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Risk Behavior for Gain, Loss and Mixed Prospects

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Abstract: This experimental study considers choice behavior of people facing prospects of three different types: *gain prospects* (no losses), *loss prospects* (no gains), and *mixed prospects* (contain both gains and losses). The data confirm that the distinction of risk behavior into these three categories of prospects is meaningful. At the aggregate level we find evidence that decision weighting, as proposed in prospect theory, is also influencing choice behavior for gain prospects and for loss prospects. A closer look at the combined data for only gain and loss prospects reveals that choice behavior is significantly influenced by the expected value of prospects: there is more risk aversion for choices among pairs of prospects with higher expected value. In the mixed domain we do not find evidence for loss aversion except for choices where one prospect is degenerate. As all choices in our experiment involve a prospect and a mean preserving spread of that prospect, we also obtain evidence regarding the validity of newly developed second order stochastic dominance principles (Levy and Levy 2002, Baucells and Heukamp 2006) which take into account key aspects of prospect theory.

Keywords: Binary Choice, Prospect Theory, Risk Aversion, Second Order Stochastic

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Dominance.

Journal of Economic Literature Classification: D81, C91

1 Introduction

Dominance criteria play an important role for decision making. They are used in economics, finance, management science and in many related disciplines (see Bawa 1982 for a listing of early literature, and the review of Levy 1992). Managers, investors, consumers and other decision makers can use them to eliminate options and strategies that are regarded inferior according to the dominance principle employed. If a dominance principle is accepted as a decision aid, then algorithms can be developed to assist the decision making process.

We designed an experiment to study dominance principles that take account of key features of prospect theory (PT), the current most popular decision theory for risk and uncertainty (Wakker 2010). Most decisions involve a considerable degree of risk and the development of appropriate dominance principles for decision under risk is ongoing. Criteria that are appreciated for prescriptive use may suffer from descriptive inaccuracy. A famous example is the much debated von Neumann and Morgenstern independence axiom (von Neumann and Morgenstern 1944, Herstein and Milnor 1953, Fishburn 1970, Luce 2000) which is regarded as a normative dominance principle for decision making under risk, and which has been challenged for its descriptive shortcomings (e.g., Allais 1953, MacCrimmon and Larsson 1979, Machina 1987, Luce 2000, Starmer 2000). The independence axiom requires that the preference between any two prospects should remain unchanged whenever common risk is introduced. So, if prospect P is preferred to prospect Q, then also the prospect "P with probability μ and otherwise R" is preferred to the prospect "Q with probability μ and otherwise R" whatever common prospect R and common positive probability μ are taken.

The independence axiom and variants of the principle have been used to develop more sophisticated decision criteria for descriptive and prescriptive use. For example, expected utility uses the full force of the principle while rank-dependent utility (Quiggin 1982, Schmeidler 1989) and prospect theory (Tversky and Kahneman 1992, Köbberling and Wakker 2003) use specific relaxations. A difficulty for the use of the independence axiom (and its weaker variants) is that it requires an a priori ranking between two prospects which may well be subjective. Different rankings of prospects may occur due to the different risk captured within each prospect and the heterogeneous risk attitudes of decision makers.

The independence axiom, however, entails itself a dominance principle that is appealing. First order stochastic dominance (FSD) requires that prospects which have higher cumulative likelihood for outcomes should be preferred. More precisely, the prospect P FS-dominates Q if, for any outcome, the cumulative likelihood of obtaining that outcome or worse is at least as high (and for some outcome higher) with Q than it is with P. FSD is a simple criterion, people agree with this principle and apply it in simple situations. Though, in nontransparent choice situations many violate this dominance criterion (see Birnbaum and Navarette (1998) and more recently Birnbaum (2005) for experimental evidence).

Although FSD can help identifying and eliminating prospects bearing unnecessary risk, in general many prospects are available and it will not be possible to compare all of them using FSD in order to select a dominant one. Among the remaining prospects a decision maker would be interested in eliminating those that are regarded as riskier than others, and thereby reduce the number of prospects further. A different principle has been invoked to aid here. Second order stochastic dominance (SSD) has been used by Rothschild and Stiglitz (1970) and Hadar and Russell (1969) to develop a measure of "Q is more risky than P." Denoting by F_R the cumulative distribution of prospect R, this principle requires that, if $\int_{-\infty}^{x}[F_P(t) - F_Q(t)]dt \leq 0$ for all outcomes x with at least one inequality being strict, P is preferred to Q. Because Q, compared to P, assigns more probability mass to at least one lower ranked outcome and does not sufficiently compensate by assigning more probability mass to better ranked outcomes, Q is regarded as more risky, and thus is dominated by P in the SSD-sense.

The theoretical implications of SSD are well understood for expected utility theory (i.e., an increasing and concave utility function; see the review in Levy 1992) and for rank-dependent utility theory (increasing and concave utility, and increasing and convex probability weighting function; see Chew, Karni and Safra 1987). Schmidt and Zank (2008) provided an analysis the implications of SSD for prospect theory (PT). Recall, that under prospect theory outcomes are modeled as deviations from a reference point, with positive deviations being gains and negative ones being losses. A PT-decision maker has utility over gains and losses and separate weighting functions for probabilities of gains and losses. In the evaluation of a prospect, utilities of gains (losses) are multiplied by decision weights which are generated by the corresponding weighting function. The gain-loss separability assumption underlying prospect theory implies that the PT-value of a mixed prospect is the sum of the separate PT-values of the gain part of the prospect (i.e., the original prospect with all losses replaced by the reference point) and the loss part of the prospect (i.e., the original prospect with all gains replaced by the reference point). Schmidt and Zank showed that SSD requires that utility is concave for gains and concave for losses but not necessarily concave at the reference point. Further, SSD implies an overall convex gain weighting function and an overall concave loss weighting function.

The theoretical implications of SSD for PT do not fit well with the empirical evidence, which suggests that utility is concave for gains but convex for losses (see Abdellaoui, Bleichrodt and Paraschiv (2007) and Wakker (2010) for summaries and discussions of recent empirical evidence) and that the weighting functions have an inverse-S shape, being concave for small probabilities and convex for large probabilities (Hogarth and Einhorn 1990, Tversky and Kahneman 1992, Wu and Gonzalez 1996, Gonzalez and Wu 1999, Abdellaoui 2000, Bleichrodt and Pinto 2000, Bleichrodt, Pinto and Wakker 2001, Etchardt-Vincent 2004, Abdellaoui, Vossmann and Weber 2005, Abdellaoui, Baillon, Placido and Wakker 2011). The theoretical implications of SSD are, however, natural because, as with expected utility and rank-dependent utility, SSD requires global risk averse behavior. Under prospect theory risk behavior is not globally consistent in the former sense because outcomes are not final wealth positions as in the afore mentioned theories but deviations from a reference point. A distinction between risk behavior for gains and separately the risk behavior for losses seems meaningful. Additionally, loss aversion (utility is steeper for losses than for similar sized gains; see Wakker and Tversky (1993) for a definition) suggests additional aversion to increases in risk when gains are traded off against losses of similar size.

