Risk Taking in Mixed Gambles

Luís Santos-Pinto   José Mata   Thomas Åstebro*

Abstract

We propose a task for eliciting attitudes towards risk which offers an economical way of uncovering heterogeneity in risk preferences. The task consists of accepting or rejecting mixed gambles that provide a gain with probability p and a loss with probability 1-p. Using mixed gambles allow us to simultaneously evaluate all features of risk preferences proposed by prospect theory. We find that roughly two thirds of the subjects behave according to prospect theory and one third as expected utility maximizers. Probability weighting matters the most in explaining decisions followed by diminishing sensitivity to outcomes. No evidence of loss aversion is found.

JEL Codes: C91; D81.

Keywords: Risk; Skew; Probability Weighting; Loss Aversion; Experiment.

*Luís Santos-Pinto, Faculty of Business and Economics, University of Lausanne, LuisPedro.SantosPinto@unil.ch; José Mata, Nova School of Business and Economics, Lisbon, jmata@fe.unl.pt; Thomas Åstebro, HEC-Paris, astebro@hec.fr.

We thank James Cox, Erik Eyster, Botond Koszegi, and Peter Wakker for various comments and suggestions. We also thank seminar and conference participants at HEC Paris, University of Lausanne, Economic Science Association World Meeting in Copenhagen, International Meeting on Behavioral and Experimental Economics in Barcelona, and D-TEA Workshop in Paris. Support from HEC Foundation, NOVA FORUM and Fundação para a Ciência e Tecnologia is gratefully acknowledged.

1 Introduction

Decisions made when agents confront risky alternatives are conventionally explained by expected utility (EU) theory preferences. Different utility functions (concave, linear, or convex) defined over final wealth states reflect diminishing, constant, or increasing marginal utility for wealth and thus aversion, neutrality or love for risk.

The evidence from the field and the lab, however, shows that attitudes towards risk deviate systematically from EU predictions (see Schoemaker, 1982 and Starmer, 2000 for reviews). This becomes very obvious when skewed payoffs are involved. For example, people buy insurance against damage to their telephone wiring at \$0.45 per month, worth \$0.26 in expectation (Cicchetti and Dubin, 1994) and the average homeowner pays \$100 to reduce the deductible from \$1000 to \$500 in his insurance policy, which is worth \$25 in expectation (Sydnor, 2010). Symmetrically, public lotteries are extremely popular despite a return of only \$0.53 on the dollar and people who gamble on horses tend to overbet on long-shots with low probability of winning large returns rather than on favorites with the greatest expected return (long documented since Griffith, 1949 and McGlothlin, 1956). Laboratory evidence also shows that, many prefer gambles that offer a low expected value but also a low probability of a large gain (Wu and Gonzalez, 1996; Abdellaoui, 2000; Bleichrodt and Pinto, 2000) and are averse to gambles that offer a low probability of a large loss even if these gambles have a high expected value (Laury et al., 2009).

Rank dependent utility (RDU) and prospect theory (PT) are alternatives to EU that offer explanations for these risky choices. These allow choices to be determined also by probability weighting (Quiggin, 1982), diminishing sensitivity to monetary outcomes, loss aversion, and reference points (Kahneman and Tversky 1979, 1992).

Given the empirical evidence reported above and the attention that alternatives to EU have received, it is surprising that most field and laboratory experiments which need to control for variations in risk attitudes still assume that individuals behave according to EU axioms. All methods commonly used to measure utility, such as the probability, certainty equivalence, and lottery equivalence methods are not able to accommodate any departure from EU, such as probability weighting and loss aversion, and are therefore problematic when a large number of individuals violate EU axioms.

One of the reasons why field work still does not routinely account for non-EU patterns of behavior is because many of the laboratory experiments that have attempted to distinguish between EU and non-EU types (Abdellaoui et al., 2007; Conte et al., 2010; Bruhin et al., 2010) elicit a substantial number of decisions per subject and are thus rather impractical to execute in field experiments, or in lab experiments when risk elicitation is not the main experiment.[1]

We propose a simple and compact lottery-choice task that is suitable for eliciting attitudes towards risk in field experiments which: i) uses only 30 decisions per subject, ii) asks subjects to make decisions across different skew conditions, iii) uses mixed gambles, and iv) uses monetary incentives in a symmetric way across the gain and loss domains. This task is more eco-

---

[1] An exception is Abdellaoui et al. (2008) who elicit choices in the gain, loss and mixed domains in a compact way.

nomical than previous risk attitude elicitations, and it allows us to uncover heterogeneity in risk attitudes across individuals, and evaluate the contribution of all the different behavioral features of RDU and PT.

The task consists of accepting or rejecting mixed gambles that vary in expected value, variance, and skew. The gambles are divided into three skew conditions each composed of ten gambles. In the "negative skew" condition each gamble offers a large loss with probability 0.1 and a small gain with probability 0.9. In the "zero skew" condition each gamble offers a small loss and a small gain with equal probability. In the "positive skew" condition each gamble offers a large gain with probability 0.1 and a small loss with probability 0.9.

We classify subjects non-parametrically into different risk preference types according to the choices made across the three skew conditions and without making any functional form assumptions about subjects' preferences. We classify 31% as EU, 61% as PT, and 8% as displaying other choice behavior. Making decisions consistent with EU is not related to demographic characteristics except gender: the EU group contains 16% females while the PT group contains 47%. Most (56%) EU subjects display risk averse behavior, whereas risk seekers and risk neutrals are, respectively, 26% and 18%. Of those classified as PT, 41% (25% of the whole sample) simultaneously reject at least one mixed gamble with positive mean and negative skew and accept at least one mixed gamble with negative mean and positive skew. Women and younger individuals are more likely to display this "bipolar" attitude towards risk. To our knowledge this is the first paper which documents the size of the population with bipolar preferences to positive and negative skew.

We use the samples defined by these different groups to estimate structural decision models. First, we estimate two separate models, one for the subjects classified as EU and another for those classified as PT. At this stage we use RDU models, which have EU as a special case in which subjects do not distort probabilities. The obtained results are consistent with our non-parametric classification: EU subjects are found not to distort probabilities while PT subjects do.

Next, for PT subjects, we estimate a set of PT models, in which we include all the different behavioral features of risk preferences proposed by PT. Estimations reveal that probability weighting plays the most important role in explaining the behavior of PT subjects. Estimations also show that diminishing sensitivity to outcomes matters and that probability weighting is different in the gain and loss domains. However, there is no evidence of loss aversion. Findings are robust to a variety of modeling assumptions.

2 Experimental Design

We offer subjects a task with three sets of choices. Each set of choices was designed in price-list style with 10 decision rows. Each decision row was a choice between a mixed gamble (accept) and a certain amount of zero (reject). The certain amount is kept fixed across the three sets of choices so subjects see it as a reference point.

Let X_i^j denote gamble i in set of choices j, where $i \in \{1, 2, ..., 10\}$ and $j \in \{N, Z, P\}$, where N denotes negative, Z zero, and P positive skew. Let $E(X_i^j)$, $V(X_i^j)$, and $S(X_i^j)$, denote, respectively, the mean, variance, and skew (unstandardized third moment) of gamble X_i^j.

The positive skew gamble i is $X_i^P = (0.1, (15 - i)x; 0.9, -x)$, the zero skew gamble i is $X_i^Z = (0.5, 1.2x; 0.5, -0.2ix)$, and the negative skew gamble i is $X_i^N = (0.9, x; 0.1, -(3 + i)x)$, where $x > 0$. These gambles satisfy conditions that enable us to classify subjects into different risk preference groups according to the number of gambles accepted in each skew condition.

The gambles' means satisfy:

$$E(X_i^N) = E(X_i^Z) = E(X_i^P) = \frac{6 - i}{10}x, \text{ for all } i, \tag{1}$$

that is, the mean of the *i-th* gamble is the same in all skew conditions and equal to $(6 - i)x/10$. Hence, the ten gambles in each skew condition are ordered in terms of expected value. The expected value is positive for the first five gambles, zero for the sixth gamble, and negative for the last four gambles.

The gambles' variances satisfy the following conditions:

$$V(X_i^Z) < V(X_i^N) < V(X_i^P), \text{ if } i \leq 5, \tag{2}$$

and

$$V(X_i^Z) < V(X_i^N) = V(X_i^P), \text{ if } i = 6, \tag{3}$$

and

$$V(X_i^Z) < V(X_i^P) < V(X_i^N), \text{ if } i \geq 7. \tag{4}$$

Condition (2) tells us that for the first five gambles, the variance of the *i-th* gamble in the zero skew condition is smaller than the variance of the *i-th* gamble in the negative skew condition which, in turn, is smaller than the variance of the *i-th* gamble in the positive skew condition. Condition (3) says that for zero mean gambles, the variance of the negative and positive skew gambles is identical and greater than the variance of the zero skew gamble. Finally, condition (4) tells us that for the last four gambles, the variance of the *i-th* gamble in the zero skew condition is smaller than the variance of the *i-th* gamble in the positive skew condition which, in turn, is smaller than the variance of the *i-th* gamble in the negative skew condition.

The gambles' skews satisfy:

$$S(X_i^N) < S(X_i^Z) = 0 < S(X_i^P), \text{ for all } i, \tag{5}$$

that is, gambles in the negative, zero, and positive skew conditions have negative, zero and positive third moments, respectively.

Subjects' choices in the three skew conditions allow us to determine subjects' risk types. Since the first five gambles have positive mean and the last four have negative mean, subjects should begin each set of choices by preferring the gamble and then switching to the certain amount. The switch points in the three skew conditions enable us to distinguish EU from PT subjects. The switch points also allow us to classify EU subjects into risk neutral averse, and seeking and PT subjects into inverse s-shape probability weighting, s-shape probability weighting, and others.[2]

The classification method is described in detail in Appendix A. To explain the intuition behind it consider the following examples.

A subject who switches from the gamble to the certain amount in decision row 6 across the three skew condition is classified as a risk neutral EU

---

[2] In inverse s-shape probability weighting, small probabilities are overweighted and large probabilities are underweighted. Conversely, in s-shape probability weighting, large probabilities are overweighted and small probabilities are underweighted.

individual since he accepts gambles with positive mean and rejects gambles with non-positive mean.

A subject who switches from the gamble to the certain amount in rows 2, 4 and 2 in the negative, zero and positive skew conditions, respectively, is classified as a risk averse EU individual. This subject rejects all gambles with non-positive mean and rejects some gambles with positive mean. Additionally, he accepts more gambles in the zero skew condition than in the other skew conditions because, for any given mean, the zero skew gamble has a lower variance than the negative and positive skew gambles.

A subject who switches from the gamble to the certain amount in rows 9, 7 and 9 in the negative, zero and positive skew conditions, respectively, is classified as a risk seeking EU individual. This subject accepts all gambles with non-negative mean and accepts some gambles with negative mean. Additionally, he accepts more gambles in the negative and positive skew conditions than in the zero skew condition because, for any given mean, the negative and positive skew gambles have higher variance than the zero skew gamble.

