# Uncertainty and the Demand for Insurance

(PRELIMINARY)

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**Abstract**

We investigate the determinants of insurance demand under uncertainty about underlying risks. We use demand elicitation surveys on a representative sample of US households in which we vary risks and the degree of uncertainty about them. We find that uncertainty in the form of compound and ambiguous risks can lead to large increases in individual demand for insurance. We also find that risk aversion and uncertainty aversion are negatively related in the population. We show that preferences that rely on expected utility for the evaluation of known (objective) risks cannot explain the data. In contrast, we prove that second-order anticipated utility exhibiting probability weighting can rationalize the observed patterns and be tractably estimated. Our preference estimates imply substantial overweighting of small probabilities and underweighting of large probabilities. We find that preference heterogeneity is largely driven by substantial heterogeneity of probability weighting of known (objective) risks.

*JEL classification: D12, D14, D81, G22, J33*

*Keywords*: risk, uncertainty, ambiguity, insurance, compound risk, probability weighting, incentivized survey

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# 1 Introduction

Insurance markets play a central role in the economy. In the United States, insurance premiums amount to $1.2 trillion each year, or about 7% of gross domestic product.[1] Arguably the most critical task faced by consumers in these markets is the assessment of their underlying risks in the presence of uncertainty and complex information about those risks. In this context, laboratory experiments using lottery choices have documented that individuals are ambiguity averse and have difficulty reducing compound lotteries (Halevy, 2007). This suggests that willingness-to-pay (WTP) for insurance should be higher under uncertainty than under known risks. That is, uncertainty averse consumers would be willing to pay an "uncertainty premium" to obtain insurance, on top of the risk premium associated with aversion to known risks.

However, while there is a growing literature on the estimation of risk preferences from insurance data, little is known about the nature of uncertainty preferences in the population and the overall impact of uncertainty on insurance demand. This paper aims to fill this gap by analyzing the demand for insurance under uncertainty and by estimating the distribution of uncertainty preferences in the population. We overcome the inherent lack of observability of demand determinants using an incentivized survey on a representative sample of the U.S. population that elicits individual demand under different risk and uncertainty scenarios.

The paper makes three main contributions. First, we quantify the impact of uncertainty on insurance demand and document key empirical regularities of WTP for insurance under uncertainty. Second, we theoretically identify conditions on uncertainty preferences needed to explain these patterns and characterize a class of preferences that can rationalize the data. Finally, equipped with this characterization, we estimate the distribution of uncertainty preferences in the population and examine the degree and sources of preference heterogeneity. We also show how to partially identify uncertainty preferences and do welfare analysis using field data from insurance markets.

In our survey, over 4,000 individuals representative of the U.S. population are given monetary incentives to reveal their WTP to fully insure a hypothetical product that has a known value. Respondents make a series of decisions in which we exogenously vary both the risk probability that the product looses its value and the degree of uncertainty about the risk probability. We introduce uncertainty by making risk probability a random variable, and either inform agents about its distribution (*compound risks*) or its possible range of values (*ambiguous risks*). We elicit agents' WTP under both known

[1] See https://www.iii.org/fact-statistic/facts-statistics-industry-overview.

risks, in which agents are given the actual risk probability, and unknown risks (we split the sample of respondents between compound and ambiguous risks). The survey includes rich sociodemographic information, including measures of financial literacy and cognitive ability.

Our data reveals several key patterns of demand behavior. First, uncertainty significantly increases individuals' willingness to pay (WTP) for insurance. To measure its magnitude, we define the uncertainty premium as the difference in WTP between a given unknown risk and the known risk whose probability equals the mean probability of the unknown risk. We observe uncertainty premia as high as 100% of the actuarially fair price of insurance, especially at low risk probabilities. Importantly, we find that the uncertainty premium is negatively correlated to the risk premium across individuals, implying that the more risk averse agents tend to be less uncertainty averse. Finally, we find that both the uncertainty premium and the risk premium go down as risk probabilities go up, with the risk premium becoming significantly negative at high risk probabilities. To check for external validity we implement a laboratory experiment and analyze existing experimental data from previous studies on risk and ambiguity attitudes. In both cases we find similar patterns as those exhibited by our survey data.

We explore the ability of different models of choice under uncertainty to explain the data. We show that uncertainty preferences that reduce to expected utility for the evaluation of known risks cannot rationalize agents' choices, as is the case for most models of ambiguity aversion (e.g., maximin expected utility (Gilboa and Schmeidler, 1989) and smooth ambiguity aversion (Klibanoff et al., 2005)). This is because probability weighting is needed to explain the fact that a majority of individuals switch from risk averse (positive risk premium) to risk loving (negative risk premium) as risk probabilities go up. Accordingly, we propose a simple generalization of recursive anticipated utility (Segal, 1987), which we call *second-order anticipated utility*, featuring two probability weighting functions, one for risk probabilities and another for the uncertainty distribution (of risk probabilities). We identify natural conditions for such preferences to be consistent with observed patterns. Specifically, an individual will exhibit a positive uncertainty premium if on average she weighs uncertain distributions more than an expected utility maximizer. In addition, we show that a negative correlation between uncertainty and risk premia arises if more risk averse individuals are less sensitive to changes in risk probabilities, while the switch between risk aversion and risk loving can be explained by overweighting (resp. underweighting) of small (large) risk probabilities.

The paper, to the best of our knowledge, provides the first estimate of the distribution of uncertainty preferences in the US population. To do so, we propose a Bayesian hierarchical model in which individual WTP for insurance is determined by second order anticipated utility preferences. We use a flexible functional form for probability weighting functions, given by the two-parameter Prelec function (Prelec, 1998) commonly used in the experimental literature. The hierarchical structure of the model assumes that individual-level preference parameters are drawn from population-level distributions. Our Bayesian approach yields an estimate of the full distribution of preference parameters at the individual level, enabling us to do an in-depth analysis of sources of heterogeneity and their relationship with socio-demographic charteristics. We find that individuals' attitudes toward uncertainty are much more homogeneous than their risk attitudes, and that preference heterogeneity is largely driven by wide heterogeneity in the probability weighting of known risks. Nonetheless, the vast majority of individuals exhibit overweighting of low to moderate probabilities, regardless of whether such probabilities correspond to know risks or are associated with uncertainty distributions. Individuals with higher levels of financial literacy and cognitive ability tend to exhibit lower probability distortions, suggesting that less sophisticated agents are over-represented in insurance markets.

Our estimation exploits the observed variation of risk and uncertainty of our data, which is typically absent in insurance market data. To overcome these data limitations, we also provide a theoretical characterization of the uncertainty premium that does not require full identification of the probability weighting function for uncertain distributions. We illustrate how this characterization reduces the data requirements needed to estimate the preference parameters governing insurance demand under uncertainty, making it amenable to empirical work using field data.

The paper's results have several implications. First, uncertainty can lead to a substantial misallocation of insurance by increasing aggregate demand and by introducing selection effects in insurance markets. Higher demand is associated with the presence of an uncertainty premium, while its negative correlation with risk attitudes can induce more risk averse agents not to buy insurance while less risk averse agents do so. We explore the welfare and policy implications of these effects in a companion paper (Gandhi et al., 2020). Second, abstracting from uncertainty in the empirical estimation of risk preferences can introduce significant biases. From a modeling perspective, our results highlight the need to incorporate probability weighting in *both* risk and uncertainty preferences. Finally, our estimation approach highlights the advantages of generating distributional estimates of individual preferences, since they provide a much more comprehensive picture of the determinants of insurance demand.

In what follows, Section 2 provides a discussion of our contribution to related work. Section 3 summarizes the survey design. Section 4 describes our main empirical findings. Section 5 identifies preferences that account for the empirical patterns. We estimate the distribution of uncertainty preferences in Section 6. Section 7 concludes.

# 2 Related Literature

This paper contributes to the literature that uses insurance take-up and claims data to study the demand for insurance (Einav et al., 2010; Jaspersen, 2016) by studying the impact of uncertainty. Most of existing work focus on estimating risk preferences under the assumption that consumers do not face uncertainty about underlying risks (Sydnor, 2010; Barseghyan et al., 2011; Einav et al., 2012), or that preferences are unrelated to information frictions (Handel and Kolstad, 2015; Handel et al., 2019). Our results highlight the need to account for uncertainty in order to obtain unbiased preference estimates. In addition, we provide a direct, non-parametric evidence of the need for preferences to incorporate probability weighting, which supports existing results that rely on the structural estimation of risk preferences (Barseghyan et al., 2013).

Our study is related to the experimental literature exploring the relationship between risk and uncertainty preferences. Existing work has looked at the relationship between ambiguity and risk attitudes (Cohen et al., 1987; Einhorn and Hogarth, 1986; Di Mauro and Maffioletti, 2004; Chapman et al., 2020) and has documented a positive association between compound lottery aversion and ambiguity aversion (Halevy, 2007; Abdellaoui et al., 2015; Chew et al., 2017). We build on this literature by providing a comprehensive empirical analysis of these relationships in the US population. Specifically, our dataset covers most of the spectrum of risk probabilities and includes rich variation in uncertainty, allowing us to look at the impact of uncertainty on insurance demand and to measure the correlation of risk and uncertainty premia at different underlying risk probabilities.

Regarding the theoretical literature on risk and uncertainty preferences, the majority of models reduce to expected utility when risks are known. Two notable exceptions exhibiting probability weighting of known risks are recursive anticipated utility (Segal, 1987) and the model of Dean and Ortoleva (2017). We build on the work of Segal (1987) by proposing a variant of recursive anticipated utility that allows for probability weighting functions to be different across risk and uncertainty domains. This class of preferences are well-suited for empirical work, since they allow for both under- and over-weighting of probabilities, which we show is necessary to explain the data, and can be tractably estimated using flexible functional forms.

## 3 Data

We conducted an incentivized survey with a representative sample of the U.S. population who are part of the online panel Understanding America Study (UAS) at the University of Southern California. Over four thousand respondents participated in the survey, which included rich socio-demographic information as well as measures of cognitive ability and financial literacy.[2] Appendix A provides summary statistics of the respondents.

In the survey, we asked each participant to make a series of 10 decisions. Each participant was told to be the owner of a machine, which was described to have some probability $p$ of being damaged. An undamaged machine paid out 100 virtual dollars (equivalent to 5 USD) to the subject at the end of the survey, while damaged machines paid out nothing. The probability of damage, including information $I$ given to the participant about $p$, was varied in each decision. Specifically, we considered the following information environments:

(i) *known risks*: $I$ represents the underlying risk probability, i.e., $I = p$.

(ii) *Unknown risks*: $I$ represents either a range of probabilities centered around $p$ (ambiguous risk) or the uniform distribution on such a range (compound risk), i.e., $I = [p - \varepsilon, p + \varepsilon]$ or $I = U[p - \varepsilon, p + \varepsilon]$, with $\varepsilon \in (0, \min\{p, 1 - p\}]$.

We elicited maximum willingness to pay for full insurance using the Becker-DeGroot-Marschak mechanism (Becker et al., 1964),[3] where the actual price of insurance was drawn at random from the uniform distribution on $(0, 100)$. Appendix I contains the survey instructions. We divided participants into four groups, as described in Table 1. Participants received a block of decisions with 5 risk probabilities under known risk, and a block of decisions with 5 probability ranges under unknown risks. The order of blocks was randomized, but the order of probabilities within each block was kept constant and was ordered from smallest to largest. In addition, half of the participants received a range noting that 'all numbers within this range are equally likely'

[2] All 5,674 UAS panel members were recruited to complete the survey online, and 4,534 respondents accessed and completed the survey. 62 respondents started but did not complete the survey and are excluded from our analysis.

[3] This is a common mechanism in similar experiments, for instance see Halevy (2007).

Table 1: Summary of Decisions Presented to Respondents, Survey 1

| Group | Decision # (within block) | (1) Probability of Loss (%) | (2) Range Probability (%) |
|---|---|---|---|
| | 1 | 5 | 3-7 |
| | 2 | 10 | 1-19 |
| 1 | 3 | 20 | 13-27 |
| | 4 | 50 | 46-54 |
| | 5 | 80 | 68-92 |
| | 1 | 5 | 1-9 |
| | 2 | 10 | 3-17 |
| 2 | 3 | 20 | 18-22 |
| | 4 | 40 | 28-52 |
| | 5 | 70 | 61-79 |
| | 1 | 2 | 1-3 |
| | 2 | 10 | 6-14 |
| 3 | 3 | 20 | 8-32 |
| | 4 | 40 | 38-42 |
| | 5 | 90 | 83-97 |
| | 1 | 2 | 0-4 |
| | 2 | 10 | 8-12 |
| 4 | 3 | 20 | 16-24 |
| | 4 | 30 | 21-39 |
| | 5 | 60 | 48-72 |

Notes: Respondents were assigned to one of four groups, and were presented both the probabilities described in (1) and (2) in the order displayed here. Half of respondents were told that each probability in the range is equally likely, while half were not given information about the probability distribution within a range.

while the other half did not receive this information. Hence, the former group was subject to compound risk, while the latter group faced ambiguous risks. This design feature allowed us to check for potential differences in attitudes towards two common sources of uncertainty in insurance markets, the perception of risks as the realization of a series of bad shocks and the lack of precise information about the distribution of shocks, respectively.

One decision from each block was randomly chosen to be actually implemented. At the end of the survey participants were asked a question eliciting their ability to reduce compound lotteries, and received $1 for a correct answer. Participation in all parts of the survey required approximately 15 minutes, and participants earned $10 for survey completion plus $8.6 on average on incentives associated with insurance questions.[4]

[4]It is common in the UAS to combine multiple studies in one survey session. As such, prior to completing the experiment, participants also received a series of un-incentivized questions designed to evaluate understanding of annuity products for another project (?).

# 4 Empirical Analysis

This section presents the main empirical patterns of determinants of insurance demand under uncertainty. First, we illustrate the magnitude of risk and uncertainty premia and estimate their correlation structure, correcting for potential bias due to measurement error in WTP. In what follows, to facilitate comparisons, we report underlying risk probability $p$, WTP, as well as risk and uncertainty premia in percentages. Note that, since the magnitude of the potential loss is 100 virtual dollars, the actuarially fair price of insurance against known risk $p \in (0, 100)$ is given by $p$.

We denote by $W(I)$ the WTP for insurance given information $I$. The risk premium associated with risk $p$ is given by $\mu(p) := W(p) - p$. Finally, we define the uncertainty premium associated with compound risk $I = U[p - \varepsilon, p + \varepsilon]$ or ambiguous risk $I = [p - \varepsilon, p + \varepsilon]$ as $\mu(I) := W(I) - W(p)$. Accordingly WTP for insurance against unknown risk $I$ can be decompose as the sum of the actuarially fair price of insurance, the risk premium and the uncertainty premium:

$$W(I) = p + \mu(p) + \mu(I).$$

## 4.1 Risk Premium

Figure 1 displays the average risk premium at each possible $p$, both for the overall sample and by household income. The 0 line represents risk neutrality. A clear pattern emerges from the figure: average risk aversion decreases as losses become more likely, suggesting that agents transition from exhibiting significant risk aversion at small probabilities to becoming risk lovers at very high $p$. Table B.2 in Appendix B reports the estimates and their statistical significance. In addition, we find risk premium to be widely heterogeneous: its standard deviation ranges from 25% to 30%. Despite the heterogeneity, the switch from risk averse to risk loving seems to be around 60% for most income levels. While the figure shows a swtich from positive to negative of the average risk premium, we find that roughly 50% of individuals exhibit a mix of risk aversion, neutrality and risk loving at different probabilities.

## 4.2 Uncertainty premium

Turning to the impact of uncertainty, as we show in Appendix B, we do not find major differences in uncertainty premium across compound and ambiguous risks. Accordingly, we pool the data of both types of unknown risks together in the empirical analysis

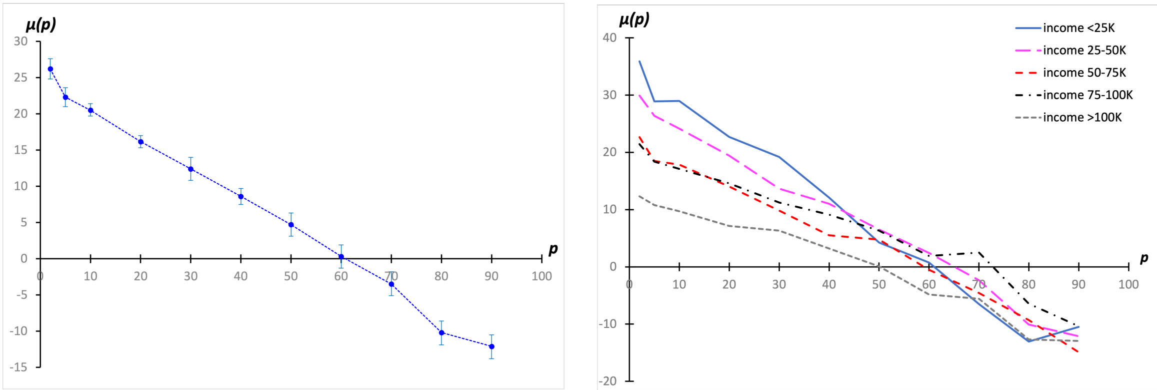


Figure 1: Average Risk Premium at Different Probabilities (bars represent 95% confidence intervals).

and, unless noted otherwise, use $I(p, \varepsilon)$ to denote compound and ambiguous risks with support $[p - \varepsilon, p + \varepsilon]$.

Figure 2 presents the average uncertainty premium at each possible $p$. Each data point shows the size of the range of probabilities associated with it, given by $2\varepsilon$. Since our design includes two range sizes for most of the probabilities, the graph displays two lines, respectively associated with small and big ranges.[5]

On average, agents exhibit significantly large uncertainty premia at $p < 50\%$ when range sizes are big, leading to an increase in WTP as high as 100% of the expected loss. Smaller range sizes still elicit a strong response for $p < 50\%$. Uncertainty premium decreases with risk probability $p$, which is consistent with the finding by Abdellaoui et al. (2015) that aversion to compound and ambiguous lotteries increases as winning probability goes up. Uncertainty premium is less heterogeneous than risk premia, with a standard deviation between 14% and 20%. We do not find major differences in the uncertainty premium by ability to reduce compound lotteries (see Table B.5 in Appendix B).