Accounting for the evidence regarding utility curvature for gains and that for losses, Levy and Levy (2002) proposed restrictions on the general SSD-principle. Prospect stochastic dominance (PSD) requires SSD for gain part of prospects but for loss part of prospects the opposite of SSD (i.e., a preference for the dominated prospect) is demanded. The Markowitz stochastic dominance (MSD), inspired by the utility curvature proposed in Markowitz (1952), requires SSD for the loss part of prospects and the opposite of SSD for the gain part of prospects. For prospects with equal mean PSD predicts the opposite of MSD, but this may not hold for prospects that have different means. Levy and Levy ran experiments involving mixed prospects containing both gains and losses and interpreted their results as evidence for MSD and, hence, as evidence against PT. Accounting for probability weighting as in the modern PT model of Tversky and Kahneman (1992), Wakker (2003) demonstrated that the choice behavior observed by Levy and Levy is, however, consistent with PT. A similar result was concluded in the study of Baucells and Heukamp (2004). The latter authors argued, in Baucells and Heukamp (2006), for further adjustments of PSD, which take into account inverse-S probability weighting and also loss aversion as suggested in modern PT.

While the study of Levy and Levy (2002) is inconclusive about violations of modern PT, the findings of Baltussen, Post and van Vliet (2006) show that choice behavior between mixed prospects may not always be in agreement with PT predictions. They reconsider a specific choice task of Levy and Levy that involved a choice between a mixed prospect F and another one, G, that results from F through simultaneous increases in risk for the gain part and also for the loss part of F. They design an "intermediate" mixed prospect, H, which agrees with F on the gain part but has increases in risk that only involve losses. As a result they obtain additional information about risk behavior among mixed prospects with common gains and among mixed prospects with common losses. This way they identify descriptive inaccuracies of PT and provide evidence regarding the PSD and MSD principles of Levy and Levy (2002).

This paper presents new empirical tests of SSD and its restrictions PSD and MSD taking account of the empirical evidence regarding probability weighting and loss aversion, and compares the findings with the predictions based on PT. We present data from a laboratory experiment involving binary choices over small to moderate scale prospects which involve real stakes. The 90 participants had to decide between a prospect and an SSD-dominated transformation of that prospect in 95 binary choices. We consider three broader conditions within which further refinements are identified: choices among prospects where all outcomes are gains, choices among prospects that involve only losses, and choices among mixed prospects that involve both gains and losses of similar size. It is well-known that SSD implies aversion to mean preserving spreads (MPS), also known as strong risk aversion (the latter requiring SSD only if the prospects have the same mean). Within a choice task we present prospects that have the same mean, hence we obtain evidence about risk behavior in the strong sense, and information about how this behavior may be affected by the nature of prospects, that is, by gain, loss, or mixed prospects.

Recall, that the afore mentioned classification of choices among gain, loss and mixed prospects accounts only for the sign of the outcomes in those prospects. It does not account for potential biases caused by probability weighting, which are also an important component of risk behavior (see Wakker 2001, 2010) and an essential component of PT. To account for the widely documented sensitivity towards probabilities, we employ MPSs which use small, medium and large cumulated probabilities. Our analysis, therefore, provides new evidence concerning the SSD criteria of Levy and Levy (2002) and the extensions developed in Baucells and Heukamp (2006). However, because in all these criteria the adjusted SSD-principles apply to the gain part and separately to the loss part of prospects, those principles implicitly assume gain-loss separability as is done in PT. Therefore, any violation of gain-loss separability will put a question mark to both PT and these new SSD criteria. The choices between mixed prospects in our experiments are therefore designed to provide evidence on whether the new SSD principles apply to this more realistic domain of prospects and indirectly also provide evidence for the gain-loss separability assumption of prospect theory.

The next section presents notation and is followed by a section with details of the experiment. The results are presented in Section 4, with a discussion provided in Section 5. Concluding remarks are presented in Section 6.

2 Notation

A *prospect* is a simple distribution over monetary outcomes. In general we write $P = (p_1, x_1; \ldots; p_n, x_n)$ for the prospect that gives probability p_i to outcome $x_i \in \mathbb{R}$ for $i = 1, \ldots, n$, where n is a natural number ($p_i \geq 0, \sum_{i=1}^n p_i = 1$). We assume that in a prospect outcomes are ordered from best to worst, i.e., $x_1 \geq \cdots \geq x_k \geq 0 > x_{k+1} \geq \cdots \geq x_n$. We assume that $0 \in \mathbb{R}$ is the reference point, so that positive outcomes are *gains* and negative outcomes are *losses*. Accordingly, if a prospect has no losses we call it a *gain prospect* and if it has no gains we call it a *loss prospect*, otherwise we call it a *mixed prospect*.[3]

A probability *weighting function*, ($w : [0, 1] \to [0, 1]$, $w(0) = 0, w(1) = 1$) is a strictly increasing function that maps the probability interval into itself, with fixed points at 0 and at 1.[4]

A preference relation $\succcurlyeq$ is assumed on the set of prospects. As usual we use

[3]Because degenerate lotteries are identified with the corresponding outcome, the prospect prospect $(0; \ldots; 0)$, that has no gains and no losses, is identified with the reference outcome 0.

[4]Empirically founded probability weighting functions are *inverse-S* shaped, i.e., concave for small probabilities and convex for large probabilities and steeper than the 45-degree line at 0 and at 1. E.g., Tversky and Kahneman 1992, Prelec (1998), Diecidue, Schmidt and Zank (2009) or Abdellaoui, l'Haridon and Zank (2010). They usually have an additional fixed point in $(0, 1)$.

$P \succcurlyeq Q$ to indicate weak preference; the symbols $\succ$ and $\sim$ denote strict preference and indifference, respectively ($\preccurlyeq$ and $\prec$ are as usual).

Prospect Theory (PT) holds if prospects are ranked using the PT-functional explained next: There exists a continuous strictly increasing utility function $u : \mathbb{R} \to \mathbb{R}$ with $u(0) = 0$, and two weighting functions w^+ and w^- such that the prospect $P = (p_1, x_1; \ldots, p_n, x_n)$ is evaluated according to

$$PT(P) = \sum_{i=1}^{k} \pi_i^+ u(x_i) + \sum_{i=k+1}^{n} \pi_i^- u(x_i),$$

with decision weights, $\pi_i^+, \pi_i^-, i = 1, \ldots, n$, determined through

$$\begin{aligned} \pi_i^+ &= w^+(\sum_{j=1}^{i} p_j) - w^+(\sum_{j=1}^{i-1} p_j) \\ \text{and } \pi_i^- &= w^-(\sum_{j=i}^{n} p_j) - w^+(\sum_{j=i+1}^{n} p_j). \end{aligned}$$

Under PT the weighting functions are uniquely determined and the utility function is unique up to multiplication by a positive number (i.e., utility is a ratio scale). Foundations for PT and discussions of the related literature can be found in Wakker (2010).

Next we recall the proposed variants of second order stochastic dominance and look at the implications for PT. To simplify the exposition and to relate the implications to the experiment and the testable hypotheses of this paper we restrict attention to implications for prospects with five equally likely outcomes.[5] Hence, we suppress probabilities from the further notation and write $P = (x_1; \ldots; x_5)$. In our experiment we consider only binary choices among prospects with the same expected value in order to restrict attention to mean-preserving spreads (MPS) and to discuss the implications of the various variants of preference or aversion to MPSs for PT. For prospect $P = (x_1; \ldots; x_5)$ and $i \in \{1, \ldots, 5\}$ we write $(y)_i P$ for the prospect where we have replaced outcome x_i with y. Whenever we use this notation

[5] In the experiment we use prospects in which each outcome has probability 1/5; outcomes that are equal are displayed with the coalesced probabilities, e.g., two 1/5 chances of obtaining £5 are presented as a single 2/5 chance for £5.

it is implicit that $x_{i-1} \geq y \geq x_{i+1}$, that is, the ranking of outcomes from best to worst is maintained for the new prospect. For $\varepsilon > 0$ we define a *mean-preserving spread* (MPS) of P as the prospect $(x_i + \varepsilon)_i (x_j - \varepsilon)_j P$ for some $i, j \in \{1, \ldots, 5\}$ with $i < j$.