A subject who switches from the gamble to the certain amount in rows 3, 6 and 8 in the negative, zero and positive skew conditions, respectively, is classified as a PT individual with inverse s-shape probability weighting. Rejection of three positive mean gambles with negative skew, acceptance of all positive mean gambles with zero skew, and acceptance of one negative mean gamble with positive skew is consistent with overweighting small probabilities and underweighting large ones.

Finally, a subject who switches from the gamble to the certain amount in rows 8, 6 and 3 in the negative, zero and positive skew conditions, respectively, is classified as a PT individual with s-shape probability weighting. Acceptance of one negative mean gamble with negative skew, acceptance of all positive mean gambles with zero skew, and rejection of three positive gambles with positive skew is consistent with overweighting large probabilities and underweighting small ones.

We run the experiment with two levels of stakes ($x = 5$ CHF and $x = 10$ CHF hereafter called the 1x stake and 2x stake conditions, respectively). Subjects in the 1x stake condition are faced with the three sets of choices displayed in Tables 1, 2, and 3 (the columns with expected value and the variance of the lotteries were not shown to subjects). In the 2x stake condition stakes are twice as high.

insert Tables 1, 2, and 3 here

The order of skew conditions were randomly assigned and counterbalanced. A total of 109 subjects participated in the experiment, 70 in the 1x stakes condition and 39 in the 2x stakes condition. In order to provide incentive for truthful revelation of preferences, subjects were randomly paid for one of their choices. Each subject received a show-up fee of 10 CHF. Since subjects could not walk away from the laboratory making losses all subjects were endowed with the maximum possible loss they could incur in the experiment (65 CHF in the 1x stake condition and 130 CHF in the 2x stake condition).

In the laboratory, we are challenged to implement losses that are viewed by subjects as “true losses” and not just lesser gains. In order to minimize a house-money effect and therefore to make losses more real, one week before the experiment took place subjects who would be assigned to the 1x stake condition received an email where they were told: "Next week you will participate in an experiment on decision making under risk. You will be paid 10 CHF as compensation for your time spent. Additionally, you will be given 65 CHF and you will keep the 65 CHF with 90% probability." Subjects who would be assigned to the 2x stake condition received a similar email, the only difference being that 65 CHF was replaced by 130 CHF.

The goal of this email was to induce subjects to think that their (probabilistic) reference point regarding rewards from the experiment is close to the actual expected earnings. If this manipulation was successful, then a subject who comes out of the laboratory with less than the expected earnings will feel like he suffered a loss and one that comes out with more will feel like he has made a gain. After completing the three sets of choices subjects answered demographic questions and returned questionnaires. A random lottery incentive system was then applied (see Appendix C for further details on the experimental set-up and Appendix D for the instructions to subjects).

3 Choices and Skew Conditions

Table 4 displays the acceptance of gambles in each skew condition. Recall that a risk neutral individual accepts lotteries 1 to 5, is indifferent between accepting or rejecting lottery 6, and rejects lotteries 7 to 10.

insert Table 4

The first line in Table 4 tells us that, out of 10 gambles, individuals accept, on average, 3.69, 5.27, and 6.94 in the negative, the zero and the positive skew conditions. Thus, on average, individuals are willing to reject a small stake positive mean gamble to avoid facing a small probability of incurring a large loss (first-order risk averse behavior towards negative skew bets). In contrast, on average, individuals are willing to accept a small stake negative mean gamble in exchange for a small probability of attaining a large gain (first-order risk seeking behavior towards positive skew bets). Finally, on average, individuals accept fifty-fifty gambles with positive mean and reject fifty-fifty gambles with negative mean (risk neutral towards fifty-fifty bets).

The remaining lines of Table 4 display the number of subjects with different acceptance patterns in each skew condition. The number of subjects who reject at least one gamble with positive mean goes from 68 (out of 109) in the negative skew condition to 31 (zero skew) and then to 20 (positive skew condition). The number of subjects who accept at least one gamble with negative mean is 18 in the negative skew condition, 18 in the zero skew condition, and 59 in the positive skew condition. As in most price-list style experiments, some subjects switch more than once from taking the gamble to rejecting it (6, 2 and 4 subjects in the different skew conditions).

Table 5 shows the results of regressions using the number of accepted gambles as the dependent variable. Apart from a constant, column 1 includes two dummies indicating the skew conditions the results being, of course, consistent with those in Table 4. Moreover, the differences in lottery choice patterns across skew conditions are statistically significant: on average, subjects accept more gambles (1.606 and 3.284) in the zero and positive skew conditions than in the negative skew condition.

insert Table 5 here

Column 2 includes dummy variables to control for the magnitude of the stakes and for the order in which choices were presented to subjects. None of these effects is significant and results for the skew conditions do not change. Results are also robust to the inclusion of demographic controls. Column 3 shows that females and those who were raised in Switzerland are less likely to accept playing the gambles, but our main results remain unchanged. These are the only two demographic characteristics that were found to be related to the propensity to accept gambles. The other demographic variables are not related to the number of accepted gambles, and including them in the regression does not change the results meaningfully (column 4).

4 Subject Classification

Applying the classification criteria (explained in Appendix A) to our data leads to the results in Table 6. The first result is that 34 subjects (31%) are classified as EU, 67 (61%) as PT, while 8 subjects (8%) have multiple switching points in at least one skew condition. This result is broadly compatible with Conte et al. (2010) and Bruhin et al. (2010) who find that 20% can be classified as EU and 80% as PT.

insert Table 6 here

Making decisions consistent with EU does not seem much related to observable demographic characteristics, except in what gender is concerned. Indeed, the EU sample contains 16% of females while the PT sample contains 47%, the difference being significant at any conventional level. Again, this finding is consistent with Bruhin et al. (2010) who find that their EU group is dominated by the behavior of male individuals exhibiting near rational probability weighting.

From the 34 EU subjects, 19 are risk averse, 9 are risk seekers, and 6 risk neutral. From the 67 PT subjects, 51 make choices consistent with inverse s-shape probability weighting, 4 with s-shape probability weighting, 12 belong to the category others. The finding that the majority of PT subjects display inverse s-shaped probability weighting (or likelihood insensitivity) is in line with previous research (see Wakker, pp. 204).

Among the 51 inverse s-shape PT subjects, there is a group of 27 (25% of our total sample) who simultaneously reject at least one mixed gamble with positive mean and negative skew and accept at least one mixed gamble with negative mean and positive skew. We call this group "bipolar risk types". While it is well understood that prospect theory implies that people may simultaneously bet on sufficiently unlikely gains as well insure against sufficiently unlikely losses, the size of this group has not been previously estimated.

The 27 bipolar risk types differ from others with respect to gender and age. Females account for 36% in the non-bipolar sample, and for 65% in the bipolar sample. Bipolar risk types are younger (20.8 years of age against 22.7). Both comparisons are significantly different at the 5% level.

5 Estimation of Decision Models

In this section we estimate structural models of choice under risk for each of the groups defined in Table 6. The estimated models parametrically incorporate all of the features of PT proposed by Tversky and Kahneman: risk aversion, nonlinear probability weighting, reference-dependence, diminishing sensitive to outcomes, and loss aversion. This allows us to clarify the contribution of these proposed features of risk preferences for subjects' observed choices, although this clarification is conditioned on assuming particular functional forms. We therefore test whether using some typical alternative functional forms for probability weighting and utility functions change our conclusions. The discussion focus on testing rank dependent utility (Section 5.1) and prospect theory (Section 5.2).

We further allow for the possibility that subjects might state their preferences with some error by using a specification due to Fechner (1966). In this specification $\Pr(Choice = X_i^j) = \Phi[(U_{X_i^j} - u_c)/\sigma]$, where $\Pr(Choice = X_i^j)$ is the probability that the individual accepts lottery X_i^j, $U_{X_i^j}$ is the value of accepting lottery X_i^j, u_c is the value of rejecting lottery X_i^j (i.e., getting the certain amount c), σ is the parameter that represents the standard deviation of the normally distributed decision errors, and Φ denotes the standard normal cumulative distribution.

We estimate the relevant parameters by maximum likelihood (see Harrison and Rutström, 2008) and report standard errors clustered at the individual level, to allow for correlation across decisions and treatments in the choices made by each individual.

5.1 Rank Dependent Utility

According to rank dependent utility (Quiggin, 1982) the value of a gamble X which yields a gain of $g > 0$ with probability p and a loss of $l < 0$ with probability $1 - p$ is

$$\begin{aligned} RDU(w + X) &= \pi_1 u(w + g) + \pi_2 u(w + l) \\ &= h(p)u(w + g) + [1 - h(p)]u(w + l), \end{aligned} \tag{6}$$

where $u(y)$ is the utility function and $h(p)$ is the probability weighting function. To model the utility function we use exponential utility (constant absolute risk aversion):

$$u(w + x) \begin{cases} \frac{1 - e^{-\beta(w+x)}}{\beta}, & \beta \neq 0 \\ w + x, & \beta = 0 \end{cases}, \tag{7}$$

where x is the outcome of a gamble. The parameter β determines the curvature of the utility function. When $\beta > 0$ there is risk aversion, when $\beta = 0$ risk neutrality, and when $\beta < 0$ there is love for risk. Exponential utility has been widely used in economics and it generally fits experimental data on utility measurement well (e.g. Abdellaoui et al. 2007).

To model probability weighting we use as our base model the one-parameter probability weighting function in Goldstein and Einhorn (1987):

$$h(p) = \frac{p^\eta}{p^\eta + (1 - p)^\eta}, \tag{8}$$

where the parameter η determines the degree of probability weighting. When $\eta = 1$ there is no probability weighting and we are back to EU. If $\eta \in (0, 1)$, the function captures the inverse s-shape pattern where low probabilities are upweighted and high probabilities are downweighted. If $\eta > 1$ we have an s-shape pattern where low probabilities are downweighted and high probabilities are upweighted. In the sensitivity analysis we also compare results when using Prelec's (1998) probability weighting function.

insert Table 7 here

The results of estimating this decision model separately for the EU and PT groups are reported in Table 7. The coefficient β is not significantly different from zero for the EU and PT groups which suggests that, on average, linear utility is a good description of subjects' utility function under RDU. EU subjects do not seem to distort probabilities, as the estimate for η is not significantly different from 1.[3] For PT subjects, on the other hand, η is significantly less than 1, which means that, on average, PT subjects upweight small probabilities and downweight large probabilities.

5.2 Prospect Theory

According to prospect theory (Kahneman and Tversky, 1979; 1992), the value of a gamble X that offers a gain $g > 0$ with probability p and a loss $l < 0$ with probability $1 - p$ is

$$\begin{aligned} PT(X|r) &= \pi_1 u(g|r) + \pi_2 u(l|r) \\ &= h^+(p)u(g|r) + h^-(1-p)u(l|r), \end{aligned} \tag{9}$$

where h^+ and h^- are the gain and loss probability weighting functions, respectively, u is the gain-loss utility, and r represents some fixed referent, usually the status-quo.[4]

---

[3] We also estimate the two-parameter Goldstein and Einhorn (1987) probability weighting function $h(p) = \frac{bp^\eta}{bp^\eta + (1-p)^\eta}$, with $\eta, b > 0$. When $b = 1$ we have an inflection point at $p = 0.5$. For both the EU and PT samples we find an estimate for b that is not significantly different from 1.

