Loss Aversion, Diminishing Sensitivity, and the Effect of Experience on Repeated Decisions

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ABSTRACT

Three experiments are presented that explore the assertion that loss aversion and diminishing sensitivity drive the effect of experience on choice behavior. The experiments are focused on repeated choice tasks where decision makers choose repeatedly between alternatives and get feedback after each choice. Experiments 1a and 1b show that behavioral tendencies that were previously interpreted as indications of loss aversion in decisions from experience are better described as products of diminishing sensitivity to absolute payoffs. Experiment 2 highlights a nominal magnitude effect: A decrease in the magnitude of the nominal payoffs eliminates the evidence for diminishing sensitivity. These and related previous results can be captured with a model that assumes reliance on small samples of subjective experiences, and accelerated diminishing sensitivity.

Key words: Myopic loss aversion, Prospect theory, Learning, Reflection effect, Explorative sampler.

INTRODUCTION

According to the loss aversion hypothesis (Kahneman & Tversky, 1979), the disutility of a loss is larger than the utility of an equivalent gain. Empirical research suggests that this hypothesis captures an important property of the effect of experience on choice behavior. For example, Benartzi and Thaler (1995) rely on the loss aversion hypothesis to explain why many investors have not learned to prefer stocks over bonds even after more than a century in which the average return of stocks was much larger than that of bonds (Mehra & Prescott, 1985).[1] According to this explanation, bonds are preferred because they eliminate the risk of (subjectively) costly losses. Another interesting example is provided by Camerer et al.'s (1997) analysis of the behavior of taxi drivers in New York City. This analysis suggests a loss aversion explanation to the observation that drivers tend to work more hours on bad days when the per-hour wage is low but quit earlier on good days in which the wage per-hour is high; a behavioral pattern that contradicts the prediction of the standard theory of labor supply. The authors suggest that the drivers set their reference point on the daily income target and act as if they are loss averse by trying to minimize the possibility of falling short of that reference point.[2]

However, direct experimental tests of the loss aversion hypothesis lead to contradictory conclusions. Whereas Thaler et al. (1997; and see Barron & Erev, 2003) found deviations from maximization that can be explained by the loss aversion hypothesis, the results reported by Katz (1964) show no evidence of loss aversion.

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[1] Mehra and Prescott call this phenomenon "The Equity Premium Puzzle." Benartzi and Thaler (1995) explain this puzzle with "Myopic Loss Aversion" (MLA) which is a combination of two behavioral concepts: myopia (the tendency to evaluate outcomes frequently) and loss aversion. Note that both concepts are equally necessary in explaining the puzzle.

[2] This suggestion was recently criticized by Ferber (2005).

The main goal of the current study is to improve our understanding of the descriptive value of the loss aversion hypothesis in decisions from experience: contexts where decision makers are not presented with information about the possible outcomes and their likelihoods but have to rely on personal experience.[3] In order to achieve this goal we start with an analysis of the problems studied by Thaler et al. (1997).

MIXED GAMBLES AND MIXED RESULTS

Thaler et al. (1997; and see Gneezy & Potters, 1997) examined the role of loss aversion in a simplified stock market. Their 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 nonnegative outcome. Investment in the stock increased the expected return by a factor of four, but was associated with high variability and frequent losses. The decisions were made from experience: the participants did not receive any description of the relevant payoff distributions, and had to rely solely on their feedback that was presented graphically[4] after each trial. The results reveal that the (low expected value) bond attracted about 60% of the investments. To confirm that the attractiveness of the bond reflected loss aversion (rather than risk aversion), Thaler et al. added the "Gain" condition. This condition was identical to the mixed condition, except that a constant was added to all payoffs to eliminate the possibility

[3] Previous research have showed that decisions from experience are different from one-shot decisions that are based on descriptions of the prospects' outcomes and likelihoods (e.g., Barron & Erev, 2003; Hertwig, Barron, Weber, & Erev, 2004).
[4] i.e., the returns for "bonds" and "stocks" were presented in bar graphs.

of losses. In support of the loss aversion hypothesis, this addition increased the attractiveness of the stock.

Barron and Erev (2003) ran a simplified replication of Thaler et al.'s study using a "clicking paradigm": In each of the 200 trials of their study, the participants were asked to select between (click on one of) two unmarked keys (instead of investing tokens). Each selection was rewarded with a draw from the key's payoff distribution. As in the original study the participants did not receive a description of the different distributions, but had to base their decisions on the feedback they received from previous choices. The feedback included a numerical presentation of the obtained payoff. Two problems were compared. Problem "Mixed" was a replication of the mixed condition in Thaler et al., while Problem "Gain" was a variant of the gain condition. The exact payoff distributions in these problems are presented below:

Problem Mixed (Barron & Erev, 2003, following Thaler et al., 1997)

S	A draw from a truncated (at zero) normal distribution with a mean of 25 and standard deviation of 17.7. (Implied mean of 25.63.)	P(S) = 0.70
R	A draw from a normal distribution with a mean of 100 and standard deviation of 354.	

Problem Gain (Barron & Erev, 2003, following Thaler et al., 1997)

S	A draw from a normal distribution with a mean of 1225 and standard deviation of 17.7.	P(S) = 0.49

R A draw from a normal distribution with a mean of 1300 and standard deviation of 354.

The results replicated the pattern observed by Thaler et al. Over the 200 trials the choice rate of the safer, low-expected-payoff, prospect (S) was 70% in Problem Mixed (when R was associated with frequent losses), and only 49% in Problem Gain. In order to clarify the relationship of their results to the loss aversion hypothesis, Thaler et al. used a simplified and myopic variant of prospect theory (Kahneman & Tversky, 1979). The simplification implied by this model involves the assumption of a linear weighting function. The added myopic term asserts that the decision makers consider one decision at a time (rather than considering the payoff distribution implied by a sequence of decisions).

Specifically, Thaler et al. (1997) assumed that choice behavior reflects an attempt to maximize expected subjective value, and the subjective value of outcome x is given by prospect theory's value function. That is,

$$(1) \quad sv(x) = \begin{cases} x^{\alpha} & if \quad x \geq 0 \\ -\lambda(-x)^{\beta} & if \quad x < 0 \end{cases}$$

Under prospect theory the parameter λ>1 captures loss aversion and parameters α and β capture (assuming (0< α ,β <1) diminishing sensitivity to increases in the absolute payoffs. According to the diminishing sensitivity assumption the subjective impact of a change in the absolute payoff decreases with the distance from zero (see Tversky & Kahneman, 1992, and motivating observations in Stevens, 1957). As noted by Thaler et al. the high S rate in Problem Mixed is predicted by the assertion of a strong loss aversion (high λ). For example, with $\lambda = 2.25$ (and $\alpha = \beta = 1$), the expected subjective values in Problem Mixed are approximately -21 from R, and +26 from S. With these parameters, the model implies that R is much more attractive in Problem Gain.

The loss aversion explanation of the pattern discovered by Thaler et al. has many attractive features. It is clear, simple, sufficient, and it clarifies the relationship of the results to a wide set of phenomena that can be naturally explained with the loss aversion hypothesis. However, the loss aversion assertion is not necessary. The same pattern can be captured with diminishing sensitivity. This is the case even under prospect theory (Kahneman & Tversky, 1979), the model used by Thaler et al.: when α is low, S is more attractive in the mixed condition even without loss aversion (i.e., with $\lambda = 1$). Under this “diminishing sensitivity” explanation, S is more attractive in the mixed problem because all the payoffs with the same payoff-sign seem similar. For example, with $\alpha = \beta = .5$ (and $\lambda = 1$), the expected subjective values in Problem Mixed are 4.4 from R, and 4.9 from S. With these parameters the model implies similar subjective expected values from R and S in Problem Gain. Notice that Simon's (1955) step-level "satisficing" utility function is an extreme version of the current diminishing sensitivity hypothesis.

Thaler et al.’s selection of the loss aversion explanation was justified by the usage of prospect theory with the parameters estimated by Tversky and Kahneman (1992): $\alpha = \beta = .88$, $\lambda = 2.25$. With these parameters the results are driven by loss aversion. However, there are good reasons to doubt the generality of these parameters to the current context. First, many estimations of prospect theory parameters yielded lower α values. For example, Camerer and Ho's (1994) data imply[5] $\alpha = .37$, and Wu and Gonzalez's (1996) data imply α values around 0.5. A second and more important reason is the observation that the loss aversion explanation is inconsistent with previous studies of choice behavior in repeated choice tasks. A clear violation of this explanation is provided by Katz (1964). Katz's study included 400 trials. In each trial the participants were asked to guess which of two light bulbs (S or R) would be turned on. The two bulbs were equally likely to be on. Guessing S was safer: The implied payoff was +1 if the guess was correct and –1 otherwise. Guessing R was riskier: The implied payoff was +4 if the guess was correct and –4 otherwise. The participants received no prior information concerning the relevant probabilities, but had to rely on the feedback they received after each trial. The implied choice problem is:

Problem Katz (Katz, 1964)

S	+1 with probability 0.5	P(S) = 0.49
	-1 otherwise	
R	+4 with probability 0.5	
	-4 otherwise	

The loss aversion assertion that losses loom larger than equivalent gains implies that most people should avoid the larger loss (of -4) and prefer Option S. In violation of this prediction the participants were indifferent between the two options. Notice that Katz's results can be captured by the diminishing sensitivity hypothesis; this

[5] Camerer and Ho (1994) did not report α, but Wu and Gonzalez repeated their estimation procedure using their data and found $\alpha = .37$ (see footnote 12 in Wu & Gonzalez, 1996).

hypothesis implies random choice in Katz's Problem. In addition, the results can be captured with a refinement of the loss aversion hypothesis that entails aversion to the possibility of losing (see Erev, Bereby-Meyer & Roth, 1999; Erev & Barron, 2005).

EXPERIMENT 1a: LOSS AVERSION OR DIMINISHING SENSITIVITY?

The main goal of Experiment 1a was to compare the loss aversion and the diminishing sensitivity explanations of Thaler et al.'s results. We employed the basic clicking paradigm used by Barron and Erev (2003) to replicate Thaler et al.'s results, and focused on the following Problems:

Problem 1 (Mixed)

S 0 with certainty

R +1000 with probability 0.5

-1000 otherwise

Problem 2 (Gain)

S 1000 with certainty

R 2000 with probability 0.5

0 otherwise

Note that in Problem 1 (Mixed) choosing the safer option eliminates the probability of losses. Therefore, the loss aversion hypothesis predicts a higher proportion of S choices in Problem 1 (Mixed) than in Problem 2 (Gain). According to this hypothesis the association of Option R with frequent losses in Problem 1 will decrease its attractiveness. The diminishing sensitivity hypothesis predicts the opposite pattern: random choice in Problem 1 and a strong preference to select S in Problem 2. This is because in Problem 1 the possible gain and loss are of the same distance (1000) from the reference point (0) and thus cancel each other out. In Problem 2, however, the diminishing sensitivity hypothesis implies that the subjective value of the even chance to win 2000 or nothing is reduced at a higher rate than the subjective value of the sure gain of 1000. As control conditions, Experiment 1 also examines Problems 3 and 4 (presented in Table 1): Both hypotheses imply a higher rate of S choices in Problem 3 than in Problem 4.

<u>Experimental design and procedure</u>

The participants in the experiment were 45 Technion students. The experiment used a within-participant design. Each participant was seated in front of a personal computer and was presented with each of the four problems presented in Table 1 for a block of 100 trials. Participants were told that the experiment would include several independent sections, in each of which they would operate a different "computerized money-machine" with two buttons for an unspecified number of trials. Each section involved a repeated play of one of the four problems. In each trial the participants were asked to select one of the buttons. Each selection followed with a presentation of its outcome in points (a draw from the relevant distribution). For example, a selection of Gamble R in Problem 1 (Mixed) resulted in a random draw from a binomial distribution that pays +1000 with probability of 0.5 and -1000 otherwise. This outcome appeared on the selected key and was added to the "accumulated earnings" score. The participants were told that their goal was to maximize their earnings. The points accumulated during the experiment were converted to cash at the rate of .01 Agarot (.0023 US cent) per 1 point. Final payoffs ranged between 26 Sheqels ($6.19) and 30 Sheqels ($7.14). The whole procedure lasted about 40 minutes.

The participants received a description of the conversion from points to cash, but did not receive prior information concerning the process that generates the payoff in points (the games' payoff structure), nor were they informed in advance that the experiment included four sections of 100 trials each (see a translation of the instructions in Appendix A). Before each section they were simply notified that a new game was about to start. In Sections 2, 3 and 4, they were also told that the new game differed from the previous games. Thus, the participants had to rely on their obtained feedback: the realized payoffs after each choice.

The order of the problems was randomized over participants. The assignment of alternatives to buttons was randomly determined for each participant at the beginning of each section and was fixed during the section.

Results

The right-hand column in Table 1 presents the proportion of S choices over the 100 trials in each of the four problems. A comparison of the proportion of S choices in Problems 1 and 2 reveals that the safer option was *less* popular when it eliminated the probability of losses (51% in Problem 1) than when losses were not possible (70% in Problem 2). In order to evaluate the significance of this pattern we calculated for each participant the difference between the proportion of S choices in the Mixed problem (Problem 1) and the proportion of S choices in the Gain problem (Problem 2). This difference was denoted the Mixed-Gain (hereafter referred to as "MG") score. The mean MG score was -0.19 (SD = .33), indicating a significant “reversed loss aversion” tendency, $t(44) = -3.85$, $p < .0005$. This result is predicted by the diminishing sensitivity hypothesis, and contradicts the predictions of the loss aversion hypothesis. Additional support for the diminishing sensitivity hypothesis comes from the examination of Problems 3 and 4. In these problems, the safer option tended to be more popular in the mixed problem (76% in Problem 3) than in the gain problem (66% in Problem 4). This difference is also significant (mean MG score = 0.10, SD = .27, $t(44) = 2.51$, $p < .02$).

Figure 1 presents the learning curves in these problems (the predictions of the explorative sampler model to be discussed below are presented on the right column of the graph). The results show that the difference between the mixed and gain conditions in each pair of problems increases over time.

