How does the way we represent lotteries affect risk preferences?*

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14th November 2023

In a risk preference elicitation experiment, we manipulate the way we represent lotteries. We represent probabilities, payoffs, or both at the same time. We find that the representation has no effect on the raw, elicited certainty equivalents. We find, however, a significant effect on the structural parameters estimated via maximum likelihood.

Keywords: risk preferences, lottery format, lottery representation, expected utility, rank-dependent utility, maximum likelihood, maximum simulated likelihood
JEL Codes: C91, D81

*We gratefully acknowledge financial support from the Network for Integrated Behavioural Science. The experiment reported in this paper was approved by the Vienna Center for Experimental Economics ethics committee.

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1 Introduction

Over the years researchers have used many methods to measure risk preferences.[1] They have also represented lotteries in many ways. In Figure 1 we illustrate this diversity with only a few examples. While some researchers use only an alphanumeric representation (Figure 1a), most also include a visual representation. Most often only the probabilities are visually represented (Figures 1b and 1c), sometimes both probabilities are payoffs are (Figure 1d). Payoffs are never represented alone.

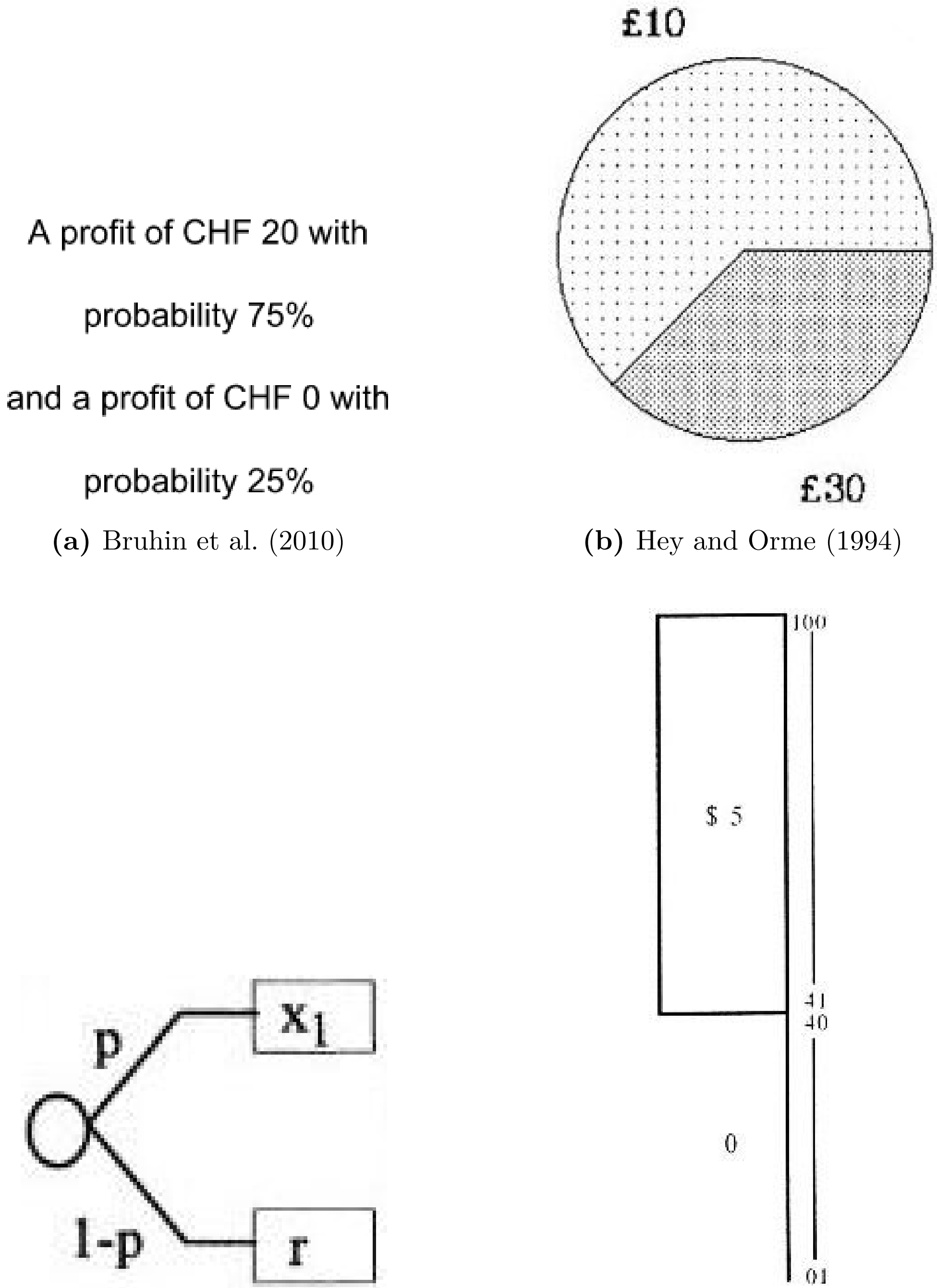
While there is a large literature comparing the pros and cons of the different elicitation methods,[2] we know little whether the choice of a lottery representation makes a difference. Harrison and Rutström (2008a, Appendix A) reviewed different lottery representations and concluded: 'To date no systematic comparison of these different methods have been performed and there is no consensus as to what constitutes a state of the art representation'. Sizeable literatures outside of economics, for example the risk communication literature (Stone et al., 1997) and the medical decision-making literature (Oudhoff and Timmermans, 2015), suggest that the way we represent lotteries do affect people's judgements.

Finding whether the representation matters is an important question for at least three audiences. Experimentalists need to know whether they introduce a bias in their experiments when they choose a particular representation. Consumers of experimental results need to know whether they can trust results obtained using different representations. If the representation matters, theorists can build new models to explain this result.

We show that the choice of lottery representation is not innocuous. In our experiments, we manipulate the representation while keeping the elicitation method fixed. Our representation allows us to represent probabilities or payoffs or both in a controlled way and to separate the effect of representing each attribute. When looking at the raw response data, we find no difference between the different representations. But when we estimate risk preference parameters using a structural model, we find that the choice of representation matters.

[1]To give only a few examples: pairwise choice (Camerer, 1989; Hey and Orme, 1994), the bissection method (Abdellaoui, 2000), multiple price lists (Holt and Laury, 2002), certainty equivalent elicitation (Bruhin et al., 2010), and the bomb task (Crosetto and Filippin, 2013).

[2]See for example Harbaugh et al. (2010), Charness et al. (2013), Pedroni et al. (2017), Crosetto and Filippin (2016) and Holzmeister and Stefan (2021)



(a) Bruhin et al. (2010)
(b) Hey and Orme (1994)
(c) Abdellaoui (2000)
(d) Camerer (1989)

Figure 1: Different lottery representations used in different experiments.

In our baseline, we use an alphanumeric representation of lotteries and thus describe lotteries to subjects using words and numbers, such as “A win of €25.00 for numbers between 1 and 25, and a win of €10.00 for numbers between 26 and 100”. Then, in our pictorial treatments, we add visual representations in which the visual display of a lottery attribute is proportional to its value. When we represent probabilities, we use horizontal space to show the range of winning numbers. When we represent payoffs, we use vertical space to show the amount of money won. When we represent both probabilities and payoffs, we combine both types of representation.

We use the elicitation method of Bruhin et al. (2010) to measure risk preferences for 25 lotteries. Compared to other elicitation methods such as the one of Holt and Laury (2002), this method has the advantage of mapping the evaluation of lotteries to a single scale, the money scale via certainty equivalents. We refine the method of Bruhin et al. (2010) by using an iterative procedure to obtain more precise certainty equivalents.

When we look at certainty equivalents reported by subjects, we see that, compared to a simple alphanumeric representation, all visual representations result in higher certainty equivalents. However, none of the differences are statistically significant.

