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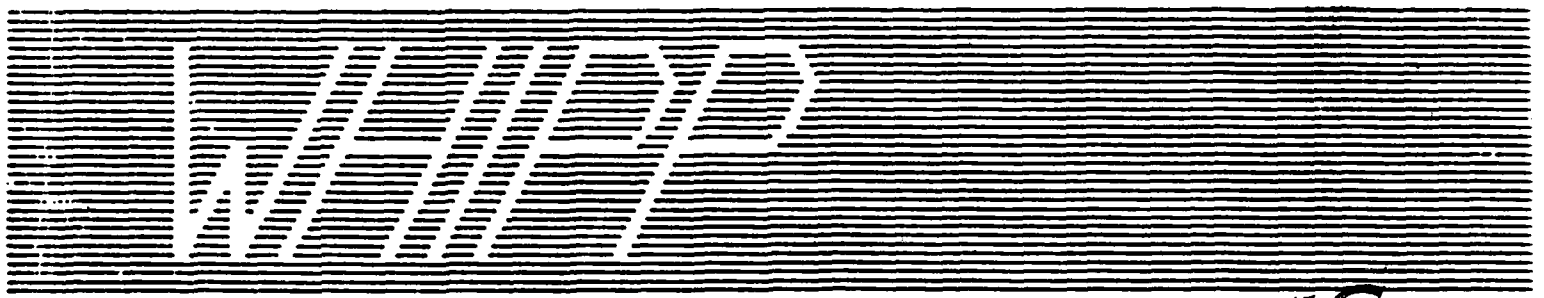
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REFLECTION IN PREFERENCES FOR MULTIOUTCOME LOTTERIES

Sandra L. Schneider
and
Lola L. Lopes

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number) Classical theories of risky decision making assume that people are risk averse. This means, in part, that people tend to reject gambles or lotteries in favor of actuarially equivalent sure things. According to prospect theory (Kahneman and Tversky, 1979), however, risk aversion applies primarily to lotteries involving gains. In the domain of losses, people are hypothesized to be primarily risk seeking, tending to prefer a gamble to an actuarially equivalent sure loss. This switch of risk preference from the domain of gains to the domain of losses is termed the reflection effect.		

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Kahneman and Tversky presented evidence supporting the reflection effect using a limited set of two-outcome gambles. The present study examined the robustness of the reflection effect for multioutcome lotteries both within subjects and across subjects differing in risk style. Consistent with the findings of Hershey and Schoemaker (1980) for the two-outcome case, the results demonstrate that the reflection effect is weak and irregular both at the group and at the individual level.

The data show that subjects chosen for risk aversion on the basis of preferences in tasks such as those used by Kahneman and Tversky are, as expected, risk averse over essentially all types of gain lotteries. For losses, however, such subjects are not uniformly risk seeking as would be predicted by the reflection hypothesis. Instead, reflection appears to occur only for gamble pairs which include a sure thing or a gamble with a riskless component. On the other hand, subjects chosen on the same basis for risk seeking appear to be uniformly risk seeking for losses, but for gains are sometimes risk seeking and sometimes risk averse. The latter preferences, which are supportive of reflection, occur reliably only for gambles with riskless components.

We interpret the data in terms of prospect theory's hypothesized value and probability weighting functions and argue that the data cannot be adequately accounted for in terms of the joint action of these two functions. However, the value function alone can describe the preferences of risk averse subjects for gains and of risk seeking subjects for losses. We discuss the characteristics of lotteries and of individuals that may underlie these consistent patterns of preference and relate our data to alternative views of risky choice proposed by Hagen (1969) and by Lopes (1984; in press).



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REFLECTION IN PREFERENCES FOR MULTIOUTCOME LOTTERIES

Since the time of Bernoulli, economists have noted that most people prefer a certain outcome to a gamble of equal expected value. This phenomenon is known as risk aversion. Bernoulli (1738) proposed that such preferences arise because people maximize the expected utility of options. He suggested that the subjective value, or utility, of money is a marginally decreasing function of objective value. Because such a function is concave everywhere, a person maximizing expected utility will always prefer a sure thing to a risky option of equal expected value.

Although the expected utility model is the cornerstone of many current theories of risky decision making, recent evidence (Kahneman and Tversky, 1979; Fishburn and Kochenberger, 1979; Laughunn, Payne, and Crum, 1980; and Williams, 1966) has suggested that when potential losses are involved most people prefer a risky option to a certain outcome of equal expected value; that is, they are risk seeking in the domain of losses.

Kahneman and Tversky (1979) labelled this switch from risk averse preferences for gains to risk seeking preferences for losses the reflection effect. In part because modern expected utility theory typically does not account such reflection, Kahneman and Tversky have developed what they believe to be a more descriptive and comprehensive model of preferences under risk. This model, embodied in what Kahneman and Tversky call prospect theory, describes individual decision making under risk as consisting of two separate stages. First, prospects are psychologically edited in order to simplify their representation, and second, the edited prospects are evaluated in terms of subjective value and probability weighting functions.

The present article focuses on the evaluation stage, with particular emphasis on the occurrence of the reflection effect. An outline of the essential features of prospect theory is presented, followed by a discussion of the conditions theoretically necessary for the occurrence of reflection. Next, what little empirical evidence exists regarding the reflection effect is considered. Finally, the present study is introduced as an expanded test of the reflection effect.

The Basics of Prospect Theory

Prospect theory is a complex axiomatic description of decision making under risk. Rather than discussing it in detail, we will consider only those portions of the theory that are relevant to the present study. Kahneman and Tversky (1979) propose that, before prospects are evaluated, they are psychologically represented through the application of several editing operations. Of primary importance for the reflection effect is that outcomes are coded relative to some reference point, usually, but not always, the status quo. Thus, decision makers are seen as thinking in terms of gains and losses rather than final asset positions.

Once the prospects have been edited, they are evaluated. First, the outcomes and associated probabilities in each edited prospect are interpreted according to a subjective value function and a probability weighting function. These subjective interpretations are then integrated quantitatively, using a format similar to that used by expected utility theorists, to determine the overall worth of each of the prospects. The prospect with the maximum worth is then identified and chosen.

The Value Function

Prospect theory's value function (which we will call "the PT value function") is presented in Figure 1. The function is concave for gains but convex for losses, giving the function an 'S' shape. This shape implies that choices will be risk averse for gains, yet risk seeking for losses.¹

Insert Figure 1 about here

Another property of the value function is that the convex portion of the function is steeper than the concave portion. This implies that the psychological impact of any given loss is greater than the psychological impact of a gain of the same amount.

The Probability Weighting Function

Kahneman and Tversky (1979) propose that objective probabilities are weighted according to "the impact of events on the desirability of prospects and not merely the perceived likelihood of these events" (p. 280). The properties of these probability weights are illustrated in the function in Figure 2 which is adapted from that provided by Kahneman and Tversky (1982).² In this function, large and intermediate probabilities are underweighted while small probabilities are overweighted. The apparent discontinuities at the ends of the weighting function indicate that extremely large probabilities are psychologically equated with certainty, while extremely small probabilities are ignored.

Insert Figure 2 about here

The underweighting of large and intermediate probabilities can cause the sum of the weighted probabilities in a two-outcome prospect to equal less than one. Kahneman and Tversky (1979) call this property subcertainty. The property implies that risky prospects with two outcomes will usually be underweighted relative to certain prospects. Thus subcertainty enhances preferences for sure things for gains and preferences for risky prospects for losses.

According to Kahneman and Tversky (1979), subcertainty will generally apply even if one of the objective probabilities in a two-outcome prospect is overweighted. However, if a small probability is associated with the only non-zero outcome in a prospect, subcertainty will not apply. In this case, the overweighting of the small probability may lead to a preference for the 'long shot' over a small certain gain and to a preference for a small sure loss over a small chance of a large loss.

The Reflection Effect

The reflection effect for any pair of lotteries is a reversal in preference induced by a change in the sign of all of the outcomes. Two of the five problems used by Kahneman and Tversky (1979) to demonstrate reflection are presented in Table 1. Problems 3 and 7 are prospect pairs in the gain formulation and problems 3' and 7' are the same pairs in the loss formulation. Beneath the pairs are the percentage of subjects preferring each prospect and the number of subjects responding to each problem.

Insert Table 1 about here

In both problems 3 and 7, notice that the majority of subjects made the risk averse choice, while in problems 3' and 7', the majority of subjects chose the riskier prospect. (Because neither prospect in problem 7 represents a sure thing, the risk averse choice is identified as the prospect with the greater absolute worth according to the PT value function.) This is the type of preference reversal suggested by prospect theory.

However, another form of reflection could conceivably occur, consisting of risk seeking preferences for gains accompanied by risk averse preferences for losses. The conditions supporting both types of reflection are discussed below.

Prospect Theory's Predictions

Taken by itself, the PT value function virtually always predicts the occurrence of reflection from risk averse choices for gains to risk seeking choices for losses. However, the characteristics of the probability weighting function make it more difficult to determine exactly when the joint effects of the value and probability weighting functions will support reflection. A second difficulty involves the final form of edited prospects. However, if the prospect pair consists of a two-outcome prospect and a sure thing of equal expected value, it is possible to specify a range of preferences that will be consistent with the value and probability weighting functions given the limited number of final forms that the edited prospects may take. Unfortunately, the conclusions drawn will only refer to prospect pairs in this form. For all other pairs, the most that can be said is that reflection should almost always

occur, but the type of reflection cannot be specified a priori.

For any prospect pair consisting of a two-outcome prospect having one outcome equal to zero and a sure thing of equal expected value, the property of subcertainty implies risk averse preferences for gains and risk seeking preferences for losses whenever the amount of underweighting of probabilities exceeds that of overweighting. However, when the overweighting of probabilities exceeds the underweighting, there must be a tradeoff between the effect of the value function and the effect of the probability weighting function. Remember that the value function supports risk averse preferences for gains and risk seeking preferences for losses, whereas the overweighting of probabilities supports just the opposite. Consequently, with small amounts of overweighting, preferences will continue to be risk averse for gains and risk seeking for losses. But when the amount of overweighting is large, preferences for gains will be risk seeking and for losses will be risk averse. Although the type of reflection differs, the effect still occurs in both of these cases. However, because the value function is steeper for losses than for gains, there will be some intermediate amount of overweighting that leads to risk averse preferences for both gains and losses. It is only in this case that reflection is not expected to occur.

