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REFLECTION EFFECT IN STOCHASTIC SPECIFICATION (*STRONG, CPT*) OF PAIRWISE CHOICE UNDER RISK

Abstract. *The paper presents the results of two stochastic specifications of experimental data obtained in the pairwise choice experiment. In the estimated specifications the strong utility stochastic model was used. A comparative analysis of the results of stochastic specifications based on two decision theories: Rank-Dependent Expected Utility and Cumulative Prospect Theory was performed, which allowed to draw two conclusions. Specification based on CPT structure is more effective in modelling choices over lotteries that contain both gains and losses. However, the reflection effect is observed only in the results of estimation based on RDEU structure. In the estimations with CPT structure the reflection effect did not occur.*

Keywords: *choice under risk, Cumulative Prospect Theory, stochastic specification, strong utility model, pairwise choice experiment*

JEL Classification: D01, D81 ,C91

1. Introduction

Thirteen years after the publication of famous article in which Kahneman and Tversky presented their Prospect Theory, they published another paper and proposed algorithmized version of their concept. Due to construction adopted, where decisions weights are imposed on cumulative probabilities, the authors called it "Cumulative Prospect Theory" (Tversky and Kahneman, 1992). Cumulative Prospect Theory (CPT), although less popular than its original version, was subject to a number of analyses (Chateauneuf and Wakker, 1999, Wakker and Tversky, 1993). Formulating of algorithm, an undoubted advantage of the aforementioned theory, enabled researchers to use it in their studies and analyses based, among other things, on stochastic specifications (Wilcox, 2008).

The subject of this article is to examine the possibility of using stochastic specifications for the analysis of experimental data of pairwise choice under risk. Authors' main area of interest is the assessment of the usefulness of obtained results for the economic interpretation of individual behaviour. A comparative analysis of two stochastic specifications was used as a research method.

2. Algorithmizing the reflection effect

Prospect theory presented by Kahneman and Tverski in 1979 combined conventional thinking about choice theory with heuristic models. It retained the concept of utility function, yet introduced the elements of decision-making heuristics at the initial stage of assessing the alternatives. While this element of the theory ceased to be emphasized with time, its two other typical aspects have become inherent elements of choice theory. These are reference point and reflection effect. As a result of empirical research conducted by the authors, they formulated value function (money utility) well-known in the literature on the subject (Starmer, 2000). The function:
- is concave for gains and convex for losses;
- is steeper in the domain of losses (Figure 1).

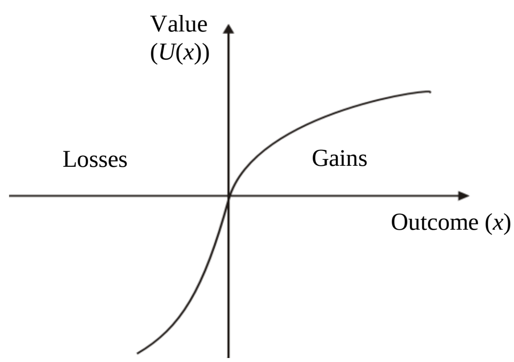

Figure 1. Valuation of results in prospect theory

Source: D. Kahneman, A. Tversky, *Prospect theory: an analysis of decisions under risk*, „Econometrica", 47/1979, p. 279.

Reverseing curve, illustrating reflection effect, was to present the results which has revealed that preferences for negative outcome (losses) are mirror reflection of preferences for positive outcome (gains) (Kahneman i Tversky, 1979). This characteristic was expressed in the form of algorithm in CPT theory.

Applying CPT model requires formulating basic notions of choice under risk. Decision problems are subject to analysis conducted as part of the aforementioned theory. At the same time, in the case of decision problem under risk, the consequence of a given decision is a random. Furthermore, it is usually assumed that the choice is made over lotteries. Lottery is a set of cash payments that can be obtained and the distribution of probability they will be obtained.

Let *X* be a set of consequences not burdened with any risk (under certainty), then $x_i \in X$ is a consequence that will arise under certain state of nature. It is assumed that *X* set is a set of monetary outcomes. Let $x_1, x_2, ..., x_n \in X$. The lottery is a pair $((x_1, x_2, ..., x_n), (p_1, p_2, ..., p_n))$, $p_j \geq 0$, $\sum_{j=1}^{n} p_j = 1$ and is expressed in the following way:

$$L = (x_1, p_1; x_2, p_2; ...; x_n, p_n), \tag{1}$$

where p_i is the probability of obtaining the payoff x_i. Vector $(x_1, x_2, ..., x_n)$ is referred to as context, whereas vector $(p_1, p_2, ..., p_n)$ is probability distribution (Wilcox, 2008).

