Online Appendix "Uncertainty Attitudes, Subjective beliefs and Decisions under Uncertainty"

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A Appendix: Extended Literature Review

In this Appendix we discuss related literature in more detail. Our work contributes to different streams of literature and creates new linkages between them. We now discuss these in turn starting with literature on subjective expectations.

Recent research in this literature has combined data on choices with data on stated beliefs to make inferences on taste parameters in various domains, including health, education, career choice and crime (Arcidiano, Hotz, Maurel, & Romano, 2020; Delavande, 2008; Delavande & Kohler, 2016; Delavande & Zafar, 2019; Giustinelli, 2016; Lochner, 2007; van der Klaauw & Wolpin, 2008; Wiswall & Zafar, 2015). Of particular relevance to our substantial application on financial decisions is research documenting that individuals who expect higher stock market gains are more likely to hold stock, e.g. Dominitz and Manski (2007), Hurd et al. (2011) or Ameriks, Kezdi, Lee, and Shapiro (2020). To our knowledge, our paper is the first to use beliefs data within a structural model that goes beyond the standard SEU model. In the health domain Giustinelli et al. (2022b) present a model of long-term care decisions with imprecise probability of future dementia using the maximin and minimax-regret criteria but do not structurally estimate it. This departure from SEU turns out to be economically relevant to make inference on how individuals respond to changes in beliefs.

Our work also relates to literature using field data to ask whether agents use non-standard expected utility models. This literature is reviewed in Barseghyan et al. (2018). For example, Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2013) estimate a structural model of insurance choice using rich insurance deductible data and find that probability weighting plays an important role (see also Barseghyan, Molinari, and Teitelbaum (2016)). In the domain of finance and insurance, existing studies, reviewed in Barberis (2013), find patterns consistent with prospect theory. This line of work typically assumes that individuals hold subjective beliefs that are equal to objective probabilities (risk). We adopt a different identification strategy that takes a data-driven approach and relies on individual-specific data on uncertainty attitudes and subjective beliefs. Although our models are not assumption-free, we do not need to make assumptions on subjective beliefs and we elicit probability weighting parameters, under the source function method, separately from subjective beliefs, hence allowing for heterogeneous uncertainty attitudes. This separate elicitation means that in our setting individuals may have heterogeneity in subjective beliefs and also have heterogeneity in how they weight their subjective beliefs.

Our paper also complements existing work studying how ambiguity attitudes shape decision-

making under uncertainty. Focusing on stock markets, Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016); Dimmock et al. (2021) and Dimmock, Kouwenberg, and Wakker (2016) study attitudes to uncertainty in a sample representative of the US and Dutch population, respectively. They find for example that ambiguity aversion is negatively related with stock market participation, and the fraction of assets allocated to equity and foreign stock ownership. We complement these findings by jointly eliciting ambiguity attitudes, including weighting under ambiguity, loss aversion, and probability-weighting under risk under the source function approach instead of focusing on only one of these characteristics and by combining these data with subjective beliefs within a structural framework.

From a methodological point of view we follow the subjective beliefs literature as we *directly* elicit subjective beliefs from survey respondents and use these belief data to make inferences about decision-making (Bachmann et al., 2023). Prior work has elicited subjective probabilities using choice-based methods, in which beliefs are inferred from a series of decisions made by respondents (Abdellaoui, Bleichrodt, & l'Haridon, 2021; Baillon, 2008; Baillon, Huang, Selim, & Wakker, 2018). This includes work that has shown that it is also possible to reveal probability intervals from choices (Abdellaoui et al., 2021). This approach has been applied, for example, to estimate heterogeneity in stock market beliefs using a household panel (von Gaudecker & Wogrolly, 2022). Compared to the subjective beliefs literature which uses stated probabilities, these methods have the advantage of being choice-based and (usually) incentivized. The downside is, however, that it is very costly in terms of survey time to elicit subjective beliefs for a great variety of outcomes as we do in this paper. There is also an extensive literature on value elicitation in psychology (Fischhoff & Bruine de Bruin, 1999). One innovation in our work is that we allow respondents to express perceived ambiguity within a stated probability design, by asking for a range in the subjective probability of interest. As pointed out by Giustinelli, Manski, and Molinari (2022a), existing research on ambiguity, or imprecise probabilities, has largely been theoretical or experimental, and we still know little about how it impacts decision-making. See also Ilut and Schneider (2023). This innovation is important when modeling decisions beyond the SEU model, in particular for multiple prior subjective expected utility. Eliciting imprecise probabilistic beliefs is still rare (Manski and Molinari (2010), Giustinelli and Pavoni (2017), Giustinelli et al. (2022b), Giustinelli et al. (2022a), Delavande, Del Bono, and Holford (2025)).

Finally, our research contributes to the literature on determinants of uncertainty attitudes, particularly going beyond risk aversion. One of our findings is a negative relation between risk and

ambiguity attitude, something that also Dimmock, Kouwenberg, and Wakker (2016) report, while Chapman et al. (2022) and Stango and Zinman (2023) report mildly positive correlation between their measures of ambiguity and risk aversion. Some experimental studies done in the lab document that prior experience of ambiguity impacts risk attitudes (Mengel, Tsakas, & Vostroknutov, 2016). Other lab studies report a positive overall correlation among risk and uncertainty attitudes (Bossaerts et al., 2010; Charness & Gneezy, 2010; Kocher & Trautmann, 2013) and some do not find a statistically significant correlation (Cohen et al., 2011). In terms of individual characteristics, the existing literature has primarily focused on the determinants of risk attitudes (e.g., Barsky, Juster, Kimball, and Shapiro (1997), Dohmen et al. (2011), von Gaudecker et al. (2011), Noussair et al. (2014)). There is much less evidence on gender or age differences in loss or ambiguity aversion in representative samples and to our knowledge our study is one of the few to jointly study these more general measures of uncertainty attitudes in a representative sample. We find that gender and age are important determinants of other measures, not just risk aversion, although the sign and size of the effect differs across different types of uncertainty attitude with, for example, women being more risk and loss averse than men (see also von Gaudecker et al. (2011)), but less ambiguity averse (see also Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016), Sutter et al. (2013), or l'Haridon et al. (2018)). Falk et al. (2018), Chapman et al. (2022), and Stango and Zinman (2023), also obtain measures in representative surveys of some of the preference parameters that we study, and others that we do not. These studies do not cover the same range of uncertainty attitudes and do not elicit subjective beliefs.

B Decision-theoretic models

This appendix contains a more detailed discussion of the decision-theoretic models we use in this paper. Before we describe the models we briefly outline the setting used in Section 4, where we incorporate these into the random utility framework for empirical analysis.

B.1 Setting

A decision-maker faces a binary choice $\mathcal{B} \in \{B, NB\}$ to either engage in a behavior (B) or not (NB). There are two binary events that influence the decision-maker's payoff: E and its complement E^c. We define $u_{\mathcal{E}}$ as the Bernoulli utility associated with experiencing event $\mathcal{E} \in \{E, E^c\}$, $C_{\mathcal{B}}$ as the cost of engaging in behavior $\mathcal{B} \in \{B, NB\}$ and we introduce a taste component $\epsilon_{\mathcal{B}}$ known to the

decision-maker but unobserved by the econometrician as in Mc Fadden (1981). We assume that event E yields higher utility than event E^c, i.e. $u_E \geq u_{E^c}$. As an example, consider B as 'getting a flu vaccine' and NB as 'not getting one'. Event E would be 'not getting the flu' which would have have utility u_E while E^c would be 'getting the flu' and have utility u_{E^c}.

The behavior $\mathcal{B}$ can influence the likelihood of the event $\mathcal{E}$. Let $p(\mathcal{E}|\mathcal{B})$ denote the individual-specific subjective probability that $\mathcal{E}$ occurs conditional on engaging in behavior $\mathcal{B}$ and $\mathbf{P}(\mathcal{E}|\mathcal{B}) = [\underline{p}(\mathcal{E}|\mathcal{B}), \bar{p}(\mathcal{E}|\mathcal{B})] \subseteq [0,1]$ denote the individual-specific range of probabilities if the individual expresses a range. In our example, $p(E|B)$ would be an individual specific probability of not getting the flu after being vaccinated, while $\mathbf{P}(E|B) = [\underline{p}(E|B), \bar{p}(E|B)]$ denotes the individual specific range of probabilities as expressed by the individual. We explore decision-making under both subjective expected utility (SEU) and its generalizations encompassing various models, which we describe in turn.

B.2 Subjective Expected Utility

Under the SEU model, the utility from choice $\mathcal{B}$ is as follows.

$$\mathbb{U}_{SEU}(\mathcal{B}) = p(E|\mathcal{B})u_E + (1 - p(E|\mathcal{B}))\, u_{E^c} - C_{\mathcal{B}} + \epsilon_{\mathcal{B}} \tag{12}$$

As usual under SEU, the event utilities are weighted by the respective probabilities, i.e. u_E (respectively, u_{E^c}) by $p(E|\mathcal{B})$ (respectively, by $(1 - p(E|\mathcal{B}))$ in the overall utility evaluation. In the flu vaccine example, this equation would simply express the subjective expected utility from getting the vaccine (B) or not getting the vaccine (NB).

B.3 Generalisations of SEU

We examine two categories of models which generalize SEU. In our setting of binary choices, both of these generalizations imply that event utilities u_E, u_{E^c} are weighted by specific transformations of the respective probabilities. The first category is a version of prospect theory (Tanaka et al. (2010), Wakker (2010)). The second category is a version of the multiple-priors model, which is applicable when an individual behaves as if they have a range of probabilities rather than a single, precise probability (Gilboa and Marinacci (2013), Wakker (2010)).

B.3.1 Prospect theory

We consider special cases of prospect theory to our setting. Within prospect theory, we first consider a version of the RDU model which incorporates probability weighting and then a restricted version (PT) of prospect theory which additionally incorporates reference dependence and loss aversion. For these, using the source function approach, we distinguish the case in which the RDU and PT models are applied to choices under risk (as perceived by the decision-maker), labeled RDU-Risk and PT-Risk respectively, and the case in which these are applied to choices under ambiguity, labeled RDU-Ambiguity and PT-Ambiguity respectively.[1]

Under the RDU model we consider, the overall utility $\mathbb{U}_{RDU}(\mathcal{B})$ of choice $\mathcal{B}$ is

$$\mathbb{U}_{RDU}(\mathcal{B}) = \pi(p(E|\mathcal{B}))u_E + (1 - \pi(p(E|\mathcal{B})))\, u_{E^c} - C_{\mathcal{B}} + \epsilon_{\mathcal{B}}. \tag{13}$$

For the PT model, we suppose that reference-point payoff and corresponding Bernoulli utility is 0. Suppose under choice $\mathcal{B}$, event E is a gain event, i.e. $u_E \geq 0$ while E^c is a loss event, i.e. $0 \geq u_{E^c}$. In the paper, we consider two formulations of overall utility.