Experimental Tests of the Reflection Effect

As part of a recent study, Payne, Laughhunn, and Crum (1982) asked 128 experienced managers to choose between a single pair of two-attribute lotteries in which each attribute had two potential outcomes each associated with a probability of 50%. The pair of lotteries was presented both for gains and for losses. Payne, et al., found that 62% of the managers' preferences were risk

averse for gains and 59% were risk seeking for losses. They also found that 33% of the managers reversed preferences from the risk averse choice for gains to the risk seeking choice for losses. These results are generally consistent with prospect theory, though much weaker than would be expected.

A more thorough examination of the reflection effect was conducted by Hershey and Schoemaker (1980). They showed, first, that significant patterns of preference reversal measured across subjects at the group level do not necessarily imply the existence of a significant number of preference reversals at the level of the individual, and second, that the reflection effect is generally weak and unlawful regardless of how it is measured.

In making the former point, Hershey and Schoemaker (1980) noted that in the five problems that Kahneman and Tversky (1979) used to demonstrate reflection, a significant majority of one group of subjects preferred the risk averse prospects for gains whereas a significant majority of another group of subjects preferred the risk seeking prospects for losses. Unfortunately, in such a between subjects design, direct measures of individual preference reversals are not possible. Nevertheless, Hershey and Schoemaker showed that, even if the same subjects had given preferences in both domains, the results in three of the five problems would not necessarily imply a significant number of individual preference reversals. (The two problems presented in Table 1 are those that do imply a significant number of individual preference reversals.)

In three separate experiments, Hershey and Schoemaker (1980) looked for reflection both in terms of individual and group preferences using prospect pairs consisting of a two-outcome prospect and a certain prospect of equal expected value. The probabilities and amounts of prospect pairs were systematically varied across problems in which the risky prospect had no

riskless component in the first experiment, and in which the risky prospect did have a riskless component in the second experiment. (A prospect has a riskless component if there is some sure minimum amount other than zero that can be expected to be won or lost.) In both experiments, consistent patterns of preference reversal failed to occur regularly at either the group level or the individual level. In the third experiment, Hershey and Schoemaker collected preferences for three prospect pairs from over 200 subjects. They reasoned that, from such a large sample, any relation among preferences would surely be detected if present. Significant preference reversal was found in only one of the problems at the group level. However, individual preference reversals occurred in all three problems for significantly more than 50% of the subjects.

In the third, successful, experiment, Hershey and Schoemaker asked subjects to explain the reasons, if any, for their preferences. Although only half of the subjects gave reasons, Hershey and Schoemaker found that the reasons given for gains generally did not parallel the reasons given for losses. This suggests that the characteristics of prospects that are perceived as most desirable for gains are not necessarily those that are perceived as most undesirable for losses.

Looking at individual reversals across all three experiments, Hershey and Schoemaker (1980) noted that the most prevalent form of preference reversal consists of risk averse preferences for gains and risk seeking preferences for losses. Although this appears to be consistent with prospect theory, these reversals were as likely to occur for prospects where probabilities were presumably overweighted as they were for prospects where probabilities were presumably underweighted. Hershey and Schoemaker question the generalizability of the reflection effect pointing out that it is most likely to occur with

small amounts, extreme probabilities, and extremely large amounts.

An Expanded Test of Prospect Theory's Reflection Effect

Because the predictions of prospect theory are complex, tests of the theory have involved only simple gambles with few outcomes. Although the data cast doubt on the strength and regularity of the reflection effect, there are several psychological issues regarding the effect that remain to be examined.

Many of the choice situations faced by individuals in real life involve more than two possible outcomes. In the present experiment we study preferences for multioutcome lotteries, with particular focus on reflection.³

Another concern of psychological interest involves differences in preferences across individuals. In all of the studies of preferences under risk, there have been some subjects whose preferences are predominantly risk seeking for gains rather than risk averse. This suggests that there may well be a significant subpopulation for which the PT value function is completely inadequate (as is the negatively accelerated utility function in traditional expected utility theory). However, an examination of the reflection effect for these subjects may indicate whether such subjects' preferences can be represented by a value function with an 'inverse S' shape (implying risk seeking preferences for gains and risk averse preferences for losses) or whether the differences in their preferences are more drastic.

To examine this issue, subjects in the present experiment were chosen according to their preferences for potential gains in choice problems similar to those used by Kahneman and Tversky (1979). Those who consistently chose the sure thing were considered risk averse for gains while those who consistently chose the gamble were considered risk seeking for gains. This not only allows for a test of the reflection effect across subjects whose attitudes toward risk

seem to differ markedly, but also allows for a comparison of risk taking tendencies from two-outcome to multioutcome gambles.

Method

Subjects

The subjects were 30 male and 30 female Introductory Psychology students at the University of Wisconsin-Madison. They were selected on the basis of a risk style survey included in the general departmental questionnaire administered in the spring of 1984.

Subjects participated in the experiment for credit toward their course grade. In addition, they were informed that they would be given the chance to win approximately \$1.00.

Stimuli

The stimuli were nine multioutcome lotteries similar to those used by Lopes (1984) plus a \$100 sure thing. Each of the lotteries had 100 tickets with 10 to 23 possible outcomes ranging between \$0 and \$439. The expected value of each lottery was \$100. The stimulus set can be seen in Figure 3. Each '#' symbol in a lottery represents a single ticket equal in value to the amount listed on the lefthand side of the same row.

Insert Figure 3 about here

To establish a convenient labelling system for the lotteries, the value of each was calculated according to Kahneman and Tversky's (1982) proposed value function for gains. The lotteries were then ordered from greatest (1) to least

(9) value. Each of the lotteries, then, is identified by the number corresponding to this ordering, whereas the \$100 sure thing is referred to as ST.

The stimulus set was chosen to provide a representative sample of multioutcome lotteries having equal expected values. As shown in Figure 3, three of the lotteries used were symmetric and the remaining six were asymmetric. The symmetric lotteries represent situations involving an equal probability of all outcomes (6), a disproportionately large probability of intermediate outcomes (5), and a disproportionately large probability of extreme outcomes (7). The asymmetric lotteries represent a variety of combinations of positive or negative skew and high or low variance. Notice, in addition, that lotteries 1 and 2 have riskless components: each has some minimum non-zero amount that is certain to be won (or lost).

Design

The experiment was designed to determine the effects of a single within-subject variable and two between-subject variables on subjects' preferences between lotteries presented in pairs.

A gain condition and a loss condition made up the two levels of the within-subject variable of potential outcome. In the gain condition, the non-zero outcomes of the lotteries and the sure thing represented gains, while in the loss condition, the non-zero outcomes and the sure thing represented losses. The lotteries shown in Figure 3 represent only those used in the gain condition; the same set was also used in the loss condition by simply preceding all outcomes with a minus sign. (Note that distributions that are positively skewed for gains become negatively skewed for losses and vice versa.)

The primary between-subject variable was risk style. Subjects were assigned to one of two risk style groups on the basis of their responses to the risk style survey mentioned earlier. The five choice problems presented in this survey were similar to those used by Kahneman and Tversky (1979). In each problem, the subject had to choose between a two-outcome gamble in which one outcome was zero and the other was a potential gain and a sure thing of equal actuarial value. Fifteen males and 15 females were selected from the group of respondents who preferred the sure thing in all five problems. In accord with conventional economic usage, this group of subjects was designated risk averse (RA). The remaining 15 males and 15 females were selected from the group of respondents who preferred a sure thing only once or not at all; these subjects were designated risk seeking (RS).

A secondary between-subject variable was introduced to assess the effect of stimulus format. One third of the subjects were presented lotteries with amounts listed in ascending order with ZERO at the bottom of the distribution (as illustrated in Figure 3) for both gains and losses, one third of the subjects were presented lotteries with amounts listed in descending order with ZERO at the top of the distribution for both gains and losses, and one third of the subjects were presented lotteries with amounts listed in ascending order for gains but in descending order for losses. Ten RA and ten RS subjects were randomly assigned to each of the three format groups.

The 45 unique pairs possible from a stimulus set of ten were presented to subjects in random order three times and subjects were asked for their preferences. This 135 pair series was presented to each subject once for the gain condition and once for the loss condition. The order of presentation of lotteries within each pair was randomly determined. Half of the RA subjects

and half of the RS subjects were randomly assigned to participate in the gain condition first; the remainder participated in the loss condition first.

Procedure

An Apple II Plus computer was used both to display stimuli and to record responses. The computer was placed on a table in a soundproof booth. A joystick was placed to the left of the computer immediately in front of a video monitor.

For both the gain and loss conditions, each trial began with the presentation of one of the lotteries from a given pair on the computer screen. In order to view the second lottery of the pair, the subject moved the joystick to the right. Each subject was permitted to look at the lotteries as long as desired and to switch the joystick to the left or right to view each of the lotteries in the pair as often as desired. The subject's choices were made by displaying the preferred lottery on the screen and then pressing a decision button located on the joystick.

The experiment was conducted in two sessions. In the first session, lasting about 45 minutes, either the gain or loss condition of the preference task was completed. The gain and loss instructions differed according to whether the subject was told that he or she would (hypothetically) be allowed to draw a single ticket at random from the chosen lottery for gains or be forced to draw a single ticket at random from the chosen lottery for losses. The explanation of the task and the stimulus set included the following:

Each lottery that you will see has exactly 100 tickets and you should assume that if you select a lottery then you will be able to (have to) draw one of the tickets at random and receive (pay) the amount that it indicates. In fact, after the experiment, you will be

allowed (required) to actually draw a ticket from a modified version of one of these lotteries and add (deduct) the amount indicated on the ticket from the earnings you are to receive for participating in this experiment. The lottery you are allowed to (must) draw from will depend on your stated preferences in this task.

However, I want to be sure to emphasize that there are no right or wrong answers in this experiment. We are interested in your preferences about how chances are distributed over prizes (losses). In fact, we designed all the lotteries so that they would be equivalent except for how the chances are distributed. I'll explain what I mean. If any lottery is played many, many times, there will be some average amount of money per play that you can expect to win (lose) in the long run. This is called the expected value of the lottery. Each of the lotteries in this part of the experiment has an expected value of \$100 (-\$100), which means that if you were allowed (forced) to play any of them for a long, long time, on the average you would win (lose) \$100 per play.

But, obviously, the lotteries differ from one another in terms of the amounts that a person is likely to win (lose) on a single play. And it is your preferences concerning these differences that we are interested in studying.

Five practice pairs of lotteries, chosen to represent each of the ten possible stimuli, were then presented to familiarize the subject with the task, stimuli, and equipment.

In the second session, which took place within a week of the first and lasted approximately one hour, the remaining condition in the preference task

was completed following both a shorter set of instructions emphasizing changes from the previous condition and five practice trials. A five minute rest interval was provided between the preference task and the final portion of the experiment which involved a rating-type judgment task. This latter task was of a pilot nature and will not be discussed further.

