Risky Insurance: Insurance Portfolio Choice with Incomplete Markets*

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Preliminary

We use a new survey to document significant perceived counterparty risk in annuity, life insurance, and long-term care insurance markets. We find that nonpayment risk significantly predicts insurance product ownership. In fact, annuity and long-term care insurance markets would be approximately twice as large if products were perceived as risk-free. To interpret our measures, we develop a new lifecycle model of the joint demand for these three products that allows for uninsurable counterparty risk and other dimensions of incomplete markets. We find that these risks significantly decrease insurance demand, and, as a result, welfare costs of sub-optimal insurance portfolios are small. However, the welfare costs of counterparty risk and incomplete markets – whether real or perceived – are large relative to a complete market benchmark.

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1 Introduction

> "There is really no mystery about [why people don't buy] long term health insurance. The reason it seems to defy reason is because your assumptions are flawed. .... My father had emphysema and the insurance company fought tooth and nail to prevent paying for years. ... And of course, only paying 50 to 80% of what they owed him. Not that they were stupid, but that they were greedy. If we believed they would pay what they should when they should, we'd buy. It's not what the odds are on that lottery ticket, it is what are the odds you'll get paid if you win." – Anonymous Reader[1]

A large number of financial products are available that directly address many of the the lifecycle risks that face Americans. Life insurance insures an individual against early death and provides a vehicle to transfer money to an individual's future 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 (LTC) insurance provides coverage of expensive health and care costs should an individual ever 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 to meet their desired insurance. 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. (2016), Mommaerts (2015)). In recent work, 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 of risk measures that define necessary conditions for an optimal insurance portfolio, characterize the optimal consumption path, and estimate substantial welfare losses due to households

[1]This quote comes from an email sent to the authors following press coverage of their previous work (Ameriks et al. (2016)) on long term care insurance. This statement was unprompted and there was no prior interaction with the corresponding individual, who granted permission to quote his message upon the author's request.

holding sub-optimal insurance portfolios.

In this paper we develop both a new dataset and a new model to shed new light on consumer demand for annuities, life insurance, and LTC insurance. We first design a new survey to measure the expected distribution of insurance policy payments and other imperfections in insurance markets. We then incorporate these measures into a model that allows for uninsurable counterparty non-payment risk, price wedges between purchase and selling prices, maximum age for new policy issuance, uninsurable health risk, and uninsurable aggregate risk. Both our new measures and new model were designed in tandem to help determine whether consumer choices or insurance markets themselves are sub-optimal.

Our study makes several contributions that advance understanding of consumer insurance demand. First, we show that perceived counterparty risk is substantial in all three insurance markets we study. Our elicited distributions of expected payouts imply that the average consumer expects to receive 87.2% of the promised payout from a typical life 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 .23 for life insurance, .29 for annuities, and .32 for LTC insurance. Thus, the three risk measures we focus on in this study all indicate that life insurance is perceived as the most safe and and LTC insurance as most risky, although consumers perceive higher risk in insurance markets than what would be inferred from historical observation.

Our second key finding is that these 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 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 score, risk aversion, propensity to plan, and financial literacy) and overall suggest that perceived risk is a barrier to 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 markets as risk-free, while life insurance ownership rates would be over nine percentage points higher.

Our third key contribution is development and use of a new lifecycle model of joint insurance demand to interpret our data. In addition to modeling uninsurable counterparty non-payment risk consistent with our survey measures, we also account for price wedges between purchase and selling prices and maximum age for new policy and calibrate these model features to match products available in the market. We additionally allow for uninsurable health, medical expense, and aggregate risk. This study 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 realistically captures the decision problem households face in retirement.

After accounting for product risks and market imperfections, the model predicts insurance holdings in line with those observed empirically: consumer demand for annuities and long-term care insurance is very low, and demand for life insurance is significantly limited. Furthermore, we find that while all modeled market imperfections limit demand, uninsurable counterparty risk is the most important source of incomplete markets, especially for annuities and long-term care insurance. Finally, in our incomplete markets model the welfare costs of sub-optimal insurance products holdings are negligible. However, similar to Koijen et al. (2016), we find large welfare costs of approximately 6% annual consumption relative to a complete markets benchmark. We conclude that household deviations from optimal insurance portfolios are small given the products they perceive as available to purchase, but 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 counterparty 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 serious 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. This pattern is consistent with annuity and life insurance companies being more subject to interest rate risk, as large premiums are typically paid up front. Finally, we included a number randomization and internal consistency checks in our survey desgn. 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.[2]

Our paper relates to a number of recent literatures and studies. 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

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

(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%, 7.7%, and 3.3% for life insurance, annuities, and LTC insurance, respectively, 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 model, 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 extend this paper's complete market framework to characterize optimal insurance holdings in an incomplete market setting, and show that this extension has significant implications for interpreting 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 a large number of studies that attempt to understand the demand function 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. (2016), 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.

More broadly, are study also fits with an active literature studying the determinants of late-in-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 (Hubbard et al. (1994)Palumbo (1999),Anderson et al. (2004), De Nardi et al. (2010), uninsurable LTC expenditure (Kopecky and Koreshkova (2014), Lockwood (2016), Ameriks et al. (2015)) 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 slow wealth decumulation in retirement.

Mroe broadly, this study relates to an influential literature that measures and models 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 equitiesCurcuru et al. (2004), Fagereng et al. (2016b). We contribute to this literature by demonstrating that incomplete insurance product markets have significant affects on consumer choices and welfare, thus highlighting the importance of measuring and modeling market incompletions in a new domain.

