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Risk and Rationality: The Effect of Incidental Mood on Probability Weighting *

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Abstract

When valuing risky prospects, people tend to overweight small probabilities and to underweight large probabilities. Nonlinear probability weighting has proven to be a robust empirical phenomenon and has been integrated in decision models, such as cumulative prospect theory. Based on a laboratory experiment with real monetary incentives, we show that incidental emotional states, such as preexisting good mood, have a significant effect on the shape of the probability weighting function, albeit only for women. Women in a better than normal mood tend to exhibit mood-congruent behavior, i.e. they weight probabilities of gains and losses relatively more optimistically. Men's probability weights are not responsive to mood state. We find that the application of a mechanical decision criterion, such as the maximization of expected value, immunizes men against effects of incidental emotions. 40% of the male participants indeed report applying expected values as decision criterion. Only a negligible number of women do so.

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1 Introduction

In the past decades, the canonical economic model of decision under risk, expected utility theory, has been severely challenged. A large number of alternative theories were introduced in the wake of experiments suggesting that people systematically violate the axioms of expected utility theory (for a review see Starmer 2000). Particularly, people do not weight utilities linearly by the corresponding probabilities, but rather overestimate small probabilities and underestimate large probabilities. This phenomenon led Kahneman and Tversky (Kahneman and Tversky 1979; Tversky and Kahneman 1992) to incorporate a nonlinear probability weighting function as a core component in their prospect theory. But why would people weight objectively given probabilities? Kahneman and Tversky justify the shape of the probability weighting function by the psychological principle of diminishing sensitivity. Diminishing sensitivity holds that the psychological impact of a marginal change will decrease as we move further away from a reference point. This prinicple 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.

At the theoretical level, 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. While these endeavors offer a technical rationale for the shape of the probability weighting function, several generalizations of expected utility theory (Bell 1982, Gul 1991, Loomes and Sugden 1986, Wu 1999) invoke emotions to explain observed behavior. Recently, Walther (2003) has derived a nonlinear transformation of probabilities from the assumption of anticipated emotions of elation and disappointment occurring when uncertainty is resolved.

While anticipated emotions can be conveniently integrated into economic models of choice, this is not the case for immediate emotions experienced at the moment of decision making. These immediate emotions may be affective responses to the decision target or they may be purely incidental emotions, like mood states or emotions carried over from recent experiences, which have no causal link to the decision at hand. That immediate emotions with respect to the decision target may affect the shape of the probability weighting function has been shown by Rottenstreich and Hsee (2001). They report that people tend to be less responsive to probabilities when they respond to emotion-laden targets such as a kiss by one's favorite movie star or an electric shock, than in the case of comparatively pallid monetary outcomes.

As far as incidental emotions are concerned, there is a large body of empirical evidence on their effects on judgment and decision making (Loewenstein and Lerner 2003, Pham in press). 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). In these studies, probabilities are typically not presented as objective numbers but have to be assessed subjectively. Wright and Bower (1992) also detect a susceptibility effect. When judging more frequently occurring events participants exhibit higher susceptibility to mood states than when judging less frequently occurring events.

Isen and her colleagues contest the validity of mood-congruent behavior in the context of risk taking, however (Isen and Labroo 2003, Isen and Patrick 1983). They argue that more optimistic probability judgment does not necessarily lead to a higher willingness to accept a given lottery. In situations where the risk is real or sizable, positive affect leads to reduced risk-taking in comparison with control subjects. This phenomenon can be explained by mood maintenance theory. According to this theory, people in a good mood stand to lose their affective state as well as their monetary stake, and therefore behave more cautiously. The study by Kliger and Levy (2003), using weather conditions as a proxy for state of mood, indeed finds that good mood is associated with investors being less willing to tolerate risk in real capital market decisions and that bad mood is associated with higher risk tolerance.

If incidental mood states influence decisions under risk the effect could work via two pathways. Mood states could either affect the valuation of monetary outcomes or the shape of the probability weighting function or both. To our knowledge, this question has not been investigated so far. We conjecture that, in the context of financial decision making, the valuation of emotionally rather pallid monetary outcomes will not be as susceptible to incidental affect as the probability weights. This hypothesis seems particularly plausible in the light of the empirical evidence on the shape of the value function. Estimates based on experimental data typically exhibit near linear value functions (Fehr-Duda et al. 2006, Fox et al. 1996) with risk taking attitudes reflected mainly by the probability weighting function. We therefore hypothesize that incidental mood states affect the shape of the probability weighting function rather than the value function. In the case of mood-congruent reactions, people in good moods should weight probabilities of gains and of losses relatively more optimistically than people in a neutral state. If Isen's conjecture of mood maintenance is correct, however, we should observe the opposite effect.