When the rating task was completed, the subject actually participated in two modified versions of the stimulus lotteries, one for gains and one for losses, in which all amounts were replaced by 1/100 of their previous value. For each drawing, the subject randomly selected a pair of lotteries from a set of nine cards held face-down by the experimenter. After examining the subject's data to determine which lottery was preferred, the subject was given the option to play the preferred lottery or take the +\$1.00 sure thing (regardless of the preference data). The total amount given to the subject was the sum of the ticket values from the gain and loss drawings plus \$1.00, providing that this amount was not negative or zero. In this way, the expected value of each subject's earnings was held constant at \$1.00.

Before being verbally debriefed by the experimenter, the subject was asked to briefly describe how he or she had made the choices between lotteries in each of the conditions. These statements were later used in the analysis only to identify possible patterns of responses indicative of choice strategies.

Results and Discussion

The data for the experiment are the number of times a subject chose a particular lottery out of the total number of times that the lottery was available for choice. Since each lottery was paired three different times with

each of the other nine stimuli, the maximum number of times that a lottery could be chosen was 27 (9 pairs x 3 presentations) and the minimum was zero.

Preliminary analysis revealed that the stimulus format manipulation had no effect on lottery preferences, $F < 1$. For this reason all further analyses have been conducted after pooling over the format variable.

Figures 4 and 5 give the mean choice data for gain and loss lotteries given by RA and RS subjects, respectively. The lotteries are labelled from greatest (1) to least (9) value according to their relative worth given the PT value function. The \$100 sure thing is labelled ST.

Insert Figures 4 and 5 about here

Obviously, there are differences in lottery preference between gains and losses, $F(9, 486) = 31.02$, $p < .001$, and between risk styles, $F(9, 486) = 22.08$, $p < .001$, but what is important is the extent to which prospect theory provides an accurate description of the pattern of the differences. The three major questions to be answered are: (1) Do preferences reverse from gains to losses? (2) Are lottery preferences in the two formulations consistent with the PT value function? and (3) Does incorporating the probability weighting function into the assessment improve the description of lottery preferences? A subsidiary analysis is also included to examine whether some lottery pairs elicit a greater degree of preference reversal than others.

Throughout the analyses, the differences in preference between RA and RS subjects will be highlighted. Because prospect theory was designed to describe the preferences of RA persons, it is reasonable to expect that the prospect theory description of preferences will most closely fit the preferences of RA

subjects. Nevertheless, it will be interesting to see how well prospect theory can handle the preferences of RS subjects.

Primary Analysis

Preference Reversal

Examination of mean preference scores. If subjects literally reverse preferences from gains to losses, the correlation coefficient relating gain preferences to loss preferences will be approximately -1.00. A correlation between mean preference scores for gains and mean preference scores for losses yielded a coefficient of -.490 for RA subjects as a group and a correlation of +.228 for RS subjects as a group. Neither of these coefficients is significant. In fact, the positive RS coefficient is in the direction opposite what would be expected if preference reversals were consistently occurring.

Examination of individual preference scores. On the face of it, it seems that relatively little preference reversal occurred from gains to losses, especially among RS subjects. However, if subjects disagree among themselves about lottery preferences either for gains or for losses, this could disguise the presence of reflection at the group level. For this reason, correlation coefficients relating gain and loss preference scores have been calculated for each subject individually.

Only 14 of the 60 subjects (9 RA, 5 RS) show a significant tendency to reverse their preferences from gains to losses, $r < -.632$, $p < .05$. Even more surprising is the finding that a full one third of both RA and RS subjects (10 RA, 13 RS) have positive correlation coefficients, suggesting some tendency to actually maintain preferences from gains to losses. For five RS subjects and one RA subject, this tendency to maintain preferences from gains to losses is significant, $r > +.632$, $p < .05$. So even at the level of the individual,

preference reversal is not particularly common.

Value Function

The PT value function was designed to explain a pattern of reversal in which preferences are risk averse for gains and risk seeking for losses. Because reflection is generally weak, subjects' preferences must often deviate in important ways from what would be expected given such a value function.

To determine the locus of deviations, the value of each of the lotteries was calculated according to the value function and prospect evaluation equations provided by Kahneman & Tversky (1979, 1982). Although the value function is assumed to vary somewhat across individuals, Kahneman & Tversky assert that reasonable approximations to the function are

$$v(x) = x^{2/3}$$

for gains and

$$v(x) = - (|x|)^{3/4}$$

for losses, where x is the objective value of one of the outcomes in a prospect. The evaluation equations are

$$V(x,p;y,q) = \pi(p) v(x) + \pi(q) v(y)$$

for prospects with no riskless component, and

$$V(x,p;y,q) = v(y) + \pi(p) [v(x) - v(y)]$$

for prospects with a riskless component (i.e. lotteries 1 and 2). In these equations x and y are objective outcomes and $\pi(p)$ is the weight given to the probability p . Both evaluation equations were expanded in the conventional way to accommodate multioutcome prospects.

Our strategy in exposition is to focus initially on the predictions generated by the PT value function, ignoring for the moment the effects of

probability weighting (i.e., $\pi(p)$ is set equal to objective probability). Once this is finished, additional analyses are presented that consider the simultaneous operation of the value and probability weighting functions.

Examination of mean preference scores. In Figures 4 and 5 (above) lotteries are ordered according to the predictions of the PT value function. For gains, the ST should be most preferred followed by lottery 1, and so on, with lottery 9 being least preferred. For losses, just the opposite pattern is predicted.

Correlation coefficients have been calculated to test the relation between predicted number of choices (i.e., for gains, 27 times for the ST, 24 times for lottery 1, etc.) and the average number of times the subjects within each group actually chose each lottery. For this correlation, the closer the coefficient is to +1.00, the more similar subjects' mean preference ordering is to the predicted value function ordering.

As is evident in Figure 4, the RA group of subjects come very close to the preference ordering derived from the value function for gains, $\underline{r} = +.977$, $\underline{p} < .001$. However, for losses, the RA preference ordering bears only a weak resemblance to the value function ordering, $\underline{r} = +.475$, n.s. For RS subjects, Figure 5 reveals a lack of any clear relation between predicted and actual preference scores for gains, $\underline{r} = -.193$, n.s. For losses, on the other hand, the RS preference ordering virtually coincides with the ordering predicted from the PT value function, $\underline{r} = +.940$, $\underline{p} < .001$.

Overall, these data indicate that RA subjects are generally risk averse for gains but not consistently risk seeking for losses. The RS group in contrast are not predominantly risk averse for gains, but are consistently risk seeking for losses. So the value function captures a portion of both RA and RS

subjects' preferences, but does not do so completely for either group. Notice that, in the absence of the risk style dichotomy, the appearance of reflection might be enhanced artifactually. That is, since RA subjects are risk averse for gains and RS subjects are risk seeking for losses, combining preferences across risk style could produce an illusion of a reversal phenomenon at the individual level when none actually exists.

Examination of individual preference scores. As noted earlier, mean preference scores tend to conceal individual differences in subjects' preferences. Because of this, individual correlation coefficients have been computed for each subject. Figure 6 is a scatterplot showing the correlation coefficients for gain preferences and for loss preferences for each of the 60 subjects. The range of possible correlation coefficients for gains is listed on the abscissa, that for losses is listed on the ordinate. The dotted lines running across the figure at $\pm .632$ on both axes represent the .05 cutoff for significant correlations. RA correlation coefficients are represented by filled circles and RS coefficients are represented by open circles. The points on the graph which are enclosed within a square identify the subjects who showed significant reflection.

Insert Figure 6 about here

The scatterplot reaffirms that for gains most RA subjects conform to the preference ordering given by the PT value function. This is illustrated by the fact that over two-thirds of the RA subjects have significant positive correlation coefficients for gains. However there is clear disagreement among the RA subjects as to the best preference ordering for loss lotteries. Only

one-third of the RA subjects have significant positive correlation coefficients for losses.

Conversely, a majority of RS subjects conform to the predicted preference ordering for losses. The preference ordering of over half of the RS subjects is significantly positively correlated with the value function preference ordering for losses. However the RS subjects disagree among themselves about the preference ordering for gain lotteries, with only one-fifth of these subjects having a significant positive correlation coefficient for gains.

Notice in the upper right-hand corner of the scatterplot that the responses of less than 20% of the 60 subjects (7 RA and 4 RS) are significantly risk averse for gains and significantly risk seeking for losses as predicted by the PT value function. Understandably, almost all of these subjects have significant correlation coefficients for reflection as well. On the other hand, not a single subject had a significant negative correlation coefficient for both gains and losses (lower left-hand corner of scatterplot), eliminating any possibility of a value function that implies risk seeking for gains and risk aversion for losses. It is also worth noting that only one subject had a significant tendency to be risk averse for both gains and losses. This is evidence against any theory that postulates a value function that is concave everywhere, including traditional utility theory.

Finally, in the center of the scatterplot, notice that the responses of 16 of the 60 subjects (5 RA and 11 RS) do not significantly correlate at all with the value function preference orderings. Surprisingly, two of these 16 subjects do have significant preference reversal correlations. These two patterns demonstrate that even when reflection does occur, it cannot always be explained by the 'S' shape of the value function.

Probability Weighting Function

Thus far it has been established that the reflection effect is much weaker for multioutcome lotteries than what is implied by the PT value function. However, according to prospect theory, the evaluation of lotteries depends also on the probability weighting function, which may substantially alter the preference orderings that are implied by the value function operating in isolation.

To determine first what the implied preference ordering for lotteries would be when probability weights are included in the prospect evaluation equation, it was necessary to obtain values from the probability weighting function. Unfortunately, the function has not been described mathematically, so it was necessary to measure the graphed function (Kahneman & Tversky, 1982). In order to provide for greater generality, we also worked with several close variations of the function. These included additive shifts, multiplicative shifts, and power variations. In all cases, the function retained the basic properties of overweighting of small probabilities, underweighting of large probabilities, and monotonicity.

Looking at each of these variations in the probability weighting function separately, the probability weights associated with the objective probabilities in each lottery were identified. The probability weights for each of the lotteries were then incorporated into the equations for prospect worth to determine the preference ordering of the stimulus lotteries. Note that the approximation of the probability weighting function being considered had no effect on the prospect worth of the \$100 sure thing since $\pi(1)$ is always equal to one.