We additionally relate to a number of studies 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 resolve this question by (1) showing that perceived counterparty 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. (2016a) demonstrate that this channel is important in matching empirical portfolio holdings with a lifecycle 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 purchase. 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 thus contribute 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 the considered insurance markets and treat counterparty risk as exogenous, this study provides new measures of consumers beliefs regarding the default risk from insurance providers that potentially provide new insights into sources of financial instability.

In short, this paper develops new data and a new model that are related to a number of literatures that study insurance markets and product choice. 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 empirical measures. Section 5 describes the baseline model, including all market imperfections and incompletions, and details our calibration approach. Section 6 analyzes predictions from our empirical model and calculates the welfare costs of sub-optimal insurance product holdings. Finally, Section 8 concludes.

2 Data

Our study uses two data sets. First, we use a sample 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 custom designed to measure perceptions of insurance policies (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. All measures of perceived risk and market incompletions in insurance markets come from our UAS sample, while all model inputs, including stochastic processes, moments used in calibration, are provided by the HRS. In addition, in some exercises we will calculate model predictions and welfare costs using HRS respondents. In these instances, we will sample from the state distribution observed in the

HRS.

Because, after appropriate reweighting, both the HRS and our UAS samples are representative of the population of older Americans, measures taken from each data set can be applied to the other 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 or 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. Additionally, 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 – the main objects of interest in this study – are plotted by age in Figure 1. Several patterns are clear in this figure. First, as stated in the introduction, ownership of insurance products late-in-life is fairly low, especially for annuities and LTC insurance. At normal retirement ages of 65-67, 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. (2016); Braun et al. (2016)). Second, we observe higher ownership rates for life insurance, with approximately 60% of households owning a policy at normal retirement age. In addition,, consistent with patterns documented in Hong and Rìos-Rull (2012), life-insurance ownership falls steadily with age as term policies that were purchased earlier in life to insure their children's welfare expire. Overall, Figure 1 indicates little appetite for ownership of insurance products at older ages.

Additionally, at times we will sample from the distribution of state variables in the HRS when initiating our structural model. Although our primary analysis focuses on our UAS survey sample, using HRS sample allows us to verify our key findings in a large sample and to eliminate concerns regarding the external validity of our findings. In this analyses, we restrict to the three most recent HRS cohorts and measure all variables as observed in the 2015 HRS.[3] In Column (1) of Table 1 we present summary stats for this sample of individuals.

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

Table 1: **Demographic Characteristics and Other Summary Statistics for the HRS and UAS samples.** Variables in Column (1) indicate the mean for the HRS, while Column (2) indicates the mean for our UAS sample.

	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

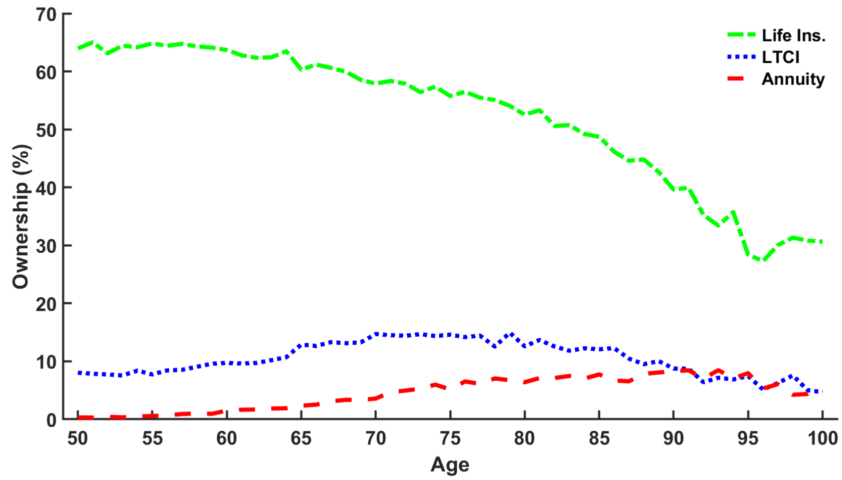


Figure 1: **Age profiles of ownership rates for annuities, life insurance, and long-term care insurance in the HRS.**

2.2 Survey Sample from the UAS Study.

The Understanding America Study (UAS) is an internet panel maintained by the USC Dornsfife center that permits researchers the possibility to purchase survey time. 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 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 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 availailable on all UAS surveys. 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 of 2018, and response rate among UAS panel participants that were invited to complete the suvey was 82%.[4] 1104 respondents began the survey, while 1088 completed the survey. Among those that completed the survey, item nonresponse was small but present. For example, 1055 respondents answered all questions related to life insurance, 1046 answered all questions related to annuities, and 1040 answered all questions

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

related to LTC insurance. In all subsequent analysis, to maximize sample size we do not hold the respondents fixed when analyzing different products. However, in unshown analyses we confirm that all results are robust to restricting to individuals that responded to all key data items.

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 to Spanish we purposefully sampled only English speaking households, and as a result our sample is less Hispanic and more white. Some of the differences suggest unexplainable differences between our survey sample and the HRS, including that wealth and income in our UAS. For example, our survey sample is slightly wealthier and has higher income than the HRS. However, overall the two samples compare favorably, and 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 perfections or answer quality. For example, we merge 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 with our data set. 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 counterparty risk. Our key survey instruments are motivated by those developed in Luttmer and Samwick (2018), who first measure the 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 Counterparty Risk and Certainty Equivalence

Our survey consists of three modules that ask each respondent about perceived risk in each insurance market studied (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 and/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 counterparty 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 size randomly determined), and ask them to imagine the best policy of this type that they could buy in the market today. Having fixed a policy in mind we then proceed to 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 fulll payment promised in their contract:

> Suppose that you own an annuity that promises to pay $[5000] 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 (e..g, [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.[5]

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

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 risk in the market) makes this choice once for a risk-free contract that is either promises to 25%, 50%, 75%, 80%, or 90% of the promised payout of the policy they have been anchored upon, 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 the exact certainty equivalent measure for each respondent, and therefore do note (as in Luttmer and 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 maps out 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 Counterparty Risk

In addition to the core measures described above, our survey also collects a number of additional counterparty risk measures in a supplemental survey module. Each respondent completes a supplement corresponding to exactly one insurance product, with the supplement they received being randomly determined.[6] These additional measures, which are described below, are designed to provide additional insights into the sources of and nature of perceived counterparty 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 counterparty risk. For example, we ask respondents how much work it will be to collect on 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?
>
> 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.