We then estimate risk preference parameters using a structural model and maximum likelihood techniques. We consider both expected utility and rank-dependent utility models. We perform the estimation in different ways: at the sample level where we decompose the effect of the treatments on the different parameters; and at the individual level where we estimate the models for each subject, then compare the distribution of parameters between treatments. We also estimate a random coefficient model using maximum simulated likelihood, in which we recover individual estimates post estimation and then also compare these recovered coefficients between treatments.

All these estimations point towards the same conclusion: while representing only probabilities or payoffs has no impact on the structural parameters, representing both decreases the curvature of the utility function of money and thus makes subjects less risk averse. We find an increase of about 11% in the curvature parameter, moving a concave utility function of money towards linearity. This is true both under expected utility and under rank-dependent utility. On the other hand, none of the representations affect the parameters of the probability weighting function.

We also observe that the representation has an effect on decision noise. In particular, our results suggest that representing probabilities alone increases noise, while representing both probabilities and payoffs decreases it. We also see that representing payoffs alone tend to increase the number of times subjects report multiple switching points when facing a lottery.

To the three audiences, we can thus say the following. To the experimentalists, we say that the representation has an effect on the elicited parameters, even if it does not affect the raw certainty equivalents. In particular, our results suggest that representing probabilities or payoffs alone may not be the best choice, as it results in either more noise or more mistakes. The consumers of experimental results can be reassured that, while the representation matters, we do not see radical differences between the representations. Well-known regularities—people are risk-averse, the probability weighting function is inverse S-shaped—are true no matter the representation. Finally, to the theorists, we offer a new puzzle: representing both probabilities and payoffs makes subjects less risk-averse.

We also offer a set of lotteries representations that have been tested. Subsequent researchers can use our lottery representations, knowing whether and how they affect risk preferences. We have open-sourced and released them on GitHub as `lottery.js`. With a few steps they can be easily integrated into any web-based experimental software such as Qualtrics, oTree (Chen et al., 2016), or LIONESS (Giamattei et al., 2020).

Related literature Habib et al. (2017) and Segovia et al. (2022) have also looked at the effect of lottery representations on risk preferences, but they have done so in the context of the elicitation method from Holt and Laury (2002). In this method, subjects make repeated pairwise choices between lotteries. Most often, the lotteries are organised in a table with varying probabilities or payoffs. As a consequence, the introduction of the lottery representation affects two or more lotteries at the same time. By contrast, our elicitation method allows our treatments to always affect only one lottery at a time. Since our method elicits certainty equivalents, we can also directly map the effects into a single monetary scale.

Habib et al. (2017) compare an alphanumeric representation to a visual representation in which probabilities and payoffs are always represented together in a 3D pie chart. As such, they do not represent each attribute independently. Instead, they manipulate whether only the 3D pie chart is provided or both the alphanumeric representation and the 3D pie chart are provided. Despite these differences, they also find that representing both probabilities and payoffs—in their case with 3D pie charts—makes subjects less risk averse.

The representations used by Segovia et al. (2022) are the closest to ours. They also use horizontal and vertical space to represent independently or jointly probabilities and payoffs. Their representation and their experiment are set up to allow them to collect eye-tracking data. Contrary to us, they do not find an effect of the lottery representation.

2 Experimental design

The goal of our experiment is to test different lottery representations and tease out the effect of representing each attribute. We start from a standard risk-elicitation task and add our different lottery representations. All comparisons are made between-subject.

2.1 Baseline

We build on Bruhin et al. (2010). Subjects face 25 lotteries, whose order is randomised for each subject. The lotteries are displayed in Table 1.[3] For each of the 25 lotteries, subjects report their certainty equivalent using tables. For each row of the tables, subjects choose between the left option, Option A, and the right option, Option B. Option A is always the same lottery in a given table, and Option B is a sure amount of money. It starts high at the top of the table, and decreases as we go down the table.

[3]These are the 'gain' lotteries from Bruhin et al. (2010), with the amounts in Swiss francs divided by two to convert them to Euros. This conversion ensures that the lotteries in our experiment have about the same purchasing power as in Bruhin et al. (2010). In 2003, when Bruhin et al. (2010) conducted their experiments in Switzerland, the net average income was 63 909.65 CHF. In 2022, when we conducted our experiments in Austria, it was 35 837.40 €. Therefore, to keep payoffs comparable we need to divide the payoffs in Bruhin et al. (2010) by $63\,909.65/35\,837.40 \simeq 1.78$, which we rounded to 2. (Source: OECD, `https://stats.oecd.org/index.aspx?queryid=55145`)

Table 1: Lotteries used in the experiment (x_1 and x_2 in Euros).

p_1	x_1	p_2	x_2	First increment	Second increment	Third increment
0.05	10	0.95	0	1	0.1	
0.05	20	0.95	5	1.5	0.15	
0.05	25	0.95	10	1.5	0.15	
0.05	75	0.95	25	5	0.5	
0.1	5	0.9	0	0.5		
0.1	10	0.9	5	0.5		
0.1	25	0.9	0	2.5	0.25	
0.25	10	0.75	0	1	0.1	
0.25	20	0.75	5	1.5	0.15	
0.25	25	0.75	10	1.5	0.15	
0.5	5	0.5	0	0.5		
0.5	10	0.5	5	0.5		
0.5	20	0.5	5	1.5	0.15	
0.5	25	0.5	0	2.5	0.25	
0.5	25	0.5	10	1.5	0.15	
0.5	75	0.5	0	7.5	0.75	0.075
0.75	10	0.25	0	1	0.1	
0.75	20	0.25	5	1.5	0.15	
0.75	25	0.25	10	1.5	0.15	
0.9	5	0.1	0	0.5		
0.9	10	0.1	5	0.5		
0.9	25	0.1	0	2.5	0.25	
0.95	10	0.05	0	1	0.1	
0.95	20	0.05	5	1.5	0.15	
0.95	25	0.05	10	1.5	0.15	

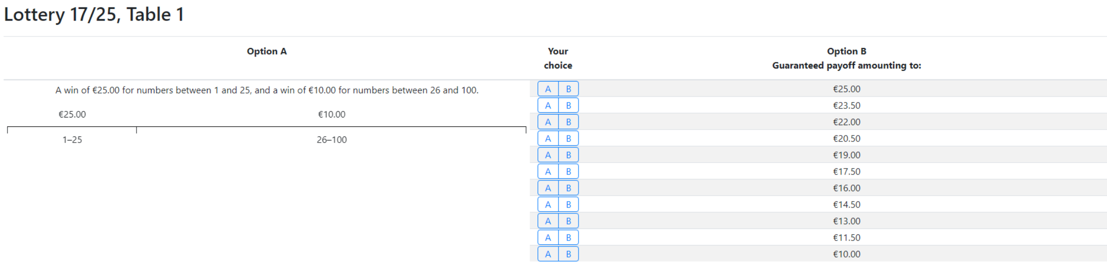


Figure 2: Example of a task

The only substantial modification we make to Bruhin et al. (2010) is the use of an iterative procedure inspired by Andersen et al. (2006) in order to get more precise certainty equivalents. Subjects first see a table with 11 certainty equivalent uniformly distributed between the largest and smallest amount of money in the lottery. Then, if the switching point is interior, subjects see a second table where the sure amounts are uniformly distributed between the sure amounts where the subject switched in the first table. We stop generating tables for a given lottery when the step between two sure amounts is lower than 0.5 €.

Figure 2 provides an example with the lottery $(25\,€, 0.25\ ;\ 10\,€, 0.75)$: the sure amounts range between 25 € and 10 €, so the increment is $(25-10)/10 = 1.5\,€$. If a subject chooses Option B with a sure amount of 22 € but Option A with 20.50 €, the second table would feature sure amounts ranging between 22 € and 20.50 €, with an increment equal to $(22-20.5)/10 = 0.15\,€$. Therefore, for this particular lottery, subjects only see two tables.

