Loss Aversion in Decisions under Risk and the Value of a Symmetric Simplification of Prospect Theory

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Abstract

Three studies are presented that examine alternative interpretations of the loss aversion assertion (Kahneman and Tversky (1979)). The first two studies reject a "strong" interpretation: In violations of this interpretation the choice rate of the risky option was higher given prospects with mixed payoffs (gain and losses) than given prospects with nonnegative payoffs. The third study rejects a "moderate" interpretation of loss aversion: It shows that the elimination of the loss aversion assumption from prospect theory increases the theory's predictive value. The results demonstrate the value of a simplified version of prospect theory that assumes a symmetric value function (with diminishing sensitivity relative to the reference point), a symmetric probability weighting function (that implies a certainty/possibility effect) and a stochastic response rule.

Keywords: Stochastic models, Cumulative prospect theory, Predictive value.

JEL Classification: C91, D01.

1. INTRODUCTION

The loss aversion assertion, one of the assumptions that underlie prospect theory (Kahneman and Tversky (1979)), implies that losses loom larger than gains. That is, the absolute subjective value of a specific loss is larger than the absolute subjective value of an equivalent gain. This assertion was shown to provide an elegant explanation to a wide set of important behavioral phenomena. Famous examples are the endowment effect (Kahneman, Knetsch and Thaler (1990)), the status quo bias (Samuelson and Zeckhauser (1988)), and the equity premium puzzle (Benartzi and Thaler (1995)). The significance of loss aversion is highlighted in Camerer’s (2000) review of the practical implications of prospect theory: seven of the 10 examples are direct derivations of the loss aversion hypothesis.

However, direct empirical evidence for loss aversion is surprisingly hard to find. In order to clarify the unique status of the loss aversion assertion it is constructive to return to Kahneman and Tversky’s (1979) classical paper. Prospect theory is designed to capture three (main) behavioral assertions: The certainty/possibility effect (overweighting of low probability outcomes), diminishing sensitivity (risk aversion in the gain domain and risk seeking in the loss domain), and loss aversion. The first two assertions are described before the presentation of the theory, and are motivated with simple experiments. Moreover, it is shown that these assumptions are necessary to capture robust deviations from the common implementations of expected utility theory (that assumes risk aversion, see e.g., Pratt (1964)). The third assertion, loss aversion, is added during presentation of the theory, and is not supported by experimental data. Kahneman and Tversky note that “…most people find symmetrical bets of the form (x, .50; -x, .50) distinctly unattractive” (Kahneman and Tversky (1979), p. 279), but none of their experimental problems include bets that involve both gains and losses (hereafter, referred to as “mixed gambles”).

In order to evaluate more recent examinations of loss aversion it is constructive to distinguish between three interpretations of this assertion. The strongest interpretation asserts that “an individual with the preferences described by cumulative prospect theory is only mildly risk averse for gambles involving only gains, but strongly risk averse for gambles that entail potential losses.” (Thaler, Tversky, Kahneman, and Schwartz (1997), p. 651). This interpretation implies that the implications of loss aversion are stronger than the implications of diminishing sensitivity (that imply risk aversion in the gain domain).

A second interpretation, referred to as the "moderate interpretation," implies that the loss aversion assertion improves (on average) the predictive power of prospect theory. This interpretation is weaker than the previous one as it allows for the possibility that loss aversion can be less influential, at least in some settings, than diminishing sensitivity.

The weakest interpretation implies that there are settings in which observed behavior cannot be captured with prospect theory without the loss aversion assertion. For example, it has been noted that when individuals have to choose once between pairs of mixed gambles with the same expected value and relatively large stakes they tend to prefer the safer ones (e.g., Brooks and Zank (2005)). This trend cannot be captured by prospect theory without the requirement of asymmetry around the reference point.

Most recent studies of loss aversion have focused on the weak interpretation. Theoretical analyses of this issue highlight elegant methods that can be used to separate the loss aversion parameter from other parameters in the prospect theory model (e.g., Kobberling and Wakker (2005), Schmidt and Zank (2005)). Empirical studies that use these methods show clear evidence for loss aversion (Bleichrodt, Pinto, and Wakker (2001), Abdellaoui, Bleichrodt, and Paraschiv (in press)). Whereas these studies are elegant and important, their implications are limited to this “weak” interpretation. Specifically, they do not imply that the loss aversion assertion improves (on average) the predictive power of prospect theory.

Rather, they imply that under certain conditions and assumptions the loss aversion assertion cannot be rejected.[1]

The strong and moderate interpretations of loss aversion have been rarely addressed with direct empirical research. We know of only two experimental studies that have tried to evaluate the "strong" interpretation of the loss aversion assertion. The first one is described in Tversky and Kahneman (1992). In order to evaluate loss aversion, Tversky and Kahneman tried to extract the premium that people ask for playing the riskier gamble in two problems that included pairs of mixed gambles.[2] They then compared the risk premium of the two mixed gambles with the premium that participants asked for a linear positive translation of these gambles to strictly positive ones. The risk premium for mixed gambles was about two times larger than the risk premium for gambles with non-negative outcomes.

The second examination of strong loss aversion is described in Thaler et al. (1997). In this study, two conditions were compared: the basic condition, referred to here as “Mixed”, included 200 independent trials. In each trial, the participants were asked to allocate 100 tokens between two “assets”: A safe bond and a risky stock. Investment in the bond always resulted in a non-negative outcome. Investment in the stock increased the expected return by a factor of four, but was associated with high variability and frequent losses. The participants did not receive a description of the relevant payoff distributions, and had to rely on their feedback that was presented after each trial. The results reveal that the (high expected value) stock attracted only 40% of the investments. To confirm that the unattractiveness of the stock reflected loss aversion (rather than risk aversion), Thaler et al. added the “Gain” condition.

