JENA ECONOMIC RESEARCH PAPERS

2009 – 088

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www.jenecon.de

ISSN 1864-7057

The JENA ECONOMIC RESEARCH PAPERS is a joint publication of the Friedrich Schiller University and the Max Planck Institute of Economics, Jena, Germany. For editorial correspondence please contact markus.pasche@uni-jena.de.

Impressum:

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D-07743 Jena
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Understanding the Two Components of Risk Attitudes: An Experimental Analysis

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November 1, 2009

Abstract

Economics and management science share the tradition of ordering risk aversion by fitting the best expected utility (EU) model with a certain utility function to individual data, and then using the utility curvature for each individual as the sole index of risk attitude. (Cumulative) Prospect theory (CPT) has demonstrated various empirical deficiencies of EU and introduced the weighting of probabilities as an additional component to capture risk attitude. However, if utility curvature and probability weighting were strongly correlated, the utility curvature in EU alone, while not properly describing risky behavior in general, would still capture most of the variance regarding degrees of risk aversion. This study shows, however, that such a strong correlation does not exist. Though, most individuals exhibit concave utility and convex probability weighting, the two components show no correlation. Thus neglecting one component entails a loss.

Keywords: risk attitudes, cumulative prospect theory, experimental study
JEL classification: C91, D81

*We thank Peter Wakker for detailed and valuable comments. This paper was presented at the APESA meeting 2009 in Haifa, at the SMYE 2009 in Istanbul, and in an earlier version at the Cognitive Lunch Series in at the University of Indiana, Bloomington. Comments and suggestions of participants are gratefully acknowledged.

1 Introduction

In expected utility (hereafter EU) theory, attitudes towards risk originate from changes in marginal utility (i.e. the curvature of utility function). Consequently in economics and management science it has been a common tradition to capture risk attitudes captured by fitting the best EU model with certain utility function to individual data, and then using the utility curvature for each individual as the sole index of risk attitude. Kahneman and Tversky (1979) have demonstrated various empirical deficiencies of that view. In (cumulative) prospect theory (hereafter *CPT*) they call for the consideration of an additional component to assess risk attitude: the weighting of probabilities. In line with these findings, Wakker (1994) argues that the utility function describes an intrinsic appreciation of money, prior to probability or risk, and that understanding risk attitude as originating from the perception of probabilities would be more natural.

In this study we explore the relation of these two components of risk. Can an individual be risk seeking in one and risk averse in the other dimension? Are those two components truly independent and thus necessary for the assessment of risk attitude? Because, advancements such as CPT would be less practically relevant if the two components of risk attitudes, utility curvature and probability weighting, were significantly positively correlated. While not properly describing risk behavior in general, the utility curvature would still capture most of the variance regarding degrees of risk aversion. In this study we focus on the gain domain, hence the other components of CPT play no role. Our data from a controlled laboratory experiment shows that, while most individuals in our study exhibit concave utility and convex probability weighting, there is no correlation between these two components. This provides further evidence that measuring risk attitude through the curvature of utility is not sufficient for describing decision making under risk, and that neglecting any one entails a loss.

A prerequisite for such an investigation is a careful measurement of the two components. Two elicitation methods are common: the parametric and the trade-off Wakker and Deneffe (1996, hereafter TO) method. In this paper we employ the latter method. The parametric method, while it provides useful insights about the shape of both functions, has a serious drawback: the joint fitting of utility and probability weighting, making the parameter estimates of these functions interdependent. The TO method is so far the only method that allows for a separate measurement of utility and probability weighting. It has been used by Abdellaoui (2000), van de Kuilen et al. (2009), Abdellaoui et al. (2005), and Kobberling and Wakker (2005). Since our aim is to look at the interplay of the two components, it is crucial to tear utility apart from probability weighting. This makes the TO method especially desirable. In the present paper we mostly rely on the version introduced by Abdellaoui (2000). The detailed procedure is outlined in the following sections.

The paper is organized as follows. Section **2** sketches the TO method and experimental procedure, Section **3** reports the results, and Section **4** concludes.