[6]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 counterparty risk in this order ensures that are core measures are uncontaminated by these additional questions.

- 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]% 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. 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 counterparty risk metrics as most risky. In practice, we define a set of responses as rationalizable 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.

The questions in this final section, as well as the randomizations built directly into the design of the survey, primarily serve to provide metrics against which we can check response qualities. In Section 4.5 we discuss how responses to these questions and other patterns in responses inform the credibility of the risk measures constructed in this survey.

4 Survey Results

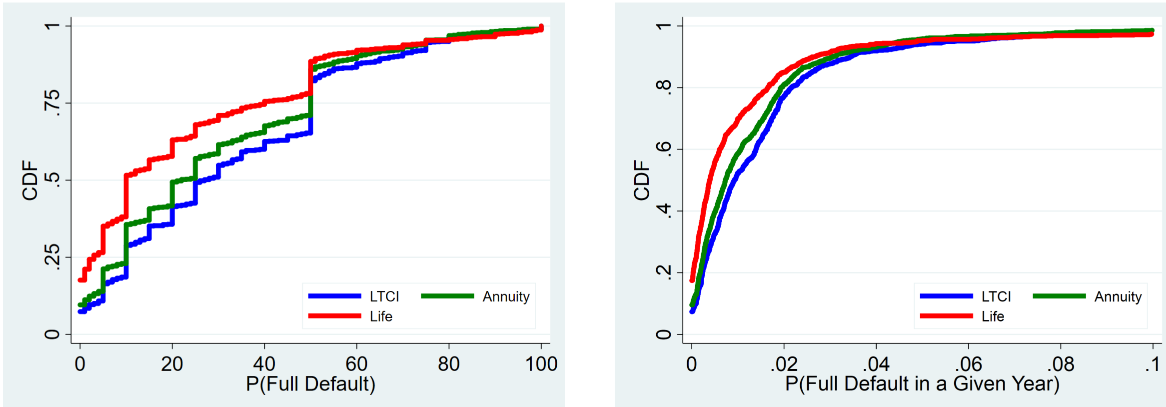
We collected 1088 complete responses to the survey described in the previous section, with the average respondent taking 17 minutes to complete the survey. In this section we present measures of perceived risk, relate them to behavioral measures, and consider internal and external response credibility. 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 Counterparty Risk Measures

Our core survey modules provide three key metrics of perceived counterparty risk: the probability of full default (i.e., the policy becomes worthless and makes no future payments), the expected value of payments when a claim is contractually promised, and the standard deviation of the perceived distribution of these promised payments. We each of these risk metrics, in order, in this section.

Figure 2, Panel (a) presents the population CDF of reported probabilities of full-default. There are three key takeaways from this figure. First, 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 no chance of a full default in life insurance markets, with even less doing so for annuities (11%) and LTCI (10%), respectively. Second, the perceived probability that a policy becomes worthless at some point is surprisingly large, with mean (median) probabilities of .29 (.22), .23 (.10), .32 (.27) for annuities, life, and LTCI, respectively. These probabilities are far higher than the full default probabilities observed empirically. Finally, 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. Panel (b) shows similar patterns, although smaller default probabilities, after these probabilities have been transformed to annual probabilities using estimated mortality rates.

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. In each figure, the measures are normalized by the claim amount, meaning that statistics may be interpreted as the 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%



(a) Full Default Probability (Lifetime)

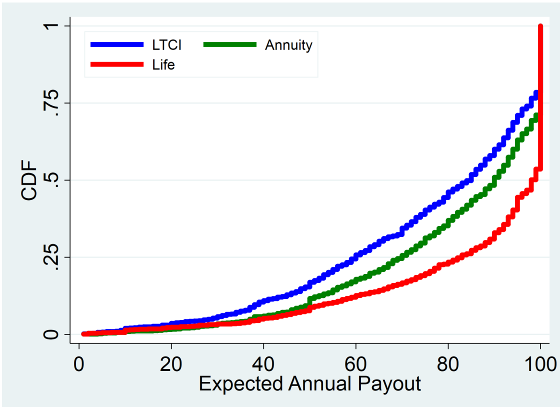
(b) Full Default Probability (Annual)

Figure 2: **Probability of Full Default.** Panel (a) presents the reported probability of full default at some point during the respondent's lifetime. Panel (b) presents these responses transformed to an annual probability of full default, Annual full default probabilities are calculated based on a respondents age, gender, and estimated health and mortality probabilities under the auxiliary assumption that annual default probabilities are time invariant.