This paper addresses the question of mood effects by estimating the parameters of prospect theory on the basis of experimental data. The data were elicited in an experiment on real gains and losses framed as investment and insurance decisions. While we do not have a gender-specific hypothesis on the relationship between mood and probability weights, we will analyze the data and present the results 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, particularly for investment gains, significantly stronger underweighting of large probabilities than do male curves.

2 Experimental Design

In the following section we describe the experimental setup and procedures. The experiment, programmed in Z-Tree (Fischbacher in press) took place in Zurich in 2003. We recruited students of various fields at the University of Zurich and the Swiss Federal Institute of Technology Zurich. We elicited certainty equivalents for 50 two-outcome lotteries. 25 of the lotteries were framed as choices between risky and certain investment gains ("gain domain"). The remaining 25 decisions were presented as choices between uncertain 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. In the present study, we chose to analyze contextually framed choices because deviations from linear probability weighting tend to be more pronounced for contextual decisions than for abstract gamble choices (Fehr-Duda et al. 2006). Gains and losses ranged from zero Swiss Francs to 150 Swiss Francs with probabilities p of 5, 10, 25, 50, 75, 90, and 95%. The lotteries for the gain domain are presented in Table 1 (outcomes x_1 and x_2 are denominated in Swiss Francs). The expected payoff per participant 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.

Table 1: Gain Lotteries

p	x_1	x_2	p	x_1	x_2	p	x_1	x_2
0.05	20	0	0.25	50	20	0.75	50	20
0.05	40	10	0.50	10	0	0.90	10	0
0.05	50	20	0.50	20	10	0.90	20	10
0.05	150	50	0.50	40	10	0.90	50	0
0.10	10	0	0.50	50	0	0.95	20	0
0.10	20	10	0.50	50	20	0.95	40	10
0.10	50	0	0.50	150	0	0.95	50	20
0.25	20	0	0.75	20	0			
0.25	40	10	0.75	40	10			

The lotteries appeared in random order on a computer screen (see Figure 1). 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 participants had to indicate whether they preferred the lottery or the certain payoff for each of these certain payoffs. The lottery's certainty equivalent was calculated as the arithmetic mean of the smallest certain amount preferred to the lottery and the following certain amount on the list when the participant had for the first time indicated preference for the lottery. For example,

Figure 1: Design of Computer Screen

Decision situation: 22						
	Option A	Your Choice:				Option B Guaranteed payoff amounting to:
1		A		o	B	20
2		A		o	B	19
3		A		o	B	18
4		A		o	B	17
5		A		o	B	16
6		A		o	B	15
7	A profit of CHF 20 with	A		o	B	14
8		A	o		B	13
9	probability 75%	A	o		B	12
10		A	o		B	11
11	and a profit of CHF 0 with	A	o		B	10
12		A	o		B	9
13	probability 25%	A	o		B	8
14		A	o		B	7
15		A	o		B	6
16		A	o		B	5
17		A	o		B	4
18		A	o		B	3
19		A	o		B	2
20		A	o		B	1
		OK				

if the participant had decided as indicated by the small circles in Figure 1 her certainty equivalent would amount to 13.5 Swiss Francs. When participants switched from preferring the certain amount to preferring the lottery more than once, we applied the following rule: If the participant had switched back and forth for more than two lotteries, all her decisions were excluded from the data set. For fewer errors, only the participant'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.

At the end of the experiment, the participants had to fill out a questionnaire eliciting information on a number of socioeconomic variables, such as age, gender, and income, as well as state of mood. When the participants had completed the questionnaire, one of their choices was randomly selected for payment by rolling dice. Participants were paid in private afterward. The participants could work at their own speed, the vast majority of them needed less than an hour to complete the experiment including the questionnaire.

