

# **Explaining heterogeneity in utility functions by individual differences in decision modes**

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modes

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## Abstract

The curvature of utility functions varies between people. We suggest that there is a relationship between individual differences in preferred decision mode (intuition vs. deliberation) and the curvature of the individual utility function. If a person habitually prefers a deliberative mode, the utility function should be nearly linear, while it should be curved when a person prefers the intuitive mode. In this study the utility functions of the subjects were assessed using a lottery-based elicitation method and related to a measurement of the habitual mode preference for intuition and deliberation. Results confirm that people who prefer the deliberative mode have a utility function that is more linear than for people who prefer the intuitive mode. Our findings indicate a stronger affective bias of subjective values in intuitive than deliberate decision makers. While deliberative decision makers may have rather used the stated values, intuitive decision makers may have additionally integrated affective reactions towards the stimuli into the decision.

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## Introduction

For decades psychologists and economists have investigated the relationship between stimuli and the perception and processing of stimuli. In psychophysics, for example, the relation between stimulus intensity (e.g. weight) and the related sensation (e.g. the perception of heaviness) is described in Fechner's law (Fechner, 1860). In the judgment and decision making literature, prospect theory (Kahneman & Tversky, 1979, Tversky & Kahneman, 1992) describes the relation between varying amounts of money and its perceived utility. As a common denominator of this "psychophysical numbing" (Fetherstonhaugh, Slovic, Johnson, & Friedrich, 1997, p.297) we find curved, non-linear relationships between the variation of a stimulus and the subjective feelings towards the stimulus variation. For most people, value functions are typically concave (i.e. constant increments of scope yield successively smaller increments of value) and inversely s-shaped, which is usually interpreted as risk-averse decision behavior when gambling for monetary gains and as risk-seeking behavior in gambles with loss outcomes (Abedellaoui, 2000; Gonzalez & Wu, 1999; Tversky & Fox, 1995). However, the parameter of curvature varies as the subjective perception of the stimuli also varies between people.

Examples for curved utility functions can be easily demonstrated in the consumer domain. Imagine that you buy a new VCR for \$400 at the dealer near you instead of \$ 395 in a different shop miles away. You may think, "Well, it's only \$5. So what?" However, when you know that your favorite wine costs only \$5 in a shop far away, whereas it costs \$ 10 at a shop near you, you might feel that it is a wonderful opportunity and find yourself on the long way to the other store. Your subjective feeling of the utility of the \$5 difference depends on the reference total amount of money (\$10 vs. \$400). The increment of utility for the same amount of money is smaller as the scope increases.

In addition to the automatic subjective valuation by feelings, humans are able to use (meta)cognition, a deliberative, conscious reflection of the problem at hand. Previous research has

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shown that priming participants to use cognitive strategies makes the effect of subjective feelings disappear. For example, Bless, T. Betsch, and Franzen (1998) showed that the framing effect disappears when the problem is subtly framed as a statistical problem. Thus, when you work on your personal monthly accounts, you will know, of course, that \$5 is \$5 and that you (luckily) saved them with the wine and not with the VCR. Metacognitive comprehension, a deliberative mode of thinking, can overcome the automatic subjective feelings and allow you to value \$5 as \$5. With this frame, the utility function should not be curved but instead approach linearity.

It is an established method to compare people's choices between risky monetary gambles to assess their utility function. The gambles used are of the kind "win \$x with the probability of p vs. win \$y with the probability of (1 - p)". Linearity of the utility function means that the utility of a risky monetary lottery is determined by the multiplication of the stated monetary value and its probability. If people place subjective values on the stated monetary outcomes (given the probability is held constant to exclude effects of probability weighting), the utility function becomes curved (i.e. it deviates from linearity). Moreover, the utility function can indicate a person's risk attitude; when people have the choice between a gamble and a sure payoff, the majority actually prefers the sure payoff over the gamble, even if the two prospects have the same expected monetary values. This preference for the sure payoff is an example of a risk-averse decision and is a consequence of people placing subjective evaluations on the stated monetary outcomes. With positive monetary outcomes, the observation of risk-averse decisions is reflected in a concave utility function: The stronger the influence of subjective values, the more the decision can deviate from the decision of an expected value maximizer.

Hsee and Rottenstreich (2004) suggest that the value function differs depending on the decision mode. They label the two opposed modes as "valuation by calculation" vs. "valuation by feelings". They suggest "that concavity arises in part because most real-world valuations mix calculation and feeling. ... In such mixes, greater reliance on feeling yields greater concavity," (p. 28). Besides the fact

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that a decision-maker can engage only in one mode at a time, there is strong evidence that individuals differ in the way they habitually use the affective-intuitive or deliberative decision mode (e.g. Betsch, 2004; Langan-Fox & Shirley, 2003). People with a preference for intuition base most of their decisions on affect, resulting in fast, spontaneous decisions, whereas people with a preference for deliberation tend to make slower, elaborated, and cognition-based decisions (Betsch, 2004).

Intuitive processing means following instant, effortless evaluation processes (Hogarth, 2001) involving automatic, affective (good vs. bad) reactions. Various models capture the intuitive mode as a complementary concept to a deliberative, effortful, planned and analytic way of making decisions (e.g. Chaiken, 1980; Epstein, 1983; Hogarth, 2001). Intuitive people ask themselves, “How do I feel about it?”, while deliberative people ask, “How do I think about it?” (for differences regarding this question format c.f. Verplanken, Hofstee, & Janssen, 1998).

A rational, unemotional person, for example Star Trek’s Mr. Spock, might buy the cheaper VCR as well as the cheaper wine because \$5 is \$5. Unlike Spock’s colleague Mr. McCoy: he is an emotional human, following sudden feelings and intuitions. McCoy might have bought the cheap wine and the more expensive VCR – as most of us probably would have. While Spock’s utility function should be linear, suggesting a risk-neutral attitude, McCoy’s should be curved, suggesting a risk-averse attitude.

