Journal of Risk and Uncertainty (2025) 70:147–170
https://doi.org/10.1007/s11166-024-09448-0

An experiment on outcome uncertainty

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Accepted: 10 December 2024 / Published online: 2 April 2025

Abstract
We report the evidence of a multi-stage lab experiment on individual decision making under ambiguity, where the latter is characterized by the (partial or) absence of information on some monetary values in the support of the lottery distributions. This complements the standard treatment of uncertainty where decision makers know the monetary prizes, but probabilities are uncertain. We use both a structural and a non-structural approach when analyzing subjects' behavior under risk, compound risk, and outcome ambiguity. Our main finding is that subjects are risk-averse and ambiguity lovers in that they evaluate more optimistically uncertain payoffs under ambiguity compared to compound risk. We also study how subjects evaluate scenarios with uncertain outcomes: 60% of choices are consistent with the Expected Utility paradigm, while 40% of them are better described by a heuristic we label as "naïve," in which the order of integration of Expected Utility is reversed (that is, they first form a point estimate of the uncertain payoffs, and then they evaluate the lotteries' expected utility). Finally, we also find that risk and ambiguity aversion are positively correlated.

Keywords Experimental economics · Individual decision making · Risk · Compound risk and ambiguity · Uncertain outcomes

JEL classification D81 · D90

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1 Introduction

In its common usage, the term *uncertainty* refers to some incomplete objective information on multiple aspects of the environment that may affect the overall consequences of our decisions: we may be uncertain about the nature or magnitude of some future events, their likelihood, their timing, etc.… However, dating back from the seminal work of Knight (1964), the economic discussion within decision theorists has been mostly confined to a very specific kind of uncertainty, that is, uncertainty about *probabilities*: *"Even though the business man could not know in advance the results of individual ventures, he could operate and base his competitive offers upon accurate foreknowledge of the future if quantitative knowledge of the probability of every possible outcome can be had…*" (Knight, 1964, p. 199). Building upon this idea of "Knightian uncertainty", Ellsberg (1961) associates the term *ambiguity* with situations in which individuals seem to act upon criteria that violate a well-defined process of formation of (subjective) probabilities.

These influential works have radically inspired the—nowadays substantial, both theoretical and experimental—literature on decision making under ambiguity, which relies on the idea that uncertainty about probabilities is the only relevant domain of ambiguity. This is a natural implication of the Bayesian approach: whatever uncertain environment can be reduced to a simple lottery (see Savage, 1954, among others) where each uncertain state can be associated with some (objective or subjective) probability. For example, a lottery that gives "*X* or nothing" with a 50:50 chance (when *X* could be either \$5 or \$10, with some probability *p* and *1-p*, respectively), under Von Neumann and Morgensten's (1953) axiom of *Reduction Of Compound Lotteries* (ROCL, see Segal, 1990), should be considered as equivalent to a simple lottery which gives payoffs 0, 5, and 10 with probability $\frac{1}{2}$, $\frac{p}{2}$, and $\frac{1-p}{2}$, respectively. This explains why ROCL allows to frame a situation of uncertain payoffs in terms of a situation of uncertain probabilities. By the same token, a similar argument can be applied for other dimensions that may be the object of ambiguity in real-life decisions (take, for example, time of delivery of payments).

However, the experimental literature on these matters has shown consistent violations of ROCL in a wide variety of economic domains. Halevy (2007), for example, reports violations of ROCL in an experiment based on Ellsberg (1961). This implies that subjects who face compound lotteries are not always able of reducing them properly. The importance of studying compound lotteries has been also emphasized by Abdellaoui et al. (2015): people do not always know how to compound and, because of this, compound risk has to be distinguished from simple risk alone. Similarly, people do not always know how to assign subjective probabilities to uncertain events and, because of this, compound risk has to be distinguished from ambiguity. In this respect, Harrison et al. (2015) show violations of ROCL in experiments when more than one decision is played by subjects and only one is randomly paid (this is, actually, the standard protocol for payment in current multi-stage experimental practice, including this paper). They conclude that subjects potentially view simple and compound random processes as different. This is directly related with what we do in this paper, by considering uncertainty about payoffs as distinct from uncertainty about probabilities. This would imply that it is essential not only to compare risk with ambiguity, but also to consider the intermediate case of compound risk.

If ROCL has limited empirical content, then a natural question arises: *can we treat ambiguity about outcomes as equivalent as ambiguity about probabilities?* The goal of this paper is exactly to study how individuals behave when decisions are framed as situations where uncertainty is associated to outcomes (i.e., monetary payoffs), rather than probabilities.[1] Specifically, we want to study (if and) how the level of information about outcomes affects subjects' behavior. To this aim, we report the evidence from a multi-stage experiment in which we randomize, between subjects, the level of information over some monetary prizes of the lotteries subjects are asked to choose between. In the *risk* treatment (TR2) subjects perfectly observe all prizes; in the *compound risk* treatment (TR1) they do not know the actual prizes but are informed about their ranking and that they are draws from a uniform distribution; in the *ambiguity* treatment (TR0) they just know their ranking. The experiment develops along two (order balanced) stages. In Stage 1, we replicate the classic Random Lottery Pair choice experiment (RLP, Hey & Orme, 1994) with (un)certain prizes, depending on the treatment (25 rounds). Stage 1 is built around choices between two lotteries over four fixed monetary prizes (between €0 and €15 in our experiment). In our treatments TR0 and TR1 we tell subjects that the intermediate prizes, call them Y and X, are integers strictly between €0 and €15, with $Y < X$. In the compound risk treatment, TR1, subjects are informed about the distribution of Y and X; in the ambiguity treatment, TR0, they are not. In Stage 2, we follow Fox and Tversky (1995) by eliciting subjects' Certainty Equivalent (CE)—under the same information conditions—of the 50 lotteries used in Stage 1. While RLP has been proved to be ideal protocol to identify the relevant parameters of our structural estimations, we use CE elicitation data to provide non-parametric tests and reduced form regressions that simply rely on the comparison of the CE distributions.

In this way, we can read our experimental evidence by way of two complementary statistical techniques. First, we compare subjects' CE elicited in Stage 2 under the three information conditions and look for treatment effects using non-parametric tests and running random-effect panel regressions. Using our full dataset from both Stage 1 and Stage 2, we also perform some structural estimations where we estimate the curvature of a standard Constant Relative Risk Aversion (CRRA) utility function (which identifies, in our estimation strategy, subjects' risk attitudes) and—simultaneously, in the compound risk and ambiguity treatments TR1 and TR0—the curvature of a probability weighting function associated with the (subjective in TR0, objective in TR1) beliefs over realizations of Y and X. Intuitively, a concave (convex) probability weighting function is associated with an optimistic (pessimistic) attitude to the probabilities of the uncertain possible values.

