SURPRISE IN DECISION MAKING UNDER UNCERTAINTY

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Abstract

In four experiments we investigate over- and underweighting of probabilities in decisions under risk. To account for this phenomenon we propose a view of the probability weighting function as a composite of cognitive and emotional processes and suggest that there is no single weighting function but two separate weighting functions for each process. Data obtained from a rating as well as three choice experiments, using both between and within subjects designs, generally support the proposed view. Given this broader perspective, cognitive "biases" or "errors" may turn out as highly intelligent solutions to maximize utility.

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Surprise in Decision Making under Uncertainty

People quite often make decisions without knowing exactly the outcomes of their choices. Whether a person plans to begin college or whether a firm decides to introduce new products, the final outcomes of these choices are barely known in advance. Such decision situations are typically evaluated by two basic features of the possible outcomes: the attractiveness of the outcomes (i. e. expected profit or gain) and their likelihood of occurrence.

As a formal approach expected utility (EU) theory emerged as a guiding framework of how to make rational decisions. According to EU-theory, a rational decision maker will maximize his or her utility by choosing the option with the highest overall utility, which is calculated by $U = p * u(x) + (1 - p) * u(0)$ for a prospect to win \$x with probability *p* and nothing otherwise. That is, the utility of each outcome x is weighted by its probability of occurrence.

Despite its astonishing simplicity and elegance further research has established systematic deviations from EU-theory (e.g. Kahneman & Tversky, 1979; Kahneman, Slovic, & Tversky 1982). One of these deviations is that people do not weight probabilities linearly but tend to overweight small and underweight large probabilities. This leads to an inverse S-shaped probability weighting function that is first concave and then convex.

Formally, such deviations are best captured by prospect theory (Kahneman & Tversky, 1979; Pommerehne, Schneider, & Zweifel, 1982; Tversky & Kahneman, 1992), which replaces the objective probabilities *p* by decision weights W (p) such that $U = W(p) * v(x)$ for a prospect to win \$x with probability *p* and nothing otherwise.

For probability there are two natural reference points–certainty and impossibility–that correspond to the endpoints of the scale. The overweighting of small and underweighting of large probabilities thus implies diminishing sensitivity; i.e., increasing the probability of winning a prize by a probability of .1 has more impact when it changes the probability of winning from .9 to 1.0, or from 0 to .1, than when it changes the probability from, say, .3 to .4 or from .6 to .7. This gives rise to a weighting function that is concave near impossibility and convex near certainty. Such a function overweights small probabilities and underweights moderate and high probabilities (Tversky & Fox, 1995, p. 270; see also Allais, 1953; Camerer & Ho, 1994; Hogarth & Einhorn, 1990; Wu & Gonzalez, 1996).

Thus, based on a large amount of empirical data, the form of the probability weighting function is widely agreed upon and this weighting of probabilities serves as a well established model for decisions under risk. However, the psychological causes for over- and underweighting have only barely been addressed so far. The present article is an attempt to fill this gap by suggesting a view of the probability weighting function as a compromise between cognitive and emotional processes.

Emotions in Decision Making

Most theories of decision making focus on cognitive processes and are silent about the role of emotions. Savage (1954) proposed anticipated regret as a determinant to influence decisions, and later Bell (1982) and Loomes and Sudgen (1982) systematically incorporated emotions into a theory of choice. Disappointment theory (Bell, 1985) incorporates anticipated elation and disappointment to an uncertain outcome, depending on whether an uncertain outcome has turned out positive or negative (see also Loomes & Sudgen, 1982; Mellers et al., 1997; van Dijk & van der Pligt, 1997). Regret theory assumes comparisons between choices and captures anticipated regret and rejoicing when one learns that a different choice would have produced a better or worse outcome, respectively. Importantly, however, both disappointment and regret theory state that decision makers unscrupulously anticipate all possible outcomes of the decision task and therefore have to face a high cognitive work load; accordingly, decision makers are supposed to anticipate all possible gains, non-gains, losses, and non-losses.

However, there are important reasons that limit the generality of the view of decision makers as extensive problem solvers who anticipate all possible decision outcomes. Firstly, Simon's (1955) satisficing principle asserts that people only have limited problem solving capacities and often do not have the time, motivation, or ability to imagine all possible decision outcomes in advance. More specifically, decision makers generally are not looking for the best or optimal, but for a satisfying solution of a decision task. If so, decision makers may try to simplify a complex decision task by anticipating only a small part of all possible outcomes. Additionally, the social psychology literature strongly emphasizes the view of persons as "cognitive misers" (see Fiske & Taylor, 1991), thereby suggesting that people try to minimize cognitive effort whenever possible. Secondly, and in line with this reasoning, prospect theory (Kahneman & Tversky, 1979)–which is based on adaptation level theory (Helson, 1964)–asserts that people are especially sensitive to environmental changes. That is, persons adapt to the status quo which serves as a neutral reference point and then evaluate changes from this neutral reference point. If so, decision makers may more easily anticipate gains and losses than non-gains and non-losses, because the latter do not constitute changes from their neutral reference point. Taken together, the view of people as "cognitive misers" together with their more pronounced sensitivity to changes than to non-changes offers the intriguing hypothesis that decision makers would be able to simplify the decision task by just anticipating gains or losses but neglecting non-gains or non-losses. The outline of this paper rests on this assumption.