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[1] Notice that the significance of the distinction between the moderate and weaker interpretations depends on the assumptions made about the “accuracy” of the model. Under the assumption that the model is accurate, support for the weak interpretation (the observation that the loss aversion is necessary to capture behavior in one setting), implies that the moderate interpretation is supported too. However, if the model is only a “potentially useful approximation” then support for the weak interpretation does not imply support for the moderate interpretation. It is possible that a certain assumption is necessary to capture behavior in one case, but it impairs predictive value in a wider set of situations. We return to this issue in the discussion.

[2] The risk premium was evaluated by estimating the value of x that makes the prospect ($a, 0.5; $b, 0.5) as attractive as ($c, 0.5; $x, 0.5) where $c < a < b$, see Tversky and Kahneman (1992) p. 312.

This condition was identical to the mixed condition, except that a constant was added to all payoffs to eliminate the possibility of losses. In support of the loss aversion hypothesis, this addition increased the attractiveness of the stock.

Thaler et al.'s study has many attractive features. The results are surprising, replicable (see replication in Barron and Erev (2003); and related findings in Gneezy and Potters (1997)), and closely related to an extremely important empirical phenomenon. However, two features of that study question the implication of the results to the strong loss aversion assertion. The first feature involves the distinction between decisions under risk (the focus of prospect theory), and decisions from experience. Thaler et al. studied decisions from experience; the participants in their study did not receive a description of the payoff distribution. Rather, the experiment lasted 200 trials, and the decision makers received feedback after each trial.

A second relevant feature involves the payoff distributions. As noted in Erev, Ert and Yechiam (2007) the loss aversion hypothesis is only one of two properties of prospect theory that can be used to capture the experimental results with such payoffs. The second property is the diminishing sensitivity hypothesis. Thus, the observed results of Thaler et al. can be captured with prospect theory without assuming loss aversion. Moreover, the experiment conducted by Erev et al. favors the diminishing sensitivity hypothesis over the loss aversion hypothesis in decisions from experience.

The main goal of the current research is to extend the search for the correct interpretation of the loss aversion assertion. We start with two studies that examine the strong interpretation of loss aversion in decisions under risk. These studies show clear violations of this interpretation. When the payoffs are relatively low, the typical decision maker exhibits risk neutrality in choice among mixed gambles. This pattern is observed in decisions with hypothetical payoffs (Study 1) and in decisions with real payoffs (Study 2). Moreover, the addition of a constant to all payoffs that transforms the problems to the gain domain increases risk aversion in contrast to the strong loss aversion interpretation.

Study 3 explores wider data sets in order to evaluate the moderate interpretation of loss aversion. Recall that under this interpretation the loss aversion assumption increases the predictive power of prospect theory. Estimation of the prospect theory model rejects this hypothesis: The analysis demonstrates that a simplified 3-parameter version of prospect theory that assumes symmetry between gain and losses is a better predictor of the experimental data than the full model that includes the loss aversion parameters.

2. EVALUATION OF THE STRONG INTERPRETATION OF LOSS AVERSION

We start our analysis with an evaluation of the strong interpretation of loss aversion assertion. The evaluation is based on two studies that compare behavior in problems that involve mixed gambles and in positive linear transformations of these problems (created by an addition of a constant to all payoffs) that involve no losses. Study 1 is focused on hypothetical gambles and Study 2 studies the robustness of the results to real (low stakes) payoffs.

2.1 Study 1 – Hypothetical Choice between Simple Prospects

Study 1 is focused on the following four problems: (The outcomes represent payoffs in Sheqels ($1= 4.2 Sheqel). The P(R) values presented on the right summarize the main results and will be discussed below)

Problem Mixed 1	S	0 with certainty	
	R	+1000 with probability 0.5 -1000 otherwise	P(R)= 0.50
Problem Gain 1	S	1000 with certainty	
	R	2000 with probability 0.5 0 otherwise	P(R)= 0.24
Problem Mixed 2	S	1000 with probability 0.5 -1000 otherwise	
	R	4000 with probability 0.5 -4000 otherwise	P(R) = 0.37
Problem Gain 2	S	5000 with probability 0.5 3000 otherwise	
	R	8000 with probability 0.5 0 otherwise	P(R) = 0.13

Note that Problem Gain 1 was created by adding 1000 to all the payoffs in Problem Mixed 1 and Gain 2 was created by adding 4000 to all the payoffs in Problem Mixed 2.

Experimental Design

The four problems were presented to the participants in a short one-page questionnaire. They were simply asked to circle the prospect they prefer in each of the problems. The order of the four problems was balanced over participants.

Seventy Technion students served as participants in the current study. Thirty-four of them were asked to fill in the experimental questionnaire during the first class of the course "Decision Making." The remaining participants were asked to fill in the experimental questionnaire after they completed an experiment on social choice (a replication of Chareness and Grosskopf (2001)). There was no significant difference between these two groups' responses.

Results

The choice rates of the risky options are presented to the right of the four problems. The first pair of problems reveals higher proportion of risk taking (50%) in Problem Mixed 1 than in Problem Gain 1 (24%). A similar pattern was observed in the second pair. The proportions of risky choices were 37% in Problem Mixed 2, and only 13% in Problem Gain 2. These differences are significant ($t(69) = 3.09$, $p < .003$; $t(69) = 3.89$, $p < .0003$; for the differences in first and second pair respectively).

Over the two pairs, the proportion of choices in the riskier option increased from 18% on average to 44% ($t(69) = 4.49$, $p < .0001$) when the riskier option was associated with losses, in sharp contrast to the strong loss aversion interpretation. The participants behaved as if the risky option was more attractive when it was associated with possible losses.