When studying subjects' beliefs over the uncertain outcomes, Y and X, we consider two alternative identification strategies: one—which we call *sophisticated*—follows a standard process of expected utility maximization with subjective

[1] This choice environment has been studied, from a theoretical perspective, by Herrero and Villar (2014).

probabilities; while in the other—which we call *naïve*—the order of integration is reversed: subjects are assumed *i)* first, to form subjective point beliefs over Y and X and then *ii)* maximize the expectation (objective, since prize probabilities are known in all three information conditions) of their value function. The sophisticated specification is the one established as normative by the literature. On the other hand, we think of our naïve specification as a realistic behavioral heuristic that subjects may use in the decision setting under consideration.[2]

Our main findings are that our subjects are *risk averse* and *ambiguity lovers*: they are more optimistic about the values of Y and X under ambiguity rather than compound risk. We also estimate the ex-ante probability that subjects' decisions are being generated by a naïve vs. a sophisticated cognitive frame. In this respect, approximately 50% of our subjects' choices follow a sophisticated evaluation and the remaining 50% follow a naïve evaluation. Finally, we also run subject-by-subject estimations of our structural models to study more in detail heterogeneity in attitudes toward risk and ambiguity. Here we find that subjects' risk aversion (measured by the curvature of the postulated value function) and ambiguity aversion (measured by the curvature of our postulated probability weighting function) are positively correlated. This means that more risk averse individuals are also more pessimistic about the realization of the uncertain payoffs. As for observable heterogeneity, that is, the source of heterogeneity we can distill from our debriefing questionnaire, we support the existing evidence on gender risk aversion effect (in that females are more risk averse than males, see Charness & Gneezy, 2012, among others) and cognitive ability effects (in that more reflective subjects are more risk averse, see Cueva et al., 2016, among others).

The remainder of the paper is arranged as follows. In Section 2 we survey the literature which we consider relevant for our research. Section 3 presents our experimental design, while in Section 4 we describe our dataset and provide some preliminary descriptive statistics as well as our reduced form results. In Section 5 we present our structural results, including pool estimates of the naïve and sophisticated model (Section 5.4) together with subject-by-subject estimates (Section 5.5). Finally, Section 6 concludes, followed by appendices containing further statistical evidence, additional details of our design and translation from Spanish of the experimental instructions.

2 Related literature

Our paper contributes to the literature on decision making under ambiguity, where—in case ROCL does not hold—uncertainty about outcomes cannot be reduced to uncertainty about probabilities. As for the model identification, we use an approach

[2] In the Appendix we also consider a third behavioral alternative, which we call *super naïve,* where we do not assume that subjects are assigning subjective probabilities to all the possible values of Y and X when they evaluate the lotteries but form point expectations of Y and X directly (results in Table A.8). As Table A.9. shows, our structural estimates of the naïve and super naïve models are—for all practical purposes—indistinguishable.

which is similar to that of Gneezy et al. (2015): although the estimation of all parameters is simultaneous, we identify the curvature of the value function using the observations of our risk treatment TR2 (under a standard expected utility framework). By contrast, attitudes toward compound risk and ambiguity are reflected by shifts in the curvature of the weighting function of the probabilities of the uncertain values Y and X. To ease identification and interpretation of results, we follow Andersen et al. (2014) and impose exponential weighting: agents can only be either optimistic/neutral/pessimistic when estimating the likelihood of the uncertain prizes.

Our paper also contributes to the (scarce) experimental literature that enlarges the scope of ambiguity outside the frame of uncertainty about probabilities. There are several finance papers that try to analyze if and how imprecision in outcomes, apart from in probabilities, may affect market conditions. Extending "imprecision" to the outcomes dimension has resulted in mixed evidence. Gonzalez-Vallejo et al. (1996) and Kuhn and Budescu (1996) find "vagueness aversion" in both probabilities and outcomes. Similar to our result of ambiguity seeking, Budescu et al. (2002) find evidence for "vagueness seeking" in outcomes through a pricing task, and Du and Budescu (2005) find similar result by eliciting CE.[3]

The closest references to our study are the experimental papers of Eichberger et al. (2015) and Eliaz and Ortoleva (2016). Both papers build their experimental design upon the classic Ellsberg's (1961) experiment on lottery choices under ambiguity. Eichberger et al. (2015) introduce a novel source of uncertainty associated to outcomes. They follow Ellsberg's urn experiment with an important modification: prizes are delivered in an envelope, and subjects do not know their exact amount. They fix two different amounts that subjects may receive and run two treatments: compound risk and ambiguity. In the compound risk treatment subjects know the probability of receiving each of the two prizes; in the case of ambiguity they do not. In the experiment, the two sources of uncertainty (probabilities and prizes) are independent, meaning that the uncertainty associated to probabilities and the uncertainty associated to prizes are not correlated. They find that fewer subjects prefer to bet on events with known probabilities once the second source of uncertainty (outcomes) is in place, compared to the classic Ellsberg's frame. By contrast, in our setting subjects—depending on the treatment—cannot avoid uncertainty. The lower preference for certain events when a second source of uncertainty found by Eichberger et al. (2015) resembles our finding of more optimistic subjective evaluations of uncertain outcomes under ambiguity compared with compound risk. Eliaz and Ortoleva (2016) also build their experimental design upon Ellsberg's (1961) urn experiment introducing three sources of uncertainty: outcomes, probabilities, and time. Their modification of Ellsberg's (1961) original setting consists of using the urn composition not only to specify the winning probabilities, but also the amount of the prizes and time of delivery. Therefore, the three sources of ambiguity are perfectly correlated. Under these conditions, they find that no uncertainty is preferred to uncertainty on any single dimension and to uncertainty in multiple dimensions. That is, when

[3] Onay et al. (2013) also show evidence for "imprecision seeking" in outcomes in pricing tasks and, more recently, Huber and Rose (2019) also find imprecision seeking in outcomes using reservation prices.

subjects can escape from uncertainty, they do so. However, when subjects cannot escape from uncertainty, they prefer situations with correlated uncertainty in more than one dimension than uncertainty in a single dimension. They also find that, when only probabilities are uncertain, only 11% of the participants choose the option with more exposure to uncertainty. However, when the prize is uncertain as well as the winning probabilities, more than half of the participants who chose the sure option in the original choice problem now switches to the uncertain one.

While ambiguity aversion is assumed in many applications of economics and finance, there are some studies that have found, as well as ours, heterogeneous attitudes to ambiguity. This is the case of Halevy (2007), where 35% of the subjects are categorized as ambiguity lovers. Bossaerts et al. (2010) and Tymula et al. (2013) reinforce the importance of taking into account the fact that ambiguity attitudes are heterogeneous across agents. Kocher et al. (2018) find love for ambiguity when lotteries involve monetary losses or small probabilities. Our results are also in line with those of Andersen et al. (2014), who find two underlying forces moving in opposite directions when analyzing subjects' evaluation of lotteries and subjective probabilities: a concave curvature of the utility function (indicating risk aversion) and a concave curvature of the weighting function (indicating an optimistic evaluation of winning probabilities).

3 Experimental design

The two protocols that are at the basis of our experimental design are CE elicitation and RLP. With respect to the former, the CE elicitation protocol has been used, among others, by Tversky and Kahneman (1992) and Fox and Tversky (1995). This protocol consists of finding a certain amount whose value is, for the subject, equivalent to the value of the lottery under consideration. These CE help us to study, non-parametrically, how subjects' behavior differs across our (informational) treatments: risk, compound risk, and ambiguity. About the latter, the RLP protocol has been proposed by Hey and Orme (1994). This protocol consists of eliciting attitudes under risk by proposing subjects' binary choices over lotteries with the same prize support (four prizes, from €0 to €15, in our case). These lotteries are random combinations of probabilities associated to the four possible prizes, probabilities that are always multiples of 1/8 in the interval [0,1]. We modify the standard RLP setting by introducing uncertainty over the two intermediate prizes, denoted by Y and X, with $Y < X$.