[4] If one restricts attention to two outcome gambles, like we do here, the 1979 and the 1992 versions of prospect theory are identical.

There are different definitions of loss aversion in the literature and it is still not clear which one is the best (see Schmidt and Zank, 2005; Abdellaoui et al., 2007). Here we follow Köbberling and Wakker's (2005) definition, which assumes that $u(x|r)$ is a composition of a loss aversion index $\lambda > 0$, reflecting the different processing of gains and losses, and basic utility of gains and losses. Formally,

$$u(x|r) = \begin{cases} u^+(x|r) & \text{if } x \geq r \\ -\lambda u^-(-x|r) & \text{if } x < r \end{cases}. \tag{10}$$

where u^+ is the basic utility from gains, and u^- the basic utility from losses. If people pay more attention to losses, λ exceeds 1, and u is steeper for losses than for gains.[5]

To estimate the PT model we take $r = 0$, $u(0|0) = 0$, and we adopt the exponential specification to parameterize the basic utility of gains

$$u^+(x|0) = \begin{cases} \frac{1-e^{-\beta^+ x}}{\beta^+}, & \beta^+ \neq 0 \\ x, & \beta^+ = 0 \end{cases}, \tag{11}$$

and the basic utility of losses

$$u^-(-x|0) = \begin{cases} \frac{1-e^{-\beta^-(-x)}}{\beta^-}, & \beta^- \neq 0 \\ -x, & \beta^- = 0 \end{cases}. \tag{12}$$

---

[5] The function u has a kink at r and is smooth everywhere else. The kink is caused by loss aversion, and does not reflect an intrinsic value of outcomes. That is, it is plausible that the basic utility function is differentiable at r. Thus, they define the loss aversion index as $\lambda = u'_{\uparrow}(x|r)/u'_{\downarrow}(x|r)$, where $u'_{\uparrow}(x|r)$ denotes the left, and $u'_{\downarrow}(x|r)$ the right derivative of u at r (both derivatives are assumed to exist and be positive and finite). If the loss aversion index is equal to 1, there is no loss aversion. If the index is greater than 1, the agent is loss averse.

The parameters β^+ and β^- determine basic utility of gains and losses, respectively. When β^+ and β^- are positive, there is diminishing sensitivity to outcomes since $u(x|0)$ is concave over gains and convex over losses. When β^+ and β^- are negative, there is increasing sensitivity to outcomes since $u(x|0)$ is convex over gains and concave over losses. Under (11) and (12) both the utility for gains and the utility for losses have derivative 1 at 0 and, thus, the basic utility functions are differentiable at 0. Consequently, Köbberling and Wakker's (2005) definition of loss aversion can be computed under exponential utility. The exponential specification also has the desirable feature that if $\lambda \geq 1$ then we have not only loss aversion in the sense of Köbberling and Wakker (2005), but also loss aversion in the sense of Kahneman and Tversky (1979), that is, for any gain x, $-U(-x|r) \geq U(x|r)$.

As before, we adopt Goldstein and Einhor's (1987) specification to parameterize probability weighting, but we allow the degree of probability weighting (η) to be different in the gain and loss domains (η^+ and η^-, respectively). When η^+ and η^- are both less than unity, there is inverse s-shape probability distortion over gains and losses. When η^+ and η^- are both greater than unity, there is s-shape probability distortion over gains and losses.

Table 8 reports the results of estimating four alternative PT specifications. The first specification assumes loss aversion is the main factor behind reference dependence. The second assumes that loss aversion and differences in the basic utilities of gains and losses are the main factors behind reference dependence. The third assumes that loss aversion and differences in probability weighting in the gain and loss domains are the main factors behind reference dependence. The fourth and last specification allows for all kinds of gain-loss asymmetries to occur simultaneously.

insert Table 8 here

Column (1) reports the results for the first specification where we assume common probability weighting and basic utility functions (a single η and a single β). The estimate for β is 0.011 which implies diminishing sensitivity to outcomes. The estimate for η is 0.72 which implies inverse s-shape probability weighting. The estimate for the loss aversion parameter λ is 0.88 which indicates that, on average, PT subjects are not loss averse.

The PT model seems to be preferable to the RDU model. Recall that our results for the RDU model indicated that linear utility was not rejected ($\beta = 0$ in Table 7). If one constrains β to be 0, the RDU model can be seen as a more general case of the PT model where λ is constrained to be equal to 1. With these constraints, both the RDU and the PT model yield the same estimates (not reported here). However, in the context of the PT model, the constraint $\beta = 0$ is clearly rejected, and so the PT model is preferred.

In column (2) we allow β to differ over gains and losses, while assuming a common probability weighting parameter (a single η). The estimates for β^+ and β^- are 0.015 and 0.09, respectively, indicating diminishing sensitivity to outcomes. We find that the estimates of β^+ and β^- are not statistically significantly different ($p_{value} = 0.1859$). The estimate for the probability weighting parameter η is the same as in model 1. Finally, the estimate for λ is slightly smaller than the one obtained in model 1.

Conversely in column (3) we allow for differences in probability weighting over gains and losses but assume a common basic utility (a single β). The estimate for β is almost identical to the one in model 1. The estimates for η^+ and η^- of 0.68 and 0.75 are not statistically significantly different ($p_{value} = 0.3742$). The estimate for λ is not significantly different from unity.

In column (4) we estimate the most general PT model. The estimates for β^+ and β^- of 0.021 and 0.005 are statistically significantly different ($p_{value} = 0.0403$). The estimate for β^+ is significantly greater than zero but the estimate for β^- is not significantly different from zero. This indicates concavity in the gain domain and linearity in the loss domain. The estimates for η^+ and η^- of 0.55 and 0.89 are statistically significantly different ($p_{value} = 0.0264$). The estimate for η^+ is significantly less than unity but the estimate for η^- is not significantly different from unity. This indicates inverse s-shape probability weighting in the gain domain and linear probability weighting in the loss domain. Finally, the estimate for λ is not significantly different from unity.

In a nutshell, the PT models, like the RDU model, provide support for inverse s-shape probability weighting. However, the implied levels of inverse s-shape probability distortion are stronger in the PT models than the RDU model.[6] This happens because the PT models also provide support for diminishing sensitivity to outcomes which leads to choices that go in the opposite direction of inverse s-shape probability weighting (see Appendix E).

---

[6] In the RDU model an estimate for η of 0.86 implies decision weights $\pi_1 = 0.87$ and $\pi_2 = 0.13$ for negative skew lotteries and $\pi_1 = 0.13$ and $\pi_2 = 0.87$ for positive skew lotteries. In the most general PT specification the estimates for η^+ and η^- of 0.55 and 0.89, respectively, imply $\pi_1 = h^+(0.9) = 0.77$ and $\pi_2 = h^-(0.1) = 0.12$ for negative skew lotteries and $\pi_1 = h^+(0.1) = 0.23$ and $\pi_2 = h^-(0.9) = 0.87$ for positive skew lotteries. Note that in the PT model there is subadditivity for negative skew lotteries since $h^+(0.9) + h^-(0.1) = 0.89$, and superadditivity for positive skew lotteries since $h^+(0.1) + h^-(0.9) = 1.10$.

Additionally, within the context of PT models, the estimations indicate that reference-dependence gain-loss asymmetries are driven mainly by differences in probability weighting in the gain and loss domains, differences in the basic utilities of gains and losses also play a role, but there is no loss aversion.

5.3 Heterogeneity within PT Subjects

Table 9 reports the results of estimating a PT model for the 51 inverse s-shape PT subjects. The table also reports the estimates for the two inverse s-shape PT subgroups: the 27 bipolar risk types, and the 24 non-bipolar risk types. The other PT subgroups have too few observations to generate meaningful results.

insert Table 9 here

Column 1 in Table 9 shows the estimates for the 51 subjects who make choices consistent with inverse s-shape probability weighting. The estimation constrains λ to be 1 since λ is very close to 1 and not significantly different from 1 in the unconstrained estimation. This is the largest PT subgroup and, not surprisingly, its estimates are close to those obtained for the whole PT sample.

Column 2 reports the parameter estimates for the bipolar risk types. The estimate for β is not significantly different from 0. The estimates for η^+ and η^- are 0.43 and 0.73, respectively. These estimates imply very strong inverse s-shape probability weighting since $\pi_1 = h^+(0.9) = 0.72$ and $\pi_2 = h^-(0.1) = 0.17$ for negative skew lotteries and $\pi_1 = h^+(0.1) = 0.28$ and

$\pi_2 = h^-(0.9) = 0.83$ for positive skew lotteries.

The parameter estimates for the non-bipolar risk types are reported in column 3. The estimate for β is not significantly different from 0. The estimates for η^+ and η^- are 0.79 and 0.93, respectively. These estimates imply $\pi_1 = 0.85$ and $\pi_2 = 0.11$ for negative skew lotteries and $\pi_1 = 0.15$ and $\pi_2 = 0.88$ for positive skew lotteries.

5.4 Heterogeneity within EU Subjects

For completeness, Table 10 reports the results of estimating the RDU model for the EU subgroups.

insert Table 10 here

The signs of the estimates of β are consistent with the predictions of the non-parametric classification: positive and significantly greater than zero for risk averse subjects, negative and significantly smaller than zero for the risk seeking subjects, and not significantly different from zero for the risk neutral.

The decomposition of the EU sample into risk averse, seeking, and neutral groups leads to some indications of probability weighting in the risk seeking group. Estimates for η are not significantly different from one for the risk averse and risk neutral group. However, the estimate for η for the risk seeking group is equal to 0.90 and is statistically different from one.

5.5 Robustness

Our estimations yield a very clear message: nonlinear probability weighting plays the most important role in explaining the choices of PT subjects. More specifically, nonlinear probability weighting is consistently statistically significant, while the shape of the utility function varies across the RDU (linear) and PT (concave for gains and convex/linear for losses) specifications, and there is no evidence whatsoever of loss aversion.

These results were obtained assuming an exponential utility function and Goldstein and Einhorn's (1987) probability weighting function. In Appendix F we perform the estimations replacing Goldstein and Einhorn's (1987) probability weighting function with Prelec's (1998) and obtain essentially the same estimates when we estimate the RDU model in the EU and PT samples. We find that there are some differences between using Prelec's or Goldstein and Einhorn's probability weighting functions when we restrict attention to the PT sample. For example, under Prelec probability weighting there is less support for inverse s-shape probability weighting in models 1 and 3 than under Goldstein and Einhorn probability weighting. However, both probability weighting functions lead essentially to the same estimates in the most general PT specification.

