzzle in dramatic form, yet for a non-standard population. This is even larger than the difference in demands we observed for ADLI, and suggests that the model over-estimation of demand can not be accounted for by respondents' unfamiliarity to the ADLI product. Figure 6 documents visually that the classic annuity puzzle is present in the VRI sample, with actual ownership and model predicted ownership drastically different.

9 Conclusion

While long-term care is expensive and the need for it pervasive, very few Americans hold long-term care insurance (LTCI). We use the newly-created Vanguard Research Initiative (VRI) panel to investigate the factors that low observed LTCI holdings reflect. Our preference estimates indicate that ideal LTCI would be far more widely held than are products in the market, and in large quantities. While providing a partial explanation for this under-insurance puzzle, we find that flaws in existing products do not fully explain it. Nor do they fully explain the annuity puzzle, which we also identify in our sample. Our results derive from quantitative survey methods that may be of broader applicability.

References

- ABEL, A. B., AND M. WARSHAWSKY (1988): “Specification of the Joy of Giving: Insights from Altruism,” *The Review of Economic Statistics*, 70(1), 145–149.
- ALTONJI, J., F. HAYASHI, AND L. KOTLIKOFF (1997): “Parental Altruism and Inter Vivos Transfers: Theory and Evidence,” *Journal of Political Economy*, 105, n6.
- AMERIKS, J., J. BRIGGS, A. CAPLIN, M. D. SHAPIRO, AND C. TONETTI (2015): “Long Term Care Utility and Late in Life Saving,” *Vanguard Research Initiative Working Paper*.
- AMERIKS, J., A. CAPLIN, S. LAUFER, AND S. VAN NIEUWERBURGH (2011): “The Joy of Giving or Assisted Living? Using Strategic Surveys to Separate Public Care Aversion from Bequest Motives,” *Journal of Finance*, 66(2), 519–561.
- AMERIKS, J., A. CAPLIN, M. LEE, M. D. SHAPIRO, AND C. TONETTI (2014): “The Wealth of Wealthholders,” *Vanguard Research Initiative Working Paper*.
- ARROW, K. (1974): “Optimal Insurance and Generalized Deductibles,” *Scandinavian Actuarial Journal*, 3, 1–42.
- ATTANASIO, O. (2015): “The Determinants of Human Capital Formation During the Early Years of Life: Theory Measurement and Policies,” *Journal of the European Economic Association*, forthcoming.
- ATTANASIO, O., AND S. CATTAN (2015): “Inferring Beliefs about the Production Function,” *mimeo*.
- ATTANASIO, O., F. CUNHA, AND P. JERVIS (2015): “Eliciting Beliefs about the Production Function,” *mimeo*.
- BARCZYK, D., AND M. KREDLER (2015): “Altruism, Exchange, Attachment to the House, or by Accident—Why do People Leave Bequests?,” *mimeo*.
- BARRO, R., AND G. BECKER (1988): “A Reformulation of the Economic Theory of Fertility,” *Quarterly Journal of Economics*.
- BARRO, R. J. (1974): “Are Government Bonds Net Wealth?,” *The Journal of Political Economy*, 82(6), 1095–1117.
- BARSKY, R. B., F. T. JUSTER, M. S. KIMBALL, AND M. D. SHAPIRO (1997): “Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study,” *Quarterly Journal of Economics*, 112, 537–579.
- BECKER, G. S. (1974): “A Theory of Social Interactions,” *Journal of Political Economy*, 82(61).
- BERNHEIM, B. D., A. SHLEIFER, AND L. H. SUMMERS (1985): “The Strategic Bequest Motive,” *The Journal of Political Economy*, 93(6), 1045–1076.
- BESHEARS, J., J. J. CHOI, D. LAIBSON, AND B. C. MADRIAN (2008): “How are Preferences Revealed?,” *Journal of Public Economics*, 92(8), 1787–1794.
- BESHEARS, J., J. J. CHOI, D. LAIBSON, B. C. MADRIAN, AND S. P. ZELDES (2012): “What Makes Annuity More Appealing?,” *mimeo*.
- BRAUN, R. A., K. A. KOPECKY, AND T. KORESHKOVA (2015): “Old, Sick, Alone and Poor: A Welfare Analysis of Old-Age Social Insurance Programs,” *working paper*.
- BROWN, J. (2007): “Rational and Behavioral Perspectives on the Role of Annuities in Retirement Planning,” *NBER Working Papers*, 13537, 1–32.

- BROWN, J. R., AND A. FINKELSTEIN (2007): “Why is the Market for Long-term Care Insurance so Small?,” *Journal of Public Economics*, 91, 1967–1991.
- (2008): “The Interaction of Public and Private Insurance: Medicaid and the Long-Term Care Insurance Market,” *The American Economic Review*, pp. 1083–1102.
- (2011): “Insuring Long-Term Care in the United States,” *The Journal of Economic Perspectives*, pp. 119–141.
- BROWN, J. R., G. S. GODA, AND K. MCGARRY (2013): “State-Dependent Utility and Insurance Purchase Decisions,” *working paper*.
- CARROLL, C. D. (1997): “Buffer-Stock Saving and the Life Cycle/Permanent Income Hypothesis,” *The Quarterly Journal of Economics*, 112(1), 1–55.
- CUTLER, D. (1996): “Why Don’t Markets Insure Long-Term Risk?,” *mimeo*.
- DE NARDI, M. (2004): “Wealth Inequality and Intergenerational Links,” *Review of Economic Studies*, 7, 743–768.
- DE NARDI, M., E. FRENCH, AND J. JONES (2010): “Differential Mortality, Uncertain Medical Expenses, and the Saving of Elderly Singles,” *Journal of Political Economy*, 118, 49–75.
- DE LAVANDE, A., AND S. ROHWEDDER (2008): “Eliciting Subjective Probabilities in Internet Surveys,” *Public Opinion Quarterly*, 72(5), 866–891.
- EVANS, W., AND W. K. VISCUSI (1991): “Estimation of State-Dependent Utility Functions Using Survey Data,” *Review of Economics and Statistics*, 73(1), 94–104.
- FINKELSTEIN, A., E. LUTTMER, AND M. NOTOWIDIGDO (2009): “Approaches to Estimating the Health State Dependence of the Utility Function,” *American Economic Review: Papers and Proceedings*, 99(2), 116–121.
- (2013): “What Good is Wealth without Health? The Effect of Health on the Marginal Utility of Consumption,” *Journal of European Economic Association*, 11, 221–258.
- FINKELSTEIN, A., AND K. MCGARRY (2006): “Multiple Dimensions of Private Information: Evidence from the Long-Term Care Insurance Market,” *American Economic Review*, 96(4), 938–958.
- FRENCH, E., AND J. JONES (2011): “The Effects of Health Insurance and Self Insurance on Retirement Behavior,” *Econometrica*, 79, 693–732.
- GENWORTH (2013): “Genworth 2013 Cost of Care Study,” Discussion paper, Genworth.
- GOURINCHAS, P.-O., AND J. PARKER (2002): “Consumption Over the Life Cycle,” *Econometrica*, 70(1), 47–89.
- HACKMANN, M. B. (2015): “Incentivizing Better Quality of Care: The Role of Medicaid and Competition in The Nursing Home Industry,” *mimeo*.
- HENDREN, N. (2013): “Private Information and Insurance Rejections,” *Econometrica*, 81(5), 1713–1762.
- HONG, J. H., J. PIJOAN-MAS, AND J.-V. RIOS-RULL (2013): “Health Heterogeneity and Preferences,” *working paper*.
- HONG, J. H., AND J.-V. RIOS-RULL (2007): “Social Security, Life Insurance and Annuities for Families,” *Journal of Monetary Economics*, 54(1), 118–140.
- (2012): “Life Insurance and Household Consumption,” *The American Economic Review*, 102(7), 3701–3730.