3.1 Sessions

We run 12 experimental sessions at the Laboratory for Theoretical and Experimental Economics (LaTEx) at the Universidad de Alicante. A total of 279 students has been recruited among the undergraduate population using the Orsee recruitment platform (Greiner, 2004). Subjects were provided with a written copy of the instructions, which were read aloud by the experimental proctor—the same person for all sessions—and we let subjects ask about any doubt they may have had. All sessions ended with a debriefing questionnaire to collect subjects' individual socio-demographics and psycho-social attitudes (see Section 3.5 for details). Each session lasted, on average, 90 minutes. The experimental sessions were computerized.[4]

3.2 Treatments

The experimental layout consists in two stages, order balanced across sessions[5]:

1 **Stage 1:** Random Lottery Pair elicitation protocol (RLP, Hey & Orme, 1994): 25 rounds.
2 **Stage 2:** Certainty Equivalent elicitation (CE, Tversky & Kahneman, 1992): 50 rounds.

Both stages are built around 50 "basic lotteries", i.e., probability distributions over four monetary prizes, €0 < €Y < €X < €15, paired in 25 binary choices. Treatment conditions (randomized between-subjects) are defined with respect to the level of information about the intermediate payoffs, Y and X. In all sessions, for all subjects, Y and X are integers from €1 to €14, drawn from a uniform distribution without replacement.

- In the **Risk** treatment (TR2) Y and X are communicated to subjects at all times.
- In the **Compound Risk** treatment (TR1) we acknowledge that $X > Y$ are integers drawn from a uniform distribution between 1 and 14.
- In the **Ambiguity** treatment (TR0) nothing is told to subjects (neither the values, X and Y, nor the stochastic process that generates them), what they only know is that $X > Y$ are integers between 1 and 14.

Subjects know, as it is explained in the instructions, that they face the same uncertain payoffs Y and X during the entire experiment.

3.3 Stage 1: RLP

In Stage 1, subjects are asked to go through a sequence of 25 binary choices in a (between-subject) random order. The 25 pair of probability distributions are exactly those of Hey and Orme (1994) randomized over four sets of fixed prizes: (0,Y,X), (0,Y,15), (0,X,15), and (Y,X,15); which means that all the lotteries are designed to have a support of a maximum of three prizes.[6]

The user interface of Phase 1 is shown in Fig. 1. Two lotteries are displayed on the screen: each prize probability corresponds to a specific color and this color assignment is kept throughout all rounds. Subjects are requested to select their preferred lottery by pressing the corresponding button. By analogy with Hey and Orme

[4] The experiment was programmed and conducted with the software z-Tree (Fischbacher, 2007). Translated versions of the instructions can be found in Appendix.

[5] Mann-Whitney non parametric statistics cannot reject the null of no difference in the distributions of lottery choices (Stage 1) and CE (Stage 2) conditional on the order.

[6] Table A.1 in the Appendix reports the exact lottery pairs used in the experiment.

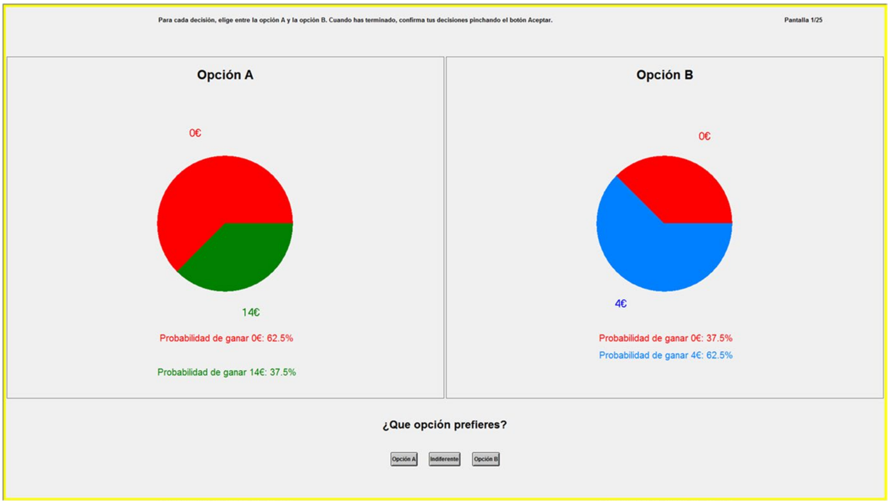

Fig. 1 Stage 1 user interface for the Risk treatment

(1994), subjects are not forced to express a strict preference for either lottery, i.e., they are also allowed to express indifference.[7]

3.4 Stage 2: CE elicitation

In Stage 2, subjects are asked to elicit their CE for each of the 50 basic lotteries played in Stage 1. This is done by pairing the lottery in question ("Option B") with a fixed amount, from €0 to €15. Subjects have to make 16 decisions per screen. We compute the CE of a lottery as the amount under Option A the first time they switch from B to A, minus €0.5 (see Fig. 2).

3.5 Debriefing and payment

A debriefing questionnaire was administered at the end of the experiment consisting of: i) questions about socio-demographics, such as gender, parents' education and wealth, educational achievement, field of study, weekly budget, and Body Mass Index (BMI, Keys et al., 1972); ii) questions about subjects' personality measured through a reduced version of the classic Big Five test (John et al., 1991); iii) questions about subjects' cognitive ability using the Cognitive Reflection Test (CRT, Frederick, 2005).[8]

[7] Expressed indifference corresponds to 4.07% of total observations: 5.3% (3.02%) [3.96%] as for treatment TR2 (TR1) [TR0], respectively. Differences between TR0 and TR1 (TR0 and TR2) [TR1 and TR2] are statistically significant at a 10% (5%) [1%] level under a non-parametric Mann-Whitney statistics, respectively.

[8] Big Five and CRT tests are described in the Appendix.

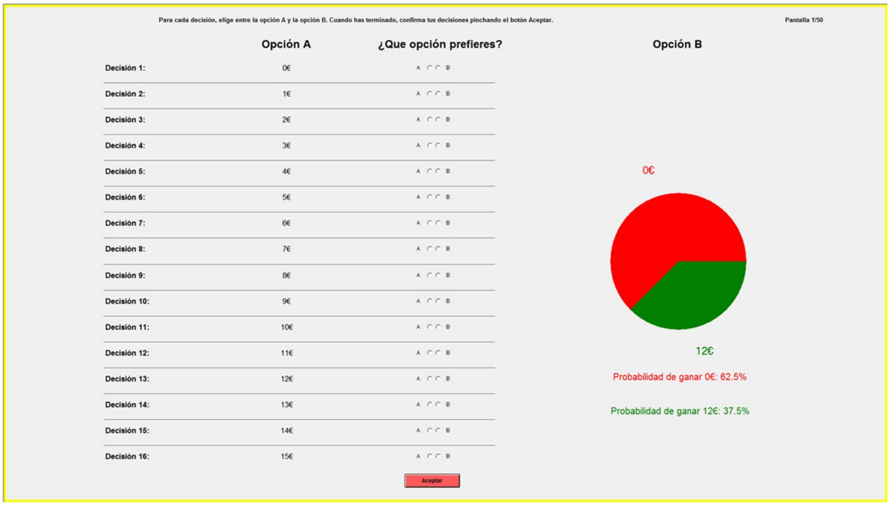

Fig. 2 Stage 2 user interface for the Risk treatment

One decision at random was selected for each stage at the end of the experiment and subjects received the sum of the monetary payoffs associated with the two payoff relevant decisions. Subjects received, on average, €14. No feedback was delivered at any time along the experiment.

4 Descriptive statistics and reduced form results

We have a sample of 279 subjects with 89 (94) [96] subjects playing under TR2 (TR1) [TR0], respectively. Table A.2. (in the Appendix) shows some descriptive statistics of our sample: 49% are female and the average age is 23 years old ±4 s.d. Table A.2. also provides information on individual characteristics and CRT and BIG5 personality test scores. As expected, descriptive personal variables are not statistically different at a 5% level across treatments.