An examination of the four problems’ order of presentation does not reveal a consistent effect, $F(3, 176) = 1.75$, NS. Nevertheless, to examine the robustness of the difference between Problem 1 and 2 we performed a between-participant analysis that avoids the risk of an order effect. This analysis focuses on the first problem presented to the participants. The observed S rates are 34% in Problem 1 (n=11), and 69% in Problem 2 (n=11). The difference is significant, $t(20) = -3.18$, $p < .005$. Thus, the between-participant analysis agrees with the within-participant analysis.

Another interesting order-related analysis involves the possibility of a "house money" effect and/or a "break even" effect (see Thaler & Johnson, 1990) which assert that decision makers’ risk taking is affected by past gains and losses. The “house money” effect asserts that risk taking is facilitated by previous gains. According to the “break even” effect risk taking is facilitated by previous losses but only under the possibility of eliminating these losses. A generalization of these effects to the current setting implies that the accumulated payoffs shift the relevant reference point, and this shift can increase risk taking. The house money effect can be used to predict more risk seeking after gains, and the break even effect can be used to predict more risk seeking after losses. In order to evaluate the house money effect we compared the behavior of the 11 participants who faced Problem 1 first (without house money) with the behavior of the other 34 participants who gained significant amounts before facing Problem 1. The results show no indication of a house money effect: Participants took more risk without house money (66% over the 11 participants than faced Problem 1 first) than with house money (44% over the remaining 34 participants; $t(43) = 2.30$, $p < .03$, for the difference between the two groups).

In order to evaluate the break even effect we re-analyzed the behavior of the participants that started the experiment with Problem 1. The analysis focused on the decisions that were made in trials 11 to 100. Seven of the 11 participants experienced both negative accumulated payoff and accumulated payoff of zero during these 90 trials. Only one of these seven participants exhibited more risk seeking given negative accumulated payoffs. The other six took more risk while the accumulated payoff was 0. Thus, they did not exhibit the break even effect.

To summarize, the results support the diminishing sensitivity hypothesis and contradict the loss aversion hypothesis. This pattern does not appear to be a product of a house money and/or break even effects. The clearest evidence against the loss aversion assumption is provided in Problem 1 in which half the participants preferred the risky option despite the high loss involved with this option.

EXPERIMENT 1b: DIMINISHING SENSITIVITY OR ZERO AVOIDANCE?

According to one interpretation of the results of Experiment 1a, the relative low choice rate of the safe alternative in Problem 1 reflects an attempt to avoid the payoff "0". This interpretation is consistent with previous demonstrations that boredom can facilitate risk taking in laboratory tasks (e.g., Lei, Noussair, & Plott, 2001). Specifically, one could speculate that participants were bored by repeatedly getting nothing and this facilitated their risk taking. Experiment 1b evaluates this zero avoidance hypothesis by focusing on the following pair of problems:

Problem 5 (Mixed)

S	+200 with probability 0.5	P(S) = 0.43
	-200 otherwise	
R	+1000 with probability 0.5	
	-1000 otherwise	

Problem 6 (Gain)

S	1200 with probability 0.5	P(S) = 0.72
	800 otherwise	
R	2000 with probability 0.5	
	0 otherwise	

The current problems differ from Problems 1 and 2 of Experiment 1a in that the safer alternative (S) is a gamble. Thus, if the pattern observed in Experiment 1a (more S choices in Problem 2 compared to Problem 1) is a product of zero avoidance then the difference between the problems should decrease. The zero avoidance predicts higher S rate in Problem 5 than in Problem 1. The diminishing sensitivity assumption, however, predicts that the differences in risk taking between the current problems will be similar to the differences observed between Problems 1 and 2. Specifically, it predicts 50% risk taking in Problem 5 (because the magnitude of the positive and negative values is symmetrically distributed around zero), and a strong preference to S in Problem 6 since the value of 2000 in R is discounted to a higher degree than the values of the safer alternative.

Experimental design and procedure

The participants in the experiment were 30 Technion students. The current experiment used the same design and procedure as the first experiment with the exception that it was focused on problems 5 and 6, presented above.

Results

A comparison of the proportion of S choices in Problems 5 and 6 reveals that the safer option was *less* popular when it reduced losses (43% in Problem 5) than when losses were not possible (72% in Problem 6). The mean MG score was -0.28 (SD = .40), which implies a significant "reversed loss aversion" tendency, $t(29) = -3.92$, $p < .0005$. This result is predicted by the diminishing sensitivity hypothesis but cannot be explained with the zero avoidance hypothesis. Additional support for the diminishing sensitivity hypothesis comes from the observation that the proportion of risk taking in Problem 5 was not significantly different than 50%, $t(29) = -1.34$, NS.

Figure 2 presents the learning curves in the Problems 5, and 6 (the predictions of the explorative sampler model are presented in the right column of the graph). Similarly to the learning curves in Experiment 1a, the difference between the two conditions increases over time.

As in Experiment 1a, no order effects were found in the current experiment, $F(1, 28) = 0.48$, NS. Analyzing only the first ordered problems does not change the pattern of results: the proportion of safe choices remains lower in Problem 5 (45%) than in Problem 6 (64%).

EXPERIMENT 2: THE NOMINAL MAGNITUDE EFFECT

The diminishing sensitivity hypothesis, supported above, appears to be inconsistent with the observation that the main regularities documented in previous studies of decisions from experience can be captured with models that assume risk neutrality (see Erev & Barron, 2005). One possible resolution of this inconsistency is based on the observation that most of the problems considered by Erev and Barron involve low nominal payoffs, while the problems studied above involve high nominal payoffs. Under this explanation, the apparent inconsistency reflects a nominal magnitude effect: On average, decision makers exhibit risk neutrality when the nominal values are low, and they behave as if their value function is S shaped (i.e., risk aversion in the gain domain, and risk seeking in the loss domain) when the nominal payoffs are high.[6]

The current experiment examined this “nominal magnitude” hypothesis by studying the four problems presented in Table 3 under two “nominal magnitude” conditions. The left-hand column in Table 3 presents the basic version of the four problems. Under Condition Low, the feedback after each choice was a draw from the distribution presented in the basic gamble column in Table 3. Condition High was identical to Condition Low except that the payoffs in points were multiplied by a

[6] A similar argument was suggested by Holt and Laury (2002). They noted that relative risk aversion tends to increase with higher stakes. According to the current hypothesis diminishing sensitivity (that implies risk aversion in the gain domain) increases with nominal payoffs (even when the actual stakes do not change).

hundred, and the conversion rate from points to money was divided by a hundred. In other words, the nominal values in the high condition differed in two orders of magnitude from the nominal values in the Low condition. Thus, the typical payoff in Condition Low involved several points, and the typical payoff in Condition High involved several hundred points. Nevertheless, the two conditions were economically identical: The sole objective difference between the two point magnitude conditions was the addition of a decimal point to the feedback in Condition Low.

In order to evaluate the robustness of the results, Problems 7 and 8 were associated with bimodal distributions and Problems 9 and 10 were associated with normal distributions. Note that in Problems 7 and 9 the risky option is associated with frequent losses, whereas the safer option is not. Following Thaler et al. (1997), Problems 8 and 10 (the "gain" problems) were created by the addition of a constant to Problems 7 and 9 (the "mixed" problems) respectively.

The nominal magnitude hypothesis predicts a difference between the two conditions. Specifically, it predicts that the proportion of S choices in the mixed problems (7 and 9) will be higher than in the gain problems (8 and 10) in Condition High but not in Condition Low.

<u>Experimental design and procedure</u>

Experiment 2 compared two between-participant groups (i.e., High and Low point magnitudes). Each group faced the four problems presented in Table 3, using a within-participant design: Each participant was faced with each of the four problems for a block of 100 trials. One hundred Technion students who did not participate in the first experiment, served as paid participants in the current study. Fifty were randomly assigned to Condition Low, and the other 50 were assigned to Condition

High. The procedure was identical to Experiment 1, with the exception that the current study focuses on the problems presented in Table 3. The instructions were as in Experiment 1. The participants did not know the payoff distributions but they were told the exact rate in which their points would be converted to money. The conversion rates in this experiment were 2 agorot (about 0.46 US cent) per 1 point in Condition Low and 0.02 agorot (about 0.0046 US cent) per 1 point in Condition High. Final payoffs ranged between 32 Sheqels ($7.61) and 39 Sheqels ($9.28).

Results

The right-hand columns in Table 3 present the (mean and median) proportion of S choices over the 100 trials in each of the four problems under the two conditions. The results reveal a clear nominal magnitude effect. In Condition Low the safer option was slightly *less* popular in the mixed problems when it eliminated the probability of loss (49% in Problem 7, and 49% in Problem 9) than in the gain problems (55% in Problem 8, and 53% in Problem 10). The mean MG score was -0.05 (SD = .27). This difference is not significantly different than 0, and it reflects no evidence for the pattern implied by the diminishing sensitivity effect.

In Condition High, however, the safer option tended to be more popular in the mixed problems when it eliminated the probability of loss (57% in Problem 7, and 60% in Problem 9) than in the gain problems (47% in Problem 8, and 50% in Problem 10). In this condition the mean MG score was 0.10 (SD = .22). This difference is significant, $t(49) = 3.34$, $p < .002$.

Comparison of the two conditions reflects the pattern predicted by the nominal magnitude hypothesis. The mean MG score in Condition High (0.10) is significantly higher than the mean MG score in Condition Low (-0.05; $t(98) = 3.05$, $p < .003$).

The learning curves are presented in Figure 3 (together with the predictions of the explorative sampler model). They show that the pattern described above is robust to experience. Indeed, the difference between the two point magnitude conditions slightly increases over time.

A QUANTITATIVE SUMMARY AND ALTERNATIVE ABSTRACTIONS

Experiment 2 takes one step toward relating the current results to previous experimental studies of decisions from experience; it shows that the apparent difference between Experiment 1 and the previous experimental studies of decisions from experience, reviewed by Erev and Barron (2005), can be a product of a nominal magnitude effect. The main goal of the current section is to take another step in the same direction; it tries to refine the models proposed by Erev and Barron in order to capture the current findings. Specifically, it searches for a model that can capture the diminishing sensitivity and payoff magnitude effects as well as the main regularities considered by Erev and Barron with a single set of parameters.

The models proposed by Erev and Barron were designed to address two robust deviations from maximization (of expected payoffs) that were not considered above. The first deviation is the payoff variability effect (see Myers & Sadler, 1960): High payoff variability reduces sensitivity to payoff difference. The second deviation can be described as underweighting of rare (low probability) events (see Barron & Erev, 2003; Yechiam & Busemeyer, 2005). Erev and Barron's analysis shows that both deviations can be captured with the assertion that decisions from experience are driven by best reply to small samples of experiences (see related assumptions in Kareev, 2000; Osborne & Rubinstein, 1998; Hertwig et al., 2004; Erev, Glozman and Hertwig, in press; Hochman & Erev, 2007; Biele, Erev & Ert, 2007). According to this assertion the decision maker recalls a small set of past experiences with each alternative, and selects the alternative that is associated with the better average experiences in the recalled set. Lebiere, Gonzalez and Martin (2007) extend this analysis and show the value of a model that assumes similarity-based weighting. This model implies high sensitivity to small sample of experiences (experiences in "similar" situations) and lower sensitivity to other experiences.

We believe that the diminishing sensitivity pattern, documented above, can be used to improve our understanding of the effect of small samples on choice behavior. Specifically, we hypothesize that the addition of the diminishing sensitivity assumption to models that assume oversensitivity to small samples, can improve the value of these models. The current section evaluates this optimistic hypothesis by considering variants of the explorative sampler model described below. The analysis focuses on the effect of the abstraction of diminishing sensitivity on the model's fit of the 14 experimental conditions considered here and the results summarized by Erev and Barron (2005).

The explorative sampler model

The model can be summarized with the following assumptions:

A1: Exploration and exploitation. The agents are assumed to consider two cognitive strategies: exploration and exploitation (see Gittins, 1979; and Denrell & March, 2001, for discussions of the value of this distinction).

Exploration implies a random choice. The probability of exploration is 1 in the very first trial, and depends on the availability of information concerning the forgone payoffs in the following trials. When this information is available the probability of exploration in trial t>1 is 0< ε <1 -- a free parameter. When information concerning the forgone payoffs is not available, the probability of exploration reduces toward an asymptote (at ε) with experience. The effect of experience on the probability of exploration depends on the number of trials (*T*) in the experiment. Exploration diminishes quickly when *T* is small, and slowly when *T* is large.[7] This assumption is quantified as follows:

(2) $$P(Explore_t) = \varepsilon^{\frac{t-1}{t+T^{\delta}}},$$

where δ is a free parameter that captures the sensitivity to the length of the experiment.

A2: Experiences and sampling. The experiences with each alternative include the set of observed outcomes yielded by this alternative in previous trials. In addition, when feedback is limited to the obtained payoff, the subjective value of the very first outcome is recalled as an experience with all the alternatives.

Under exploitation the agent draws (with replacement) a sample of m_t past experiences with each alternative. All previous experiences are equally likely to be sampled. The value of m_t at trial t is assumed to be randomly selected from the set {1, 2,…… κ} where κ is a free parameter.

The sampling algorithm is assumed to depend on the available information. When feedback is limited to the obtained payoffs the sampling from the experiences with the different alternatives is independent. When the foregone payoffs are known

[7] Implicit in this abstraction is the simplification assumption that the decision makers know the value of *T*. This assumption is incorrect, but it is likely to provide good approximation of the estimated number. Since the decision makers know the expected length of the experiment in minutes, and the number of subsections, it is natural to assume that they can develop a good estimate of *T*.

(the decision makers receive complete feedback that includes the payoff from the unselected alternatives), the distinct samples are perfectly correlated. The decision maker selects one set of m_t trials, and the outcomes in those trials are used to determine the values of the different alternatives.

