Online Appendix-Higher Order Risk Attitudes: New Model Insights and Heterogeneity of Preferences

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Appendix A The fourfold pattern to risk over outcome magnitude and probabilities

Cumulative prospect theory accommodates the fourfold pattern to risk over outcome probabilities, that is, as the probability increases from low to high, risk preferences change from risk seeking to risk aversion over gains, while those preferences change from risk aversion to risk seeking over losses. This is because, as Scholten and Read (2014) point out, prospect theory retained some of the notions introduced by Markowitz (1952) such as reference dependence and loss aversion, but introduced new ones such as probability weighting and a singly inflected value function. Scholten and Read provide an insightful account about the possible reasons the fourfold pattern to risk over outcome magnitude was not addressed by Kahnemann and Tversky. Furthermore, Scholten and Read (2014) contribute to this literature by showing that it is in principle possible for a CPT specification to account for both fourfold patterns. This is the case for a value function $v(.)$ and a weighting probability function $w(.)$ that meet the following condition for the case of a lottery that pays x with probability p and nothing otherwise ($m > 1$):

$$\frac{v\left(mx\right)}{v\left(\frac{1}{p}mx\right)} > w\left(p\right) > \frac{v\left(x\right)}{v\left(\frac{1}{p}x\right)}. \tag{a1}$$

Therefore, a necessary condition is that the value function has to be decreasingly elastic. Although this theoretical insight is certainly appealing, it faces practical limitations. The reason is that, even within decreasingly elastic value functions, inequalities (a1) are only met for a limited number of cases. We illustrate this point in Figure A.1. Following Scholten and Read, we use a normalised logarithmic value function, $v(x) = \frac{1}{a}\left(\log\left(1 + ax\right)\right)$, and the Tversky and Kahnemann probability weighting functions $w(p) = \frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{1/\gamma}}$. We use the following range of parameter values consistent with the literature: $\alpha \in [0.01, 0.1]$, $\gamma \in [0.50, 0.95]$. We use a payoff value $x = 25$ and $p \in [0.01, 0.35]$, such that lowest expected payout is 0.25 as in Scholten and Read experimental data. The red shaded areas are the ones for which (a1) is met. Similar result is obtained for different values of m. As payoff value x is increased, the number of instances for which conditions (a1) are met decreases substantially. Actually, the largest value of x where (a1) holds is $x = 40$ (shown in blue in Figure A.1).