In the following sections we investigate the psychological causes for over- and underweighting by assuming limited problem solving capacities. Specifically, we investigate typical gain non-gain gambles, where people can win for instance $160 with probability p = .3 and nothing otherwise. Importantly, because of limited problem solving capacities and a more pronounced sensitivity to changes (gains) than to non-changes (non-gains) we assume just anticipated surprise for possible gains–but not anticipated disappointment for possible non-gains–as a cause for the shape of the probability weighting function. That is, in contrast to disappointment theory we hypothesize that decision makers just anticipate possible gains but do not anticipate non-gains. Therefore, we propose anticipated surprise (elation) alone, without anticipated disappointment as a cause for the curvature of the probability weighting function. Previous research (e.g. Josephs, Larrick, Steele, & Nisbett, 1997; Larrick & Boles, 1995; Ritov, 1996; Zeelenberg & Beattie, 1996; Zeelenberg & Beattie, 1997) has found that decision makers only anticipate regret when they know in advance that they will get to hear the outcome of the non-chosen alternative. Because this is not the case in our experiments below, the proposed theory herein stands closer to disappointment than to regret theory. We start our analyses by pointing to the insufficiency of the standard interpretation of the probability weighting function.

Insufficiency of the Standard Interpretation of the Probability Weighting Function

As stated above, the standard interpretation of the probability weighting function states that changes near the endpoints of the probability scale have stronger impacts than changes spaced away from these endpoints. Findings that are explained by such differential weighting are usually referred to as impossibility- and certainty effect (Allais, 1953; Allais & Hagen, 1979; Kahneman & Tversky, 1979). However, the certainty and impossibility effect per se are not enough to explain over- and underweighting, because constant under- or constant overweighting would also be in line with both effects (see Figure 1). Thus, we are still looking for an explanation of the specific shape of the probability weighting function.

Some short reflection on the probability weighting function offers an additional perspective to the standard interpretation of the certainty and impossibility effect. According to prospect theory, U = W (p) * v (x) for the prospect to win $x with probability *p*, and nothing otherwise. That is, compared to a linear weighting function *p*, a person derives more utility from low and less utility from high probabilities. This is a direct corollary from prospect theory, which states that people overweight low and underweight large probabilities.

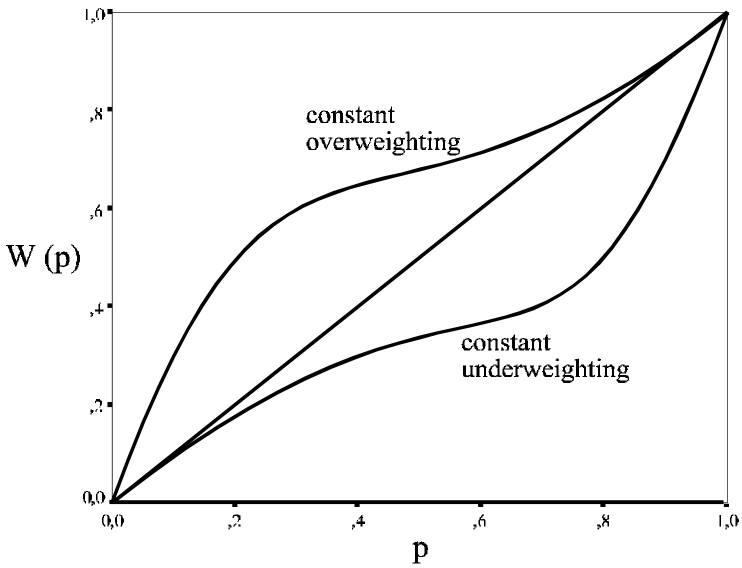

Figure 1. Possible weighting functions that would also satisfy the impossibility and certainty effect.

Given this new interpretation, one may ask why people derive relatively more utility from low and relatively less utility from high probabilities. To account for both phenomena, we propose the experience of surprise as an additional (emotional) source of utility.

An Additional Source of Utility: Surprise

Imagine two people. Both are winning a price of $10, however with different chances for winning. For person A the probability was .5, and for person B the probability was .1. Now we ask a simple question: "Who will be happier after winning, A or B?" That is, we ask for affective reactions after having won. Note that the amount won is the same for both A and B. Therefore, if it were only the amount which was relevant, A and B should not differ in their evaluations of their happiness after having won the price. If so, an experiment, should end up with a 50:50 split.

We suggest, however, that A and B differ in their experienced utility and hypothesize that after winning B is happier than A, despite the fact that B had lower odds than A. Hints are given by daily experience. For example, to increase the joy of a birthday or Christmas present people often do not tell the other what he or she will receive. Or, unexpected deaths cause more and longer pain for the bereaved than expected ones (Bowlby, 1969). More generally, surprising events exert a stronger emotional impact on persons than expected ones.

Two Sources of Utility: Cognitive and Emotional Utility

As stated, the probability weighting function W (p) as well as the above example points to a second source of utility to influence decisions under risk. Accordingly, we suggest two different sources of utility: a cognitive utility (Uc) and an emotional utility (Ue), where Uc refers to the usual expected utility derived from the rational choice model (Uc = *p* * v (x)). Psychologically, Uc captures the long-term utility of possession, whereas Ue captures the short term utility of winning–a distinction similar to the duality of "Having" versus "Being". To calculate Uc and Ue algebraically, we propose the following equations:

$$Uc = p * v(x) \quad (1)$$

$$Ue = We(p) * v(x) \quad (2)$$

with

Uc	Cognitive Utility (expected utility from rational choice model)
Ue	Emotional Utility derived from surprise
p	Objective probability
We (p)	Weighting function for emotional utility
v (x)	Value function on $x

To specify the weighting function We (p) for the emotional utility, Figure 2 is helpful. Some assumptions can be inferred from the two lines. Important assumptions are that the weighting function for the emotional utility We (i) is convex and (ii) runs counter to the objective probability p.

Support for a convex, nonlinearly decreasing weighting function for the emotional utility (utility derived from surprise) comes from habituation experiments, in which expected events cause increasingly less intensive responses (Staddon & Higa, 1996).