- HUBBARD, R. G., J. SKINNER, AND S. P. ZELDES (1994): "Expanding the Life-Cycle Model: Precautionary Saving and Public Policy," *The American Economic Review*, pp. 174–179.
- HURD, M. D. (1989): "Mortality Risk and Bequests," *Econometrica*, 57(4), 779–813.
- JUSTER, F. T. (1966): "Consumer Buying Intentions and Purchase Probability: An Experiment in Survey Design," *Journal of the American Statistical Association*, 61(315), 658–696.
- KIMBALL, M. S., C. R. SAHM, AND M. D. SHAPIRO (2008): "Imputing Risk Tolerance from Survey Responses," *Journal of the American Statistical Association*, 103, 1028–1038.
- KOIJEN, R. S. J., S. VAN NIEUWERBURGH, AND M. YOGO (2015): "Health and Mortality Delta: Assessing the Welfare Cost of Household Insurance Choice," *Journal of Finance*, forthcoming.
- KOIJEN, R. S. J., AND M. YOGO (2015): "The Cost of Financial Frictions for Life Insurers," *American Economic Review*, forthcoming.
- KOPECKY, W., AND T. KORESHKOVA (2014): "The Impact of Medical and Nursing Home Expenses and Social Insurance Policies on Savings and Inequality," *American Economic Journal: Macroeconomics*, 6, 29–72.
- KOTLIKOFF, L. J., AND L. H. SUMMERS (1981): "The Role of Intergeneration Transfers in Aggregate Capital Accumulation," *Journal of Political Economy*, 89(4), 706–732.
- LAIBSON, D., A. REPETTO, AND J. TOBACMAN (2007): "Estimating Discount Functions with Consumption Choices over the Lifecycle," Discussion paper, National Bureau of Economic Research.
- LAITNER, J., D. SILVERMAN, AND D. STOLYAROV (2014): "Annuitized Wealth and Post-Retirement Saving," *working paper*.
- LIGHT, A., AND K. MCGARRY (2003): "Why parents play favorites: Explanations for unequal bequests," Discussion paper, National Bureau of Economic Research.
- LILLARD, L., AND Y. WEISS (1997): "Uncertain Health and Survival: Effects on End of Life Consumption.," *Journal of Business and Economic Statistics*, 15(2), 254–68.
- LOCKWOOD, L. (2012): "Bequest Motives and the Annuity Puzzle," *Review of Economic Dynamics*, 15(2), 226–243.
- (2014): "Bequest Motives and the Choice to Self-Insure Late-Life Risks," *working paper*.
- MANSKI, C. F. (1990): "The Use of Intentions Data to Predict Behavior: A Best Case Analysis," *Journal of the American Statistical Association*, 85(412), 934–940.
- (2004): "Measuring Expectations," *Econometrica*, 72(5), 1329–1376.
- MCGARRY, K. (1999): "Inter Vivos Transfers and Intended Bequests," *Journal of Public Economics*, 73(3), 321–351.
- MODIGLIANI, F. (1986): "Life Cycle, Individual Thrift and the Wealth of Nations," *American Economic Review*, 76(3), 297–313.
- PALUMBO, M. (1999): "Uncertain Medical Expenses and Precautionary Saving near the End of the Life Cycle," *Review of Economic Studies*, 66, 395–421.
- PAULY, M. V. (1990): "The Rational Nonpurchase of Long-Term-Care Insurance," *Journal of Political Economy*, 98(1), 153–168.

- PAWEENAWAT, A., AND R. M. TOWNSEND (2012): "Village Economic Accounts: Real and Financial Intertwined," *The American Economic Review Papers and Proceedings*, 102(3), 441–446.
- RUBIN, D. B. (2004): *Multiple Imputation for Nonresponse in Surveys*, vol. 81. John Wiley & Sons.
- VAN DER KLAUW, W., AND K. I. WOLPIN (2008): "Social Security and the Retirement and Savings Behavior of Low-income Households," *Journal of Econometrics*, 145(1-2), 21–42.
- VISCUSI, W. K., AND W. EVANS (1990): "Utility Functions that Depend on Health Status: Estimates and Economic Implications," *American Economic Review*, 80(3), 353–374.
- WISWALL, M., AND B. ZAFAR (2015): "Determinants of College Major Choice: Identification using an Information Experiment," *Review of Economic Studies*, 82(2), 791–824.
- YAARI, M. (1965): "Uncertain Lifetime, Life Insurance, and the Theory of the Consumer," *The Review of Economic Studies*, 32(2), 137–150.
- ZELDES, S. P. (1989): "Optimal Consumption with Stochastic Income: Deviations from Certainty Equivalence," *The Quarterly Journal of Economics*, 104(2), 275–298.

A Model Appendix

This section presents the consumer choice model and model for insurance demand as first presented in Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015). See Online Appendix: Modeling for further description and computation of optimal decision rules.