A3: Regressiveness, diminishing sensitivity, and choice. The recalled subjective values of the outcome *x* from selecting alternative *j* at trial *t* is assumed to be affected by two factors: regression to the mean of all the experiences with the relevant alternative (in the first t-1 trials), and diminishing sensitivity. Regression is captured with the assumption that the regressed value is $R_x = (1-w)x + (w)A_j(t)$, where $0 < w < 1$ is a free parameter and $A_j(t)$ is the average outcome from the relevant alternative.[8]

Diminishing sensitivity is captured with a variant of prospect theory's (Kahneman and Tversky, 1979) value function that assumes

(3)
$$sv(x) = \begin{cases} R_x^{\alpha_t} & if \quad R_x \geq 0 \\ -(-R_x)^{\alpha_t} & if \quad R_x < 0 \end{cases}$$

Where $\alpha_t = (1+V_t)^{(-\rho)}$, $\rho \geq 0$ is a free parameter, and V_t is a measure of payoff variability. V_t is computed as the average absolute difference between consecutive obtained payoffs in the first t-1 trials (with an initial value at 0). The parameter ρ captures the effect of diminishing sensitivity: large ρ implies quick increase in diminishing sensitivity with payoff variability.

[8] Implicit in this regressiveness (the assumption $0 < w < 1$) is the assumption, introduced by Lebiere, Gonzalez and Martin (2007), that all the experiences are weighted (because all the experiences affect the mean). This implicit assumption is necessary to capture a thought experiment in which the decision maker chooses between "1000 with certainty" and the gamble "1001 .9; 0 otherwise".

The estimated subjective value of each alternative at trial *t* is the mean of the subjective value of the alternative's sample in that trial. Under exploitation the agent selects the alternative with the highest estimated value.

Estimation and results.

In order to evaluate the model, we simulated virtual replications of the 14 conditions described above and the 40 conditions reviewed by Barron and Erev (2005, see Table 4[9]). The simulated participants arrived at their choices on the basis of the model's assumptions. Thus, we can compare the choice proportions predicted by the model to the empirically observed choice proportions. The following five steps were taken in each trial:

1. The trial decision mode (exploration or exploitation) was determined (using Equation 2). If the selected type was exploration, one option was randomly chosen and the process moved to step 3.
2. The following actions were taken in the case of exploitation.
    a. The sample size used by the agent (m_t) was determined.
    b. A sample of m_t outcomes was drawn with replacement from the experience with each alternative.
    c. The alternative with the higher mean subjective value in the sample was selected.

[9] The 40 conditions were run under three experimental paradigms. Under the "Probability Learning" (PL) paradigm the decision maker is asked to predict which of two mutually distinctive events will occur in the next trial, and can see when the trial ends which event occurred. Under the "Minimal Information" (MI) paradigm the individual is asked during every trial to select one of two unmarked buttons, and gets feedback concerning the payoff of the chosen button. The "Complete Feedback" (CF) paradigm is similar to the Minimal Information paradigm with the exception that the decision maker is presented with the values of both buttons after each choice, but her payoff is determined by the selected button.

3. The outcomes were realized by drawing from the objective payoff distributions.
4. The experiences (observed outcomes) were stored.
5. The measures of the payoff variance (V_t), and the average payoffs ($A_j(t)$) were updated.

The model's parameters were estimated (using a grid search method with mean squared deviation criteria) to simultaneously fit the 54 experimental conditions. The estimated parameters were $\rho = 0.15$, $w = 0.3$, $\delta = 0.55$, $\varepsilon = 0.08$ and $\kappa = 6$. Tables 4 and 5 and the right panels in Figures 1, 2, and 3 present the implied predictions. These exhibits show that the model reproduces the main patterns of the results. Specifically, the model reproduces the three very different effects of the addition of a constant to all the payoffs. As in the human data this addition: (i) increases the rate of choosing Safe in the upper panel of Figure 1 and in Figure 2, (ii) decreases the rate of choosing Safe in the lower panel on Figure 1 and under the high condition in Figure 3, and (iii) has little effect under the Low condition in Figure 3. In addition to the qualitative reproduction, the model provides good quantitative fit of the aggregated results: The mean square deviation (MSD) between the observed and predicted proportions presented in Table 4 and 5 is .0044. This score is similar to the MSD scores of the best models in Erev and Barron's (2005) analysis. Thus, the refined model is as accurate as these models in capturing Erev and Barron's data, and outperforms these models in capturing the current data.

Alternative abstractions

Two alternative abstractions of the diminishing sensitivity assertion were examined. The first uses Equation 1's abstraction of the diminishing sensitivity assumption. Notice that this abstraction allows loss aversion and assumes constant diminishing sensitivity. The MSD score of the model with this subjective value function is minimized with the parameters α = 0.7, λ = 1.3, δ = 0.55, ε = 0.08 and κ = 6: The MSD score is 0.0087. The relatively high MSD score reflects the fact that the estimated parameters cannot describe the patterns observed in experiment 1and that Equation 1's power value function cannot capture the nominal magnitude effect.

A second alternative abstraction adds the possibility of loss aversion to Equation 3's power function. It assumes Equation 4 subjective value function:

$$(4) \qquad sv(x) = \begin{cases} R_x^{\alpha_t} & if \quad R_x \geq 0 \\ -\lambda(-R_x^{\alpha_t}) & if \quad R_x < 0 \end{cases}$$

The analysis of this model shows that the addition of the loss aversion parameter does not improve the fit. Optimal fit is obtained with λ = 1. Thus the MSD score and the other parameters are identical to those of the simpler model that use Equation 3's abstraction.

Shortcomings and possible extensions

The explorative sampler model has three major shortcomings. The first involves the fact that the model under-predicts some of the sequential dependencies in the data. Specifically it under-predicts the tendency to select the alternative with the best recent outcome, and the tendency to repeat recent choices. Biele et al. (2007)

show that this limitation can be corrected with the assumption that recency and inertia are products of decision modes that are not modeled here.

A second shortcoming involves the (implicit) assumption of a static environment. The explorative sampling model ignores the possibility that the environment can change. Hochman and Erev (2007; and Biele et al., 2007) show that this shortcoming can be corrected with the assumption of contingent sampling. Under this assumption the sampling is contingent on an assessment of the state of the environment.

A third shortcoming involves the assumption that the probability to select the different modes is independent of the experience. Erev and Barron (2005) highlight one solution to this problem. Under their solution the probability of selecting each mode is determined by a reinforcement learning process (and see related ideas in Stahl, 2000 and Rieskamp & Otto, 2006).

Loss aversion and individual differences

The analysis presented above focuses on the behavior of the typical participant. Thus, it suggests that on average, participants are equally explorative to gains and losses, but does not imply that equal sensitivity to gains and losses is general. Indeed, sensitivity to gains compared to losses is at the heart of many of the current theories of individual differences (e.g., Gray, 1994; Higgins, 1997) and of learning models that seek to study decisions at the individual level (e.g., Busemeyer & Stout, 2002; Wallsten et al., 2005; Yechiam et al., 2006). The current findings do not contradict these models. What the current findings imply is that across individuals, in the conditions studied here the loss aversion tendency is balanced, so that there are only small differences in the average loss aversion across different individuals.

GENERAL DISCUSSION

The original goal of the current research was to improve our understanding of the effect of loss aversion on decisions from experience. We hoped to propose a refined abstraction of loss aversion that could explain why the effect of experience appears to be sensitive to loss aversion in some settings (Thaler et al., 1997) but not in others (Katz, 1964). The experimental results led us in a different direction: They suggest that the effect of experience in repeated decisions does not appear to reflect loss aversion for the average participant.

The clearest evidence against the hypothesis that the typical decision maker exhibits loss aversion is provided by Problem 1. The typical participant was indifferent between the status quo (payoff of 0) to an equal chance to win 1000 and lose 1000. This result contradicts Kahneman and Tversky's (1979) original definition of loss aversion (losses loom larger than gains), and Erev and Barron's (2005) revised abstraction (an effort to minimize the probability of losses).

In addition, the current results demonstrate that previous findings that were interpreted as evidence for loss aversion in decisions from experience are better described with the assertion of a strong diminishing sensitivity effect. For example, the tendency to prefer safe outcomes that ensure a positive return over risky outcomes with a much higher average return (Thaler et al., 1997; Barron & Erev, 2003) is explained with the assertion of low sensitivity to the difference between the different gains.

Finally, the results suggest that the extent to which decision-makers exhibit the diminishing sensitivity effect is a function of the nominal payoff magnitude. Strong diminishing sensitivity was observed when the feedback involved a gain or loss of hundreds of points, but not when the payoff involved several points. Indeed, when the nominal payoffs were low, the modal behavior exhibited risk neutrality.

The effect of loss aversion on experience in natural settings

The current results appear to be inconsistent with the observation that the loss aversion hypothesis provides an elegant explanation for the effect of experience in many natural decision environments (see Thaler & Benarzi, 1995; Camerer et al., 1997). Under one explanation of this inconsistency, it reflects a difference between "small decisions" (the situations examined here), and bigger decisions (situations in which the absolute difference between the expected values of the different alternatives is high).

A second feasible explanation is based on the observation that there are many alternative explanations for the empirical phenomena interpreted as indications of loss aversion. For example, the suggestion that many individuals are under-invested in the stock market, analyzed by Benartzi and Thaler (1995), can be explained through the diminishing sensitivity hypothesis supported here.[10]

We believe that additional research is needed in order to compare the two explanations. The current data cannot be used to determine if the behavioral tendencies observed here are likely to emerge in big decisions.

[10] Notice that there are many natural investment problems in which the loss aversion and diminishing sensitivity hypotheses lead to different predictions. One example involves the choice between an individual stock and an index fund. It is commonly assumed that an index fund is associated with same expected return as an individual stock but with less variability (risk). Thus, as in Katz (1964), loss aversion implies a bias toward the index fund, while the diminishing sensitivity hypothesis implies random choice. Recent research suggests that individual investors deviate from the textbook model in the direction of selecting individual stocks (e.g., Blume & Friend, 1975; Kelly, 1995; Barber & Odean, 2000).

Loss aversion in decisions under risk, and in riskless choice

Another important disclaimer involves the role of loss aversion in decisions that are based on a description of the relevant payoff distributions. The current results do not question the validity of the loss aversion hypothesis in the context of decisions under risk (one-shot choices among numerically described lotteries), the focus of Kahneman and Tversky (1979).[11] Nor do they do so in the context of riskless choice (see Shapira, 1981; Tversky & Kahneman, 1991). The current results do suggest that the loss aversion phenomenon is less general than we originally believed.

One interesting relationship between the current findings and loss aversion studies in other contexts involves the possibility that loss aversion can be a forecasting error (Kermer, Driver-Linn, Wilson, & Gilbert, 2006). According to this assertion people overestimate the impact of potential losses on their actual behavior. The current findings support this assertion by showing that people do not overweight experienced losses compared to gains in their decisions.

Interpretations and implications of the nominal magnitude effect.

The nominal magnitude effect, documented in Experiment 2, is consistent with Holt and Laury's (2002) observation that relative risk aversion tends to increase with the magnitude of (nominal) payoffs. These findings seem to challenge recent abstractions of risk taking that assume constant relative risk aversion (e.g., Weber, Shafir, & Blais, 2004).

We believe that the most important implication of the nominal magnitude effect is the identification of a boundary condition for the diminishing sensitivity effect. It implies that when the nominal (and objective) payoffs are low, choice

[11] However, recent research (Schmidt & Traub, 2002; Ert & Erev, 2007) does question the robustness of the loss aversion hypothesis in decisions under risk.

behavior can be captured with a simple model that assumes risk neutrality. Only when the nominal magnitudes are large is the diminishing sensitivity assumption important. The explorative sampler model presents one abstraction of this observation.

Derivation of additional implications requires better understanding of the factors that contribute to this effect. Two factors are likely to be particularly important. The first involves perceptual sensitivity. The perception of large nominal values is more demanding, and likely to involve a stronger perceptual bias.

Obviously, however, the nominal values dimension is only one of many dimensions that can affect perceptual bias. For example, graphical presentation of the outcomes (of the type used by Thaler et. al, 1997) is likely to enhance diminishing sensitivity. Another interesting manipulation involves a presentation of foregone payoff (the payoff from the alternative that was not selected). Ert and Erev (in preparation) ran a replication of Experiment 1 with information concerning foregone payoffs. Their results replicate the qualitative pattern described above, but reveal smaller differences between the two conditions that can be captured with the assertion that the presentation of foregone payoff decreases diminishing sensitivity.

A second factor involves generalization. It is possible that the presentation of large nominal values increases the tendency to generalize from previous experiences with decisions that involve more substantial amounts of money. This assertion implies a relationship between the nominal magnitude effect and Holt and Laury's (2002) incentive effect.

Potential practical implications: The example of safety rules

An attempt to derive the potential practical implications of the current results reveals two difficulties. First, as suggested above, the current data cannot be used to determine if the behavioral tendencies observed here are likely to emerge in big decisions. Second, the explorative sampler model that captures the main results highlights two behavioral tendencies, “diminishing sensitivity” and “reliance on small samples”, that can lead to contradictory predictions.

We believe that these difficulties reduce the set of environments that can be reliably analyzed based on the current results, but they do not eliminate this set; there are many environments in which small decisions (involving small absolute differences between the expected values of the different alternatives) have consequential economic implications. Moreover, in many of these cases, the two tendencies captured by explorative sampler model reinforce each other. For an example consider the value of enforcing safety rules. Specifically, think about situations in which decision makers have to choose between a safe and a riskier action. A concrete example involves a pedestrian (human or chicken) and a road that he, she, or it plans to cross when the pedestrian light is red. This decision maker has to choose between waiting for the green light (the safer option), and crossing during the red light (the riskier option).

The risky option is likely to lead to a gain of few seconds, but there is a small probability that it will lead to a much larger loss. Thus, a naïve generalization of the loss aversion hypothesis suggests that the decision maker is likely to deviate from expected utility maximization in the direction of being “too cautious.” The current results lead to the opposite prediction. Diminishing sensitivity implies bias toward risk seeking because it implies insufficient sensitivity to the large potential losses. A bias in the same direction is predicted by the assumed reliance on small samples: Since low probability events are less likely to be realized given small samples, the decision maker is likely to behave as if he or she believes that "it won't happen to me." Therefore, the two psychological assumptions abstracted in the explorative sampler model imply a bias towards risk taking in this set of situations. Consequently, the current analysis suggests that the value of the enforcement of safety rules is likely to be larger than the value estimated under the assumption of loss aversion or even rational choice.