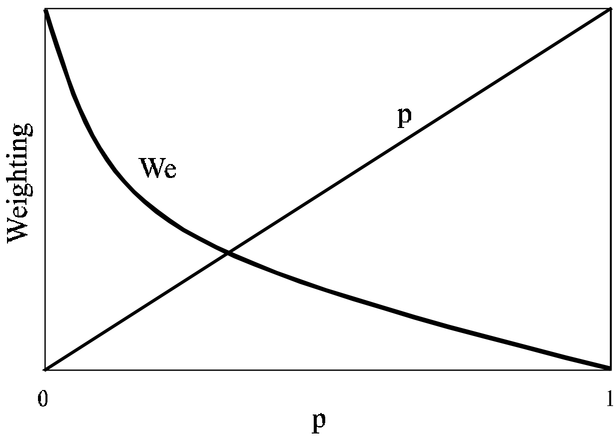

Figure 2. Predicted weighting functions We (p) and p for emotional and cognitive utility, respectively.

The distinction between two separate systems has long been recognized by philosophers, poets, and scientists. Within recent psychology Morling and Epstein (1997) clearly stated the idea: "A rational system operates according to people's understanding of conventional rules of logic and evidence, and is often concerned with long-term consequences. It is conscious, deliberate, analytical, predominantly verbal, and relatively affect-free. An experiential system uses heuristics rather than logical rules, is intimately associated with affect, and is concerned primarily with short-term, immediate consequences and concrete experience. It is preconscious, automatic, intuitive, associationistic, and predominately nonverbal. The two systems are conceptually separate but interact" (p. 1269; see also Epstein, 1994).

Having characterized the main features of the emotional weighting function We, the question of how the cognitive and emotional utility interact to influence overall utility is still open. The next section addresses this issue.

The Interaction of the Cognitive and Emotional Utility

As mentioned, we do not only have to be explicit on the two different sources of utility, we must also be explicit on the interaction of these two different kinds of utility. For this purpose we suggest overall utility as the weighted sum of cognitive utility Uc and emotional utility Ue. That is

$$U = wc * Uc + we * Ue \quad (3)$$

with

Uc Cognitive utility, derived from expected utility model

Ue Emotional utility, derived from surprise

wc Weighting function for Uc

we Weighting function for Ue

substituting Uc and Ue by equation (1) and (2) it follows

$$U = (wc * p + we * We\ (p)) * v(x) \quad (4)$$

following prospect theory U = W (p) * v (x); therefore,

$$W\ (p) = wc * p + we * We\ (p) \quad (5)$$

According to equation (5) we assume that prospect theory's probability weighting function W (p) is the weighted sum of the objective probabilities *p* and the weighting function for surprise We (p). Therefore, we propose separate weighting functions wc and we for each source of utility (see Figure 3). We suggest higher weighting of *p* near the endpoints of zero and one of the probability scale, whereas We is more heavily weighted in the middle of the probability scale. That is, a person will not choose an impossible gain ($p = 0$), although the utility derived from surprise may be extremely high. Conversely, a person will no` ` måLIoïe a sure prospect, only because the utility derived from surprise is zero. To the contrary, the middle of the probability scale should offer the largest freedom to weight the utility derived from surprise. Secondly, we suggest a negative relationship between emotional and cognitive utility; i.e. high weighting of the cognitive utility results in low weighting of the emotional utility and vice versa. More formally, we assume that the sum of the two weighting functions equals 1 (wc + we = 1). Thirdly, because the probability weighting function W (p) deviates only modestly from rational decisions, we suggest higher weighting of the cognitive compared to the emotional utility. Figure 3 depicts all three assumptions and shows the weighting functions wc and we for the cognitive and emotional utility, respectively.

To summarize: From the literature we know that probabilities influence decisions not directly. Their influence is better described by a weighting function defined over the objective probabilities such that low probabilities are overweighted and medium and large probabilities are underweighted. We propose that this pattern of over- and underweighting is a consequence of two different components of probabilities; a cognitive component which captures the long-term utility of possession and an emotional component which captures the short-term utility of derived from the experience of winning. According to equation (5) we suggest the probability weighting function W (p) as a composite consisting of the objective probabilities *p* for the cognitive utility and the weighting function We (p) for the emotional utility, each multiplied by its weighting function wc and we, respectively.

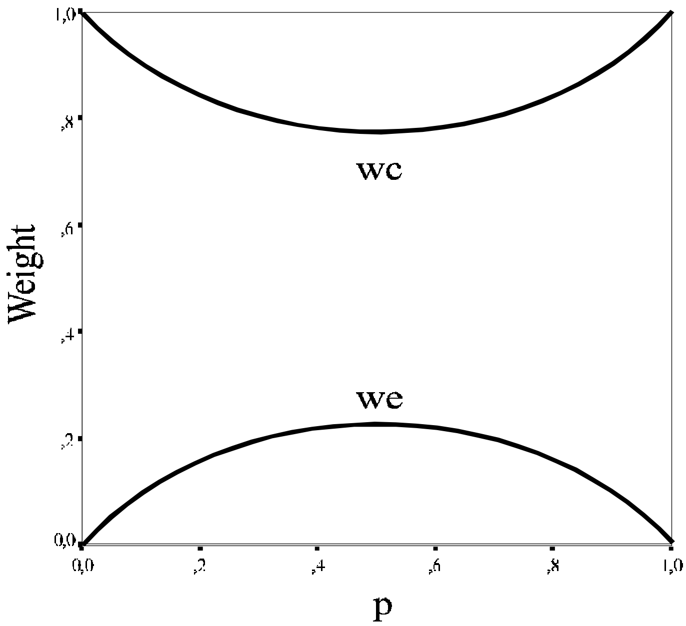

Figure 3. Predicted weighting functions wc and we for the cognitive and emotional utility, respectively.

