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The Determinants of Decision Time

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Abstract

This paper estimates the determinants of decision time for different types of decision maker in the context of an experimental investigation of multiple prior models of behaviour under ambiguity. Four models are considered: Expected Utility, Smooth, Rank Dependent Expected Utility and Alpha model. The results of a mixture model which assigns subjects to types enable us to distinguish the factors influencing the decision time of each of these four types. We find that the different types are influenced by different factors. In general, the Rank Dependent type takes more time, followed by the Smooth, the Expected Utility and finally the Alpha type, whose decision time is always the lowest. Our results reflect the relative complexity of the preference functionals used by the different types. Consequently, the importance of looking at the process of pairwise choices rather than simply at the choice made is raised to the attention of theorists and analysts.

JEL classification: C23; C24; C91; D81

Keywords: decision time; choice under uncertainty; censored regression

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1 Introduction

This paper estimates the determinants of the time taken by subjects to make decisions in experiments. A number of factors may impinge on decision time: the complexity of the decision problem, its familiarity (which may change as the experiment proceeds), and the positioning of a particular decision task in the overall sequence facing the subject. The characteristics of the subject may also be important, particularly the way that the subject processes and analyses decision problems. Using an experiment on decision-making under ambiguity as a vehicle, this paper explores the importance of these reasons and others. The results are of importance for the optimal choice of tasks in experiments and for the understanding of subjects' decision-making processes. Our paper complements the results of Rubenstein (2013), though his analysis is more concerned with the relationship between response time and error. Our work also adds to the results of Moffatt (2005); we will explain more later.

In particular, the experiment was designed to discover the *type* of each subject; specifically the preference functional used by each subject - the set of possible functionals being an important subset of the many theories of behaviour under ambiguity current in the literature.[1] This subset consisted of the Expected Utility model (EU), the Smooth ambiguity Model (SM) of Klibanoff et al. (2005), the Rank Dependent model (RD) which was originally proposed by Quiggin (1982), and the Alpha expected utility Model (AM) of Ghirardato et al. (2004). In EU the decision-maker (DM) is perceived as working with subjective probabilities; SM is a *multiple prior* model and proceeds by assuming that, while the DM does not know the true probabilities, he or she has a set of possible probabilities, and attaches probabilities to each member of this set, and works with an expectation of some function of expected utility for each member of this set; RD assumes that the DM weights their subjective probabilities; AM also posits a set of possible probabilities with the DM deciding on the basis of a weighted average of the lowest and highest expected utilities over this set.

These different models suggest different stories about the cognitive processing of decision problems by subjects. We might expect that different processing methods may lead to different decision times. This is one of the things that we explore. Rather more obviously, we examine the effect of the position of a particular decision problem in the sequence of problems presented to the subject during the experiment. One might expect that decisions might get easier as the subject gets familiar with the type of problem presented; at the same time, boredom and/or fatigue may set in. More importantly, the complexity and nature of a problem may well affect behaviour: some problems might be perceived as being more obvious than others. This may be something that is different for different types of subject. We tease out these different effects.

Section 2 below outlines the experiment from which we got the data; section 3 describes the econometric assumptions underlying our analysis; section 4 reports our results; and section

[1] A survey can be found in Etner et al. (2012).

5 concludes.

2 The experiment

The data analysed here is based on the experiment reported in Conte and Hey (2013). Here we recall only those features of it that are essential for the understanding of the analysis described in the rest of this present paper.

In order to create a setting appropriate for the preference functionals examined in the paper, the experimental design is such that lotteries are defined by probabilities, and the set of possible probabilities and the probability of each member of this set are observable.[2]

Subjects face 49 tasks, each involving a choice between two two-stage lotteries.[3] Each two-stage lottery consists of several one-stage lotteries. A one-stage lottery is composed of a certain number of red balls and a certain number of blue balls. Each task starts out with two two-stage lotteries being portrayed on the computer screen, one of the two two-stage lotteries is designated the "unchanging lottery" and the other the "changing lottery". For each of the two lotteries, the computer selects one of the one-stage lotteries at random (termed the "actual lottery"). This is the lottery that will be played out for real at the end of the experiment if that task is selected.

A task proceeds as follows. The subject is first asked to choose a "winning colour" (blue or red) for that task. Secondly, he or she is asked to choose which of the two lotteries is preferred. Then, one of the one-stage lotteries (that is not the "actual lottery") is selected at random by the computer and eliminated from the "changing lottery"; thus, there is one less one-stage lottery in the "changing lottery". The subject is asked once again which is his or her preferred lottery. The computer software will continues eliminating one of the one-stage lotteries from the changing lottery, and then asking the subject to choose between one of the two lotteries, until there is just one one-stage lottery left in the "changing lottery". Subjects are forced to wait for 5 seconds before they can make a decision between the two lotteries.

At the end of the experiment, for each subject, one of the 49 tasks is selected. The "winning colour" chosen by the subject for that task is recalled. Then, a round from that task is selected at random and the subject's stated preference at that time are checked. According to the choice made, the corresponding "actual lottery" is played for real. If the extracted ball is of the "winning colour", then the subject is paid an extra €40 additional to the €7.5 of the show-up fee. If it does not, then there is no extra payment.

The experiment was conducted in, and financed by, the experimental lab of the Max

[2]Purists may well argue that it does not present an ambiguous situation to the subjects, but a two-stage probabilistic situation. The reason is that the paper is meant to investigate the SM and AM models in which there is a set of possible probabilities. That set is specified; otherwise, there would have been no way to fit the models. But this does not detract from the present paper, where we are looking at the determinants of decision time.

[3]This may seem a large number; it was determined by extensive pre-experiment simulation.

Planck Institute of Economics, Jena, Germany, directed by Professor Werner Güth, with subjects recruited using the ORSEE system (Greiner, 2004).

3 The weighted random-effects tobit model of decision times

Let us denote a generic one-stage lottery by $O(r, R)$, where R is the number of balls and r ($0 \leq r \leq R$) is the number of winning balls (the winning colour is chosen *ex ante* by the subject). Each of these R balls has equal probability of being drawn. Let us denote a two-stage lottery by $\mathcal{R}(r_1, r_2, \ldots, r_{\tilde{R}}; R)$, where r_j's represents the number of winning balls in the j's one-stage lottery and $\tilde{R}$ is the number of one-stage lotteries (priors) comprised in the two-stage lottery, so that $j = 1, \ldots, \tilde{R}$. For the sake of convenience, let us denote $\mathcal{R} = \mathcal{M}$, $R = M$, $r = m$ and $\tilde{R} = \tilde{M}$, when the lottery is of the unchanging type, and $\mathcal{R} = \mathcal{N}$, $R = N$, $r = n$ and $\tilde{R} = \tilde{N}$, when the lottery is of the changing type.

Let y^*_{it} be the (latent) time subject i takes to make a decision in choice problem t and let x_{it} be a vector of characteristics of the two lotteries involved in the choice problem. Consider the log-linear regression model with individual-specific random effects under the hypothesis that subject i is of type $\tau \in \{EU, SM, RD, AM\}$

$$\log(y^*_{it}) = \gamma^\tau + x'_{it}\beta^\tau + \alpha^\tau_i + \epsilon^\tau_{it} \tag{1}$$

for $i = 1, \ldots, 149$ and $t = 1, \ldots, 256$. Here, γ^τ is an intercept, β^τ is a vector of coefficients, α^τ_i is the individual-specific random effect $NID(0, \sigma^{\tau 2}_\alpha)$, and ϵ^τ_{it} is an idiosyncratic error term $NID(0, \sigma^{\tau 2}_\epsilon)$, independent of α^τ_i and of anything else in the model.

