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Understanding the Two Components of Risk Attitudes: An Experimental Analysis

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Abstract

Cumulative Prospect Theory (PT) introduced the weighting of probabilities as an additional component to capture risk attitudes. However, this addition would be a less significant challenge to expected utility theory (EU) if utility curvature and probability weighting showed strong positive correlation. In that case the utility curvature in EU alone, while not properly describing risky behavior in general, would still capture most of the variance of individual risk aversion. This study provides experimental evidence that such a strong and positive correlation does not exist. Although most individuals exhibit concave utility and convex probability weighting, the two components show no strong positive correlation.

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

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1 Introduction

In expected utility theory (hereafter EU), the attitude towards risk originates from changes in marginal utility (i.e., the curvature of the utility function). As a result, risk attitudes are traditionally caputred by fitting the best EU model and then using the individual utility curvature as the sole index of risk attitude. Kahneman and Tversky (1979) demonstrated various empirical deficiencies of that view. In (cumulative) prospect theory (hereafter PT) they added a second component to assess risk attitudes, namely the weighting of probabilities. Wakker (1994) gave an intuitive interpretation on the distinct roles that these two components play in the assessment of risk attitudes: Utility describes an intrinsic appreciation of money prior to probability or risk, while risk attitude originates from the perception of probabilities.

Studies testing PT or measuring these two components of risk attitudes are abundant (see, e.g. Harrison and Rutstrom, 2008, for a review). Yet to the best of our knowledge, no study has so far addressed the relation between these two components. Previous literature has either been silent on this relation or implicitly assumed independence. Addressing this question is, however, important, since PT would pose a less significant challenge to EU if the two components, utility curvature and probability weighting, were significantly and positively correlated (more concave in utility corresponds to more underweighting in probability). In that case, one could argue that the utility curvature in EU – while not properly describing risk behavior in general – would still capture most of the variance regarding degrees of risk aversion, making the other component of risk redundant.

In this study we investigate the relation between these two components of risk. Are they truly unconnected? Can an individual be risk seeking in one component and risk averse in the other? Results from our controlled laboratory experiment suggest that this may well be the case. While most individuals in our study exhibit concave utility and convex probability weighting, we find no significant positive correlation between the two components. In a broader context, our results provide further evidence that measuring risk attitude through the curvature of utility alone may not be sufficient to describe decision making under risk, and that neglecting either of the two components entails a loss.

Since our aim is to understand the interplay of utility and probability weighting, a clean measurement of the two components is essential. In this study we employ the trade-off method (hereafter TO) (Wakker and Deneffe, 1996) to measure risk attitude, which is the only method to date that allows for an independent measurement of the two components. Among others, Abdellaoui (2000), Abdellaoui et al. (2005), and van de Kuilen and Wakker (2009) have employed the TO method. In this paper we mostly rely on the TO as introduced by Abdellaoui (2000). The rest of the paper is organized as follows: Section **2** outlines the procedure and experimental setup; technical details are in the Appendix. Section **3** contains the main results. The paper closes with a discussion and a conclusion in Sections **4** and **5**.

2 The TO Method and Experimental Setup

We restrict ourselves to PT for gains and binary lotteries with objective probabilities. Let $(x_{i+1},p;x_i)$ denote a prospect yielding x_{i+1} with probability p and x_i otherwise. When $x_i < x_{i+1}$ this prospect is evaluated by $w(p)u(x_{i+1}) + [1-w(p)]u(x_i)$ in PT, where the utility function $u(\cdot)$ is assumed to be strictly increasing over the outcome space $[0,\infty)$, and the probability weighting function $w(\cdot)$ is increasing over the probability space $[0,1]$, with $w(0)=0$ and $w(1)=1$.