All in all, subjects see a single table for 6/25 lotteries, two tables for 18/25 lotteries, and three tables for only one lottery. We calculate the certainty equivalent as the average between the last sure amount for which the subject chose Option B and the next, smaller amount.[4]

For our iterative procedure to work, we require subjects to have a unique switching point in the table. If they try to submit a table with multiple switching points or if they switch instead from Option A to Option B, they see an error message and are asked to change their answers. We keep track of the number of times a subject

[4]By contrast, all lotteries in Bruhin et al. (2010) appeared in a single table of 20 lines. Since different lotteries have different ranges between their maximum and minimum payoffs, different tables have also different sure amount increments, ranging from 0.5 CHF to 5 CHF. Therefore, one potentially makes a greater error when computing the certainty equivalent for lotteries with a larger spread. Our iterative procedure alleviates this issue.

tried to incorrectly submit a table. Subjects can still submit a table in which they have chosen Option A or Option B everywhere; in that case they do not see the next table, if any.

In the Baseline, lotteries are represented alphanumerically, such as "A win of 25.00 € for numbers between 1 and 25, and a win of 10.00 € for numbers between 26 and 100". From this Baseline we have three treatments, which are all displayed in Figure 3.

2.2 Probabilities represented

Our first treatment is similar in all aspects to the Baseline, except that in addition to the alphanumeric representation, the probability dimension of the lotteries is represented visually via the partition of the horizontal box below a lottery's payoffs, as shown in Figure 3a.

2.3 Payoffs represented

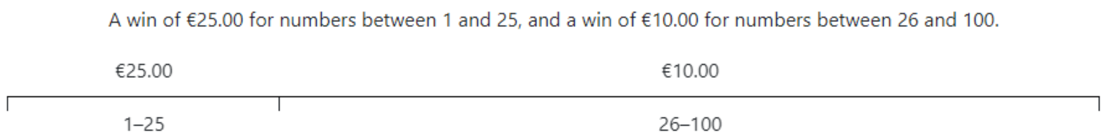
Our second treatment is similar in all aspects to the Baseline, except that in addition to the alphanumeric representation, the payoff dimension of the lotteries is represented visually via the height of the box drawn to contain each lottery's non-zero payoffs, as shown in Figure 3b. The tallest bar corresponds to the largest winning amount in the experiment, and all other bars are scaled with respect to it.

2.4 Probabilities and payoffs represented

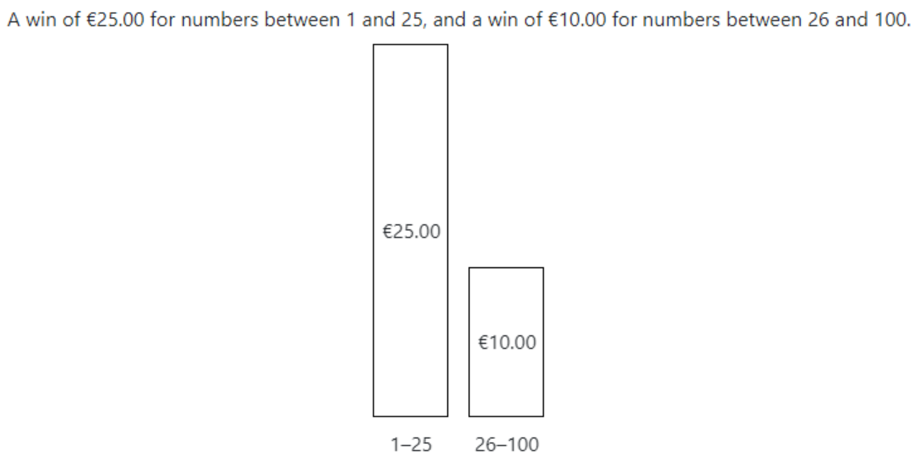
Our last treatment is similar in all aspects to the Baseline, except that in addition to the alphanumeric representation, we employ both of the visual cues introduced in the previous two treatments. Hence, the lotteries are represented as shown in Figure 3c. The resulting area corresponds to the expected value of the lottery.

2.5 Incentives and implementation details

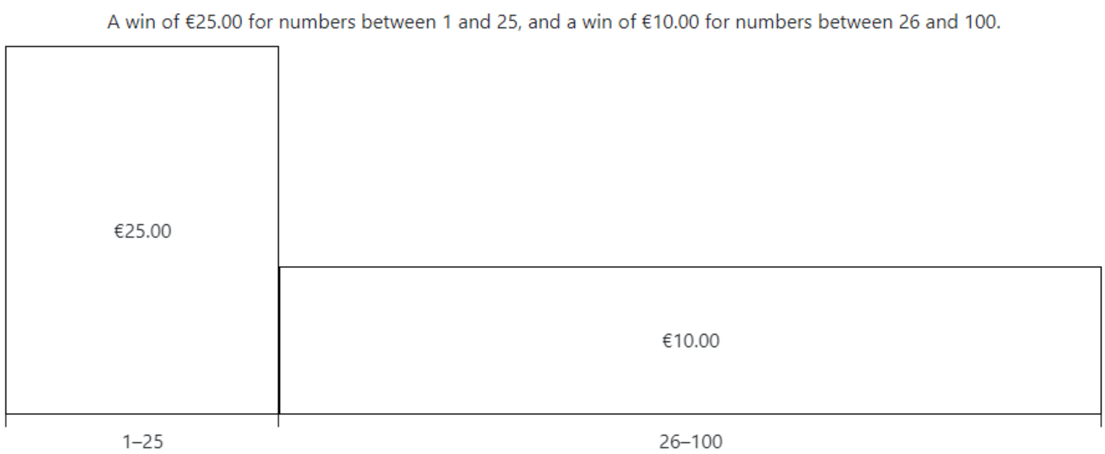
At the end of the experiment and independently for each subject, we selected a lottery and a row in its first table. If, for this row, subjects had chosen Option A, then they would play the lottery by drawing a numbered chip from a bag of 100



(a) Probabilities represented



(b) Payoffs represented



(c) Probabilities and payoffs represented

Figure 3: The different lottery representations

chips. If, for this row and the next row, they had chosen Option B, they would receive the sure amount of money of the row randomly chosen. Finally, if they had chosen Option B for this row, but Option A for the next row, we would draw a row at random in the second table and repeat the process; unless this was the last available table, in which case subjects would simply receive what they had chosen.

The experiment took place at the laboratory of the Vienna Center of Experimental Economics of the University of Vienna between March and June 2022. Sessions lasted about one hour and subjects earned on average 13.73 € from the lotteries, plus a show-up fee of 4 €. We had 119 subjects in the baseline, 119 in the probability treatment, 120 in the payoff treatment, and 120 in the both treatment. Our experiment was pre-registered.[5]

3 Results

3.1 Certainty equivalents

We start by looking at raw certainty equivalents. Figure 4 reports the mean certainty equivalent reported in each treatment. We see that all representations result in higher mean certainty equivalents than the baseline, where only an alphanumeric representation of the lottery was provided. However, no difference is statistically significant. In Appendix A.3 we report the results of a regression of the certainty equivalent on the treatment dummies in which we further control for lottery, lottery order, session, and the number of times a subject tried to submit an incorrect table. We still find no statistically significant difference between the baseline and any of the treatments.

We also look at whether some lotteries respond better to the treatments than others. In Table 2 we show that lotteries with a zero outcome received a significantly higher certainty equivalent when both probabilities and payoffs are represented. In Appendix A.3 we look at other lottery characteristics on top of having a zero outcome: the standard deviation or being left- or right-skewed. We find that only the interaction between the treatment and having a zero outcome is significant.