Since the typical probability of filing an insurance claim in most insurance markets is substantially lower than 50%, the fact that we observe large uncertainty premia at $p < 50\%$ points to a strong effect of uncertainty on insurance demand.

## 4.3 Relationship Between Risk and Uncertainty premium

We next look at the correlation between the risk premium and the uncertainty premium, normalized by range size. We do so for each probability $p$ separately to control for the negative relationship between $p$ and both $\mu(p)$ and $\mu(I)$.

[5] Table B.2 in Appendix B shows the average uncertainty premium at each $p$ by group.

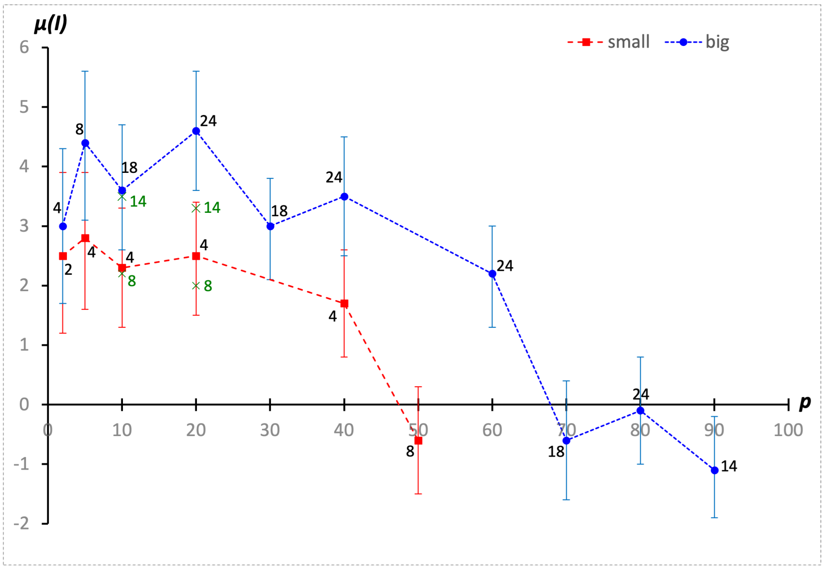


Figure 2: Uncertainty premium at Different Probabilities (point labels represent range size and bars represent 95% confidence intervals).

Figure 3 plots the correlation coefficients, showing that risk and uncertainty premia are negatively correlated at all risk probabilities, with all coefficients being significant at the 1% level. Furthermore, the correlation coefficient is remarkably invariant to underlying risk $p$ regardless of whether we control for individual characteristics (partial correlation) or not (total correlation): it consistently lies between $-0.24$ and $-0.35$, even after controlling for cognitive ability, financial literacy and demographic background.[6]

An important concern with the estimates of the correlation between risk and uncertainty premia is that they may be biased downward due to measurement error in WTP induced by the elicitation mechanism. The effect of such measurement error goes beyond the typical attenuation bias, given that $W(p)$ enters with a positive sign in $\mu(p) = W(p) - p$ while it enters with a negative sign in $\mu(I) = W(I) - W(p)$. To correct for these biases, we follow the obviously related instrumental variable (ORIV) approach proposed by Gillen et al. (2019), which is based on the idea of using additional measures of the same variable as instruments. Appendix C.0.1 describes the derivation of the ORIV estimator for $corr(\mu(p), \mu(I))$ and presents the estimates for different $p$. We obtain similar magnitudes and significance levels as those shown in Figure 3.

[6] Table C.6 in **??** reports the total correlation coefficients in columns two and four and shows that they are highly significant. The partial correlation coefficients are virtually identical and therefore omitted.

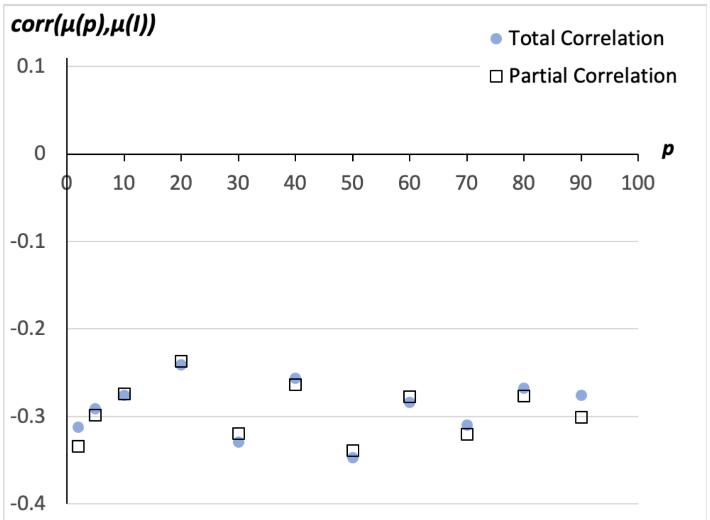


Figure 3: Correlation Coefficients between Risk Premium and Uncertainty Premium.

## 4.4 External Validity

Our empirical results are confirmed by a companion laboratory experiment with about 120 undergraduate students at the University of Wisconsin-Madison and by the analysis of publicly available experimental data. The experiment design included a similar set of decision questions. We also added an additional treatment for all subjects, *multiplicative risks* to check the robustness of our results to alternative forms of compound risks. Elicitation mechanisms and payments were similar to those in the survey. Appendix H provides a full description of the experiment as well as detailed results.

We find that both risk and uncertainty premia are decreasing in risk probability $p$ (Figure H.5). The only major difference is that subjects in the experiment were significantly less risk averse. In addition, risk and uncertainty premia exhibit a negative correlation of similar magnitude: estimates lie between $-0.24$ and $-0.35$, even after controlling for both measurement error and personal characteristics (Table H.10). Finally, we analyze covariates of uncertainty premium with the experimental data and find that qualitatively similar results (see Appendix H.4).

Our analysis of the correlation between risk and uncertainty premium using data from three prominent experimental studies on uncertainty preferences (Halevy, 2007; Abdellaoui et al., 2015; Chew et al., 2017) shows that correlation coefficients are significantly negative and large in magnitude (see Appendix C.0.2). In a recent paper, Chapman et al. (2020) find a mild negative correlation using objective lotteries and bets on ambiguous urns.

## 5 Uncertainty Preferences

We focus on two main families of preferences, namely, *EU-based* preferences, i.e., those that reduce to expected utility (EU) when evaluating known risks, and *probability-weighting* preferences which apply non-identity weights to probabilities.

The family of EU-based preferences includes most of the proposed models of uncertainty preferences: $\alpha$-maximin expected utility and variational preferences (Maccheroni et al., 2006), which include maximin expected utility (Gilboa and Schmeidler, 1989) and multiplier preferences (Hansen and Sargent, 2001) as special cases, as well as smooth ambiguity preferences (Klibanoff et al., 2005) and uncertainty averse preferences Cerreia-Vioglio et al. (2011). Since preferences reduce to EU under known risks. That is, the value of binary risk $(p, -1; 1-p, 0)$ involving a loss of $-1$ with probability $p$ for an agent with initial wealth $w$ is given by

$$EU(p) = pu(w-1) + (1-p)u(w). \tag{1}$$

As show below, EU-based preferences cannot explain the data on WTP for insurance against known risks, unless we resort to non-standard functional forms of utility. In contrast, uncertainty preferences involving probability-weighting can generate risk premium patterns similar to those illustrated in Figure 1. Two leading examples are recursive anticipated utility (Segal, 1987) and multiple priors–multiple weighting preferences (Dean and Ortoleva, 2017). We restrict attention to the former since it allows for flexible weighting functions, whereas the latter requires concave probability weighting functions, which we show below cannot explain the risk premium data.

The idea behind recursive anticipated utility is to represent unknown risks as a two-stage lottery and to apply probability weights recursively. The second-stage lottery represents know risks, in our case $(p, -1; 1-p, 0)$, while the first stage lottery is a probability distribution over $p$, e.g., $U[p-\varepsilon, p+\varepsilon]$, representing the decision maker (DM) beliefs about $p$. Recursive anticipated utility evaluates unknown risks by first obtaining certainty equivalents of second-stage lotteries, and then evaluate the distribution over certainty equivalents induced by the first-stage lottery. In order to apply these preferences to ambiguous risks, it is assumed that the DM has a subjective probability distribution $F(p)$ over known risks.

While recursive anticipated utility uses the same weighting function for both stages, we allow for different probability weighting functions across stages. We call such preferences *second order anticipated utility* (SOAU)and they are characterized by probability-weighting functions $\pi_k$ and utility functions $u_i$ at each stage $k = 1, 2$. Both $\pi_k$ and $u_k$

are increasing with $\pi_k(0) = 0$ and $\pi_k(1) = 1$.

Known risks $(p, -1; 1-p, 0)$ are evaluated by applying weighting function $\pi_2$ to loss probability $p$ and by using $u_2$ to evaluate changes to final wealth.[7] Accordingly, the DM's valuation of $p$ is given by

$$V(p) = \pi_2(p)u_2(w-1) + (1-\pi_2(p))u_2(w). \tag{2}$$

To isolate the effect of probability weighting, consider the case of linear utility $u_2(x) = x$. The certainty equivalent of risk $p$ is $-\pi_2(p)$ and thus the risk premium is given by $\mu(p) = \pi_2(p) - p$.

The evaluation of unknown risk $I$ given by probability distribution $F(p)$ over known risks involves the evaluation of certainty equivalents using utility $u_1$ and the application of weighting function $\pi_1$ to the distribution of certainty equivalents induced by $F$. Let $y(p)$ be the certainty equivalent of risk $p$, and $G(y)$ the distribution of certainty equivalents. If $G$ is continuous and has full support in $[\underline{y}, \bar{y}]$, the value of $I$ is given by

$$V(I) = u_1(\underline{y}) + \int_{\underline{y}}^{\bar{y}} u_1'(y)(1-\pi_1(G(y))dy. \tag{3}$$

The next proposition characterizes the value of unknown risks of the form $I(p,\varepsilon) = U[p-\varepsilon, p+\varepsilon]$ with $\varepsilon \in (0, \min\{p, 1-p\}]$ under SOAU with linear utility $u_1(x) = u_2(x) = x$. Assuming linear utility isolates the role of probability weighting in explaining the data. All proofs are in Appendix D.

**Proposition 1.** *The value of unknown risk $I(p,\varepsilon)$ under SOAU with linear utility is given by*

$$V_w(I(p,\varepsilon)) = -\pi_2(p-\varepsilon) - 2\varepsilon \int_0^1 \pi_2'(p+\varepsilon(2z-1))\pi_1(1-z)\, dz. \tag{4}$$

*In addition, the uncertainty premium of $I(p,\varepsilon)$ is*

$$\mu(I(p,\varepsilon)) = \varepsilon \int_0^1 \left[\pi_2'(p+\varepsilon z)\pi_1\left(\frac{1-z}{2}\right) - \pi_2'(p-\varepsilon z)\left(1-\pi_1\left(\frac{1+z}{2}\right)\right)\right] dz. \tag{5}$$

[7] The weighting function is applied over the cdf of outcomes. Alternative formulations involve applying weights $\hat{\pi}_k(z) = 1 - \pi_k(1-z)$ to the decumulative distribution of outcomes. Following Segal (1987), we use this formulation since it is more convenient when dealing with binary risks.

Since the functional form of the uncertainty premium does not lend itself to an easy interpretation, we define the "marginal uncertainty premium" $\mu_0(p)$ as the limit of the uncertainty premium, normalized by range size, as $\varepsilon \to 0$. The uncertainty premium associated with unknown risk $I(p,\varepsilon)$ can be well approximated by $\varepsilon\mu_0(p)$ as long as $\pi_2$ exhibits little curvature in the range $[p-\varepsilon, p+\varepsilon]$.

**Proposition 2.** *Let* $\mu_0(p) := \lim_{\varepsilon\to 0} \frac{\mu(I(p,\varepsilon))}{\varepsilon}$ *denote the marginal uncertainty premium at* $p$*. SOAU with linear utility implies that*

$$\mu_0(p) = \pi_2'(p)(2E\pi_1 - 1), \tag{6}$$

*where* $Ew_1 = \int_0^1 \pi_1(z)dz$ *is the expected value of first-stage probability weights.*

Expression (6) shows that the marginal uncertainty premium only depends on the sensitivity of the risk premium to changes in $p$, measured by the slope of $\pi_2$, and on the average of first stage weights ($E\pi_1$). In particular, $\mu_0(p)$ is increasing in the average first-stage weight $\pi_1$, being positive whenever there is overweighting on average, i.e., $Ew_1 > 0.5$. In addition, the more sensitive the risk premium is to changes in $p$ the larger the magnitude of $\mu_0(p)$. Intuitively, individuals whose risk attitudes are insensitive to changes in loss probability exhibit little variation in WTP for insurance across different $p$, and thus do not react strongly to the (initial) introduction of uncertainty.

Next, we provide a series of results showing that, while EU-based preferences cannot explain the pattern exhibited by risk premium, SOAU preferences can rationalize the three key empirical facts documented above.

## 5.1 Risk Premium

As the next proposition formally establishes, EU-based models cannot explain the switch from risk aversion to risk loving as $p$ goes up without resorting to non-standard utility functions involving concave-then-convex utility at small stakes. We also show in Appendix E that adding a reference point (deterministic or stochastic) to the utility function does not help reconcile the model with the data. In contrast, a probability weighting function featuring overweighting of small probabilities and underweighting of large ones can rationalize the behavior of the risk premium. An example is the inverted s-shaped weighting function commonly found in experiments on risk prefrences (e.g., Gonzalez and Wu, 1999).

**Proposition 3.** *Assume that there exists* $p^* \in [0,1]$ *such that* $\mu(p) > 0$ *for* $p < p^*$ *and* $\mu(p) < 0$ *for* $p > p^*$.

(i) ***Expected utility***: *if the DM has initial wealth $w$ and maximizes expected utility under known risks then the upper convex envelope of $u(x)$ is below the line connecting $u(w-1)$ and $u(w)$ for all $x \in (w-1, w-p^*)$ and its lower concave envelope is above such line for all $x \in (w-p^*, w)$.*

(ii) ***Probability-weighting***: *if the DM maximizes anticipated utility with linear utility then $\pi_2(p) > p$ for $p \in [0, p^*)$ and $\pi_2(p) < p$ for $p \in (p^*, 1]$.*

## 5.2 Uncertainty premium

SOAU preferences can rationalize the pattern illustrated in Figure 2. To see how, recall that the marginal uncertainty premium at small ranges is given by $\pi_2'(p)(2E\pi_1 - 1)$. Hence, if preferences exhibit overweighting of 1st-stage probabilities on average ($E\pi_1 > 0.5$) and a 2nd-stage weighting function $\pi_2(p)$ that is steeper at smaller $p$, then the marginal uncertainty premium is larger at smaller $p$.

## 5.3 Correlation between Risk and Uncertainty Premia

The next result provides two possible ways by which a population of individuals with SOAU preferences can exhibit a negative correlation between risk and uncertainty premia. The first one involves more risk averse individuals being less sensitive to changes in risk than comparatively less risk averse individuals. This seems like a natural behavioral explanation: more risk averse individuals have a stronger incentive to avoid risks and thus might be less sensitive to variation in underlying risks. Intuitively, they may be cautious and willing to 'overpay' for insurance, regardless of whether underlying risks turn out to be smaller or larger than expected. The second explanation is less plausible since it involves a negative relationship between probability weighting across stages, i.e., individuals who have higher second order weights exhibit lower first-order weights. Such negative relation is hard to reconcile with the notion that risk averse agents dislike 'randomness.'

**Proposition 4.** *Consider two DM $i, j$ satisfying $\pi_{2i}(p) > \pi_{2j}(p)$ for some $p \in (0,1)$. Then $\mu_i(p) > \mu_j(p)$ and*

(i) *if $\pi_{2i}'(p) < \pi_{2j}'(p)$ and $E\pi_{1i} \leq E\pi_{1j}$ then $\mu_{0i}(I(p,\varepsilon)) < \mu_{0j}(I(p,\varepsilon))$;*

(ii) *if $\pi_{2i}'(p) \leq \pi_{2j}'(p)$ and $E\pi_{1i} < E\pi_{1j}$ then $\mu_{0i}(I(p,\varepsilon)) < \mu_{0j}(I(p,\varepsilon))$.*

The proof is immediate and therefore omitted.

One way to test whether SOAU can generate the negative correlation is to estimate the slope of $\pi_2$ and the average of first-stage weights $E\pi_1$ at the individual level using the following two-step approach. First, for each subject $i$ we estimate $\pi'_{i2}$ by running the following linear regression using the observations $t = 1, \cdots, 5$ on WTP for insurance against known risks:

$$W_{it} = a_i + b_i p_{it} + \nu_{it}, \quad t = 1, \cdots, 5. \tag{7}$$

Since $W(p) = \pi_2(p)$, $\hat{b}_i$ is an estimate of $\pi'_{i2}(p)$. Second, we regress $\hat{b}_i$ on the uncertainty premium associated with unknown risks, normalized by range size:

$$\frac{\mu_{it}}{\varepsilon_{it}} = \alpha_k \hat{b}_{it} + \xi_{it}. \tag{8}$$

Since $\mu_0 = \pi'_2(p)(2E\pi_1 - 1)$ we can estimate $E\pi_1$ using $\hat{E}\pi_{i1} = \frac{\hat{\alpha}_k+1}{2}$. Table 2 presents the average estimates of $\pi'_{i2}(p)$ and $E\pi_1$ in the population, as well as its cross-sectional correlation with risk and uncertainty premia. The latter confirms the hypothesis that risk averse agents exhibit lower sensitivity to changes in underlying risk probabilities, inducing a negative correlation between risk and uncertainty premia. Figure 4 shows that such negative correlation is mostly driven by individuals with the lowest sensitivity. Specifically, individuals with $\pi'_{i2}$ estimates at the bottom quintile of its distribution exhibit significantly higher risk premium and significantly lower uncertainty premium than the rest of subjects.

