Risky Insurance: Life-cycle Insurance Portfolio Choice with Incomplete Markets*

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Preliminary Results

[Link to most updated version]

We provide survey evidence that individuals believe there is substantial nonpayment risk in annuity, life insurance, and long-term care insurance (LTCI) products. Using simple statistical analysis we show that nonpayment beliefs predict insurance ownership and that the insurance ownership rate would be much larger if people believed there was zero nonpayment risk. To better quantify how nonpayment risk affects insurance ownership and how different features of insurance products affect consumer welfare, we develop an incomplete-markets life-cycle model of the demand for life insurance, annuities, LTCI, and a risk free bond. We incorporate features of real-world insurance products such as perceived nonpayment risk, high loads above actuarial fair prices, and quantity restrictions (e.g., age restrictions on purchases, short-selling constraints). Both high prices and nonpayment risk substantially decrease insurance ownership. Compared to our rational expectations baseline, the welfare loss from suboptimally owning zero insurance is 0.4 percent in consumption equivalent units. If the products had no risk and were sold at actuarially fair prices, the welfare cost of zero insurance ownership is much larger at 7.9 percent. If subjective beliefs are wrong and payments are always made, correcting beliefs increases welfare by 4 percent.

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1 Introduction

A large number of financial products are available that directly address many of the life-cycle risks Americans face. Life insurance insures an individual against early death and provides a vehicle to transfer money to an individual's estate. Annuities insure an individual against outliving their wealth by providing an income stream that is guaranteed for as long as the insured individual is alive. Long-term-care insurance (LTCI) provides coverage of expensive health and care costs should an individual need assistance with the activities of daily living or require a stay in a nursing home. Furthermore, the products that are available in the market have a variety of maturities and payoff structures, making it possible for consumers to choose a customized portfolio of annuity, life insurance, and LTC insurance policies. Despite a rich set of available insurance options, most individuals choose not to participate in these insurance markets: only 6% of individuals aged 60-65 own a private annuity, 30% own a private life insurance policy, and 10% own a private LTC insurance policy.

Given this puzzling lack of insurance, a number of studies have attempted to understand consumer demand for annuities (Brown (2001), Inkmann et al. (2011)), life insurance (Bernheim (1989), Inkmann and Michaelides (2012), Hong and Rìos-Rull (2012)), and long-term care insurance (Brown and Finkelstein (2008), Lockwood (2012), Ameriks et al. (2018), Mommaerts (2015)). Most closely related to our paper, Koijen et al. (2016) highlighted the importance of considering the demand for these three products jointly to account for overlap in payouts across states. In a model with complete markets, Koijen et al. (2016) develop two risk measures that define necessary conditions for an optimal insurance portfolio, characterize the optimal life-cycle consumption path, and estimate substantial welfare losses due to households holding sub-optimal insurance portfolios.

In this paper we develop both a new dataset and a new model to better understand consumer demand for annuities, life insurance, and LTC insurance. We first design a new survey to measure the expected distribution of insurance policy payments. We then incorporate these measures into an incomplete markets life-cycle model of demand for life insurance, annuities, LTC insurance, and risk free bonds. The model features uninsurable health and mortality risk and the insurance products have uninsurable non-payment risk, cost more than the acturially fair price, have wedges between purchase and selling prices, are subject to short-selling constraints, and there is a maximum age for new policy issuance.

Our study makes several contributions that advance understanding of consumer insurance demand. First, we show that perceived nonpayment risk is substantial in all three of the insurance markets we study. Our elicited distributions of expected payouts imply that on average consumers expect to receive 87.2% of the promised payout from a typical life insurance policy, 81.5% for annuities, and 76.2% for LTC insurance, with standard deviations of payouts averaging 16.7%, 21.5% and 23.9%, respectively. In addition, the full default probability—defined as the probability that a policy becomes worthless and makes no subsequent payment prior to the policy's contractual expiration—is 0.23 for life insurance, 0.29 for annuities, and 0.32 for LTC insurance. Our three risk measures all indicate that life insurance is perceived as the most safe and that LTC insurance is the most risky. Consumers perceive much higher risk in insurance markets than what would be inferred from historical observations of insurer default, possibly suggesting high paperwork or contractual complications as the main barrier to full payment.

Our second key contribution is a statistical analysis of subjective beliefs and insurance ownership. Individual's perceived risks are highly correlated with actual insurance product holdings. For example, respondents with higher expected payouts are significantly more likely to own life insurance, respondents reporting higher standard deviations of annual payments and higher full default probabilities are significantly less likely to own annuities, and respondents with higher full default probabilities are significantly less likely to own LTC insurance. While the direction of causality can not be fully determined from such cross-sectional analyses, the negative relationship between perceived risk and policy ownership are robust to including demographic controls and behavioral measures (e.g., proxies for trust, cognitive ability, risk aversion, propensity to plan, and financial literacy) and overall suggest that perceived risk reduces policy ownership. In fact, counterfactual predictions of probit regressions indicate that annuity and LTC insurance ownership rates would be twice as high if households were to perceive insurance products as risk-free, while life insurance ownership rates would be over nine percentage points higher.

Our third key contribution is the structural model analysis. To better quantify how nonpayment risk affects insurance ownership and how different features of insurance products affect consumer welfare, we develop an incomplete-markets life-cycle model of the demand for life insurance, annuities, LTCI, and a risk free bond. Health and mortality are the key risks in the model. We incorporate features of real-world insurance products such as perceived nonpayment risk, high loads above actuarial fair prices, wedges between the purchase and resale prices for insurance products, and quantity restrictions (e.g., age restrictions on purchases, short-selling constraints). We employ a mix of calibration and estimation so that insurance in the model reflects products actually available in the market. This paper is the first of which we are aware to study the joint demand for annuities, life, and LTC insurance in an incomplete market model that reflects the decision problem households face as they age into retirement.

To quantify the model we need to select values for parameters that control properties of insurance products, health and mortality risk, income, preferences, and rates of return. We use the estimated nonhomothetic health-state-dependent utility function from Ameriks et al. (2020) with one extension: we allow the strength of the bequest motive to vary over the life cycle. We also follow that paper in estimating income age profiles and health and mortality risk using Health and Retirement Study (HRS) data, but in this paper we work with a population that is representative of older Americans. We calibrate loads above actuarially fair prices on insurance products to those reported in Hong and Rìos-Rull (2012) for life insurance and Brown and Finkelstein (2008) for annuities and LTC insurance. Finally, we choose rates of return on risk free bonds, the discount rate used to determine actuarial fair prices, the household discount factor and intertemporal elasticity of substitution, and the a parameter that controls the life-cycle profile of bequest motives to match the 25th, 50th, and 75th percentiles of the wealth distribution by age and the average ownership rate of the 3 insurance products.

The model predicts insurance holdings in line with those observed empirically: consumer ownership of annuities and long-term care insurance is very low, and ownership of life insurance is far from universal. Furthermore, we match the life-cycle pattern of insurance ownership, which is not a targeted moment. Both high prices and nonpayment risk substantially decrease insurance ownership. Compared to our baseline, the welfare loss from sub-optimally owning zero insurance is 0.4 percent in consumption equivalent units. If the products had no risk and were sold at actuarially fair prices, the welfare cost of zero insurance ownership is much larger at 7.9 percent. This large welfare cost of suboptimal insurance ownership is reminiscent of the complete markets analysis in Koijen et al. (2016). Thus, we conclude that the welfare costs of suboptimally low insurance ownership is small given the products available in the market and, simultaneously, risky and incomplete insurance markets result in significant welfare losses to older consumers.

Because many of our main findings are derived from survey responses, we take a number of steps to establish the credibility of our key measures and findings. In addition to insurance product ownership, we find that our subjective expectations of nonpayment risk correlate with other behavioral measures in intuitive ways. For example, respondents that have experienced financial fraud in the past report higher probabilities of full default. In addition, several patterns in the data suggest that respondents were thoughtful when answering the survey. For example, respondents expect lower payouts from annuities and life insurance during economic downturns, while expectations of long-term care insurance payouts are invariant to aggregate fluctuations. Finally, we included a number of randomization and internal consistency checks in our survey design. We find that randomized framings and orderings do not predict survey responses, while approximately 85% of respondents ranked the riskiness of insurance products in a manner consistent with their perceived risks.[1]

1.1 Relation to the Literature

In terms of measurement, our paper is most similar to Luttmer and Samwick (2018), which measures the perceived nonpayment risk surrounding Social Security. Our key survey instrument is derived from that used in this study, and applies the bins-and-balls method (Delavande and Rohwedder (2008)) to elicit the subjective payment distribution for each respondent. We also follow Luttmer and Samwick (2018) and measure indifference points between insurance policies currently available and a policy that offers certain, but lower, payouts. These certainty equivalent measures imply risk premia of 5.7% for life insurance, 7.7% for annuities, and 3.3% for LTC insurance, which are comparable to the 8% risk premia Luttmer and Samwick (2018) estimate for Social Security. Although similar in measurement methodology, our study focuses on more and different types of assets, thus providing additional insights into the perception of financial risks in retirement.

In terms of the model and research question, our paper is most similar to Koijen et al. (2016), which provides the key insight that demand for annuities, life, and LTC insurance should be studied jointly given the overlap in payouts from these products. We compliment that paper's complete-market framework by characterizing optimal insurance holdings in an incomplete market setting, and show that this extension has significant implications for the welfare costs of observed household insurance holdings. Whereas Koijen et al. (2016) find substantial welfare costs from sub-optimal portfolio choice we find that foregone gains are much smaller after modeling the products that consumers perceive as being available in the market.

In addition to these two studies, this paper contributes to a number of broader literatures. First, we relate to papers that study the demand for annuities (Yaari (1965), Brown (2001), Davidoff et al. (2005), Inkmann et al. (2011)), life insurance (Bernheim (1989), Inkmann and Michaelides (2012), Hong and Rìos-Rull (2012)), and long-term care insurance Brown and Finkelstein (2008), Lockwood (2012), Ameriks et al. (2018), Mommaerts (2015). In addition, a few studies have previously considered the joint demand for annuities and life insurance (Inkmann et al. (2011), Hubener et al. (2013)), while the aforementioned Koijen et al. (2016) study considers demand for all three insurance products. We contribute to this literature by characterizing joint demand for insurance products in a model with incomplete markets and by incorporating nonpayment risk.

Our study also contributes to the literature that studies the determinants of late-in-

[1] All results are robust to restricting our sample to households that pass this internal consistency check.

life saving behavior. As noted in Poterba et al. (2013), households spend down their wealth slowly in retirement. A number of studies have tried to explain this slow draw-down by allowing for uninsurable medical expense risk (Hubbard et al. (1994), Palumbo (1999), Anderson et al. (2004), De Nardi et al. (2010), uninsurable LTC spending risk (Kopecky and Koreshkova (2014), Lockwood (2016), Ameriks et al. (2020)) and a strong bequest motive (Hurd (1989), Nardi (2004), Kopczuk and Lupton (2007), Love et al. (2009), Lockwood (2012)) in incomplete market models. The model that we use is similar to the models used in these studies and incorporates many of the key features that generate slow wealth decumulation in retirement.