A preference $\succcurlyeq$ satisfies *second-order stochastic dominance* (SSD) if $P \succcurlyeq (x_i + \varepsilon)_i (x_j - \varepsilon)_j P$ for any MPS $(x_i + \varepsilon)_i (x_j - \varepsilon)_j P$.[6] Such a preference is exhibiting *aversion* to MPSs; a *preference* for MPSs requires $P \preccurlyeq (x_i + \varepsilon)_i (x_j - \varepsilon)_j P$ for any MPS; and *neutrality* or insensitivity means $P \sim (x_i + \varepsilon)_i (x_j - \varepsilon)_j P$ for all MPSs. According to Schmidt and Zank (2008), if PT holds and $\succcurlyeq$ satisfies SSD, then the utility function u is concave for gains and concave for losses (but not necessarily concave at 0). Further, the weighting function for gain probabilities is convex and the weighting function for losses is concave. Additional implications hold for the derivatives of utility at 0 and the derivatives of the probability weighting functions (see Schmidt and Zank 2008, Theorem 1).

Levy and Levy (2002) proposed adjustments to SSD to take into account the S-shape form of utility as suggested by Kahneman and Tversky (1979) and to take into account the inverse-S shape form of utility as suggested by Markowitz (1952). In our setup, a preference $\succcurlyeq$ satisfies *prospect stochastic dominance* (PSD) if $P \succcurlyeq (x_i + \varepsilon)_i (x_j - \varepsilon)_j P$ for any MPS $(x_i + \varepsilon)_i (x_j - \varepsilon)_j P$ with $x_j - \varepsilon \geq 0$ and $P \preccurlyeq (x_i + \varepsilon)_i (x_j - \varepsilon)_j P$ for any MPS $(x_i + \varepsilon)_i (x_j - \varepsilon)_j P$ with $x_i + \varepsilon \leq 0$. In other words, PSD implies that SSD holds for gain prospects and the opposite of SSD holds for loss prospects. Using the results of Theorem 1 in Schmidt and Zank (2008) one obtains, as a corollary, the following implications of PSD for PT: utility is concave for gains and convex for losses; further, the weighting function for gain probabilities is convex as is the weighting function for loss probabilities. Note that no implications for behavior regarding MPSs involving an increment in both gains and losses follow

[6]Because we restrict attention to prospects that have the same mean this definition makes sense. It should, however, be noted that SSD is, in general, also defined for prospects without equal means. That general definition implies our definition used here but the reversed implication does not hold.

from PSD. The opposite of PSD is called *Markowitz stochastic dominance* (MSD) and requires $P \preccurlyeq (x_i+\varepsilon)_i(x_j-\varepsilon)_jP$ for any MPS $(x_i+\varepsilon)_i(x_j-\varepsilon)_jP$ with $x_j-\varepsilon \geq 0$ and $P \succcurlyeq (x_i+\varepsilon)_i(x_j-\varepsilon)_jP$ for any MPS $(x_i+\varepsilon)_i(x_j-\varepsilon)_jP$ with $x_i+\varepsilon \leq 0$. It should be clear what the corresponding implications for utility and weighting functions are under PT.

The previous SSD-principles have implications for the probability weighting functions that are not in line with the four-fold pattern of risk attitudes under PT (Tversky and Kahneman 1992). This pattern requires probability weighting functions to be inverse-S shaped (i.e., concave for small probabilities and convex for large ones). To account for this effect, Baucells and Heukamp (2006) proposed further adjustments to PSD. They note that most inverse-S shaped probability weighting functions can be described by two parameters $0 \leq c \leq d \leq 1$ such that concavity of the weighting function holds on $[0, d]$ and convexity holds on $[c, 1]$. The case $c = d$ is particularly interesting because then the parameters denote the inflection point of the weighting function that has a natural interpretation as measure for elevation as discussed, e.g., in Gonzalez and Wu (1999) and Abdellaoui, et al. (2010).[7]

Baucells and Heukamp (2006) proposed *prospect weighted stochastic dominance* (PWSD), which requires PSD only if the decumulative probability of x_i is above some $c^+ \in (0, 1)$, the parameter for gain probabilities, if $x_j - \varepsilon \geq 0$ and the cumulative probability of x_j is above some $c^- \in (0, 1)$, the parameter for loss probabilities, if $x_i + \varepsilon \leq 0$, respectively. Under PT the implications are similar to those of PSD, except that the shape of weighting functions is determined only for probabilities in the range $[c^+, 1]$ for gain probabilities, respectively, $[c^-, 1]$ for loss probabilities. The dual analog principle of *Markowitz weighted stochastic dominance* (MWSD) requires MSD only if the decumulative probability of x_j is below some $d^+ \in (0, 1)$, the parameter for gain probabilities, if $x_j - \varepsilon \geq 0$ and the cumulative probability of x_i is below some $d^- \in (0, 1)$, the parameter for loss probabilities, if $x_i+\varepsilon \leq 0$, respectively,

[7] The case $c = d$ occurs naturally in the parametric probability weighting functions of Goldstein and Einhorn (1987), Tversky and Kahneman (1992), Baker, Lattimore and Witte (1992), Prelec (1998) and Diecidue et al. (2009).

with the analogous dual consequences to PWSD for utility and probability weighting functions under PT.

Thus far we have not discussed preference or aversion to MPSs which involve a transfer of ε from a gain to a loss. Schmidt and Zank (2005) discussed a related principle of loss aversion. *Loss aversion* (LA) holds if $P \succcurlyeq (x_i + \varepsilon)_i(x_j - \varepsilon)_j P$ for any MPS $(x_i + \varepsilon)_i(x_j - \varepsilon)_j P$ with $x_i > 0 > x_j$. The opposite of LA is called *gain seeking* (GS). Schmidt and Zank showed that LA holds if utility for losses is steeper than the utility for gains adjusted by a ratio of decision weights for gains and losses. This LA condition was tested in an experiment involving small stakes by Brooks and Zank (2005) where it was confirmed.

In this study we expand on these earlier works and present an experiment taking account of all the above mentioned SSD variations.

3 Experiment

The experiment consisted of several binary choices between a prospect and an MPS of that prospect. Ninety (28 female and 62 male) graduate and undergraduate students in economics from the University of Manchester took part in this study. They were initially sent an e-mail message in which the nature of the experiment was briefly described. The message contained a link to a web page that presented information about the experiment, which were the instructions (see Appendix A). The students were asked to respond if they intended to participate in this experiment. This message was sent to all students enrolled in economics or a related subject in 2004 (approximately 1000 students). Those who responded were asked to attend the experiment, which was held in groups in a computer room during March 2004 (with sessions varying from 2 to 13 individuals). Participants attended one experimental session, which took approximately 40 minutes on average to complete.

The majority of prospects in the experiment involved losses, and a difficulty with real losses concerns their implementation. Benartzi and Thaler (1999) offered participants the option of earning money (i.e., a job) if losses from the experiment would exceed a certain level. A more common practice is to give participants an initial endowment. This endowment can be a flat payment for participation (Cohen, Jaffray and Said 1985, Camerer 1989, Battalio, Kagel and Jiranyakul 1990, Harless 1992, Harless and Camerer 1994, Myagkov and Plott 1997, Di Mauro and Mafioletti 2002, Smith, Dickhaut, McCabe and Pardo 2002, Mason, Shogreen, Settle and List 2005, Brooks and Zank 2005) or earned otherwise during the experiment (see Laury and Holt 2000). It is then assumed that participants (instantly) integrate that payment into their wealth and that subsequent choices will not be affected by this income. Typically, the payment and therefore also the stakes in those experiments range from small to moderate. The design of our study was similar in that the flat payment plus the outcome of a randomly chosen prospect was promised for completing the experiment.

