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PARAMETER INTERACTIONS IN CUMULATIVE PROSPECT THEORY IN RELATION TO PROBABILITY WEIGHTING

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ABSTRACT. Tversky and Kahneman's cumulative prospect theory assumes symmetric probability cumulation with regard to the reference point in decision weights. Theoretically, this model should be fixed despite a change in the direction of probability cumulation. We investigate this phenomenon by proposing an alternative model with one-direction probability cumulation. By doing so, we create a reference model that allows us to verify the parameter interactions in cumulative prospect theory specifications. We apply the simultaneous parametric fitting of utility and weighting functions using binary choice data from our own incentivized choice experiment (N = 70). We consider two parametric forms of probability weighting functions, namely, the one-parameter Tversky–Kahneman and two-parameter Prelec functions. We find that the Prelec function is sufficiently flexible to make these two models equivalent, thereby preserving the stability of the utility parameters. We also observe parameter interactions in the other specifications, especially with the Tversky–Kahneman weighting function.

Keywords: cumulative prospect theory, parameter interactions, rank-dependent utility, decision weights

Introduction

Prospect theory is a widely recognized economic decision theory describing choice under risk. It not only explains experimental results but also can provide evidence for field data (Barberis, 2013). In particular, as it can justify many of the observed effects in contrast to expected utility theory, it has been welcomed as groundbreaking. Prospect theory suggests a mechanism to generate four risk attitude patterns through the combination of a probability weighting scheme (decision weights) and a value transformation (utility). These risk patterns are generally found to be consistent with experimental results (Zeisberger, Vrecko, & Langer, 2012).

Over time, prospect theory has entered into the main canon for teaching economics, attracting researchers outside the narrow decision theory field who want to apply it to a broader context in different disciplines. Despite its widespread popularity, however, the application of the theory is difficult. The original prospect theory (OPT) formulation is no longer used and the confirmed ability to explain data actually refers to cumulative prospect theory (CPT) (Tversky & Kahneman, 1992), a second-generation theory (Schmidt, Starmer, & Sugden, 2008) known as simply "prospect theory" (e.g., Zeisberger et al., 2012).

The main features of OPT are (1) the subjective assessment of the gains and losses made separately such that the value function (i.e., utility function) over gains is concave and that over losses is convex, (2) the subjective perception of risk typically overweighting small and underweighting large probabilities (i.e., an inverse S-shaped probability weighting function), and (3) loss aversion due to the assumption that the value function for losses is steeper than that for gains (Kahneman & Tversky, 1979). CPT introduces certain features not covered by OPT associated with the decision weights, which have a considerable impact on the evaluation of the decision problem. Although the probability weighting function is a common characteristic of CPT and OPT, the weighting scheme in CPT assumes the modification of cumulated probabilities and results in the further transformation of the initial probabilities assigned to the outcomes. The modification originated from the Rank-Dependend Utility (RDU) model developed by Quiggin (1982); however, CPT introduced a symmetry in probability cumulation that is not present in the RDU model. Consequently, the decision weights in CPT, are defined in such a way that downward comparisons of the probability weights to the reference point are made for gains, while upward comparisons to the reference point are made for losses (Wakker, 2010). As a result, unlike in OPT, the decision weights in CPT depend on the outcomes' ranking positions (Tversky & Kahneman, 1992).

Applying CPT in practice poses another difficulty because of the need to calibrate the theoretical model with unknown parameters using observed data from multiple subjects. Some researchers simply take the median values of the estimates in Tversky and Kahneman (1992) as the estimates of the representative subject or its benchmark (Barberis & Huang, 2008; Barberis, Mukherjee, & Wang, 2016). However, this practice is often criticized because a subject having the whole set of parameters close to the median values of the estimates may not exist. Indeed, Harrison and Ross (2017) argued that such an approach is methodologically inaccurate and does not meet standards of scientific rigor.

On the other hand, fitting the CPT model for individual subjects or panel data is a challenge, posing numerous issues to consider regarding the required choice of data elicitation and model estimation methods. There are two main groups of methods that can be applied here: parametric and non-parametric ones.

Nonparametric methods proved to deliver satisfying results in terms of confirming of the CPT's shapes of the utility and probability weighting functions (Abdellaoui, 2000; Abdellaoui, Barrios, & Wakker, 2007; Abdellaoui, Bleichrodt, & Kammoun, 2013; Abdellaoui, Vossmann, & Weber, 2005; Erner, Klos, & Langer, 2013; Etchart-Vincent, 2004; Fennema & Assen, 1999; Patalano et al., 2020). But the methods are based on sequential elicitation, resulting from specific experimental design in order to obtain necessary data structure. Consequently, there are limitations to apply those methods in various contexts.

On the contrary, parametric approach allows for fitting "more natural" data, and was tested in numerous studies (Booij, Praag, & van de Kuilen, 2010; Gao, Sun, Yang, Meng, & Qu, 2021; Glöckner & Pachur, 2012; Murphy & Brincke, 2018; Nilsson, Rieskamp, & Wagenmakers, 2020; Tanaka, Camerer, & Nguyen, 2010; Toubia, Johnson, Evgeniou, & Delqui´e, 2013; Vrecko & Langer, 2013; Wu & Gonzalez, 1996). However, some authors raised concerns about its ability to identify the behavioral parameters of CPT which led to developing non-parametric approach (Abdellaoui, Diecidue, & Öncüler, 2011; Abdellaoui, L'Haridon, & Paraschiv, 2011; Schmidt & Traub, 2002; Stott, 2006; van de Kuilen & Wakker, 2011).

Although employing nonparametric methods passes by methodological problems of parametric ones, it does not improve them. We believe that this issue can be addressed, and therefore we focus on simultaneous estimation of CPT parameters within parametric approach.

We aim to investigate the stability of parameter estimates when CPT is used to fit the data. Our focus is on the symmetric cumulation of probabilities in the weighting scheme incorporated in CPT, which we compare with the one-direction cumulation of probabilities as in RDU. Since the latter approach has not thus far been explored in the literature, we call the CPT model with one-direction cumulation "rank- dependent prospect theory" (RPT), referring to the rank but not sign dependence of the probability weights. Furthermore, we discuss the conditions for the two models to be equivalent and interpretation of the probability weighting function parameters. We expect that comparing the estimates from these two weighting schemes will help reveal any patterns of parameter interactions, should they be present. Specifically, we identify two main issues to address in this investigation.

First, the structure of the multi-parameter CPT model may result in an undesirable interaction among the parameters. If the two key transformations in CPT, namely the utility (value) function and the probability weighting function, interact with each other, even small changes in the parameterization setup may result in large variations in the estimated parameters. Stott (2006) observed such an interaction when testing different parametric forms of the transformations in CPT. He found that the best performing transformation in one function (e.g., utility function) critically depends on which function is used for the other (e.g., probability weighting function). In conclusion, he suggested using less complicated (single-parameter) transformations to reduce the interaction effect. Zeisberger et al. (2012) systematically investigated the interaction effects among CPT parameters. While examining the time stability of the preferences, they identified the difficulty caused by the interdependency among the parameters such that seemingly different parameter sets could produce similar preference structures. They explained this effect using the certainty equivalent elicitation method and concluded that the interaction of the probability weighting with the value function is systematic and highly relevant when measuring preferences and their stability (Zeisberger et al., 2012).

In this context, we focus on the stability of the parameters estimates when the weighting scheme is manipulated. That led us to examining how the symmetry around the reference point in the weighting scheme affects estimates of the utility function, especially the utility loss aversion parameter. Specifically, we compare two variants of the weighting scheme under two popular parametric families of probability weighting functions, the one-parameter form of Tversky–Kahneman (referred to as TK hereafter) and two-parameter Prelec form (referred to as Pr). These are considered to be representative of a general form of the weighting function (Gonzalez & Wu, 1999; Stott, 2006).

The second issue is the aspect of "probability loss aversion" discussed by Schmidt and Zank (2008). Fundamentally, this phenomenon arises from the interaction between the parameters of the utility function and the probability weighting function. In CPT, the loss aversion is represented in the utility function as a kink in the reference point. However, "probability loss aversion" describes a scenario where loss aversion behavior may be incorporated within the model through decision weights, specifically when the weights are larger in the loss domain than in the gain domain.

Harrison (2013, p. 115) stated that the loss aversion effect may be transferred to the decision weights when the researcher, assuming the same probability weighting function for gains and losses, "miraculously finds that utility loss aversion is empirically significant." In other words, it is suggested that probability loss aversion might be observed when the model using a common probability weighting function is compared to a model with separate weighting functions for gains and losses.

The literature offers partial confirmation of this observation. For instance, Glöckner and Pachur (2012) reported CPT estimates when assuming the same and separate probability weighting functions in the gain and loss domains. In all model variants, the utility loss aversion parameter was statistically significant and larger than 1 (ranging from 1.05 to 1.99). Furthermore, the median estimates they reported show that introducing a separate parameter for the probability weighting function in the loss domain systematically reduced the utility loss aversion parameter.

Additionally, Harrison and Ross (2017) claimed that little evidence shows observed loss aversion being related to utility loss aversion. Rather, the evidence points to probability weighting as a source of loss aversion since the probability weights diverge from the initial probability distributions attached to the decision problem. This aspect of CPT has yet not been properly investigated and is becoming more of interest. Taking the intuition proposed by Harrison (2013) about common and separate probability weighting functions in the gain and loss domains as a working hypothesis, we compare those two variants to quantify the change in the utility loss aversion parameter.

The investigation of these two issues – namely, parameter interactions in general and probability loss aversion – requires data that thoroughly covers not only the gain outcomes domain but also the loss domain and the mixed frames (comprising both positive and negative outcomes). The mass of evidence on CPT is based on gain frame data only, which is inconclusive when comparing the rank-dependent formulation for probability weighting (RDU) with CPT since the two models provide the same estimates in the gain domain (Harrison & Ross, 2017). Moreover, the majority of evidence is based on hypothetical outcomes, especially when losses are concerned. To obtain data suited to our investigation, we conducted an incentivized experiment that included in the incentives system the possibility of gains and the risk of losses.

The remainder of this paper is organized as follows. In the next section, we consider the symmetry of weights scheme around the reference point and introduce the modified model. Section 3 describes the experimental design and collection of the choice data. Section 4 presents the model and estimation method followed by a discussion of our main results.

1. Symmetry in the weighting scheme relative to the reference point in CPT

1.1. CPT formulation

Addressing the problems with OPT, mainly its susceptibility to violations of stochastic dominance, Tversky and Kahneman (1992) developed CPT based on Quiggin's (1982) RDU. The risky prospect (or lottery) is a pair X, P, where $X = (x_1, x_2, \dots, x_n)$ denotes the potential outcomes and P is the probability distribution of X, also denoted by $L = (x_1, p_1;\ x_2, p_2;\ \dots;\ x_n, p_n)$. In both theories, RDU and CPT, the value of the prospect is evaluated as the following expected value:

$$V(L) = \sum_r w_r \cdot U(x_r) \tag{1}$$

where w is the decision weight depending on the cumulative distribution function, while the $U(\cdot)$ function is the utility of the outcome as final wealth assuming asset integration in RDU and the value of the outcome as a loss or gain in CPT. The choice is a result of the maximization of the prospect value.

Further, the lottery is ordered in both theories: $x_1 < x_2 < \dots < x_n$. The decision weights in the RDU model are determined by

$$w_r = \pi(\Pr(X \geq x_r)) - \pi(\Pr(X \geq x_{r+1})), \quad \text{for } r = 1, \dots, n-1,$$
$$w_n = \pi(p_n).$$

Here, the decision weight of outcome x_r ($r = 1, \dots, n-1$) depends on the probability of obtaining at least x_r ($X \geq x_r$) and the probability of obtaining more than x_r ($X \geq x_{r+1}$). Therefore, the perspective is oriented "toward the best outcomes," a weighting scheme also described in terms of "gain-ranks" (Wakker, 2010) or decumulative probabilities (Tversky & Kahneman, 1992).