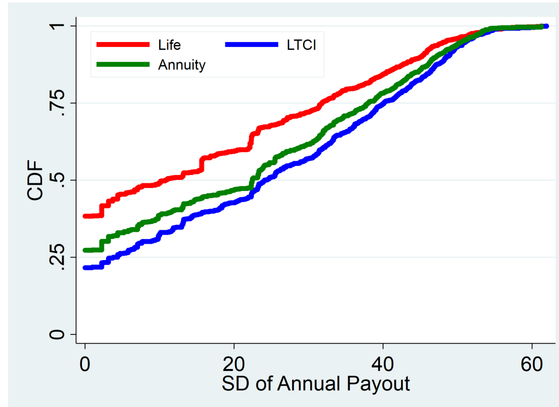
of the promised claim amount. Consumers perceive even more risk for annuities and LTCI, reporting mean (median) expected payouts of 82% (90%) and 76% (85%) of the qualified claim amounts, respectively. Panel (b) shows that in addition to expecting to receive a lower payout than promised, consumers perceive 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 policy returns and payouts. Thus, we conclude that regardless of the actual risk associated with insurance policies, consumers view insurance purchases as risky. Additionally, there appears to be a clear ranking of insurance policy 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, lower payout as a share of promised 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, and LTCI policy for a risk-free policy offering 75-80% of the promised payments. This indicates that typical respondents



(a) Full Default Probability (Lifetime)



(b) Full Default Probability (Annual)

Figure 3: **Probability of Full Default.** Panel (a) presents the reported probability of full default at some point during the respondent's lifetime. Panel (b) presents these responses transformed to an annual probability of full default, Annual full default probabilities are calculated based on a respondents age, gender, and estimated health and mortality probabilities under the auxiliary assumption that annual default probabilities are time invariant.

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

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

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 argument. 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 large. For annuities in particular the risk premia 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 a high risk premia to hold them.

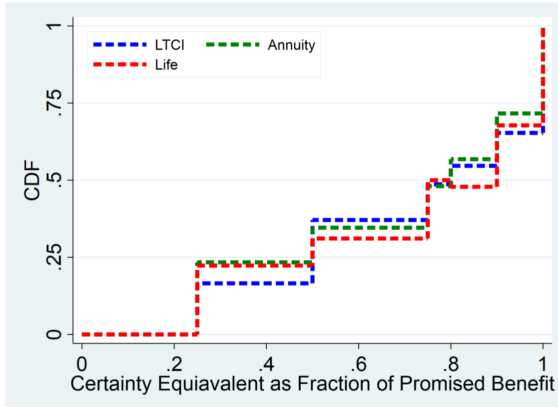


Figure 4: **Certainty Equivalent Distributions.**

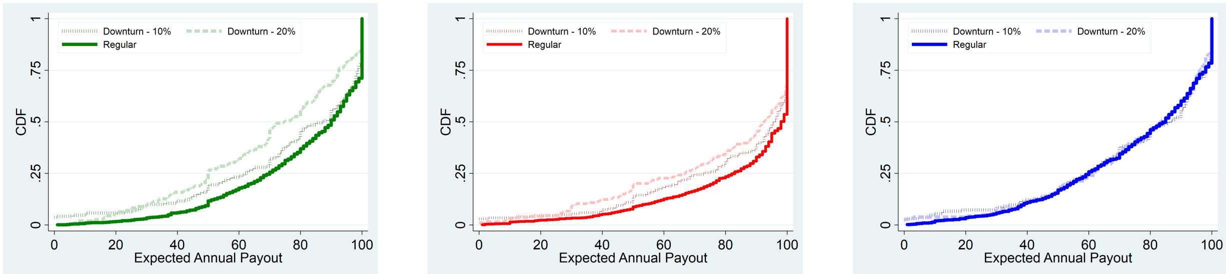
4.2 Other Survey Measures

In addition, to our three main measures of counterparty risk, we analyze several other risk metrics as well. 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 that 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.[7] These patterns are quite striking, interesting, and suggest that the sources of risk associated with different insurance policies varies. One potential explanation is that whereas LTC insurance policy risk is generally associated with claim denial due to subjective state verification by insurance companies, 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.

Finally, Figure 6 plots the CDF for the perceived probability of full default conditional on nonpayment in a given year where a payment is promised for an annuity and LTC insurance policy. Relative to Figure 2, there is a clear rightward shift in these CDFs, indicating a higher probability of full default. This suggests that respondents expect these two events to be related, and perceive insurance companies as more likely to fully default after first missing promised payments.

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

[7] Although unshown, we also find no change in probability of full default with changes in aggregate state



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

Figure 5: **Probability of Full Default.** Panel (a) presents the reported probability of full default at some point during the respondent's lifetime. Panel (b) presents these responses transformed to an annual probability of full default, Annual full default probabilities are calculated based on a respondents age, gender, and estimated health and mortality probabilities under the auxiliary assumption that annual default probabilities are time invariant.

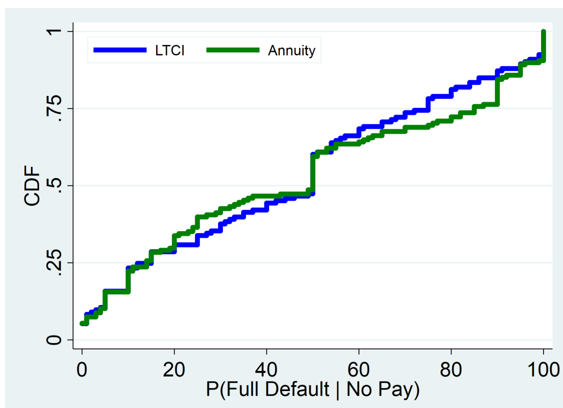


Figure 6: **Probability of full default conditional on nonpayment.**

4.3 Counterparty Risk and Insurance Ownership

Our survey shows that perceived counterparty risk in insurance markets 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. Although unshown, all regressions include controls for age, wealth, income, education, marital status, race, health, household size, and retirement.[8]

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

[8]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.