4.1 Consistency

To the extent to which in the structural estimations of Section 5 we frame subjects' behavior within the realm of specific parametric models of behavior (along with all the implicit auxiliary assumptions that come with them), we are interested in a prior check on whether observed behavior satisfies basic consistency conditions compatible with our postulated theoretical setup and (if and how) inconsistency is linked with ambiguity or other individual characteristics.

Standard behavioral restrictions (namely, first-order stochastic dominance and transitivity) require that subjects' decisions in Stage 2 (CE elicitation) satisfy two conditions (remember that they take 16 decisions per screen):

Condition 1. They start (end) by choosing the lottery (sure) option, since it is first-order stochastically dominated by the sure payment (lottery) in the first (last) round, respectively.

Condition 2. They switch only once at some point along the sequence (due to transitivity).

In this respect, around 15% of the total number of choices are "inconsistent" (13.4% of choices under TR0, 15.2% under TR1, and 16.3% under TR2, respectively) in that either condition 1 or 2 are not met. Differences between TR2 and TR1 are not statistically significant according to the non-parametric Mann-Whitney test (MW). Differences between TR2 and TR0 are significant at a 1% level. Differences between TR1 and TR0 are statistically significant at a 5% level. It seems that inconsistencies are more frequent the more information provided.

We use a linear probability model (LPM) with random effects using the probability of inconsistent answers as dependent variable. LPM results are presented in Table A.3. in the Appendix and show that no variable has a significant effect on the probability of inconsistent answers. In the remainder of the paper, we shall run our regressions using these variables as controls.

We assume that 10% or less of inconsistent answers on behalf of a subject may be due to distraction or misunderstanding in a specific moment along the experiment, therefore, for the subsample we consider "consistent observations", by completely dropping subjects' stage when more than five periods—over 50—are inconsistent. For our regressions in Sections 4.2 and 4.3, we use only Stage 2 consistent observations, to the extent to which, in case of multiple switching, CE cannot be calculated precisely. In Section 5, instead, we use observations from both stages 1 and 2 and we present results both for the entire pool sample, as well as for consistent observations.

4.2 Non-structural results

In the reminder of this paper, without loss of generality, we normalize prizes within the unit interval. Given that in our three treatments the same 50 lotteries are played, we can analyze subjects' behavior non parametrically, comparing the CE by lottery and treatment. In Table 1, columns 2–4 (9–11) report the average CE by treatment of the 25 left (right) lotteries, respectively. CE are ordered by greyscale (the lighter, the greater). Columns 5–7 (12–14) report the significance level of the Mann-Whitney tests where a pairwise comparison between treatment pairs is made under the null that assumes equal average CE between treatments.

We can appreciate how the CE of the lotteries are, in most cases, greater in TR0 than in TR1, and greater in TR1 than in TR2. This shows that subjects seem to evaluate lotteries more optimistically the lower the level of information provided about the intermediate prizes. MW tests reject the null across treatments with a 5% significance level for most lotteries. The least evident difference is the one between TR1 and TR0. The average CE under risk is 0.434, the average CE under compound risk is 0.472 and the average CE under ambiguity is 0.509, and the differences between averages are always statistically different at 1% significance.

Figure 3 tracks the Kernel densities of the individual CE for our 50 lotteries by treatment. Here can outlook the difference between the distribution of TR2 compared with those of the uncertain treatments (TR1 and TR0).

4.3 Reduced form regressions

Table 2 reports the estimated coefficients of a random effect linear regression where the CE is the dependent variable and covariates are treatment dummies and individual characteristics (IC_i: socio-demographics, cognitive ability, and personality traits). We also control for lottery fixed effects, $Lottery_l$, and assume an individual-specific random effect, τ_i, as well as a lottery-specific idiosyncratic error, ϵ_{il}:

$$CE_{il} = \beta_0 + \beta_1 TR0_{il} + \beta_2 TR1_{il} + \beta_3 Lottery_l + \beta_4 IC_i + \tau_i + \epsilon_{il}.$$

We use TR2 as a baseline. Treatment effects for TR0 (TR1) are 0.0739 (0.037), respectively, both significant at 1%. Also, the treatment effect for TR0 is significantly higher than that of TR1 (see the row of Table 2 reporting the estimate of the difference, TR1–TR0). These results (column 1) are robust to the two additional

Table 1 Mann-Whitney average Certainty Equivalent differences test

(1) Left Ls	(2) TR0	(3) TR1	(4) TR2	(5) TR2 vs TR1	(6) TR2 vs TR0	(7) TR1 vs TR0	(8) Right Ls	(9) TR0	(10) TR1	(11) TR2	(12) TR2 vs TR1	(13) TR2 vs TR0	(14) TR1 vs TR0
1	0.297	0.289	0.292				1	0.346	0.299	0.174	***	***	*
2	0.583	0.517	0.446	***	***	***	2	0.589	0.576	0.512	***	***	
3	0.658	0.566	0.675	***		***	3	0.608	0.560	0.564			
4	0.646	0.612	0.600		**		4	0.644	0.609	0.594		**	
5	0.567	0.524	0.531		*	**	5	0.563	0.542	0.467	***	***	
6	0.344	0.328	0.169	***	***		6	0.398	0.355	0.360			
7	0.630	0.573	0.572		**	**	7	0.631	0.611	0.579	*	***	
8	0.420	0.392	0.370		**		8	0.451	0.385	0.365		***	**
9	0.601	0.573	0.508	***	***		9	0.457	0.432	0.265	***	***	
10	0.508	0.472	0.440		***		10	0.548	0.503	0.434	***	***	**
11	0.639	0.555	0.504	**	***	***	11	0.627	0.572	0.568		**	**
12	0.329	0.337	0.184	***	***		12	0.358	0.318	0.328			**
13	0.495	0.463	0.395	***	***		13	0.512	0.489	0.450	**	***	
14	0.505	0.498	0.418	***	***		14	0.614	0.582	0.596			
15	0.449	0.421	0.331	***	***		15	0.502	0.465	0.448		**	
16	0.633	0.599	0.563		***	*	16	0.604	0.580	0.548	*	***	
17	0.714	0.659	0.748	***		***	17	0.719	0.665	0.668		**	***
18	0.317	0.286	0.288		**		18	0.358	0.319	0.272	*	***	**
19	0.254	0.224	0.216		**	**	19	0.230	0.225	0.131	***	***	
20	0.513	0.493	0.516				20	0.522	0.503	0.472			
21	0.494	0.436	0.359	***	***	**	21	0.431	0.388	0.319	***	***	
22	0.504	0.447	0.407	***	***	**	22	0.490	0.455	0.416	*	***	
23	0.641	0.611	0.591		**	*	23	0.632	0.557	0.522		***	***
24	0.552	0.503	0.454	***	***	**	24	0.547	0.507	0.477		***	*
25	0.407	0.379	0.326	**	***		25	0.364	0.334	0.313		**	

Note: (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ for the null of equal means). In column 1, Left lotteries indexes are shown and in column 8, Right lotteries indexes. In columns 2–4 and 9–11, average CE for each lottery and for each information treatment are presented. In columns 5–7 and 12–14, Mann-Whitney tests are reported for the information treatment pairs indicated. TR0 (TR1) [TR2] correspond to the Ambiguity (Compound Risk) [Risk] treatments, respectively.