The fixed payment in this study was £17 (approximately US$30 at the time of the experiment) and the stakes in the prospects varied from £−15 to £15. Similar stakes have been used, for example, in Camerer (1989), Starmer and Sugden (1989), Battalio, Kagel and Jiranyakul (1990), Hogarth and Einhorn (1990), Hey and Orme (1994), Beattie and Loomes (1997) and Brooks and Zank (2005), and have generated meaningful results. The actual payments at the end of the experiment ranged between £2 and £32 (including the fixed payment), with the average of actual payments being £13.69.

The experiment was held on computers, using an interface supported by a standard web browser familiar to students. Participants, seated at reasonable distance between themselves, were directed to a web page containing the instructions which the experimenter read aloud. Participants were informed that they had to respond to 105 tasks (the last 10 tasks consisted of repeated randomly chosen tasks, but this was not mentioned to the participants). It was explained that a task consisted of choosing between two prospects (called gambles in the instructions), and that indifference was not allowed.

A prospect was framed as picking a ball from a bag that contains 15 balls numbered consecutively from 1 to 15, each equally likely to be drawn. The bag, containing the 15 white table-tennis balls, was shown at the beginning of the experiment. On the computer screen, a prospect was presented as 15 colored balls with amounts of money underneath those balls. Identical outcomes were coalesced and corresponded to balls of the same color. Participants were informed about the range of outcomes $[-15, 15]$, and that their final payment was made up of a fixed amount (£17) which they would get if they answered all tasks and to which the outcome of a randomly selected choice would be added. That latter prospect was played for real, that is, each participant picked a ball from the bag, the obtained outcome was added to (or, in the case of losses, subtracted from) the fixed payment, and later a cheque was sent to the participant (see Cubitt, Starmer and Sugden (1998) for a discussion about the appropriateness of using this random incentive scheme). Details about the address of the participants and the earnings from the experiment were collected on a separate form at the end of the experimental session, where each participant was also asked to state the minimum they were willing to pay from their own money in order to retake the experiment (see Appendix B).

Recall that each of the 95 tasks in the experiment consisted of choosing between one prospect and a second one that dominated the first in the SSD-sense. To account for the distinction into gains and losses, we implemented a gain condition (22 choices where neither prospect involves losses), a loss condition (22 choices where neither prospect involves gains), and a mixed condition (51 choices where each prospect contains both gains and losses). Further, within each condition, we designed different tasks to account for a possible effect of probability weighting. These are explained next.

The Gain Prospects Tasks. The tasks in the gain condition are presented in Table 1. A prospect is displayed as five outcomes of equal likelihood. These probabilities (1/5) are not mentioned in the table. Within a task, the left prospect refers to the more risky one, in the SSD-sense. Outcomes in the table are ranked from best to worst for each prospect. In the experiment the presentation of prospects and tasks was different to the presentation in Table 1. Equal outcomes were coalesced, the order of outcomes was not ranked in a systematic way and differed between prospects within and across tasks, and the position of the more risky prospect (left or right on the computer screen) and the order of appearance of the tasks on screen were randomized.

Task No.	Outcomes Riskier Prospect						Outcomes Safer Prospect					No of S-choices	Different from mean
WR-tasks													
52	15	0	0	0	0		3	3	3	3	3	56**	
53	10	0	0	0	0		2	2	2	2	2	51	
54	5	0	0	0	0		1	1	1	1	1	43	**
SYM-tasks													
55	15	10	5	5	0		10	10	5	5	5	48	
56	10	10	5	0	0		10	5	5	5	0	58***	
57	5	5	3	0	0		5	3	3	2	0	65***	**
STR-tasks													
58	15	5	5	0	0		10	5	5	5	0	54**	
59	10	5	5	0	0		5	5	5	5	0	41	***
60	15	15	5	5	0		15	10	5	5	5	65***	**
61	10	10	5	5	0		10	5	5	5	5	59***	
62	15	5	0	0	0		10	5	5	0	0	61***	
63	10	5	0	0	0		5	5	5	0	0	35	***
64	15	15	15	5	0		15	15	10	5	5	66***	**
65	10	10	10	5	0		10	10	5	5	5	71***	***
GER-tasks													
66	15	7	2	2	0		10	7	5	2	2	57**	
67	10	5	1	1	0		5	5	5	1	1	26	***
68	15	11	11	6	0		11	11	10	6	5	64***	**
69	10	6	6	5	0		6	6	5	5	5	48	
70	15	15	11	2	0		15	11	10	5	2	53**	
71	11	10	6	2	0		11	6	5	5	2	54***	
72	15	11	4	0	0		11	10	5	4	0	62***	
73	10	6	4	0	0		6	5	5	4	0	62***	

Note: Significant deviations from 45 according to a one-tailed binomial test at the 10%, 5% and 1% are designated with *, **, and ***, respectively.

Table 1: Tasks in the Gain Condition

For a prospect with equally likely outcomes, an elementary MPS can be seen as subtracting $\varepsilon > 0$ from a higher ranked, larger outcome and simultaneously adding ε to a lower ranked outcome. In Table 1 we highlight, for each prospect, the affected outcomes where a shift of ε occurred, noting that all remaining outcomes were common. An exception to this were the tasks 52–54, which involve a risky and a safe prospect, and which provide evidence about the risk behavior in the weak sense of preference for expected value. This condition is termed weak risk (WR) condition.

Tasks 55–57 involve symmetric spreads where ε is shifted from the (second) best to the (second) worst outcomes, and is referred to as the symmetric increases in risk (SYM) condition. Under Tversky and Kahneman's (1992) prospect theory with inverse-S shaped weighting functions, decision weights for these outcomes do not differ much, hence one would expect that utility curvature is mainly influencing choice behavior. This is different for Tasks 58–65 where this symmetry is deliberately not respected and shifts occur from best (intermediate) to intermediate (worst) outcomes. For these tasks, which we refer to as strong risk (STR), decision weighting may influence preferences.

In contrast to the previously described choices of the gain condition, Tasks 66–73 involve spreads where the shift of the amount ε changes the ranking of outcomes in the safer prospect. This makes the shift less transparent and may potentially influence preferences. These task are referred to as the general increases in risk (GER) condition.

The Loss Prospects Tasks. The tasks 74–95 refer to the loss condition and are presented in Table 2. These tasks result from the gain tasks by multiplying each outcome in a prospect with -1. Hence, these tasks correspond to the original gain tasks with prospects reflected around 0.