We also relate to papers that measure and model how uninsurable risk and incomplete markets affect consumer behavior. Studies of uninsurable labor income have been shown to have significant impact on asset prices (Krusell and Smith (1998), Gomes and Michaelides (2008), Storesletten et al. (2007), Guvenen (2009)) and consumption inequality (Blundell et al. (2008)). At an individual level, higher exposure to uninsurable background risk has been shown to make consumers less willing to invest in equities (Curcuru et al. (2004), Fagereng et al. (2016)). We contribute to this literature by demonstrating that incomplete insurance markets have significant affects on consumer choices and welfare, thus highlighting the importance of measuring and modeling these features in a new domain.

We additionally relate to a number of studies that have examined how trust and counterparty risk affect demand for assets. In the case of annuities, several studies have noted that small probabilities of nonpayment can make individuals unwilling to participate in annuity markets (Lopes and Michaelides (2007), Pashchenko (2013), Jang et al. (2013)), but there is no consensus as to whether this is a significant or insignificant channel for limiting annuity demand. We address this question by (1) showing that perceived nonpayment risk in annuity markets is large and (2) it significantly limits annuity ownership. In equity markets, a small perceived probability of nonpayment or loss of capital is widely acknowledged as a cause of nonparticipation. Guiso et al. (2008) show evidence that more trusting individuals are willing to participate in equity markets and Fagereng et al. (2016) demonstrate that this channel is important for matching empirical portfolio holdings with a life-cycle model. Our study demonstrates that similar perceived risks are important in explaining consumer behavior in insurance markets as well.

Our study also contributes to an active literature that studies how subjective beliefs regarding investments and financial decisions are correlated with actual consumer behavior (see Manski (2004) for a survey on measuring beliefs and their importance in explaining behavioral observations). Most directly comparable, Beshears et al. (2014) find that perceived risks and investments limit annuity purchases. Additionally, a number of recent studies have established that subjective beliefs of house price returns significantly predict home purchase decision (Armona et al. (2018)), while Adelino et al. (2018) show that the second moment of the expected return distribution is highly predictive as well. Additionally, expectations of returns have been shown to affect investment in the stock market (Hurd et al. (2011)), human capital (Wiswall and Zafar (2017)), and labor market search effort (Conlon et al. (2018)). Our finding that expectations of insurance product returns predict ownership contributes to the mounting evidence that subjective expectations are an important determinant of consumer behavior.

Finally, we tangentially relate to an active literature that examines the investments and financial stability of insurance providers (Merrill et al. (2012), Becker and Opp (2013), Becker and Ivashina (2015), Ellul et al. (2015)). Recent work on life insurance providers (Koijen and Yogo (2015), Koijen and Yogo (2016)) suggests that the growth of shadow insurance is a growing risk in the stability of these market, suggesting that the perceived counterparty risk consumers report might not be without merit. Although we do not model the supply side of insurance markets and treat nonpayment risk as exogenous, this study provides new measures of consumer beliefs of nonpayment risks from insurance providers that potentially provide new insights into sources of financial instability.

The remainder of the paper is structured as follows: Section 2 introduces the data set, including documenting patterns in observed insurance product holdings. Section 3 outlines our survey, while Section 4 analyzes survey responses and examines their relationship with product ownership and other individual characteristics. Section 5 describes the baseline structural model and details our quantification approach. Section 6 analyzes predictions from our structural model and calculates the welfare gains associated with insurance products, under scenarios that vary consumer beliefs and properties of the insurance products. Finally, Section 7 concludes.

2 Data

Our study uses two data sets. First, we use a sample of participants in the Understanding America Study (UAS), a representative American Internet panel of approximately 6,000 individuals hosted by the University of Southern California Dornsife center. Our sample of 1040 respondents consists of all UAS participants that are over age 45 and responded in May-June of 2018 to a survey that we purpose-designed to measure perceptions of insurance products (see Section 3 for details). Because the UAS does not have a significant panel dimension that is useful both in calibrating our structural model and measuring the dynamics of insurance ownership, we supplement our survey with observations from the Health and

Retirement Study (HRS). The HRS is a nationally representative panel study of more than 37,000 Americans over age 50 that provides high quality measures of health, income, asset, and insurance dynamics from 1991 to the present. We use the UAS sample to measure insurance nonpayment risk and perform statistical analysis of how nonpayment risk correlates with key variables at the individual level. We use the HRS to calibrate the stochastic process for health and longevity risk, health cost shocks, and income age profiles. Since, after appropriate reweighting, both the HRS and the UAS samples are representative of the population of older Americans, we are comfortable taking some measures from each data without significant concerns regarding external validity. In this section, we first present some facts on insurance ownership taken from the HRS, before providing more details on our UAS sample.

2.1 HRS and Dynamics of Insurance Ownership

We use the HRS to estimate health, income, wealth, medical expense, and insurance dynamics that are inputs and moments targeted in calibrating our structural model described in Section 5. Our estimation of these profiles and processes follow literature standards, so methodological details are relegated to Appendix B. Estimated wealth, income, health, and medical expense profiles are consistent with those previously documented in the literature, and are presented when discussing our calibration strategy in Section 5.

Ownership rates of annuities, life insurance, and LTC insurance are plotted by age in Figure 1. We note several clear patterns. First, ownership of insurance products late-in-life is fairly low, especially for annuities and LTC insurance. At a typical retirement ages of 65, we find that approximately 12% of all households own a LTC insurance policy and less than 5% of all households own a private annuity, consistent with the previously documented annuity puzzle (Yaari (1965), Modigliani (1986)) and LTC insurance puzzle (Ameriks et al. (2018); Braun et al. (2016)). Second, we observe higher ownership rates for life insurance, with approximately 60% of households owning a policy at age 65. In addition, consistent with patterns documented in Hong and Rìos-Rull (2012), life-insurance ownership falls steadily with age as term policies that individuals purchased earlier in life to insure their children's welfare expire. Overall, Figure 1 indicates limited demand by older Americans for the annuity or LTC insurance products available in the market.

When simulating our model, our initial condition for the distribution of state variables is drawn from the HRS data. Although our primary analysis focuses on our UAS survey sample, using the HRS sample allows us to document certain key facts in a widely understood data set as well as reduce concerns about small sample issues. In this analysis, we measure all variables

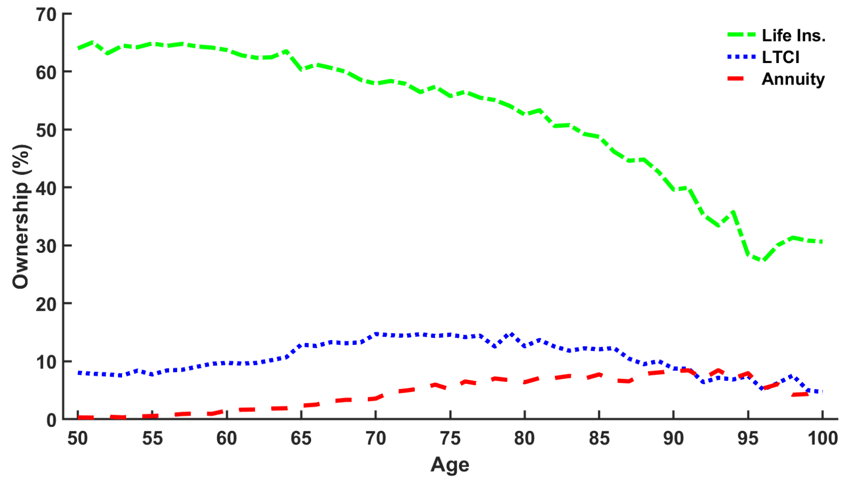


Figure 1: **Age profiles of ownership rates for annuities, life insurance, and long-term care insurance in the HRS.**

as observed in the 2015 HRS and restrict attention to the three youngest HRS cohorts.[2] In Column (1) of Table 1 we present summary statistics for this sample of individuals.

2.2 Survey Sample from the UAS Study.

The Understanding America Study (UAS) is an internet panel maintained by the USC Dornsfife center. Researchers can pay to field their survey questions to this panel. Survey respondents are randomly invited to join the panel (i.e., there is no voluntary selection into the UAS). Upon joining, they participate periodically in survey modules designed by various research teams. Survey modules are programmed and tested by the UAS team before being sent to the field, where respondents are paid for the time they spend on each survey module. In addition, the UAS periodically collects measures of general interest to researchers. For example, every two years all UAS participants complete a version of the HRS survey that the UAS team has adapted to be more amenable to a self-administered web survey. Thus, measures such as health, labor force participation, financial holdings, and various behavioral measures are available for all UAS participants. In addition, all UAS survey modules become publicly available after a one year embargo, and respondents can be linked across surveys by a unique UAS ID. For more information on the UAS, including data and recruitment protocol, we refer the reader to `https://uasdata.usc.edu/`.

Our survey was fielded in May 2018, and the response rate among UAS panel participants

[2]We exclude older cohorts because they were sampled in the early 1990s, and so by construction are significantly older than our UAS sample by 2015.

Table 1: **Demographic Characteristics and Other Summary Statistics for the HRS and UAS samples.** We report the mean values for each variable. Column (1) is from the the HRS and Column (2) from the UAS.

	HRS (1)	**UAS** (2)
Male	.47	.51
Age	59.2	61.4
Retired	.28	.36
Education		
High School	.46	.52
Some College	.29	.26
College & Above	.25	.18
Married	.69	.59
Race		
White	.75	.88
Black	.16	.09
Hispanic & other	.09	.04
Health		
Good	.72	.81
Bad	.24	.16
LTC	.04	.03
Income (K $)	64	130
Wealth (K $)	280	573
Insurance Product Ownership		
Annuity	.06	.11
Life Insurance	.61	.56
LTCI	.09	.11
N	10,234	1,040

that were invited to complete the survey was 82%.[3] 1104 respondents began the survey, while 1088 completed the survey, with an average response time of 17 minutes. Among those that completed the survey, there was very little item non-response. For example, 1055 respondents answered all questions related to life insurance, 1046 answered all questions related to annuities, and 1040 answered all questions related to LTC insurance. In all subsequent analysis, to maximize sample size we do not hold the respondents fixed when analyzing different products.

Summary statistics from our UAS sample are presented in Column (2) of Table 1. We observe some differences between our UAS sample and the HRS. Some of these differences are explainable by our sampling procedure. For example, because we did not translate our survey into Spanish we purposefully sampled only English-speaking households, and as a result our sample is less Hispanic and more white. Some of the differences are not obviously explained by sample strategies, e.g., our survey sample is wealthier and has higher income than the HRS. Most importantly, insurance product ownership rates are quite close across the two data sets.

In addition to measures in our survey, UAS respondents can be linked to a number of other measures collected in prior UAS surveys. Some measures, including age, gender, marital status, household size, labor market status, and other standard controls are preloaded into each survey data set. Less standard measures are not included in the data set provided by the UAS team, but may have been collected in prior UAS surveys and can be linked by fixed respondent IDs. We therefore reviewed the available data and stored or constructed a number of behavioral measures that are potentially informative of risk perceptions or survey response quality. For example, we merge into our data set self-reported trust measures, cognitive scores, financial literacy measures, numeracy scores, indicators of whether respondents have experienced fraud in the last two years, subjective risk aversion, and measures of the propensity to plan. In addition, we construct measures of stock returns experienced between ages 18-25 using data available on Bob Shiller's website and merge into our data set by birth year. In some of the empirical analyses in the remainder of this paper, we will include these behavioral measures as controls in addition to a standard set of demographic covariates.

