

Long-term Care Insurance, Annuities, and the Under-Insurance Puzzle

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Abstract

Recent research suggests that costly private long-term care introduces a strong precautionary saving motive for individuals late in life. This finding suggests significant demand for long-term care insurance (LTCI) that seems at odds with observed low holdings of private LTCI. This paper develops two different methods to measure demand for a type of LTCI that addresses many flaws of the products typically available in the market. The first uses a structural life-cycle model to estimate demand for each survey respondent as a function of individual-specific preferences and state variables. The second is derived from a survey-based measure of stated desire to purchase. Both imply demand higher than observed private LTCI holdings. The difference between model and stated demand is large, positive, and suggests missing motives in the model related to intergenerational transfers. Similar patterns hold in an analysis of annuity demand.

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1 Introduction

Recent research suggests that costly private long-term care introduces a strong precautionary saving motive for individuals late in life. Although this implies that demand for long-term care insurance (LTCI) should be high, less than 10% of the population holds private LTCI (Lockwood (2014)). Unfortunately the long-term care insurance products that are available in the market are far from ideal due to default risk, possible increases in future premia, high loads, and a potentially adversarial claims process. It is unclear whether these features are the primary cause of low observed LTCI purchases or whether insurance against the need for long-term care is not highly valued. Desirable LTCI products may not only be of private value, but also of great public value, since provision of government provided care is placing ever-increasing pressure on public finances (Brown and Finkelstein (2008), Brown, Goda, and McGarry (2013)). Better understanding of the determinants of LTCI demand is necessary for identifying the potential gains from improved public or private insurance options.

This paper develops two distinct measures of demand for a type of long-term care insurance that addresses many flaws of the products typically available in the market. Demand is measured for a relevant population of older wealthholders from the newly created Vanguard Research Initiative (VRI). First, we estimate demand using a structural life-cycle model that features a flexible specification of preferences. We develop survey-based methods that enable estimation of person-specific preference parameters, which give rise to model-estimated demand for insurance products for each survey respondent. The second estimate of demand is derived from a survey-based measure of stated desire to purchase. In addition, we measure subjective expectations related to health and longevity. Stated demand is estimated to be particularly high for those who expect longer stays in long-term care facilities and who regard public long-term care to be of particularly low quality relative to private care.

For both measurements demand is higher than observed private LTCI holdings might suggest. However, directly elicited demands are significantly lower than are the model-based estimates. One possible reason for this divergence may be lack of respondent familiarity with the product on offer. Since the LTCI products currently available in the market have many characteristics that make them undesirable, we ask about a type of LTCI called “Activities of Daily Living Insurance” (ADLI), an Arrow security that pays out automatically whenever the policy holder has difficulties with such activities as eating, dressing, bathing, walking across a room, etc. While steps were taken to test and shore up comprehension of this hypothesized product, unfamiliarity may nevertheless reduce stated demand.

That unfamiliarity may not be the whole story is revealed by considering an insurance product with which many in our sample are familiar: annuities. When we use our model to estimate demand for actuarially fair annuities, we similarly find high demand by many individuals. When we compare these estimates with stated demands, we find that the model overpredicts by an even greater margin. The vast majority of respondents express little to no interest in actuarially fair annuities despite the estimated model predicting high such demand.

In combination, the results indicate that there is an “under-insurance” puzzle. There appears to be far lower interest in insurance of late in life spending risks than current models predict. This lower than model-predicted level of interest in insurance among older asset holders raises the possibility our model is mis-specified. To study potential model mis-specification, we develop an econometric method that compares

model and stated demand to identify causes for the differences in the demand measures. This method is applied to test how the restricted modeling of inter-generational linkages affects the estimates of demand.

While many forms of inter-generational altruism have been modeled in the theoretical literature, the model we use in estimating demand follows the standard approach in the quantitative literature of capturing bequest motives with a “warm glow” bequest utility function (De Nardi (2004)). In practice it is understood that, in addition to leaving bequests, many people make significant inter-vivos transfers to their children and other dependents (McGarry (1999)). We measure such inter-vivos transfers in our sample, and find evidence that they contribute significantly to the difference between model implied and stated demands. Looking separately at ADLI and actuarially fair annuities, we find that those who have in the past made transfers to their family have particularly low stated demand relative to model-based demand. This suggests that an unmodeled motive or risk related specifically to intergenerational transfers contributes to the large difference in our demand measurements. Hence modeling missing intergenerational motives may be important if we are to better understand potential demand for modified insurance products.

As the above makes clear, this method for estimating individual specific model-implied demand and testing the specification of life-cycle models is survey-based. Key to the tests are “strategic survey questions” (SSQs) that enable estimation of model parameters at the individual level.¹ These questions ask respondents to specify behavior in detailed scenarios that are particularly revealing of preference parameters. Each SSQ corresponds to a simple optimization problem, and survey responses can be mapped to optimal policies to identify preference parameters. Estimating heterogeneous preferences is essential for understanding behavior. Early simple structural models failed to match statistics of the empirical distributions of asset and insurance product holdings, leading to so-called “puzzles.” More recent research that builds richer models of institutional features, risks, and motives still generate puzzles, and non-structural statistical analysis suggests conditioning on more observables still leaves a large fraction of the variation in the data unexplained. Thus, a large amount of behavior seems to be explained by unobservables, with preferences being a leading candidate. A problem we address with SSQs is that almost any behavior can be explained with complete freedom to set preferences and there is little other data available to jointly discipline preferences and behavior. See Koijen, Van Nieuwerburgh, and Yogo (2015) for more on this issue and a different approach to estimating heterogeneous preferences by explicitly targeting insurance product holdings. This method of using SSQs to estimate preferences and comparing model based and measured stated demands is applicable to a wide range of problems.

Section 2 introduces the model that we estimate in the paper and provides background material on the long-term care insurance and annuity markets. 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 parameter estimates. Section 6 derives model-based and stated preference estimates of demand for ADLI. Section 7 re-estimates both demand measures for actuarially fair annuities. Section 8 demonstrates the impact of family transfers on the gap between model and stated demand estimates. Section 9 concludes.

¹Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011), Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015)) use such questions in more aggregated form, while Barsky, Juster, Kimball, and Shapiro (1997) pioneered the use of surveys to identify individual preferences.

2 Background

Model

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. 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 (see Gourinchas and Parker (2002) for 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, while De Nardi, French, and Jones (2010) allows persistent health expense risk, with all finding that health expenses introduce a significant precautionary saving motive. Bequests have long been accepted as an important saving motive, with Kotlikoff and Summers (1981) and Hurd (1989) modeling and estimating their contributions to wealth accumulation. De Nardi (2004) introduced a flexible end of life bequest functional form, and estimated a luxury bequest motive individuals with large resources. This modeling strategy has been more recently adapted in De Nardi, French, and Jones (2010), Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011), and Lockwood (2014), with similar qualitative conclusions. Lupton and Kopczuk (2007) identifies a similar motive amongst those without children, further suggesting bequest motives to be more broadly important for savings.

A feature that is increasingly recognized as important in the literature concerns health state utility. Finkelstein, Luttmer, and Notowidigdo (2013) highlights the importance of this dependence in savings patterns, while Kojien, Van Nieuwerburgh, and Yogo (2015) and De Nardi, French, and Jones (2010) estimate a lower marginal utility when in poor health. In other work using the VRI data set, Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015) allow for a separate utility when an individual is in need of long-term care and find precautionary motives associated with LTC to be significantly more important than bequest motives as drivers of late in life saving behavior. Saving motives driven by LTC are active for individuals with less than \$50,000 in annual income and wealth less \$400,000 (a large majority of the U.S. population). By contrast, the estimated bequest utility parameters suggest that the corresponding motive contributes only modestly to late in life savings.

Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015) estimate a common set of preference parameters for the entire population. In the current paper we take advantage of the richness of the data in the VRI to estimate parameters of this model at the individual level. An outline of this model is presented below, while the consumer decision problem is included in Appendix A.

The model considers consumers who are heterogeneous over wealth, income age-profile, age, gender, initial health status ($s \in \{0, 1, 2, 3\}$), and preferences. The health and health cost state evolves according to a Markov process conditional on age, gender, and prior health status. Consumers start at age t_0 and live to be at most $T-1$ years old, where in our parameterization t_0 corresponds with age 55 and T corresponds with age 108. Each period, consumers choose ordinary consumption ($c \in [0, \infty)$), savings (a'), expenditure when in need of long-term care ($e_{LTC} \in [\chi, \infty)$), and whether to use government care ($G \in \{0, 1\}$). The model groups consumers into five income groups with deterministic age-income profiles.² Each consumer has

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

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 Appendix D.2 shows 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 ($s \in \{0, 1\}$), consumers value consumption according to standard CRRA preferences with parameter σ . Utility when in need of LTC ($s = 2$) associated with expenditure level e_{LTC} is

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

Capturing the fact that LTC provision is essential for those in need and private long-term care is expensive, there is a minimum level of expenditure needed to obtain private LTC, i.e., $e_{LTC} \geq \chi_{LTC}$. Finally upon death ($s = 3$), the agent receives no income and pays all mandatory health costs. Any remaining wealth is left as a bequest, b , which the consumer values with warm glow utility

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

Both ADL state and bequest preferences 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 seen as 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 not in the ADL state ($s = 1$ or 2) the government provides a consumption floor, $c = \omega_G$. A consumer who needs LTC ($s = 2$) has access to government-provided care is loosely based on the institutions of Medicaid. If a consumer needs LTC and uses government care, the government provides $e_{LTC} = \psi_G$. The value ψ_G parameterizes the consumer's value of public care, since that parameter essentially determines the utility of an individual who needs LTC and chooses to use government care. There is no borrowing, and the retiree cannot leave a negative bequest.