2.2 Study 2 – Choosing between simple prospects for real money

The second study is designed to evaluate the robustness of the results of Study 1 to the experimental paradigm. Specifically, it focuses on decisions for real money by using a variant of Problems Mixed 2 and Gain 2 as follows (the outcomes represent payoffs in Sheqels):

Problem	S	10 with probability 0.5	
Mixed 3		-10 otherwise	
	R	20 with probability 0.5	P(R) = 0.58
		-20 otherwise	
Problem	S	30 with probability 0.5	
Gain 3		10 otherwise	
	R	40 with probability 0.5	P(R) = 0.31
		0 otherwise	

Experimental Design

Seventy two Technion students served as paid participants in the current study. The experiment used a within-participant design. Each participant was seated in front of a computer screen and was then presented with each of the two problems shown above. In each problem, participants were asked to mark the prospect they prefer to play. The order of the problems was balanced over participants. At the end of the experiment one problem was randomly selected and played. The participants' payoff was determined according to their choice in the selected problem.

In order to facilitate the generation of real losses, participants were recruited for two experiments: the one that is reported here, and another one that involves repeated choice in four simplified partially observable Markov decision problems. We refer to the current experiment as the "target" experiment and the other one as "filler." The earning from the filler experiment was at least 20 Sheqels, but no more than 32 Sheqels. The order of the experiments was counterbalanced: 36 participants were presented with the target experiment before the filler; the other 36 were presented with the target experiment after the filler. Participants were told that in a case they lose in the target experiment, their loss would be subtracted from their earnings in the filler experiment. We believe that this method of studying real losses is more natural than paying participants a fixed amount from which they can win or lose.[3] That is, when participant actually "work" for their money there is a higher possibility that they integrate the stakes more quickly to their current wealth (see also Holt and Laury (2002) for a similar argument) thereby decreasing the possibility of a "house money" effect (Thaler and Johnson (1990)). Final Payoffs of the target experiment ranged between a loss of 20 Sheqels and a win of 40 Sheqels (-$4.8 and +$9.5).

Results

The choice rates of the risky options are presented to the right of the two problems. The results replicate the pattern observed in Experiment 1. Again, the proportions of risky choices were much higher in the mixed problem (0.58) than in the gain domain (0.31).[4] This

[3] The fixed amount approach is, nevertheless, a common method in studies that involve losses (e.g., Battalio, Kagel, and Jiranyakul (1990), Brooks and Zank (2005), Harless (1992)).

[4] We also checked for possible order effects: neither the ordering of the two problems, nor the ordering of the two experiments had an effect on the current results. In all four orders the proportion of risky choice in Problem Mixed 3 was extensively higher than in Problem Gain 3. It is also worth noticing that the proportion of risk taking in Condition Mixed 3 is not significantly different than 50% ($t(71) = 1.42$, NS).

reversal of the prediction of the strong loss aversion interpretation is significant ($t(71) = 3.6$, $p < .001$). The similarity of the current results to these observed in Study 1 suggests that the reversal of the strong loss aversion hypothesis is robust to decisions with real (small stakes) incentives.

3. THE PREDICTIVE VALUE OF A SYMMETRIC SIMPLIFICATION OF PROSPECT THEORY

The results presented above reject the strong interpretation of the loss aversion assertion; they highlight a clear reversal of the predictions of this interpretation. The implications of Study 1 and 2 to the weaker interpretations of the loss aversion hypothesis are less obvious. For example, under a stochastic variant of prospect theory, strong diminishing sensitivity can mask the effect of loss aversion in some cases. The objective of the current study is to examine the moderate interpretation of loss aversion: it evaluates the usefulness of the loss aversion assumption to the prediction of behavioral data by using three different datasets that summarize choice behavior between risky prospects. For this purpose, the current examination compares different variants of prospect theory using Busemeyer and Wang (2000) generalization criteria. Two of the datasets were collected in the studies described below. The third dataset was collected by Wu and Markle (2005).

3.1 Study 3a: 39 interesting problems

In order to clarify the relationship of the current analysis to the analysis performed by Kahneman and Tversky (1979), we chose to collect data on problems that are similar to the problems they analyzed. Specifically we focused on 13 (of the 18) problems studied in the

1979 paper,[5] and on two variants of each of these problems. Table 1 presents the 39 problems. Problems 1-13 are replications of the problems used by Kahneman and Tversky (1979). Each of these problems includes a hypothetical choice between a safe and a risky prospect with one non-zero outcome. Problems 14-26 were created by subtracting the value of the safer payoff from both prospects in Problems 1-13 respectively. For example, Problem 1 focuses on choices between S (2,400, .34; 0) and R (2500, .33; 0).[6] Subtracting the safer payoff of 2400 from both prospects creates a new decision problem (Problem 14) with mixed gambles S (0, .34; -2400) and R (100, .33; -2400). Problems 27-39 were created by another subtraction of the safer payoff from the original problems (1-13). In the current example, Problem 27 involves a choice between S (-2400, .34; -4800) and R (-2300, .33; -4800).

< Insert Table 1>

Experimental Design

Thirty Technion students participated in the current study and were paid 20 Sheqels ($4.8) for showing up. The experiment used a within-participant design. Each participant was seated in front of a computer screen and was then presented with each of the 39 problems presented in Table 1. The problems were presented in random order.

Results

The right most column of Table 1 presents the proportion of R choices that were observed in Kahneman and Tversky (1979). The second right most column presents the proportions of R choices in the current study. A comparison of these two columns reveals

[5] The problems that were studied in Kahneman and Tversky (1979) and were excluded from the current analysis are Problems 1, 13, and 13' which include more than two possible outcomes in one of the gambles, and Problems 5 and 6 that referred to choice between hypothetical tours.

[6] The notation (x, p; y) refers to a prospect that yields outcome x with probability of p, and y otherwise. The outcomes refer to Israeli currency as in Kahneman and Tversky (1979).

that all the trends, observed in the 13 problems of the Kahneman and Tversky's (1979) study, were replicated. The correlation between the two studies is $r = 0.84$ ($p < .0001$).