The first formulation yields the overall utility $\mathbb{U}_{PT}(\mathcal{B})$ of $\mathcal{B}$ as

$$\mathbb{U}_{PT}(\mathcal{B}) = \pi(P(E|\mathcal{B}))u_E + (1 - \pi(P(E|\mathcal{B})))\, \lambda u_{E^c} - C_{\mathcal{B}} + \epsilon_{\mathcal{B}}. \tag{14}$$

where $\pi(\cdot) : [0,1] \to [0,1]$ is the source function under which probabilities are weighted, $\lambda \geq 0$ denotes the parameter that measures loss aversion.

This is a restricted version of PT where we assume that the same source function applies for gains and losses similar to Tanaka et al. (2010) and we assume that the decision weights add up to one across the gain and loss events, which corresponds to assuming a duality condition on the source-based weighting function (Abdellaoui et al., 2005). The results for this formulation are presented and discussed in section 4.4.

The second formulation retains the assumption of the same source function across gains and losses similar to Tanaka et al. (2010), but does not assume that the decision weights add up to one across the gain and loss events. The second formulation yields the overall utility $\hat{\mathbb{U}}_{PT}(\mathcal{B})$ of $\mathcal{B}$ as

$$\hat{\mathbb{U}}_{PT}(\mathcal{B}) = \pi(P(E|\mathcal{B}))u_E + \pi\left(1 - (P(E|\mathcal{B}))\right) \lambda u_{E^c} - C_{\mathcal{B}} + \epsilon_{\mathcal{B}}. \tag{15}$$

[1] See Wakker (2010) for a comprehensive discussion of the general RDU and PT models under risk and ambiguity.

Under this formulation, for choice scenario j, B_j is chosen over NB_j if and only if $\hat{\mathbb{U}}_{PT}(B_j) > \hat{\mathbb{U}}_{PT}(NB_j)$.

Assuming that the unobserved components $\epsilon_{\mathcal{B}_j}$ are iid extreme value type I, the probability of choosing B_j takes the standard logit form

$$\Pr(B_j) = \Pr\left(\epsilon_{NB_j} - \epsilon_{B_j} < \Delta\hat{U}_j^{PT}\right). \tag{16}$$

where $\Delta\hat{U}_j^{PT} = \hat{\mathbb{U}}_{PT}(B_j) - \hat{\mathbb{U}}_{PT}(NB_j)$ is the utility difference given by

$$\begin{aligned} \Delta\hat{U}_j^{PT} = & \quad \left[\pi\left(p(E_j|B_j)\right) - \pi\left(p(E_j|NB_j)\right)\right] \cdot u_{E_j} \\ & + \left[\pi\left((1-p(E_j|B_j))\right) - \pi\left((1-p(E_j|NB_j))\right)\right] \cdot \lambda u_{E_j^c} \\ & - \left[C_{B_j} - C_{NB_j}\right]. \\ = & \quad \hat{\Pi}_j^1 \cdot u_{E_j} + \hat{\Pi}_j^2 \lambda u_{E_j^c} - \left[C_{B_j} - C_{NB_j}\right], \end{aligned} \tag{17}$$

where $\hat{\Pi}_j^1 = \left[\pi\left(p(E_j|B_j)\right) - \pi\left(p(E_j|NB_j)\right)\right]$ and $\hat{\Pi}_j^2 = \left[\pi\left((1-p(E_j|B_j))\right) - \pi\left((1-p(E_j|NB_j))\right)\right]$.

The estimation results for this formulation are shown in Table E.11 and are qualitatively similar to those for the first formulation. In particular, the loss aversion parameter is not significant for any of the choice scenarios.

As discussed in Wakker (2010), the general PT model allows for different weighting functions for gain events and loss events.

B.3.2 Multiple-prior model

The second category of models is based on the multiple-prior model for decision-making (see Gilboa and Marinacci (2013), Wakker (2010) for an overview). This model is relevant if the individual behaves as if they hold a range of probabilities, instead of a precise probability. In the version, denoted MP, of the multiple-prior model we consider, $\mathbf{P}(E|\mathcal{B})$ denotes the range of probabilities for event E conditional on choice $\mathcal{B}$ with $\underline{p}(E|\mathcal{B})$ and $\bar{p}(E|\mathcal{B})$ denoting the lower and upper bound respectively of the range. For each probability $p \in \mathbf{P}(E|\mathcal{B})$, there is a corresponding subjective expected utility $(pu_E + (1-p)u_{E^c})$. The lowest possible subjective expected utility is given weight $\phi \in [0,1]$ while the highest possible subjective expected utility is given weight $(1-\phi)$.

Specifically, for each choice $\mathcal{B}$, we consider the following overall ϕ-max-min utility.

$$\begin{aligned}\mathbb{U}_{MP}(\mathcal{B}) &= \phi \min_{p\in\mathbf{P}(E|\mathcal{B})} [pu_E + (1-p)u_{E^c}] + (1-\phi) \max_{p\in\mathbf{P}(E|\mathcal{B})} [pu_E + (1-p)u_{E^c}] - C_{\mathcal{B}} + \epsilon_{\mathcal{B}} \\ &= (u_E - u_{E^c}) \left(\phi \underline{p}(E|\mathcal{B}) + (1-\phi)\, \bar{p}(E|\mathcal{B})\right) + u_{E^c} - C_{\mathcal{B}} + \epsilon_{\mathcal{B}} \\ &= \Phi_{\mathcal{B}_j} \cdot u_{E_j} + \left(1 - \Phi_{\mathcal{B}_j}\right) \cdot u_{E_j^c} - C_{\mathcal{B}_j} + \epsilon_{\mathcal{B}_j} \qquad (18)\end{aligned}$$

where the second equality obtains because $u_E \geq u_{E^c}$ and so the lowest expected utility is obtained at the lower bound $\underline{p}(E|\mathcal{B})$ while the highest expected utility is obtained at the upper bound $\bar{p}(E|\mathcal{B})$. The case of $\phi = 1$ corresponds to the max-min expected utility model associated with Gilboa and Schmeidler (1989). The model with $\phi \in (0,1)$ is also referred to as the Hurwicz criterion and is sometimes also referred to as the 'alpha-max-min' model.[2]

In this formulation, ϕ is a measure of a respondent's degree of ambiguity aversion and $(\bar{p}(E|\mathcal{B}) - \underline{p}(E|\mathcal{B}))$ is a measure of the respondent's perceived ambiguity about the event E. We refer to $\Phi_{\mathcal{B}} = \left(\phi \underline{p}(E|\mathcal{B}) + (1-\phi)\, \bar{p}(E|\mathcal{B})\right)$ as the *weighted probability under the MP model*. For individuals who have an exact probability in mind, $\underline{p}(E|\mathcal{B}) = \bar{p}(E|\mathcal{B}) = p(E|\mathcal{B})$ and their decision-making is based on the SEU model.

C Appendix: Additional Information on Procedures

In this section we describe the procedures used to elicit measures of risk, loss, and ambiguity attitude in more detail.

C.1 Module I: Simple Risk and Ambiguity Aversion

In this module participants were asked two simple questions as shown in Figure C.1. We do not use these in this paper.

C.2 Module II: Utility Curvature (Risk Attitude)

In this module participants made a sequence of ten choices between two "wheels of fortune". After a screen where we explained them how a wheel of fortune works, we then told them in each decision problem "We will spin one of these two wheels of fortune for you. You can pick whether we spin wheel A or wheel B. Wheel A has x red and $10 - x$ blue zones. Wheel B has x grey and $10 - x$

[2] As noted previously, we use ϕ instead of 'alpha' to avoid confusion with the probability weighting parameter α.

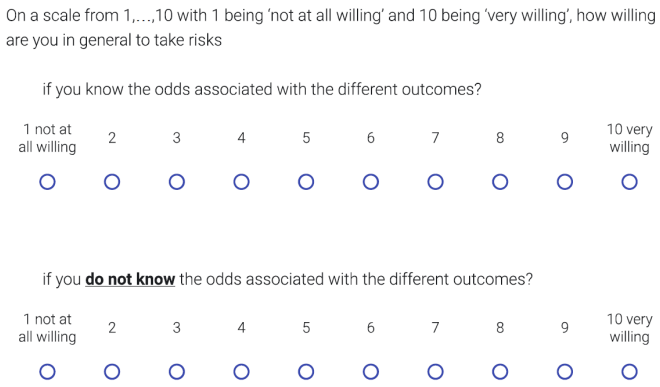


Figure C.1: Screenshot of module I questions.

yellow zones", where x ranged from 1 to 10 across the ten decision problems. We then asked them "Which wheel would you like us to spin for you? Please choose one below". Figure C.2 shows the wheels the way the participants saw them on the screen. As in the Holt and Laury (2002) prospect list, the outcomes in each of the zones were always those shown in the figure.

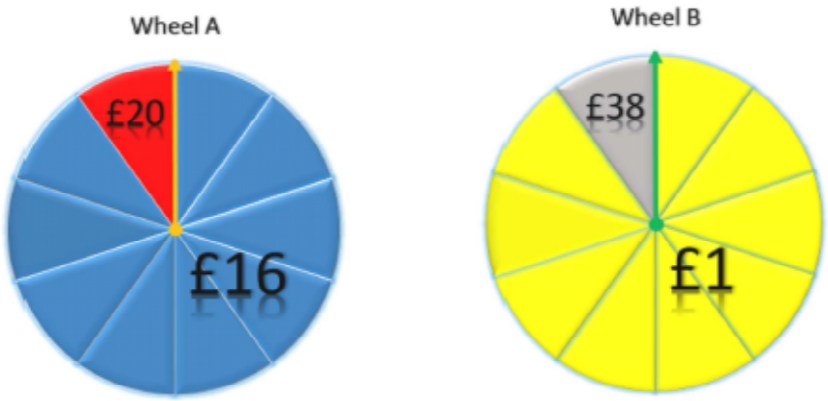


Figure C.2: Wheels A and B for the $\frac{1}{9}$ probability ($x = 1$).

C.3 Module III: Utility Curvature (Risk Attitude), Loss Aversion, and Source Function for Risk (Probability-Weighting under Risk)

Table C.1 shows the prospects used in Module III. Participants were shown two wheels of fortune. Wheel A and Wheel B with similar illustrations as in Figure C.2 above, but where some outcome was represented with a "?". In questions III.1-III.4 respondents indicated a switch-point where they would like to switch from spinning wheel A to wheel B. The different possible values/prospects are indicated in the square brackets in Table C.1. Questions III.5 and III.6 simply ask a choice between two prospects (wheels of fortunes). Before starting this module there was a screen explaining to respondents how a wheel of fortune works.