We argue that the subjective assessment of intuitive people should be more influenced by affective reactions (c.f. Loewenstein, Weber, Hsee, & Welch, 2001) than the subjective assessment of deliberative people. The subjective values of deliberatives (i.e. deliberative people) should correspond more closely to the stated monetary values presented. The individual preference for intuition and deliberation should therefore be related to the shape of people’s value function. Concretely, we claim that the monetary utility function of people with a preference for deliberative decision-making deviates less from linearity than that of non-deliberative decision makers. Conversely, the more intuitive a

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person is when it comes to decision-making, the more that person's utility function should deviate from the linear form (i.e. it should be more curved).

## Method

### Overview

This hypothesis was tested in a lottery-based study presented in this paper. First, we assessed subjects' utility functions, based on a sequence of individually-adapted lottery questions in which the lottery probabilities were kept equal to avoid the potentially perturbing effect of individually-different probability weighting. Then, subjects filled in an inventory assessing their Preference for Intuition and Deliberation (PID, Betsch, 2004). Based on the lottery choices, we were able to estimate an index for the curvature of the utility function that we related to the individual preference for deliberation and intuition.

### Subjects and Design

A total of 200 students from the University of Mannheim participated in a study in groups (maximum 17 per group). The sample was obtained in two separate blocks (Sample 1 = 68 subjects, Sample 2 = 132); the procedure differed only minimally (see Procedure).

### Procedure

Upon entering the lab, subjects in both samples were told that they would have to make many decisions regarding lotteries with two alternatives. As the study was computer-based, the two lotteries (A and B) were presented simultaneously on the computer screen. Subjects were instructed to indicate their choice by clicking on the respective button for lottery A or B. After a selection was made, the next lottery appeared on the screen. Subjects were not constrained by time and answered all lottery questions at their leisure.

At the end of the procedure, the first sample answered the PID questionnaire by clicking on one of five radio buttons indicating their agreement with the statements. The second sample took part in 3

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more unrelated studies before they answered the PID inventory, which was identical to the first sample. This order was chosen in attempt to prevent an influence of the value function elicitation procedure on the PID values. The time elapsed between the value function elicitation and the PID inventory was approximately 45 minutes. After the procedure subjects from both samples were thanked, debriefed, and dismissed.

In order to provide incentives and to enhance motivation, one of the subjects in each session in the first sample was randomly selected to play for a real monetary pay-off based on his or her choices made in one of the lottery tasks. Since the outcomes of the lotteries were up to €6000, we informed the subjects that the randomly selected person played for 1% of the positive outcomes (i.e. the gains) presented in the lotteries. We dropped this procedure in the second sample and found no change in results. In the next section we describe the materials in more detail.

## Materials

Value function elicitation. A value function assigns a subjective value, or utility, to a stated (objective) value. To approximate such a function, it is necessary to elicit a number of points of this function for every individual (for an illustration cf. Figure 1).

\*\*\* insert Figure 1 about here \*\*\*

Various methods exist to construct individual value functions (i.e. to assess these points) from observed decisions in a series of monetary gambles (Farquhar, 1984). Our elicitation mechanism is based on a method proposed by Abdellaoui (2000) in which seven points are elicited separately for both the gain and loss domains  $\{x_0 \text{ to } x_6\}$ . To elicit one single point  $x_i$ , subjects are required to make five decisions between lotteries. The lottery outcomes are adapted based on the prior decision of the subjects, in order to determine (after five iterations) an outcome  $x_i$  for which the subject is indifferent between the two lotteries, A and B. This indifference is achieved as follows: If the subject prefers lottery B to lottery A, then the value of  $x_i$  in lottery B is decreased such that lottery B is less attractive.

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Conversely, if the subject prefers lottery A to lottery B, then the value of  $x_i$  is increased such that lottery B becomes more attractive. These steps are repeated five times for all elicited points  $x_i$ . Based on the  $x$  values it is possible to estimate two parameters, alpha ( $\alpha$ ) and beta ( $\beta$ ). Alpha describes the utility function in the gain domain, and beta describes the function in the loss domain. Appendix A gives a detailed description of the method and calculation of  $\alpha$  and  $\beta$ .

Alpha and beta characterize the risk attitude of the individuals in the sense of a measure of proportional risk attitude (Eisenführ & Weber, 2003). Standard nonlinear least squares regression is used to estimate  $\alpha$  and  $\beta$ , for gains and losses. A value of  $\alpha$  and  $\beta$  equal to 1 denotes a linear utility function on gains and losses, respectively. If  $\alpha$  is larger than 1, the utility function is convex and the individual is risk-seeking for gains, if  $\alpha$  is smaller than 1, the individual is risk-averse for gains, since the utility function is concave (for  $\beta$ , vice versa).

We use the absolute difference between the risk parameters,  $\alpha$  and  $\beta$ , and 1 as a measure for the curvature of the utility function; the higher the value is, the more the utility function is curved (i.e. the more it deviates from a linear function; see Figure 2). Therefore, we define  $a = |\alpha - 1|$  and  $b = |\beta - 1|$  as indices for curvature (i.e. for the deviation of the particular utility functions from a linear function).