The problem of choice consists in finding such lottery *L* in the set of all possible alternatives that will maximize the value (utility) determined by choice theory. The most basic model is von Neumann-Morgenstern expected utility model (EUT). In this case, the value of lottery *L* is determined as expected utility of monetary outputs *V*(*L*) = EU(*L*). As for the lottery of the form (1), utility is calculated by the following formula:

$$V(L) = \sum_{i=1}^{n} p_i \cdot U(x_i), \tag{2}$$

where U: $X \rightarrow \mathbb{R}$ is utility of money function that assigns numerical value to monetary outcome o (Lindgren, 1971). The shape of utility of money curve reflects (in expected utility theory) attitude towards risk faced by the individual. Utility curve for a risk-averse person is concave, utility curve for a risk lover is convex, whereas straight line characterizes neutral attitude towards risk.

Choice model adopted in CPT is the modification of Rank Dependent Expected Utility Theory (RDEU) proposed by Quiggin (1982). Compared to EUT, a novelty consists in modelling non-linear probabilities, i.e. decision weights, through cumulative probabilities. This stems from the assumption according to which the assessment of probability of a given outcome depends on position occupied by this outcome among other results (e.g. if it is the best or the worst). Quiggin concludes that if the weight of probability assigned to a given outcome depends on its position, non-linear psychological changes are made not in single, but cumulative probabilities (Sokolowska 2005).

As for the theory under discussion, outcomes x_i are analyzed in order. If x_1 is the lowest outcome, whereas x_n is the highest one, in RDEU theory decision-maker maximizes the value of function with weights:

$$\begin{aligned} w_i &= \pi(p_i + ... + p_n) - \pi(p_{i+1} + ... + p_n), \quad \text{for } i = 1,...,n-1, \\ w_i &= \pi(p_i), \quad \text{for } i = n. \end{aligned} \tag{3}$$

There is a distinction between decision weights (w) and probability weights (π). The following interpretation is suggested: probability weighting function reflects the "psychophysics of risk", i.e. the way in which individuals subjectively "distort" objective probability; decision weight determines the extent to which probability weights affects value function $V(\cdot)$. Rank Dependent Expected Utility function

$$V(L) = \sum_i w_i \cdot U(x_i) \tag{4}$$

is monotonic with respect to payoffs and satisfies the stochastic dominance.

In CPT, just as in the theory developed by Quiggin, the payments of a given random prospect are ordered from the lowest to the highest, yet indexed differently. It is assumed that the set X contains neutral value (reference point), denoted by 0, to which x_0 is assigned. Subsequently, positive values (gains) are indexed by positive indices $(x_i, i > 0)$, whereas negative ones (losses) - by negative indices $(x_i, i < 0)$. Lottery is strictly positive (strictly negative) when all the payoffs are positive (negative). The lottery that provides both positive and negative outcomes is called mixed lottery. Then $L^+ = (x_i^+, p_i)$ is a positive part of mixed lottery L, whereas $L^- = (x_i^-, p_i)$ is its negative part.

$$\begin{aligned} x_i^+ &= x_i, \text{ for } x_i > 0 \quad \text{and} \quad x_i^+ = 0, \text{ for } x_i \le 0, \\ x_i^- &= x_i, \text{ for } x_i < 0 \quad \text{and} \quad x_i^- = 0, \text{ for } x_i \ge 0. \end{aligned} \tag{5}$$

Since random prospect is ordered, negative indices are assigned in proper order to negative outcomes, whereas positive indices - to positive outcomes.

The way in which people determine the lotery value in CPT compared to RDEU theory remained unchanged. Algorithm for lottery valuation is expressed in the form of equation (4). However, weighting function w takes various forms depending on whether it refers to positive or negative outcome. It is assumed that $w_i = w_i^+$ for $i \ge 0$ and $w_i = w_i^-$ for $i < 0$. Weighting function w was derived from the theory developed by Quiggin (Tversky and Kahneman, 1992):

$$\begin{aligned} w_i^+ &= \pi^+(p_i + ... + p_n) - \pi^+(p_{i+1} + ... + p_n), \quad \text{for } 0 \le i \le n-1, \\ w_i^- &= \pi^-(p_{-m} + ... + p_i) - \pi^-(p_{-m} + ... + p_{i-1}), \text{ for } 1-m \le i \le 0, \end{aligned} \tag{6}$$

$w_n^+ = \pi^+(p_n)$ and $w_{-m}^- = \pi^-(p_{-m})$.