The main innovation of CPT in comparison to RDU is the introduction of sign dependence, which is clear as regards the value function, but not so obvious regarding probability weighting. In CPT, the lottery is not only ordered, but also split into positive and negative parts as

$$x_1 < \cdots < x_k < \cdots < x_n, \tag{2}$$

where x_k is a (neutral outcome) reference point, $x_k = 0$. The positive and negative parts of the lottery $L^+ = \{X^+, P^+\}, L^- = \{X^-, P^-\}$ with

$$x_r^+ = \begin{cases} x_r, & x_r \geq 0, \\ 0, & x_r < 0, \end{cases} \quad x_r^- = \begin{cases} 0, & x_r > 0, \\ x_r, & x_r \leq 0, \end{cases} \tag{3}$$

are evaluated separately. This means that the utility function may have different parameters for the loss and gain domains; however, there are reasons for using the same parameters, as we discuss later. Most importantly, the weighting scheme differs depending on the lottery part, with the weights for the positive (w_r^+) and negative (w_r^-) parts defined by[1]

$$w_n^+ = \pi^+(p_n),$$
$$w_r^+ = \pi^+\big(\Pr(X \geq x_r)\big) - \pi^+\big(\Pr(X \geq x_{r+1})\big), \quad \text{for } r = k, \dots, n-1,$$
$$w_r^- = \pi^-(\Pr(X \leq x_r)) - \pi^-(\Pr(X \leq x_{r-1})), \quad \text{for } r = 2, \dots, k,$$
$$w_1^- = \pi^-(p_1).$$

For gains, the weights are based on decumulative probabilities as in RDU. For losses, conversely, the weight of a loss x_r ($r = 2, \dots, k$) depends on the probability of the outcome not exceeding x_r and the probability of the outcome being worse than x_r. Hence, the perspective for negative outcomes is "toward the worst outcomes" or, in other words, based on "loss-ranks" or cumulative probability. Compared to RDU, CPT introduces symmetry in probability cumulation around the reference point, accompanied by separate weighting functions, w^+ and w^-. The consequences of this symmetric weighting scheme are discussed in the following section.

1.2. The role of symmetry in the weighting scheme in CPT

Explaining the origin of symmetry in the scheme of rank-dependent weights, Tversky and Kahneman (1992) argued that "in keeping with the spirit of prospect theory, we use the decumulative form for gains and the cumulative form for losses. This notation is vindicated by the experimental findings." One can hardly find in the literature more explanation or arguments for such approach than this quoted statement. To the best of our knowledge, the issue of symmetry in weighting scheme was not addressed by previous empirical studies.

In fact, whether the direction of cumulation matters at all is debatable. As explained by Wakker (2010, pp.219-222), the rank-dependent model may be defined equivalently using both gain-ranks and loss-ranks. However, the weighting function applied in the gain-ranks (decumulative) approach is not necessarily the same weighting function as in the loss-ranks (cumulative) one. For those two approaches to be equivalent, the probability weighting function

[1] We use the notation inversely compared with Tversky and Kahneman (1992), of $\pi(\cdot)$ for the probability weighting function and w for the decision weight, following Starmer (2000).

must be symmetric, i.e., $\pi(p) = 1 - \pi(1-p)$. When the symmetry is not satisfied, the two approaches are not equivalent, however, there is the duality between the gain-rank weighting function π_g and loss-rank weighting function $\pi_l(p)$

$$\pi_l(p) = 1 - \pi_g(1-p); \quad \pi_g(p) = 1 - \pi_l(1-p),$$

yet neither requires the symmetry condition since they are different functions.

Since most research refutes symmetry in the probability weighting function, the question remains of whether a change in the cumulation direction in the loss domain affects the model estimates. Wakker (2010) was convinced that it should not, however argued, that the two approaches offer different interpretations of the parameters of the probability weighting function. He provided the example that the convex probability weighting function of gain-ranks is equivalent to the concave probability weighting of loss-ranks.

Although, from a theoretical point of view, the argumentation is clear, this may not be the case for fitted data. The estimations of CPT and its variant using one-direction probability cumulation could differ for three reasons. First, the information may be asymmetric (i.e., the choice data may not provide sufficient information for the entire range of losses and probabilities). Second, the parameter estimates of the probability weighting function and utility function may interact. Third, the limited parametric form of the probability weighting function may not allow for the smooth adjustment needed to change the cumulation direction.

In light of these three possibilities, it is important to investigate how the change in cumulation direction within the weighting scheme, specifically in the loss domain, affects the parameter estimates, which is the contribution of this study. This task, to the best of our knowledge, has not previously been undertaken.

1.3. RPT: a CPT variant with a one-directional weighting scheme

In this study, we compare the estimates of the CPT model with its modification, where the direction of probability cumulation is the same in both the gain and the loss domains. To distinguish the two models, we call the modified variant RPT, referring to the rank- and sign-dependent utility model given by Luce and Fishburn (1991) to CPT. While the name "prospect theory" covers the sign dependence of the utility function, "rank and sign" refers to the weights.

For comparison purposes, RPT can be considered to be a compromise between the RDU and CPT models in the sense that (i) the value (utility) function is as in prospect theory, (ii) the weighting scheme is in line with RDU's gain-ranks, and (iii) it allows for both (i.e., the same and different probability weighting function parameters in the gain and loss domains). Therefore, for the ordered lottery (as in (2)), the model maximizes

$$V_{RPT}(L) = \sum_{r=1}^{k-1} \left(\pi^-\left(\Pr(X^- \geq x_r)\right) - \pi^-\left(\Pr(X^- \geq x_{r+1})\right)\right) \cdot U(x_r)$$
$$+ \sum_{r=k}^{n} \left(\pi^+\left(\Pr(X^+ \geq x_r)\right) - \pi^+\left(\Pr(X^+ \geq x_{r+1})\right)\right) \cdot U(x_r),$$

where X^- and X^+ refer to the negative and positive parts of the lottery as in CPT defined in (3).

We compare the RPT and CPT estimations in four variants, according to the scheme presented in Table 1. The model implementations cover the variants with the same parameters of the probability weighting function for gains and losses and parameters for gains and losses estimated separately, indicated by the subscripts 1 and 2, respectively. In the first situation, no probability loss aversion exists because of the symmetry in the weights in CPT, while the second allows for probability loss aversion in both models. In addition, two parameterizations of the probability weighting function are applied: the TK form and two-parameter Pr form.

Table 1. The eight models tested in the experiment

	Probability weighting functions in the loss and gain domains			
Weight cumulation	common		sign-dependent	
One-direction	$RPT_{1,TK}$	$RPT_{1,Pr}$	$RPT_{2,TK}$	$RPT_{2,Pr}$
Symmetric	$CPT_{1,TK}$	$CPT_{1,Pr}$	$CPT_{2,TK}$	$CPT_{2,Pr}$
	Number of weighting function parameters / Total number of parameters			
	1 / 3	2 / 5	2 / 5	4 / 6
	Value function in relation to RDU			
One-direction (RPT)	$V_{RDU}(L^+,\pi)+V_{RDU}(L^-,\pi)$		$V_{RDU}(L^+,\pi^+)+V_{RDU}(L^-,\pi^-)$	
Symmetric (CPT)	$V_{RDU}(L^+,\pi)+V_{RDU}(L^-,\pi^*)$		$V_{RDU}(L^+,\pi^+)+V_{RDU}(L^-,(\pi^-)^*)$	

Note: $V_{RDU}(L,\pi)$ is the RDU value of lottery L assuming probability weighting function π. π^* is symmetric function $\pi^*(p)=1-\pi(1-p)$.
Source: *own compilation*

Introducing one-directional weight cumulation under RPT is an alternative to CPT's way of incorporating rank-dependent weights into OPT. Notably, CPT was not the first attempt to merge prospect theory with rank-dependent weighting. Starmer and Sugden (1989) proposed RPT defined as $V(L)=V_{RDU}(L^+,\pi)+V_{RDU}(L^-,\pi^*)$, where $\pi^*(p)=1-\pi(1-p)$. We refer to this model as CPT_1, representing the CPT variant with common probability weighting function and symmetric weight cumulation.

For clarity, Table 1 presents a summary of the four model variants we examine, showing the model structure in relation to RDU. This representation highlights the duality in loss domain between the probability weighting functions of RPT and CPT. The adopted research scheme aims to answer two research questions.

1. How does the separate estimation of the probability weighting function parameters in the gain and loss domains change the estimates compared with the same parameters and is probability loss aversion therefore observed?
2. How does the change in the direction of probability cumulation in the loss domain affect the estimates?

To answer the first question, the models with subscript 1 are compared with the models with subscript 2. To answer the second, we compare CPT with RPT. Such comparisons should allow us to verify the interactions between the parameters and thus check the stability of the estimates.

2. Experimental design

The estimated models are based on the experimental data from the incentivized binary choice under risk experiment conducted in the laboratory at the University of Gdańsk. This computerized experiment was performed using an application specially created for the research purpose. The subjects were undergraduate students who volunteered for the survey. The average age of the participants was 21 and about 65% were women.

The main part consisted of two types of sessions: (i) training sessions, in which participants could learn the rules and experimental procedures as well as familiarize themselves with the reward system, and (ii) data-gathering sessions for the model estimation. Specifically, two data-gathering sessions were conducted with a one-week span between them. In addition, the training sessions allowed participants to win a certain amount of money to use in the gambling tasks, as the decisions included not only gain lotteries but also loss and mixed lotteries. Hence, participants could incur a loss in a single session. However, to address ethical concerns about participants potentially losing their own money, we ensured that each participant received at least a minimum reward to cover the time cost of participation.

Of the recruited 77 subjects, 70 completed both data-gathering sessions, and the models were estimated for those subjects. There were 80 decision problems in each session. The choice of decision problems was based on the HILO structure (Camerer, 1995) and the studies of Loomes and Sugden (1998) and Harrison and Swarthout (2016) under the assumption that the output domain was between -100 PLN and 100 PLN in 10 PLN increments (10 PLN is equal to 2.3 EUR). The set of decision problems used in the experiment is presented in the supplementary materials (Table 4).