As subjects in our experiment are forced to wait for at least 5 seconds before reporting their preferred lottery, we assume that those who take less than 5.5 seconds (inclusive of the 5 waiting seconds) to make a decision would have possibly been able to do it within the 5 waiting seconds. Essentially, we concede 0.5 seconds reaction time to those subjects who have already made up their mind during the waiting time.[4] Hence, the observed decision time, y_{it}, represents a left-censored version of y^*_{it}, so that the observational rule is

$$\begin{aligned} y_{it} &= y^*_{it} \quad \text{if} \quad y^*_{it} > 5.5 \\ y_{it} &= 5.5 \quad \text{if} \quad y^*_{it} \leq 5.5 \end{aligned} \tag{2}$$

So far, this is a standard random-effects tobit model, where subject i's likelihood contribution is given by

[4]We note that the experimental software rounded to the nearest integer the time at which each decision problem is shown to players. This results in an approximation in the range of $(-0.5, 0.5)$ seconds. This rounding was completely random.

$$l_i^\tau = \Pr\left(y_{i1}, \ldots, y_{i256} | x_{i1}, \ldots, x_{i256}, \beta\right) = \int_{-\infty}^{\infty} \prod_t f\left(y_{it} | x_{it}, \alpha_i^\tau, \beta^\tau\right) g\left(\alpha_i^\tau\right) d\alpha_i^\tau \qquad (3)$$

where $g\left(\alpha_i^\tau\right)$ is the normal density function with mean 0 and variance $\sigma_\alpha^{\tau 2}$ evaluated at α_i^τ and $f\left(y_{it} | \mathbf{x}_{it}, \alpha_i^\tau, \beta^\tau\right)$ is given by

$$\begin{aligned} f\left(y_{it} | x_{it}, \alpha_i^\tau, \beta^\tau\right) &= \frac{1}{\sqrt{2\pi\sigma_\epsilon^{\tau 2}}} \exp\left\{-\frac{1}{2}\frac{\left(y_{it} - x_{it}'\beta^\tau - \alpha_i^\tau\right)^2}{\sigma_\epsilon^{\tau 2}}\right\} && \text{if} \quad y_{it} > 5.5 \\ &= 1 - \Phi\left(\frac{x_{it}'\beta^\tau + \alpha_i^\tau}{\sigma_\epsilon^\tau}\right) && \text{if} \quad y_{it} = 5.5 \qquad (4) \end{aligned}$$

The total log-likelihood is

$$logL^\tau = \sum_{i=1}^{149} \omega_i^\tau \, log(l_i^\tau) \qquad \tau \in \{EU, SM, RD, AM\} \qquad (5)$$

The peculiarity of our model is in the regression weight ω_i^τ, which takes on a role of primary importance in our analysis, in that it enables us to discriminate the factors influencing the decision times of the four different types of player as identified by a mixture model by Conte and Hey (2013). In fact, we use as weights the posterior probabilities obtained from such a mixture model.[5] Our approach is meant to give more importance to the observations from subjects who are more likely classified as the type whose decision time's rule are investigated, and less importance to the others.[6]

In the next sections, we will draw graphs and derive effects based on the estimation results obtained from the maximisation of Equation 1, and we will also make predictions on real data. In doing this, we will set to 0 the variance of the error term in Equation 1, $\sigma_\epsilon^{\tau 2}$, following the standard routine. Anyhow, we have to take into account that here we are assuming that the decision time, y_t^*, follows a lognormal distribution with a mean that is itself a random variable following a normal distribution with mean $\gamma^\tau + x_t'\beta^\tau$ and variance $\sigma_\alpha^{\tau 2}$. This is of crucial importance when the expected value of the decision time is computed, which is $E(y^*) = \exp\left(\gamma^\tau + x_t'\beta^\tau + \sigma_\alpha^{\tau 2}/2\right)$.

[5] Conte and Hey (2013) split the sample into estimation sample and prediction sample and calculate two types of posterior type-probabilities: from the estimates and from the predictions. Here, we report and discuss the results obtained by using the posterior probabilities of the estimation, but we did not notice any relevant difference from the results obtained from the posterior probabilities of the prediction.

[6] Conte and Hey (2013) also assign subjects to type according to the highest posterior probability. We have performed our type-wise analysis using for each type only those observations from the subjects who are assigned to the type under investigation. Such a procedure produced results quantitatively comparable to the ones we get from the type-weights approach described here.

variable	definition	EU	SM	RD	AM
$totalnumberofballs$ (C)	$M \times \tilde{M} + N \times \tilde{N}$	+***	+**	+***	
$M + N$ (C)	the number of balls in each of the two-stage lotteries in the unchanging two-stage lottery **plus** the number of balls in each of the two-stage lotteries in the changing two-stage lottery	-***			
$\tilde{M} + \tilde{N}$ (C)	the number of one-stage lotteries in the unchanging two-stage lottery **plus** the number of one-stage lotteries in the changing two-stage lottery	-***		-***	
$-\lvert M - N\rvert$ (S)	the **negative absolute difference** between the number of balls in each of the two-stage lotteries in the unchanging two-stage lottery and the number of balls in each of the two-stage lotteries in the changing two-stage lottery	-*			
$-\lvert\tilde{M} - \tilde{N}\rvert$ (S)	the **negative absolute difference** between the number of one-stage lotteries in the unchanging two-stage lottery and the number of one-stage lotteries in the changing two-stage lottery	-***	+**	+***	
$-\lvert \sum_{j=1}^{\tilde{M}} m_j - \sum_{k=1}^{\tilde{N}} n_k\rvert$ (S)	the **negative absolute difference** between the number of winning balls in the unchanging two-stage lottery and the number of winning balls in the changing two-stage lottery	+***	+**	+***	
$identical$ (S)	1 if the unchanging and changing lottery are identical		-***		-*
$\mathbf{1}(\mathcal{M}$ is symmetric) (B)	1 if unchanging lottery is symmetric (if interchanging the winning and losing balls does not change the lottery)		-***	-***	
$\mathbf{1}(\mathcal{N}$ is symmetric) (B)	1 if changing lottery is symmetric (if interchanging the winning and losing balls does not change the lottery)		-***	-**	
$\mathbf{1}$(both $\mathcal{M}$ and $\mathcal{N}$ are symmetric) (B)	1 if both unchanging and changing lotteries are symmetric		+***	-***	
$\mathbf{1}$(both $\mathcal{M}$ and $\mathcal{N}$ are symmetric) $\times\mathbf{1}$(round = 1) (B)	1 if both unchanging and changing lotteries are symmetric and it is round 1		-***	-***	

Table 1: Description of variables other than *order*, *round* and $\lvert\hat{\Delta}\rvert$. A column for each of the four types is added to indicate the sign of the estimated coefficient and its significance level according to the regression estimates in Table 3. The letters C, S and B, which follow the name of each variable, indicate that the variable measures complexity, similarity or that it is between the two, respectively. $\mathcal{M}$ ($\mathcal{N}$) indicates an unchanging (changing) two-stage lottery. M (N) is the number of balls in each of the one-stage lotteries in the unchanging (changing) two-stage lottery. $\tilde{M}$ ($\tilde{N}$) is the number of one-stage lotteries in the unchanging (changing) two stage lottery. m_j (n_j) is the number of winning balls in the j-th one-stage lottery in the unchanging (changing) two stage lottery.

4 Estimation

4.1 Decription of regressors

As previously noted, for each of the four types of player, $\tau \in \{EU, SM, RD, AM\}$, Equation 5 is maximised using as weights the relevant posterior probabilities from the estimates, ω_i^τ, $i = 1, \ldots, 149$, separately for each type.

The regressors we use are described in what follows. A summary of notation can be found in Table 1. The complete estimation results are in Table 3.

We include both the variable *order*, which indicates the position in the sequence of tasks in which a particular task is presented to the player, and the variable *round*, which represents the position in the elimination sequence of the task in which a particular choice problem is encountered (we note that the number of rounds varies from task to task - Table 2 gives the detail). The use of these variables is aimed at modelling two effects that one would reasonably expect in the participants, that is learning and fatigue.