6 Discussion and Conclusions

We propose a simple and compact lottery-choice task that is suitable for eliciting attitudes towards risk in field experiments or in lab experiments where risk elicitation may not be the main experiment. Risk attitudes are elicited using mixed gambles with positive, zero and negative skew. Therefore, our work goes beyond prior experimental research focusing on eliciting risk attitudes using lotteries involving only gains (e.g., Brunner et al., 2007; Åstebro et al., 2008; Ebert and Wiesen, 2009; and Deck and Schlesinger, 2010) or lotteries involving either only gains or only losses (e.g. Holt and Laury, 2002; Fehr-Duda et al.,2010; and Bruhin et al., 2010). This brings the experimental task closer to real world risky decisions which typically involve gain-loss gambles.

We use a non-parametric classification method to decompose the sample into EU and PT subjects without making functional form assumptions about subjects' preferences. This contrasts to prior experimental research that assumes specific functional forms of utility and probability weighting to study risk attitudes.[7] The parametric approaches are easy to estimate and interpret, but they suffer from a contamination effect: a misspecification of the utility function will also bias the estimated probability weighting function and vice versa (Abdellaoui, 2000; Harrison and Rutström, 2008).

We only use 30 decisions per subject to uncover heterogeneity in risk attitudes. In comparison, experimental research with finite mixture models may elicit as much as 500 decision per subject (e.g. Harrison and Rutström, 2009; Conte et al., 2010; Bruhin et al., 2010).[8] Of course, one limitation of our study is that since individuals only make 30 decisions (which are equivalent to eliciting three switching points) we cannot perform individual

---

[7] For example, Harrison and Rutström (2009) assume power utility and the one parameter probability weighting function introduced by Tversky and Kahneman (1992), Tanaka et al. (2010) assume power utility and Prelec (1998) one parameter probability weighting.

[8] In Harrison and Rutström (2009) the goal is to estimate the probability that any one lottery choice is consistent with EU or not, irrespective of the identity of the decison maker. In Conte et al. (2010) and Bruhin et al. (2010) the goal is to classify individuals as EU or non-EU types.

level estimations of preference parameters.

In our sample, we find that 31% can be classified as EU, 61% as PT, and 8% have multiple switching points in at least one skew condition. Conte et al. (2010) and Bruhin et al. (2010) find that when subjects face gambles involving only gains or only losses, 20% can be classified as EU and 80% as PT. Hence, our result is compatible with Conte et al. (2010) and Bruhin et al. (2010) but was obtained using a task that requires much lighter subject cognitive loads and computational efforts. Field experiments that need to use an individual measure of risk attitudes as an input should take this heterogeneity into account. If there is heterogeneity, as other research has suggested and our data confirms, basing risk preference elicitation procedures on a single preference theory is inappropriate and may lead to biased results. Our task offers a simple tool to perform such measurement.

Our maximum likelihood estimations reveal that, on average, PT subjects display inverse s-shape probability weighting in all of our specifications. Hence, most people apparently prefer lotteries with positive skew because they overweight the odds of unlikely gains and dislike lotteries with negative skew because they overweight the probability of unlikely losses. This finding is consistent with Conte et al. (2010) and Bruhin et al. (2010) who find evidence of inverse s-shape probability weighting in their PT samples. The finding is also consistent with evidence from fields studies. For example, both Snowberg and Wolfers (2010) and Jullien and Salanié (2000) find that inverse s-shape probability weighting dominates in explaining why there is overbetting on the long-shot horse while favorites are underbet. In the context of insurance choices, Cohen and Einav (2007) and Barseghyan et al.

(2010) find preferences in which inverse s-shape probability weighting plays the most important role and loss aversion is irrelevant. Still, our estimations also indicate that the PT model is preferable to the RDU model for explaining choices in the PT group, as most PT subjects display diminishing sensitivity to outcomes relative to a reference point.

Since we use mixed lotteries we can evaluate all features of risk preferences proposed by prospect theory. Most of prior experimental work typically has been limited to testing a subset of the behavioral features of PT. For example, Abdellaoui (2000) and Bruhin et al. (2010) use lotteries involving either only gains or only losses and estimate probability distortion parameters for the gain and loss domains but do not estimate a loss aversion parameter since that is neither feasible nor meaningful. Tversky and Kahneman (1992) and Abdellaoui et al. (2007) study all features of risk preferences proposed by prospect theory but use hypothetical choices. Abdellaoui et al. (2008) use real incentives for lotteries with only gains but not for lotteries with only losses or with gains and losses. As far as we know, there are only two other studies that analyze all aspects of prospect theory using monetary incentives for all types of lotteries: Harrison and Rutström (2009) and Tanaka et al. (2010).

Our estimations show that, on average, PT subjects display diminishing sensitivity to outcomes. We find support for concavity in the gain domain and either convexity or linearity in the loss domain. This is consistent with findings from studies that report utility curvature for gains and losses: utility for losses displays diminishing sensitivity in most cases but losses are evaluated more linearly than gains. Recall that diminishing sensitivity to outcomes leads to choices that go in the opposite direction of inverse s-shape probability weighting. That is, it leads to first-order risk seeking towards negative skew gambles and first-order risk aversion towards positive skew gambles. However, the estimations show that the impact of inverse s-shaped probability weighting on choices dominates the impact of diminishing sensitivity to outcomes.

We also find more upweighting of low probabilities for gains than for losses. Fehr-Duda et al. (2010) obtain similar results using a partially different experimental treatment and estimation method; they observed relative risk aversion over increasing gains but an incoherent pattern of risk preferences over increasing losses. These patterns were explained by estimating inverse s-shape probability weighting which changed markedly towards less optimistically perceived odds when gains rose for the PT sample, while probability weighting remained unchanged when losses rose.

Finally, our estimations also reveal that our sample of PT subjects does not display loss aversion. This result is consistent with Ert and Erev (2010), and Fehr-Duda et al. (2010) as well some field evidence (e.g. Barseghyan et al. 2010), but stands in contrast to the many studies which interpret rejection of fifty-fifty gain-loss gambles with positive mean as loss aversion (e.g., Gachter et al. 2007). Our results support the idea that loss aversion is volatile and depends on framing (see Wakker 2010, pp. 265).

In a nutshell, our experiment proposes a simple task that allows the study of risk attitudes without assuming an EU framework and to uncover heterogeneity in these attitudes. This is an important contribution since the existing evidence on risk attitudes shows that a large fraction of subjects display non-EU preferences and there is a wide distribution of risk preferences. We offer an economical way of uncovering such preferences that can be used in the field. The use of mixed gambles allows us to evaluate the role played by all the different behavioral features of risk preferences proposed by PT.

Tables

Table 1: Choices in the Positive Skew Domain (1x stake)

Choice	Lottery (L)	Accept	Reject	$E(L)$	$V(L)$
1	90% of -5 CHF, 10% of 70 CHF			2.50	506
2	90% of -5 CHF, 10% of 65 CHF			2.00	441
3	90% of -5 CHF, 10% of 60 CHF			1.50	380
4	90% of -5 CHF, 10% of 55 CHF			1.00	324
5	90% of -5 CHF, 10% of 50 CHF			0.50	272
6	90% of -5 CHF, 10% of 45 CHF			0	225
7	90% of -5 CHF, 10% of 40 CHF			-0.50	182
8	90% of -5 CHF, 10% of 35 CHF			-1.00	144
9	90% of -5 CHF, 10% of 30 CHF			-1.50	110
10	90% of -5 CHF, 10% of 25 CHF			-2.00	81

Note: The last two columns were not displayed to experimental subjects.

Table 2: Choices in the Zero Skew Domain (1x stake)

Choice	Lottery (L)	Accept	Reject	$E(L)$	$V(L)$
1	50% of -1 CHF, 50% of 6 CHF			2.50	12
2	50% of -2 CHF, 50% of 6 CHF			2.00	16
3	50% of -3 CHF, 50% of 6 CHF			1.50	20
4	50% of -4 CHF, 50% of 6 CHF			1.00	25
5	50% of -5 CHF, 50% of 6 CHF			0.50	30
6	50% of -6 CHF, 50% of 6 CHF			0	36
7	50% of -7 CHF, 50% of 6 CHF			-0.50	42
8	50% of -8 CHF, 50% of 6 CHF			-1.00	49
9	50% of -9 CHF, 50% of 6 CHF			-1.50	56
10	50% of -10 CHF, 50% of 6 CHF			-2.00	64

Note: The last two columns were not displayed to experimental subjects.

Table 3: Choices in the Negative Skew Domain (1x stake)

Choice	Lottery (L)	Accept	Reject	$E(L)$	$V(L)$
1	10% of -20 CHF, 90% of 5 CHF			2.50	56
2	10% of -25 CHF, 90% of 5 CHF			2.00	81
3	10% of -30 CHF, 90% of 5 CHF			1.50	110
4	10% of -35 CHF, 90% of 5 CHF			1.00	144
5	10% of -40 CHF, 90% of 5 CHF			0.50	182
6	10% of -45 CHF, 90% of 5 CHF			0	225
7	10% of -50 CHF, 90% of 5 CHF			-0.50	272
8	10% of -55 CHF, 90% of 5 CHF			-1.00	324
9	10% of -60 CHF, 90% of 5 CHF			-1.50	380
10	10% of -65 CHF, 90% of 5 CHF			-2.00	441

Note: The last two columns were not displayed to experimental subjects.

Table 4: Acceptance of Lotteries across Skew Conditions

Acceptance Behavior (lottery choice category)	Negative Skew	Zero Skew	Positive Skew
Average number of lotteries accepted	3.69	5.27	6.94
Reject all lotteries	20	1	9
Accept 1, reject 2 to 10	11	2	1
Accept 1 and 2, reject 3 to 10	17	4	4
Accept 1 to 3, reject 4 to 10	11	11	3
Accept 1 to 4, reject 5 to 10	9	13	3
Accept 1 to 5, reject 6 to 10	11	38	16
Accept 1 to 6, reject 7 to 10	6	20	10
Accept 1 to 7, reject 8 to 10	1	3	5
Accept 1 to 8, reject 9 and 10	3	4	4
Accept 1 to 9, reject 10	2	2	3
Accept all	12	9	47
Multiple Switchers	6	2	4
Total	109	109	109

Table 5: Regression Results: Number of Accepted Lotteries

	(1)		(2)		(3)		(4)	
Constant	3.661	(0.298)	3.601	(0.384)	3.766	(0.689)	4.138	(1.669)
Zero skew	1.606^a	(0.359)	1.608^a	(0.362)	1.606^a	(0.351)	1.605^a	(0.347)
Positive skew	3.284^a	(0.434)	3.287^a	(0.436)	3.284^a	(0.430)	3.284^a	(0.431)
2x stake			-0.093	(0.329)				
Order (2nd)			0.121	(0.403)				
Order (3rd)			0.152	(0.382)				
Female					-0.758^b	(0.318)	-0.708^c	(0.375)
Raised in Swzt					-0.709^b	(0.285)	-0.774^b	(0.315)
Age							0.019	(0.043)
Parents decide							-0.551	(0.525)
People in house							0.030	(0.168)
Single							0.534	(0.525)
Student							-0.032	(0.366)
R^2	0.179		0.179		0.209		0.246	
$\bar{R}^2$	0.174		0.167		0.199		0.195	

Note: Robust standard errors in parentheses. Letters a, b and c indicate significance at 1%, 5%, and 10%, respectively. Column 4 also includes sets of dummies for years of schooling (4) and household income (8). None of the two sets is significant.