Task No.	Outcomes Riskier Prospect						Outcomes Safer Prospect					No of S-choices	Different from mean
WR-tasks													
74	0	0	0	0	-15		-3	-3	-3	-3	-3	29***	*
75	0	0	0	0	-10		-2	-2	-2	-2	-2	25***	**
76	0	0	0	0	-5		-1	-1	-1	-1	-1	26***	**
SYM-tasks													
77	0	-5	-5	-10	-15		-5	-5	-5	-10	-10	38*	
78	0	0	-5	-10	-10		0	-5	-5	-5	-10	39	
79	0	0	-3	-5	-5		0	-2	-3	-3	-5	24***	***
STR-tasks													
80	0	0	-5	-5	-15		0	-5	-5	-5	-10	39	
81	0	0	-5	-5	-10		0	-5	-5	-5	-5	49	***
82	0	-5	-5	-15	-15		-5	-5	-5	-10	-15	29***	*
83	0	-5	-5	-10	-10		-5	-5	-5	-5	-10	32***	
84	0	0	0	-5	-15		0	0	-5	-5	-10	43	
85	0	0	0	-5	-10		0	0	-5	-5	-5	58	***
86	0	-5	-15	-15	-15		-5	-5	-10	-15	-15	33***	
87	0	-5	-10	-10	-10		-5	-5	-5	-10	-10	30***	
GER-tasks													
88	0	-2	-2	-7	-15		-2	-2	-5	-7	-10	47	**
89	0	-1	-1	-5	-10		-1	-1	-5	-5	-5	57	***
90	0	-6	-11	-11	-15		-5	-6	-10	-11	-11	29***	*
91	0	-5	-6	-6	-10		-5	-5	-5	-6	-6	32***	
92	0	-2	-11	-15	-15		-2	-5	-10	-11	-15	33***	
93	0	-2	-6	-10	-11		-2	-5	-5	-6	-11	47	**
94	0	0	-4	-11	-15		0	-4	-5	-10	-11	32***	
95	0	0	-4	-6	-10		0	-4	-5	-5	-6	37**	

Note: Significant deviations from 45 according to a one-tailed binomial test at the 10%, 5% and 1% are designated with *, **, and ***, respectively.

Table 2: Tasks in the Loss Condition

The Mixed Prospects Tasks. Table 3 presents Tasks 1–51 which we call the mixed condition. These tasks are also grouped in WR (Tasks 1–6), SYM (Tasks 7–27), STR (Tasks 28–39), and GER (Tasks 40-51). It should be mentioned that in this condition the WR-tasks are a special cases of SYM-tasks, which in turn are special cases of STR-tasks, and the latter are special cases of GER-tasks.

Task No.	Outcomes Riskier Prospect						Outcomes Safer Prospect					No of S-choices	Different from mean
WR-tasks													
1	15	15	0	-15	-15		0	0	0	0	0	48	
2	10	10	0	-10	-10		0	0	0	0	0	38	
3	5	5	0	-5	-5		0	0	0	0	0	47	
4	15	0	0	0	-15		0	0	0	0	0	45	
5	10	0	0	0	-10		0	0	0	0	0	30	***
6	5	0	0	0	-5		0	0	0	0	0	40	
SYM-tasks													
7	15	0	0	0	-15		10	0	0	0	-10	47	
8	10	0	0	0	-10		5	0	0	0	-5	42	
9	5	0	0	0	-5		2	0	0	0	-2	39	
10	15	9	0	-9	-15		10	9	0	-9	-10	51	
11	10	3	0	-3	-10		5	3	0	-3	-5	49	
12	5	2	0	-2	-5		2	2	0	-2	-2	44	
13	15	8	5	0	-15		10	8	5	0	-10	42	
14	10	4	2	0	-10		5	4	2	0	-5	47	
15	5	2	1	0	-5		2	2	1	0	-2	36	*
16	15	0	-5	-8	-15		10	0	-5	-8	-10	51	
17	10	0	-2	-4	-10		5	0	-2	-4	-5	51	
18	5	0	-1	-2	-5		2	0	-1	-2	-2	53**	*
19	15	15	5	-15	-15		15	10	5	-10	-15	40	
20	10	10	3	-10	-10		10	5	3	-5	-10	45	
21	5	5	2	-5	-5		5	2	2	-2	-5	34	**
22	15	15	0	-15	-15		15	10	0	-10	-15	57***	**
23	10	10	0	-10	-10		10	5	0	-5	-10	46	
24	5	5	0	-5	-5		5	2	0	-2	-5	41	
25	15	15	-5	-15	-15		15	10	-5	-10	-15	39	
26	10	10	-3	-10	-10		10	5	-3	-5	-10	47	
27	5	5	-2	-5	-5		5	2	-2	-2	-5	46	

Task No.	Outcomes Riskier Prospect					Outcomes Safer Prospect					No of S-choices	Different from mean
STR-tasks												
28	15	0	0	-15	-15	10	0	0	-10	-15	44	
29	10	0	0	-10	-12	5	0	0	-5	-12	50	
30	5	0	0	-5	-6	2	0	0	-2	-6	45	
31	15	15	0	0	-15	15	10	0	0	-10	50	
32	12	10	0	0	-10	12	5	0	0	-5	57***	**
33	6	5	0	0	-5	6	2	0	0	-2	32	***
34	15	0	-15	-15	-15	10	0	-10	-15	-15	44	
35	10	0	-10	-12	-12	5	0	-5	-12	-12	47	
36	5	0	-5	-6	-6	2	0	-2	-6	-6	41	
37	15	15	15	0	-15	15	15	10	0	-10	48	
38	12	12	10	0	-10	12	12	5	0	-5	50	
39	6	6	5	0	-5	6	6	2	0	-2	58***	**
GER-tasks												
40	15	0	-12	-12	-15	10	0	-10	-12	-12	49	
41	10	0	-8	-8	-10	5	0	-5	-8	-8	41	
42	5	0	-4	-4	-5	2	0	-2	-4	-4	45	
43	15	12	12	0	-15	12	12	10	0	-10	36	
44	10	8	8	0	-10	8	8	5	0	-5	59***	***
45	5	4	4	0	-5	4	4	2	0	-2	31	***
46	15	15	12	-12	-15	15	12	10	-10	-12	46	
47	12	10	8	-8	-10	12	8	5	-5	-8	56**	**
48	8	5	4	-4	-5	8	4	2	-2	-4	47	
49	15	12	-12	-15	-15	12	10	-10	-12	-15	49	
50	10	8	-8	-10	-12	8	5	-5	-8	-12	52*	
51	5	4	-4	-5	-8	4	2	-2	-4	-8	24	***

Note: Significant deviations from 45 according to a one-tailed binomial test at the 10%, 5% and 1% are designated with *, **, and ***, respectively.

Table 3: Tasks in the Mixed Condition

4 Results

The results of the experiment are presented at aggregate and individual level. First, we recall the predictions of the different SSD-variants. SSD predicts a preference for the safer prospect for each task.[8] PSD predicts a preference for the safer prospect

[8]The descriptions "safer" or "riskier" are short for "safer in the SSD-sense" or "riskier in the SSD-sense," respectively.

for all tasks in the gain condition, and a preference for the riskier prospect for all tasks in the loss condition. For choices between our mixed prospects, PSD makes no prediction. MSD makes the opposite predictions to PSD for tasks in the gain condition and for the tasks in the loss conditions, but no predictions for tasks in the mixed condition. LA predicts a choice of the safer prospect in all mixed tasks, while GS predicts a choice for the riskier prospect in all mixed tasks; LA and GS make no predictions for gain or loss tasks.

The predictions of PWSD (MWSD) require assumptions about the parameters c^+, c^- (d^+, d^-). Given the design of our study we set $c^+ = c^- = 0.2$ $(d^+, d^- = 0.8)$. PWSD predicts a preference for the safer prospect in the gain tasks 56&57, 60&61, 64&65, and 70&71 and a preference for the riskier prospect in the loss tasks 78&79, 82&83, 86&87, and 92&93. MWSD predicts a preference for the riskier prospect in gain tasks 56&57, 58&59, 62&63, and 72&73 and a preference for the safer prospect in loss tasks 78&79, 80&81, 84&85, and 94&95.