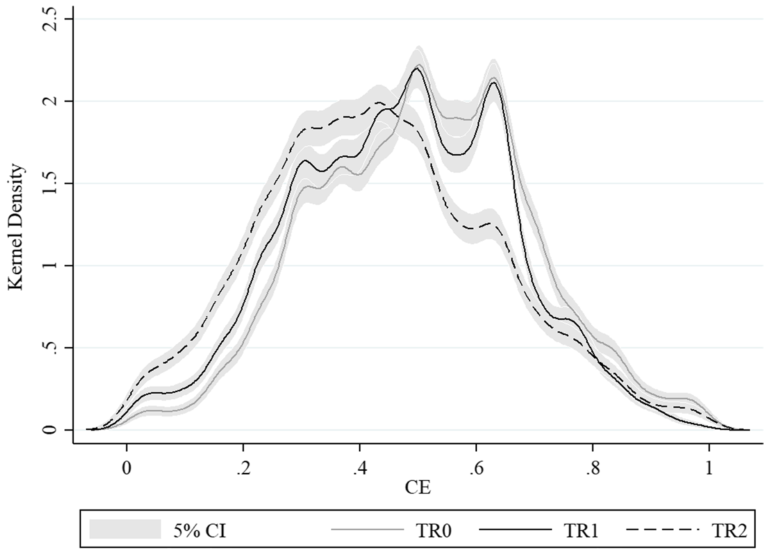

Fig. 3 Kernel density of the individual Certainty Equivalent. Grey: density under ambiguity. Black: density under compound risk. Dashed line: density under risk. Confidence intervals at a 5% significance level drawn in light grey. TR0 (TR1) [TR2] correspond to the Ambiguity (Compound Risk) [Risk] treatments, respectively

specifications of the model, where we control for individual characteristics such as gender, age, BMI, the room/household size ratio, and the weekly budget (column 2), and when we also control for cognitive abilities and personality traits (column 3).[9]

5 Structural estimations

We believe it is important to parameterize the decision-making process of our subjects and estimate structural parameters that might be directly comparable with previous (and future) studies. Our structural estimations give us a richer interpretation of subjects' behavior and a better explanation on their lottery evaluations from which our results arise. For our structural estimations we use data from both stages, 1 and 2. Our identification strategy involves the estimation of a single curvature for subjects' utility function, identifiable with the marginal utility of money, common to all treatments, and the estimation of attitudes toward compound risk vs. ambiguity via a parametric probability weighting function associated to the unknown probabilities (probabilities associated to the possible values that the uncertain prizes may take). We are interested in checking the internal validity of two alternative models: one based on the classic normative model of Expected Utility and another, based on

[9] The full set of estimated coefficients (including controls) can be found in Table A.4 in the Appendix.

Table 2 Certainty Equivalent random effect linear regression. Asterisks indicate significance from 0. TR0 (TR1) correspond to the Ambiguity (Compound Risk) treatments, respectively

Dependent variable	(1) CE	(2) CE	(3) CE
$TR0$	0.0739***	0.076***	0.0767***
	(0.014)	(0.014)	(0.014)
$TR1$	0.037***	0.0379***	0.0392***
	(0.014)	0.0392***	(0.014)
$TR1 - TR0$	−0.036***	−0.0381***	0.037***
	(0.014)	(0.014)	(0.014)
Cons	0.2529***	0.3009***	0.3171***
	(0.012)	(0.038)	0.076
Lottery Fixed Effects	Yes	Yes	Yes
Individual socio-characteristics	No	Yes	Yes
Cognition and personality	No	No	Yes
Observations	11,798	11,798	11,798

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

an intuitive heuristics, which we interpret as a plausible behavioral alternative. By way of a mixture model, we can also estimate the ex-ante probability with which our observations are generated by either latent behavioral process. Finally, in Section 5.5, we perform a subject-by-subject estimation of our behavioral models to grasp a better understanding of the heterogeneity—both observable and unobservable—in the attitudes of our subjects' pool toward risk and payoffs' uncertainty.

5.1 Identification strategy

We look at a situation in which an individual has to make a choice between two lotteries (Stage 1) or a binary choice between a lottery and a sure amount (Stage 2). Each lottery corresponds to a known probability distribution over four prizes, $0<Y<X<1$. We first set the decision framework in which the intermediate prizes, Y and X, are known (TR2).

Let $L^k = \left\{0, Y, X, 1; p_0^k, p_Y^k, p_X^k, p_1^k\right\}, k = -1, 1$ denote a lottery, where $k=-1$, 1 represents the left (right) lottery, respectively, of the choice in Stage 1, where subjects make 25 decisions of this kind. In Stage 2, the same 50 lotteries are played against a sure amount between 0 and 1: the left lottery will be the sure amount, call it S, earned with probability 1 ($L^{-1}=\{S;1\}$). Under a standard VNM framework, the individual evaluates the expected utility of lottery k, $U(L^k)$, as follows:

$$U\left(L^k\right) = u(0) \cdot p_0^k + u(Y) \cdot p_Y^k + u(X) \cdot p_X^k + u(1) \cdot p_1^k,$$

which simplifies to $U\left(L^k\right) = u(Y) \cdot p_Y^k + u(X) \cdot p_X^k + p_1^k$ once we substitute, without loss of generality, $u(0)=0$ and $u(1)=1$.

In our structural estimations, we employ a Constant Relative Risk Aversion (CRRA) utility function defined over the monetary prizes:

$$u_i(z) = \frac{z^{1-\rho_i}}{1-\rho_i} \text{ if } \rho_i \neq 1$$

$$u_i(z) = \ln(z) \text{ if } \rho_i = 1,$$

with $\rho = 0$ $(\rho > 0)[\rho < 0]$ identifying risk neutrality (aversion) [loving], respectively.

We need extra parameters to study the evaluation of the lotteries under uncertain intermediate prizes (TR1 and TR0). In the instructions subjects are told that *Y* and *X* are integers between 1 and 14 with the order restriction Y < X. After normalization, *Y* and *X* are values from the interval $\left[\frac{1}{15}, \frac{14}{15}\right]$. For our estimations, we adapt the probability distribution of the first and the second order statistics (min and max, respectively) of a two size sample without replacement from a discrete uniform distribution from $\frac{1}{15}$ to $\frac{14}{15}$ (Nagaraja, 1992). The corresponding densities are given by:

$$f_Y(z) = \frac{\binom{z-1}{1-1}\binom{N-z}{n-1}}{\binom{N}{n}} = \frac{\binom{z-1}{1-1}\binom{14-z}{2-1}}{\binom{14}{2}} = \frac{14-z}{91} \tag{1}$$

$$f_X(z) = \frac{\binom{z-1}{2-1}\binom{N-z}{n-2}}{\binom{N}{n}} = \frac{\binom{z-1}{2-1}\binom{14-z}{2-2}}{\binom{14}{2}} = \frac{z-1}{91} \tag{2}$$

where *N*—the amount of numbers in the population—is 14, *n*—the amount of numbers we get for our sample—is 2, and *z* is the order position in the population of the number whose density we need to compute. Given the above density functions, we can compute the expected values of Y and X:

$$E(Y) = \sum_{z=1}^{14} \frac{z}{15} \cdot f_Y(z) = \frac{1}{3} \quad E(X) = \sum_{z=1}^{14} \frac{z}{15} \cdot f_X(z) = \frac{2}{3}.$$

As anticipated, attitudes toward compound risk/ambiguity are proxied by the curvature of an exponential probability weighting function, as proposed by Quiggin (1982), that we anchor to the first and second order statistics of the uniform distribution, (1) and (2). That is to say, since in TR0 we provide no information on the distribution of *Y* and *X*, we impose, also in this case, a uniform distribution and let subjects differ in the curvature of the weighting function between treatments:

$$w(\pi) = \pi^{\gamma_{TR}},$$

where $\gamma_{TR} > 0$.