Aside from our focal variable, mood state, we included a number of controls when estimating the parameters of prospect theory. These variables are supposed to control for income, experience with financial decisions, and knowledge of statistical concepts. They stem from the answers to the questionnaire and are defined as follows. GOODMOOD is a binary variable constructed from the answers to the question "How do you feel today?" Participants indicated whether they were feeling worse or better than usual by marking a number between 0 ("bad") and 5 ("very good") with values between 2 and 3 meaning "as usual". The majority of participants, namely 52%, were feeling as usual, fewer than 10% reported to be feeling worse than usual. Participants were assigned GOODMOOD = 1 when they indicated values of 4 or 5, they were assigned GOODMOOD = 0 otherwise. To capture potential effects of calculating expected payoffs, we constructed the dummy variable EXVALUE. Participants 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 participants explicitly mentioned that they had calculated the lotteries' expected payoffs; some others described a procedure which closely resembled the calculation of the expected value. The dummy variable EXVALUE was assigned the value of 1 for participants in these two categories, for everyone else the variable was set to zero. INCOME is measured in 1'000 Swiss Francs and refers to the participants' average monthly disposable income. SEMESTER denotes the number of semesters enrolled at the university. Finally, the binary variable for investment experience, INVEST, was assigned a value of 1 if the participant herself had already made investments in stocks, bonds, options or other financial instruments; INVEST = 0 otherwise.

Summary statistics by gender are shown in Table 2. We tested all these variables with respect to gender differences. 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 the expected value as benchmark for decision making. EXVALUE = 1 for 20 men, but only for 3 women (Mann-Whitney test significant at p-value < 0.001)[1]. This difference is quite surprising as about half of our female subjects are students at the Swiss Federal Institute of Technology

[1]For this reason, EXVALUE was not included in estimating the female parameters.

Table 2: Summary Statistics for the Explanatory Variables

	Women			
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
GOODMOOD	0.375	0.484	0	1
EXVALUE	0.075	0.264	0	1
INCOME	1.005	0.679	0.250	3.500
SEMESTER	3.148	1.785	2	8
INVEST	0.249	0.433	0	1
	Men			
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
GOODMOOD	0.381	0.486	0	1
EXVALUE	0.399	0.490	0	1
INCOME	1.045	0.529	0.250	2.000
SEMESTER	3.923	2.226	2	12
INVEST	0.300	0.458	0	1

with highly technical and mathematical curricula. Men have significantly higher incomes, have spent more semesters at the university, and are more likely to be familiar with investment decisions. 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).

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. Figure 2 exhibits median risk premia sorted by the probability of the lotteries' highest gain or loss, respectively. Median RRPs display the familiar fourfold pattern of risk attitudes: Participants 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 incidental mood affects risk taking behavior? 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 presented in the next section, is needed for that purpose. To answer the question with respect to overall risk taking behavior, we correlate measured risk premia with GOODMOOD. For men, the null hypothesis that RRP and GOODMOOD are independent cannot be rejected at all levels of probability for both gains and losses. We observe highly significant Spearman rank correlations for women, however (see Table 3, particularly in the upper probability range in the gain domain and in the middle range in the loss domain). Correlation coefficients are mostly negative, indicating that GOODMOOD is associated with lower risk premia, i.e. with relatively more risk seeking behavior. Therefore, the descriptive analysis supports the mood congruence hypothesis for women. At this stage of analysis, neither mood-congruence nor mood-maintenance effects seem to be detectable in men's behavior.