3.2 Study 3b: 200 mostly randomly selected Problems

The second dataset considered here was composed of two parts. The first, "basic", part includes Problem Mixed 1 and Gain 1,[7] and 98 randomly selected problems. The random problems were of the form: (S with certainty) or (R_1 with probability of p, and R_2 otherwise). The four parameters were selected using the following algorithm:

The values of R_1 and R_2 were determined by draws from the uniform set [-10000, 10000] and rounding to the nearest integer divisible by 100. The value of p was randomly selected from the set {.001, .01, .1, .2, .3, .4, .5, .6, .7, .8, .9, .99, .999}. The value of S was determined by a draw from [EV_R-1000, EV_R+1000] where $EV_R = pR_1 + (1-p)R_2$ and rounding to the nearest integer divisible by 5.[8]

This selection method resulted with 28 problems in the gain domain, 17 problems in the loss domain, and 55 problems with mixed gambles. The second part, referred to as the "reflected part," was created by multiplying each of the payoffs of the first 100 problems by -1. For example, the "reflected" version of Problem 1 (presented in Table 2) included a choice between a sure outcome of 5580, and a risky prospect that promised 4900 with probability of 0.60, and 9100 otherwise. Together, the two parts ensure that the full dataset is balanced with regard to the expected value associated with options S and R. The full dataset is presented in Table 2.

[7] Problem Mixed 1 and Gain 1 were added to the dataset as control problems in order to assess the robustness of the behavioral trends to the size of the dataset of problems. The similarity between the results in these problems and the results of studies 1 and 2 suggests that the effect of the size of the dataset is not large.

[8] We chose to focus on randomly selected problems in order to decrease the risk of a selection bias (i.e., producing models that capture interesting problems as in Kahneman and Tversky (1979) but fail to capture problems that are less interesting but might be more common).

Experimental Design

Forty Technion students participated in the current study and were paid 20 Sheqels ($4.8) for showing up. Each participant was seated in front of a personal computer and was then presented with 100 problems. Twenty participants were assigned to the "100-basic" problems presented in Table 2. The other 20 participants were assigned to the "100-reflected" problems. Participants in each condition were asked to choose once between S and R in each of the 100 problems that were randomly ordered.

< Insert Table 2 >

Results

The proportions of risky choices in the "100-basic" problems are presented in Column "Prisk basic" in Table 2. The proportions of risky choices in the "100-relected" problems are presented in Column "Prisk reflect" in this table. As one might expect, the proportions of R choice in the 100 basic problems are negatively correlated (r = -.82) with the proportions of R choice in the "reflected" problems.

3.3 The Predictive value of Cumulative Prospect Theory

The current analysis focuses on two variants of cumulative prospect theory (Tversky and Kahneman (1992), Tversky and Wakker (1995), Wakker and Tversky (1993)): The original 5-parameter abstraction, and a stochastic generalization of this abstraction.

Cumulative prospect theory

According to cumulative prospect theory, decision-makers are assumed to select the prospect with the highest weighted value. The weighted value of Prospect X that pays x_1 with probability p_1 and x_2 otherwise is:

$$\text{WV(X)} = V(x_1)\pi(p_1) + V(x_2)\pi(p_2) \tag{1}$$

where $V(x_i)$ is the subjective value of outcome x_i, and $\pi(p_i)$ is the subjective weight of outcome x_i.

The subjective values are given by a value function that can be described as follows:

$$V(x_i) = \begin{cases} x_i^{\alpha} & if \quad x_i \geq 0 \\ -\lambda_0 |x_i|^{\beta} & if \quad x_i < 0 \end{cases} \tag{2}$$

The parameters $0 < \alpha < 1$ and $0 < \beta < 1$ capture the assumption of diminishing sensitivity in the gain and the loss domain respectively. The parameter λ_0 (λ in the original notations) captures the basic idea of the loss aversion assertion; when $\lambda_0 > 1$ losses loom larger than gains (as explained below, two additional features of the model affect the abstraction of loss aversion).

The subjective weights are assumed to depend on the outcomes' rank, sign, and on a cumulative weighting function. When the two outcomes are of different sign, the weight of outcome *i* is:

$$\pi(p_i) = \begin{cases} \dfrac{p_i^{\gamma}}{(p_i^{\gamma} + (1-p_i)^{\gamma})^{1/\gamma}} & if \quad x_i \geq 0 \\ \dfrac{p_i^{\delta}}{(p_i^{\delta} + (1-p_i)^{\delta})^{1/\delta}} & if \quad x_i < 0 \end{cases} \tag{3}$$

The parameters $0 < \gamma < 1$ and $0 < \delta < 1$ capture the tendency to overweight low-probability outcomes.

When the outcomes are of the same sign, the weight of the most extreme outcome (largest absolute value) is computed with equation (3) (as if it is the sole outcome of that sign), and the weight of the less extreme outcome is the difference between that value and 1.

In order to clarify the abstraction of loss aversion under cumulative prospect theory it is convenient to set $\beta = \alpha(\lambda_1)$, and $\delta = \gamma(\lambda_2)$. Under this abstraction, cumulative prospect theory has three free parameters that abstract loss aversion λ_0, λ_1, and λ_2, and one free parameter for each of the other main psychological assumptions: Diminishing sensitivity is captured by α, and overweighting of rare outcomes is captured by γ.[9]

Cumulative prospect theory with a stochastic response rule.

The second model considered here is a generalization of cumulative prospect theory that assumes a stochastic response rule. The motivation to consider this generalization comes from experimental studies that examine situations in which people were faced with the same problem more than once. These studies show a large variation between repeated choices that cannot be explained with the assertion of a change in the decision maker state and/or information. For example, Wakker, Erev and Weber (1994) found that when the gambles are of similar expected value, the average decision maker changes her preference in 34% of the cases.