[5] https://osf.io/z2fjp

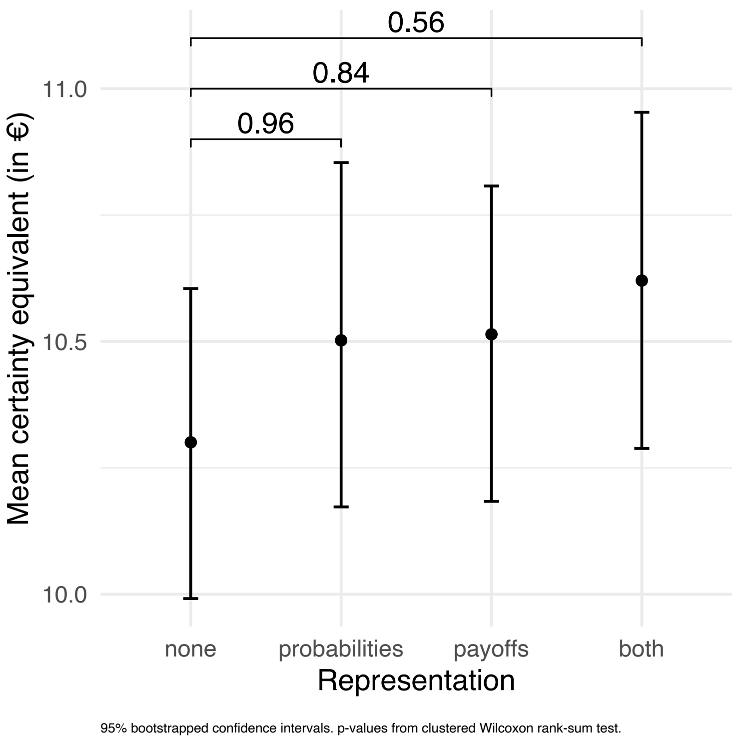


Figure 4: Mean certainty equivalents in each treatment.

Table 2: Effect of representations on certainty equivalents for lotteries with and without zero outcomes, OLS.

	(1)	(2)
Intercept	19.36^{***}	19.69^{***}
	(0.23)	(0.52)
Representing probabilities	-0.06	-0.06
	(0.23)	(0.23)
Representing payoffs	-0.04	0.14
	(0.23)	(0.73)
Representing both	0.00	0.20
	(0.24)	(0.76)
Lotteries with zero outcome	-17.02^{***}	-17.00^{***}
	(0.25)	(0.25)
Lotteries with zero outcome × Representing probabilities	0.35	0.34
	(0.22)	(0.22)
Lotteries with zero outcome × Representing payoffs	0.24	0.24
	(0.22)	(0.22)
Lotteries with zero outcome × Representing both	0.57^{**}	0.58^{**}
	(0.21)	(0.21)
Lottery order		-0.03^{***}
		(0.01)
Number submissions with multiple switch		0.04
		(0.03)
Number submissions with switch in wrong direction		0.96^{*}
		(0.45)
Lottery dummy	✓	✓
Session dummy	✗	✓
R^2	0.74	0.74
n	10 335	10 335

Notes. Standard errors clustered on subjects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.2 Structural estimations

3.2.1 Sample-level estimation

We now move to structural estimation. For that, we first need to specify a structural model. The lotteries can be written as $\mathcal{L} = \Big(p, x_1; (1-p), x_2\Big)$ with $x_1 > x_2$. The utility of the lottery is given by

$$U(\mathcal{L}) = w(p) \cdot u(x_1) + w(1-p) \cdot u(x_2)$$

where w is a probability weighting function and u is a utility function of money. When $w(p) = p$, U is expected utility; otherwise, it is rank-dependent utility.

We follow closely Bruhin et al. (2010). For u we use the power, CRRA utility function $u(x) = x^\alpha$. Since we have 0 outcomes in the experiment, we have to restrict $\alpha \geq 0$. For w we use the Goldstein and Einhorn (1987) probability weighting function

$$w(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma}$$

with $\gamma \geq 0$ and $\delta \geq 0$.

In the experiment, subjects report certainty equivalents CE. Denote by $\hat{\text{CE}}$ the certainty equivalent derived from the model above:

$$\hat{\text{CE}} = u^{-1}\Big(w(p) \cdot u(x_1) + w(1-p) \cdot u(x_2)\Big).$$

To take the model to the data, we add Fechner errors ϵ to the certainty equivalents such that $\text{CE} = \hat{\text{CE}} + \epsilon$ with $\epsilon \sim \mathcal{N}(0, \sigma^2)$. In other words, subjects make mistakes when reporting their certainty equivalents; such mistakes are mean-zero and are independently and identically distributed across lotteries.

We estimate the parameters via maximum likelihood.[6] We start by estimating the parameters on the whole sample, in effect assuming that all subjects have the same parameters. Therefore, we estimate $\theta = (\alpha)$ in the case of EU and $\theta = (\alpha, \gamma, \delta)$ in the case of RDU, as well as the noise parameter σ. For the certainty equivalent of lottery $n \in \{1, \ldots, 25\}$ reported by subject $i \in \{1, \ldots, I\}$ the contribution to

[6] We use **R** (R Core Team, 2023) with the `maxLik` package (Henningsen and Toomet, 2011). We rely on the BFGS algorithm with numerical derivatives.

the likelihood is the density

$$f(\mathrm{CE}_{i,n};\theta,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\left(\mathrm{CE}_{i,n} - \hat{\mathrm{CE}}_{i,n}(\theta)\right)^2}{2\sigma^2}\right)$$

and the sample log-likelihood $\ln L(\theta,\sigma;CE) = \sum_{i=1}^{I}\sum_{n=1}^{25} \ln f(\mathrm{CE}_{i,n};\theta,\sigma)$.

To capture the effect of the representation on the parameters, we decompose them as

$$\begin{aligned}
\alpha &= \alpha_0 + \mathbb{1}_{\text{probabilities}}\,\alpha_{\text{probabilities}} + \mathbb{1}_{\text{payoffs}}\,\alpha_{\text{payoffs}} + \mathbb{1}_{\text{both}}\,\alpha_{\text{both}},\\
\delta &= \delta_0 + \mathbb{1}_{\text{probabilities}}\,\delta_{\text{probabilities}} + \mathbb{1}_{\text{payoffs}}\,\delta_{\text{payoffs}} + \mathbb{1}_{\text{both}}\,\delta_{\text{both}},\\
\gamma &= \gamma_0 + \mathbb{1}_{\text{probabilities}}\,\gamma_{\text{probabilities}} + \mathbb{1}_{\text{payoffs}}\,\gamma_{\text{payoffs}} + \mathbb{1}_{\text{both}}\,\gamma_{\text{both}},\\
\sigma &= \sigma_0 + \mathbb{1}_{\text{probabilities}}\,\sigma_{\text{probabilities}} + \mathbb{1}_{\text{payoffs}}\,\sigma_{\text{payoffs}} + \mathbb{1}_{\text{both}}\,\sigma_{\text{both}},
\end{aligned}$$

where $\mathbb{1}_{\text{treatment}}$ is an indicator function equal to 1 if we are in the specified treatment and equal to 0 otherwise.

Table 3 shows the results. We see that, both under EU and under RDU, representing both probabilities and payoffs increases by about 11% the curvature parameter of the utility function of money α. The representations have no effect on the parameters of the probability weighting function. Therefore, the increase in α corresponds to a decrease in risk aversion.

Further, the representations affect differently the noise parameter σ depending on whether we assume EU or RDU: under EU, representing probabilities or payoffs increases σ while representing both does not; under RDU, representing probabilities or both increases σ while representing payoffs does not.

Our estimates are in line with the previous literature. For example, despite the difference in sample, currency, and procedures, our estimates of δ and γ—0.94 and 0.33—are similar to those found in Bruhin et al. (2010, Table V, CPT Types, Pooled)—0.926 and 0.377. We observe more curvature of u than Bruhin et al. (2010), but we are still within the ranges commonly found in the literature: when comparing the estimates reported in the literature, Stott (2006, Table 5) finds estimates for α of a power utility function ranging between 0.19 and 0.89, while we find 0.53 and 0.59 for EU and RDU.