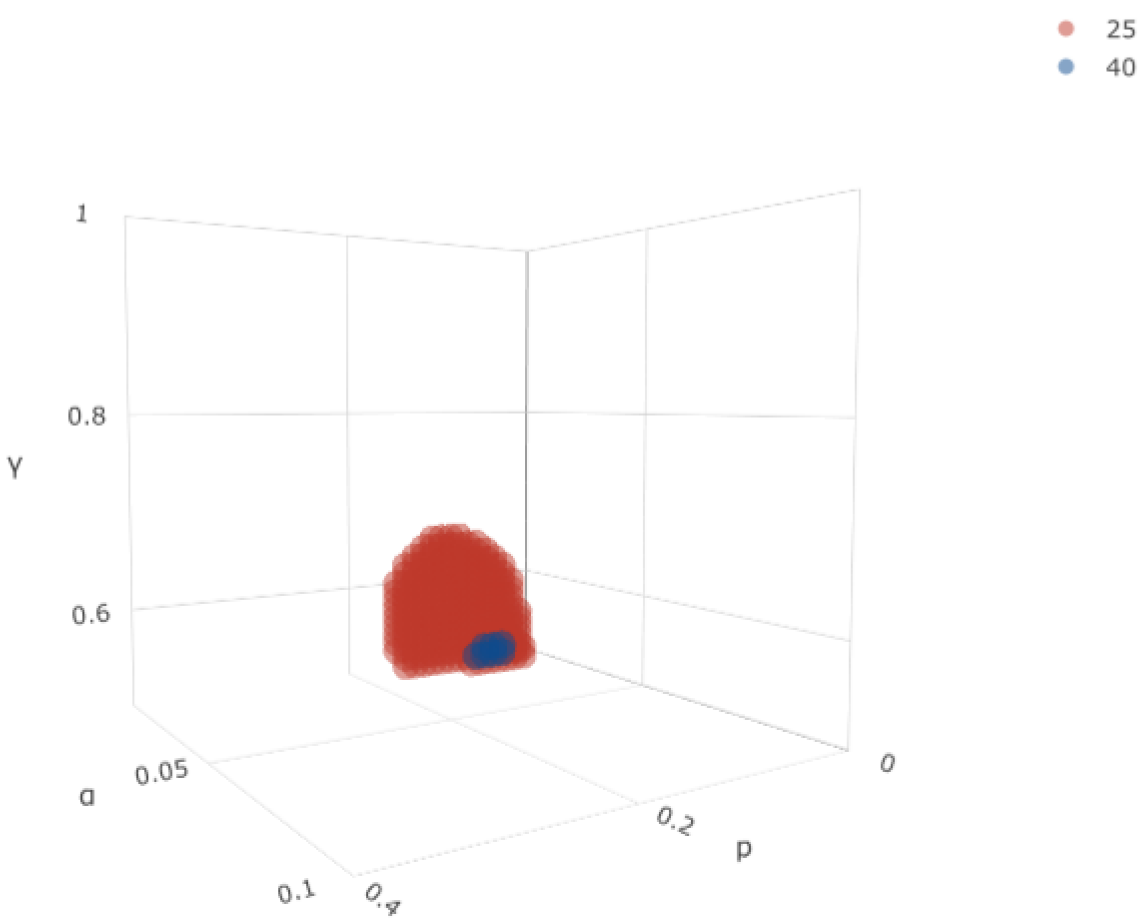

Figure A.1: Combination of parameters for which the inequality holds $\frac{v(mx)}{v\left(\frac{1}{p}mx\right)} > w\left(p\right) > \frac{v(x)}{v\left(\frac{1}{p}x\right)}$

Appendix B Two additional reference points: MinMax and X at Max P

In addition to the reference points considered in Section 3 of this paper, Baillon et al. (2020) examined two additional deterministic reference points: MinMax and X at Max P. The use of these two reference points in the literature is scarce. We are not aware of any study on higher order risk preferences, either theoretical or empirical, that employ these two reference points. Nevertheless, we present below the analytical derivations of the valuation of lottery pairs to elicit third and fourth order risky choices assuming these two reference points under two different model specifications, the M model and a CPT model.

B.1 MinMax

B.1.1 Third order risky choice

We recall the probabilities and outcomes of the lottery pair of order 3 are the following

$$\begin{aligned} B_3 &: \quad 0.5, W+X-k_2; 0.25, W+X+e_1; 0.25, W+X-e_1 \\ A_3 &: \quad 0.5, W+X; 0.25, W+X-k_2+e_1; 0.25, W+X-k_2-e_1. \end{aligned}$$

There are two possible reference points for this lottery pair. First, when $k_2 \geq e_1$, the MinMax reference point is $W+X$.

For the M model of utility defined in (1), the expected utility of the lottery pair is

$$\begin{aligned} U(B_3) &= -\lambda 0.5 \left(1 - e^{-\beta(k_2)^\eta}\right) + 0.25 \left(1 - e^{-\rho\beta(e_1)^\eta}\right) - \lambda 0.25 \left(1 - e^{-\beta(e_1)^\eta}\right) \\ U(A_3) &= -\lambda 0.25 \left(1 - e^{-\beta(k_2-e_1)^\eta}\right) - \lambda 0.25 \left(1 - e^{-\beta(k_2+e_1)^\eta}\right). \end{aligned}$$

For the CPT model, we assume a specification with a power value function, parameter $\alpha \in [0,1]$, loss aversion parameter λ, and an inverse-S-shaped probability weighting function, $w(p)$, where $w^+(p)$ and $w^-(p)$ are the probability weighting functions for gains and losses, respectively. In this case, the subjective expected values, $V(\bullet)$, are the following

$$V(B_3) = w^{+}(0.25)\,(e_1)^{\alpha} - \lambda w^{-}(0.5)\,(k_2)^{\alpha} - \lambda\left(w^{-}(0.75) - w^{-}(0.5)\right)(e_1)^{\alpha}$$
$$V(A_3) = -\lambda w^{-}(0.25)\,(k_2 - e_1)^{\alpha} - \lambda\left(w^{-}(0.5) - w^{-}(0.25)\right)(k_2 + e_1)^{\alpha}.$$

Second, when $e_1 > k_2$, the MinMax reference point becomes $W + X - k_2 + e_1$.

For the M model, the expected utility of the lottery pair is

$$U(B_3) = -\lambda 0.5\left(1 - e^{-\beta (e_1)^{\eta}}\right) + 0.25\left(1 - e^{-\rho\beta (k_2)^{\eta}}\right) - \lambda 0.25\left(1 - e^{-\beta (2e_1 - k_2)^{\eta}}\right)$$
$$U(A_3) = -\lambda 0.5\left(1 - e^{-\beta (e_1 - k_2)^{\eta}}\right) - \lambda 0.25\left(1 - e^{-\beta (2e_1)^{\eta}}\right).$$

For the CPT model, the subjective expected values are the following

$$V(B_3) = w^{+}(0.25)\,(k_2)^{\alpha} - \lambda w^{-}(0.25)\,(2e_1 - k_2)^{\alpha} - \lambda\left(w^{-}(0.75) - w^{-}(0.25)\right)(e_1)^{\alpha}$$
$$V(A_3) = -\lambda w^{-}(0.25)\,(2e_1)^{\alpha} - \lambda\left(w^{-}(0.75) - w^{-}(0.25)\right)(e_1 - k_2)^{\alpha}.$$

Our analysis reveals that the M DM can exhibit in both cases either prudent or imprudent choices, depending on the value of the model parameters and payoff sizes, although the imprudent choice is present for a wider range of parameter values. However, we find that the CPT DM chooses B_3, except if the loss aversion parameter λ exceeds extreme values such as 6.