Table 2: Components of uncertainty premium

| Regression Estimates | | |
|---|---|---|
| Estimate | Average | Std. error |
| $\pi'_2(p)$ | 0.61 | 0.59 |
| $E\pi_1$ | 0.52 | 1.06 |
| Correlation[a] | | |
| | Risk premium | Info premium |
| $\pi'_2(p)$ | -0.15*** | 0.12*** |
| $E\pi_1$ | -0.01 | 0.02*** |
| No. Obs. | 4,442 | |

[a] Statistical significance: *p-value $<$ 0.10, **p-value $<$ 0.05, ***p-value $<$ 0.01.

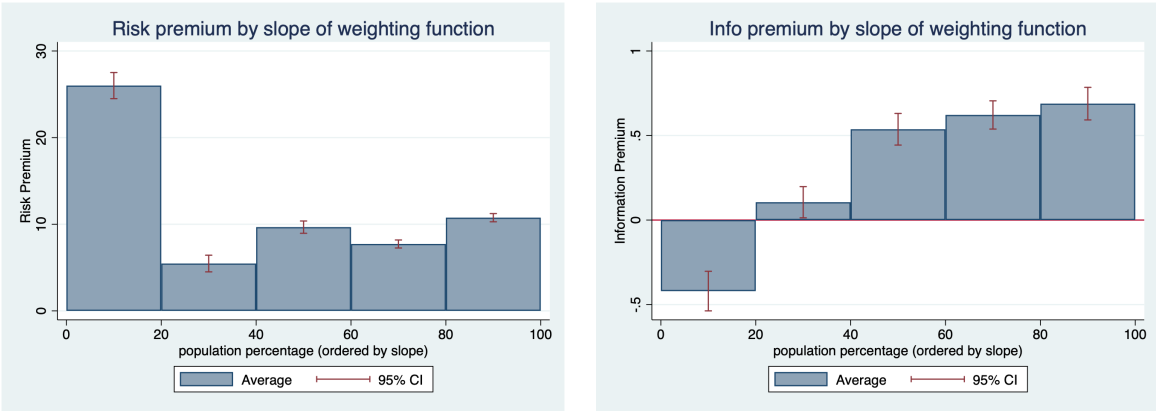


Figure 4: Average Risk and uncertainty premium at different estimates of $\pi'_{i2}$.

# 6 Preference Estimation

This section presents our approach to estimate the distribution of SOAU preferences in the population and analyzes some of its key features, namely, the typical shape of weighting functions, the degree of heterogeneity and the distribution of preferences across different socio-demographic characteristics.

Our approach is based on the decomposition of WTP into the sum of risk and uncertainty premium, which under linear utility takes on the following form by Proposition 1:

$$W(I(p,\varepsilon)) = p + \mu(p) + \mu(I(p,\varepsilon))$$
$$= \pi_2(p) + \varepsilon \int_0^1 \left[ \pi'_2(p+\varepsilon z)\pi_1\left(\frac{1-z}{2}\right) - \pi'_2(p-\varepsilon z)\left(1-\pi_1\left(\frac{1+z}{2}\right)\right)\right] dz. \quad (9)$$

We impose a parametric form on $\pi_k$ and estimate them at the individual level using a hierarchical Bayesian model. Specifically, we assume that weighting functions in (9) have a 2-parameter Prelec functional form:

$$\pi_k(p) = e^{-\beta_k(-\log(p))^{\alpha_k}}, \qquad \alpha_k, \beta_k > 0, \quad k = 1, 2. \quad (10)$$

This functional form is commonly used to model rank-dependent utility and allows for linear, concave, convex, as well as s-shaped and inverted s-shaped weighting functions, as illustrated by Table 3 and Figure 5. Lower values of $\beta_k$ globally lead to higher weights $\pi_k(p)$, i.e., to comparatively higher risk aversion, while parameter $\alpha_k$ mostly affects the shape of $\pi_k$, determining whether small probabilities are overweighted and large probabilities underweighted ($\alpha < 1$) or vice versa ($\alpha > 1$).[8] The Prelec weighting

Table 3: Prelec weighting function

| *Shape of* $\pi_k$ | $\alpha_k$ | $\beta_k$ |
|---|---|---|
| Linear | 1 | 1 |
| Concave | 1 | $< 1$ |
| Convex | 1 | $> 1$ |
| Inverted s-shape | $< 1$ | any |
| s-shape | $> 1$ | any |

function crosses the diagonal once at $p^* = e^{-\beta^{1/(1-\alpha)}}$ for all $\alpha \neq 1$. Accordingly, $\alpha < 1$ implies overweighting of probabilities in $[0, p^*]$. Note that $e^{-\beta^{1/(1-\alpha)}}$ is decreasing in $\beta$ for all $\alpha < 1$, implying that smaller $\beta$ lead to a larger interval $[0, p^*]$ of overweighted probabilities. Let $\theta = (\alpha_1, \beta_1, \alpha_2, \beta_2)$ be the parameter vector of Prelec weighting

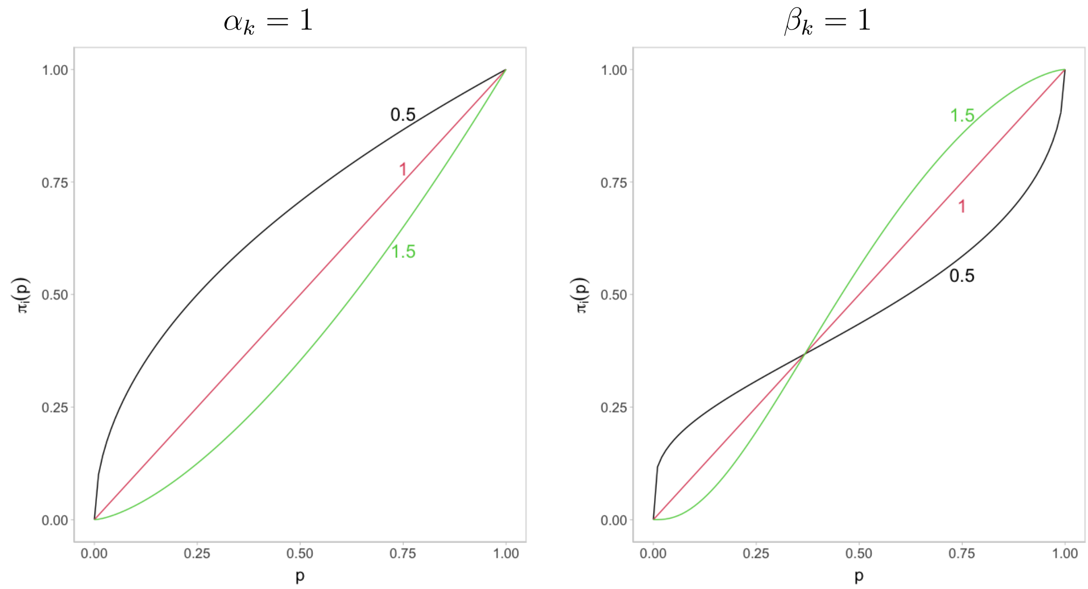


Figure 5: Prelec weighting functions for different values of $\beta_k$ (left) and $\alpha_k$ (right).

functions (10) and let $W(\cdot;\theta)$ denote the resulting WTP function given by (9). Our goal is to estimate the distribution of $\theta$ in the population. To do so, we assume that agent $i$'s *observed* WTP for insurance against $I_{it} = I(p_{it}, \varepsilon_{it})$ is given by the random variable $W_{it}$ whose mean is determined by $W(I_{it}; \theta_i)$, where $\theta_i$ represents the agent's weighting function parameters. Letting $W_{it}$ to be random allows for the possibility of

[8]Specifically, the slope of $\pi_k(p)$ at $p = 0$ is infinity for $\alpha_k < 1$ and zero for $\alpha_k > 1$, whereas the opposite is true at $p = 1$.

mistakes or for random preferences. Notice that, since $W(I_{it};\theta_i)$ falls inside the interval $(0,1)$ for $p \in (0,1)$, we could assume that $W_{it}$ follows a continuous distribution with support in $(0,1)$ such as the beta distribution. However, a non-negligible subset of subjects sometimes report WTP of zero or one. Accordingly, we instead assume that $W_{it}$ follows a flexible zero-one inflated beta distribution, which allows for the possibility that $W_{it}$ takes on values in $\{0,1\}$. The distribution has two point masses, at 0 and 1, and follows a beta distribution on $(0,1)$. That is, $W_{it}$ follows mixture distribution

$$f(\mathrm{w}|I_{it},\theta_i,q,q_1,\phi) = \begin{cases} q(1-q_1) & \mathrm{w}=0 \\ qq_1 & \mathrm{w}=1 \\ (1-q)Beta(W(I_{it};\theta_i)\phi,(1-W(I_{it};\theta_i))\phi) & \mathrm{w}\in(0,1), \end{cases} \tag{11}$$

where $q = Pr(W_{it} \in \{0,1\})$, $q_1 = Pr(W_{it} = 1|W_{it} \in \{0,1\})$, and $\phi$ is the precision of the beta distribution. Unlike the weighting function parameter vector $\theta_i$, which is allowed to vary across individuals, we set these three parameters at the population level since we only have ten observations per individual.

We next build a hierarchical model by assuming that $\alpha_{ik}$ and $\beta_{ik}$ are drawn from population-level distributions with support on the positive real line. Specifically, we set the prior distribution of $\alpha_{ik}$ for $k = 1,2$ to be lognormal, with the population-level mean and standard deviation of $\log\alpha_{ik}$ given by $\alpha$ and $\sigma_\alpha$, respectively. Similarly, the prior distribution of $\beta_{ik}$ is lognormal with parameters $\beta$ and $\sigma_\beta$.

We close the model by specifying hyperprior distributions for population-level parameters. First, we assume a standard normal prior for $\alpha$ and $\beta$, which is centered around the values associated with linear probability weighting and its unit variance yields an informative but dispersed prior.[9] Second, we choose a half t-student prior for standard deviations of Prelec parameters $\theta_i$. Third, we choose a gamma prior for the precision of the Beta distribution $\phi$. Finally, we let the probability parameters $q_0$ and $q_1$ to have beta priors given by $Beta(1,1)$.[10]

[9]For values of $\alpha$ or $\beta$ larger than five the weighting function becomes very close to a step function, so having a vague hyperprior that places a substantial mass above those values is not going to lead to significantly different weighting functions while affecting the ability of the model to converge.

[10]We have tried alternative hyperprior specifications and have not found significant differences in our estimates.

Accordingly, our hierarchical model is given by

$$\begin{aligned}
W_{it} &\sim f(\cdot|I_{it}, \theta_i, q_0, q_1, \phi), \quad \theta_i = (\alpha_{1i}, \beta_{1i}, \alpha_{2i}, \beta_{2i}) \\
\alpha_{ik} &\sim Lognormal(\alpha, \sigma_\alpha), \quad k = 1, 2 \\
\beta_{ik} &\sim Lognormal(\beta, \sigma_\beta), \quad k = 1, 2 \\
\alpha &\sim Normal(0, 1) \\
\beta &\sim Normal(0, 1) \\
\sigma_\alpha &\sim \text{Half-student } t(3, 0, 2.5) \\
\sigma_\beta &\sim \text{Half-student } t(3, 0, 2.5) \\
\phi &\sim Gamma(1, 2) \\
q_h &\sim Beta(1, 1), \quad h = 0, 1.
\end{aligned} \tag{12}$$

Our main goal is to estimate the posterior distribution of $\theta_i$ for each subject in the sample, and use the estimated posteriors to learn about the distribution of uncertainty preferences in the population, e.g., the distribution of the individual median values of $\theta_i$. In order to do so, we excluded 245 individuals (5.4% of the sample) reporting WTP of always zero or always one in all their choices. Such choices either reflect non-truthfull responses or are associated with infinite degrees of risk love and risk aversion, respectively.

The estimation involves two main hurdles. First, the model is a high-dimensional non-linear model. Second, computing the distribution of WTP involves an integral with no closed-form solution. These features make the model difficult to estimate and computationally demanding. To overcome these hurdles we code and fit our model in Stan (Stan Development Team, 2019), a probabilistic modeling language that allows for Bayesian inference with Markov Chain Monte Carlo (MCMC) sampling. Stan is ideally suited for non-linear models and provides built-in functions such as numerical integration. In addition, it has an adaptive sampling algorithm (No U-turn sampler or NUTS) that facilitates MCMC convergence and allows for within-chain parallel computing to speed up the estimation.[11] The estimation involved two chains with different starting values and 2,000 iterations each. Standard convergence tests were satisfactory, with almost all parameters exhibiting effective sample sizes greater than 0.75 (see Appendix F for details).

Figure 6 depicts the posterior distributions of individual median values for the four Prelec parameters and the distribution of individual-level standard deviations, while

[11] We fit our model using the R interface CmdStanR (Gabry and Češnovar, 2021).

Table 4 presents the population-level estimates.[12] The distributions of medians give a measure of heterogeneity of weighting functions in the population while the std. deviation distributions reflect the precision of individual-level estimates. Summary statistics of these distributions are presented in Table 4. The distribution of median values re-

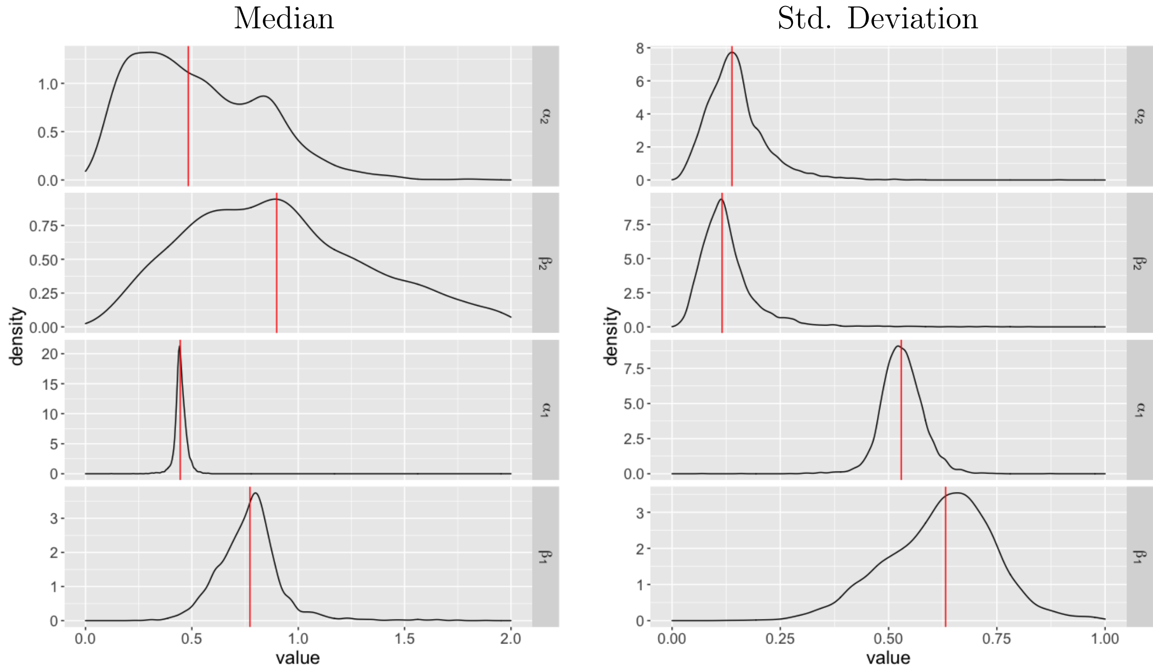


Figure 6: Posterior density of median values (left) and standard deviations (right) of $\theta_i$. Red lines represent distribution medians.

veals several aspects of risk and uncertainty preferences. First, $\alpha_{2i}$ and $\beta_{2i}$ exhibit substantial dispersion, implying that the 2nd-stage weighting function $\pi_{2i}$. In contrast, median values of $\alpha_{1i}$ and $\beta_{1i}$ are much more concentrated leading to a relatively homogeneous 1st-stage weighting function $\pi_{1i}$. Second, individual estimates of 2nd-stage weighting parameters are much more precise than 1st-stage estimates given that the former exhibit much lower standard deviations. This is likely due to the fact that, since 1st-stage weights only affect the uncertainty premium while 2nd-stage weights affect both the risk and uncertainty premia, all individual observations are effectively used to estimate $\alpha_{2i}, \beta_{2i}$ while one half of the observations contain information about $\alpha_{1i}, \beta_{1i}$.

The population-level parameter estimates in Table 4 help us measure the tendency to report extreme values of WTP as well as the degree of randomness/deviations of WTP responses with respect to SOAU preferences. On average, the estimated proba-

[12] We obtain similar results using mean rather than median values.

Table 4: Model Estimates: Population-level Parameters

| Parameter | Median | Std. deviation |
|---|---|---|
| $q_0$ | 0.0688 | 0.0012 |
| $q_1$ | 0.852 | 0.0071 |
| $\phi$ | 16.2 | 0.140 |
| $\alpha$ | -0.831 | 0.0137 |
| $\beta$ | -0.222 | 0.0096 |
| $\sigma_\alpha$ | 0.768 | 0.0122 |
| $\sigma_\beta$ | 0.639 | 0.0076 |
| Log Probability[a] | 6560 | 137 |
| No. Obs. | 39,950 | |
| No. Individuals | 4,268 | |

[a] Unnormalized log density of the model.

bility of reporting WTP of 0 or 1 is about 7%, with most of these choices being one (85%). This gives us a rough measure of irrationality, in the sense that such values imply a violation of stochastic dominance. The precision of the beta distribution is about 16, which suggests that, while WTP is clearly informed by preferences it exhibits substantial randomness.[13]

What do these parameter distributions tell us about the distribution of individual preferences? First, they show that the vast majority of individuals exhibit inverted S-shape weighting functions in both probability stages, given that median values of $\alpha_{1i}$ are below one, while $\alpha_{2i}$ is lower than one for 93% of individuals. In addition, almost all median values of $\beta_{1i}$ and a majority of $\beta_{2i}$ are below one, implying overweighting of probabilities in a range $[0, p^*]$ with $p^* > e^{-1} \approx 0.368$.[14]

To learn more about the distribution of SOAU preferences we look at the joint density of weighting parameters $(\alpha_{ik}, \beta_{ik})$ for $k = 1, 2$, shown in the top row of Figure 7. Confirming the above results regarding marginal distributions, the joint distribution of $(\alpha_{i2}, \beta_{i2})$ is highly dispersed, with most of the mass roughly placed in the lower triangle of rectangle $[0, 1.5] \times [0, 3]$. This implies that, despite wide heterogeneity of risk preferences, virtually no agent exhibits risk love at low probabilities and $\alpha_{i2}$ and $\beta_{i2}$ are negatively correlated. The peak of the joint density, depicted in the bottom-left graph of Figure 7, occurs at $\alpha_{i2} = 0.86$, $\beta_{i2} = 0.92$, leading to a weighting function relatively

[13]For instance, if the mean WTP is 0.5, the interquartile range associated with a precision of 16.2 is $[0.416, 0.584]$.