Question	Choice to spin		modelled on
	Wheel A:	Wheel B	Tanaka et al. (2010)
III.1	$(0.3 * 40 + 0.7 * 10)$	$(0.1 * 5 + 0.9 * [0, 75, 85, 95, 105, 125, 150, 185, 220, 300, 400, 600, 1000])$ GBP	Series 1
III.2	$(0.9 * 40 + 0.1 * 30)$	$(0.7 * 5 + 0.1 * [0, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 110, 120])$ GBP	Series 2
III.3	$(0.5 * 1 + 0.5 * (-4))$	$(0.5 * 30 + 0.5 * [0, -4, -8, -12, -16, -21, -26, -30])$ GBP	Series 3
III.4	$(0.5 * 1 + 0.5 * (-8))$	$(0.5 * 30 + 0.5 * [0, -4, -8, -12, -16, -21, -26, -30])$ GBP	Series 3
III.5	$(0.5 * 25 + 0.5 * (-4))$	$(0.5 * 30 + 0.5 * (-21))$ GBP	Series 3
III.6	$(0.5 * 4 + 0.5 * (-4))$	$(0.5 * 30 + 0.5 * (-21))$ GBP	Series 3

Table C.1: Prospects used in Module III.

The switching point (the critical value from which on wheel B is spun) in prospect choice III.1 (which lies entirely in the gains domain) can be rationalized by a number of combinations of (γ, α). The same is true for the switching point in III.2. However, III.1 and III.2 are chosen in such a way that a higher switching point implies a higher α and lower γ in III.2, while both α and γ increase as the switching point increases in III.2 (see Tanaka et al. (2010)). This design allows to identify a unique interval for each α and γ consistent with a pair of choices in III.1 and III.2 of which we take the midpoint as estimated (γ^w, α_R). Following Tanaka et al. (2010) we approximate (γ^w, α_R) to the nearest 0.05 increment and use the approximate values at the boundaries if participants do not switch.

Following Tanaka et al. (2010) we assume a range of $[0, 1.4]$ for α and we assign inferred values of alpha to the nearest point on a grid with step-size 0.05, i.e. $0, 0.05, ..., 1.35, 1.4$. Finally, we estimate the loss aversion parameter λ from the Tanaka et al. (2010) specification using participants' choices in prospects III.3-III.6 and the (γ^w, α_R) identified above.

C.4 Module IV: Ambiguity Attitude and Source Function for Ambiguity

To measure ambiguity attitude and the parameter for weighting under the source function for ambiguity, we elicit certainty equivalents for wheels with colours displayed (denoted R wheels in the paper) and for wheels with colours obscured (denoted A wheels in the paper), as illustrated in Figure C.3.

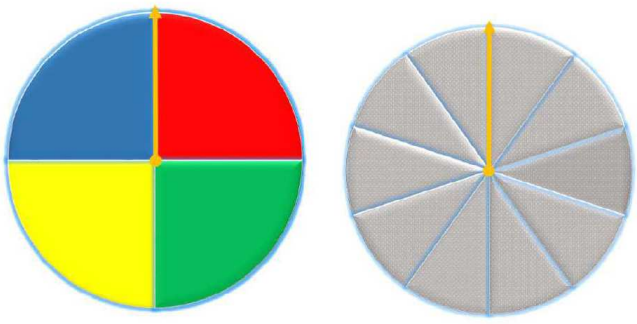


Figure C.3: Examples of wheels used to elicit ambiguity attitude.

Table C.2 shows all the prospects used in Module IV. For each of the questions we tell participants which colours are winning (indicated in bold in the table) and then elicit their certainty equivalent.

Question	Wheel Type	Colours	Winning Probability	Prize
IV.1	R	**Red**, Blue, **Yellow**, Green	0.5	20 GBP
IV.2	R	**Red**, Blue, Yellow, Green	0.25	20 GBP
IV.3	R	**Red**, Blue, **Yellow**, **Green**	0.75	20 GBP
IV.4	R	**Red**, Blue, **Yellow**, Green	0.5	40 GBP
IV.5	A	**Red**, Blue, **Yellow**, Green	0.5	20 GBP
IV.6	A	**Red**, Blue, Yellow, Green	0.25	20 GBP
IV.7	A	**Red**, Blue, **Yellow**, **Green**	0.75	20 GBP
IV.8	A	**Red**, Blue, **Yellow**, Green	0.5	40 GBP

Table C.2: Prospects used in Module IV. For wheel type A, "winning probability" corresponds to "ambiguity-neutral probability".

To accommodate a non-neutral ambiguity attitude while still using subjective probabilities, the wheels A and R can be treated as two different sources of uncertainty (Fox and Tversky (1998); Abdellaoui et al. (2011); Chew and Sagi (2008)). To allow for different attitudes toward different sources, we can allow for the same subjective probability of similar events but allow these to be weighted differently for each source. For example, let $\mathbf{RB}_A$ (respectively $\mathbf{RB}_R$) denote the event of wheel A stopping with the arrow on red or blue (respectively, wheel R stopping with the arrow on red or blue).

We can assign the subjective probability of 0.5 to $\mathbf{RB}_A$ and to $\mathbf{RB}_R$, which is termed the *ambiguity neutral* probability (Dimmock, Kouwenberg, and Wakker (2016); Chew and Sagi (2008)). Then $\pi_A(0.5)$ denotes the weighted probability of the event $\mathbf{RB}_A$ and $\pi_R(0.5)$ denotes the weighted probability of event $\mathbf{RB}_R$. Similarly, for every winning event in wheel R with probability $p\%$, we use p as the ambiguity neutral probability for the corresponding event in wheel A. Then using the indicated certainty equivalent CE_p^A, we can obtain the weighting parameter α_A corresponding to choices for A wheels as shown in (5). Dimmock, Kouwenberg, and Wakker (2016) and Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016) demonstrate how eliciting matching probabilities directly also provides a direct measure of local ambiguity attitude, i.e. attitude at a specific p. Dimmock, Kouwenberg, and Wakker (2016), Baillon et al. (2018), and Baillon, Halevy, and Li (2022) show how global ambiguity attitude can be summarized by a global ambiguity aversion measure and a global ambiguity-generated likelihood insensitivity measure which can be obtained using parameters from a linear weighting function.

C.5 Module V: Outcomes

Table C.3 lists the choices we asked about in Module V.

Table C.3: choices

	(1) Mean	(2) n
Health		
"Did you get a flu vaccine last year?" (H1a)	0.398	902
"Will you get a flu vaccine next year?" (H1b)	0.400	902
"Do you smoke cigarettes at all nowadays" (H3)	0.094	904
"Have you had a cervical screening (pap smear) in the last three years" (H4)	0.582	478
Financial		
"How often do you buy national lottery tickets (e.g. Lotto, Euromillions)?" (F1)	0.648	894
"We will ask you about any savings and investments you may have....Stocks and shares ISAs or PEPs?" (F2)	0.296	756

Note: H4 is only asked to women. All the decisions are binary (yes/no) except F1 where the set of answers was: "Never, Almost Never, Sometimes, Fairly Often and Very Often".

C.6 Module VI: Subjective beliefs

In Module VI we elicited subjective beliefs for the choices described in Table 3. The precise list of questions was as follows.

"On a scale from 0% to 100%, where 0% means "no chance of happening" and 100% means "totally likely to happen", please tell me how likely it is that the following event will happen in your life in the future.

- "How likely is it that you will get the flu in the next 12 months?"
- "How likely is it that you will get cervical cancer in the next 15 years"? (asked to women only)
- "How likely is it that mutual fund shares invested in stocks will have grown by 5 percent or more in the next year?"
- "How likely is it that a man (woman) will develop lung cancer if (s)he smokes at least one cigarette a day for 20 years?"(asked about the same gender as respondent).

Please enter a number between 0 and 100"

For each of the questions - after they indicated a number - all participants were asked "When you said xxx % just now, did you mean this as an exact number or do you have a range of numbers in mind?". They then ticked a box indicating either "exact number" or "range". Only if they indicated "range", they were asked "What range of numbers did you have in mind when you said xxx % ?". Figure C.4 illustrates a sequence of (up to) three questions with which subjective probabilities were elicited.

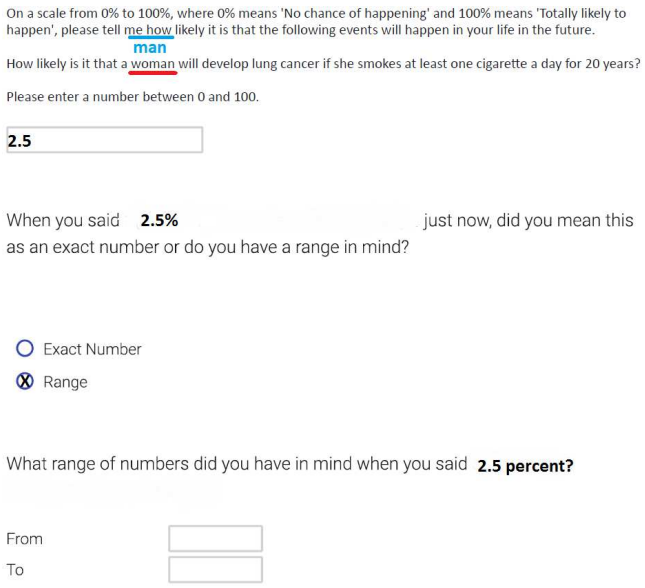


Figure C.4: An illustration of a sequence of (up to) three questions with which subjective probabilities were elicited.

C.6.1 Derivation of ϕ for the MP model

We use the estimates of α_R and α_A and the elicited beliefs to obtain individual- and event-specific estimates of ϕ for the MP model (9) as follows. In order to do this, we make specific parametric assumptions, which we don't directly test. Our assumption and formulation is based on a similar exercise in Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2015) (see the discussion in their Sections 3.2 and 3.3 which shows how a matching probability can be linked to a specific formulation of a multiple-prior model). There is no obvious way to link parameters from a prospect theory model to those of a multiple prior model in full generality to our knowledge.

For ease of notation, we drop the j index in what follows. Suppose the probability interval has the form

$$\mathbf{P}(E|\mathcal{B}) = [(1-\delta)p, (1-\delta)p + \delta] \tag{19}$$

where p is the ambiguity neutral probability and δ is the length of the interval (see e.g. Dimmock et al. (2015)). First, using the stated probability ranges provides event- and individual specific estimates of δ, from which we can calculate p using (19). Then, we obtain ϕ using p and the concept of matching probability as follows (see also e.g. Dimmock et al. (2015)). For the choice of $\mathcal{B}$, given ambiguity-neutral p, the matching probability $m(p) \in [0,1]$ is characterised by the following.

$$\pi_R(m(p))(u_E - u_{E^c}) + u_{E^c} = (\pi_A(p))(u_E - u_{E^c}) + u_{E^c}, \tag{20}$$

where π_R and π_A are the probability-weighting function under risk and the weighting function under

ambiguity respectively. We then use our estimates of α_R and α_A to obtain $m(p)$ from

$$\begin{aligned} m(p) &= \pi_R^{-1}\left(\pi_A\left(p\right)\right) \\ &= \exp\left(-\left(-\ln p\right)^{\frac{\alpha_A}{\alpha_R}}\right) \end{aligned} \tag{21}$$

Under the MP model (9) with the probability interval form in (19), the utility of action $\mathcal{B}$ is

$$[\phi(1-\delta)p + (1-\phi)((1-\delta)p+\delta)](u_E - u_{E^c}) + u_{E^c} = [(1-\delta)\,p + (1-\phi)\,\delta](u_E - u_{E^c}) + u_{E^c}. \tag{22}$$

In turn, this implies that given δ, p, $m(p)$, and ϕ are related as follows.

$$m(p) = (1-\delta)\,p + (1-\phi)\,\delta, \tag{23}$$

Table E.7 presents descriptive statistics of the event-specific ϕ.