Relations to Other Models

Compared to disappointment theory (Bell, 1982, 1985) some fundamental differences exist: Firstly, disappointment theory assumes that decision makers anticipate both elation for gains and disappointment for non-gains, whereas our model assumes that decision makers simplify the decision task by just anticipating gains but ignoring non-gains. Following prospect theory they are more prone to anticipate changes than non-changes from a neutral reference point. Secondly, our model assumes a compromise between cognitive and emotional processes, a notion which is absent in disappointment theory. Psychologically we assume that cognitive and emotional processes exclude each other: Higher weighting of surprise leads to lower weighting of cognitive calculations and vice versa.

Overview over our Experiments

To test our theoretical hypotheses we conducted four experiments. Experiment 1 is a rating experiment; and experiments 2, 3, and 4 are based on choices. In experiment 1 we do the groundwork and measure the utility derived from expected and unexpected gains. The experiments 2-4 (i) try to replicate the overall probability weighting function W (p) and (ii) to investigate the weighting function for surprise We (p). This is done to estimate the unmeasurable weighting functions wc and we, since when we know W (p) and We (p) it is possible to calculate wc and we algebraically to see whether their shapes are in line with the model (see figure 3).

Experiment 1

Experiment 1 was done to estimate the emotional utility resulting from gambles. Participants simply had to indicate how happy they would be with a specified win.

Method

Twenty-one participants from an introductory Psychology class at the University of Salzburg volunteered to participate in study 1 (15 females, 6 males, *AM* = 21.4 years, *SD* = 4.1). Participants were asked to imagine having participated in a lottery and having won. Then they were presented with a series of gambles described by the probability of winning and the amount won. We varied 9 probability levels (.01, .05, .1, .3, .5, .7, .9, .95, .99) and 3 different winning amounts ($4, $40, $120). By completely crossing probabilities and amounts, we ended up with 27 different gambles. Participants had to evaluate each gamble on a scale from 0 (would not at all be happy) up to 6 (would be really happy). To control for order effects, four different orders of gambles were produced.

Results and Discussion

The results are shown in Figure 4. We averaged over the 3 amounts of money and found that the emerging picture was very similar to the one we expected. These findings show a convex utility function with higher levels of happiness for lower probabilities. That is, small probabilities cause disproportionally more happiness than high probabilities.

Ue thus has the expected shape. We suggest that the emotional component can be best understood as a psychophysical function of *surprise*, dependent on the levels of probabilities. It is important to distinguish this psychophysical function for the emotional component from a psychophysical function that captures subjective estimates of probabilities, which people derive from real world events. That is, the subjective estimate of a probability and the emotional reaction to this estimate are two different processes. To control for the former, in all experiments herein subjects receive prefabricated, stated probabilities.

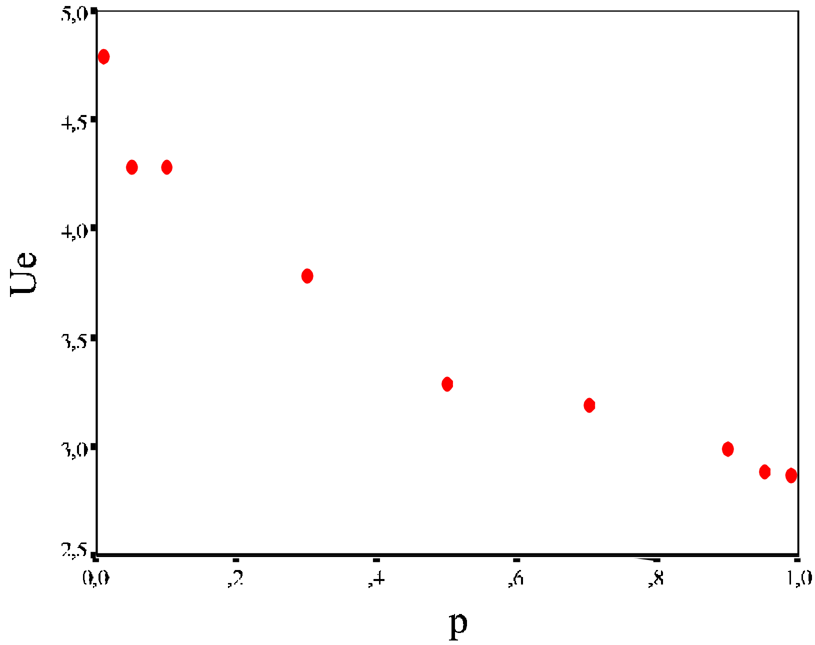

Figure 4. Medians for experienced joy about winning money, plotted as a function of probability.

Experiments 2-4

Each of these experiments consisted of two sessions. Session 1 always explored the probability weighting function W (p), session 2 always explored the weighting function We (p) for the emotional utility Ue. Experiment 2 used a between, and the experiments 3 and 4 were within subjects designs. In experiments 3 and 4 the order of the sessions was reversed.

Method

Participants. Participants were students from the University of Linz. The participants in the second experiment were 31 students (15 males, 16 females, *AM* = 23.3 years, *SD* = 4.4) for session 1, and 26 students (11 males, 15 females, *AM* = 24.8 years, *SD* = 4.5) for session 2. The participants in the third experiment were 50 students (31 males, 19 females, *AM* = 24.0 years, *SD* = 4.0). The participants in the fourth experiment were 32 students (25 males, 7 females, *AM* = 23.5 years, *SD* = 4.4).