[14]Since $p^* = e^{-\beta^{1/(1-\alpha)}}$ is decreasing in $\beta$ for all $\alpha < 1$, the smallest $p^*$ when $\beta \leq 1$ is associated with $b = 1$.

close to the risk neutral benchmark. Nonetheless, the joint distribution is quite asymmetric, with $\alpha_{i2}$ typically falling well below one, i.e., most agents exhibit substantial risk aversion (overweighting) at low probabilities and risk loving (underweighting) at high probabilities. This is illustrated by the weighting function associated with the median (of median) values of $\alpha_{i2}$ and $\beta_{i2}$ (see bottom-left graph of Figure 7).

In contrast, the joint density of $(\alpha_{i1}, \beta_{i1})$ is highly concentrated along the diagonal of rectangle $[0.4, 0.5] \times [0.5, 1]$, with the mode given by $\alpha_{i1} = 0.44$, $\beta_{i1} = 0.8$. Accordingly, these estimates suggest that all agents in the population significantly overweigh (underweighs) 1st-stage probabilities below (above) 0.5, as illustrated in bottom-right graph of Figure 7).

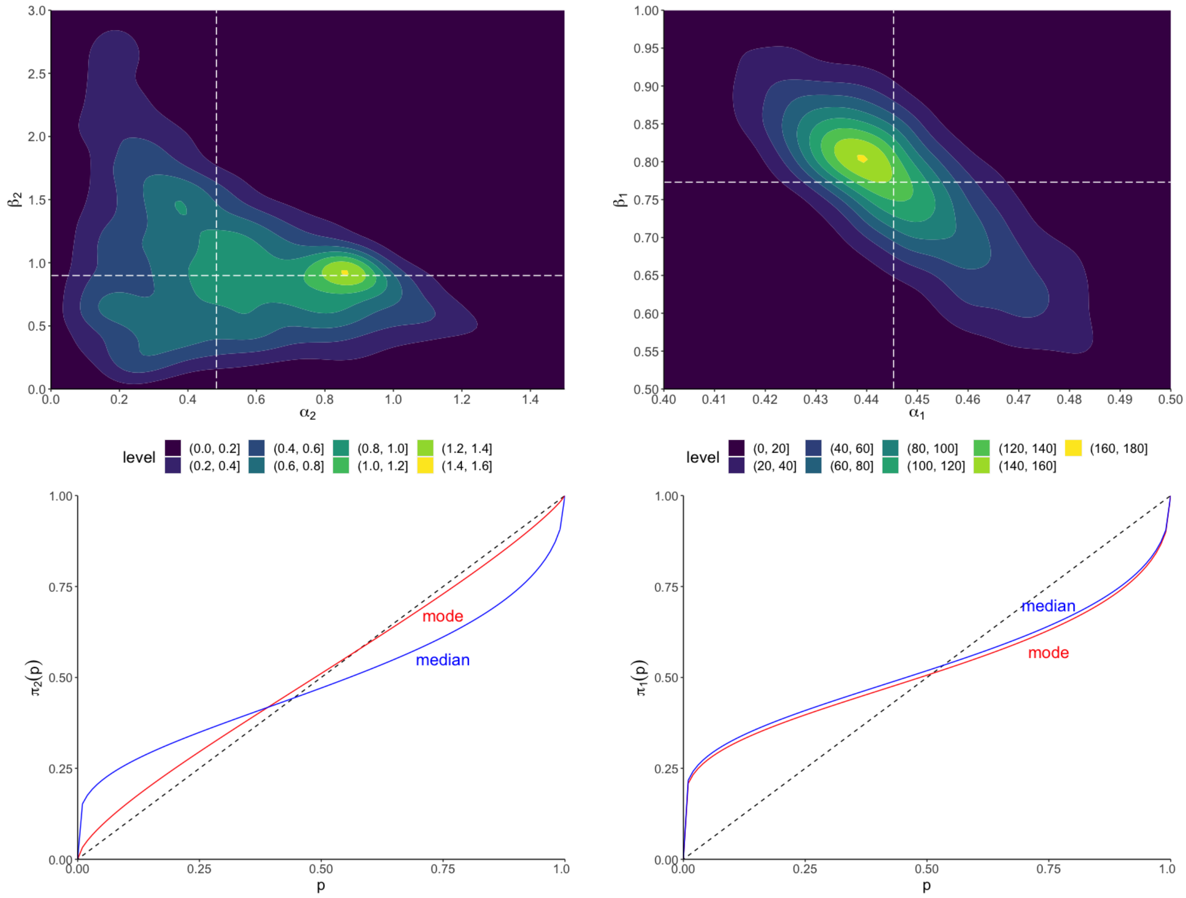


Figure 7: Top panel: Posterior joint density of median values of $(\alpha_{i2}, \beta_{i2})$ (left) and $(\alpha_{i1}, \beta_{i1})$ (right); white lines represent median values of each parameter. Bottom panel: 2nd-stage weighting function (left) and 1st-stage weighting function (right); the mode represents the weighting function associated with the mean of the distribution and the median refers to the weighting function associated with the median (of median) values of each parameter.

The dispersion of 2nd-stage weighting functions leads to wide heterogeneity in risk preferences. Since 1st-stage weighting functions are very homogeneous one might conclude that heterogeneity in risk preferences drives heterogeneity in uncertainty preferences. However, this is unclear because the uncertainty premium depends on the *slope* of $\pi_2$ and the *level* of $\pi_1$. One way to understand the relative contribution of each weighting function to the heterogeneity of uncertainty preferences is to look at their relative contribution to the variation of the marginal uncertainty premium $\mu_0(p) = \pi_2'(p)(2E\pi_1 - 1)$. Using the above joint distribution we compute the standard deviation of $\pi_2'(p)$ for $p \in (0.1, 0.9)$ and the standard deviation of $2E\pi_1$.[15] We find that the standard deviation of $\pi_2'(p)$ ranges between 0.26 and 0.44, while the std. deviation of $2E\pi_1$ is about 0.12. These differences are much smaller than the large differences in heterogeneity between $\pi_2$ and $\pi_1$ exhibited by the joint distributions in Figure 7, although 2nd-stage weights still contribute between two to four times more to the heterogeneity of marginal uncertainty premia than 1st-stage weights.

## 6.1 Sociodemographic Differences

We next analyze potential differences in the distribution of preferences across different sociodemographic characteristics. Specifically, we plot the joint distribution of 2nd-stage weighting parameters by income, age and gender (Figure 8), and also by financial literacy and cognitive ability (Figure 9).

There are some differences across groups, with higher income individuals and men exhibiting less probability mass at low values of $(\alpha_{i2}, \beta_{i2})$ than lower income individuals and women respectively, but overall heterogeneity remains substantial across groups. The starkest differences appear when we compare groups by financial literacy and cognitive ability test scores. The distribution of $(\alpha_{i2}, \beta_{i2})$ is more concentrated at higher values for individuals with scores above the median, with very little mass in the rectangle $[0, 0.5] \times [0, 1]$. In addition, both have a peak close to linear weighting. In contrast, the distribution of those with scores lower than the median score exhibit substantial mass in $[0, 0.5] \times [0, 1]$.

We do not find any meaningful differences in the joint distribution of 1st stage weights across these characteristics, and thus we do not present them here. This is not surprising, given that the distribution $(\alpha_{i1}, \beta_{i1})$ is very concentrated.

These results are confirmed by the estimates from regressing risk and uncer-

[15] We avoid extreme values of $p$ since the slope of $\pi_2$ tends to infinity (or zero) under the Prelec functional form.

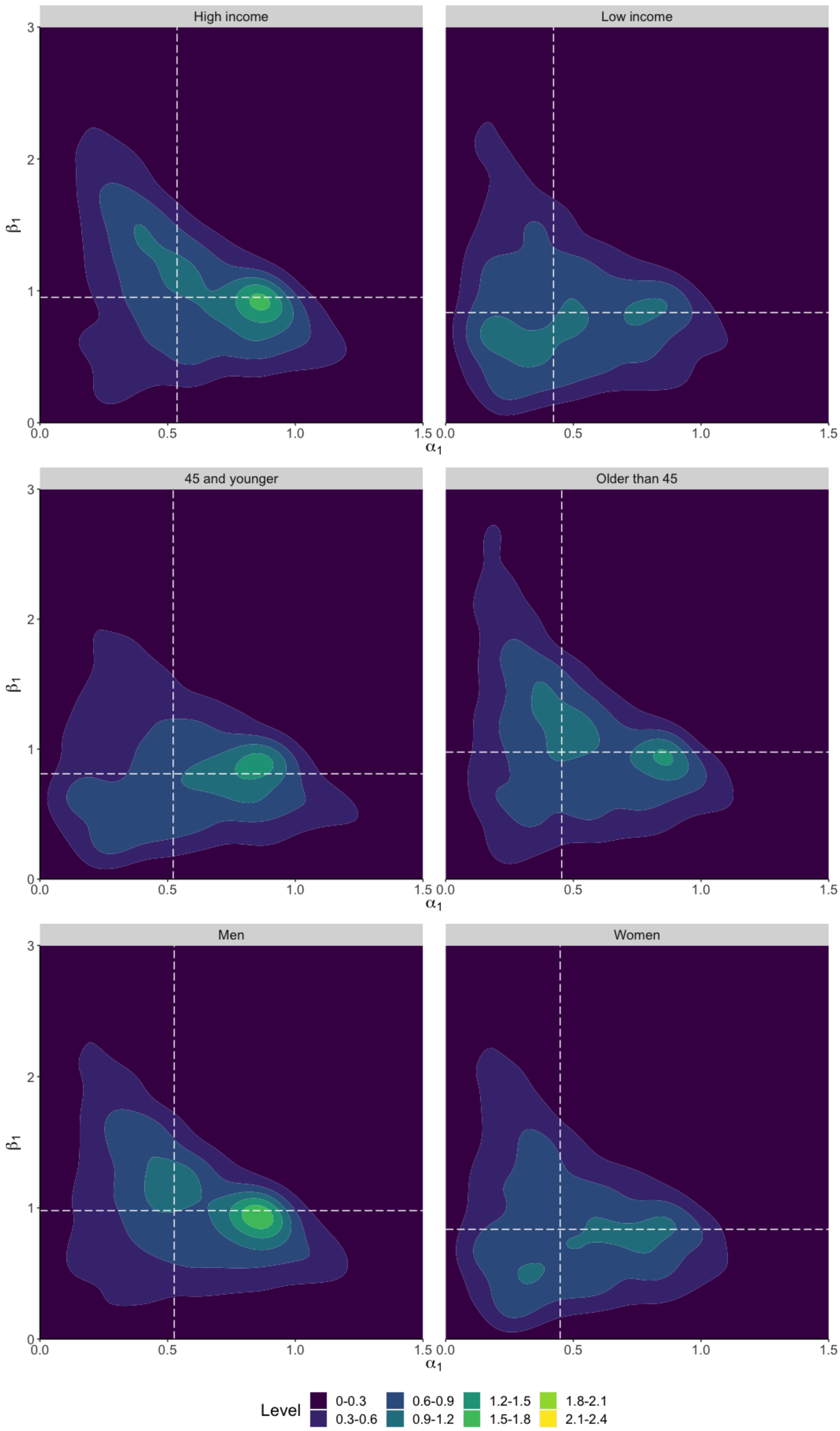


Figure 8: Joint distribution of median values of $(\alpha_{2i}, \beta_{2i})$ by selected demographics.

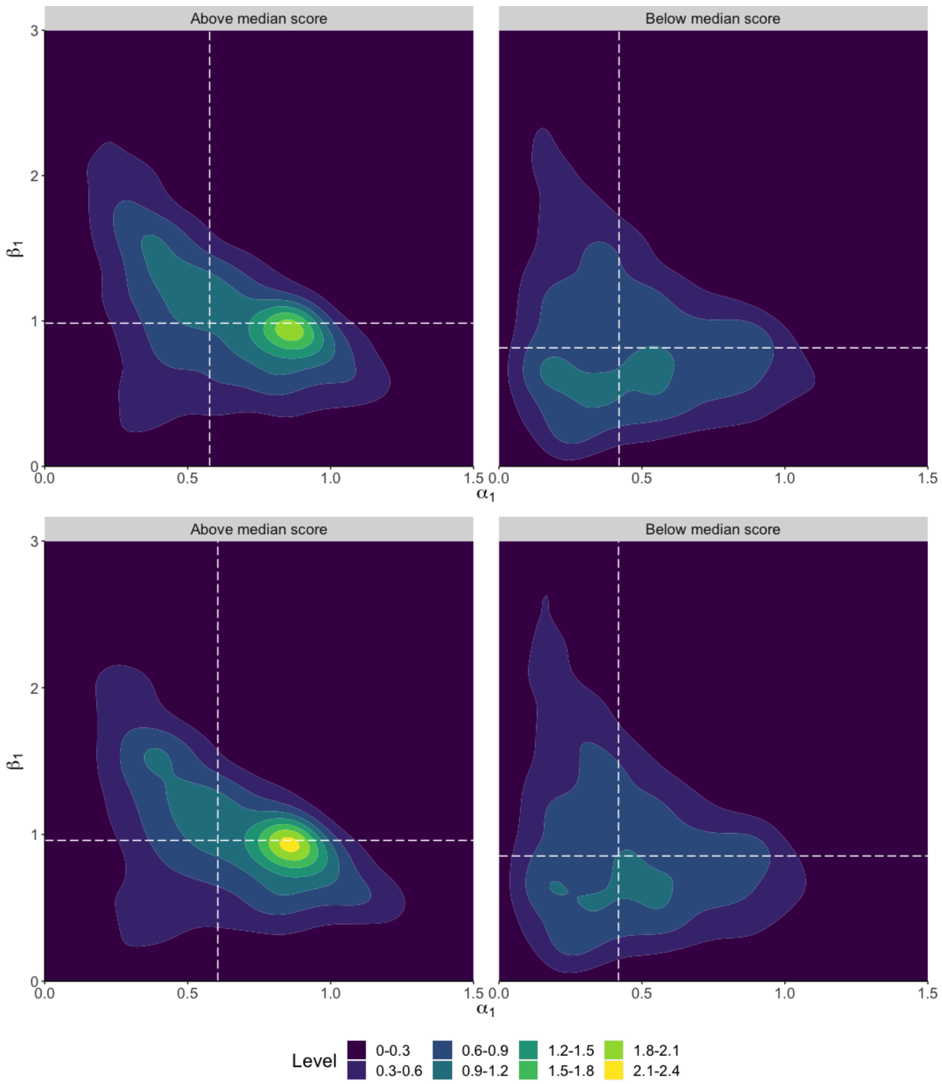


Figure 9: Joint distribution of median values of $(\alpha_{2i}, \beta_{2i})$ by financial literacy (top) and cognitive ability (bottom).

tainty premia on various sociodemographic characteristics, which are presented in Appendix G. They also suggest that policy interventions aimed at reducing uncertainty, i.e., by requiring insurers to provide simple risk estimates to consumers, might have a disproportionate positive impact on less sophisticated consumers.

## 6.2 Partial Identification with Limited Data

Our preference estimation takes advantage of the richness of our incentivized survey data. However, data from insurance markets often lacks information about the uncertainty about risks faced by individuals. In such contexts, is it even possible to estimate individual preferences? One approach would be to use data from insurance choices across domains, e.g., auto insurance and home insurance, to partially estimate preferences by using a linear approximation of the 2nd-stage weighting function $\pi_2$. Since information and uncertainty about risks varies across domains, we can use them as proxies for uncertainty, while the linear approximation makes the uncertainty premium proportional to the slope of $\pi_2$. Specifically, under linear approximation $\pi_2(p) = a + bp$, the WTP for insurance against unknown risk $(p, \varepsilon)$ is given by

$$W(p, \varepsilon) = \pi_2(p) + \varepsilon\mu_0(p) = a + bp + \varepsilon b(2E\pi_1 - 1) = a + bp + c\varepsilon. \tag{13}$$

In principle, we can estimate this linear regression from data $\{W_{it}, p_{it}, \varepsilon_t\}_i$, where $t$ represents the insurance domain. While $p_{it}$ and $\varepsilon_t$ are not observed, $p_{it}$ can be measured using empirical claim rates, as is the typically done in the empirical insurance literature, and the volatility of claim rates in each domain can serve as a proxy for $\varepsilon_t$.

Expression (13) also serves to illustrate the potential effects of abstracting from the presence of uncertainty in the estimation of risk preferences. As an example, not including $\varepsilon_t$ in the linear regression implied by (13) translates into omitted variable bias, leading to a biased intercept and a higher (lower) slope estimates depending on whether risk $p$ and uncertainty $\varepsilon$ are positively or negatively correlated.

# 7 Conclusion

Our study uncovers the impact of uncertainty on insurance demand and uncovers key features about the nature and distribution of risk and uncertainty attitudes. There are several takeaways from our analysis, which point to methodological changes, policy interventions and potential avenues for future research. Such implications of our analysis acquire particular relevance given that we find similar patterns across multiple data sources.