Positive part of function w^+ is exactly the same as in RDEU theory, whereas w^- is a formula transformed in such a way so that probabilities refer to the lowest and not to the highest payment. w_i^- is interpreted as a difference between weighted probability of achieving the outcome at least so unfavourable as x_i and weighted probability of achieving the outcome worse than x_i.

Function π is probability weighting function. In this case it may be different for positive and negative payoffs. Due to its construction and resemblance to the theory formulated by Quiggin, CPT model is referred to as "sign- and rank- dependent model". As for CPT, Tversky and Kahneman adopted probability weighting function $\pi(\cdot)$ which is inverted S-shaped function (Figure 2).

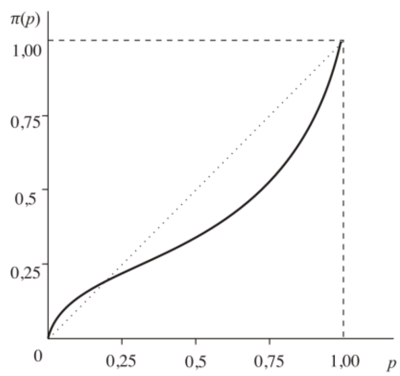

Figure. 2. Probability weighting function

Source: Handa J., Risk, Probabilities, and a New Theory of Cardinal Utility, „Journal of Political Economy” 1977, Vol. 85, pp. 113-114.

Function presented in Figure 2 illustrates regularity as to subjective perception of probability, which consists in overweighing extremely low probabilities and underestimating medium and high probabilities. The literature offers several forms of probability weighting function (Handa, 1977). Since empirical research is aimed at estimating stochastic specification (Strong, CPT), it is essential to adopt certain form of weighting function with parameters that will additionally have to be estimated in econometric model. One-parameter form of function is adopted:

$$\pi(p) = \frac{p^\alpha}{(p^\alpha + (1-p)^\alpha)^{1/\alpha}}, \tag{7}$$

where α is one of parameters estimated as part of the model.

3. Stochastic specification

The aforementioned theories are deterministic choice models that do not model the variation of decisions. Nevertheless, it is known that facing the same decision problem, people are prone to change their choice over time. Choosing between loteries A and B, a given person will choose A and another time he/she will choose B although circumstances are much the same. Therefore, stochastic specifications are better for modelling individual choices.

In stochastic models of choice, preferences are represented by properly selected deterministic choice theory that is referred to as core theory or structure (Loomes and Sugden, 1995). Structure is function *V* that assigns values to every lottery under examination (utility of lottery) so that for any pair of loteries *A* and *B*

$$V(A)\text{-}V(B) \geq 0 \iff \mathbf{P}(A, B) \geq 0{,}5, \quad (8)$$

where $\mathbf{P}(A, B)$ denotes probability that *A* will be chosen from the pair $\{A, B\}$.

The process of constructing stochastic preference theory on the basis of deterministic theory is known as stochastic specification (Loomes et al., 2002). Stochastic specification is composed of the following pair: (stochastic model, structure).

The example of stochastic specification discussed in the present paper is based on Strong Utility Model. This model has been axiomatized for the first time by Gerard Debreu in 1958 (Machina, 1985). It is often referred to as Fechner's model. It assumes that decision-makers maximize utility function that includes stochastic distorting element. As for the literature on the subject from the past eight years, this type of modelling can be found in publications by Hey and Orme (1994).

Stochastic choice model is called strong utility model when there exists the increasing function $F: \mathbb{R} \longrightarrow [0, 1]$, that satisfies the following conditions:

(i) $F(0) = 0{,}5$,

(ii) $F(\mathrm{x}) = 1 - F(-\mathrm{x})$,

and such that

$$\mathbf{P}(A, B) = F(\lambda \cdot [V(A) - V(B)]). \quad (9)$$

λ is a parameter $\lambda \in \mathbb{R}$. It is sometimes called precision parameter for a given individual. It is often assumed that $\lambda=1$. This parameter enables one to introduce minor changes to forecasts, depending on individual who makes a decision. At the same time it does not interfere significantly in the construction of model as the argument of function is the difference $V(A)\text{-}V(B)$, which is not strictly determined .In fact the value $V(A)\text{-}V(B)$ depends (for any structure) on utility scale adopted (which stems from the affinity of utility function). Therefore, since the model reflects not so much utility itself as preferences delineated by deterministic structures and due to the property (ii) of function *F*, the fact that parameter λ will take any value will not change the nature of forecast (Wilcox, 2008).