3 Survey Description

In this section we describe our measurement of perceived nonpayment risk. Our key survey instruments are motivated by those developed in Luttmer and Samwick (2018), who first

[3]This response rate is a lower bound, as the survey link was removed once the number of purchased responses had been reached

measure the perceived distribution of Social Security benefits and the certainty equivalent to that distribution for each survey respondent. The difference of the expected value of payouts and the certainty equivalent measure yields the risk premia, i.e., the compensation an individual would require to hold the risk associated with payment uncertainty. While we adopt the Luttmer and Samwick (2018) baseline survey instrument, we tailor it in a number of ways to better inform risks in insurance markets. In this section, we provide details of our survey instrument.

3.1 Measuring Nonpayment Risk and Certainty Equivalence

Our survey consists of three modules that ask each respondent about perceived risk for each insurance product (annuity, life, and LTC). To avoid and permit testing for anchoring of responses, we randomize the order in which respondents receive modules. Within each module, respondents are first asked whether they are familiar with or own that specific type of insurance policy. For those that own an insurance policy, we collect details of the specific policy that they own (e.g., policy size) and ask them to consider this policy when reporting nonpayment risk. For those that do not own an insurance policy of the type measured in each module, we provide them details of how the indicated insurance works, prompt them with a policy of an indicated benefit size (with benefit sizes randomly determined), and ask them to imagine the best policy of this type that they think they could buy in the market today. Having fixed a policy in mind we then ask them about their perceptions of risk associated with this policy. To provide a concrete example of our survey instrument, for the remainder of this section we will focus on annuities, with survey modules for life and LTC insurance implemented analogously.

We first ask respondents about the probability of full default. Specifically, we ask the following:

> Suppose that you own an annuity that promises to pay $[5000] each year for the rest of your life. Suppose further that you never trade this annuity for cash and hold the contract until the end of your life.
>
> We are now interested in the percent chance that the annuity becomes worthless due to no fault of your own at any point before the end of your life. This means that the annuity permanently stops making payments. This might occur if the insurance company goes out of business, they claim you violated a clause in the contract, or they ruled the policy void for some other reason.

What is the percent chance this occurs?

Respondents than indicate their responses on a slider which updates to remind them what their choice indicates as they move between zero and one hundred.

We then proceed to collect the perceived distribution of payments in a year where the respondent qualifies for a claim. We use the bins-and-balls technique developed in Delavande and Rohwedder (2008) that prompts respondents to place balls in categories based on the likelihood indicated events will occur. In the first screen, respondents are asked to indicate whether they will receive no payment, a fraction of their promised payment, or the full payment promised in their contract:

Suppose that you own an annuity that promises to pay $[20,000] each year for the rest of your life. We would now like to focus on what might happen just during the next calendar year.

You have been given 20 balls to put in the following bins. Each bin describes a scenario that involves the annuity payment that you are supposed to receive next year. The more likely you think a bin is, the more balls you should put in that bin.

What do you think will happen to the annuity payment next year?

I will receive no payment/I will receive a payment less than I am supposed to receive/I will receive a payment at least as large as I am supposed to receive

Respondents are then asked to reassign balls placed in the middle bin into 5 bins ([1-20, ... , 81-99]) to indicate the fraction of the payment they expect to receive conditional on receiving less than contractually promised.

You put [13] ball(s) in the bin marked ”I will receive a payment less than I am supposed to receive.” Please distribute those balls in the following bins. The more likely you think a bin is, the more balls you should put in that bin.

If you do receive a payment that is less than you are supposed to receive, how much do you think you would get?

This provides a complete characterization of the distribution of payments respondents expect to receive, which we can then use to calculate the expected value and standard deviation of expected annual payouts as a fraction of the amount promised in the contract.[4]

After collecting the distribution of payments, we ask respondents whether they would be willing to accept a risk-free contract that offers certain payments of a value below those contractually promised. Each respondent (that reported at least some nonpayment risk) makes this choice once for a risk-free contract that either promises 25%, 50%, 75%, 80%, or 90% of the promised payout of the policy under consideration, with the fraction randomly determined. Specifically, we ask:

> The way you put balls into various bins shows that you expect to receive about [83]% of your annuity payment next year. It also shows that you could receive more or less than [83]% of the promised payment.
>
> Let's call this distribution of possible payments, as described by you using the bins and balls, your "uncertain payments." So, your uncertain payments are whatever payments you think you might receive next year.
>
> We are now interested in how you value having a contract with no uncertainty. Imagine a contract that is guaranteed to pay [75]% of your annuity payment with no risk of the insurance company not paying out as promised. This is like having all 20 balls on this certain percentage. This contract is unbreakable and cannot be changed by anybody. This contract has no risk, but is guaranteed to pay less than the full promised amount of your original contract.
>
> Would you rather have:
>
> - Guaranteed payment equal to [75]% of the annuity payment you are supposed to receive. or
> - Uncertain payments around an expectation of [83]% of the annuity payment you are supposed to receive?

Because each respondent only responds to this question once we do not collect precise certainty equivalent measure for each respondent, and therefore do not (as in Luttmer and

[4]In calculating expected values and standard deviations we assume that balls correspond to the midpoint of their final bins.

Samwick (2018)) recover the distribution of risk-premia among respondents. However, the fraction of people that would accept the risk-free contract for each level of payout gives the population CDF of certainty equivalent measures that can then be used to calculate summary statistics like mean and median certainty equivalent measures, and by extension, the mean and median of the population risk-premia.

3.2 Additional Measures of Nonpayment Risk

In addition to the core measures described above, our survey also collects a number of additional nonpayment risk measures in a supplemental survey module. Each respondent completes a supplement corresponding to one insurance product, with the supplement they received randomly determined.[5] These additional measures, which are described below, are designed to provide additional insights into the sources and characteristics of perceived nonpayment risk.

First, for annuities and LTC insurance, we ask respondents to report the probability of full default conditional on a policy not paying out in a given year:

> Earlier you put [5] balls in the bin indicating "I will receive no payment at all". Suppose that this actually happened.
>
> In the case that you receive no payment next year, what is the percent chance that the annuity never makes another payment at any point in the future? This might occur if the insurance company goes out of business, they claim you violated a clause in the contract, or they ruled the policy void for some other reason.

Additionally, we ask respondents for more details about the nature of the perceived nonpayment risk. For example, we ask respondents how much work it will be to receive payments from their insurance policy:

> In general, how much effort do you think you will need to put in to receive the annuity payments you are promised?

[5] Specifically, respondents receive the supplement that corresponds to the third insurance product that they respond about in the core, randomly ordered, survey modules. Collecting supplemental measures about perceived nonpayment risk in this order ensures that our core measures are not influenced by these additional subsequent questions.

For example, this could include you or your family members doing paperwork, talking with claims officers, talking with doctors, hiring lawyers, or other such activities.

Please choose one of the following:

- No effort at all.
- A small amount of effort.
- A medium amount of effort.
- A large amount of effort.

We next ask respondents to report the probabilities of full-default and the perceived payment distribution conditional on an economic downturn. In particular, we prompt respondents to consider a scenario where the stock market has decreased by a randomly determined amount:

We are now interested in the chance that the insurance company will meet the policy's obligations under different economic conditions.

Specifically, suppose that the stock market decreases by [10/20/30]% next year.

Respondents then report full-default probabilities and the subjective distribution of perceived payments in the next year through a series of survey questions nearly identical to those used to construct our core risk measures, with the conditioning language presented above added.

3.3 Other Survey Measures

After responding to survey modules for annuities, life, and LTC insurance, the survey concludes with a final section that asks respondents to reflect on their survey responses. The questions in this final section, as well as the randomization in the design of the survey, primarily serve to provide metrics to check survey response quality. In Section 4.5 we discuss how responses to these questions and other patterns in responses inform the credibility of the constructed risk measures.

We first ask respondents to rank life, annuities, and LTC insurance in order from least to most risky. This question primarily serves as a check for internal consistency, as we would expect respondents to rank products with higher reported nonpayment risk metrics as most risky. In practice, we define a set of responses as not internally incoherent if at least one of the core risk metrics is largest for the policy type rated as "most risky" in this question.

We next ask respondents to report the factors that influenced their responses (e.g., personal experiences, family/friends' experiences, government intervention, policy complexity, the aggregate economy, trust in salespeople, other/free response). Finally, respondents were asked to report how confident they were in their responses, and how much thought they had given to insurance policies and chances of nonpayment prior to the survey.

4 Survey Results

In this section we present measures of perceived risk, relate them to individual charactersitics and behaviors, and consider response credibility. All figures and analyses in this section use population weights provided by the UAS, and thus may be interpreted as indicating measures for a representative sample of American's over age 45.

4.1 Perceived Nonpayment Risk Measures

Our core survey modules provide three key metrics of perceived nonpayment risk: the probability of full default (i.e., the policy becomes worthless and makes no future payments), the expected value of payments conditional on a qualifying event, and the standard deviation of the perceived distribution of these promised payments.

Figure 2, Panel (a) presents the population CDF of reported probabilities of full-default. Although there is substantial heterogeneity in perception of this risk, the vast majority of respondents assign positive probability to a full default occurring. Only 19% of respondents report zero probability of a full default in life insurance markets, with even less doing so for annuities (11%) and LTCI (10%).There appears to be a clear ordering of perceived risk, with respondents viewing life insurance as least likely to default and LTCI as most likely to default. The median respondent expects life insurance to default in any given year with probability 0.3 percent, annuities with probability 0.5 percent, and LTCI 1 percent. These probabilities are far higher than the full default probabilities observed empirically.

Figure 3 presents the population CDFs for the mean (Panel (a)) and standard deviations (Panel (b)) of the perceived payments in a given year where the policy holder qualified for a claim. For annuities a qualifying event is being alive, for life insurance it is dying, and for LTCI it is needing help with 2 or more activities of daily living. In each figure, the measures are normalized by the full claim amount. Thus, the variables should be interpreted as the