A.1 Extended Model Presentation

The Consumer Problem

The consumer takes r as given and chooses a' , c , e_{ADL} , and G to maximize utility. The consumer problem, written recursively, is,

$$\begin{aligned}
 V(a, y, t, s, h, g) = & \max_{a', c, e_{ADL}, G} \mathbb{I}_{s \neq 3} (1 - G) \{U_s(c, e_{ADL}) + \beta E[V(a', y, t + 1, s', h')]\} \\
 & + \mathbb{I}_{s \neq 3} G \{U_s(\omega_G, \psi_G) + \beta E[V(0, y, t + 1, s', h')]\} + \mathbb{I}_{s=3} \{v(b)\} \\
 \text{s.t.} \\
 a' = & (1 - G)[(1 + r)a + y(t) - c - e_{ADL} - h] \geq 0 \\
 e_{ADL} \geq & \chi \text{ if } (G = 0 \wedge s = 2) \\
 e_{ADL} = & \psi_G \text{ if } (G = 1 \wedge s = 2) \\
 c = & \omega_G \text{ if } (G = 1 \wedge (s = 0 \vee s = 1)) \\
 b = & \max\{(1 + r)a - h', 0\} \\
 U_s(c, e_{ADL}) = & \mathbb{I}_{s \in \{0,1\}} \frac{c^{1-\sigma}}{1-\sigma} + \mathbb{I}_{s=2} (\theta_{ADL})^{-\sigma} \frac{(e_{ADL} + \kappa_{ADL})^{1-\sigma}}{1-\sigma} \\
 v(b) = & (\theta_{beq})^{-\sigma} \frac{(b + \kappa_{beq})^{1-\sigma}}{1-\sigma}.
 \end{aligned}$$

The value function has three components, corresponding to the utility plus expected continuation value of a living individual who does not use government care, that of one who does choose to use government care, and the warm glow bequest utility of the newly deceased individual.¹² Note that a person using government care has expenditure levels set to predetermined public care levels and zero next period wealth. The budget constraint shows that wealth next period is equal to zero if government care is used, and is otherwise equal to the return on savings plus income minus chosen expenditures minus health costs. The individual cannot borrow, cannot leave a negative bequest, and private expenditure when in need of help with ADLs must be at least χ .

A.2 Insurance Demands

Insurance products are priced conditional on age, health status, and gender. The price of an insurance product is denoted by $p(t, s, g)$, such that spending \$ $\tilde{y} \times p(t, s, g)$ purchase payout \tilde{y} per year when the insurance-relevant states are realized. In the case of annuities, income is paid every year, and in the case of ADLI it is paid only in years when $s = 2$.

¹²Technically, there is a fifth health state that is reached (with certainty) only in the period after death and is the absorbing state, so that the consumer only receives the value of a bequest in the first period of death.

Taking prices as given, demand for insurance is calculated as

$$D(a, y, t, s, h, g) = \arg \max_{\tilde{y}} V(a - p(t, s, g)\tilde{y}, \hat{y}, t, s, h, g) \quad (\text{A.1})$$

$$\hat{y} = y(t) + \tilde{y},$$

where \hat{y} is the income stream including insurance payouts and V is the value function evaluated at the new wealth level and income stream. Note that without insurance, income is deterministic and only age-dependent. Purchasing insurance makes the new income stream (\hat{y}) stochastic through its dependence on age and health. To calculate $D(a, y, t, s, h, g)$ consumer optimal policies are computed over a grid of \tilde{y} and the \tilde{y} that maximizes the value function is obtained by interpolation.

Prices. Prices are first calculated to be actuarially fair conditional on age, health, and gender. Actuarially fair is defined to be the price such that the agency selling the product makes zero profit in expected value.

The realized period payouts for annuities and ADL insurance depend on health state s . An annuity pays out while $s = 0, 1$ or 2 , while ADLI pays out while only when $s = 2$. Thus, the vector of period payouts across health states $s \in \{0, 1, 2, 3\}$ for annuities is

$$\vec{y} = [\tilde{y}, \tilde{y}, \tilde{y}, 0]',$$

while for ADLI it is,

$$\vec{y} = [0, 0, \tilde{y}, 0]'$$

Let \vec{s} be an indicator vector that has elements s_i for $i \in \{0, 1, 2, 3\}$ equal to zero for $s \neq i$ and equal to 1 if $s = i$. The insurance product is priced to equal the expected discounted stream of payments. Thus, an insurance product that pays out \vec{y} per period for a person of age t , gender g , with current health status s has price

$$p(t, s, g) = \vec{s} \times \left[\sum_{i=0}^{T-t} \frac{1}{(1+r)^i} \prod_{k=0}^i \pi_g(s'|t+k, s) \right] \times \vec{y}. \quad (\text{A.2})$$

B Validation Exercises

This appendix presents results from validation exercises for key survey instruments. It first examines how SSQ responses correlate with other variables, and then examines how stated annuity demand correlates with relevant variables. Corresponding exercises for SSQ 3 and stated ADLI demand are presented in the paper.

B.1 SSQ Validation

SSQ 1 Table B.1 regresses SSQ 1 responses on the respondents ownership of equity. Respondents that do not own equity exhibit some evidence that they would be less willing to risk future income for a chance at doubling income. Such individuals would be considered more risk averse.

SSQ 2 Table B.2 presents results of a regression of SSQ 2 responses on respondent characteristics. There is evidence that respondents that own LTCI assign more wealth to the ADL state, indicating a greater preference for wealth when in need of help with ADLs.

SSQ 3 Table B.2 presents results of a regression of SSQ 3 responses on respondent characteristics.

SSQ 4 Table B.4 presents results of a regression of response to SSQ 4 on covariates, including the respondents opinion of government care. Specifically, the variable of interest is an indicator of whether the respondent indicates a more favorable view of publicly provided LTC than the median respondent. Respondents that have a more favorable opinion of publicly provided LTC assign a higher indifference point to SSQ 4, signifying that they would be less willing to forgo the government care option at low wealth levels.

B.2 Other Validation

Stated Annuity Demand Table B.6 presents a tobit regression of demographic and other covariates on stated demand for annuities. Here it is shown that higher than expected longevity significantly predicts stated purchase of the ideal annuity products.