B.1.2 Fourth order risky choice

The payoffs of the two zero-mean independent risks can be different, $e_2 > e_1$. In this case, we recall the probabilities and outcomes of the two lotteries are the following

$$B_4 : 0.25, W + X + e_2; 0.25, W + X + e_1; 0.25, W + X - e_1; 0.25, W + X - e_2$$
$$A_4 : 0.5, W + X; 0.125, W + X + e_2 + e_1; 0.125, W + X + e_2 - e_1;$$
$$0.125, W + X - e_2 + e_1; 0.125, W + X - e_2 - e_1.$$

The MinMax reference point is $W + X + e_2$.

For the M model, the expected utility values of the lottery pair are given by

$$
\begin{aligned}
U(B_4) &= -\lambda 0.25\left(1-e^{-\beta(e_2-e_1)^\eta}\right)-\lambda 0.25\left(1-e^{-\beta(e_2+e_1)^\eta}\right)-\lambda 0.25\left(1-e^{-\beta(2e_2)^\eta}\right)\\
U(A_4) &= -\lambda 0.5\left(1-e^{-\beta(e_2)^\eta}\right)+0.125\left(1-e^{-\rho\beta(e_1)^\eta}\right)-\lambda 0.125\left(1-e^{-\beta(e_1)^\eta}\right)\\
&\quad -\lambda 0.125\left(1-e^{-\beta(2e_2-e_1)^\eta}\right)-\lambda 0.125\left(1-e^{-\beta(2e_2+e_1)^\eta}\right).
\end{aligned}
$$

For the CPT model, the value of the prospects are given by

$$
\begin{aligned}
V(B_4) &= -\lambda w^-(0.25)(2e_2)^\alpha-\lambda\left(w^-(0.5)-w^-(0.25)\right)(e_1+e_2)^\alpha-\lambda\left(w^-(0.75)-w^-(0.5)\right)(e_2-e_1)^\alpha\\
V(A_4) &= w^+(0.125)\,(e_1)^\alpha-\lambda w^-(0.125)\,(2e_2+e_1)^\alpha-\lambda\left(w^-(0.25)-w^-(0.125)\right)(2e_2-e_1)^\alpha\\
&\quad -\lambda\left(w^-(0.75)-w^-(0.25)\right)(e_2)^\alpha-\lambda\left(w^-(0.875)-w^-(0.75)\right)(e_1)^\alpha.
\end{aligned}
$$

Our analysis reveals that the M DM can exhibit either temperate or intemperate choices, depending on the value of the model parameters and payoff sizes, although the intemperate choice is present for a wider range of parameter values. However, we find that the CPT DM makes the temperate choice.

Overall, taking into consideration both third and fourth order risky choices, we find that the predictions of the two models under this reference point are similar to the case of MaxMin.

B.2 X at Max P

B.2.1 Third order risky choice

In the third order lottery pairs, there is one payoff in each lottery with equal probability of 0.5. Following Baillon et al. (2020), we take as the reference point the payoff of the A lottery. Therefore, the reference point is $W+X$.

There are two cases. First, when $k_2 \geq e_1$, the value of the lottery pair is the same as in the case under MinMax examine above.

Second, when $e_1 > k_2$, for the M model, the expected utility of the lottery pair is

$$
\begin{aligned}
U(B_3) &= -\lambda 0.5\left(1-e^{-\beta(k_2)^\eta}\right)+0.25\left(1-e^{-\rho\beta(e_1)^\eta}\right)-\lambda 0.25\left(1-e^{-\beta(e_1)^\eta}\right)\\
U(A_3) &= 0.25\left(1-e^{-\rho\beta(-k_2+e_1)^\eta}\right)-\lambda 0.25\left(1-e^{-\beta(k_2+e_1)^\eta}\right).
\end{aligned}
$$

For the CPT model, the subjective expected values are the following

$$
\begin{aligned}
V(B_3) &= w^+(0.25)\,(e_1)^\alpha - \lambda w^-(0.25)\,(e_1)^\alpha - \lambda\left(w^-(0.75) - w^-(0.25)\right)(k_2)^\alpha \\
V(A_3) &= w^+(0.25)\,(e_1 - k_2)^\alpha - \lambda w^-(0.25)\,(k_2 + e_1)^\alpha .
\end{aligned}
$$

B.2.2 Fourth order risky choice

The reference point under X at max P is $W + X$. Therefore, the implications for both models are the same as under the reference point average payout described in Section 3.2.

Appendix C Stimuli

Table C.1: List of choice tasks from Deck and Schlesinger (2010).

Task	Order	Option B	Option A
1	3	$[30, 30 + 25 + [25, -25]$	$[30 + 25, 30 + [25, -25]$
2	4	$[15 + [5, -5], 5 + [5, -5]]$	$[15, 15 + [5, -5] + [5, -5]]$
3	3	$[12.5, 12.5 + 9 + [5, -5]$	$[12.5 + 9, 12.5 + [5, -5]$
4	4	$[15 + [9, -9], 15 + [1, -1]]$	$[15, 15 + [9, -9] + [1, -1]]$
5	3	$[12.5, +12.5 + 1 + [5, -5]$	$[12.5 + 1, +12.5 + [5, -5]$
6	4	$[55 + [25, -25], 55 + [25, -25]]$	$[55, 55 + [25, -25] + [25, -25]]$
7	3	$[10.5, +10.5 + 9 + [1, -1]$	$[10.5 + 9, +10.5 + [1, -1]$
8	4	$[55 + [5, -5], 55 + [45, -45]]$	$[55, 55 + [5, -5] + [45, -45]]$
9	3	$[12.5, +12.5 + 5 + [5, -5]$	$[12.5 + 5, +12.5 + [5, -5]$
10	3	$[14.5, +14.5 + 1 + [9, -9]$	$[14.5 + 1, +14.5 + [9, -9]$