Methodologically, our work emphasizes the need to account for uncertainty in the estimation of preferences and suggests ways to do so even with limited data. It also highlights the need to develop models of uncertainty preferences that incorporate probability weighting and proposes a class of preferences amenable to empirical estimation. From an econometrics perspective, our preference estimation exercise illustrates the potential of Bayesian hierarchical methods to obtain distributional estimates that allow for a comprehensive analysis of agent heterogeneity.

The paper highlights that different types of information frictions affect markets in different ways. Whereas frictions about insurance contracts (e.g., information about coverage, pricing, transaction costs) tend to depress demand for those contracts (Handel and Kolstad, 2015; Bhargava et al., 2017; Handel et al., 2019; Domurat et al., 2019), we show that uncertainty about risks increases insurance demand and can lead to selection effects. These differences imply that friction-mitigation policies aimed at improving welfare need to be tailored to the specific frictions being targeted. In particular, policies aimed at regulating disclosure of known risk estimates can have large welfare effects, primarily benefiting less-sophisticated lower-income consumers. While conducting a welfare analysis is beyond the scope of this paper, we do so in a companion paper Gandhi et al. (2020).

Finally, the sources of agents' reaction to unknown risks remain elusive. Most of the sociodemographic variables traditionally associated with risk attitudes, such as income or education, lack explanatory power when it comes to uncertainty preferences. This implies that information frictions cannot be controlled for in empirical work by simply conditioning on observable characteristics.

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# Appendix A Descriptive Statistics

Table A.1 presents the summary statistics of the main sociodemographic variables of households in the UAS in Surveys 1 and 2.

Table A.1: Descriptive Statistics - UAS

| Variable | Mean | Std. Dev. |
|---|---|---|
| Age | 48.34 | 15.52 |
| Female | 0.57 | 0.49 |
| Married | 0.59 | 0.49 |
| Some College | 0.39 | 0.49 |
| Bachelor's Degree or Higher | 0.36 | 0.48 |
| HH Income: 25k-50k | 0.24 | 0.43 |
| HH Income: 50k-75k | 0.20 | 0.40 |
| HH Income: 75k-100k | 0.13 | 0.34 |
| HH Income: Above 100k | 0.20 | 0.40 |
| Black | 0.08 | 0.27 |
| Hispanic/Latino | 0.10 | 0.29 |
| Other Race | 0.10 | 0.30 |
| Financial Literacy (range: 0-100) | 67.52 | 22.11 |
| Cognitive Ability | 50.70 | 8.66 |
| No. Individuals | 4,442 | |

# Appendix B Statistical Analysis of WTP

In this section we present the average WTP under known risk ($W(p)$) and the uncertainty premium. We report both averages for the whole sample, and also distinguishing by whether decisions involved ambiguous ranges. Finally, we use our incentivized quiz about reducing compound risks, to contrast average WTP by subjects' ability to reduce compound lotteries.

Table B.2 presents whole sample averages and reports both whether WTP are different from risk probabilities and whether uncertainty premium is significantly different from zero using one-sided paired $t$-tests.

**Ambiguity** Tables B.3 and B.4 show the effect of presenting agents with non-ambiguous versus ambiguous ranges. There is no clear effect of ambiguity on the

Table B.2: WTP for Insurance: Pooled Compound and Ambiguous Risk

| | Group 1 | | Group 2 | | Group 3 | | Group 4 | |
|---|---|---|---|---|---|---|---|---|
| $p$ | $W(p)^a$ | $\mu(I)^{b,c}$ | $W(p)$ | $\mu(I)$ | $W(p)$ | $\mu(I)$ | $W(p)$ | $\mu(I)$ |
| 2 | | | | | 28.2*** | 2.5*** (2) | 28.3*** | 3.0*** (4) |
| 5 | 25.8*** | 2.8*** (4) | 28.9*** | 4.4*** (8) | | | | |
| 10 | 28.5*** | 3.6*** (18) | 31.4*** | 3.5*** (14) | 31.4*** | 2.2*** (8) | 30.9*** | 2.3*** (4) |
| 20 | 34.1*** | 3.5*** (14) | 36.8*** | 2.5*** (4) | 36.6*** | 4.6*** (24) | 37.1*** | 2.0*** (8) |
| 30 | | | | | | | 42.4*** | 3.0*** (18) |
| 40 | | | 48.1*** | 3.5*** (24) | 49.1*** | 1.7*** (4) | | |
| 50 | 54.7*** | -0.6* (8) | | | | | | |
| 60 | | | | | | | 60.3 | 2.2*** (24) |
| 70 | | | 66.5*** | -0.6 (18) | | | | |
| 80 | 69.8*** | -0.1 (4) | | | | | | |
| 90 | | | | | 77.9*** | -1.1** (14) | | |

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<)\ p$: *p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<)\ 0$: *p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.
[c] Range sizes in parenthesis.

uncertainty premium. Overall, effects seem to be quantitatively of the same order of magnitude.

**Ability to reduce compound lotteries.** Table B.5 shows the average WTP associated with the range used in the incentivized question that asked subjects to compute the underlying failure probability. There are no substantial differences in uncertainty premia between those who answered correctly and those who did not correctly reduce the range, except for the last 2 ranges, in which those who reduced the range properly actually exhibit a higher WTP.

Table B.3: WTP for Insurance: Compound Risk $I = U[p-\varepsilon, p+\varepsilon]$

| | Group 1 | | Group 2 | | Group 3 | | Group 4 | |
|---|---|---|---|---|---|---|---|---|
| $p$ | $W(p)^a$ | $\mu(I)^{b,c}$ | $W(p)$ | $\mu(I)$ | $W(p)$ | $\mu(I)$ | $W(p)$ | $\mu(I)$ |
| 2 | | | | | 29.2*** | 2.3** (2) | 28.5*** | 2.8*** (4) |
| 5 | 25.3*** | 2.6*** (4) | 29.2*** | 3.4*** (8) | | | | |
| 10 | 27.6*** | 4.1*** (18) | 32.0*** | 2.9*** (14) | 32.0*** | 2.1*** (8) | 30.1*** | 3.0*** (4) |
| 20 | 32.8*** | 3.6*** (14) | 37.6*** | 1.7*** (4) | 37.2*** | 4.4*** (24) | 35.9*** | 2.7*** (8) |
| 30 | | | | | | | 41.5*** | 4.0*** (18) |
| 40 | | | 48.4*** | 3.9*** (24) | 49.9*** | 1.4** (4) | | |
| 50 | 53.0*** | 0.03 (8) | | | | | | |
| 60 | | | | | | | 60.3 | 3.1*** (24) |
| 70 | | | 66.8*** | 0.0 (18) | | | | |
| 80 | 67.7*** | 0.8* (4) | | | | | | |
| 90 | | | | | 78.2*** | -0.8* (14) | | |

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<)\ p$: *p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<)\ 0$: *p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.
[c] Range sizes in parenthesis.

Table B.4: WTP for Insurance: Ambiguous Risk $I = [p - \varepsilon, p + \varepsilon]$.

| | Group 1 | | Group 2 | | Group 3 | | Group 4 | |
|---|---|---|---|---|---|---|---|---|
| $p$ | $W(p)^a$ | $\mu(I)^{b,c}$ | $W(p)$ | $\mu(I)$ | $W(p)$ | $\mu(I)$ | $W(p)$ | $\mu(I)$ |
| 2 | | | | | 27.2*** | 2.8*** (2) | 28.1*** | 3.3*** (4) |
| 5 | 26.2*** | 2.9*** (4) | 28.7*** | 5.4*** (8) | | | | |
| 10 | 29.4*** | 3.1*** (18) | 30.7*** | 4.1*** (14) | 30.7*** | 2.4*** (8) | 31.7*** | 1.6*** (4) |
| 20 | 35.4*** | 2.9*** (14) | 36.1*** | 3.3*** (4) | 36.1*** | 4.7*** (24) | 38.2*** | 1.2** (8) |
| 30 | | | | | | | 43.3*** | 2.0*** (18) |
| 40 | | | 47.8*** | 3.1*** (24) | 48.3*** | 2.0*** (4) | | |
| 50 | 56.4*** | -1.2** (8) | | | | | | |
| 60 | | | | | | | 60.3 | 1.2** (24) |
| 70 | | | 66.3*** | -1.2** (18) | | | | |
| 80 | 71.9*** | -1.1** (4) | | | | | | |
| 90 | | | | | 77.5*** | -1.4** (14) | | |

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) p$: *p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) 0$: *p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.
[c] Range sizes in parenthesis.

Table B.5: WTP by Ability to Reduce Compound Lotteries

| | | Correct | | | Incorrect | | |
|---|---|---|---|---|---|---|---|
| Decision | $p$ | $W(p)^a$ | $\mu(I)^b$ | $n$ | $W(p)$ | $\mu(I)$ | $n$ |
| Range | | | | | | | |
| 3-7 | 5 | 22.6*** | 2.7*** | 658 | 34.2*** | 2.7** | 247 |
| 3-17 | 10 | 26.3*** | 3.3*** | 484 | 37.3*** | 3.3*** | 417 |
| 8-32 | 20 | 30.6*** | 5.2*** | 523 | 42.4*** | 3.9*** | 539 |
| 21-39 | 30 | 38.7*** | 4.0*** | 655 | 48.5*** | 1.2* | 406 |

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) p$: *p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) 0$: *p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.

# Appendix C Robustness and External Validity

### C.0.1 Measurement Error Correction

This section provides estimates of the correlation between risk and uncertainty premium that correct for potential biases due to measurement error. To formally show the problem, let $\hat{W}(I) = W(I) + \varepsilon_I$ be the elicited WTP under information $I$, where $\varepsilon_I$ is a random variable representing classical measurement error. Accordingly, the elicited risk premium is given by $\hat{\mu}(p) = \mu(p) + \varepsilon_p$ and the elicited uncertainty premium is given by $\hat{\mu}(I) = \mu(I) + \varepsilon_I - \varepsilon_p$. Assuming that measurement errors are independently drawn and that they are independent of $W(\cdot)$, the correlation between $\hat{\mu}(I)$ and $\hat{\mu}(p)$ is given by

$$corr(\hat{\mu}(I), \hat{\mu}(p)) = \frac{cov(\mu(I), \mu(p)) - Var(\varepsilon_p)}{\sqrt{(Var(\mu(I) + Var(\varepsilon_I - \varepsilon_p))(Var(\mu(p) + Var(\varepsilon_p))}}.$$

Hence, the numerator is negatively biased while the denominator is biased upwards, making both the direction and the size of the bias indeterminate.

However, if we have duplicate measures of the risk premium, $\hat{\mu}(p)$ and $\hat{\mu}^d(p) = \mu(p) + \varepsilon_p^d$ we can use $\hat{\mu}^d(p)$ as an instrument for $\hat{\mu}(p)$ in a regression of $\hat{\mu}(I)$ on $\hat{\mu}(p)$. Since errors are independent across measures the measurement error in $\hat{\mu}(I)$, given by $\varepsilon_I - \varepsilon_p$, is independent of the measurement error $\varepsilon_p^d$ in $\hat{\mu}^d(p)$, making the latter a valid instrument. Accordingly, the regression coefficient $\hat{\beta}$ delivers a consistent estimate of $\frac{cov(\mu(I), \mu(p))}{Var(\mu(p))}$. If, in addition, we have an additional measure $\hat{\mu}^d(I)$ of the uncertainty premium, the correlation between the risk and uncertainty premia can be consistently estimated using

$$\widehat{corr}(\mu(p), \mu(I)) = \hat{\beta}\sqrt{\frac{\widehat{cov}(\hat{\mu}(p), \hat{\mu}^d(p))}{\widehat{cov}(\hat{\mu}(I), \hat{\mu}^d(I))}}, \tag{14}$$

where $\widehat{corr}$ and $\widehat{cov}$ represent sample correlation and covariance, respectively.

Gillen et al. (2019) exploit the use of duplicate measures or *replicas* to obtain not only consistent but also efficient estimates via stacked IV regressions, one per available replica, with the remaining replicas acting as instruments. They call their approach an *obviously related instrumental variable* (ORIV) regression and show how to obtain consistent correlation estimates and bootstrapped standard errors.

To obtain replicas of risk and uncertainty premia, we take advantage of the fact that our experimental design elicits subjects' WTP for insurance for multiple risk probabilities. Specifically, we use the linear interpolation of risk premium associated with the probability points adjacent to $p$ as the second measure of $\mu(p)$. That is, if $p' < p$ and $p'' > p$ are the loss probabilities closest to $p$ in the experimental design, the replicas of risk and uncertainty premia are given by

$$\hat{\mu}^d(p) = \mu(p')\frac{p'' - p}{p'' - p'} + \mu(p'')\frac{p - p'}{p'' - p'},$$

$$\hat{\mu}^d(I) = \mu(I')\frac{p'' - p}{p'' - p'} + \mu(I'')\frac{p - p'}{p'' - p'},$$

where $I'$ and $I''$ represent the unknown risks respectively associated with $p'$ and $p''$. We normalize uncertainty premium by dividing it by range size and perform the linear interpolation using the normalized premia.

Table C.6 shows the ORIV correlation for probabilities with adjacent probabilities on both sides (column three). The estimates are of similar magnitude if not slightly more negative. These results indicate that the negative relationship between risk and uncertainty premia is not an artifact of measurement error.

Table C.6: Correlation between risk and insurance premia

| $p$ | correlation[a] | ORIV correlation[b] |
|---|---|---|
| 2 | -0.312*** | - |
| 5 | -0.291*** | - |
| 10 | -0.276*** | -0.310*** |
| 20 | -0.241*** | -0.319*** |
| 30 | -0.329*** | -0.324*** |
| 40 | -0.256*** | -0.353*** |
| 50 | -0.347*** | -0.306*** |
| 60 | -0.284*** | - |
| 70 | -0.309*** | - |
| 80 | -0.267*** | - |
| 90 | -0.276*** | - |

[a] Statistical significance: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] p-values for ORIV correlation are computed using bootstrapped standard errors.

### C.0.2 Correlation in Existing Experimental Data

The remarkable invariance of our correlation estimates raises the question whether we have uncovered a robust feature of uncertainty preferences or whether they are just a byproduct of our specific survey design. We address this question by replicating our analysis in our companion laboratory experiment, which is described below, and by computing the correlation between risk premium and compound risk premia in the data of some of the most prominent studies looking at the relationship between ambiguity and compound risk attitudes, namely the papers by Halevy (2007), Abdellaoui et al. (2015) and Chew et al. (2017).

As Table C.6 shows, correlation coefficients are significantly negative in all the datasets. Interestingly, since the data in Abdellaoui et al. (2015) includes three different probabilities we were able to calculate the ORIV correlation for $p = 1/2$, which turns out to be identical to the ORIV correlation of $-0.3$ in our data.[16]

[16] Abdellaoui et al. (2015) use compound lotteries in their 'hypergeometric CR' treatment, preventing

Table C.7: Correlation between risk and insurance premia

| $p$ | Study | N | correlation | ORIV correlation |
|---|---|---|---|---|
| 50 | This paper - UAS | 1,043 | -0.347*** | -0.306*** |
| 50 | This paper - Experiment | 119 | -0.401*** | -0.299*** |
| 50 | Halevy (2007) - $2 treatment | 104 | -0.557*** | - |
| 50 | Halevy (2007) - $20 treatment | 38 | -0.542*** | - |
| 8.33 | Abdellaoui et al. (2015)[c] | 115 | -0.418*** | - |
| 50 | Abdellaoui et al. (2015)[d] | 115 | -0.365*** | -0.310** |
| 91.67 | Abdellaoui et al. (2015) | 115 | -0.518*** | - |
| 50 | Chew et al. (2017) | 188 | -0.493*** | - |

[a] Statistical significance: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] p-values for ORIV correlation are computed using bootstrapped standard errors.
[c] Correlation between the known risk premium and hypergeometric CR premium.
[d] ORIV correlation from the Abdellaoui et al. (2015) dataset is computed using the average risk premium under simple lotteries with winning probabilities 1/12 and 11/12 as a replica for the risk premium at probability 1/2.

# Appendix D Omitted Proofs

*Proof of Proposition 1.* Under linear utility $u(x) = x$ the certainty equivalent of known risk $(q, -1; 1-q, 0)$ is $-\pi_2(q)$. Since this expression is decreasing in $q$, the distribution of certainty equivalents induced by the uniform distribution on $[p-\varepsilon, p+\varepsilon]$ is given by

$$G(y) = Pr(q \geq \pi_2^{-1}(-y)) = 1 - \frac{\pi_2^{-1}(-y) - p + \varepsilon}{2\varepsilon} = \frac{p + \varepsilon - \pi_2^{-1}(-y)}{2\varepsilon},$$

where $\pi_2^{-1}$ denotes the inverse of $\pi_2$. In addition, the lowest and highest certainty equivalents are respectively associated with the highest and lowest loss probabilities, i.e., $\underline{y} = -\pi_2(p+\varepsilon)$ and $\bar{y} = -\pi_2(p-\varepsilon)$. Accordingly, expression (3) leads to

$$V_w(I(p,\varepsilon)) = -\pi_2(p-\varepsilon) - \int_{-\pi_2(p+\varepsilon)}^{-\pi_2(p-\varepsilon)} \pi_1\left(\frac{p+\varepsilon-\pi_2^{-1}(-y)}{2\varepsilon}\right) dy.$$

Applying the change of variable $t = \pi_2^{-1}(-y)$ we obtain

$$V_w(I(p,\varepsilon)) = -\pi_2(p-\varepsilon) - \int_{p-\varepsilon}^{p+\varepsilon} \pi_2'(t)\pi_1\left(\frac{p+\varepsilon-t}{2\varepsilon}\right) dt.$$

A second change of variable $z = \frac{t-p+\varepsilon}{2\varepsilon}$ implies that $2\varepsilon dz = dt$ and that the new limits of integration are $\underline{z} = 0$ and $\bar{z} = 1$, leading to expression (4).