The predicted preference ordering for lotteries varied somewhat for both gains and losses with different approximations to the probability weighting function. However, some parts of the preference ordering did not change. According to virtually all of the approximations, the most preferred lottery for gains (and least preferred for losses) should have been lottery 8, followed by lottery 6. For those approximations where the amount of underweighting of probabilities approached that found in the measured approximation to π , the least preferred lotteries for gains (and most preferred for losses) in order of decreasing (increasing) value should have been lotteries 1, ST, and 3. Lotteries 2 and 4, for almost all approximations to π , should (should not) have been preferred to lotteries 9, 5, and 7 for gains (losses) but the preference ordering between 2 and 4 as well as between 9, 5, and 7 was subject to change depending on the particular approximation to π being considered.

Examination of mean preference scores. Once again, correlation coefficients have been calculated to examine the relation between the average number of times the subjects within each group actually chose each lottery and the number of times a lottery would be chosen given the predicted preference ordering. Since the probability weighted preference ordering is subject to some fluctuations in lottery positions, the number of times a lottery would theoretically be chosen was estimated as follows. For those lotteries that maintain their position in the theoretical preference ordering across approximations to the probability weighting function, the number of times a lottery would be chosen was assigned as before (i.e., for gains, 27 times for lottery 8, 24 times for lottery 6, 6 times for lottery 1, 3 times for the ST, and 0 times for lottery 3). For those lotteries that have fluctuating positions depending on the approximation, the number of times each lottery

would be chosen was assigned as the mean number of times it would be chosen in each of the positions it might occupy in the different orderings (i.e., for gains, 19.5 times for lotteries 2 and 4, and 12 times for lotteries 9, 5, and 7). Since the theoretical preference scores are only estimates, the significance of these correlations was not tested. Nevertheless, the direction and size of the resulting correlation coefficients should capture a general relation if any exists.

The only positive correlation between subject preference scores and probability weighted preference scores is $+0.228$ for RS subjects for gains. This is small enough not to suggest any general tendency for preferences to be ordered according to probability weighted predictions. The coefficient of -0.399 found for RA subjects for losses even suggests a general inconsistency between actual and predicted preferences. The somewhat larger negative correlation coefficients of -0.453 for RA preferences for gains and -0.565 for RS preferences for losses suggest similar inconsistencies, but this is to be expected since these latter preferences were reasonably well described on the basis of the value function alone.

Examination of individual preference scores. Although the group data suggests a lack of any notable positive relation between obtained and predicted preference scores, mean preference scores may conceal individual patterns in preferences. In view of this, individual correlation coefficients were also calculated. Figure 7 is a scatterplot showing the correlation coefficients for both gains and losses for each of the 60 subjects. RA correlation coefficients are once again represented by a filled circle and RS coefficients by an open circle. The range of possible correlation coefficients for gains is listed on the abscissa, that for losses on the ordinate. This time the points on the

graph which are enclosed by a square represent the correlation coefficients of the 16 subjects whose preference scores were not significantly related to the preference scores derived from the value function alone for either gains or losses.

Insert Figure 7 about here

The lack of any strong positive relation between obtained and predicted preference scores is obvious from the aggregation of points in the center of the graph. The most obvious general pattern is that the majority of RA subjects have negative correlation coefficients for gains and that the majority of RS subjects have negative correlation coefficients for losses. Once again, this is understandable since strong positive relations with the theoretical value function preference orderings have already been established in these two cases.

For losses, only one fourth of the RA subjects have positive correlation coefficients and, in almost all cases, the correlation is very weak. Probability weighted preference scores are somewhat better descriptions of RS subjects' preferences for gains. Here, slightly over one half of the subjects have positive correlation coefficients, and although most of these are weak, there are a few coefficients that suggest some tendency for preferences to approach the ordering predicted from probability weighted preference scores.

Even for the 16 subjects whose preferences were not significantly correlated with value function predicted preferences, using probability weights does not improve the description of actual preferences. Although the only five subjects to have positive correlation coefficients for both gains and losses

are within this group of 16 subjects, the correlations are weak, being less than +.45 for gains and less than +.20 for losses. Finally, notice the two points in Figure 7 that have been marked with an 'X'. These points represent the coefficients of the two subjects who show a significant tendency to reverse their preferences from gains to losses. It was pointed out earlier that the significant preference reversal in these two cases could not be explained on the basis of value function predicted preferences. As Figure 7 illustrates, neither can the preference reversals be explained on the basis of probability weighted predicted preferences.

Summary and Evaluation of Primary Analysis

The reflection effect across multioutcome lotteries is weak and unreliable across subjects. Even though the PT value function can account for some of the data when operating in isolation, the interaction of the probability weighting and value functions should provide the best descriptions of the data, but this is clearly not the case.

The inability of probability weighted predicted preferences to describe actual preferences may be due, at least in part, to a rather peculiar property of the probability weighting function when applied to multioutcome lotteries. This property operates as follows. Generally, as the number of outcomes in a lottery increases, so does its predicted value. Specifically, whenever there are more than about eight outcomes in a lottery and the probabilities of these outcomes are distributed relatively equally or are skewed toward the largest amounts, the degree of overweighting of the probabilities less than about .12 easily overcomes the degree of underweighting of large probabilities. Put another way, as the ratio of small probabilities to large probabilities in a lottery increases, all else being equal, the effect of overweighting of small

probabilities will at some point surpass the effect of underweighting of large probabilities.

Kahneman & Tversky (1979) discuss the phenomenon of subcertainty in the two-outcome case, in which underweighting of both (or sometimes only one) of the objective probabilities in the prospect causes the total weighted probabilities involved to sum to less than one. Although it is not discussed in prospect theory, their probability weighting function also implies 'supercertainty' for the multioutcome case; that is, when all of the probabilities in a multioutcome lottery are overweighted, the sum of weighted probabilities for the lottery may be greater than one producing a preference for a risky option over a sure thing for gains (and vice versa for losses). Thus, prospect theory's probability weighting function implies that the attitudes of persons toward certainty may reverse simply on the basis of an increase in the number of potential outcomes in a prospect.

The prediction of supercertainty might be debated on the grounds that multioutcome lotteries would be simplified to yield fewer subjective outcomes during the editing phase. With fewer subjective outcomes, the probabilities would be larger, most likely resulting in the underweighting of the probabilities rather than overweighting. However, reliable and finely graded responses of subjects to such lotteries in previous research (Lopes, 1984) make it doubtful that multioutcome lotteries are reduced to only a few outcomes.

Subsidiary Analysis

Although the reflection effect is weaker than would be expected on the basis of prospect theory, the evidence presented thus far suggests that reflection will occur for some subjects across some lotteries. The following

analysis concerns the strength of the reflection effect across lottery pairs at both group and individual levels. The data for the analysis are the number of subjects in each risk style group predominantly preferring each lottery within a pair. There were a total of 30 scores per risk style group for each lottery pair, both for gains and for losses.

Group preferences. In this analysis, the risk averse (ra) and the risk seeking (rs) members of each lottery pair have been determined according to the PT value function. Subjects are said to agree in their preferences when a lottery in a pair is preferred by significantly more than 50% of subjects.

RA subjects agree with one another and conform to the preference ordering implied by the value function for gains in almost all pairs. For only 11 of the 45 pairs, is there no significant agreement. For losses, RA subjects do not agree as often. Although lottery 9 and lottery 8 should be the most desirable loss lotteries, at least according to the value function, when one or the other of these lotteries appears in a pair, RA subjects tend to disagree in their preferences. When lottery 9 and lottery 8 are not members of the pair, however, risk seeking preferences predominate when the ST, lottery 1, or lottery 2 are involved. Because these three entail some sure loss, Kahneman and Tversky's (1979) hypothesis that certainty is undesirable for losses is at least partially supported. For the remaining pairs of loss lotteries, RA subjects most often disagree in their preferences.

A very different pattern of preferences emerges for RS subjects. These subjects consistently agree with one another and conform to the preference ordering implied by the value function for losses. For only 14 of the 45 loss pairs is there no agreement as to which member is preferred. For gains, however, a significant majority of subjects agree only that lottery 1 is the

preferred choice in most of the pairs in which it appears. In almost all other cases, RS subjects disagree in their preferences, although a near-significant majority often select the rs lottery.

Kahneman and Tversky (1979) demonstrated the existence of the reflection effect by pointing out that the significant majority of preferences for gains are opposite the significant majority of preferences for losses. Using this same criterion, RA subjects show significant reflection across only 16 of the 45 lottery pairs while RS subjects show significant reflection across only four pairs.

Individual preferences. Although the reflection effect is described by Kahneman and Tversky (1979) in terms of ra - rs choices (i.e., ra for gains and rs for losses), choices that are rs - ra are equally representative of the reflection effect. Similarly, ra - ra and rs -rs preference relations are both representative of preference maintenance. This examination of lottery pair preference relations tests whether significantly more than 50% of subjects' responses to matched pairs of gain and loss lotteries represent preference reversal or preference maintenance.

For RA subjects, preference reversals occur for significantly more than 50% of subjects for 13 of the 24 lottery pairs in which the ra member of the pair is the ST, lottery 1, or lottery 2. There is also significant preference reversal when lottery 5 is paired with lottery 7. In the remaining 31 pairs preference reversal and preference maintenance occur about equally often.

A more pronounced lack of significant majority preference relations exists for RS subjects. For 40 of the 45 pairs, preference reversal and preference maintenance occur with approximately equal frequency. In one of the five cases in which significant majority preference relations do occur (lottery 8 paired

with lottery 9), it represents preference maintenance. Not surprisingly, the four cases in which significant preference reversals occur involve lottery 1 or 2, the lotteries with riskless components. (It may be of interest to note that 3 of these 4 pairs were not significant at the group level.)

General Discussion

Taken together, the data demonstrate that the reflection effect is weak and irregular across lotteries and across subjects. Although the PT value function does predict fairly well the simple preferences of RA subjects for gains and RS subjects for losses, it does poorly insofar as reflection is concerned. Sometimes preferences reflect from gains to losses, and sometimes they don't. Furthermore, allowing for probability weighting effects does not provide a better fit to the data, at least for our multioutcome lotteries. In fact, it generally does the opposite, undoing the partial good fit provided by the value function.

Of course, it is unreasonable to expect that any theory will be able to account for every choice made by every person. However, it should be able to describe and account for the major differences, as well as similarities, among risk preferences. We discuss in what follows three aspects of the decision making process that at present are inadequately handled by prospect theory. These include: (1) the relation between individual gain and loss preferences, (2) the characteristics of lotteries that affect preferences, and (3) the characteristics of individuals that affect preferences.