List of choice tasks from Deck and Schlesinger (2010). $[x, y]$ indicates a lottery with chances 50:50 of getting either x or y. The first column refers to the corresponding name of the task from the data source. Choice of option B indicates risk aversion, prudence and temperance for the 2^{nd}, 3^{rd} and 4^{th} order respectively.

Table C.2: List of choice tasks from Deck and Schlesinger (2014).

Task	Order	Option B	Option A
4	2	$[5+5, 10]$	$[5, 10+5]$
5	2	$[2+8, 4]$	$[2, 4+8]$
6	2	$[10+5, 15]$	$[10, 15+5]$
7	2	$[2+3, 4]$	$[2, 4+3]$
8	2	$[20+30, 40]$	$[20, 40+30]$
9	2	7	$[4, 10]$
10	2	10	$[1, 19]$
11	3	$[5, 10+[-2, 2]]$	$[5+[-2, 2], 10]$
13	3	$[5, 10+[-4, 4]]$	$[5+[-4, 4], 10]$
14	3	$[2, 4+[1, -1]]$	$[2+[1, -1], 4]$
15	3	$[20, 40+[10, -10]]$	$[20+[10, -10], 40]$
16	3	$[8, 10+[2, -2]]$	$[8+[2, -2], 10]$
17	3	$[12, 14+[1, -1]]$	$[12+[1, -1], 14]$
18	4	$[[10, 24]+[14, 20], [14, 20]+[10, 24]]$	$[[14, 20]+[14, 20], [10, 24]+[10, 24]]$
19	4	$[[5, 12]+[7, 10], [7, 10]+[5, 12]]$	$[[7, 10]+[7, 10], [5, 12]+[5, 12]]$
21	4	$[[5, 12]+[1, 16], [1, 16]+[5, 12]]$	$[[1, 16]+[1, 16], [5, 12]+[5, 12]]$
22	4	$[14+12B, 24+12A]$	$[14+12A, 24+12B]$
23	4	$[7+11B, 12+11A]$	$[7+11A, 12+11B]$
24	4	$[1+11B, 18+11A]$	$[1+11A, 18+11B]$

List of choice tasks from Deck and Schlesinger (2014). $[x, y]$ indicates a lottery with chances 50:50 of getting either x or y. The first column refers to the corresponding name of the task from the data source. Choice of option B indicates risk aversion, prudence and temperance for the 2^{nd}, 3^{rd} and 4^{th} order respectively.

Table C.3: List of choice tasks from Noussair et al. (2014)

Task	Order	Option B	Option A
Riskav 1	2	20	$[65, 5]$
Riskav 2	2	25	$[65, 5]$
Riskav 3	2	30	$[65, 5]$
Riskav 4	2	35	$[65, 5]$
Riskav 5	2	40	$[65, 5]$
Prud 1	3	$[90 + [20, -20], 60]$	$[90, 60 + [20, -20]]$
Prud 2	3	$[90 + [10, -10], 60]$	$[90, 60 + [10, -10]]$
Prud 3	3	$[90 + [40, -40], 60]$	$[90, 60 + [40, -40]]$
Prud 4	3	$[135 + [30, -30], 90]$	$[135, 90 + [30, -30]]$
Prud 5	3	$[65 + [20, -20], 35]$	$[65, 35 + [20, -20]]$
Temp 1	4	$[90 + [30, -30], 90 + [30, -30]]$	$[90, 90 + [30, -30] + [30, -30]]$
Temp 2	4	$[90 + [30, -30], 90 + [10, -10]]$	$[90, 90 + [30, -30] + [10, -10]]$
Temp 3	4	$[90 + [30, -30], 90 + [50, -50]]$	$[90, 90 + [30, -30] + [50, -50]]$
Temp 4	4	$[30 + [10, -10], 30 + [10, -10]]$	$[30, 30 + [10, -10] + [10, -10]]$
Temp 5	4	$[70 + [30, -30], 70 + [30, -30]]$	$[70, 70 + [30, -30] + [30, -30]]$

List of choice tasks from Noussair et al. (2014). $[x, y]$ indicates a lottery with chances 50:50 of getting either x or y. The first column refers to the corresponding name of the task from the data source. Choice of option B indicates risk aversion, prudence and temperance for the 2nd, 3rd and 4th order respectively.

Appendix D Simulations

In this appendix, we describe two extensive Monte Carlo simulation exercises and report their results. The scope of the simulations is two-fold. First, we want to confirm that the statistical method employed in the paper is able to identify the different model specifications as well as to discriminate among them. Second, we want to confirm that the tasks selected in the new experiment are useful to empirically estimate and classify subjects across the alternative choice models.