Summary

The current analysis rejects the hypothesis that loss aversion drives the effect of experience on repeated decisions. Rather, it suggests that the main behavioral regularities observed for the average participant in previous studies of decisions from experience reflect two robust tendencies: diminishing sensitivity relative to a reference point, and reliance on small samples.

Appendix A: The Instructions for the Experimental Task

“Hello,

In this experiment you will play a number of different games. In each game you will operate a money machine. Each button press will lead to winning or losing a number of points (depending on the button you choose). Your goal in the experiment is to win as many points as possible. There could be differences in the number of points produced by each of the buttons. Your final bonus will be determined by the total number of points earned in the game (100 points = 1 Agora). For your information, it is highly likely that the machine would be different for each participant.

Good luck”.

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Table 1: The problems studied in Experiment 1a and the aggregate results

Basic problems				Proportion of S (safe) choices	
		Verbal description	Notation	Mean (SD)	Median
1	S:	0 with certainty	0	0.51	0.50
	R:	1000 with probability 0.5 -1000 otherwise	(1000, .5; -1000)	(.29)	
2	S:	1000 with certainty	1000	0.70	0.74
	R:	2000 with probability 0.5 0 otherwise	(2000, .5; 0)	(.21)	
		Mixed-Gain (MG) Score		*-0.19*	*-0.16*
				(.33)	
3	S	400 with certainty	400	0.76	0.82
	R	1400 with probability 0.5 -600 otherwise	(1400, .5; -600)	(.21)	
4	S	1400 with certainty	1400	0.66	0.64
	R	2400 with probability 0.5 400 otherwise	(2400, .5; 400)	(.23)	
		Mixed-Gain (MG) Score		*0.10*	*0.08*
				(.27)	

The left-hand columns present the 4 basic problems studied in Experiment 1a in which participants chose repeatedly between a safer option (S) and riskier option (R). The right-hand columns present the main results over the 100 trials run in the two conditions.

Table 2: The problems studied in Experiment 1b and the aggregate results

Basic problems				Proportion of S (safe) choices	
		Verbal description	Notation	Mean (SD)	Median
5	S:	200 with probability 0.5 -200 otherwise	(200, .5; -200)	.43	.47
	R:	1000 with probability 0.5 -1000 otherwise	(1000, .5; -1000)	(.28)	
6	S:	1200 with probability 0.5 800 otherwise	(1200, .5; 800)	.72	.81
	R:	2000 with probability 0.5 0 otherwise	(2000, .5; 0)	(.31)	
		Mixed-Gain (MG) Score		*-.28*	*-.34*
				(.40)	

The left-hand columns present the two basic problems studied in Experiment 1b in which participants chose repeatedly between a safer option (S) and riskier option (R). The right-hand columns present the main results over the 100 trials run in the two conditions.

Table 3: The problems studied in Experiment 2 and the aggregate results.

				Proportion of S (safe) choices			
Basic problems				Condition Low		Condition High	
		Verbal description	Notation	Mean (SD)	Median	Mean (SD)	Median
7	S:	A draw from the interval (0,1)	0 + u(0,1)	0.49 (.33)	0.45	0.57 (.28)	0.62
	R:	A draw from the interval (-1,0) with probability 0.5 A draw from the interval (2,3) otherwise	(-1, .5; 2) + u(0,1)				
8	S:	A draw from the interval (3,4)	3 + u(0,1)	0.55 (.25)	0.52	0.47 (.24)	0.47
	R:	A draw from the interval (2,3) with probability 0.5 A draw from the interval (5,6) otherwise	(2, .5; 5) + u(0,1)				
9	S	A draw from a truncated (at zero) normal distribution with a mean of 0.25 and standard deviation of 0.177 (implied mean of 0.256)	TN(.25, .177, 0)	0.49 (.30)	0.47	0.60 (.26)	0.64
	R	A draw from a normal distribution with a mean of 1 and standard deviation of 3.54	N(1, 3.54)				
10	S	A draw from a truncated (at 12) normal distribution with a mean of 12.25 and standard deviation of 0.177 (implied mean of 12.256)	TN(12.25, .177, 12)	0.53 (.26)	0.53	0.50 (.26)	0.51
	R	A draw from a normal distribution with a mean of 13 and standard deviation of 3.54	N(13, 3.54)				
		Mixed-Gain Score (MG)		*-0.05 (.27)*	*-0.01*	*0.10 (.22)*	*0.11*

The left-hand columns present the four basic problems studied in Experiment 2 in which participants chose repeatedly between a safer option (S) and riskier option (R). The right-hand columns present the main results over the 100 trials run in the two conditions: In Condition Low the presentation of payoffs on the experimental screen matched the verbal description in the left side of the Table. In Condition High these payoffs were multiplied by 100.

Table 4: Comparison of the results and the predictions of the explorative sampler model

				Proportion of S (safe) choices	
Experiment	Problem	R (risky)	S (safe)	Observed	Explorative Sampler
1a					
0	1	(1000, .5; -1000)	0	0.51	0.47
	2	(2000, .5; 0)	1000	0.72	0.73
+400	3	(1400, .5; -600)	400	0.75	0.73
	4	(2400, .5; 400)	1400	0.65	0.60
1b					
±200	5	(1000, .5; -1000)	(200, .5; -200)	0.43	0.51
	6	(2000, .5; 0)	(1200, .5; 800)	0.72	0.73
2					
Low	7L	(2, .5; -1) +u(0,1)	0 +u(0,1)	0.49	0.44
	8L	(5, .5; 2) + u(0,1)	3+ u(0,1)	0.55	0.40
	9L	N(1.00, 3.54)	TN(0.25, 0.177) truncated at 0	0.49	0.45
	10L	N(13.00, 3.54)	TN(12.25, 0.177) truncated at 12	0.53	0.43
High	7H	(200, .5; -100) +u(0,100)	0 +u(0,100)	0.62	0.61
	8H	(500, .5; 200) + u(0,100)	200+ u(0,100)	0.52	0.43
	9H	N(100, 354)	TN(25, 17.7) truncated at 0	0.60	0.55
	10H	N(1300, 354)	TN(1225, 354) truncated at 1200	0.50	0.44

Notice that the letter added to the problem number in Experiment 2 reflects the nominal magnitude condition: L for Low, and H for High. The Explorative Sampler column refers to the predicted proportion of S choices under the Explorative Sampler model.

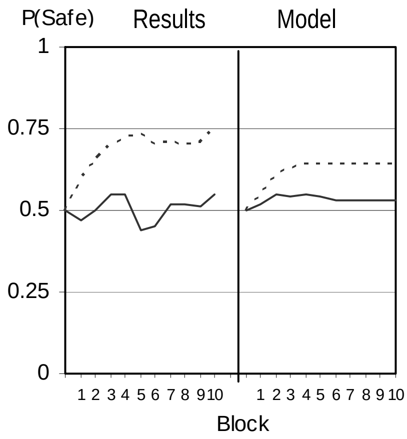
Table 5: Comparison of the results and the explorative sampler model predictions in the problems studied by Erev and Barron (2005).

Problem and paradigm	Number of Trials	Alternative H	Alternative L	Proportion of (L) choices: Observed	Proportion of (L) choices: Explorative Sampler
1 MI	200	(11)	(10)	0.16	0.08
2 MI	200	(11)	(1, .5; 19)	0.32	0.38
3 MI	200	(1, .5; 21)	(10)	0.42	0.56
4 MI	200	(-10)	(-11)	0.07	0.08
5 MI	200	(-10)	(-1, .5; -21)	0.46	0.48
6 MI	200	(-1, .5; -19)	(-11)	0.52	0.43
7 CF	200	(11)	(10)	0.06	0.04
8 CF	200	(1, .5; 21)	10	0.37	0.45
9 CF	200	-10	-11	0.06	0.04
10 CF	200	-10	-1, .5; -21	0.45	0.45
		Problems 11-14: G is the gamble (-5, .5; +5)			
11 MI	200	N(21,3)	N(18,3)	0.15	0.20
12 MI	200	N(21,3)	N(18,3) + G	0.24	0.28
13 MI	200	N(21,3)+G	N(18,3)	0.41	0.30
14 MI	200	N(21,3)+G	N(18,3) + G	0.38	0.32
		Problems 15-20: H= (x if E; -x if not-E) L=(-x if E; x if not-E)			
15 PL	400	x=1, p(E) =.6		0.40	0.31
16 PL	400	x =10, p(E) =.6		0.38	0.30
17 PL	400	x=1, p(E) =.7		0.23	0.20
18 PL	400	x =10, p(E) =.7		0.20	0.20
19 PL	400	x=1, p(E) =.8		0.23	0.21
20 PL	400	x =10, p(E) =.8		0.12	0.12
21 MI	400	(4, .8; 0)	(3)	0.36	0.40
22 MI	200	(4, .2; 0)	(3, .25; 0)	0.48	0.46
23 MI	200	(32, .1; 0)	(3)	0.71	0.74
24 MI	200	(32, .025; 0)	(3, .25; 0)	0.69	0.68
25 MI	200	(-3)	(-32, .1; 0)	0.60	0.70
26 MI	200	N(100,354)	TN(25, 17.7)	0.69	0.54
27 MI	200	N(1300, 354)	N(1225, 17.7)	0.48	0.41
28 MI	200	N(1300, 17.7)	N(1225, 17.7)	0.16	0.08
		Problems 29-35: H=(G if E; B if not-E) L=(B if E; G if not-E)			
29 PL	300	P(E) =.75, G=5, B=0		0.17	0.15
30 PL	300	P(E)=.75, G=5, B= -5		0.05	0.16
31 PL	500	P(E)=.7, G=6, B= 2		0.20	0.20
32 PL	500	P(E)=.7, G=4, B= 0		0.22	0.20
33 PL	500	P(E)=.7, G=2, B= -2		0.11	0.20
34 PL	500	P(E)=.7, G=0, B= -4		0.13	0.20
35 PL	500	P(E)=.7, G=-2, B= -6		0.18	0.20
		Problems 36-39: P(E) =.7; P(F)=.9 H=(G if E&F, B if not-E&F, 0 otherwise) L = (B if E&F, G if not-E&F, 0 otherwise)			
36 PL	550	G=6, B=2		0.17	0.20
37 PL	550	G=-2, B=-6		0.18	0.20
38 MI	550	G=6, B=2		0.22	0.27
39 MI	550	G=-2, B=-6		0.22	0.25
40 MI	400	(-3)	(-4, .8; 0)	0.40	0.35

The left-hand columns present the 40 problems studied by Erev and Barron (2005) and the observed results (prop. of L choices in the first 100 trials). The paradigms are: MI = minimal information, CF = complete feedback, and PL= probability learning. The notation (x,p;y) describes a gamble that pays x with probability p, y otherwise. The notation (x if E; y if not-E) implies a gamble that pays x if E occurs and y otherwise. N(x,y) means a draw from a normal distribution with mean x and standard deviation y, TN(25,17.7) is a truncated (at zero) normal distribution. Alternative H is associated with higher expected value than Alternative L. The right-hand column presents the prediction of the explorative sampler model.

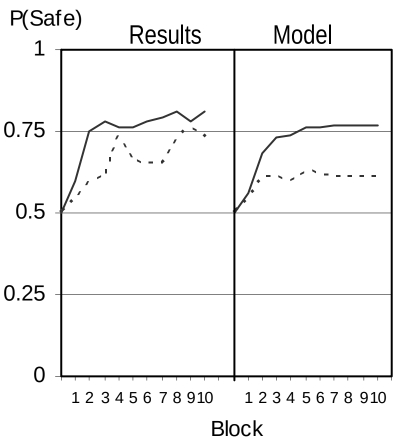
Figure 1. Proportion of safe choices in 10 blocks of 10 trials and the sensitive sampler model's predictions in each of the four problems studied in Experiment 1a.

1.a Problems 1 & 2:



Problem		S (safe)	R (risky)
1	Mixed	0	(1000, .5; -1000)
2	Gain	1000	(2000, .5; 0)

1.b Problems 3 & 4:

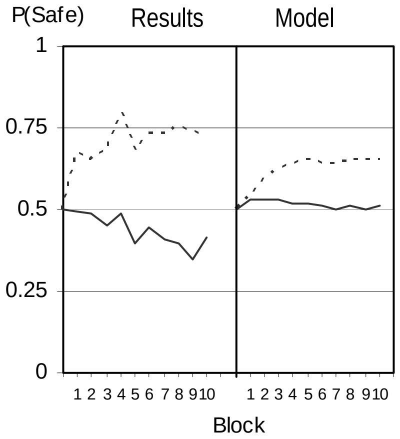


Problem		S (safe)	R (risky)
3	Mixed	400	(1400, .5; -600)
4	Gain	1400	(2400, .5; 400)

The notation (*X, p; Y*) refers to a gamble that yields a payoff of *x* with probability *p* and *y* otherwise.

Figure 2. Proportion of safe choices in 10 blocks of 10 trials and the sensitive sampler model's predictions in each of the pair of problems studied in Experiment 1b.

Problems 5 & 6:



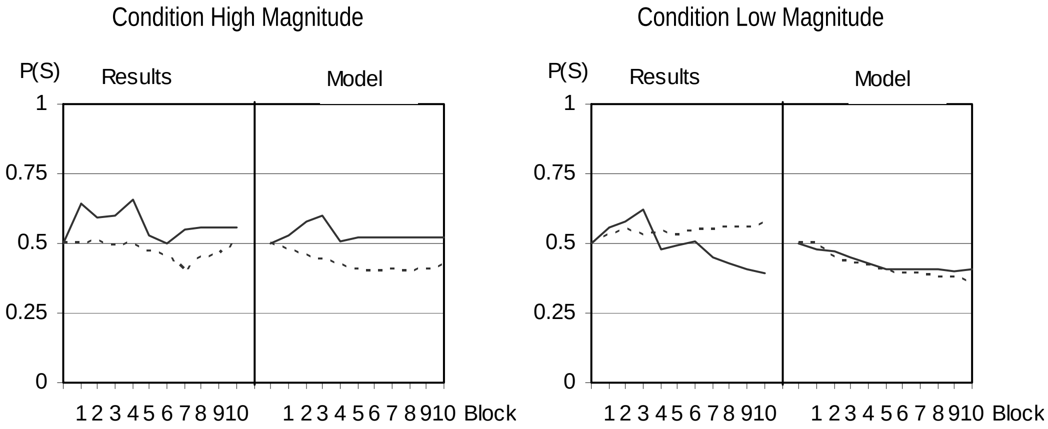
Problem		S (safe)	R (risky)
5	Mixed	(200, .5;-200)	(1000, .5; -1000)
6	Gain	(1200, .5; 800)	(2000, .5; 0)

The notation (*X, p; Y*) refers to a gamble that yields a payoff of *x* with probability *p* and *y* otherwise.