We use the response rule proposed by Erev, Roth, Slonim and Barron ((2005) and see a similar idea in Busemeyer (1985)). When the decision maker is asked to select between Prospect R (r1 with probability p(r); r2 otherwise) and Prospect S (s1 with probability p(s); s2 otherwise), this rule implies that the probability that R will be selected is

[9] Overweighting of rare outcomes can be also explained by diminishing sensitivity under the assumption that the two end points of the probability function (0 and 1) serve as reference points (e.g., Gonzalez and Wu (1999)).

$$\Pr(R) = \frac{e^{WV(R)(\mu/D)}}{e^{WV(R)(\mu/D)} + e^{WV(S)(\mu/D)}} \quad (4)$$

The parameter μ captures payoff sensitivity, and D is the absolute distance between the cumulative functions implied by the two prospects. The computation of D requires a normalization of the weights of the different outcomes. The normalized weight of outcome x_1 is

$$\pi_n(x_1) = \frac{\pi(x_1)}{\pi(x_1) + \pi(x_2)} \quad (5)$$

Assuming $x_1 > x_2$, the cumulative normal value of gamble X at point z ($0 \le z \le 1$) is

$$CNP(X,z) = \begin{cases} V(x_1) & if \quad z \le \pi_n(x_1) \\ V(x_2) & if \quad z > \pi_n(x_1) \end{cases} \quad (6)$$

D is the absolute distance between the cumulative normal payoffs of the two prospects. A representation of this value computation is presented in Figure 1.

< Insert Figure 1 >

3.3.1 Estimation and equivalent number of observations

In the first stage of the current analysis we estimated the parameters of the two models for the data sets described above. The estimation was based on a simplex optimization method (Nedler and Mead (1965)) using a means squared error criteria.[10] That is, we searched for the parameters that minimize the squared distance between the observed results

[10] To reduce the risk of programming errors the analysis was conducted independently with two programs. One in SAS (version 9.1) and the other in MATLAB (version 7.1).

(1 if the participant selected the risky prospect, 0 otherwise) and the prediction of the model of the probability that the risky gamble will be selected (1 or 0 in the case of the original model, and a number between 0 and 1 in the case of the stochastic model). The estimation was obtained under the constraint of a single set of parameters for all the participants, and all the problems in the relevant dataset.

At the second stage of the analysis we estimated simplified versions of the two models that include constraints on the value of the loss aversion related parameters (λ_0, λ_1, and λ_2). The third stage of the analysis focused on two generalization tasks. We used the estimated models to predict behavior in two different datasets that were not used during the estimation. One of the two generalization datasets was collected and analyzed by Wu and Markle (2005; see Table 1, p. 8). The second generalization dataset was one of the two presented in Study 3; the one that was not used during the relevant estimation.

As in the estimation stage, the generalization analysis focused on MSE scores. To clarify the interpretation of these scores they were also converted to the model's Equivalent Number of Observation (ENO, see Erev, Roth, Slonim and Barron (in press)). The ENO of a model is an estimation of the size of the experiment that has to be run to obtain predictions that are more accurate than the model's prediction. For example, if a model has an ENO of 10, its prediction of the probability of R choice in a particular problem, is expected to be as accurate as the prediction that is based on the observed proportion of R choices in an experimental study of that problem with 10 participants. This score is computed as ENO = $S^2/(MSE-S^2)$ where S^2 is the pooled variance over problems. That is, S^2 is the estimate of the MSE score of an accurate model, and ENO increases when the MSE decreases toward its minimal value.

Table 3 presents the main results. It shows that the constraints (setting λ_0, λ_1, and/or λ_2 to equal 1) increase the MSE of the model in the fitted data. This increase is not large and not surprising (the addition of free parameter can only improve the fit). More interesting is the observation that the constraints improve the models' predictive power. Indeed, the elimination of the loss aversion assertion (setting $\lambda_0 = 1$, $\lambda_1 = 1$, and $\lambda_2 = 1$) maximizes the models' ENO in all the comparisons!

< Insert Table 3 >

Under one explanation of the negative effect of the loss aversion parameter, it reflects data over-fitting. Whereas we cannot rule out this possibility, we took few steps to reduce this risk. The most important step involves the comparison of the 4-parameter and the 3-parameter models. When a 4-parameter model is estimated based on 200 randomly selected problems (and 20 decision-makers per problem), the risk of over-fitting should not be large (unless the contribution of the relevant factor is small).

The results also highlight the value of the stochastic generalization of cumulative prospect theory. This 1-parameter addition increases the ENO from less than 2, to more than 10 in most comparisons.

We believe that the current results question the value of the moderate interpretation of the loss aversion assertion. The addition of loss aversion impaired the predictive value (the ENO) of the variants of cumulative prospect theory we examined. It seems that a simplified symmetric variant of the model, that avoids the loss aversion assertion, maximizes the model's predictive value.

4. DISCUSSION

The loss aversion assertion is one of the best-known implications of behavioral decision research. Many studies demonstrate that this assertion can be used to explain important economic phenomena (e.g., Benartzi and Thaler (1995), Camerer (2000), Rabin

(1998)). Yet, direct tests of this assertion are surprisingly scarce. The current research tries to address this gap. The first two studies test a strong interpretation of loss aversion. This interpretation, assumed in many of the applications of the loss aversion assertion, implies lower risk taking in problems that involve only gains than in problems that involve possible losses (e.g., Thaler et al. (1997)). The results reject this prediction. In fact, the opposite pattern was observed. The participants exhibit stronger risk aversion tendency while choosing between nonnegative prospects than while choosing between mixed prospects.