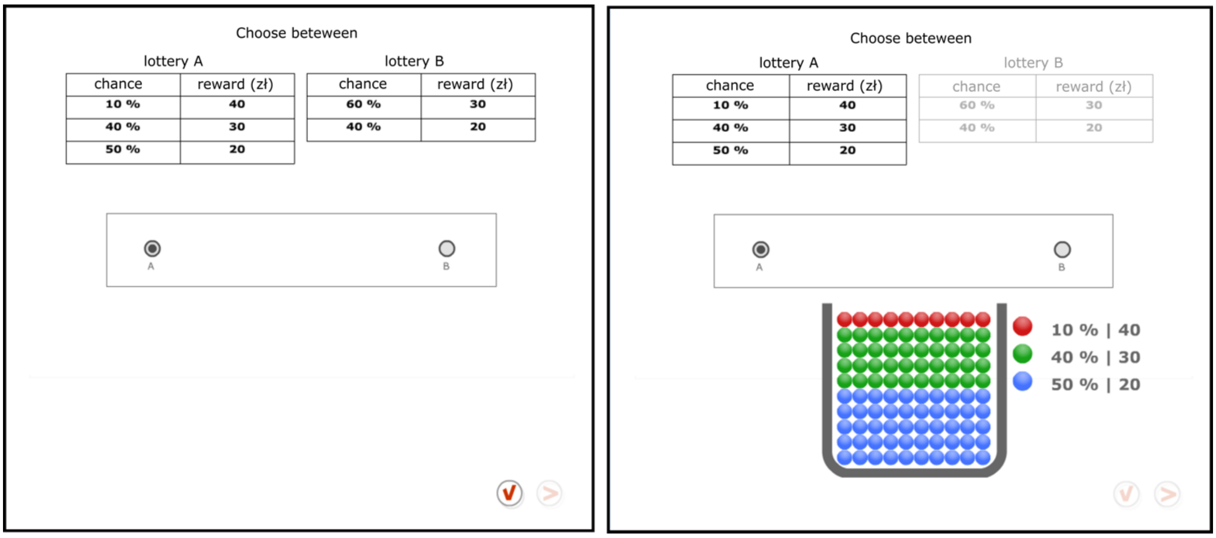

Figure 1. Decision problem presentation in the experiment
Source: *own elaboration*

Decisions were framed in the standard gamble format presented in Figure 1. Three types of lotteries were used: positive, negative, and mixed lotteries (32, 32, and 16 decision problems in each session, respectively). Although the set of decision problems was fixed, the problems were displayed to each subject in a random order (i.e., each participant received his/her decision problems in a different order). After each choice, the chosen lottery was played using an animation presenting an urn with 100 colored balls, representing the lottery's distribution. Next, the draw of the ball was animated, and the resulting outcome of the choice was presented on the screen. Therefore, after each choice, subjects learned the results of their choices, but no sum or balance of all the choices' results was presented. The majority of the participants needed less than half an hour to complete each session.

The incentive system was as follows. At the end of each session, four decision problems were randomly selected for payment, two of which were positive lotteries with one negative and one mixed. At the end of each session, the subject learned which decision problems had been selected. Finally, the previously displayed results of those four choices were added to the subject's reward balance.

While every lottery could have affected the result, there was greater chance of a positive result than a loss. The resulting rewards of the subjects varied from 90 PLN to 420 PLN with an average value of 242 PLN (or 57 EUR).

3. Model and estimation method

3.1. Parametrizations

Utility function

We consider a power utility function in the form of x^{α} for $x \geq 0$ and $\alpha > 0$. The function is monotonically increasing and is linear if $\alpha = 1$, strictly concave if $0 < \alpha < 1$, and convex if $\alpha > 1$. Parameter α therefore represents outcome sensitivity. However, the function has singularity as $\alpha \to 0$. To ensure continuity in parameter α and keep the reference point at 0 so that $U(0) = 0$, we express the power utility function, in line with (Wakker, 2008), as

$$v(x) \equiv v(x;\alpha) = \begin{cases} \dfrac{(1+x)^{\alpha} - 1}{\alpha} & \text{if } x > 0,\ \alpha > 0, \\ \log(1+x) & \text{if } x > 0,\ \alpha = 0. \end{cases}$$

To cover negative outcomes, we use an asymmetric extension and define the utility function with $\lambda > 0$ as

$$U(x) = \begin{cases} v(x) & \text{if } x \geq 0, \\ -\lambda v(-x) & \text{if } x < 0. \end{cases}$$

In general, different powers α of the utility function for gains and losses may be considered. However, to measure loss aversion with parameter λ, we assume a common α parameter in the whole domain as proposed by Köbberling and Wakker (2005) and Harrison and Swarthout (2016).

Probability weighting function

Two parametric forms are considered. While these are two of the most frequently used functions, they vary in terms of flexibility.

A standard one-parameter family (TK) is defined as

$$\pi(p) \equiv \pi_1(p;\gamma) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}, \quad 0 \leq p \leq 1,\ 0 < \gamma \leq 1.$$

This satisfies that $\pi(0) = 0$ and $\pi(1) = 1$ and $0 \leq \pi(p) \leq 1$ for $0 \leq p \leq 1$ and can exhibit the inverse S-shaped phenomenon covering both concave (small p) and convex (large p) regions. The function is well defined for $\gamma = 1$ with $\pi(p) = p, 0 \leq p \leq 1$; however, when $\gamma = 0$, it becomes a zero function except at 1, creating a discontinuity. Moreover, the function is not necessarily monotonically increasing for $0 < p < 0.5$ when γ is small $(0 < \gamma < 0.28)$. The parameter γ captures probability sensitivity.

A more flexible two-parameter family (Pr) function is defined as

$$\pi(p) \equiv \pi_2(p;\delta,\gamma) = \exp[-\delta\{-\log(p)\}^{\gamma}], \quad 0 < p < 1,\ \delta > 0,\ \gamma > 0,$$

with $\pi(0) = 0$ and $\pi(1) = 1$. The function is linear in p on the log-log scale, satisfying $\log\big(-\log\pi(p)\big) = \log\delta + \gamma\log(-\log p)$; therefore, it is monotonically increasing. When $\gamma = 1, \pi(p) = p^{\delta}$ and does not include the one-parameter family as a special case. The δ parameter controls the elevation and the γ parameter controls the curvature (probability sensitivity).

In both cases, when combined with positive and negative outcomes, the corresponding weight functions π^{+} and π^{-} are allowed to have different parameters (denoted with the subscripts p and n in the gain and loss domains, respectively).

3.2. Estimation method

Given the binary outcomes of the choices for each subject from the several combinations of the lotteries, we formulate a binary regression model and obtain the maximum likelihood estimates.

Denote by Y the outcome of the game $(X^A, P^A, X^B, P^B) = (L^A, L^B)$ with 1 indicating that lottery A is selected over lottery B. Then, Y follows a Bernoulli random variable with the success probability μ, where

$$\mu = \Pr(Y = 1) = F\big(V(L_A) - V(L_B)\big),$$

under a link function $F(\cdot)$ and $V(\cdot)$ is given in (1). Here, we use a logit link function with $F(a) = e^a/(1 + e^a)$ for $-\infty < a < \infty$. Observe that

$$V(L_A) - V(L_B) = \sum_{r=1}^{m} w_r^A U(x_r) - \sum_{r=1}^{m} w_r^B U(x_r) = \sum_{r=1}^{m} (w_r^A - w_r^B) U(x_r).$$

w_r and U are functions of the parameters, say θ, and the number of parameters depends on the scenarios. Hereafter, we simply write $\mu = \mu(\theta; x, p)$. Let y be the realization of Y. The likelihood function for the model is given by

$$L(\theta) = \mu(\theta; x, p)^y \{1 - \mu(\theta; x, p)\}^{1-y}.$$

To deal with multiple outcomes, we write $y_1, \ldots, y_n$ as the realizations from $Y_j \sim \text{Bernoulli}(\mu_j), j = 1, \ldots, n$. Assuming that the outcomes are independent given the subject and the subject uses the same mechanism to make a choice with the same set of parameters θ for different lottery sets (x_j, p_j) so that $\mu_j = \mu(\theta, x_j, p_j)$, the corresponding log-likelihood function can be written as

$$\ell(\theta) = \sum_{j=1}^{n} \Big\{ y_j \log\Big(\mu\big(\theta; x_j, p_j\big)\Big) + \big(1 - y_j\big) \log\Big(1 - \mu\big(\theta; x_j, p_j\big)\Big) \Big\}.$$

The maximum likelihood estimates are defined as the value that maximizes the likelihood function:

$$\hat{\theta} = \arg\max \ell(\theta).$$

4. Results and discussion

4.1. Interaction between the parameters: Estimation results

We fit the eight specifications in Table 1 to the participants' data. We then compare the RPT and CPT estimates to investigate the interaction between the utility and probability weighting function parameters. According to the theory, the two models are equivalent, with the RPT probability weighting function being a symmetric reflection of the CPT probability weighting function. We verify whether this fact can be observed in the estimates when applying simultaneous parametric fitting to the utility and weighting functions. To confirm this observation, we should observe (1) no difference between the RPT and CPT utility function parameters and (2) a difference between the RPT and CPT probability weighting function parameters (for models with separate functions in the gain and loss domains, only in the loss domain).

Table 2. Median estimates for the parameters

Specification	$RPT_{1,TK}$	$CPT_{1,TK}$	$RPT_{1,Pr}$	$CPT_{1,Pr}$	$RPT_{2,TK}$	$CPT_{2,TK}$	$RPT_{2,Pr}$	$CPT_{2,Pr}$
Parameter	Median estimates for the parameters and interquartile range							
α	0.57 (0.36)	0.55 (0.43)	0.57 (0.20)	0.52 (0.35)	0.52 (0.37)	0.62 (0.28)	0.52 (0.22)	0.52 (0.22)
λ	0.65 (1.37)	0.49 (0.91)	0.51 (0.71)	0.87 (1.97)	0.96 (2.05)	0.50 (0.58)	1.02 (1.09)	1.05 (1.23)
γ	1.07 (0.48)	1.05 (0.42)	—	—	—	—	—	—
γ_n	—	—	—	—	1.30 (1.03)	1.32 (0.97)	—	—
γ_p	—	—	—	—	1.04 (0.35)	1.05 (0.39)	—	—
δ	—	—	0.79 (0.69)	0.74 (0.48)	—	—	—	—
γ	—	—	1.26 (0.53)	1.25 (0.75)	—	—	—	—
δ_n	—	—	—	—	—	—	1.47 (3.31)	1.19 (1.13)
γ_n	—	—	—	—	—	—	1.75 (1.87)	1.45 (1.53)
δ_p	—	—	—	—	—	—	0.72 (0.38)	0.71 (0.42)
γ_p	—	—	—	—	—	—	1.20 (0.62)	1.23 (0.69)
Criterion	Performance							
Median $-lnL$	90.40	90.80	85.84	85.78	87.98	90.41	80.74	80.27
Median AIC	186.79	187.59	179.67	179.56	183.97	188.83	173.48	172.54
Median accuracy	0.67	0.66	0.71	0.7	0.67	0.69	0.73	0.74

Note: $AIC = 2k - 2lnL$, where k is the number of free parameters.

Source: *own elaboration*

Table 2 presents the medians of the estimated parameters together with the interquartile range. Only specifications with a Pr sign-dependent probability weighting function in the gain and loss domains conform to the theory since no significant difference between $RPT_{2,Pr}$ and $CPT_{2,Pr}$ is observed in utility parameters α, λ or the gain domain probability weighting function δ_p and γ_p estimates. Consistently, the parameters in the loss domain probability weighting function differ, both δ_n and γ_n being lower for $CPT_{2,Pr}$than for $RPT_{2,Pr}$. The other three specifications exhibit differences between RPT and CPT in the utility function estimates (especially, loss aversion λ), while the estimates of the probability weighting function parameters do not differ significantly. These findings, suggesting some interaction between the parameters, show the limited benefits of the most popular specification, $CPT_{2,TK}$.

Common probability weighting function variants are included in the analysis for comparison purposes. According to the hypothesis that probability loss aversion takes precedence over utility loss aversion, we should expect to observe a larger λ in the common probability weighting function variant than in the sign-dependent one. However, we find no such effect in our analysis. Contrarily, the variants with distinct probability weighting functions produced higher λ values, which contradicts the probability loss aversion.

Table 2 shows the average performance of the models. Firstly, the medians of the log-likelihoods are given; however, as the RPT and CPT models are not nested, this approach is not suitable for making comparisons. The second measure comprises the Akaike information criterion (AIC), which controls for the number of free parameters and therefore is more suitable for comparisons between different CPT (or RPT) specifications as they differ by the number of parameters. The difference between RPT and CPT specifications in terms of AIC median values can be observed only for sign-dependent specifications with TK weighting function; the visual comparison of AIC distributions for eight models (Figure 9 in Supplementary materials) reveal differences within RPT-CPT pairs for models with Pr common weighting function and with TK separate weighting functions. For the remaining two specifications, i.e., common TK variant and sing-dependent Pr variant, the AIC distribution is invariant to the direction of probability cumulation.