When $\gamma_{TR} < 1$, we have a concave weighting function, which means individuals are somewhat "optimistic" about the uncertain outcomes probabilities.

5.2 Naïve vs. sophisticated

As we mentioned earlier, we consider two stylized decision rules for choices over lotteries with uncertain outcomes: one, based on the normative principle of expected utility maximization (what we call *sophisticated* evaluation), another that we consider a natural heuristics when subjects decide under uncertain outcomes (what we call *naïve* evaluation). Let's present these two alternatives in turn.

The sophisticated model consists of including the utility of each of the possible values of Y and X times its probability (objective or subjective) in the evaluation of the lottery, computing in this way its expected utility. The only modification we apply to the expected utility model, as anticipated, is the introduction of a weighting function to identify treatments effects:

$$U^S(L) = u(0) \cdot p_0 + \left[\sum_{z=1}^{14} u(z) \cdot w\big(f_Y(z)\big)\right] \cdot p_Y + \left[\sum_{z=1}^{14} u(z) \cdot w\big(f_X(z)\big)\right] \cdot p_X + u(1) \cdot p_1. \quad (3)$$

In the naïve model, the order of integration is reversed: subjects first estimate Y and X as the (weighted) expected values of the uncertain payoffs, and then evaluate lotteries by way of expected utility. We think that this is a very intuitive heuristic of evaluating lotteries with uncertain outcomes. This is equivalent to say that, under the naïve heuristic, subjects first form a point belief of Y and X and then choose between lotteries conditional on these point beliefs:

$$U^N(L) = u(0) \cdot p_0 + u\Big(\sum_{z=1}^{14} z \cdot w\big(f_Y(z)\big)\Big) \cdot p_Y + u\Big(\sum_{z=1}^{14} z \cdot w\big(f_X(z)\big)\Big) \cdot p_X + u(1) \cdot p_1. \quad (4)$$

These two models (sophisticated and naïve) collapse when $\rho = 0$, i.e., when individuals are risk neutral. While individuals can still have different attitudes to uncertainty, we cannot distinguish between a sophisticated and a naïve evaluation when they are risk neutral because the two models collapse into the same one in this particular case.

We also estimate an additional model in which we do not impose any explicit process for the belief formation process of Y and X, apart from the order: each subject i figures out the values of Y_i and X_i with the only restriction of $X_i > Y_i$. The estimation of this alternative specification, which we call *super naïve*, can be found in the Appendix.

5.3 Likelihoods and mixture model

Let $C_{it} = -1$ ($C_{it} = 0$) [$C_{it} = 1$] if subject i has chosen lottery $k = -1$ (is indifferent) [has chosen lottery $k = 1$] in decision round t, respectively. In our structural model the probability of choosing a lottery is linked to the difference in payoffs, as follows:

$$\Pr\big(C_{it} = 1\big) = \Pr\left[U_i\big(L_t^1\big) - U_i\big(L_t^{-1}\big) \geq \theta\right],$$

where $U_i\big(L_t^k\big)$ is the evaluation of lottery k by individual i at round t and θ is the difference between the left and right lottery i.i.d. idiosyncratic error terms.

$U_i(L_t^1) - U_i(L_t^{-1}) = \Delta U_{it}$ is the difference of lotteries evaluations calculated and used to define the cumulative probability of the observed choice.

Subjects are told in the instructions that an expression of indifference would mean that the computer would choose one of the lotteries by them, both with the same probability, in the case of that period was selected for payment. To take into account the "indifference" responses we assume that such choices implied a 50:50 mixture of the likelihoods of choosing left and right lotteries.[10]

We estimate this response model by maximum likelihood assuming that the error terms follow a logistic distribution. Let $\ell_{it} = \frac{\exp(\Delta U_{it})}{1+\exp(\Delta U_{it})}^{I(C_{it}=1)} \cdot \frac{\exp(\Delta U_{it})}{1+\exp(\Delta U_{it})}^{\frac{1}{2}I(C_{it}=0)} \cdot \frac{1}{1+\exp(\Delta U_{it})}^{\frac{1}{2}I(C_{it}=0)} \cdot \frac{1}{1+\exp(\Delta U_{it})}^{I(C_{it}=-1)}$. Then, the log-likelihood function is:

$$\begin{aligned}\mathcal{L}(\rho,\gamma) &= \sum_{i,t} \ln \ell_{it} \\ &= \sum_{i,t}\left[\ln\left(\frac{\exp(\Delta U_{it})}{1+\exp(\Delta U_{it})}\right)\cdot I(C_{it}=1) + \frac{1}{2}\ln\left(\frac{\exp(\Delta U_{it})}{1+\exp(\Delta U_{it})}\right)\cdot I(C_{it}=0)\right. \\ &\left. + \frac{1}{2}\ln\left(\frac{1}{1+\exp(\Delta U_{it})}\right)\cdot I(C_{it}=0) + \ln\left(\frac{1}{1+\exp(\Delta U_{it})}\right)\cdot I(C_{it}=-1)\right]\end{aligned}$$

For the estimation, we take all the observations as a pool and then correct errors clustering at the individual level. The estimated coefficients are reported in Tables A.5–6 in the Appendix and discussed in Section 5.4.

We are now interested in specify and estimate a grand log-likelihood function considering our models as two data generating processes. For this purpose, we develop a mixture model where q^S denotes the probability that our data is generated by the sophisticated model, and $q^N = (1 - q^S)$ the probability that our data is generated by the naïve model. The grand log-likelihood can be written as the probability weighted average of the conditional likelihoods:

$$\mathcal{L}\left(\rho^S, \gamma^S, \rho^N, \gamma^N, q^S\right) = \sum_{i,t} \ln\left[\left(q^S \times \ell_{it}^S\right) + \left(q^N \times \ell_{it}^N\right)\right].$$

Table 3 reports the estimated coefficients of this mixture model.

5.4 Estimated coefficients

As already described, we jointly estimate the curvature of our CRRA utility function with the parameter, ρ, and the Compound/Ambiguity aversion with the treatment dependent parameter, γ_{TR}.

We present the results of our mixture model for the entire sample and only for the consistent observations in Table 3, clustering at the individual level in all cases.[11]

[10] Our treatment of indifference follows the estimation strategy developed by Papke and Wooldridge (1996).

[11] Results for each of the conditional likelihoods (sophisticated and naïve models), when estimated separately can be found in the Appendix in Tables A.5. and A.6.

Table 3 Mixture model (naïve vs. sophisticated). Asterisks indicate significance from 0. TR0 (TR1) correspond to the Ambiguity (Compound Risk) treatments, respectively

	All		Only Consistent	
	NAÏVE	SOPHISTICATED	NAÏVE	SOPHISTICATED
q^S	0.525		0.615*	
	(−0.125–1.175)		(−0.072–1.303)	
ρ	0.749***	0.748***	0.759***	0.759***
	(0.741–0.757)	(0.740–0.756)	(0.753–0.766)	(0.752–0.766)
γ_{TR1}	0.946***	0.976***	0.99***	0.987***
	(0.889–1.004)	(0.961–0.991)	(0.934–1.046)	(0.973–1.001)
γ_{TR0}	0.874***	0.955***	0.886***	0.960***
	(0.825–0.922)	(0.942–0.968)	(0.835–0.937)	(0.947–0.973)
$\Delta\gamma_{TR0-TR1}$	−0.073*	−0.021**	−0.104***	−0.027***
	(−0.15–0.004)	(−0.040 - −0.001)	(−0.182 - −0.026)	(−0.046 - −0.008)
Pseudolikelihood	−112,095.27		−92,294.721	
Observations	230,175	230,175	195,743	195,743
Cluster (id)	279	279	279	279