Figure 3. Proportion of safe choices under high and low point magnitudes, and the sensitive sampler model's predictions in 10 blocks of 10 trials in each of the four problems studied in Experiment 2.

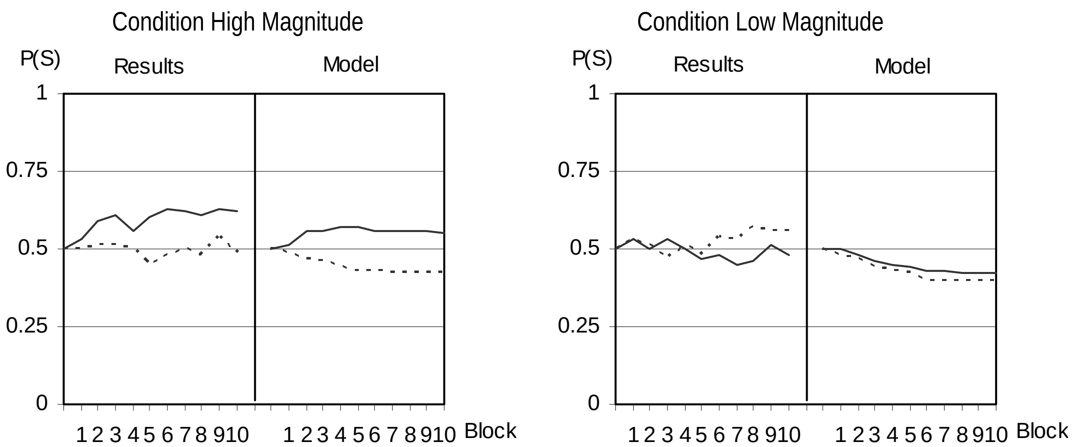
3.a Problems 7 & 8:

Problem		S (safe)	R (risky)
—— 7	Mixed	0+u(0,1)	(2, .5;-1)+u(0,1)
- - - - 8	Gain	3+u(0,1)	(5, .5;2)+u(0,1)



3.b Problems 9 & 10:

Problem		S (safe)	R (risky)
—— 9	Mixed	TN(0.25, 0.177, 0)	N(1.00, 3.54)
- - - - 10	Gain	TN(12.25, 3.54, 12)	N(13.00, 3.54)



The left-and right-hand columns present the results and the predictions of the sensitive sampler model respectively in each of the point magnitude conditions (High and Low). The notation (*X, p; Y*) refers to a gamble that yields a payoff of *x* with probability *p* and *y* otherwise. The notation u(*V, Z*) refers to a draw from a uniform distribution between *v* and *z*. The notation N(*B, F, P*) refers to a draw from a normal distribution with mean of *B*, standard deviation of *F*, and the payoff is truncated at point *P*.

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Ido Erev is the ATS' Women's Division Professor of Industrial Engineering and Management at the Technion, and a Marvin Bower fellow at HBS (in 2007-2008). His current research focuses on decisions from experience and the economics of small decisions. Examples of implications include the design of rule enforcement systems and training methods.

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Loss aversion in the eye and in the heart: The Autonomic Nervous System's responses to losses

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Loss aversion in the eye and in the heart: The Autonomic Nervous System's responses to losses

Abstract

The common view in psychology and neuroscience is that losses loom larger than gains, leading to a negativity bias in behavioral responses and Autonomic Nervous System (ANS) activation. However, evidence has accumulated that in decisions under risk and uncertainty individuals often impart similar weights to negative and positive outcomes. We examine the role of the ANS in decisions under uncertainty, and its consistency with the behavioral responses. In three studies, we show that losses lead to heightened autonomic responses, compared to equivalent gains (as indicated by pupil dilation and increased heart rate) even in situations where the average decision maker exhibits no loss aversion. Moreover, in the studied tasks autonomic responses were not associated with risk taking propensities. These results are interpreted by the hypothesis that losses signal the subjective importance of global outcome patterns.

Keywords: decision making, autonomic arousal, loss aversion

Introduction

In the past two decades numerous studies in diverse areas of psychology have suggested that bad is stronger than good, that is, that negative experiences have greater influence on the individual than positive experiences (see Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Rozin & Royzman, 2001; Vaish, Grossmann, & Woodward, 2008). For example, research has shown that first impressions are more affected by unfavorable than by favorable information (Fiske, 1980) and that well being is more affected by negative than by positive social interactions (Rook, 1984). Studies of decisions under certainty similarly showed that the threat of losing a potential reward has larger effect on performance than the promise of gaining the same reward (Costantini & Hovig, 1973; Ganzach & Karshai, 1995). Additionally, researchers have recorded more physiological arousal (Bechara, Damasio, Tranel, & Damasio, 1997; Löw, Lang, Smith, & Bradley, 2008; Satterthwaite, et al., 2007) following negative events than following positive events (for related findings involving brain activity, see Tom, Fox, Trepel, & Poldrack, 2007). For example, Satterthwaite et al. (2007) administered a task where the participants guessed which of two cards would turn up higher, and received positive or negative feedback according to their success. The results showed that pupil diameter (PD), an index of autonomic activation (Andreassi, 2000), became larger following negative feedback. These findings are assumed to denote a negativity bias, since autonomic nervous system (ANS) arousal, which accompanies emotional or cognitive responses to psychological stimuli (Andreassi, 2000; Annoni, Ptak, Caldara-Schnetzer, Khateb, & Pollermann, 2003; Cacioppo, Tassinary, & Berntson, 2007), has been shown to serve as a physiological correlate for behavioral responses to incentives (Heitz, Schrock, Payne, & Engle, 2007; Sokol-Hessner et al., 2009).

However, examinations of behavioral response to losses in decision making under risk and uncertainty have failed to replicate the negativity bias (Ert & Erev, 2008; Erev, Ert, & Yechiam, 2008; Erev et al., in press; Kermer, Driver-Linn, Wilson, & Gilbert, 2006; Kortizky & Yechiam, in press; Rozin & Royzman, 2001; Yechiam & Ert, 2007; 2009). These studies have demonstrated that increased sensitivity to negative outcomes is not exhibited in the classic laboratory decision making paradigms. Specifically, Kahneman and Tversky (1979) argued that because losses loom larger than gains most people would not accept gambles with mixed symmetric losses (i.e., gaining or losing an amount with the same likelihood). In reality, people tend to be indifferent, on average, between these gambles and their certainty equivalents.

On top of the recent accumulated evidence showing that individuals do not exhibit increased behavioral sensitivity to negative outcomes, due to several methodological considerations, it could be argued that the physiological results in support for a negativity bias are equivocal. Namely, in several of these studies, gains and losses were not symmetrical in magnitude (e.g., Sokol-Hessner et al., 2009), frequency (e.g., Bechara et al., 1997) or both (e.g., Tom et al., 2007), so firmest conclusions are not permitted (Baumeister et al., 2001). For instance, in Tom et al. (2007) and in Sokol-Hessner et al. (2009), losses were always smaller than their equivalent gains. Thus, the observed negativity bias in these studies could be confounded by diminishing sensitivity to large outcomes (Kahneman and Tversky, 1979), which affected gains more than losses. Similarly, these studies did not include a control condition which incorporates no losses. Thus, their results cannot differentiate increased sensitivity to negative outcomes from increased sensitivity to performance failure (i.e., error versus success, see e.g., Critchley, Tang, Glaser, Butterworth, & Dolan, 2005), consistent with the error related negativity phenomenon (e.g., Frank, Woroch & Curran, 2005), or from increased sensitivity to risk in general, consistent with affect-based decision models (e.g., Clore, Schwarz, & Conway, 1994; Damasio, 1996; Loewenstein, Weber, Hsee, & Welch, 2001).

In the current study we aimed to disentangle the role of losses in decision making, by examining the behavioral response to losses and its physiological correlates in decisions under uncertainty with symmetric gains and losses. In addition, we included an appropriate control condition to differentiate the effect of absolute losses from that of relative losses, in order to compare an assertion of arousal following losses to arousal following errors.

To do so, we evaluated three contrasting predictions. The first prediction builds on the suggestion of Erev et al. (2008) that decisions under uncertainty represent a distinct context in which people have no special sensitivity to losses, as opposed to riskless decisions (see also Ert & Erev, 2008). This is explained by the argument that because in decisions under uncertainty (and risk) the same alternative produces both gains and losses, people’s tendency to maintain some level of risk (and avoid boredom and monotonicity) implies no discounting of small to moderate losses compared to equivalent gains (Yechiam & Ert, 2007). Assuming that autonomic arousal also reflects the subjective indifference to losses in such decisions, then both behavior and ANS arousal should not exhibit the negativity bias.

The second prediction, which is referred to as the individual differences prediction, builds on findings of individual differences in the subjective weighting of losses and gains (Busemeyer & Stout, 2002; Sokol-Hessner et al., 2009; Worthy, Maddox, & Markman, 2007). It assumes that while the ANS is more sensitive to losses than gains in robust settings (as demonstrated above), behavioral loss aversion only emerges for individuals with relatively high level of arousal following losses. Consequently, only *some* people exhibit behavioral loss aversion. Additionally, under this account a positive correlation is expected between arousal following losses and risk aversion with symmetric gains and losses.

The third and final prediction suggests that losses signal a potential threat in the environment and hence leads to increased arousal (see Critchley, Mathias, & Dolan, 2002). However, they affect the subjective significance of *whole* outcome patterns and not only the loss component. Accordingly, losses increase the perceived risk associated with choice alternatives (Yechiam, 2009). Since people are differentially affected by the perceived risk level (i.e., some people are risk averse and stay away from high risk situations while others are risk seeking and prefer them over their certainty equivalents), the increased arousal should not be associated with the individual's tendency to take risk. We shall refer to this last account as the Loss signals Risk (LSR) hypothesis. Findings consistent with this hypothesis were reported by Coombs and Lehner (1981, 1984) who showed that for a lottery where individuals have an equal chance of winning or losing $10, adding $10 to the loss increased perceived risk more than adding the same amount to the gain.[1]

It should be noted that since autonomic arousal is assumed to represent the impact of emotional responses to negative and positive outcomes (Sokol-Hessner et al., 2009), the first two contrasting predictions are actually both consistent with affect-based decision-models (e.g., the *risk-as-feelings* hypothesis by Loewenstein et al., 2001; the *somatic-marker* hypothesis by Damasio, 1996), which argue that affect experienced at the moment of decision making is used to evaluate the level of risk,

[1] Yet these findings have the possible problem of individuals not being able to clearly define the term risk independently from loss.

and to then direct behavior, even in the face of divergent cognitive information. Similar to these models, our first two predictions argue that the affect indexed by autonomic arousal should be consistent with behavioral choices. The LSR hypothesis is different because it suggests that the role of losses in decisions under risk and uncertainty is not realized as a simple affect preceding one's choices, but rather is part of a computation involving an integration of expected gains and losses (thus predicting no direct linkage between affect following losses, indexed by arousal, and subsequent choices).

To test these predictions, we conducted three studies. The first two studies measured the change in PD following gains compared to losses. PD was used since it is considered an immediate and direct index of autonomic activation, which is directly related to cognitive and emotional processes (Andreassi, 2000; Bradley, Miccoli, Escrig, & Lang, 2008; Granholm & Steinhauer, 2004). In addition, PD has been found to be relatively sensitive to monetary incentive used in decision making tasks, even compared to more common ANS measures such as skin conductance (Heitz et al., 2007). Study 3 replicated Study 1's results using Heart-Rate (HR), a more commonly studied ANS measure (Andreassi, 2000; Malik, 1996). Together, the three studies indicate that autonomic indices display a negativity bias even when behavior is not negatively biased. Moreover, the results are consistent with the LSR hypothesis, showing no association between autonomic responses to losses and behavioral tendencies to avoid them.

Study 1: Effects of gains and losses on pupil diameter

In this study, the participants were administered decision tasks involving absolute or relative monetary losses. In addition to examining their behavioral choices, we also recorded their autonomic activity, as indexed by the effect of losses (and gains) on their pupil dilation. The participants played for points with a conversion rate of 1 New Israeli Shekel (NIS) per 10 point earned. In the first (within-subject) condition, referred to as the Mixed Condition, one choice alternative resulted in a 50/50 chance of gaining or losing 2 points and the other resulted in a 50/50 chance of gaining or losing 1 point. The second condition, labeled All-Gains, offered a similar dilemma, with the exception that a fixed value of 3 points was added to all payoffs (i.e., one alternative produced 1 or 5 points and the other produced either 2 or 4 points, with equal probability). This All-Gains condition was created to preserve the risk level while eliminating the possibility of incurring losses.

Method

Participants

Twenty-five healthy undergraduates from the Technion – Israel Institute of Technology (13 females; mean age, 23.8 years, SD = 1.9) participated in the experiment. All participants were free of neurological and psychiatric history and had normal or corrected 20/20 vision. Participants were given a show-up fee of NIS 20 and were additionally paid according to the amount earned in the experimental task.

Procedure

Participants were presented with a computerized “money machine”, which consisted of two unmarked buttons, an obtained payoff counter, and an accumulated payoff counter. Each selection of one of the buttons was followed by a presentation of the obtained payoff, (e.g., -2 or +2 in the risky option under the Mixed condition) on the selected button and on the obtained payoff counter for two seconds, and an updating of the accumulated payoff counter which was presented constantly. The minimal inter-trial interval was 2 seconds, and the number of trials in each condition was 60.