\*\*\* insert Figure 2 about here \*\*\*

Individual preference for intuition and deliberation (PID). To assess preferences in making decisions intuitively or deliberatively, we use the Preference for Intuition and Deliberation scale (PID; Betsch, 2004). The measurement consists of 18 questions: nine items assessing the habitual preference for deliberation (PID-D) and nine items assessing the preference for intuition (PID-I). On a 5-point scale anchored at 1 (“I don’t agree.”) and 5 (“I totally agree.”), subjects answered questions regarding their decision-making habits. PID-D consists of items such as, “I prefer making detailed plans to leaving things to chance” or “I think before I act.” PID-I includes items such as, “With most decisions it makes sense to rely on your feelings” or “I carefully observe my deepest feelings” (the complete PID

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inventory is included in Appendix B). In prior studies (total  $N > 2500$ ; Betsch, 2004) the scale proved as reliable (Cronbach's  $\alpha$  for PID-D varied between 0.78 and 0.84, for PID-I between 0.78 and 0.81), and the 2-dimensional structure was confirmed. The inventory captures a habitual preference that is stable over time. A preference for a decision mode influences decision-making especially in unconstrained situations (e.g. no time pressure, enough resources, etc.).

People with high scores on deliberation have been shown to be conscientious perfectionists with a high need for structure (Betsch, 2004, Study 3). They aim at maximizing rather than satisficing their decision outcome. On the other hand, highly intuitive people are speedy decision-makers and tend to score high on social and emotion-bound personality dimensions like extraversion, agreeableness, and openness for experience.

## Results

As no differences between the samples were obtained for the parameters describing the utility functions (alpha and beta), PID-I and PID-D (all  $F_s < 1.2$ ), the data of the two samples were combined. From the total of 200 subjects, 15 were found to be outliers in terms of the standard error and were therefore deleted<sup>1</sup>.

For data analysis, we first calculated correlations between the curvature indices and the PID values. Based on the two subscales PID-I and PID-D subjects could further be classified as high or low intuitive and high or low deliberative.

In line with previous findings (e.g. Betsch, 2004), the subjects in general had a significantly greater preference for deliberation (PID-D = 3.7,  $\underline{sd} = 0.63$ ) than preference for intuition (PID-I = 3.3,  $\underline{sd} = 0.63$ ),  $t(185) = -4.9$ ,  $p < 0.001$ .

The median of the coefficient estimates of the power function on gains ( $\underline{\alpha}$ ) was 0.92, with a mean standard error ( $\underline{se}$ ) of the nonlinear least squares estimation of 0.06 ( $\underline{M\alpha} = 0.95$ ,  $\underline{sd} = 0.45$ ). In the loss domain the median  $\beta$  equaled 0.90 ( $\underline{se} = 0.05$ ;  $\underline{M\beta} = 0.99$ ,  $\underline{sd} = 0.04$ )<sup>2</sup>. The coefficients of

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determination of the nonlinear regression approach 1 (the mean  $R^2$  is 0.995 for  $\alpha$  and 0.995 for  $\beta$ ). In total, the results regarding subjects' risk attitudes are consistent with the predictions of prospect theory (Tversky and Kahneman, 1992) and subsequent work based on prospect theory.

The Relationship between Preference for Intuition and Deliberation (PID) and the Curvature of the Utility Function. We hypothesized that high values of deliberation (PID-D) should coincide with a less curved utility function. Conversely, subjects with a greater degree of intuition (PID-I) should have more curved utility functions.

Based on this hypothesis, we expected that both curvature indices,  $a = |\alpha - 1|$  and  $b = |\beta - 1|$ , would be positively correlated with a preference for intuition and negatively correlated with a preference for deliberation. This was supported by our data: A high preference for deliberation was found to be negatively and significantly related to the curvature of the utility function in the gain domain,  $r_a$  (Pearson's correlation coefficient) =  $-.20$ ,  $p < 0.01$ , and in the loss domain,  $r_b = -0.15$ ,  $p < 0.05$ . Similarly, a high preference for intuition was significantly positively correlated with the curvature index on both the gain ( $r = 0.18$ ,  $p < 0.05$ ) and the loss domain ( $r = 0.21$ ,  $p < 0.01$ ). Thus, more deliberative decision-makers had less curved, or more linear, utility functions, while more intuitive decision makers had more curved, or less linear, utility functions. This hypothesis found further support in an overall test<sup>3</sup>. Though the intuition and deliberation dimensions of the PID were not highly negatively correlated ( $r = -.36$ ,  $p < .001$ ), we defined  $c = \text{PID-I} - \text{PID-D}$  as an overall measure for the preference for intuition ( $M_c = -.37$ ,  $sd = 1.0$ ). Higher values of  $c$  indicate a higher preference for intuition. Our hypothesis that  $c$  is positively correlated with the curvature indices  $a$  and  $b$  was strongly supported by the data (see Table 1, rows 1 and 2).

\*\*\* insert table 1 about here \*\*\*

Partitioning the sample. Do our correlation findings reflect a relationship between habitual preferences for a decision mode and the curvature of the utility function, or do they rather stem from a

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systematic relationship between specific risk attitudes and the habitual preference for a certain decision mode? To investigate the robustness of our statistical findings, in particular to see whether the results are only driven by specific subgroups of the sample, we subdivided the sample into various partitions.

Table 1 presents the results from the sample partitioned based on the curvature estimates of the utility functions (i.e. based on their risk attitude). All correlation results held for the subgroups. If risk-seeking subjects on the gain domain (i.e. we excluded the subjects with  $\alpha \geq 1$ ) or subjects that were risk-averse on the loss domain (i.e., we excluded the subjects with  $\beta \geq 1$ ) were excluded, the correlation results are only marginally significant.

Next, we partitioned the sample based on the PID-classification of the subjects. We divided them into extreme groups based on a median split method. We will refer to the high intuitive, low deliberative group as to the intuitives and to the low intuitive, high deliberative group as deliberatives.

The sample means of the curvature estimates  $\alpha$  and  $\beta$  did not differ significantly between the PID extreme groups. Two t-tests for unpaired samples for  $\alpha$  and  $\beta$  comparing the extreme groups yield t-values smaller than 1 (i.e. no significant differences) for both deliberatives ( $\underline{M}\alpha = 0.94$ ,  $\underline{M}\beta = 0.91$ ) and intuitives ( $\underline{M}\alpha = 1.00$ ,  $\underline{M}\beta = 0.97$ ).