The Long-term Care Insurance Market

The type of long-term care insurance product we describe in the VRI and use in our modeling is very different from prevailing forms of long-term care insurance available on the private market. Currently, the typical structure of LTC policies involves consumers paying periodic premiums in exchange for an insurer's promise to reimburse certain LTC-related expenses, under certain conditions, subject to certain (generally restrictive) limits. For example, Brown and Finkelstein (2011) define a typical purchased policy "as a policy that covers institutional and home care with a 60-day deductible, a four-year benefit period, and a \$150 maximum daily benefit with a 5 percent per year escalation rate." They estimate that such a policy could potentially cover only two-thirds of the expected present discounted value of LTC expenses at age 65.

Beyond these basic limitations, there are several design features of existing, real-world LTC policies that

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

may make them unattractive from a consumer point of view. For example, while most policies are “guaranteed renewable,” LTC policy holders are subject to the important risk of an increase in required premium rates to maintain continuing coverage. If they cannot pay higher rates, they can lose their coverage. Insurers cannot raise premiums on individual LTC policies in isolation, but, subject to regulatory approval, they can increase (and in several well-publicized changes have increased) rates for groups or “classes” of policyholders to reflect errors in actuarial underwriting assumptions or other factors. In addition, policy benefit triggers, especially for tax-qualified LTC policies, can be restrictive. Stallard (2011) (as cited in Rubin, Crowe, Fisher, Ghaznaw, McCoach, Narva, Schaulewicz, Sullivan, and White (2014)) “finds that about half of [the elderly] disabled population does not meet the eligibility requirements for tax qualified LTC insurance policies due to not satisfying either HIPAA’s ADL trigger definitions or its cognitive impairment trigger.” Finally, LTC insurance may be subject to significantly higher cost loads than are typical for life annuities or other forms of insurance. Brown and Finkelstein (2011) estimate loads (costs) of 32 cents per dollar of hypothetical, actuarially fair benefits. For all of these reasons, we believe there to be quite significant differences between the hypothetical product described in our work and the real-world options generally available to consumers.⁴

The Annuity Market

Insurance contracts offering fixed nominal or, less commonly, fixed inflation-adjusted life annuities are currently available for purchase in private markets. Brown, Mitchell, Poterba, and Warshawsky (2001) describe many of the relevant institutional details of the immediate annuity market in the U.S. Current annuity products and providers can be found using a simple internet search for “retirement income”.

Indicative pricing of such contracts is available from services such as ImmediateAnnuities.com. Given the wide availability of annuity products, the reasons why they are so little used by retirees remain puzzling to many economists (the issue is well summarized in Warshaswksy (2013), Chapter 3)).

A natural explanation of low demand for annuities would be high price. Study of the typical cost of annuities available in the private market relative to hypothetical, actuarially fair versions was first undertaken by Friedman and Warshawsky (1988) and Friedman and Warshawsky (1990). Others have revisited and updated these estimates. Mitchell, Poterba, Warshawsky, and Brown (1999) report the ratio of actually available annuity payouts to hypothetical actuarially fair equivalents of roughly 0.85-0.95. While such costs are not insignificant, there is general consensus that such loads would not significantly impact demand in a standard life-cycle framework. Other than pricing deviations, the only significant dimension of difference between the hypothetical annuity contract we describe in our modeling and questions and one currently available in the market is that a completely risk free annuity is not attainable in the real world. We maintain that neither of these sets of issues represents a significant material difference between annuity contracts available publicly and the hypothetical version we describe to panelists and use in our modeling.

⁴This calls into question the ability to use financial choices to infer motives. In general, recovery of utility parameters from such choices rests on strong identifying assumptions regarding product features and consumer information.

3 The VRI and the Survey Instruments

3.1 The Sample

This paper draws on the newly developed Vanguard Research Initiative (VRI). Respondents are Vanguard clients 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.⁵ 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. As detailed below, 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.

As of August 2014, the VRI consists of three completed surveys (see <http://ebp-projects.isr.umich.edu/VRI/sur> for links to all three surveys). 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.

We make essential use in this paper not only of the data from VRI survey 1, but also from VRI surveys 2 and 3. VRI 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. VRI 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 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 though 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. Key statistics of the sample used in this paper is presented in in Table 1.

⁵In these interviews, respondents are shown Internet survey instruments and given in-person interviews to assess their comprehension: see Section 4 for further details.

Wealth Levels	Mean	10p	25p	50p	75p	90p		
Full Sample	745,274	115,000	271,720	543,191	1,012,263	1,587,400		
Employer Only	557,026	52,473	168,150	392,926	836,400	1,161,000		
Demographics		Education		Health			Gender	
	Sample Size	No College	College or higher	Poor\ Fair	Good	Very Good\ Excellent	Male	Female
Full Sample	1087	25.7%	74.3%	5.2%	22.5%	72.2%	44.3 %	55.7%
Employer Only	162	37.7%	62.3%	4.3%	29.0%	66.7%	54.9%	45.1%

Table 1: **Characteristics of Final Sample:** 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 necessary survey questions to produce all estimates needed in this paper. In addition, this table presents details from our employer subsample. This sample not only meets the above requirements, but also entered Vanguard through an employer sponsored plan.

3.2 Stated Demand for Insurance

As indicated above, VRI survey 2 includes stated preference questions on the demand for improved long-term care insurance. The challenge in gathering this demand is that, by definition, it concerns a form of insurance that is not available in the market place. The demand questions were therefore preceded by a definition of the health state that is commonly regarded as provoking need for long-term care. We define this in the survey as needing significant help with the activities of daily living (ADLs) such as “eating, dressing, bathing, walking across a room, and getting in or out of bed.” To reinforce, we make this definition available in a hover button whenever *ADL appears. As detailed in Section 4, we test subject comprehension of this definition prior to gathering information on demand for insurance.

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.

Note that typical risks associated with insurance products available in the market are absent by design. For example, we state explicitly that payouts are determined by an impartial third party to remove concerns about the receipt of money and the claims process. We also provide an associated hover button whenever ADL insurance is mentioned that refers to it as: “An insurance policy that pays benefits in any month in which the policy holder needs help with ADLs. The cash benefits are immediately available to the policyholder to be used for any purpose.”

When gathering stated demand information, we price the product 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. Responses to these questions are considered in Section 6.

Our 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. Responses are analyzed in Section 7.

Strategic Survey Questions

SSQs 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 LTC and leaving a bequest, starting with the introduction of the subject of interest and the scenario itself.

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.

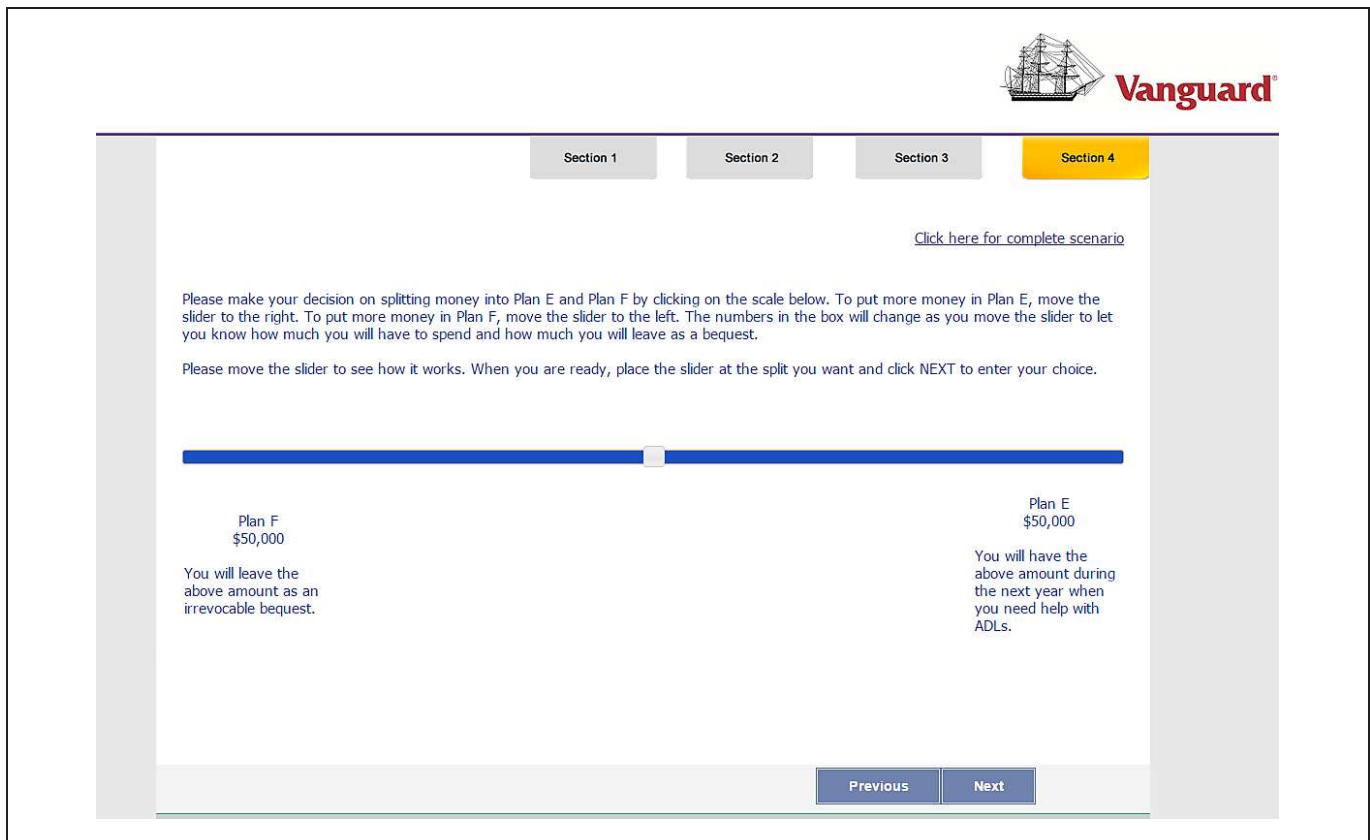
- Plan E is reserved for your spending. From Plan E, you will need to pay all of your expenses, including long-term care and any other wants, needs, and discretionary purchases.
- Plan F is an irrevocable bequest.