The third study evaluates a weaker interpretation of the loss aversion assertion. Under this interpretation, referred to as the moderate interpretation, the quantification of loss aversion in prospect theory improves the theory's predictive value. The results reject this hypothesis too; analysis of three wide data sets demonstrates that the abstraction of the loss aversion hypothesis impairs the predictive value of prospect theory.

At first glace, the current results appear to question the value of behavioral decision research. That is, they suggest that the reliance on "descriptive" models creates an illusion of "descriptive" conclusions. However, we believe that a more careful evaluation of the current results supports the opposite conclusion; it highlights the potential of behavioral decision research. Our optimistic conclusion is based on the observation that the data do not imply that the behavioral models we considered (variants of cumulative prospect theory) fail. On the contrary, they suggest that cumulative prospect theory can be more elegant than we originally thought. A simplified 3-parameter variant of this model that assumes symmetry between gain and losses provides surprisingly good predictions of choice behavior.

The variant of cumulative prospect theory, supported here, captures three behavioral regularities. The first two regularities are the ones that have motivated the original version of prospect theory: Diminishing sensitivity, and overweighting of low probability events. The third regularity, stochastic choice, appears less interesting, but it is not less important. The abstraction of this regularity increases the ENO of the model from less than 2 to more than 10 in most of the comparisons we analyzed.

Weaker interpretations of the loss aversion assertion

It is important to emphasize that the current results do not reject the weak interpretation of the loss aversion assertion. Specifically, we do not question the robustness of the observation that in certain settings choice behavior cannot be captured with prospect theory without the abstraction of loss aversion (e.g., Abdellaoui et al. (in press)). In addition, we do not question the possibility that certain individuals behave as if they are loss averse (Schmidt and Traub (2002), Brooks and Zank (2005)). The current analysis only suggests that these "loss aversion inducing situations" and "loss averse individuals" may not be very common (in the space of situations we considered).[11] This suggestion is supported by two observations. First, it is easy to find situations in which people exhibit the reversal of the strong loss aversion assertion. Second, the addition of the loss aversion abstraction to cumulative prospect theory impairs the theory predictions of the aggregate behavior in a wide set of situations.

We believe that the main difference between the current research and previous studies of the loss aversion hypothesis involves the working assumption concerning the role of the relevant models. Most previous studies examined the loss aversion assertion under the working assumption that a particular theory is accurate. Under this working assumption, a single experimental result can be used to reject a particular model (like the simplified variant of cumulative prospect theory supported here). The current analysis, in contrast, treats descriptive models as potentially useful approximations that can be used to predict behavior

[11] In a recent experimental test of loss aversion, Schmidt and Traub (2002) arrived to a similar conclusion. When trying to classify individuals by their loss attitude, 33% of the participants were classified as “loss averse”, 24% as “loss seeking” and most participants (42%) exhibited “loss neutrality.” The authors concluded: “our results suggest that this conclusion (*i.e.*, *that loss aversion is a good description of decision behavior in general*) should be taken with some cautious” (Schmidt and Traub (2002), p. 246).

in a particular set of situations. Under this working assumption, a single observation has limited implication. The value of a model is captured by its predictive value (and can be quantified by its ENO).[12]

Summary

The current analysis leads to a set of negative and a set of positive conclusions. The negative conclusions are related to the loss aversion assertion. The results highlight clear reversals of the predictions of two interpretations of this assertion. In violation of the strong interpretation, risk aversion in choice among mixed prospects (that involve gains and losses) is weaker than in a choice among prospects with nonnegative payoffs. In addition, the abstraction of loss aversion impairs the predictive value of prospect theory. The positive conclusions are related to the value of the behavioral regularities that motivated the original presentation of prospect theory: diminishing sensitivity relative to the status quo, and overweighting of low probability outcomes. The results show that a simplified symmetric version of prospect theory that captures these regularities and assume stochastic choice has surprisingly high predictive value.

[12] The current approach does not imply that the violations of the model should be ignored. Rather it tries to avoid complex models that capture interesting violations but impair predictive value. In a follow-up research (Ert and Erev (2007)) we explore the conditions under which loss-aversion, and reversed loss-aversion, are likely to emerge. Our results suggest that the critical conditions involve contextual variables that are ignored by prospect theory. For example, many people reject the bet (-1000, .5; +1000) when they are asked to select between “Accept” or “Reject”, but prefer this bet over (0 with certainty). Similar contextual variables can account to the difference between the current results and Tversky and Kahneman’s (1992) evaluation of loss aversion.