2 The TO Method and Experimental Setup

We only consider CPT for gains and binary lotteries. Let $(p : x_{i+1}, 1-p : x_i)$ denote a prospect yielding x_{i+1} with prob p and x_i otherwise. When $x_i < x_{i+1}$ this prospect is evaluated as $w(p)u(x_{i+1}) + [1 - w(p)]u(x_i)$ by CPT, where the utility function $u(\cdot)$ is assumed to be strictly increasing over the outcome space $X = [0, \infty)$, and the probability weighting function $w(\cdot)$ is increasing over probability space $P = [0, 1]$, with $w(0) = 0$ and $w(1) = 1$.

The TO method elicits utility and probability weighting separately in two consecutive steps. In the first step (TO), a standard sequence of outcomes $x_1, \ldots, x_n$, i.e., equally spaced outcomes in terms of utility, is constructed, and in the second step (PW) this sequence of outcomes is used to construct a sequence of probabilities. More specifically, in TO a x_{i+1} is determined to make the subject indifferent between $A : (p, x_{i+1}; 1-p, r)$ and $B : (p, x_i; 1-p, R)$, where p, r, and R are exogenous parameters. With x_{i+1} at hand, similarly a x_{i+2} is then determined to make the subject indifferent between $A : (p, x_{i+2}; 1-p, r)$ and $B : (p, x_{i+1}; 1-p, R)$. According to CPT the two indifference relations imply:

$$
\begin{aligned}
&[1-w(p)]u(R)+w(p)u(x_i)=[1-w(p)]u(r)+w(p)u(x_{i+1}),\\
&[1-w(p)]u(R)+w(p)u(x_{i+1})=[1-w(p)]u(r)+w(p)u(x_{i+2}),\\
\Rightarrow\quad &u(x_{i+2})-u(x_{i+1})=u(x_{i+1})-u(x_i) \qquad (1)
\end{aligned}
$$

Combining the upper two equations leads to equation (1), which states that the outcomes (x_i, x_{i+1}, x_{i+2}) are equally distributed on the utility axis. Starting with certain x_0, and constructing recursively n times, we obtain a standard sequence of $x_0, x_1, \dots, x_n$.

In PW, the obtained standard sequence of outcomes $x_0, x_1, \dots, x_n$ is used to determine a standard sequence of probability weights. For each $x_i, i = 1, \cdots, n-1$, a p_i is varied to make the subject indifferent between a lottery $A : (p_i, x_0; 1-p_i, x_n)$ and a certain outcome $B : (x_i)$. By CPT the indifference implies:

$$
w(p_i)u(x_n)+(1-w(p_i))u(x_0)=w(1)u(x_i) \qquad (2)
$$

$$
\Rightarrow w(p_i)=\frac{u(x_i)-u(x_0)}{u(x_n)-u(x_0)}, \quad \forall i=1,\dots,n-1. \qquad (3)
$$

By (1), we know that $u(x_{i+1}) - u(x_i)$ is constant. Hence, the above equation can be simplified into $w(p_i) = i/n$, for $i = 1, \dots, n-1$. The elicited values of $p_1, p_2, \dots, p_n$, along with the fact that $w(p_i) = i/n$, allow us to estimate the shape $w(p)$.

The experiment was conducted in June 2008 with 124 Jena university undergraduate students. In total we ran 4 sessions. Each session lasted about 50 minutes. In the experiment the parameters were fixed as follows: $p = 0.5$, $r = 0$, $R = 10$, and $x_0 = 20$. We elicited 6 points for utility, and 5 points for probabilities. The difference is obtained by modified bisection method[1]. We used 8 iterations to obtain the indifference for each x_i, and about 7 iterations to obtain each p_i. A consistency check was carried out for each x_i by repeating the 7^{th} choice. For probabilities we checked for consistency by eliciting a p_6 such that $(x_3) \sim (x_4, p_6; x_2, 1-p_6)$, which should equal to p_3 according to CPT. This makes 54 rounds for the TO part and about 42 rounds for the PW part. Out of each part one round was individually selected at random, the preferred lottery was played, and resulting amounts paid to the participant. The average earning was 16 Euros. [2]

[1] A more detailed description of the TO and the bisection method can be found in the Appendix 1.