As far as models under analysis are concerned, it is assumed that choice is determined by subjective value of the lottery $V(\cdot)$, however it is a non-observable value. On the other hand, one can observe the choices that have been made. Therefore, random variable can be defined:

$$y = \begin{cases} 1, & \text{when A is choosen,} \\ 0, & \text{when B is choosen.} \end{cases}$$

Then $\mathbf{P}(A,B) = \Pr(y=1)$.

The stochastic strong utility model (9)is the function of the utility difference (V-distance). Let $A = (x_{-m}, p_{-m}{}^{A}; x_{-m+1}, p_{-m+1}{}^{A}; ...; x_0, p_0{}^{A}; x_1, p_1{}^{A}; x_2, p_2{}^{A}; ...; x_n, p_n{}^{A})$ and $B = (x_{-m}, p_{-m}{}^{B}; x_{-m+1}, p_{-m+1}{}^{B}; ...; x_0, p_0{}^{B}; x_1, p_1{}^{B}; x_2, p_2{}^{B}; ...; x_n, p_n{}^{B})$. Then, in line with CPT model (4), the argument of stochastic choice function will take the following form (9):

$$V(A) - V(B) = r_{-m} \cdot U(x_{-m}) + r_{-m+1} \cdot U(x_{-m+1}) + ... + r_0 \cdot U(x_0) + r_1 \cdot U(x_1) + ... + r_n \cdot U(x_n),$$

where $r_i = w_i{}^{A} - w_i{}^{B},\ (i = -m, -m+1, ..., 0, 1, ..., n)$.

Subsequently $w_i{}^{A}$ and $w_i{}^{B}$ are calculated on the basis of equation (6). Furthermore, it is assumed that function $\pi(p)$ takes the form presented in equation (7).

Estimated parameters of the model are the utilities of money outcomes $U(x_i)$, $i = -m, -m+1, ..., 0, 1, ..., n$ and the parameter of probability weighting function α. It is usually assumed that function F is cumulative distribution functionof the normal or logistic distribution. In the first case the probit model is developed, whereas in the latter - logit model (Gruszczyński, 2010). In the analysis under discussion, probit model was adopted. The results of probit model estimation were obtained by means of maximum likelihood method for each and every subject.

4. Empirical research

For the purpose of stochastic specification (Strong, CPT), data derived from experimental research was used. The research was conducted at the University of Gdansk in 2008 with the participation of students (Babula, 2010). It referred to multiple choices from lottery pairs and was aimed at analyzing the changeability of choices with reference to selected lotteries[1]. Twenty-nine people participated in the experiment. Results obtained during 7 stages were used in order to estimate stochastic specification. Each phase was completed after a three-day interval. Each person provided 195 answers, which altogether totalled 5655 answers to questions presented.

[1] Due to the specificity of experiment (referring to abstract objects such as lotteries) its results will not become outdated. In the literature, the results of experiments and analyses conducted by other researchers have already been used for analyzing the models. For instance, in order to compare various stochastic specifications Wilcox (2008) used data derived from the experiment carried out by Hey and Orme (1994).

Web application was used for presenting decision problems and registering the answers provided by the students.

Financial elements of motivational incentives were used in the experiment. As a result, all the students participating in the experiment have completed it. Answers that should be eliminated as chance decisions and taken without due attention was not observed while analyzing the results of the experiment.

As for the experiment, the control of significant factors consisted in proper selection of decision pairs (pairs of lotteries) which were presented to the students. Thirty-five decision problems were used in the experiment. Students were presented with them in random order during particular stages. HILO structure was used for describing decision problems (Camerer, 1995). This structure is a simple set of choices construed on the basis of three payments: the highest (located in upper vertex of probability simplex), average (located in bottom left vertex) and the lowest one – bottom right vertex. On each simplex (Fig. 3) seven points were marked to represent lotteries that are matched in pairs illustrating decision problems. The problems are marked with numbers, from 1 to 35, five problems are presented on each probability triangle.