The participants were instructed to repeatedly select a button in order to maximize their earning, while their PD was recorded. Participants were also informed that they would earn NIS 1 for every 10 points won in the experiment. The payoffs were contingent on the participants’ choices, as indicated above. In addition, in order to make the incentive structure less obvious, a constant of 0.1-0.5 (in 0.1 intervals) was randomly added or subtracted from the sampled payoff in every trial.

Payoffs were delivered in a deterministic fashion: each task started with either a gain/relative-gain or a loss/relative-loss, and in each choice alternative (independently) the sign of the payoff was switched on each trial. This was done so as to eliminate possible surprise effects that would be non-symmetric with respect to gains and losses. In addition, the order of the two experimental conditions was controlled. Half of the participants were presented first with the Mixed condition, followed by the All-Gains condition, while for the other half this order was reversed. Similarly, half of the participants were presented with a gain/relative-gain in the first trial, followed by a loss/relative-loss in the second trial, while for the other half this order was reversed.

PD data acquisition

Eye-tracking data was collected using ViewPoint PC 60 EyeFrame system (Arrington Research, Scottsdale, Arizona). The system operates with a single tiny camera and an infrared illuminator mounted on a lightweight frame facing toward the participant's dominant eye, and supported by comfortable head straps. It records pupil data at approximately 30 frames per second (fps). Pupil data was measured as the diameter of the pupil in response to gains and losses in the window of 0.5 seconds before the stimulus onset to 2.0 seconds after stimulus onset. Pupil data was averaged to produce a data step every 250 milliseconds. The participants' heads were fixed by a head and chin rest during the whole session. New sixteen-point calibrations and validations were performed prior to the start of each session.

Results

The proportion of risky choices [P(Risky)] across all trials in Study 1 was 0.46 in the Mixed condition and 0.51 in the All-gains condition (Figure 1A). A t-test for paired samples revealed no significant difference between P(Risky) in the two conditions [$t(24) = -0.89$, $p = .38$]. In addition, both proportions were not significantly different from the 50% chance level [$t(24) = -1.25$, $p = .22$; $t(24) = 0.26$, $p = .80$, respectively]. As been shown in several recent studies of decisions under uncertainty (e.g., Erev et al., 2008; Kermer et al., 2006; Kortizky & Yechiam, in press; Yechiam & Ert, 2007), our results indicated that behaviorally, participants did not prefer outcomes with lower losses, nor exhibited more risk aversion in the Mixed condition as would be predicted if losses were overweighted.[2]

On the other hand, absolute losses in the Mixed condition were associated with larger average PDs compared to absolute gains (Figure 1B). This was not observed for the All-Gains condition (Figure 1C). Two by two repeated measures analyses of variance (ANOVA) were conducted for each of the epochs with payment (gains versus losses; either absolute or relative) and condition (Mixed versus All-Gains) as within subject variables. The results showed a significant interaction between payment and domain in the epochs of 625-875 ms [$F(1, 24) = 4.106$, $p = 0.05$].

Post-hoc paired-sample t-test analyses revealed that in the Mixed condition the increased arousal following losses was significant in the epochs of 625 ms to 1125 ms after the stimulus onset [625-875 ms: $t(24) = -2.63$, $p = .01$, and 875-1125 ms: $t(24) = -2.33$, $p = .03$, respectively]. These results were replicated for separate choice alternatives (i.e., risky versus safe) (Figure 2A and 2B), suggesting that the negativity bias is robust and does not reflect mere risk aversion. However, these findings were not observed in the All-Gains condition (i.e., *relative* losses did not lead to more arousal than relative gains) (Figure 1C). Thus, a gap appeared between the behavioral loss-indifferent choices and the autonomic negatively biased responses.

We next evaluated the contrasting predictions of the individual-differences and LSR hypotheses by examining if individuals who respond to losses by increasing their arousal (compared to gains) also exhibit more loss aversion. Focusing on the Mixed condition, we calculated the correlation between the unique arousal experienced upon losses [625-1125 ms. following the onset of the outcome

[2] No gender differences was found for the behavioral or for the physiological responses in Study 1, as well as in the other studies reported in this paper. Thus, for conciseness, the data for females and males was collapsed.

presentation: PD(Losses) – PD(Gains)] and the proportion of choices from the safe alternative which produces lower magnitude losses. The results showed no significant correlation ($r = -0.06$, $p = .76$). This pattern of results supports the LSR hypothesis (although it should be interpreted with caution due to the small sample size), and suggests that individual differences in contingent arousal do not seem to affect the tendency to avoid losses.

Finally, the individual consistency between arousal following losses and loss sensitivity was examined. Because the number of losses from the risky alternatives for each participant was relatively small, we focused on the tendency to switch choices following losses (from either the safe or risky alternative) as the behavioral indicator for loss sensitivity: the so called "loss-shift" tendency (Erev et al., in press). For each participant, the correlation between arousal in response to a loss (in time *t*) and the decision to switch choices afterwards (in *t+1*) was calculated for 29 trials (0 = no switch; 1 = switch). The results showed that on average, the correlation was near zero (average $r = -0.007$, $SD = 0.22$ in the epochs of 625 ms to 1125 ms after the stimulus onset). A one-sample t-test analysis revealed that the average correlation was not significantly different from zero [$t(49) = -0.235$, $p = 0.815$]. Similarly, only two of the participants showed a significant correlation ($p < 0.05$) during these epochs which was in the direction of the individual differences hypothesis. Thus, these findings further support the LSR hypothesis and show that increased arousal in response to losses does not affect the tendency to avoid losses by switching to another alternative.

Study 2: Replication with natural numbers

The results of Study 1 could be interpreted as indicating that in decisions under uncertainty the ANS is more sensitive to losses than participants' choice behavior.

However, an alternative interpretation is that the enhanced autonomic arousal was the results of the effort in processing negative numbers (Tzelgov, Ganor-Stern, & Maymon-Schreiber, 2008). Study 2 was designed to contrast these two interpretations. For this purpose the +/- signs were represented by randomly selected colors (either green or red) so that natural rather than negative numbers denoted the magnitude of penalties.

Method

Participants

Nineteen healthy undergraduates from the Technion (13 females; mean age, 24.1 years, SD = 2.6) who did not take part in Study 1 participated in the experiment. All participants were free of neurological and psychiatric history and had normal or corrected 20/20 vision. Participants were given a show-up fee of NIS 30 and were additionally paid according to the amount earned in the experimental task.

Procedure

The procedure was identical to that of Study 1 (Mixed condition). However, the +/- signs were represented by randomly selected colors (either green or red). Specifically, participants were randomly assigned to one of two conditions. In the first condition (n = 10) negative outcomes were represented by red colored buttons and positive outcomes were represented by green colored buttons. In the second condition the colors were reversed. Participants were instructed about the meaning of the two colors. A manipulation check conducted after task completion revealed that all participants associated the color with its correct meaning (reward or penalty). Additionally, the accumulated payoff was also presented graphically, and its color matched the color assigned to positive or negative outcomes, depending on the sign of the accumulated sum. Finally, to ensure that the effect is not limited to small nominal magnitudes (Harinck, Van Dijk, Van Beest, & Mersmann, 2007), nominal payoff values were multiplied by 10.

PD data acquisition

Recording of physiological data were conducted as in Study 1.

Results

Virtually the same pattern of results was found as in Study 1. The aggregated proportion of P(Risky) across all trials was 0.48 (Figure 3A), and not below chance level [t(18) = -0.68, p = .50]. At the same time, losses were associated with significantly larger PDs on average, in the epochs of 375-625 ms [t(18) = -1.74, p = .09] and 625-875 ms [t(18) = -4.44, p < .001] after the stimulus onset (Figure 3B). This pattern remained when choices were held constant (Figure 4).

We next calculated the correlation between the unique arousal experienced upon losses in the Mixed condition [625-1125 ms. following the stimulus onset: PD(Losses) – PD(Gains)] and the proportion of choices from the safe alternative which produces lower magnitude losses. The results show no significant correlation (r = 0.31, p = .19), again suggesting that loss sensitivity is completely independent from the individual's arousal level following losses, as predicted by the LSR hypothesis.

Finally, as in Study 1, the correlation between arousal in response to loss and the decision to switch choices following this loss was calculated separately for each participant. The result of this analysis showed that on average, the correlation was close to zero (average r = 0.04, SD = 0.15 in the epochs of 625 ms to 1125 ms after the stimulus onset). A one-sample t-test analysis revealed that this correlation is indeed not significantly different from zero [$t(37) = 0.888$, $p = 0.380$]. In fact, not even a single participant showed a significant correlation ($p < 0.05$) during these epochs. Thus, consistent with the LSR hypothesis, increased arousal in response to losses did not predict the tendency to switch choices after experiencing losses.

Study 3: Effects of gains and losses on Heart Rate

In this study we sought to examine the generality of the current results for other measures of autonomic arousal. We chose the HR, a common measure of cognitively-related ANS activity (Andreassi, 2000). In this final study participants were administered the same task as in Study 1, while there autonomic activity, as indexed by HR, was monitored.

Method

Participants

Twenty-two healthy undergraduates from the Technion (8 females; mean age, 23.7 years, SD = 1.5) who did not take part in Studies 1 and 2 participated in the experiment. All participants were free of neurological and psychiatric history. Participants were given a fixed rate fee of NIS 20 and were additionally paid according to the amount earned in the experimental task.

Procedure

The procedure was identical to that of study 1 except for the minimal inter-trial interval, which was set to 15 seconds to minimize residual effects of prior outcomes.

HR data acquisition

HR data was obtained using the SitePAT-200 (Itamar Medical Ltd., Keisaria, Israel), a photo-cell sensor plethysmograph, shaped as a finger cup, which is placed at the end of the first finger of the non-dominant hand (see e.g., Karasik et al., 2002). The participants' non-dominant hand was fixed on a hand rest during the whole session. The rate of data acquisition was 100 Hz, averaged to about 1 sample per second. HR data is presented as the number beats of the heart in a minute. HR was measured in the window of 2 seconds before the stimulus onset to 5 seconds after stimulus onset.

Results

The proportion of risky choices across all trials in Study 3 was 0.5 in the Mixed condition and 0.49 in the All-gain condition (Figure 5A). A t-test for paired samples revealed no significant difference between P(Risky) in the two conditions [$t(21) = 0.107$, $p = 0.92$]. In addition, both proportions were not significantly different from the 50% chance level [$t(21) = 0.034$, $p = 0.97$; $t(21) = -0.10$, $p = 0.92$, respectively]. Thus, similar to Studies 1 and 2, our results indicated that participants did not exhibit any increased sensitivity to negative outcomes in their behavioral choices.

On the other hand, absolute losses in the Mixed condition were associated with higher average HR compared to absolute gains (Figure 5B). A two by two repeated measures ANOVA (conducted as in Study 1) revealed a significant interaction between payment and domain in the epoch of 1-2 seconds following the outcome presentation [($F(1,21) = 4.121$, $p = 0.05$]. Consistent with the results of Study 1, this interaction suggests that the increased sensitivity of the autonomic activation index to negative outcomes was the result of a unique response to absolute losses.

Post-hoc paired-sample t-test analyses revealed that in the Mixed condition, the difference was significant in the epochs of 0-1 and 1-2 seconds after the stimulus onset [$t(21) = -2.137$, $p < .05$, and $t(21) = -2.607$, $p < .02$, respectively]. However, these findings were not observed in the All-Gains condition (i.e., *relative* losses did not lead to more arousal than relative gains) (Figure 5C). Thus, as in Studies 1 and 2, a gap appeared between the behavioral loss-indifferent choices and the autonomic negatively biased responses. The same pattern of results was observed for separate choice alternatives (i.e., risky versus safe) but for conciseness this examination is not presented.

As in the previous studies, we next evaluated the contrasting predictions of the individual-differences and LSR hypotheses by examining if individuals who respond to losses by increasing their arousal also exhibit more loss aversion. Focusing on the Mixed condition, we calculated the correlation between the unique arousal experienced upon losses [1-2 seconds after the stimulus onset: HR(Losses) – HR(Gains)] and the proportion of choices from the safe alternative which produces lower magnitude losses. The results showed no significant correlation ($r = -0.06$, $p = .78$). Thus, in support of the LSR hypothesis, individual differences in contingent arousal did not correlate with the tendency to avoid losses.

Finally, for each participant, the correlation between arousal in response to a loss and the tendency to switch choices following this loss was calculated. The result showed that the average correlation was close to zero (average $r = -0.03$, $SD = 0.19$ in the epoch of 1-2 seconds after the stimulus onset). A one-sample t-test analysis revealed that this correlation was not significantly different from zero [$t(41) = -1.259$, $p = 0.215$]. Similarly, only one participant showed a significant correlation ($p < 0.05$) during this epoch which was in the direction of the individual differences hypothesis.

Thus, these findings correspond to the PD findings, and provide converging support for the LSR hypothesis, suggesting that for the majority of the participants, increased arousal in response to losses does not affect the tendency to avoid the alternative producing the losses; even though there was, on average, increased HR following losses than following equivalent gains.

General discussion

The present studies replicate recent findings indicating no behavioral sensitivity to negative outcomes in experience based decisions (Erev et al., 2008; Kermer et al., 2006), but at the same time show that this pattern of behavior is accompanied by a negativity bias in autonomic arousal. Two potential explanations were suggested to account for such findings: an individual-differences explanation suggesting that loss averse individuals are more aroused by losses than by equivalent gains, and the LSR hypothesis arguing that losses increase the subjective significance of whole outcome patterns (i.e., both gains and losses). Our results reject the individual-differences hypothesis and support the LSR hypothesis, by showing no correlation between autonomic arousal following losses (pupil size changes, heart rate) and the loss sensitivity of individual decision makers.

The LSR hypothesis appears to tie together the findings in decisions under certainty and uncertainty. In decisions under certainty where outcome patterns are either all gains or all losses, the subjective significance of whole outcome patterns involving losses is larger than those involving gains. Consequently, people show loss aversion in these tasks (e.g., Costantini & Hovig, 1973). However, in decisions under uncertainty with mixed outcomes the subjective significance of the whole history of payoffs is balanced, as it includes both gains and losses. As a result, the increase in autonomic activity following losses is not translated into a tendency to avoid such mixed outcomes, even for individuals with very high arousal following losses. Some of these individuals do avoid the risky outcomes signaled by losses, but others approach them.