To assess the robustness of these findings, in Appendix A.4 we estimate the

Table 3: Sample-level estimation, decomposition of the structural parameters.

	EU	RDU
α_0	0.53^{***}	0.59^{***}
	(0.01)	(0.01)
$\alpha_{\text{probabilities}}$	0.03	0.03^{*}
	(0.01)	(0.01)
α_{payoffs}	0.01	0.03
	(0.01)	(0.01)
α_{both}	0.06^{***}	0.07^{***}
	(0.01)	(0.02)
δ_0		0.94^{***}
		(0.01)
$\delta_{\text{probabilities}}$		-0.01
		(0.02)
δ_{payoffs}		-0.01
		(0.02)
δ_{both}		-0.01
		(0.02)
γ_0		0.33^{***}
		(0.01)
$\gamma_{\text{probabilities}}$		-0.02
		(0.02)
γ_{payoffs}		-0.02
		(0.02)
γ_{both}		0.02
		(0.02)
σ_0	5.07^{***}	4.11^{***}
	(0.05)	(0.14)
$\sigma_{\text{probabilities}}$	0.35^{***}	0.31^{*}
	(0.10)	(0.15)
σ_{payoffs}	0.22^{*}	0.18
	(0.10)	(0.15)
σ_{both}	0.17	0.30^{*}
	(0.09)	(0.15)
Log Likelihood	$-31\,819.80$	$-29\,755.04$

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

same functional forms but independently for each subject. We also estimate the distribution of the parameters in a random coefficient framework using maximum simulated likelihood (see Conte et al., 2011 and von Gaudecker et al., 2011 for similar approaches). We find the same qualitative results: representing both probabilities and payoffs increases the curvature parameter of the utility function of money α, and the representations have no effect on the parameters of the probability weighting function γ and δ. In terms of the noise parameter σ, we find some evidence that representing only probabilities increases noise while representing both probabilities and payoffs decreases it.

3.2.2 Mixture model

We also estimate a mixture model in the manner of Harrison and Rutström (2008b). We assume that a proportion of observations p^{EU} follows EU and that a proportion of observations $1-p^{\mathrm{EU}}$ follows RDU, and estimate p^{EU} in addition to the parameters of each model. Instead of decomposing the parameters between treatment, as we did previously, we now decompose p^{EU} as

$$p^{\mathrm{EU}} = p_0^{\mathrm{EU}} + \mathbb{1}_{\mathrm{probabilities}}\, p_{\mathrm{probabilities}}^{\mathrm{EU}} + \mathbb{1}_{\mathrm{payoffs}}\, p_{\mathrm{payoffs}}^{\mathrm{EU}} + \mathbb{1}_{\mathrm{both}}\, p_{\mathrm{both}}^{\mathrm{EU}}.$$

p_0^{EU} gives the baseline proportion of EU observations, while the other parameters show how the proportion changes with the representation.

Table 4 shows the results. We estimate that about 40% of the observations can be attributed to EU. Representing both probabilities and payoffs increases the proportion of EU observations to about 45%, a 12% increase.

3.3 Switching points and decision times

We finally analyse a number of secondary outcomes that we also measured in our experiment.

We measured the number of times subjects tried to submit tables where they switched in the wrong direction, meaning they switched from the lottery on the left to the certainty equivalents on the right. By doing so, they essentially violate first-order stochastic dominance. Compared to the baseline, we find some evidence that this was higher when representing payoffs only (clustered Wilcoxon rank-rum

Table 4: Mixture model.

	Estimate (SE)
α^{EU}	1.13^{***}
	(0.01)
α^{RDU}	0.55^{***}
	(0.01)
δ	0.94^{***}
	(0.01)
γ	0.18^{***}
	(0.01)
σ^{EU}	1.69^{***}
	(0.05)
σ^{RDU}	4.52^{***}
	(0.05)
p_0^{EU}	0.40^{***}
	(0.02)
$p_{\mathrm{probabilities}}^{\mathrm{EU}}$	0.00
	(0.02)
$p_{\mathrm{payoffs}}^{\mathrm{EU}}$	-0.01
	(0.02)
$p_{\mathrm{both}}^{\mathrm{EU}}$	0.05^{*}
	(0.02)
Log Likelihood	$-28\,352.95$

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

test, $p = 0.058$). The other treatments do not differ significantly from the baseline ($p > 0.218$).

We also measured the number of times subjects tried to submit tables with multiple switching points. Such behaviour can indicate random behaviour or a misunderstanding of the task. We find some evidence that the number of switches in the wrong direction is higher when we represent payoffs only (clustered Wilcoxon rank-rum test, $p = 0.068$); the other treatment again do not show any significant differences ($p > 0.452$).

Finally, we measured the time subjects took to submit each table. We do not find any difference between the treatments ($p > 0.23$).

4 Discussion and conclusion

In our experiments, we manipulate the way we represent lotteries while keeping the elicitation method fixed. We find that the choice of representation does matter and affects the risk preferences elicited.

Our representations use horizontal and vertical bars to represent probabilities and payoffs. We note that pie charts are another popular way of representing probabilities in the risk preference literature. We chose our particular representation because it allows us to manipulate probabilities and payoffs independently. Further, there is still a large debate around the appropriateness of pie charts to represent proportions (Spence, 2005).[7]

Our most consistent result is that representing both probabilities and payoffs makes subjects less risk averse. Previous research using different elicitation methods with different representations in different contexts has reached a similar conclusion (Friedman et al., 2022; Habib et al., 2017), so this result appears to be a regularity. While our experiment was not designed to explain this result, we can offer some leads. When we represent both probabilities and payoffs, we essentially display the expected value of a lottery. This extra information might provide an anchor to subjects and help them report their risk preferences. We can also think of a salience

[7]Some studies find that pie charts perform worse (Cleveland and McGill, 1984), and others, that they perform better (Simkin and Hastie, 1987). It is also unclear what people really respond to when facing a pie chart (Kosara, 2019; Skau and Kosara, 2016). Further, pie charts are not well suited to represent probabilities that are not multiples of 25%, and discrimination between a 5% and a 10% probability on a pie chart is difficult (Spence, 2005).

(Bordalo et al., 2012) or focusing (Kőszegi and Szeidl, 2013) channel: attention is more heavily directed to the represented attribute; both attributes thus need to be represented if one does not want to favour one attribute to the detriment of the other.

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Appendices

Appendix A Additional results and figures

A.1 Certainty equivalents by lottery

In Figure A1 we look at mean certainty equivalents for each lottery.

A.2 Standardised absolute deviations from expected value

We also look at how certainty equivalents vary during the course of the experiment. To do that, we compute normalised absolute differences from the expected value of a lottery

$$\bar{\mathrm{CE}} = \frac{|\mathrm{CE} - \mathrm{EV}|}{\mathrm{EV}}$$

and regress on $\bar{\mathrm{CE}}$ treatment dummies, the lottery number, the interaction between the two, and controls. The results of this regression are in Table A1. We see that, overall, representing payoffs results in higher normalised absolute difference from the expected value. However, as the experiment progresses, the difference shrinks.

A.3 Certainty equivalent regressions

Table A2 report the results of an ordinary least square regression of certainty equivalent on treatment dummies. In model (1) we add lottery dummies to control for the fact that different lotteries had different expected values. In model (2) we further control for

- the order of the lottery in the experiment, which was randomised for each subject;
- the number of times a subject tried to submit a table with multiple switching points;
- the number of times a subject tried to submit a table with a switching point in the wrong direction; and finally,
- session effects by adding session dummies.

The effect of the treatment remain statistically insignificant in all models.

Table A1: Effect of treatments and lottery number on $\bar{\text{CE}}$, OLS regression.