We should make clear that, in each task, subjects are first asked to choose which colour they want as a winning colour for that task and that, only after having chosen their winning colour, they start with the first round of choices between the two lotteries. Hence, we use an indicator for the first round in each decision task, $\mathbf{1}(round = 1)$, to control for the peculiarity of the decision time in the first round of a task, which includes the time to choose the winning colour.[7] Given the characteristics of the first round and the use of a dummy variable to capture its effect, in the first round, the variable *round* is purged of the time taken to decide the winning colour.

Along similar lines to Moffatt (2005), we add variables to control for the complexity level of a choice problem (the more information one gets, the longer the time he or she spends in the decision process), an individual measure of closeness to indifference (this, in our framework, has to vary with player's type), and measures of objective similarity (two lotteries can be close in terms of evaluation but not necessarily identical in visual terms). All these variables are built in a way that takes into account both the characteristics of a task and of the choice problem in a particular round of that task. In other words, they change between tasks and also within the rounds of a particular task.

The complexity of a decision problem is modelled by three variables: $totalnumberofballs$, $M + N$ and $\tilde{M} + \tilde{N}$. The first represents the dimension of the decision problem ($M \times \tilde{M} + N \times \tilde{N}$). The second is meant to capture the dimension of the one-stage lotteries. The third measures the number of one-stage lotteries in a decision problem, that is the number of priors involved in the decision. Essentially, these indicators account for the dimensionality of the decision problem from three different points of view, each of these might play a peculiar role in the evaluation of the preferred lottery by the different types of player. It is worth noting that, while $M + N$ is constant within a certain task, $\tilde{M} + \tilde{N}$ changes with the round number of the task sequence. In particular, $\tilde{N}$ decreases by one at each elimination of a one-stage lottery. We do not expect these two indicators to be effective for any particular type of player. With the exception of the AM type, all the other types are expected to take into account all the one-stage lotteries in a decision task, and so to be sensitive to both the number of one-stage lotteries and the dimension of the one-stage lotteries included in the task.

As measures of objective similarity we use $-|M - N|$, $-|\tilde{M} - \tilde{N}|$, $-|\sum_{j=1}^{\tilde{M}} m_j - \sum_{k=1}^{\tilde{N}} n_k|$ and *identical*. All these variables, which are measured in absolute values, are meant to

[7]Here, $\mathbf{1}(.)$ has the standard meaning of an indicator function that takes the value 1 when the statement in the brackets is true; it is 0 otherwise.

capture how different the changing and the unchanging lottery are in physical terms. It is worth noting that the first three are preceded by a negative sign. This is done so that the larger the value taken by the variable the more similar the lotteries are. More specifically, $-|M-N|$ captures the negative absolute difference in the dimensions of the one-stage lotteries. It essentially indicates how different the one-stage lotteries are in terms of number of balls. $-|\tilde{M}-\tilde{N}|$ indicates the negative absolute difference in the number of priors involved in the decision choice. Finally, $-|\sum_{j=1}^{\tilde{M}} m_j - \sum_{k=1}^{\tilde{N}} n_k|$ is the negative absolute difference between the number of winning balls between the two two-stage lotteries. The smaller these variables the more different the two lotteries. When these variable are close to zero, it means that the two two-stage lotteries share some similarities. However, if all these measures equal 0 simultaneously, the two two-stage lotteries might not be exactly the same lottery.[8] For this reason, we add a dummy variable named *identical* which takes the value 1 if the two lotteries are exactly the same lottery, 0 otherwise.[9]

Halfway between complexity and similarity stand the three dummy variables $\mathbf{1}(\mathcal{M}$ is symmetric), $\mathbf{1}(\mathcal{N}$ is symmetric) and $\mathbf{1}$(both $\mathcal{M}$ and $\mathcal{N}$ are symmetric). A two-stage lottery is symmetric if, after exchanging the winning colour by the losing colour, one obtains the same lottery. The symmetry of a lottery gauges complexity in that it is visually easy to detect without being required to count the number of balls contained in the two lotteries. It also captures similarity because, besides the number of balls being different, subjects can perceive two lotteries as being similar because they share the characteristic of being symmetric.

As far as closeness to indifference is concerned, we follow the approach described in Moffatt (2005, page 375, Equation 12) using the estimation results in Conte and Hey (2013). In contrast to Moffatt (2005), Conte and Hey (2013) estimate a 4-type mixture model, where three out of four models are characterised by a single parameter, except for the EU type whose functional has no parameter at all. Hence, for each subject i conditional on being of a particular type, we calculate the posterior expectation of the parameter of interest which characterises the functional for that type. Finally, we use the so-obtained parameters to calculate for each subject's decision problem, conditional on being of a certain type, the absolute valuation differential. We will refer to such absolute valuation differential as $|\hat{\Delta}_{EU}|$, $|\hat{\Delta}_{SM}|$, $|\hat{\Delta}_{RD}|$ and $|\hat{\Delta}_{AM}|$ in the Expected Utility, Smooth Model, Rank Dependent model and Alpha Model case, respectively.[10]

[8] Consider, for example, the two lotteries $\mathcal{R}(1,2;3)$ and $\mathcal{R}(0,3;3)$. These share the number of one-stage lotteries, the number of balls in the one-stage lotteries, and the number of winning balls, but they are different, nevertheless.

[9] As a measure of objective similarity, Moffatt (2005) calculates the Euclidean distance between the probability vectors of the two lotteries. Here, we are unable to do the same because the structure of our two-stage lottery is such that it cannot be represented by a single probability vector.

[10] The hats over the Δ's indicate that they are obtained by using the Maximum Simulated Likelihood estimates of the parameters from Tab. 3 in Conte and Hey (2013). The procedure is explained in Moffatt (2005).

4.2 Regression results

The regression results are reported in Table 3. The table is organised in four columns, one for each type. It will be noted that not all variables enter into all four columns; the entries for *order* (and its powers), *round* and $|\hat{\Delta}_\tau|$, $\tau \in \{EU, SM, RD, AM\}$, were decided by using likelihood-ratio tests at a 5% significance level for each type separately.

We now turn to an interpretation of these estimates. We start with *order*, which clearly is highly significant, not only in and of itself but also in its powers. Figure 1 displays the expected decision time against task order per type based on the estimation results of Table 3. The formula used is $E\left(\hat{y}_t^{*\tau}\right) = exp(\hat{\gamma}^\tau + x_t'\hat{\beta}^\tau + \hat{\sigma}_\alpha^{\tau 2}/2)$, with all the regressors other than *order* and its relevant powers set to 0. This latter should be noted carefully when interpreting this figure, since the other variables have different effects and importance for the different types. Indeed as Figure 5 (which we shall discuss later) shows, it is actually the case that the RD decision-makers take the most time, then the SM take less in general and then the EU and finally the AM, who take the least time. Because all the regressors (apart from those involving *order*) are put equal to zero, the *absolute* values of the expected decision time in Figure 1 are associated with a sort of "neutral" task, that is a task with no characteristics. What Figure 1 is showing is the effect of *order* on decision time. Both the slope and the level of the curves in Figure 1 change with the effect of the other regressors. This is due to the log-linear specification of our model. In fact, the effects of the regressors on the decision time has to be interpreted in percentage terms. For example, the fact of the two lotteries being symmetric accounts for a decrease in the decision time of 25.87 percentage points for a RD subject. The curves in Figure 1 represent a useful reference with respect to which one should interpret the effects of the other regressors and, in particular, of the variables showed in Figures 2 and 3. We will be more clear about this later.