Figure 2: Median Relative Risk Premia by Probability

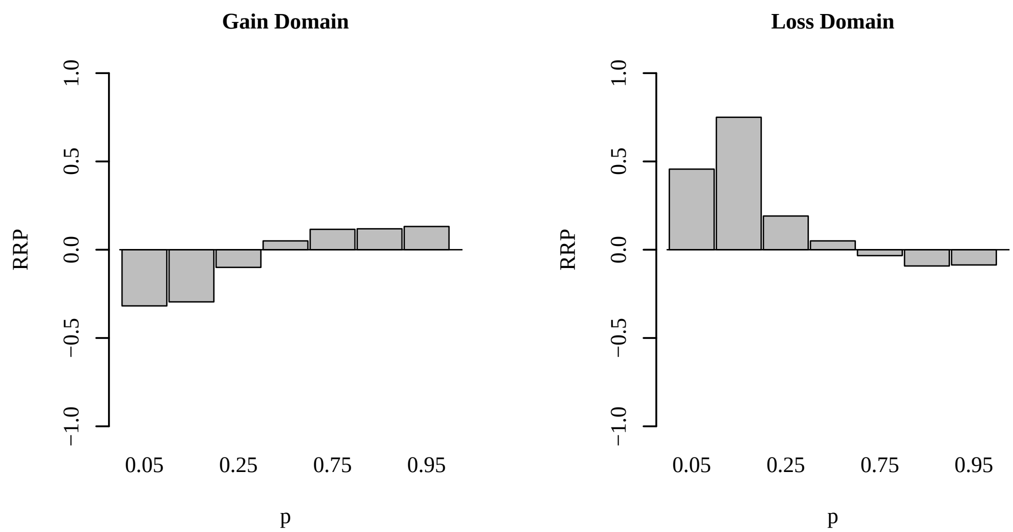


Table 3: Correlations of RRP with GOODMOOD

				Women			
Probability	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
Gains							
Correlation	0.005	0.028	-0.068	-0.184	-0.261	-0.076	-0.269
p-Value	0.955	0.762	0.464	0.004	0.004	0.410	0.003
Losses							
Correlation	-0.091	-0.173	-0.127	-0.187	-0.220	-0.102	-0.168
p-Value	0.257	0.060	0.170	0.004	0.016	0.266	0.067

4 Econometric Model

The 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 our assumptions on how an individual evaluates a lottery, i.e. we specify how she values monetary outcomes and weights probabilities. Second, we specify the relationship between the parameters of the behavioral model and the variables which presumably influence the size 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 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 written as

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

A number of different functionals have been proposed to model the value function. An obvious candidate for the value function is a sign-dependent power functional which can be conveniently interpreted and has turned out to be the best compromise between parsimony and goodness of fit (Stott 2006). The exponents are identifiable because our experimental design includes a number of binary lotteries with two non-zero outcomes.

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

A variety of functionals for modeling probability weights $w(p)$ has been described 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):

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

We favor this specification because the parameters have a neat psychological interpretation (Gonzales 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. The larger the value of δ, the more elevated the curve, ceteris paribus. 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 hypotheses into hypotheses on the relative sizes of the parameter estimates. Specifically, if mood congruence holds, 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. In case of the susceptibility effect in the gain domain, i.e. when responsiveness to mood rises with increasing probability, we also expect a positive effect on the estimate for γ. As probability weights typically depart most strongly from linear weighting in the upper range of probabilities, the total effect of an increase in the slope parameter and in the elevation parameter should result in the expected susceptibility pattern.

In total, we have to estimate six behavioral parameters: α, β, γ and δ for gains, as well as γ and δ for losses. Next we specify the core component of our econometric model, the relationship between the behavioral parameters and the variables which may have an influence on their size. In principle, individual characteristics may affect the size of 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, EXVALUE, INCOME, SEMESTER, and INVEST. The coefficients θ_k, $k = 0, ..., K$, capture the average effect of the explanatory variables on the behavioral parameters. The estimates for the individual behavioral parameters are obtained by inserting the individual values for z_k into each of the equations (5). If all the θ_k, $k = 1, ..., K$, were zero, i.e. if individual characteristics did not exert an influence on behavior, the estimation procedure would result in estimates for the constant θ_0 only. Consequently, the behavioral parameters would be the same for each individual. What does the mood congruence hypothesis imply for the coefficients of GOODMOOD with respect to the probability weights? Clearly, for δ the respective coefficient should be positive for gains, and negative for losses. In case of mood maintenance, the opposite signs should prevail.

Finally, since prospect theory 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 $ce = \hat{ce} + \epsilon$. Note that the predicted certainty equivalent, $\hat{ce}$, is a function of all the six different behavioral parameters $\psi(\theta_0, ..., \theta_K)$. There may be different sources of error resulting in accidentally wrong answers, such as carelessness, hurry or inattentiveness (Hey and Orme 1994). The Central Limit Theorem supports the assumption that these errors are normally distributed with zero mean and simply add white noise [2].

5 Results

Estimating the econometric model by maximum likelihood yields estimates for the coefficients θ_k of the explanatory variables and, in turn, for the parameters of the value and the probability weighting functions. As the correlation analysis has shown, GOODMOOD is significantly

[2] Heteroskedasticity resulting from lottery-specific, domain-specific, and individual-specific errors are accounted for by the estimation procedure.

correlated with risk taking behavior, at least for women. With the parameter estimates at our disposal, we are now able to answer the question whether good mood rather affects the valuation of monetary outcomes or the weighting of probabilities. For this purpose, we estimated three models with differing degrees of generality and conducted a series of likelihood ratio tests. First, we estimated the full model, model *I*, as described in the previous section, i.e. taking account of the presumed linear relationship between all the behavioral parameters and GOODMOOD. Second, we estimated a restricted model, model *II*, with only the parameters of the probability weighting functions depending on the explanatory variables. Third, we restricted model *II* even further by omitting all the explanatory variables. The resulting model *III* yields only representative behavioral parameter estimates.