Table 6: Groups and Mean Number of Lotteries Accepted

Groups	N	(%)	Skew		
			Neg.	Zero	Pos.
EU					
Risk neutral	6	(5.5)	5.33	5.17	5.67
A1: $a^N, a^Z, a^P \in \{5, 6\}$					
Risk averse	19	(17.4)	1.79	4.42	2.95
A2: $\min(a^N, a^P) \leq \max(a^N, a^P) < a_Z \leq 5$					
A3: $\min(a^N, a^P) < \max(a^N, a^P) \leq a_Z \leq 5$					
A4: $a^N = a^Z = a^P = 0$					
Risk seeker	9	(8.3)	9.11	7.22	9.89
A5: $6 \leq a^Z < \min(a^N, a^P) \leq \max(a^N, a^P)$					
A6: $6 \leq a^Z \leq \min(a^N, a^P) < \max(a^N, a^P)$					
A7: $a^N = a^Z = a^P = 10$					
All EU	34	(31.2)	4.35	5.29	5.26
PT					
Inverse s-shape	51	(46.8)	2.25	5.31	8.80
B1: $a^N \leq a^Z < a^P$					
B2: $a^N < a^Z \leq a^P$					
S-shape	4	(3.7)	7.75	2.75	1.25
B3: $a^P \leq a^Z < a^N$					
B4: $a^P < a^Z \leq a^N$					
Others					
C1: $a^Z < \min(a^P, a^N)$	6	(5.5)	8.33	4.83	8.83
C2: $a^Z > \max(a^P, a^N)$	3	(2.8)	1.33	6.00	1.67
C3: $a^N = a^Z = a^P = k \in \{1, 2, 3, 4\}$	1	(0.9)	2.00	2.00	2.00
C4: $a^N = a^Z = a^P = k \in \{7, 8, 9\}$	2	(1.8)	8.50	8.50	8.50
All PT	67	(61.5)	3.27	5.19	7.93
Multiple Switchers	8	(7.3)	4.38	5.75	5.88
All subjects	109	(100.0)	3.69	5.27	6.94

Table 7: EU and PT Subjects: RDU model with CARA Utility and Goldstein and Einhorn (1987) Probability Weighting

	EU		PT	
β	-0.00006	(0.001)	-0.001	(0.001)
η	0.99	(0.01)	0.86^*	(0.03)
σ	3.22^*	(0.65)	4.58^*	(0.61)
LL	-590		-1131	
Subjects	34		67	

Note: Clustered standard errors in parentheses. The superscript * indicates significance at 5%. For β and σ relative to 0. For η relative to 1.

Table 8: PT Subjects: PT model with CARA Utility and Goldstein and Einhorn (1987) Probability Weighting

	(1)		(2)		(3)		(4)	
β	0.011^*	(0.005)			0.012^*	(0.004)		
β^+			0.015^*	(0.005)			0.021^*	(0.007)
β^-			0.009^*	(0.005)			0.005	(0.005)
η	0.72^*	(0.05)	0.72^*	(0.05)				
η^+					0.68^*	(0.07)	0.55^*	(0.10)
η^-					0.75^*	(0.06)	0.89	(0.09)
λ	0.88^*	(0.05)	0.81^*	(0.08)	0.93	(0.07)	0.86	(0.08)
σ	1.60^*	(0.24)	2.55^*	(0.35)	2.73^*	(0.38)	2.61^*	(0.38)
LL	-1079		-1076		-1079		-1063	
Subjects	67		67		67		67	

Note: Clustered standard errors in parentheses. The superscript * indicates significance at 5%. For β, β^+, β^-, and σ relative to 0. For η, η^+, η^-, and λ relative to 1.

Table 9: PT Inverse S-Shape Subjects: PT model with CARA Utility and Goldstein and Einhorn (1987) Probability Weighting

	All		Bipolar		Non-Bipolar	
β	0.0085^*	(0.0035)	0.0126	(0.0068)	-0.0007	(0.0036)
η^+	0.61^*	(0.0506)	0.43^*	(0.0854)	0.79^*	(0.0578)
η^-	0.78^*	(0.0584)	0.73^*	(0.0940)	0.93	(0.0801)
σ	2.52^*	(0.3569)	2.23^*	(0.4874)	2.92^*	(0.5356)
LL	-678		-299		-343	
Subjects	51		27		24	

Note: Clustered standard errors in parentheses. The superscript * indicates significance at 5%. For β and σ relative to 0. For η^+, η^-relative to 1.

Table 10: EU Subjects: RDU model with CARA Utility and Goldstein and Einhorn (1987) Probability Weighting

	Risk averse		Risk seeker		Risk neutral	
β	0.0045^*	(0.0015)	-0.0284^*	(0.0022)	-0.0020	(0.0013)
η	0.97	(0.0250)	0.90^*	(0.0368)	0.99	(0.0033)
σ	1.72^*	(0.4272)	7.97^*	(1.2392)	1.82^*	(0.7118)
LL	-300		-62		-63	
Subjects	19		9		6	

Note: Clustered standard errors in parentheses. The superscript * indicates significance at 5%. For β and σ relative to 0. For η relative to 1.

References

Abdellaoui, Mohammed (2000). "Parameter-free Elicitation of Utility and Probability Weighting Functions," *Management Science*, 46, 1497-1512.

Abdellaoui, Mohammed, Bleichrodt, Han and Corina Paraschiv (2007). "Loss Aversion under Prospect Theory: a Parameter-free Measurement," *Management Science*, 53 , 1659-1674.

Abdellaoui, Mohammed, Bleichrodt, Han and Oliver L'Haridon (2008). "A Tractable Method to Measure Utility and Loss Aversion under Prospect Theory," *Journal of Risk and Uncertainty*, 36, 245-266.

Arrow, Kenneth (1971). *Essays in the Theory of Risk Bearing*, Chicago, IL: Markham Publishing Company.

Åstebro, Thomas, Mata, José, and Luis Santos-Pinto, (2008). "Preference for Skew in Lotteries: Evidence from the Laboratory," Working Paper SSRN.

Barberis, Nicholas, Huang, Ming and Richard Thaler (2006). "Individual Preferences, Monetary Gambles, and Stock Market Participation: A Case for Narrow Framing," *The American Economic Review*, 96, 1069-1090.

Barseghyan, Levon, Molinari, Francesca, Ted, O'Donoghue and Joshua Teitelbaum (2010). "The Nature of Risk Preferences: Evidence from Insurance Choices," Working paper, SSRN.

Bleichrodt, Han, Pinto, José, and Peter Wakker (2001). "Using Descriptive Findings of Prospect Theory to Improve the Prescriptive Use of Expected Utility," *Management Science*, 47, 1498-1514.

Bleichrodt, Han and José Pinto (2000). "A Parameter-free Elicitation of the Probability Weighting Function in Medical Decision Analysis," *Management*

Science, 46, 1485-1496.

Brunner, Tobias, Levinsky, René, and Jianying Qiu (2007). "A Note on Skewness Seeking: An Experimental Analysis," *Jena Economic Research Papers*, 079.

Bruhin, Adrian, Fehr-Duda, Helga, and Thomas Epper (2010). "Risk and Rationality: Uncovering Heterogeneity in Probability Distortion," *Econometrica*, 78, 4, 1375–1412.

Camerer, Colin (1992). "Recent Tests of Generalizations of Expected Utility Theory," in Ward Edwards, ed., *Utility: Theories, Measurement, and Applications*, Kluwer: Norwell, MA, 1992, pp. 207-251.

Chiu, Henry (2010). "Skewness Preference, Risk Taking and Expected Utility Maximisation," *The Geneva Risk and Insurance Review*, 35, 108-29.

Cicchetti, Charles and Jeffrey Dubin (1994). "A Mi-croeconometric Analysis of Risk Aversion and The Decision to Self-Insure," *Journal of Political Economy*, 102, 1, 169-86.

Cohen, Alma and Liran Einav (2007). "Estimating Risk Preferences from Deductible Choice," *The American Economic Review*, 97, 3, 745-788.

Conlisk, John. (1989). "Three Variants on the Allais Example," *The American Economic Review*, 79, 3, 392-407.

Conte, Anna, Hey, John and Peter Moffat (2010). "Mixture Models of Choice under Risk," forthcoming in *Journal of Econometrics.*

Deck, Cary and Harris Schlesinger (2010). "Exploring Higher-Order Risk Effects," forthcoming in *Review of Economic Studies.*

Ebert, Sebastian and Daniel Wiesen (2009). "An Experimental Methodology for Testing for Prudence and Third-Order Preferences," Bonn Econ Discussion Papers, 21.

Ert, Eyal, and Ido Erev (2008). "The Rejection of Attractive Gambles, Loss Aversion, and the Lemon Avoidance Heuristic," *Journal of Economic Psychology* 29, 715-723.

Ert, Eyal and Ido Erev (2010). "On the Descriptive Value of Loss Aversion under Risk," Working paper, Harvard Business School.

Fechner, Gustav (1966). *Elements of Psychophysics*, New York: Holt, Rinehart and Winston.

Fehr-Duda, Helga, Bruhin, Adrian, Epper, Thomas and Renate Schubert (2010). "Rationality on the Rise: Why Relative Risk Aversion Increases with Stake Size," *Journal of Risk and Uncertainty*, 40, 2, 147-180.

Gachter, Simon, Johnson, Eric and Andreas Herrmann (2007). "Individual-Level Loss Aversion in Riskless and Risky Choices," Centre for Decision Research and Experimental Economics Discussion Paper Series, ISSN 1749-3293.

Goldstein, William and Hillel Einhorn (1987): "Expression Theory and the Preference Reversal Phenomena," *Psychological Review*, 94, 236–254.

Golec, Joseph, and Maury Tamarkin (1998). "Betters Love Skewness, Not Risk, at the Horse Track," *Journal of Political Economy*, 106, 205–225.

Gonzalez, Richard and George Wu (1999). "On the Shape of the Probability Weighting Function," *Cognitive Psychology*, 38, 129-166.

Greiner, Ben (2004). "An Online Recruiting System for Economic Experiments," In Forschung und wissenschaftliches Rechnen 2003. GWDG Bericht

63, ed. Kurt Kremer and Volker Macho, 79-93. Göttingen: Ges. für Wiss.

Griffith, R. M. (1949). “Odds Adjustments by American Horse-Race Bettors,” *The American Journal of Psychology*, 62, 2, 290–294.

Harless, David and Colin Camerer (1994). “The Predictive Utility of Generalized Expected Utility Theories,” *Econometrica*, 62, 6, 1251-1289.

Harrison, Glenn and Elisabet Rutström, (2008). “Risk Aversion in the Laboratory,” *Research in Experimental Economics*, 12, 41-196.

Harrison, Glenn and Elisabet Rutström (2009). “Expected Utility Theory and Prospect Theory: One Wedding and a Decent Funeral,” *Experimental Economics*, 12, 133-158.