The Relation Between Individual Gain and Loss Preferences

Reflection. If a general relation does exist between gain and loss preferences, it is doubtful that it can be adequately described in terms of

reflection. Evidence from the present experiment suggests that individuals differ greatly in their general tendencies to reverse or maintain preferences. In addition, the kind of relation that occurs most frequently differs across lottery pairs. For pairs involving a lottery with a riskless component reflection tends to occur. However, for most pairs involving high variance lotteries preference maintenance is more common. In this latter case, it should be pointed out that the preferences underlying the tendency toward maintenance differ across the two risk style groups. RA subjects generally avoid the high variance lotteries in both domains while RS subjects generally prefer them.

Consistent with the findings for multioutcome lotteries, Hershey and Schoemaker (1980) also found irregular gain-loss preference relations across two-outcome lotteries. In only 7 of their 28 problems did significant reflection occur, typically in lottery pairs involving small amounts, extreme probabilities, and/or very large amounts. Because all of their lottery pairs had a sure thing as one of the members, preference relations between purely risky prospects could not be established. However, they did show that three of the five examples of reflection presented by Kahneman and Tversky (1979) do not necessarily imply a significant number of preference reversals at the level of the individual. It is noteworthy that two of these inconclusive pairs involved purely risky prospects.

Our data suggest that relatively little reflection occurs at the individual level unless one of the lotteries contains a riskless component. Taken in conjunction with the fact that risk aversion for gains was supported for RA subjects and risk seeking for losses was supported for RS subjects, it is possible that the apparent frequency of preference reversal between purely

risky prospects may be inflated by pooling over subjects with distinct, and in some ways, opposing risk preferences.

Reasoning processes. In addition to what has already been discussed, Hershey and Schoemaker (1980) hypothesized that if relations do exist between individuals' gain and loss preferences, there ought to be some symmetry involved in the reasoning behind their preferences. In their third experiment, they asked subjects to supply the reasons, if they were aware of any, for their preferences for three different gamble pairs both for gains and for losses. The stated reasons were then coded as mentioning the sure amount, the probability, the uncertain amount, or some combination of these components of the gambles. From the coded statements, Hershey and Schoemaker concluded that the only pair for which reasoning was based on the same component(s) across the gain and loss formulations was that in which an extreme probability was involved. From this preliminary evidence, the possibility of preference relations based on symmetries in reasoning about the particular components of gambles seems doubtful.

In a similar vein, subjects were asked at the end of the present experiment to briefly describe how they had made their choices. Although the statements were not collected for the purpose of statistical analysis, the responses do suggest some interesting tendencies that may bear on the relation between reasoning processes in the gain and loss domains.

Within each domain, the vast majority of responses indicated two basic points of view. For gains, subjects generally reported that they (1) tried to make sure that they would win something or (2) tried to choose the lottery with the best chance to win some large amount at the risk of winning nothing or a very small amount. For losses, subjects generally reported that they (1) tried

to make sure that they wouldn't lose the largest amount or (2) tried to choose the lottery with the best chance of losing nothing or a small amount at the risk of losing some very large amount. The similarities between the two points of view across domains are obvious. Notice that viewpoint (1) in both domains would generally lead to risk averse choices and that viewpoint (2) in both domains would generally lead to risk seeking choices.

As one might guess, the tendency of subjects to have one of the two viewpoints for gains did not, overall, seem to correspond in any consistent fashion with the viewpoints reported for losses. In fact, most of the subjects indicated an awareness of their own subjective tradeoff between the two viewpoints, and some even suggested strategies to determine for which lottery pairs each of the viewpoints should be adopted. For instance, in the domain of losses, eight of the 60 subjects suggested a strategy similar to the following: Compare the largest amounts to be lost in each lottery. If the difference is large, choose the lottery with the smallest maximum loss (viewpoint (1)). If the difference is small or zero, choose the lottery with the best chance of losing nothing or only a small amount (viewpoint (2)).

Even this cursory evidence suggests that there is no easily identifiable and consistent relation between gain and loss preferences. However, it also suggests that if a relation does exist, it may not focus on the particular components of the lotteries or on general tendencies toward risk aversion or risk seeking within either domain. Rather, relations between gain and loss preferences may be determined by individual interpretations of the best tradeoffs between more and less risky options depending on the characteristics of those options. Certainly, all of the evidence taken together does suggest that any relation between gain and loss preferences will only become apparent

when the characteristics of individuals and lotteries that underlie differences in preference can be identified.

The Characteristics of Lotteries that Affect Preferences

Lottery preference patterns. In the present experiment, subjects generally agreed that lotteries with a riskless component were highly desirable for gains and most often undesirable for losses. Subjects also generally agreed that the sure thing was undesirable for losses.

For many of the other lottery pairs, RA and RS subjects showed a tendency to disagree with one another in their preferences, but often in a consistent fashion. For instance, the majority of RA subjects found the sure thing highly desirable for gains while the majority of RS subjects most often preferred a lottery to the sure thing. Across many of the remaining pairs, RA subjects tended to make risk averse choices for both gains and losses whereas RS subjects tended to make risk seeking choices.

Even the disagreements within risk style groups seem to reflect consistent reasoning patterns. For example, there was some disagreement among RA subjects regarding the desirability of the high variance negatively skewed loss lotteries. Some of these subjects reported that they couldn't afford to lose the very highest amounts in these lotteries, while others reported that they were willing to risk the large loss in order to obtain the greatest chance of losing nothing or a small amount. (Notice that this corresponds to individual differences in the evaluation of the tradeoff between viewpoint (1) and viewpoint (2) discussed in the previous section.)

Similarly, in the two-outcome case, the data provided by Hershey and Schoemaker (1980) reveal consistent patterns of preference with certain types of gambles. For losses, gambles with a riskless component are most often

preferred to a sure thing of equal expected value. For gains, when faced with a choice between a sure thing and a purely risky prospect having a potential outcome of \$10,000 or more, the sure thing will most often be preferred. If Hershey and Schoemaker had subdivided their subjects on the basis of risk style or some other relevant dimension, richer and clearer patterns might have emerged. But even without subdivisions, it appears that the sure thing, gambles with riskless components, and gambles with large potential outcomes appear to have relatively distinct impacts on risk processing.

Important lottery characteristics in prospect theory. In prospect theory, the characteristics of prospects believed to be important in risky decision making are, for the most part, implicit in the evaluation phase. The centrality in the theory of the value function and the probability weighting function imply that amounts and probabilities are the characteristics of prospects that affect preferences. Additionally, prospects with riskless components are evaluated somewhat differently than prospects with no riskless components, which suggests that this factor also affects preferences. On the face of it, this breakdown of lotteries into characteristics seems quite reasonable. The separation of risky and riskless components is particularly well taken given the evidence for patterns in preferences based on this differentiation.

However, according to prospect theory, risky and riskless components of prospects, in the form of amounts and probabilities, are integrated into a single overall impression that by itself cannot retain information regarding particularly salient or important characteristics of prospects. Furthermore, the impact of amounts and probabilities is specified generally by the shapes of the value and probability weighting functions, implying that the relative

importance of each of the amounts and probabilities is predetermined by the shapes of these functions and that the result of the evaluation across prospects will yield a pattern of preferences that is everywhere consistent with these shapes.

As noted throughout, the evidence from both the present study and the study by Hershey and Schoemaker (1980) demonstrates that the implications of prospect theory are generally not supported by individual preference data. Neither are the implications supported by reports of reasoning strategies. Even when these reports were coded in terms of probabilities and amounts (Hershey and Schoemaker, 1980), there was no evidence that subjects used these components in a consistent fashion when evaluating lotteries.

Given this, it seems surprising that predictions based on the PT value function alone can capture most of the preferences of RA subjects for gains and of RS subjects for losses. However, it should be remembered that the same function (operating either alone or in conjunction with the probability weighting function) cannot describe the remaining preferences or the relations existing between gain and loss preferences. This may indicate that the process leading to preferences is different than that embodied in prospect theory.

Distributional approaches to risky decision making. Prospect theory is structurally similar to the family of expected utility models, differing from them primarily in the particulars of the transformations applied to values and probabilities. Other approaches to risky decision making have focused on the distributional properties of lotteries, two of which will be discussed here. The first approach shows how perceptions of and attitudes toward the moments of distributions might be included as explicit and critical aspects of risky decision making. The second approach introduces a representation of lotteries

that may illuminate the characteristics of lotteries that are psychologically important in risk processing. Neither approach will be described in detail here, only the implications relevant to the present discussion.

Hagen (1969) argues that perceptions of and attitudes toward risk depend on several interrelated factors besides probabilities and outcomes. He asserts that a person's feelings at the time of the decision will be influenced by the dispersion and skewness of the distribution of subjective outcomes. When dispersion is small, the desirability of lotteries is generally enhanced. As dispersion increases, all else being equal, desirability begins to decline, and at some point becomes realistically unacceptable. Skewness, on the other hand, affects preferences according to its sign, with positive skewness being associated with hope and negative skewness with fear. Hagen postulates that risky choice necessarily involves tradeoffs among these distributional components. Our subjects' verbal responses also suggested such tradeoffs.

Similarly, Lopes (1984; in press) argues that the distributional characteristics of lotteries are essential both in perceptions of risk and in preferences between risks. However, she suggests that the relevant distributional characteristics of lotteries are not moments per se but rather reflect distributional inequality, a measure that taps dispersion and skewness simultaneously. Lopes proposes that risks are mentally represented and processed in terms of their cumulative properties, with outcomes at the low end of distributions receiving greater weight, at least for risk averse people.

Lopes also stresses the role of aspiration level in risky choice. Although the idea of aspiration level is not new (Siegel, 1957; Simon, 1955), theories of risky decision making ordinarily pay it little attention. For example, in prospect theory an aspiration level may provide the reference point

for the value function (Kahneman and Tversky, 1979; Payne, Laughunn, and Crum, 1980), but most frequently the reference point is set at the status quo. In Lopes' theory, the aspiration level plays a more adaptive role, similar to the role played by aspirations in Simon's (1955) process of satisficing. In this view, aspiration levels not only underlie individual differences in willingness to assume risk, but also actively organize the choice process by reflecting current external demands and by tracking current opportunities. Thus, candidate lotteries serve not only as potential choices but also as frameworks against which other lotteries are evaluated.

The Characteristics of Individuals that Affect Preferences

That preferences under risk will be affected by certain characteristics of individuals seems intuitively obvious. However, many theories of risky decision making, including prospect theory, do not acknowledge this directly. In the present experiment, subjects were differentiated on the basis of risk style group, and the differences in preferences between these two groups were shown to be significant. However, even within groups, preferences often differed dramatically, indicating the need to identify additional or more appropriate characteristics of individuals that affect preferences.