The first likelihood ratio test was applied to model *I* and the restricted model *II*. The null hypothesis that both models explain behavior equally well cannot be rejected for both sexes (p-value for women: 0.066, men: 0.201). This means that including GOODMOOD or the other controls does not help in explaining the curvature of the value functions. Therefore we should prefer the more parsimonious model *II*. The respective likelihood ratio test of model *II* against the representative agent model *III* detects a highly significant difference in fit, however: Model *II* is clearly preferred (p-value < 0.001 for both women and men). This means that including the explanatory variables in the estimation of the probability weighting function parameters greatly improves model fit. Therefore, we only present the parameter estimates for model *II* in Table 4. 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 [3]. 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.

Before we turn to the effect of mood state, we briefly discuss our findings on the average parameter estimates. In all cases, value function exponents are close to one, only women's β is statistically different from one. This finding means that value functions are essentially linear

[3] The additional variable GMOODxEV will be explained below.

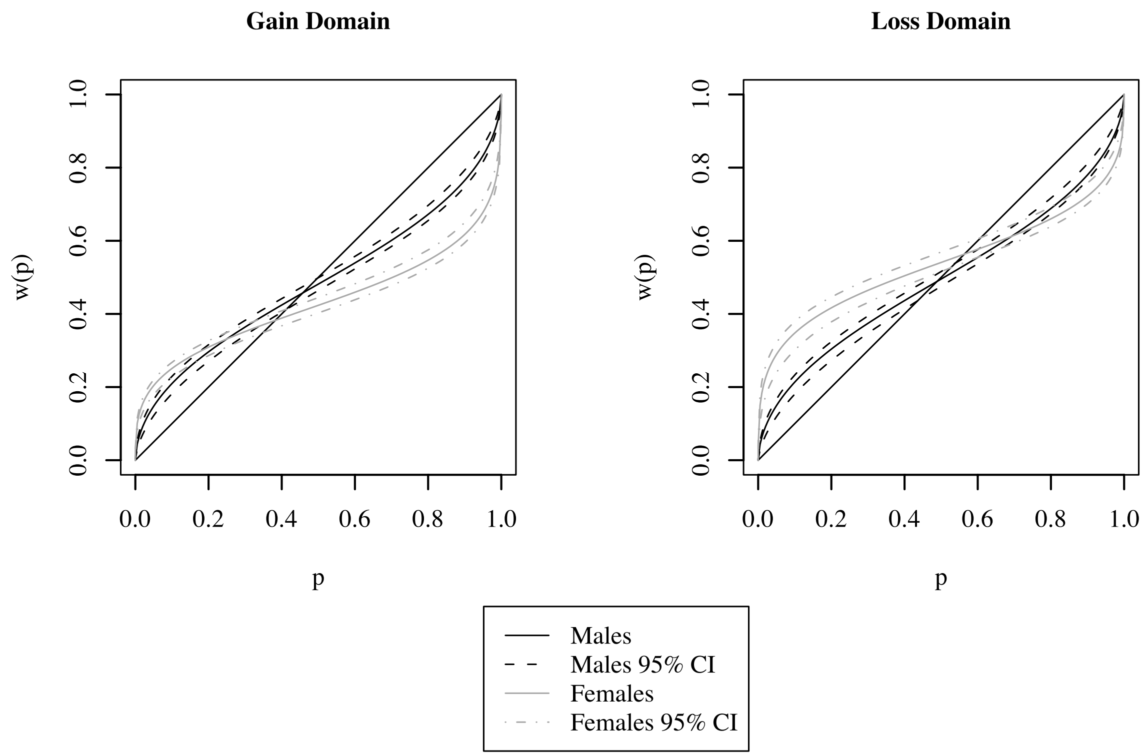
Table 4: Parameter Estimates $\hat{\theta}_k$

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

Figure 3: Gender-Specific Probability Weights



with women exhibiting a slight degree of loss aversion. The parameters of the probability weighting functions show a gender-specific pattern: The women's functions are more curved than the men's. Figure 3 displays the average male and female probability weighting curves for both domains. Since the bootstrapped 95%-confidence bands partially diverge the average woman is significantly more risk averse over the range of probabilities typically associated with risk averse behavior.

So far we have asserted that GOODMOOD does not affect the valuation of outcomes, but does it affect probability weights? The mood-congruence 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. This hypothesis can be made more concrete for the functional form we have chosen. The parameter γ is mainly responsible for the slope of the curve, δ essentially governs its elevation. We therefore expect good mood to predominantly affect δ, the elevation parameter, namely positively for gains and negatively for losses. The same reasoning applies for the mood-maintenance hypothesis, albeit with changed signs.

