Estimating Uncertainty Preferences with Probability Weighting: Evidence from a Representative Survey

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Abstract

Individuals likely face uncertainty about underlying risks in insurance and financial markets. To characterize demand for financial products, it is therefore necessary to understand preferences toward both known and uncertain risks. We survey a representative sample of US households to estimate such preferences. We observe three main patterns and show that they can be modeled by incorporating probability weighing in both risk and uncertainty domains: 1) individuals exhibit uncertainty aversion, 2) individuals switch from risk averse to risk loving as risks become more likely and 3) risk and uncertainty aversion are negatively correlated. We find that probability weighting is much more heterogeneous in the risk domain than in the uncertainty domain. While individuals overweigh small probabilities and underweigh large probabilities across domains, probability distortion is lower among individuals with higher financial literacy and cognitive ability. We suggest how to account for unobserved uncertainty when estimating risk preferences from observational data.

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

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

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1 Introduction

Understanding the nature of individual preferences is key to conducting economic analysis of markets in which agents face risks, such as insurance and financial markets. One way to understand the nature of preferences is to use observational data on decision-making and recover preferences under certain assumptions. A growing literature does this using insurance decisions in observational data.[1] This literature characterizes risk attitudes under the assumption that agents have full information about the risks they face. One of the main takeaways of this literature is the need to incorporate probability weighting over risks in preference estimation (Barseghyan, Molinari, O'Donoghue and Teitelbaum, 2013).

However, it is likely that consumers do not have full information about their underlying risks and instead are uncertain about the risks that they face. For example, consumers may perceive the probability of suffering a loss to be between between 5 and 15% rather than exactly 10%. This uncertainty could also come in the form of difficulty reducing compound risks - e.g., having trouble assessing overall risk when the risk of damage to a roof is a combination of the risk of hail and the risk of a poorly built roof. Recent evidence shows that indeed economic agents often perceive risks in terms of probability ranges (Bachmann et al., 2020) and that consumers exhibit aversion to ambiguous and compound risks.[2] This suggests that whether risks are known or uncertain is a determinant of insurance demand.

Therefore, to fully characterize preferences in financial markets, it is important to consider preferences over both known risks and uncertain risks. However, it is not possible to estimate preferences in both the risk and uncertainty domains with observational data alone. As noted by Stantcheva (2022), a solution in this situation is to conduct surveys to uncover preferences. We therefore survey a representative sample of over 4,000 households in the United States. We elicit respondents' willingness to pay (WTP) for insurance against a loss in three scenarios: known (simple) risks, compound risks and ambiguous risks in the form of probability ranges.

This paper makes two main contributions. First, we theoretically show the need to incorporate probability weighting in both the risk and uncertainty domain to explain the empirical patterns in the data. These patterns involve 1) agents switching from risk aversion to risk loving as risks become more likely, 2) being uncertainty averse on

[1]See Barseghyan et al. (2016) for a review of existing work.

[2]The evidence of ambiguity aversion and compound lotteries is extensive. See for instance the evidence of aversion to ambiguous risks (Cohen et al., 1987; Einhorn and Hogarth, 1986; Di Mauro and Maffioletti, 2004; Chapman et al., 2020) and the review on higher order risk attitudes by Trautmann and van de Kuilen (2018).

average and 3) exhibiting a negative relation between risk and uncertainty aversion. We also find that agents' reaction to the introduction of uncertainty is much more homogeneous than their risk attitudes. Second, we estimate the joint distribution of risk and uncertainty preferences in the population and examine the degree and sources of preference heterogeneity. In a companion paper, we report on the three above-mentioned results and evaluate the welfare implications thereof, but do not provide the theory or estimate preferences as we do here (Gandhi et al., 2022).

Preference models that are linear in probabilities cannot satisfactorily explain the switch from risk averse to risk loving exhibited by a majority of survey respondents. In contrast, rank-dependent utility exhibiting overweighting (resp. underweighting) of small (large) probabilities can produce this switch. However, rank-dependent utility is, by definition, restricted to deal with known risks so it cannot explain our results when uncertainty about risks are introduced. A way to overcome this limitation is to model uncertain risks as two-stage risks and extend probability-weighting preferences to this domain. According to this approach, the second stage represents known risks, given by probabilities over final outcomes, while the first stage captures uncertainty via a probability distribution over known risks. Segal (1987) introduced a recursive version of rank-dependent utility that applies the same probability weighting function to both first- and second-stage distributions. We propose a generalization of these preferences, which we call *second-order anticipated utility*, that features two probability weighting functions, one for risk probabilities and another for the uncertainty distribution of risk probabilities. Allowing for different weighting functions is needed to generate the observed differences in heterogeneity across the risk and uncertainty domains. We theoretically identify conditions for such preferences to be consistent with the patterns in our data. To do so, we look at the change in WTP for insurance caused by the introduction of a small degree of uncertainty about risk probabilities. We call this change in WTP the *marginal uncertainty premium* and characterize it for second-order anticipated utility. It is given by the average probability weight in the uncertainty domain and the slope (or sensitivity) of the weighting function in the risk domain. We show that an individual is uncertainty averse, defined as having a positive marginal uncertainty premium, if on average she weighs distributions over risk probabilities more than an expected utility maximizer. We also prove that a negative correlation between the marginal uncertainty premium and the risk premium arises if higher risk aversion is associated with a lower sensitivity to changes in risk probabilities. We empirically confirm this association by estimating at the individual level the slope of the second stage weighting function. We find that agents with flatter slopes exhibit significantly higher risk premia. Intuitively, risk averse individuals are willing to pay a generous premium for insurance to avoid being exposed to a loss, regardless of the exact probability of its occurrence, thus exhibiting a lower sensitivity to changes in this probability.

To the best of our knowledge, this paper presents the first estimate of the joint distribution of risk and uncertainty preferences using a representative sample of the US population. To obtain these estimates, we adopt a Bayesian hierarchical model in which WTP for insurance is determined by second-order anticipated utility preferences. 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 pin down the relative contribution of probability weighting in the risk and uncertainty domains to preference heterogeneity and their relationship with sociodemographic characteristics. 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. Further, the majority of individuals overweight low to moderate probabilities, regardless of whether such probabilities correspond to known or uncertain risks. In terms of sociodemographic differences, we find that individuals with higher financial literacy and cognitive ability exhibit lower probability distortions.

Our preference estimation yields three main takeaways. First, the relatively homogeneous response to uncertainty suggests that policies aimed at improving information about underlying risks in insurance markets may be beneficial for most consumers, regardless of their risk attitudes and sociodemographic background. Second, the link between financial literacy and probability weighting suggests that less sophisticated agents might be over-represented in insurance markets. We explore these welfare implications in a companion paper (Gandhi et al., 2022). Finally, from a methodological perspective, our results highlight the need to control for uncertainty in the estimation of risk preferences. In this context, we show how we can exploit the functional form of the marginal uncertainty premium to correct for the presence of unobserved uncertainty in observational data.

In what follows, Section 2 provides a discussion of our contribution to related work. Section 3 summarizes the survey design. Section 4 summarizes the empirical patterns reported in Gandhi et al. (2022). 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 on the estimation of preferences that uses insurance take-up and claims data by studying the impact of uncertainty. Most existing work focuses on estimating risk preferences under the assumption that consumers know their distribution of underlying risks (Sydnor, 2010; Barseghyan et al., 2011, 2013; Einav et al., 2012), or the assumption that preferences are unrelated to information frictions (Handel and Kolstad, 2015; Handel et al., 2019). In this context, our paper brings insights from experimental economics work on ambiguity aversion to the empirical insurance literature by providing a methodology to estimate the joint distribution of risk and uncertainty preferences and applying it to the US population. A related paper is the analysis of ambiguity attitudes with lotteries on a representative sample by Dimmock et al. (2016).

Regarding the theoretical literature on 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 differ 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.

From a modeling perspective, our results extend to the uncertainty domain the insights from Barseghyan, Molinari, O'Donoghue and Teitelbaum (2013), who show the need for probability weighting on the estimation of risk preferences. We also show how to partially estimate uncertainty preferences even with limited data, as is typically the case in the field. Finally, our estimation approach highlights the advantages of generating distributional estimates of individual preferences, since they provide a more comprehensive picture of key determinants of insurance demand. Our companion paper explores the welfare implications of uncertainty in insurance markets, but does not model preferences theoretically (Gandhi et al., 2022).