It will be noticed that all the curves are downward sloping and convex. Moreover, for all types, there is a similar pattern of decision time: a noticeable decrease in decision time is observed in the first 10 tasks; the reduction in decision time then slows down for all types, except for AM. Indeed AM's expected decision time seems to mildly increase in the last ten rounds. Summarising, we observe a significant reduction in the amount of time spent deciding over task. More precisely, we observe a consistent pattern for all the types: time spent decreases with experience, but its effect becomes marginally weaker with accumulated experience.

Let us now turn to the other variables. Both the first round dummy ($\mathbf{1}(round = 1)$) and the variable *round* have an effect on decision time that depends on the point in the sequence of tasks where a certain task is played, that is the effect of these two variables is not constant throughout the sequence of tasks. In order to appreciate their effects on the expected decision time, we refer to Figures 2 and 3. Both figures indicate by how much the lines in Figure 1 shift, on average, when a particular round (the first round in the case of Figure 2 and rounds 1 to 7

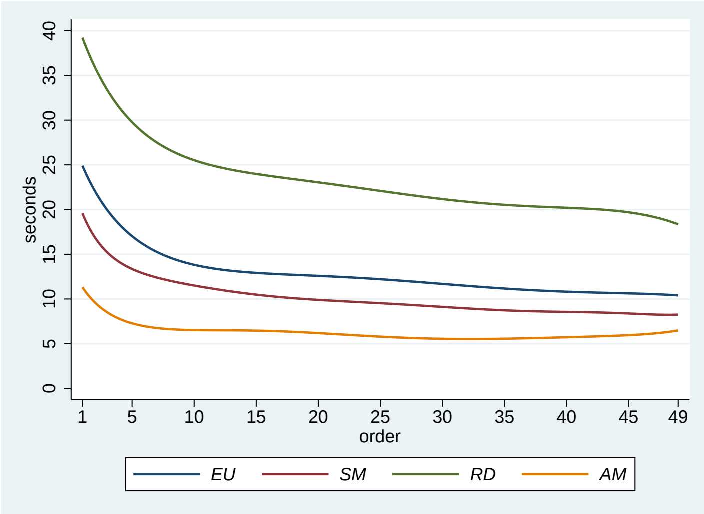

Figure 1: Expected decision time (in seconds) against task order per type based on estimation results in Table 3. The formula used is $E(\hat{y}_t^{*\tau}) = exp(\hat{\gamma}^\tau + x_t'\hat{\beta}^\tau + \hat{\sigma}_\alpha^{\tau 2}/2)$, with all the variables in x_t other than *order* set to 0.

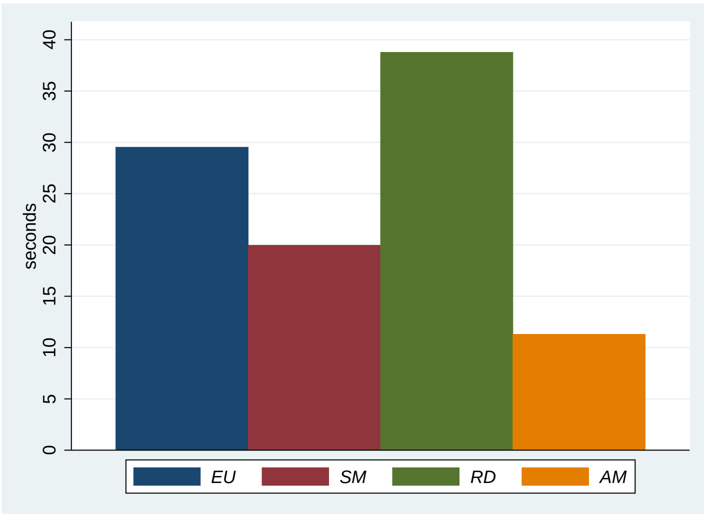

Figure 2: Marginal effect of $\mathbf{1}(round = 1)$ on expected decision time (in seconds) per type based on the estimation results in Tab. 3. All the variables other than γ, *order* and $\mathbf{1}(round = 1)$ are set to 0. The chart shows by how much, on average, the lines in Figure 1 move when the first round of a task is played.

in the case of Figure 3) in a task is played.[11] Once again it should be noted that all variables except those shown in the figures are put equal to zero. The decisions in the first round of a task seem to be very time consuming for a *RD* (who takes almost 40 additional seconds,

[11]Let us just recall here that the difference between the effect of the first round on the expected decision time captured by $\mathbf{1}(round = 1)$ and $round = 1$ is that the former captures the effect of the time spent deciding the "winning colour" and the latter isolates the effect of playing the first round of a task on the expected decision time if players were not to decide about the "winning colour".

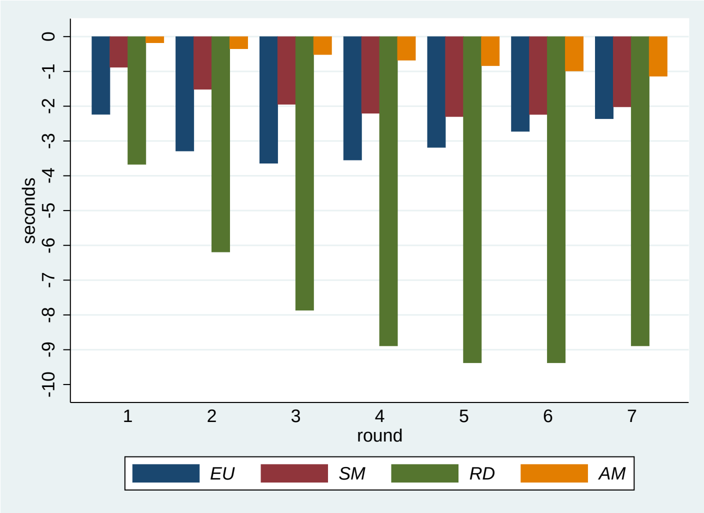

Figure 3: Marginal effect of round on expected decision time (in seconds) per type based on the estimation results in Tab. 3. All the variables other than γ, *order* and *round* are set to 0. The chart shows by how much, on average, the lines in Figure 1 move when a certain round number of a task is played. The bars indicate the cumulative effect of round on expected decision time.

on average) and much faster for an AM (who takes 12 additional seconds, on average), the additional time taken by the other two types is about 25 seconds, on average. Figure 3 shows that an RD type experiences quite a large decrease (up to 9 seconds in round 5, on average) in decision time when the task is made of many rounds. The decision time decreases also for EU (SM) up to round 3 (5), but much less than for RD, with a gain of about 3 (1.9) seconds on average. The expected decision time seems to decrease mildly with rounds (about 0.7 seconds).

We now examine the effect of the three variables modelling the *complexity* of a decision problem, $totalnumberofballs$, $M+N$ and $\tilde{M}+\tilde{N}$. Table 3 shows that all three variables are significant for a EU, none of the three are significant for an AM, just $totalnumberofballs$ is significant for an SM, and both $totalnumberofballs$ and $\tilde{M}+\tilde{N}$ for an RD. In terms of magnitude, the decision time increases with the number of balls involved in the choice for all types except for AM (which is understandable in the light of what an AM decision-maker does); it decreases with the total dimension of the one stage lotteries for an EU and decreases with the total number of priors for EU and RD.

Of the variables that capture the *objective similarity* of the lotteries, $-|M-N|$, $-|\tilde{M}-\tilde{N}|$, $-|\sum_{j=1}^{\tilde{M}} m_j - \sum_{k=1}^{\tilde{N}} n_k|$ and $identical$, the first has a mildly negative effect only for an EU. The negative absolute difference in the number of priors has a negative effect for EU, a positive effect for SM and RD and no significant effect for AM. The decision time significantly increases with the negative absolute difference in the number of winning balls of the two lotteries involved in the decision for all the types except AM. We attribute this finding to the fact that the higher the difference in winning balls between the two lotteries the easier is to visualise which lottery is the "best" in terms of winning balls. It is even possible that subjects, after a number of tasks and rounds, develop visual rules of thumb whose content is not captured by the other variables. Finally, two identical lotteries decrease the decision time of both a SM and (but only slightly) of an AM.