D.1 Simulation 1: Assessment of the econometric method

The objective of the first simulation exercise is to explore whether the statistical method employed here can successfully identify and discriminate among the different model specifications using the experimental designs analysed in this paper, and the model selection method we are using to classify subjects, i,e, calculation of the Bayes Factor based on the Marginal Log-Likelihood. The Bayes factor is known to balance the quality of the fit versus the model complexity, and it therefore, rewards highly predictive models and penalises models with "wasted" parameter space.

We define a *specification* as the combination of a decision model and a reference point. We have 2 decision models (M and CPT) and three reference points (SQ, AP and MaxMin), giving a total of 6 specifications. Depending on the value of the parameters of some of those specifications, EUT is nested within them. The simulation follows a number of steps. For each of the six specifications, and for a given set of choice tasks, we assume a set of behavioural parameters and we generate an artificial dataset consisting of the choices of 100 subjects. We subsequently run a cross-estimation exercise where all the specifications are used to estimate that dataset. For each iteration, we check whether it is possible to identify the data generating specification and recover the behavioural parameters that generated the simulated dataset. We repeat this process 100 times. For the set of behavioural parameters, we used values that fall within a range that can be considered as representative for the utility curvature, the probability weighting and the precision (noise) (see Scholten and Read, 2014; Noussair et al., 2014, Abdellaoui et al. 2021). We have repeated the simulation exercise for various levels of noise and the results reported below remain qualitatively identical. Here we report the results of a *medium* value of the parameter ϕ that is usually observed empirically.

The values of the parameters for all the specifications are listed in Table D1. Following the assumptions of the Hierarchical Bayesian modeling, for each iteration of the simulation, the parameters of the individual subjects are drawn from a Normal distribution centered around the true parameter values. Finally, for the set of choice tasks we are using the lotteries from DS10. The reason behind this choice is that, from all the experimental data we analyse and report in this study, the experimental design of DS10 is the less informative one as far as our objective to estimate parametric models is concerned. In particular, DS10 includes only 10 pairwise choices (6 tasks for third order and 4 tasks for fourth order risk preferences) and therefore, it is expected to be the most challenging dataset in terms of identification and estimation of the models.

Table D2 reports the mean aggregate absolute value of the Log-Marginal Likelihood for all the 36 cross-specification combinations. The specifications across the rows represent the true DGP, while the specifications across the columns represent the estimated ones. For instance, in the first row, the DGP is M/SQ and the entry in each cell of that row is the average value of the marginal likelihood when the corresponding column model is the estimated one. Across the diagonal is when the true and the estimated models coincide. Hence, if identification is feasible, one would expect the entry on the diagonal to be the smallest number for each of the rows (here a lower value of the likelihood indicates a better fit of the model). This pattern is confirmed in Table D2. In every row, the diagonal element is always the minimum, confirming that, on average, the true DGP is identified. This evidence suggests that the different specifications are not observationally indistinguishable.

Table D3 reports the pairwise comparison of specifications based on the value of the Bayes Factor. Again, the specification in the rows represent the true DGP, and the ones in the columns the estimated one. For example, in the first row, where M/SQ is the the DGP, the number of times the M/SQ was classified as the best model when each of the other specifications was assumed, is reported. As expected, the diagonal element is always 0 as the Bayes Factor is 1. Then, for instance, when M/SQ is compared to M/AP, the former was identified as the best model for each of the simulations, while when M/SQ was compared to CTP/SQ, the model was classified best in 93% of the simulations. Overall, it appears that, on average, the true DGP can be identified with confidence.

Finally, we examine whether the value of the parameters can be successfully recovered. Tables D4-D9 report the median estimates from this cross-estimation exercise. Following the standard practice, we have constrained the upper bounds of the parameters. For the M model, we have set the upper bound of α to 0.1, of η to 2 and λ to 5. For the CPT model, we have set the upper bound of α and γ to 2, and λ to 5. For example, Table D4 reports the estimates when the true DGP is M/SQ and each of the six model specifications has been employed to estimate the dataset. The results of this table show that the recovered values are quite close to the true ones (0.041 for parameter α compared to the true value of 0.05, and 1.193 for the η parameter compared to the true value of 1.200). However, when a different model specification is estimated, we obtain parameter estimates that differ substantially from the true ones. For example, $\alpha = 0.000$ and $\eta = 1.945$ in the case of M/AP, and $\alpha = 0.098$, almost twice the true value, and $\eta = 1.507$ in the case of M/MaxMin. Similarly, when CPT is estimated, we obtain large estimates for both the probability weighting function and the utility curvature, with $\gamma > 1$ implying over-weighting of all probabilities, or $\alpha > 1$ implying risk seeking behaviour. A similar pattern is observed for the remaining 5 cases.