	SSQ 1a	SSQ 1b
<i>health</i> = 2	51820.39	4577.15
	148016.4	60297.43
<i>health</i> = 3	-254075	-9763.45
	233914.1	95292.02
\mathbb{I}_{child}	21949.49	35864.12
	74096.31	30142.98
<i>Income</i> ₂	-196330.9	-46709.57
	101100.7	41201.9
<i>Income</i> ₃	-316462.5	-112584.3
	98212.77	39991.2
<i>Income</i> ₄	-135844.6	-52029.15
	93559.62	38184.55
<i>Income</i> ₅	-39303.15	-43237.25
	108913.7	44183.73
<i>College</i>	96727.29	28818.99
	69355.65	28297.14
<i>College</i> × \mathbb{I}_{child}	903.49	805.99
	3177.12	1294.83
<i>log(wealth)</i>	-1833.62	332.61
	1794.45	731.11
<i>Male</i>	-23140.47	-28701.33
	66943.85	27381.4
<i>age</i> (<i>age</i> > 65)	-500.65	-7.9
	541.01	220.35
<i>health</i> = 2	-639.29	217.33
	3924.86	1600.32
<i>health</i> = 3	5801.16	313.83
	6639.63	2675.35
\mathbb{I}_{child}	-1016.28	-957.56
	2156.52	877.07
<i>College</i>	-2420.02	-683.45
	1969.77	803.96
<i>Income</i> ₂	5765.48	1038.82
	2931.69	1195.36
<i>Income</i> ₃	8753.84	2816.97
	2751.53	1121.51
<i>Income</i> ₄	3815.64	1119.21
	2691.29	1098.53
<i>Income</i> ₅	2328.34	952.99
	3023.17	1226.63
<i>Male</i>	-86.77	806.92
	1918.18	784.07
<i>age</i> (<i>age</i> > 65)	6.15	.1
	5.58	2.27
<i>health</i> = 2	2.71	-1.46
	26.36	10.76
<i>health</i> = 3	-43.69	-3.2
	43.75	17.59
\mathbb{I}_{child}	6.49	6.45
	15.89	6.46
<i>College</i>	15.27	5.04
	14.01	5.72
<i>Income</i> ₂	-41.03	-7.19
	21.17	8.63
<i>Income</i> ₃	-62.35	-19.41
	19.7	8.04
<i>Income</i> ₄	-25.56	-7.17
	19.3	7.88
<i>Income</i> ₅	-15.17	-5.71
	21.62	8.77
<i>Male</i>	-0.27	-5.77
	13.71	5.61
<i>log(wealth)</i> (<i>age</i> > 65)	536.18	-126.28
	1159.92	472.98
<i>health</i> = 2	-1326.26	-1037.21
	2291.14	929.92
<i>health</i> = 3	5643.29	-22.94
	4714.76	2028.67
\mathbb{I}_{child}	1225.35	-86.69
	1241.8	506.21
<i>College</i>	-299.56	-541.12
	1294.8	528.6
<i>Income</i> ₂	-158.95	717.79
	1637.89	669.73
<i>Income</i> ₃	963.09	932.14
	1822.71	741.41
<i>Income</i> ₄	-430.14	607.54
	1707.42	696.37
<i>Income</i> ₅	-3441.69	341.51
	1954.97	798.62
<i>Male</i>	2604.11	158.17
	1079.51	439.69
<i>No Equity</i>	-2549.43	-2227.90
	(3602.17)	(1474.09)

Table B.1: **External Validation of SSQs 1:** This table presents the results from a Tobit regression of SSQ 1 responses on the listed covariates.

	SSQ 2a	SSQ 2b	SSQ 2c
<i>health = 2</i>	216809	330652.7	171480.8
	193648.6	169075.6	108307.5
<i>health = 3</i>	27639.55	129319	64253.95
	457716	399369.5	255493.2
\mathbb{I}_{child}	-94709.72	-118787.1	-64341.91
	92970.93	81126.98	51895.1
<i>Income₂</i>	170909.8	30931.03	101794.4
	124488	108542	69809.84
<i>Income₃</i>	-90240.3	-26306.3	114192.79
	117430.6	102438.4	65676.66
<i>Income₄</i>	134728.9	177960.5	97857.93
	119066	103881.5	66400.64
<i>Income₅</i>	118028.5	131094.7	64648.36
	135344	118072.4	75475.5
<i>College</i>	-14634.9	-71411.91	-53432.36
	84284.3	73533.78	47149.3
<i>College</i> × \mathbb{I}_{child}	3893.04	-1007.31	1258.71
	3535.3	3082.12	1972.11
<i>log(wealth)</i>	-582.61	-2323.67	-70.15
	1981.81	1730.06	1105.61
<i>Male</i>	-125291.9	-118064.42	8752.03
	82119.78	71581.74	45809.04
<i>age</i> (<i>age > 65</i>)	-657.77	-511.57	-215.49
	646.44	563.89	360.45
<i>health = 2</i>	-6937.17	-9904.41	-5289.08
	5305.8	4632.47	2968.7
<i>health = 3</i>	-1563.83	-2362.23	-2699.85
	13646.87	11904.91	7617.97
\mathbb{I}_{child}	3333.37	3726.04	2354.85
	2763.82	2411.55	1542.32
<i>College</i>	65.01	579.9	1092.61
	2411.85	2104.48	1349.18
<i>Income₂</i>	-4750.11	-51.33	-2506.54
	3658.18	3188.81	2051.78
<i>Income₃</i>	2590.74	1218.69	-105.97
	3357.83	2929.07	1877.63
<i>Income₄</i>	-3489.72	-3535.15	-2960.94
	3488.41	3043.42	1945.05
<i>Income₅</i>	-3050.86	-2672.07	-1557.97
	3838.8	3348.66	2140.4
<i>Male</i>	3873.98	3572.11	-673.01
	2387.09	2081.08	1331.54
<i>age</i> (<i>age > 65</i>)	10.32	5.76	2.25
	6.8	5.93	3.79
<i>health = 2</i>	49.56	70.64	38.24
	36.13	31.54	20.22
<i>health = 3</i>	12.26	24.63	19.49
	92.96	81.11	51.91
\mathbb{I}_{child}	-25.68	-27.76	-18.54
	20.65	18.02	11.52
<i>College</i>	-2.67	-4.37	-7.93
	17.39	15.17	9.73
<i>Income₂</i>	34.61	-59	19.1
	26.74	23.3	15
<i>Income₃</i>	-17.58	-7.98	3.06
	24.31	21.21	13.6
<i>Income₄</i>	23.82	25.06	22.88
	25.39	22.15	14.16
<i>Income₅</i>	25.19	19.97	12.57
	27.84	24.28	15.52
<i>Male</i>	-26.42	-25.58	6.03
	17.31	15.09	9.65
<i>log(wealth)</i> (<i>age > 65</i>)	-113.69	746.99	391.54
	1340.11	1169.55	747.8
<i>health = 2</i>	1880.91	862.6	350.38
	2681.1	2341.03	1495.07
<i>health = 3</i>	539.01	-7287.75	1795.15
	6038.72	5260.01	3362.38
\mathbb{I}_{child}	-1289.21	-463.38	-866.37
	1383.93	1207.31	772.5
<i>College</i>	1524.7	4167.39	1109.97
	1463.63	1276.92	816.39
<i>Income₂</i>	-963.11	-2026.25	-1743.59
	1837.25	1603.5	1025.93
<i>Income₃</i>	-314.01	-1633.12	-1761.08
	1998.84	1744.65	1114.86
<i>Income₄</i>	-1023.64	-4393.58	-459.18
	1999.26	1744.97	1115.4
<i>Income₅</i>	-2438.55	-3407.81	-1407.05
	2133.08	1861.97	1190.86
<i>Male</i>	-1112.99	-432.8	-757.24
	1213.83	1058.75	676.93
<i>Average ADL Cost</i>	-0.01	0	0
	(.01)	(.01)	(.01)
<i>Prob. Family Cares for ADLs OwnLTCI</i>	-47.83**	-22.75	-13.59
	(24.10)	(20.99)	(13.43)
	2453.63	2104.12	1799.09**
	(1514.04)	(1319.88)	(844.02)
<i>Opinion of Public ADL Facility Above Median Expect. of ADL state</i>	3881.26**	2969.87**	1212.60
	(1528.67)	(1332.84)	(851.27)
	-479.20	630.93	258.90
	(1212.27)	(1056.65)	(675.50)