The four variables which account for the symmetry of the two lotteries seem to be relevant only for a SM and a RD decision maker. All of them have a negative effect on decision time except for $\mathbf{1}$(both $\mathcal{M}$ and $\mathcal{N}$ are symmetric), whose effect is positive for SM.[12] It should be noted, though, that the contemporaneous symmetry of the two lotteries implies indifference for an EU decision maker. This may speak for the reason the symmetry-related variables are not statistically significant for that type.

As previously explained, the importance of the closeness to indifference, modelled by the variable $|\hat{\Delta}_\tau|$ and its powers, is type specific. Therefore, it is discussed separately for each type because we cannot compare the difference in utility evaluation across types, as they miss a common metric.[13] Figure 4 shows the effect of these measures of closeness to indifference as a proportion of the expected decision time. For example, for RD a $|\hat{\Delta_{RD}}| = 0.05$ reduces the expected decision time by 20% (because it multiplies the expected decision time by 0.8) and a $|\hat{\Delta_{RD}}| = 0.65$ reduces the expected decision time by 50% (because it multiplies the expected decision time by 0.5). For EU and AM decision makers, the effect of the absolute utility gap on time spent on the decision time is almost negligible. More precisely we find that any utility gap only mildly reduces decision time. However, looking at the effect of such a utility gap on the decision time of the SM and RD types, the effect appears highly significant, especially for the RD type. For both types, moving away from indifference in the range (0, 0.25) determines a reduction in the decision time of about 17% for SM and 50% for RD. Such a reduction increases by another 5% for and 10% the farther away we move up from the indifference point for SM and RD, respectively. The effect of these measures of closeness to indifference is, in general, non linear and very different among types (it is only mildly significant and linear for AM, but this was to be expected, since this type of decision makers do not consider all the one-stage lotteries when making a choice). Overall we can roughly confirm the results obtained by Moffatt (2005) as far as the RD type is concerned and to a lesser extent the SM type: when people are evaluating lotteries that have almost the same value they take more time deciding. However this does not seem to be true for the EU and AM types.

The significance and magnitude of the random effects, σ_α, testify that there is a large heterogeneity in the population whatever the type.

Figure 5 shows the predicted average decision time (in seconds) per round per task based

[12] Changing lotteries are always symmetric in the first round (because they contain all the possible priors) and may be symmetric or not in the following rounds, depending on the random elimination sequence explained in Section 2. Hence, the effect of the symmetry of the changing lottery can be partially captured by the first round dummy. For this reason we have added the interaction effect $\mathbf{1}$(both $\mathcal{M}$ and $\mathcal{N}$ are symmetric)$\times\mathbf{1}$(round $= 1$).

[13] The $|\hat{\Delta}|$'s vary from 0 to 0.67, 0.86, 0.81 and 0.87 for EU, SM, RD and AM, respectively.

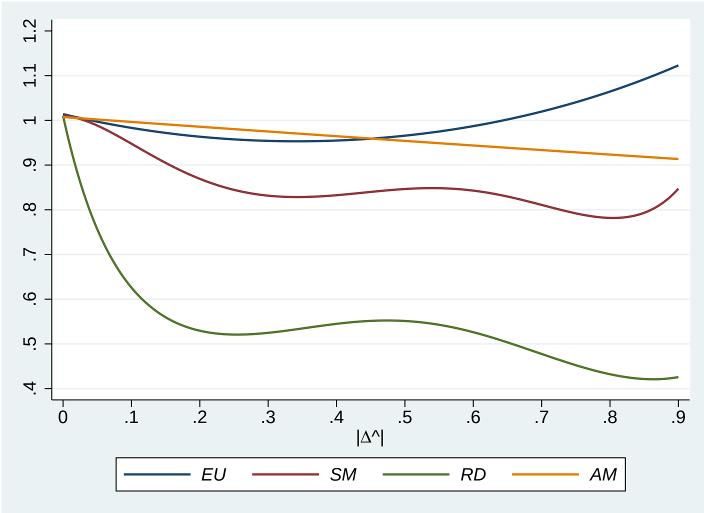

Figure 4: Estimated multiplicative effect of absolute utility gap on decision time per type based on estimation results in Table 3.

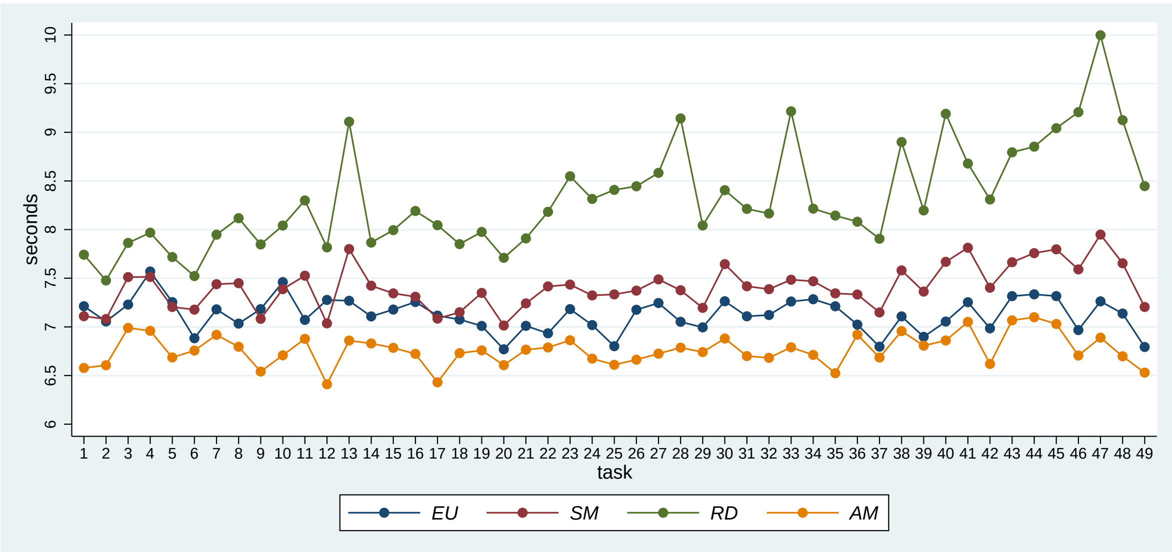

Figure 5: Predicted average decision time (in seconds) per round per task. The prediction has been performed on the tasks actually used in the experiment. The average decision time has been computed by setting $\mathbf{1}(round = 1)$ and $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric}) \times \mathbf{1}(round = 1)$ to 0.

on the estimation results in Tab. 3. Given the structure of our experimental task with an "unchanging lottery" and a "changing lottery" from which one one-stage lottery is randomly selected out at each round, each task has a different composition in terms of lotteries, except for the first round. For example, the changing lottery in task 1 (see Tab. 2), that is $\mathcal{N}(0, 1, 2, 3; 3)$ in round 1, might become one of the following 4 two-stage lotteries, after only one round, depending on the one-stage lottery that is randomly eliminated: $\mathcal{N}(0, 1, 2; 3)$, $\mathcal{N}(0, 1, 3; 3)$, $\mathcal{N}(0, 2, 3; 3)$, $\mathcal{N}(1, 2, 3; 3)$. Hence, for each subject, each task has its own history.

In order to take into account the variety of each task consequent to the elimination sequences for predicting the decision time of each task, we use the elimination sequences actually experienced by the subjects in our sample. Since tasks are composed of different rounds, we set the coefficient on $\mathbf{1}(\text{round} = 1)$ and $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric}) \times \mathbf{1}(\text{round} = 1)$ to 0. In fact, the effect of the time to choose the "winning colour", which is quite substantial, would influence much more the predicted average decision time per round of the tasks with a low number of rounds that those with a higher number of rounds, where such an effect is dissipated. The $|\hat{\Delta}_\tau|$'s used in the prediction have been derived, for each type, using the mean of the parameter of interest which characterises the functional for that type, as derived in Conte and Hey (2013).