We first discuss the results for the women's parameter estimates. 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 a significant effect on the shape of the probability weighting function, however, since γ and δ cannot move totally independently from each other. Whether the total effect of GOODMOOD on probability weighting is significant, has to be judged by constructing confidence bands for the average good-mood curve and for its no-good-mood counterpart. Figure 4 depicts these curves for both domains. The black curves 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 Figure 4 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.

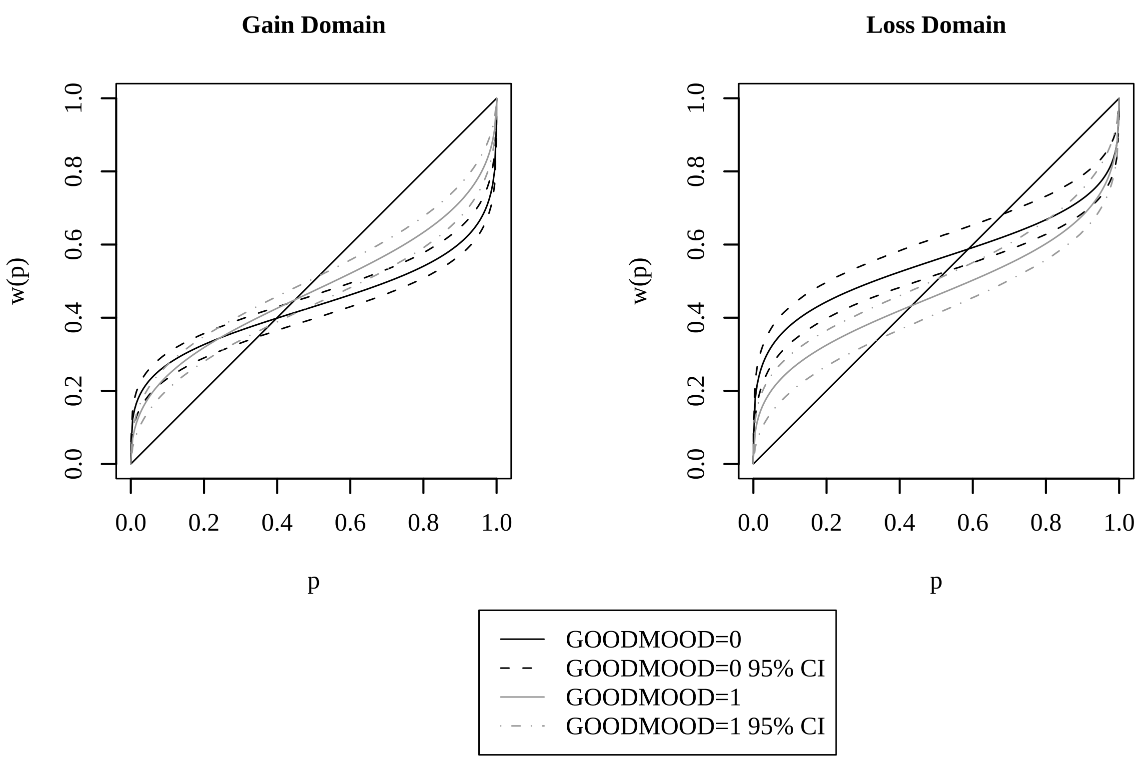
We now turn to the estimates for the female curve in the loss domain. GOODMOOD does not have a significant effect on the slope parameter γ, but it does have an effect on δ. Again, the coefficient has the expected sign: It is negative, i.e. probabilities of losses are less strongly weighted, and it exhibits a large absolute value. As the graph on the right hand side of Figure 4 shows, 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 findings of the behavioral model confirm the observed correlations depicted in Table 3. The prediction of the mood-congruence 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 good mood for more probable gains and less probable losses.

Inspection of the men's side of Table 4 reveals that, aside from the constant, 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 weighting curves: 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, men who report computing expected values essentially behave as expected value maximizers. The curves are clearly S-shaped for the group of men who did not declare calculating 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 when evaluating lotteries the effect of good mood is captured by the coefficient of GOODMOOD alone. In accordance with the mood

Figure 4: GOODMOOD-Effect on Women's Probability Weights



congruence 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. Does this change in δ suffice to significantly change the overall shape of the curves? As Figure 5 shows, over some range of probabilities 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 most likely not strong enough in our data to manifest itself in changed 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, people who apply the criterion adhere more closely to linear weighting and may therefore be less responsive to mood states. 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 Figure 6 present the respective curves with their confidence bands for men with EXVALUE = 1. As the the coefficients have already suggested, the confidence bands overlap totally. Good mood does not have any effect on men who calculate expected values. Therefore, for this group of men, which constitutes 40% of the male participants, 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 therefore are likely to find no effect at the behavioral level consistent with the observed lack of significant correlations between relative risk premia and GOODMOOD.