Table B.2: **External Validation of SSQs 2:** This table presents the results from a Tobit regression of SSQ 2 responses on the listed covariates.

	<u>SSQ 3a</u>	<u>SSQ 3b</u>	<u>SSQ 3c</u>
<i>health = 2</i>	261809	661755.4	961421.3
	293615.1	349715.4	436963.9
<i>health = 3</i>	187294.8	381007.3	198659
	462587.1	499853	627722.4
\mathbb{I}_{child}	-134071.3	-187987.1	-204805.6
	145072.6	168479.6	211666.3
<i>Income₂</i>	-307547.4	-185016.9	-152676.5
	190256	218024	274415.4
<i>Income₃</i>	43979.78	-16872.74	-29093.17
	185448.9	215908.5	272140.2
<i>Income₄</i>	-286470.1	-301802.1	-439482.8
	176980.9	208099.1	261054.7
<i>Income₅</i>	-80584.98	-202072.2	-396469
	206404.6	239534.4	300100.6
<i>College</i>	-46890.27	119334.13	5620.16
	130770.8	152896.5	191972.6
<i>College</i> × \mathbb{I}_{child}	11797.9	12002.77	9292.02
	6284.26	7216.57	9045.34
<i>log(wealth)</i>	-3581.32	-1575.04	2496.8
	3457.73	4016.37	5040.52
<i>Male</i>	-34101.14	86280.99	363627
	127469.4	148721.2	186810.3
<i>age (age > 65)</i>	-164.42	-1302.91	-1996.16
	1088.41	1266.46	1590.65
<i>health = 2</i>	-7521.85	-20018.03	-29438.54
	7866.07	9360.25	11669.27
<i>health = 3</i>	-6687.42	-15512.65	-10529.1
	13235.35	14062.63	17755.18
\mathbb{I}_{child}	3033.09	6238.59	8111.47
	4256.18	4950.62	6221.82
<i>College</i>	820.69	-3025.9	-188.55
	3694.52	4328.14	5437.3
<i>Income₂</i>	8713.25	5252.71	5193.32
	5507.56	6321.22	7957.62
<i>Income₃</i>	-2880.88	-3335.35	-2705.87
	5204.29	6063.17	7644.19
<i>Income₄</i>	8350.58	7829.39	11602.11
	5023.63	5920.48	7436.37
<i>Income₅</i>	423.76	4642.77	10837.62
	5725.21	6646.24	8319.67
<i>Male</i>	374.7	-1608.61	-8593.76
	3639.52	4255.68	5346.33
<i>age (age > 65)</i>	.65	7.75	13.6
	11.25	13.07	16.42
<i>health = 2</i>	48.8	129.61	192.93
	52.31	62.19	77.64
<i>health = 3</i>	58.58	105.01	86.23
	87.65	92.45	116.72
\mathbb{I}_{child}	-20.3	-43.97	-58.75
	31.62	36.73	46.16
<i>College</i>	-13.47	12.31	-3.59
	26.29	30.81	38.71
<i>Income₂</i>	-59.41	-32.04	-39.14
	39.76	45.56	57.37
<i>Income₃</i>	26.59	31.57	23.14
	37.31	43.46	54.81
<i>Income₄</i>	-56	-50.39	-84.1
	35.96	42.41	53.31
<i>Income₅</i>	1.73	-25.42	-74.06
	40.98	47.54	59.52
<i>Male</i>	1.58	13.28	64.38
	26.06	30.46	38.29
<i>log(wealth) (age > 65)</i>	436.46	4001.91	5616.93
	2327.56	2709.86	3400.97
<i>health = 2</i>	1661.61	7382.29	11179.93
	4619.91	5367.99	6750.91
<i>health = 3</i>	-1638.91	13450.09	7531.17
	8776.63	9537.8	11635.58
\mathbb{I}_{child}	26.73	-4238.26	-7484.71
	2457.27	2818.94	3534.13
<i>College</i>	3861.75	1716.64	-1037.11
	2514.71	2944.04	3699.65
<i>Income₂</i>	15.74	-1162.29	-1323.86
	3175.09	3698.08	4650.32
<i>Income₃</i>	2374.08	7598.69	8223.39
	3439.65	4038.21	5083.9
<i>Income₄</i>	-1133.39	1126.24	3625.33
	3477.04	4055.33	5079.73
<i>Income₅</i>	3454.55	1074.25	963.79
	3648.97	4301.77	5417.53
<i>Male</i>	62.05	-3198.79	-6397.56
	2103.6	2454.36	3084.73
<i>Average ADL Cost</i>	.03	.05**	.07**
	(.02)	(.02)	(.03)
<i>Prob. Family Cares for ADLs Above Median</i>	-56.33	-90.82*	-135.51**
	(40.86)	(47.95)	(60.41)
<i>Transfers</i>	-4858.13**	-9401.06***	-11331.22***
	(2307.98)	(2697.35)	(3391.45)
<i>Opinion of Public ADL Facility</i>	-2423.81*	80.29	1466.69
	(1358.17)	(1586.00)	(1991.96)

Table B.3: **External Validation of SSQs 3:** This table presents the results from a Tobit regression of SSQ 3 responses on the listed covariates.