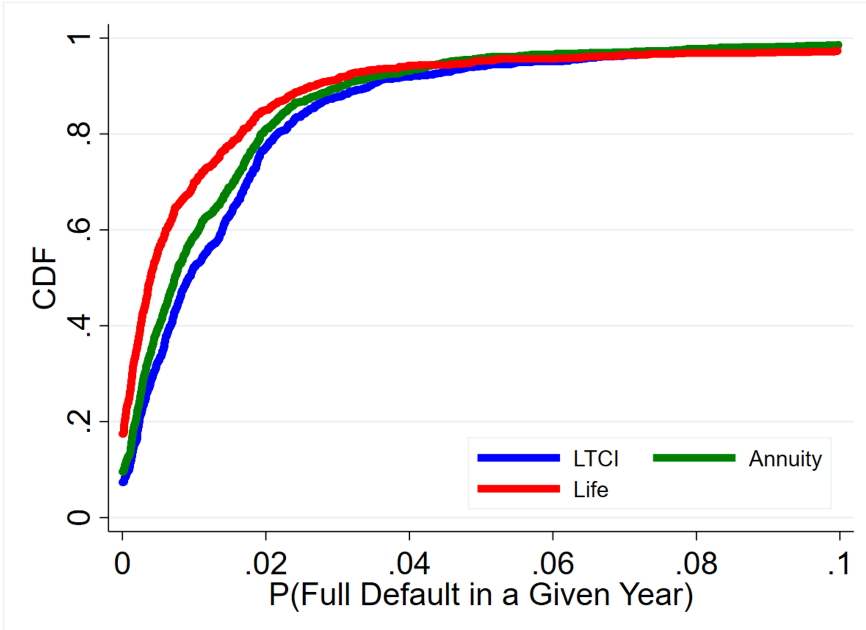
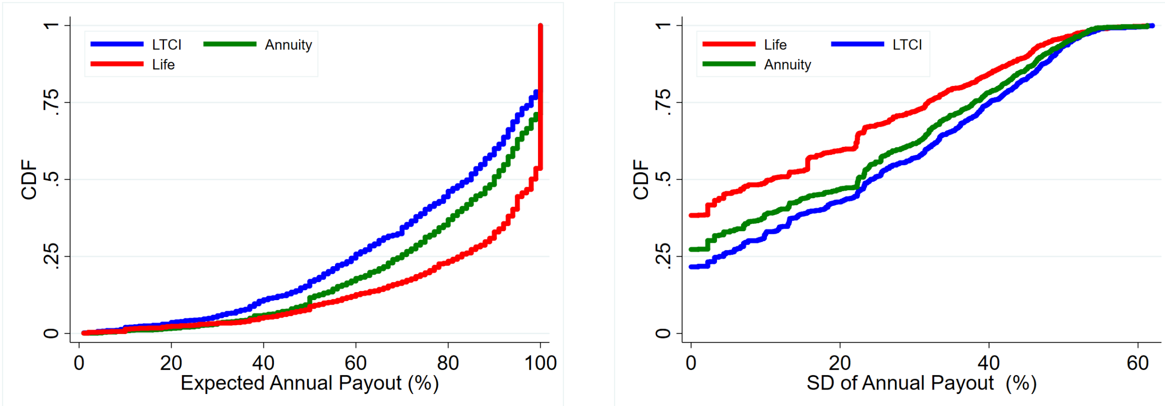


Figure 2: **Annual Probability of Full Default.**

fraction of the promised claim that is expected to actually be paid. In Panel (a) we again observe that many respondents perceive substantial payment uncertainty. For life insurance, although almost half of all respondents expect the policy to pay the full promised amount, consumers on average expect to only received 87% of the promised claim amount. Consumers perceive even more risk for annuities and LTCI, reporting mean (median) expected payouts of 82% (90%) and 76% (85%) of the qualified claim amounts, respectively. Panel (b) shows that in addition to expecting to receive a lower payout than promised, consumers perceive substantial uncertainty in the payout they will receive in each market. On average (at median), perceived payment distributions imply standard deviations of 16% (11%), 22% (22%), 23% (24%) of the promised payment amount for life, annuity, and LTC insurance policies, respectively.

Combined, these figures document our first key result: In all three insurance markets considered, and by all three risk metrics constructed, consumers perceive substantial uncertainty in insurance product payouts. Whether or not there is actually such risk in the market does not change the fact that consumers view life-cycle insurance products as risky. Additionally, there appears to be a clear risk ranking of insurance types, with life insurance being relatively safe, LTC insurance being relative risky, and annuities in the middle.

To provide insight into how consumers value this uncertainty, we next examine the population distributions of certainty equivalent measures in Figure 4. Each point on these CDFs indicate the fraction of the population that would prefer a certain payout at a lower share of



(a) Expected Annual Payout

(b) Standard Deviation of Annual Payout

Figure 3: **Subjective Annual Payout Risk** Conditional on a qualifying event occurring, Panel (a) presents the CDF of the mean of the expected payment distribution and Panel (b) presents the CDF of the standard deviation of the expected payment distribution.

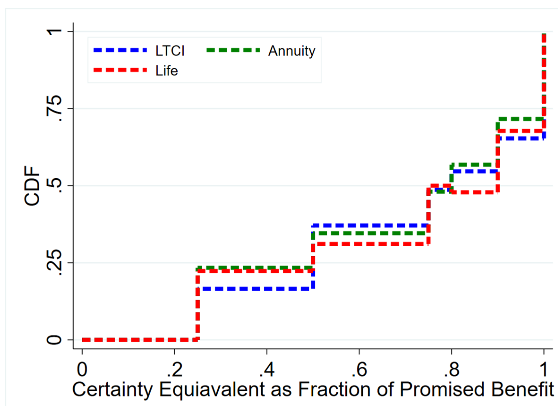


Figure 4: **Certainty Equivalent Distributions.**

the promised payout instead of holding the risk associated with the actual policy. We first observe that certainty equivalent measures are relatively similar across types of insurance policies. At the median, respondents would trade an actual annuity, life insurance, and LTCI policy for a risk-free policy offering 75-80% of the promised payments. This indicates that typical respondents dislike policy risk, and would be willing to forego a substantial share of the promised policy payment to remove this risk.

Table 2 formalizes this point. In this Table, Column (1) presents the average expected payout (as share of promised payout), Column (2) presents the mean certainty equivalent implied by the CDFs in Figure 4, while Column (3) presents the risk premia (defined as the difference between Column (1) and Column (2)) associated with each type of insurance policy. We find that the risk premia associated with each type of insurance policy is quite

Table 2: **Average Expected Payouts, Certainty Equivalent Measures, and the Implied Risk Premia for Life, Annuities, and LTC Insurance**

	Mean Expected Value (1)	**Mean Certainty Equivalent (2)**	**Risk Premia (3)**
Life	87.16	81.43	5.72
Annuity	81.51	73.79	7.72
LTCI	76.17	72.90	3.27

large. For annuities, in particular, the risk premium is nearly 8%, a level that is comparable to the well-documented, puzzlingly high risk premia associated with publicly traded equities. Overall, Table 2 suggests that not only do respondents view insurance policies as risky, but they require high risk premia to hold them.

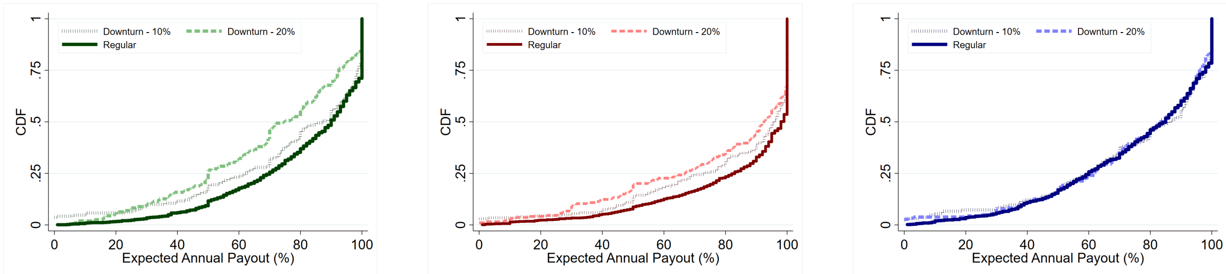
4.2 Other Survey Measures

In addition to our three main measures of nonpayment risk, we also analyze several other measures of risk. First, Figure 5 presents the perceived annual payments in different, randomly determined, aggregate states that are proxied by different stock market returns. Relative to the baseline, we find that respondents expect annuity and life insurance payments to decrease in economic downturns, as indicated by the shift in the CDFs to the left conditional on a stock market decrease of 10% and even further left for a decrease of 20%. Interestingly, we observe no corresponding shift for LTC insurance payments.These patterns suggest that the sources of risk associated with different insurance policies varies. Speculatievely, perhaps LTC insurance risk is generally associated with claim denial due to subjective state verification by insurance companies, while annuity and life insurance risk is more associated with the balance sheet of insurance companies. At the very least, this pattern of responses indicates a certain level of sophistication for survey respondents.

Overall, our supplemental measures of nonpayment risk provide several insights into the situations and manners in which individuals expect insurance companies to meet their contractual obligations.

4.3 Nonpayment Risk and Insurance Ownership

Our survey shows that perceived nonpayment risk in insurance products is large. However, in isolation they do not establish whether perceived risk affects consumer demand. To explore the relationship between demand and perceived risk, in Table 3 we regress indicators of ownership on our risk and other behavioral measures. All regressions include controls for



(a) Annuity (b) Life Insurance (c) LTC Insurance

Figure 5: **Expected Payout Distribution Conditional on Different Aggregate Stock Market Conditions.** This figure reproduces Figure 3a in "Regular" times, and also reports survey responses for times when the price of the aggregate stock market is down by 10 percent in a year or down by 20 percent.

age, wealth, income, education, marital status, race, health, household size, and retirement.[6]

We find that our risk measures are highly predictive of product ownership. For annuities (Column (1)), we find that a higher default probability is associated with lower ownership probability, as is a higher standard deviation of perceived payments. Both of these effects are significant at p-values$<.001$. For life insurance (Column (2)), a higher expected value of payout upon death is highly predictive of ownership, with the effect again significant at p-values$<.001$. Additionally, although not significant, higher full default probabilities are again associated with lower ownership probabilities for life insurance. For LTC insurance (Column (3)) we again find that a full default probability predicts lower ownership at p-values$<.001$, while higher standard deviations of perceived payouts is associated with lower ownership probabilities, although the effect is not significant. In Columns (4)-(6) we show that these results hold even after including a large set of other individual characteristics measures. These measures have little predictive power in excess of our risk measures.

[6]These controls are not shown due to space limitations but predict ownership in intuitive ways: for example, wealth, income, and education level are all found to significantly predict ownership of all three products.

Table 3: **Regression of Ownership on Risk Metrics**

	Own Annuity (1)	Own Life (2)	Own LTCI (3)	Own Annuity (4)	Own LIfe (5)	Own LTCI (6)
Annuity Payment Exp. Value	-0.0018			-0.0005		
	(0.212)			(0.373)		
Annuity Full Def. Prob	-0.0021***			-0.0020***		
	(0.000)			(0.000)		
Annuity Payment SD	-0.0043**			-0.0029***		
	(0.002)			(0.000)		
Life Payment Exp. Value		0.0046***			0.0045**	
		(0.001)			(0.003)	
Life Full Default Prob		-0.0015			-0.0013	
		(0.129)			(0.142)	
Life Payment SD		-0.0006			-0.0002	
		(0.686)			(0.896)	
LTCI Payment Exp. Value			0.0007			0.0006
			(0.111)			(0.181)
LTCI Full Default Prob			-0.0023***			-0.0022***
			(0.000)			(0.000)
LTCI Payment SD			-0.0009			-0.0010
			(0.195)			(0.136)
Trust				0.0188	-0.0063	0.0162
				(0.091)	(0.758)	(0.241)
Cognitive Score				-0.0007	-0.0033	0.0004
				(0.747)	(0.271)	(0.852)
Financial Literacy Score				-0.0112	-0.0662*	-0.0083
				(0.459)	(0.019)	(0.609)
Numeracy Score				-0.0079	0.0207	-0.0240
				(0.560)	(0.319)	(0.101)
Experienced Fraud				0.0298	0.0545	-0.0031
				(0.549)	(0.375)	(0.941)
Risk Aversion				-0.0072	-0.0160	-0.0015
				(0.252)	(0.072)	(0.776)
Propensity to Plan				0.0137	-0.0013	0.0016
				(0.243)	(0.947)	(0.888)
Early Stock Returns				0.1474	-0.5123	-0.7936
				(0.757)	(0.441)	(0.122)
N	1055	1046	1040	1055	1046	1040
R^2	0.170	0.132	0.129	0.268	0.218	0.179
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In addition to significantly predicting ownership, the magnitudes of these effects are economically meaningful, as documented in Table 4. Column (1) presents the predicted ownership rates for our survey sample. Columns (3)-(5) show the marginal effect on ownership probability from increasing the indicated risk measure by one standard deviation. Most

Table 4: **Counterfactual Predictions of Probit Regressions Under Various Specifications of Risk Perception.**

			Maginal Effects, 1 Std. Dev. Increase		
	P(Own)	**P(Own|No Risk)**	**Exp. Value**	**Full Default**	**Std. Dev.**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Annuity	.12	.24	-.010	-.017	-.030
Life	.57	.66	.111	-.042	-.010
LTCI	.10	.23	.039	-.046	-.003

importantly, Column (2) shows the predicted ownership probability if all respondents were assumed to perceive the insurance products as risk free.