Goodness-to-fit of the models was captured by accuracy measure. Accuracy represents the percentage of correctly predicted choices from the fitted model with a threshold 0.5. The most flexible specifications, $CPT_{2,Pr}$ and $RPT_{2,Pr}$, outperform the other models, the former giving slightly better accuracy. Moreover, allowing for separate parameters in the loss and gain domains in specifications with the TK function does not improve accuracy in comparison to the variant with common parameters. Visual comparison of accuracy distributions within RPT-CPT pairs (Figure 10 in Supplementary materials) demonstrates the lack of significance of the direction of probability cumulation on the goodness-to-fit of the model.

4.2. Interpreting parameter estimates: Discussion

The outcome sensitivity of the utility function (Table 2), quantified by the α parameter, falls within the typical range. These estimates confirm that the outcome sensitivity parameter is similar to those reported in other studies, ranging from 0.23 (Camerer & Ho, 1994) to 1.34 (Gao et al., 2021).

Compared with previous studies, the median values for loss aversion parameter λ in the first three pairs of models are below 1, which is unexpected but occurs partly because we only impose a minimal constraint in the estimation that λ is non-negative without any model selection. We adopt this approach to investigate the parameters' interactions across the specifications. Our results are not the first instance of observing low values for λ.

Nilsson et al. (2020) reported a median value of 0.78 for λ in their analysis, utilizing different parameters of the utility function for gains and losses. This value improved to 0.97 when employing a common utility function parameter across both domains. The value of λ being 1 (individual models and median) is reported by Rieskamp (2008), where 1 is the parameter's lower boundary.

Another study by Abdellaoui et al. (2013) also reported λ equal to 1, but the value was obtained from the calculations based on the loss aversion definition by Köbberling and Wakker (2005) rather than estimation within the model. Murphy and Brincke (2018) reported a median value around 1 for λ as well.

The TK probability weighting function parameters greater than 1 are higher than the median values reported in most other studies (Glöckner & Pachur, 2012; Nilsson et al., 2020; Rieskamp, 2008; Tversky & Kahneman, 1992; Zeisberger et al., 2012). Median estimates close to one were reported in Stott (2006) and Harrison and Rutström (2009). On the other hand, estimates of the Pr probability weighting function parameters are more typical compared to the TK parameters. This is because greater volatility in parameter estimates can be observed across studies for the Pr function (Abdellaoui, Diecidue, & Öncüler, 2011; Balcombe & Fraser, 2015; Bouchouicha & Vieider, 2017; Stott, 2006; van de Kuilen & Wakker, 2011).

Although we encountered occasional issues with singular cases, at least three of the considered models provided stable estimates for each subject. Given the isolated instability observed in a small number of cases, we further examined the tasks (stimuli) to assess their effectiveness in capturing revealed preferences. Specifically, we aimed to determine whether the subjects were sufficiently responsive to the stimuli. To investigate this, we calculated the correlation between the choice proportions and the difference in expected values (EV) of lotteries for each game. The left side of Figure 2 displays a scatter plot illustrating that as the expected value (EV) of one lottery increases relative to the other, the proportion of selecting that lottery also increases. The correlation coefficient for this relationship was 0.56 ($p < 0.01$). The concentration of observations in the center of the plot results from the relatively large number of games with equal EV. The positive relationship between the value of the lottery and the likelihood of its selection indicates that, overall, subjects paid attention to the tasks.

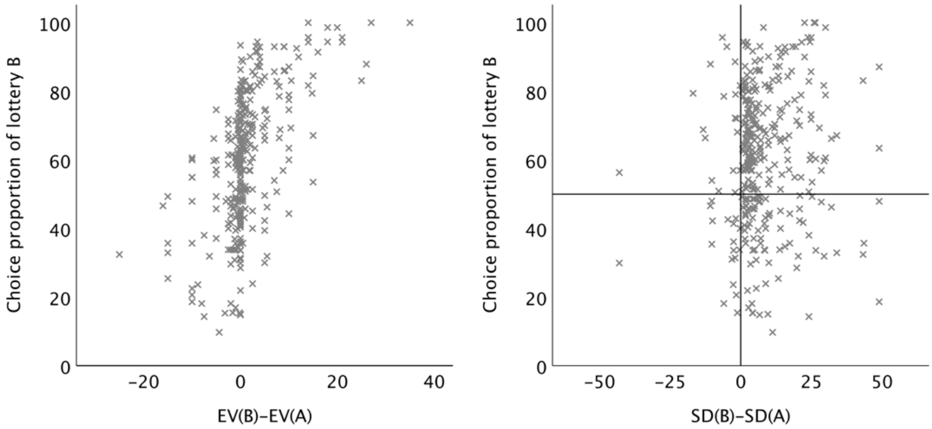

Figure 2. Scatter plot of the difference of the expected value (left) and difference of the standard deviation (right) of lottery B and lottery A, and the proportion of subjects using lottery B
Source: *own elaboration*

The right side of Figure 2 illustrates the frequency of choosing the riskier lottery when the risk is measured by the standard deviation (SD) of the lottery. The concentration of the observations in the top-right quarter of the plot indicates a dominant preference for risky lotteries in the observed choice behavior. While such risk-seeking behavior is not typical in experimental results on binary choice under risk, this observation aligns with the parameters' estimates obtained from the models, suggesting that the estimated models accurately captured revealed preferences.

We believe that immediate feedback in the repeated experience of binary choices is the feature of our experimental design that induced risk-seeking behavior. We found partial support for this statement in previous studies. While some studies on the impact of feedback on risk attitude found that feedback reduces risk-taking (Li et al., 2023), the opposite conclusion is drawn when viewed through the moderating effect of learning and experience. Hertwig, Barron, Weber, and Erev (2004) found a significant difference between decisions from experience and decisions from description. In the feedback and experience condition, where subjects gradually acquired knowledge about the payoff distributions, the rate of risky choices was significantly higher compared to the description treatment, which provided a description of the two options. On the other hand, Abdellaoui, L'Haridon, and Paraschiv (2011) found no difference between the description and experience conditions.

Numerous studies have shown that immediate feedback facilitates learning and gaining experience (Kulik & Kulik, 1988). Subsequently, experienced subjects are found to make choices more in line with the expected value, reducing risk aversion behavior. Melesse and Cecchi (2017) investigated the risky choices of farm households and found that market experience attenuates risk aversion. Ert and Haruvy (2017) showed that repeated experience of the Holt-Laury test caused subjects to transition from revealing risk aversion to displaying risk neutrality. Bradbury, Hens, and Zeisberger (2015) found that simulated experience improved participants' understanding of risk and prompted them to select riskier financial products, leading to higher risk-taking behavior. Similar results were obtained by Kaufmann, Weber, and Haisley (2013), who found that experience sampling, as a method to communicate risk to investors, increased risky allocations.

Regarding the findings related to loss aversion, we investigate whether our results further contribute to the existing evidence challenging loss aversion. The mixed results in relation to loss aversion were found by several authors (Ert & Erev, 2013; Mukherjee, Sahay, Pammi, & Srinivasan, 2017; Rakow, Cheung, & Restelli, 2020; Zeif & Yechiam, 2022). Specifically, we focus on the specifications with Pr sign-dependent probability weighting function, as we found it to be the least susceptible to parameter interactions. Based on the $CPT_{2,Pr}$ specification, we found that 36% of the subjects exhibit distinct loss aversion ($\lambda > 1.5$), while 23% of the subjects show mild loss aversion or neutrality towards such effects ($0.9 < \lambda \leq 1$). These results support the conclusion of significant heterogeneity in our findings, indicating diverse choice behavior across subjects. Consequently, in line with our findings on risk aversion, we attribute such low or nonexistent loss aversion to the immediate feedback and learning effect.

4.3. Insight into the parameter interactions: Clustered data

To mitigate the effect of heterogeneity to investigate the parameter interactions, we group subjects according to their response pattern using hierarchical clustering with a binary distance measure. The results of this data clustering are presented in the Supplementary materials (Figure 11). We identify four groups of subjects that are reasonably well separated and then compare the models' estimates grouped by these clustered classes (median estimates for the parameters by cluster group are provided in Table 3 in the Supplementary materials). Such data clustering also allows us to check the validity of the data by distinguishing the six subjects under suspicion of making ill-considered choices (i.e., causing most of the models' identification problems). Those six subjects are excluded from further analysis.

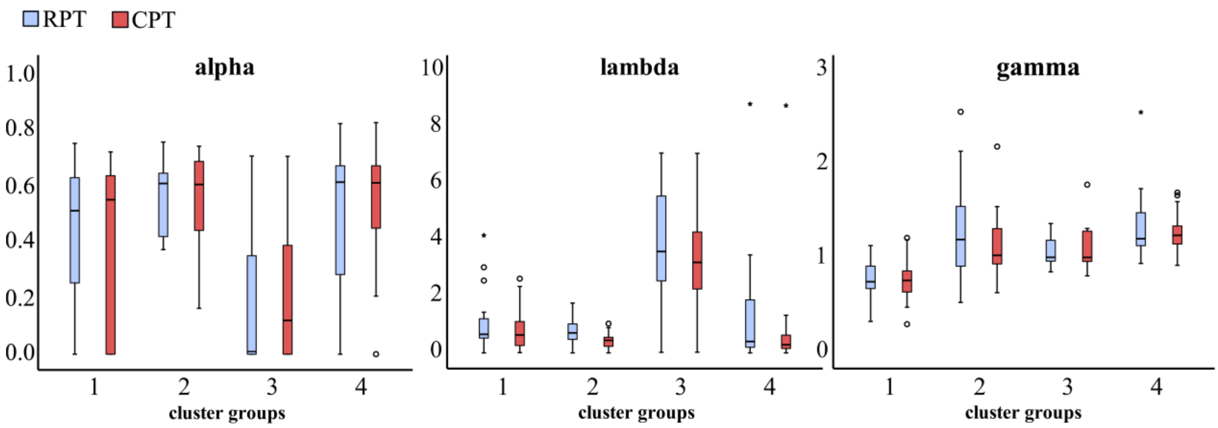

Figure 3. Distributions of the parameters by cluster for specifications with the TK common weighting function
Source: *own study*

Figure 3 shows the distributions of the estimates of the basic model with three adjustable parameters (i.e., a variant with the TK common parameter probability weighting function). No significant differences between the RPT and CPT estimates are observed for this specification. The utility function estimates are similar for clusters 1, 2, and 4, while cluster 3 gathers the subjects with distinctly lower utility α estimates accompanied with higher loss aversion λ in comparison to the other groups. However, the median estimates of probability weighting function parameter γ is lower in cluster 1 than in the other groups. The change in symmetry around the reference point has little impact on this specification with the common probability weighting function for gains and losses.