	SSQ 4a
<i>health = 2</i>	328966.3
	168832.9
<i>health = 3</i>	123210.2
	398848.8
<i>I_{child}</i>	-120307.1
	80996.29
<i>Income₂</i>	32040.73
	108336.1
<i>Income₃</i>	-26966.6
	102248
<i>Income₄</i>	177631.4
	103687.7
<i>Income₅</i>	131333
	117857.3
<i>College</i>	-71243.37
	73469.16
<i>College × I_{child}</i>	-947.55
	3083.67
<i>log(wealth)</i>	-2347.48
	1726.65
<i>Male</i>	-117828.5
	71447.2
<i>age (age > 65)</i>	-537.91
	563.62
<i>health = 2</i>	-9864
	4624.73
<i>health = 3</i>	-2172.14
	11888.91
<i>I_{child}</i>	3765
	2407.24
<i>College</i>	579.1
	2102.24
<i>Income₂</i>	-102.55
	3182.62
<i>Income₃</i>	1243.69
	2923.84
<i>Income₄</i>	-3519
	3037.66
<i>Income₅</i>	-2667.61
	3342.34
<i>Male</i>	3560.36
	2077.11
<i>age (age > 65)</i>	6.03
	5.93
<i>health = 2</i>	70.35
	31.49
<i>health = 3</i>	23.3
	81
<i>I_{child}</i>	-28.06
	17.98
<i>College</i>	-4.38
	15.16
<i>Income₂</i>	-0.22
	23.26
<i>Income₃</i>	-8.17
	21.17
<i>Income₄</i>	24.94
	22.11
<i>Income₅</i>	19.91
	24.24
<i>Male</i>	-25.5
	15.06
<i>log(wealth) (age > 65)</i>	789.27
	1168.38
<i>health = 2</i>	886.33
	2339.83
<i>health = 3</i>	-7334.56
	5250.18
<i>I_{child}</i>	-439.64
	1208.16
<i>College</i>	4156.92
	1274.89
<i>Income₂</i>	-1977.59
	1600.51
<i>Income₃</i>	-1643.31
	1741.79
<i>Income₄</i>	-4406.33
	1742.05
<i>Income₅</i>	-3422.36
	1858.67
<i>Male</i>	-421.36
	1056.55
<i>Average ADL Cost</i>	0
	(0.01)
<i>Prob. Family Cares for ADLs</i>	-22.50
	(21.01)
<i>OwnLTCl</i>	2109.29
	(1317.40)
<i>Above Median Transfers</i>	-380.25
	(1171.00)
<i>Opinion of Public ADL Facility</i>	3009.23**
	(1330.27)
<i>Above Median Expect. of ADL state</i>	648.18
	(1056.36)

Table B.4: **External Validation of SSQ 4:** This table presents the results from a Tobit regression of SSQ 4 responses on the listed covariates.

	$\mathbb{I}_{ADLI>0}$	<u>Annual Income</u>
<i>health = 2</i>	-35.17	4137143
	24.05	1995000
<i>health = 3</i>	-8750	
	15861.9	
\mathbb{I}_{child}	15.27	-196415.2
	8.15	270847.3
<i>Income₂</i>	1.47	-548517.5
	10.49	457084.7
<i>Income₃</i>	-6.23	234276
	9.95	380592
<i>Income₄</i>	-13.69	-77500.67
	11.03	426575.9
<i>Income₅</i>	-17.17	-6604.63
	12.79	478531.8
<i>College</i>	8.87	64067.34
	7.65	315808.7
<i>College</i> × \mathbb{I}_{child}	-0.07	-1369.07
<i>log(wealth)</i>	.29	10301.92
	.25	-4065.91
<i>Male</i>	.16	6834.3
	.22	-337211.3
	7.78	291195.2
<i>age (age > 65)</i>	.11	-3135.5
	.06	2097.8
<i>health = 2</i>	.92	-112708.5
	.65	54061.62
<i>health = 3</i>	22.56	
	413.02	
\mathbb{I}_{child}	-0.46	5721.66
	.25	8034.33
<i>College</i>	-0.19	-2824.54
	.22	9191.58
<i>Income₂</i>	.01	16372.04
	.31	13545.7
<i>Income₃</i>	.14	-5174.92
	.29	10980.82
<i>Income₄</i>	.41	3725.05
	.33	12554.39
<i>Income₅</i>	.51	974.81
	.37	14012.25
<i>Male</i>	-0.05	11467.44
	.23	8636.75
<i>age (age > 65)</i>	0	22.48
	0	21.42
<i>health = 2</i>	-0.01	738.74
	0	352.9
<i>health = 3</i>	-0.15	0.61
	2.71	4.42
\mathbb{I}_{child}	0	-34.93
	0	60.02
<i>College</i>	0	16.08
	0	67.78
<i>Income₂</i>	0	-122.06
	0	100.72
<i>Income₃</i>	0	38.65
	0	80.23
<i>Income₄</i>	0	-19.89
	0	92.66
<i>Income₅</i>	0	-11.26
	0	104.25
<i>Male</i>	0	-87.3
	0	64.08
<i>log(wealth) (age > 65)</i>	-0.27	752.09
	.11	4472.24
<i>health = 2</i>	.01	9343.24
	.22	9226.73
<i>health = 3</i>	1.53	
	81.61	
\mathbb{I}_{child}	.02	-1885.54
	.11	4469.36
<i>College</i>	-0.29	3777.48
	.12	4672.79
<i>Income₂</i>	-0.14949.81	
	.15	5870.34
<i>Income₃</i>	.11	-4806.51
	.16	6119.17
<i>Income₄</i>	0	-6353.76
	.17	6481.67
<i>Income₅</i>	.14	-45.55
	.19	6892.53
<i>Male</i>	.11	-1269.41
	.1	3940.67
<i>Average ADL Cost</i>	8.7e-7	.03*
	(1.3e-6)	(.02)
<i>Prob. Family Cares for ADLs Above Median Transfers</i>	.00	.70
	(.00)	(23.78)
<i>Opinion of Public ADL Facility</i>	.07	459.04
	(.11)	(1403.37)
	-.13	-2053.17
	(.13)	(1571.91)

Table B.5: **Validation of Surveyed ADLI Demand Measure:** This table presents how stated ADLI demand is predicted by other covariates. Column 1 presents the results of a probit regression of the ADLI purchase decisions, and column 2 presents an OLS regression on the level of ADLI income demanded for those with positive demand.