Inspecting the last column in Tables 1–3, one observes that there is considerable variation in the number of individuals choosing the safer prospect across tasks in the gain and the number of individuals choosing the riskier prospect across tasks in the loss condition, but little variation in the number of choices for the safer prospect across tasks in the mixed condition. Moreover, according to a one tailed binomial test at the 5% significance level, in a large number of tasks in the gain (loss) condition a significant majority chooses the safer (riskier) prospect, while in nearly all tasks of the mixed condition the number of choices for the safer prospect deviates insignificantly from 45 (i.e., from 50% of the total number of participants). Overall, there seems to be some evidence in favor of PSD (and PWSD) rejecting MSD (and MWSD) but little evidence for LA or GS. A more detailed analysis is required to address the variation in the number of safe choices in both the gain and loss tasks. This analysis is presented in the next subsections, where the findings are also contrasted to predictions of the PT-model of Tversky and Kahneman (1992).

4.1 Results for the Gain Condition

This subsection presents results for the gain condition, initially at the aggregate level and then at the level of the individuals.

4.1.1 Aggregate Data for Gain Prospects

First we test whether the observed choices in Table 1 are random (the null hypothesis, $H_0 : \mu = 45$) or not. The alternative hypothesis is that the safer prospect is chosen in line with the prediction of SSD and PSD (i.e., $H_A : \mu > 45$). The penultimate column in Table 1 reports significance values for this test at $10\%, 5\%$, and 1% indicated by *, ** and ***, respectively. For the majority of choices (68%) the alternative hypothesis is accepted at the 5% level. There is however some variation in the number of safer prospects chosen across tasks. The last column in Table 1 reports significant deviations from the overall mean number of safe choices across all tasks according to a two tailed binomial test (i.e., $H_0 : \mu - 54.5 = 0$ vs. $H_A : \mu - 54.5 \neq 0$). In nine tasks we observe significant deviations from the overall mean number of safer choices at the 5% level.

We observe from Table 1 that in tasks 56&57, 60&61, 64&65, and 70&71 (the PWSD-gain tasks) a significant majority of subjects chooses the safer prospect, in line with PWSD. Considering tasks 56&57, 58&59, 62&63, and 72&73 (the MWSD-gain tasks) we observe that in one task a significant majority of subjects chooses the riskier prospect but that in six tasks a significant majority prefers the safer prospect, such that we can conclude that there is no support for MWSD in the gain condition.

4.1.2 Data for Gain Prospects at the Level of Individuals

We are now interested to see whether the findings in the previous subsection are replicated at the level of individuals. For this we classify individuals as PSD (MSD) if across all gain tasks they choose the safer (riskier) prospect significantly more often than the riskier (safer) prospect according to a binomial test at the 5% level. Similarly, we classify individuals as PWSD (MWSD) if across PWSD-gain tasks

(MWSD-gain tasks) they choose the safer (riskier) prospect significantly more often than the riskier (safer) prospect according to a binomial test at the 5% level.

Table 4 presents the results.

Tasks Gain\Choices	Majority Safe	Majority Risky	Unclassified
All tasks	32	6	52
PWSD-tasks	31	1	58
MWSD-tasks	26	6	58

Table 4: PSD and PWSD behavior for gain tasks

Table 4 confirms that the majority of individuals are unclassified, that a large number of individuals choose significantly more often a safer prospect, and that very few individuals choose significantly more often the riskier prospect. We can safely reject MSD or MWSD behavior for the large majority of individuals.

4.2 Results for the Loss Condition

The results of this subsection are also presented at both the aggregate and the individual level.

4.2.1 Aggregate Data for Loss Prospects

We test whether the observed choices in Table 1 are random (the null hypothesis, $H_0 : \mu = 45$) or not. The alternative hypothesis is that the riskier prospect is chosen in line with the prediction of PSD (i.e., $H_A : \mu < 45$). The penultimate column in Table 2 reports significance values for this test at $10\%, 5\%$, and 1% indicated by *, ** and ***, respectively. For the majority of choices (59%) the alternative hypothesis is accepted at the 5% level. Again we observe some variation in the number of riskier prospects chosen across loss tasks. The last column in Table 2 reports significant deviations from the overall mean number of safe choices across all tasks according to a two tailed binomial test (i.e., $H_0 : \mu - 32.72 = 0$ vs. $H_A : \mu - 32.72 \neq 0$). In eight tasks we observe significant deviations from the overall mean number of safer choices at the 5% level.

We observe from Table 2 that in tasks 78&79, 82&83, 86&87, and 92&93 (the PWSD-loss tasks) a significant majority of subjects chooses the riskier prospect in six tasks, in line with PWSD. Considering tasks 78&79, 80&81, 84&85, and 94&95 (the MWSD-loss tasks) we observe that in one task a significant majority of subjects chooses the safer prospect and that in three tasks a significant majority prefers the riskier prospect, such that we can conclude that there is little support for MWSD in the loss condition.

4.2.2 Data for Loss Prospects at the Level of Individuals

Next we report the results from the loss tasks at the level of individuals. In analogy to the gain tasks, we classify individuals as PSD (MSD) if across all loss tasks they choose the riskier (safer) prospect significantly more often than the safer (riskier) prospect according to a binomial test at the 5% level. Similarly, we classify individuals as PWSD (MWSD) if across PWSD-gain tasks (MWSD-gain tasks) they choose the riskier (safer) prospect significantly more often than the safer (riskier) prospect according to a binomial test at the 5% level.

Table 5 presents the results.

Tasks Loss\Choices	Majority Risky	Majority Safe	Unclassified
All tasks	27	6	57
PWSD-tasks	22	6	62
MWSD-tasks	17	9	64

Table 5: PSD and PWSD behavior for loss tasks

Table 5 confirms that the majority of individuals are unclassified, and that the number of individuals who choose significantly more often a riskier prospect is significantly higher than the number of individuals choosing significantly more often the safer prospect. We can reject MSD or MWSD behavior for the large majority of individuals.

4.3 Results for the Mixed Condition

In this subsection we focus on the mixed condition and report results at the aggregate and individual level.

4.3.1 Aggregate Data for Mixed Prospects

We test whether the observed choices in Table 3 are random (the null hypothesis, $H_0 : \mu = 45$) or not. The alternative hypothesis is that the safer prospect is chosen in line with the prediction of LA (i.e., $H_A : \mu > 45$). The penultimate column in Table 3 reports significance values for this test at $10\%, 5\%$, and 1% indicated by *, ** and ***, respectively. For a small minority of choices (12%) the alternative hypothesis is accepted at the 5% level. We observe some variation in the number of safer prospects chosen across mixed tasks. The last column in Table 3 reports significant deviations from the overall mean number of safe choices across all tasks according to a two tailed binomial test (i.e., $H_0 : \mu - 45.02 = 0$ vs. $H_A : \mu - 45.02 \neq 0$). In just ten tasks we observe significant deviations from the overall mean number of safer choices at the 5% level. The aggregate data does not seem give much support for either LA or GS.

4.3.2 Data for Mixed Prospects at the Level of Individuals

We classify individuals LA or GS if their choices over all mixed tasks deviates significantly from 50% in the corresponding direction according to a one tailed binomial test at the 5%-level. We find that 30 individuals (33%) are LA, 27 (30%) are GS, and 33 individuals (37%) are unclassified.

4.4 Results for Combined Gain and Loss Conditions

In this subsection we look at data from the gain and loss tasks to obtain further insights.[9] First, we estimate PT parameters and subsequently we look at behavior

[9]There is little variation in the mixed tasks, which suggests that that data provides little information about behavior beyond that reported in the previous subsection.

whengain tasks are reflected into loss tasks. Finally, we look at explanations for the variation in the number of safe choices across tasks.