3 Data

Our data includes a survey of 4,442 US households who are part of the Understanding America Study (UAS) at the University of Southern California. The UAS is a representative panel of households who regularly complete surveys online. We merged our survey data with rich sociodemographic information and measures of cognitive ability and financial literacy available on UAS panel members.[3] Appendix A provides summary statistics of the respondents.

Participants made a series of 10 decisions. In each decision, participants were told they were the owner of a machine, which had some probability p of being damaged. An undamaged machine paid out 100 virtual dollars (equivalent to 5 USD), while damaged machines paid out nothing. In each decision, participants indicated their maximum WTP to fully insure the machine. The actual price of insurance was drawn at random from a uniform distribution on $(0, 100)$, and participants acquired the insurance if their WTP was above the drawn price and not otherwise.[4]

Participants faced two different environments, *known risks* and *uncertain risks*, each involving a block of 5 decisions. One decision from each environment was randomly selected to be paid out at the end of the survey. In the known risks environment, participants were informed of the value of risk probability p in each decision. In the uncertain risks environment, the risk probability was drawn from the uniform distribution $U[p-\varepsilon, p+\varepsilon]$, with $\varepsilon \in (0, \min\{p, 1-p\}]$. Individuals were either told that the risk probability belonged to the range $[p-\varepsilon, p+\varepsilon]$ or that all values in $[p-\varepsilon, p+\varepsilon]$ were equally likely. The former case represents ambiguous risks, since agents do not observe the distribution of p, while the latter case corresponds to compound risks that reduce to p.

We divided participants into four groups. Each group received the set of risk probabilities and probability ranges described in Table 1. To isolate the effect of uncertainty on individual demand for insurance, the probability ranges faced by a participant were centered around the values of p associated with her decisions under known 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. Half of participants received ambiguous risks and half received compound 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. Overall, p varied between 2% and 90%, while range sizes (2ε) varied from 2%

[3] 5,674 UAS panel members ages 30 and over 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.

[4] This approach is also called the Becker-DeGroot-Marschak mechanism (Becker et al., 1964) and is commonly used in similar studies, e.g., Halevy (2007).

to 24%. Appendix F contains the survey instructions.

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

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.

Table 1: Summary of Decisions Presented to Respondents

4 Empirical Patterns

This section summarizes the main empirical patterns of insurance choices under uncertainty documented in Gandhi et al. (2022). Gandhi et al. (2022) illustrate the magnitude of risk and uncertainty premia and estimate their correlation structure, correcting for potential bias due to measurement error. 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 known risk p is given by $\mu(p) := W(p) - p$. 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 decomposed as the sum of the actuarially fair price of insurance, the risk premium and the uncertainty premium: $W(I) = p + \mu(p) + \mu(I)$.

Fact 1: Risk premium decreasing in p. Figure 1 displays the average risk premium at each p, both for the overall sample and by household income. The 0 line represents risk neutrality. Average risk aversion decreases as losses become more likely, suggesting that agents transition from exhibiting significant risk aversion at small p to becoming risk loving at very high p. Individual regressions show that for about 76% of agents risk premium is decreasing in risk probability, with 47% predicted to switch from risk aversion to risk loving as p increases. Interestingly, although individuals with higher incomes tend to display smaller risk premia than individuals with lower incomes, the switch from a positive to a negative risk premium seems to be around $p = 0.6$ for most income levels.

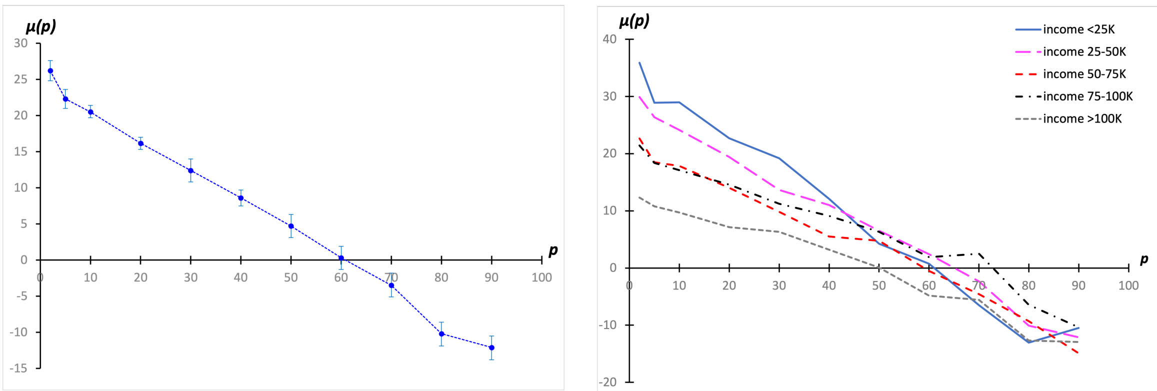

Figure 1: Average Risk Premium at Different Probabilities (bars represent 95% confidence intervals).

Fact 2: Positive uncertainty premium at low and moderate p. Figure 2 presents the average uncertainty premium at each possible p.[5] Data points are labeled with the size of the range of probabilities associated with them, given by 2ε. On average, agents exhibit large uncertainty premia at $p < 50\%$, which are higher at big ranges than at small ranges. These lead to an increase in WTP as high as 100% of the expected loss for big ranges. The uncertainty premium decreases with risk probability p, which is consistent with the findings by Hogarth and Kunreuther (1989) and Abdellaoui et

[5] Gandhi et al. (2022) do not find systematic differences in average uncertainty premia across compound and ambiguous risks so they pool the data for both types of uncertain risks.

al. (2015) that aversion to compound and ambiguous lotteries increases as winning probability goes up.

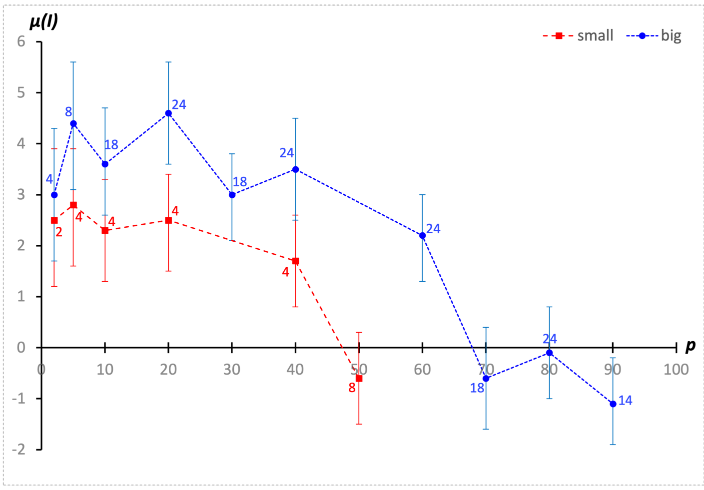

Figure 2: Uncertainty Premium at Different Risk Probabilities (point labels represent range size and bars represent 95% confidence intervals).

Fact 3: Negatively correlated risk and uncertainty premia. Figure 3 plots the correlation coefficients for each p, showing that risk and uncertainty premia are negatively correlated at all risk probabilities, with all coefficients significant at the 1% level. Correlation coefficients are remarkably invariant to underlying risk p, consistently lie between -0.24 and -0.35, and do not substantially change after controlling for individual characteristics such as cognitive ability, financial literacy, and sociodemographics (partial correlations). Gandhi et al. (2022) show that the negative correlation is robust to measurement error and is also present in experimental data from prominent studies on ambiguity and compound risk attitudes (Halevy, 2007; Abdellaoui et al., 2015; Chew et al., 2017).

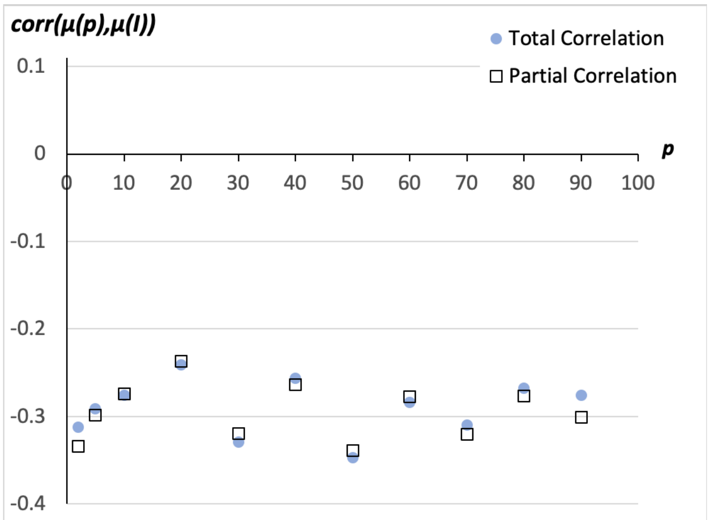

Figure 3: Correlation Coefficients between Risk Premium and Uncertainty Premium.