In Figure 5 we observe how the decision time for an RD is substantially higher than that for the other three types (mean=8.32, min=7.48, max=10.0), regardless of the task, while the predicted average decision time for AM is always the lowest (mean=6.76, min=6.41, max=7.10). The predicted average decision time for EU (mean=7.12, min=6.77, max=7.57) and SM (mean=7.40, min=7.01, max=7.94) is quite similar when the one-stage lotteries of the unchanging lottery are characterised by a low number of balls, but higher for SM with respect to EU otherwise. The peaks that can be observed, mostly in the second part of the figure, for both RD and SM essentially correspond to the tasks where the "unchanging lottery" is not symmetric.

5 Conclusions

Rather obviously, decision time decreases, at a decreasing rate, throughout the experiment for all types of subject. What is interesting is the different behaviour of the different types. Not only do different types have different preference functionals, but they also seem to be processing the problems differently. Indeed there seems to be a connection between the type of subject and the way they think about their decisions.

Let us now remind ourselves of the different preference functionals. Here we consider the evaluation of a typical two-stage lottery consisting of $\tilde{R}$ one-stage lotteries, where the j'th of these has r_j balls of the winning colour and R balls in total. Let us number these so that $r_1 < r_2 < ... < r_{\tilde{R}}$. We normalise the utility function (present in all the functionals) so that the utility of winning is 1 and that of losing 0. We have

$$EU \qquad \left[\frac{r_1}{R} + \frac{r_2}{R} + ... + \frac{r_{\tilde{R}}}{R}\right] / \tilde{R}$$

$$SM \qquad \left[\phi\left(\frac{r_1}{R}\right) + \phi\left(\frac{r_2}{R}\right) + ... + \phi\left(\frac{r_{\tilde{R}}}{R}\right)\right] / \tilde{R}$$

$$RD \quad \sum_{j=1}^{\tilde{R}} f\left(\frac{r_j}{R}\right)\left[f\left(\frac{\tilde{R}-j+1}{\tilde{R}}\right)-f\left(\frac{\tilde{R}-j}{\tilde{R}}\right)\right]$$

$$AM \qquad a\frac{r_1}{R}+(1-a)\frac{r_{\tilde{R}}}{R}$$

It is eminently clear from these expressions that the AM preference functional is easiest to apply in that it involves fewest terms. Equally clear is that RD is by far the most difficult. EU and SM look similarly difficult in the number of terms that need to be processed, though SM does involve applying a function to the fractions which can be readily seen from the experimental screen. In terms of the number of items on the screen that need to be noted (or counted) by the subject, once again AM seems the simplest, followed by EU and SM while RD appears to have more things to count and/or process. It is therefore particularly interesting and natural that the RD subjects take the longest, followed by EU and SM while AM take the shortest: our classification seems to be capturing *processes* as well as types. The initial processing cost for a new problem, as evidenced in Figure 2, also shows that RD takes the most time and AM the least. For RD it may be the case that they implicitly calculate the various terms involving $f(.)$ right at the beginning of a problem and then use those calculated values through the various rounds - hence explaining the large reductions through the rounds as shown in Figure 3. The EU type also reduces the decision time through the rounds, but nowhere nearly as fast at RD. Probably as a consequence of AM being fast to begin with, their reductions through the rounds are very small.

The complexity variable $totalnumberofballs$ is highly significant and positive for EU, SM and RD, though understandably not significant for AM as this type does not look at all the two lotteries. The magnitude of the effect is greatest for RD, followed by EU and then SM. However it should be noted, when thinking about the EU type, that for them in addition both $M+N$ and $\tilde{M}+\tilde{N}$ are highly significant with sizeable *negative* coefficients, thus offsetting some of the effects of $totalnumberofballs$. This offset does not occur for SM types, suggesting that complexity may be less important for EU than for SM; this seems reasonable in the light of the formulae above - which indicates that the SM type have to apply a function to the same arguments as the EU type. It should also be noted that for the RD types the complexity variable $\tilde{M}+\tilde{N}$ is negative and highly significant.

As far as the similarity variables are concerned, their interpretation must depend on the way one views the subjects as processing the decision problems. Theory does not really help us here: it implicitly assumes that a valuation is made of each lottery independently and then these valuations are then compared. The theory does not (can not) postulate that a subject, when making a pairwise choice, simplifies the problem by eliminating things in common in the two lotteries. The evidence contained in Table 3 suggests that, for the EU type, similarity, as measured by $-|M-N|$ and $-|\tilde{M}-\tilde{N}|$, *decreases* decision time while $-|\sum_{j=1}^{\tilde{M}} m_j - \sum_{k=1}^{\tilde{N}} n_k|$

increases it. This is as one would suspect. However, for the SM and RD types, similarity increases decision time. This is a surprising result, and may be a consequence of the decision processes that these types use. Interestingly symmetry also reduces decision time for the SM and RD types. One interpretation of these findings may be that the SM and RD types, knowing their preference functional is difficult to implement, simplify the decision problem before applying their functionals. Strictly speaking they should not be doing this.

However, we are reminded of the original version of Prospect Theory of Kahneman and Tversky (1979) in which there is an editing phase before the evaluation phase. This editing phase has been 'sanitised out' in Rank Dependent which is a refinement of the original version of Prospect Theory. Perhaps, though, this is what our RD subjects were doing?

Finally, we have some interesting findings with respect to the effect on decision time of the estimated utility gap between the two lotteries. Moffatt (2005) found that decision time decreased with this gap. This fits with the idea of a decision-maker being more certain about the 'correct' decision when the two lotteries seemed further apart in terms of his or her preferences. At the same time, to a theorist, it may seem a bit odd: if the lotteries are close together in terms of the subject's preferences, then it does not really matter which they choose. We find that our RD subjects, and to a lesser extent the SM subjects, behaved similarly to Moffatt's, though this was not the case for the EU and AM types, as Figure 4 shows. It may be that in our context for the latter types the perception of the utility gap did not affect choices, in that each lottery was evaluated independently of the other, as the theory says it should.

In conclusion our analysis shows that different factors influence the decision time for different types. We have hinted that this may be a consequence of the way subjects process decision problems. This suggests that the theorists should investigate the process of pairwise choice, rather than seeing this as being arrived at by simply calculating the value of each lottery and comparing them. Perhaps we need to return to the original version of Rank Dependent – that is, Kahneman and Tversky's Prospect Theory?