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TABLE 1

THE 39 PROBLEMS THAT WERE EVALUATED IN STUDY 3a

	S1	P(s)	S2	R1	P(r)	R2	Prisk	Prisk (KT79)
1	2400	0.34	0	2500	0.33	0	0.72	0.83
2	3000	1	0	4000	0.8	0	0.28	0.20
3	3000	0.25	0	4000	0.2	0	0.76	0.65
4	3000	0.9	0	6000	0.45	0	0.38	0.14
5	3000	0.002	0	6000	0.001	0	0.69	0.73
6	500	1	0	1000	0.5	0	0.38	0.16
7	-3000	1	0	-4000	0.8	0	0.79	0.92
8	-3000	0.25	0	-4000	0.2	0	0.38	0.42
9	-3000	0.9	0	-6000	0.45	0	0.59	0.92
10	-3000	0.002	0	-6000	0.001	0	0.24	0.30
11	-500	1	0	-1000	0.5	0	0.72	0.69
12	5	1	0	5000	0.001	0	0.72	0.72
13	-5	1	0	-5000	0.001	0	0.48	0.17
14	0	0.34	-2400	100	0.33	-2400	0.9	.
15	0	1	0	1000	0.8	-3000	0.66	.
16	0	0.25	-3000	1000	0.2	-3000	0.9	.
17	0	0.9	-3000	3000	0.45	-3000	0.66	.
18	0	0.002	-3000	3000	0.001	-3000	0.76	.
19	0	1	0	500	0.5	-500	0.38	.
20	0	1	0	-1000	0.8	3000	0.41	.
21	0	0.25	3000	-1000	0.2	3000	0.21	.
22	0	0.9	3000	-3000	0.45	3000	0.48	.
23	0	0.002	3000	-3000	0.001	3000	0.14	.
24	0	1	0	-500	0.5	500	0.45	.
25	0	1	0	4995	0.001	-5	0.59	.
26	0	1	0	-4995	0.001	5	0.31	.
27	-2400	0.34	-4800	-2300	0.33	-4800	0.62	.
28	-3000	1	0	-2000	0.8	-6000	0.76	.
29	-3000	0.25	-6000	-2000	0.2	-6000	0.55	.
30	-3000	0.9	-6000	0	0.45	-6000	0.79	.
31	-3000	0.002	-6000	0	0.001	-6000	0.93	.
32	-500	1	0	0	0.5	-1000	0.76	.
33	3000	1	0	2000	0.8	6000	0.48	.
34	3000	0.25	6000	2000	0.2	6000	0.34	.
35	3000	0.9	6000	0	0.45	6000	0.21	.
36	3000	0.002	6000	0	0.001	6000	0.21	.
37	500	1	500	0	0.5	1000	0.41	.
38	-5	1	-5	4990	0.001	-10	0.69	.
39	5	1	5	-4990	0.001	10	0.31	.

Note: each raw represent a decision problem between prospect S (S1, P(s); S2) and prospect R (R1, P(r); R2). Column Prisk presents the proportion of R choices in each problem. Column Prisk (KT79) presents the proportion of risky choices observed in Kahneman and Tversky (1979).

TABLE 2

THE 200 PROBLEMS THAT WERE EVALUATED IN STUDY 3b

	1-50 "BASIC" PROBLEMS							51-100 "BASIC" PROBLEMS					
	S	R1	Pr	R2	Prisk basic	Prisk reflect		S	R1	Pr	R2	Prisk basic	Prisk reflect
1	-5580	-4900	0.6	-9100	**0.2**	**0.95**	51	8500	9300	0.3	7300	**0.3**	**0.9**
2	-9075	5000	0.001	-9100	**0.8**	**0.35**	52	3625	5000	0.01	3600	**0.8**	**0.5**
3	-2300	-2000	0.9	-6400	**0.3**	**0.75**	53	-2500	-2500	0.7	-2600	**0.15**	**0.75**
4	4560	4900	0.9	-8500	**0.15**	**0.95**	54	-4400	8200	0.2	-8800	**0.5**	**0.5**
5	2700	3200	0.9	-1600	**0.2**	**0.65**	55	5700	9900	0.6	-3100	**0.3**	**0.7**
6	2080	5200	0.1	1300	**0.4**	**0.85**	56	3495	3500	0.99	2800	**0.3**	**0.8**
7	900	900	0.7	500	**0.15**	**0.95**	57	-6255	-3900	0.01	-6300	**0.7**	**0.45**
8	8600	8700	0.999	-3100	**0.3**	**0.9**	58	2100	2100	0.6	1800	**0**	**0.95**
9	3300	3300	0.5	1800	**0.1**	**0.95**	59	7450	7500	0.999	-7400	**0.3**	**1**
10	8000	8000	0.6	6900	**0.2**	**0.9**	60	4100	8900	0.5	-2700	**0.35**	**0.75**
11	2280	5000	0.1	1600	**0.55**	**0.75**	61	-1840	3700	0.4	-7200	**0.5**	**0.5**
12	2450	2500	0.99	-3600	**0.15**	**0.95**	62	-5800	-5600	0.9	-8400	**0.35**	**0.9**
13	3700	6300	0.6	-2700	**0.3**	**0.75**	63	-6260	-6100	0.4	-6900	**0.35**	**0.85**
14	-5220	8900	0.1	-7900	**0.65**	**0.35**	64	2050	3700	0.5	-1600	**0.15**	**1**
15	7450	8600	0.5	4300	**0.3**	**1**	65	-2380	3600	0.01	-2500	**0.8**	**0.35**
16	-3000	-2900	0.7	-4700	**0.2**	**0.95**	66	-120	3200	0.4	-4000	**0.5**	**0.55**
17	-7075	7300	0.001	-7100	**0.8**	**0.25**	67	5400	5500	0.99	-2600	**0.3**	**0.85**
18	3005	3900	0.001	3000	**0.75**	**0.55**	68	3850	8200	0.5	-2500	**0.25**	**0.7**
19	-3350	9600	0.1	-5900	**0.55**	**0.4**	69	-8080	2600	0.001	-8100	**0.8**	**0.25**
20	2970	3000	0.99	-800	**0.3**	**0.9**	70	-4420	4300	0.01	-4600	**0.6**	**0.35**
21	9550	9600	0.99	5400	**0.3**	**1**	71	-695	4600	0.01	-800	**0.8**	**0.1**
22	900	7300	0.5	-7500	**0.3**	**0.45**	72	7140	9000	0.8	-5300	**0.25**	**1**
23	7980	8300	0.3	7500	**0.35**	**0.9**	73	220	6500	0.3	-3900	**0.3**	**0.6**
24	8885	8900	0.999	-6000	**0.3**	**0.95**	74	1660	3300	0.6	-3300	**0.3**	**0.8**
25	-7280	2300	0.001	-7300	**0.85**	**0.2**	75	-200	2400	0.7	-9600	**0.35**	**0.45**
26	-5740	-5500	0.6	-8600	**0.1**	**0.85**	76	4340	4800	0.4	2500	**0.35**	**0.9**
27	5000	5100	0.8	-400	**0.05**	**0.9**	77	3495	3500	0.99	3000	**0.45**	**0.9**
28	-4295	-500	0.001	-4300	**0.8**	**0.4**	78	-6240	600	0.2	-9200	**0.45**	**0.45**
29	-4200	2200	0.1	-5800	**0.45**	**0.45**	79	8850	8900	0.99	6000	**0.35**	**0.7**
30	-7340	300	0.01	-7500	**0.7**	**0.5**	80	-4800	-4800	0.8	-5900	**0.15**	**0.8**
31	-610	6300	0.3	-5000	**0.4**	**0.5**	81	-4995	-1100	0.001	-5000	**0.8**	**0.3**
32	3250	5600	0.5	-1100	**0.15**	**0.95**	82	-5250	5900	0.1	-7600	**0.75**	**0.35**
33	-3050	-3000	0.7	-3800	**0.3**	**0.9**	83	-3405	6100	0.01	-3600	**0.8**	**0.4**
34	1580	1600	0.4	1500	**0.45**	**0.85**	84	-2940	-1300	0.4	-5700	**0.45**	**0.75**
35	6275	9900	0.01	6200	**0.65**	**0.4**	85	-4530	5900	0.1	-6800	**0.6**	**0.3**
36	6420	7100	0.7	1500	**0.25**	**0.95**	86	2040	6000	0.6	-6400	**0.15**	**0.6**
37	1190	1200	0.99	-2400	**0.1**	**0.95**	87	-7300	1600	0.1	-9400	**0.65**	**0.4**
38	1590	1600	0.999	-4800	**0.25**	**0.85**	88	-4300	-900	0.5	-9700	**0.5**	**0.45**
39	-1395	-1400	0.99	-2900	**0.15**	**0.8**	89	6760	7400	0.1	6600	**0.6**	**0.45**
40	3420	5300	0.8	-9100	**0.15**	**0.8**	90	9195	9200	0.999	-5900	**0.2**	**0.95**
41	-3860	6900	0.3	-9900	**0.55**	**0.45**	91	4180	6100	0.2	2900	**0.25**	**0.95**
42	4650	4700	0.7	1200	**0.25**	**0.9**	92	4350	10000	0.5	-3300	**0.55**	**0.9**
43	-3270	-1900	0.7	-9800	**0.45**	**0.7**	93	5960	8000	0.6	400	**0.2**	**0.95**
44	9340	9600	0.7	5400	**0.3**	**0.95**	94	4900	4900	0.6	4000	**0.25**	**0.95**
45	5400	5500	0.99	-3600	**0.35**	**0.85**	95	700	9300	0.4	-6700	**0.45**	**0.4**
46	-20	3900	0.6	-8400	**0.4**	**0.45**	96	-2080	8700	0.01	-2300	**0.7**	**0.4**
47	-5295	4800	0.01	-5500	**0.65**	**0.15**	97	-2485	3500	0.001	-2500	**0.85**	**0.4**
48	4560	4800	0.2	4400	**0.5**	**0.65**	98	-9610	-9600	0.9	-9800	**0.35**	**0.85**
49	120	8800	0.001	100	**0.7**	**0.35**	99	0	1000	0.5	-1000	**0.7**	**0.45**
50	-320	3300	0.4	-4400	**0.4**	**0.55**	100	1000	2000	0.5	0	**0.3**	**0.7**