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 inclusion of a large battery of other behavioral measures. Interestingly, these behavioral measures have little predictive power in excess of our risk measures, as indicated by the lack of significance on most of their coefficients.

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

	Own Annuity	Own Life	Own LTCI	Own Annuity	Own LIfe	Own LTCI
	(1)	(2)	(3)	(4)	(5)	(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 economic magnitudes of these effects are economically meaningful, as documented in Table 4. Column (1) presents the predicted ownership rates for our survey sample in it's baseline specification. Columns (3)-(5) show the marginal effect on ownership probability from increasing the indicated risk measure

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

by one standard deviation. Most 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. To summarize, we predict that ownership probabilities would be more than twice as high for annuities and LTCI, while life insurance ownership would increase notably, if perceived risk was removed. Of course, this analysis comes with the caveat that these estimated relationships are only locally identified, and so the predicted effect of removing all perceived risk is potentially larger or smaller than indicated here. 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 Counterparty 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 behavioral controls. 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 risk as lower. This suggests that some of the negative risk perceptions of insurance products reflects a lack of understanding.

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

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

In addition, we find that having experienced fraud in the past is associated with higher 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 counterparty risk, although it is unclear whether this reflects noise in these proxies. Although unshown, we find that perceived risk is decreasing in education and weatlh. Overall, we conclude that our risk measures vary with behavioral and demographic covariates in intuitive ways.

4.5 Response Quality and Credibility

Many of the findings in this study hinge critically on the credibility of the subjective belief measures that we collected. We thus took great care to both design our survey in a way that did not bias responses and allowed 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 included in Tables 3 and 5 (unshown).

A second key built in check of response quality is our qualitative question, as described in Section 3.3that asks respondents to rank policies by perceived riskiness. Although such qualitative questions are sometimes difficult to interpret, this question provides a natural check for internal consistency. We define a set of responses as rationalizable if neither the most or least risky rated insurance product is rated as the least or most risky insurance product by all three risk measures. By this metric, we find that 84% of all respondents are rationalizable, or that their responses aren't mutually 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. More importantly, our finding that perceived risk measures correlate with product ownership in meaningful ways establishes external validity of our measures. 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 7 suggest 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

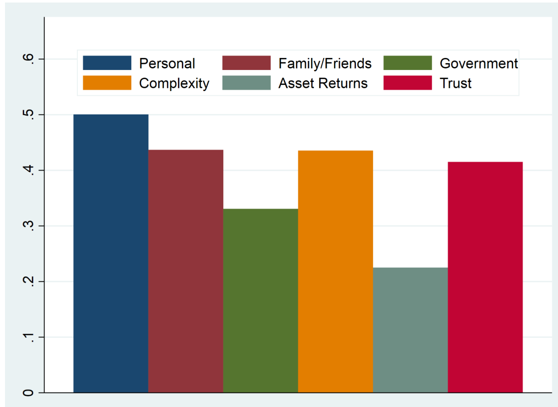


Figure 7: **Factors considered when responding to survey**

asked about in our survey prior to responding. Overall, these patterns suggest respondents took their charge seriously and answered questions in meaningful ways.

5 Model

To analyze demand for annuities, life insurance, and long-term care insurance, we turn to a heterogeneous agent, incomplete market model of insurance portfolio choice. In the model, agents begin each period with an endowment of liquid wealth (B_t), insurance holdings (A_t^k), and income profile (Y_t), and choose how much to consume, save, and invest in insurance products subject to age (t), health status s, sex (f), and the aggregate state of the economy (G). In this section we provide a full specification of the decision problem, including all motives and stochastic processes.

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 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 is dead. The health transitions are Markov, dependent upon age and sex, and given by transition matrix $\Gamma_{t,f}$, where death is modeled as an absorbing state.

Health also determine 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 ($\mathbb{E}[HC_{t,s,f}] < \mathbb{E}[HC_{t+1,s,f}]\ \forall t$), and are significantly larger than in the LTC than normal state ($\mathbb{E}[HC_{t,0,f}] << \mathbb{E}[HC_{t,1,f}]\ \forall t$).

Aggregate Risk The state of the economy G evolves stochastically to reflect aggregate economic fluctuations, so $G = 0$ when the the economy is in an expansio and $G = 0$ when in a recession. The aggregate state follows a Markov process denoted Λ, with

$$G' \sim \Lambda_{|G}.$$

The aggregate state affects income and asset returns, as further detailed below.

Preferences Households have CRRA preferences defined over a consumption good C_t. Preferences are allowed to vary according to health state through marginal utility multipliers θ_s, with $\theta_0 = \theta_1 = 1$. The household's preferences are denoted

$$\begin{aligned} V_t &= \frac{\theta_s}{1-\sigma} C_t^{1-1/\sigma} + \beta \mathbb{E}\left[\mathbb{I}_{s_t \neq 3} V_{t+1} + \mathbb{I}_{s_t = 3} \nu(b)\right] \\ \nu(b) &= \frac{\theta_3}{1-\sigma} (b + \kappa_3)^{1-1/\sigma} \end{aligned}$$

where $\nu(b)$ denotes preferneces overa n end of life bequest b.

Income Agents have a set retirement income 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 assume that agents fall into one of 5 income quintiles, each of which scales the average income profile linearly and determines income for the remainder of life.

Because the focus of this model is asset and insurance product demands and because retirement income is generally not viewed as risky, in our baseline model we do not allow for income uncertainty. However, in later exercises we allow for income to evolve stochastically with exposure to the aggregate economic state according to a Markov process denoted

$$Y^{t+1} \sim F_{Y|Y_t, G'}.$$

Assets Agents can invest in four different assets. First, an agent can invest in a bond (B_t) that offers a return of r_G, with $r_0 > r_1$, signifying that returns are higher when are higher when the economy is in an expansion than a recession.