	$\mathbb{I}_{Annuity>0}$	Annual Income
<i>health = 2</i>	7.56	-539809.3
	14.71	828177.9
<i>health = 3</i>	-382.63	
	21803.5	
\mathbb{I}_{child}	2.11	489864.3
	7.52	433986.9
<i>Income₂</i>	-11.13	-650398.1
	11.7	713924.1
<i>Income₃</i>	-5.08	-561198.8
	10.22	575556.1
<i>Income₄</i>	-10.99	-63707.01
	10.66	620626.4
<i>Income₅</i>	-0.93	-1357453
	11.39	628743.9
<i>College</i>	10.82	782709.9
	7.88	521418.5
<i>College</i> × \mathbb{I}_{child}	.02	20749.13
	.26	15317.19
<i>log(wealth)</i>	0	14199.52
	.16	9095.58
<i>Male</i>	-10.14	-142571.6
	6.95	404240.8
<i>age (age > 65)</i>	-0.03	-1628.25
	.05	3074.37
<i>health = 2</i>	-0.12	15937.89
	.41	23780.41
<i>health = 3</i>	12.68	
	635.29	
\mathbb{I}_{child}	-0.14	-9169.25
	.23	12951.32
<i>College</i>	-0.37	-14484.77
	.23	15434.44
<i>Income₂</i>	.36	18182.17
	.35	22317.03
<i>Income₃</i>	.23	16137.72
	.3	16782.75
<i>Income₄</i>	.25	-314.35
	.31	18244.12
<i>Income₅</i>	.11	33009.45
	.33	18499.73
<i>Male</i>	.37	901.97
	.21	12256.99
<i>age (age > 65)</i>	0	22.14
	0	32.64
<i>health = 2</i>	0	-112.46
	0	168.96
<i>health = 3</i>	-0.08	
	4.39	
\mathbb{I}_{child}	0	57.62
	0	97.43
<i>College</i>	0	101.92
	0	114.95
<i>Income₂</i>	0	-136.56
	0	167.12
<i>Income₃</i>	0	-121.97
	0	122.86
<i>Income₄</i>	0	-7.1
	0	134.33
<i>Income₅</i>	0	-243.58
	0	136.76
<i>Male</i>	0	-8.79
	0	90.75
<i>log(wealth) (age > 65)</i>	.09	1974.98
	.11	6482.71
<i>health = 2</i>	-0.26	-2263.24
	.2	12457.69
<i>health = 3</i>	-7.44	
	203.81	
\mathbb{I}_{child}	.2	-11609.16
	.11	6275.52
<i>College</i>	.05	-22809.94
	.13	8492.08
<i>Income₂</i>	-0.02	3367.27
	.16	10117.55
<i>Income₃</i>	-0.162	272.13
	.16	10238
<i>Income₄</i>	.22	9110.46
	.18	10397.79
<i>Income₅</i>	-0.08	19251.01
	.18	10208.37
<i>Male</i>	-0.17	9558.85
	.1	5723.87
<i>Above Median</i>	.25***	1750.89
<i>Life Expectancy</i>	(.10)	(5465.68)

Table B.6: **Validation of Surveyed Annuity Demand Measure:** This table shows how annuity demand is predicted by various covariates. Our measure of longevity is whether an individual's expectation on the probability of living for 10-20 years is above or below median, conditional on current age.

C Exploring the Model Predicted and Stated Demand Gap

In this section we develop an econometric method that utilizes the difference between model estimated and stated demand to identify sources of model mis-specification. As developed in Section 6, ADL insurance demand as predicted by the model can be expressed as D_i . In addition, we assume stated demand can be expressed as a function of the same state variables, denoted S_i . Define η_i as the individual difference between model and stated demand,

$$\eta_i = D_i - S_i$$

Finally, assume that this difference η_i can generally be expressed as a function of modeled state variables x_i , preference parameters Θ_i , and other, undetermined state variables q_i . Thus,

$$\eta = G(x, \Theta, q).$$

G is thus a generic function of our demand measurement error that allows for differences in demand measures from two distinct sources. First, differences in demand measurements could be caused by mis-specification of included model elements as dictated by Θ and x . For example, mis-specification of the functional form of preferences could cause systematic variation in η_i as a function of Θ , while use of incorrect health transition probabilities (which we model only as a function of x) could cause η_i to be dependent upon included state variables gender and age. A second cause of differences in demand measurement could be omission of relevant state variables q from our modeled demands D_i . For example, the model in this paper does not consider the effect of children and family on the saving and insurance purchase decisions. Similarly, private information about individuals' health is omitted from the model but presumably affects stated demand.

Each of these variable sets could affect both measures of demand. Preferences Θ and x are the factors that are modeled, reflecting opinions of the model-builders that they are the relevant variables in stated insurance purchase decisions. Omitted variables q could affect decisions two ways. First, in recovering parameters Θ , SSQ responses are interpreted as being determined by a limited number of factors. Omission of these factors from the model could impact this interpretation and thus affect modeled demand. In addition, stated demand is possibly affected by factors that aren't considered in the model. Given that most factors affect both demand measures simultaneously, it is difficult to determine exactly how each will affect the difference between modeled and stated demand. In general, however, one would expect omitted variables that discourage purchase of insurance products to be associated with lower model differences. Similarly, model mis-specification that encourages demand for insurance products might be associated with larger differences in demand measures. Thus, omitted risks that encourage precautionary holding of liquid wealth should correspond to larger demand differences, while overstated insurable risks should correspond to smaller differences in demand measures.