As for the experiment, choices were made about decision problems in three contexts (0, 100, 200), (0, -100, -200) and (0, 200, 400). Probability distribution in the aforementioned contexts may be reduced to distribution in one general context

$$(-200, -100, 0, 100, 200, 400)$$

through assigning zero probabilities to respective payoffs.

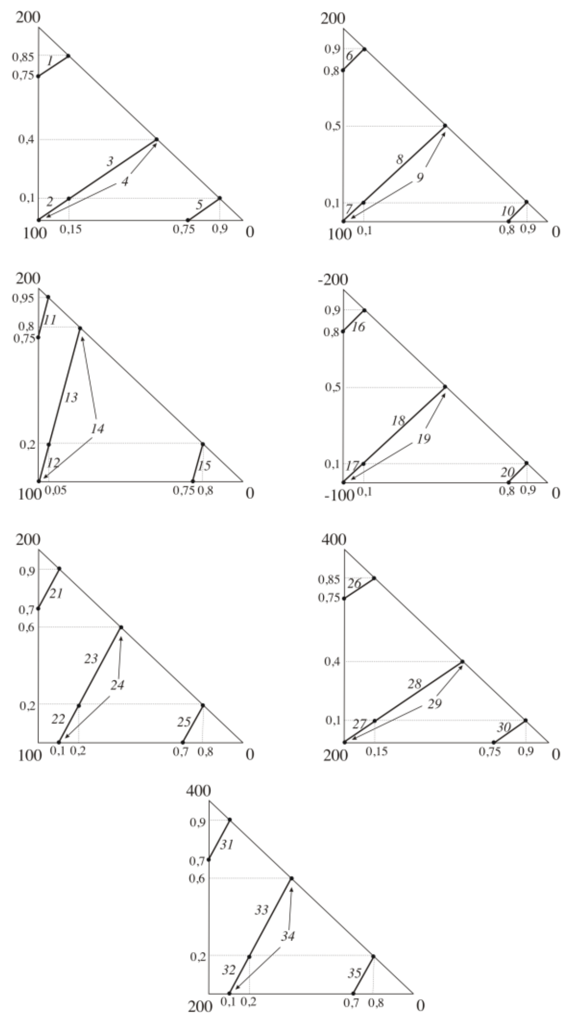

Figure. 3. Choices numbered 1 to 35 that students participating in the experiment were presented with

Source: own elaboration.

Model parameters were estimated for the general context. In order to collect data essential for estimation, decision weights w were calculated for each lottery (each probability distribution), and so was the difference between these weights, for different values of parameters α. Furthermore, for the purpose of model estimation it is assumed that the utility of zero outcome is zero $U(0)=0$. The model takes the following form:

$$\mathrm{P}(A,B)=F(r_{-2}\cdot U(-200)+r_{-1}\cdot U(-100)+r_1\cdot U(100)+r_2\cdot U(200)+r_3\cdot U(400)).$$

Hence, parameters $U(-100)$, $U(-200)$, $U(100)$, $U(200)$ and $U(400)$ are estimated in probit model without absolute term.

5. Results of estimation

Thanks to stochastic specifications, twenty-nine models were estimated. Estimation was completed during two stages. At first, models constructed for each person participating in the experiment were subject to estimation - respectively for different levels of α and paying attention to the fact that the parameter may take different values for positive part of the lottery (α^+) and its negative part (α^-). It should be highlighted that the value of parameter α (due to the fact that the graph of function $\pi(p)$ is in line with its economic interpretation) fell within the interval [0.3, 0.9][2]. Subsequently, model with the highest log-likelihood was selected and with significant parameters at the 5 percent level.

For the sake of comparing how modelling of reflection effect (with the use of probability weighting function) affects the results of estimation in the analysis under discussion, stochastic specification (*Strong, RDEU*) was estimated as well. The process of estimation was analogical, however formula (3) was used for determining decision weights.

The models were estimated individually – independently for each individual. The results for person with code number 1 will be discussed in detail (Figure 4).