[2] We used ztree (Fischbacher, 2007) for experimental software and ORSEE (Greiner, 2004) to manage

3 Results

We report the results in two steps. Starting with general results for utility and probability weighting, we proceed with the classification of them in terms of their curvature, and finally turn to our main result: the relation between the curvature of utility and probability weighting.

3.1 Classification of utility functions

Consistency was checked for each participant by repeating the 7^th choice pair of each x_i. Preference reversal occurred in 30% of the cases. This number may seem large. However, the remaining interval for the inference of x_i at the 7^th choice is already quite small. This value is also comparable to the findings in Starmer and Sugden (1989) (26.5%) and Camerer (1989) (31.6%), which suggests that the elicited x_i are rather reliable.[3]

We classified the participants' utility function using $u(x) = x^{\alpha}$, which is often used in the literature. It may seem surprising that though we favor the non-parametric TO method over parametric fitting, we still fit a power utility function. Our purpose is not to obtain a precise α for each individual, rather we are only interested in a ranking among subjects, and the estimated αs provide enough information to this end. The sequence of values, $x_0, x_1, ..., x_6$ enables us to estimate α for each subject. An $\alpha < 1$ implies a concave, an $\alpha \approx 1$ implies a linear, and an $\alpha > 1$ implies a convex utility function. For a linear utility we set a tolerance level of $0.9 < \alpha < 1.1$. According to this classification 68 subjects have concave ($\alpha < 0.9$), 27 subjects have linear ($0.9 < \alpha < 1.1$), and 29 subjects have convex ($\alpha > 1.1$) utility functions. We found results to be robust to variations in this tolerance level.

participants' invitation. An English translation of the original instructions is attached in the Appendix 2.

[3]Note that for x_1, when the interval is rather small, preference reversal occurs in 39% of the cases, while it lowers to 23% for x_6. This further emphasizes that preference reversal was a result of the rather small choice interval.

	Utility			Probability weighting				
	α	Non-parametric	Both		γ	Non-parametric		Both
concave	68	67	55	convex	91	convex	81	79
convex	29	9	5	concave	23	concave	4	4
linear	27	25	6	linear	5	S	15	–
						Inverse S	19	–

Table 1: Classification of utility and probability weighting, first according to parametric fitting, second to the non-parametric method, and finally to both criteria.

Since a wrong choice of parametric specification may bias results, we also used the non-parametric difference method to check for the robustness of the above classification. Similar to Abdellaoui (2000), we calculated the first order difference $\Delta'_i = |x_i - x_{i-1}|$ for $i = 0, ..., 6$ and the second order difference $\Delta''_j = \Delta'_{j+1} - \Delta'_j$ for $j = 1, ..., 5$. With these criteria, we classified

- 67 subjects as concave, with $\Delta''_j > 2$ for 3 or more out of 5 times,
- 25 as linear, with $\Delta''_j < -2$ for 3 or more out of 5 times, and
- 9 subjects as convex, with $-2 \leq \Delta''_j \leq 2$ for 3 or more out of 5 times.

The remaining 23 subjects could not be classified with this method. As shown in table (1), majority are consistent with both classification methods, especially subjects with concave utility functions[4]. Hence, α reasonably captures the shape of the utility function.

3.2 Classification of probability weighting functions

Here, too, we checked for consistency by comparing $(x_6, p_3; x_0) \sim (x_3)$ and $(x_4, p'_3; x_2) \sim (x_3)$. The two probabilities should be equal ($p_3 = p'_3$) according to CPT. Indeed, the

[4]The seemingly inconsistent result between α and the difference method in the linear category is mostly because estimating an α uses all 7 points, whereas the difference method often ignores some points entirely. Subject 65 is an typical example. His elicited payoff points are $(20, 37, 47, 57, 67, 77, 87)$, which is linear according to the difference method, but $\alpha = 1.4579$.

median values of p_3 and of p'_3 are equal to 0.5, and they are not significantly different (paired Wilcoxon signed rank test $p > 0.10$.[5]).