Comparing Columns (1) and (2) shows that perceived risk has significant effects on the overall ownership rates. For annuities, if products were perceived as risk free this exercise suggests that ownership probability would double from .12 to .24, while life insurance ownership rates would increase from .57 to .66. Most strikingly, this exercise suggests extremely large increases in LTC insurance ownership probabilities, from .10 to .23. Of course, this analysis comes with the caveat that these estimated relationships are only locally identified and this model is not the reduced form of any structural model we have developed. In Section 6 we revisit this issue when we examine predictions from our structural model under different assumed risk perceptions.

4.4 What Determines Perceptions of Nonpayment Risk in Insurance Markets?

Having established that beliefs of risks explain behavior, we next turn to examining the sources of these beliefs. To do so, we regress each of our three risk measures for each product on demographic and other individual characteristics. Because our measures are all bounded between zero and one-hundred (with the exception of the standard deviation of payments, for which only the lower bound applies), we estimate tobit regressions with the appropriate lower and upper bounds. The results from these regressions are presented in Table 5.

Several intuitive patterns emerge from these regressions. First, we find that households with higher cognitive and financial literacy scores perceive lower risk. This suggests that some of the negative risk perceptions of insurance products reflects a lack of understanding or belief in the inability to successfully negotiate with insurance companies should an issue arise. In addition, we find that having experienced fraud in the past is associated with higher

Table 5: **Tobit regressions of risk measures on demographic and behavioral controls.**

	(1) ann_exp_value	(2) life_exp_value	(3) ltci_exp_value	(4) ann_sd	(5) life_sd	(6) ltci_sd	(7) full_def_prob_life	(8) full_def_prob_ann	(9) full_def_prob_ltci
trust	1.4253	2.2886	0.2788	-1.3812	-1.1120	-0.3979	-0.4504	0.1632	-0.8615
	(0.165)	(0.113)	(0.787)	(0.202)	(0.313)	(0.662)	(0.673)	(0.846)	(0.374)
cog_score	0.2966	0.3589	0.0929	-0.1480	-0.1314	0.0930	-0.3178*	-0.3782**	-0.3898**
	(0.059)	(0.096)	(0.565)	(0.346)	(0.493)	(0.501)	(0.039)	(0.006)	(0.007)
finlit_score2	6.8144***	3.5791	4.4049**	-2.6490	-1.4613	-1.0548	-5.1882*	-2.4366	-2.1181
	(0.000)	(0.145)	(0.010)	(0.147)	(0.437)	(0.469)	(0.017)	(0.180)	(0.236)
num_score	0.3493	1.7149	2.5265*	0.3791	-1.1370	-2.7133*	-2.2504	-1.0665	-2.2378
	(0.775)	(0.293)	(0.047)	(0.747)	(0.415)	(0.012)	(0.078)	(0.324)	(0.051)
exp_fraud2	-0.1197	-2.1701	-3.2417	0.8327	2.4689	0.6859	10.1234	7.4495*	10.6057**
	(0.980)	(0.618)	(0.505)	(0.838)	(0.565)	(0.854)	(0.058)	(0.046)	(0.003)
risk_subj	0.7951	-0.1573	-0.3824	-0.6904	0.1052	0.1386	-0.0101	0.2508	0.5388
	(0.158)	(0.795)	(0.498)	(0.163)	(0.839)	(0.760)	(0.983)	(0.612)	(0.282)
plan_ahead	-2.6690*	-1.5754	-3.2523**	2.6458*	2.9525**	0.7277	0.0171	0.9158	-0.6763
	(0.017)	(0.208)	(0.008)	(0.012)	(0.009)	(0.407)	(0.989)	(0.396)	(0.538)
cohort_rreturn	-69.2280***	-33.0117	-47.3129*	74.7321***	59.3517**	35.2781	56.5205*	44.6014*	43.7751*
	(0.001)	(0.277)	(0.042)	(0.000)	(0.009)	(0.060)	(0.012)	(0.018)	(0.042)
_cons	126.7772***	99.1973**	114.9519***	-48.9317*	-43.8391	-9.5041	-3.8482	-0.4265	20.4084
	(0.000)	(0.007)	(0.000)	(0.031)	(0.101)	(0.667)	(0.884)	(0.984)	(0.399)
/									
var(e.ann_exp_value)	607.0701***								
	(0.000)								
var(e.life_exp_value)		862.5435***							
		(0.000)							
var(e.ltci_exp_value)			716.8971***						
			(0.000)						
var(e.ann_sd)				525.7375***					
				(0.000)					
var(e.life_sd)					660.6357***				
					(0.000)				
var(e.ltci_sd)						463.9210***			
						(0.000)			
var(e.full_def_prob_life)							709.8695***		
							(0.000)		
var(e.full_def_prob_ann)								550.2486***	
								(0.000)	
var(e.full_def_prob_ltci)									636.8367***
									(0.000)
N	1058	1055	1044	1058	1051	1044	1081	1081	1082
R^2									

p-values in parentheses

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

perceived risk, especially for full default probabilities. We also find that propensity to plan predicts perceived risks, as does stock returns experienced between ages 18-25. Interestingly, we do not find that self-assessed trust and risk aversion predict beliefs of nonpayment risk, although it is unclear whether this reflects noise in these proxies.

4.5 Response Quality and Credibility

Many of the findings in this study rely on the credibility of the subjective belief measures. The survey was designed to allow for ex-post testing of response quality. For example, the order of survey modules and the policy amounts for individuals that did not already own a given type of insurance, were randomly assigned. Reassuringly, we find that this random order and random framing is insignificant when computing statistics in Tables 3 and 5.

A second key built-in check of response quality is our qualitative question, as described in Section 3.3, that asks respondents to rank policies by perceived riskiness. Although such qualitative questions are sometimes difficult to interpret, this question provides a natural check on internal consistency. We define a set of responses as internally coherent if the most risky rated insurance product according to the qualitative question is not rated as the least risky insurance product by all three quantitative risk measures and similarly for the least risky rated product. By this metric, we find that 84% of all respondents are not inconsistent. Furthermore, in Appendix A we analyze this subsample separately, and find that results in Tables 3 and 5 are unchanged.

In addition, several features of survey responses provide evidence of answer quality. For example, we find clear, consistent ordinal rankings of the perceived riskiness of insurance products across individuals. More importantly, our finding that perceived risk measures correlate with product ownership in meaningful ways establishes external validity of our measures, linking subjective expectations questions to observed behavior. Similarly, conditional expectations suggest that respondents perceive aggregate risk as affecting annuity and life insurance payouts, but not LTC insurance. This is consistent with the greater interest rate risk insurance companies face in annuity and life insurance markets.

Finally, self-evaluation measures suggest that respondents were confident in their responses. Figure 6 suggests that respondents considered a number of reasonable factors when responding to the survey. Furthermore, only 17% of respondents report being unconfident in their answers, while only 9% of respondents report having not given any thought to the issues asked about in our survey prior to responding. Overall, these patterns suggest respondents took their charge seriously and answered questions in meaningful ways.

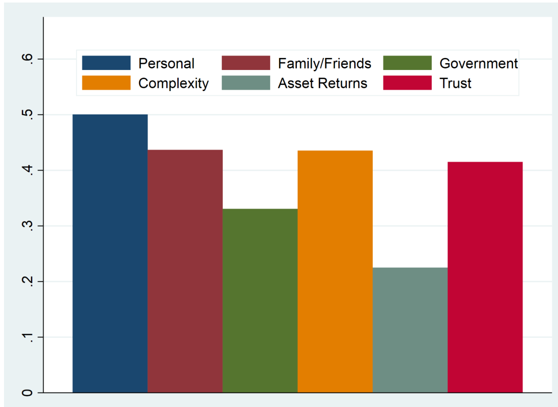


Figure 6: **Factors considered when responding to survey**

5 Model

To better quantify how nonpayment risk affects insurance ownership and how different features of insurance products affect consumer welfare, we develop an incomplete-markets life-cycle model of the demand for life insurance, annuities, LTCI, and a risk free bond. In this section we detail the model and our quantification strategy.

Agents are heterogeneous in exogenous state variables age (t), health status s_t, sex (f), and income age-profile (Y_t). Health and mortality are the key risks in the model and are captured by exogenous stochastic s_t transitions. Individuals begin each period with a quantity of risk free bonds (B_t) and insurance holdings (D_t^k) for each type of insurance k and an associated annual premium for life insurance and LTCI, and choose how much to consume, save, and invest in insurance products. The model incorporates features of real-world insurance products such as perceived nonpayment risk, high loads above actuarial fair prices, wedges between the purchase and resale prices for insurance products, and quantity restrictions (e.g., age restrictions on purchases, short-selling constraints). We use a mix of calibration and estimation to set parameters that determine preferences, risks, and choice sets.

5.1 Model Details

Demographics and Health An agent aged t_0 will live to be at most T years old, with sex denoted $f = 1$ if female and $f = 0$ if male. Each period, the agent realizes its health status s which evolves stochastically between $s = 0$ if normal, $s = 1$ if bad, $s = 2$ if the agent requires LTC, and $s = 3$ if the agent dies this period. The health evolves according to a Markov transition matrix $\Gamma_{t,f}$ which is a function of age and sex.

Health also determines the exogenous health costs ($HC_{t,s,f}$) that an agent must pay when alive. These costs, which are dependent on age, sex, and current health status, are realized between periods $t-1$ and t and are essentially a stochastic negative shock to liquid wealth. Health costs are distributed according to CDF $F_{HC|t,s,f}$, are increasing in expected value with age and health status.

Preferences Households have time-separable, health-state dependent non-homothetic preferences for consumption C_t and have a warm-glow bequest motive. Flow utility ν_s is

$$\nu_s(C_t) = \theta_{s,t}^{-\sigma} \frac{(C_t + \kappa_s)^{1-\sigma}}{1-\sigma}$$

This follows the specification of utility in Ameriks et al. (2020), where the key innovation was to allow for nonhomothetic utility in the LTC health state, analogous to how bequest utility is modeled following Nardi (2004). The new feature in this paper relative to Ameriks et al. (2020) is that $\theta_{s,t}$ varies with age. In practice, we allow $\theta_{3,t}$ to vary with age to capture, in a parsimonious way, an age-varying desire to leave a bequest, perhaps driven by the changing economic needs of children as they age.

Income Agents have a fixed retirement income age-profile that pays an amount Y_t each year they are alive. This income is the sum of all labor income, social security payments, and payments from defined benefit plans. We model agents as having one of 5 potential paths, estimated from a quintile regression on earnings in the HRS.

Because the focus of this model is asset and insurance product demands and because retirement income (especially social security and defined benefit plan payments) is generally not as risky as prime-age labor income, in our baseline model we do not allow for income uncertainty. This allows us to reduce the state space of the model and facilitates computation.