To prove the second part of the proposition, note that the uncertainty premium

us from obtaining a replica of the uncertainty premium given that such lotteries are hard to compare across $p$. Nonetheless, the ORIV correction can still be performed by using a replica of the risk premium at 1/2, obtained via linear interpolation with probabilities 1/12 and 11/12.

satisfies $V_w(I(p,\varepsilon)) = -\mu(I(p,\varepsilon)) - \mu(p) - p$. Since $\mu(p) = \pi_2(p) - p$, we have that

$$\mu(I(p,\varepsilon)) = -\pi_2(p) + \pi_2(p-\varepsilon) + 2\varepsilon \int_0^1 \pi_2'(p+\varepsilon(2z-1))\pi_1(1-z)\,dz.$$

By the fundamental theorem of calculus we can express $\pi_2(p)$ as

$$\pi_2(p) = \pi_2(p-\varepsilon) + \int_{-\varepsilon}^{0} \pi_2'(p+t)dt = \pi_2(p-\varepsilon) + 2\varepsilon \int_0^{1/2} \pi_2'(p+\varepsilon(2z-1))dz,$$

where the last equality follows from the change of variable $z = \frac{t+\varepsilon}{2\varepsilon}$. Hence,

$$\mu(I(p,\varepsilon)) = -2\varepsilon \int_0^{1/2} \pi_2'(p+\varepsilon(2z-1))dz + 2\varepsilon \int_0^1 \pi_2'(p+\varepsilon(2z-1))\pi_1(1-z)\,dz$$

$$= -2\varepsilon \int_0^{1/2} \pi_2'(p+\varepsilon(2z-1))\left(1-\pi_1(1-z)\right)dz + 2\varepsilon \int_{1/2}^1 \pi_2'(p+\varepsilon(2z-1))\pi_1(1-z)\,dz.$$

The last expression leads to (5) by applying the change of variable $z' = 1-2z$ to the first integral and $z' = 2z-1$ to the second integral. □

*Proof of Proposition 2.* Dividing both sides of (5) and taking the limit as $\varepsilon \to 0$ we obtain

$$\lim_{\varepsilon\to 0}\frac{\mu(I(p,\varepsilon))}{\varepsilon} = \pi_2'(p)\left[\int_0^1 \pi_1\left(\frac{1-z}{2}\right)dz + \int_0^1 \pi_1\left(\frac{1+z}{2}\right)dz - 1\right]$$

$$= \pi_2'(p)\left[2\int_0^{1/2} \pi_1(z')\,dz' + 2\int_{1/2}^1 \pi_1(z')\,dz' - 1\right] = \pi_2'(p)\left[2\int_0^1 \pi_1(z')\,dz' - 1\right].$$

□

*Proof of Proposition 3. Part (i)*: We prove first the condition regarding the lower concave envelope. The expected utility of risk $(p,-1;1-p,0)$ is given by $pu(w-1)+(1-p)u(w)$. A positive risk premium for $p \in (0,p^*)$ involves $u(w-p) > pu(w-1)+(1-p)u(w)$. Letting $x = w-p$ we get that $u(x) > x(u(w)-u(w-1)) + u(w)(1-w) + wu(w-1)$. Since the RHS is linear in $x$ the strict inequality implies that we can always find a concave function $g(x)$ satisfying $u(x) \geq g(x) >$

$x(u(w) - u(w-1)) + u(w)(1-w) + wu(w-1)$ for all $x \in (w-p^*, w)$. The proof for the upper convex envelope is similar and therefore omitted.

*Part (ii):* The risk premium under linear utility $u(x) = x$ is given by $\mu(p) = \pi_2(p) - p$ so the condition is immediate. □

# Appendix E Reference-Dependent Preferences

We show in this section that adding reference dependence to EU-based uncertainty preferences cannot explain the risk premium patterns without resorting to non-standard functional forms of the utility function.

Reference-dependent preferences involve taking expectations over the utility of changes w.r.t. a reference point $x^*$, given by the function $v(x - x^*)$. Reference points can be deterministic or stochastic. Regarding stochastic reference points, which were introduced by Kőszegi and Rabin (2006), when evaluating WTP for full insurance, it is natural to make the lottery $(p, -1; 1-p, 0)$ the reference point. In this case, Sprenger (2015) has shown that stochastic reference point leads to risk neutrality when choosing a deterministic outcome (full insurance), thereby predicting a risk premium equal to zero for all $p$. Accordingly, we focus on deterministic reference points.

The value of known risk $(p, -1; 1-p, 0)$ for a DM with initial wealth $w$ and reference point $x^*$ is given by

$$V_r(p) = pv(w - 1 - x^*) + (1-p)v(w - x^*). \tag{15}$$

Two popular choices of reference points are either initial wealth $(x^* = w)$ or expected final wealth $(x^* = w - p)$ as in the model of dissapointment aversion (Bell, 1985; Loomes and Sugden, 1986; Gul, 1991). They respectively lead to

$$V_r(p) = pv(-1) + (1-p)v(0) \tag{16}$$

and

$$V_r(p) = pv(-1+p) + (1-p)v(p). \tag{17}$$

The next results shows that for reference-dependent preferences to explain the risk premium data we would need to resort to non-standard utility functions that switch between concavity/convexity or between loss averse/gain loving as wealth changes go above some threshold $p^* \in (0, 1)$.

**Proposition 5.** *Assume that there exists $p^* \in [0, 1]$ such that $\mu(p) > 0$ for $p < p^*$ and $\mu(p) < 0$ for $p > p^*$. If the DM maximizes expected utility $v(x - x^*)$ over gains/losses with respect to reference point $x^*$ then*

*(iii.a) if $x^* = w$ then the upper convex envelope of $v(z)$ is below the line connecting $v(-1)$ and $v(0)$ for all $z \in (-1, -p^*)$ and then its lower concave envelope above the line for all $z \in (-p^*, 0)$;*

*(iii.b) if $x^* = w - p$ then $\frac{v(0)-v(p-1)}{1-p} > \frac{v(p)-v(0)}{p}$ (loss averse) for all $p \in [0, p^*)$ and $\frac{v(0)-v(p-1)}{1-p} < \frac{v(p)-v(0)}{p}$ (gain loving) for all $p \in (p^*, 1]$.*

*Proof.* *Part (iii.a)*: If the reference point is current wealth, then the expected value of risk $(p, -1; 1-p, 0)$ is given by $pv(-1) + (1-p)v(0)$. A positive risk premium implies $v(-p) > pv(-1) + (1-p)v(0)$. Hence, the proof follows from applying the same argument in the proof of part (i) of Proposition 3 to $v$ instead of $u$ for the range of losses $(-p^*, 0)$.

*Part (iii.b)*: If the reference point is expected final wealth $y-p$, then the expected value of risk $(p, -1; 1-p, 0)$ is given by $pv(p-1) + (1-p)v(p)$. A positive risk premium implies

$$v(0) > pv(p-1) + (1-p)v(p) \Rightarrow p\left(v(0) - pv(p-1)\right) > (1-p)\left(v(p) - v(0)\right),$$

which proves the condition. □

# Appendix F Bayesian Estimation

This section presents some convergence tests of the MCMC sampling both within and between chains. Initial values for chain 1 were set to $\alpha = -0.7, \beta = -0.36, \sigma_\alpha = \sigma_\beta = 0.4, \phi = 4, q = 0.1, q_1 = 0.8$ and $\alpha_i = \beta = i = 0.5$ for all $i$. Initial values for chain 2 were set to $\alpha = \beta = 0.1, \sigma_\alpha = \sigma_\beta = 2, \phi = 2, q = 0.3, q_1 = 0.6$ and $\alpha_i = \beta = i = 1.1$ for all $i$.

Figure F.1 shows that the traces of the last (post warm-up) 1,000 iterations of both chains mix well, with the two chains exploring the same region of parameter values. Overall, there was only one divergent iteration out of 2,000.

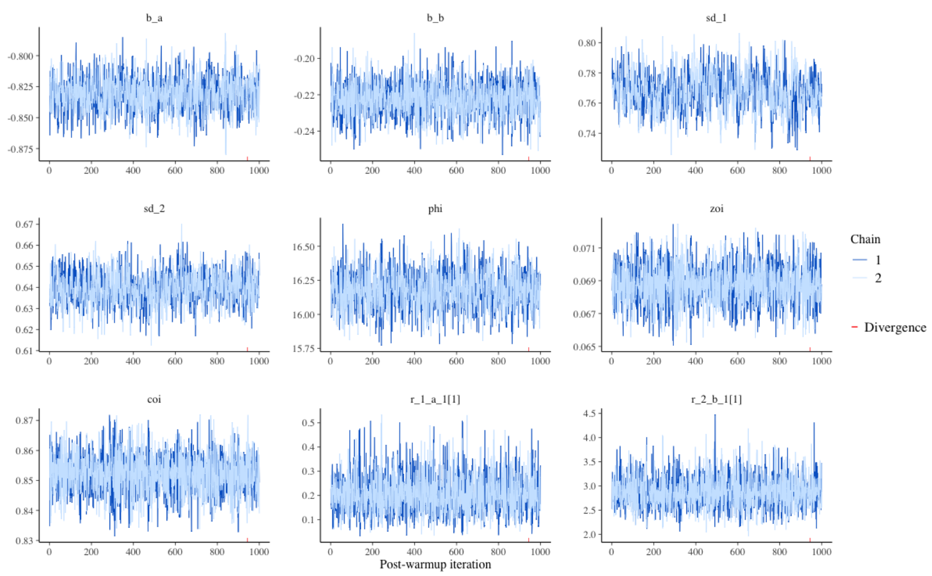


Figure F.1: Traces of selected parameters.

A typical statistic to check for convergence to a common distribution is the split-$\hat{R}$, which measures the ratio of the average variance of draws within each chain to the variance of the pooled draws across chains. Such ratios should be one if the chains have converged. If the chains have not converged to a common distribution, the split-$\hat{R}$ statistic will be greater than one. A common threshold for divergence is 1.05. Figure F.2 shows the values of split-$\hat{R}$ for all the parameters (over 17,000). All of the values are extremely close to 1.

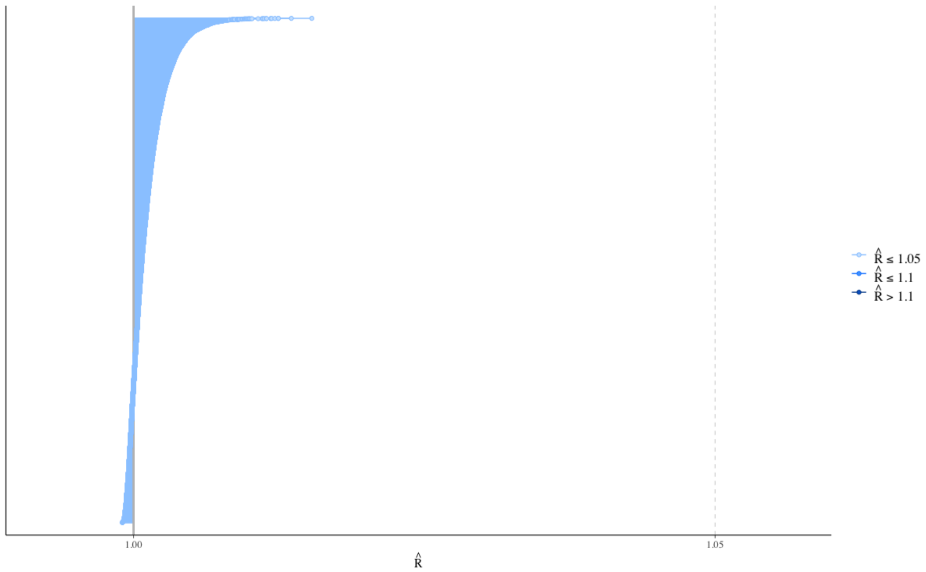


Figure F.2: Split-$\hat{R}$ of model parameters.

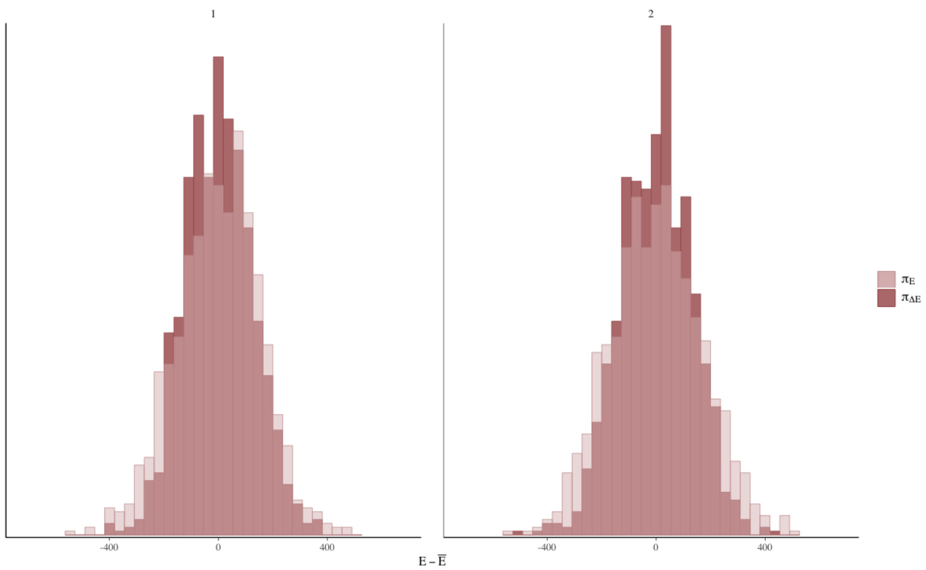


Figure F.3: Energy distributions for chain 1 (left) and chain 2 (right).

Figure F.3 plots for each chain the marginal energy distribution $\pi_E$ and the first-differenced distribution $\pi_{\Delta E}$. Both histograms overlap nicely and show an absence of heavy tails, which are challenging for sampling.

Finally, Figure F.4 shows the ratio of effective sample size ($N_{eff}$) to actual sample size ($N$) for all model parameters. this ratio estimates the fraction of independent draws from the posterior distribution. The ratio is larger than 0.75 for almost all parameters, implying low autocorrelation of MCMC draws.[17]

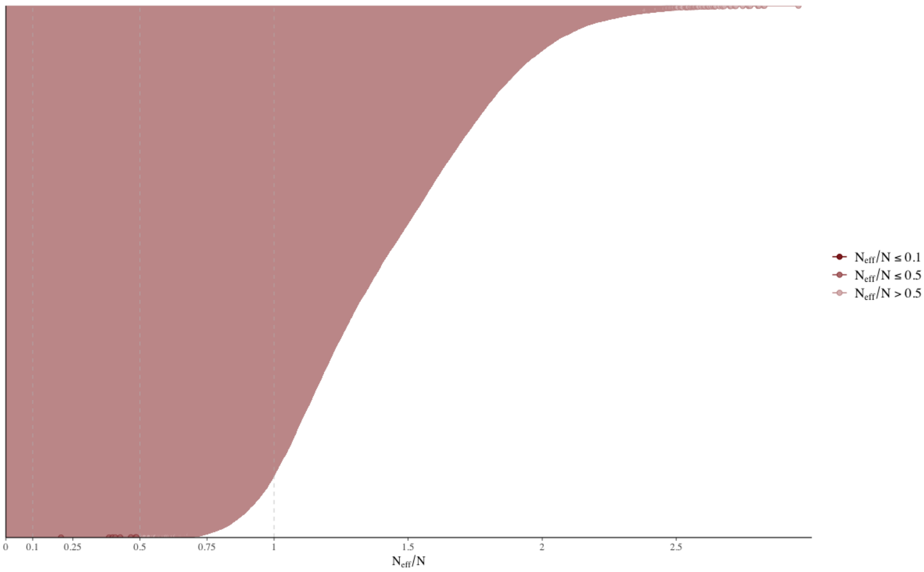


Figure F.4: Effective sample size ratio of model parameters.

# Appendix G Covariates of WTP

Table G.8 shows the results of regressing uncertainty premium on range size, whether the information about the range is ambiguous, the error in the quiz regarding reducing compound risk (normalized by range size), financial literacy and cognitive ability, as well as sociodemographic variables. All the regressions control for risk probability $p$ and for whether the known risk scenario was presented before uncertain risks or if the order was reversed (p-values are adjusted to control for multiple hypothesis testing). The first column shows the regression estimates without controlling for risk attitudes ($\mu(p)$), while the second column does control for risk attitudes.

Several conclusions emerge from these estimates. First, risk attitudes are by far the most important covariate of uncertainty premium: Risk premium accounts for about 9% of the overall variation of the uncertainty premium, while the rest of variables combined only account for a $R^2$ of 3%. Second, the table reflects the relationship between risk probabilities and range sizes depicted in Figure 2, namely, the wider the range and the lower the risk probability the higher the uncertainty premium. In contrast,

[17] A ratio greater than one implies negative autocorrelation leading to a smaller variance of the mean estimate than the one obtained from independent draws of the true posterior.