Though there was no difference in means, there was a significant difference between highly deliberative ( $\underline{sd}\alpha = 0.27$ ,  $\underline{sd}\beta = 0.21$ ) and intuitive subjects ( $\underline{sd}\alpha = 0.50$ ,  $\underline{sd}\beta = 0.50$ ) in the standard deviations of the mean curvature estimates, which is consistent with our hypothesis: A variance ratio test for the difference in the standard deviation of  $\alpha$ ,  $\underline{F}(57,62) = 3.4$ ,  $p < 0.001$ , and  $\beta$ ,  $\underline{F}(57,62) = 5.7$ ,  $p < 0.001$ , suggests that the standard deviations are significantly higher for intuitives. That is, the  $\underline{\alpha}$ - and  $\underline{\beta}$ -values of intuitives deviated considerably more from their means than the  $\underline{\alpha}$ - and  $\underline{\beta}$ -values of deliberatives, which suggests that intuitives had a more curved utility function than deliberatives.

The results from the subgroup analysis provide further evidence that our data do not suggest a systematic relationship between the preference for a decision mode and a certain risk attitude.

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However, as we have hypothesized, there is instead a systematic relationship between the preference for a decision mode and the degree of curvature of individual utility functions. In sum, our findings are neither driven by only one specific subgroup of the sample, nor by differences between the PID extreme groups in their mean curvature estimates.

The last two rows of the subgroup analysis in Table 1 address an important interpretative point of our analysis: They show that the results still hold even if we delete all subjects with linear utility functions from the sample, that is, if we exclude all subjects whose behavior follows an expected-value calculation.

Decision Times. Decisions based on affect should be faster compared to deliberative decisions because affect is quickly accessible (cf. affective primacy hypothesis, Zajonc, 1980). Comparing decision times between the extreme groups (intuitive vs. deliberative decision-makers) allows to track the process used to make the lottery decisions. Deliberative subjects ( $\underline{M} = 412$  seconds) take significantly more time to complete both lottery tasks than intuitives ( $\underline{M} = 308$  seconds), unpaired- $t(94) = 2.26, p < 0.05$  (one-tailed)<sup>4</sup>.

In order to exclude the possibility that intuitive subjects just clicked in a non-systematic way, which would have also led to faster decision times and more curved utility functions, we compared intuitives' and deliberatives' mean standard error of the coefficient estimates of  $\alpha$  and  $\beta$ . If intuitive subjects had clicked in a non-systematic way, they would have given answers that were systematically inconsistent with a regular and smooth utility function, such as the power function (cf. Figure 2) that is assumed by our utility function estimation approach. In an unpaired samples t-test, which included only subjects that did not have a linear utility function (i.e. a standard coefficient estimation error of zero), the mean standard errors did not differ between deliberative subjects ( $\underline{se} = 0.06$ ) and intuitive subjects ( $\underline{se} = 0.07$ ), unpaired- $t(202) = -1.3, p > 0.10$  (one-tailed)<sup>4</sup>, showing that our results cannot be explained by unmotivated intuitive subjects giving arbitrary answers to the lottery questions.

## Discussion

In this study we showed that the curvature of individual value functions, assessed with an established elicitation method, were correlated with an individual preference for intuitive and deliberative decision-making. The more people prefer deliberative strategies, the more linear their utility functions were. On the contrary, the more intuitive a person was, the more curved the utility function was. The effect was stable for various partitions of the sample.

This effect might have occurred because intuitive and deliberative decision-makers used different sources of information. While deliberatives may have used rather the stated values as presented by the experimenter, intuitive decision makers might have additionally integrated affective reactions towards the stimuli into their decisions. Intuitives might “go beyond the information given” (Bruner, 1957, p.41) and bias their judgment with additional affective information, while deliberates might tend to bias their judgment less with subjective evaluations. Although we have not directly shown this in the current setting, there are several findings that support this assumption.

First, if intuitive subjects rely on quickly accessible affect, their reaction times should have been shorter compared to deliberative decision-makers who tend to reflect on their decisions. Indeed, this was the case in our sample and this is in line with findings from Betsch (2004): The time needed to finish the 64 lottery choices was significantly shorter for intuitive subjects compared to deliberative subjects. In Betsch’s (2004) study, intuitive subjects indicated faster decision making than deliberative decision makers on a self-report scale. Furthermore, subjective evaluation happens automatically, but a meta-cognitive correction needs extra time, which might have caused the prolonged decision time for deliberative decision-makers. Second, the faster decisions of intuitive decision makers were not a result of random clicking or a lack of motivation. The standard error of the utility estimates was not significantly higher for intuitives compared to deliberatives. Third, deliberative people tend to be maximizers of the objective expected values, which was demonstrated by the nearly linear shape of

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their utility functions. Again in line with findings by Betsch (2004), preference for deliberation (PID-D) correlated significantly with maximization ( $r=.27$ ), a construct expressing the tendency to make optimal objective decisions as opposed to subjectively satisfying decisions (Schwartz et al., 2002). Maximizing is a highly cognitive process, involving conscious weighting, information search, for example, which requires more cognitive capacity than affective-intuitive, satisfying decisions.

Finally, in an unpublished pilot-study, we simply asked subjects after the utility elicitation procedure to what extent they relied on affect vs. calculation. Deliberatives reported that they calculated in 9% of the cases, whereas intuitive decision-makers reported that they calculated in only 5% of the cases. On the other hand, self-reports additionally showed that intuitive decision-makers (56%) used significantly more affect than deliberative decision makers (41%), the interaction effect was significant,  $p < 0.05$ . It seems unlikely that deliberatives actually “calculate” in the literal sense (also given the fact that the mean time used for the 32 lottery decisions was max. 5 minutes). However, the self-report data on strategy use in addition to the decision time differences in this study indicate that deliberative decision makers did indeed perform more time-consuming cognitive operations.