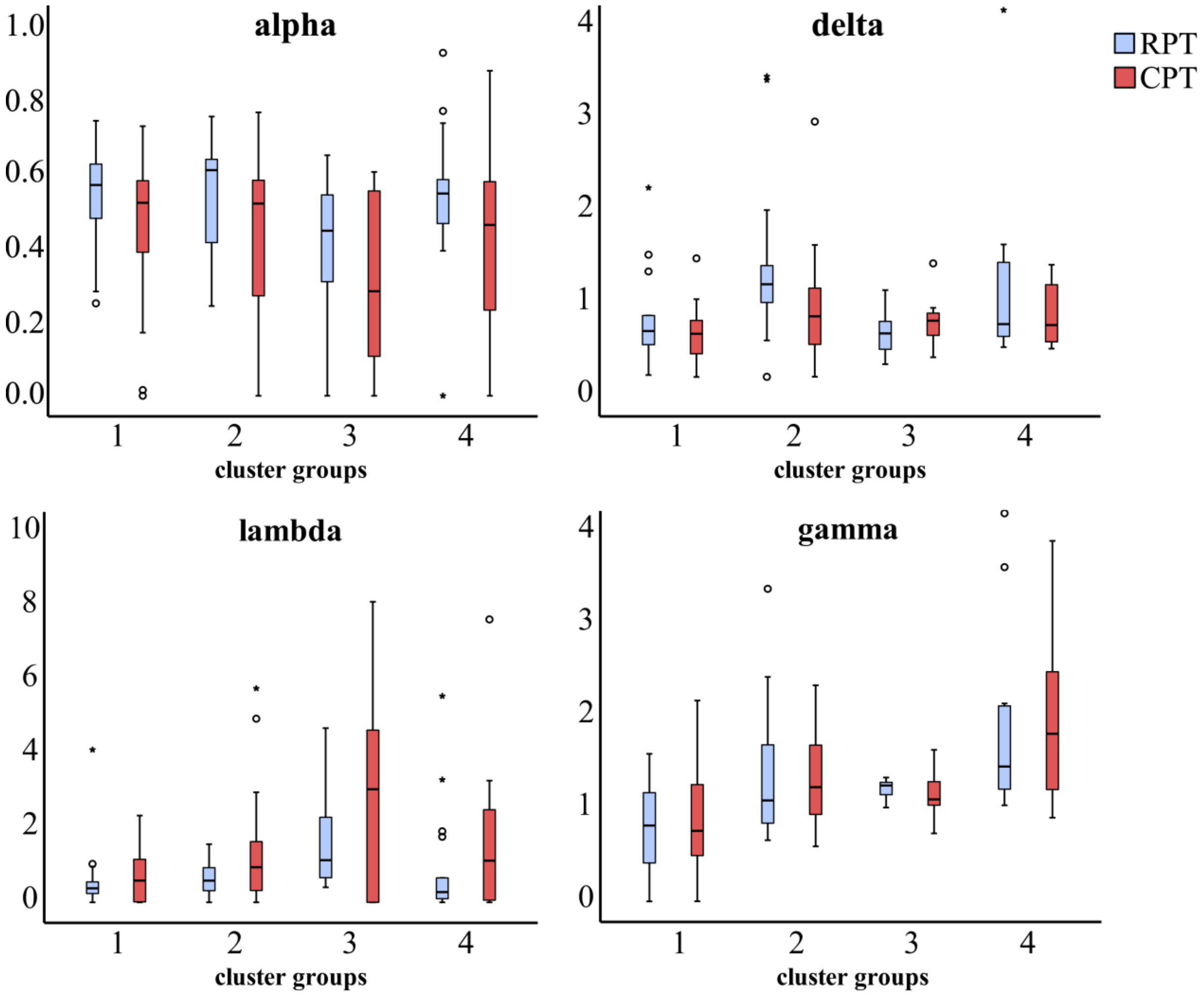

Figure 4. Distributions of parameters by cluster for specifications with the Pr common weighting function
Source: *own study*

Figure 4 shows the distributions of the parameters in clusters for the specification with the Pr common probability weighting function variant. For all the clusters, the utility α estimates are higher for RPT accompanied with lower λ estimates in comparison to CPT. No systematic differences between RPT and CPT regarding the probability weighting function parameters δ and γ can be observed. Generally, the change in the probability cumulation direction in the weighting scheme causes an adjustment mostly in the utility function, revealing the interaction between the utility and probability weighting functions.

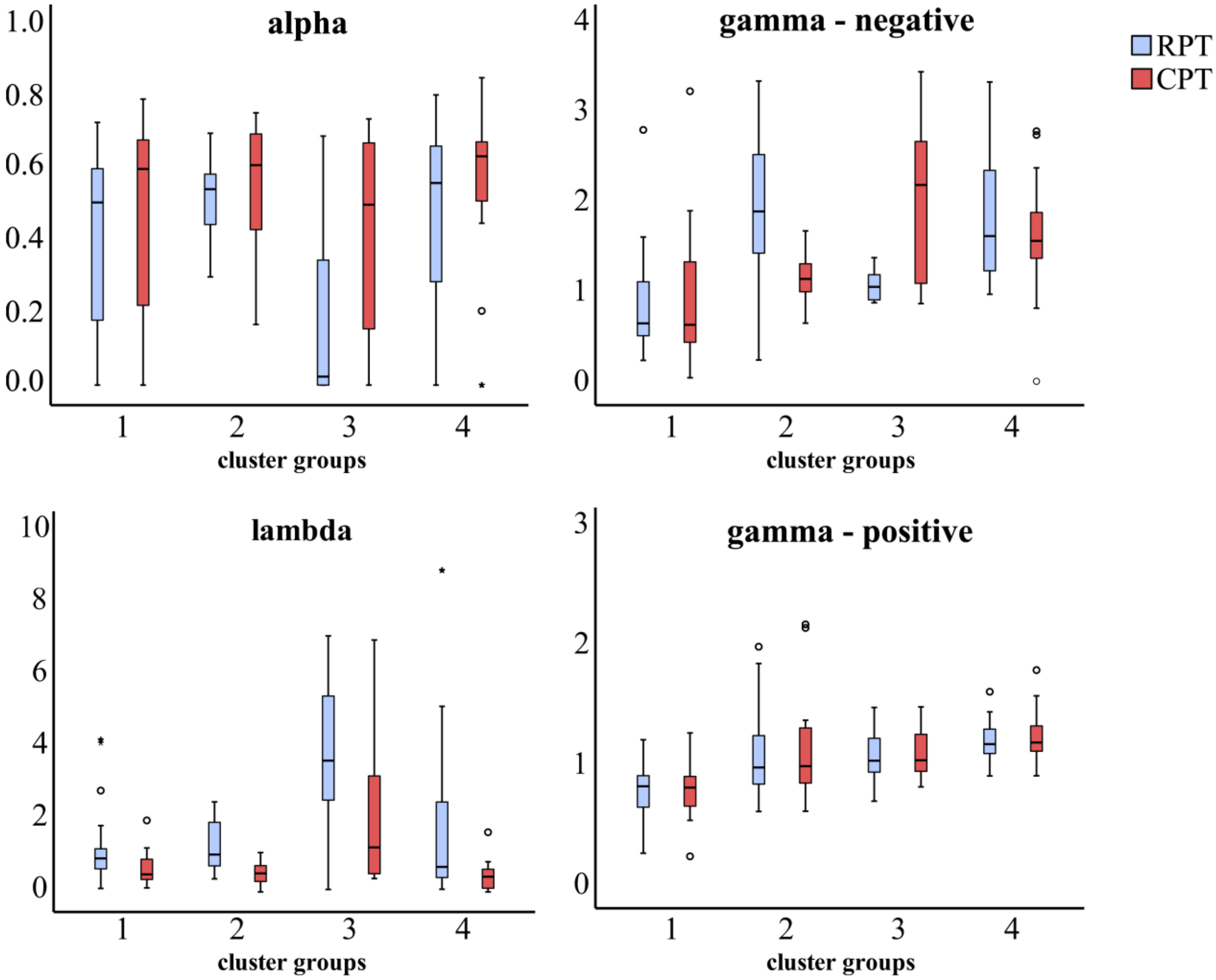

Figure 5. Distributions of the parameters by cluster for specifications with the TK sign-dependent weighting functions
Source: *own study*

The third specification covers the typical CPT model with the TK probability weighting function. Figure 5 presents the distributions of the parameters in clusters. The differences in the utility function parameters for CPT and RPT are clear. For all the cluster groups, the utility α parameters are systematically larger for CPT accompanied by systematically smaller λ parameters in comparison to RPT, again suggesting that the parameters interact. This finding complements the previous specifications.

The probability weighting function parameters for the gain domain are relatively stable, with minor differences between clusters. No differences between CPT and RPT are observed as expected because the algorithms in the gain domain are identical. However, large variation in the γ_n estimates is observed for the loss domain. While the estimates of CPT and RPT are similar in clusters 1 and 4, large differences are noted in clusters 2 and 3; however, these differences are in opposite directions, which causes all the median values in the sample to appear to be similar. Cluster 2 gathers subjects for whom the CPT probability weighting function γ_n estimates are relatively low; after adjusting the RPT algorithm variant, the estimates increase significantly. The opposite is observed in cluster 3, where relatively high estimates are obtained for CPT and much smaller ones for RPT.

Figure 6 presents the typical utility and probability weighting functions for the chosen subjects and for both the common and the separate TK probability weighting functions. We present the representative subjects' curves as opposed to the median values' curves in response to the objection that no subject might link these median estimates. To avoid such bias, for each cluster, we present the subject whose set of estimates is the closest to the median values.

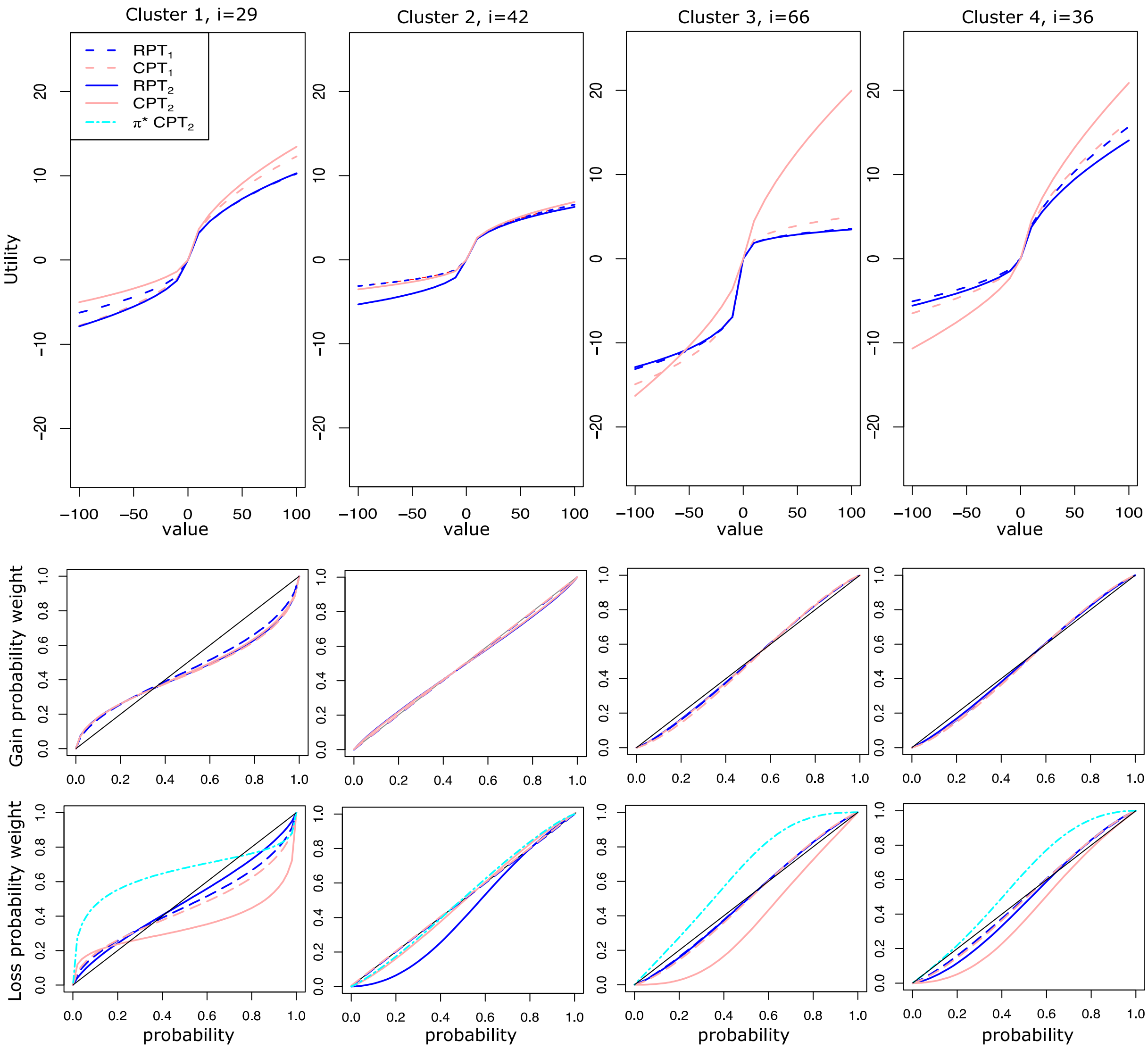

Figure 6. Utility and probability weighting functions for each cluster's representative subject for models with the TK weighting functions
Source: *own study*