6 Discussion

The estimation of our econometric model has yielded the following main insights. Consistent with our initial hypothesis, incidental good mood does not affect the valuation of monetary

Figure 5: GOODMOOD-Effect on Men's Probability Weights: EXVALUE = 0

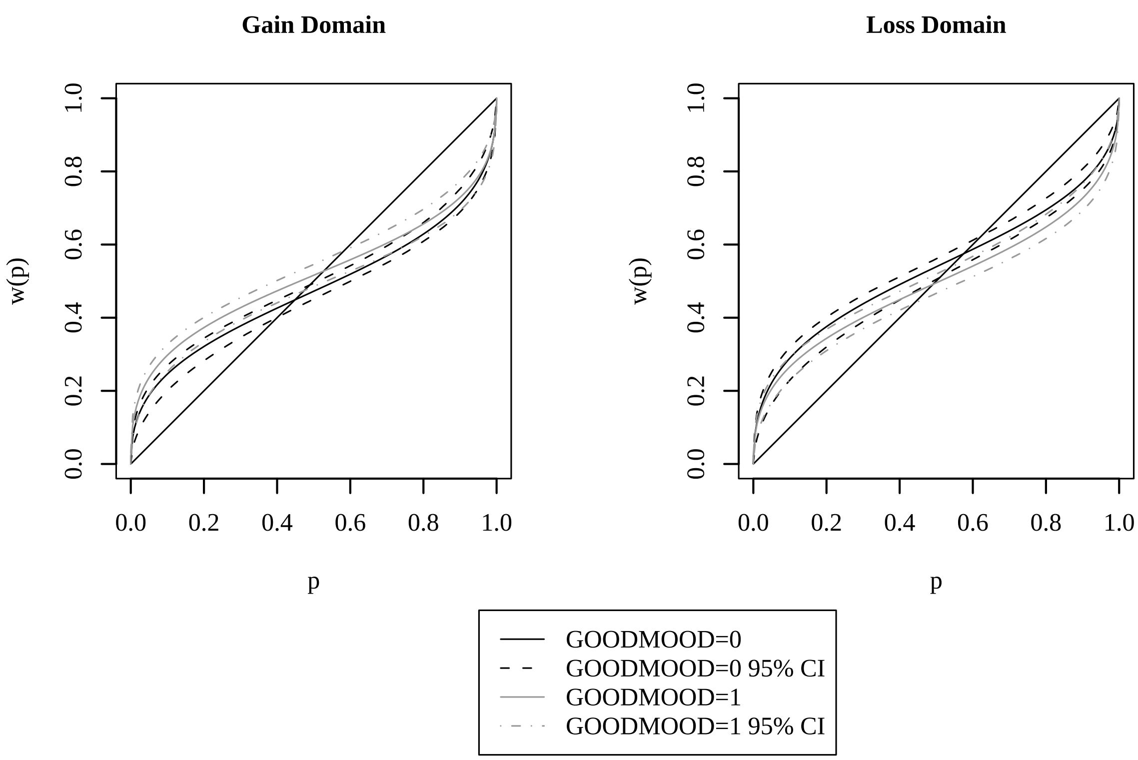
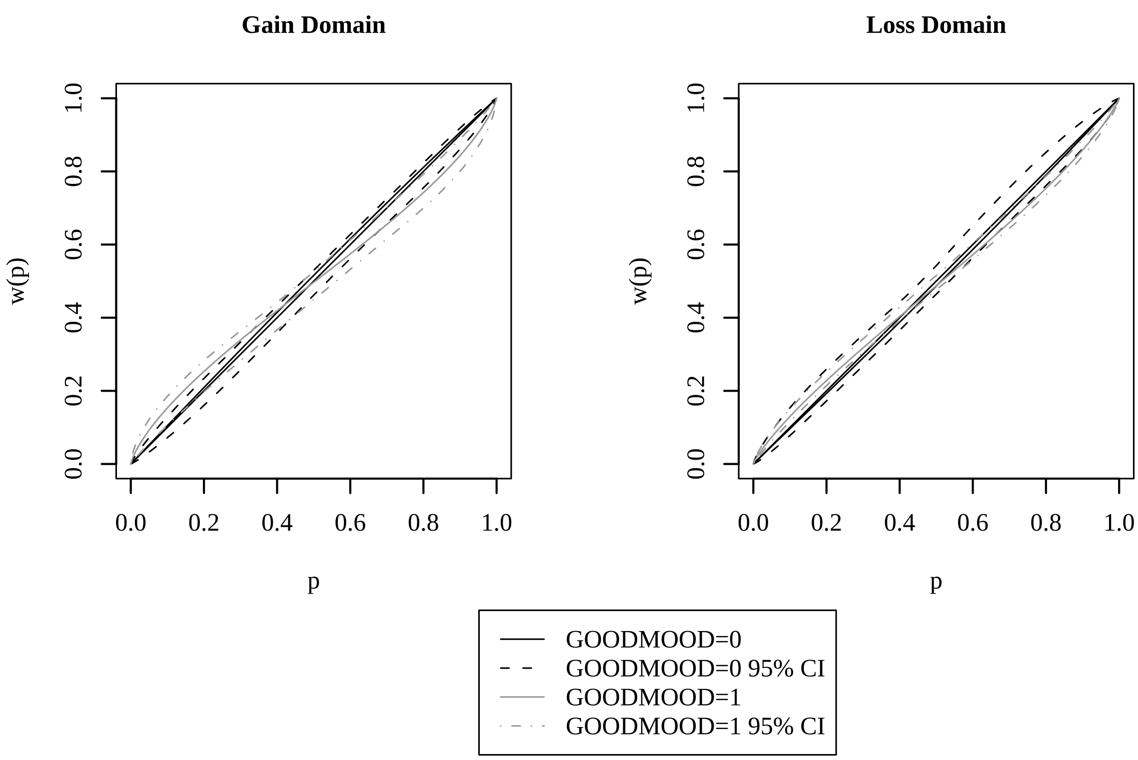