Holt, Charles, and Susan Laury (2002). “Risk Aversion and Incentive Effects,” *American Economic Review*, 92(5), 1644-55.

Jullien, Bruno and Bernard Salanié (2000). “Estimating Preferences under Risk: The Case of Racetrack Bettors,” *Journal of Political Economy*, 108(3), 503-530.

Kahneman, Daniel and Amos Tversky (1979). “Prospect Theory: An Analysis of Decision Making under Risk,” *Econometrica*, 47, 263-292.

Köbberling, Veronika, and Peter Wakker (2005). “An Index of Loss Aversion,” *Journal of Economic Theory*, 122, 119-131.

Laury, Susan, McInnes, Melayne, and Todd Swarthout (2009). “Insurance Decisions for Low-Probability Losses,” *Journal of Risk and Uncertainty*, 39, 17-44.

McGlothlin,William (1956). “Stability of Choices among Uncertain Alternatives,” *The American Journal of Psychology*, 69, 4, 604–615.

Prelec, Drazen (1998). “The Probability Weighting Function,” *Econometrica*, 60, 497-528.

Quiggin, John (1982). “A Theory of Anticipated Utility,” *Journal of Economic Behavior and Organization*, 3, 323-343.

Schmidt, Ulrich and Horst Zank (2005). “What is Loss Aversion?” *Journal of Risk and Uncertainty*, 30, 157-167.

Schoemaker, Paul (1982). “The Expected Utility Model: It’s Variants, Purposes, Evidence and Limitations,” *Journal of Economic Literature*, Vol. 20, 529-563.

Segal, Uzi and Avia Spivak (1990), “First-order versus Second-order Risk Aversion,” *Journal of Economic Theory*, 51, 111-125.

Snowberg, Eric and Justin Wolfers (2010). “Explaining the Favorite-Longshot Bias: Is Risk Love or Misperceptions?” forthcoming in *Journal of Political Economy.*

Starmer, Chris (2000). “Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk,” *Journal of Economic Literature*, Vol. 38, 332-382.

Sydnor, Justin (2010). “(Over)Insuring Modest Risks,” forthcoming in *American Economic Journal: Applied Economics.*

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). “Risk and Time Preferences: Experimental and Household Survey Data from Vietnam,” *The American Economic Review*, Vol. 100: 1, 557–571.

Tversky, Amos and Daniel Kahneman (1992). “Advances in Prospect Theory: Cumulative Representation of Uncertainty,” *Journal of Risk and Un-*

certainty, 5, 297-323.

Wakker, Peter (2010). *Prospect Theory for Risk and Uncertainty*, Cambridge University Press, New York.

Appendix A: Classification Rules

For presenting the criteria that classifies subjects into groups, let $a^j_{k,l}$ denote the number of gambles an individual accepts in skew condition j when he faces gambles k to l, where $k < l \in \{2, ..., 10\}$ and $j \in \{N, Z, P\}$. Furthermore, to simplify notation, let the total number of gambles an individual accepts in skew condition j be denoted by $a^j = a^j_{1,10}$.

Subjects are classified into groups according to the choices they made in the three skew conditions as described in Table 6. The table also displays the number of subjects in each group and the mean number of lotteries accepted by each group across skew conditions.

We start with classifying subjects as either EU, PT, or multiple switchers. The last category contains subjects who switch more than once from accepting to rejecting lotteries in a given skew condition. Hence, we only retain as EU or PT those subjects that have a unique switching point in each skew condition.

insert Table 6 here

A narrow framing EU individual (EU individual from now on) does not integrate the gambles with labor income, wealth and/or background risks. Hence, an EU individual compares the utility of rejecting the gamble and keeping the endowment, $u(w)$, with the expected utility of accepting the gamble X^j_i, $E[u(w + X^j_i)]$.

An EU individual rejects lottery X^j_i when $E[u(w + X^j_i)] < u(w)$, accepts lottery X^j_i when $E[u(w + X^j_i)] > u(w)$, and is indifferent between acceptance or rejection of lottery X^j_i when $E[u(w + X^j_i)] = u(w)$. The choices of an EU individual are driven only by the shape of his utility function and he can be risk neutral (linear u), averse (concave u), or seeking (convex u).

A risk neutral EU individual compares the mean of each lottery to zero, rejects all lotteries with a negative mean and accepts all lotteries with a positive mean. Since our first five lotteries have positive mean and our last four lotteries have negative mean, a risk neutral EU individual accepts the first five lotteries and rejects the last four, that is, $a^j_{1,5} = 5$ and $a^j_{7,10} = 0$ for all j. Therefore, the choices of risk neutral EU individual are given by $a^N, a^Z, a^P \in \{5, 6\}$. This condition is referred to as A1 in Table 6.

A risk averse EU individual rejects negative mean lotteries, that is, he rejects X^j_i with $i \geq 7$ for all j. Additionally, he also rejects lotteries X^P_6, X^Z_6, and X^N_6 since these are mean-preserving spreads of the sure amount 0. Hence, a risk averse EU individual rejects lotteries X^j_i with $i \geq 6$ for all j, that is, $a^j_{6,10} = 0$ for all j. This implies that for a risk averse EU individual $a^j \leq 5$ for all j, the inequality being strict for at least one j.

A risk seeking EU individual accepts positive mean lotteries, that is, he accepts X^j_i with $i \leq 5$ for all j. Additionally, he also accepts lotteries X^P_6, X^Z_6, and X^N_6 since these are mean-preserving spreads of 0. Hence, a risk seeking EU subject accepts lotteries X^j_i with $i \leq 6$ for all j, that is, $a^j_{1,6} = 6$ for all j. This implies that for a risk seeking EU individual $a^j \geq 6$ for all j, the inequality being strict for at least one j.

Chiu (2010) establishes a skewness-comparability condition on probability distributions that is necessary and sufficient for any decision-maker's preferences over the distributions to be determined by the first three moments of the distributions. Under the condition, an EU maximizer's preferences for a larger mean, a smaller variance, and a larger third moment are shown to parallel, respectively, his preferences for a first-degree stochastic dominance improvement, a mean-preserving contraction, and a downside risk increase. He also shows that all Bernoulli gambles satisfy the skewness-comparability condition and therefore individuals' choices between Bernoulli gambles can be understood as trade-offs between mean, variance, and skewness. That is, we can write

$$E[u(w + X_i^j)] = U(w, E(X_i^j), V(X_i^j), S(X_i^j)) = U(Y_i^j).$$

Finally, he shows that when a decision-maker's preferences over gambles only depends on their means, variances, and third moments, then aversion to larger variances implies risk aversion and precludes taking fair gambles whatever the strength of the skewness preference.

Chiu's (2010) results and conditions (1), (2), and (5) impose additional constraints on the choices of risk averse EU individuals. First, a risk averse EU individual who is indifferent to skew has $U(Y_i^Z) > U(Y_i^N) > U(Y_i^P)$ for all $i \leq 5$. This implies either $a^Z > a^N \geq a^P$ or $a^Z \geq a^N > a^P$. Second, a risk averse EU individual who dislikes skew has $U(Y_i^Z) \geq U(Y_i^N) > U(Y_i^P)$ for all $i \leq 5$. This implies either $a^Z > a^N \geq a^P$ or $a^Z \geq a^N > a^P$. Third, a risk averse EU individual who likes skew and whose aversion to risk is low relative to love for skew has $U(Y_i^Z) \geq U(Y_i^P) > U(Y_i^N)$ for all $i \leq 5$. This implies either $a^Z \geq a^P > a^N$ or $a^Z > a^P \geq a^N$. Fourth, a risk averse EU individual who likes skew and whose aversion to risk is high relative to love for skew has $U(Y_i^Z) > U(Y_i^N) \geq U(Y_i^P)$ for all $i \leq 5$. This implies either $a^Z > a^N \geq a^P$ or $a^Z \geq a^N > a^P$. The non-redundant conditions are summarized as A2 and A3 in Table 6. Finally, an extremely risk averse EU individual can reject all gambles, that is, $a^j = 0$ for all j (A4).

Similarly, Chiu's (2010) results and conditions (1), (4), and (5) impose additional constraints on the choices of risk seeking EU individuals. First, a risk seeking EU individual who is indifferent to skew has $U(Y_i^N) > U(Y_i^P) > U(Y_i^Z)$ for all $i \geq 7$. This implies either $a^N > a^P \geq a^Z$ or $a^N \geq a^P > a^Z$. Second, a risk seeking EU individual who dislikes skew has $U(Y_i^N) > U(Y_i^P) \geq U(Y_i^Z)$ for all $i \geq 7$. This implies $a^N > a^P \geq a^Z$ or $a^N \geq a^P > a^Z$. Third, a risk seeking EU individual who likes skew and whose love for risk is low relative to love for skew has $U(Y_i^P) > U(Y_i^N) \geq U(Y_i^Z)$ for all $i \geq 7$. This implies either $a^P > a^N \geq a^Z$ or $a^P \geq a^N > a^Z$. Fourth, a risk seeking EU individual who likes skew and whose love for risk is high relative to love for skew has $U(Y_i^N) \geq U(Y_i^P) > U(Y_i^Z)$ for all $i \geq 7$. This implies either $a^N \geq a^P > a^Z$ or $a^N > a^P \geq a^Z$. The relevant conditions are summarized as A5 and A6 in Table 6. Finally, an extremely risk seeking EU individual can accept all gambles, that is, $a^j = 10$ for all j (A7).[9]

A subject whose choices meet none of the conditions A1-A7 but which have a unique switching point in each skew condition is called a PT subject. We classify PT subjects into three groups according to the pattern of probability weighting: those whose choices are consistent with inverse s-shape probability weighting, s-shape probability weighting, and others (see Table 6 under PT heading). Those with non-unique switching points are listed in the second to last row in Table 6.

A PT subject whose choices are consistent with inverse s-shape probability weighting can (i) accept less or the same number of lotteries in the

---

[9] Appendix B applies the classification scheme to the choices of an EU individual with exponential utility and an endowment of 65 CHF.

negative skew condition than in the zero skew condition and accept less lotteries in the zero skew condition than in the positive skew condition (B1), or (ii) accept less lotteries in the negative skew condition than in the zero skew condition and accept less or the same number of lotteries in the zero skew condition than in the positive skew condition (B2).

A PT subject whose choices are consistent with s-shape probability weighting can (i) accept less or the same number of lotteries in the positive skew condition than in the zero skew condition and accept less lotteries in the zero skew condition than in the negative skew condition (B3), or (ii) accept less lotteries in the positive skew condition than in the zero skew condition and accept less or the same number of lotteries in the zero skew condition than in the negative skew condition (B4).

A PT subject whose choices meet none of the conditions (B1)-(B4) is considered to belong to the category others. This category can be decomposed into four subgroups: those who accept less lotteries in zero skew condition than the minimum of the lotteries accepted in the negative and positive skew conditions (C1), those who accept more lotteries in the zero skew condition than the maximum of the lotteries accepted in the negative and positive skew conditions (C2), those who accept the same number of lotteries in the three skew conditions and $a^j_{1,10} \in \{1, 2, 3, 4\}$ (C3), and those who accept the same number of lotteries in the three skew conditions and $a^j_{1,10} \in \{7, 8, 9\}$ (C4).