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 $(LTCI)$. The products differ by the health states s in which they promise to pay out. Specifying D_t^k to be a 3×1 vector for dividends of asset k, where row s is defined as the payout in state s at age t from owning one unit of owning asset k, allows us to write

$$\begin{aligned} D_t^{Ann} &= [1, 1, 0] \\ D_t^{LI} &= [0, 0, 1] \\ D_t^{LTC} &= [0, \mathbb{E}\left[HC_{t,2,f}\right], 0]. \end{aligned}$$

Using the above payoff vectors, the actuarially fair price, the price at which a risk neutral insurance company is indifferent to trading $p^k_{t_0,s_0,f,G_0}$ units of asset k for an insured individual aged t_0, in health state s_0, in aggregate conditons G_0, of sex f for one unit of bonds B_t, is denoted $p^k_{t_0,s_0,f,G_0}$. This price can be written as

$$(1) \qquad p^k_{t_0,s_0,f,G_0} = v'_{s_0} \sum_{t=t_0+1}^{T} v'_{G_0} \Lambda^{t-t_0} \left[\frac{1}{(1+r_0)^{t-t_0}}, \frac{1}{(1+r_1)^{t-t_0}} \right]' \times v'_{s_0} \Gamma^{t-t_0}_{t,f} \left[D^k_t \right]$$

where v_s is a 3×1 vector with a one in row s and zeros elsewhere and v_G is a 2×1 vector with a one in row G and zeros elsewhere. Similarly, one can denote the face value of an agent's policy that promises to pay $\bar{D}^k$ units of annual dividends $A_t^k(\bar{D}^k)$

$$\begin{aligned} A_t^k(\bar{D}^k) &= v'_s \sum_{t=t_0+1}^{T} v'_{G_0} \Lambda^{t-t_0} \left[\frac{1}{(1+r_0)^{t-t_0}}, \frac{1}{(1+r_1)^{t-t_0}} \right]' \times v'_{s_0} \Gamma^{t-t_0}_{t,f} \left[D^k_t \times \bar{D}^k \right] \\ &= p^k_{t_0,s_0,f,G_0} \times \bar{D}^k. \end{aligned}$$

Thus for given a price $p^k_{t_0,s_0,f,G_0}$ knowing A_t^k and $\bar{D}^k$ are equivalent, allowing us to only save A_t^k as a state variable in the consumer decision problem.

Although $p^k_{t_0,s_0,f,G_0}$ denotes the actuarially fair price, we allow for the possibility that agents transact at less favorable prices. In particular, we let λ^k_+ denote the load on and λ^k_- denote the transaction cost to selling insurance product k. Thus a net purchaser of asset k pays $p^k_{t_0,s_0,f,G_0}(1+\lambda^k_+)$, and a net seller receives $p^k_{t_0,s_0,f,G_0}(1-\lambda^k_-)$ for each unit of A_t^k transacted.

We denote the net transactions of each each agent to product k at age t as W_t^k. Thus, the law of motion on holdings A_t^k can be written as:

$$A^k_{t+1} = \left(A^k_t + W^k_t\right) \frac{p^k_{t+1,s',f,G'}}{p^k_{t,s,f,G}}.$$

The intertemporal budget constraint on bonds can thus be written as:

$$\frac{B_{t+1}}{1+r} = B_t + Y_t - HC_{t,s,f} - C_t \\ + \sum_k \left[D_{t+1}^k (A_t^k | s') - W_t^k p_{t,s,f}^k \left(1 - \lambda_-^k \mathbb{I}_{W_t^k < 0} + \lambda_+^k \mathbb{I}_{W_t^k > 0}\right)\right]$$

We augment the above budget constraint with two additional restrictions. First, agents are not allowed to purchase insurance products after age t_{max}, despite being able to withdraw from existing policies. In practice, we implement this constraint by imposing $W_{t,s}^k < 0$ if $t > t_{max}$. Second, we impose a no short-sale constraint on all assets by requiring $B_{t+1} \geq 0$ and $A_{t+1}^k \geq 0 \; \forall k$ (equivalently, $W_t^k \geq -A_t^k$).

For LTC insurance, we impose additional constraints to capture the reality of the market. In particular, we impose a no partial insurance constraint, restricting agents to hold either none or exactly one unit of the insurance product. In practice, this means that:

$$\bar{D}^{LTC} = 1$$

$$W_{t,s}^k \in \begin{cases} \{0, -A_t^{LTCI}(1)\} \; if \; A_t^{LTCI} = A_t^{LTCI}(1) \\ \{0, A_t^{LTCI}(1)\} \; if \; A_t^{LTCI} = 0. \end{cases}$$

Finally, for all insurance products we allow for two types of counterparty risk. First, with probability $q^{k,A}(X_t)$ the insurance company does not provide the per-period payment as promised in the contract, resulting in $D_{t+1}^k(A_t^k|s') = 0$. Second, with probability $q^{k,A}(X_t)$ the insurance company defaults on the face-value of the contract, resulting in $A_{t+1}^k = 0$. Both of these sources of default are unpriced in Equation 1, and we do not at this point take a stance about what, if anything, might cause insurance companies to default on their promised payments.

Government Insurance Consumption is insured by the government through a minimum consumption level $\bar{C}$. If agents are not able to spend at least this amount, they receive transfers

$$Tr_t = \max \left[0, \bar{C} - B_t - Y_t - \sum_k A_t^k p_{t,s,f}^k \left(1 - \lambda_-^k \mathbb{I}_{W_t^k < 0}\right)\right]. \tag{2}$$

To receive government insurance, an agent must liquidate all wealth holdings and receives exactly enough to meet the consumption floor. Following the rules of Medicaid, agents then enter next period with no sources of wealth besides retirement income.