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 measure comprehension, 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, the nature of the claims process, etc. 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, as well as what their allocation implies. The exact presentation can be seen in the frame below:



The screenshot shows a survey interface with four sections at the top: Section 1, Section 2, Section 3, and Section 4 (highlighted in yellow). A link "Click here for complete scenario" is located below the sections. The main content area contains the following text:

Please make your decision on splitting money into Plan E and Plan F by clicking on the scale below. To put more money in Plan E, move the slider to the right. To put more money in Plan F, move the slider to the left. The numbers in the box will change as you move the slider to let you know how much you will have to spend and how much you will leave as a bequest.

Please move the slider to see how it works. When you are ready, place the slider at the split you want and click NEXT to enter your choice.

A horizontal slider is shown with a white handle. Below the slider, the following information is displayed:

Plan F
\$50,000
You will leave the above amount as an irrevocable bequest.

Plan E
\$50,000
You will have the above amount during the next year when you need help with ADLs.

At the bottom of the interface, there are two buttons: "Previous" and "Next".

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.

Having spent such a long time setting up the scenario and aiding comprehension, we stayed within the scenario and 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 LTC. 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 test questions. The results of these tests are summarized in the next section.

As noted above, 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 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,

	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) $W = \$50K, \pi = 0.75$	$\sigma, \theta_{LTC}, \kappa_{LTC}$
SSQ 3	Allocation between ADL and bequest states	ADL expenditure and bequest	(a) $W = \$100K$ (b) $W = \$150K$ (c) $W = \$200K$	$\sigma, \theta_{LTC}, \kappa_{LTC}$ $\theta_{beq}, \kappa_{beq}$
SSQ 4	Indifference between public and private LTC	ADL expenditure and bequest	(a) Public Care Available	$\sigma, \theta_{LTC}, \kappa_{LTC}$ $\theta_{beq}, \kappa_{beq}, \psi_G$

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.

we posed specific questions about each SSQ, with broadly encouraging and informative results. Aggregate versions of the iModerate style questions were posed after respondents had completed the production survey. Results are presented in Section 4.

3.3 Transfer and Other

In the analysis that follows we make use of many data items in addition to those identified above. Specifically, from VRI 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 LTC insurance. From VRI Survey 3 we use data on family transfers (see Section 8), 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.

4 Credibility of 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 the ADLI questions, there were 6 such questions in total. More than 50 percent 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 error 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.

	ADLI	SSQ 1	SSQ 2	SSQ 3	SSQ 4
Number of questions	5	6	9	3	2
All correct, 1 st try	57.9%	46.3%	18.6%	55.4%	77.3%
All correct, 2 nd try	81.9%	75.1%	55.5%	81.9%	94.1%
≤ 1 wrong, 2 nd try	94.4%	93.4%	80.8%	96.2%	99.5%

Table 3: **Responses to SSQ test 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?	
Response	Percent	Response	Percent	Response	Percent
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: **Survey Comprehension Questions:** Each respondent was asked each of the three questions presented above. Response statistics are recorded for each.

4.2 Respondent Feedback and SSQ Design

As indicated above, broad questions on responses to the SSQs were placed at the very end of the production survey. As shown in Table 4, the results are broadly encouraging. Nearly 90% of respondents found the tradeoffs either very clear or somewhat clear. Furthermore, more than 80% indicated that they placed 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% had given the underlying issues at least a little thought before taking the survey.

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. As indicated, these questions came in distinct blocks. When changing the allocation within a scenario, internal coherence would require a strong positive correlation in responses. 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.

	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. Responses are grouped by SSQ. Of key interest are the correlations between SSQs of the same type.

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. As noted above, 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 variations indicate systematic patterns in responses. Most respondents allocate almost all of their portfolio to the ADL state when wealth is \$100,000, about 2/3 to the ADL state when wealth is \$150,000, but only about half when wealth is \$200,000, as illustrated in Figure 1.

In addition to being internally coherent, another measure of validity comes from checking whether individual responses to SSQs are predicted by behaviors 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.

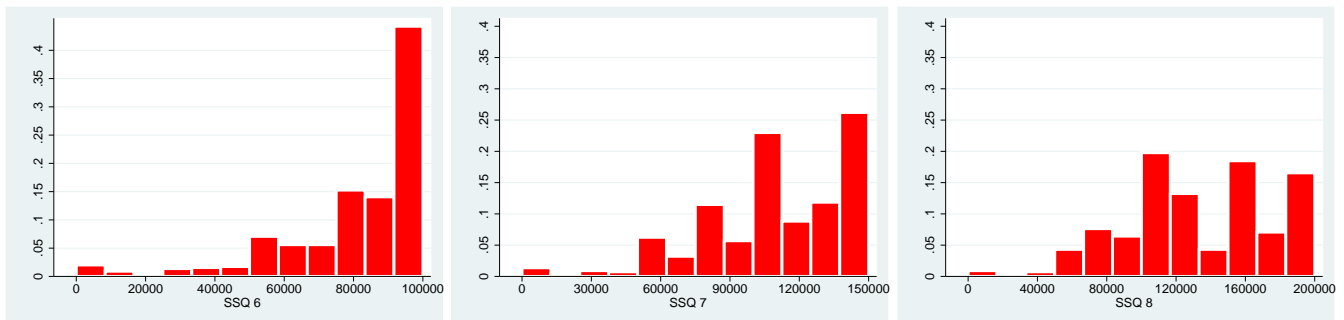


Figure 1: **SSQ 3 Response Distributions:** We ask SSQ 3, the SSQ presented in the section above, for wealth values of \$100,000, \$150,000, and \$200,000. The response distributions are presented above in this order.

		SSQ 3a	SSQ 3b	SSQ 3c
$(age > 65)$		1.30e5 (0.59)	-3557.638 (0.99)	49607.993 (0.89)
$health = 2$		2.63e05 (0.37)	7.68e5* (0.03)	1.06e06* (0.02)
$health = 3$		2.49e5 (0.57)	4.58e5 (0.33)	-1.75e5 (0.76)
\mathbb{I}_{child}		-2.82e5 (0.09)	-2.90e5 (0.14)	-3.33e5 (0.17)
College		-1.02e5 (0.36)	49332.720 (0.70)	50321.901 (0.75)
College $\times\mathbb{I}_{child}$		9935.221 (0.11)	8621.403 (0.23)	5549.966 (0.54)
$age \times$	$(age > 65)$	-4348.725 (0.52)	-2226.858 (0.78)	-4281.466 (0.67)
	$health = 2$	-7699.025 (0.33)	-2.26e4* (0.02)	-3.11e4** (0.01)
	$health = 3$	-8761.577 (0.48)	-1.79e4 (0.17)	556.269 (0.97)
	\mathbb{I}_{child}	8080.385 (0.11)	9485.066 (0.10)	11764.178 (0.11)
	College	2712.858 (0.38)	-804.234 (0.83)	-1059.120 (0.82)
$age^2 \times$	$age > 65$	34.136 (0.48)	20.490 (0.72)	31.259 (0.66)
	$health = 2$	51.153 (0.33)	147.686* (0.02)	204.916** (0.01)
	$health = 3$	72.035 (0.38)	120.549 (0.16)	11.500 (0.91)
	\mathbb{I}_{child}	-57.775 (0.12)	-68.353 (0.12)	-85.804 (0.12)
	College	-24.277 (0.28)	-0.875 (0.97)	4.075 (0.90)
$log(wealth) \times$	$(age > 65)$	702.512 (0.73)	4881.074* (0.04)	7611.172** (0.01)
	$health = 2$	1851.048 (0.68)	6277.758 (0.24)	8181.801 (0.22)
	$health = 3$	-185.238 (0.98)	14533.872 (0.12)	5979.731 (0.60)
	\mathbb{I}_{child}	-1563.677 (0.41)	-4817.499* (0.03)	-7320.232** (0.01)
	College	2217.297 (0.19)	509.498 (0.80)	-59.311 (0.98)
Reported Average ADL Care Cost		0.031 (0.13)	0.054* (0.03)	0.064* (0.03)

Table 6: **External Verification of SSQs 3:** This table presents the results from a tobit regression of SSQ 3 responses on the listed covariates.