5 Modeling Uncertainty Preferences

We next explore the ability of models of choice under uncertainty to explain the data. We first propose a generalization of recursive anticipated utility (Segal, 1987), which we call *second-order anticipated utility* (SOAU). In Subsection 5.1, we discuss the ability of SOAU to explain our data. In particular, fitting the data requires two probability weighing functions, one for risk probabilities and another for the distribution of risk probabilities. This class of preferences is needed because, as we show in Subsection 5.2, alternative models of ambiguity aversion cannot explain the data without resorting to non-standard functional forms.

5.1 Second Order Anticipated Utility

The SOAU class of preferences that we introduce below can explain the data patterns that we observe, namely, the switch from risk aversion to risk loving as p goes up, a positive uncertainty premium decreasing in p, and a negative correlation between risk and uncertainty premia. SOAU is a generalization of rank-dependent utility (Quiggin, 1982) to allow for ambiguity and compound risk attitudes.

The idea behind SOAU is to represent uncertain risks as a two-stage lottery and to apply probability weights recursively. The second-stage lottery represents known risks, in our case $(p, -1; 1-p, 0)$, where the size of the loss is normalized to be -1. 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. SOAU evaluates uncertain risks by first obtaining certainty equivalents of second-stage lotteries, and then using the distribution over certainty equivalents induced by the first-stage lottery. In order to apply these preferences to uncertain risks, it is assumed that the DM has a subjective probability distribution over known risks.

More specifically, SOAU are characterized by probability-weighting functions π_k and utility functions u_i at each stage $k = 1, 2$. Both π_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 π_2 to risk probability p and by using u_2 to evaluate changes to final wealth.[6] Accordingly, the DM's valuation of p when her initial wealth is w is given by

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

The evaluation of uncertain risks 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 π_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

$$V(I) = u_1(\underline{y}) + \int_{\underline{y}}^{\bar{y}} u_1'(y)(1-\pi_1(G(y))dy. \tag{2}$$

To isolate the effect of probability weighting, we consider the case of linear utility $u_k(x) = x,\ k = 1, 2$. This implies that the certainty equivalent of risk p is $-\pi_2(p)$ and thus the risk premium is given by $\mu(p) = \pi_2(p) - p$. Accordingly, a higher weight $\pi_2(p)$ represents a higher aversion to risk p.

Our goal is to characterize the uncertainty premium associated with uncertain risks $U[p-\varepsilon, p+\varepsilon]$, which correspond to compound risks or to ambiguous risks under uniform beliefs. To do so we define the "marginal uncertainty premium" $\mu_0(p)$ to be the limit of the uncertainty premium, normalized by range size, as $\varepsilon \to 0$. It captures the reaction of the DM to the initial introduction of uncertainty and can be used to provide a linear approximation of the uncertainty premium associated with uncertain risk $I(p, \varepsilon)$.

The next proposition shows that the marginal uncertainty premium depends on the slope of second stage weights and the average of first stage weights. The proof as well

[6]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.

as a characterization of the uncertainty premium for any value of ε is in Appendix B.

Proposition 1. *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*

$$\mu_0(p) = \pi_2'(p)(2E\pi_1 - 1), \tag{3}$$

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

Expression (3) has an easy interpretation. In particular, $\mu_0(p)$ is increasing in the average first-stage weight π_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, i.e., the bigger the slope π_2', the larger the magnitude of $\mu_0(p)$. Intuitively, individuals whose risk attitudes are insensitive to changes in risk probability exhibit little variation in WTP for insurance across different p, and thus do not react strongly to the (initial) introduction of uncertainty.

Equipped with the characterization of risk premium ($\mu(p) = \pi_2(p) - p$) and the marginal uncertainty premium ($\mu_0(p) = \pi_2'(p)(2E\pi_1 - 1)$), we formally show that SOAU can rationalize the above patterns in a natural way. The first result deals with the behavior of the risk and uncertainty premia w.r.t. p and the second result identifies conditions for the negative correlation between risk and uncertainty premia. We omit the proofs of the next two propositions since they follow directly from the characterization of the risk and marginal uncertainty premia.

Proposition 2. *If preferences are given by SOAU with linear utility then the following statements are true.*

(i) If the DM overweighs small 2nd-stage probabilities and underweighs large ones, i.e., there exist $p^* \in (0,1)$ such that $\pi_2(p) > p$ if $p < p^*$ and $\pi_2(p) < p$ for $p > p^*$, then the DM is risk averse w.r.t. risk $p < p^*$ and risk loving for $p > p^*$.

(ii) If the DM overweighs 1st-stage probabilities on average, i.e., $E\pi_1 = \int_0^1 \pi_1(z)dz > 0.5$, then the marginal uncertainty premium $\mu_0(p)$ is positive for all $p \in (0,1)$.

(iii) If the 2nd-stage weighting function becomes less sensitive as p goes up in $[\underline{p}, \overline{p}]$, i.e., $\pi_2'(p)$ is decreasing at all $p \in [\underline{p}, \overline{p}]$, then the marginal uncertainty premium is decreasing in $[\underline{p}, \overline{p}]$.

Overweighting-then-underweighting, overweighting on average and diminishing sensitivity for non-extreme probabilities are typically satisfied by the inverted s-shape functional forms commonly used in rank-dependent utility and prospect theory, such as the Prelec weighting function (Prelec, 1998). In contrast, uncertainty preferences that require concave weighting functions, as is the case with multiple-prior multiple-weighting preferences proposed by (Dean and Ortoleva, 2017) cannot explain the switch from risk aversion to risk loving.

The next proposition provides an intuitive condition that generates a negative correlation between risk and uncertainty premia. It involves more risk averse individuals being less sensitive to changes in risk than comparatively less risk averse individuals, provided their average 1st-stage weights are similar. 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 overly cautious and willing to 'overpay' for insurance, regardless of whether underlying risks turn out to be smaller or larger than expected.

Proposition 3. *Consider two individuals i, j with preferences given by SOAU with linear utility and weighting functions π_{ik}, π_{jk}, $k = 1, 2$, such that $E\pi_{1i} \leq E\pi_{1j}$.*

If individual i has a higher and flatter second-stage weighting function at risk probability p than individual j (i.e, $\pi_{2i}(p) > \pi_{2j}(p)$ and $\pi'_{2i}(p) < \pi'_{2j}(p)$), then i exhibits a higher risk premium and a lower marginal uncertainty premium than j at p (i.e., $\mu_i(p) > \mu_j(p)$ and $\mu_{0i}(p) < \mu_{0j}(p)$).

To test the predictions of Proposition 3 we estimate π'_2 and $E\pi_1$ at the individual level using the following two-step approach. First, for each subject i we estimate π'_{2i} by regressing p on WTP for insurance against known risks:

$$W_{it} = a_i + b_i p_{it} + \nu_{it}, \quad t = 1, \cdots, 5 \tag{4}$$

Since $W(p) = \pi_2(p)$, $\hat{b}_i$ is an estimate of $\pi'_{2i}(p)$. Second, we regress $\hat{b}_i$ on the uncertainty premium associated with unknown risks, normalized by range size:

$$\frac{\mu_{it}}{\varepsilon_{it}} = \alpha_i \hat{b}_i + \xi_{it}. \tag{5}$$

Given that $\mu_0(p) = \pi'_2(p)(2E\pi_1 - 1)$, we can estimate $E\pi_{1i}$ using $\hat{E}\pi_{1i} = \frac{\hat{\alpha}_i + 1}{2}$. Table 2 presents the average estimates of $\pi'_{i2}(p)$ and $E\pi_{1i}$ in the population, as well as its cross-sectional correlation with risk and uncertainty premia. The latter confirms the hypothesis that risk averse agents tend to 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, respondents with π'_{i2} estimates at the bottom quintile of its distribution exhibit significantly higher risk premium and significantly lower uncertainty premium than the rest of the respondents.

Regression Estimates		
Estimate	Average	Std. error
$\pi'_2(p)$	0.61	0.59
$E\pi_1$	0.52	1.06
Correlation[a]		
	Risk premium	Uncertainty 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.