An alternative explanation of the results might be that the current experience-based tasks were insensitive to the asymmetric effect of losses on human behavior, which appears in robust settings (e.g., Baumeister et al., 2001; Rozin & Royzman, 2001). Yet note that this argument also implies that the current task represents a situation where ANS activation is more sensitive to losses than behavioral choices, as been demonstrated by the results of our experiments. In other words, the current task represents a situation where despite of no behavioral loss aversion, a negativity bias exists in autonomic arousal, at the group and individual levels. This indicates a boundary condition for the risk-as-feeling hypothesis (Loewenstein et al., 2001) which posits a direct link between emotional responses and behavior. The LSR hypothesis argues that the link is less direct and specific and involves computations which take into account assessments concerning the global situations (i.e., the effect of both gains and losses).

More generally, we suggest that affects and emotions can be diffused from their original sources and used as a means to appraise global situations. A pertinent example is the effect of anger on signaling the extremity of an attitude in negotiations (Abelson, 1995). Anger, a negative emotion, is not used only as a key to inferring the negativity of the anger expresser, but also to communicate that the global issue under consideration is important to the to the expresser (Frank, 1988; Fridlund, 1991, 1994; Hinde, 1985; Keltner & Haidt, 2001; Morris & Keltner, 2000). Accordingly, it has some positive effects in negotiation dynamics (Brett, Shapiro, & Lytle, 1998;

Gottman & Levenson, 1992; Friedman et al., 2004). Thus, in this example the response to the negative emotion (anger) extends beyond the direct (negative) weighting of the person which expresses it, and into the global assessment of a situation which has positive and negative aspects. The LSR hypothesis makes a similar claim about the effect of losses, suggesting that the threatening emotional reaction they invoke is used to signal information concerning the global risk level, which is a function of both gains and losses.

Another finding of the current paper which diverges from current affect-based theories involves the assertion that risk, by its nature, activates emotional responses to signal threat (e.g., Loewenstein et al., 2001). The current findings indicate that losses, rather than risk itself, may serve as markers of risk level. Our interpretation of these findings is that losses, even minor ones, are an important natural signal of risk. Consequently, their absence could "fool" the affective system into responding as if there is no risk involved in experiential choices. This view is consistent with the special role of actual losses indicated in prospect theory (Kahneman, & Tversky, 1979) yet it is interesting that it appears in ANS activation, even though this activation is not translated into behavioral choices.

Additionally, the LSR hypothesis has some implications to the study of individual differences in risk taking. In particular, a common view suggests that sensitivity to gains versus losses is a psychological construct which affects risk taking behavior in a roughly linear manner (e.g., Busemeyer & Stout, 2002). In contrast, the LSR hypothesis is more consistent with models suggesting that risk level modulates risk taking behavior (Brachinger & Weber, 1997; Ert & Yechiam, 2009; Keller, Sarin, & Weber, 1986). Sokolowska and Pohorille (2000) have proposed one way in which these two constructs interact. They suggested that when risk level is very high the weighting of gains and losses has a lower impact on choice behavior (and the alternative is rejected). The LSR hypothesis suggests a second possible interaction: when losses are available, risk is signaled, and the subjective attitude towards risk has a larger impact. Further studies should examine these postulated interactions.

Finally, the current findings also go beyond error-based explanations of the negativity bias. It has been shown that error processing (i.e., performance failure) activates the ANS (Critchley et al., 2005). However, in the current context, this error-based explanation would suggest a similar pattern of results in the Mixed and the All-gains conditions, since both conditions represent the same degree of performance failure (relative to the reference point). The current results, showing that ANS activation was only larger following absolute losses suggests that negative outcomes trigger a distinct autonomic response, even compared to errors.

Potential limitations of the current study include the fact that the LSR hypothesis predictions included a main effect (of arousal following losses compared to gains) but also a null correlation between arousal and behavioral choices. Though inconsistent with studies showing that autonomic arousal is highly implicated in decision processes (Bechara et al., 1997; Critchley et al., 2001; Gerdes, 2006; Loewenstein et al., 2001), this null correlation can be interpreted as denoting complete breakup between autonomic arousal and decision processes involving risk taking. Future studies should further validate the argument of the LSR hypothesis concerning the signaling role of the autonomic system. For example, the LSR hypothesis implies that in *very high* levels of risk, the arousal following losses would be correlated with the tendency to avoid risk for most individuals.[3]

[3] While individuals tend to be risk neutral in low to moderate risk level, high risk levels lead to risk aversion (Erev et al., 2008; Holt & Laury, 2002)

Another open question concerns the temporal dynamics of the autonomic responses. It is interesting to note that the differences in autonomic responses to gains and losses occurred at about 1 second after the presentation of the outcome. Previous findings using PD have shown differences in a similar timeframe of approximately 1 second in the response to stimuli of different subjective significance such as in the response to relevant versus irrelevant text words (e.g., Oliveira, Aula, & Russell, 2009), and to positively or negatively marked words (Bierman et al., 2009). However, the significance of this time period is yet unclear.

Conclusions

The present findings show that in decisions under uncertainty, the response of the ANS is negatively biased. However, the simple interpretation of this bias as an indicator of the subjective significance of losses is inconsistent with the data. Even at the individual level, those showing high arousal did not tend to avoid losses to a greater extent. These results suggest a special role of losses in signaling the risk levels of global situations or environments, which has the ecological benefit of allowing individuals to tailor their behavioral choices to their preferred risk level (Yechiam, 2009). The current study represents the first psychophysiological test of this hypothesis, and clearly more research is needed to validate it.

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Figure 1: Study 1 results. (A) Proportion of participants selecting the risky option in the two experimental conditions. Trials are presented in blocks of 15. (B) Average pupil diameter in the Mixed condition as a function of the event type (gain versus loss). Time zero denotes the outcome presentation onset. Significant differences are marked by black dotted lines. (C) Average pupil diameter in the All-Gains condition as a function of the event type (relative gain versus relative loss).

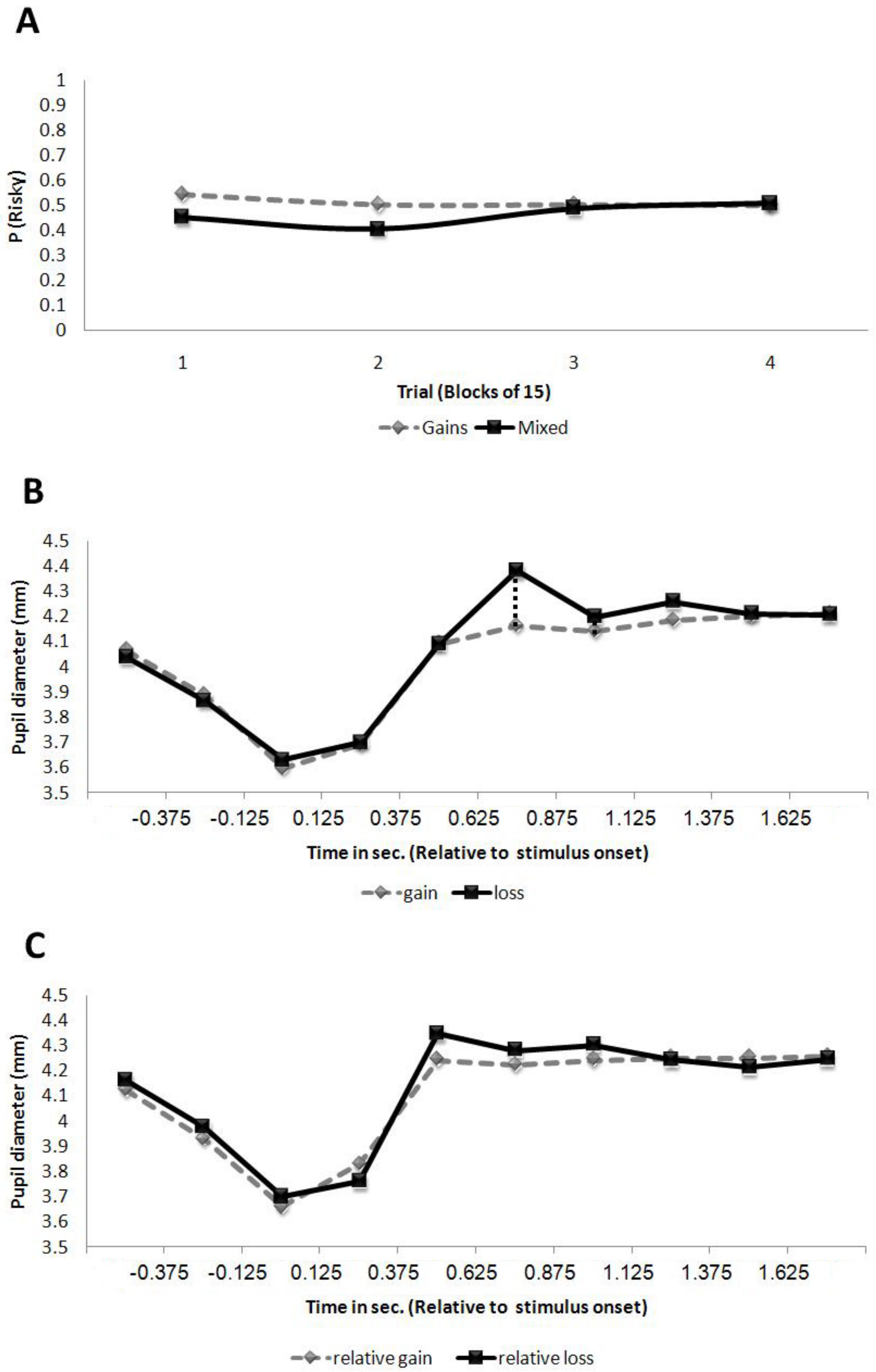


Figure 2: Detailed pupil diameter results for the Mixed condition of Study 1. (A) Average pupil diameter as a function of the event type (gain versus loss) for the safe choices only. Time zero denotes the outcome presentation onset. Significant differences are marked by black dotted lines. The results indicate that in the epoch of 625-875 ms, pupil diameters were significantly larger following negative than following positive outcomes ($p < .01$). (B) Average pupil diameter as a function of the event type (gain versus loss) for the risky choices only. The results indicate that in the epochs of 625-1375 ms pupil diameters were significantly larger following negative outcomes ($p < .05$).

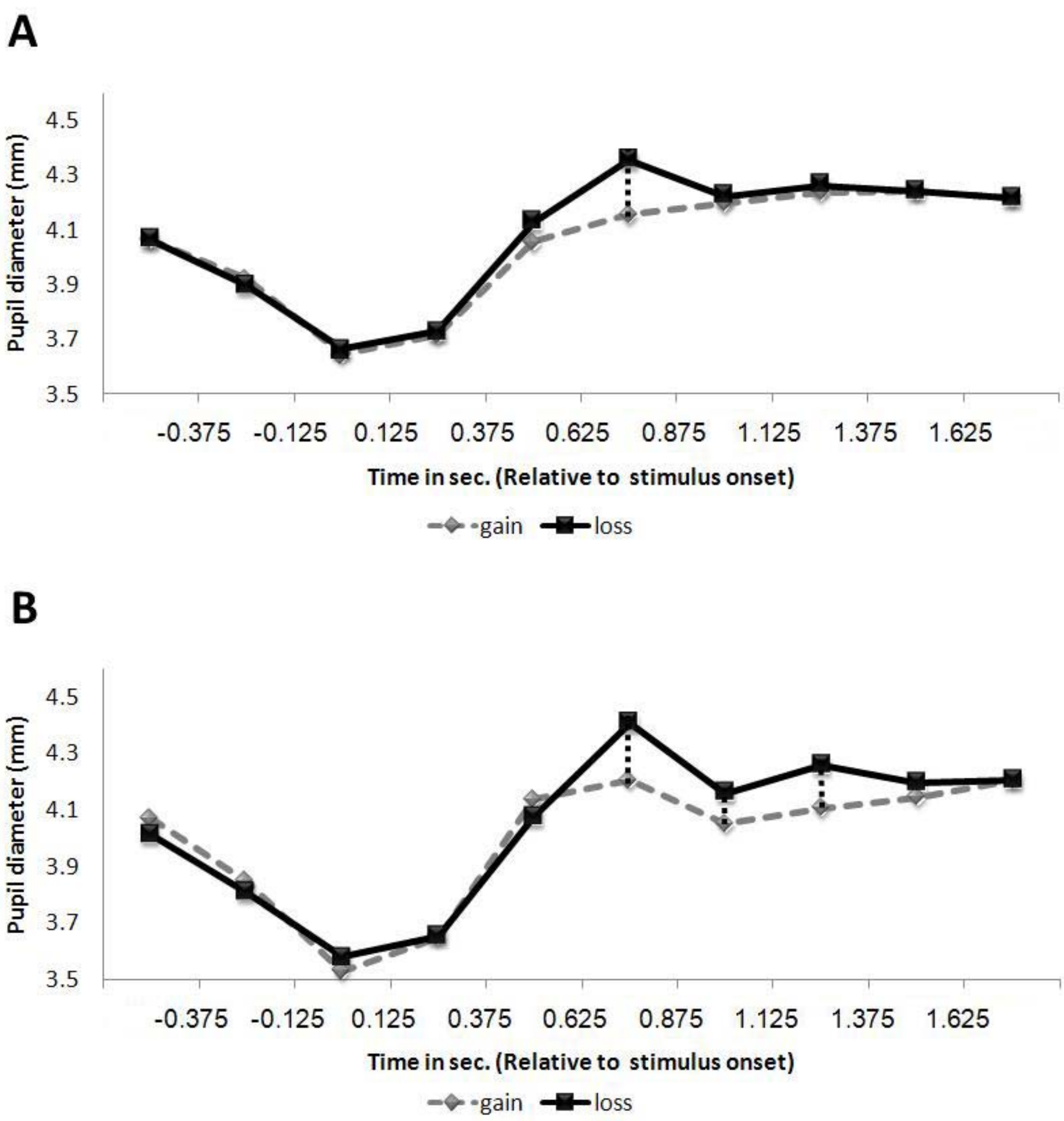
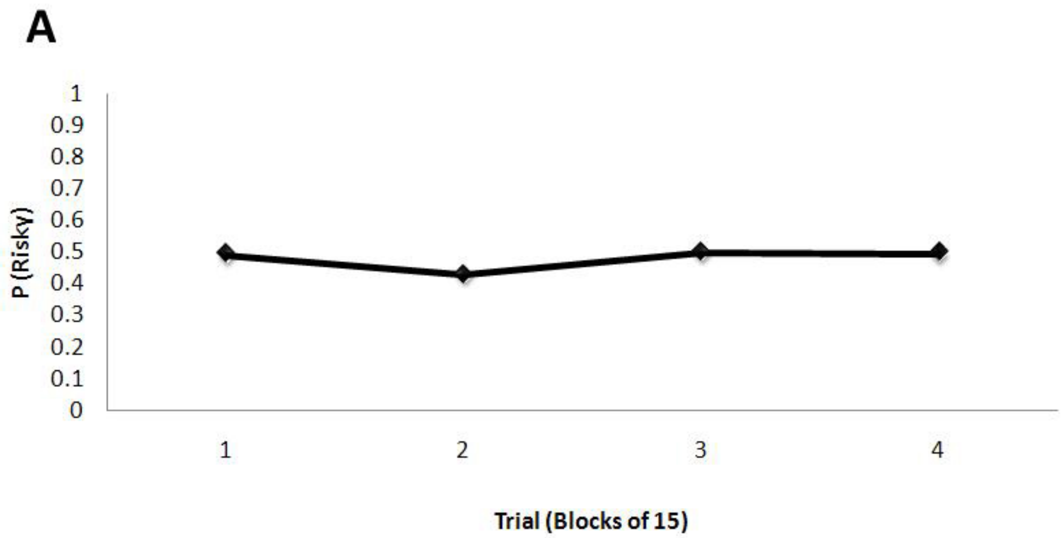


Figure 3: Study 2 (color version) results. (A) Proportion of participants selecting the risky option. Trials are presented in blocks of 15. (B) Average pupil diameter as a function of the event type (gain versus loss). Time zero denotes the outcome presentation onset. Significant differences are marked by black dotted lines.