Note that having children is a strong predictor of allocating less money to the ADL state, as might be expected based on likely differences in underlying bequest motives. We also observe evidence that individuals who believe ADL costs are larger 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 in the SSQ scenario. Appendix B.1 documents that fundamental internal and external consistency conditions hold for the other three SSQs as well.

5 Parameter Estimates

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 parameterizations. This is in contrast to Barsky, Juster, Kimball, and Shapiro (1997) and Kimball, Sahm, 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, Sahm, 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 a 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

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

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

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

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.

Formal 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_{LTC} , and κ_{LTC} determine responses to SSQs 1 and 2, and identification of these parameters rests largely on these questions. The 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:

$$\begin{aligned} \max_{z_3^1, z_3^2} & \theta_{LTC} \frac{(z_3^1 + \kappa_{LTC})^{1-\sigma}}{1-\sigma} + \theta_{beq} \frac{(z_3^2 + \kappa_{beq})^{1-\sigma}}{1-\sigma} \\ \text{s.t.} & z_3^1 + z_3^2 \leq W \\ & z_3^1 \geq 0; z_3^2 \geq 0. \end{aligned} \quad (3)$$

The optimal allocation rule is given by

$$z_3^1 = \begin{cases} 0 & \text{if } \theta_{bequest}(W + \kappa_{beq})^{-\sigma} - \theta_{LTC}(\kappa_{LTC})^{-\sigma} > 0 \\ W & \text{if } \theta_{LTC}(W + \kappa_{LTC})^{-\sigma} - \theta_{bequest}(\kappa_{beq})^{-\sigma} > 0 \\ \frac{\left(\frac{\theta_{bequest}}{\theta_{LTC}}\right)^{-1/\sigma} (W + \kappa_{beq})^{-\kappa_{LTC}}}{\left(+\left(\frac{\theta_{bequest}}{\theta_{LTC}}\right)^{-1/\sigma}\right)} & \text{otherwise} \end{cases} \quad (4)$$

Conditional on σ , θ_{LTC} , and κ_{LTC} , 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 3 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.⁶

5.2 Parameter Estimates

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.⁷ Comparison with the bottom row does, however, show consistency in qualitative patterns. Furthermore, previous estimates with homogenous preferences are contained between the 25th – 75th percentiles of the estimated parameter distribution. The median marginal estimates suggest a relative risk aversion parameter $\sigma = 4.52$, LTC expenditure as a necessity ($\kappa_{LTC} < 0$) with high marginal valuations ($\theta_{LTC} > 1$), bequests as a 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.⁸

The parameter sets are reasonably well identified. The individual component of the response error ($\bar{\sigma}$) is estimated to be between 0 and .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 LTC 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

⁶The parameters ω_G and β are not identified by any of the SSQs, and thus are calibrated to standard values from the literature.

⁷Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015) estimates a single population parameter set and matches both SSQ and wealth moments.

⁸To 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: $\frac{\bar{\psi}^{1-\sigma}}{1-\sigma} = \theta_{LTC} \frac{(\psi_G + \kappa_{LTC})^{1-\sigma}}{1-\sigma}$.

Marginal Distribution of Parameters

	σ	θ_{LTC}	κ_{LTC}	θ_{beq}	κ_{beq}	ψ_G
10%	2.04	<0.01	-82.44	<0.01	3.23	19.97
25%	3.02	0.05	-50.65	0.04	11.70	39.75
50%	4.52	2.14	-9.45	17.89	125.72	59.99
75%	6.74	99.45	46.23	108.33	362.64	99.87
90%	10.11	>1000	148.81	>1000	781.45	178.34
Median Standard Errors	.13	.98	10.71	1.37	18.44	.35
Ameriks, et.al 2015	5.85	1.57	-45.65	0.59	7.88	85.11

Correlations of Parameters

	σ	θ_{ltc}	κ_{ltc}	θ_{beq}	κ_{beq}	ψ_G
σ	1.00					
θ_{ltc}	0.24	1.00				
κ_{ltc}	-0.10	0.34	1.00			
θ_{beq}	0.21	0.05	0.15	1.00		
κ_{beq}	-0.14	-0.06	0.30	0.21	1.00	
ψ_G	0.11	0.15	0.19	0.04	0.05	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.

monetary equivalent to the public care option.

6 ADLI Demand

6.1 Model-Based Calculation

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% annual return. Actuarially fair is defined such that the agent selling this product makes zero expected profit. Actuarially fair pricing requires the further assumption that health transitions are common amongst all agents as calculated from the 1996-2010 HRS.⁹ 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 any error in demand measurement caused by parameter mismeasurement and yields an unbiased estimate of demand. For the remainder of the paper, all reported demands and summary statistics reflect these unbiased estimates.

6.2 Model-Based ADLI Demand

When we calculate ADLI demand for each individual in our sample, we find that 37.2 percent of respondents have no interest whatever. For those who have interest, the resulting demand is presented in Figure 2. The largest category comprises those who demand between \$0 and \$100,000 of income in any year in which they need assistance with ADLs, although a non-trivial number demand significantly more.

Heterogeneity in estimated ADLI demands in our sample derives in large part from differences in preferences. Table 8 presents the mean and median parameter sets for individuals that are estimated to have positive or zero ADLI demand. Note first that respondents estimated to purchase ADLI are significantly more risk averse than those that do not, consistent with the standard relationship between risk aversion and insurance demand. We find also that individuals who purchase ADLI have a much stronger preference for expenditure when in the ADL state. In fact, these individuals have a median κ_{LTC} of -16.25 compared to 7.31, meaning that individuals we estimate to purchase ADLI are more likely to view ADL state expenditure as a necessity. Furthermore, the marginal utility multiplier θ_{LTC} is significantly larger for those that purchase ADLI, with a median value 4.66 as opposed to 0.53. Purchasers also unambiguously assign a lower valuation

⁹See Online Appendix: Estimation for details of the calculation of health transition functions.

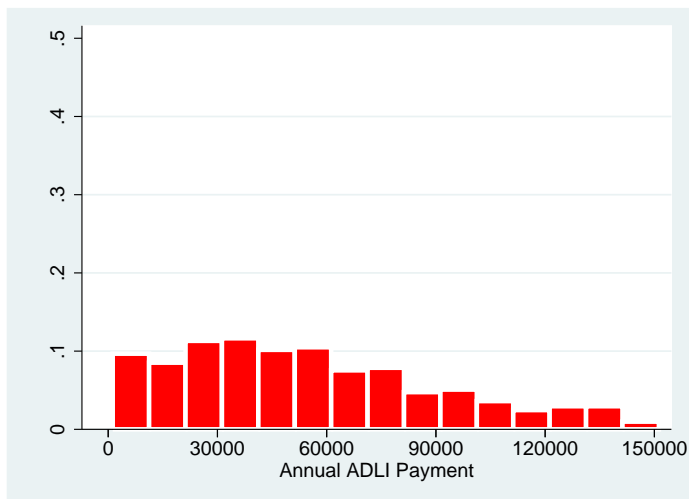


Figure 2: **Model Implied ADLI Demand:** This figure presents the level of ADLI income demanded for our those individuals that our model estimates to have positive demand. We omit the 32.1 percent of individuals for whom demand is zero.

		ADL Insurance Demand					
		σ	θ_{LTC}	κ_{LTC}	θ_{beq}	κ_{beq}	ψ_G
Don't Buy	Mean	4.25	131.68	32.94	312.79	319.08	58.85
	Median	3.69	.53	7.31	11.33	236.19	39.99
Buy	Mean	5.73	236.82	-20.06	393.71	162.70	44.98
	Median	4.95	4.66	-16.25	24.93	75.98	25.02

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.

to a free government care option, ψ_G , as would be expected. Similar such patterns hold for mean parameter values.

Effects of the bequest motives on ADLI purchases are theoretically ambiguous. On one hand, bequests decrease desire for insurance, as bequests increase the value of liquid wealth at the end of life. However, ADLI also insures the estate against being depleted by large expenditures when in the ADL state, so this product also partly insures bequests. The estimates support the second motive as being dominant, as individuals that are estimated to purchase ADLI have stronger bequest motives. When comparing median κ_{beq} for those that we estimate do and do not purchase ADLI, the lower values, 75.98 as opposed to 236.19, suggest that individuals that do purchase ADLI view bequests as less of a luxury good. In addition, we find that θ_{beq} is larger for those that purchase ADLI (24.93) than those that do not (11.33), implying a higher marginal valuation. Again, similar such patterns hold for mean parameter values.

