 DOI: 0.1037/xlm0000607

Are we attracted by losses? Boundary conditions for the approach and avoidance effects of losses

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Abstract: The majority of the literature on the psychology of gains and losses suggests that losses lead to an avoidance response. Several studies, however, have shown that losses can also lead to an approach response, whereby an option is selected more often when it produces losses. In five studies we examine the boundary conditions for these contradictory approach and avoidance effects. The results show that an approach response emerges only when losses are produced by a highly advantageous choice alternative and when participants have ample unbiased direct or vicarious experience with this alternative. Additionally, the avoidance response to losses is also not ubiquitous and emerges when alternatives producing losses are experienced as disadvantageous. Thus, the findings suggest that both the approach and avoidance effects of losses exist and can be accounted for by increased investment of cognitive resources with losses (i.e., loss attention). Additionally, the findings clarify the loss attention account in indicating that losses increase exploitative behavior based on experienced outcomes, a process which can be locally optimal.

Keywords: learning; experience; problem solving; loss aversion; loss attention.

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Penalties are known to have complex consequences and even Skinner (1971), a firm advocate of the disutility of penalties, asserted that they can have a positive effect on classroom attention because “by paying attention the students escape from the threat of punishment (and reinforce the teacher for threatening it)” (Skinner, 1971, p. 28). In forced selections among alternatives as well, financial losses can lead to two contradictory behavioral responses. Typically it is assumed that losses lead to a preventative response, namely avoidance of alternatives producing losses. This is a basic principle of a diverse set of theories including rational choice (e.g., von Neumann & Morgenstern, 1944), achievement motivation (Atkinson, 1964), and conditioning (e.g., Thorndike, 1935). Additionally, it has been found that losses are avoided more than gains are sought after (e.g., Tversky & Kahneman, 1992; Bereby-Meyer & Erev, 1998; Maddox, Baldwin, & Markman, 2006; Pope & Schweitzer, 2011; Saguy & Kteily, 2011). This asymmetry was explained by constructs such as loss aversion, i.e., the increased subjective weight of losses compared to equivalent gains (Kahneman & Tversky, 1979); loss avoidance, i.e., the tendency to reduce the likelihood of losses (Payne, Laughhunn, & Crum, 1980); and loss attention, i.e., increased attention when losses are possible, which can facilitate the avoidance of disadvantageous or detrimental alternative containing losses (Yechiam & Hochman, 2013a). Yet losses have also been found to lead to an approach response (Yechiam & Hochman, 2013a; Yechiam, Retzer, Telpaz, & Hochman. 2015). This type of response occurs when an advantageous alternative produces minor losses, thus losses lead to more choices from the advantageous alternative even though it also produces losses. This approach effect of losses was argued to be driven by the increased attention and cognitive performance brought about by losses (Yechiam &

Hochman, 2013b). In the current studies we evaluate the boundary conditions for these contradictory effects of losses on approach and avoidance.

Specifically, we revisit previous findings showing that minor losses produced by a highly advantageous choice alternative increase the likelihood of its selection, compared to a similar alternative with no losses (Yechiam & Hochman, 2013a; Yechiam et al., 2015). We evaluate whether this behavioral pattern is replicable, whether it is robust to changes in the risky alternative's payoff structure, and whether it requires experience (i.e., familiarity) with the alternative producing losses. The latter notion is consistent with studies in various domains showing that experience eases negative emotions. Pertinent examples include the reduction of negative feelings associated with objects following repeated interaction with them (Foa & Kozak, 1986; Robinson & Elias, 2005) and the reduction of food aversions through repeated tasting (Rozin & Schiller, 1980; Zandstra, De Graaf, Mela, & Van Staveren, 2000).

Most existing models of decisions from experience do not assume that losses lead to a paradoxical approach effect, because this effect is inconsistent with the assumption of dominance (von Neumann & Morgenstern, 1944). Under this assumption, reducing the value of an outcome associated with a given alternative should never improve the utility of the alternative. This notion is embedded in the utility functions of most reinforcement learning models (e.g., Sutton & Barto, 1998; Camerer & Ho, 1999; Sarin & Vahid, 2001; Yechiam & Busemeyer, 2005; Erev & Haruvy, 2015) as well as instance based learning models (e.g., Gonzalez & Dutt, 2011). In these models either losses are given more weight than gains or less weight than gains, but they can never be given a "negative weight" leading to an approach response. The notion of loss attention (Yechiam &

Hochman, 2013b) suggests that rather than being given a negative weight, losses increase the investment of cognitive resources (see e.g., Taylor, 1991; Yechiam & Hochman, 2013b) which typically increases the sensitivity to the task outcome (in situations where cognitive investment is not already very high).