The dashed lines represent the variants with a common parameter for the probability weighting function in both the gain and the loss domains, and the solid lines the separate parameters versions of CPT and RPT in red and blue, respectively. Fitting our experimental data using models with the TK probability weighting function yields large differences between subjects' utility functions, while the probability weighting function does not show large diversity. For all the considered models, the probability weighting functions for the gain domains are close to linear as well as close to the shapes obtained for the common parameter variant (i.e., they do not show large probability transformations). By contrast, the difference in the probability weighting function in the loss domain for the CPT_2 model is pronounced.

The light blue lines in the bottom row charts are the symmetric shapes of the probability weighting function for CPT loss (solid red). The lines close to the curves of the probability weighting function for RPT loss (solid blue) show evidence of the equivalence of RPT and

CPT. In specifications with the TK probability weighting function, those two lines (i.e., CPT symmetric and RPT loss probability weighting curves) are not close. Therefore, the CPT and RPT models differ in this case.

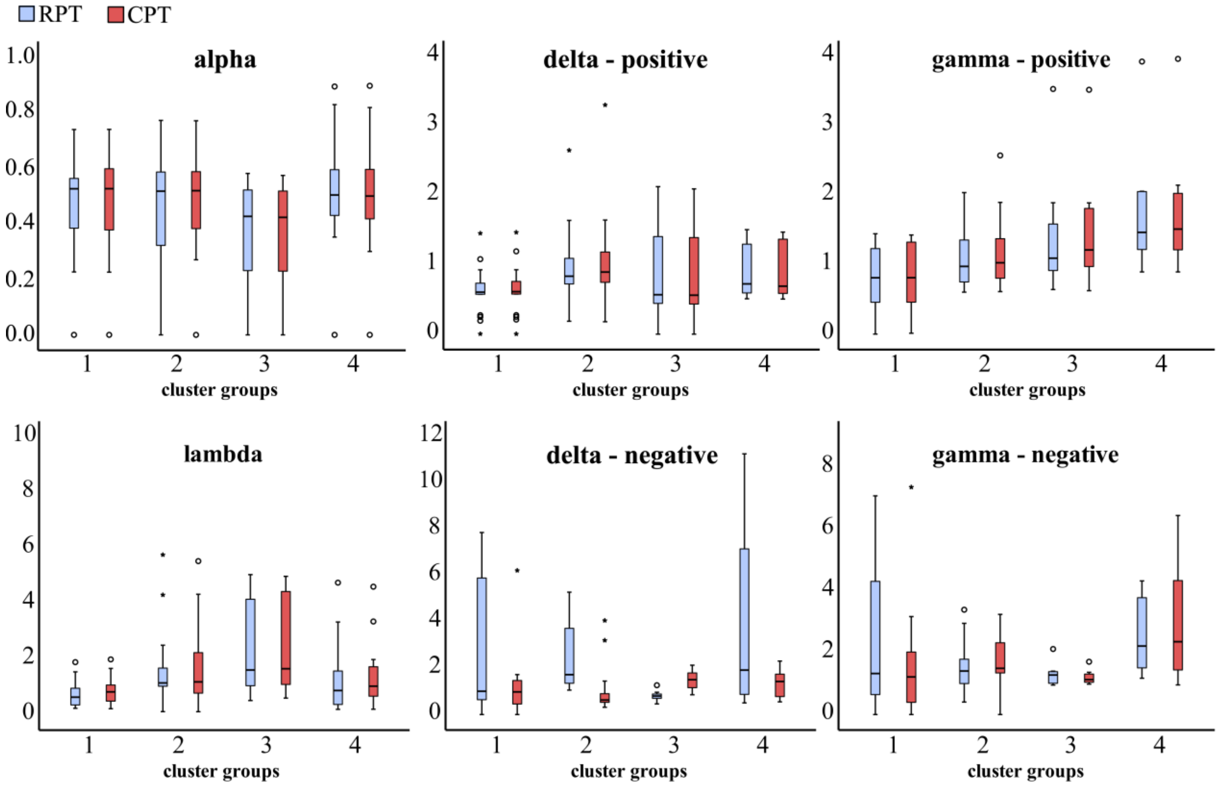

Figure 7. Distributions of the parameters by cluster for the specifications with the Pr sign-dependent weighting functions
Source: *own study*

Finally, Figure 7 presents the distributions of the estimates of the most flexible specification with the Pr probability weighting function parametric form using separate parameters for the gain and loss domains. In this specification, the desired similarity in utility estimates between CPT and RPT is obtained. While differences between clusters are noticeable in the utility parameters, no clear distinction can be observed between the CPT and RPT estimates. The probability weighting function in the gain domain is similar. Consequently, in line with the theory, an adjustment to the change in the weighting scheme is observed in the estimates of the probability weighting function in the loss domain, especially regarding the elevation (δ_n).

Figure 8 shows representative subjects' utility curve and probability weighting functions for the specifications with the Pr function. This figure provides evidence of the successful adjustment between CPT and RPT. For all the representative subjects, the utility and gain probability weighting curves in the two models are alike. Moreover, the light blue lines representing the symmetric CPT curves in the bottom row charts fit the RPT curves (dark blue) well, which proves the equivalence of $RPT_{2,Pr}$ and $CPT_{2,Pr}$.

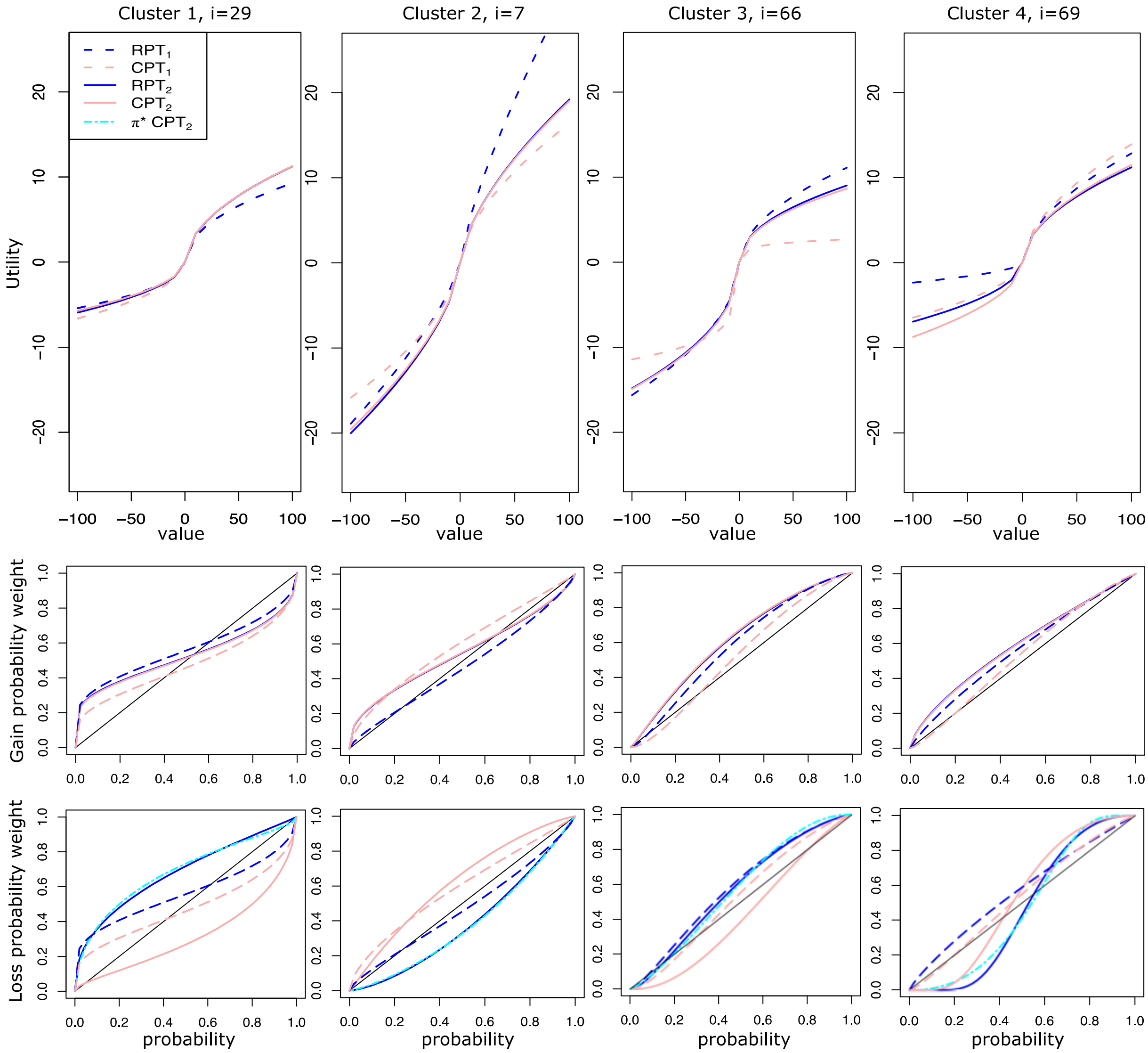

Figure 8. Utility and probability weighting functions for each cluster's representative subject for models with the Pr weighting functions
Source: *own study*

Conclusion

Prospect theory is based on two subjective scales, namely, the transformations of value and probability. Edwards (1954) expressed his concern that utilities and subjective probabilities are not independent and therefore a model may fail to predict risky choices. There is a risk that certain data characteristics are acquired by the utility function parameters, possibly overlapping the probability-specific effects. The inability to separate those two components leading to the parameter interactions is thus regarded as a major drawback of the model specification.

We tested the parameter interactions by comparing the CPT model with its modified version that assumes one-direction probability cumulation (i.e., the RPT model). The change in probability cumulation should not affect the estimates of the utility and probability weighting function parameters in the gain domain. The two-parameter Pr weighting function succeeded in this task, while the application of the most popular one-parameter TK function gave different sets of estimates for CPT than for RPT, revealing the interaction. Such flexibility of the weighting function is a crucial characteristic allowing us to separate the utility and probability weighting function parameters. In this regard, our conclusion is contrary to Stott's (2006) suggestion for coping with the problem by reducing the number of parameters using a simple one-parameter weighting function.