6.3 Stated ADLI Demand

Our second measure of ADLI demand is derived from the survey instrument described in Section 3.2. As described therein, respondents are first asked whether they would like to purchase any amount of this product,

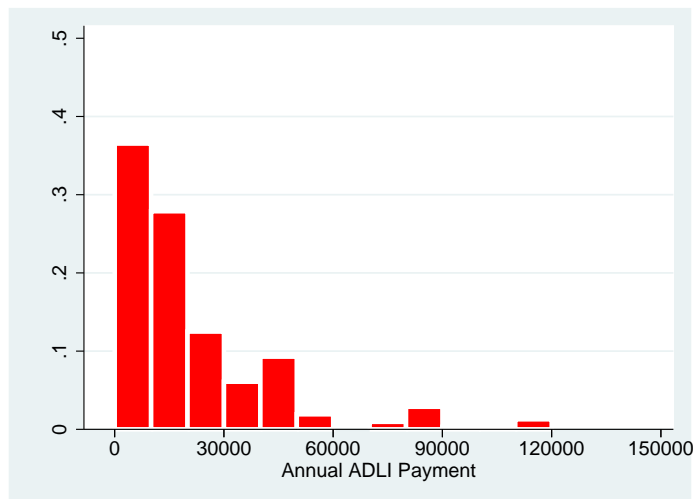


Figure 3: **Surveyed ADLI Demand:** This figure presents the level of stated ADLI income demanded for our those individuals that indicated positive demand. We omit the 71.2 percent of individuals for whom stated demand is zero.

to which 29.2 percent answer affirmatively. They are then asked how much they would purchase, generating the demand distribution presented in Table 10. Note that 40 percent of respondents reporting positive demand indicate a desire to purchase more than \$20,000, while the 95th percentile of the demand distribution is \$42,000.

In Table 9 we examine how stated demands correlate with demographic and economic characteristics, as well as other survey measures. Specifically, “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. If a variable indicates a higher preference for wealth in the ADL state, it should have a significant, positive coefficient in one or both of these regressions.

In the first column, we conduct a probit estimation of the purchase decision as a function of other survey measures. Here we find that respondents who report higher probabilities of experiencing extended time in the ADL state are more likely to purchase. 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. We see this more strongly when examining the level of purchases in the second column, as such individuals purchase \$2,500 less. Few demographic variables (other than male) are significant, likely reflecting actuarially fair pricing conditional on gender, age, and health status.

6.4 Comparison of Estimates

The above section suggests that ADLI demand as modeled is demanded by 67.9 percent of individuals, while only 29.2 percent of surveyed individuals state they would purchase the same product. Furthermore,

		$\mathbb{I}_{ADLI>0}$	Annual ADLI Income
<i>age</i> > 65		-1.165 (0.91)	1.35e5 (0.36)
<i>health</i> = 2		-25.866 (0.15)	-9.33e4 (0.60)
<i>health</i> = 3		-924.201 (0.97)	-1.99e5 (0.41)
\mathbb{I}_{child}		5.061 (0.47)	-1.17e5 (0.24)
College		0.838 (0.86)	1.11e5 (0.10)
College $\times\mathbb{I}_{child}$		-0.121 (0.63)	-185.539 (0.96)
<i>age</i> \times	<i>age</i> > 65	0.076 (0.80)	-3522.618 (0.39)
	<i>health</i> = 2	0.698 (0.14)	2507.131 (0.60)
	<i>health</i> = 3	23.840 (0.97)	5695.019 (0.40)
	\mathbb{I}_{child}	-0.174 (0.41)	3263.831 (0.28)
	College	-0.023 (0.87)	-3538.212 (0.07)
<i>age</i> ² \times	<i>age</i> > 65	-0.001 (0.76)	22.631 (0.44)
	<i>health</i> = 2	-0.005 (0.15)	-14.108 (0.66)
	<i>health</i> = 3	-0.156 (0.97)	-37.455 (0.40)
	\mathbb{I}_{child}	0.001 (0.43)	-22.773 (0.31)
	College	0.000 (0.80)	24.901 (0.07)
$\log(wealth)\times$	$\ln wealth_{(age > 65)}$	-0.076 (0.37)	-97.287 (0.94)
	<i>health</i> = 2	-0.064 (0.74)	-1082.721 (0.70)
	<i>health</i> = 3	1.582 (0.99)	-1203.653 (0.80)
	\mathbb{I}_{child}	0.079 (0.33)	123.723 (0.92)
	College	-0.036 (0.61)	961.193 (0.36)
Reported Average ADL		0.000	0.032
Care Cost		(0.45)	(0.07)
Ranking Public to Private		-0.089	-2400.321**
ADL Facility (1-5)		(0.13)	(0.01)
Probability Years Needing		0.005**	24.346
	Help with ADLS>3	(0.00)	(0.33)

Table 9: **Validation of Surveyed ADL demand measurement:** This table presents how stated ADLI purchases are predicted by other covariates. Column 1 presents the results of a probit regression of the ADLI purchase decisions, and column 2 presents a tobit regression on the level of ADLI income demanded. P-values are included in parentheses.

	ADLI							
	mean	p5	p10	p25	p50	p75	p90	p95
Modeled Demand	44,245	0	0	1,669	25,215	68,636	117,331	153,441
Stated Demand	7,179	0	0	0	0	6,000	24,000	42,000
Simulated-Ideal	37,047	-18,200	-6097	0	19,976	61,949	109,748	144,231

Table 10: **Distribution of Differences in ADLI Demand:** This table presents the distribution of each of the ADLI demand measures. 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.

in comparing the distributions of demand presented in Rows 1 and 2 of table 10, 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. Thus, at the aggregate level, the model over-predicts demand for ADL insurance, for both the purchase decision and the level purchased. With regard to whether or not to purchase, one potential reason for the large gap is that pre-existing LTC insurance holdings may have caused individuals that would otherwise desire ADLI not to demand any more. When we include those individuals with prior LTC coverage amongst those that would purchase ADLI, we find that 43.5 percent of respondent either already own LTC insurance or report positive demand in the survey. Thus, stated demand for positive ADLI holdings is below that implied by the model even after including pre-existing coverage.

The overestimation of ADLI demand is more pronounced on the intensive margin. When looking at the distribution of differences in the third row of Table 10. Here we observe a median demand difference of \$17,500 and a mean difference of \$35,000, suggesting for most individuals that the model significantly over-predicts the level of demand. Note that the third row measures percentiles of difference, not differences of percentiles, so that it does not equal the difference between the top two rows.

7 Annuity Demand

Since ADLI is a product that does not exist in practice, part of the explanation for the large difference between demand measurements may be unfamiliarity. In this section we repeat the previous exercises for actuarially fair annuities. As discussed in Section 2, the annuity market is more developed than the market for LTC insurance 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 4.

We also collect stated annuity demand measures, the distribution of which is presented in Table 11. Despite being told explicitly that the offered annuity has no risk of default, is perfectly indexed for inflation, and is fairly priced based on gender, age, and current health, respondents reported little interest in this product. Only 22.9 percent of respondents indicated they would purchase any of this product. The lack of

	Annuity							
	mean	p5	p10	p25	p50	p75	p90	p95
Modeled Demand	45,159	1,827	2,917	8,488	28,832	66,501	113,932	145,418
Stated Demand	34,85	0	0	0	0	0	10,000	20,000
Simulated-Ideal	41,676	-2,764	1,707	6,517	25,741	64,645	109,914	144,950

Table 11: **Distribution of Differences in Annuity Demand:** This table presents the distribution of each of our Annuity demand measures. 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.

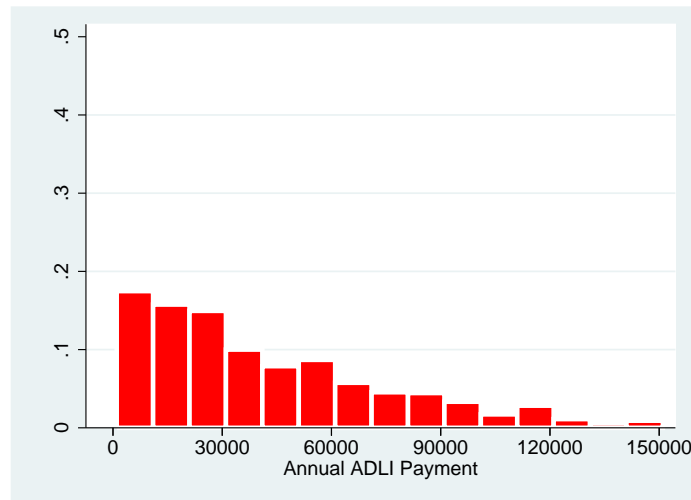


Figure 4: **Model Implied Annuity Demand:** This figure presents the annuity demand from the model for the 96.1% of individuals that our model predicted to have positive demand.