	β (SE)
Intercept	4.26^{***}
	(0.19)
Representing probabilities	0.05
	(0.06)
Representing payoffs	$0.17^{\bullet}$
	(0.10)
Representing both	0.10
	(0.11)
Lottery number	0.00
	(0.00)
Representing probabilities × lottery number	0.00
	(0.00)
Representing payoffs × lottery number	-0.01^{**}
	(0.00)
Representing both × lottery number	0.00
	(0.00)
Lottery dummy	✓
Session dummy	✓
R^2	0.48
n	10 335

Notes. Standard errors clustered on subjects.
$^{\bullet}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2: Effect of representations on certainty equivalents, OLS.

	(1)	(2)
Intercept	2.49^{***}	2.85^{***}
	(0.18)	(0.50)
Representing probabilities	0.10	0.10
	(0.26)	(0.26)
Representing payoffs	0.07	0.26
	(0.26)	(0.75)
Representing both	0.26	0.47
	(0.27)	(0.78)
Lottery order		-0.03^{***}
		(0.01)
Number submissions with multiple switch		0.05
		(0.03)
Number submissions with switch in wrong direction		0.95^{**}
		(0.45)
Lottery dummy	✓	✓
Session dummy	✗	✓
R^2	0.74	0.74
n	10 335	10 335

Notes. Standard errors clustered on subjects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

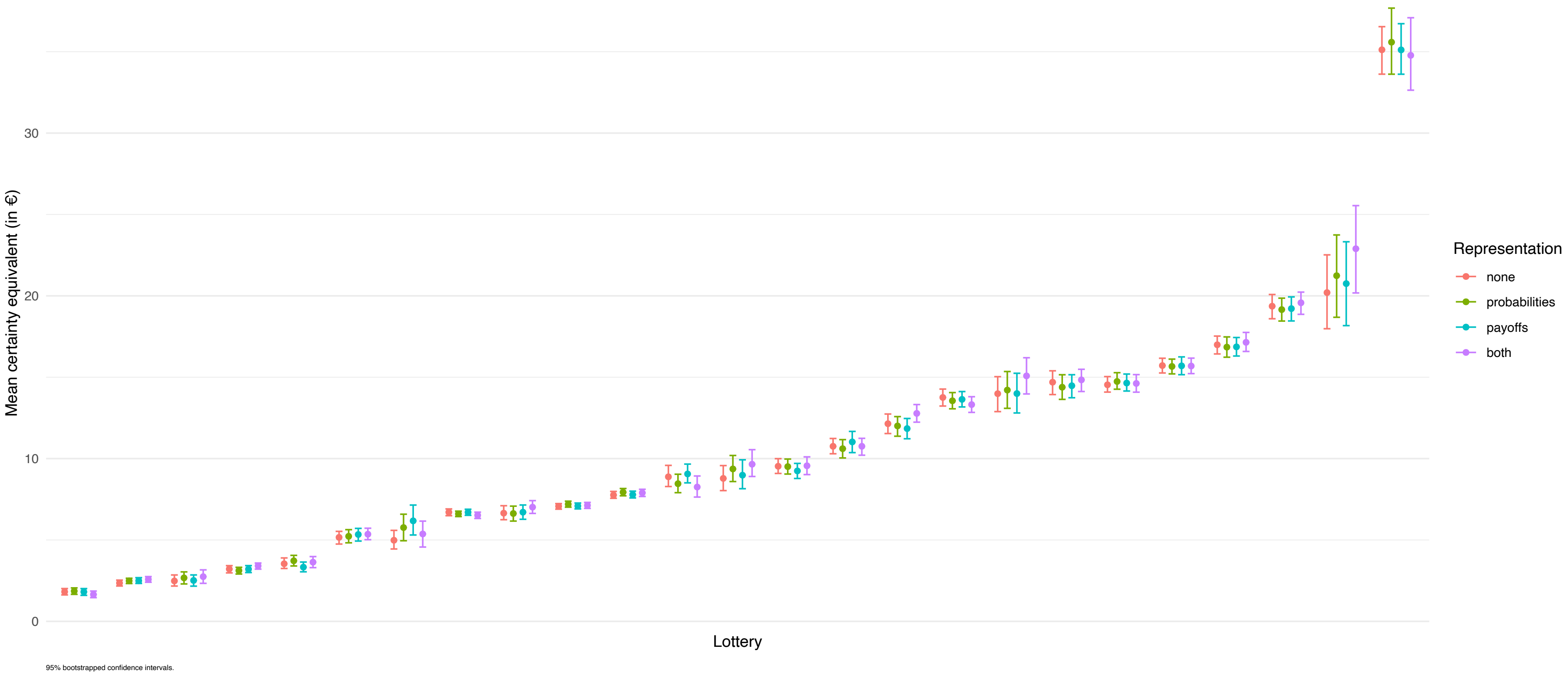

Figure A1: Mean certainty equivalents for each lottery and in each treatment.

Table A3: Effect of representations on certainty equivalents for lotteries with different characteristics, OLS.

	(1)	(2)
Intercept	8.61^{***}	9.32^{***}
	(2.02)	(2.08)
Representing probabilities	-0.06	-0.04
	(0.35)	(0.35)
Representing payoffs	0.08	0.24
	(0.37)	(0.77)
Representing both	-0.40	-0.23
	(0.34)	(0.74)
Lotteries with zero outcome	-7.49^{***}	-7.46^{***}
	(0.16)	(0.16)
Lotteries with zero outcome × Representing probabilities	0.29	0.29
	(0.17)	(0.17)
Lotteries with zero outcome × Representing payoffs	0.23	0.23
	(0.17)	(0.17)
Lotteries with zero outcome × Representing both	0.37^{*}	0.38^{*}
	(0.17)	(0.17)
Left-skewed lottery	9.08^{***}	8.74^{***}
	(1.84)	(1.85)
Left-skewed lottery × Representing probabilities	-0.12	-0.13
	(0.28)	(0.28)
Left-skewed lottery × Representing payoffs	-0.17	-0.14
	(0.27)	(0.27)
Left-skewed lottery × Representing both	0.26	0.29
	(0.26)	(0.27)
Right-skewed lottery	4.97^{**}	4.61^{*}
	(1.80)	(1.81)
Right-skewed lottery × Representing probabilities	0.04	0.03
	(0.24)	(0.25)
Right-skewed lottery × Representing payoffs	-0.02	0.00
	(0.20)	(0.21)
Right-skewed lottery × Representing both	-0.19	-0.17
	(0.26)	(0.26)
Standard deviation	0.51^{***}	0.50^{***}
	(0.06)	(0.06)
Standard deviation × Representing probabilities	0.02	0.02
	(0.05)	(0.05)
Standard deviation × Representing payoffs	0.01	0.01

	(0.05)	(0.05)
Standard deviation × Representing both	0.07	0.07
	(0.05)	(0.05)
Lottery order		-0.03^{***}
		(0.01)
Number submissions with multiple switch		0.05
		(0.03)
Number submissions with switch in wrong direction		0.93^{*}
		(0.45)
Lottery dummy	✓	✓
Session dummy	✗	✓
R^2	0.74	0.74
n	10 335	10 335

Notes. Standard errors clustered on subjects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.4 Additional structural estimations

A.4.1 Individual-level estimation

Here, instead of estimating the parameters at the sample level, as we did in the main text, we estimate the parameters independently for each subject, meaning that for each subject i we obtain estimates of θ_i and σ_i. The subject log-likelihood is

$$\ln L_i(\theta_i, \sigma_i; \mathrm{CE}_i) = \sum_{n=1}^{25} \ln f(\mathrm{CE}_{i,n}; \theta_i, \sigma_i).$$

The model converges and we can recover estimates and standard errors for 444 subjects (out of 457) under EU and for 434 subjects under RDU.[8]

Figure A2 shows box plots of the estimated parameters under EU, and Figure A3, under RDU. As before, we find that representing both payoffs and probabilities increases α. Under RDU, we do not observe a statistically significant effect of the representations on the parameters of the probability weighting function, δ and γ. Finally, we find that representing both probabilities and payoffs decreases σ under EU, while representing probabilities increases σ under RDU.