Regarding model performance, we found that the change in the direction of probability cumulation does not affect the goodness-to-fit of the model, while still influencing certain estimated parameter values.

Our results add new insights into the parameter interactions in prospect theory specifications. As a part of the study of parameter interactions, we challenge the conjecture that we should observe probability loss aversion when comparing CPT with its variant assuming a common weighting function, which is the model defined by Starmer and Sugden (1989). We did not observe the expected larger utility loss aversion parameter for the model with a reduced number of parameters, implying that probability loss aversion is unlikely.

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Supplementary materials

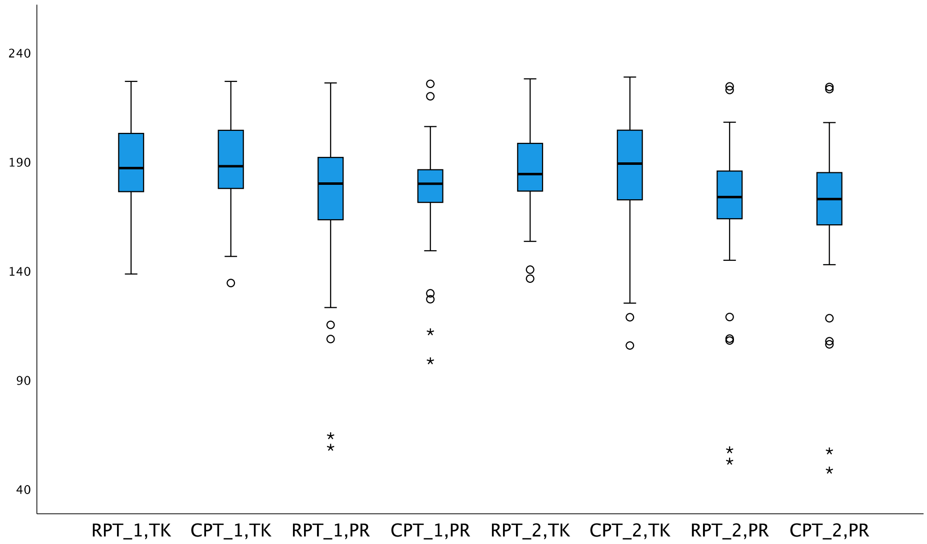

Figure 9. Akaike information criterion (AIC) distributions across specifications
Source: *own study*

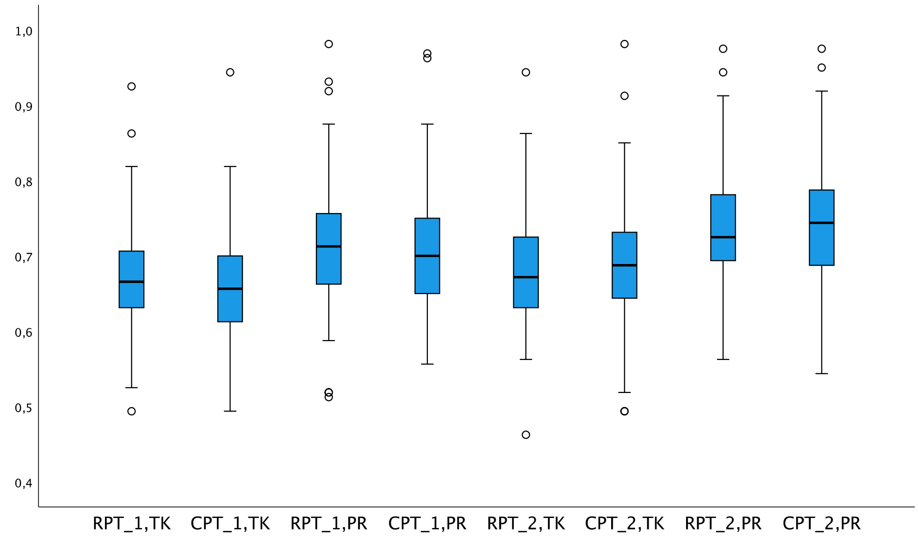

Figure 10. Accuracy distributions across specifications
Source: *own study*

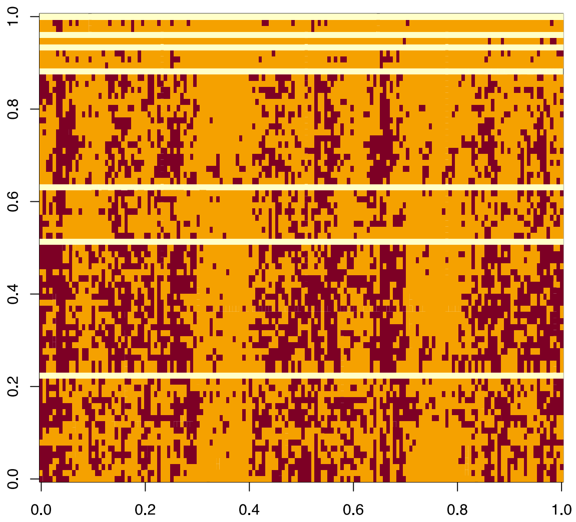

Figure 11. Data clustered with binary distance
Source: *own study*

Table 3. Median estimates for the parameters by cluster group

Cluster	1 N=17		2 N=21		3 N=8		4 N=18	
	RPT	CPT	RPT	CPT	RPT	CPT	RPT	CPT
	TK common weighting function (one-param.)							
α	0.51	0.54	0.60	0.60	0.01	0.12	0.61	0.60
λ	0.66	0.63	0.71	0.44	3.59	3.21	0.40	0.29
γ	0.76	0.77	1.21	1.04	1.02	1.02	1.21	1.25
$-lnL$	91.19	93.22	90.40	90.84	88.53	88.52	95.07	96.18
	Pr common weighting function (two-param.)							
α	0.57	0.52	0.61	0.52	0.45	0.28	0.55	0.46
λ	0.38	0.59	0.58	0.95	1.14	3.05	0.28	1.12
δ	0.70	0.67	1.21	0.86	0.67	0.81	0.77	0.76
γ	0.82	0.76	1.09	1.24	1.25	1.10	1.46	1.81
$-lnL$	86.42	83.66	88.17	86.85	80.03	86.99	87.72	86.35
	TK sign-dependent weighting functions (two-param.)							
α	0.51	0.60	0.54	0.61	0.02	0.50	0.56	0.63
λ	0.93	0.48	1.04	0.51	3.64	1.23	0.69	0.42
γ_n	0.69	0.67	1.93	1.18	1.09	2.22	1.65	1.60
γ_p	0.85	0.84	1.00	1.02	1.06	1.06	1.20	1.21
$-lnL$	90.81	93.20	87.24	90.75	88.41	86.36	94.01	95.78
	Pr sign-dependent weighting functions (four-param.)							
α	0.53	0.53	0.52	0.52	0.43	0.42	0.50	0.50
λ	0.63	0.82	1.14	1.18	1.61	1.65	0.87	1.03
δ_n	1.01	0.98	1.72	0.63	0.80	1.50	1.92	1.43
γ_n	1.33	1.22	1.41	1.50	1.28	1.13	2.22	2.36
δ_p	0.60	0.61	0.83	0.89	0.57	0.56	0.72	0.69
γ_p	0.81	0.81	0.97	1.03	1.09	1.21	1.46	1.51
$-lnL$	79.23	79.18	82.97	83.48	78.57	77.94	83.17	83.96

Source: *own study*

Table 4. The set of decision problems used in the experiment

		Lottery A						Lottery B					
No	Ses	x_1	p_1	x_2	p_2	x_3	p_3	x_1	p_1	x_2	p_2	x_3	p_3
1	1	0	0	50	0.25	100	0.75	0	0.15	50	0	100	0.85
2	1	0	0.15	50	0.25	100	0.6	0	0.3	50	0	100	0.7
3	1	0	0	50	0.5	100	0.5	0	0.3	50	0	100	0.7
4	1	0	0	50	0.5	100	0.5	0	0.15	50	0.25	100	0.6
5	1	0	0	50	1	100	0	0	0.15	50	0.75	100	0.1
6	1	0	0	50	1	100	0	0	0.6	50	0	100	0.4
7	1	0	0.15	50	0.75	100	0.1	0	0.6	50	0	100	0.4
8	1	0	0.75	50	0.25	100	0	0	0.9	50	0	100	0.1
9	1	-100	0.75	-50	0.25	0	0	-100	0.85	-50	0	0	0.15
10	1	-100	0.6	-50	0.25	0	0.15	-100	0.7	-50	0	0	0.3
11	1	-100	0.5	-50	0.5	0	0	-100	0.7	-50	0	0	0.3
12	1	-100	0.5	-50	0.5	0	0	-100	0.6	-50	0.25	0	0.15
13	1	-100	0	-50	1	0	0	-100	0.1	-50	0.75	0	0.15
14	1	-100	0	-50	1	0	0	-100	0.4	-50	0	0	0.6
15	1	-100	0.1	-50	0.75	0	0.15	-100	0.4	-50	0	0	0.6
16	1	-100	0	-50	0.25	0	0.75	-100	0.1	-50	0	0	0.9
17	1	20	0	30	0.25	40	0.75	20	0.15	30	0	40	0.85
18	1	20	0.15	30	0.25	40	0.6	20	0.3	30	0	40	0.7
19	1	20	0	30	0.5	40	0.5	20	0.3	30	0	40	0.7
20	1	20	0	30	0.5	40	0.5	20	0.15	30	0.25	40	0.6
21	1	20	0	30	1	40	0	20	0.15	30	0.75	40	0.1
22	1	20	0	30	1	40	0	20	0.6	30	0	40	0.4
23	1	20	0.15	30	0.75	40	0.1	20	0.6	30	0	40	0.4
24	1	20	0.75	30	0.25	40	0	20	0.9	30	0	40	0.1
25	1	-40	0.75	-30	0.25	-20	0	-40	0.85	-30	0	-20	0.15
26	1	-40	0.6	-30	0.25	-20	0.15	-40	0.7	-30	0	-20	0.3
27	1	-40	0.5	-30	0.5	-20	0	-40	0.7	-30	0	-20	0.3
28	1	-40	0.5	-30	0.5	-20	0	-40	0.6	-30	0.25	-20	0.15
29	1	-40	0	-30	1	-20	0	-40	0.1	-30	0.75	-20	0.15
30	1	-40	0	-30	1	-20	0	-40	0.4	-30	0	-20	0.6
31	1	-40	0.1	-30	0.75	-20	0.15	-40	0.4	-30	0	-20	0.6
32	1	-40	0	-30	0.25	-20	0.75	-40	0.1	-30	0	-20	0.9
33	1	0	0	50	0.3	100	0.7	0	0.1	50	0	100	0.9
34	1	0	0.2	50	0.6	100	0.2	0	0.4	50	0	100	0.6
35	1	0	0.1	50	0.9	100	0	0	0.4	50	0	100	0.6
36	1	0	0.1	50	0.9	100	0	0	0.2	50	0.6	100	0.2
37	1	0	0.5	50	0.3	100	0.2	0	0.6	50	0	100	0.4
38	1	0	0.4	50	0.6	100	0	0	0.6	50	0	100	0.4
39	1	0	0.4	50	0.6	100	0	0	0.5	50	0.3	100	0.2
40	1	0	0.7	50	0.3	100	0	0	0.8	50	0	100	0.2
41	1	-100	0.7	-50	0.3	0	0	-100	0.9	-50	0	0	0.1
42	1	-100	0.2	-50	0.6	0	0.2	-100	0.6	-50	0	0	0.4
43	1	-100	0	-50	0.9	0	0.1	-100	0.6	-50	0	0	0.4
44	1	-100	0	-50	0.9	0	0.1	-100	0.2	-50	0.6	0	0.2
45	1	-100	0.2	-50	0.3	0	0.5	-100	0.4	-50	0	0	0.6
46	1	-100	0	-50	0.6	0	0.4	-100	0.4	-50	0	0	0.6
47	1	-100	0	-50	0.6	0	0.4	-100	0.2	-50	0.3	0	0.5
48	1	-100	0	-50	0.3	0	0.7	-100	0.2	-50	0	0	0.8
49	1	-20	0	-10	0.2	40	0.8	-20	0.1	-10	0	40	0.9
50	1	-20	0.1	-10	0.8	40	0.1	-20	0.5	-10	0	40	0.5
51	1	-20	0	-10	1	40	0	-20	0.5	-10	0	40	0.5
52	1	-20	0	-10	1	40	0	-20	0.1	-10	0.8	40	0.1
53	1	-20	0.5	-10	0.4	40	0.1	-20	0.7	-10	0	40	0.3
54	1	-20	0.4	-10	0.6	40	0	-20	0.7	-10	0	40	0.3
55	1	-20	0.4	-10	0.6	40	0	-20	0.5	-10	0.4	40	0.1
56	1	-20	0.8	-10	0.2	40	0	-20	0.9	-10	0	40	0.1
57	1	-20	0	-10	0.4	40	0.6	-20	0.1	-10	0	40	0.9
58	1	-20	0.1	-10	0.6	40	0.3	-20	0.25	-10	0	40	0.75