Table D.1: Simulation parameters

		M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
	α	0.050	0.050	0.050	-	-	-
	β	-	0.040	0.040	-	-	-
M	η	1.200	1.200	1.200	-	-	-
	λ	-	1.500	1.500	-	-	-
	ϕ	5.000	5.000	5.000	-	-	-
	α	-	-	-	0.750	0.750	0.750
CPT	γ	-	-	-	0.650	0.650	0.650
	λ	-	-	-	-	1.500	1.500
	ϕ	-	-	-	5.000	5.000	5.000

Notes: The Table reports the true values of the simulation parameters. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

Table D.2: Log-Marginal Likelihoods

	M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
M/SQ	**1128.58**	1144.20	1141.75	1133.49	1137.59	1140.95
M/AP	1073.87	**944.37**	1121.19	1227.78	989.25	1006.08
M/MAXMIN	1254.54	1082.97	**1061.93**	1261.80	1269.86	1280.56
CPT/SQ	897.99	900.45	893.32	**868.38**	874.84	875.59
CPT/AP	1231.10	1152.59	1196.50	1114.32	**1091.59**	1112.84
CPT/MAXMIN	748.36	750.62	721.12	707.06	709.45	**692.17**

Notes: The Table reports the mean aggregate Log-Marginal Likelihood for all the 36 possible combinations between true and assumed models based on 100 simulations. The row specification is the true data generating process ,while the column specification is the estimated one. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

Table D.3: Classification based on Bayes Factor

	M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
M/SQ	0	100	100	93	100	100
M/AP	100	0	100	100	100	100
M/MAXMIN	100	100	0	100	100	100
CPT/SQ	100	100	100	0	100	100
CPT/AP	100	100	100	93	0	88
CPT/MAXMIN	100	100	100	94	100	0

Notes: The Table reports frequency with which each row model is classified better than each column model, based on the value of the Bayes Factor. The row specification is the true data generating process ,while the column specification is the estimated one. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

Table D.4: Estimates when M/SQ is the true DGP

		M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
	α	0.041	0.000	0.098	-	-	-
	s.d.	0.019	0.000	0.006	-	-	-
	β	-	0.098	0.005	-	-	-
	s.d.	-	0.012	0.006	-	-	-
M	η	1.193	1.945	1.507	-	-	-
	s.d.	0.211	0.129	0.358	-	-	-
	λ	-	0.44	1.147	-	-	-
	s.d.	-	0.574	0.251	-	-	-
	ϕ	7.886	1.945	1.507	-	-	-
	s.d.	7.996	0.129	0.358	-	-	-
	α	-	-	-	0.811	1.938	1.918
	s.d.	-	-	-	0.076	0.092	0.188
CPT	γ	-	-	-	0.989	1.288	1.054
	s.d.	-	-	-	0.102	0.199	0.06
	λ	-	-	-	-	0.248	2.353
	s.d.	-	-	-	-	0.308	1.175
	ϕ	-	-	-	22.954	0.137	0.06
	s.d.	-	-	-	3.572	0.044	0.044

Notes: The row specification is the true data generating process ,while the column specification is the estimated one. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

Table D.5: Estimates when M/AP is the true DGP

		M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
	α	0.000	0.052	0.005	-	-	-
	s.d.	0.000	0.037	0.001	-	-	-
	β	-	0.030	0.048	-	-	-
	s.d.	-	0.018	0.031	-	-	-
M	η	2.000	1.240	1.127	-	-	-
	s.d.	0.000	0.201	0.277	-	-	-
	λ	-	1.716	0.900	-	-	-
	s.d.	-	0.857	0.412	-	-	-
	ϕ	0.179	1.240	1.127	-	-	-
	s.d.	0.021	0.201	0.277	-	-	-
	α	-	-	-	1.126	1.515	0.998
	s.d.	-	-	-	0.018	0.126	0.068
	γ	-	-	-	2.000	1.612	0.921
	s.d.	-	-	-	0.000	0.132	0.052
CPT	λ	-	-	-	-	2.877	0.717
	s.d.	-	-	-	-	0.265	0.279
	ϕ	-	-	-	0.402	0.421	15.198
	s.d.	-	-	-	0.056	0.134	5.142

Notes: The row specification is the true data generating process ,while the column specification is the estimated one. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

Table D.6: Estimates when M/MAXMIN is the true DGP

		M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
	α	0.001	0.026	0.042	-	-	-
	s.d.	0.000	0.003	0.015	-	-	-
	β	-	0.001	0.025	-	-	-
	s.d.	-	0.000	0.022	-	-	-
M	η	2.000	2.000	1.141	-	-	-
	s.d.	0.000	0.000	0.102	-	-	-
	λ	-	0.266	1.322	-	-	-
	s.d.	-	0.031	0.240	-	-	-
	ϕ	0.022	2.000	1.141	-	-	-
	s.d.	0.001	0.000	0.102	-	-	-
	α	-	-	-	1.277	1.845	1.016
	s.d.	-	-	-	0.064	0.023	0.127
CPT	γ	-	-	-	1.337	2.000	0.994
	s.d.	-	-	-	0.489	0.000	0.106
	λ	-	-	-	-	1.466	0.899
	s.d.	-	-	-	-	0.110	0.613
	ϕ	-	-	-	3.860	0.102	13.475
		-	-	-	2.827	0.020	7.582

Notes: The row specification is the true data generating process ,while the column specification is the estimated one. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