Full Decision Problem Let $X_t = \{t, s, G, Y_t, f\}$ and $X_{t+1} = \{t+1, s', G', Y_{t+1}, f\}$ denote exogenous state variables. The consumer decision problem can be fully expressed as:

$$V_t(B_t, A_t^{ANN}, A_t^{LI}, A_t^{LTC}, X_t) = \max_{B_t, W_t^{ANN}, W_t^{LI}, W_t^{LTC}, C_t} \Big((1 - \beta \mathbb{I}_{s \neq 2}) \theta_s C_t^{1-1/\psi} +$$

$$\beta \mathbb{I}_{s \neq 2} E \left[V_{t+1}(B_{t+1}, A_{t+1}^{ANN}, A_{t+1}^{LI}, A_{t+1}^{LTC}, X_{t+1})^{1-\rho} \right]^{\frac{1-1/\psi}{1-\rho}} \Big)^{\frac{1}{1-1/\psi}}$$

$$\begin{aligned}
&\textit{subject to:} && Tr_t = \max \left[0, \bar{C} - B_t - Y_t - \sum_k A_t^k p_{t,s,f}^k \left(1 - \lambda_-^k \mathbb{I}_{W_t^k < 0} \right) \right] \\
&\textit{where if } Tr_t = 0 && \frac{B_{t+1}}{1+r} = B_t + Y_t - HC_{t,s,f} - C_t \\
& && \quad + \sum_k \left[D_{t+1}^k (A_t^k | s') - W_t^k p_{t,s,f}^k \left(1 - \lambda_-^k \mathbb{I}_{W_t^k < 0} + \lambda_+^k \mathbb{I}_{W_t^k > 0} \right) \right] \\
& && \hat{D}_{t+1}^k (A_t^k | s') = \begin{cases} D_{t+1}(A_t^k | s') & \textit{with prob} \;\; 1 - q^{k,D}(X_t) \\ 0 & \textit{with prob} \;\; q^{k,D}(X_t) \end{cases} \\
& && A_{t+1}^k = \begin{cases} \left(A_{t,}^k + W_t^k \right) \frac{p_{t+1,s',f}^k}{p_{t,s,f}^k} & \textit{with prob} \;\; 1 - q^{k,A}(X_t) \\ 0 & \textit{with prob} \;\; q^{k,A}(X_t) \end{cases} \\
& && W_t^k \geq -A_t^k \\
& && W^{LTC} = \in \begin{cases} \{0, -A_t^{LTCI}(1)\} & \textit{if} \;\; A_t^{LTCI} = A_t^{LTCI}(1) \\ \{0, A_t^{LTCI}(1)\} & \textit{if} \;\; A_t^{LTCI} = 0 \end{cases} \\
& && W_t^k < 0 \; \textit{if} \; t > t_{max} \\
&\textit{and if } Tr_t > 0 && C_t = \bar{C} \\
& && \frac{B_{t+1}}{1+r} = 0 \\
& && A_k^{t+1} = 0 \\
&\textit{and laws of motion:} && s' \sim \Gamma_{t,f|s} \\
& && G' \sim \Lambda_{|G} \\
& && Y_{t+1} \sim F_{Y|Y_t, G'} \\
& && HC_{t+1,s,f} \sim F_{HC|t+1,s,f}
\end{aligned}$$

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 incompletions 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 affect demand for insurance products before moving on to our main findings.

First, on all insurance products we impose a maximum age at which agent's 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. Thus, we set $t_{max} = 80$ to capture the lack of insurance policies available at older ages. Because LTC risk and survival can extend well beyond age 80, this restriction forces forces households to trade off between pre-committing money that is not available in the interim against an inability to insure in the future and potentially limit demand for these products.

A second source of imperfection in the market we model are price wedges that require that an agent pay a more than actuarially fair price to purchase the product and receive a less than actuarially fair price when selling the product. Theoretically, these price wedges have two effects. First, agent's 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, $\lambda_+^k - \lambda_-^k$, generates different marginal payoffs between states that can not be insured with the modeled assets. In our baseline calibration we assume a 10 percentage point spread for annuities and life insurance. For LTC insurance, we assume that each annual premium entails a 10% load, and that the amount paid in is never recoverable (i.e., coverage is dropped when an individual stops paying premiums). Practically, this amounts to setting $\lambda_-^{LTC} = 1$

A third significant deterrent to holding the offered products is the counterparty risk, captured by the probabilities that the insurance company will default on the face value and per-period payment $q^{k,A}(X_t)$ and $q^{k,D}(X_t)$. Allowing for these default probabilities provides two deterrents to insurance purchase. First, because the product price defined in Equation 1 does not factor in default, the price of the insurance policy is worse than actuarially fair. More importantly however, allowing for counterparty risk introduces un-insurable 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. We calibrate these probabilities to match the average annual full default probabilities and expected value

Table 6: **Baseline Calibration - Preferences**

Time Preference - $\beta = .96$	**Risk Aversion -** $\sigma = 4$
Bequest motive - $\theta_3 = 10$	**Bequest motive -** $\kappa_3 = 20$
LTC motive - $\theta_2 = 1.3$	

of the payout distributions described in Section 4.

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

As final incorporated deterrent to insurance product purchase is the uninsurable aggregate risk captured by exogenous state variable G_t. In our baseline model, returns to wealth and perceived counterparty risk are both a function of G, introducing the possibility that possibility that insurance products don't pay out as promised in states when wealth is low, making them less attractive. In section 7 we further allow for aggregate risk to affect retirement income, further increasing background risk to explore it's effect on consumer insurance product demand.