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Table 2

task	unchanging lottery	changing lottery	total number of balls	$\tilde{M}+\tilde{N}$	$-\vert\tilde{M}-\tilde{N}\vert$	$-\vert\sum_{j=1}^{\tilde{M}} m_j - \sum_{k=1}^{\tilde{N}} n_k\vert$	$\vert\hat{\Delta}_{EU}\vert$	$\vert\hat{\Delta}_{SM}\vert$	$\vert\hat{\Delta}_{SQ}\vert$	$\vert\hat{\Delta}_{AM}\vert$
1	$\mathcal{M}(1,2;3)$	$\mathcal{N}(0,1,2,3;3)$	13.5	4.5	-1	-1.70	.153	.183	.158	.158
2	$\mathcal{M}(0,1,2,3;3)$	$\mathcal{N}(0,1,2,3;3)$	19.5	6.5	-1.5	-2.13	.152	.155	.157	.149
3	$\mathcal{M}(0,1,2,3,4;4)$	$\mathcal{N}(0,1,2,3;3)$	27.5	7.5	-2.5	-6.31	.146	.153	.151	.138
4	$\mathcal{M}(0,3;3)$	$\mathcal{N}(0,1,2,3,4;4)$	18	5	-1.4	-3.68	.132	.170	.138	.129
5	$\mathcal{M}(1,2;3)$	$\mathcal{N}(0,1,2,3,4;4)$	18	5	-1.4	-3.47	.134	.161	.139	.138
6	$\mathcal{M}(0,1,2,3;3)$	$\mathcal{N}(0,1,2,3,4;4)$	24	7	-1.4	-2.81	.133	.143	.138	.126
7	$\mathcal{M}(0,1,2,3,4;4)$	$\mathcal{N}(0,1,2,3,4;4)$	32	8	-2	-3.85	.143	.149	.148	.140
8	$\mathcal{M}(0,1,2,3,4,5;5)$	$\mathcal{N}(0,1,2,3,4;4)$	42	9	-3	-9.04	.132	.140	.137	.126
9	$\mathcal{M}(0,3;3)$	$\mathcal{N}(0,1,2,3,4,5;5)$	23.5	5.5	-1.8	-6.06	.118	.150	.124	.108
10	$\mathcal{M}(1,2;3)$	$\mathcal{N}(0,1,2,3,4,5;5)$	23.5	5.5	-1.8	-6.18	.126	.145	.131	.127
11	$\mathcal{M}(0,1,2,3,4;4)$	$\mathcal{N}(0,1,2,3,4,5;5)$	37.5	8.5	-1.8	-4.26	.123	.124	.129	.113
12	$\mathcal{M}(0,3;3)$	$\mathcal{N}(0,1,2,3,4,5,6;6)$	30	6	-2.3	-9.33	.114	.155	.121	.105
13	$\mathcal{M}(0,1,2,3,4,5;5)$	$\mathcal{N}(0,1,2,3,4,5,6;6)$	54	10	-2.3	-5.85	.117	.120	.123	.107
14	$\mathcal{M}(0,1,3,4;4)$	$\mathcal{N}(0,1,2,3;3)$	23.5	6.5	-1.5	-4.26	.149	.157	.153	.145
15	$\mathcal{M}(0,4;4)$	$\mathcal{N}(0,1,2,3,4;4)$	20	5	-1.4	-3.10	.131	.166	.136	.126
16	$\mathcal{M}(0,4;4)$	$\mathcal{N}(0,1,2,3,4,5;5)$	25.5	5.5	-1.8	-5.42	.126	.157	.132	.116
17	$\mathcal{M}(0,4;4)$	$\mathcal{N}(0,1,2,3,4,5,6;6)$	32	6	-2.3	-8.50	.110	.152	.116	.103
18	$\mathcal{M}(2,3;5)$	$\mathcal{N}(0,1,2,3;3)$	17.5	4.5	-1	-1.88	.153	.185	.159	.160
19	$\mathcal{M}(0,2,3,5;5)$	$\mathcal{N}(0,1,2,3;3)$	27.5	6.5	-1.5	-6.25	.148	.153	.153	.142
20	$\mathcal{M}(0,5;5)$	$\mathcal{N}(0,1,2,3,4;4)$	22	5	-1.4	-2.88	.138	.167	.144	.131
21	$\mathcal{M}(2,3;5)$	$\mathcal{N}(0,1,2,3,4;4)$	22	5	-1.4	-2.88	.135	.162	.141	.141
22	$\mathcal{M}(0,2,3,5;5)$	$\mathcal{N}(0,1,2,3,4;4)$	32	7	-1.4	-4.05	.134	.140	.139	.127
23	$\mathcal{M}(0,5;5)$	$\mathcal{N}(0,1,2,3,4,5;5)$	27.5	5.5	-1.8	-4.94	.121	.162	.127	.116
24	$\mathcal{M}(2,3;5)$	$\mathcal{N}(0,1,2,3,4,5;5)$	27.5	5.5	-1.8	-4.91	.123	.143	.129	.127
25	$\mathcal{M}(0,2,3,5;5)$	$\mathcal{N}(0,1,2,3,4,5;5)$	37.5	7.5	-1.5	-4.14	.121	.124	.127	.110
26	$\mathcal{M}(0,5;5)$	$\mathcal{N}(0,1,2,3,4,5,6;6)$	34	6	-2.3	-7.62	.114	.146	.121	.105
27	$\mathcal{M}(2,3;5)$	$\mathcal{N}(0,1,2,3,4,5,6;6)$	34	6	-2.8	-7.69	.116	.142	.122	.119
28	$\mathcal{M}(0,1,5;6)$	$\mathcal{N}(0,1,2,3;3)$	25.5	5.5	-1	-6.93	.226	.228	.236	.186
29	$\mathcal{M}(2,3,4;6)$	$\mathcal{N}(0,1,2,3;3)$	25.5	5.5	-1	-5.27	.158	.191	.163	.163
30	$\mathcal{M}(0,2,4,6;6)$	$\mathcal{N}(0,1,2,3;3)$	31.5	6.5	-1.5	-8.22	.159	.163	.164	.154
31	$\mathcal{M}(0,1,3,5,6;6)$	$\mathcal{N}(0,1,2,3;3)$	37.5	7.5	-2.5	-11.28	.148	.156	.153	.142
32	$\mathcal{M}(0,2,3,4,6;6)$	$\mathcal{N}(0,1,2,3;3)$	37.5	7.5	-2.5	-11.33	.158	.168	.163	.151
33	$\mathcal{M}(2,3,4,5,6;6)$	$\mathcal{N}(0,1,2,3;3)$	37.5	7.5	-2.5	-13.79	.235	.252	.243	.238

34	$\mathcal{M}(0,1,2,4,5,6;6)$	$\mathcal{N}(0,1,2,3;3)$	43.5	8.5	-3.5	-14.24	.157	.161	.161	.152
35	$\mathcal{M}(0,1,2,3,4,5,6;6)$	$\mathcal{N}(0,1,2,3;3)$	49.5	9.5	-4.5	-17.23	.149	.158	.153	.143
36	$\mathcal{M}(0,6;6)$	$\mathcal{N}(0,1,2,3,4;4)$	24	5	-1.4	-2.68	.136	.167	.142	.131
37	$\mathcal{M}(2,4;6)$	$\mathcal{N}(0,1,2,3,4;4)$	24	5	-1.4	-2.72	.128	.148	.133	.131
38	$\mathcal{M}(0,1,5;6)$	$\mathcal{N}(0,1,2,3,4;4)$	30	6	-1.2	-5.55	.227	.217	.240	.169
39	$\mathcal{M}(0,3,6;6)$	$\mathcal{N}(0,1,2,3,4;4)$	30	6	-1.2	-3.66	.132	.145	.138	.125
40	$\mathcal{M}(0,1,2,6;6)$	$\mathcal{N}(0,1,2,3,4;4)$	36	7	-1.4	-7.46	.179	.170	.199	.122
41	$\mathcal{M}(0,2,4,6;6)$	$\mathcal{N}(0,1,2,3,4;4)$	36	7	-1.4	-6.04	.132	.140	.137	.125
42	$\mathcal{M}(0,1,2,4,5,6;6)$	$\mathcal{N}(0,1,2,3,4;4)$	48	9	-3	-12.17	.132	.139	.137	.122
43	$\mathcal{M}(0,6;6)$	$\mathcal{N}(0,1,2,3,4,5;5)$	29.5	5.5	-1.8	-4.61	.126	.156	.132	.113
44	$\mathcal{M}(2,4;6)$	$\mathcal{N}(0,1,2,3,4,5;5)$	29.5	5.5	-1.8	-4.61	.123	.141	.129	.125
45	$\mathcal{M}(2,3,4;6)$	$\mathcal{N}(0,1,2,3,4,5;5)$	35.5	6.5	-1.5	-3.94	.118	.136	.123	.119
46	$\mathcal{M}(0,1,2,5;6)$	$\mathcal{N}(0,1,2,3,4,5;5)$	41.5	7.5	-1.5	-6.71	.206	.198	.220	.150
47	$\mathcal{M}(0,1,2,3,5;6)$	$\mathcal{N}(0,1,2,3,4,5;5)$	47.5	8.5	-1.8	-8.37	.182	.182	.192	.153
48	$\mathcal{M}(0,1,2,4,5,6;6)$	$\mathcal{N}(0,1,2,3,4,5;5)$	53.5	9.5	-2.5	-9.27	.126	.130	.133	.115
49	$\mathcal{M}(0,6;6)$	$\mathcal{N}(0,1,2,3,4,5,6;6)$	36	6	-2.3	-7.14	.118	.151	.126	.108