Table G.8: Covariates of uncertainty premium and Risk Premium

| | $\mu(I)$ | $\mu(I)$ | $\mu(p)$ |
|---|---|---|---|
| Risk Probability | -0.06*** | -0.14*** | -0.41*** |
| | (0.01) | (0.01) | (0.01) |
| Range Size | 0.11*** | 0.11*** | |
| | (0.01) | (0.01) | |
| Ambiguity | 0.54 | 0.50 | |
| | (0.33) | (0.32) | |
| $\mu(p)$ | | -0.19*** | |
| | | (0.01) | |
| Financial literacy | -0.15 | -0.45 | -1.71** |
| | (0.23) | (0.23) | (0.50) |
| Average Cognitive Score | 0.49 | 0.30 | -1.34* |
| | (0.24) | (0.23) | (0.48) |
| Quiz Error | -0.06 | 0.22 | |
| | (0.09) | (0.09) | |
| Age | -0.05 | -0.04 | 0.08 |
| | (0.07) | (0.06) | (0.14) |
| $Age^2/100$ | 0.04 | -0.01 | -0.24 |
| | (0.07) | (0.06) | (0.13) |
| Female | -0.64 | 0.11 | 3.90*** |
| | (0.35) | (0.35) | (0.76) |
| Married | -0.60 | -0.73 | -0.59 |
| | (0.37) | (0.36) | (0.83) |
| Some College | 0.29 | 0.01 | -1.22 |
| | (0.48) | (0.47) | (1.02) |
| Bachelor's Degree or Higher | 0.28 | -0.15 | -2.19 |
| | (0.54) | (0.54) | (1.16) |
| Hh Income: 25k-50k | 0.45 | 0.53 | 0.21 |
| | (0.54) | (0.53) | (1.16) |
| Hh Income: 50k-75k | 0.38 | -0.11 | -2.82 |
| | (0.60) | (0.58) | (1.26) |
| Hh Income: 75k-100k | 0.75 | 0.59 | -0.97 |
| | (0.62) | (0.62) | (1.41) |
| Hh Income: Above 100k | 0.29 | -0.85 | -6.38*** |
| | (0.62) | (0.62) | (1.33) |
| Non-Hispanic Black | -1.70 | -1.21 | 2.58 |
| | (0.75) | (0.71) | (1.53) |
| Spanish/Hispanic/Latino | 0.31 | 0.30 | 0.04 |
| | (0.70) | (0.70) | (1.37) |
| Other Race/Ethnicity | -0.12 | 0.10 | 1.23 |
| | (0.66) | (0.63) | (1.24) |
| Reverse Order | 4.64*** | 4.13*** | -2.51*** |
| | (0.33) | (0.32) | (0.71) |
| $R^2$ | 0.03 | 0.13 | 0.20 |
| $N$ | 19,050 | 19,050 | 19,432 |

All regressions include a constant and standard errors are clustered. Regressions including $\mu(p)$ are IV regressions with the linear interpolation of adjacent risk premia as the instrument for $\mu(p)$. Bonferroni-adjusted $p$-values: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

whether the range is ambiguous or not does not lead to significant differences in the uncertainty premium. Information attitudes do not seem to be driven by misperception of risks, as measured by the error in the incentivized quiz about reducing compound risk (normalized by range size). Third, cognitive and socio-demographic variables do not seem to significantly drive information attitudes. In contrast, gender, income, as well as cognitive ability and financial literacy are significantly associated with risk attitudes. The third column in Table G.8 shows that individuals with higher financial literacy and cognitive ability are less risk averse. Similarly, being male and earning an income above $100k are associated with lower risk aversion. These relationships are consistent with previous studies about risk attitudes (Outreville, 2014).

Finally, we find significant order effects, with higher uncertainty premia associated with the reverse order, i.e., when agents were asked about WTP for unknown risks first. This may suggest that being exposed to known risk may have an anchoring effect on WTP for insurance against unknown risks.[18]

# Appendix H Experiment

## H.1 Design

The laboratory experiment was conducted at the BRITE Laboratory for economics research and computerized using ZTree (Fischbacher, 2007). Participants were recruited from a subject pool of undergraduate students at the University of Wisconsin-Madison. A total of 119 subjects participated in 9 sessions, with an average of 13 subjects participating in each session. Upon arriving to the lab, subjects were seated at individual computers and given copies of the instructions. After the experimenter read the instructions out loud, she administered a quiz on understanding (see Appendix I for the complete instructions and quiz provided to subjects).

Each participant made 52 insurance decisions individually and in private. In each decision period, the subject was the owner of a unit called the A unit. The A unit had some chance of failing, and some chance of remaining intact. Intact A units paid out 100 experimental dollars to the subject at the end of the experiment, while failed A units paid out nothing. The probability of A unit failure, including the information available about said probability, was varied in each decision.

In each decision period, we elicited the maximum willingness to pay for full insurance using the Becker-DeGroot-Marschak mechanism. Subjects moved a slider to indicate how much of their 100 experimental dollar participation payment they would like to use to pay for insurance. Then, the actual price of insurance was drawn at random using a bingo cage from a uniform distribution on (0,100). If WTP was equal to or greater than the actual price, the subject paid the actual price, which assured that the A unit would be replaced if it failed. On the other hand, if WTP was less than the actual price, the subject did not pay for insurance and lost the A unit if there was a failure.

We randomized subjects to two different treatments; No Ambiguity group and

[18] No such order effects seem to be present in our lab experiment (see Table H.11 in Appendix H.4).

Ambiguity group. All subjects faced multiple information environments; in that sense, our design includes both within- and between- subject components.

We start by explaining the decisions faced by the No Ambiguity group. We divide the decisions into 4 different 'blocks' of 13 decisions each. In each 'block' of decisions, we asked subjects to state their maximum WTP for an expected rate of failure of between 2% and 98%, as described in Table H.9. The four 'blocks' were as follows: 1) Probability of Loss, which provided full information about the failure rate, 2) Range Small, which provided a small range of possible probabilities of failure, 3) Range Big, which provided ranges of greater size, and 4) Multiplicative Risks.[19] It was clearly explained that within the Range blocks, the actual probability of failure would be chosen from within the range with all integer numbers equally likely. Multiplicative Risks imply a loss only if both probabilities are realized. As can be noted from Table H.9, each decision within the block has a corresponding decision with the same expected probability across information environments for ease of comparison.

Both Multiplicative Risks and Range blocks constitute a decision that involves solving a compound risk problem. Along the range treatments, we chose Small and Big range in order to vary levels - Big Range is somewhat more imprecise than Small range.

The Ambiguity group faced similar decisions to the No Ambiguity group (as denoted by Table H.9, except that the actual selection of the probability of failure for the Range 'blocks' was left ambiguous. Specifically, subjects were told that the actual probability is within the range but is unknown.

Subjects made decisions one at a time, but had a record sheet in front of them summarizing the ranges and probabilities for all 52 decisions. To control for any order effects, we conducted the experiment using 4 different possible orders, assigned at random to each session: (1, 2, 3, 4); (2, 3, 4, 1)' (3, 4, 1, 2) and (4, 1, 2, 3). Following the decision rounds, subjects also completed a quiz testing their ability to reduce compound lotteries and a short demographic questionnaire.

At the end of the experiment, only one of the decisions was selected at random and paid out, and no feedback on outcomes was given until the end, so we consider each decision made an independent decision. At the end of the experiment, we first randomly selected one decision to be the 'decision-that-counts.' Then, we randomly selected the actual price of insurance. Finally, we used the reported probability of failure in the 'decision-that-counts' to randomly choose whether or not the A unit would fail. All random selections were carried out using a physical bingo cage and bag of orange and white balls rather than a computerized system to assure transparency.

Earnings in experimental dollars were converted to US dollars at the rate of 10 experimental dollars = $1. Participation required approximately one hour and subjects earned an average of about $29.5 each.[20]

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[19] In the experiment itself, these were called 'Known Failure Rate' (1), 'Uncertain Failure Rate' (2 and 3), and 'Failure Rate Depends on Environmental Conditions' (4)

[20] In this paper, we report only on the insurance choice experiment, which was conducted at the beginning of the session. However, subjects stayed to participate in another risk task after the insurance task was over. The time and earnings reported above exclude the additional task time and payout.

Table H.9: Experiment Treatments

| Decision # (within block) | (1) Probability of Loss (%) | (2) Range Small (%) | (3) Range Big (%) | (4) Multiplicative Risks 1st; 2nd, (%) |
|---|---|---|---|---|
| 1 | 2 | 1-3 | 0-4 | 40; 5 |
| 2 | 5 | 3-7 | 1-9 | 10; 50 |
| 3 | 10 | 3-17 | 1-19 | 40; 25 |
| 4 | 20 | 16-24 | 8-32 | 25; 80 |
| 5 | 30 | 29-31 | 21-39 | 85; 35 |
| 6 | 40 | 38-42 | 28-52 | 50; 80 |
| 7 | 50 | 46-54 | 38-62 | 66; 76 |
| 8 | 60 | 58-62 | 48-72 | 86; 70 |
| 9 | 70 | 69-71 | 61-79 | 75; 93 |
| 10 | 80 | 76-84 | 68-92 | 95; 84 |
| 11 | 90 | 83-97 | 81-99 | 92; 98 |
| 12 | 95 | 93-97 | 91-99 | 99; 96 |
| 13 | 98 | 97-99 | 96-100 | 99; 99 |

## H.2 Risk and Uncertainty Premium

The experiment confirms the results found in both surveys. Both risk premium and uncertainty premium are decreasing in risk probability $p$, as shown in Figure H.5. The only difference is that subjects in the experiment were significantly less risk averse.

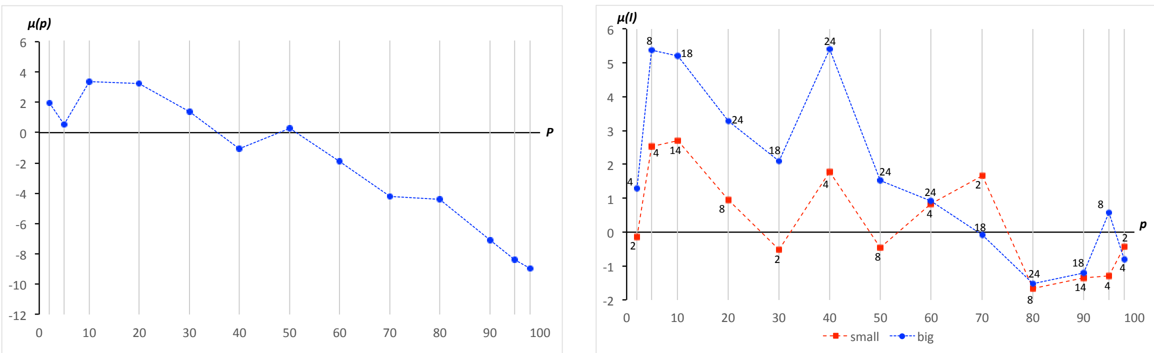


Figure H.5: Average Risk and Uncertainty Premia at Different Probabilities.

The effects of multiplicative risks are much stronger than those associated with ranges. Figure H.6 shows the comparison of uncertainty premia for multiplicative risk and range treatments. Whereas the uncertainty premium associated with multiplicative risks also declines as $p$ goes up, it is still large at $p \leq 80\%$. A possible explanation for this disparity is that multiplicative risks are perceived as more complex. Using the incentivized quiz about reducing both range and multiplicative risks, Table H.14 shows that the inability to reduce lotteries seems to increase WTP under multiplicative risks.

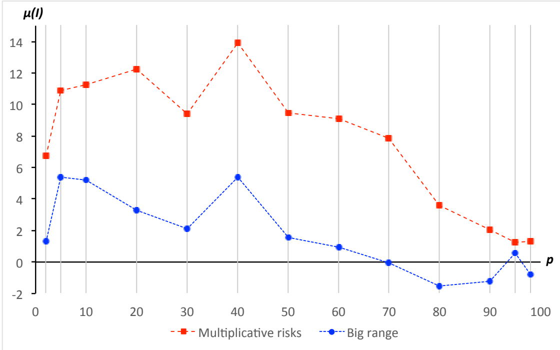


Figure H.6: uncertainty premium of Big Range and Multiplicative Risk Treatments

## H.3 Relationship Between Risk and Uncertainty Premium

Table H.10 presents the correlation coefficients for different $p$ between risk and uncertainty premia, as well as the ORIV correlation coefficients. To perform the ORIV correction we use the linear interpolation of adjacent risk premia as a replica of risk premium. We do not use replicas of the uncertainty premium given the lack of a direct comparability of uncertainty premium between different multiplicative risks.[21]

Table H.10: Correlation between risk and insurance premia – Experiment

| | Range | | Multi-Risk | |
|---|---|---|---|---|
| $p$ | correlation[a] | ORIV correlation[b] | correlation | ORIV correlation |
| 2 | -0.197** | - | -0.249** | - |
| 5 | -0.120 | -0.059 | -0.166** | -0.012 |
| 10 | -0.214** | 0.210 | -0.304*** | -0.333* |
| 20 | -0.394*** | -0.405*** | -0.315*** | -0.268*** |
| 30 | -0.567*** | -0.499 | -0.388*** | -0.301*** |
| 40 | -0.203** | -0.428* | -0.239*** | -0.192*** |
| 50 | -0.401*** | -0.299*** | -0.378*** | -0.366*** |
| 60 | -0.240*** | -0.289** | -0.347*** | -0.254*** |
| 70 | -0.374*** | -0.299*** | -0.372*** | -0.373*** |
| 80 | -0.388*** | -0.425*** | -0.402*** | -0.373*** |
| 90 | -0.459*** | -0.529*** | -0.525*** | -0.530*** |
| 95 | -0.538*** | -0.596*** | -0.539*** | -0.529*** |
| 98 | -0.569*** | - | -0.587*** | - |

[a] Statistical significance: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] p-values for ORIV correlation are computed using bootstrapped standard errors.

[21]Not having a replica for the uncertainty premium implies that the ORIV correlation is consistent as long as the variation in each replica of the risk premium due to measurement error is identical (Gillen et al., 2019).

Table H.11: Covariates of uncertainty premium and Risk Premium - Experiment

| | $\mu(I)$ | | | | $\mu(p)$ |
|---|---|---|---|---|---|
| | Range | | Multi-Risk | | |
| Risk Probability | -0.04* | -0.07*** | -0.07 | -0.15*** | -0.12*** |
| | (0.01) | (0.01) | (0.04) | (0.04) | (0.03) |
| Probability Range | 0.25** | 0.18 | | | |
| | (0.08) | (0.08) | | | |
| (Probability Range)$^2$ | -0.01 | -0.01 | | | |
| | (0.00) | (0.00) | | | |
| 1st Stage Probability | | | -0.04 | 0.00 | |
| | | | (0.03) | (0.03) | |
| Ambiguity | -0.28 | 0.17 | | | |
| | (1.21) | (1.24) | | | |
| Quiz Score | -0.12 | -0.26 | 0.39 | 0.30 | |
| | (0.47) | (0.46) | (0.48) | (0.51) | |
| Quantitative Major | 1.35 | 0.88 | -2.11 | -3.10 | -2.84 |
| | (1.41) | (1.49) | (2.17) | (2.34) | (3.02) |
| Statistics Course | 1.88 | 1.52 | -2.73 | -3.11 | -3.22 |
| | (1.97) | (1.86) | (2.74) | (2.94) | (4.04) |
| Cumulative GPA | 0.88 | 1.30 | -0.12 | 0.28 | 1.20 |
| | (0.96) | (0.91) | (1.53) | (1.47) | (1.59) |
| CRT Score | -0.46 | -0.28 | -3.09*** | -3.35*** | 0.15 |
| | (0.56) | (0.55) | (0.86) | (0.90) | (1.13) |
| $\mu(p)$ | | -0.15*** | | -0.31*** | |
| | | (0.04) | | (0.07) | |
| Age | -0.20 | -0.18 | 1.48*** | 1.62*** | 0.15 |
| | (0.09) | (0.09) | (0.18) | (0.16) | (0.22) |
| Female | 0.27 | -0.19 | 3.63 | 1.88 | -4.56 |
| | (1.43) | (1.54) | (1.87) | (1.99) | (2.63) |
| Years in College | -0.18 | -0.13 | -0.36 | -0.27 | 0.96 |
| | (0.76) | (0.81) | (1.16) | (1.29) | (1.69) |
| Black/African American | -2.51 | -2.69 | -2.92 | -2.12 | -0.19 |
| | (3.88) | (4.03) | (8.40) | (9.38) | (3.86) |
| Asian | -1.97 | -2.21 | -1.61 | -1.44 | 0.94 |
| | (1.53) | (1.40) | (2.14) | (2.20) | (3.45) |
| Hispanic | 3.14 | 5.50 | 0.71 | 4.47 | 10.30 |
| | (1.66) | (2.23) | (3.18) | (3.81) | (6.07) |
| Reverse Order | -2.21 | -1.64 | -1.67 | -1.34 | 4.08 |
| | (1.21) | (1.24) | (1.64) | (1.65) | (2.42) |
| $R^2$ | 0.04 | 0.13 | 0.14 | 0.28 | 0.09 |
| $N$ | 3094 | 2618 | 1547 | 1309 | 1547 |

All regressions include a constant and standard errors are clustered. Regressions including $\mu(p)$ are IV regressions with the linear interpolation of adjacent risk premia as the instrument for $\mu(p)$. Bonferroni-adjusted $p$-values: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

## H.4 Covariates of Uncertainty Preferences in the Laboratory

Table H.11 presents the regression estimates from the experiment. We run separate regressions for the range and multiplicative risk treatments. In the latter regressions we include the first stage risk probability since it is associated with negative skeweness (Dillenberger and Segal, 2017).[22] We also include as proxies for financial literacy whether the subject's major is quantitative (life sciences, natural sciences, economics and business, and engineering majors) and whether she took an economic course. GPA and the number of correct answers in the cognitive reflection test (CRT) (Frederick, 2005) are proxies for cognitive ability.

The results in terms of the explanatory power of risk premium largely replicate the findings using the UAS data. The regression $R^2$ goes from 0.03 to 0.14 in the range treatment and from 0.14 to 0.28 for multiplicative risks. Neither ambiguity nor skeweness seem to significantly affect uncertainty premia. Interestingly, a higher cognitive ability (CRT score) is significantly associated with a lower uncertainty premium only in the multiplicative risks treatment, potentially reflecting the fact that these risks are more complex than range risks and thus elicit a higher reaction in subjects with lower ability. In terms of demographics only age is statistically significant in the multi-risk treatment.

Unlike the field experiment, order effects are not significant. To measure them we consider whether the subjects answered the known risk questions first or faced the reverse order, meaning that the answer questions of the respective treatment (range or multiplicative risks) first.

## H.5 Analyisis of WTP

Table H.12 presents the average WTP under known risk as well as the uncertainty premium across treatments. The table also reports both whether $W(p)$ is different from $p$ and whether the uncertainty premium is different from zero according to one-sided paired $t$-tests.

Table H.13 shows the comparison of presenting agents with non-ambiguous versus ambiguous ranges. No clear pattern emerges, with uncertainty premium being sometimes smaller and other times larger under ambiguity.

Finally, we check whether the results might be solely driven by subjects' lack of understanding of how to reduce compound lotteries. The next table shows the WTP and risk premia of subjects that answered correctly an incentivized quiz asking them to compute the underlying failure probability of some of the above scenarios. There were six questions in the quiz, three for ranges and three regarding compound risks. Table H.14 presents the results. While the magnitude of $\mu(I)$ is higher on average for those who respond incorrectly, subjects that reduce compound risks still exhibit significant uncertainty premia, especially under multiplicative risks.