A universal classification of probability weighting requires careful consideration. Previous experiments find mostly inverse S, but S, linear, convex, and concave shaped probability weighting functions as well. For proper classification, we first checked each subject's array of p_i for patterns. Note that the pattern of probability weighting is best discovered when p is close to 0 or 1, where probability weighting is suspected to be most severe, while the middle range, i.e., when p is close to 0.5, patterns are less obvious. Thus a crude but simple way to detect patterns is to compare w_1 with p_1 and w_5 with p_5). A convex probability weighting implies $w_1 < p_1$ and $w_5 < p_5$, while a concave probability weighting implies $w_1 > p_1$ and $w_5 > p_5$, an inverse S-shaped probability weighting implies $w_1 > p_1$ and $w_5 < p_5$, and finally an S-shaped probability weighting implies $w_1 < p_1$ and $w_5 > p_5$. Based on these criteria, we classified 81 subjects as convex, 4 subjects as concave, 19 subjects as inverse S-shaped, and 15 subjects as S-shaped.

Having learned the general pattern of probability weighting, we then fitted the data parametrically to obtain a curvature index for each individual. Recognizing that parametric fittings are sensitive to functional form, we assume two families of functions for probability weighting: $w(p) = p^\gamma$ and $w(p) = \frac{p^\nu}{[p^\nu+(1-p)^\nu]^{\frac{1}{\nu}}}$

[5] The mean difference $p_3 - p'_3 = -0.015$, and the mean and median absolute difference is respectively 0.16 and 0.11

[6] To avoid convergence to local minimal when estimating $w(p) = \frac{p^\nu}{[p^\nu+(1-p)^\nu]^{\frac{1}{\nu}}}$, we used a wide range of starting points, from 0.2 to 4 at an increment of 0.2.

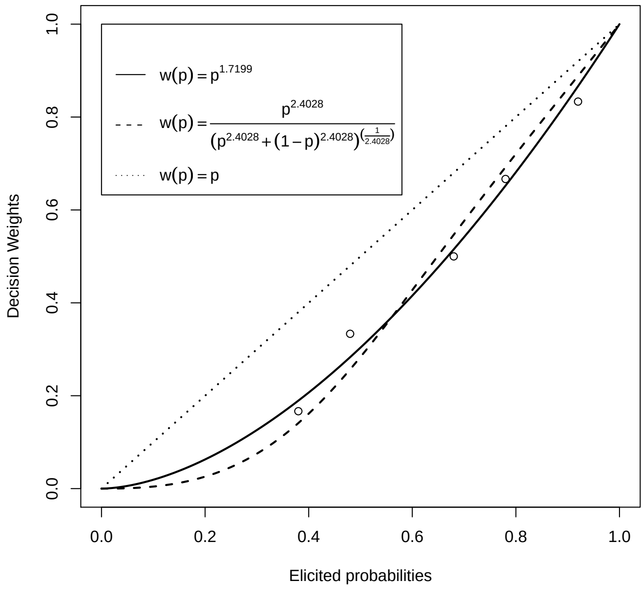

Figure 1: Parametric fittings of median data.

later discussion we shall mainly rely on γ, and use ν as a robustness check.

This finding is surprising given that majority of previous literature found inverse S probability weighting. In particular, since we used almost the same method as in Abdellaoui (2000), who also found inverse S to be prevailing. Our result is not unique though. Also van de Kuilen (2008) and van de Kuilen et al. (2009) find results similar to ours. The major difference between our study and Abdellaoui (2000) is that he used a much larger stake size.[7] This may suggest that the relation between stake size and probability weighting might not be as innocent as we thought. Possibly probabilities are more distorted when the stake size exceeds certain level. Answering this question is however beyond the scope of the current study.