Appendix D: EU Choices–Exponential Utility

Table 11 maps the choices of a EU individual with an exponential utility along the three skew conditions with different values for risk aversion (the parameter β) and gives the subject classification for each case.

insert Table 11 here

Table 11 shows that the theoretical and our choice classification coincide in all cases except in the two cases close to risk neutrality. Of course, in theory, an individual is risk neutral only when $\beta = 0$. As choices made by individuals with values of β in the close vicinity of zero choices satisfy A1 and therefore, these individuals are classified as risk neutral, despite being slightly risk loving, $\beta \in (-0.0039, 0)$, or slightly risk averse, $\beta \in (0, 0.0038]$.

This mismatch between the theoretical and the choice classification for slight risk averse and slight risk seeking subjects happens in all experiments that use a multiple price list design to elicit risk attitudes (see, for example, Holt and Laury, 2002).

Table 11: Gambles Accepted by an EU Individual with Exponential Utility

Range for β	Risk profile	Gambles accepted in N,Z,P	Condition
$\beta \leq -0.0653$	seeker	10,10,10	A7
$-0.0652 < \beta \leq -0.0549$	seeker	10,9,10	A5
$-0.0548 < \beta \leq -0.0414$	seeker	10,8,10	A5
$-0.0413 < \beta \leq -0.0370$	seeker	10,7,10	A5
$-0.0369 < \beta \leq -0.0238$	seeker	10,7,9	A5
$-0.0237 < \beta \leq -0.0222$	seeker	10,6,9	A5
$-0.0221 < \beta \leq -0.0122$	seeker	10,6,8	A5
$-0.0121 < \beta \leq -0.0111$	seeker	10,6,7	A5
$-0.0110 < \beta \leq -0.0093$	seeker	9,6,7	A5
$-0.0092 < \beta \leq -0.0069$	seeker	8,6,7	A6
$-0.0068 < \beta \leq -0.0052$	seeker	7,6,7	A6
$-0.0051 < \beta \leq -0.0039$	seeker	7,6,6	A6
$-0.0039 < \beta < 0$	seeker	6,6,6	A1
$\beta = 0$	neutral	5 or 6 in each condition	A1
$0 < \beta \leq 0.0038$	averse	5,5,5	A1
$0.0038 < \beta \leq 0.0051$	averse	5,5,4	A3
$0.0051 < \beta \leq 0.0068$	averse	4,5,4	A2
$0.0068 < \beta \leq 0.0092$	averse	4,5,3	A2
$0.0092 < \beta \leq 0.0111$	averse	4,5,2	A2
$0.0111 < \beta \leq 0.0121$	averse	4,5,1	A2
$0.0121 < \beta \leq 0.0126$	averse	3,5,1	A2
$0.0126 < \beta \leq 0.0221$	averse	3,5,0	A2
$0.0221 < \beta \leq 0.0332$	averse	2,5,0	A2
$0.0332 < \beta \leq 0.0369$	averse	2,4,0	A2
$0.0369 < \beta \leq 0.0603$	averse	1,4,0	A2
$0.0603 < \beta \leq 0.0822$	averse	0,4,0	A2
$0.0822 < \beta \leq 0.1604$	averse	0,3,0	A2
$0.1604 < \beta \leq 0.3046$	averse	0,2,0	A2
$0.3046 < \beta \leq 0.5080$	averse	0,1,0	A2
$0.5080 < \beta$	averse	0,0,0	A4

Note: The choices shown are for a utility $u = [1 - e^{-\beta(65+x)}]/\beta$.

Appendix C: Details on Experimental Design

The experiment was performed in the IEW-lab at University of Zurich. All subjects were students of the University of Zurich or the Swiss Federal Institute of Technology Zurich (ETH). Economists and psychologists were excluded from the subject pool. We used the recruitment system ORSEE (Greiner, 2004). Each subject participated in only one session. Subjects in both stake conditions were randomly allocated to each of the six possible sequences of skew conditions.

To make sure that subjects fully understood the procedures and the payoff consequences of the available actions, each subject had to read a detailed set of instructions before the session started and was allowed to ask clarifying questions. After subjects read the instructions and completed the three sets of choices they answered demographic questions. After completing the demographic questions all subjects returned their questionnaires to the experimenter.

After that subjects' earnings were determined. The choice of which skew condition was used to determine earnings (decision set A, B, or C) was made using a six-sided die. Subjects were told that: "If the outcome of the six-sided die is either 1 or 2, decision set A counts, if the outcome is either 3 or 4, decision set B counts, and if the outcome is either 5 or 6 decision set C counts."

The decision used to determine earnings (decisions 1 through 10) and the realization of the lottery associated with that decision was made using a ten-sided die. Subjects were told that: "We will use a ten sided-die to determine your payoffs. A volunteer will throw this die twice, once to select one of the ten decisions to be used, and a second time to determine the payoff if you chose 'Accept' for that lottery."

One experimenter announced the outcome of the dice orally and another one wrote them on a whiteboard. Each subject was paid according to his or her choices and the realizations of the six-sided and ten-sided dice.

The mean earnings of subjects in the 1x stake condition were 79.18 CHF and 173.74 CHF in the 2x stake condition (excluding the 10 CHF show-up fee). Total earnings paid to subjects including show-up fees were 13,409.00 CHF.

Appendix D: Experimental Material

Research Study

Decision-Making under Risk

Instructions

Read these instructions carefully as your understanding of them will affect your ability to earn money.

Your decision sheet shows a table with ten decisions listed on the left. Each decision is a choice between "Accept" and "Reject" the Lottery. If you Accept the lottery you have the chance of either winning or losing some money. If you Reject the lottery you will not earn anything and you will not lose anything – your payoff will be zero.

You will make ten choices and record these by ten check marks, but only one of them will be used in the end to determine your earnings. Before you start making your ten choices, please let me explain how these choices will affect your earnings for this part of the experiment.

We will use a ten-sided die to determine payoffs; the faces are numbered from 1 to 10 (the "0" face of the die will serve as 10.) After you have made all of your choices, we will throw this die twice, once to select one of the ten decisions to be used, and a second time to determine your payoff if you chose "Accept" for that Lottery.

Even though you will make ten decisions, only one of these will end up affecting your earnings, but you will not know in advance which decision will be used. Obviously, each decision has an equal chance of being used in the end.

Now, please look at Decision 1 at the top of Example Problem Set on the next page. If you Accept the Lottery you will earn 50.00 CHF if the throw of the ten sided die is 1, and you will lose 5.00 CHF if the throw is 2-10. The other Decisions are similar, except that as you move down the table, the value of the highest payoff decreases. For each Decision you are asked to choose whether or not you want to take the gamble by checking the Accept or Reject columns.

This table is just an example and is not to be used to make real decisions. The problems for which you will be asked to make decisions have a similar structure, but the magnitudes of the gains and losses will be different, as well as the numbers on the dies that will determine if you make a gain or a loss.

Your gains - You may win or lose money if you Accept the Lottery. If you win you will be paid the amount won; if you lose you will have to pay the amount lost. The maximum amount that you can lose in the gambles is CHF 65. However, because we don't want you to end with less money than you started out you will be given CHF 65 from which we will deduct any loss that you may experience. In addition, you will be paid an additional CHF 15 as a compensation for your time spent.

There will be a total of three problem sets (A B, and C), each composed of ten decisions. In each problem set the gains, losses and chances to win will be different. In the end we will only use one of the three problem sets to determine your earnings. The choice of which problem set to use to determine earnings will be made by using a six-sided die. Each problem set has the same probability of being chosen. If the outcome of the six sided die is either 1 or 2, problem set A counts, if the outcome is either 3 or 4 set B counts, and if the outcome is either 5 or 6 set C counts.

To summarize, in each problem set you will make ten choices: for each choice you will have to decide between Accept or Reject the Lottery. You may choose Accept for some decisions and Reject for other decisions, and you may change your decisions and make them in any order. When you are finished with making all ten choices you will move on to the next problem set. This will be repeated three times. After the three problems sets are done, we will ask you a few demographic questions about yourself.

At the end, a randomly chosen participant will first cast a six sided die, numbered from 1 to 6, and then a 10-sided die, numbered 0 to 9 to select the decision which determines your earnings. The 6-sided die will decide which problem will be used and the 10-sided die will decide which decision will be used to determine your gains or losses. The same participant will then throw the 10-sided die again to choose whether you win or lose on that Lottery if you decided to Accept that lottery. You will be paid all earnings in cash when finished.

Are there any questions? Now you may begin making your choices. Please, do not talk with anyone while we are doing this; raise your hand if you have a question.

Problem Set A

Instructions

Your decision sheet shows ten decisions listed on the left. Each decision is a choice between "Accept" and "Reject" the Lottery. If you Accept the lottery you have the chance of either winning or losing some money. If you Reject the lottery you will not earn anything and you will not lose anything – your payoff will be zero.

You will make ten choices and record these by ten check marks, but only one of them will be used in the end to determine your earnings.

In this problem set, the gains and losses associated to each choice is different from before. Also, note that whether there will be gains or losses may be determined by different numbers on the dice. Once you have completed your choices you will move on to the next problem set. Earnings will be determined at the end of the study.

Please check whether you Accept or Reject each lottery

Problem Set B

Instructions

As before, your decision sheet shows ten decisions listed on the left. Each decision is a choice between "Accept" and "Reject" the Lottery. If you Accept the lottery you have the chance of either winning or losing some money. If you Reject the lottery you will not earn anything and you will not lose anything – your payoff will be zero.

You will make ten choices and record these by ten check marks, but only one of them will be used in the end to determine your earnings.

In this problem set, the gains and losses associated to each choice is different from before. Also, note that whether there will be gains or losses may be determined by different numbers on the dice. Once you have completed your choices you will move on to the next problem set. Earnings will be determined at the end of the study.

Please check whether you Accept or Reject each lottery

Problem Set C

Instructions

As before, your decision sheet shows ten decisions listed on the left. Each decision is a choice between "Accept" and "Reject" the Lottery. If you Accept the lottery you have the chance of either winning or losing some money. If you Reject the lottery you will not earn anything and you will not lose anything – your payoff will be zero.

You will make ten choices and record these by ten check marks, but only one of them will be used in the end to determine your earnings.

In this problem set, the gains and losses associated to each choice is different from before. Also, note that whether there will be gains or losses may be determined by different numbers on the dice. Once you have completed your choices you will move on to the next problem set. Earnings will be determined at the end of the study.