Assets Agents can invest in four different assets. First, an agent can invest in a bond (B_t) that offers a return of r. Agents are unable to borrow in bond markets, so $B_t \geq 0$.

In addition, agents can invest in three insurance products, indexed by k: a life annuity (Ann), a whole life insurance policy (LI), or long-term care insurance (LTC). Agents can purchase any of the insurance products up until a maximum age $t_{max,k}$. This captures a real world feature that after a certain age insurers, perhaps concerned with adverse selection, will not sell to individuals.

The insurance products differ in the health states s in which they promise to pay out. Let $\bar{D}^k$ be a 4×1 vector of dividends of asset k, where row s is defined as the payout in state s from owning one unit of insurance asset k: $\bar{D}^{Ann} = [1,1,1,0]'$; $\bar{D}^{LI} = [0,0,0,1]'$; $\bar{D}^{LTCI} =$

$[0, 0, 1, 0]'$.

Annuities are purchased by making a lump-sum payment of bonds. We denote the net transactions in annuities at age t as W_t^k. Thus, the law of motion on holdings D_t^{Ann} can be written as:

$$D_{t+1}^{Ann} = D_t^{Ann} + W_t^{Ann}. \tag{1}$$

Individuals owning life insurance and LTCI pay annual premia. For individuals who want to reduce their insurance holdings, annuities can be sold for some cash value, while individuals owning life insurance and LTCI can simply stop paying the premia.

Purchase prices and annual premia are set as a markup λ_+^k over the actuarially fair price. Annuities are sold at a markdown below the acturially fair price λ_-^{ANN}. The acturially fair price, denoted as $p_{t_0,s_0,f}^k$, is the price at which a risk neutral insurance company earns zero expected profits by selling a unit of insurance product k to an individual aged t_0, in health state s_0, of sex f. We allow for the rate r_I used by insurers to discount future cash flows to differ from the rate of return the household receives on its risk free bonds.

For an annuity, the actuarially fair lump-sum unit cost is computed as:

$$p_{t_0,s_0,f}^{Ann} = \sum_{t=t_0+1}^{T} \frac{1}{(1+r_I)^{t-t_0}} \times v_{s_0}' \left(\prod_{j=t_0}^{t} \Gamma_{j,f} \right) \bar{D}^{ANN} \tag{2}$$

where v_{s_0} is a 4×1 vector with a one in row s_0 and zeros elsewhere.

For life insurance and LTCI, the price paid is in the form of a constant annual premium. This annual premium is computed such that insurers expect to earn zero profits under the assumption that the product will be held until death (no lapse). This payment can be represented as the consumer shorting an annuity to the insurer with yearly payment:

$$p_{t_0,s_0,f}^k = \frac{\left[\sum_{t=t_0+1}^{T} \frac{1}{(1+r_I)^{t-t_0}} \times v_{s_0}' \left(\prod_{j=t_0}^{t} \Gamma_{j,f} \right) \bar{D}^k \right]}{p_{t_0,s_0,f}^{ANN}}, \quad \text{for } k \in \{LI, LTCI\} \tag{3}$$

For life insurance and LTCI the annual premium is locked in at the time of purchase, and is thus a state variable. To keep the state space computationally tractable, we only allow individuals to hold at most one life insurance and one LTCI policy at a time. If they want to change their LI or LTCI holdings, they must let their old contract lapse and can purchase a new contract at current prices.

Additionally, we do not allow for short-sales of insurance products, so $D_{t+1}^k \geq 0$.

Default Probabilities We allow for two types of default for each insurance product. First the insurance company might fully default on the value of the contract. Practically, this means that with probability $q^{k,FD}$ the promised future dividends (D^k_{t+1}) are set to zero in the next period:

$$D^k_{t+1} = \begin{cases} D^k_t + W^k_t & \textit{with prob} \;\; 1 - q^{k,FD} \\ 0 & \textit{with prob} \;\; q^{k,FD} \end{cases} \tag{4}$$

Second, the insurance company may default on the promised payment in a given period. In this case, instead of receiving the promised dividend payment $\hat{D}^k_{t+1} = D^k_{t+1}$ the agent receives a payment of $\hat{D}^k_{t+1} = 0$. This occurs with probability $q^{k,D}$:

$$\hat{D}^k_{t+1} = \begin{cases} D^k_{t+1} & \textit{with prob} \;\; 1 - q^{k,D} \\ 0 & \textit{with prob} \;\; q^{k,D} \end{cases} \tag{5}$$

For simplicity, we do not currently model uncertainty over the fraction of a qualified payment an individual we receive. Instead, we model an annual nonpayment as a binary variable, in which individuals either receive the full contractual value or zero. We calibrate $q^{k,D}$ so that the expected payment is equal to the mean of the expected payment distribution from the survey. We hope to model a richer partial nonpayment probability distribution in line with that measured in our survey in the future.

Government Insurance Consumption is insured by the government through a minimum consumption level $\bar{C}$. To receive government insurance, an agent must give all of its wealth to the government and in return consumes $\bar{C}$. Following the rules of Medicaid, agents then enter next period zero bond and insurance insurance holdings, i.e., $B_{t+1} = D^k_{t+1} = 0$ for all k.

Intertemporal Budget Constraints We now collect the results from above and specify the intertemporal budget constraints that track the evolution of bonds.

The law of motion for risk-free bonds can be written as:

$$\begin{aligned} \frac{1}{(1+r)} B_{t+1} = & B_t + Y_t + v'_{s_t} \sum_k D^k_t \hat{D}^k_t - C_t - HC_t - p^{LTCI}_{i,t} - p^{LI}_{i,t} \\ & - W^{ann}_t p^{ann}_{t,s,f} \left(1 - \lambda^{ann}_{-} \mathbb{I}_{W^{ann}_t < 0} + \lambda^{ann}_{+} \mathbb{I}_{W^{ann}_t > 0}\right) \end{aligned} \tag{6}$$

The individual starts the period with some bond and insurance holdings, earns income, receives payments from insurance products if a qualifying event occurs and the insurance product pays, consumes, pays health costs, pays premia on life insurance and LTCI, and receives or pays income from the sale or purchase of annuities. $p_{i,t}^{LTCI}$ and $p_{i,t}^{LI}$ are set at the time of purchase of the contracts and are constant unless choosing to change the quantity of insurance owned as described above.

Full Decision Problem We now specify the full decision problem solved by each agent. Let $X_t = \{s_t, Y_t, f\}$ and $X_{t+1} = \{s_{t+1}, Y_{t+1}, f\}$ denote exogenous state variables. The consumer decision problem is:

$$
\begin{aligned}
V_t(B_t, D_t^{ANN}, D_t^{LI}, D_t^{LTC}, X_t, p_i^{LTCI}, p_i^{LI}) = \max\{&V_t^{GOV}(B_t, D_t^{ANN}, D_t^{LI}, D_t^{LTC}, X_t, p_i^{LTCI}, p_i^{LI}), \\
&V_t^{PRIV}(B_t, D_t^{ANN}, D_t^{LI}, D_t^{LTC}, X_t, p_i^{LTCI}, p_i^{LI})\}
\end{aligned}
$$

where:

$$
\begin{aligned}
V_t^{GOV}(B_t, D_t^{ANN}, D_t^{LI}, D_t^{LTC}, X_t, p_i^{LTCI}, p_i^{LI}) &= \nu_s(\bar{C}_s) + \beta \mathbb{E}\left[V_{t+1}(B_{t+1}, 0, 0, 0, X_{t+1}, 0, 0)\right] \\
\textit{where} \quad B_{t+1} &= Y_{t+1} - HC_{t+1,s',f}
\end{aligned}
$$

i.e. they consume minimum consumption $\bar{C}_s$ and give up all their insurance holdings going into period $t+1$, and

$$
\begin{aligned}
V_t^{PRIV}(B_t, D_t^{ANN}, D_t^{LI}, D_t^{LTC}, X_t, p_i^{LTCI}, p_i^{LI}) = & \max_{W_t^{ANN}, D_{t+1}^{LI}, D_{t+1}^{LTC}, C_t} \nu_s(C_t) \\
& + \beta \mathbb{E}\left[V_{t+1}(B_{t+1}, D_{t+1}^{ANN}, D_{t+1}^{LI}, D_{t+1}^{LTC}, X_{t+1}, p_{i,t+1}^{LTCI}, p_{i,t+1}^{LI})\right] \\
where \quad & \frac{1}{(1+r)} B_{t+1} = B_t + Y_t + v'_{s_t} \sum_k D_t^k \hat{D}_t^k - C_t - HC_t - p_{i,t}^{LTCI} - p_{i,t}^{LI} \\
& - W_t^{ann} p_{t,s,f}^{ann} \left(1 - \lambda_-^{ann} \mathbb{I}_{W_t^{ann}<0} + \lambda_+^{ann} \mathbb{I}_{W_t^{ann}>0}\right)
\end{aligned}
$$

$$
\begin{aligned}
& \hat{D}_{t+1}^k = \begin{cases} D_{t+1}^k & with\ prob\ \ 1 - q^{k,D} \\ 0 & with\ prob\ \ q^{k,D} \end{cases} \\
& D_{t+1}^k = \begin{cases} D_t^k + W_t^k & with\ prob\ \ 1 - q^{k,FD} \\ 0 & with\ prob\ \ q^{k,FD} \end{cases} \\
& D_{t+1}^k \geq 0 \\
& W_t^{Ann} \leq 0 \quad \text{if} \quad t > t_{max} \\
& D_{t+1}^k = D_t^k \vee 0 \quad \text{if} \quad t > t_{max} \quad \text{for} \quad k \in \{LI, LTC\} \\
& p_{i,t}^k = \begin{cases} p_i^k & \text{if} \quad D_t^k = D_{t-1}^k \\ p_{t-1,s,f}^k D_t^k & \text{if} \quad D_t^k \neq D_{t-1}^k \end{cases} \quad \text{for} \quad k \in \{LI, LTC\}
\end{aligned}
$$

with stochastic processes

$$
\begin{aligned}
& s' \sim \Gamma_{t,f|s} \\
& HC_{t+1,s,f} \sim F_{HC|t+1,s,f}
\end{aligned}
$$

and prices

$$
\begin{aligned}
p_{t_0,s_0,f}^{Ann} &= \sum_{t=t_0+1}^{T} \frac{1}{(1+r_I)^{t-t_0}} \times v'_{s_0} \left(\prod_{j=t_0}^{t} \Gamma_{j,f}\right) \bar{D}^k \\
p_{t,s,f}^{LI} &= \left[\sum_{t'=t+1}^{T} \frac{1}{(1+r_I)^{t'-t}} \times v'_s \left(\prod_{j=t}^{t'} \Gamma_{j,f}\right) \bar{D}^{LI}\right] / p_{t_0,s_0,f}^{Ann} \\
p_{t,s,f}^{LTCI} &= \left[\sum_{t'=t+1}^{T} \frac{1}{(1+r_I)^{t'-t}} \times v'_s \left(\prod_{j=t}^{t'} \Gamma_{j,f}\right) \bar{D}^{LTCI}\right] / p_{t_0,s_0,f}^{Ann}
\end{aligned}
$$

5.2 Risks, Costs, and Incomplete Markets

The model above is similar to the complete markets model considered in Koijen et al. (2016), but incorporates several sources of non-insurable risks, costs, and market frictions that might deter agents from purchasing insurance products. Because modeling these features and exploring how they affect demand for insurance is a main contribution of this study, it is worthwhile to explain modeling choices and discuss their effect on demand for insurance products before moving on to our main findings.