D Appendix: Robustness Checks

This section discusses different robustness checks and extensions of our main results.

LASSO regressions As an additional test of the importance of prospect theory, which in our setting incorporates weighted (subjective) probability, we use LASSO regressions as a data-driven method to assess the relative predictive power of (unweighted) reported probabilities and weighted probabilities across models (Zou, 2006). LASSO is well suited for comparing the informativeness of competing variables that may be correlated. This method allows us to test whether weighted probabilities provide explanatory value beyond (unweighted) reported probabilities and observable characteristics, without imposing strong a priori restrictions on the model.[3] This complements our structural approach by offering a flexible, model-agnostic perspective on the empirical relevance of weighted probabilities. Specifically, the dependent variable is one of the binary choices above, and the prediction variables are the complete set of demographic characteristics as well as each of the probabilities used in the six different decision-making models we consider, as shown in Table 5.

Table E.8 indicates with an **X** the variables the LASSO regression includes in the prediction model among the six probabilities. The results are strikingly robust: for all outcomes, a weighted probability

[3]Cunha, Elo, and Culhane (2022) adopt a similar approach to evaluate whether maternal subjective beliefs provide information in addition to socio-economic status to predict investments in the human capital of children.

from prospect theory is always selected while the (unweighted) reported probability is only selected in some contexts. The weighted probability from the MP model is never selected. Although from a theoretical point of view, we do not expect individuals to rely both on the weighted probabilities and (unweighted) reported probabilities, the LASSO results support the empirical importance of weighted probability in understanding decisions made under uncertainty.

Robustness to different assumptions on conditional health probabilities As discussed in Section 4.2.3, we assume that respondents perceive a zero probability of contracting the flu if vaccinated, a zero probability of developing lung cancer if they do not smoke, and a zero probability of cervical cancer if they undergo screening. We recognize that these may be strong assumptions, so we replicate our main analysis under alternative assumptions. First, we set these probabilities to 0.01. For the MP model, we assume that the lower bound is zero and the upper bound is 0.02 (instead of assuming they are both zero). In a second robustness exercise, we set them to objective risks obtained from the medical literature. In particular, we assume a 3.5% probability of getting the flu if vaccinated (Jayasundara, Soobiah, Thommes, Tricco, & Chit, 2014), a 2% probability of getting cervical cancer if screened (Malagón et al., 2018), and a 1.35% probability of developing lung cancer for non-smokers (Villeneuve & Mao, 1994). For the MP models, we set the lower bound to zero and the upper bounds to twice these risk levels. The results, presented in Appendix Tables E.9 and E.10, yield conclusions that align with those in Table 7. For instance, the RDU-Ambiguity model continues to provide the best fit for cervical cancer screening, while the SEU and PT models perform similarly for the flu vaccine.

Relaxing the assumption that the decision weights add up to one across the gain and loss events As discussed in Section B.3.1, our baseline specification assumes that the decision weights add up to one across the gain and loss events in the *PT* variant. We relax this assumption and estimate equation (16). The results are presented in Table E.11 and are very similar to those in our baseline specification, indicating that our main findings are not driven by this additivity assumption.

Alternative functional form for the probability weighting function As in Tanaka et al. (2010), our experimental module was designed primarily to recover individual-specific parameters of the Prelec (1998) probability weighting function, which is widely used due to its flexibility in capturing inverse-S shaped weighting patterns. Nevertheless, we also use the experimental data to recover individual-specific weights under a simpler power function, separately for risk and ambiguity.

While this is a less ideal fit for the experimental design, it allows us to test the robustness of our findings to alternative functional forms. For the small share of respondents (approximately 5%) for whom we are unable to estimate a valid power parameter, we impute the common value of $\alpha = 0.145$ estimated from the homogeneous model in Section 4.3. This approach ensures comparability with our main analysis by retaining the full sample.

The results largely support the main conclusions (see Appendix Tables E.12 and E.13). For flu vaccination, lung cancer, and stock market participation, the power weighting RDU-Risk and RDU-Ambiguity models perform comparably to the SEU benchmark in both in-sample fit and out-of-sample predictive performance (e.g., CV-AUC around 0.77 for flu and around 0.66 for lung cancer across all models, with marginally better fit based on the AIC for the RDU-Ambiguity model for the flu). For lottery participation, as with the Prelec functional form, power weighting RDU-Risk and RDU-Ambiguity models substantially outperform SEU, delivering much lower AIC (1032 vs. 1048) and higher CV-AUC (0.635 for RDU-Ambiguity vs. 0.611 for SEU). In contrast, for cervical cancer screening, the power-based models no longer dominate as they did under the Prelec specification. Overall, these results show that even under another parametric assumption for the weighting function, the core finding remains robust: RDU models either match or outperform SEU in explaining real-world decision-making under uncertainty.

Smoothing versus probability weighting We explore whether the better fit of RDU models is partly due to their ability to smooth (unweighted) reported probabilities, which often exhibit heaping at 0, 50, and 100. To investigate this, we focus on cervical screening and lottery choices, where the AIC for RDU models is substantially lower than for SEU models. Rather than using individual-specific weighting parameters α, we assign each respondent a random α drawn from the empirical distribution of α_R and estimate equation (10) to obtain an AIC. This procedure is repeated 500 times.

Appendix Figure F.5 shows the distribution of AIC values obtained through this procedure. Comparing these to the AIC values reported in Tables 7 and 8, we see that the SEU model's AIC typically lies near the center or upper end of the distribution, while the AICs for the RDU models are consistently near the lower bound—indicating a better fit when individual-specific probability weights are used instead of random weights. The fact that the SEU model's AIC does not lie at the extreme right of the distribution suggests that smoothing may contribute to the improved fit of the RDU models. Nonetheless, the results clearly indicate that the superior fit of the RDU models is not

primarily due to smoothing of (unweighted) reported probabilities.

Heterogeneity in u Although our main estimation accounts for the heterogeneity in beliefs, probability weighting parameters, and loss aversion, it assumes a common value of u across individuals. To relax this assumption, we allow u to vary for individuals with $\gamma > 0$. The results, presented in Appendix Tables E.14 and E.15, show that our main conclusions remain robust.

E Appendix: Additional Tables

This section presents additional tables from the empirical analysis. Table E.1 shows the share of respondents reporting a range of probabilities, the average range size and the number of participants (N) for different baseline probabilities p and events.

	No Flu			*No cervical cancer*			*No lung cancer*			*Stock value increases*			*Win the lottery*		
	Share range	Range size	N	Share range	Range size	N	Share range	Range size	N	Share range	Range size	N	Share range	Range size	N
Panel A															
$0 < p \leq 0.25$	0.235	0.195	52	0.185	0.050	29	0.409	0.352	68	0.472	0.121	425	0.434	0.090	801
$0.25 < p \leq 0.49$	0.625	0.228	33	0.400	0.138	10	0.557	0.338	109	0.490	0.316	103	0.700	0.257	11
0.5	0.503	0.361	183	0.418	0.453	79	0.477	0.426	192	0.484	0.466	196	0.371	0.600	37
$0.5 < p \leq 0.75$	0.602	0.232	104	0.621	0.249	30	0.582	0.247	157	0.591	0.291	67	0.000		2
$0.75 < p \leq 1$	0.481	0.138	494	0.452	0.132	296	0.555	0.134	325	0.537	0.240	43	0.364	0.495	11
Panel B															
Not 0, 0.5, 1	0.576	0.169	531	0.504	0.165	251	0.554	0.214	629	0.537	0.195	517	0.499	0.105	582
0, 0.5 or 1	0.348	0.298	335	0.266	0.249	193	0.463	0.408	222	0.410	0.367	317	0.294	0.111	280
Panel C															
Not 0.5	0.487	0.164	683	0.444	0.145	365	0.546	0.214	659	0.492	0.185	638	0.436	0.096	825
0.5	0.503	0.361	183	0.418	0.453	79	0.477	0.426	192	0.484	0.466	196	0.371	0.600	37

Table E.1: Share of respondents reporting a range of probabilities, average range size and number of participants (N) for different baseline probabilities p and events.

Tables E.2 and E.3 focus on the association of uncertainty attitudes with outcomes not used in main analysis. The outcomes are binary response to whether they would accept a free holiday in Tunisia shortly after the terror attacks (Free Holiday). Insurance is a count variable on how many of five possible insurances (extra car, home, life, holiday, health) they currently hold.

	Free Holiday		Insurance	
	(1)	(2)	(3)	(4)
$1-\gamma$	-0.092***	-0.095***	-0.018	-0.007
	(0.026)	(0.026)	(0.066)	(0.067)
$AA_{0.5}$		-0.057		0.314*
		(0.069)		(0.176)
Constant	0.375***	0.380***	2.903***	2.868***
	(0.020)	(0.021)	(0.050)	(0.053)
Observations	861	852	857	848
R-squared	0.014	0.015	0.000	0.004
Mean Dep. Var.	0.339	0.339	2.898	2.898

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.2: Association of risk attitude (module II) and ambiguity attitude with outcomes not used in main analysis. The outcomes are binary response to whether they would accept a free holiday in Tunisia shortly after the terror attacks (Free Holiday). Insurance is a count variable on how many of five possible insurances (extra car, home, life, holiday, health) they currently hold.

	Free Holiday		Insurance	
	(1)	(2)	(3)	(4)
$1-\gamma^{\omega}$	-0.015	-0.027	-0.041	-0.039
	(0.038)	(0.042)	(0.026)	(0.029)
λ		-0.007**		0.007***
		(0.003)		(0.002)
Constant	0.701***	0.732***	0.486***	0.485***
	(0.101)	(0.065)	(0.078)	(0.083)
Observations	808	795	805	792
R-squared	0.089	0.082	0.186	0.194

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.3: Association of risk attitude (utility curvature) and loss aversion parameter from module III with outcomes not used in main analysis. The outcomes are binary response to whether they would ac accept a free holiday in Tunisia shortly after the terror attacks (Free Holiday). Insurance is a count variable on how many of five possible insurances (extra car, home, life, holiday, health) they currently hold.

Table E.4 shows linear regressions of probability weighting parameters on demographic characteristics.