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

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

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

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

$$w(p_i)u(x_n) + [1 - w(p_i)]u(x_0) = w(1)u(x_i) \Rightarrow w(p_i) = \frac{u(x_i) - u(x_0)}{u(x_n) - u(x_0)}, \quad \forall i = 1, \ldots, n-1. \quad (2)$$

By (1), we know that $u(x_{i+1}) - u(x_i)$ is constant, and the above equation can be simplified in $w(p_i) = i/n$, for $i = 1, \ldots, n-1$. The elicited values of $p_1, p_2, \ldots, p_{n-1}$, 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.[1] We fixed the parameters at: $p = 0.5$, $r = 0$, $R = 10$, and $x_0 = 20$. We elicited 6 points for utility and 5 points for probabilities. Indifference was obtained by the modified bisection method, using 8 iterations for each x_i, and 7 iterations to obtain each p_i.[2] A consistency check for each x_i was carried out by repeating the 7^{th} choice. For probabilities we checked for consistency by eliciting a p_3' such that $(x_3) \sim (x_4, p_3'; x_2)$, which should equal to p_3 according to PT. This resulted in 54 rounds for the UT part and 42 rounds for the PW part. One round of each part was individually selected at random, the preferred lottery was played, and the resulting amounts was paid privately and individually to the participant. The average earning was 16 €, with a min of 8 and max of 46 €.[3]

[1] We ran 4 sessions, with 32 subjects in 3 sessions and 28 subjects in one session. Each session lasted about 90 minutes. The experiment included two further parts. Those results are reported in Qiu and Steiger (2009).

[2] A detailed description of the TO and the modified bisection method can be found in Appendix 1. The procedure to elicit p_i was made variable (7 or 9 iterations) to accommodate inconsistent choices. However, this turned out to be unnecessary.

[3] We used ztree (Fischbacher, 2007) for experimental software and ORSEE (Greiner, 2004) to manage invitations to participants. An English translation of the original instructions is attached in the Appendix 2.

3 Results

3.1 Consistency and Reliability

We repeated the $7^t h$ choice pair of each x_i to check for consistency. Preference reversal occurred in 30% of the cases. This seemingly large number may originate from the small remaining interval for the inference of x_i at the $7^t h$ choice[4] and is comparable to the findings in Starmer and Sugden (1989) (26.5%) and Camerer (1989) (31.6%). In PW, we checked for consistency by comparing $(x_6,p_3;x_0) \sim (x_3)$ and $(x_4,p'_3;x_2) \sim (x_3)$. According to PT, the two probabilities should be equal ($p_3 = p'_3$). Indeed, the median values of p_3 and p'_3 are equal to 0.5, and they are not significantly different (paired Wilcoxon signed rank test $p > 0.10$.).[5]

3.2 Classification of utility functions

To classify each utility function, we calculated a ratio (denoted by τ_u) of the area above the (linearly normalized) utility function and the rectangular area between (x_0, 0) and (x_6, 1).[6] This ratio classified the concavity, convexity or linearity of the utility function in a non-parametric way. For each subject, money was measured on the x-axis (from x_0 to x_6) and utility was measured on the y-axis (from 0 to 1, at an increment of 1/6). We calculated the area above these points (with linear approximation) and then normalized this measure by dividing the area by $1 \times (x_6 - x_0)$. This gave a measure of τ_u between 0 and 1, with risk aversion decreasing with the increase in τ_u. We classified 26 subjects with a τ_u between $0.47 \leq \tau_u \leq 0.53$ as having linear utility functions. With this measure, 71 subjects had concave ($\tau_u < 0.47$) and 27 subjects had convex ($\tau_u > 0.53$) utility functions.

[4] Note that for x_1, when the interval is rather small (the difference was less than 2), preference reversal occurs in 39% of the cases, while it lowers to 23% for x_6. This suggests that preference reversal is to some extent the result of small choice intervals. For larger intervals reversal is reduced yet still remains.

[5] The mean difference $p_3 - p'_3 = -0.015$, and the mean and median absolute difference are 0.16 and 0.11 respectively. The means are $p_3 = .6615$ and $p'_3 = .6766$.

[6] Note that we calculated the area above, not below, the curve, i.e. the area between $u = 1$ and the utility curve. This gives τ_u the same property as α of $u(x) = x^\alpha$: an increase in τ_u and α both implies less risk aversion.

	Utility		
	τ_u	Difference	Both
concave	71	67	59
convex	27	9	6
linear	26	25	12

Table 1: Classification of utility, first according to the area ratio, then to the non-parametric method, and finally to both criteria

As a control, we also employed a non-parametric difference method to check for robustness of the above classification. Similar to Abdellaoui (2000), we took the first order difference $\Delta'_i = |x_i - x_{i-1}|$ for $i = 1, ..., 6$ and the second order difference $\Delta''_j = \Delta'_{j+1} - \Delta'_j$ for $j = 1, ..., 5$. We classified 67 subjects as concave (with $\Delta''_j > 2$ for 3 or more out of 5 times), 9 subjects as convex (with $\Delta''_j < -2$ for 3 or more out of 5 times), and 25 subjects as linear (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, the majority of subjects was consistent with both classification methods, in particular those with concave utility functions. As a robustness check we also assumed a power form utility function $u(x) = x^\alpha$ and estimated an α for each individual with his/her sequence of values $x_1, x_2, ..., x_6$ using an OLS regression $\log(u(x)) = \text{Intercept} + \alpha \log(x) + \epsilon$, where $\epsilon \approx N(0, \sigma^2)$. We found that the mean α equals 0.9316 and the median equals 0.8744 (Std error equals 0.0299), and that 74 αs are significantly different from 1 (at 5% significant level), with 58 αs are significantly smaller than 1 and 18 αs are significantly larger than 1. The two measures (τ_u and α) are highly and positively correlated (Spearman's $\rho = 0.6877$, $p < 0.01$), which supports the use of τ_u as a measure of utility curvature.

3.3 Classification of probability weighting functions

A classification of probability weighting requires careful consideration. Previous experiments found mostly inverse S, but also S, linear, convex, and concave shaped probability weighting functions. First, we checked each subject's array of p_i for patterns. The pattern of probability weighting is best discovered when p is close to 0 or 1, where probability

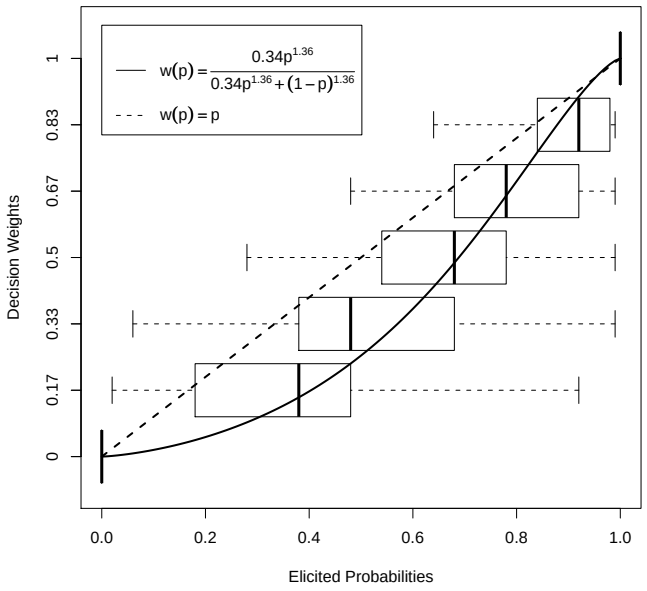


Figure 1: Boxplot of the probability weighting. The curve $w(p) = \frac{0.46p^{1.08}}{0.46p^{1.08}+(1-p)^{1.08}}$ is fitted with median data.

weighting is supposed to be most pronounced. Thus a simple way to detect patterns is to compare w_1 with p_1 and w_5 with p_5. We classified a probability weighting as convex (or optimistic) when $w_1 < p_1$ and $w_5 < p_5$, as concave (or pessimistic) when $w_1 > p_1$ and $w_5 > p_5$, as inverse S-shaped when $w_1 > p_1$ and $w_5 < p_5$, and as S-shaped when $w_1 < p_1$ and $w_5 > p_5$. Based on these criteria, 83 subjects were convex, 4 subjects concave, 19 subjects inverse S-shaped, and 18 subjects S-shaped. Figure 1 gives a boxplot of the probability weights. The data pattern clearly favors a convex probability weighting.

Knowing the general pattern of probability weights, we took the area below the (linearly normalized) probability weights as a measure of pessimism. We used probabilities as x-axis (from p_1 to p_5) and decision weights as y-axis (from 0 to 1, at an increment of $1/6$). We calculated the area below these points (with linear approximation) to obtain a ratio (denoted by τ_p) between 0 and 1. The magnitude of τ_p states whether a subject, *in general*, overweights or underweights probabilities. In order to highlight the different components of risk attitudes, we classify subjects as pessimistic, neutral, and optimistic if their $\tau_u < 0.47$, $0.47 \leq \tau_u \leq 0.53$, and $\tau_u > 0.53$, respectively. With this measure,

Probability weighting				
	τ_p	Non-parametric		Both
convex / optimism	97	convex	83	77
concave / pessimism	5	concave	4	2
linear	22	S	18	–
		Inverse S	19	–

Table 2: Classification of probability weighting, first according to the area ratio, then according to the non-parametric method, and finally according to both criteria

97 subjects were pessimistic, 23 subjects were optimistic, and 33 subjects were neutral in probability weighting. Results and a comparison to the non-parametric method are shown in Table 2. Variations in the tolerance level did not alter results dramatically.

Since τ_p is merely an index of optimism or pessimism. It does not capture the degree of inverse S or S. For robustness check, we also assumed a parametric form for the probability weighting function: $w(p) = \frac{\delta p^\nu}{\delta p^\nu + (1-p)^\nu}$. This form was introduced by Goldstein and Einhorn (1987) and has been frequently used. It allows for most common shapes of probability weighting, depending on the combination of δ and ν, with δ being an index of pessimism and optimism. With five data points $p_i, i = 1, 2, 3, 4, 5$, we estimated a δ and a ν for each subject by minimizing the sums of squared residuals[7]. The median of δ equals 0.495 (mean $\delta = 0.5679$, Std. error equals 0.0316) and ν equals 0.88 (mean $\nu = 1.0468$, Std. error equals 0.0627). As we can see from Figure 1, the fitted curve using median data clearly favors a convex probability weighting function. The high correlation between τ_p and δ (two–sided Spearman's $\rho = 0.8746$, $p < 0.01$) also suggests that τ_p captures probability weighting reasonably well.

[7]We used a wide range of values, δ from 0 to 2 at an increment of 0.01, ν from 0 to 4 at an increment of 0.04.

3.4 Central results

Our main question, to which we now turn, is the relation between utility curvature and probability weights. The results are reported in Table 3 and Figure 2. The largest group in Table 3 are the subjects with concave utility functions and pessimism in the probability weighting (55 subjects). This finding is convenient for economists, since most theoretical models rely on the assumption of risk averse agents. Our result suggests that the majority of the population may indeed be risk averse in both components (concave in utility and convex in probability weighting). There are further interesting patterns in the data. The third cell in the first row denotes the subjects with convex utility but pessimistic probability weighting. They are the second largest group in our classification (26 subjects). This is mirrored by the 4 subjects in the first cell of the third row. This cell denotes the subjects with concave utility but optimistic probability weighting.

In light of information obtained on the curvature of utility and probability weighting, a natural question is: Are subjects who are more concave in utility also more convex in probability weighting? To test this hypothesis, we ran a one–sided Spearman's ρ rank correlation test of τ_u and τ_p for all subjects. It turned out that the correlation had the wrong sign, and was not significant (Spearman's $\rho = -0.1597$, $p = 0.9617$)! The subjects with concave utility and convex probability weighting are those most often assumed in economic theories. As shown above, this is the largest group in our data and most robust to different classification methods. However, for those subjects the correlation is not significant either (one–sided Spearman's rank correlation, $\rho = 0.0701$, $p = 0.6108$). Correlating the parametric estimator δ with α gives qualitatively the same result (one–sided Spearman's ρ rank correlation test between δ and α, $\rho = 0.0761$ and $p = 0.2004$ for all subjects, and $\rho = -0.0656$ and $p = 0.317$ for subjects who are risk averse in both components).

A more general illustration of our main result is shown in Figure 2. Here the relation between τ_u and τ_p is plotted for each subject. The x-axis depicts τ_u and the y-axis depicts τ_p. Small τ_p values correspond to pessimism in probability weighting, and small τ_u values correspond to concave utility. The lower left square represents the largest group of subjects with pessimistic/convex risk attitude. As we can see, no positive correlation between τ_u and τ_p is apparent.

	Concave τ_u	Linear τ_u	Convex τ_u	Sum
Pessimistic τ_p	55	16	26	97
Neutral τ_p	12	10	0	22
Optimistic τ_p	4	0	1	5
Sum	71	26	27	124

Table 3: The two components of risk attitudes. The collums depict the utility and the rows the probability weighting

4 Discussion

The TO method requires questions to be chained. It is known that this can give subjects incentives to not answer truthfully Harrison (1986). In theory, subjects could increase their expected payoff by pretending to be more risk averse. Yet, this does not seem to be a practical problem. Van de Kuilen and Wakker (2009), who also employed the TO method, found subjects in post-experimental interviews to be unaware of the chained structure, let alone the manipulation possibilities. In our data, we checked for possible manipulation by comparing the reported x_i with the possible upper range of x_i. By our experimental design this ratio equals 0.67 for a risk neutral agent.[8] If, however, subjects reported their x_i' strategically, this ratio would be close to 1. Our data shows that the mean of the ratios is 0.80, which is consistent with a reasonable degree of risk aversion.

One may find it surprising that in our study we have mostly convex probability weighting functions while in most previous literature inverse S was prevalent – the more so because we used the same method as Abdellaoui (2000), who found inverse S to be prevailing. We have no conclusive explanation for this difference. But we suspect that it might be related to experimental procedure, subject pool, stake size, and payment method.[9] Abdellaoui used small group interviews with subjects who were acquainted with probabilities and expectations, whereas we used group sessions with subjects of diversified backgrounds. He

[8] For more detailed information, refer to Appendix 1.

[9] Unfortunately we could not use the data of Abdellaoui (2000) for comparison, as this data has been lost.

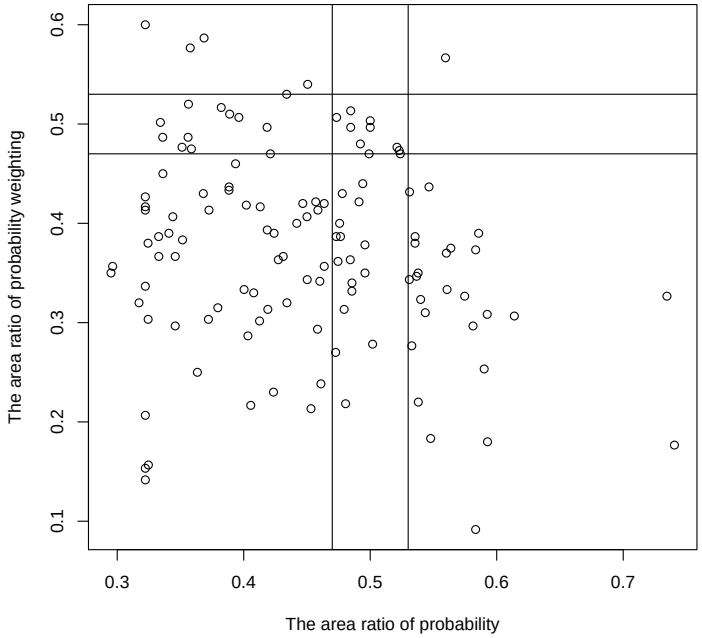


Figure 2: Distribution of the area ratios in utility and probability weighting. The largest group in the lower left corner represents the subjects who are averse in utility and pessimistic in probability weighting.

also used a much larger stake size (outcomes between U.S. $200 and U.S. $4,000) but paid only 1 out of 46 subjects on the basis of their decisions, while we used outcomes between 1 and 5 euro, and paid all subjects on the basis of their decisions. Another explanation is that the inverse S could not be detected, because the first weight elicited was $1/6$. Our results are not unique though. van de Kuilen (2009) and van de Kuilen and Wakker (2009) found similar results. Thus the shape of probability weighting is perhaps not as clear as we thought, and more research needs to be done.