Procedure. All experiments were run using a computer. For session 1 we employed the same procedure used by Tversky and Fox (1995).[1] Therein subjects made choices between a descending series of sure payments and an uncertain prospect. For instance, a person had a choice between an uncertain prospect to win $160 with probability .3 (and nothing otherwise) or a sure payment of \$50. The prize for the prospect always was \$160 and subjects determined their certainty equivalent (CE) for each of 19 different probabilities. The probabilities for the 19 prospects varied between .05 and .95, in multiples of .05. In session 1 the sure payments were always less than \$160.

Session 2 presented a different cover story. Subjects had to imagine two people who got a present. Person A got a coupon which promised a sure payment, while person B got a lottery ticket. For instance, person A got a coupon worth \$170, person B got a lottery ticket which offered to win \$160 with $p = .05$. After a week, person A exchanges the coupon and receives the expected \$170, whereas person B joins the draw and actually wins \$160. Subjects then had to decide "Who is spontaneously happier?" As in session 1 the probabilities for the 19 lottery tickets varied between .05 and .95, in multiples of .05. To avoid ceiling effects, the coupon values were presented in ascending order, evenly spaced between \$161 and \$480. Note, contrary to session 1, in session 2 the sure payments are always greater than the lottery amount (i. e. greater than \$160). This is important since it shows that in a rational sense such a question does not make sense: Who will be spontaneously happier, the one who gets more for sure or the one who gets less with some probability $p < 1$? Clearly, this is a question not aimed at a cognitive but at an emotional answer.

Results and Discussion

According to prospect theory the utility for a prospect to win \$x with probability *p* and nothing otherwise is U = W (p) * v (x). Because subjects stated their certainty equivalents (CE) for each prospect, it follows that v (CE) = W (p) * v (x) and W (p) = v (CE) / v (x). To estimate the subjective value of the certainty equivalent (CE) and the prize (x), we used a power function with an exponent of 0.88, which emerged empirically as a median estimate for subjective value (Tversky & Kahneman, 1992). We comment more on this issue in the general discussion section.

Figures 5, 6, and 7 show the median decision weights W (p) together with the probability weighting functions for the three experiments 2-4. The smooth curves in these figures were obtained by fitting the parametric form: $W(p) = a * p^b / (a * p^b + (1-p)^b)$ (see Lattimore, Baker & Witte, 1992; Tversky & Fox, 1995). The fit for another two-parameter function, $W(p) = p^a / (p^a + (1 - p)^a)^b$, Wu and Gonzales (1996), is similar with a = .79, b = 1.5 for experiment 2, a = 0.72, b = 1.35 for experiment 3, and a = 0.79, b = 0.95 for experiment 4. The findings clearly confirm previous research, by showing that people overweight low and underweight high probabilities.

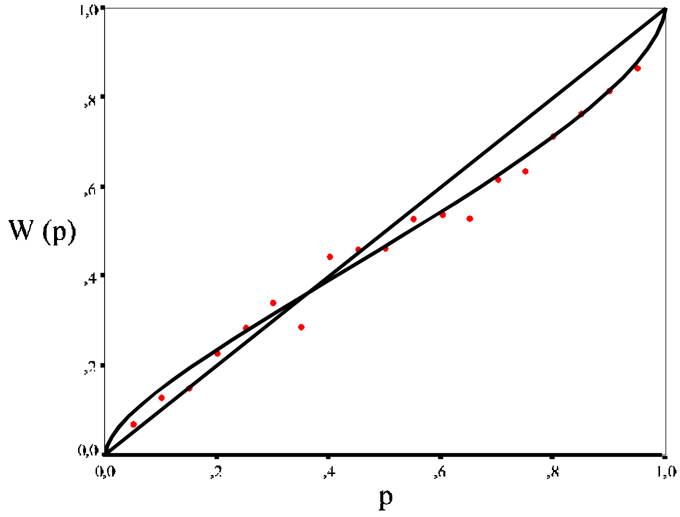

Figure 5. Median decision weights from experiment 2 plotted as a function of probability. Parameters for smooth curve: a = 0.87, b = 0.75.

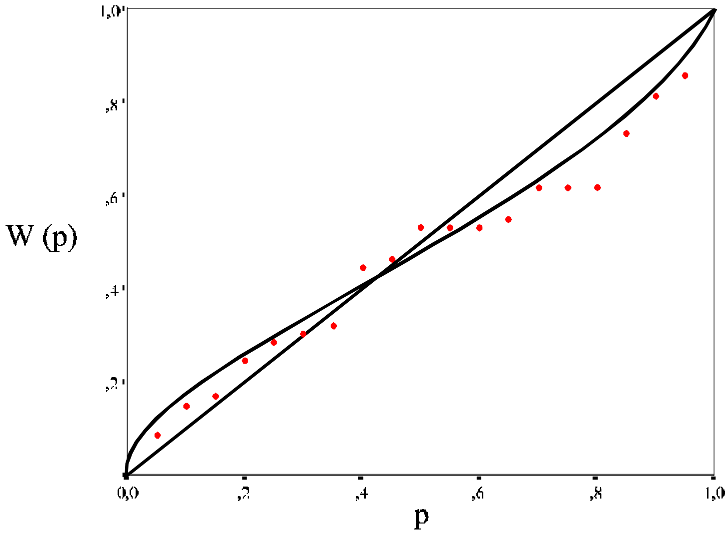

Figure 6. Median decision weights from experiment 3 plotted as a function of probability. Parameters for smooth curve: a = 0.88, b = 0.68.

Figures 8, 9 and 10 depict the medians of the emotional weighting function We (p) estimated from session 2 in the three experiments. As expected, the median intensities for We (p) decrease with higher probabilities, thereby supporting the findings of the rating study in experiment 1. Small probabilities evoke disproportionally higher levels of surprise.