A deliberative decision-maker might also have a long-term perspective on gambling. As Benartzi and Thaler (1999) showed in their studies, people are more willing to take risky alternatives when they know the distribution of long-term returns. Intuitives might go for the ad hoc, affectively attractive or safe option and show “myopic risk aversion” (Benartzi & Thaler, 1999, p.364). This can be, in the long run, a worse choice compared to taking risks. Deliberatives might maximize the long-term utility by abstracting from the sudden affect in a time consuming cognitive act.

As a limitation of this study we have to note that our explanation of the effect was not directly tested in this study. The basis of information used for the decisions was not manipulated. Johnson, Payne, and Bettman (1988) found, for example, that the display of numbers (e.g. the probability of .9 as

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9/10 or 513/570) elicits different strategies, namely calculation-based strategies vs. heuristic strategies. Such a method could be useful in future studies that further investigate the reported findings.

To summarize, in our study we found empirical evidence for the hypothesis that a habitual “individual difference” factor is able to account for the observed variation in the curvature of individual utility functions. This is another piece of evidence that both, affective and deliberative processes, play a role when people make decisions (cf. Loewenstein & O’Donoghue, 2004). On one hand, the findings in this study suggest that deliberative people use more cognitive strategies than intuitive people, and on the other hand, the data substantiates the speculation that the curvature of utility functions might come from affective evaluation and the integration of affect into the decision. This is especially the case for intuitive decision makers.

### Conclusion

The degree of curvature of the utility function is interpreted as the risk attitude of the decision-maker. Attitudes consist of affective, cognitive, and behavioral components (e.g. Breckler, 1984). One can argue that for intuitive subjects the affective part of the attitude contributes more to the overall risk attitude compared to the cognitive part (vice versa for deliberative decision-makers). Our findings suggest that intuitive people use the affective risk information contained in the lotteries when making their decisions, which might lead to the risk attitude (i.e. feeling of risk) becoming integrated in the judgment, resulting in risk-averse or risk-seeking behavior. Deliberative people, on the contrary, seem to base their decisions on the stated values rather than affect. It seems unlikely that deliberative people do not have any affective reactions to the lotteries, but they might therefore abstract from this affective information and might discount or neglect it when making their judgments (a process that requires time).

This interpretation of the observed relationship between habitual decision modes and lottery choice behavior is in line with other research as well. In Kaufmann’s (2003) study, people were

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presented with a list of return values for individual stocks, which differed in the total return and the variance of the return (i.e. the associated risk of the stock). People classified as intuitive, based on the PID scale, had a higher degree of sensitivity towards the risk of the individual stocks than the deliberatives. Similar to the findings in our study and consistent with the “risk-as-feelings-hypothesis” (Loewenstein et al., 2001), the risky stocks seem to trigger a feeling of uncertainty that particularly affects intuitive people in their evaluations of the lotteries.

In their work, Fetherstonhaugh and colleagues (1997) found, for example, that not all subjects had curved utility functions. “People ... exhibit diminished sensitivity in valuing lifesaving interventions against a background of increasing numbers of life at risk. ... Although psychophysical numbing was present in each study, its prevalence varied,” (p. 283, 297). Considering the preferred decision mode could help explain why some people value saving 4,500 people independent from the number of threatened people (e.g. 11,000 or 250,000), and why others show dramatic differences.

Although affect and risk perception are increasingly mentioned in the literature, the focus has mostly been on the influence of mood or affective states on risky decision-making (e.g. Isen, Nygren, & Ashby, 1988; Mano, 1994; Wright & Bower, 1992). In this work we consider the impact of intuitive or deliberative decision-making based on the idea that the information used for a judgment varies with respect to the individually preferred habitual decision mode. While deliberative people rather use the stated information, intuitives seem to process not only the stated values but also their subjective feeling of how safe or how good a lottery is. People using affective information (i.e. people with a preference for intuition) may be more prone to the effects of mood on their decisions in risky situations. Future studies might attempt to control for mood effects to rule out this explanation.

This study links psychometric measures with individual utility functions, the backbone of all research on individual decision-making models in the economic sciences. Our findings suggest that individually stable traits, measured based on a psychological questionnaire, might help explain

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observed economic behavior, such as finance and insurance decisions. In this context, the findings might be of particular relevance for understanding portfolio choice and stock market decisions. The question of whether or not there are stable individual differences in reasoning or decision-making competence has recently gained interest (see Parker & Fischhoff, 2005; Stanovich & West, 1998; 2000), for example in the context of investor overconfidence models (Glaser, Nöth, & Weber, 2004).

Our results suggest that people differ systematically in the way they solve simple monetary risky decision problems. We identified a person variable, the individual preference for intuition and deliberation that helps to explain heterogeneity in utility functions. The findings are further evidence that affective-intuitive and deliberative decision modes affect peoples' decisions in substantial ways. Further theoretical and empirical work on decision-making under risk and uncertainty will profit from considering different decision modes, for example by assessing the individual preference for intuition and deliberation.