Probability weighting parameters and demographic characteristics

	α_R		α_A		ϕ	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.024	-0.023	0.087	0.086	0.135**	0.133**
	(0.017)	(0.017)	(0.059)	(0.061)	(0.054)	(0.059)
Age	-0.000	-0.000	0.005***	0.004*	-0.000	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
White	-0.010	-0.012	-0.215	-0.231	0.103	0.081
	(0.031)	(0.034)	(0.153)	(0.160)	(0.098)	(0.113)
Anglican	0.108	0.054	0.087	0.222	0.170	0.118
	(0.078)	(0.098)	(0.238)	(0.326)	(0.151)	(0.213)
Catholic	0.137*	0.082	0.124	0.283	0.106	0.028
	(0.082)	(0.102)	(0.232)	(0.332)	(0.176)	(0.242)
Other Christian	0.123	0.072	0.174	0.300	-0.151	-0.216
	(0.079)	(0.097)	(0.228)	(0.300)	(0.131)	(0.202)
Other Religion	0.119	0.065	0.118	0.239	0.225*	0.183
	(0.074)	(0.094)	(0.212)	(0.307)	(0.120)	(0.184)
University		0.045		-0.021		0.060
		(0.047)		(0.198)		(0.120)
A levels		0.005		-0.011		0.025
		(0.049)		(0.198)		(0.125)
GCSC		0.042		0.158		0.003
		(0.049)		(0.213)		(0.131)
Other Qual		0.005		0.290		0.025
		(0.071)		(0.351)		(0.203)
Married		-0.003		0.003		-0.090
		(0.022)		(0.077)		(0.071)
Number Children		-0.008		-0.071***		0.014
		(0.009)		(0.027)		(0.028)
Rural		0.012		0.044		0.087
		(0.020)		(0.071)		(0.065)
Constant	0.564***	0.565***	0.282**	0.290**	-0.009	-0.003
	(0.066)	(0.066)	(0.122)	(0.124)	(0.031)	(0.034)
Observations	871	871	864	864	218	218
R-squared	0.007	0.019	0.017	0.046	0.140	0.184

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.4: Linear Regression of probability weighting parameters on demographic characteristics. α_R is the probability-weighting parameter under risk, α_A is the weighting parameter under ambiguity, ϕ is the ambiguity aversion parameter which weights probabilities in the MP model (9). The baseline for ethnicity is non-white, the baseline for religion is no religious affiliation and the baseline for highest educational or vocational qualification is no qualification. All specifications include order-fixed effects controlling for the order in which the survey modules were fielded. Even columns also include region fixed effects for eleven government office regions.

Subjective beliefs and demographic characteristics: Health Outcomes

	No Flu				No Cervical Cancer				No Lung Cancer			
	p	$\pi_R(p)$	$\pi_A(p)$	Φ	p	$\pi_R(p)$	$\pi_A(p)$	Φ	p	$\pi_R(p)$	$\pi_A(p)$	Φ
Female	-0.027	-0.015	0.030*	-0.033*					-0.027	-0.019	0.014	-0.017
	(0.018)	(0.018)	(0.018)	(0.020)					(0.018)	(0.016)	(0.014)	(0.020)
Age	0.002**	0.001	0.002***	0.001*	0.003***	0.003***	0.004***	0.003***	0.003***	0.002***	0.001***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
White	0.005	0.002	-0.037	-0.012	-0.066	-0.084	-0.139***	-0.075	0.068*	0.059*	0.006	0.071*
	(0.038)	(0.038)	(0.038)	(0.042)	(0.053)	(0.053)	(0.053)	(0.057)	(0.037)	(0.033)	(0.029)	(0.042)
Anglican	0.066	0.070	0.051	0.120	0.054	0.089	0.094	0.075	-0.211**	-0.191**	-0.127*	-0.275**
	(0.102)	(0.099)	(0.101)	(0.111)	(0.143)	(0.142)	(0.142)	(0.152)	(0.099)	(0.086)	(0.076)	(0.111)
Catholic	0.015	0.023	0.059	0.058	0.020	0.059	0.114	0.030	-0.184*	-0.187**	-0.088	-0.247**
	(0.106)	(0.103)	(0.104)	(0.115)	(0.146)	(0.145)	(0.145)	(0.156)	(0.102)	(0.089)	(0.079)	(0.115)
Other Christian	0.067	0.078	0.045	0.120	0.041	0.076	0.077	0.051	-0.158	-0.144*	-0.095	-0.231**
	(0.101)	(0.098)	(0.099)	(0.110)	(0.140)	(0.139)	(0.139)	(0.149)	(0.098)	(0.085)	(0.075)	(0.110)
Other Religion	0.041	0.051	0.038	0.091	0.030	0.065	0.038	0.045	-0.161*	-0.140*	-0.103	-0.215**
	(0.097)	(0.094)	(0.095)	(0.105)	(0.135)	(0.133)	(0.134)	(0.143)	(0.094)	(0.082)	(0.072)	(0.106)
University	-0.009	-0.013	-0.036	-0.013	0.021	0.028	-0.009	0.012	-0.088*	-0.044	-0.014	-0.065
	(0.049)	(0.048)	(0.049)	(0.053)	(0.060)	(0.059)	(0.060)	(0.064)	(0.048)	(0.042)	(0.037)	(0.054)
A Levels	-0.007	-0.021	-0.012	-0.002	0.060	0.079	0.049	0.054	-0.127**	-0.100**	-0.015	-0.109*
	(0.051)	(0.050)	(0.051)	(0.056)	(0.064)	(0.064)	(0.065)	(0.068)	(0.050)	(0.044)	(0.039)	(0.056)
GCSC	-0.011	-0.006	0.000	-0.014	0.003	0.024	0.017	0.001	-0.112**	-0.064	0.022	-0.086
	(0.051)	(0.050)	(0.051)	(0.056)	(0.064)	(0.063)	(0.065)	(0.068)	(0.050)	(0.044)	(0.039)	(0.057)
Other Qual	-0.047	-0.044	-0.038	-0.056	-0.021	-0.047	-0.027	-0.104	-0.112	-0.080	0.031	-0.102
	(0.071)	(0.069)	(0.070)	(0.077)	(0.105)	(0.104)	(0.104)	(0.112)	(0.069)	(0.060)	(0.053)	(0.078)
Married	0.019	0.024	0.005	0.042*	0.008	0.015	0.028	0.024	0.010	0.002	0.001	0.027
	(0.022)	(0.022)	(0.022)	(0.024)	(0.031)	(0.031)	(0.031)	(0.033)	(0.022)	(0.019)	(0.017)	(0.024)
Number Children	0.002	-0.002	-0.007	0.005	-0.041***	-0.046***	-0.059***	-0.041***	-0.011	-0.007	-0.014*	-0.006
	(0.010)	(0.010)	(0.010)	(0.011)	(0.014)	(0.014)	(0.014)	(0.015)	(0.010)	(0.009)	(0.008)	(0.011)
Rural	0.015	0.009	-0.007	0.001	-0.039	-0.048	-0.061*	-0.035	-0.010	-0.004	-0.020	-0.020
	(0.022)	(0.021)	(0.022)	(0.024)	(0.032)	(0.032)	(0.032)	(0.034)	(0.021)	(0.019)	(0.016)	(0.024)
Constant	0.636***	0.597***	0.503***	0.585***	0.649***	0.522***	0.463***	0.598***	0.758***	0.649***	0.544***	0.729***
	(0.067)	(0.066)	(0.066)	(0.073)	(0.094)	(0.093)	(0.093)	(0.100)	(0.065)	(0.056)	(0.050)	(0.073)
Observations	866	853	854	866	444	435	436	444	851	834	833	851
R-squared	0.052	0.041	0.059	0.049	0.081	0.100	0.171	0.087	0.077	0.072	0.054	0.070

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.5: Linear Regression of Subjective beliefs on demographic characteristics. Columns (1)-(4) focus on the subjective belief of not getting the flu, columns (5)-(8) on the subjective belief of not getting cervical cancer and columns (9)-(12) on the subjective belief of not getting lung cancer. p is the (unweighted) reported subjective belief, $\pi_R(p)$ and $\pi_A(p)$ the weighted probabilities under risk and ambiguity, respectively, and Φ the weighted probability under the MP model (9). The baseline for ethnicity is non-white, the baseline for religion is no religious affiliation and the baseline for highest educational or vocational qualification is no qualification. All specifications include order-fixed effects controlling for the order in which the survey modules were fielded and region fixed effects for eleven government office regions.

Subjective beliefs and demographic characteristics: Financial Outcomes

	Stock Value Increases				Lottery Gain			
	p	$\pi_R(p)$	$\pi_A(p)$	Φ	p	$\pi_R(p)$	$\pi_A(p)$	Φ
Female	-0.080***	-0.065***	-0.039***	-0.051***	0.035***	0.035***	0.011	0.034***
	(0.018)	(0.015)	(0.014)	(0.018)	(0.011)	(0.010)	(0.012)	(0.010)
Age	0.000	0.001	0.000	-0.000	-0.001	-0.001*	-0.002***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.031	0.026	0.017	0.041	-0.037	-0.008	0.005	-0.029
	(0.039)	(0.033)	(0.030)	(0.037)	(0.023)	(0.022)	(0.026)	(0.022)
Anglican	-0.184*	-0.173**	-0.096	-0.163	0.023	-0.008	0.050	-0.019
	(0.103)	(0.086)	(0.078)	(0.100)	(0.060)	(0.058)	(0.067)	(0.057)
Catholic	-0.199*	-0.194**	-0.123	-0.173*	0.021	0.001	0.036	-0.018
	(0.107)	(0.090)	(0.081)	(0.104)	(0.062)	(0.060)	(0.069)	(0.059)
Other Christian	-0.161	-0.152*	-0.089	-0.126	0.026	-0.022	0.019	-0.012
	(0.102)	(0.085)	(0.077)	(0.099)	(0.059)	(0.057)	(0.066)	(0.056)
Other Religion	-0.196**	-0.187**	-0.098	-0.166*	0.007	-0.031	0.024	-0.028
	(0.098)	(0.082)	(0.074)	(0.095)	(0.057)	(0.055)	(0.063)	(0.054)
University Degree	-0.024	-0.012	-0.022	0.001	0.010	0.006	0.018	0.036
	(0.051)	(0.043)	(0.039)	(0.049)	(0.029)	(0.028)	(0.032)	(0.027)
A Levels	-0.058	-0.032	-0.039	-0.004	0.030	0.032	0.018	0.048*
	(0.053)	(0.044)	(0.041)	(0.051)	(0.030)	(0.029)	(0.034)	(0.029)
GCSC	-0.047	-0.030	-0.042	-0.004	0.029	0.032	0.018	0.054*
	(0.053)	(0.044)	(0.041)	(0.051)	(0.030)	(0.029)	(0.034)	(0.029)
Other Qualif.	-0.067	-0.045	-0.018	-0.022	0.051	0.069*	0.061	0.084**
	(0.072)	(0.060)	(0.055)	(0.070)	(0.042)	(0.040)	(0.048)	(0.040)
Married	-0.016	-0.022	-0.015	0.004	-0.006	-0.014	0.002	0.005
	(0.022)	(0.019)	(0.017)	(0.022)	(0.013)	(0.013)	(0.015)	(0.012)
Number Children	0.003	0.003	0.002	0.004	0.006	0.004	0.004	0.007
	(0.010)	(0.009)	(0.008)	(0.010)	(0.006)	(0.006)	(0.007)	(0.006)
Rural	0.005	0.005	-0.005	-0.008	0.003	0.000	-0.011	-0.003
	(0.022)	(0.018)	(0.017)	(0.021)	(0.013)	(0.012)	(0.014)	(0.012)
Constant	0.429***	0.422***	0.386***	0.335***	0.083**	0.137***	0.204***	0.065*
	(0.067)	(0.056)	(0.050)	(0.064)	(0.040)	(0.038)	(0.044)	(0.038)
Observations	834	821	821	834	862	848	843	862
R-squared	0.054	0.052	0.034	0.032	0.052	0.058	0.055	0.050

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.6: Linear Regression of Subjective beliefs on demographic characteristics. Columns (1)-(4) focus on the subjective belief of stock market gains and columns (5)-(8) on the subjective belief of winning the lottery. p is the (unweighted) reported subjective probability, $\pi_R(p)$ and $\pi_A(p)$ the weighted probabilities under risk and ambiguity, respectively, and Φ is the weighted probability under the MP model (9). The baseline for ethnicity is non-white, the baseline for religion is no religious affiliation and the baseline for highest educational or vocational qualification is no qualification. All specifications include order-fixed effects controlling for the order in which the survey modules were fielded and region fixed effects for eleven government office regions.