First, on all insurance products, we impose a maximum age at which agents are able to purchase new or add to previously purchased policies. Although insurance companies could always in principle offer appropriately priced insurance products, insurers are generally unwilling to sell new policies to older individuals, possibly due to difficulty accounting for adverse selection. For example Hendren (2013) notes that LTCI applications for individuals over age 80 are automatically rejected, while MetLife notes that 98% of annuity purchases occur before age 85, and most life insurance companies stop issuing new policies to individuals between ages 80 and 90.

A second source of imperfection in the market we model is price wedges that require that an agent pay a more than actuarially fair price to purchase the product and, in the case of annuities, receive a less than actuarially fair price when selling the product. Theoretically, these price wedges have two effects. First, agents are less willing to purchase the product since it is both more expensive and worth less in the future should they decide to sell it. Second, these price wedges produce regions in the space of asset holdings where individuals are unwilling to buy or sell the product, and potentially generate the infrequent adjustment of insurance holdings that we observe empirically. Importantly, the spread between buying and selling, $\lambda_{+}^{Ann} - \lambda_{-}^{Ann}$, generates different marginal payoffs between states that can not be insured with the modeled assets.

A third significant feature of the insurance we model is the nonpayment risk, captured by the probabilities that the insurance company will default on the total value ($q^{k,FD}$) and per-period payments ($q^{k,D}$). Allowing for these nonpayment probabilities provides two deterrents to insurance purchase. First, because the product price defined in Equation 2 does not factor in default, the price of the insurance policy is worse than actuarially fair. More importantly however, allowing for nonpayment risk introduces uninsurable model states that feature potentially large losses of wealth for agents that invest in these policies, and rational agents may choose to forgo product purchase to avoid holding this risk.

A fourth modeled deterrent to insurance product purchase is uninsurable health risk. Out-of pocket health costs are known to generate a significant precautionary savings motive (see De Nardi et al. (2010), among others), and consumers may be reluctant to commit wealth to insurance products that don't cover these expenses.

In short, the model developed in this paper provides a rich environment to explore how different sources of market incompletion, costs, and risks affect demand for the three considered insurance products, and most importantly, better understand whether the low levels of insurance are rational when one accounts for a range of potential deterrents to insurance product purchase.

5.3 Model Calibration

We estimate 5 income-age profiles by running a quintile regression on HRS data, separately for men and women. Income includes labor income, defined contribution pension plans, and social security payments. We also estimate the sex and age dependent health-state transition matrix and the out-of-pocket medical health expenditure shocks using HRS data. See Appendix B for details. We also set consumption when using government care and not in need of LTC to $\bar{C}_0 = \bar{C}_1 = \$5K$.

The final parameters we set independently are those that govern insurance product characteristics.

We use the means of our original survey responses to calibrate nonpayment probabilities $q^{k,FD}$, $q^{k,D}$. We set the loads above actuarially fair pricing $\lambda_+^{ANN}, \lambda_+^{LTCI}$, from Brown and Finkelstein (2011) and λ_+^{LI} from Hong and Rìos-Rull (2012). For now, we set $\lambda_-^{ANN}, t^{max,k}$ based on our reading of industry reports.

We estimate the remaining parameters of the model using the simulated method of moments to match 3 sets of moments. We target the 25th, 50th, and 75th percentile of the wealth distribution by 5-year age bins for ages 45–80. We also target the average ownership rate of annuities, life insurance, and long-term-care insurance. Finally, we target the 9 strategic survey question (SSQ) mean responses from Ameriks et al. (2020). These SSQs place individuals in hypothetical scenarios and ask them to make choices that are designed to be highly revealing of preferences. See Appendix C for details.

The nonhomothetic health-state dependent utility functional form is taken from Ameriks et al. (2020).

All of the preference parameter values are the same as from Ameriks et al. (2020) except for σ, which is now 4.27 instead of 5.27. For the new, time varying bequest motive, we set $\theta_{3,t} = \theta_{beq,0} + (\theta_3 - \theta_{beq,0} \frac{(t-45)}{(80-45)}$. That is, the bequest parameter at age 80 and above is taken from Ameriks et al. (2020), we introduce a new parameter, $\theta_{beq,0}$, that controls the bequest motive at age 45, and the parameter $\theta_{3,t}$ changes linearly between these two values. This

Table 6: **Baseline Calibration - Insurance products**

	Annuities	Life	LTCI
Full Default ($q^{k,FD}$)	.018	.012	.023
Annual Payout Default ($q^{k,D}$)	.195	.128	.238
Price Wedge, buying (λ_{+}^{k})	.2	.25	.32
Price Wedge, selling (λ_{-}^{k})	.15	–	–
Max Purchase age ($t_{max,k}$)	70	70	70

Table 7: **Baseline Calibration - Preferences and Returns**

Time Preference - $\beta = 1.01$	**Risk Aversion** - $\sigma = 4.27$
LTC motive - $\theta_2 = 0.67$	**LTC motive** - $\kappa_2 = -37.44$
Bequest motive - $\theta_3 = 1.09$	**Bequest motive** - $\kappa_3 = 7.83$
Youth bequest motive - $\theta_{beq,0} = .13$	
Bond return - $r = 0.03$	Insurance discount rate - $r_I = 0.04$

parameter has a particularly strong impact on ownership of life insurance over the life cycle.

Model Solution In their model with complete markets, Koijen et al. (2016) provide a set of necessary conditions for optimal insurance portfolio choice as well as an analytical characterization of the welfare loss due to sub-optimal insurance product choice. Unfortunately, analytic solutions do not exist for the incomplete markets framework considered in this paper. We thus solve the model quantitatively, namely by backwards induction utilizing a 4-dimensional grid search over the $(B_t, D_t^{ANN}, D_t^{LI}, D_t^{LTCI})$. To simulate the model, we set as an initial condition the distribution of state variable values drawn from UAS survey respondents. In particular, for each respondent, we take their age, sex, income, liquid + housing wealth, and measured insurance product ownership.[7] Then we simulate the model forward, allowing individuals in the model to re-optimize their portfolios and savings over the life cycle.

6 Model Results

In this section we present preliminary results from our latest estimation of the model. Figure 7 shows that the model matches the data well for the distribution of wealth by age. There is some odd behavior in the data for wealth at older ages likely driven by small samples or cohort effects, which is also visible to a lesser degree in HRS data.

[7] We presume that the LTC and life insurance annual premiums they locked in are the ones they would have if they purchased at age 55 when healthy.

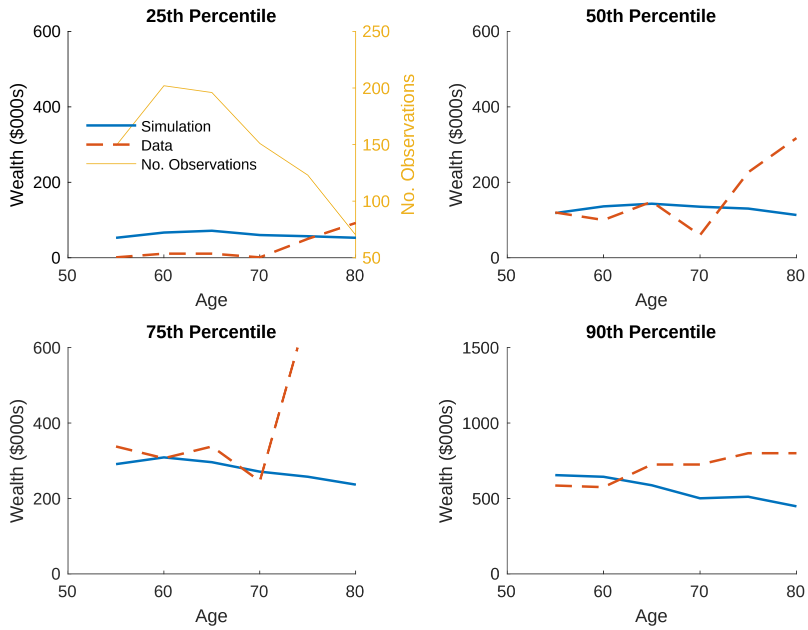


Figure 7: **Insurance Ownership: Model and Data**

Figure 8 compares measured and model-implied ownership rates for the 3 difference insurance products over the life cycle.

In the calibration we targeted the average insurance ownership rates for each of the 3 products, but the life-cycle pattern of ownership was not targeted. Overall, we match well the average ownership rates as well as the relatively flat empirical ownership profiles. However, life insurance ownership in the model is less frequent than in the data. In the data, some life insurance holdings are likely motivated by tax-advantaged savings rather than to insure against early death and our model does not have a rich enough asset structure to capture that saving motive.

In our main analysis we compute ownership rates and welfare changes that would arise if the insurance products had different characteristics. Specifically, we explore the cases of zero insurance, insurance that has zero nonpayment risk, actuarially-fair priced insurance, and the combination of no nonpayment risk and actuarially fair pricing. We then compute the consumption equivalent welfare gain (aggregating over individuals) of living in economies with different insurance product characteristics, using the zero-insurance economy as the benchmark. The results from this exercise are provided in Tables 8.

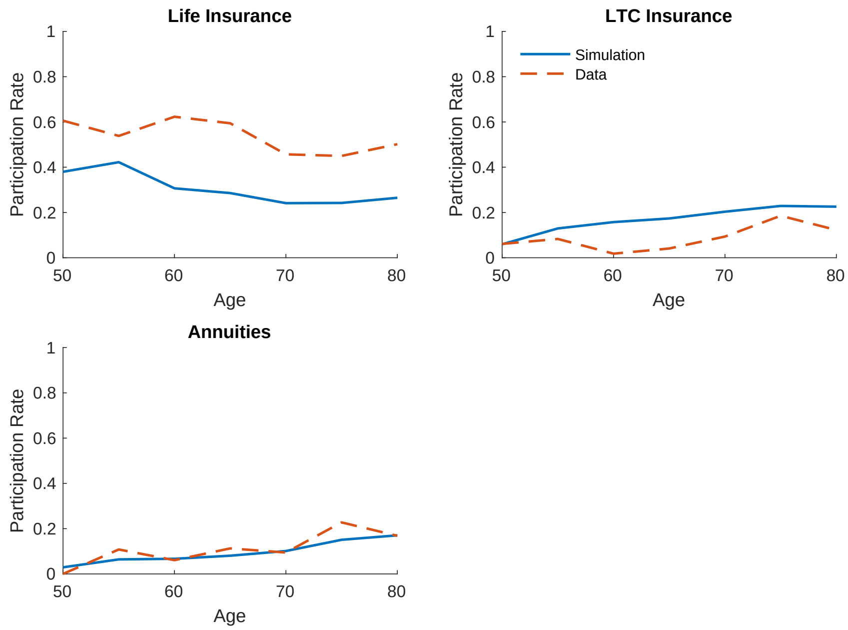


Figure 8: **Insurance Ownership: Model and Data**

6.1 Ownership and Welfare Results: Rational Expectations

Panel A of Table 8 presents the resulting model-predicted ownership rates for annuity, life, and LTC insurance for the four calibrations we consider. In column (3) we observe that in our baseline calibration, insurance demands are quite low. The ownership rate for annuities is 8.9%, life insurance is 31.5% while LTCI is 16.2%. While we closely match annuity ownership and we slightly overpredict LTCI ownership, overall the baseline model matches the data in that the vast majority of people do not own these products. Life insurance is owned by substantially fewer people in our model as in the data. This may reflect the additional tax-advantages some life insurance products with cash value provide that we do not model.