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 calibrate our model as follows. We first assume a typical aggregate transition matrix, with expansions ($G = 1$) more persistent than recessions:

$$\Lambda_{|G} = \begin{bmatrix} .5 & .5 \\ .8 & .15 \end{bmatrix}.$$

We further assume that interest rates are zero in recessions ($r_0 = 0$), and 6

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

Table 7: **Baseline Calibration - Insurance products**

	Annuities	Life	LTCI
Full Default ($q^{k,D}$)	.018	.012	.0
Annual Default ($q^{k,A}$)	.195	.128	.238
Price Wedge, buying ($\lambda^{k,+}$)	.05	.05	.05
Price Wedge, selling ($\lambda^{k,-}$)	.05	.05	-1
Max Purchase age ($t^{max,k}$)	80	80	80

characterization of the welfare loss due to sub-optimal insurance product choice. Unfortunately, analytic solutions do not exist for the the incomplete markets framework considered in this paper. We thus solve the model quantitatively, namely by backwards induction utilizing a 3-dimensional grid search over the $(B_t, A_t^{ANN} A_t^{LI})$ asset space for the case when $A_t^{LTCI} \in \{0, A_t^{LTCI}(1)\}$. Resulting optimal policies are included in Section 6.

6 Empirical Predictions of Model

In our baseline analysis, we sample state variables of UAS respondents and use them to initialize the model. For this sample of individuals, we calculate two things. First, we calculate the optimal holdings of life, annuity, and LTC insurance for the indicated states. Then, for each individual we calculate the percent increase in lifetime consumption consumption that would make them indifferent betwen their optimal and current insurance portfolio holdings. Averaging over these increases provides a measure of the average welfare costs of suboptimal insurance portfolio choice.

We repeat this exercise for four different calibrations: no counterparty risk, no price wedges or aggregate risk, and finally combine these two adjustments to obtain a near complete market benchmark.[9] The results from this exercise are provided in Table 8.

6.1 Results

Panel A of Table 8 presents the resulting model predicted demands for annuity, life, and LTC insurance demands for the four calibrations we consider.[10] In column (1) we observe that

[9]Note that markets are not complete because there does not exist insurance for out-of-pocket medical expenses and individuals are restricted to hold full or zero LTC insurance.

[10]The results in this section are preliminary and subject to change as we improve our calibration and refine results (for example, most parameters are chosen ad-hoc in this calibration, and the current simulations

Table 8: **Optimal Insurance Demands and Welfare Costs of Sub-optimal Portfolio Holdings**

	Baseline	No Counter-party Risk	No Price Wedges/ Agg Risk	Complete Markets
A. *Insurance demand*				
Annuity	27%	79%	63%	95%
Life	12%	44%	14%	81%
LTCI	16%	31%	24%	37%
B. *Welfare Cost*				
$\%\Delta C$	1.3%	4.2%	2.9%	6.6%

in our baseline calibration, insurance demands are quite low. Annuity demand is reduced to 27% while LTCI is only 16%. Both of these are reasonably close to their respective ownership rates of, respectively, 6% and 10%. In this calibration, we counterfactually predict too little life insurance demand, suggesting that our calibrated bequest motive is too weak.

Comparing Column 1 with Columns 3-4 in Table 8 provides insights into the reason for these low demands. For annuities, we find that counterparty risk plays a huge role in limiting demand: making annuities risk free increases the fraction of agents with positive demand to 79%, while removing other sources of market incompletions increases demand to 95%. Thus, we conclude that accounting for perceived counterparty risk is able to explain the vast majority of the annuity puzzle. We similarly find that our measures of counterparty risk account for the low levels of demand for life insurance in our baseline calibration. Making life insurance risk free increases optimal ownership to 44% of our sample, while removing other market imperfections increases it to 77%. Interestingly, removing price wedges alone do little to increase demand from our baseline level. For long-term care insurance, we find that turning counterparty risk does increase demand, although even in our near complete markets setting only 37% of our sample is predicted to own LTCI. This is due to our assumption of no partial LTC insurance, and the implicit government care option captured in Equation 2.

Panel B of Table 8 presents the welfare costs of sub-optimal portfolio holdings as a percentage of lifetime consumption. We find that welfare costs are small under our baseline calibration: Our model's prediction that most households should not hold most insurance matches empirical patterns reasonably well and ensures that most households hold near-optimal insurance portfolios. In fact, a substantial portion of this welfare cost is driven by

assume all respondents are male to limit computational complexity).

the implied over-investment in life insurance. In the second column we find that the welfare costs increase dramatically when our model is calibrated with risk-free insurance products, with smaller increases in welfare costs when price wedges and aggregate risk are removed in Column 3. In column 4 we find that when all of these features are removed and markets are close to complete, welfare costs exceed 6% of annual lifetime consumption.

Overall, we conclude that our sample holds near optimal insurance portfolios when the market is modeled as it is perceived by individuals. However, the cost of incompletions, imperfections, and risks in insurance markets – whether real or perceived – result in large welfare losses.

7 Alternative Specifications and Robustness

To be completed.

8 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 holdings would be much higher if insurance products were risk free. Third, we show that the welfare costs of these risks, as well as other sources of market incompletions, are large, totaling over 6% of annual 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 9: **Regression of ownership on risk metrics in our sample with internally consistent responses**

	(1) own_ann	(2) own_life	(3) own_ltci	(4) own_ann	(5) own_life	(6) 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 10: **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 Stochastic Processes

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