Returning to the model of demand differences, we assume that G can be approximated as

$$G(x, \Theta, q) \approx g_x(x) + g_\Theta(\Theta) + g_q(q). \tag{C.1}$$

This decomposition assumes that there is no effect on demand differences due to the interaction between

modeled state variables x , estimated parameter set Θ , and omitted variables q . It is thus a first order approximation to the function of interest. The separability of effects of state variable and parameter sets is primarily necessary for tractability. Further examination of this assumption does not appear to change our fundamental conclusions. The separability of omitted variables q and parameter sets Θ or state variables x likely weakens the closeness of our approximation. Given that we are primarily interested in identifying the presence of omitted factors q and not the quantitative effect however, this assumption should not be restrictive. It is only restrictive if the omitted variable q only affects the difference in demand measurements through its interaction with state variables x and Θ .

The assumptions of additive separability provide convenient interpretation. For each function g , $g \neq 0$ implies model mis-specification (relative to stated demands) related to the relevant variables. Thus, $g_x(x) \neq 0$ suggests model mis-specification related to modeled state variables, $g_\Theta(\Theta) \neq 0$ suggests model mis-specification related to preference parameters, and $g_q(q) \neq 0$ suggests model mis-specification related to omitted variables q . Furthermore, $g > 0$ suggests mis-specification that causes model demand to be overstated relative to stated demand, while $g < 0$ suggest mis-specification that causes model demand to be understated relative to stated demand. To estimate this function, we take a non-parametric approach that does not assume any functional form for g_Θ and g_x . Specifically, partition the space of feasible Θ and x into $\mathcal{P}^\Theta = \{P_k^\Theta\}_{k=1}^{K^\Theta}$ and $\mathcal{P}^x = \{P_k^x\}_{k=1}^{K^x}$ respectively. Using these partitions, define vectors $C_i^\Theta \ni \{C_{i,k}^\Theta = 1 \iff \Theta_i \in P_k^\Theta\}$ and $C_i^x \ni \{C_{i,k}^x = 1 \iff x_i \in P_k^x\}$. Finally, defining vectors $\beta_k^\Theta = g(\Theta)$ for any $\Theta \in P_k^\Theta$ and $\beta_k^x = g(x)$ for any $x \in P_k^x$, the functions of interest

$$\begin{aligned} g_\Theta(\Theta_i) &= \beta^\Theta C_i^\Theta \\ g_x(x_i) &= \beta^x C_i^x \end{aligned}$$

are approximated to arbitrary precision for sufficiently fine partitions. Finally, model-omitted variables q are examined one at a time. Given primary interest in the significance and sign of $g(q)$, we approximate g_q with a linear function, such that $g_q(q) = \Gamma q$. Substituting these expressions into equation C.1 yields

$$G(x, \Theta, q) = \beta^\Theta C_i^\Theta + \beta^x C_i^x + \Gamma q_i, \tag{C.2}$$

which we use to estimate

$$\eta_i = \beta^\Theta C_i^\Theta + \beta^x C_i^x + \Gamma q_i + \epsilon_i.$$

Equation C.3 permits testing of the null hypothesis

$$H_0 : \beta^\Theta = 0; \beta^x = 0; \Gamma = 0. \tag{C.3}$$

Rejection of the null hypothesis for β^Θ or β^x suggests that the existing state variables included in our structural model are not incorporated in a way that fully reflects their impact on demand.¹³ Similarly, a positive coefficient on Γ indicates that the variables in q cause the model to overpredict demand, while a

¹³As mentioned when discussing equation C.1, the above specification does not control for effects of the interaction between preferences and modeled state variables. Attempts to control for these effects through inclusion of first order cross-partials of Θ_i and x_i weakens precision of estimates but does not impact significance of other coefficients.

negative coefficient on Γ indicates that the variables in q cause the model to underpredict demand. It is thus reasonable to expect any variables that reflect missing risks or savings motives that are not included in our model to be estimated to have a significant positive coefficient.

To implement this estimation, we must first construct our partitions \mathcal{P}^Θ and \mathcal{P}^x . \mathcal{P}^x is constructed according to the discrete value of all state variables except wealth. Because wealth is continuous, we discretize it according to \$50,000 bins up to \$1,000,000, and \$200,000 bins thereafter. \mathcal{P}^Θ is a partition of continuous valued parameters. We discretize this by sorting individuals into partitions according to whether each parameter is above or below the population median.

C.1 Restricted Sample

This section repeats the gap analysis when the sample is restricted to individuals that do not own LTCI. Results are qualitatively consistent with those presented in Table 12, but estimates are much less precise due to the smaller sample size.

	ADLI difference							
	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>	<u>7</u>	<u>8</u>
$\mathbb{I}_{Transfers}$	4,331							4,383
	(6,672)							(7,116)
\mathbb{I}_{child}		2,660						2,046
		(7,097)						(8,171)
$\mathbb{I}_{Real Estate}$			-3,850					-2,712
			(6,697)					(6,730)
$\mathbb{I}_{College}$				-6,720				-6,243
				(6,478)				(6,805)
$\mathbb{I}_{Comp. Test}$					-6,102			-4,838
					(7,102)			(7,280)
$\mathbb{I}_{Family Care}$						547		-452
						(6,574)		(6,952)
$\mathbb{I}_{ADL help}$							-7,732	-6,943
							(6,021)	(6,086)

Table C.1: **Omitted Considerations, ADLI:** This table presents the Γ coefficient on each indicated variable from estimation of equation 7 for households that do not own LTCI. The coefficients on β^x and β^Θ are omitted, but in all estimations these coefficients are jointly significant at the 1% level. Standard Errors are included in parentheses.

C.2 Details of Covariates

This section provides summary statistics of the covariates used in the regressions presented in Section 7.3 and the tables included in this appendix.

	<u>Mean</u>	<u>Median</u>	<u>St. Dev.</u>
Total Transfers	12,762	2,500	20,068
Children	1.62	2	.47
Home Value	234,056	180,000	273,826
College Educated	0.74	1	0.44
Comprehension Test Correct	20.74	22	3.32
Prob. Family Provides ADL Care	0.20	0.10	0.26
Prob. Needing Help with ADLs >1 year	0.46	0.45	0.30

Table C.2: **Covariate Summary Statistics:** This table provides summary statistics for variables used to construct the covariates analyzed in Table 12.