Goodness of fit							
Stochastic specification	Log Likelihood				Count R-squared		
(*Strong, CPT*)	-106.3				74.9%		
(*Strong, RDEU*)	-107.4				68.2%		
Coefficients							
Stochastic specification	$\propto^-$	$\propto^+$	U(-200)	U(-100)	U(100)	U(200)	U(400)
(*Strong, CPT*)	0.7	0.8	-31.0	-14.1	4.6	7.1	9.7
(*Strong, RDEU*)	-	0.9	-119.2	-59.8	4.6	6.9	9.1

Figure. 4. Results of the estimation of stochastic specifications for chosen individual

Source: own elaboration.

[2] As for the results under analysis, parameter α changed by 0.1. It was tested and concluded that smaller leaps in the parameter would not change the results significantly. With α lower than 0.3 the function is not monotonic within the interval [0, 1], whereas for α=1 weighting function does not change probabilities ($\pi(p)=p$).

The affinity of model was measured with the use of the following two indices: log-likelihood (LL) and count R-squared, that is the proportion of correctly classified. In both cases using CPT structure for stochastic specification provides better adjustment of the model (compared to RDEU structure). Count R-squared amounting to 74.9% indicates that the model is adjusted to some extent – the model forecasts correctly about 75% of choices made by individual no. 1 out of all the choices made by this individual during the examination.

In the case of stochastic specification based on RDEU structure, maximum likelihood was achieved for parameter α=0.9. As for stochastic specification based on CPT structure, maximum likelihood was achieved for two different parameters α – for positive outcomes amounting to 0.8 and slightly lower for negative outcomes (losses), amounting to 0.7. Therefore, according to the last mentioned specification, individual under examination is more subjective in perceiving probability than in the case of the first mentioned specification (*Strong, RDEU*). The subjectivism is slightly greater when choices refer to losses, however its direction is not subject to change – low probabilities are overestimated, whereas high are understated, regardless of the fact if they refer to gains or losses.

Estimated parameters are interpreted as the utility of monetary outcomes. In accordance with the significance test for single parameter (based on statistics **z**) null hypothesis on the insignificance of parameters was rejected for each parameter with significance level amounting to 0.05.

The result is in line with the theory– the higher the outcome, the greater the utility. At the same time, coefficients for positive outcomes are similar in both specifications, unlike the utility values of negative ones. It is not surprising as both structures are identical when they refer only to gains.

On the basis of the results of both stochastic specifications, curves can be delineated to represent utility (Figure 5). In the light of prospect theory, the expected graph of the utility function is presented in Figure 1. In fact, such a curve was obtained from the stochastic specification (*Strong, RDEU*) which did not model reflection effect. Utility curve delineated thanks to the estimation based on the RDEU structure is concave for gains and convex for losses[3]. On the contrary, utility curve delineated with the use of specification (*Strong, CPT*) estimation is concave both for gains and losses.

[3] Due to limited number of choices made about losses, utility of negative payments is very sensitive to the choice of the value of parameter α. Through changing this value only slightly in specification (*Strong, RDEU*), utility close to the ones in specification (*Strong, CPT*) can be achieved. However, function changes from convex to concave in the origin of coordinates in the former case and remains unchanged in the latter case.

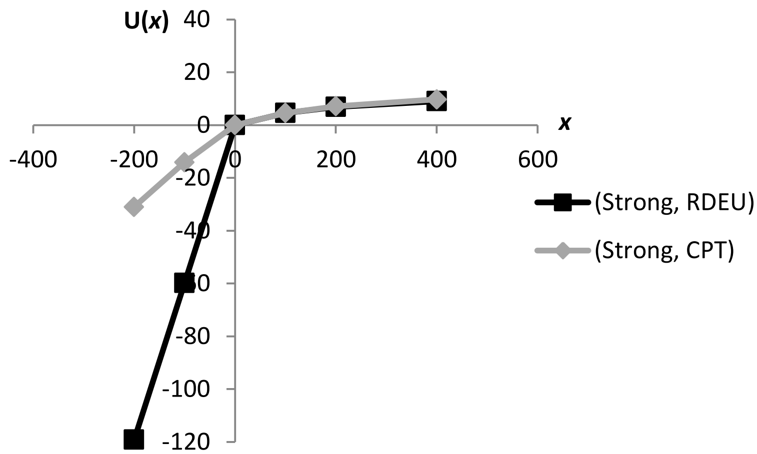

Figure. 5. Utility curve for chosen individual based on parameters of stochastic specification estimation

Source: own elaboration.