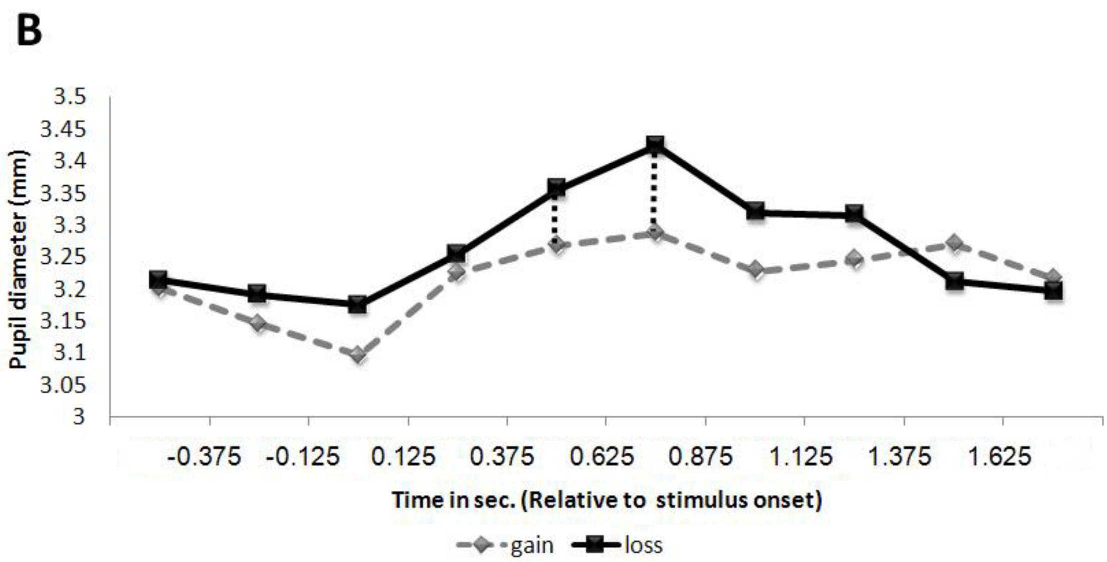


Figure 4: Detailed pupil diameter results for Study 2. (A) Average pupil diameter as a function of the event type (gain versus loss) for the safe choices only. Time zero denotes the outcome presentation onset. Significant differences are marked by black dotted lines. The results indicate that in the epochs of 625-1375 ms pupil diameters were significantly larger following negative than following positive outcomes ($p < .05$). (B) Average pupil diameter as a function of the event type (gain versus loss) for the risky choices only. The results indicate that in the epoch of 626-875 ms, pupil diameters were significantly larger following negative than following positive outcomes ($p < .05$).

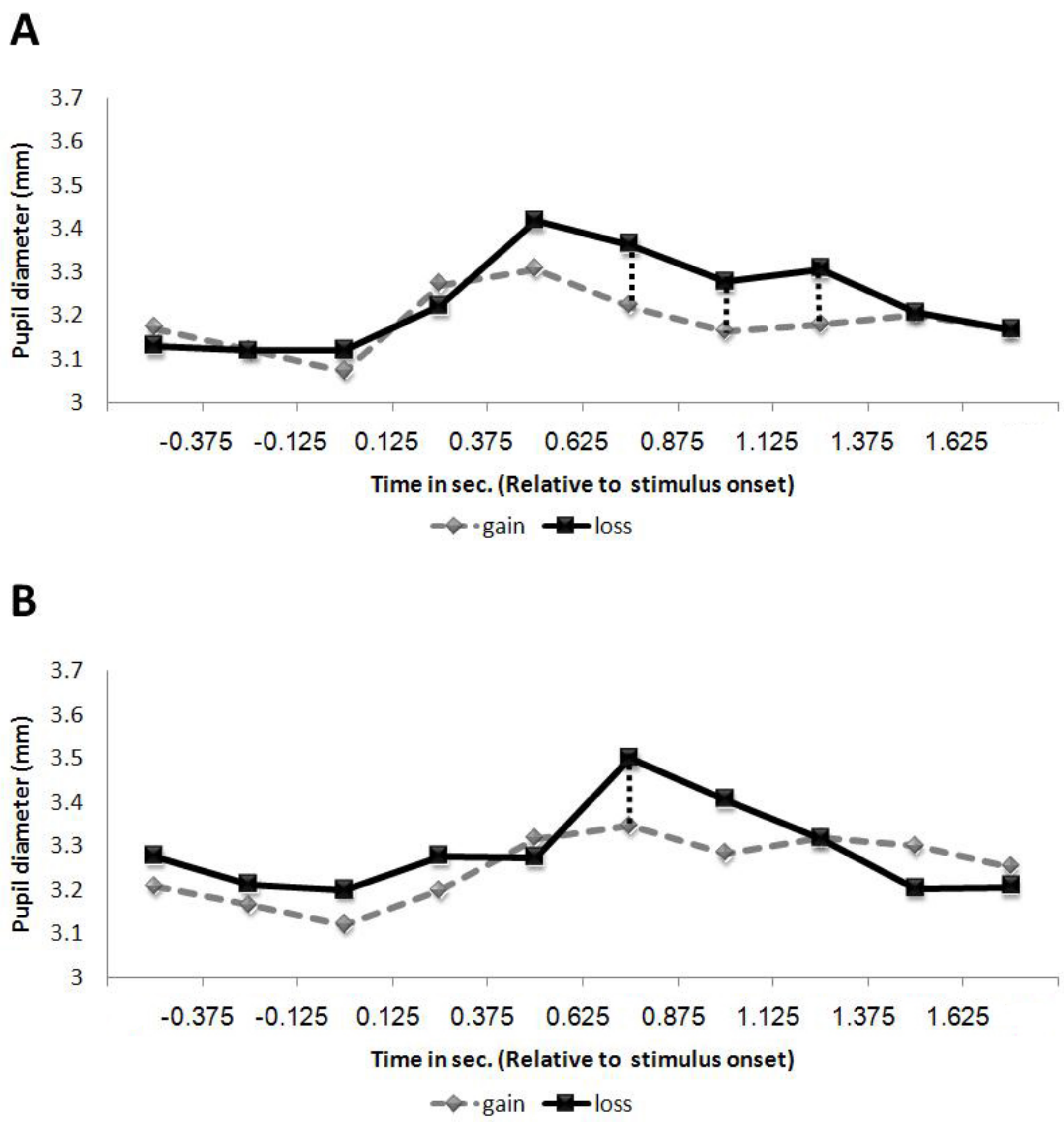
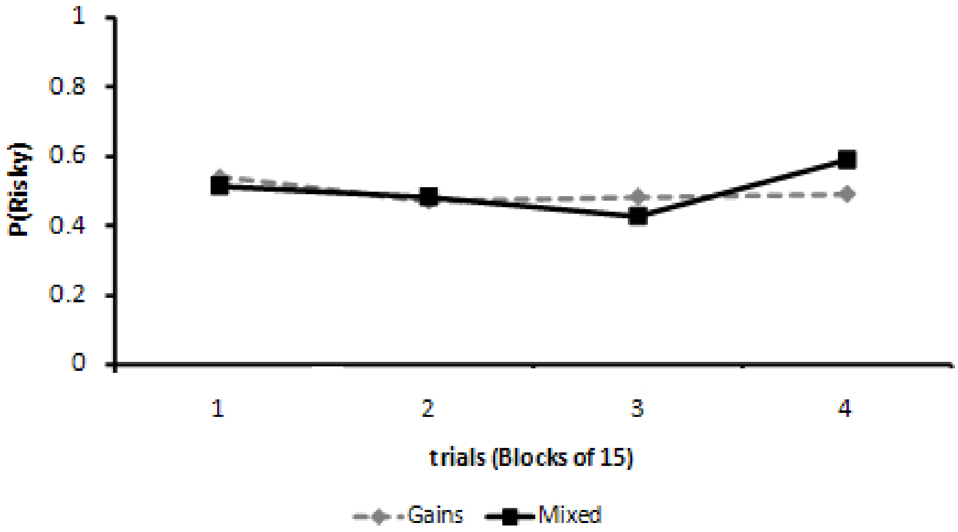
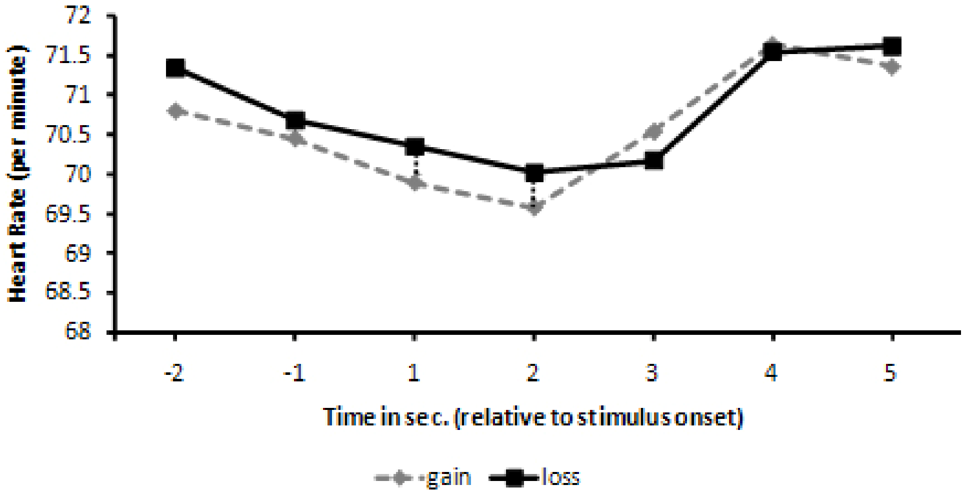


Figure 5: Study 3 results. (A) Proportion of participants selecting the risky option in the two experimental conditions. Trials are presented in blocks of 15. (B) Average heart rate in the Mixed condition as a function of the event type (gain versus loss). Time zero denotes the outcome presentation onset. Significant differences are marked by black dotted lines. (C) Average heart rate in the All-Gains condition as a function of the event type (relative gain versus relative loss).

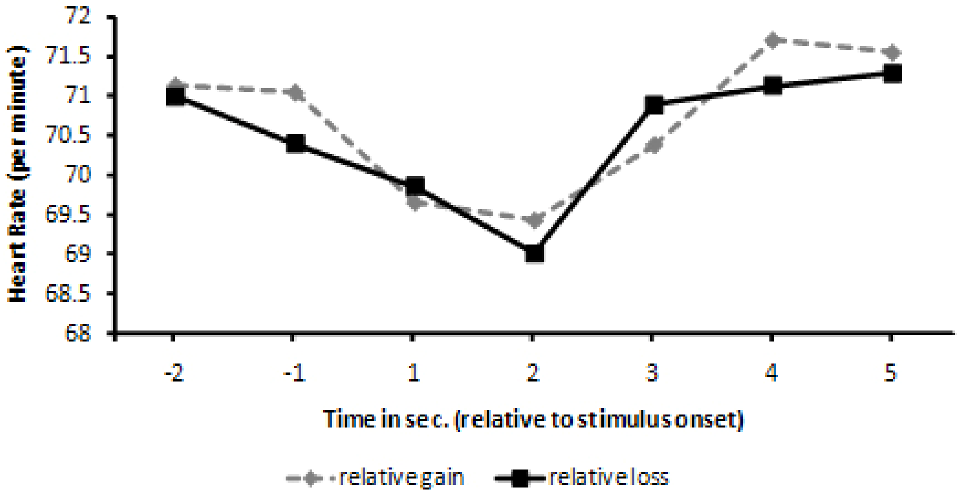
A


P(Risky)
1
0.8
0.6
0.4
0.2
0
1
2
3
4
trials (Blocks of 15)
Gains
Mixed

B


Heart Rate (per minute)
72
71.5
71
70.5
70
69.5
69
68.5
68
-2
-1
1
2
3
4
5
Time in sec. (relative to stimulus onset)
gain
loss

C


Heart Rate (per minute)
72
71.5
71
70.5
70
69.5
69
68.5
68
-2
-1
1
2
3
4
5
Time in sec. (relative to stimulus onset)
relative gain
relative loss