4.4.1 A PT-Parameter Estimation.

Recall that the preference axioms needed to derive PT do not, on their own, impose restrictions on the curvature of utility and of the curvature of the weighting functions (for a preference foundation of PT under risk, see Chateauneuf and Wakker 1999). Such restrictions follow from empirical studies (e.g., Tversky and Kahneman 1992, Abdellaoui 2000) using aggregate data. We have pooled together the data from the loss tasks and the gain tasks and obtained parameter estimates for utility and weighting functions as they were specified in Tversky and Kahneman (1992):

$$\begin{aligned} u(x) &= \begin{cases} x^{\alpha}, x \geq 0, \\ -|x|^{\beta}, x < 0, \end{cases} \\ w^{+}(p) &= \frac{p^{\gamma}}{[p^{\gamma} + (1-p)^{\gamma}]^{1/\gamma}}, 0 < \gamma < 1, \\ w^{-}(p) &= \frac{p^{\delta}}{[p^{\delta} + (1-p)^{\delta}]^{1/\delta}}, 0 < \delta < 1. \end{aligned}$$

Table 6 provides the output of a probit regression using a single agent stochastic choice model over gain and loss tasks, which finds the combination of parameters that best explains the variation in the data (see also Wu and Markle (2008) for a similar model). The parameter estimates found in the gain and loss domains are comparable to those in previous studies with somewhat lower parameter estimates for utility but larger parameters for the weighting function.[10]

[10] Adding the data for the mixed condition and a parameter, λ, for loss aversion gives similar estimates. $\lambda = 0.93$ ($se = 0.059$), is found insignificantly different from 1 (i.e., no LA and no GS).

Parameter	Estimates	Standard Errors
power gains, α	0.80	0.027
power losses, β	0.78	0.036
gain probabilities, γ	0.83	0.024
loss probabilities, δ	0.87	0.027
Log-Likelihood	-2638.58	
n	3960	

Table 6: PT-parameters

The parameters estimated in Table 6 suggest that probability weighting and utility curvature are of significant influence for the aggregate choice behavior.

4.4.2 Reflection of Behavior

Looking at Tables 1 and 2 it is apparent that the number of safe choices in a gain tasks is mirrored into a similar number of risky choices in the reflected loss task. To obtain statistical evidence for this observation we performed a difference of proportions test. Denoting p_G the proportion of safer choices in a gain task and by p_L the proportion of safer choices in a mirrored loss task, we conducted the following test:

$$H_0 : p_G - (1 - p_L) = 0 \text{ vs. } H_A : p_G - (1 - p_L) \neq 0.$$

Applying this tests only results in two significant differences (53&75 and 54&76).

Similar to Tables 4 and 5 above we classify individuals according to PSD, MSD, and PWSD behavior[11] if in both the gain and loss conditions behavior is in agreement

[11] Because very few subjects were MWSD for gains and for losses we skip the corresponding table.

with the corresponding prediction. We report the results in Table 7 for P/MSD

Tasks Gain\Loss	Majority Safer (6)	Majority Riskier (27)	Unclassified (57)
Majority Safer (32)	2	10	20
Majority Riskier (6)	0	5	1
Unclassified (52)	4	12	36

Table 7: PSD behavior for gain and loss tasks

and Table 8 presents results for PWSD:

PWSD Tasks Gain\Loss	Majority Safer (6)	Majority Riskier (22)	Unclassified (62)
Majority Safer (31)	4	10	17
Majority Riskier (1)	0	1	0
Unclassified (58)	2	11	45

Table 8: PWSD behavior for gain and loss tasks.

4.4.3 Variation in Behavior

The variation can be caused by outlier behavior (e.g., tasks 63 and 67 in the gain condition, tasks 85 and 89 in the loss condition) or heterogeneous behavior. The second explanation suggests an analysis of the effect of task type (WR, SYM, STR, or GER). It appears also that for tasks in which the largest outcome in a prospect is higher after an MPS, the number of safer choices is greater. In such tasks the expected value is higher which may have influence on choice behavior. We perform a regression analysis for potential factors that may have caused the observed variation in the number of safer choices across the gain and loss tasks. All models tested included a constant term (C), the expected value (E) of a prospect within a task, dummy variables indicating the type (WR, SYM, or STR) with GER as baseline, a dummy variable if a task is from the loss condition ($LOSS$), and interaction terms for type and condition (e.g., $LOSS * WR$). After sequentially removing those variables that have a p-value above 10% we obtain the following model with highly significant coefficients (p-value below 1%), and highest adjusted R^2, with standard errors in parenthesis below the corresponding coefficients:

$$\begin{array}{llll} \text{No. safe Choices} & = 46.77 * C & +1.59 * E & -16.92 * (LOSS * WR) \\ \bar{R}^2 = 0.569 & (1.40) & (0.24) & (5.38) \end{array}$$

This model suggest that the choice for the safer prospect within a task will increase with the prospects' expected value.

5 Discussion

The results presented in the previous section confirm that PT with the specification of Tversky and Kahneman provides comparable parameter estimates to previous studies (Abdellaoui 2000, Tversky and Kahneman 1992) for utility, but somewhat higher parameter estimates for the probability weighting functions. This suggests that probability weighting may not play a significant role for choice behavior in the tasks of this experiment. This finding is not surprising as most empirical findings regarding probability weighting suggest that probabilities in the range $(0.2, 0.8)$, as we used in the design of prospects, are treated close to linear as in expected utility. Indeed if we compare Tables 7 and 8 we observe similar distributions into the different classes, thus little variation. The only source of variation that we find in the data is related to the expected value of prospects in a task, which is positively related to the proportion of subjects preferring the safer prospect within a task.

While a concave/linear utility for gains and a linear/convex utility for losses seems to be the dominant pattern, a somewhat surprising finding is that we do not find strong evidence for loss aversion. There is an equal split of subjects into loss averse, gain seeking and unclassified. In an earlier experiment by Brooks and Zank (2005) twice as many subjects were loss averse as compared to gain seeking. A difference to Brooks and Zank is that here the likelihood associated with a reduction in losses through MPS is smaller (0.2 compared to 0.25 and 0.33). The lower likelihood may have made increases in losses less prominent and thereby inducing more neutral or gain seeking behavior.[12]

[12]Another explanation could be that the high number tasks involving mixed prospects and

Overall we find some evidence supporting PSD and PWSD with rejections for MSD and MWSD. More generally the aggregate data supports prospect theory, in particular as the latter can also accommodate the unclassified subjects in Tables 4,5,7, and 8.

6 Conclusion

In this paper we took a different approach to testing SSD-principles. Instead of selecting a single or just a few choice problems to obtain evidence in favor or against SSD, P/MSD or P/MWSD and LA/GS, we designed several tasks that took account of key aspects of prospect theory. We were able to provide a detailed analysis of behavior at the level of individuals in addition to the aggregate data analysis. We observe that no subject is revealing behavior in agreement with M(W)SD and that some individuals choose in agreement with PSD. Most notably, PT can accommodate a significantly larger number of individual behavior than any of the SSD variants, a finding that is also supported by the estimated PT-parameters. This conclusion, however, follows from observed choice behavior for gain prospects combined with the separate choice behavior for loss prospects. For mixed prospects, we find evidence against SSD, and the few loss averse individuals were matched by a similar number of gain seeking individuals.

loss prospects may have generated pessimism about gaining any amount of money out of this experiment. This would explain why most subjects were not willing to pay a large proportion of their earnings from the experiment to participate again in the same study (a finding which can be interpretted as a form of loss aversion). 82 subjects provided us with such information: on average, those who lost from their fixed payment (31 subjects earned £6.64 on average) were willing to pay $44,66\%$ of their ernings; those who gained (27 subjects earned £24.22 on average) were willing to pay 23.85% of their earnings, and those who neither gained nor lost (24 subjects received £17) were willing to pay 24.5% of their earnings to repeat the experiment.