Table 2: Components of uncertainty premium

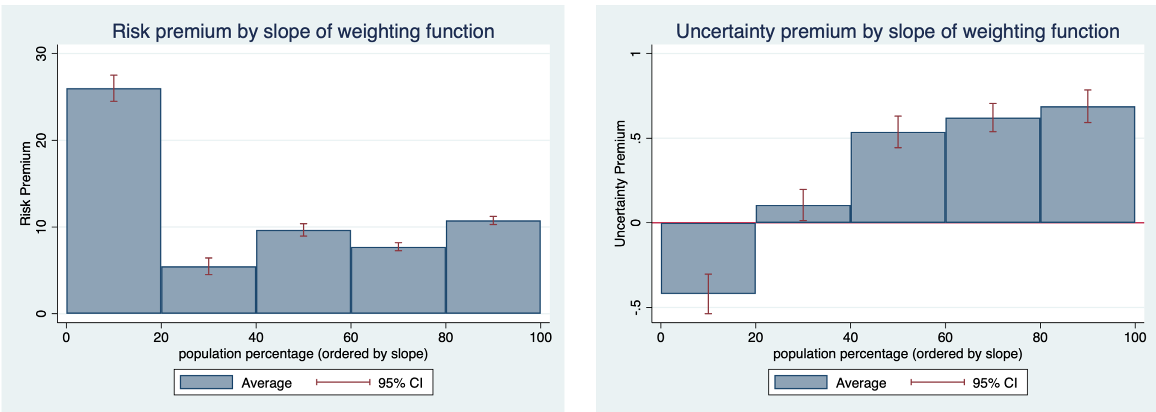

Figure 4: Average Risk and uncertainty premium at different estimates of π'_{i2}.

5.2 Alternative Preference Models

We have shown that SOAU can rationalize the empirical patterns in a natural way. The question is whether other uncertainty preferences such as existing models of ambiguity aversion can explain the data. It turns out that, as we show in Appendix C, the vast majority of ambiguity preferences proposed in the literature cannot explain the switch from risk aversion to risk loving. The reason for such a failure is that most models assume that the DM applies expected utility (EU) to evaluate known risks, which has a hard time explaining a switch in risk attitudes as the risk probability goes up. These EU-based preferences include α-maximin expected utility and variational preferences (Maccheroni et al., 2006), with 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). The same failure applies to uncertainty preferences exhibiting reference-dependent utility or multiple utility functions.

6 Preference Estimation

We next estimate the distribution of uncertainty preferences in the population. We focus on SOAU with linear utility for two reasons. First, it can account for the empirical patterns of insurance demand. Second, it nests as special cases standard forms of risk aversion (concave π_2) and risk loving (convex π_2) in the context of our data.

Our approach uses the decomposition of WTP into the sum of risk and uncertainty premium, which under linear utility takes on the following form by Lemma 1 in Appendix B:

$$
\begin{aligned}
W(I(p,\varepsilon)) &= p + \mu(p) + \mu(I(p,\varepsilon)) \\
&= \pi_2(p) + \varepsilon \int_0^1 \left[\pi_2'(p+\varepsilon z)\pi_1\left(\frac{1-z}{2}\right) - \pi_2'(p-\varepsilon z)\left(1-\pi_1\left(\frac{1+z}{2}\right)\right)\right] dz. \quad (6)
\end{aligned}
$$

We impose a parametric form on π_k and estimate them at the individual level using a hierarchical Bayesian model. Specifically, we assume that weighting functions in (6) have a 2-parameter Prelec functional form:

$$
\pi_k(p) = e^{-\beta_k(-\log(p))^{\alpha_k}}, \qquad \alpha_k, \beta_k > 0, \quad k = 1, 2. \quad (7)
$$

This functional form is commonly used in rank-dependent utility and allows for linear, concave, convex, as well as s-shaped and inverted s-shaped weighting functions, as illustrated by Figure 5. Lower values of β_k globally lead to higher weights $\pi_k(p)$, i.e., to comparatively higher risk aversion, while parameter α_k mostly affects the shape of π_k, determining whether small probabilities are overweighed and large probabilities

Shape of π_k	α_k	β_k
Linear	1	1
Concave	1	< 1
Convex	1	> 1
Inverted S	< 1	any
S-shape	> 1	any

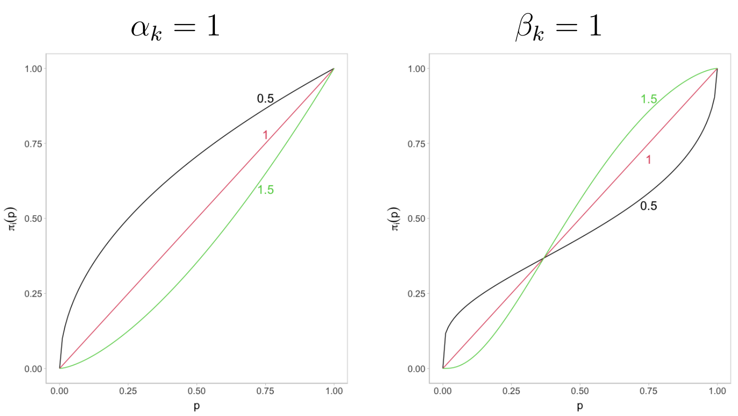

Figure 5: Prelec weighting function for different values of β_k (middle plot) and α_k (right plot).

underweighed ($\alpha < 1$) or vice versa ($\alpha > 1$).[7]

Let $\theta = (\alpha_1, \beta_1, \alpha_2, \beta_2)$ be the parameter vector of Prelec weighting functions (7) and let $W(\cdot;\theta)$ denote the resulting WTP function given by (6). Our goal is to estimate the distribution of θ 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 θ_i represents the agent's weighting function parameters. Letting W_{it} to be random allows for the possibility of mistakes or for random preferences. Notice that $W(I_{it};\theta_i)$ falls inside the interval $(0, 1)$ for $p \in (0, 1)$. However, a non-negligible subset of subjects sometimes report WTP of zero or one.[8] Accordingly, we assume that W_{it} follows a flexible zero-one inflated beta distribution, which has two point masses, at 0 and 1, and follows a beta distribution on $(0, 1)$ with mean given by $W(I_{it};\theta_i)$. That is, W_{it} follows mixture distribution

$$f(\mathrm{w}|I_{it}, \theta_i, q, q_1, \phi) = \begin{cases} q(1-q_1) & \mathrm{w} = 0 \\ qq_1 & \mathrm{w} = 1 \\ (1-q)Beta(W(I_{it};\theta_i)\phi, (1-W(I_{it};\theta_i))\phi) & \mathrm{w} \in (0,1), \end{cases} \tag{8}$$

where $q = Pr(W_{it} \in \{0, 1\})$, $q_1 = Pr(W_{it} = 1|W_{it} \in \{0, 1\})$, and ϕ is the precision of the beta distribution. Unlike the weighting function parameter vector θ_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.

[7] π_k crosses the diagonal once at $p^* = e^{-\beta^{1/(1-\alpha)}}$ for all $\alpha \neq 1$. In addition, 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 $p = 1$. Accordingly, $\alpha < 1$ (resp. $\alpha > 1$) implies overweighting (resp. underweighting) of probabilities in $[0, p^*]$.

[8] We exclude from the estimation 245 individuals reporting zero or one in all their choices.

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

We close the model by specifying hyperprior distributions for population-level parameters. First, we assume a standard normal prior for α and β, 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 θ_i. Third, we choose a gamma prior for the precision of the Beta distribution ϕ. Finally, we let the probability parameters q_0 and q_1 to have beta priors given by $Beta(1, 1)$.[10]

Accordingly, our hierarchical model is given by

$$\begin{aligned}
W_{it} &\sim f(\cdot|I_{it}, \theta_i, q_0, q_1, \phi), \quad \theta_i = (\alpha_{1i}, \beta_{1i}, \alpha_{2i}, \beta_{2i}) \\
\alpha_{ik} &\sim Lognormal(\alpha, \sigma_\alpha), \quad k = 1, 2 \\
\beta_{ik} &\sim Lognormal(\beta, \sigma_\beta), \quad k = 1, 2 \\
\alpha &\sim Normal(0, 1) \\
\beta &\sim Normal(0, 1) \\
\sigma_\alpha &\sim \text{Half-student } t(3, 0, 2.5) \\
\sigma_\beta &\sim \text{Half-student } t(3, 0, 2.5) \\
\phi &\sim Gamma(1, 2) \\
q_h &\sim Beta(1, 1), \quad h = 0, 1.
\end{aligned} \tag{9}$$

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 D 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.[11] 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

[9]For values of α or β 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.