Tables E.5 and E.6 show linear regressions of subjective beliefs on demographic characteristics for the health and financial outcomes, respectively.

	N	mean	median	SD
ϕ (Flu)	218	0.31	0	0.40
ϕ (Cervical cancer)	94	0.28	0	0.40
ϕ (Stock market)	148	0.57	0.65	0.35
ϕ (Smoking)	207	0.41	0.29	0.41
ϕ (Lottery)	29	0.66	0.91	0.38

Table E.7: Descriptive statistics of the ϕ parameter (event specific for respondents who report a range of probabilities). ϕ is the parameter from the MP model (9).

Table E.8 present LASSO regressions where the dependent variable is one of the binary choices above, and the prediction variables are the complete set of demographic characteristics as well as each of the probabilities used in the six different decision-making models we consider, as shown in Table 5. It indicates with an **X** the variables the LASSO regression includes in the prediction model among the six probabilities.

	Flu vaccine	Cervical Screening	Smoking	Lottery	Stock Market
SEU: P_j	X				X
RDU-Risk: Π_j^R	X			X	X
RDU-Ambiguity: Π_j^A	X	X	X	X	
PT-Risk: $\Pi_j^R(1-\lambda)$					
PT-Ambiguity $\Pi_j^A(1-\lambda)$	X	X			
MP: Π_j^{MP}					

Table E.8: LASSO logit regressions results: **X** indicates a variable was selected. P_j denotes the difference between (unweighted) reported probabilities. Π_j^R denotes the weighted probability difference under RDU-Risk and PT-Risk and Π_j^A denotes the weighted probability difference under under RDU-Ambiguity and PT-Ambiguity. Π_j^{MP} denotes the weighted probability difference under MP.

Panel A *Flu Vaccine*	SEU	Prospect Theory				MP
		RDU-Risk	RDU-Ambiguity	PT-Risk	PT-Ambiguity	
P_F	0.754**					
	(0.367)					
Π_F		0.968**	0.505	1.118***	0.547	
		(0.384)	(0.389)	(0.395)	(0.408)	
$\Pi_F(1-\lambda)$				0.077	0.025	
				(0.073)	(0.096)	
Π_F^{MP}						0.590
						(0.360)
Observations	828	828	828	828	828	828
McFadden R-squared	0.234	0.236	0.231	0.237	0.231	0.232
AIC	913.3	911	916.3	911.5	918.2	915
CV-RMSE	0.428	0.428	0.429	0.430	0.431	0.429
CV-AUC	0.770	0.773	0.767	0.766	0.763	0.768
Panel B *Cervical Screening*	SEU	Prospect Theory				MP
		RDU-Risk	RDU-Ambiguity	PT-Risk	PT-Ambiguity	
P_{CC}	0.671					
	(0.523)					
Π_{CC}		0.786	1.109*	0.619	1.009	
		(0.540)	(0.599)	(0.592)	(0.670)	
$\Pi_{CC}(1-\lambda)$				-0.087	-0.047	
				(0.130)	(0.155)	
Π_{CC}^{MP}						0.652
						(0.506)
Observations	424	424	424	424	424	424
McFadden R-squared	0.253	0.254	0.258	0.255	0.258	0.253
AIC	485.6	484.9	482.4	486.2	484.2	485.6
CV-RMSE	0.452	0.451	0.450	0.452	0.453	0.452
CV-AUC	0.744	0.747	0.750	0.745	0.746	0.744
Panel C *Smoking*	SEU	PT model				MP
		RDU-Risk	RDU-Ambiguity	PT-Risk	PT-Ambiguity	
P_{LC}	1.248*					
	(0.651)					
Π_{LC}		0.360	0.376	0.493	0.359	
		(0.645)	(0.544)	(0.645)	(0.548)	
$\Pi_{LC}(1-\lambda)$				0.123	-0.015	
				(0.124)	(0.156)	
Π_{LCj}^{MP}						1.120*
						(0.622)
Observations	795	795	795	795	795	795
McFadden R-squared	0.148	0.138	0.138	0.142	0.138	0.147
AIC	490.8	495.9	495.8	495.8	497.8	491.7
CV-RMSE	0.296	0.296	0.296	0.296	0.297	0.296
CV-AUC	0.675	0.660	0.657	0.658	0.650	0.673

Table E.9: Results of Structural Estimation for Health Outcomes. Relaxing the assumption that probability of getting the flu once vaccinated, cervical cancer after screening or lung cancer when not smoking is zero and assuming 0.01 instead. Panel A focuses on the decision to get a flu vaccine, Panel B on cervical screening and Panel C on smoking. It shows the coefficients of logit models. P_j denotes the difference between (unweighted) reported probabilities. Π_j is (the weighted probability difference) Π_j^R under RDU-Risk and PT-Risk and is Π_j^A under RDU-Ambiguity and PT-Ambiguity respectively. Π_j^{MP} denotes the weighted probability difference under MP. All specifications include controls for gender, ethnicity, age, a dummy for age greater than 65, education, marital status, number of children, a dummy for whether a person lives in a rural area, working, self-reported physical health, module order-fixed effects and region fixed effects for eleven government office regions. Bootstrapped standard errors (500 reps).

Panel A *Flu Vaccine*	SEU	Prospect Theory				MP
		RDU-Risk	RDU-Ambiguity	PT-Risk	PT-Ambiguity	
P_F	0.754**					
	(0.367)					
Π_F		0.955**	0.504	1.091***	0.502	
		(0.383)	(0.392)	(0.396)	(0.415)	
$\Pi_F(1-\lambda)$				0.073	-0.001	
				(0.080)	(0.098)	
Π_F^{MP}						0.602*
						(0.363)
Observations	828	828	828	828	828	828
McFadden R-squared	0.234	0.236	0.231	0.236	0.231	0.232
AIC	913.3	911.1	916.3	912	918.3	915
CV-RMSE	0.428	0.428	0.429	0.431	0.431	0.429
CV-AUC	0.770	0.772	0.767	0.766	0.763	0.768
Panel B *Cervical Screening*	SEU	Prospect Theory				MP
		RDU-Risk	RDU-Ambiguity	PT-Risk	PT-Ambiguity	
P_{CC}	0.671					
	(0.523)					
Π_{CC}		0.804	1.108*	0.617	1.026	
		(0.540)	(0.594)	(0.596)	(0.666)	
$\Pi_{CC}(1-\lambda)$				-0.099	-0.038	
				(0.136)	(0.157)	
Π_{CC}^{MP}						0.657
						(0.509)
Observations	424	424	424	424	424	424
McFadden R-squared	0.253	0.254	0.258	0.255	0.258	0.253
AIC	485.6	484.8	482.4	486	484.3	485.6
CV-RMSE	0.452	0.451	0.450	0.452	0.453	0.452
CV-AUC	0.744	0.747	0.750	0.745	0.746	0.744
Panel C *Smoking*	SEU	PT model				MP
		RDU-Risk	RDU-Ambiguity	PT-Risk	PT-Ambiguity	
P_{LC}	1.248*					
	(0.651)					
Π_{LC}		0.366	0.396	0.499	0.370	
		(0.644)	(0.548)	(0.645)	(0.554)	
$\Pi_{LC}(1-\lambda)$				0.124	-0.022	
				(0.125)	(0.160)	
Π_{LC}^{MP}						1.122*
						(0.623)
Observations	795	795	795	795	795	795
McFadden R-squared	0.148	0.138	0.139	0.142	0.139	0.147
AIC	490.8	495.9	495.7	495.8	497.7	491.7
CV-RMSE	0.296	0.296	0.296	0.296	0.297	0.296
CV-AUC	0.675	0.660	0.657	0.658	0.650	0.673

Table E.10: Results of Structural Estimation for Health Outcomes. Relaxing the assumption that probability of getting the flu once vaccinated, cervical cancer after screening or lung cancer when not smoking is zero and setting this probability to estimated parameters from the literature instead. Panel A focuses on the decision to get a flu vaccine, Panel B on cervical screening and Panel C on smoking. It shows the coefficients of logit models. P_j denotes the difference between (unweighted) reported probabilities. Π_j is (the weighted probability difference) Π_j^R under RDU-Risk and PT-Risk and is Π_j^A under RDU-Ambiguity and PT-Ambiguity. Π_j^{MP} denotes the weighted probability difference under MP. All specifications include controls for gender, ethnicity, age, a dummy for age greater than 65, education, marital status, number of children, a dummy for whether a person lives in a rural area, working, self-reported physical health, module order-fixed effects and region fixed effects for eleven government office regions. Bootstrapped standard errors (500 reps).

Panel A *Flu Vaccine*	PT-Risk	PT-Ambiguity
$\hat{\Pi}_F^1$	1.274***	1.202***
	(0.427)	(0.436)
$\hat{\Pi}_F^2\lambda$	0.086	0.088
	(0.074)	(0.079)
Observations	828	828
McFadden R-squared	0.238	0.237
AIC	910.2	911.9
CV-RMSE	0.429	0.430
CV-AUC	0.768	0.767
Panel B *Cervical Screening*	PT-Risk	PT-Ambiguity
$\hat{\Pi}_{CC}^1$	0.667	1.155
	(0.653)	(0.725)
$\hat{\Pi}_{CC}^2\lambda$	-0.089	-0.043
	(0.128)	(0.119)
Observations	424	424
McFadden R-squared	0.255	0.258
AIC	486.5	484.7
CV-RMSE	0.452	0.452
CV-AUC	0.745	0.746
Panel C *Smoking*	PT-Risk	PT-Ambiguity
$\hat{\Pi}_{LC}^1$	0.721	0.730
	(0.693)	(0.701)
$\hat{\Pi}_{LC}^2\lambda$	0.321	0.410
	(0.269)	(0.290)
Observations	795	795
McFadden R-squared	0.155	0.158
AIC	489.3	488.0
CV-RMSE	0.296	0.295
CV-AUC	0.674	0.673
Panel D *Stock Market Participation*	PT-Risk	PT-Ambiguity
$\hat{\Pi}_S^1$	0.819*	0.532
	(0.468)	(0.514)
$\hat{\Pi}_S^2\lambda$	0.022	0.037
	(0.037)	(0.044)
Observations	806	806
McFadden R-squared	0.134	0.131
AIC	926.9	929.3
CV-RMSE	0.448	0.449
CV-AUC	0.678	0.676

Table E.11: Results of Structural Estimation under Non-Additive Prospect Theory (equation (16)). Panels A–C focus on health decisions (flu vaccination (F), cervical cancer screening (CC), and smoking (LC)), and Panel D on stock market participation (S). The table reports coefficients from logit models. $\hat{\Pi}_j^1$ denotes the weighted probability difference for the gain component and $\hat{\Pi}_j^2\lambda$ denotes the weighted probability difference for the loss component scaled by the individual-specific loss aversion parameter λ for choice scenario $j \in \{F, CC, LC, S\}$ as obtained from the non-additive prospect theory in equation (17) in section B.3.1. All specifications include controls for gender, ethnicity, age, a dummy for age greater than 65, education, marital status, number of children, a dummy for whether a person lives in a rural area, working, self-reported physical health, module order fixed effects and region fixed effects for eleven government office regions. Bootstrapped standard errors (500 reps).