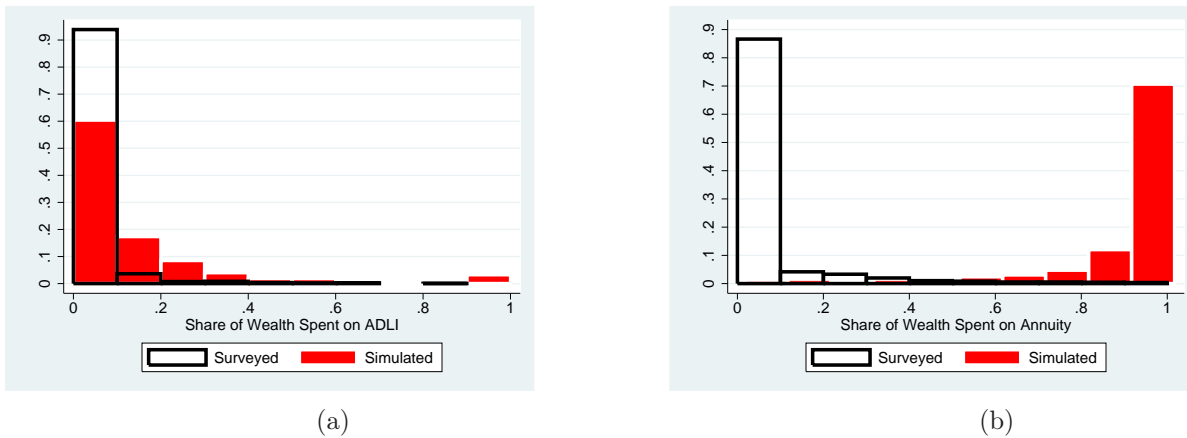


Figure 5: **Share of Wealth Used to Purchase Insurance:** The above figures present the amount of wealth spent on the relevant insurance product divided by total wealth. The left figure presents this ratio for ADLI, while the right figure presents the same results for the annuity.

interest is also exhibited in low-level of demand for 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.¹⁰ First, those with longer life expectancy are significantly more likely to have strictly positive demand than are those with lower life expectancy. As for 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 increases strongly with wealth, as expected.

The distribution of stated annuity demand is dramatically different from estimated demands. Table 11 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, the gap between what the model predicts individuals would demand and what individuals state that 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. 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 products.

8 The Under-Insurance Puzzle, Model Specification, and Transfers

Stated interest in insurance demand among older wealth-holders is well below the level suggested by models. To illustrate this finding in starkest form, Figure 5 displays the findings from the last two sections by plotting the share of wealth allocated to ADLI and annuities for both the surveyed and modeled measurements. Panel (a) of Figure 5 plots the distribution of the proportion of financial wealth that respondents are estimated to allocate to ADLI. We find that in both the survey and simulation individuals allocate fairly low shares of wealth to ADLI, although the model clearly predicts a higher wealth share.

Powerful as is the gap between estimates for ADLI, it is far more dramatic for actuarially fair annuities, as plotted in Panel (b) of Figure 5. The model implies that a very large proportion of wealth should optimally be annuitized. Stated demand, in sharp contrast, indicates very low interest: below 10 percent of wealth for almost the entire population. This figure illustrates the annuity puzzle in dramatic form, yet for a non-

¹⁰The results of this estimation are presented in Appendix B.2.

standard population. 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 purchased annuity. Given that their bequest motives are relatively low, it is optimal to annuitize the bulk of their wealth.

In Appendix D we present the same measurements when we restrict the sample to those with employer sponsored Vanguard plans. These individuals are less wealthy and more representative of the general population, as displayed in Table 1. We find that all qualitative results hold for this sample. Also in this appendix, all analysis is repeated for the case in which agents receive a risk free return of $r = .03$ on saved wealth, while insurance products are still priced using $r = .01$. Again, all qualitative results hold, further suggesting that the low demand for insurance is pervasive.

One possible explanation for findings of high modeled interest in annuities and LTCI relative to stated measures is the weak bequest motive estimated for many respondents. Lockwood (2014) shows that agents with a sufficiently strong bequest motive have little interest in either LTCI or annuities due to a preference for liquid wealth at the end of life. It is difficult to reconcile a strong bequest motive with the response distributions we observe in SSQ 3 however. In this question, an individual with a strong bequest motive should allocate the majority of wealth to the bequest state. In Figure 1 however, respondents indicate a clear preference for LTC expenditure over an end of life bequest. Thus, explaining low insurance product demands through a strong end of life bequest motive is incompatible with these survey responses. Furthermore, Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015) find that even when targeting only wealth moments, permitting an LTC state utility function drastically reduces the estimated strength of the bequest motive. This provides further evidence against strong bequests as an explanation of low insurance demand.

The blatant conflict between model predicted and stated demand for insurance raises important questions concerning model specification. Of particular interest are omitted precautionary risks that increase preference for liquid wealth in the model. Omitted risks make ADLI and annuities more undesirable in the model if these insurance products do not simultaneously provide insurance for the omitted risks.¹¹ Intuitively, omission of uninsurable risks or precautionary motives should cause larger differences between modeled and stated demands because omission of these risks causes the model to understate the desire to hold liquid precautionary wealth. Similarly, overstated risks or precautionary motives should cause smaller differences between modeled and stated demands due to overstating the desire to hold liquid precautionary wealth.

To identify omitted risks 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. To identify sources of model mis-specification, we analyze the difference between model demand (D_i) and

¹¹For analysis of how an insurance product can simultaneously insure multiple late in life risks, see Koijen, Van Nieuwerburgh, and Yogo (2015).

stated demand (S_i). Defining this difference as η_i , suppose that it can be written as

$$\begin{aligned}\eta_i &= D_i - S_i \\ \eta_i &= G(x_i, \Theta_i, q_i).\end{aligned}\tag{5}$$

Thus, model differences are assumed to be a function of modeled state variables, preferences, and omitted variables. Assuming that G is additively separable in its arguments permits the following approximation,

$$G(x_i, \Theta_i, q_i) \approx g_x(x_i) + g_\Theta(\Theta_i) + g_q(q_i).\tag{6}$$

This approximation assumes that partial derivatives across arguments are zero, and the function can thus be decomposed into differences caused by modeled state variables, preference sets, and omitted variables. Estimation of equation 6 requires specification of each function g . To avoid making parametric assumptions regarding g_x and g_Θ , we take a non-parametric approach that does not assume any functional form for g_Θ and g_x . Specifically, partitioning 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 and defining vectors $C_i^\Theta \ni \{C_{i,k}^\Theta = 1 \iff \Theta_i \in P_k^\Theta\}$ and $C_i^x \ni \{C_{i,k}^x = 1 \iff x_i \in P_k^x\}$ allows us to approximate

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

Substituting these expressions into equation 6 and assuming $g_q(q_i) = \Gamma q_i$ permits OLS estimation and testing the null hypothesis of

$$\begin{aligned}\eta_i &= \beta^x C_i^x + \beta^\Theta C_i^\Theta + \Gamma q_i + \epsilon_i \\ H_0 : \beta^\Theta &= 0; \beta^x = 0; \Gamma = 0.\end{aligned}\tag{7}$$

The above equation provides convenient interpretation. Estimation of $\beta^x \neq 0$ and $\beta^\Theta \neq 0$ indicate model mis-specification related to state variables and preferences, respectively.¹² Estimation of $\Gamma > 0$ indicates model mis-specification related to variable q that generates overdemand of insurance relative to stated demand, while $\Gamma < 0$ indicates model-mispecification that generates model underdemand of insurance. Of particular interest, one should expect a significant positive Γ for omitted precautionary risks, as proxied by q . More information on the development of this method, its derivation, the assumptions made, and construction of partitions is included in Appendix C.

A likely source of model mis-specification in the presented model is the restriction of family and intergenerational motives to an end of life bequest. Theories of intergenerational motives, while difficult to operationalize in empirical life-cycle studies, allow for richer considerations that are not captured by this motive.¹³ Of particular interest is the omission of inter-vivos transfers, which altruistic parents may save

¹²Note 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.

¹³See 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 (1987) provides discussion of different modeling approaches for rationalizing bequests.

	ADLI difference	Annuity difference
Transfers	0.348** (.097)	0.191** (.070)
$\mathbb{I}_{Transfer>20k}$	13,889* (4,659)	8,251 (4,654)
\mathbb{I}_{child}	5,025 (4697)	4,321 (4,959)

Table 12: **Other motives:** This table presents the Γ coefficient on each indicated variable 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.

precautionarily to insure the risk of liquidity constrained offspring (Light and McGarry (2003)). The developed method is thus demonstrated by examining inter-vivos transfers as a source of model mis-specification.

As described briefly in Section 3, in VRI Survey 3 we measure the total amount of financial wealth that individuals have transferred to their descendants in the last three years. We find that 67.6 percent of individuals report having transferred wealth to descendants during this time frame, with a mean (median) transfer level of \$18,900 (\$8,600). Furthermore, 25 percent of respondents indicating positive transfers report having transferred more than \$29,500 while 10 percent report having transferred more than \$60,000. These numbers suggest that inter-vivos transfer of wealth to descendants is both common and sizable.

To test for model mis-specification related to intergenerational transfer of wealth, we estimate equation 7 with q defined as the level of transfers. The results of this estimation for both ADLI and annuities are presented in the first row of Table 12. 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 drawn from the error distribution of parameter estimates. Reported coefficients and standard errors reflect this multiple imputation approach. We observe significance at the 1 percent level for both ADLI and annuity demand differences. This provides evidence that indeed omission of family and inter-vivos transfer considerations from the decision problem biases upwards the estimate of modeled demand. When repeating the estimation with q defined as an indicator of having transferred over \$20,000, we again observe significance for ADLI demand differences at the 5 percent level. Interestingly, when repeating this exercise with q defined as having a child there is no significant estimated effect. These results are presented in the second and third rows of Table 12, and indicate that the relevant model omission is the presence of an inter-vivos transfer motive and not presence of children per se.