One might object that we use parametric fitting although we advocate a non-parametric method. Again we are not interested in the value of γ or ν per se. The only reason for

[7] Abdellaoui (2000) used the outcomes between U.S. $200 and U.S. $4,000, while we used outcomes between 1 Euro and about 5 Euro.

	concave α	linear α	convex α	sum
pessimistic γ	52	18	21	91
neutral γ	1	2	2	5
optimistic γ	14	4	5	23
sum	67	24	28	119

Table 2: The two components of risk attitudes

the fitting is to obtain a clear ranking of *the curvature of probability weighting functions*, which so far only the TO method allows since it avoids the joint fitting of utility and probability. In order to highlight the different components of risk attitudes, we classified the probability weighting of subjects[8] as below. The classification result was robust for variations in the tolerance level for γ. As we can see from Table 1, most subjects are consistent with both γ and the non-parametric method.

- concave/optimistic: 23 subjects are optimistic if their probability weighting function is concave ($\gamma < 1$),
- linear/neutral: 5 subjects are linear if their probability weighting function is linear ($\gamma \approx 1$ or more precisely $0.95 < \gamma < 1.05$), and
- convex/pessimistic: 91 subjects are pessimistic if their probability weighting function is convex ($\gamma > 1$).

3.3 Central results

Now we turn to our main hypothesis: the relation between the shape of utility function and probability weighting function. The results are reported in Table (2) and Figure 2.

The largest group in Table (2) are the subjects with concave utility functions and pessimism in the probability weighting (52 subjects). This finding is amiable to economists since most theoretical models rely on the assumption that agents are risk averse. Our result suggests that the majority of the population may indeed have concave utility and

[8]When classifying all subjects using ν we find similar picture: 102 subjects with a $\nu > 1.15$, 4 subjects with a $0.95 \leq \nu \leq 1.15$, and 18 subjects with a $\nu < 0.95$.

convex probability weighting functions. There are further interesting patterns in the data. The third cell in the first row denotes the convex/pessimistic subjects. They are the second largest group in our classification (21 subjects). Mirroring this is the first cell in the third row. This cell denotes the concave/optimistic subjects. Here we have 14 subjects. These subjects have concave (respectively convex) utility functions and probability weighting functions. This is interesting since although both utility functions and probability weighting functions captures information about risk attitudes, they seem to have different foundations.

Having obtained the ordinal information regarding the curvature of utility and probability weighting, one natural question to ask is: are subjects who is more concave in utility also more convex in probability weighting? To test this hypothesis, we ran a Spearman's ρ rank correlation test between α and γ for all subjects. The correlation is insignificant (Spearman's $\rho = -0.04037$, $p = 0.6562$). We also ran the same correlation test between α and ν, and similar results showed up (Spearman's $\rho = -0.0065$, $p = 0.9428$). This finding suggests that these two components of risk are different and it is, therefore, necessary to consider both. The subjects whose utility function is concave and probability weighting function is convex are most often assumed in economic theories. As shown above, these subjects represent the largest proportion and are most robust to different classification methods, therefore we ran the same correlation test only for these subjects. The results are the similar (Spearman's $\rho = -0.1951$, $p > 0.1746$ for γ, and Spearman's $\rho = -0.0434$, $p > 0.7645$ for ν).

A more general illustration of our main result is shown in Figure 2. Here the relation between alpha and gamma is plotted for each individual participant. The x-axis depicts alpha and the y-axis the gamma. The rectangles correspond to the labeling in Table 2, with the upper left rectangle depicting the concave & pessimistic, the upper mid square the neutral pessimistic subjects, etc. In order to produce a more condensed picture the graph is limited to subjects with $\alpha < 1.5$ and $\gamma < 2$. Though most observations are in the upper left square of the graph, it can be seen that dots are randomly distributed with no apparent pattern or piling.