Risk style groups. The division of subjects into risk style groups was motivated by the desire to identify the patterns of preferences for those individuals who do not conform to the prospect theory norm. The results from these two groups demonstrate that the risk style group dichotomy does separate individuals who differ in many of their preferences. The majority of RA subjects prefer risk averse choices for gains and the majority of RS subjects prefer risk seeking choices for losses. However, the patterns of preferences

identified do not seem to be representative of pure risk styles. For both groups of subjects, the pattern breaks down in one of the two domains and, oddly enough, the breakdown occurs in different domains for each of the risk style groups. Thus, the question arises as to what this dichotomy does represent. The individuals within each group clearly differ in some respect, but it is not clear from our data what those distinguishing characteristics are, much less how they affect preferences.

Identifying relevant characteristics of individuals. In prospect theory, the characteristics of individuals are not acknowledged as important to risky decision making, except in that the slopes of the value and probability weighting functions may differ slightly across individuals. In particular, the theory assumes that the goal of all subjects in all choice situations is to maximize the weighted value of the prospects. But if this is the case, then subjects must differ dramatically in their value and probability weighting functions. What seems more likely to us is that subjects differ in their goals and in their strategies for achieving those goals.

Models of risky decision making such as those of Lopes (1984; in press) and of Hagen (1969) may be fruitful in suggesting how people represent risks and how they go about satisfying their various goals under risk. In any event, it seems that both adequate empirical description and fruitful theoretical analysis will need to rest on quite different constituents than those implied by weighted value theories such as prospect theory. These new constituents include at least some consideration of the goals and strategies that people bring to risky decision making.

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Footnotes

¹Kahneman and Tversky are not the first to propose a subjective value function that is convex for a particular range of values, nor are they the first to define a subjective value function in terms of changes in wealth, rather than final assets. Most notable are the variations to the traditional utility function presented by Friedman and Savage (1948) and by Markowitz (1959) which allow for some risk seeking preferences, and thus imply some degree of reflectivity. Despite this, Kahneman and Tversky's value function is the only function that implies the existence of the reflection effect across virtually all prospects.

²In the original figure, probabilities less than about .05 appear to be undefined. This suggests that they should be set to zero. However, it is clear from the fact that Kahneman and Tversky cite overweighting of small probabilities as a cause of people's purchase of lottery tickets and of insurance (1979, p. 281) that they do not intend that probabilities as large as .01 be ignored. Accordingly, we have extrapolated the range of the function so that it includes .01.

³Kahneman and Tversky (1979) note that additional, but as yet unspecified, editing operations may be invoked to simplify multioutcome prospects. However, they assert that the extension of prospect theory to the multioutcome case is otherwise straightforward.

Figure Captions

Figure 1. Prospect theory's hypothetical value function. From "The Psychology of Preferences" by D. Kahneman and A. Tversky, 1982, Scientific American, 248, 166. (Permission to reprint has been requested.)

Figure 2. Prospect theory's hypothetical probability weighting function. Adapted from "The Psychology of Preferences" by D. Kahneman and A. Tversky, 1982, Scientific American, 248, 168. The dotted portion of the function extrapolates the range in which the decision weight is non-zero to include $p=.01$. (Permission to reprint has been requested.)

Figure 3. Stimulus set of nine multi-outcome lotteries and a \$100 sure thing. (The code number beneath each lottery represents the relative worth of the lottery from greatest (1) to least (9) value according to prospect theory's theoretical value function.)

Figure 4. Mean preference scores of RA subjects for lotteries in the gain and loss formulations.

Figure 5. Mean preference scores of RS subjects for lotteries in the gain and loss formulations.

Figure 6. Correlations of individual subjects' preference scores for gains and for losses with predicted preference scores based on prospect theory's value function. Correlation coefficients for the RA subjects are represented by filled circles and correlation coefficients for the RS subjects are represented by open circles. The dotted lines represent the .05 cutoff for significant correlations. The points enclosed within a square identify those subjects who had a significant tendency to reverse their preferences from gains to losses.

Figure 7. Correlations of individual subjects' preference scores for gains and for losses with predicted preference scores after probability weighting. Correlation coefficients for the RA subjects are represented by filled circles and correlation coefficients for the RS subjects are represented by open circles. The points enclosed within a square identify those subjects whose preference scores were not significantly related to the preference scores derived from the value function alone for either gains or losses. The two points that have been marked with an 'X' identify the two subjects whose significant preference reversals could not be explained on the basis of value function predicted preferences.

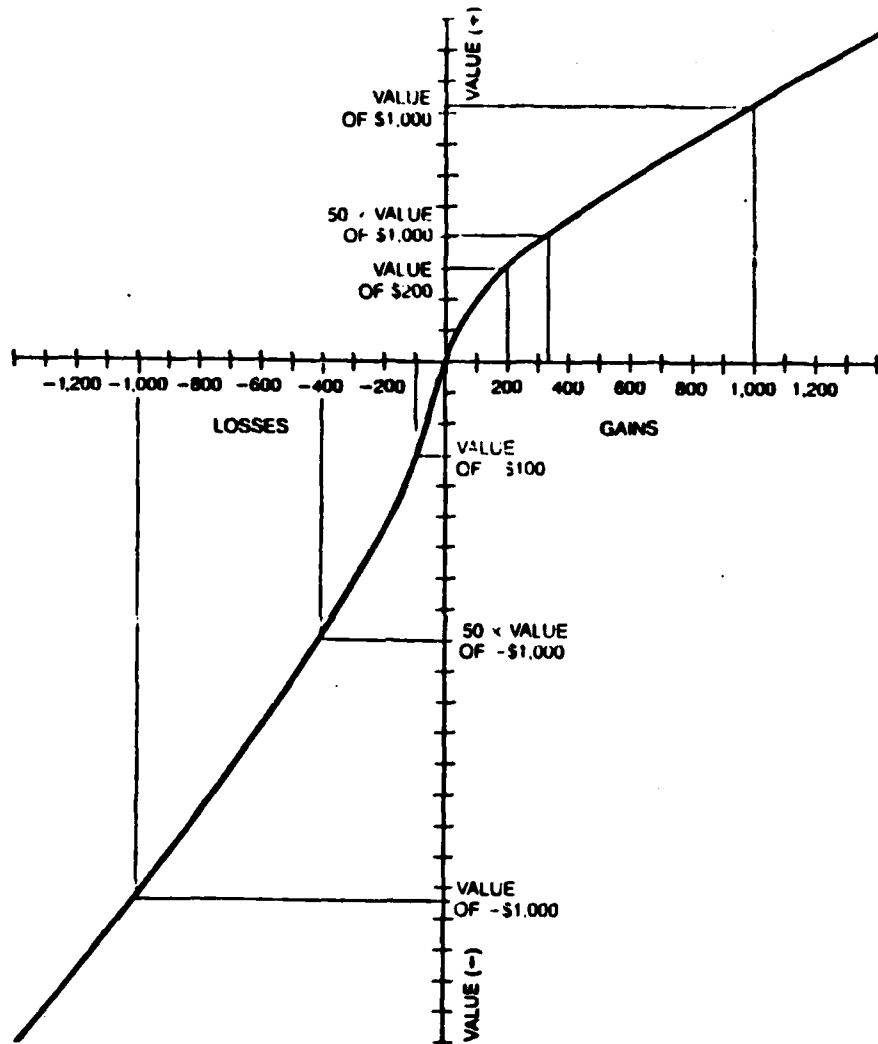


Figure 1

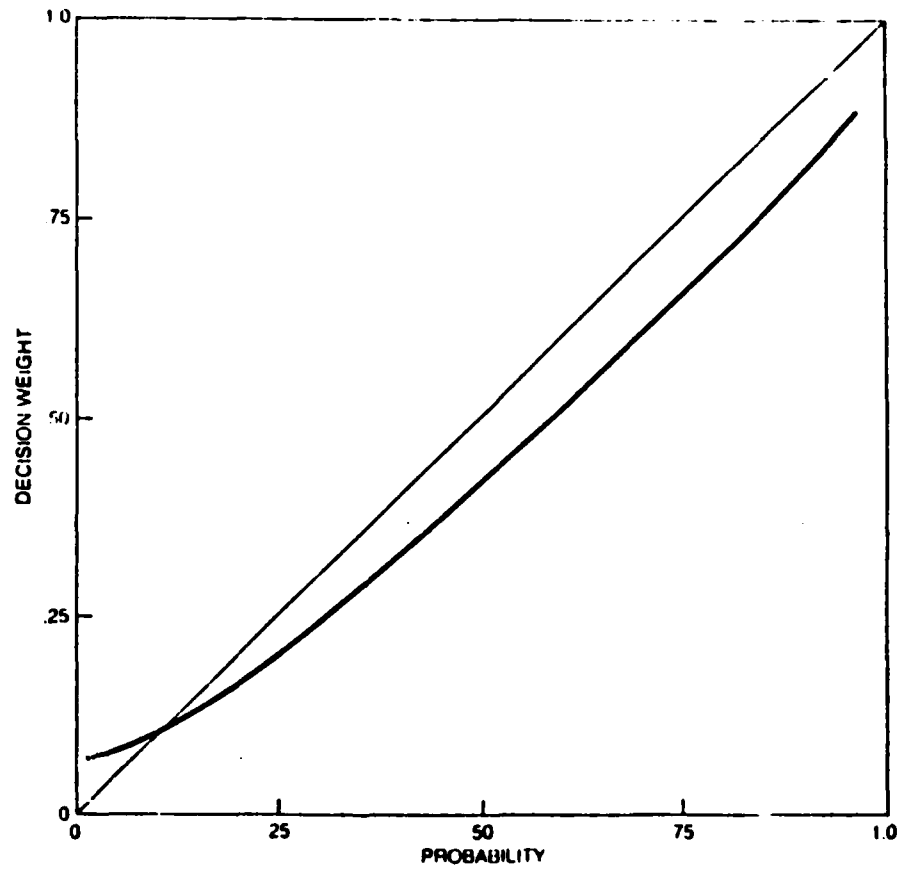
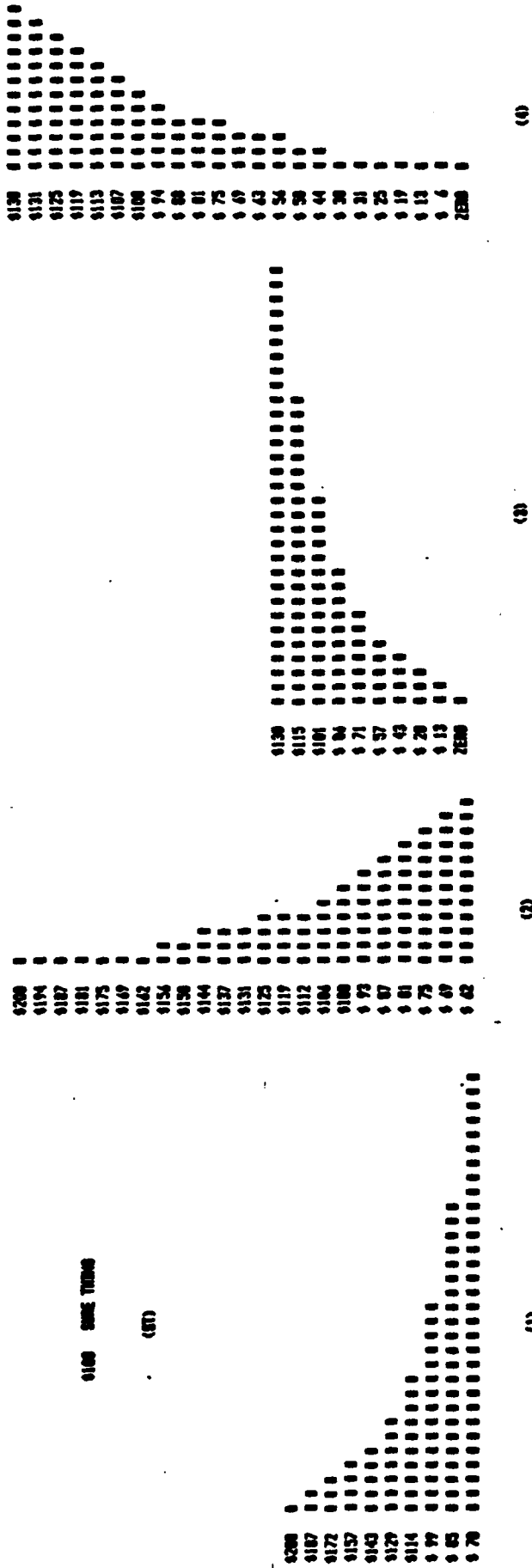