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

estimates. The distribution of median values reveals that 2nd-stage weighting is very

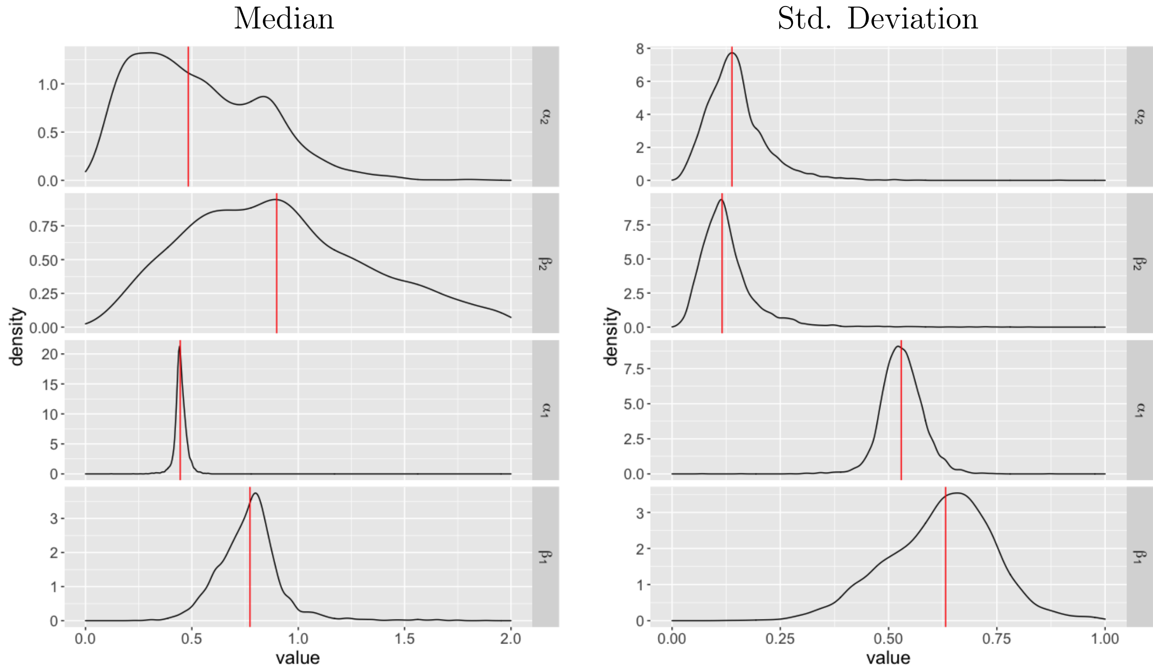

Figure 6: Posterior density of median values (left) and standard deviations (right) of θ_i. Red lines represent distribution medians.

heterogeneous, with α_{2i} and β_{2i} exhibiting substantial dispersion. In contrast, median values of α_{1i} and β_{1i} are much more concentrated leading to a relatively homogeneous 1st-stage weighting function π_{1i}.[12]

What do these parameter distributions tell us about the nature of uncertainty 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 α_{1i} are below one, while α_{2i} is lower than one for 93% of individuals. In addition, almost all median values of β_{1i} and a majority of β_{2i} are below one, implying overweighting of probabilities in a range $[0, p^*]$ with $p^* > e^{-1} \approx 0.368$.[13]

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

[12]Individual estimates of 2nd-stage weighting parameters are more precise than 1st-stage estimates given that the former exhibit much lower standard deviations. This is likely due to the fact that, since π_1 only affects the uncertainty premium while π_2 affects both the risk and uncertainty premia, all observations are effectively used to estimate α_{2i}, β_{2i} while only half contain information about α_{1i}, β_{1i}.

[13]For $\beta \leq 1$ the lowest $p^* = e^{-\beta^{1/(1-\alpha)}}$ is associated with $\beta = 1$.

of rectangle $[0, 1.5] \times [0, 3]$. Furthermore, there is a concentration of mass close to the peak of the joint density, which occurs at $\alpha_{i2} = 0.86$, $\beta_{i2} = 0.92$. Such concentration represents agents whose risk preferences are well captured by expected utility, while the mass spanning to the left captures s-shaped weighting functions that significantly overweight small probabilities. The bottom-left graph of Figure 7 illustrates these differences by depicting the range of 2nd-stage weighting functions corresponding to two vertical slices of the joint density, one at $\alpha = 0.2$ and the other at $\alpha = 0.9$.

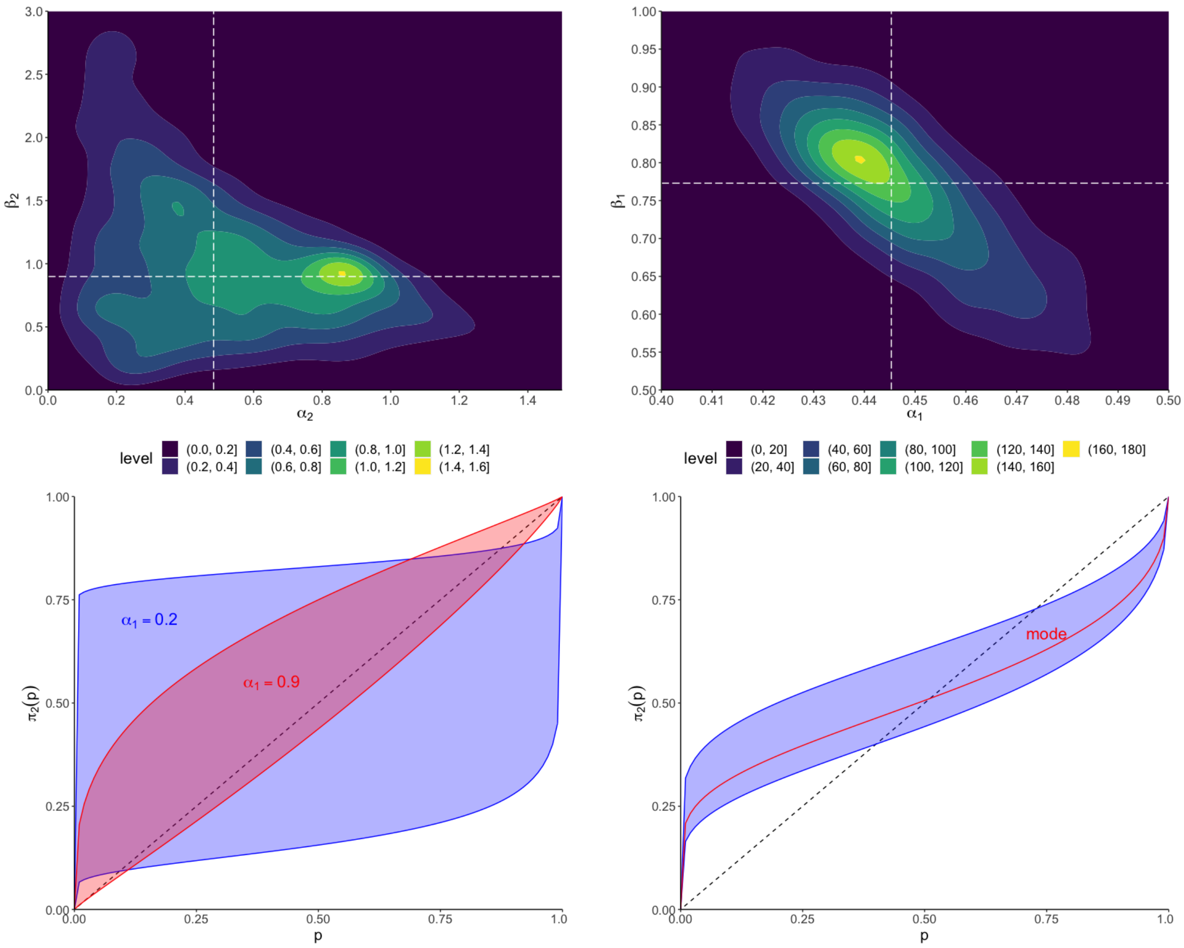

Figure 7: Top panel: Posterior joint density of median values of $(\alpha_{i2}, \beta_{i2})$ (left) and $(\alpha_{i1}, \beta_{i1})$ (right); white lines represent median values of each parameter. Left-bottom panel: 2nd-stage weighting functions for $\alpha_2 = 0.2$ and $\beta_2 \in [0.2, 2]$ (purple), and for $\alpha_2 = 0.2$ and $\beta_2 \in [0.4, 1.15]$ (red). Right-bottom panel: 1st-stage weighting functions.