Figure 6: GOODMOOD-Effect on Men's Probability Weights: EXVALUE = 1



outcomes. As far as probability weights are concerned, we find a substantial gender difference in sensitivity to self reported good mood. While the estimates of the female probability weighting functions support the mood congruence hypothesis for both gains and losses, men overall seem not to be responsive to good mood. Why is there such a substantial difference in women's and men's behavior?

In the experiment the decision situations were presented in terms of objectively given probabilities. Men seem to have a different approach from women to solving problems like these. As already noted above, a significantly higher proportion of men than of women, namely 40% versus 7.5%, stated that they used the lotteries' expected payoffs as benchmark for their decisions. A close look at the coefficients of the explanatory variables has revealed that behavior differs between men who use expected values in the evaluation of lotteries, and men who do not. The first group's probability weighting curves are near linear and the value functions are as well. This finding represents a major byproduct of our analysis: Men who report using expected values actually behave as expected value maximizers. And this group is practically immune to mood states. The other group's probability weighting functions 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 most likely not strong enough to become evident in risk taking behavior.

Another question we would like to address is the effect of incidental good mood on rational choice. If linear weighting of objective probabilities is accepted as a standard for rationality, the curvature of the probability weighting function can be interpreted as indicator of rationality. We presume that most people would prefer that their choices are not influenced by irrelevant mood states. However, women's reaction to good mood results in less strongly S-shaped probability weighting curves suggesting that better mood makes women more rational.

To sum up, our analysis has uncovered yet another aspect of gender differences in risk taking behavior. Numerous studies in psychology, sociology, and economics have demonstrated that women are generally relatively more risk averse than are men (Byrnes et al. 1999, Eckel and Grossman 2005). In the context of financial decisions, this gender difference can be explained by the differing shapes of the probability weighting function (Fehr-Duda et al.

2006). In this study, we have found women's probability weighting curves to be susceptible to preexisting good mood whereas men's are not. This lack of men's responsiveness can be traced back to two factors: Men who use the expected value criterion are not susceptible to good mood at all. Men who do not apply such a mechanical rule do exhibit mood congruent behavior, but the effect is rather weak. The mood-congruence effect might become more clearly evident, however, as the number of observations is increased. If this were the case, decision type rather than gender would be the basis for classifying behavior: prospect-theory types with S-shaped probability weighting functions who are susceptible to incidental emotions versus expected-utility-theory types with linear weighting functions who are not. Future research will have to show whether our conjecture will bear out.

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