We regard the analysis of this section as comprising a specification test for the broad class of current models of late in life spending. No version of this model that matches respondent preferences indicated by SSQ responses is consistent with the very low stated demand for actuarially fair annuities and for long-term care insurance. While the findings of this section suggest that family transfers may explain a portion of this gap, their contribution remains to be quantified. While it is conceivable that appropriately including these motives will explain much of the identified gap, there is also a chance that additional model elements remain to be uncovered. Methods analogous to those used in this section may aid in the identification of such additional elements.

9 Conclusion

We provide two new estimates of demand for ideal LTCI, one model-based and the other based on stated demand. Both estimates are larger than private holdings of LTCI, suggesting that flaws in available products contribute to the low level of observed private holdings. However, model estimated demand for ADLI is significantly higher than directly elicited demands. These same patterns hold when we repeat our analysis for actuarially fair annuities. This deviation between model and stated demand—the under-insurance puzzle—exists even for a model with heterogeneity in observables such as wealth, income, gender, age, and health, and in unobservable preferences, as estimated from SSQs. We show inter-vivos family transfers predict the differences in demand, suggesting that omitted motives related to the family contribute to the gap between demand estimates for both products.

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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_{LTC} , and G to maximize utility. The consumer problem, written recursively, is,

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

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.¹⁴ 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 LTC 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 $s = 2$.

¹⁴Technically, 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 respondents ownership of LTC insurance. There is evidence that respondents that own LTCI assign more wealth to the LTC state, indicating a greater preference for wealth when in need of help with ADLs.

SSQ 4 Table B.3 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.4 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>age</i> > 65		62507.118 (0.61)	-2.77e4 (0.58)
<i>health</i> = 2		-1.75e4 (0.91)	-4034.943 (0.95)
<i>health</i> = 3		-1.62e5 (0.45)	19869.617 (0.82)
\mathbb{I}_{child}		-4.96e4 (0.55)	13597.601 (0.68)
College		28351.511 (0.62)	-3012.214 (0.90)
College $\times\mathbb{I}_{child}$		745.551 (0.81)	546.683 (0.67)
<i>age</i> \times	<i>age</i> >65	-1837.593 (0.59)	661.134 (0.63)
	<i>health</i> = 2	988.192 (0.80)	404.873 (0.80)
	<i>health</i> = 3	3594.036 (0.55)	-568.521 (0.82)
	\mathbb{I}_{child}	1286.208 (0.60)	-503.573 (0.62)
	College	-451.145 (0.78)	97.154 (0.88)
<i>age</i> ² \times	(<i>age</i> > 65)	14.646 (0.54)	-4.336 (0.66)
	<i>health</i> = 2	-8.034 (0.76)	-2.680 (0.80)
	<i>health</i> = 3	-29.366 (0.46)	3.005 (0.85)
	\mathbb{I}_{child}	-10.191 (0.58)	3.376 (0.65)
	College	1.876 (0.87)	-0.400 (0.93)
<i>log(wealth)</i> \times	(<i>age</i> > 65)	-253.737 (0.80)	143.734 (0.73)
	<i>health</i> = 2	-577.319 (0.80)	-863.215 (0.35)
	<i>health</i> = 3	4735.577 (0.30)	-21.585 (0.99)
	\mathbb{I}_{child}	699.803 (0.47)	353.552 (0.37)
	College	-491.922 (0.58)	-199.880 (0.58)
No Exposure to Equity		-2334.575 (0.51)	-2862.973* (0.05)

Table B.1: **SSQ 1**: The above table presents a tobit estimation of SSQ 1 on the listed covariates. P-values are included in parentheses.

	SSQ 2a	SSQ 2b	SSQ 2c
Age	323.0747 *** (.000)	164.6257*** (.010)	188.5319*** (.000)
Gender	640.3033 (.762)	2276.085 (.218)	2281.926 (.052)
\mathbb{I}_{sick}	3037.052 (.285)	-579.1218 (.815)	-3016.98* (.055)
Total Wealth	-.0012401 (.180)	-.0004135 (.607)	-.0003979 (.438)
Income Group	-1127.711 (.061)	-206.842 (.693)	-142.0448 (.670)
Income Group \times Gender	-400.8133 (.628)	-1385.507 (.055)	-462.4333 (.313)
Pre-existing LTCI Ownership	1877.882 (.198)	1784.253 (.160)	1684.273 * (.037)

Table B.2: **SSQ 2:** The above table presents a tobit estimation of SSQ 2 on the listed covariates. P-values are included in parentheses.

	SSQ 4 a
Age	-194.463 (0.70)
Gender	19992.003 (0.17)
\mathbb{I}_{sick}	-8312.349 (0.68)
Total Wealth	0.004 (0.53)
Income Group	-3384.263 (0.41)
Income Group \times Gender	-2373.870 (0.68)
Positive opinion of Public LTC	11605.485* (0.03)

Table B.3: **SSQ 4:** The above table presents a tobit estimation of SSQ 4 on the listed covariates. P-values are included in parentheses.

		$\mathbb{I}_{Ann>0}$	Annuity Income Demand
$age > 65$		3.588 (0.75)	73611.844 (0.33)
$health = 3$		10.114 (0.45)	-2.99e4 (0.74)
$health = 3$		-389.996 (0.99)	-1.03e5 (0.63)
\mathbb{I}_{child}		-3.353 (0.65)	-2.20e4 (0.66)
College		-0.072 (0.99)	13708.126 (0.68)
College \times \mathbb{I}_{child}		-0.147 (0.55)	922.375 (0.58)
$age \times$	$age > 65$	-0.123 (0.70)	-1985.101 (0.35)
	$health = 2$	-0.159 (0.66)	1194.403 (0.63)
	$health = 3$	13.011 (0.99)	3704.856 (0.55)
	\mathbb{I}_{child}	0.063 (0.78)	474.486 (0.76)
	College	-0.017 (0.91)	-687.456 (0.47)
$age^2 \times$	$age > 65$	0.001 (0.69)	15.243 (0.31)
	$health = 2$	0.001 (0.61)	-7.869 (0.64)
	$health = 3$	-0.087 (0.99)	-23.949 (0.57)
	\mathbb{I}_{child}	-0.001 (0.69)	-5.387 (0.64)
	College	0.000 (0.84)	4.346 (0.53)
$\log(wealth) \times$	$age > 65$	0.042 (0.63)	-631.105 (0.24)
	$health = 2$	-0.381* (0.03)	-1087.770 (0.37)
	$health = 3$	-7.777 (0.98)	-3102.792 (0.27)
	\mathbb{I}_{child}	0.144 (0.07)	1033.073* (0.04)
	College	0.017 (0.82)	931.100* (0.04)
Subjective Survival Prob. Above Age Average		0.220* (0.01)	204.783 (0.72)

Table B.4: **Surveyed Annuity Demand:** This table shows how annuity demand is predicted by various covariates. Our measure of longevity is whether an individual expects above or below median probability of living for 10-20 years, conditional on current age.

C Estimation Appendix

C.1 Estimation of Model Misspecification

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 $\beta_i^\Theta = g(\Theta)$ for any $\Theta \in P_k^\Theta$ and $\beta_i^x = g(x)$ 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.¹⁵ Similarly, a

¹⁵As 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.

positive coefficient on Γ indicates that the variables in q cause the model to overpredict demand, while a 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.

D Robustness

This section conducts two robustness exercises to confirm our findings. First, analysis is repeated on the employer subsample to examine whether results are sample specific, or whether results hold across samples. This analysis provides no evidence that our main findings are sample specific. Next, analysis is repeated under the assumption that individuals are able to save at a 3 percent interest rate, despite products being priced at a 1 percent risk free rate. This accounts for the higher returns to wealth likely received by the VRI sample, despite the fact that we do not model the financial portfolio allocation decision.

D.1 Employer Sub-sample Analysis

This subsection presents evidence regarding SSQs, estimated preference parameters, modeled insurance product demands, and stated insurance products demands for the employer sub-sample. This subsample is drawn from individuals that are Vanguard clients through participation in an employer sponsored retirement plan. As such, these individuals did not self-select into the Vanguard client base. In addition, these individuals are not as wealthy as the larger sample and are more similar demographically to the broader U.S. population. Although we observe clear differences in our results when restricted to this sample, all results presented in the body of the paper remain unchanged qualitatively.

Figure D.1 presents all SSQ response distributions. Responses generally mirror those of the larger sample.

Table D.1 presents the parameter estimates for this sample. The parameter distributions are remarkably similar to the baseline results from the larger sample.

	σ	θ_{LTC}	κ_{LTC}	θ_{beq}	κ_{beq}	ψ_G
10%	1.95	.00	-95.15	.00	-57.21	1.11
25%	2.76	.01	-62.16	.00	-8.60	6.98
50%	3.89	1.03	-11.65	2.78	87.74	26.76
75%	6.16	26.16	32.24	999.53	336.78	56.59
90%	9.27	1000	123.58	1000	733.49	166.97
Ameriks, et.al 2015	5.85	1.57	-45.65	0.59	7.88	39.46

Table D.1: **Parameter distribution, Employer Sample:** This table presents the marginal distribution of parameter estimates for the employer sample.