A.4.2 Random coefficients estimation

Finally, as a middle-ground, we assume that the parameters are distributed in the sample according to some probability distributions and estimate the parameters of these distributions. Since $\alpha \geq 0$, $\delta \geq 0$ and $\gamma \geq 0$, we assume that the parameters are log-normally distributed:

$$\begin{aligned} \ln \alpha &\sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2), \\ \ln \delta &\sim \mathcal{N}(\mu_\delta, \sigma_\delta^2), \\ \ln \gamma &\sim \mathcal{N}(\mu_\gamma, \sigma_\gamma^2), \end{aligned}$$

In addition, we assume that these parameters are distributed independently of each other. We also assume that the noise parameter σ is the same for the whole sample.

In the case of EU, denote by $\theta_{\mathrm{EU}} = (\mu_\alpha, \sigma_\alpha)$ the parameters to estimate, and by $g_{\mathrm{EU}}(\alpha)$ the density of α. Similarly, in the case of RDU, denote by $\theta_{\mathrm{RDU}} = (\mu_\alpha, \sigma_\alpha, \mu_\delta, \sigma_\delta, \mu_\gamma, \sigma_\gamma)$ the parameters and by $g_{\mathrm{RDU}}(\alpha, \delta, \gamma)$ the joint density. In both cases we also estimate σ.

[8] Under EU, we are missing 2 subjects in baseline, 2 when probabilities are represented, 4 when payoffs are represented, and 5 when both are represented. Under RDU, we are missing 4 subjects in baseline, 6 when probabilities are represented, 5 when payoffs are represented, and 8 when both are represented.

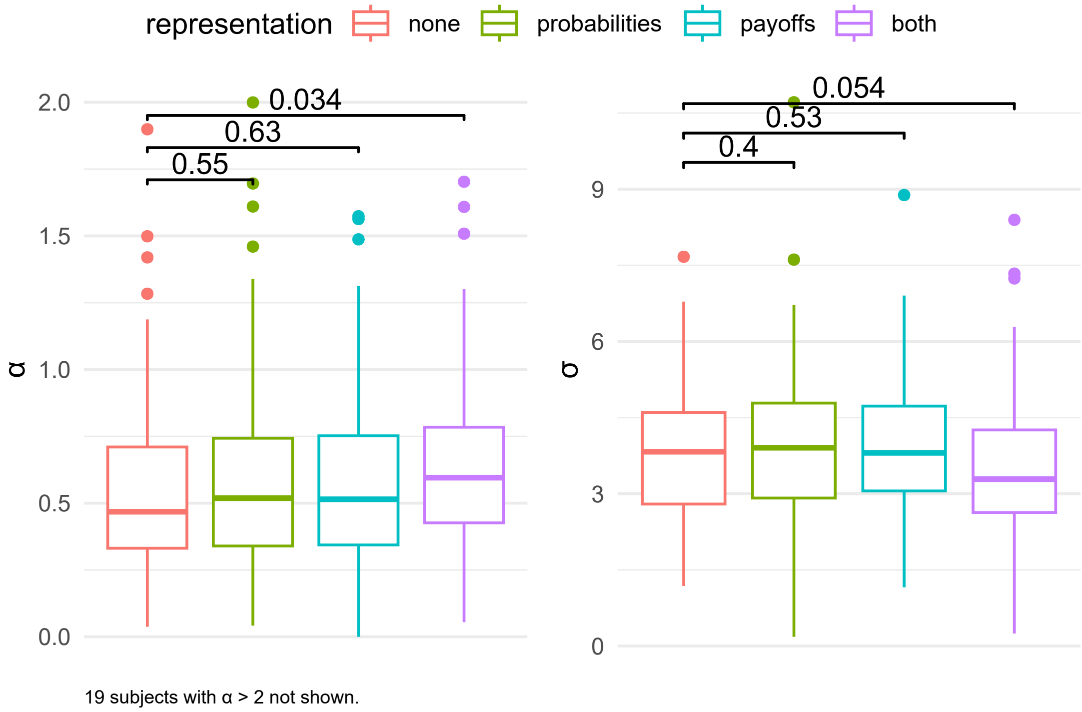

Figure A2: Box plots of the estimated parameters under EU. p-values from two-sided Wilcoxon rank-sum tests.

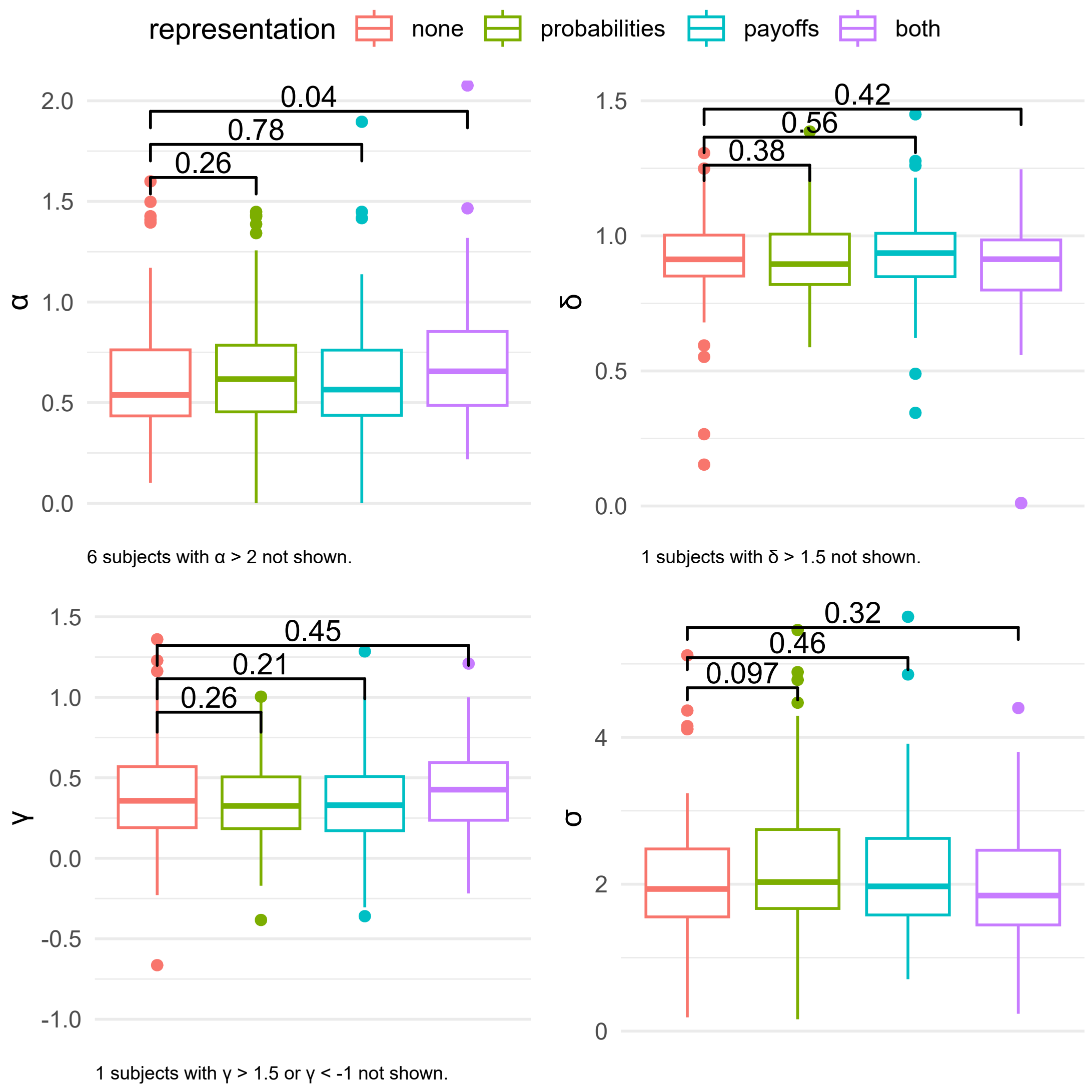

Figure A3: Box plots of the estimated parameters under RDU. p-values from two-sided Wilcoxon rank-sum tests.