Table D.7: Estimates when CPT/SQ is the true DGP

		M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
	α	0.018	0.001	0.090	-	-	-
	s.d.	0.001	0.003	0.030	-	-	-
	β	-	0.041	0.023	-	-	-
	s.d.	-	0.045	0.015	-	-	-
M	η	2.000	1.758	1.009	-	-	-
	s.d.	0.005	0.214	0.031	-	-	-
	λ	-	0.238	3.273	-	-	-
	s.d.	-	0.226	1.306	-	-	-
	ϕ	0.812	1.758	1.009	-	-	-
	s.d.	0.065	0.214	0.031	-	-	-
	α	-	-	-	0.819	1.120	0.970
	s.d.	-	-	-	0.192	0.159	0.067
CPT	γ	-	-	-	0.659	0.598	0.546
	s.d.	-	-	-	0.166	0.235	0.299
	λ	-	-	-	-	1.357	1.867
	s.d.	-	-	-	-	1.088	0.512
	ϕ	-	-	-	5.186	17.322	5.222
		-	-	-	5.265	34.880	6.240

Notes: The row specification is the true data generating process ,while the column specification is the estimated one. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

Table D.8: Estimates when CPT/AP is the true DGP

		M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
	α	0.011	0.043	0.032	-	-	-
	s.d.	0.000	0.045	0.003	-	-	-
	β	-	0.001	0.000	-	-	-
	s.d.	-	0.002	0.000	-	-	-
M	η	1.092	1.539	1.062	-	-	-
	s.d.	0.007	0.300	0.022	-	-	-
	λ	-	2.937	1.128	-	-	-
	s.d.	-	1.659	0.015	-	-	-
	ϕ	14.356	1.539	1.062	-	-	-
	s.d.	0.243	0.300	0.022	-	-	-
	α	-	-	-	1.219	0.724	0.991
	s.d.	-	-	-	0.084	0.154	0.063
CPT	γ	-	-	-	0.943	0.596	0.755
	s.d.	-	-	-	0.049	0.203	0.313
	λ	-	-	-	-	1.366	0.846
	s.d.	-	-	-	-	0.850	0.104
	ϕ	-	-	-	4.805	8.684	10.476
		-	-	-	2.675	17.958	5.949

Notes: The row specification is the true data generating process ,while the column specification is the estimated one. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

Table D.9: Estimates when CPT/MAXMIN is the true DGP

		M/SQ	M/AP	M/MAXMIN	CPT/SQ	CPT/AP	CPT/MAXMIN
	α	0.020	0.000	0.100	-	-	-
	s.d.	0.001	0.000	0.000	-	-	-
	β	-	0.011	0.033	-	-	-
	s.d.	-	0.022	0.015	-	-	-
M	η	2.000	1.460	1.000	-	-	-
	s.d.	0.000	0.258	0.000	-	-	-
	λ	-	0.617	1.824	-	-	-
	s.d.	-	0.245	0.669	-	-	-
	ϕ	1.242	1.460	1.000	-	-	-
	s.d.	0.110	0.258	0.000	-	-	-
	α	-	-	-	0.845	1.217	0.800
	s.d.	-	-	-	0.065	0.108	0.088
CPT	γ	-	-	-	0.788	0.619	0.631
	s.d.	-	-	-	0.050	0.086	0.249
	λ	-	-	-	-	2.825	1.449
	s.d.	-	-	-	-	0.623	0.128
	ϕ	-	-	-	9.837	1.719	5.625
		-	-	-	4.366	2.094	4.083

Notes: The row specification is the true data generating process ,while the column specification is the estimated one. M stands for the Markowitz model, CPT for the Cumulative Prospect Theory model. For the reference points, SQ indicates the Status Quo, AP the average payout and MAXMIN the MAXMIN.

D.2 Simulation 2: Tasks in the new experiment

The objective of the second simulation is to assist with the selection of choice tasks to use in our experiment. The selection of the experimental tasks is based on four criteria. First, we selected lottery pairs that generated different choices across the two decision models for the majority of a wide range of model parameter values. Second, we include in the experiment choice tasks with a significant probabilistic information content. That is, for increased levels of noise in the stochastic component of choice, and for a given set of parameters, we kept those tasks that would predict choice probability in favour of a lottery of at least 60%. Third, the lottery pairs selected need to provide enough information to satisfactorily recover the parameters of the DGP. Fourth, the choice tasks selected should have discriminatory power between the two models based on the value of the pairwise Bayes Factor.

This simulation is focused on the SQ reference point because is the one we endeavoured to implement through experimental procedure as described in Section 5. Like we did in simulation 1, we simulate data from an either M or CPT specification, and estimate those datasets with the two possible specifications. Table D10 reports the mean aggregate absolute value of the Log-Marginal Likelihood for all the 4 cross-specification combinations. The specifications across the rows represent the true data generating specification, while the specifications across the columns represent the estimated ones. If the method correctly identifies the model, the diagonal element should be the lowest in each row, which is the case in our simulation. In addition, we find that the true DGP specification is identified 100% of the times based on the value of the Bayes Factor. Finally, Tables D11 and D12 report the parameters that have been recovered in the estimations of the simulations. The estimates are close to the true values when the DGP coincides with the assumed specification. When the true DGP is M/SQ, the parameter in the CPT value function is close to unity, suggesting linear utility and probability distortion. When the true DGP is CPT/SQ, parameter η in the expo-power function is unity which would suggest an EUT model with exponential utility rather than the M model of utility.