Finally, Table D.2 presents product demands for all insurance products for the employer sample. The model again significantly overpredicts demand for both products. Simulated product demands are slightly lower, likely reflecting the lower wealth holdings of the employer sample. However, the stated demand for both products is far lower than model implied demand and patterns are consistent with those observed in the full sample.

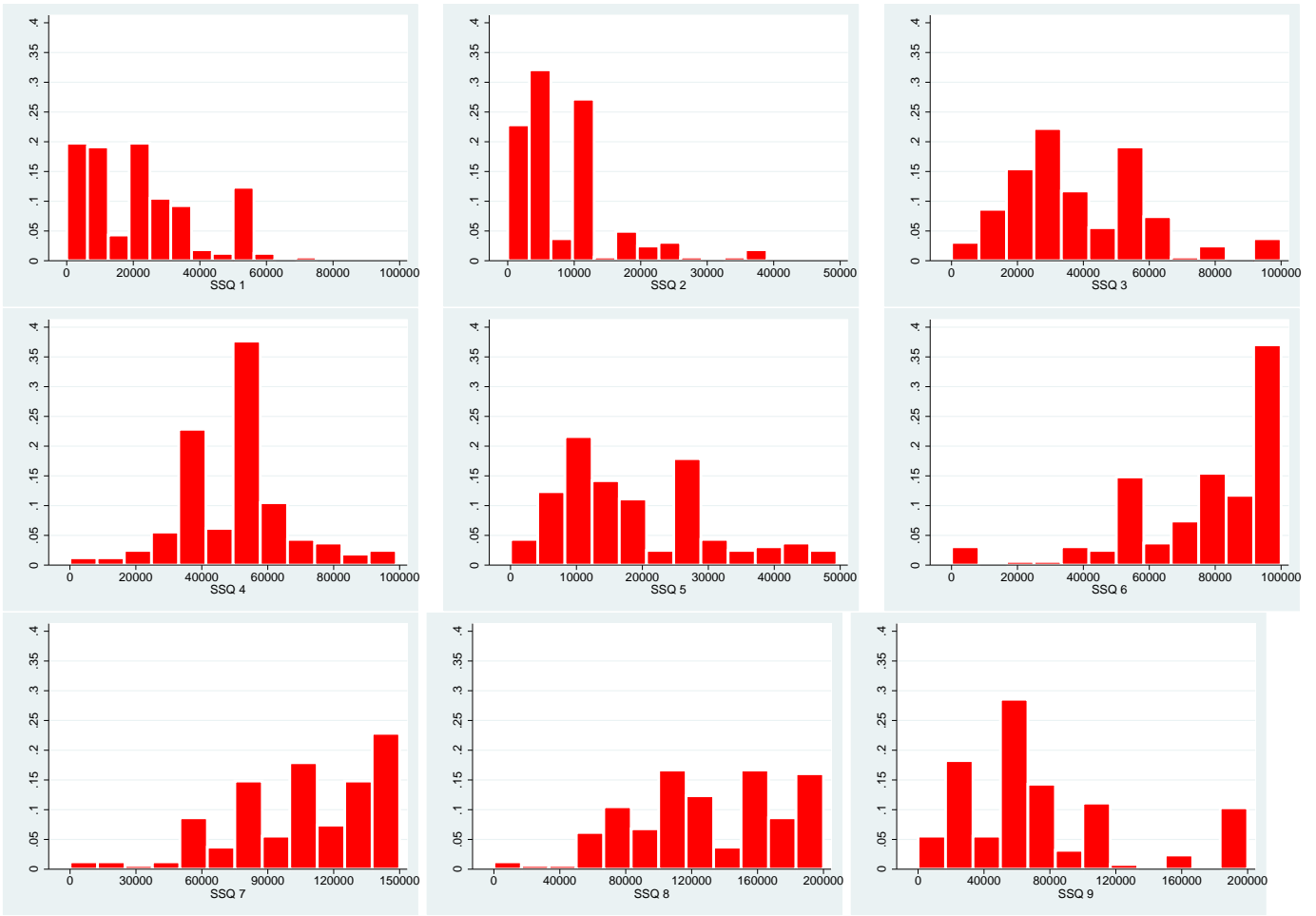


Figure D.1: **SSQ distributions, Employer Sample:** This figure presents the SSQ distribution for respondents that are members of the employer sample.

	ADLI							
	mean	p5	p10	p25	p50	p75	p90	p95
Modeled Demand	31,581	0	0	0	12,076	54,370	90,184	103,212
Stated Demand	7,179	0	0	0	0	7,200	30,000	48,000
Simulated-Ideal	21,660	-35,000	-13,400	0	8,015	44,871	79,170	92,332
	Annuity							
	mean	p5	p10	p25	p50	p75	p90	p95
Modeled Demand	28,996	0	1,310	7,130	20,408	41,586	64,989	83,368
Stated Demand	7,179	0	0	0	0	220	12,800	25,000
Simulated-Ideal	24,135	-8,771	0	2,546	16019	39,017	62,669	83,368

Table D.2: **Insurance Product Demands:** Above we present the insurance product demand estimate distributions and the distribution of differences for both annuities and ADLI, restricted to our employer sample.

	ADLI							
	mean	p5	p10	p25	p50	p75	p90	p95
Modeled Demand	39,542	0	0	0	16,967	60,403	104,651	144,640
Stated Demand	7,179	0	0	0	0	6,000	24,000	42,000
Simulated-Ideal	32,363	-23,000	-8,360	0	10,297	54,911	106,636	141,233
	Annuity							
	mean	p5	p10	p25	p50	p75	p90	p95
Modeled Demand	38,991	0	1,229	8,462	26,106	53,324	93,292	117,260
Stated Demand	3,485	0	0	0	0	0	10,000	20,000
Simulated-Ideal	35,506	-1,200	0	7,049	23,839	51,226	89,580	116,511

Table D.3: **Insurance Product Demands:** Above we present the insurance product demand estimate distributions and the distribution of differences for both annuities and ADLI, as calculated allowing for a 3 percent return.

D.2 Analysis Allowing for 3 Percent Return to Savings

This section repeats the main analysis, but allows for a 3 percent risk free return to wealth instead of the 1 percent risk free return in our baseline. However, insurance products are still priced at a 1 percent risk free return. We find that qualitative patterns of our analysis are robust to this specification of returns.

Table D.3 presents the model-estimated demands, stated demands, and the difference between the two demand measures for both annuities and ADLI when allowing a 3 percent annual return to wealth. We observe that for both products, the model implied demand is again significantly higher than the stated demand. However, comparing this table with Tables 10 and 11 shows that the model estimated demand when $r=.03$ is generally slightly below the model estimated demand when $r=.01$. The higher return on saving generally makes insurance products more expensive, thus causing decreases in model estimated demand.

Figure D.2 replicates Figure 5 when allowing a 3 percent annual return to wealth. While patterns are qualitatively the same as in Figure 5, we observe again that model estimated demands are generally lower than when $r=.01$.

Finally, we repeat estimation of equation 7 using modeled demands calculated with $r=.03$. Results are presented in Table D.4. Here we observe again that inter-vivos transfers significantly predict the difference between model and stated demands for ADLI. For annuities, there is no longer significant estimated effect.

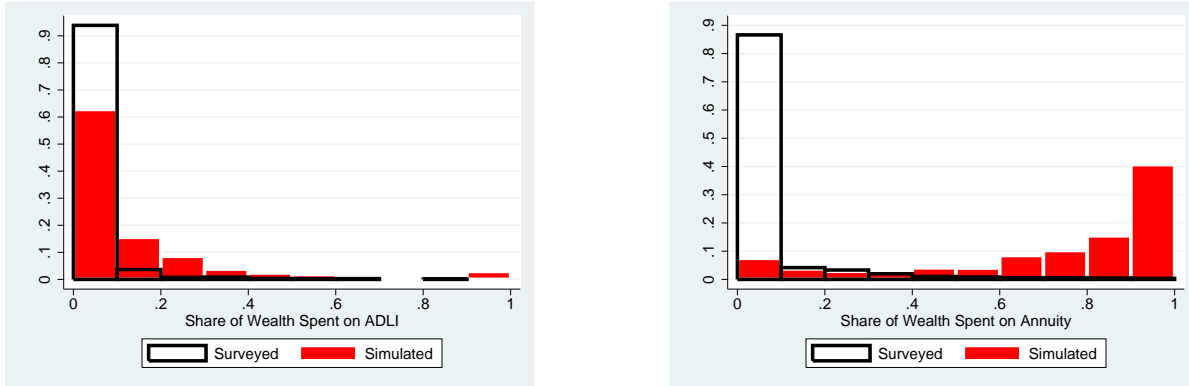


Figure D.2: **Share of Wealth used to Purchase Insurance:** The above figures present the amount of wealth spent on the relevant insurance product divided by total wealth. The left figure presents this ratio for ADLI, while the right figure presents the same results for the annuity. Here, modeled demands are calculated with 3 percent annual return to saved wealth.

	ADLI difference	Annuity difference
Transfers	.207*	.026
	(.096)	(.645)
$\mathbb{I}_{Transfer > 20k}$	10,491*	-1,978
	(.05)	(.318)

Table D.4: **Other motives:** This table presents the Γ coefficient on each indicated variable 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. P-values are included in parentheses.