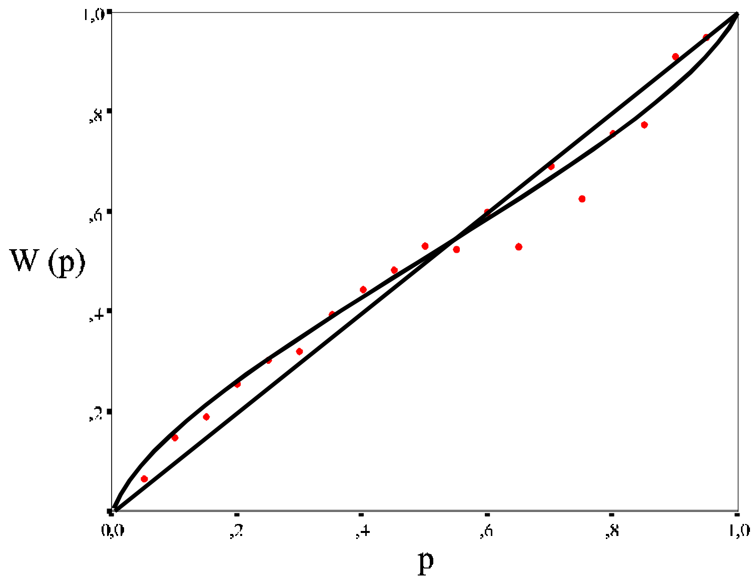

Figure 7. Median decision weights from experiment 4 plotted as a function of probability. Parameters for smooth curve: a = 1.0, b = 0.79.

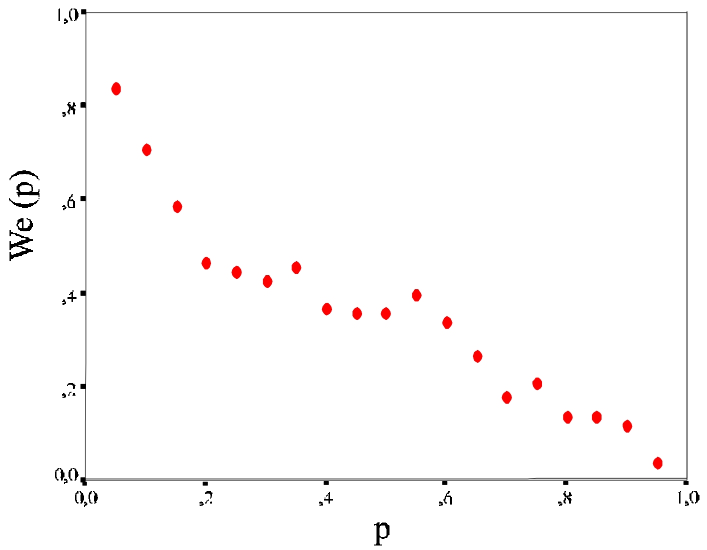

Figure 8. Weighting function We for emotional utility: Medians from experiment 2, plotted as a function of probability.

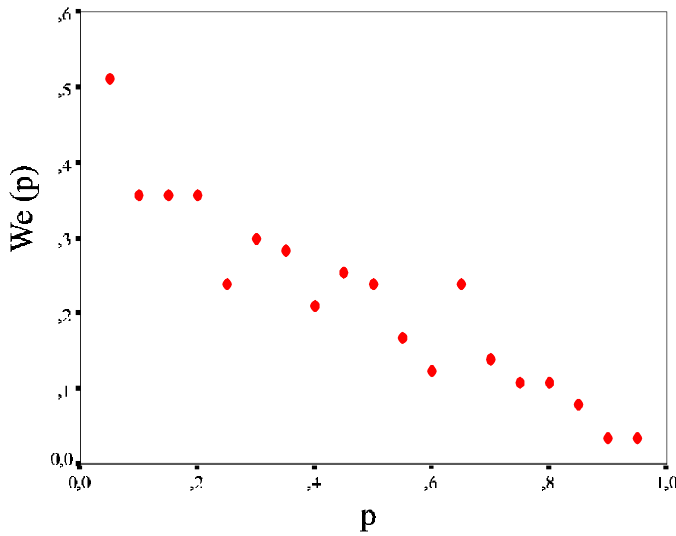

Figure 9. Weighting function We for emotional utility: Medians from experiment 3, plotted as a function of probability.

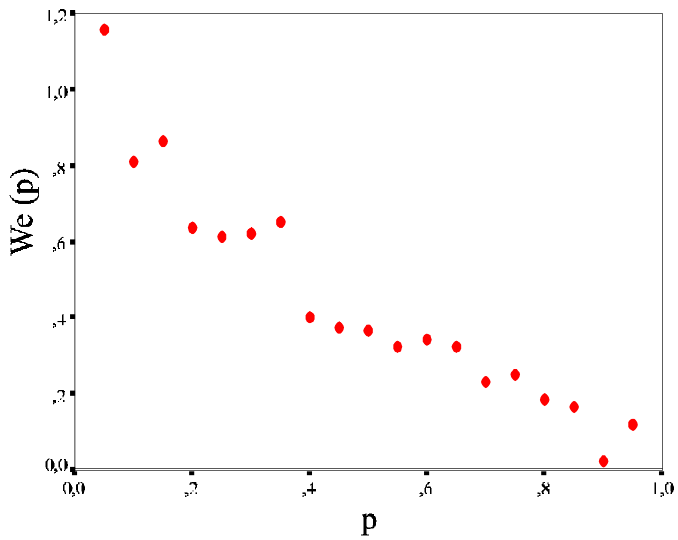

Figure 10. Weighting function We for emotional utility: Medians from experiment 4, plotted as a function of probability.