The joint density of the 25 certainty equivalents of subject i is

$$\prod_{n=1}^{25} f(\mathrm{CE}_{i,n}; \theta_i, \sigma).$$

Therefore, under EU, the contribution to the likelihood for subject i is

$$L_i(\theta_{\mathrm{EU}}, \sigma; \mathrm{CE}_i) = \int_{\mathbb{R}_+} \prod_{n=1}^{25} f(\mathrm{CE}_{i,n}; \alpha, \sigma)\, g_{\mathrm{EU}}(\alpha)\, \mathrm{d}\alpha,$$

and, under RDU,

$$L_i(\theta_{\mathrm{RDU}}, \sigma; \mathrm{CE}_i) = \iiint_{\mathbb{R}_+} \prod_{n=1}^{25} f(\mathrm{CE}_{i,n}; \alpha, \delta, \gamma, \sigma)\, g_{\mathrm{RDU}}(\alpha, \delta, \gamma, \sigma)\, \mathrm{d}\alpha\, \mathrm{d}\delta\, \mathrm{d}\gamma.$$

The sample log-likelihood is then the sum across all subjects of the logarithms of these likelihoods.

We estimate the parameters using maximum simulated likelihood (see Conte et al., 2011 and von Gaudecker et al., 2011 for similar approaches).[9] The results are in Table A4.

After the estimation, we can recover a posterior estimate of each parameter and for each subject, conditional on their n certainty equivalents. Figure A4 shows box plots of the posterior estimates of α under EU, and Figure A5, of the parameters under RDU. We obtain the same results as previously: representing probabilities and payoffs at the same time increases α both under EU and under RDU. On the other hand, under RDU, none of the representations have an effect on the probability weighting function.

[9]We use Halton sequences of length 100 per individual.

Table A4: Random coefficients estimation, maximum simulated likelihood.

	EU	RDU
μ_α	-0.58^{***}	-0.34^{***}
	(0.05)	(0.01)
σ_α	1.19^{***}	0.75^{***}
	(0.03)	(0.02)
μ_δ		-0.07^{***}
		(0.00)
σ_δ		0.10^{***}
		(0.00)
μ_γ		-1.22^{***}
		(0.03)
σ_γ		0.78^{***}
		(0.03)
σ	4.07^{***}	2.52^{***}
	(0.03)	(0.02)
Log Likelihood	$-29\,899.60$	$-25\,663.85$

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

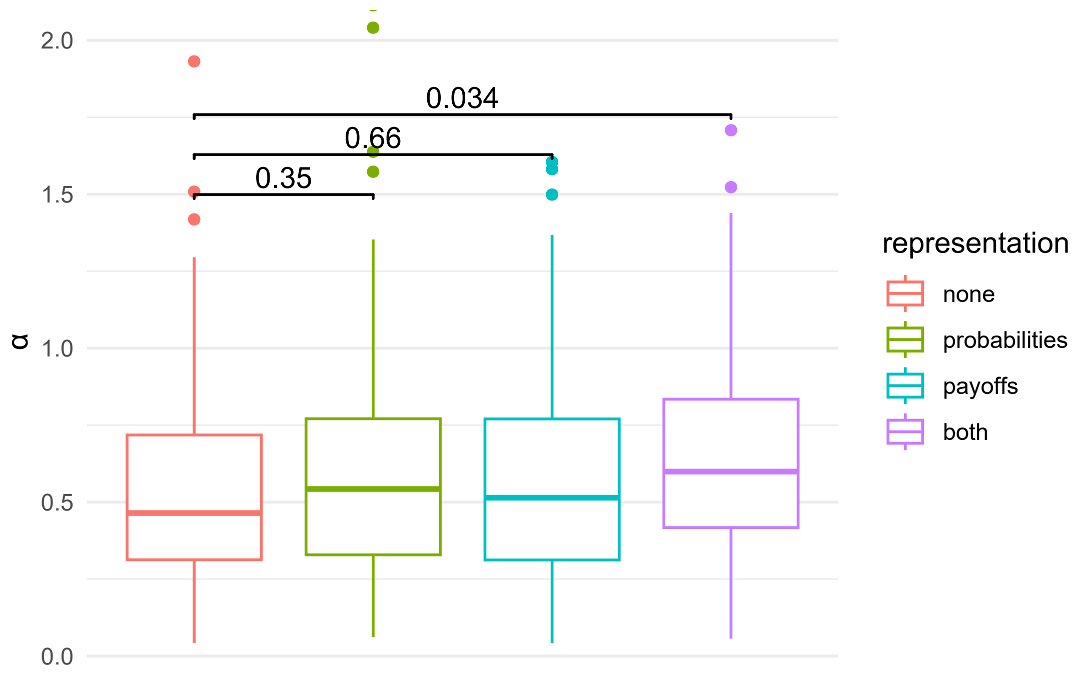

Figure A4: Box plot of the posterior estimates of α under EU. p-value from two-sided Wilcoxon rank-sum tests.

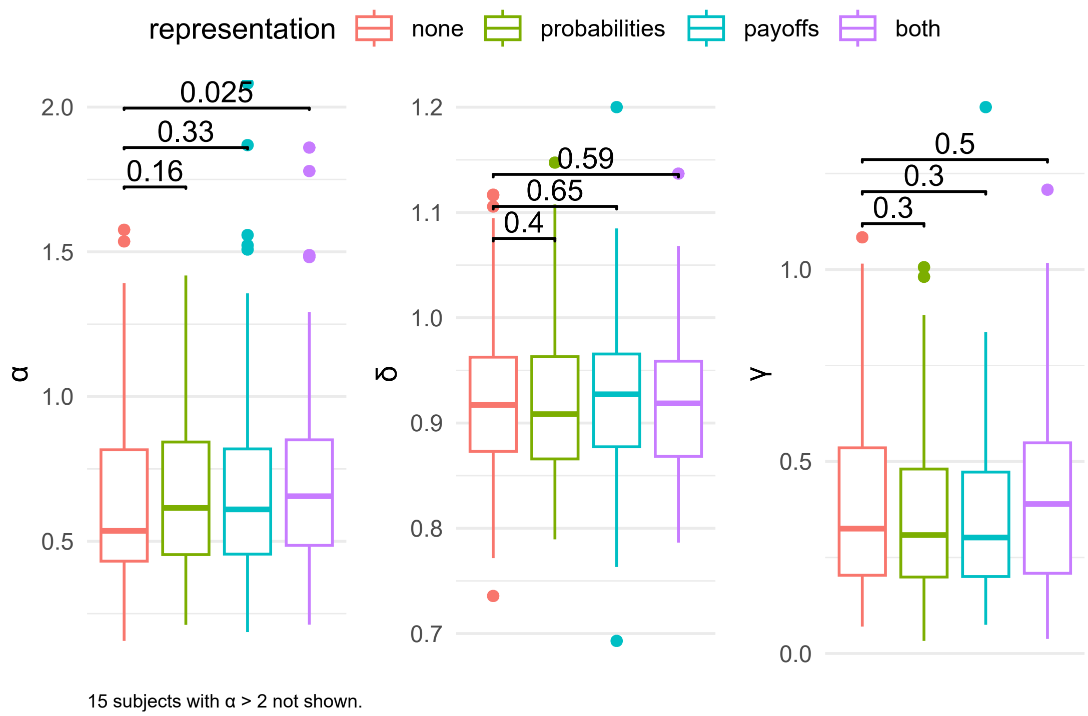

Figure A5: Box plots of the posterior estimates of the parameters under RDU. p-value from two-sided Wilcoxon rank-sum tests.