In contrast, the 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 $\alpha_{i1} = 0.44$, $\beta_{i1} = 0.8$. These estimates suggest that all agents significantly overweigh (underweigh) 1st-stage probabilities below (above) 0.5, as illustrated in the bottom-right graph of Figure 7).

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 π_2 and the *level* of π_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 computed the standard deviation of $\pi_2'(p)$ for $p \in (0.1, 0.9)$ and the standard deviation of $2E\pi_1$.[14] We find that the standard deviation of $\pi_2'(p)$ ranges between 0.26 and 0.44, while the standard deviation of $2E\pi_1$ is about 0.12. These differences are much smaller than the large differences in heterogeneity between π_2 and π_1, although 2nd-stage weights still contribute between two to four times more to the heterogeneity of the marginal uncertainty premium than 1st-stage weights.

The population-level parameter estimates (see Table D.2 in Appendix D) reveal a modest likelihood to report extreme values and substantial randomness in choice. On average, the estimated probability 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 (such values imply a violation of stochastic dominance). As an illustration of the degree of randomness, the interquartile range for a mean WTP of 0.5 is $[0.416, 0.584]$.

6.1 Differences by Sociodemographics and Cognitive Skills

We next analyze 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).

The joint distributions uncover some mild differences across sociodemographic groups. Specifically, the densities of $(\alpha_{i2}, \beta_{i2})$ for higher income individuals and men place somewhat less probability mass at low values than lower income individuals and women, respectively. However, these income and gender differences appear small given that all densities are relatively flat and place all the mass in the same lower triangle.

[14] We avoid extreme values of p because π_2' under Prelec functional form tends to infinity (or zero).

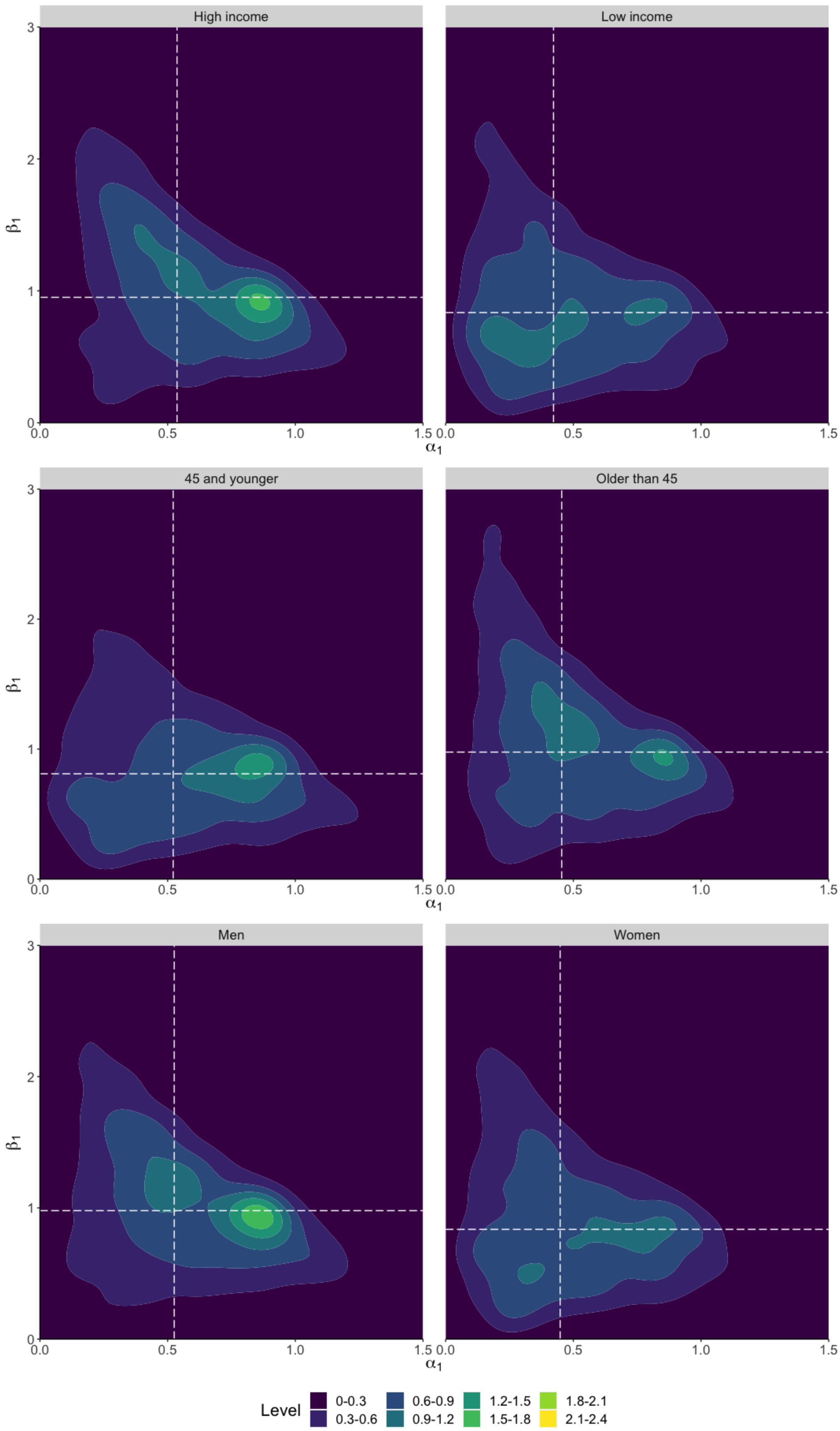

Figure 8: Joint distribution of median values of $(\alpha_{2i}, \beta_{2i})$ by selected demographics; white lines represent median values of each parameter.

In contrast, we find starker differences 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. This is unlike the distribution of those with scores lower than the median score, which places substantial mass in $[0, 0.5] \times [0, 1]$. This implies that higher probability weighting for known risks is more pronounced for individuals with lower levels of financial literacy and cognitive ability.

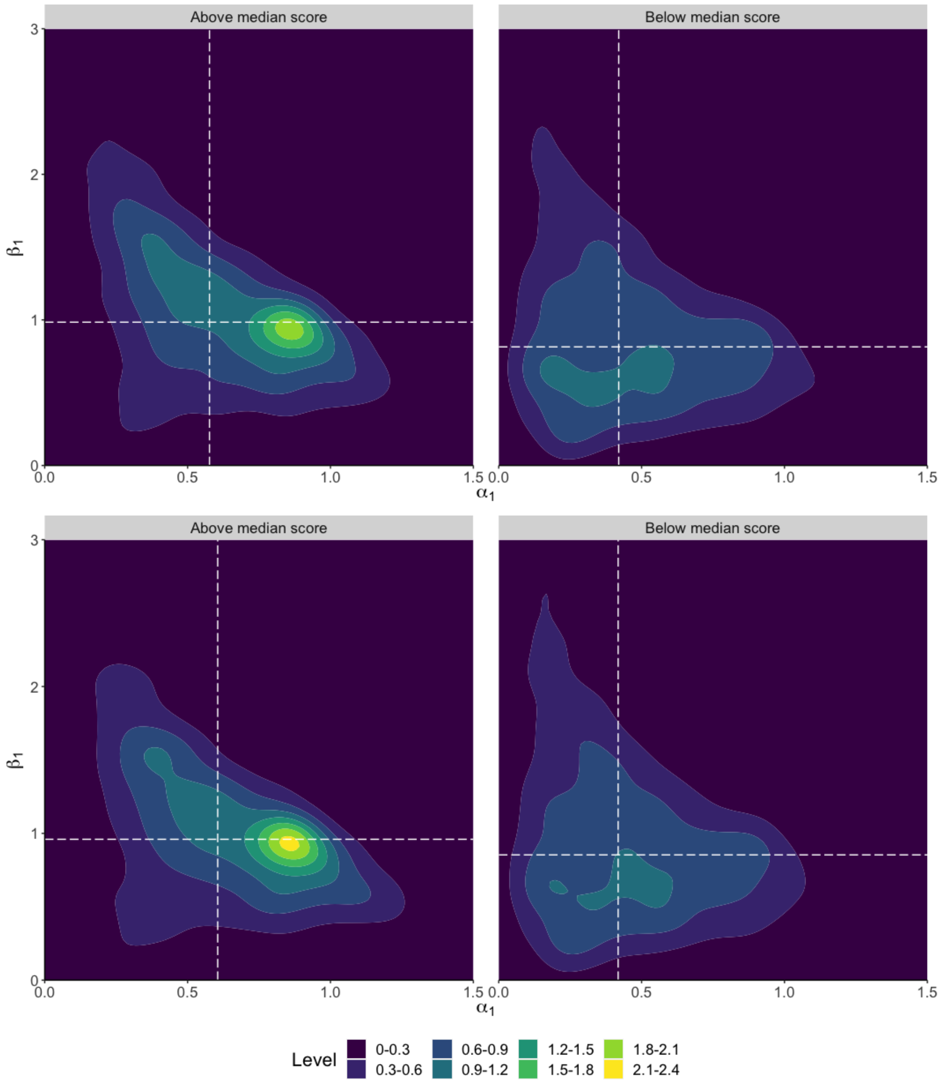

Figure 9: Joint distribution of median values of $(\alpha_{2i}, \beta_{2i})$ by financial literacy (top) and cognitive ability (bottom); white lines represent median values of each parameter.