Panel A *Flu Vaccine*	SEU	Power (RDU-Risk)	Power (RDU-Ambiguity)
P_F	0.754**		
	(0.367)		
$\Pi_F^{Power-Risk}$		0.702**	
		(0.354)	
$\Pi_F^{Power-Ambiguity}$			0.872**
			(0.393)
Observations	828	828	828
McFadden R-squared	0.234	0.233	0.235
AIC	913.3	913.7	911.6
CV-RMSE	0.428	0.428	0.428
CV-AUC	0.770	0.769	0.772
Panel B *Cervical Screening*	SEU	Power (RDU-Risk)	Power (RDU-Ambiguity)
P_{CCj}	0.671		
	(0.523)		
$\Pi_{CC}^{Power-Risk}$		0.196	
		(0.502)	
$\Pi_{CC}^{Power-Ambiguity}$			0.663
			(0.587)
Observations	424	424	424
McFadden R-squared	0.253	0.250	0.252
AIC	485.6	487.3	485.8
CV-RMSE	0.452	0.454	0.451
CV-AUC	0.744	0.740	0.745
Panel C *Smoking*	SEU	Power (RDU-Risk)	Power (RDU-Ambiguity)
P_{LC}	1.248**		
	(0.651)		
$\Pi_{LC}^{Power-Risk}$		0.593	
		(0.603)	
$\Pi_{LC}^{Power-Ambiguity}$			1.071
			(0.687)
Observations	795	795	795
McFadden R-squared	0.148	0.140	0.145
AIC	490.8	495.2	492.3
CV-RMSE	0.296	0.296	0.296
CV-AUC	0.675	0.652	0.671

Table E.12: Results of Structural Estimation for Health Outcomes under power functional form for the probability-weighting function under risk (col 2) and the weighting function under ambiguity (col 3). Panel A focuses on the decision to get a flu vaccine, Panel B on cervical screening and Panel C on smoking. It shows the coefficients of logit models. P_j denotes the difference between (unweighted) reported probabilities. Π_j is (the weighted probability difference) Π_j^R under RDU-Risk and is Π_j^A under RDU-Ambiguity. All specifications include controls for gender, ethnicity, age, a dummy for age greater than 65, education, marital status, number of children, a dummy for whether a person lives in a rural area, working, self-reported physical health, module order-fixed effects and region fixed effects for eleven government office regions. Bootstrapped standard errors (500 reps).

Panel A *Lottery Participation*	SEU	Power (RDU-Risk)	Power (RDU-Ambiguity)
P_L	1.992*		
	(1.036)		
$\Pi_L^{Power-Risk}$		1.558***	
		(0.380)	
$\Pi_L^{Power-Ambiguity}$			1.327***
			(0.287)
Observations	825	825	825
McFadden R-squared	0.0720	0.0875	0.0869
AIC	1048	1032	1032
CV-RMSE	0.472	0.468	0.467
CV-AUC	0.611	0.632	0.635
Panel B *Stock Market Participation*	SEU	Power (RDU-Risk)	Power (RDU-Ambiguity)
P_S	0.705*		
	(0.374)		
$\Pi_S^{Power-Risk}$		0.090	
		(0.262)	
$\Pi_S^{Power-Ambiguity}$			0.097
			(0.251)
Observations	806	806	806
McFadden R-squared	0.133	0.128	0.128
AIC	925.4	930	930
CV-RMSE	0.448	0.449	0.450
CV-AUC	0.681	0.674	0.673

Table E.13: Results of Structural Estimation for Financial Outcomes under power functional form for the probability weighting function under risk (col 2) and under ambiguity (col 3). Panel A focuses on lottery participation, Panel B on stock market participation. It shows the coefficients of logit models. P_j denotes the difference between (unweighted) reported probabilities. Π_j is (the weighted probability difference) Π_j^R under RDU-Risk and is Π_j^A under RDU-Ambiguity. All specifications include controls for gender, ethnicity, age, a dummy for age greater than 65, education, marital status, number of children, a dummy for whether a person lives in a rural area, working, self-reported physical health, module order-fixed effects and region fixed effects for eleven government office regions. Bootstrapped standard errors (500 reps).

Panel A *Flu Vaccine*	SEU	PT model RDU-Risk	 RDU-Ambiguity	MP
Prob	1.446**	1.532***	1.313**	1.267**
	(0.579)	(0.593)	(0.642)	(0.568)
Prob × Risk Averse	-1.133	-1.191	-0.961	-1.148
	(0.774)	(0.809)	(0.783)	(0.741)
Risk Averse	0.219	0.323	0.342	0.209
	(0.300)	(0.352)	(0.414)	(0.286)
Observations	806	806	806	806
McFadden R-squared	0.237	0.237	0.235	0.236
AIC	892	891.9	894	893.5
CV-RMSE	0.430	0.430	0.431	0.431
CV-AUC	0.770	0.770	0.768	0.768
Panel B *Cervical Screening*	SEU	PT model RDU-Risk	 RDU-Ambiguity	MP
Prob	1.579	1.591	1.389	1.386
	(1.476)	(1.278)	(1.088)	(1.342)
Prob × Risk Averse	-0.971	-0.953	-0.070	-0.762
	(1.640)	(1.456)	(1.235)	(1.503)
Risk Averse	0.076	0.147	-0.041	0.023
	(0.450)	(0.516)	(0.586)	(0.436)
Observations	414	414	414	414
McFadden R-squared	0.257	0.258	0.265	0.257
AIC	477.4	477.1	473.3	477.6
CV-RMSE	0.460	0.456	0.453	0.459
CV-AUC	0.732	0.741	0.749	0.733
Panel C *Smoking*	SEU	PT model RDU-Risk	 RDU-Ambiguity	MP
Prob	1.617	1.582	1.181	1.356
	(1.129)	(1.232)	(1.250)	(1.032)
Prob × Risk Averse	-0.732	-1.070	-0.503	-0.524
	(1.275)	(1.424)	(1.510)	(1.205)
Risk Averse	0.315	0.432	0.056	0.169
	(0.896)	(0.848)	(0.793)	(0.835)
Observations	776	776	776	776
McFadden R-squared	0.144	0.140	0.137	0.142
AIC	486.1	488.2	489.3	487
CV-RMSE	0.297	0.298	0.298	0.297
CV-AUC	0.652	0.645	0.635	0.650

Table E.14: Results of Structural Estimation with Risk Aversion Interactions for Health Outcomes. Panel A focuses on the decision to get a flu vaccine, Panel B on cervical screening and Panel C on smoking. The table shows coefficients from logit models with interactions between probability weighting and risk aversion. All specifications include controls for gender, ethnicity, age, a dummy for age greater than 65, education, marital status, number of children, a dummy for whether a person lives in a rural area, working, self-reported physical health, module order-fixed effects and region fixed effects for eleven government office regions. Bootstrapped standard errors (500 reps).

Panel A *Lottery Participation*	SEU	Prospect Theory RDU-Risk	 RDU-Ambiguity	MP
Prob	1.316	0.897	2.722**	1.176
	(1.946)	(1.362)	(1.124)	(1.753)
Prob × Risk Averse	1.069	2.961	0.539	1.402
	(2.659)	(2.145)	(1.424)	(2.547)
Risk Averse	-0.220	-0.415*	-0.236	-0.236
	(0.206)	(0.245)	(0.314)	(0.206)
Observations	803	803	803	803
McFadden R-squared	0.0733	0.0866	0.0976	0.0748
AIC	1027	1014	1002	1026
CV-RMSE	0.474	0.467	0.465	0.473
CV-AUC	0.609	0.636	0.648	0.612
Panel B *Stock Market Participation*	SEU	Prospect Theory RDU-Risk	 RDU-Ambiguity	MP
Prob	1.482**	2.117***	1.016	1.449**
	(0.618)	(0.783)	(0.944)	(0.610)
Prob × Risk Averse	-1.229*	-1.862**	-0.625	-1.206
	(0.731)	(0.901)	(1.093)	(0.793)
Risk Averse	0.172	0.385	-0.020	0.143
	(0.310)	(0.359)	(0.412)	(0.304)
Observations	784	784	784	784
McFadden R-squared	0.140	0.142	0.135	0.139
AIC	895.9	894.1	900.7	896.5
CV-RMSE	0.446	0.445	0.448	0.446
CV-AUC	0.686	0.686	0.680	0.685

Table E.15: Results of Structural Estimation with Risk Aversion Interactions for Financial Outcomes. Panel A focuses on lottery participation, Panel B on stock market participation. The table shows coefficients from logit models with interactions between probability weighting and risk aversion. All specifications include controls for gender, ethnicity, age, a dummy for age greater than 65, education, marital status, number of children, a dummy for whether a person lives in a rural area, working, self-reported physical health, module order-fixed effects and region fixed effects for eleven government office regions. Bootstrapped standard errors (500 reps).

F Appendix: Additional Figures

This section presents additional figures.