Table H.12: WTP for Insurance

| $p$ | $W(p)^a$ | Range $\mu(I)^b$ | (size) | $\mu(I)$ | (size) | Multi-Risk $\mu(I)$ |
|---|---|---|---|---|---|---|
| 2 | 3.98** | 0.14 | (2) | 1.29 | (4) | 6.74*** |
| 5 | 5.51 | 2.55** | (4) | 5.37*** | (8) | 10.88*** |
| 10 | 13.38** | 2.70*** | (14) | 5.20*** | (18) | 11.28*** |
| 20 | 23.27** | 0.94 | (8) | 3.27*** | (24) | 12.23*** |
| 30 | 31.38 | -0.51 | (2) | 2.11* | (18) | 9.41*** |
| 40 | 38.94 | 1.78** | (4) | 5.41*** | (24) | 13.88*** |
| 50 | 50.29 | -0.45 | (8) | 1.53 | (24) | 9.47*** |
| 60 | 58.11 | 0.83 | (4) | 0.92 | (24) | 9.10*** |
| 70 | 65.80** | 1.68** | (2) | -0.08 | (18) | 7.86*** |
| 80 | 75.58** | -1.66* | (8) | -1.52 | (24) | 3.60** |
| 90 | 82.92*** | -1.34* | (14) | -1.19 | (18) | 2.05 |
| 95 | 86.61*** | -1.29 | (4) | 0.57 | (8) | 1.25 |
| 98 | 89.04*** | -0.42 | (2) | -0.80 | (4) | 1.29 |

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) p$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) 0$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.

Table H.13: WTP by Ambiguity

| | Non-ambiguous Range | | | | | Ambiguous range | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $p$ | $W(p)^a$ | $\mu(I)^b$ | (size) | $\mu(I)$ | (size) | $W(p)$ | $\mu(I)$ | (size) | $\mu(I)$ | (size) |
| 2 | 3.48* | -0.45 | (2) | -0.05 | (4) | 4.46* | 0.15 | (2) | 2.56* | (4) |
| 5 | 4.77 | 2.41 | (4) | 3.55** | (8) | 6.21 | 2.67* | (4) | 7.10*** | (8) |
| 10 | 12.40 | 3.21** | (14) | 4.40*** | (18) | 14.31** | 2.21** | (14) | 5.97*** | (18) |
| 20 | 22.21 | 1.79* | (8) | 2.59* | (24) | 24.28** | 0.13 | (8) | 3.92** | (24) |
| 30 | 31.05 | -0.21 | (2) | 1.28 | (18) | 31.69 | -0.80 | (2) | 2.90* | (18) |
| 40 | 38.05 | 2.55** | (4) | 5.90*** | (24) | 39.79 | 1.05 | (4) | 4.95*** | (24) |
| 50 | 50.28 | -0.97 | (8) | 0.24 | (24) | 50.31 | 0.05 | (8) | 2.75 | (24) |
| 60 | 56.84 | 0.62* | (4) | 1.47 | (24) | 59.31 | 1.03 | (4) | 0.41 | (24) |
| 70 | 63.97** | 1.97* | (2) | 0.31 | (18) | 67.54 | 1.41 | (2) | -0.44 | (18) |
| 80 | 72.72*** | -0.12 | (8) | -0.69 | (24) | 78.30 | -3.13*** | (8) | -2.31 | (24) |
| 90 | 80.14*** | -1.19 | (14) | -0.48 | (18) | 85.56** | -1.49 | (14) | -1.87 | (18) |
| 95 | 83.26*** | 0.57 | (4) | 2.02 | (8) | 89.79** | -3.07** | (4) | -0.80 | (8) |
| 98 | 86.74*** | -0.33 | (2) | 0.05 | (4) | 91.23*** | -0.51 | (2) | -1.61 | (4) |

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) p$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) 0$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.

[22] It can be shown that lotteries with $p_1 < (>)\ 0.5$ are negatively skewed.

Table H.14: WTP by Ability to Reduce Compound Lotteries - Lab

| | | Correct | | | Incorrect | | |
|---|---|---|---|---|---|---|---|
| Decision | $p$ | $W(p)^a$ | $\mu(I)^b$ | $n$ | $W(p)$ | $\mu(I)$ | $n$ |
| Range | | | | | | | |
| 0-4 | 2 | 3.18** | 0.31 | 105 | 10.00 | 8.64 | 14 |
| 3-17 | 10 | 13.02* | 2.13** | 88 | 14.39* | 4.32** | 31 |
| 61-79 | 70 | 64.56*** | 0.32 | 89 | 69.47 | -1.24 | 30 |
| Multi-Risk | | | | | | | |
| 10; 50 | 5 | 4.69 | 9.50*** | 84 | 7.49 | 14.20*** | 35 |
| 50; 80 | 40 | 37.61 | 11.47*** | 77 | 41.38 | 18.31*** | 42 |
| 95; 84 | 80 | 73.88** | 4.10** | 50 | 76.81* | 3.23* | 69 |

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) p$:
*p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) 0$:
*p-value $< 0.10$, **p-value $< 0.05$, ***p-value $< 0.01$.

# Appendix I Instructions

## I.1 Survey

You can earn up to $10 for the next part. The amount you earn depends on the decisions you make, so you should read carefully!

We will ask you to make decisions about insurance in a few different scenarios. This time, at the end of the survey, one of the scenarios will be selected by the computer as the "scenario that counts." The money you earn in the "scenario that counts" will be added to your usual UAS payment. Since you won't know which scenario is the "scenario that counts" until the end, you should make decisions in each scenario as if it might be the one that counts.

We will use virtual dollars for this part. At the end of the survey, virtual dollars will be converted to real money at the rate of 20 virtual dollars = $1. This means that 200 virtual dollars equals $10.00.

**Each Scenario**

- You have 100 virtual dollars
- You are the owner of a machine worth 100 virtual dollars.
- Your machine has some chance of being damaged, and some chance of remaining undamaged, and the chance is described in each decision.
- You can purchase insurance for your machine. If you purchase insurance, a damaged machine will always be replaced by an undamaged machine.
- At the end, in the scenario-that-counts, you will get 100 virtual dollars for an undamaged machine. You will not get anything for a damaged machine.

**Paying for Insurance**

You will move a slider to indicate how much you are willing to pay for insurance, before learning the actual price of insurance. To determine the actual price of insurance in the "scenario that counts", the computer will draw a price between 0 and 100 virtual dollars, where any price between 0 and 100 virtual dollars is equally likely.

If the amount you are willing to pay is equal to or higher than the actual price, then:

- You pay for the insurance at the actual price, whether or not your machine gets damaged
- If damage occurs, your machine is replaced at no additional cost
- If there is no damage, your machine remains undamaged
- You get 100 virtual dollars for your machine

- That means you would earn 100 virtual dollars (what you start with) PLUS 100 virtual dollars (amount you get for machine) MINUS the price of insurance.

If the amount you are willing to pay for insurance is less than the actual price, then:

- You do not pay for the insurance
- If damage occurs, your machine is damaged and you do not get any money for your machine. That means you would earn 100 (what you start with) but you would not earn anything for your machine.
- If there is no damage, your machine remains undamaged and you get 100 virtual dollars. That means you would earn 100 virtual dollars (what you start with) PLUS 100 virtual dollars (amount you get for the machine).

This means that the higher your willingness to pay, the more likely it is that you will buy insurance.

**BASELINE BLOCK: ALL TREATMENTS**

Remember: You can earn up to $10 for the next part. The amount you earn depends on the decisions you make, so you should read carefully!

KNOWN DAMAGE RATE: The chance of your machine being damaged is 5% [10, 20, etc].

Please move the slider to indicate the maximum amount you are willing to pay for insurance.

Remember, if the amount you are willing to pay is higher than the actual price, then you will pay for insurance at the actual price, whether or not your machine is damaged. Should there be damage, your machine will be replaced and you will get 100 virtual dollars for it. If the amount you are willing to pay is less than the actual price, then you will not pay for insurance, but if damage occurs, your machine will not be replaced and you will not get any money for it.

[ Slider moves from 0 to 100 in integer increments. ]

**CONFIRMATION MESSAGE**

You have indicated you are willing to pay up to X for insurance. Continue? Y / N

**RANGE BLOCK: AMBIGUOUS RANGE**

UNCERTAIN DAMAGE RATE: The chance of your machine being damaged is between 3% and 7% [8-32 etc]. The exact rate of damage within this range is unknown.

Please move the slider to indicate the maximum amount you are willing to pay for insurance.

Remember, if the amount you are willing to pay is higher than the actual price, then you will pay for insurance at the actual price, whether or not your machine is damaged. Should there be damage, your machine will be replaced and will pay out 100 virtual dollars. If the amount you are willing to pay is less than the actual price, then you will not pay for insurance, but if damage occurs, your machine will not be replaced and will not pay out any money.

[ Slider moves from 0 to 100 in integer increments. ]

**RANGE BLOCK: NON-AMBIGUOUS RANGE**

UNCERTAIN DAMAGE RATE: The chance of your machine being damaged is between 3% and 7% [8-32 etc]. All damage rates in this range are equally likely.

Please move the slider to indicate the maximum amount you are willing to pay for insurance.

Remember, if the amount you are willing to pay is higher than the actual price, then you will pay for insurance at the actual price, whether or not your machine is damaged. Should there be damage, your machine will be replaced and will pay out 100 virtual dollars. If the amount you are willing to pay is less than the actual price, then you will not pay for insurance, but if damage occurs, your machine will not be replaced and will not pay out any money.

[ Slider moves from 0 to 100 in integer increments. ]

**QUESTION**

Before we finish, we'd like you to answer a final question. You will receive $1 for a correct answer.

Suppose a machine has a chance of being damaged between X and Y%. All damage rates in this range are equally likely. What is the average rate of damage for this machine?

The ranges to use in the question are: Group 1: range 3-7%; group 2: range 3-17%; group 3: 8-32%; group 4: 21-39%

**END SCREEN**

Thank you for participating!

The computer selected scenario X to be the "scenario that counts"

The computer selected the price of X virtual dollars for the insurance. Since the maximum you were willing to pay for insurance was X virtual dollars, you [bought/did not buy] insurance at the price of X.

The likelihood of damage for scenario X was [X%/between X% and Y%]. Your machine [was / was not] damaged and you got [ nothing / amount ] for your machine.

Based on the scenario the computer selected, your earnings for this part are X virtual dollars.

Converted to real money, your earnings are $X (X virtual dollars divided by 20).

You also earned $0 / $1 in the previous question.

A total of $X will be added to your usual UAS payment.

## I.2 Laboratory Experiment: Order 1, No Ambiguity

*Instructions for different orders are the same, except for the order of presentation.*

In this part, we will use experimental dollars as our currency. At the end of the experiment, your experimental dollars will be converted to US dollars and paid out to you in CASH with the following conversion rate:

10 experimental dollars = $1. This means 100 experimental dollars = $10.

You will start with 100 experimental dollars – this is your participation payment for this part of the experiment ($10).

You will make a series of 52 different decisions. Once all decisions have been made, we will randomly select one of those to be the decision-that-counts by drawing a number at random from a bingo cage with balls numbered from 1 to 52. Note, that since all decisions are equally likely to be chosen, you should make each decision as if it will be the decision-that-counts. Please pay close attention because you can earn considerable money in this part of the experiment depending on the decisions you make. You should think of each decision as separate from the others.

**Each Decision Period**

In each decision period, you will be the owner of a unit called an A unit. Your A unit has some chance of failing, and some chance of remaining intact. The probability of failure differs for different decision periods, so you should pay careful attention to the instructions in each decision period. In each decision period, you will have the opportunity to purchase insurance for your A unit. You can use up to 100 experimental dollars from your participation payment to purchase the insurance. If you purchase insurance, a failed A unit will always be replaced for you. At the end of the experiment, in the decision-that-counts, intact A units (those that have not failed) will pay out 100 experimental dollars. Failed A units will pay out 0 experimental dollars.

**Paying for Insurance**

You will indicate how much you are willing to pay for insurance in each decision by moving a slider. You will indicate your willingness to pay before learning the actual price of insurance for that round. To determine the actual price of insurance in the 'decision that counts', a number will be drawn at random from a bingo cage with numbers from 1 to 100. Any number is equally likely to be drawn.

If the maximum amount you were willing to pay for insurance is equal to or higher than the actual price of insurance, then: You pay for the insurance at the actual price, whether or not a failure occurs. If a failure occurs, your A unit is replaced at no additional cost to you. If there is no failure, your A unit remains intact. Your A unit always pays out 100 experimental dollars.

If the maximum amount you were willing to pay for insurance is less than the actual price of insurance, then: You do not pay for the insurance. If a failure occurs, your A unit will fail and you get no experimental dollars. If there is no failure, your A unit will remain intact and pays out 100 experimental dollars.

If you indicate you are willing to pay 0 experimental dollars for insurance, then you will never buy the insurance.

**Failure of the A unit**

After learning whether you have purchased insurance, you will find out whether your A unit has failed or not in the 'decision that counts'. The likelihood of failure depends on the specific directions in each decision. In some decisions, the likelihood of failure is known, and in some decisions, the likelihood of failure is uncertain. Let's go through some examples:

**Known Failure Rate**

In decisions with a known failure rate, the failure rate will be given to you. For example, suppose the failure rate is 15%. To determine whether your A unit will fail, we will place 100 balls in this bag. 15 will be orange and 85 will be white. Then, you will draw a ball at random. If the ball you drew is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail).

As another example, suppose the failure rate is 50%. To determine whether your A unit will fail, we will place 100 balls in this bag. 50 will be orange and 50 will be white. Again, if the ball you drew is orange, your A unit will fail and if it is white your A unit will remain intact (will not fail). In this type of decision, drawing an orange ball means your A unit fails.

**Uncertain Failure Rate**

In decisions with an uncertain failure rate, the failure rate will be given to you as a range. For example, suppose the failure rate is in the range 5% to 25%. To determine whether your A unit will fail, we will place 100 balls in this bag. Between 5 and 25 of the balls will be orange, and the remaining balls will be white. All failure rates in this range will be equally likely - a separate bingo draw will determine the number of orange balls before they are put in the bag. This means it is equally likely that there are 5, 6, 7...through 25 orange balls in the bag. Then, you will draw a ball at random. If the ball you drew is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail).

As another example, suppose the failure rate is in the range 40%-60%. To determine whether your A unit will fail, we will place 100 balls in this bag. Between 40 and 60 of the balls will be orange, and the remaining balls will be white. All numbers in this range will be equally likely. Again, if the ball you drew is orange, your A unit will fail and if it is white your A unit will remain intact (will not fail). In this type of decision, drawing an orange ball means your A unit fails.

**Failure Rate Depends on Environmental Conditions**

In decisions where the failure rate depends on environmental conditions, the A unit may only fail if environmental conditions are poor, but not if the environmental conditions are good. The likelihood of poor environmental conditions and the actual likelihood of failure are known and given to you. For example, suppose that the chance of poor environmental conditions is 50%. If the environment is poor, then there is a 30% chance of failure of the A unit. This means that we will have 2 bags with 100 balls each. In the first bag, we will put 50 orange balls and the remaining balls will be white. You will draw a ball at random from the first bag. If the ball is white, the environmental conditions are good and your A unit will not fail. If the ball is orange, the environmental conditions are poor and you will draw from the second bag. In the second bag, we will put 30 orange balls and the remaining balls will be white. You will draw a ball at random from the second bag. If the ball you drew from the second bag is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail).

As another example, suppose that the chance of poor environmental conditions is 70%. If the environment is poor, then there is a 50% chance of failure of the A unit. This means that the first bag will have 100 balls - 70 orange and the remaining white. You will draw a ball from the first bag at random. If it is white, your A unit will remain intact. If it is orange, we will prepare the second bag. The second bag will have 100 balls - 50 orange and the remaining white. You will draw a ball from the second bag at random. If the ball you drew from the second bag is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail). In this type of decision, both balls must be orange for your A unit to fail.

**In summary**

Each decision is equally likely to be the decision-that-counts. Therefore you should pay close attention to each decision you make. The likelihood of failure may be different in each decision period. Pay close attention and reference the instructions if you need to. Intact A units pay out 100 experimental dollars at the end of the experiment. Failed A units pay out nothing. In each decision period, you will decide how much you are willing to pay for insurance. If your willingness to pay is greater than or equal to the actual price of insurance, then you will buy insurance. If your willingness to pay is less than the actual price of insurance, then you will not buy insurance. This means that the higher your willingness to pay, the more likely it is that you will buy insurance. Insurance guarantees that your A unit will be replaced at no cost and will pay out 100 experimental dollars. If you bought insurance, you pay for insurance whether or not your A unit fails.

Before you begin making decisions, you will answer the next set of questions on your screen to confirm your understanding. You may refer back to instructions at any time. Please answer the questions on your screen now.

**Your decisions**

You will now have 30 minutes for this part. Please take your time when making each of the 52 decisions. There will be a 5-second delay before you can submit each of your decisions on the screen. Please also record your decisions on the record sheet.

## I.3 Laboratory Experiment: Order 1, Ambiguity in Ranges

*Instructions are the same as those without ambiguity, except for the 'uncertain failure rate' scenario. We provide just the instructions that are different from Appendix I.2.*

**Uncertain Failure Rate** In decisions with an uncertain failure rate, the failure rate will be given to you as a range. For example, suppose the failure rate is in the range 5% to 25%. To determine whether your A unit will fail, we will place 100 balls in this bag. Between 5 and 25 of the balls will be orange, and the remaining balls will be white. The exact number of orange balls is unknown and could be any number between 5 and 25. Then, you will draw a ball at random. If the ball you drew is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail).

As another example, suppose the failure rate is in the range 40%-60%. To determine whether your A unit will fail, we will place 100 balls in this bag. Between 40 and 60 of the balls will be orange, and the remaining balls will be white. Again, if the ball you drew is orange, your A unit will fail and if it is white your A unit will remain intact (will not fail). In this type of decision, drawing an orange ball means your A unit fails.