Therefore, the expected reflection effect, which in the light of prospect theory is related to the way the individual assess the monetary outcomes, can be obtained when this effect is not embeded in the construction of probability weighting function. In order to verify if such a phenomenon is systematic, the results for the remaining twenty-eight individuals were subject to analysis in this respect. Figures 6 and 7 present the results of analysis performed with reference to estimated models.

Number of individuals for whom stochastic specification (Strong, CPT) produced the following result					
	model was not estimated correctly	parameters for positive outcomes were not monotonic	parameters significant at the 0.1 level	model was estimated correctly	Total
Altogether	**5**	**2**	**6**	**16**	29
Including:	Comparison with specification results (Strong, RDEU)				
Number of models estimated correctly by (Strong, RDEU)	0	0	0	13	13
Number of models for which LL in (Strong, CPT) was higher than LL in (Strong, RDEU)	2	2	5	13	22

Figure. 6. Comparative analysis of results of stochastic specifications (Strong, CPT) and (Strong, RDEU) for 29 individuals participating in the experiment

Source: own elaboration.

With reference to stochastic specification (*Strong, CPT*), two out of all the estimated models should be rejected since parameters (interpreted as the utility of monetary outcomes) are not monotonic (Fig. 6). Furthermore, in the case of five models there is no grounds for rejecting hypothesis on the insignificance of parameters. Models were estimated correctly for twenty-two individuals participating in the experiment. At the same time, parameters for six of them were significant at 0.1 level.

Specification (*Strong, CPT*) provides much better results compared to estimation based on specification (*Strong, RDEU*) in the case of which models were estimated correctly only for thirteen students. This number would be subject to considerable increase if estimation referred to lottery in which only positive outcomes occurred. In accordance with expectations, using CPT for the lottery which outcomes include both gains and losses is more effective than using RDEU.

As for specification based on CPT structure, the adjustment of models was more effective when measured with the Log Likelihood value. Comparing the results for all the models subject to estimation, it can be stated that only in 7 out of 29 pairs of models this adjustment did not improve as a result of change from RDEU to CPT structure.

Number of models in which estimated parameters indicate:	Stochastic specification	
	(*Strong, CPT*) N = 22	(*Strong, RDEU*) N = 13
reflection effect in line with prospect theory	1	10
risk aversion towards losses	21	1
change in attitude towards risk along with output increase in the case of gains	4	2

Figure. 7. Reflection effect in parameters determined due to the estimation of stochastic specifications (Strong, CPT) and (Strong, RDEU)

Source: own elaboration.

Apart from undoubted advantages, i.e. greater number of estimated models and their better adjustment, the results are surprising since reflection effect is not present in estimated parameters interpreted as the money utilities. As for twenty-two models estimated correctly with the use of specification (*Strong, CPT*), such a property was observed only in one case (Fig. 7). In the remaining twenty-one models parameters indicated risk aversion with reference to losses. Contrary results were obtained for specification (*Strong, RDEU*) in the case of which ten out of thirteen estimated models were in line with prospect theory, whereas another two indicated (apart from risk propensity with reference to losses) change in approach to risk in the case of gains, namely from aversion to propensity towarts risk along with outcome increase. Risk aversion in the case of losses was the case only with one model.

6. Conclusion

The results of stochastic specification estimation are in line with choice theory under risk and may be subject to meaningful interpretation. Specification based on CPT structure is more effective in modelling choices over lotteries that involve both gains and losses. Furthermore, such a specification enables better goodness to fit than specification based on RDEU structure. Nevertheless, reflection effect in money utilities is not observed in the results of estimation based on CPT structure.

The construction of deterministic choice models under analysis is two-stage. According to economic interpretation of these algorithms, in the act of assessment of the lottery two independent processes of subjectivization take place. The first one refers to subjective perception of money outcomes (utility function), whereas the second one takes account of subjective perception of probability (probability weighting function). The main assumption of prospect theory, i.e. reflection effect, is ascribed to the estimation of money outcomes. However, in the algorithm of cumulative prospect theory, reflection effect is modelled also through the construction of weighting function and thus, according to the authors, gives rise to the unexpected results of estimation.

In the light of the results, it is reasonable to conduct further research aimed at determining precisely which factors underlay the results of the experiment. Addressing such issues in theoretical analysis of CPT model and repeating the experiment (yet for wider range of the lotteries) could have thrown light on this phenomenon. At this stage of analysis it can only be assumed that complex form of probability weighting function in CPT structure eliminates reflection effect as far as value estimation is concerned.

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