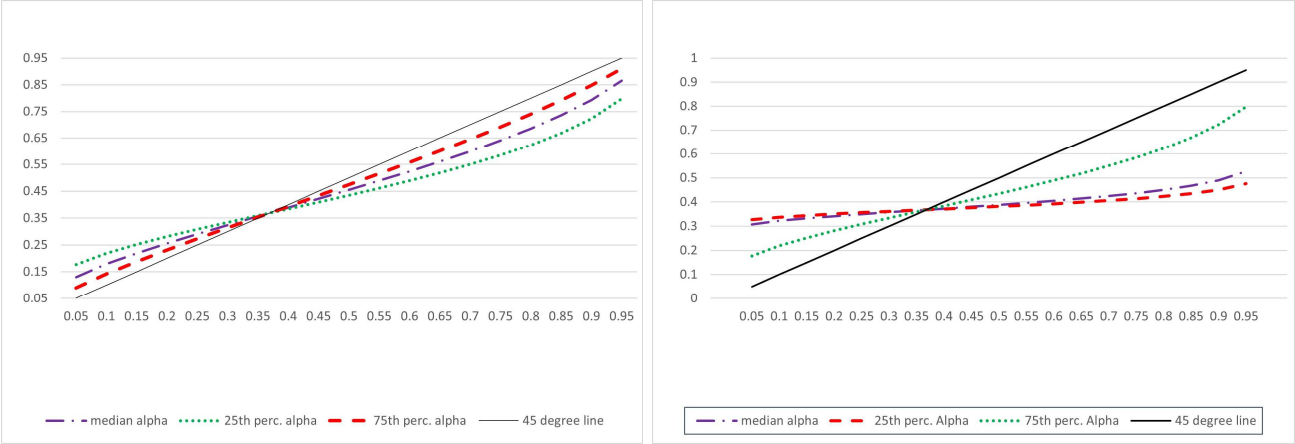


Figure F.1: Left panel: Illustration of median probability weighting function under risk ($\alpha_R = 0.65$), 25-th percentile ($\alpha_R = 0.5$) and 75-th percentile ($\alpha_R = 0.8$). Right panel: Illustration of median probability weighting function under ambiguity ($\alpha_A = 0.15$) 25-th percentile ($\alpha_A = 0.1$) and 75-th percentile ($\alpha_A = 0.5$).

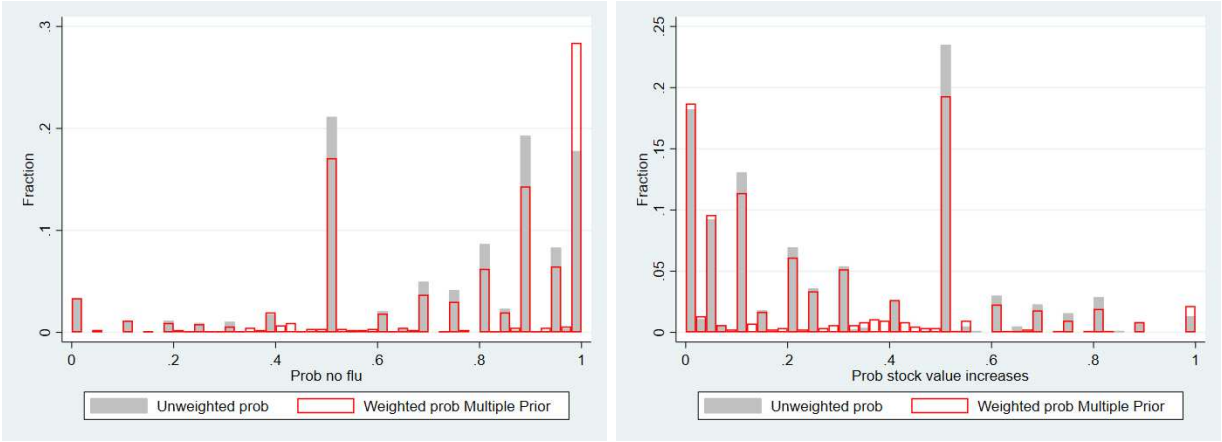


Figure F.2: Distribution of weighted probabilities for the MP model. Left panel: probability of not getting the flu; Right panel: probability of stock value increases.

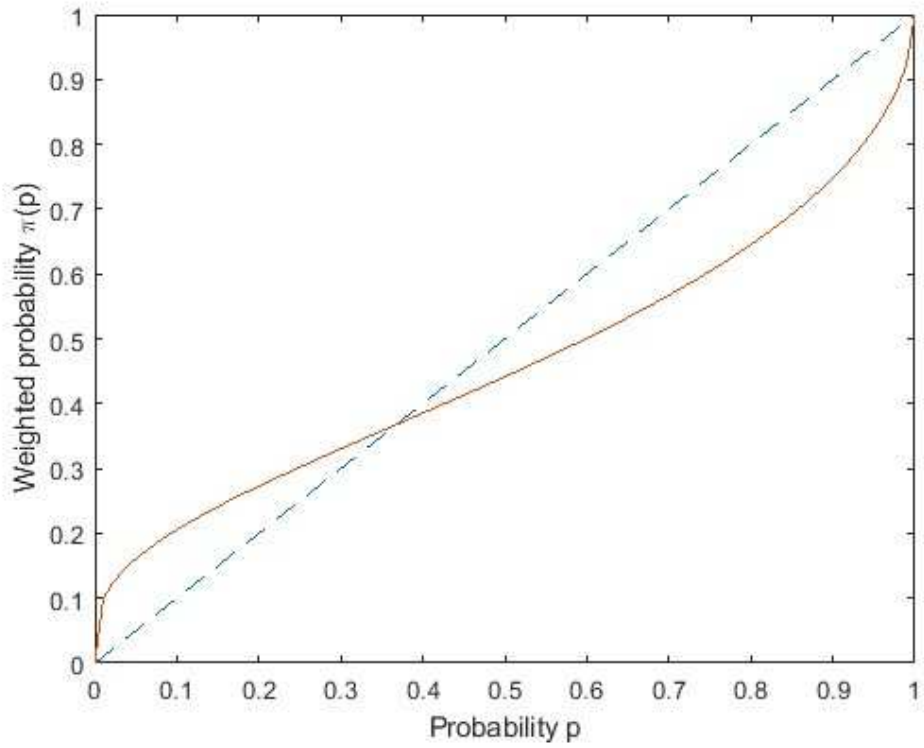


Figure F.3: The commonly found inverse-S shaped probability weighting function (solid curve). The dashed line is the 45-degree line.

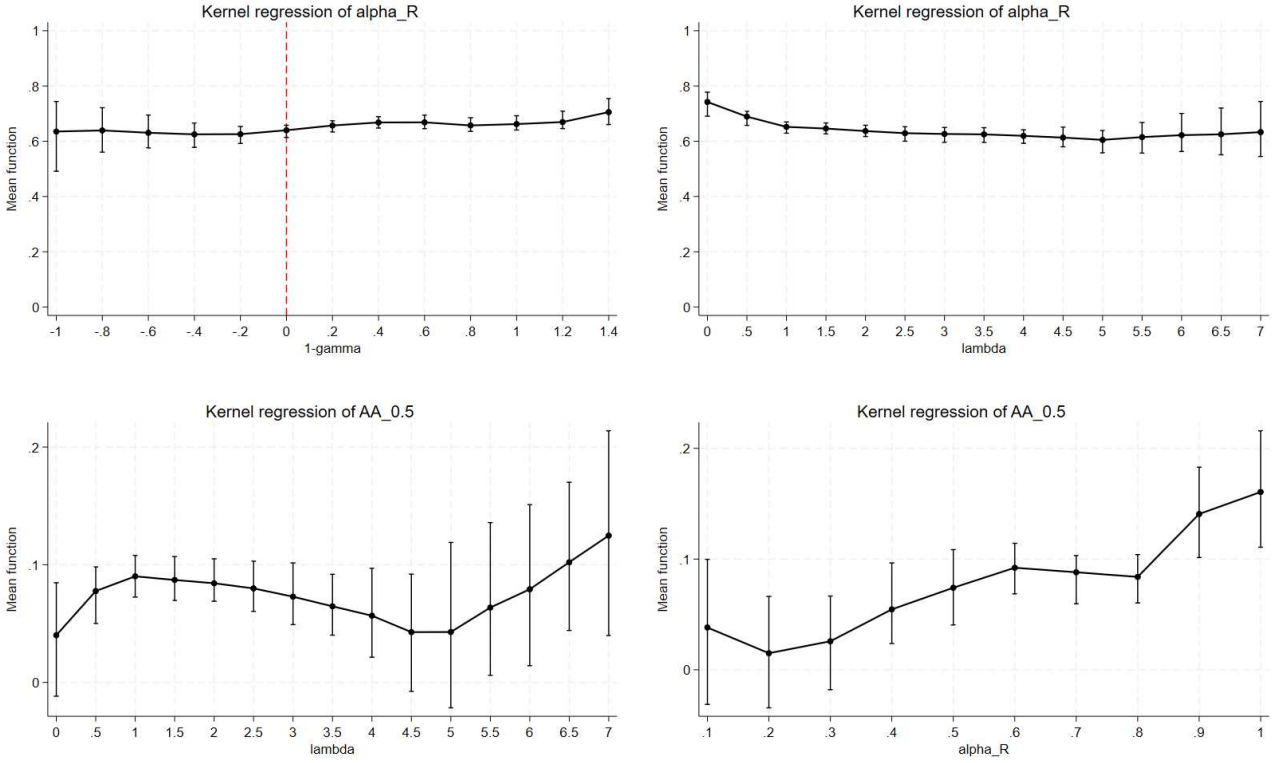


Figure F.4: Top panel: Kernel density of the probability weighting measure α_R for different levels of $1-\gamma$ (top left panel) and λ (top right panel). Bottom panel: Kernel density of the local ambiguity aversion measure $AA_{0.5}$ for different levels of λ (bottom left panel) and α_R (bottom right panel).

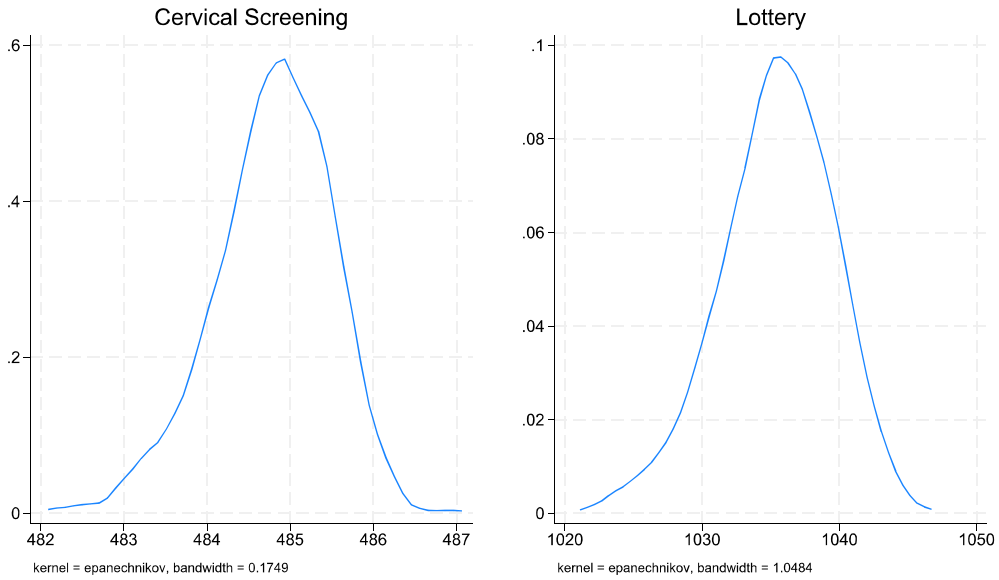


Figure F.5: Distribution of AIC under random allocation of α. Each respondent is allocated a random α from the empirical distribution of α_R. 500 repetitions. The graph shows the kernel density of the AICs obtained from estimation of equation (10).

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