Although the results of the three studies generally support our model, Figures 7 and 9 show slight deviations from the expected pattern. Recall, because we reversed the order of session 1 and session 2 for experiment 4 compared to experiment 3, both figures show the second session of a within subjects design. Hence, deviations from the expected pattern could well be attributed to order effects such that subjects had troubles to switch from one session to the other. Further support for this conjecture comes from the maximum median value in Figure 9, which is substantially lower than that of the Figures 8 and 10. That is for Figure 9, after having judged on a mainly cognitive basis in session 1, subjects might had difficulties to base their choices on purely emotional grounds, as required in session 2. Conversely, in Figure 7 subjects might had difficulties to switch from emotionally to cognitively based choices. However, despite these possible order effects, the data are generally well in line with the predictions.

Finally, the weighting functions wc and we for the objective probabilities *p* and the weighting function We for the emotional utility, respectively, may provide further support to the proposed model. We predicted functions similar to those depicted in Figure 3. To estimate the beta-weights for wc and we empirically we used the nonlinear regression:

W (p) = wc * p + (1 – wc) * We (p) (6)

W (p) ... Probability weighting function; medians obtained from session 1

p ... Objective probabilities

We (p) ... Weighting function for emotional utility; medians obtained from session 2

wc ... ($ß_o + ß_1 * p + ß_2 * p^2$), weighting function for *p*

(1 – wc) ... we; weighting function for We

Following Figure 3, for wc and we quadratic functions seem sufficient. The amounts of explained variance (R^2) for experiment 2, 3 and 4 are .99, .97, and .98, respectively[2]. Figures 11 to 13 depict the empirical weighting functions for all three experiments.

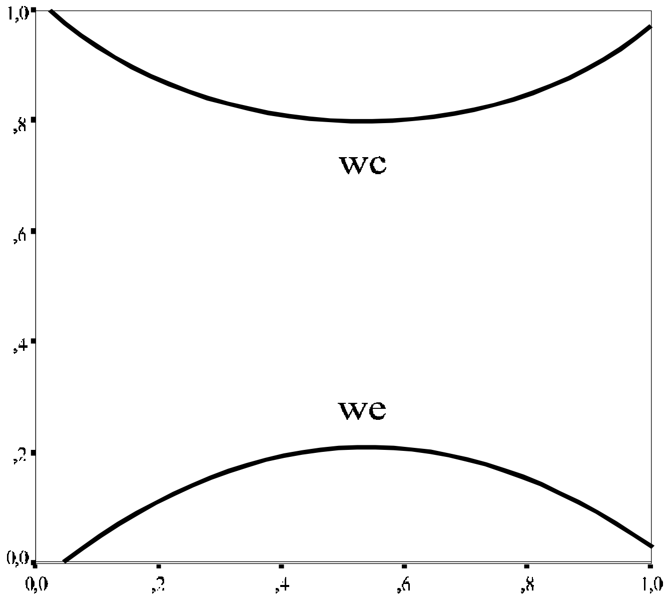

Figure 11. Empirical weighting functions we and wc for the emotional and cognitive utility, respectively, from experiment 2.

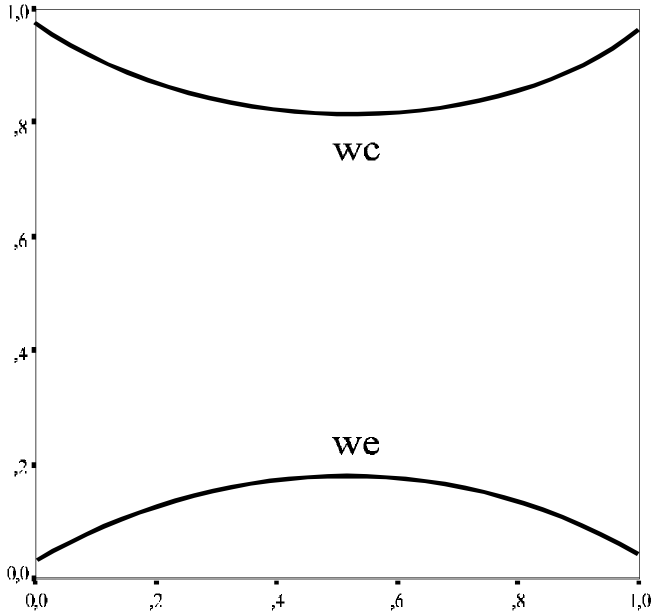

Figure 12. Empirical weighting functions we and wc for the emotional and cognitive utility, respectively, from experiment 3.

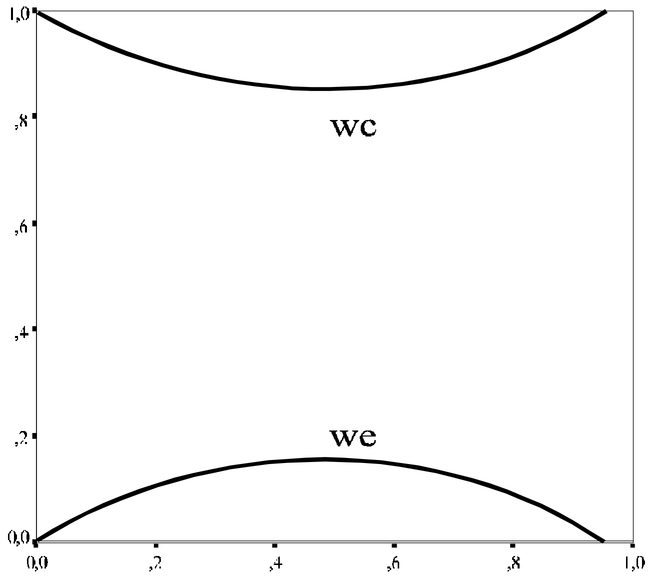

Figure 13. Empirical weighting functions we and wc for the emotional and cognitive utility, respectively, from experiment 4.