		Lottery A						Lottery B					
No	Ses	x_1	p_1	x_2	p_2	x_3	p_3	x_1	p_1	x_2	p_2	x_3	p_3
59	1	-20	0	-10	1	40	0	-20	0.25	-10	0	40	0.75
60	1	-20	0	-10	1	40	0	-20	0.1	-10	0.6	40	0.3
61	1	-20	0.4	-10	0.6	40	0	-20	0.5	-10	0.2	40	0.3
62	1	-20	0.4	-10	0.6	40	0	-20	0.55	-10	0	40	0.45
63	1	-20	0.5	-10	0.2	40	0.3	-20	0.55	-10	0	40	0.45
64	1	-20	0.6	-10	0.4	40	0	-20	0.7	-10	0	40	0.3
65	1	60	0	70	0.25	80	0.75	60	0.1	70	0	80	0.9
66	1	60	0.1	70	0.75	80	0.15	60	0.4	70	0	80	0.6
67	1	60	0	70	1	80	0	60	0.4	70	0	80	0.6
68	1	60	0	70	1	80	0	60	0.1	70	0.75	80	0.15
69	1	60	0.6	70	0.25	80	0.15	60	0.7	70	0	80	0.3
70	1	60	0.5	70	0.5	80	0	60	0.7	70	0	80	0.3
71	1	60	0.5	70	0.5	80	0	60	0.6	70	0.25	80	0.15
72	1	60	0.75	70	0.25	80	0	60	0.85	70	0	80	0.15
73	1	-80	0.75	-70	0.25	-60	0	-80	0.9	-70	0	-60	0.1
74	1	-80	0.15	-70	0.75	-60	0.1	-80	0.6	-70	0	-60	0.4
75	1	-80	0	-70	1	-60	0	-80	0.6	-70	0	-60	0.4
76	1	-80	0	-70	1	-60	0	-80	0.15	-70	0.75	-60	0.1
77	1	-80	0.15	-70	0.25	-60	0.6	-80	0.3	-70	0	-60	0.7
78	1	-80	0	-70	0.5	-60	0.5	-80	0.3	-70	0	-60	0.7
79	1	-80	0	-70	0.5	-60	0.5	-80	0.15	-70	0.25	-60	0.6
80	1	-80	0	-70	0.25	-60	0.75	-80	0.15	-70	0	-60	0.85
81	2	0	0	50	0.25	100	0.75	0	0.1	50	0	100	0.9
82	2	0	0.1	50	0.75	100	0.15	0	0.4	50	0	100	0.6
83	2	0	0	50	1	100	0	0	0.4	50	0	100	0.6
84	2	0	0	50	1	100	0	0	0.1	50	0.75	100	0.15
85	2	0	0.6	50	0.25	100	0.15	0	0.7	50	0	100	0.3
86	2	0	0.5	50	0.5	100	0	0	0.7	50	0	100	0.3
87	2	0	0.5	50	0.5	100	0	0	0.6	50	0.25	100	0.15
88	2	0	0.75	50	0.25	100	0	0	0.85	50	0	100	0.15
89	2	-100	0.75	-50	0.25	0	0	-100	0.9	-50	0	0	0.1
90	2	-100	0.15	-50	0.75	0	0.1	-100	0.6	-50	0	0	0.4
91	2	-100	0	-50	1	0	0	-100	0.6	-50	0	0	0.4
92	2	-100	0	-50	1	0	0	-100	0.15	-50	0.75	0	0.1
93	2	-100	0.15	-50	0.25	0	0.6	-100	0.3	-50	0	0	0.7
94	2	-100	0	-50	0.5	0	0.5	-100	0.3	-50	0	0	0.7
95	2	-100	0	-50	0.5	0	0.5	-100	0.15	-50	0.25	0	0.6
96	2	-100	0	-50	0.25	0	0.75	-100	0.15	-50	0	0	0.85
97	2	0	0	50	0.4	100	0.6	0	0.1	50	0	100	0.9
98	2	0	0.1	50	0.6	100	0.3	0	0.25	50	0	100	0.75
99	2	0	0	50	1	100	0	0	0.25	50	0	100	0.75
100	2	0	0	50	1	100	0	0	0.1	50	0.6	100	0.3
101	2	0	0.4	50	0.6	100	0	0	0.5	50	0.2	100	0.3
102	2	0	0.4	50	0.6	100	0	0	0.55	50	0	100	0.45
103	2	0	0.5	50	0.2	100	0.3	0	0.55	50	0	100	0.45
104	2	0	0.6	50	0.4	100	0	0	0.7	50	0	100	0.3
105	2	-100	0.6	-50	0.4	0	0	-100	0.9	-50	0	0	0.1
106	2	-100	0.3	-50	0.6	0	0.1	-100	0.75	-50	0	0	0.25
107	2	-100	0	-50	1	0	0	-100	0.75	-50	0	0	0.25
108	2	-100	0	-50	1	0	0	-100	0.3	-50	0.6	0	0.1
109	2	-100	0	-50	0.6	0	0.4	-100	0.3	-50	0.2	0	0.5
110	2	-100	0	-50	0.6	0	0.4	-100	0.45	-50	0	0	0.55
111	2	-100	0.3	-50	0.2	0	0.5	-100	0.45	-50	0	0	0.55
112	2	-100	0	-50	0.4	0	0.6	-100	0.3	-50	0	0	0.7
113	2	-20	0	-10	0.25	40	0.75	-20	0.15	-10	0	40	0.85
114	2	-20	0.15	-10	0.25	40	0.6	-20	0.3	-10	0	40	0.7
115	2	-20	0	-10	0.5	40	0.5	-20	0.3	-10	0	40	0.7
116	2	-20	0	-10	0.5	40	0.5	-20	0.15	-10	0.25	40	0.6

		Lottery A						Lottery B					
No	Ses	x_1	p_1	x_2	p_2	x_3	p_3	x_1	p_1	x_2	p_2	x_3	p_3
117	2	-20	0	-10	1	40	0	-20	0.15	-10	0.75	40	0.1
118	2	-20	0	-10	1	40	0	-20	0.6	-10	0	40	0.4
119	2	-20	0.15	-10	0.75	40	0.1	-20	0.6	-10	0	40	0.4
120	2	-20	0.75	-10	0.25	40	0	-20	0.9	-10	0	40	0.1
121	2	-20	0	-10	0.3	40	0.7	-20	0.1	-10	0	40	0.9
122	2	-20	0.2	-10	0.6	40	0.2	-20	0.4	-10	0	40	0.6
123	2	-20	0.1	-10	0.9	40	0	-20	0.4	-10	0	40	0.6
124	2	-20	0.1	-10	0.9	40	0	-20	0.2	-10	0.6	40	0.2
125	2	-20	0.5	-10	0.3	40	0.2	-20	0.6	-10	0	40	0.4
126	2	-20	0.4	-10	0.6	40	0	-20	0.6	-10	0	40	0.4
127	2	-20	0.4	-10	0.6	40	0	-20	0.5	-10	0.3	40	0.2
128	2	-20	0.7	-10	0.3	40	0	-20	0.8	-10	0	40	0.2
129	2	20	0	30	0.25	40	0.75	20	0.1	30	0	40	0.9
130	2	20	0.1	30	0.75	40	0.15	20	0.4	30	0	40	0.6
131	2	20	0	30	1	40	0	20	0.4	30	0	40	0.6
132	2	20	0	30	1	40	0	20	0.1	30	0.75	40	0.15
133	2	20	0.6	30	0.25	40	0.15	20	0.7	30	0	40	0.3
134	2	20	0.5	30	0.5	40	0	20	0.7	30	0	40	0.3
135	2	20	0.5	30	0.5	40	0	20	0.6	30	0.25	40	0.15
136	2	20	0.75	30	0.25	40	0	20	0.85	30	0	40	0.15
137	2	-40	0.75	-30	0.25	-20	0	-40	0.9	-30	0	-20	0.1
138	2	-40	0.15	-30	0.75	-20	0.1	-40	0.6	-30	0	-20	0.4
139	2	-40	0	-30	1	-20	0	-40	0.6	-30	0	-20	0.4
140	2	-40	0	-30	1	-20	0	-40	0.15	-30	0.75	-20	0.1
141	2	-40	0.15	-30	0.25	-20	0.6	-40	0.3	-30	0	-20	0.7
142	2	-40	0	-30	0.5	-20	0.5	-40	0.3	-30	0	-20	0.7
143	2	-40	0	-30	0.5	-20	0.5	-40	0.15	-30	0.25	-20	0.6
144	2	-40	0	-30	0.25	-20	0.75	-40	0.15	-30	0	-20	0.85
145	2	60	0	70	0.3	80	0.7	60	0.1	70	0	80	0.9
146	2	60	0.2	70	0.6	80	0.2	60	0.4	70	0	80	0.6
147	2	60	0.1	70	0.9	80	0	60	0.4	70	0	80	0.6
148	2	60	0.1	70	0.9	80	0	60	0.2	70	0.6	80	0.2
149	2	60	0.5	70	0.3	80	0.2	60	0.6	70	0	80	0.4
150	2	60	0.4	70	0.6	80	0	60	0.6	70	0	80	0.4
151	2	60	0.4	70	0.6	80	0	60	0.5	70	0.3	80	0.2
152	2	60	0.7	70	0.3	80	0	60	0.8	70	0	80	0.2
153	2	-80	0.7	-70	0.3	-60	0	-80	0.9	-70	0	-60	0.1
154	2	-80	0.2	-70	0.6	-60	0.2	-80	0.6	-70	0	-60	0.4
155	2	-80	0	-70	0.9	-60	0.1	-80	0.6	-70	0	-60	0.4
156	2	-80	0	-70	0.9	-60	0.1	-80	0.2	-70	0.6	-60	0.2
157	2	-80	0.2	-70	0.3	-60	0.5	-80	0.4	-70	0	-60	0.6
158	2	-80	0	-70	0.6	-60	0.4	-80	0.4	-70	0	-60	0.6
159	2	-80	0	-70	0.6	-60	0.4	-80	0.2	-70	0.3	-60	0.5
160	2	-80	0	-70	0.3	-60	0.7	-80	0.2	-70	0	-60	0.8