Figure 2



0100 SOME THING

(BT)

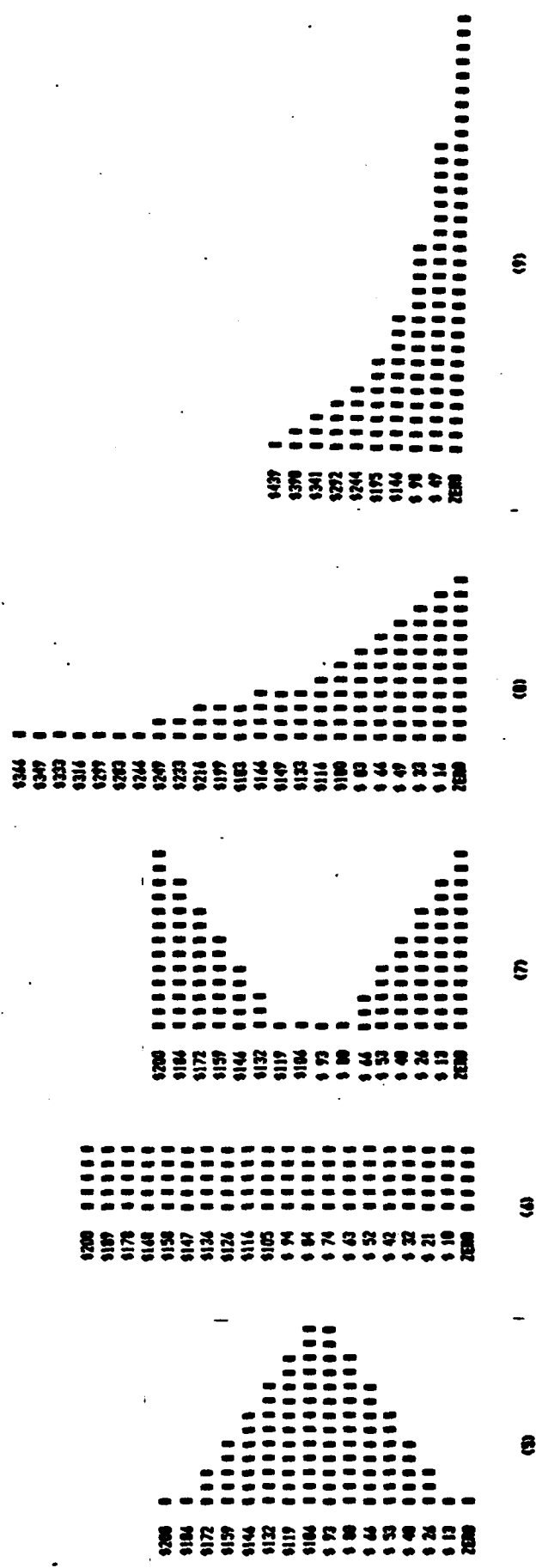


Figure 3

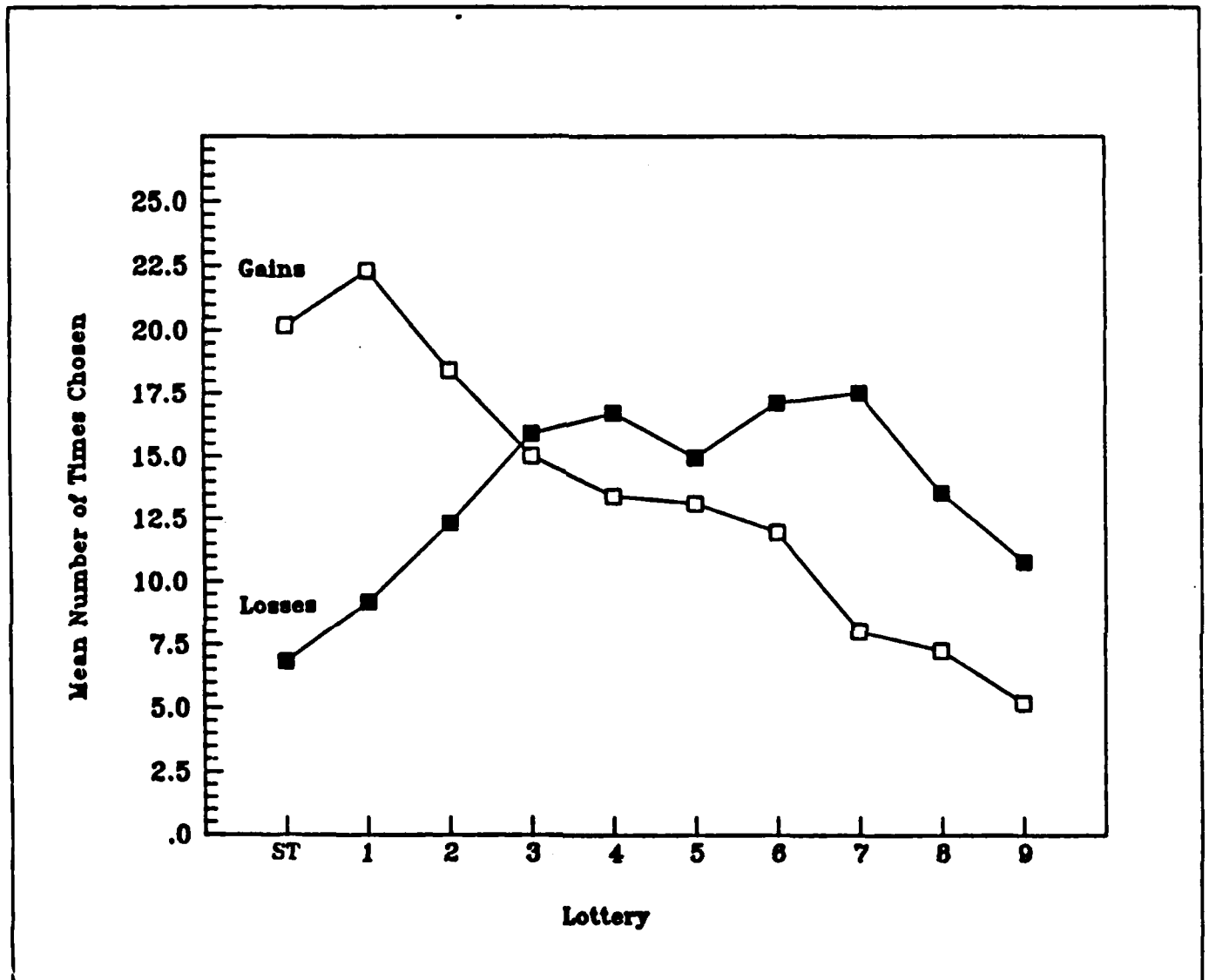


Figure 4

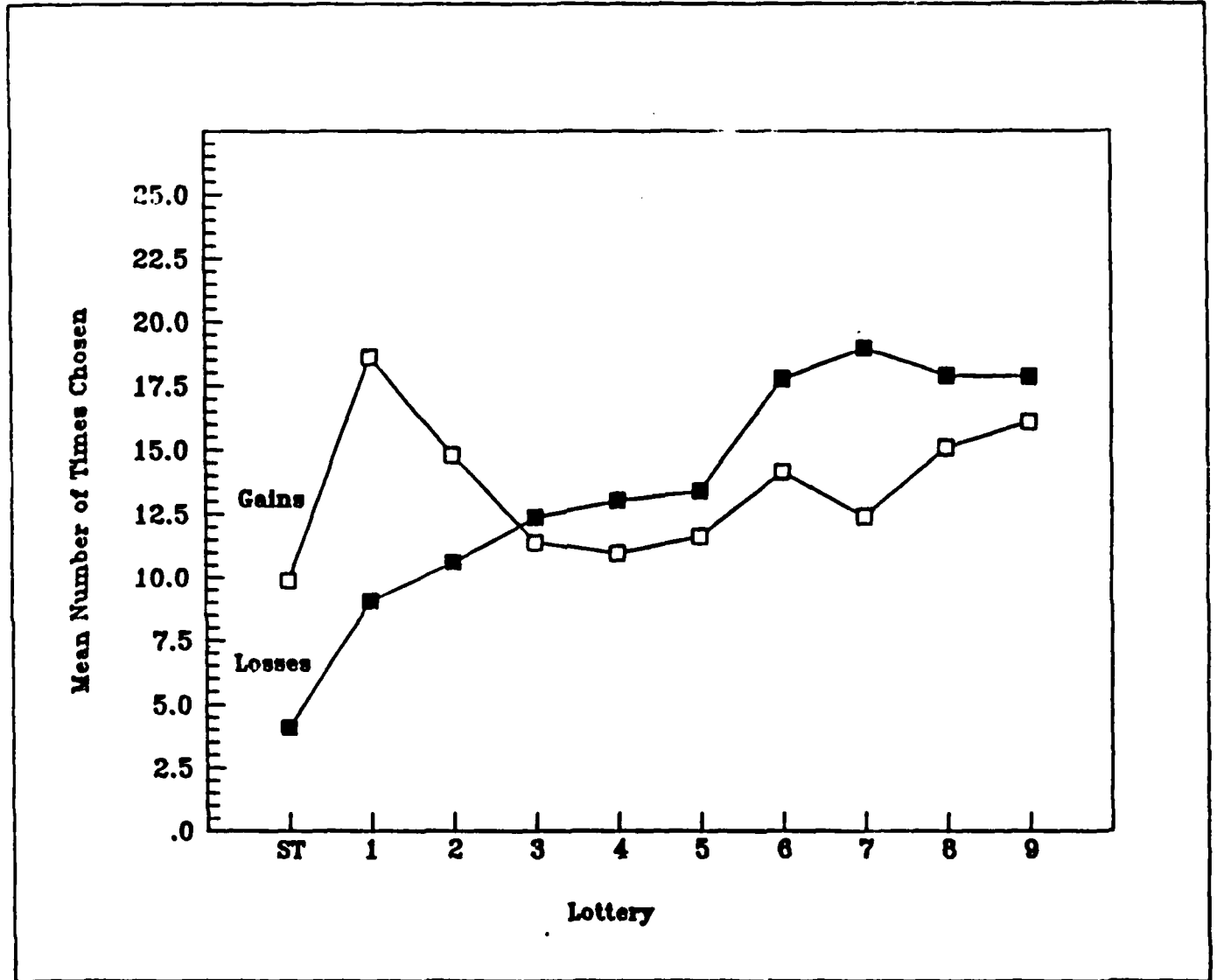


Figure 5

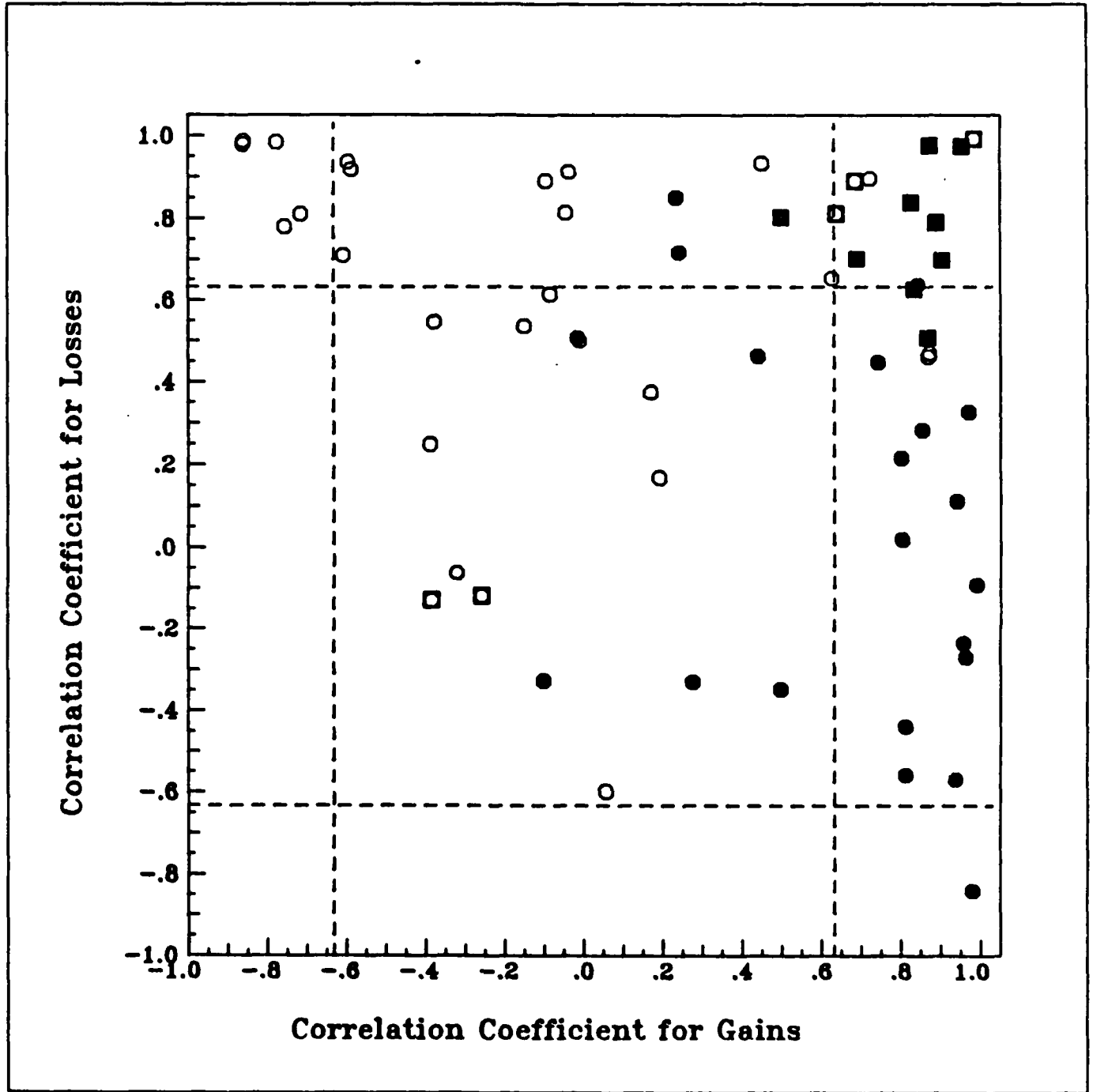


Figure 6

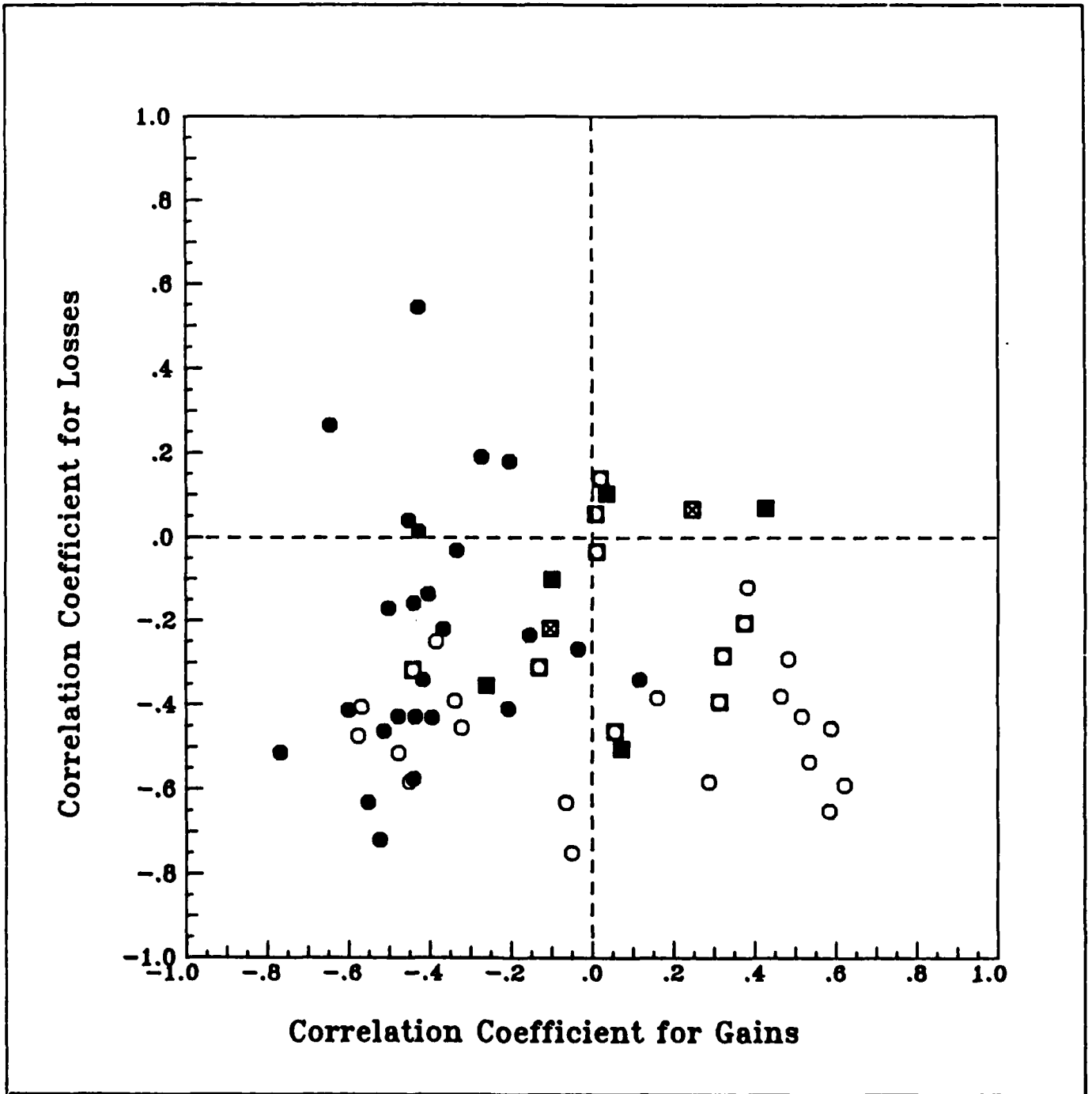


Figure 7

Table 1

Example Problems Used by Kahneman and Tversky (1979) to Demonstrate the Reflection Effect

Problem 3: Choose between

A: 4,000 with probability .80,	B: 3,000
0 with probability .20	
N = 95 (20%)	(80%)*

Problem 3': Choose between

A: -4,000 with probability .80,	B: -3,000
0 with probability .20	
N = 95 (92%)*	(8%)

Problem 7: Choose between

A: 6,000 with probability .45,	B: 3,000 with probability .90,
0 with probability .55	0 with probability .10
N = 66 (14%)	(86%)*

Problem 7': Choose between

A: -6,000 with probability .45,	B: -3,000 with probability .90,
0 with probability .55	0 with probability .10
N = 66 (92%)*	(8%)

Note. $p < .05$.

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