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Footnotes

1. The 15 excluded subjects were outliers in terms of the standard error of the coefficient estimates of the utility function: We excluded all subjects whose standard error of one of the coefficient estimates was more than one standard deviation larger than all other standard errors of coefficient estimates. High standard errors indicate unsystematic clicking, suggesting a lack of motivation. It is interesting to note that some of the deleted subjects were not only outliers in terms of the standard error of their coefficient estimates but also in terms of the time needed for the completion of the lottery questions: They needed considerably less time than all other subjects. There was no systematic relation between preference for intuition and deliberation and the occurrence of outliers.
2. Abdellaoui (2000) found 0.89 and 0.92 for the sample mean of  $\alpha$  and  $\beta$ , respectively based on a study with 40 subjects in total.
3. We are grateful to a reviewer suggesting this test to us.
4. The unpaired t-test does not assume equal variances. Therefore, the degrees of freedom are computed based on the Welch-Satterthwaite approximation.
5. For the loss domain, we used the negative of the above values as  $R$ ,  $r$  and  $x_0$ , respectively.
6. That is, we implicitly assume that individual preferences can be represented by, for example, (Cumulative) Prospect Theory. Note, however, that the value function that we elicit is indeed a von-Neumann-Morgenstern utility function. Equation (3) holds also under Expected Utility Theory, which can be shown by substituting  $p$  for  $w(p)$  in equations (1) and (2).

References

- Abdellaoui, M. (2000) Parameter-free elicitation of utility and probability weighting functions. Management Science, *46*, 1497-1512.
- Benartzi, S., & Thaler, R. H. (1999). Risk aversion or myopia? Choices in repeated gambles and retirement investments. Management Science, *45*, 364-381.
- Betsch, C. (2004). Präferenz für Intuition und Deliberation. Inventar zur Erfassung von affekt- und kognitionsbasiertem Entscheiden [Preference for Intuition and Deliberation (PID): An Inventory for Assessing Affect- and Cognition-Based Decision-Making]. Zeitschrift für Differentielle und Diagnostische Psychologie, *25*, 179-197.
- Bless, H., Betsch, T., Franzen, A. (1998). The impact of context cues on solutions to the "asian disease" problem. European Journal of Social Psychology, *28*, 287-291.
- Breckler, S. J. (1984). Empirical validation of affect, behavior, and cognition as distinct components of attitude. Journal of Personality and Social Psychology, *47*, 1191-1205.
- Bruner, J. S. (1957). Going beyond the information given. In H. E. Gruber, K. R. Hammond, & R. Jessor (Eds.), Contemporary approaches to cognition (pp. 41–69). Cambridge, MA: Harvard University Press.
- Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. Journal of Personality & Social Psychology, *39*, 752-766.
- Eisenführ, F., & Weber, M. (2003). Rationales Entscheiden (4<sup>th</sup> edition). Heidelberg, Germany: Springer.
- Epstein, S. (1983). Aggregation and beyond: Some basic issues on the prediction of behavior. Journal of Personality, *51*, 360-392.
- Farquhar, P. H. (1984). Utility Assessment Methods. Management Science, *30*, 1283-1300.
- Fechner, G. T. (1860). Elemente der Psychophysik. Leipzig, Germany: Breitkopf und Härtel.
- Fetherstonhaugh, D., Slovic, P., Johnson, S., & Friedrich, J. (1997). Insensitivity to the value of human life: A study of psychophysical numbing. Journal of Risk and Uncertainty, *14*, 283-300.
- Glaser, M., Nöth, M., & Weber, M. (2004). Behavioral Finance. In: D. J. Koehler & N. Harvey (Eds.), Blackwell Handbook of Judgment and Decision Making. Oxford: Blackwell.

## Explaining heterogeneity in utility functions

Gonzalez, R., & Wu, G. (1999). On the shape of the probability weighting function. Cognitive Psychology, *38*, 129-166.

Hogarth, R. (2001). Educating intuition. Chicago: University Press.

Hsee, C. K., & Rottenstreich, Y. (2004). Music, pandas, and muggers: on the affective psychology of value. Journal of Experimental Psychology: General, *133*, 23-30.

Isen, A. M., Nygren, T. E., & Ashby, F. G. (1988). Influence of positive affect on the subjective utility of gains and losses: It is just not worth the risk. Journal of Personality & Social Psychology, *55*, 710-717.

Johnson, E. J., Payne, J. W., & Bettman, J. R. (1988). Information displays and preference reversals. Organizational Behavior and Human Decision Processes, *42*, 1-21.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, *47*, 263-91.

Kaufmann, M. (2003). Informationsintegration unter expliziter Einstellungsbildung [Information integration under explicit attitude formation]. Unpublished manuscript, University of Heidelberg.

Langan-Fox, J., & Shirley, D.A. (2003). The Nature and Measurement of Intuition: Cognitive and Behavioral Interests, Personality and Experiences. Creativity Research Journal, *15*, 207-222.

Loewenstein, G., & O'Donoghue, T. (2004). Animal Spirits: Affective and Deliberative Processes in Economic Behavior. Working Paper, 5/4/2004. Carnegie Mellon University.

Loewenstein, G., Weber, E., Hsee, C. K., & Welch, E. (2001). Risk as feelings. Psychological Bulletin, *127*, 267-286.

Mano, H. (1994). Risk-taking, framing effects, and affect. Organizational Behavior & Human Decision Processes, *57*, 38-58.

Parker, A., & Fischhoff, B. (2005). Decision-making competence: External validation through an individual-differences approach. Journal of Behavioral Decision-Making, *18* (1), 1-27

Prelec, D (2000). Compound Invariant Weighting Functions in Prospect Theory. In D. Kahneman, & A. Tversky (Eds.), Choices, Values and Frames. Cambridge, UK: Cambridge University Press.

Explaining heterogeneity in utility functions

Schwartz, B., Ward, A., Monterosso, J., Lyubomirsky, S., White, K., & Lehman, D. R. (2002).

Maximizing versus satisficing: Happiness is a matter of choice. Journal of Personality & Social Psychology, 83(5), 1178-1197.

Stanovich, K. E., & West, R.F. (1998). Individual differences in rational thought. Journal of Experimental Psychology, 127, 161-188.

Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate. Behavioral and Brain Sciences, 23, 645-726.

Tversky, A., & Fox, C. (1995). Weighting Risk and Uncertainty. Psychological Review, 102, 269-283.

Tversky, A., & Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. Journal of Risk and Uncertainty, 5, 297-323.

Verplanken, B., Hofstee, G., & Janssen, H. J. W. (1998). Accessibility of affective versus cognitive components of attitudes. European Journal of Social Psychology, 28, 23-36.

Wakker, P. P., & Deneffe, D. (1996). Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown. Management Science, 42, 1131-1150.

Wright, W. F., & Bower, G. H. (1992). Mood effects on subjective probability assessment. Organizational Behavior & Human Decision Processes, 52, 276-291.

Zajonc, R. B. (1980). Feeling and thinking. Preferences need no inferences. American Psychologist, 35, 151-175.

FIGURES

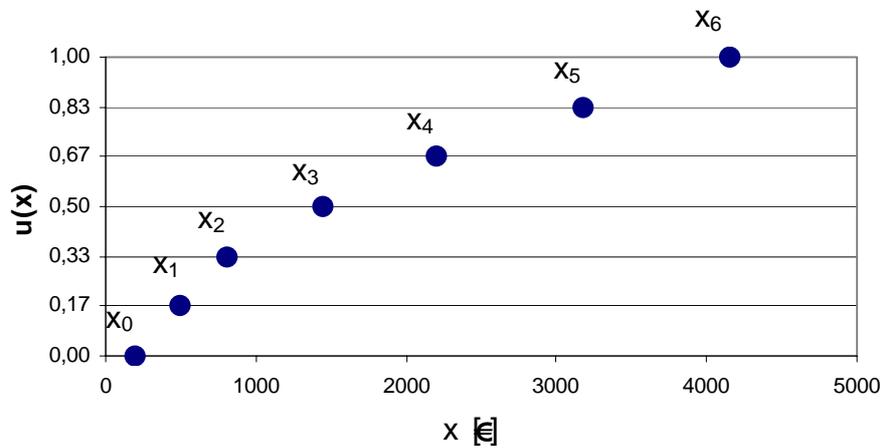


Figure 1: Utility function for gains for Individual 1. The  $x_i$  are equally spaced in terms of their utility.

This allows for the assessment of the curvature of the value function.

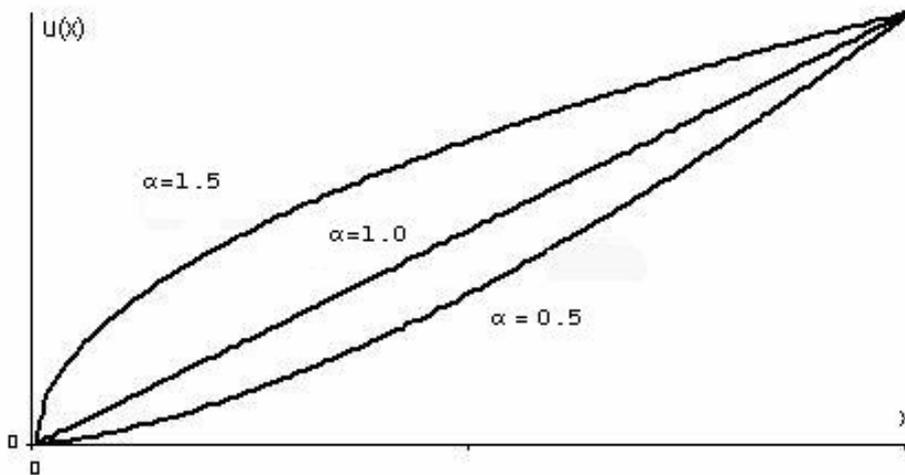


Figure 2: The utility function for gains for various values of  $\alpha$ . The absolute difference between the parameter  $\alpha$  and 1 is a measure for the curvature of the utility function.

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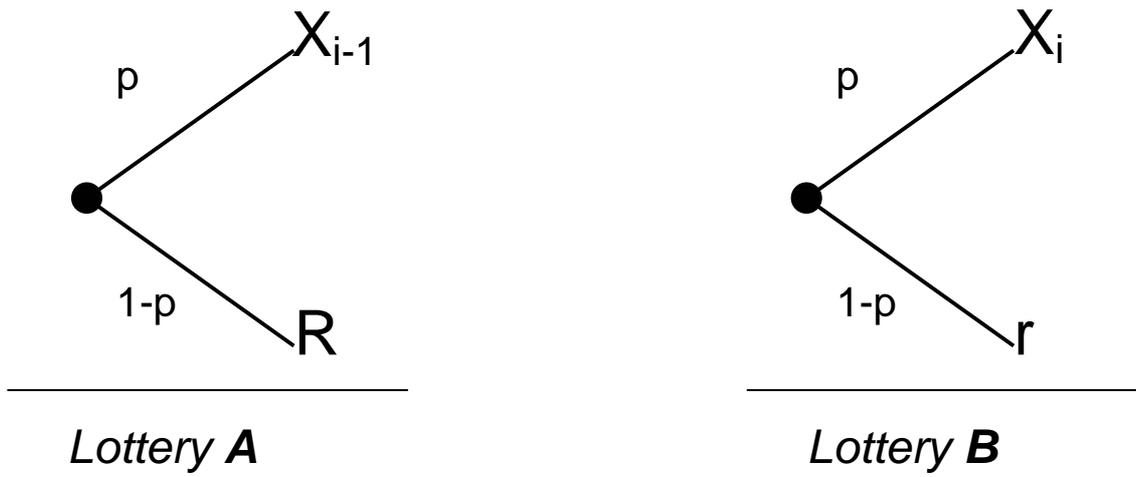


Figure 3: An example of the two presented lotteries.

TABLES

Table 1: Overall test. Correlation between overall measure of preference for intuition (c) and the curvature indices (a, b) of the utility function. The table also presents results for various sample partitions.

	<u>c</u>
<u>a</u> (N = 185)	0.23 **
<u>b</u> (N = 185)	0.23 **
<u>a</u> ( $\alpha \geq 1$ : N = 74)	0.41 ***
<u>a</u> ( $\alpha \leq 1$ : N = 136)	0.14 +
<u>b</u> ( $\beta \geq 1$ : N = 80)	0.34 **
<u>b</u> ( $\beta \leq 1$ : N = 131)	0.15 +
<u>a</u> ( $\alpha \neq 1$ : N = 160)	0.20 **
<u>b</u> ( $\beta \neq 1$ : N = 159)	0.19 **

Note: A higher c value denotes a higher preference for intuition. A higher a or b value is associated with a more curved utility function. Correlations flagged with a + are significant on the 0.10-level, \* on the 0.05 level, \*\* on 0.01, and \*\*\* on 0.001. c = PID-I – PID-D.

## APPENDIX A

### Details of eliciting the value function and risk attitude parameters ( $\alpha$ and $\beta$ ):

Individuals' utility functions for the gain and loss domains are elicited using a series of 64 individually adapted lottery choice questions presented by the computer.

The method of utility function elicitation is based on the construction of so-called standard sequences of outcomes,  $\{x_0 \text{ to } x_6\}$  (i.e. monetary outcomes that are equally spaced in terms of their utility). In our design, we use a five-step interval bisection procedure to determine an outcome  $x_1$  for which the subject is indifferent between the lotteries  $A=(x_0, p; R, 1-p)$  and  $B=(x_1, p; r, 1-p)$  (see Figure 3), where  $x_0, R, x_1$  and  $r$  denote monetary payoffs of the lottery and  $p$  and  $(1-p)$  denote the probabilities of the respective payoffs (see Figure 3). Here, we have  $0 \leq r < R < x_0 < x_1$  with  $r, R$  and  $x_0$  held constant. The answers to the first five presented lottery choice questions allow us to determine the desired  $x_1$  that achieves indifference between lottery A and B.

\*\*\* insert Figure 3 about here \*\*\*

In the next step of this procedure (i.e. the next 5 presented lotteries) we determine, again based on bisection, an  $x_2$  for which the subject is indifferent between the lotteries  $(x_1, p; R, 1-p)$  and  $(x_2, p; r, 1-p)$ . We continue this method until we have determined an  $x_6$ , (that is, until we have  $5 \times 6=30$  lottery choice questions in total, plus two consistency check questions). Another 32 questions that follow the same logic explained above are presented for the elicitation of the utility function for losses. Note that in our study we have set  $R$  to €100 and  $r$  to €0;  $x_0$  has been set to €200<sup>5</sup>. These values are based on the suggestions of Abdellaoui (2000) and Wakker and Deneffe (1996). We start every five-step bisection procedure for the elicitation of a *new*  $x_i$  with a value of  $x_i=x_{i-1}+\text{€}500$ . The interval within which we determine the new  $x_i$  via bisection is then  $[x_{i-1}, x_{i-1} + \text{€}1000]$ . Furthermore,  $p$  is set to  $2/3$  for all subjects

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and *for all lottery choices*, thus excluding the possibility of the perturbing effect of different individual probability weighting functions for the construction of the utility function.

Now, let  $u(\cdot)$  denote the value- or utility-function on the gain or the loss domain and let  $w(\cdot)$  denote the probability weighting function for the respective domain<sup>6</sup>. Then the constructed indifferences give pairs of equations of the following type:

$$w(p) u(x_i) + (1-w(p)) u(R) = w(p) u(x_{i+1}) + (1-w(p)) u(r) \quad (1)$$

$$w(p) u(x_{i+1}) + (1-w(p)) u(R) = w(p) u(x_{i+2}) + (1-w(p)) u(r) \quad (2)$$

From these two equations it follows:

$$u(x_{i+1}) - u(x_i) = u(x_{i+2}) - u(x_{i+1}) \quad (3)$$

That is, in terms of utility, the trade-off of  $x_i$  for  $x_{i+1}$  is equivalent to the trade-off of  $x_{i+1}$  for  $x_{i+2}$ .

We obtain a standard sequence of outcomes,  $\{x_0, x_1, x_2, x_3, x_4, x_5, x_6\}$ , which is, by construction, increasing for gains and decreasing for losses and uniquely characterizes the individuals' utility function, since all  $x_i$  are equally spaced in terms of their utility (see Figure 1).

Following Tversky and Kahneman (1992), we assume a power utility function that is “by far the most popular form for estimating money value” (Prelec, 2000):

$$u(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -(-x)^\beta & \text{if } x < 0 \end{cases} \quad (4)$$

APPENDIX B

Items of the Preference for intuition and deliberation scale (Betsch, 2004).

<b>Preference for deliberation</b>	$\alpha = .76$
Before making decisions I first think them through.	
Before making decisions I usually think about the goals I want to achieve.	
I don't like situations that require me to rely on my intuition.	
I prefer making detailed plans rather than leaving things to chance.	
I am a perfectionist.	
I think about a decision particularly carefully if I have to justify it.	
When I have a problem I first analyze the facts and details before I decide.	
I think before I act.	
I think more about my plans and goals than other people do.	
<b>Preference for intuition</b>	$\alpha = .77$
I listen carefully to my deepest feelings.	
I consider myself when making decisions.	
I prefer drawing conclusions based on my feelings, my knowledge of human nature, and my experience of life.	
When it comes to trusting people, I can usually rely on my gut feelings.	
I prefer emotional people.	
I like emotional situations, discussions, and movies.	
I am a very intuitive person.	
My feelings play an important role in my decisions.	
With most decisions it makes sense to completely rely on your feelings.	

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