In general, the results confirm the predictions in all three experiments. The cognitive utility is always more heavily weighted than the emotional utility, and the cognitive utility is more important near the endpoints of zero and one than in the middle of the probability scale. Furthermore, the cognitive and emotional utility are complementary to each other. Interpreted freely, this shows that people have to face reality near zero and one, whereas they have more freedom for their illusions for moderate probabilities.

General Discussion

We proposed a psychological model to account for over- and underweighting of probabilities in decisions under risk. Seen as a whole, data of four experiments corroborate the notion of the probability weighting function as a composite of cognitive and emotional processes, each weighted by a different function. Therefore, the present article elaborates on previous research in several respects: Firstly, over- and underweighting of probabilities is distinguished from impossibility and certainty effects, as shown in Figure 1, because the certainty and impossibility effect alone do not suffice to explain over- and underweighting of probabilities. Secondly, we suggest a psychophysical function for surprise as a cause to influence utility. Thirdly, the model contains a detailed formal conceptualization of the interplay between cognitive and emotional processes. Both a relatively simple paper-and-pencil rating experiment as well as three more sophisticated computer-based choice experiments for measuring the weighting functions W (p) and We (p) arrive at the same conclusion–a convergence that corroborates the validity of method and findings.

One may object that the empirical shape of the probability weighting function W (p) is crucially dependent on the shape of the value function, for which we used a power function with an exponent of .88. As mentioned, this exponent emerged as an empirical estimate for the value function (Tversky & Kahneman, 1992). However, for two reasons we do not think that the specific shape of the value function imposes a high impact on the empirical estimation of the probability weighting function W (p): Firstly, when we used a linear value function the shape of the probability weighting function was very similar to the shape we obtained when we used a power function with an exponent of .88–this finding in line with that of Tversky and Kahneman (1992). Secondly, and even more important, Wu and Gonzalez (1996) developed a method that enables the estimation of the probability weighting function W (p) without any assumptions about the value function. Again, their results support the inverted S-shape of the probability weighting function. Interestingly, they obtained an averaged exponent *b* for the probability smooth curve of .68, which comes close to our averaged exponent *b* of .74. Moreover, the averaged linear parameters *a* for the probability smooth curves are .84 and .91, for their and our experiments, respectively. In sum, although some variations in the parameters occurred, the specific exponent used for the value function does not seem to influence crucially the basic shape of the probability weighting function (see also Wu & Gonzales, 1996 for further details).

Are violations of subjective expected utility theory irrational?

We argued that unexpected events–i. e. events with a low probability of occurrence–elicit more intense emotions than expected ones. As a consequence, repeated exposure to the same stimulus leads to habituation of the organism to this stimulus; organisms thus show increasingly less intense physiological responses.

Given surprise as a ubiquitous phenomenon, the question arises whether deviations from a linear probability function constitute "cognitive errors" and "irrationalities", as the "heuristics and bias approach" has argued (see Kahneman, Slovic, & Tversky, 1982 for a review), or whether these deviations may even be rational.

Rationality is usually defined as the way of thinking that best helps people to achieve their goals, as Baron (1997) put it: "If it should turn out that following the rules of formal logic leads to eternal happiness, then it is 'rational thinking' to follow the laws of logic (assuming that we all want eternal happiness). If it should turn out, on the other hand, that carefully violating the laws of logic at every turn leads to eternal happiness, then it is these violations that we shall call 'rational'" (p. 29). Hence, it follows that a rational decision maker could maximize utility by finding some compromise between the two different sources of utility–the short term utility derived from winning and the long term utility derived from possession.

We suggest that short-term effects directly depend on the emotional utility, as we have called it. That is, in the short run low probabilities cause more utility than large probabilities, as the probability weighting function suggests. Hence, both overweighting of small and underweighting of large probabilities would be rational.

However, even in the long run overweighting of small probabilities can be rational, as the following perspective suggests. Elster and Loewenstein (1992), referring to Bentham, notice:"... much of the pleasure and pain we experience in daily life arises not from direct experience–that is, 'consumption'–but from contemplation of our own past or future..." (p. 213f). In this sense people could derive pleasure by remembering the past joyful event of winning.

The mimic of surprise, especially characterized by high eye brows, is one of six basic emotions that was correctly identified by all investigated cultures of the world (Ekman, Sorenson, & Friesen, 1969), thus supporting surprise as a fundamental, universal, and biologically transmitted emotion. Given these considerations one may ask for the specific purpose of this very general principle. We think that surprise indicates a discrepancy between a mental model and a state of the world. Because correct mental models are crucial for surviving, surprise may be the first step that motivates persons to adapt their inadequate mental models to outside conditions.

In sum, instead of interpreting deviations from a linear probability scale as "biases" or even "cognitive errors", an analysis, which considers two different sources of utility, arrives at the conclusion that nonlinearity in the weighting of probabilities may be a consequence of an intelligent compromise between two different sources of utility: the cognitive and the emotional.

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Footnotes

1 See there for a detailed description of session 1.

2 Estimating two different quadratic weighting functions wc and we, by adding three additional parameters ß$_3$, ß$_4$, and ß$_5$ for we, did not increase model fit. The beta weights β_0, β_1, β_2 for wc are 1.03, -0.89, 0.83 for experiment 2, respectively; 0.96, -0.55, 0.53 for experiment 3, and 1.0, -0.61, 0.63 for experiment 4, respectively.