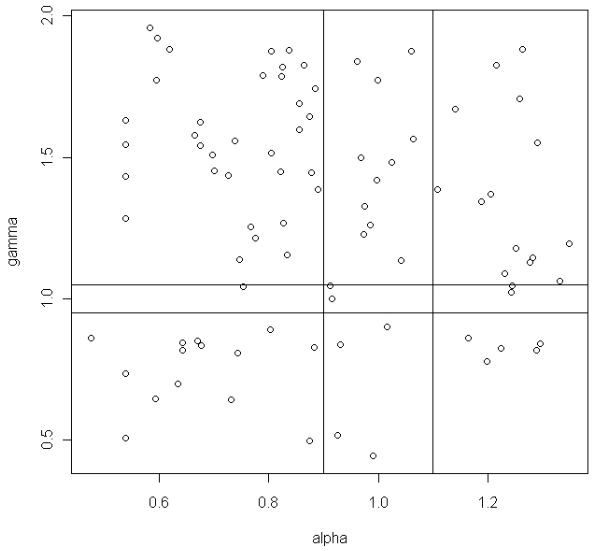

Figure 2: Distribution of alpha and gamma, for $\alpha < 1.5$ and $\gamma < 2$

4 Conclusion

It is now probably less controversial to argue that risk attitudes have two components. Yet, to the best of our knowledge no study so far looked at the relation between these two components of risk. This question is important because CPT would have been less relevant practically if the curvature of utility and probability weighting is positively significantly correlated. Then it might not be that problematic to use the curvature of utility function as the single proxy for risk attitudes.

However, our results suggest that the two components of risk attitudes capture different characteristics of individuals' risk attitudes. Although most individuals have concave utility functions and convex probability weighting functions, the two components show no significant correlation. Hence, an accurate account of risk attitude requires the measurement of both. Predictions only based on the curvature of utility functions can be quite far from real behavior, as demonstrated by the findings in numerous literature.

5 Appendix 1: the (modified) bisection choice procedure

The detailed algorithm of the (modified) bisection choice procedure is as follows:

1. Given x_i, we set a range for x_{i+1}'s indifference value. This range should be large enough to include potential indifference values for x_i, and it should be small enough to allow for a good inference of the indifference point. We used the following equation to determine this potential range was determined by the following equations:

$$\underline{x} = max\{0, (x_i + R) * 0.5 - r\} \tag{4}$$

$$\bar{x} = (x_i + R) * 1.5 - r. \tag{5}$$

   The determination of this range reflects the combined consideration of flexibility and efficiency. Let $x_m = \frac{\underline{x}+\bar{x}}{2}$ denote the middle point of the interval $[\underline{x}, \bar{x}]$. Subjects were first presented a pair of lotteries: $A = (x_i, 0.5; 10, 0.5)$ and $B = (x_{i+1}, 0.5; 0, 0.5)$, with $x_{i+1} = x_m$. To ease calculations only integers were allowed. When x_i is not a even integer, the closest even integer larger than x_i is taken.

2. If A is preferred, we know that x_{i+1} must be increased in order to achieve indifference. We thus let $x_{i+1} = \frac{x_m+\bar{x}}{2}$. Likewise, if B is preferred, x_{i+1} must be decreased. We then let $x_{i+1} = \frac{x_m+\underline{x}}{2}$.

3. Repeating this procedure 4 more times, the interval containing the indifference point will become rather small. Finally, we choose the middle point of the final interval to be x_{i+1}.

A drawback of the bisection procedure is that it is not entirely incentive compatible. If subjects are aware of the entire experimental procedure from the start, they may have an incentive to strategically misreport their choices. To see this, note that pretending to be overly risk averse, i.e. choosing A all the time, raises x_{i+1} and thus increases the mean payoff of prospects B. Since subjects are paid their preferred prospect in one randomly chosen pair, this misreporting strategy may increase their expected experimental payoff. To make it more difficult to fully grasp the bisection procedure, we added two choices at the beginning elicitation procedure. Therefore, in total eight choices were taken to elicit each point. The display of these two choices is independent from participant's choices and is expected to make the inference of the whole algorithm more difficult.

The procedure may be best understood with a numerical example. In the experiment we started the elicitation with the following pair of prospects: $A = (20, 0.5; 10) \sim B = (x_1, 0.5; 0)$. The potential range of x_1 is $[15, 45]$. Participants will then face the following sequence of choices.

No.	Alternatives	Choice	Inference
1	$A = (20, 0.5; 10)$ vs $B = (30, 0.5; 0)$	A	$x_1 \in [30, 45]$
2	$A = (20, 0.5; 10)$ vs $B = (24, 0.5; 0)$	A	$x_1 \in [30, 45]$
3	$A = (20, 0.5; 10)$ vs $B = (38, 0.5; 0)$	A	$x_1 \in [38, 45]$
4	$A = (20, 0.5; 10)$ vs $B = (34, 0.5; 0)$	A	$x_1 \in [38, 45]$
5	$A = (20, 0.5; 10)$ vs $B = (41, 0.5; 0)$	B	$x_1 \in [38, 41]$
6	$A = (20, 0.5; 10)$ vs $B = (39, 0.5; 0)$	A	$x_1 \in [39, 41]$
7	$A = (20, 0.5; 10)$ vs $B = (40, 0.5; 0)$	A	$x_1 \in [40, 41]$
8	$A = (20, 0.5; 10)$ vs $B = (41, 0.5; 0)$	B	$x_1 \in [40, 41]$

Based these choices, x_1 is set to equal to the middle point of the final range $[40, 41]$, that is, 40.5. If subjects choose A all the way, we simply set x_1 equal to the upper bound of the initial range, which is 45.[9]

Elicitation of probability weights was carried out in a similar manner. For each p_i we first presented subjects with a fixed sequence of five pairs of prospects of structure $A = (x_6, p_i; x_0, 1 - p_i)$ and $B = (x_i, p_i; x_i, 1 - p_i)$, where p_i is successively set to $.1, .9, .3, .7, .5$. Having finished these sequences for all $x_i, i = 1, \ldots, 5$, we proceeded with the bisection procedure. If there was only one switching point for p_i, two further iterations would be employed to find the point of indifference. If there were two or more switching points, a interval encompassing all switching points would be determined and a maximum of 4

[9]For the current example one may find 8 choices are too much. For later rounds, this will be necessary since x_i increases with sequence and so does the potential range of x_i.

iterations of the bisection procedure was employed to find out the indifference probability.

6 Appendix 2: Experimental Instructions

6.1 General Information

Thank you for participating in our experiment. Please end all conversations now and switch off your cell phone. Please read the instruction carefully. The money you earn will depend on the choice you make. The money will be paid to you in cash at the end of the experiment. Throughout the experiment, we shall speak of ECU (experimental currency units) rather than Euro. The exchange rate between ECU and Euro is fixed to 20 ECU= 1 Euro. Please do not communicate during the experiment, and raise your hand if you have questions. We will answer your questions individually. It is very important that you obey these rules, since we would otherwise be forced to exclude you from the experiment and hence from payment.

The Experiments consists of four parts. Each part consists of several rounds. In each round you have to make a decision. At the end of the experiment one round of each part is selected for payment. The sum of these four payments will be your final payment.

6.2 Instructions for the TO experiment

The first part of the experiment comprises 42 rounds. In each round, you will be presented with a pair of risky alternatives. Your task is to pick your preferred alternative. To make the comparisons easier, the payoffs are also presented in the upper right corner of the screen. The pairs of risky alternatives will have the following format:

[insert screen shot here]

The alternatives shown above can be better understood by using the following thinking. Imagine a big watch with one arm. In above figure, 40% of the panel is covered by white and 60% of the panel is covered by black. The arm of the watch stops equally likely at each position of the watch. Suppose now you have chosen alternative A from the above pair. Then, if the arm stops in the white area, you are paid 300 ECU, if the arm stops at the black area, you are paid 100 ECU. (Equivalent, had you chosen B you would be paid 200 in case of black and 50 in case of white)

At the end of this part of the experiment, one of your choices will be randomly selected and played, and the resulting outcome will be your experimental earning in this part.

6.3 Instructions for the PW experiment

This part is similar to the first part. Again you will be asked for your preference between two lotteries, the difference being that lottery B always gives a fixed payoff. Another difference is that the probabilities in lottery A change for each decision. Using the picture of the first part: the division of the circle between black and white changes for each decision. Please think carefully before each decision, since a confirmed choice cannot be changed.

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