TABLE 3

THE PREDICTIVE POWER OF THE DIFFERENT VERSIONS OF CUMULATIVE PROSPECT THEORY

		λ_0	α	λ_1 $\beta=\alpha(\lambda_1)$	γ	λ_2 $\delta=\gamma(\lambda_2)$	μ	Fit MSE	Generalization tests: 200 MSE *ENO*	Generalization tests: W&M MSE *ENO*
Estimated on study 3a (39 prob.)	CPT	.98	.86	1	.85	.98	---	.306	.309	.396
									1.31	*1.24*
		1.02	.86	[1]	.84	[1]	---	.306	.310	.396
									1.30	*1.24*
		[1]	.85	[1]	.8	[1]	---	.308	.285	.396
									1.61	*1.61*
	SCPT	1.53	.85	.92	.79	.98	4.52	.215	.202	.238
									6.51	*11.65*
		1.01	.81	[1]	.78	[1]	4.23	.216	.199	.237
									7.37	*12.11*
		[1]	.81	[1]	.78	[1]	4.20	.216	.199	.237
									7.43	*12.16*
									39 MSE *ENO*	
Estimated on study 3b (200 prob.)	CPT	0.95	.75	1	.68	1.1	---	.272	.343	.391
									1.42	*1.27*
		1	.86	[1]	.5	[1]	---	.274	.335	.420
									1.49	*1.07*
	SCPT	1.68	.78	.95	.75	.90	2	.188	.223	.237
									9.18	*11.72*
		1.09	.75	1	.71	1	1.98	.188	.221	.237
									10.02	*11.63*
		[1]	.77	[1]	.71	[1]	2.04	.188	.220	.237
									10.33	*12.04*

Note: CPT refers to the deterministic version of cumulative prospect theory and SCPT refers to the stochastic version. The first section of the table presents the predictions of the models that were estimated on the data of study 3a (39 problems). The second section presents the prediction estimated on the data of study 3b (200 problems). A cell with [1] refers to a parameter that was restricted to be 1. The third right-most column presents the MSE of the fitted model on the estimated data. The two right-hand columns present the MSE and ENO of the model on two prediction tasks: Predicting 3a or 3b (the one not used during the estimation), and predicting the 34 problems studied by Wu and Markle (W&M, 2005).

FIGURE 1

The cumulative utility functions of the two prospects: (r1, p(r); r2) and (s1, p(s); s2). The normalization factor D is the average distance between the two functions.