Recall that the expected pay from the experiment was £17, while the minimum one can ensure is £2. Thus, it may well be, that the frequent reoccurence of tasks with potential losses has induced many subjects to exhibit more risk neutral behavior in the SSD-sense.

Prospect theory has emerged as a reasonable compromise between empirical validity and mathematical tractability, and this accounts for much of the popularity of the model (Starmer 2000, Wakker 2010). We have, once more, confirmed PT's superiority over gain prospects and over loss prospects. Our study reinforces a distinction of behavior over gain, loss, and mixed prospects (see also Shoemaker 1990). As most real decisions that we face involve gains and losses within one alternative, the critical test for prospect theory concerns PT's predictive power for choices among mixed prospects. In the latter domain we have identified shortcomings of the theory, for the range of real stakes that we used and possibly because of the more complex non binary prospects used in this study. Additional studies seem warranted to evaluate PT's predictive power for complex multi-outcome prospects and for drawing comparisons with PT-estimates using binary prospects.

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Appendix A: "Experiments on Individual Choice" Instructions

Appendix B: "Experiments on Individual Choice" Payment Form

Experiments on Individual Choice

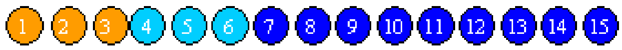
(This experiment has been approved by the Senate Committee on the Ethics of Research on Human Beings of the University of Manchester)

Welcome to this session. The aim of this experiment is to investigate how people make decisions. We will ask you to make several decisions, and will record your choice. The records will be used for scientific purposes only. Our published results will not identify any individuals. Our general interest is to observe and analyse how people make decisions. We expect that 100 or more people will participate in this experiment.

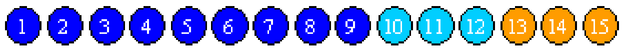
This experiment is not a test. There is no way for us to tell whether your decisions are good or bad. That is for you to judge. People are different, and faced with the same situation they will prefer to take different courses of action. What you need to consider is the fact that the amount of money that you receive by participating in this experiment depends partly on your decisions, and partly on luck.

We will ask you to perform 105 tasks. Each task consists of choosing one of two gambles. An example of a task is described below:

Choose the gamble that you would like to play:



5 -5 8



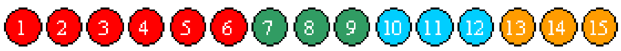
8 10 -10

○ left ○ right

Submit

After deciding which gamble to play by marking "left" or "right" and pressing the "Submit" button the next task appears.

Now we explain what a gamble is and how it is played. A complete gamble is visualised on the screen as 15 balls numbered consecutively from 1 to 15 with amounts of money underneath balls of the same colour. An example is the following gamble:



15 -3 -5 3

This is how a gamble is played: A bag contains all 15 balls. One ball is drawn at random. Each ball in the bag is equally likely to be drawn. The outcome of a gamble is the sum of money indicated underneath the drawn ball.

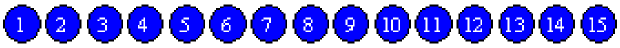
In the example above, the **red balls** indicate that **£15.00** will be gained for a ball with the number **1, 2, 3, 4, 5 or 6** on it. The **green balls** indicate that **£3.00** will be lost for a ball with the number **7, 8, or 9** on it. The **blue balls** indicate that **£5.00** will be lost for a ball with the number **10, 11, or 12** on it. Finally, the **orange balls** indicate that **£3.00** will be gained for a ball with the number **13, 14, or 15** on it.

In this experiment there will be several types of gambles. Three examples of gambles are explained below

> **Gamble type 1:** A bag contains 15 balls numbered from 1 to 15. One ball is drawn at random. Each ball in the bag is equally likely to be drawn. If the ball is numbered **1, 2, 3, 4, 5 or 6** the outcome is the amount of money indicated underneath those balls (therefore, there is a **40%** chance of getting that amount). If the ball is numbered **7, 8, 9, 10, 11, or 12**, the outcome is the amount of money indicated underneath those balls (therefore, there is a **40%** chance of getting that amount). If the ball is numbered **13, 14, or 15**, the outcome is the amount of money indicated underneath those balls (therefore, there is a **20%** chance of getting that amount). We represent this gamble with balls in the respective colours, as follows:

Gamble type 2: A bag contains 15 balls numbered from 1 to 15. One ball is drawn at random. Each ball in the bag is equally likely to be drawn. If the ball is numbered **1, 2, or 3**, the outcome is the amount of money indicated underneath those balls (therefore, there is a **20%** chance of getting that amount). If the ball is numbered **4, 5, or 6**, the outcome is the amount of money indicated underneath those balls (therefore, there is a **20%** chance of getting that amount). If the ball is numbered **7, 8, or 9**, the outcome is the amount of money indicated underneath those balls (therefore, there is a **20%** chance of getting that amount). If the ball is numbered **10, 11, or 12**, the outcome is the amount of money indicated underneath those balls (therefore, there is a **20%** chance of getting that amount). If the ball is numbered **13, 14, or 15**, the outcome is the amount of money indicated underneath those balls (therefore, there is a **20%** chance of getting that amount). We represent this gamble with balls in the respective colours, as follows:

Gamble type 3: A bag contains 15 balls numbered from 1 to 15. One ball is drawn at random. Each ball in the bag is equally likely to be drawn. If the ball is numbered **1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 or 15** the outcome is the amount of money indicated underneath those balls (therefore, there is a **100%** chance of getting that amount). We represent this gamble with balls in the respective colour, as follows:



Most gambles involve negative and positive amounts of money. In such a gamble one may lose some amount of money from the fixed payment (£17.00) that you receive if you complete all tasks. For example the gamble below indicates that you can either lose £15.00 with 20% chance, or gain £2.00 with 20% chance, or gain £10.00 with 40% chance, or gain 15 with a 20% chance.

-15 2 10 15

If you complete all tasks, then you receive a participation fee of £17.00 plus an additional amount of money determined by your decision in one randomly selected task. The computer will select this gamble after all tasks have been completed, and we will play that gamble for real. The additional amount of money ranges from £-15.00 to £15.00. Therefore the final sum of money that you receive will be a positive amount in the range of £2.00 and £32.00; it will never be negative.

There is enough time allocated for completing all tasks. You may withdraw from the experiment at any time. If you withdraw from the experiment, we will not be able to compensate you for your effort.

Take your time to make sure that you have understood everything. The window with these instructions will be accessible at all times. You may also ask the experimenters for help. Please do **not use the "Back" button** of your internet browser unless you are asked on the computer screen. Also, please do not distract (or talk to) other people taking part in the experiment. If you completed all tasks please remain seated and indicate to the experimenter that you have finished.

When you are ready to start with the tasks, press the "Proceed with the Experiment" link below, and then follow the instructions set by the computer.

Proceed with the experiment

Experiments on Individual Choice

Project: British Academy Small Research Grant SG-36804 Choice under Risk: An Experimental Investigation	
Name/Surname:	
Student Registration No.	
Address where Cheque should be sent:	
Date:	19 March 2004
Scope:	Prize for Participation in Experiment
Winning Ball:	No.
Payment:	£
Please indicate if you would like to participate again in similar experiments	Yes / No
Please indicate how much of your payment you are willing to give up in order to participate again in this experiment	£
Your Signature:	
Verified / Signed:	H. Zank: