Journal of Economic Behavior & Organization 78 (2011) 14–24

Contents lists available at ScienceDirect

Journal of Economic Behavior & Organization

journal homepage: www.elsevier.com/locate/jebo

Risk and rationality: The effects of mood and decision rules on probability weighting☆

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ARTICLE INFO

Article history:
Received 25 July 2008
Received in revised form
23 December 2010
Accepted 23 December 2010
Available online 14 January 2011

JEL classification:
D81
C49

Keywords:
Probability weighting function
Risk taking behavior
Incidental emotions
Rationality
Gender differences

ABSTRACT

Empirical research has shown that people tend to overweight small probabilities and underweight large probabilities when valuing risky prospects, but little is known about factors influencing the shape of the probability weighting curve. Based on a laboratory experiment with monetary incentives, we demonstrate that pre-existing good mood is significantly associated with women's probability weights: Women in a better than normal mood tend to weight probabilities relatively more optimistically. Many men, however, seem to be immunized against effects of incidental mood by applying a mechanical decision criterion such as maximization of expected value.

1. Introduction

In the past decades, abundant experimental evidence has challenged the canonical economic model of decision under risk, expected utility theory. A large number of findings suggest that people systematically violate the axioms of expected utility theory (for a review see Starmer, 2000). In particular, people's choices often exhibit a fourfold pattern: They are risk averse for high-probability gains and low-probability losses, and risk seeking for low-probability gains and high-probability losses. This phenomenon led Kahneman and Tversky (1979) and Tversky and Kahneman (1992) to incorporate an inverse S-shaped probability weighting function as a core component in their prospect theory.

But why would people weight objective probabilities? Kahneman and Tversky justify the shape of the probability weighting function by the psychological principle of diminishing sensitivity, i.e. the psychological impact of a marginal change decreases as one moves further away from a reference point. This principle implies a probability weighting function that is steep near the reference points, naturally taken to be impossibility and certainty, and relatively flat in the middle.[1] However,

☆ This research was supported by the Swiss National Science Foundation, Grant #100012-109907. A previous version, titled "Risk and Rationality: The Effect of Incidental Mood on Probability Weighting", is available at http://www.soi.uzh.ch/research/wp/2007.html.

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[1] Tversky and Wakker (1995) discuss the properties of the preference order that are necessary and sufficient for an S-shaped probability weighting function. Prelec (1998) as well as Gonzalez and Wu (1999) provide axiomatic foundations for specific functional forms of the weighting function.

0167-2681/$ – see front matter
doi:10.1016/j.jebo.2010.12.004

there is vast individual heterogeneity in the specific shape of the probability weighting function. So far, little is known about factors driving the curvature of the probability weighting function, let alone about determinants of individual differences. One exception is the decision maker's gender: On average, women's probability weighting curves depart more strongly from linear weighting than do men's curves (Bruhin et al., 2010).

Several generalizations of expected utility theory offer a rationale for the shape of the probability weighting function by invoking anticipated emotions (Bell, 1982; Loomes and Sugden, 1986; Gul, 1991; Wu, 1999). Recently, for instance, Walther (2003) has shown that an S-shaped transformation of probabilities may result if decision makers anticipate elation or disappointment at the time when uncertainty is resolved. His model of affective utility predicts that higher sensitivity to anticipated emotions leads to greater departures from linear probability weighting.[2]

While anticipated emotions have been integrated into economic models of behavior under risk, this is not the case for incidental emotions, like mood states or emotions carried over from recent experiences, which have no causal link to the decision at hand. In the psychology literature, there is a large body of empirical evidence on the effects of incidental emotions on judgment and decision making (Loewenstein and Lerner, 2003; Pham, 2007). Numerous studies show that incidental mood states generally have mood-congruent effects on perception and object valuation. Risks are perceived to be higher under negative moods than under positive moods (Johnson and Tversky, 1983; Wright and Bower, 1992).[3] In these studies, probabilities are typically not presented as objective numbers but have to be assessed subjectively. Wright and Bower (1992) also detected a susceptibility effect. When judging more frequently occurring events participants exhibit higher susceptibility to mood states than when judging less frequent ones.

It is an open question whether these results on probability assessment carry over to the valuation of risky prospects with stated objective probabilities. If so, risk preferences may be less stable than assumed by economic theory, and subject to factors completely irrelevant to the decision at hand. The experimental literature reports that subjects often choose differently when confronted with the same decision problems at different occasions. The percentage of subjects with preference reversals has been found to be quite substantial (Hey and Orme, 1994). While many authors would attribute this phenomenon to errors, some of this variation could well be due to sensitivity to incidental emotions.

Whereas studying mood and affect has a long tradition in psychology, economists have only recently become interested in this field of research. Examples of experimental work include Capra (2004) and Kirchsteiger et al. (2006), both of which show significant effects of mood state on behavior in games. If incidental mood also influences decisions under risk, the effect could work via two pathways. Mood states could either affect the valuation of monetary outcomes or probability weighting or both. We conjecture that, in the context of financial decision making, the valuation of monetary outcomes is less susceptible to incidental affect than are probability weights. This hypothesis seems particularly plausible in the light of experimental evidence showing that probability weights seem to be the more malleable component of risk taking attitudes (Fehr-Duda et al., 2010; Abdellaoui et al., in press). We therefore hypothesize that people in good moods should weight probabilities more optimistically, i.e. they should put a relatively higher weight on gain probabilities and a relatively lower weight on loss probabilities, than do people in a neutral state.

This paper addresses the question of individual mood effects by estimating the parameters of a sign- and rank-dependent decision model. We elicited certainty equivalents of a large number of lotteries involving real gains and losses, which enabled us to estimate individual probability weighting functions. Mood states were accounted for by a binary variable indicating whether subjects reported to be in a better than usual mood or not.

To our knowledge, this is the first experimental study that sheds light on individual differences in probability weighting.[4] In particular, we show that incidental feelings may have an effect on decision making under risk, rendering risk preferences potentially susceptible to factors irrelevant to the decision at hand. Even though there is no significant gender difference in reported mood states, we find a substantial gender effect in sensitivity to self-reported good mood: Our findings indicate that, in support of our conjecture, women in a better than normal mood tend to weight probabilities more optimistically. No such effect can be detected in average men's behavior. This finding can be explained by two factors: First, contrary to women, a considerable percentage of men use expected values as a guideline to decision making, which seems to immunize them against mood states. Moreover, we show that these men's behavior is indeed consistent with expected value maximization. Hence, the gender difference in decision strategy may also explain why the average male probability weighting curve departs less strongly from linear weighting than does the female one. Second, men who do not apply this decision rule behave congruently with good mood, but to a much lesser degree than do women.

[2] To our knowledge, this theory has not been tested systematically. However, the study by Rottenstreich and Hsee (2001) may be interpreted as preliminary evidence: The authors report that people tend to be less responsive to probabilities when they react to emotion-laden targets, such as a kiss by one's favorite movie star or an electric shock, than they do in the case of comparatively pallid monetary outcomes.

[3] Isen and her colleagues contest the validity of mood-congruent behavior in the context of risk taking, however (Isen and Patrick, 1983; Isen and Labroo, 2003). They argue that people in a good mood stand to lose their affective state as well as their monetary stake, and therefore may behave more cautiously (see also Kliger and Levy, 2003).

[4] A recent paper by Mukherjee (2010) investigates the link between probability weighting and thinking style. His data is based on four choices only and, therefore, not suitable to disentangle utility of outcomes and probability weighting. Kliger and Levy (2008) recover probability weighting functions from *market data* on asset returns and relate them to proxies of mood, such as the degree of cloud coverage.

The paper is structured as follows. Section 2 explains the experimental design and procedures. After analyzing the raw data in Section 3, the econometric model for estimating the risk parameters is specified in Section 4. Section 5 presents our results, followed by a general discussion in Section 6.

2. Experimental design and data

In the following section we describe the experimental setup and procedures.[5] We recruited 107 students, 58 men and 49 women, of various fields at the University of Zurich and the Swiss Federal Institute of Technology Zurich. From each subject, we elicited certainty equivalents for 50 two-outcome lotteries. 25 of these lotteries were framed as choices between risky and certain investment gains ("gain domain"). The remaining 25 decisions were presented as choices between risky repair costs and certain insurance costs ("loss domain"). Expected payoffs for the insurance decisions, including lottery-specific initial endowments, were equal to the expected investment payoffs. Gains and losses ranged from zero Swiss Francs[6] to 150 Swiss Francs with probabilities p of 5, 10, 25, 50, 75, 90, and 95%.[7] The expected payoff per subject amounted to 31 Swiss Francs, which was considerably more than a local student assistant's hourly compensation, plus a show up fee of 10 Swiss Francs, thus generating salient incentives.

The lotteries appeared in random order on a computer screen (see Figure A1 in the Appendix, available online). The screen displayed the respective lottery and a list of 20 equally spaced certain outcomes ranging from the lottery's maximum payoff to the lottery's minimum payoff. The subjects had to indicate whether they preferred the lottery or the respective certain payoff in each row of the list. The lottery's certainty equivalent was calculated as the arithmetic mean of the smallest certain amount preferred to the lottery and the subsequent certain amount on the list.[8]

After completion of the decision tasks, subjects had to fill out a questionnaire on socioeconomic information, such as age, gender, and income, as well as state of mood. Subsequently, one of their choices was randomly selected for payment by rolling dice. They were paid in private afterward. Subjects could work at their own speed, the vast majority of them needed less than an hour to complete the experiment including the questionnaire.

Ideally, to be able to draw inference on causal relationships, the experimenter would prefer to induce different states of mood by an appropriate procedure (Westermann et al., 1996). Given the large number of observations necessary to reliably estimate risk preference parameters, induced mood is likely not to be sufficiently persistent to last through the session. For this reason, we utilize a self-reported measure constructed from the answers to the question "How has your day been going?". Our choice of question reflects the characterization of mood as a general background feeling building up as a consequence of prior incidents or conditions in the environment (Parkinson et al., 1996). People come to the lab with a history of experiences made in the course of the day. Presumably, pleasant experiences trigger diffuse feelings of well-being and, consequently, may influence people's attitudes toward risk (Loewenstein and Lerner, 2003).[9]

The mood variable was constructed in the following way: Subjects indicated whether their day had been worse or better than usual by marking a number between 0 ("worse") and 5 ("promising") with values between 2 and 3 meaning "as usual". Subjects were assigned GOODMOOD = 1 when they indicated values of 4 or 5, they were assigned GOODMOOD = 0 otherwise. This scale naturally induces a neutral reference state and controls for subjects' propensity to feeling generally rather good or bad. The majority of subjects, namely 52%, indicated a neutral state, fewer than 10% reported their day to have been going worse than usual.[10] The remaining subjects, 37.5%, reported a better than normal state.[11]

Aside from the focal variable GOODMOOD we included a number of controls. They are defined as follows. To capture potential effects of calculating expected payoffs, we constructed a binary variable EXVALUE. Subjects were asked to "briefly explain the criteria influencing [their] decisions during the experiment". The answers to this open question were encoded in the following way. Some subjects explicitly mentioned that they had calculated the lotteries' expected payoffs; some others described a procedure which closely resembled the calculation of expected values. The binary variable EXVALUE was assigned the value of 1 for subjects in these two categories, for everyone else the variable was set to zero. INCOME

[5] The experiment, programmed in z-Tree (Fischbacher, 2007), took place in Zurich in 2003. The data was also used in Fehr-Duda et al. (2006) and Bruhin et al. (2010). Instructions are available upon request.

[6] One Swiss Franc currently equals about one U.S. Dollar.

[7] The lotteries for the gain domain are presented in Table A1 in the Appendix, available online.

[8] When subjects switched from preferring the certain amount to preferring the lottery more than once, we applied the following rule: If the subject had switched back and forth for three or more lotteries, all her decisions were excluded from the data set. For fewer errors, only the subject's inconsistent decisions were ignored. In total, we analyze 50 men's data and 40 women's data after excluding 9 women's and 8 men's responses.

[9] Our question constitutes an indirect way of tapping mood. In order to validate our approach we asked subjects both our indirect question and a direct one "Rate how you feel" on an otherwise identical scale (Capra et al., 2010) during another experiment with comparable monetary incentives, comparable duration and similarly cognitively demanding tasks. One group of subjects was confronted with the direct question first and the indirect question later in the questionnaire, the other group received the questions in reversed order. The answers to the different types of mood questions are highly significantly correlated (Spearman rank correlations 0.66 and 0.60 with p-value <0.001, respectively).

[10] Because of the low percentage of bad-mood reports we could not investigate the effects of bad mood on behavior.

[11] The question was asked after completion of the experimental tasks, but before subjects were informed about their payoffs. Therefore, one might be concerned whether we measured mood effects originating from the experiment itself rather than pre-existing mood. Again, we have strong evidence against such a possibility: In another experimental session, subjects' ratings of "How has your day been going?" remained absolutely stable irrespective of whether the question was asked before or after the decision tasks (Spearman rank correlation 0.95, p-value <0.001). Therefore, we are confident to have reliably measured pre-existing affective state.

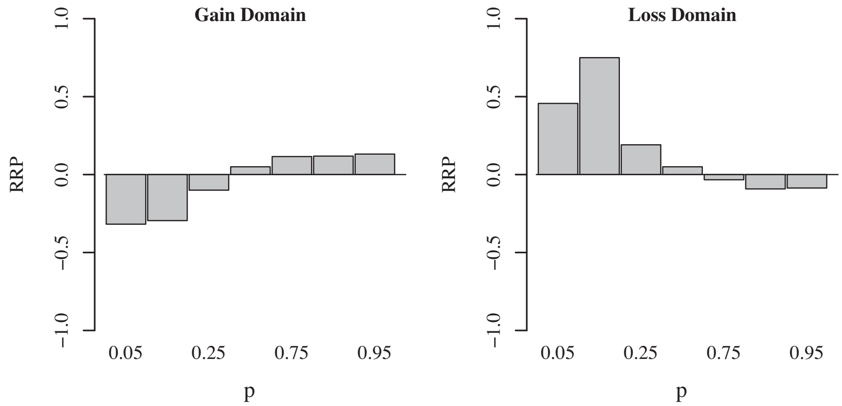

Fig. 1. Median relative risk premia by probability.

was measured in 1000 Swiss Francs and refers to the subjects' average monthly disposable income. SEMESTER denotes the number of semesters enrolled at university. Finally, the binary variable for investment experience, INVEST, was assigned a value of 1 if the subject herself had already made investments in stocks, bonds, options or other financial instruments; INVEST = 0 otherwise.

We tested all these variables with respect to gender differences.[12] Each one of the variables EXVALUE, INCOME, SEMESTER, and INVEST exhibits significant gender differences (judged by a Mann–Whitney test at conventional levels of confidence): There are significantly more men than women using expected values as a benchmark for decision making. 20 men, but only 3 women do so (*p*-value of Mann–Whitney test < 0.001).[13] This difference is quite surprising as about half of our female subjects are students at the Swiss Federal Institute of Technology with highly technical and mathematical curricula. Men have significantly higher incomes and have spent more semesters at university. Men are also more likely to be familiar with investment decisions (30% vs. 25%). GOODMOOD, however, does not show a gender effect. The percentage of men in a better than usual mood, 38.1%, is about the same as the corresponding percentage of women, 37.5% (*p*-value of Mann–Whitney test equals 0.698). In order to account for heterogeneity with respect to these factors, it is important to include them in the estimation procedure.

3. Descriptive analysis

Observed risk taking behavior can be conveniently summarized by relative risk premia $RRP = (ev - ce)/|ev|$, where ev denotes the lottery's expected value and ce stands for the observed certainty equivalent. $RRP > 0$ indicates risk aversion, $RRP < 0$ risk seeking, and $RRP = 0$ risk neutrality. Fig. 1 exhibits median risk premia sorted by the probability of the lotteries' highest gains or losses, respectively. Median *RRP* s display the familiar fourfold pattern of risk attitudes: subjects are risk averse for small-probability losses and large-probability gains, they are risk seeking for small-probability gains and large-probability losses.

Do we find any support for our hypothesis at the descriptive level, namely that subjects act congruently with their incidental mood states? At this level of analysis we cannot distinguish between effects on the valuation of outcomes and effects on probability weighting. A behavioral model, such as the one presented in Section 4, is needed for that purpose. To answer the question with respect to overall risk taking behavior, we checked whether measured risk premia differed significantly between subjects with GOODMOOD = 1 and those with GOODMOOD = 0.

For men, the null hypothesis that RRP and GOODMOOD are unrelated cannot be rejected. We observe highly significant differences for women at several levels of probability, however (see Table 1, particularly in the upper probability range). Differences in the median *RRP* s are mostly negative, indicating that GOODMOOD = 1 is associated with lower risk premia, i.e. with relatively more risk seeking behavior. Therefore, the descriptive analysis supports our conjecture that mood affects behavior, at least for women. At this stage of analysis, no mood effects seem to be detectable in men's behavior.

4. Econometric model

One objective of the current paper is disentangling the effect of mood state on outcome valuation from its effect on probability weighting. For this purpose we use an econometric model consisting of three components. First, we describe the behavioral model, i.e. our assumptions on how individuals evaluate risky prospects. Second, we specify the relationship

[12] Summary statistics by gender are shown in Table A2 in the Appendix, available online.
[13] For this reason, EXVALUE was not included when estimating the female parameters.

Table 1
Relationship of RRP with GOODMOOD

Women Probability	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Gains							
RRP-difference*	0.004	−0.227	−0.029	−0.100	−0.166	−0.025	−0.117
p-value**	0.956	0.763	0.463	0.005	0.004	0.409	0.003
Losses							
RRP-difference*	−0.012	−0.056	−0.000	−0.095	−0.335	−0.500	−0.476
p-value**	0.257	0.060	0.170	0.004	0.017	0.326	0.068

* Median RRP for GOODMOOD = 1 minus median RRP for GOODMOOD = 0.
** Mann–Whitney test.

between the parameters of the behavioral model and the variables that presumably influence the magnitude of these parameters. Third, in order to be able to estimate the parameters by maximum likelihood, we have to specify our assumptions on the distribution of the error term added on to the deterministic evaluation of lotteries.

In the following, we discuss the parameterization of the behavioral model. According to a sign- and rank-dependent model, as assumed for example by cumulative prospect theory, an individual values a two-outcome lottery $\mathcal{L} = (x_1, p_1; x_2)$, where $|x_1| > |x_2|$ by

$$v(\mathcal{L}) = v(x_1)w(p_1) + v(x_2)(1 - w(p_1)). \tag{1}$$

The function $v(x)$ describes how monetary outcomes x are valued, whereas the function $w(p)$ assigns a subjective weight to every outcome probability p. The individual's certainty equivalent $\hat{ce}$ can then be expressed as

$$\hat{ce} = v^{-1}\left[v(x_1)w(p_1) + v(x_2)(1 - w(p_1))\right]. \tag{2}$$

An obvious candidate for the value function is a sign-dependent power function:[14]

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -(-x)^{\beta} & \text{otherwise.} \end{cases} \tag{3}$$

A variety of options for modeling probability weights $w(p)$ have been discussed in the literature (Quiggin, 1982; Tversky and Kahneman, 1992; Prelec, 1998). We use the two-parameter specification suggested by Goldstein and Einhorn (1987) and Lattimore et al. (1992), which has proven to account well for individual heterogeneity (Wu et al., 2004):

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}, \quad \delta \geq 0, \ \gamma \geq 0. \tag{4}$$

We favor this specification because the parameters have an intuitive psychological interpretation (Gonzalez and Wu, 1999). The parameter δ largely governs the elevation of the curve, whereas the parameter γ largely governs its slope. The smaller the value of γ, the more strongly the probability weighting function deviates from linear weighing. In this sense, γ represents an index of rationality. The larger the value of δ, the more elevated the curve, ceteris paribus. Therefore, δ can be interpreted as an index of optimism. Linear weighting is characterized by $\gamma = \delta = 1$. In a sign-dependent model, the parameters may take on different values for gains and for losses.

Moreover, this specification of the probability weighting function allows us to translate our general conjecture into a hypothesis on the relative magnitude of parameter values. If good mood increases risk tolerance, the probability weighting curve for good-mood persons should be more elevated in the gain domain, i.e. the parameter estimate for δ should be significantly higher than for control subjects; in the loss domain, it should be lower.

While we do not have a gender-specific hypothesis on the relationship between mood and probability weights, we estimate the model separately by gender. The reason for this approach is the following: As Fehr-Duda et al. (2006) have shown, average female probability weighting functions differ from male ones in a specific way: Female curves tend to be relatively more S-shaped and exhibit significantly stronger underweighting of large probabilities than do male curves. In order to avoid too many tedious interaction terms, we decided to estimate gender-specific models rather than a general one.[15] In total, we estimate six gender-specific behavioral parameters: α, γ and δ for gains, as well as β, γ and δ for losses.

Next we specify the core component of our econometric model, the relationship between the behavioral parameters and the variables that may have an influence on their values. In principle, individual characteristics may affect the magnitude of

[14] This specification of the value function seems to lack a prominent feature of prospect theory, loss aversion. As Köbberling and Wakker (2005, p. 125) argue, loss aversion measures a decision maker's *attitude toward mixed gambles*, encompassing both gains and losses. However, our lottery design does not contain any mixed gambles. When there are only single-domain lotteries and a parameter of loss aversion λ is introduced in the conventional way, i.e. by assuming $v(x) = -\lambda(-x)^{\beta}$ for $x < 0$ and $\lambda > 0$, loss aversion λ is not identifiable: λ cancels out in the definition of the certainty equivalent $\hat{ce}$ of a loss lottery $(x_1, p; x_2)$ with $x_1 < x_2 \leq 0$, as $\lambda(-\hat{ce})^{\beta} = \lambda(-x_1)^{\beta}w(p) + \lambda(-x_2)^{\beta}(1 - w(p))$ holds for *any* value of λ.

[15] Results remain qualitatively unchanged when estimating a pooled model including the relevant interaction terms. Results are available upon request.

the parameters of the value functions as well as of the probability weights. Therefore, we assume the following relationship to hold for each single behavioral parameter ψ:

$$\psi = \theta_0 + \theta_1 z_1 + ... + \theta_K z_K, \tag{5}$$

where the dependent variable ψ represents any one of the parameters α, β, and the domain-specific γ and δ; z_k, $k = 1, ..., K$, are the individual explanatory variables GOODMOOD, INCOME, SEMESTER and INVEST. EXVALUE features solely in the male model as there is only a small number of women reporting the calculation of expected values. The coefficients θ_k, $k = 0, ..., K$, capture the average effect of the explanatory variables on the behavioral parameters. According to our hypothesis, the respective coefficient of GOODMOOD in the equation for δ should be positive for gains and negative for losses.

Finally, since our behavioral model explains *deterministic* choice we have to add an error term ε in order to estimate the parameters of the model based on the elicited certainty equivalents *ce* which can then be written as $ce = \hat{ce} + \varepsilon$. Note that the predicted certainty equivalent $\hat{ce}$ is a function of all the six different behavioral parameters $\psi(\theta_0, ..., \theta_K)$. We assume that these errors are normally distributed with zero mean. The estimation procedure accounts for heteroskedasticity resulting from lottery-specific, domain-specific, and individual-specific errors.

5. Results

5.1. Model selection

Estimating the econometric model by maximum likelihood yields estimates for the coefficients of the explanatory variables $\hat{\theta}_k$ and, in turn, for the parameters of the value and the probability weighting functions. As the descriptive analysis has shown, risk taking behavior is significantly associated with GOODMOOD, albeit only for women. With the parameter estimates at our disposal, we are now able to answer the question whether good mood affects the valuation of monetary outcomes or probability weighting. For this purpose, we estimated three gender-specific models with differing degrees of generality and conducted a series of likelihood ratio tests. First, we estimated the full model as described in the previous section, i.e. taking account of the presumed linear relationship between each one of the behavioral parameters and the explanatory variables. Second, we estimated an intermediate model with only the parameters of the probability weighting functions depending on the explanatory variables. Third, we restricted the model even further by omitting all the explanatory variables. The resulting least general model yields only representative behavioral parameter estimates.

The first likelihood ratio test was applied to the full model and the intermediate model. For both genders, the null hypothesis that these models explain behavior equally well cannot be rejected (p-values 0.066 (women), 0.201 (men)). This means that including GOODMOOD or the other controls does not contribute to explaining the curvature of the value functions. Therefore, the more parsimonious model should be preferred. The respective likelihood ratio test of the intermediate model against the representative agent model detects a highly significant difference in fit, however: The intermediate model is clearly preferred (p-value < 0.001 for both women and men). This means that including the explanatory variables when estimating probability weights greatly improves explanatory power. Therefore, we only present the parameter estimates for the intermediate model in Table 2. The table displays, by gender and domain, the coefficients $\hat{\theta}_k$ of the explanatory variables for γ and δ as well as the average values for all the behavioral parameters.[16] The variables INCOME, SEMESTER, and INVEST were included as controls. Standard errors are estimated by the percentile bootstrap method with 4,000 replications (Efron, 1979). Coefficients which are significant at 5% or less are displayed with an asterisk.

5.2. Mood effects

So far we have asserted that GOODMOOD does not significantly affect the valuation of monetary outcomes, but does it affect probability weights? Our hypothesis predicts more optimistic probability weighting, i.e. people in good mood should put a higher weight on gain probabilities and a lower weight on loss probabilities than do people who are not in a better mood than usual. As discussed in Section 4, this hypothesis implies that good mood should predominantly affect δ, the elevation parameter, namely positively for gains and negatively for losses. We first discuss our results on women's parameter estimates.

5.2.1. Mood effects on women's probability weights

In the gain domain, both coefficients of GOODMOOD for γ and δ are significantly positive. As expected, GOODMOOD has a stronger effect on δ, the elevation of the curve, but it also influences the slope of the probability weighting function. Given that the average female probability weighting function is rather flat in the middle part (average γ equals 0.377), GOODMOOD has a steepening effect, i.e. the resulting curve deviates less strongly from linear weighting.

Significance of both coefficients does not necessarily imply an overall significant effect on the shape of the probability weighting function, however, since γ and δ cannot move totally independently from each other. Whether the effect of GOODMOOD on probability weighting is significant has to be judged by comparing the confidence bands for the average good-mood curves with their no-good-mood counterparts. Fig. 2 depicts these curves for both domains. The black curves

[16] The additional variable GMOODxEV will be explained below. Findings on average parameter estimates are discussed in the Appendix, available online.

Table 2
Parameter estimates $\hat{\theta}_k$

Gains	Women			Men		
	α	γ	δ	α	γ	δ
Constant	0.981*	0.320*	0.662*	0.983*	0.547*	1.082*
	(0.045)	(0.039)	(0.059)	(0.020)	(0.064)	(0.070)
GOODMOOD		0.152*	0.143*		−0.039	0.171*
		(0.039)	(0.058)		(0.040)	(0.076)
EXVALUE					0.546*	0.170
					(0.080)	(0.093)
GMOODxEV					−0.194	−0.249
					(0.102)	(0.134)
Controls		Yes	Yes		Yes	Yes
Average	0.981	0.377	0.809	0.983	0.628	0.983
Losses	Women			Men		
	β	γ	δ	β	γ	δ
Constant	1.173*	0.306*	1.228*	1.016*	0.546*	0.963*
	(0.080)	(0.055)	(0.235)	(0.015)	(0.089)	(0.093)
GOODMOOD		0.080	−0.412*		−0.026	−0.189*
		(0.059)	(0.154)		(0.042)	(0.075)
EXVALUE					0.514*	−0.222
					(0.103)	(0.132)
GMOODxEV					−0.125	0.191
					(0.104)	(0.127)
Controls		Yes	Yes		Yes	Yes
Average	1.173	0.364	1.112	1.016	0.653	1.044

* Significant at 5%; bootstrapped standard errors in parentheses.
Controls: INCOME, SEMESTER, INVEST.

represent the average woman's probability weights with their 95%-confidence bands for GOODMOOD = 0, the gray curves for GOODMOOD = 1. All the other variables are evaluated at their means. The graph on the left-hand side of Fig. 2 shows that the confidence bands overlap for the lower range of probabilities, but diverge for the upper range. Being in a better than normal mood is associated with less underweighting of large probabilities, i.e. the average woman in a better than normal mood is less pessimistic about high-probability gains.

We now turn to the estimates for the female curve in the loss domain. GOODMOOD does not have a significant effect on the slope parameter γ, but it does have an effect on δ. The coefficient has the expected negative sign and exhibits a large absolute value, i.e. loss probabilities receive substantially lower weights. As the graph on the right hand side of Fig. 2 shows,

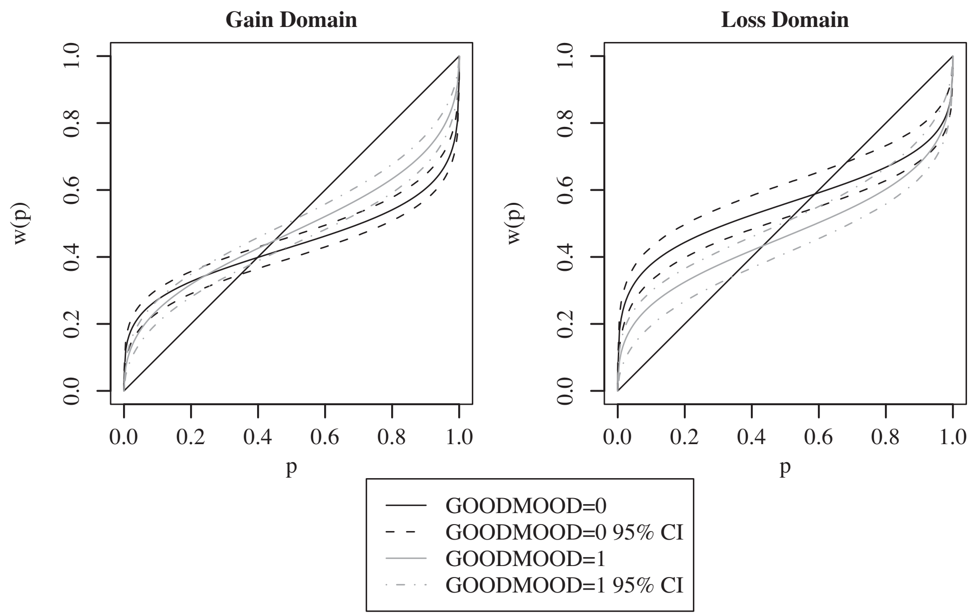

Fig. 2. GOODMOOD-effect on women's probability weights.

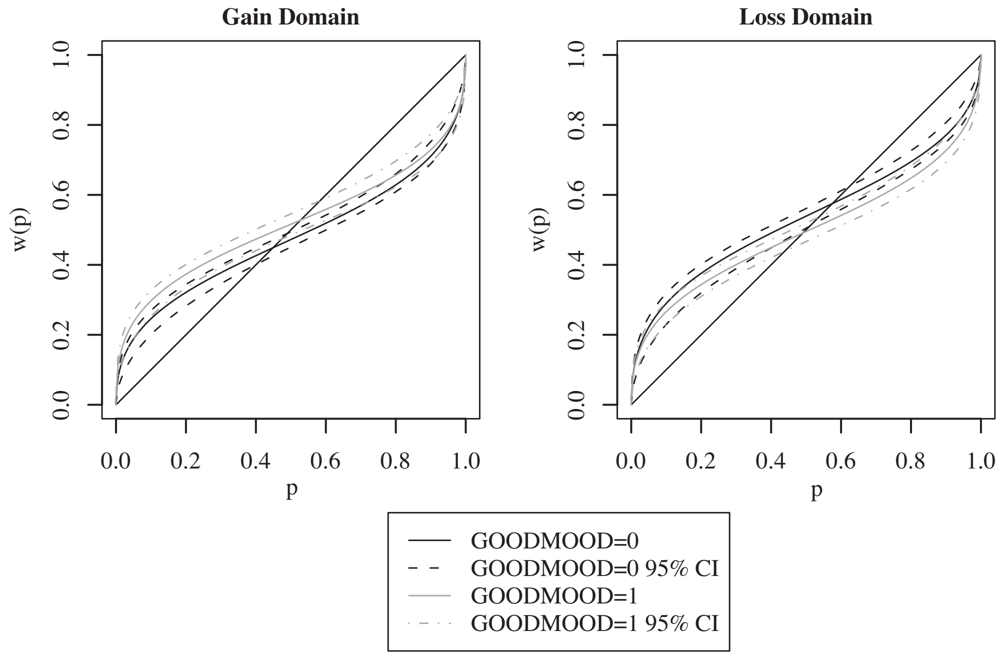

Fig. 3. GOODMOOD-effect on men's probability weights: EXVALUE = 0.

the 95%-confidence bands for the average curves constructed with GOODMOOD = 1 and GOODMOOD = 0, respectively, do not overlap for a considerable range of probabilities. For probabilities up to roughly 0.6, an average women in a good mood is significantly more optimistic. Due to the large coefficient of δ, the mood effect is somewhat more pronounced for losses than for gains. To sum up, for women, GOODMOOD has a significant effect on the shape of the probability weighting function for both gains and losses. For the range of probabilities which are typically associated with risk averse behavior, good-mood women are significantly less pessimistic than women who are not in a better than usual mood. The estimates of the behavioral model are consistent with our findings in Table 1. Our hypothesis can thus be supported.

Are women more susceptible to mood state at higher levels of probability? Inspection of estimated probability weighting graphs for GOODMOOD = 1 and GOODMOOD = 0 in the gain domain shows that the curves diverge with increasing probability. The opposite is the case for losses. We find a susceptibility effect, albeit of a different nature as the one discussed by Wright and Bower (1992). Women tend to be increasingly responsive to incidental feelings for more probable gains and less probable losses, i.e. for the range of probabilities where typically risk averse behavior is observed.

5.2.2. Mood effects on men's probability weights

Inspection of the men's side of Table 2 reveals that EXVALUE has by far the strongest influence on γ. For both gains and losses, the application of the expected value criterion is associated with a much steeper probability weighting curve. And indeed, it can be shown that men with EXVALUE = 1 exhibit near linear probability weights: In the gain domain the estimated average parameter values equal 0.99 for γ and 1.13 for δ; in the loss domain we find 0.98 for γ and 0.88 for δ. Therefore, as their value functions are also roughly linear, men who report computing expected values essentially behave as expected value maximizers. The curves are clearly S-shaped for the group of men who do not adhere to expected values. Since EXVALUE exerts such a strong influence on the curvature of the probability weighting functions, its effect might override any impact of good mood. We therefore included an interaction term of EXVALUE with GOODMOOD, GMOODxEV, in the estimation. GOODMOOD measures the mood effect on all men, irrespective of decision strategy. GMOODxEV captures the additional effect of good mood on men with EXVALUE = 1. In the following, we discuss the effect of good mood for both groups of men separately.

For men who do not use expected values, we have to inspect the coefficients of GOODMOOD alone. In accordance with our hypothesis we find a significant effect in the estimates for δ: The coefficient of GOODMOOD is significantly positive for gains, elevating the curve, and significantly negative for losses, depressing the curve. The coefficients exhibit about the same order of magnitude. Do these effects on δ suffice to significantly change the overall shapes of the curves? Fig. 3 shows that, over some range, probability weighting by good-mood men is almost significantly more optimistic. But even though good mood results in a change in the elevation of the probability weighting curves, the effect is not strong enough to manifest itself in differing risk taking behavior.

What about the men who apply the expected value criterion? In this case, the sum of the coefficients of GOODMOOD and the interaction term GMOODxEV is relevant for judging the effect of incidental mood on probability weighting. Presumably,

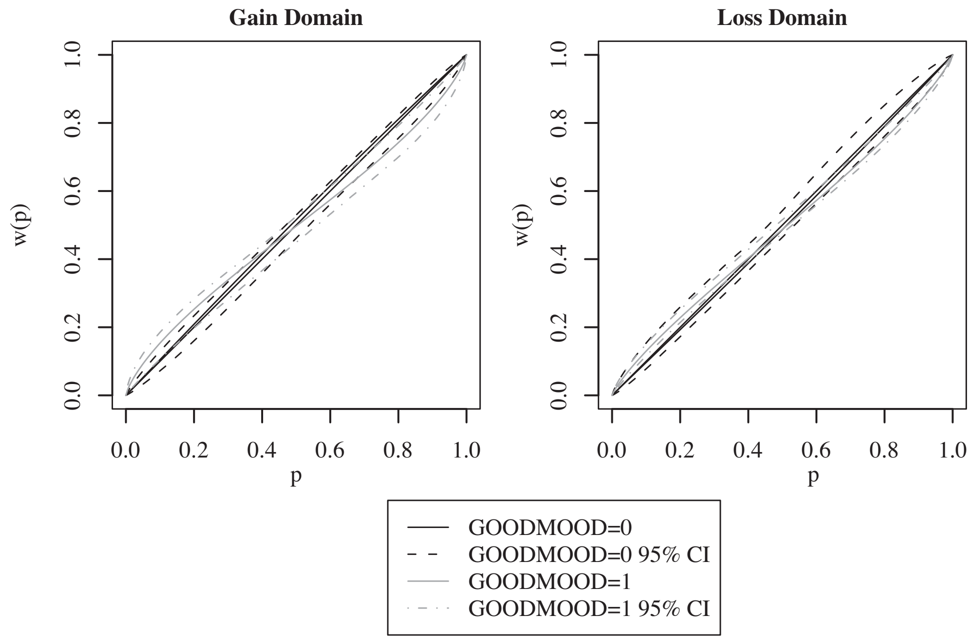

Fig. 4. GOODMOOD-effect on men's probability weights: EXVALUE = 1.