Please check whether you Accept or Reject each lottery

Table 12: Example Problem Set (not to be used for actual decisions)

Decision	Lottery	Accept	Reject
1	50 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
2	45 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
3	40 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
4	35 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
5	30 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
6	25 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
7	20 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
8	15 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
9	10 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
10	5 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		

Table 13: Problem Set A

Decision	Lottery	Accept	Reject
1	70 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
2	65 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
3	60 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
4	55 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
5	50 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
6	45 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
7	40 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
8	35 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
9	30 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
10	25 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		

Table 14: Problem Set B

Decision	Lottery	Accept	Reject
1	6 CHF if the throw of the die is 1-5 -1 CHF if the throw of the die is 6-10		
2	6 CHF if the throw of the die is 1-5 -2 CHF if the throw of the die is 6-10		
3	6 CHF if the throw of the die is 1-5 -3 CHF if the throw of the die is 6-10		
4	6 CHF if the throw of the die is 1-5 -4 CHF if the throw of the die is 6-10		
5	6 CHF if the throw of the die is 1 -5 CHF if the throw of the die is 2-10		
6	6 CHF if the throw of the die is 1-5 -6 CHF if the throw of the die is 6-10		
7	6 CHF if the throw of the die is 1-5 -7 CHF if the throw of the die is 6-10		
8	6 CHF if the throw of the die is 1-5 -8 CHF if the throw of the die is 6-10		
9	6 CHF if the throw of the die is 1-5 -9 CHF if the throw of the die is 6-10		
10	6 CHF if the throw of the die is 1-5 -10 CHF if the throw of the die is 6-10		

Table 15: Problem Set C

Decision	Lottery	Accept	Reject
1	-20 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
2	-25 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
3	-30 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
4	-35 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
5	-40 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
6	-45 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
7	-50 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
8	-55 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
9	-60 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		
10	-65 CHF if the throw of the die is 1 5 CHF if the throw of the die is 2-10		

Appendix E: PT Choices–Opposing Forces

Here we show that inverse s-shape probability weighting leads to choices that go in the opposite direction of diminishing sensitivity to outcomes. More precisely, we show that inverse s-shape probability weighting (with an inflection point at 0.5) implies accepting at least one positive skew gamble with negative mean and rejecting at least one negative skew gamble with positive mean whereas diminishing sensitivity to outcomes implies rejecting at least one positive skew gamble with positive mean and accepting at least one negative skew gamble with negative mean.

Taking $r = 0$ and $u(0|0) = 0$, a PT agent with gain-loss utility given by (10) rejects gamble X if

$$h^+(p)u^+(g) - \lambda h^-(1-p)u^-(-l) < 0,$$

or

$$\lambda \frac{h^-(1-p)}{h^+(p)} > \frac{g}{-l} \frac{u^+(g)/g}{u^-(-l)/(-l)}. \tag{13}$$

If the inequality holds in the opposite direction the agent accepts gamble X.

Proposition 1: If a PT agent only displays inverse s-shape probability weighting with an inflection point at 0.5, then he (i) accepts the six positive skew gambles with non-negative mean and accepts at least one positive skew gamble with negative mean, and (ii) rejects the five negative skew gambles with non-positive mean and rejects at least one negative skew gamble with positive mean.

Proof of Proposition 1: Consider a PT agent who displays inverse s-shape probability weighting with an inflection point at 0.5 and who must decide between accepting or rejecting the positive skew gamble with zero mean $X_P = (p, g; 1-p, l)$, where $g > -l$ and $p = \frac{-l}{g-l} < 0.5$. To rule out loss aversion, diminishing sensitivity to outcomes, and differences in probability weighting across the gain and loss domains we set $\lambda = 1$, $u^+(x) = x$ for $x \geq 0$, $u^-(-x) = x$ for $x < 0$, $h^+(p) = h(p)$ and $h^-(1-p) = 1 - h(p)$. Hence, (13) becomes $\frac{1-h(p)}{h(p)} > \frac{g}{-l}$. Inverse s-shape probability weighting with an inflection point at 0.5 implies $p < h(p) < 0.5$. This agent accepts gamble X_P since $p < h(p)$ and $p = \frac{-l}{g-l}$ imply $\frac{1-h(p)}{h(p)} < \frac{g}{-l}$. Now suppose the same agent must decide between accepting or rejecting the negative skew gamble with zero mean $X_N = (p, g; 1-p, l)$, where $g < -l$ and $p = \frac{-l}{g-l} > 0.5$. Inverse s-shape probability weighting with an inflection point at 0.5 implies $0.5 < h(p) < p$. This individual rejects gamble X_N since $h(p) < p$ and $p = \frac{-l}{g-l}$ imply $\frac{1-h(p)}{h(p)} > \frac{g}{-l}$. Hence, if inverse s-shape probability distortion with an inflection point at 0.5 is sufficiently strong, this agent will accept at least one positive skew gamble with negative mean and reject at least one negative skew gamble with positive mean.

Proposition 2: If a PT agent only displays diminishing sensitivity to outcomes, then he (i) rejects the five positive skew gambles with non-positive mean and rejects at least one positive skew gamble with positive mean, and (ii) accepts the six negative skew gambles with non-negative mean and accepts at least one negative skew gamble with negative mean.

Proof of Proposition 2: Consider a PT agent who only displays diminishing sensitivity to outcomes and must decide between accepting or rejecting gamble X_P. To rule out loss aversion, differences in sensitivity to outcomes across the gain and loss domains, and probability weighting we set $\lambda = 1$, $u^+(x) = u(x)$ for $x \geq 0$, $u^-(-x) = u(x)$ for $x < 0$, $h^+(p) = p$, and

$h^{-}(1-p) = 1-p$. Hence, (13) becomes $\frac{1-p}{p} > \frac{g}{-l}\frac{u(g)/g}{u(-l)/l}$. Since $g > -l$, diminishing sensitivity to outcomes implies $\frac{u(g)/g}{u(-l)/l} < 1$. This agent rejects gamble X_P since $\frac{u(g)/g}{u(-l)/l} < 1$ and $p = \frac{-l}{g-l}$ imply $\frac{1-p}{p} < \frac{g}{-l}\frac{u(g)/g}{u(-l)/l}$. Now suppose the same agent must decide between accepting or rejecting gamble X_N. Since $g < -l$, diminishing sensitivity to outcomes implies $\frac{u(g)/g}{u(-l)/l} > 1$. This agent accepts gamble X_N since $\frac{u(g)/g}{u(-l)/l} > 1$ and $p = \frac{-l}{g-l}$ imply $\frac{1-p}{p} < \frac{g}{-l}\frac{u(g)/g}{u(-l)/l}$. Hence, if diminishing sensitivity to outcomes is sufficiently strong, this agent will reject at least one positive skew gamble with positive mean and accept at least one negative skew gamble with negative mean.

Appendix F: Sensitivity Analysis

Here we check the sensitivity of our results to an alternative form of nonlinear probability weighting. To do that we perform our main estimations replacing Goldstein and Einhorn's (1987) probability weighting function by Prelec's (1998): $h(p) = \exp(-(-\ln p)^{\eta})$, where $\eta > 0$. When $\eta < 1$ we have inverse s-shape and when $\eta > 1$ we have s-shape probability weighting. When $\eta = 1$ there is no probability weighting. This function has an invariant fixed and inflection point at $p = 1/e \simeq 0.37$. The estimates obtained for EU and PT subjects are reported in Tables 16 and 17, respectively.

Table 16: EU and PT Subjects: RDU model with CARA Utility and Prelec (1998) Probability Weighting

	EU		PT	
β	-0.0001	(0.0013)	-0.0017	(0.0011)
η	0.99	(0.0138)	0.87^{*}	(0.0276)
σ	3.21^{*}	(0.6403)	4.78^{*}	(0.6407)
LL	-590		-1138	
Subjects	34		67	

Note: Clustered standard errors in parentheses. The superscript * indicates significance at 5%. For β and σ relative to 0. For η relative to 1.

Column 1 in Table 16 tells us that, on average, the estimate for β is not significantly different from zero and that EU subjects do not seem to distort probabilities, as the estimate for η is not significantly different from 1. Column 2 in provides estimates for PT subjects using the RDU model. The estimate for η is 0.87 and is significantly less than 1. This estimate for η implies decision weights $\pi_1 = 0.87$ and $\pi_2 = 0.13$ for negative skew lotteries, $\pi_1 = 0.5$ and $\pi_2 = 0.5$ for zero skew lotteries, and $\pi_1 = 0.13$ and $\pi_2 = 0.87$ for positive skew lotteries. These decision weights are very close to the ones obtained with the RDU model under Goldstein and Einhorn's (1987) probability weighting function.

Table 17: PT Subjects: PT model with CARA Utility and Prelec (1998) Probability Weighting

	(1)		(2)		(3)		(4)	
β	0.0017	(0.0013)			0.0018	(0.0011)		
β^+			0.0164*	(0.0052)			0.0211*	(0.0073)
β^-			-0.0084^*	(0.0043)			0.0048	(0.0048)
η	0.94	(0.0366)	0.71*	(0.0489)				
η^+					0.97*	(0.0127)	0.53*	(0.1056)
η^-					1.04	(0.0339)	0.85	(0.0835)
λ	1.03*	(0.0083)	0.71*	(0.0747)	1.02	(0.1149)	0.79*	(0.0892)
σ	3.31*	(0.4396)	2.40*	(0.3487)	2.91*	(0.3746)	2.40*	(0.3793)
LL	-1096		-1073		-1085		-1067	
Subjects	67		67		67		67	

Note: Clustered standard errors in parentheses. The superscript * indicates significance at 5%. For β, β^+, β^-, and σ relative to 0. For η, η^+, η^-, and λ relative to 1.

Table 17 provides estimates for PT subjects using the four specifications of the PT model. In models 1 and 3 we don't find diminishing sensitivity to outcomes since β is not statistically significantly different from 0. In model 1 we also don't find evidence for probability weighting since η is not statistically significantly different from 1. In model 3 there is statistical evidence for probability weighting but this is not economically significant since the estimate for η is very close to 1. In model 1 there is statistical evidence for loss aversion but this is not economically significant since the estimate for λ is very close to 1. Finally, in model 3 there is no evidence for loss aversion.

In model 2 we find support for concave utility in the gain and loss domains since β^+ is significantly greater than 0 and β^- is significantly less than 0. We also find evidence for inverse s-shape probability weighting since the estimate for η is 0.71. Finally, the estimate for λ is significantly less than 1.

In model 4 the estimates for β^+ and β^- of 0.021 and 0.004 are statistically significantly different ($p_{value} = 0.0492$). The estimate for β^+ is significantly greater than zero but the estimate for β^- is not significantly different from zero. This indicates concavity in the gain domain and linearity in the loss domain. The estimates for η^+ and η^- of 0.53 and 0.85 are statistically significantly different ($p_{value} = 0.0349$). The estimate for η^+ is significantly less than unity but the estimate for η^- is not significantly different from unity. This indicates inverse s-shape probability weighting in the gain domain and linear probability weighting in the loss domain. The estimates for η^+ and η^- imply $\pi_1 = h^+(0.9) = 0.76$ and $\pi_2 = h^-(0.1) = 0.13$ for negative skew lotteries and $\pi_1 = h^+(0.1) = 0.24$ and $\pi_2 = h^-(0.9) = 0.87$ for positive skew lotteries. Finally, the estimate for λ is significantly less than 1.