Unlike 2nd-stage weights, we do not find any meaningful differences in the distribution of 1st-stage weights across these characteristics, with most individuals reacting to the introduction of uncertainty by overweighting the likelihood of small risks p. These results are confirmed by regressing risk and uncertainty premia on various sociodemographic characteristics, which are presented in Appendix E.

6.2 Partial Identification with Limited Data

Our estimation takes advantage of the richness of our incentivized survey data. However, data from insurance markets often lacks information about the uncertainty faced by individuals. Is it possible to estimate individual preferences in such contexts? One approach would be to use choice data across domains, e.g., auto insurance and home insurance, to partially estimate preferences via a linear approximation of the 2nd-stage weighting function π_2. Since information and uncertainty about risks varies across domains, they can proxy for uncertainty, while the linear approximation makes the uncertainty premium proportional to the slope of π_2. Specifically, under linear approximation $\pi_2(p) = a + bp$, WTP for insurance against unknown risk (p, ε) is given by

$$W(p, \varepsilon) = \pi_2(p) + \varepsilon\mu_0(p) = a + bp + \varepsilon b(2E\pi_1 - 1) = a + bp + c\varepsilon. \tag{10}$$

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 ε_t are not observed, p_{it} can be measured using empirical claim rates, as is typically done in the empirical insurance literature, and the volatility of claim rates in each domain can serve as a proxy for ε_t.

Expression (10) also serves to illustrate the potential effects of abstracting from the presence of uncertainty in the estimation of risk preferences. Omitting ε from (10) leads to an upward or downward bias in slope estimate b depending on whether risk p and uncertainty ε are positively or negatively correlated.

7 Conclusion

It is likely that consumers understand underlying risks in insurance markets to varying degrees. Hence, to fully understand preferences in these markets, it is important to incorporate preferences toward uncertain risks. Given that such preferences cannot easily be estimated from observational data, in this paper we use incentivized surveys to elicit risk and uncertainty preferences from a representative sample of US households.

Our paper makes two main contributions. First, we theoretically show the need to incorporate probability weighting in both the risk and uncertainty domain to explain the observed empirical patterns in individual demand for insurance. Second, equipped with this characterization, we estimate the joint distribution of risk and uncertainty preferences in the population and examine the degree and sources of preference heterogeneity.

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. 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.

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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.

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	

Table A.1: Descriptive Statistics - UAS

Appendix B Additional Results and Omitted Proofs

We first provide a full characterization of the uncertainty premium.

Lemma 1. *The value of uncertain risk $I(p,\varepsilon) := U[p-\varepsilon, p+\varepsilon]$ under SOAU with linear utility is given by*

$$V_w(I(p,\varepsilon)) = -\pi_2(p-\varepsilon) - 2\varepsilon \int_0^1 \pi_2'(p+\varepsilon(2z-1))\pi_1(1-z)\, dz. \tag{11}$$

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

$$\mu(I(p,\varepsilon)) = \varepsilon \int_0^1 \left[\pi_2'(p+\varepsilon z)\pi_1\left(\frac{1-z}{2}\right) - \pi_2'(p-\varepsilon z)\left(1-\pi_1\left(\frac{1+z}{2}\right)\right)\right] dz. \tag{12}$$

The uncertainty premium given by (12) depends on two factors. The first is the sensitivity to changes in risk probabilities, captured by the slope of the second stage weighting function π_2'. The second is the level of first stage weights π_1, with higher first stage weights leading to higher uncertainty premia.[15]

Proof of Lemma 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 π_2^{-1} denotes the inverse of π_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 (2) 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 (11).

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

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

[15] Higher π_1 increases the positive term and lowers the negative term in the integrand of (12).

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 (12) by applying the change of variable $z' = 1-2z$ to the first integral and $z' = 2z-1$ to the second integral. □

Proof of Proposition 1. Dividing both sides of (12) by ε and taking the limit as $\varepsilon \to 0$ we obtain

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

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

where the integrals in the left-hand side of the last equality are derived via changes of variable $z' = \frac{1-z}{2}$ and $z' = \frac{1+z}{2}$, respectively. □

Appendix C Alternative Preferences

We show in this section that EU-based uncertainty preferences cannot explain the risk premium patterns without resorting to non-standard functional forms of the utility function. In addition, we show that adding reference dependence or allowing for a set of utility functions such as the multi-prior multi-utility model of Riella (2015) exhibit the same problems as EU-based models.

First, we focus on EU-based preferences. Since they reduce to EU under known risks, the value of binary risk $(p,-1;1-p,0)$ given initial wealth w is

$$EU(p) = pu(w-1) + (1-p)u(w). \tag{13}$$

The evaluation of uncertain risks of the form $I(p,\varepsilon)$ then typically involves an optimization problem over expected utility of known risks or computing the expected value of some non-linear function of EU of known risks. An example of the former approach are variational preferences

$$V(I(p,\varepsilon)) = \min_{p' \in [0,1]} \left(EU(p') + c(p'; p, \varepsilon) \right),$$

where c is a cost function that depends on beliefs.[16] The smooth ambiguity model follows the expectations approach. Under the belief that $p \sim U[p-\varepsilon, p+\varepsilon]$, the value of the uncertain risk is given by

$$V(I(p,\varepsilon)) = \int_{p-\varepsilon}^{p+\varepsilon} \phi(EU(p'))dp',$$

where ϕ is an increasing function.

As the next proposition formally establishes, EU-based models and preferences with concave weighting functions cannot explain the switch from risk aversion to risk loving as p goes up without resorting to non-standard s-shape type functional forms.

Proposition 4. *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 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 $x \in (w-p^*, w)$.*

Proof. 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. $\square$

Either adding a reference point (deterministic or stochastic) to the utility function or allowing for multiple utility functions, such as in cautious expected utility (Riella, 2015; Cerreia-Vioglio et al., 2015), does not help to explain the switch. In the former case, reference-dependent preferences must exhibit a switch between loss aversion to gain loving, while in the latter case the set of utilities considered by the DM cannot contain concave utility functions.

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

[16] For instance, maximin EU is associated with cost function $c(p'; p, \varepsilon) = 0$ if $p' \in [p-\varepsilon, p+\varepsilon]$ and $c(p'; p, \varepsilon) = \infty$ otherwise.

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

$$V_r(p) = pv(w - 1 - x^*) + (1 - p)v(w - x^*). \tag{14}$$

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

$$V_r(p) = pv(-1) + (1 - p)v(0) \tag{15}$$

and

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

The next result 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 4 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. $\square$

The multi-prior multi-utility model of Riella (2015) a value of $I(p, \varepsilon)$ given by

$$V(I(p, \varepsilon)) = \min_{p' \in [p-\varepsilon, p+\varepsilon]} \min_{u \in \mathcal{U}} u^{-1}(p'u(w - 1) + (1 - p)u(w)),$$

where $\mathcal{U}$ is a set of increasing utility functions normalized to yield the same utility level at $w-1$ and w. The next proposition establishes that $\mathcal{U}$ cannot include concave utility functions if the DM switches from risk aversion to risk loving as p goes up.