For a robust check of our central hypothesis, we also analyzed Bleichrodt and Pinto's 2000 data. Bleichrodt and Pinto (2000) mainly found inverse S-shaped probability weighting. We calculated τ_u and τ_p for their data. The one–sided Spearman's ρ rank correlation test between τ_u and τ_p gives qualitatively the same result: $\rho = -0.4328$ ($p = 0.999$). We assumed a power form $u(x) = x^\alpha$ for utility functions and $w(p) = \frac{\delta p^\nu}{\delta p^\nu + (1-p)^\nu}$ for probability weighting functions, and estimated the α, δ, and ν by minimizing the sum

of squared residuals. The one–sided Spearman's ρ rank correlation test between α and δ gives qualitatively the same result: $\rho = -0.4469$ ($p = 0.9993$). These results suggest that our result is neither limited to our data nor to the shape of the probability weighting function.

5 Conclusion

In view of numerous studies exploring risk attitudes, it is now probably less controversial to argue that risk attitudes have two components. Yet to the best of our knowledge, no study has so far addressed the relation between these two components of risk. This question is important because PT would have been a less significant challenge to EU if the curvature of utility and probability weighting had been strongly correlated.

In this paper, we elicited risk attitudes using the trade-off method. We classified utility and probability weighting for each individual subject and analyzed the relation between the two components. We found that, although most individuals exhibit concave utility and convex probability weighting, the two components show no positive correlation. This suggests that the curvature of utility alone is an insufficient proxy for risk attitudes, and that an accurate account of risk attitudes requires the measurement of both.

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6 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:

$$\underline{x} = max\{0, (x_i + R) * 0.5 - r\} \quad (3)$$

$$\bar{x} = (x_i + R) * 1.5 - r. \quad (4)$$

   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: $A = (x_i, 0.5; 10)$ and $B = (x_{i+1}, 0.5; 0)$, 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.[10]

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 $A = (x_6, p_i; x_0)$ and $B = (x_i, p_i; x_i)$, 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, an interval encompassing all switching points would be determined and a maximum of 4 iterations of

[10] 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.

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

7 Appendix 2: Experimental Instructions

The experiment was carried out in June 2008 in the computerized laboratory of the Max Planck Institute in Jena. We ran 4 sessions, with 32 subjects in 3 sessions and 28 subjects in one session. Each Session lasted about 90 minutes. Participants could not observe each other's choices. Rounds for payment were chosen individually and participants were paid out privately and individually at the end of the experiment.

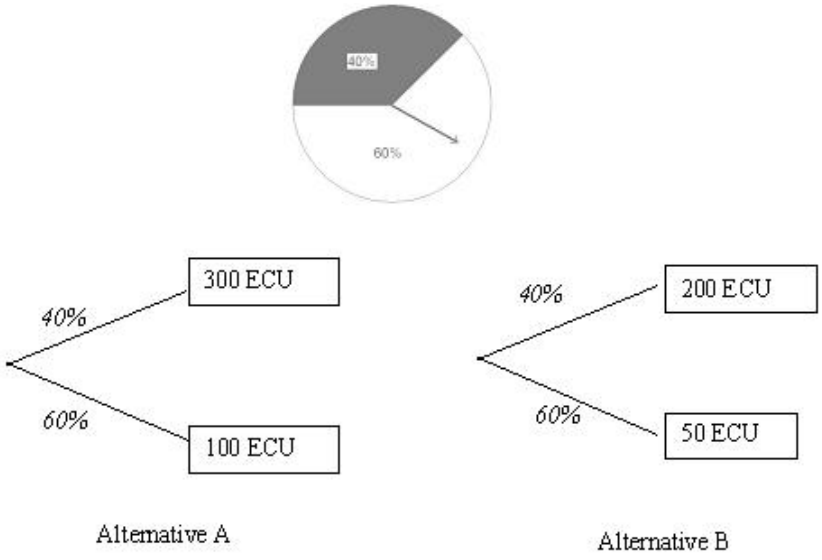
7.1 General Information

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.

7.2 Instructions for the UT 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:

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.

7.3 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.