Note: 95% Confidence Intervals in parenthesis *** $p<0.01$, ** $p<0.05$, * $p<0.1$

As Table 3 shows, both models (sophisticated and naïve) display very similar behavioral patterns. When we look at the results considering only the consistent observations (columns 3 and 4), we find a curvature parameter, ρ, equal to 0.76 for both naïve and sophisticated specifications. This tells us that our subjects have a diminishing marginal utility of money. Harrison and Rutström (2008) conclude that there is a systematic evidence that subjects in laboratory experiments behave as if they were risk averse. Hey and Orme (1994) conclude, through different estimation methods to ours, that their utility function is concave, and Holt and Laury (2002, 2005) show that subjects are moderately risk averse in the lab. Using the data from Hey and Orme (1994) and assuming the same CRRA functional form as ours, Harrison and Rutström (2008) estimate a constant relative risk aversion parameter of 0.8 (against that of 0.76 in our case). Using data from Harrison and Rutström (2009), a replication of Hey and Orme (1994) with gains and losses, the authors estimate a constant relative risk aversion parameter equal to 0.761 for gains. Andersen et al. (2008), who study both, risk and time preferences, estimate a CRRA coefficient of 0.74.

About the compound/ambiguity aversion parameter, γ, we can see how under TR1 γ is not statistically different from 1, which means that our estimates are consistent with the idea that people are following our experimental instructions and evaluate uncertain payoffs using the first and second order statistics of a discrete uniform distribution without replacement. However, in TR0, γ is lower than 1 (i.e., the probability weighting function is concave) which means that subjects are assigning to the possible values of the uncertain outcomes greater probabilities than for the uniform distribution. Furthermore, consistently with the results of Sections 4.2 and 4.3, the difference in concavity between TR1 and TR0 is statistically significant at the 1%

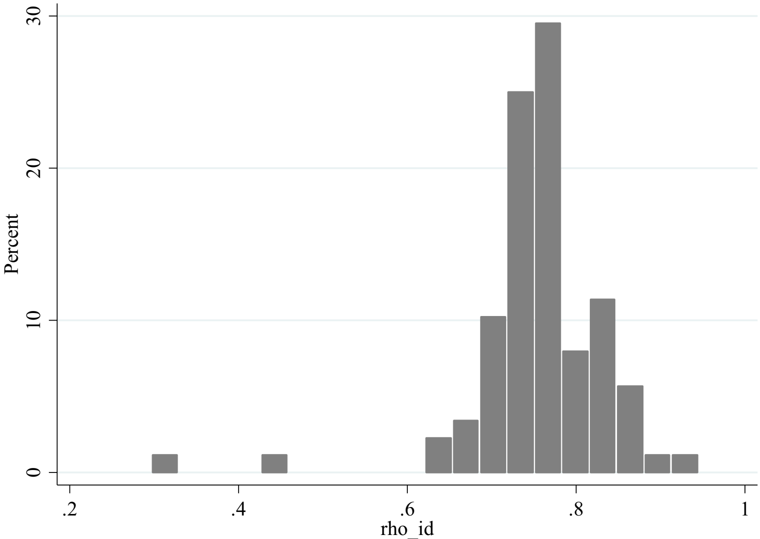

Fig. 4 Histogram of the distribution of the curvature of the value function (ρ) in the Risk treatment. Only 1 out of 88 estimations is not statistically different from 0 at the 5% level

level. As for the estimation of the mixture model, q^S, is around 50% (depending on whether we look at the consistent subjects, or at the full sample), which means that half of our observations are generated by the sophisticated model and half by the naïve model. Not surprisingly, the probability of sophisticated reasoning is higher in the consistent subsample.

5.5 Heterogeneity

All the structural analysis so far has been performed by deriving pool estimates, that is, estimating a constant measuring a "representative attitude" for the entire population. This is, of course, only a first-order approximation. In this section, we shall follow Cabrales et al. (2010) and Giaccerini and Ponti (2018) by exploring issues related with heterogeneity within our subject pool by estimating our models subject-by-subject, to have *i)* a better grasp on how our individual structural parameters (indicating *unobservable* heterogeneity) distribute across our subject pool and *ii)* how they depend on the *observable* heterogeneity distilled by our debriefing questionnaire.

As for the analysis of unobservable heterogeneity, we start with ρ, that is, the parameter that we use to measure the curvature of the utility function/risk attitude. We estimate ρ for those subjects playing in TR2 (where risk attitudes are not confounded with issues related with ambiguity), with Fig. 4 reporting its distribution. As Fig. 4 shows, the null of risk neutrality is not rejected for just 1 subject in the sample, all the other can be defined as risk averse, with a greater density of estimations between values 0.7 and 0.8. In other words, it seems that risk attitudes are, in general, rather uniform across our sample. This is in line with the relevant literature in the field (take, e. g., Harrison & Rutström, 2008).

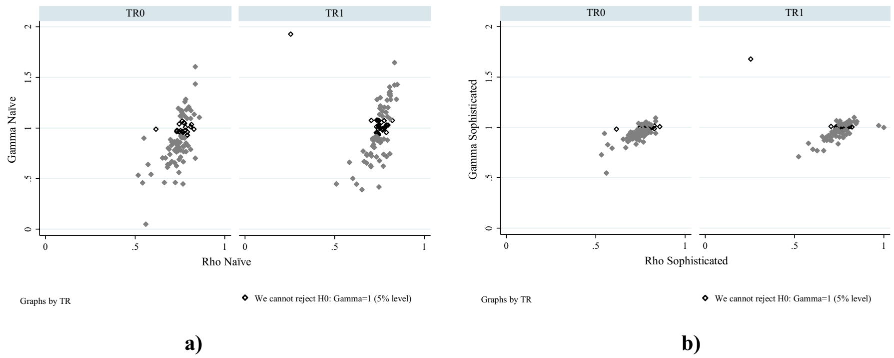

Fig. 5 Subject-by-subject estimated parameters for the curvature of the value function (ρ) and the curvature of the probability weighting function (γ) under the naïve (Panel **a**) and sophisticated (Panel **b**) model. TR0 (TR1) correspond to the Ambiguity (Compound Risk) treatments, respectively

However, this is not the case of ambiguity attitudes, for which we estimate, subject-by-subject, the two models in the paper defined as *naïve* and *sophisticated*.[12] We estimate the naïve model for subjects under TR1 and TR0. Our parameter estimations are tracked in Panel *a)* of Fig. 5. While risk attitudes seem to be homogeneous across our sample (in that all our subjects but one are described as risk averse), this is not the case as far as the curvature of the probability weighting function is concerned. In this case, 51% (25%) [24%] are defined by our naïve model as optimistic (neutral) [pessimistic] in the evaluation of the uncertain outcomes, respectively.[13] If we study the correlation between ρ and γ, we find a positive correlation (0.73 in TR1 and 0.62 in TR0, in both cases statistically significant at the 1% level). In other words, subjects who are more risk averse, are also more pessimistic in their uncertain outcome probability evaluation, and this positive correlation is stronger under Ambiguity than under Compound Risk.

We repeat the same estimations under the sophisticated model, where the coefficient distribution is reported in Panel *b)* of Fig. 5. Again, while almost everybody is classified as risk averse (we have only one risk neutral subject), there are heterogeneous attitudes about ambiguity, where 59% (23%) [18%] of our subject pool is defined by our sophisticated model as optimistic (neutral) [pessimistic] toward payoff uncertainty, respectively. Also in this case, there is also a positive and strong correlation between the two estimated parameters (0.73 in TR1 and 0.72 in TR0, in both cases statistically significant at the 1% level).