Proposition 6. *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 has multi-prior multi-utility preferences then the upper convex envelope of u is below the line connecting $u(w-1)$ and $u(w-p^*)$ for all $u \in \mathcal{U}$.*

Proof. The minimum certainty equivalent of p associated with a utility function in $\mathcal{U}$ is given by $\min_{u \in \mathcal{U}} u^{-1}(p'u(w-1) + (1-p)u(w))$. Since the risk premium $\mu(p)$ is below p for $p > p^*$ the minimum certainty equivalent must be above $w-p$. Since utilities are normalized to have the same values at $w-1$ and w, they all share the same EU line connecting $u(w-1)$ and $u(w)$. But this implies that $EU(p) > u(w-p)$ for all $u \in \mathcal{U}$ and all $p \in (p^*, 1)$. That is, all utility functions in the set $\mathcal{U}$ are below the EU line for values in $(w-1, w-p^*)$, yielding the result. □

Appendix D Bayesian Estimation

The estimation of Bayesian model (9) 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. We fit our model using the R interface CmdStanR (Gabry and Češnovar, 2021).

We run two Markov chains with 2,000 iterations each. 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. We first present convergence tests of the MCMC sampling both within and between chains and then provide the population-level-parameter estimates.

Figure D.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.

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 D.2

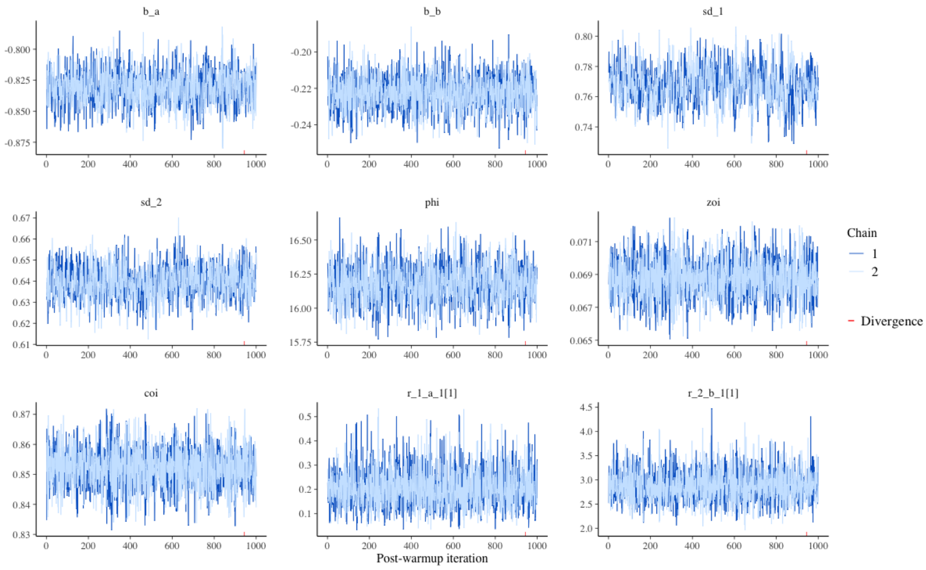

Figure D.1: Traces of selected parameters.

shows the values of split-$\hat{R}$ for all the parameters (over $17,000$). All of the values are extremely close to 1.

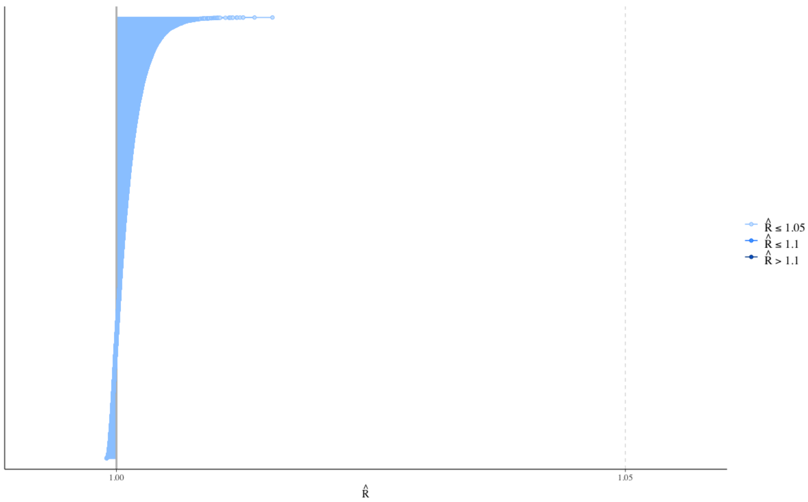

Figure D.2: Split-$\hat{R}$ of model parameters.

Figure D.3 plots for each chain the marginal energy distribution π_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 D.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

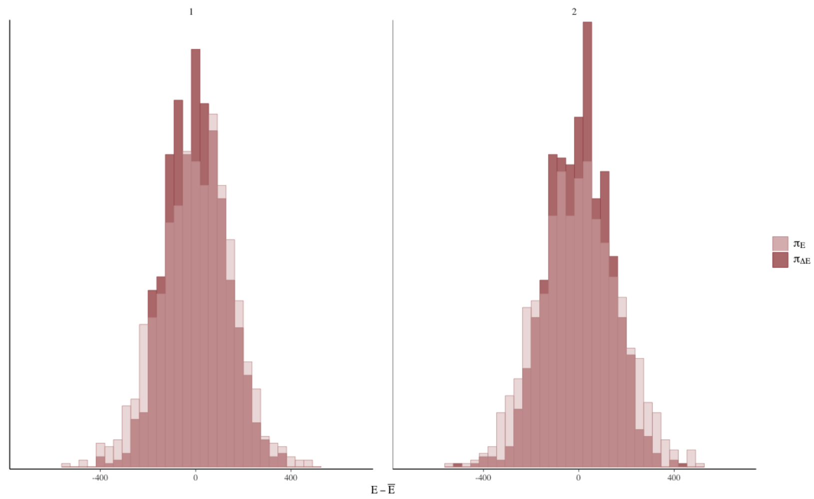

Figure D.3: Energy distributions for chain 1 (left) and chain 2 (right).

parameters, implying low autocorrelation of MCMC draws.[17]

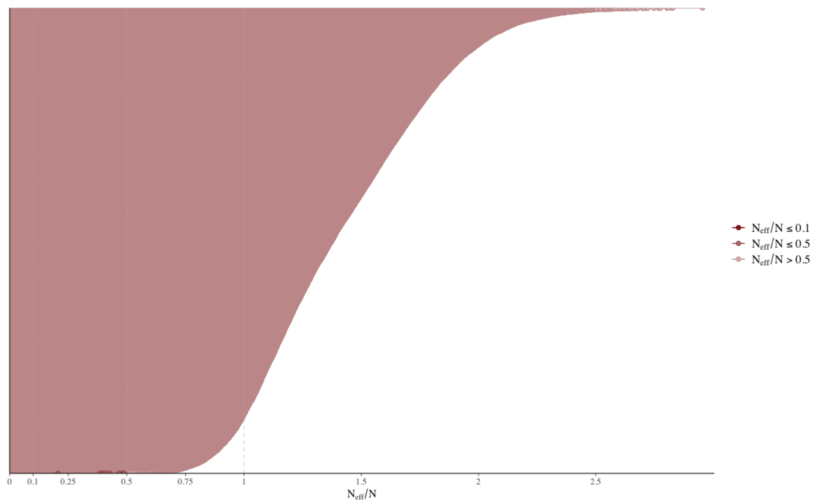

Figure D.4: Effective sample size ratio of model parameters.

Table D.2 presents the population-level parameter estimates. They measure the tendency to report extreme values of WTP as well as the randomness of WTP responses with respect to SOAU preferences. On average, the estimated probability 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.

[17] A ratio greater than one implies negative autocorrelation leading to a smaller variance of the mean

Parameter	Median	Std. deviation
q	0.0688	0.0012
q_1	0.852	0.0071
ϕ	16.2	0.140
α	-0.831	0.0137
β	-0.222	0.0096
σ_α	0.768	0.0122
σ_β	0.639	0.0076
Log Probability[a]	6560	137
No. Obs.	39,950	
No. Individuals	4,268	

[a] Unnormalized log density of the model.

Table D.2: Model Estimates: Population-level Parameters

Appendix E Covariates of WTP

Table E.3 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, whether the range is ambiguous or not does not lead to significant differences in the uncertainty premium. Third, gender, income, as well as cognitive ability and financial literacy are significantly associated with risk attitudes. The third column in Table E.3 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

estimate than the one obtained from independent draws of the true posterior.

	$\mu(I)$	$\mu(I)$	$\mu(p)$
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: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table E.3: Covariates of uncertainty premium and Risk Premium first. This may suggest that being exposed to known risk may have an anchoring effect on WTP for insurance against unknown risks.

Appendix F Instructions

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.