Table D.10: Log-Marginal Likelihood

	M/SQ	CPT/SQ
M/SQ	**1487.205**	3662.528
CPT/SQ	1392.478	**1260.302**

Notes: The Table reports the mean aggregate Log-Marginal Likelihood for all the four possible combinations between true and assumed models based on 100 simulations. The row model is the true data generating process ,while the column model is the assumed model. M/SQ stands for the Markowitz model with Status Quo reference point, CPT for the Cumulative Prospect Theory model with Status Quo reference point.

Table D.11: Estimates when M/SQ is the true DGP

Parameter	M/SQ	Parameter	CPT/SQ
α	0.049	α	0.989
s.d.	0.004	s.d.	0.010
η	1.161	γ	0.645
s.d.	0.041	s.d.	0.025
ϕ	3.915	ϕ	4.954
s.d.	0.839	s.d.	0.527

Notes: The row specifications represent the true data generating process and the column ones the assumed specification. M/SQ stands for the Markowitz model with Status Quo reference point, CPT for the Cumulative Prospect Theory model with Status Quo reference point.

Table D.12: Estimates when CPT/SQ is the true DGP

Parameter	M/SQ	Parameter	CPT/SQ	
α	0.093	α	-	0.753
s.d.	0.003	s.d.	-	0.032
η	1.001	γ	-	0.658
s.d.	0.003	s.d.	-	0.020
ϕ	9.227	ϕ	-	3.168
s.d.	0.036	s.d.	-	0.360

Notes: The row specifications represent the true data generating process and the column ones the assumed specification. M/SQ stands for the Markowitz model with Status Quo reference point, CPT for the Cumulative Prospect Theory model with Status Quo reference point.

Appendix E Screenshot

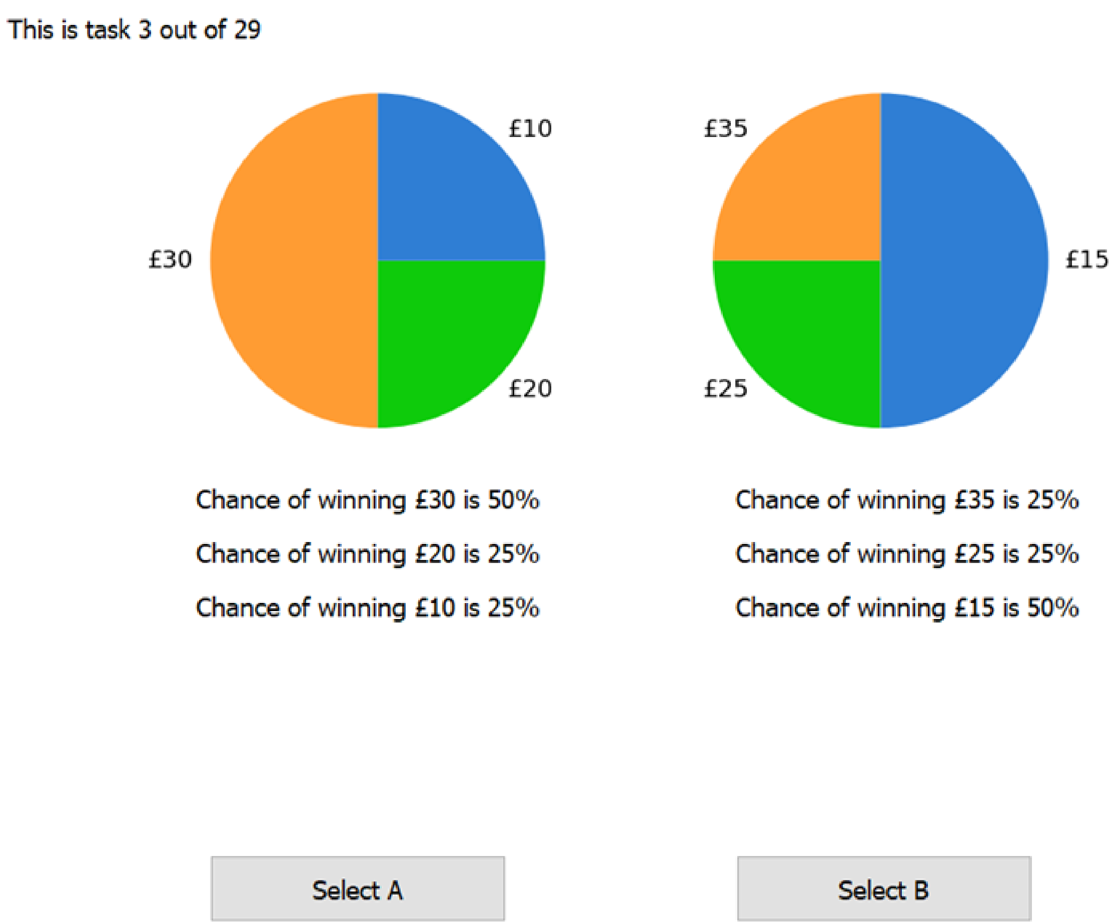

Figure E.1: Screenshot of the experimental interface

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