Table 8: **Insurance Demand and Welfare Costs of Sub-optimal Portfolio Holdings: Rational Expectations**

	Data	No Insurance	Baseline	No Price Wedges	No Nonpayment Risk	No Price Wedges or Nonpayment Risk
A. *Insurance Ownership*						
LI	53.9%	0.0%	31.5%	41.4%	79.7%	89.3%
LTC	8.7%	0.0%	16.2%	19.7%	33.7%	57.5%
Ann	10.7%	0.0%	8.9%	17.4%	54.8%	66.7%
B. *Welfare Gains*						
Consumption Equivalent	-	-	0.4%	1.3%	5.2%	7.9%

Comparing the Column 3 with Columns 4-6 in Table 8 provides insights into the reason for these low demands. For annuities, we find that the 20 percent load above actuarial fair pricing plays a sizable role in limiting demand: pricing annuities at zero markup increases the fraction of agents with positive demand to 17%. Nonpayment risk has an even larger effect on annuity ownership, as changing products to have zero nonpayment risk increases the ownership rate to 55 percent. The combination of zero nonpayment risk and zero markups over the actuarial price leads to a 67 percent ownership rate. We similarly find that removing nonpayment risk and price markups has a large effect on life insurance ownership. Making life insurance risk free increases optimal ownership from 32% to 80%, removing markups increases it to 41%, while the combination of those two factors leads to 89% ownership. For long-term care insurance, we find that removing nonpayment risk increases demand to 55%, removing markups increases it to 17%, while the combination of those two factors leads to 67% ownership. Even with zero nonpayment risk, actuarially-fair pricing, and risk averse individuals, not all individuals choose to purchase insurance. This is in part due to state-dependent preferences and in part due to implicit government care option. In summary, individuals in our model are very sensitive sensitive to nonpayment risk, which significantly reduces ownership rates for all three insurance products. Accounting for real-world characteristics of insurance products has a large effect on insurance ownership.

Panel B of Table 8 presents the welfare gains associated with the different asset market cases, measured in consumption equivalent units. That is, it is the amount that consumption would need to be increased in all states in the world without these 3 insurance products existing to be indifferent to living in the world described by each case. We find that welfare costs are small under our baseline calibration. Most individuals optimally choose not to own any of the 3 insurance products, and ownership of LTCI and annuities is very low, so the welfare gain from being able to purchase the optimal amount of insurance in our baseline economy compared to an economy in which the only asset is a risk free bond is small at 0.4%. In the fourth column we find that the welfare gains nearly triple to 1.3% when insurance prices have zero markup. There is an even larger 5.2% increases in welfare when insurance has zero nonpayment risk as seen in Column 5. In Column 6 we find that when insurance is priced with zero markups and there is zero nonpayment risk the welfare gains over autarky are 7.9% of annual lifetime consumption. This huge welfare gain shows that individuals face substantial life-cycle risks of needing LTC and uncertain death timing and that they want to insure against this risk. Put another way, a complete market analysis—which is closer to our final case of no markups and no nonpayment risk—might suggest that there are large welfare losses from holding suboptimally-low amounts of insurance, but this incomplete market analysis that tries to capture key properties of real-world insurance products suggests much smaller welfare losses from low insurance ownership. A main conclusion of the paper is that the risk of nonpayment and the large markups over actuarial fair prices prevents individuals from insuring themselves against these risks using products available in the market, at a substantial welfare cost.

6.2 Ownership and Welfare Results: Subjective Beliefs

Table 9: **Insurance Demand and Welfare Costs of Sub-optimal Portfolio Holdings: Subjective Non-Payment Beliefs & Payments Always Made**

	Data	No Insurance	Baseline	No Price Wedges	No Nonpayment Risk	No Price Wedges or Nonpayment Risk
A. *Insurance Ownership*						
LI	53.9%	0.0%	31.8%	41.7%	79.7%	89.3%
LTC	8.7%	0.0%	18.5%	18.9%	33.7%	57.5%
Ann	10.7%	0.0%	9.3%	20.9%	54.8%	66.7%
B. *Welfare Gains*						
Consumption Equivalent	-	-	1.4%	2.7%	5.2%	7.9%

The results presented in Table 8 were computed assuming that individuals have rational expectations, i.e., the probability of nonpayment equaled individuals' beliefs about the probability of nonpayment. Finally, in Table 9 we present a welfare analysis when individuals do not have rational expectations. For this exercise we hold the nonpayment beliefs fixed but change the insurance payout process so that payment are always made. Individuals in this exercise have the same optimal policy rules as in the previous exercise, since their beliefs are unchanged, so the only difference in insurance ownership will come from different values of the state variables arising from different insurance payouts. Since the insurance qualifying events (needing LTC or death) tend to happen at older ages, after insurance can no longer be purchased, this alternative exercise generates insurance ownership rates very similar to that of the rational expectations exercise. The welfare numbers are, however, different. Now, the baseline is 1.4% better than the autarky no-insurance case, since receiving payments is better than not receiving payments. Perhaps even more interesting is the comparison of 1.4% to the 5.2% welfare gain in the no-nonpayment-risk column. For this subjective beliefs case in which there is zero-nonpayment risk, insurance pays individuals whenever there is a qualifying even in both in the baseline and no-nonpayment-risk case. The difference in welfare is completely driven by the difference in insurance purchases. When individuals know there is zero nonpayment risk, they substantially increase their ownership of insurance products: life insurance from 32% to 80%, annuities from 9% to 55%, and LTCI from 19% to 34%. If this were the true model of the world, just correcting individuals mistaken fears about nonpayment risk would lead to large increases in insurance ownership and large welfare gains.

7 Discussion

This paper provides three novel findings. First, we show that many consumers perceive significant risks in purchasing insurance products due to non-payment and default by insurance companies. Second, we provide compelling evidence that these perceived risks matter for insurance product choice: statistical and structural analyses both suggest ownership rates would be much higher if insurance products were risk free and actuarially-fair priced. Third, we show that the consumer welfare costs of these nonpayment risks and high prices are large, totaling almost 8% of lifetime consumption. Overall, our study suggests incomplete markets and perceived risks are often overlooked but important determinants of insurance holdings by consumers. In addition, our study highlights the importance of measuring and modeling the products consumers perceive as available when conducting welfare analyses and designing policy to affect consumer choice.

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A Analysis of UAS survey subsample with internally consistent responses

Table A.1: **Regression of ownership on risk metrics in our sample with internally consistent responses**

	(1)	(2)	(3)	(4)	(5)	(6)
	own_ann	own_life	own_ltci	own_ann	own_life	own_ltci
ann_exp_value	-0.0017			-0.0002		
	(0.270)			(0.770)		
full_def_prob_ann	-0.0016**			-0.0016**		
	(0.008)			(0.004)		
ann_sd	-0.0045**			-0.0027***		
	(0.004)			(0.001)		
life_exp_value		0.0046***			0.0038*	
		(0.001)			(0.015)	
full_def_prob_life		-0.0015			-0.0012	
		(0.129)			(0.174)	
life_sd		-0.0006			-0.0006	
		(0.686)			(0.701)	
ltci_exp_value			0.0009			0.0008
			(0.050)			(0.118)
full_def_prob_ltci			-0.0022***			-0.0022***
			(0.000)			(0.000)
ltci_sd			-0.0010			-0.0010
			(0.208)			(0.163)
trust				0.0225	-0.0133	0.0214
				(0.058)	(0.551)	(0.151)
cog_score				-0.0013	-0.0028	0.0015
				(0.585)	(0.393)	(0.558)
finlit_score2				-0.0000	-0.0755*	0.0003
				(1.000)	(0.014)	(0.987)
num_score				-0.0214	0.0199	-0.0348*
				(0.161)	(0.385)	(0.042)
exp_fraud2				0.0517	0.0800	0.0186
				(0.378)	(0.238)	(0.704)
risk_subj				-0.0085	-0.0142	-0.0025
				(0.210)	(0.147)	(0.660)
plan_ahead				0.0004	-0.0159	0.0024
				(0.974)	(0.444)	(0.843)
cohort_rreturn				-0.0824	-0.5042	-0.8261
				(0.869)	(0.457)	(0.144)
N	871	1046	856	871	862	856
R^2	0.141	0.132	0.142	0.246	0.234	0.198
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: **Tobit regressions of risk measures on demographic and behavioral controls, sample with internally consistent responses.**

	(1) ann_exp_value	(2) never_def_prob_life	(3) ann_sd	(4) life_exp_value	(5) never_def_prob_ann	(6) life_sd	(7) never_def_prob_ltci	(8) ltci_exp_value	(9) ltci_sd
main									
trust	0.1855	-0.2577	-0.7070	1.3690	1.3169	-0.3861	-2.0044*	0.3406	-0.4151
	(0.855)	(0.812)	(0.446)	(0.261)	(0.157)	(0.694)	(0.043)	(0.752)	(0.605)
cog_score	0.2363	0.4034*	-0.0933	0.3813	0.1936	-0.1091	0.4867**	0.1479	-0.0176
	(0.169)	(0.021)	(0.565)	(0.090)	(0.206)	(0.542)	(0.003)	(0.393)	(0.891)
finlit_score2	5.9770**	4.7221*	-2.0708	0.6433	1.9868	0.7930	1.5694	3.6353	-0.5710
	(0.002)	(0.011)	(0.254)	(0.782)	(0.221)	(0.647)	(0.303)	(0.052)	(0.669)
num_score	0.8866	2.1226	-0.3404	1.8751	1.1263	-1.6830	0.8036	2.8365*	-2.7947**
	(0.514)	(0.113)	(0.781)	(0.274)	(0.318)	(0.214)	(0.494)	(0.038)	(0.004)
exp_fraud2	3.0947	-10.1457*	-3.3082	-1.0436	-7.0727*	0.0553	-9.9046**	-1.3876	-2.3892
	(0.553)	(0.043)	(0.454)	(0.818)	(0.045)	(0.989)	(0.005)	(0.798)	(0.530)
rational	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
risk_subj	0.5937	0.2764	-0.4378	-0.7318	-0.0563	0.8557	-0.1707	-0.2562	0.2187
	(0.311)	(0.580)	(0.367)	(0.275)	(0.911)	(0.099)	(0.730)	(0.660)	(0.610)
plan_ahead	-1.2719	0.3207	1.3106	-0.2452	0.1293	1.5910	1.6552	-1.8149	-0.4275
	(0.316)	(0.785)	(0.247)	(0.860)	(0.906)	(0.161)	(0.129)	(0.183)	(0.645)
N	872	888	872	868	888	864	889	857	857
R^2									
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

p-values in parentheses

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

B Estimation of Income and Health Processes (TBD)

In this section we describe our estimation of health, medical expense, and income profiles that either serve as inputs into the structural model. All processes and profiles are obtained by applying the estimation strategy described below to the full HRS sample.

C Simulation and Estimation of Jointly-Determined Model Parameters (TBD)

In this section we describe how we compute optimal policies for individuals in the model, how we simulate the model, how we construct sample moments of wealth, insurance ownership rates, and strategic survey questions from the data, and how we use the simulated method of moments to estimate model parameters.