Table 2: The 49 decision tasks faced by the participants. Each task is made of two two-stage lotteries, an unchanging lottery ($\mathcal{M}(.;.)$) and a changing lottery ($\mathcal{N}(.;.)$). The generic two-stage lottery is displayed as $\mathcal{R}(r_1, r_2, \ldots, r_{\tilde{R}}; R)$, where r_j's represents the number of winning balls in the j's one-stage lottery, R is the number of balls in the one-stage lotteries composing the two-stage lottery and $\tilde{R}$ is the number of one-stage lotteries (priors) comprised in the two-stage lottery, so that $j = 1, \ldots, \tilde{R}$. In the tasks above, it is assumed that the blue is the winning colour. The table also displays the mean value assumed by some task-specific variables used in Tab. 3. It is worth noting that, while the variables $totalnumberofballs$, $\tilde{M}+\tilde{N}$ and $-|\tilde{M}-\tilde{N}|$ change within task (depend only on the round) but not between subjects, the variables $-|\sum_{j=1}^{\tilde{M}} m_j - \sum_{k=1}^{\tilde{N}} n_k|$ and $|\hat{\Delta}_\tau|$, $\tau \in \{EU, SM, RD, AM\}$, depend on the elimination sequence and, consequently, change between subjects. The calculation of $|\hat{\Delta}_\tau|$, $\tau \in \{EU, SM, RD, AM\}$, has been based, for each type, on the mean of the parameter of interest which characterises the functional for that type, as derived in Conte and Hey (2013).

Table 3

	τ			
	EU	*SM*	*RD*	*AM*
γ^{τ}	3.3411***	3.1715***	3.8057***	2.6293***
	(0.1224)	(0.0737)	(0.1153)	(0.1594)
order	-0.1508***	-0.2432***	-0.1438***	-0.2376***
	(0.0092)	(0.0270)	(0.0187)	(0.0311)
$order^2$	0.0112***	0.0402***	0.0148***	0.0288***
	(0.0011)	(0.0075)	(0.0031)	(0.0053)
$order^3$	-0.0004***	-0.0040***	-0.0008***	-0.0017***
	(0.0001)	(0.0010)	(0.0002)	(0.0004)
$order^4$	6.97e-06***	0.0002***	0.0000***	0.0000***
	(1.25e-06)	(0.0001)	(8.34e-06)	(0.0000)
$order^5$	-4.50e-08***	-8.70e-06***	-3.63e-07**	-7.65e-07***
	(9.98e-09)	(2.77e-06)	(1.45e-07)	(2.46e-07)
$order^6$	–	1.83e-07***	2.10e-09**	4.46e-09***
		(6.34e-08)	(9.61e-10)	(1.64e-09)
$order^7$	–	-2.07e-09***	–	–
		(7.70e-10)		
$order^8$	–	9.75e-12**	–	–
		(3.85e-12)		
$\mathbf{1}(round = 1)$	1.1343***	1.0519***	0.9176***	1.0245***
	(0.0496)	(0.0278)	(0.0465)	(0.0709)
round	-0.2389***	-0.0994***	-0.1881***	-0.0234***
	(0.0694)	(0.0117)	(0.0198)	(0.0079)
$round^2$	0.0526***	0.0097***	0.0171***	–
	(0.0174)	(0.0014)	(0.0024)	
$round^3$	-0.0032**	–	–	–
	(0.0014)			
$totalnumberofballs$ $(M \times \tilde{M} + N \times \tilde{N})$	0.0088***	0.0036**	0.0106***	-0.0043
	(0.0023)	(0.0016)	(0.0026)	(0.0042)
$M + N$	-0.0299***	0.0006	-0.0016	0.0191
	(0.0071)	(0.0049)	(0.0083)	(0.0131)
$\tilde{M} + \tilde{N}$	-0.0430***	-0.0112	-0.0426***	0.0265
	(0.0116)	(0.0080)	(0.0136)	(0.0214)
$-\|M - N\|$	-0.0081*	0.0032	0.0080	-0.0027
	(0.0043)	(0.0030)	(0.0051)	(0.0086)
$-\|\tilde{M} - \tilde{N}\|$	-0.0170***	0.0068**	0.0097**	0.0005
	(0.0040)	(0.0028)	(0.0048)	(0.0080)
$-\|\sum_{j=1}^{\tilde{M}} m_j - \sum_{k=1}^{\tilde{N}} n_k\|$	0.0059***	0.0024**	0.0047***	0.0035
	(0.0014)	(0.0010)	(0.0017)	(0.0028)
identical	0.0061	-0.0929***	-0.0622	-0.1091*
	(0.0366)	(0.0240)	(0.0421)	(0.0660)
$\mathbf{1}(\mathcal{M}$ is symmetric$)$	-0.0099	-0.0731***	-0.1904***	-0.0104
	(0.0134)	(0.0093)	(0.0165)	(0.0272)
$\mathbf{1}(\mathcal{N}$ is symmetric$)$	-0.0041	-0.0667***	-0.0899**	0.0085
	(0.0326)	(0.0219)	(0.0370)	(0.0592)
$\mathbf{1}($both $\mathcal{M}$ and $\mathcal{N}$ are symmetric$)$	-0.0225	0.0861***	-0.2587***	0.0239
	(0.0367)	(0.0234)	(0.0470)	(0.0629)
$\mathbf{1}($both $\mathcal{M}$ and $\mathcal{N}$ are symmetric$) \times \mathbf{1}($round $= 1)$	-0.0358	-0.0976***	-0.1895***	-0.0325
	(0.0394)	(0.0270)	(0.0451)	(0.0735)
$\|\hat{\Delta}_{\tau}\|$	-0.3610***	-0.0973	-6.9497***	-0.1087*
	(0.1071)	(0.2502)	(0.4492)	(0.0598)

$\lvert\hat{\Delta}_\tau\rvert^2$	0.5272***	-8.3773***	25.0067***	–
	(0.1855)	(2.4222)	(2.8022)	
$\lvert\hat{\Delta}_\tau\rvert^3$	–	34.3979***	-35.3987***	–
		(9.1865)	(6.4435)	
$\lvert\hat{\Delta}_\tau\rvert^4$	–	-48.9950***	16.6760***	–
		(14.5929)	(4.8647)	
$\lvert\hat{\Delta}_\tau\rvert^5$	–	23.3141***	–	–
		(8.1244)		
σ_α	0.1666***	0.1427***	0.1435***	0.1216***
	(0.0192)	(0.0120)	(0.0191)	(0.0325)
σ_ϵ	0.3230***	0.3074***	0.3315***	0.2772***
	(0.0025)	(0.0017)	(0.0029)	(0.0051)
Log-likelihood	-3695.5	-6073.9	-2854.1	-464.5
$\sum_{i=1}^{149} \omega_i^\tau$	38.805	73.375	29.518	7.301
observations	38144	38144	38144	38144
subjects	149	149	149	149

Table 3: Estimation results of the random-effects Tobit model weighted with posterior type-probabilities. 5914 (32230) observations are left-censored (uncensored). ***, ** and * denote a p-value < 0.01, < 0.05 and < 0.10, respectively.