We can also look at the *observable* heterogeneity, that is, how the individual parameters depend on subjects' characteristics we distill from the debriefing questionnaire. With this purpose, we run an Estimated Dependent Variable (EDV) model where the dependent variables are the estimated individual parameters. When we run a regression where the dependent variable is estimated, the residuals can be split

[12] Results subject by subject for the super naïve model are in the Appendix.

[13] These proportions are computed as percentages of the individual estimated γ that are statistically lower, not different from or greater than 1 at the 5% level, respectively.

into two (additive) components: one is the sampling error, the difference between the "true" value of the dependent variable and its estimation; the other is the idiosyncratic random shock that belongs to the regression even if the dependent variable were directly observed. To identify each component, we employ a two-stage estimation approach: the parameters are first estimated for each individual as described above and, in a second stage, an EDV regression is run in which the estimated parameters from the first stage are used as dependent variables. We use the Feasible Generalized Least Squares (FGLS) estimator proposed by Lewis and Linzer (2005), useful for our case in which the standard errors of the estimated dependent variable are known.[14] We estimate the variance of the component of the regression residual that is not due to sampling of the dependent variable, $\hat{\sigma}$, and we build (joint with the known sampling error, ω) a set of weights to use in a Weighted Least Squares regression, which gives us estimates asymptotically efficient. Results are reported in Table A.7 in the Appendix. In general, we find that the individual characteristics distilled from the debriefing survey are not correlated with the estimated attitudes to both risk and ambiguity. If we analyze characteristics one by one, we find that under TR2 there is a positive and significant (at 5% confidence) effect of Female on ρ, in that females are more risk averse. This result disappears for subjects under TR1 and TR0. There is also a weak positive effect of Female on γ, telling us that females are more pessimistic when evaluating uncertainty. This is not surprising because this effect of gender on risk and ambiguity attitudes has already been reported by the literature (see, among others, Eckel & Grossman, 2008). As for cognitive ability, there is a positive and significant effect for subjects under TR1 and TR0 on ρ and γ, telling us that those subjects classified as reflective, are more risk and uncertainty averse than the residual group (see Cueva et al., 2016).

6 Conclusion

Broadly speaking, the theoretical discussion about ambiguity has been polarized by three alternative approaches. The first strand of literature identifies ambiguity with the coexistence of multiple priors: take, for example, Gilboa and Schmeidler's (1989) MaxMin Expected Utility, or the model of Alpha-MaxMin Expected Utility of Ghirardato et al. (2004), which has the great advantage of not imposing, a priori, an ambiguity averse attitude on behalf of our subjects (hypothesis that is actually rejected by our own experimental evidence). The second strand identifies attitudes toward ambiguity with shifts in the curvature of the value function, like in Klibanoff et al. (2005). Finally, the third strand of literature -initiated by Kahneman and Twersky (1979)- uses probability weighting functions to identify ambiguity attitudes. Along these lines, Abdellaoui et al. (2015) assume that the decision maker can assign subjective probabilities to events generated by a specific source (i.e., probabilistic sophistication within sources of ambiguity) and then use a source-dependent probability weighting function to transform these into decision weights. The difference in the source-dependent probability weighting function reflects ambiguity attitude. By analogy with this approach, we take, instead, the

[14] This method was firstly suggested by Hanusek (1974) for the case in which the dependent variables are estimated regression coefficients.

difference between risk, compound risk, and ambiguity to identify ambiguity attitudes via different curvatures of the probability weighting function (assumed linear in TR2, as a benchmark for comparison).

The love for ambiguity we find in our—both structural and non-structural—empirical analysis may come as a surprise, given the substantial amount of evidence that, using variations of Ellsberg's classic urn experiment, finds exactly the opposite. In this respect, the non-parametric results of Table 1 (where, for 46 lotteries out of 50, the CE under ambiguity is the highest, and differences are most often significant) are especially striking in that they do not rely on the same stringent assumptions as our structural estimations. We believe that this result deserves some discussion. We should notice that we are not the first to find instances of love for ambiguity in specific experimental domains. For example, Andersen et al. (2014) identify both a concave utility and probability weighting functions under structural assumptions very similar to ours (although under a rather different decision frame). Some finance studies also find "imprecision seeking" in the context of outcomes, as we already discussed in Section 2. Kocher et al. (2018) find ambiguity neutrality or seeking when introducing losses or lower likelihoods in the decision problems. Going towards a decision setting closer to our Stage 2, Fox and Tversky (1995) elicit the CE of risky vs. ambiguous binary lotteries under two frame conditions (randomized between subjects). Under the "Comparative" frame subjects have to elicit their CE for *both* the risky and the ambiguous prospect; under the "Noncomparative" frame half of the subjects are exposed to the CE elicitation of the risky (ambiguous) prospects only, respectively. Under this design, they find ranking reversal of average CE, with the risky prospects being ranked higher (lower) in the Competitive (Noncompetitive) condition respectively: "*Hence, ambiguity aversion seems to require a direct comparison between the clear and the vague bet; an awareness of missing information is not sufficient*…" (p. 590). In other words, our information conditions TR0 to TR2 randomize between subjects the level of ambiguity of their decisions; the direct choice between risk and ambiguity—typical of Ellsberg-type experiments—is allowed neither in Fox and Tversky (1995) nor in our experiment. This may have important consequences in the way in which subjects value lotteries and suggest that ambiguity—exactly as risk—attitudes may well be context specific and greatly vary across different elicitation tasks.[15]

Moreover, our results, as well as those of Eichberger et al. (2015) and Eliaz and Ortoleva (2016), tell us about the importance of the dimension presented as uncertain for individuals' choice behavior. Analyzing all the possible dimensions of uncertainty under a unified framework seems to be the natural following step in this research. Can we directly compare how individuals behave in uncertain situations framed as uncertainty in different dimensions? Eliaz and Ortoleva (2016) already answer this question in the case of correlated uncertainties. What about independent uncertainties across different dimensions? Many real-life situations present a framework in which uncertainty occurs in different dimensions, and they are not necessarily correlated.

15 Ahn et al. (2014) also find high heterogeneity in the attitudes toward ambiguity (as well as weighting) in a portfolio choice experiment in which subjects can invest in assets characterized by different degrees of ambiguity.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11166-024-09448-0.

Acknowledgements We thank Carmen Beviá, Han Bleichrodt, Raffaele Miniaci, and seminar participants at the University of Chicago, Universidad de Alicante, and LUISS Guido Carli Roma for comments and suggestions. A special thank goes to the Editor in charge and an anonymous referee for their supportive and mindful remarks. We are also grateful to Carlos Belando, Lourdes Garrido, Josefa Zaragoza, María Mestres, Haihan Yu, and Vita Zhukova for their precious research assistance. This paper has been revised while Giovanni Ponti was visiting the Department of Economics at the European University Institute in Florence. He would like to thank Andrea Ichino and all people at the EUI for their kind hospitality. The usual disclaimers apply. Financial support from the Spanish Ministry of Science and Innovation (Grants PID2019-107081GB-I00 and PID2022-142356NB-I00) and Generalitat Valenciana (Prometeo 2013/037, Prometeo/2021/073 and Research Groups 3/086) is gratefully acknowledged.

Author contribution CH, JA, and GP developed the research concept and designed the study; MS wrote the code of the software for the experiment; JA collected the data; PA, JA, DT, and GP analyzed the data; JA and GP drafted the manuscript with comments from CH and DT. All authors approved the final version of the manuscript for submission.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature.

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