people who apply the criterion adhere more closely to linear weighting and may therefore be less responsive to other factors. For δ, the coefficients of GMOODxEV indeed have the opposite signs from the corresponding coefficients of GOODMOOD, which means that the mood effect is counteracted by the application of the expected value criterion. Moreover, we can ascertain that the sums of the coefficients of GOODMOOD and GMOODxEV are not significantly different from zero. The graphs in Fig. 4 present the respective curves with their confidence bands for men with EXVALUE = 1. As the coefficients have already suggested, the confidence bands overlap. Good mood does not have any effect on men who calculate expected values. Therefore, for this group of men, who comprise 40% of the male subjects, risk taking behavior is not responsive to mood state.

In total, men's behavior is either not responsive to good mood at all, or only weakly so. We are therefore likely to find no effect at the aggregate behavioral level, consistent with the lack of a significant relationship between observed relative risk premia and GOODMOOD.

6. Discussion

Imagine you are facing a risky decision and assess all your options. Should how your day has been going so far color your judgment? Presumably, you will answer in the negative as would probably most people. However, we find strong evidence that people's risk taking behavior is susceptible to incidental affect and that this susceptibility is more pronounced for women. Women who report that their day has been going better than usual exhibit two kinds of behavioral effects: First, they weight probabilities more optimistically and, second, their probability weighting curves depart less strongly from linearity. If linear weighting of objective probabilities is accepted as a standard of rationality, good mood seems to promote more rational behavior.

Contrary to women's reactions, men overall seem not to be responsive to good mood. However, a closer look reveals that a crucial variable in explaining this gender difference in behavior is decision strategy: A significantly higher proportion of men than of women stated that they used expected lottery payoffs as a benchmark for their decisions. Men employing this strategy by and large behave as expected value maximizers, i.e. their value functions as well as their probability weighting functions are near linear irrespective of mood state. Adherence to decision rules such as the expected value criterion, therefore, seems to immunize decision makers against incidental affect. The other male group's probability weighting functions, however, are of the typical kind, i.e. they are inverted S-shaped. These men do react congruently to good mood but, in our data, the effect is not strong enough to be visible in overall risk taking behavior. Mood effects might become more clearly evident as the number of observations is increased.

Interestingly, Kliger and Levy (2008) find that, at the level of market transactions, probability weighting functions are more strongly S-shaped on days with a high degree of cloud coverage and in the fall, when daylight becomes progressively scarce. The authors attribute their finding to bad mood triggered by weather and seasonal conditions. On good days people seem to be relatively more rational than on bad days, which is consistent with our results.

As mood builds up as a consequence of prior experiences and conditions in the environment, not only clear skies and warm temperatures may induce pleasant feelings, but also what previously happened in the course of the day. In particular, fortunate outcomes from prior decisions might raise people's mood and, consequently, make them relatively more risk seeking. The idea that prior outcomes may affect subsequent risk-taking behavior is discussed by another strand of the empirical literature: When faced with sequential gambles people are more willing to take risks if they made money on prior gambles (Thaler and Johnson, 1990; Gertner, 1993; Gneezy et al., 2003). This result has become known as the *house money effect*, because it is reminiscent of the expression "playing with the house money" used to describe gamblers' increased willingness to bet when ahead. Attempts at explaining this behavioral regularity have centered on reference wealth effects and outcome-dependent loss aversion (Neilson, 1998; Barberis et al., 2001), both of which pertain to characteristics of the value function. In the light of our findings, the mechanism behind decreasing risk aversion may be good mood resulting from prior gains. In this case, the channel through which the house money effect operates is optimistic probability weighting. In their seminal paper, Thaler and Johnson already discuss the possibility of mood driving the house money effect (1990, p. 658). We are not aware of any conclusive evidence that could discriminate between the alternative explanations. It may well be the case that, depending on the circumstances, one or the other is the dominant factor.[17] Thaler and Johnson conclude that "Perhaps the most important conclusion to be reached from this research is that making generalizations about risk-taking preferences is difficult" (p. 660). Twenty years of research later we cannot help but agree.

Numerous studies in psychology, sociology, and economics have demonstrated that, generally, women are relatively more risk averse than are men (Byrnes et al., 1999; Eckel and Grossman, 2005; Fehr-Duda et al., 2006). In this study, we have identified a decisive gender difference in decision strategy. In situations that are characterized by objectively given probabilities men are significantly more likely to calculate expected lottery payoffs. However, as Borghans et al. (2009) have recently shown, the gender difference in valuations of *uncertain* prospects shrinks substantially when objective probabilities are not available anymore: Men react much more strongly to increasing ambiguity than do women. Future research will have to show whether there is a significant difference in men's and women's decision rules when expected values have lost their meaning.

Appendix A. Supplementary Data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2010.12.004.

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[17] For instance, Weber and Zuchel (2005) elicit risk preferences in a two-stage betting game by employing the strategy method. Obviously, in this case mood should not play a role because people make their second-stage choices contingent on first-stage outcomes before the lotteries are played out. A house money effect emerges in only one of their treatment conditions.

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