The loss attention account can be formulized with a simple softmax model (Luce, 1959; Daw et al., 2006) assuming increased payoff sensitivity in tasks involving losses compared to those involving only gains. As demonstrated below, this model predicts that since losses facilitate sensitivity to expected value, they only lead to an approach response for highly advantageous risky alternatives. Alternatively, one could construct a learning model in which negligible losses trigger more risk seeking (similar to prospect theory's prediction for the loss domain; Kahneman & Tversky, 1979), e.g., due to an additional excitement when taking risk. This alternative model predicts that when a risky alternative produces minor losses this leads to an approach response irrespective of the expected value of the alternative (i.e., not only for an advantageous alternative). A similar prediction is made by notion of emotional contrast (Slovic, Finucane, Peters, & MacGregor, 2002) according to which an alternative producing large gains is more appealing when it also produces minor losses, regardless of the alternative's expected value.

Table 1 summarizes previous studies of approach responses driven by losses in forced-choice decisions. As shown in Table 1, in Yechiam and Hochman (2013a) and Yechiam et al. (2015) the relative preference of a risky alternative producing a large gain or a minor loss (e.g., +200 or -1 with equal probability) over a safe alternative (e.g., 35 for sure) was higher compared to where the risky alternative did not produce minor losses (e.g., +200 or +1 with equal probability). Thus, adding a minor loss to the risky alternative increased its attractiveness over the safe alternative.[1] However, this effect did not emerge in Erev, Ert, Plonsky, Cohen, and Cohen (2017). One major difference between these studies is that in Erev et al. (2017) expected value differences between risky and safe alternatives were smaller than in Yechiam et al.'s studies. We examine the effect of reduced expected value differences in Study 1 and 2. A second major difference is that Yechiam et al's studies had 100 trials whereas Erev et al.'s (2017) study only included 25 trials. It is therefore possible that the approach response requires sustained experience with the alternative producing losses (i.e., seeing multiple outcomes of that alternative).

Consistent with the notion that the approach response requires experience, increased choice of the risky alternative producing minor losses (compared to minor gains) in Yechiam and Hochman (2013a; Problem 1 in Table 1) and Yechiam et al. (2015; Problem 3 in Table 1) was only found after roughly 25 choices had been made. On the other hand, in Yechiam and Hochman (2013a) an approach response to losses was also found in one-shot decisions from description, where participants receive information about possible outcomes but do not get experience (Table 1, Problem 1, right most columns). This may suggest that experience is not a prerequisite for the approach response to losses. Thus, whether ample experience with the alternative producing losses is required for an approach effect of losses remains an open question.

[1] Note that the approach effect only occurred when the risky alternative producing the loss was advantageous in terms of expected value (e.g., in Problems 1 and 3, but not in Problems 2 and 4). This is consistent with the notion of loss attention, as demonstrated in Figure 1.

We conducted a series of studies to evaluate the robustness of the approach effect of losses and the conditions giving rise to it. It has been suggested that Amazon Mechanical Turk (MTurk) workers show greater avoidance of losses than student participants (Wolfson & Bartkus, 2013; see also Paolacci, Chandler, & Ipeirotis, 2010). We therefore began by testing whether the approach response found in the lab by Yechiam, Hochman, and colleagues can be replicated on MTurk. This was followed by examining the robustness of the effect to variations in probabilities and outcomes. Finally, we examined specific hypotheses driven by the possible effect of experience on reduced avoidance and increased approach to potential losses.

Quantitative Simulation

In order to derive quantitative predictions for the effect of losses, we conducted a simulation. Following Yechiam and Hochman (2013a) we adopted a simple softmax choice rule (Luce, 1959; Daw et al., 2006) to account for the approach effect of losses and predict its boundary conditions with respect to expected value differences between alternatives. Additionally, we added an assumption of diminishing marginal utility which exists in many models of decisions making (e.g., Kahneman & Tversky, 1979; Erev et al., 2008; 2017; Ahn et al., 2008).[2]

According to this softmax rule the probability of selecting alternatives is a function of their expectancies, representing the outcomes predicted upon selecting them, and random noise:

[2] According to this notion, the subjective impact of a change in the absolute payoff decreases with the distance from zero (see motivating observations in Stevens, 1957).

$$\mathrm{P}[j] = \frac{e^{\theta \cdot E_j}}{\sum_j e^{\theta \cdot E_j}} \ , \tag{1}$$

The probability (P) of selecting an alternative j is assumed to be a function of the distance between its expectancy (E_j) and the expectancy of other available alternatives, but to also be affected by random noise. The Parameter θ controls the sensitivity of the choice probabilities to the expectancies. θ of zero implies random choice, and as $\theta \rightarrow \infty$ this increases the likelihood of basing one's decision on the expectancies. Given no bias in the prediction of outcomes, higher values of θ imply greater expected value maximization. Under the loss attention account it is assumed that for tasks with losses θ is higher than for tasks with no losses ($\theta_{Loss} > \theta_{Gain}$).

We approximated E_j as the mean experienced utility of j, across participants, as follows:

$$E_j = \sum_i p_{i,j} \cdot sgn(x_{i,j}) \cdot |x_{i,j}|^{\alpha} \ , \tag{2}$$

For an alternative with i outcomes, the expectancy is the sum of each outcome's probability p multiplied by the sign of the outcome (using the signum function defined as follows: $sgn(x) = -1$ if $x < 0$; $sgn(x) = 0$ if $x = 0$; $sgn(\mathrm{x}) = 1$ if $x > 1$) and by its adjusted absolute magnitude where α is the degree of the utility function's concavity/convexity. The three parameters of the model are therefore θ_{Loss}, θ_{Gain}, and α.

The parameters of the model were estimated based on the two studies of decisions from experience with ample number of trials (100 trials): Yechiam and Hochman (2013b) and Yechiam et al. (2015). Following the extant experimental literature (e.g., Ahn et al., 2008; Erev, Ert, & Yechiam, 2008, Erev et al., 2017) the estimated value of α was constrained between 0 and 1 (implying diminishing marginal utility) and the estimated value of θ_{Loss} and θ_{Gain} was bounded between 0 and 10. Parameter estimation was conducted using an evolutionary algorithm (Coello, Lamont, & Van Veldhuizen, 2007) implemented in Microsoft Solver Foundation 3.1, with the following parameters: mutation rate = 0.075, population size = 100, random seed = 0, and convergence = 0.00001. The mean RMSD across conditions was 0.117.[3] The results showed that the estimated θ for the Gain condition was θ_{Gain} = 0.120; while for the Loss condition it was θ_{Loss} = 0.232; considerably higher. Additionally, a substantial degree of diminishing marginal utility was observed, with α = 0.68 (a similar value to that found in Erev et al., 2008; 2017). We then used these estimated parameters to generate predictions for a set of different problems.

First, we examined the effect of changes in the positive amount of the risky alternative. The predicted probability of selecting the risky alternative appears on the left panel of Figure 1. The simulated predictions indicate that the approach effect of losses is expected to diminish when the risky alternative's positive outcome is reduced (and expected value differences between alternatives are reduced as well). These predictions were examined in Study 1b.

Next, we examined the predicted effect of changes in the probability *p* of the risky alternative's positive event. As can be seen, the approach response is expected to increase with the increased probability of the positive outcome, up to a ceiling point, while low

[3] By comparison, if we force $\theta_{Gain} = \theta_{Loss}$ then RMSD is 0.150 (a 28% decrease in accuracy).

probabilities are predicted to eliminate the effect (at p = .4) and finally reverse it (at p = .3). Note that this latter prediction emerges even though the risky alternative is still advantageous; owing to diminishing marginal utility. These predictions were evaluated in Study 2.

In order to evaluate the effect of experience, we also examined the effect of getting feedback from the selected option only, thus biasing individuals' experience once they began avoiding the risky option. We could not use the current simulation to derive quantitative predictions for the effect of this manipulation (because without foregone payoffs the probability of the outcome is contingent on participants' choices). However, the results of the simulation do provide qualitative predictions. Under the hot stove effect (Denrell & March, 2001) an individual will stop selecting the risky alternative when its experienced average outcome is lower than that of the safe alternative. In a setting where an individual only sees the outcomes from the selected alternative, this implies a reduction in the actual frequency of getting positive payoff from the risky alternative compared to its population mean (e.g., 50% in Problem 1). Figure 1 suggests that if the frequency of getting the high positive payoff from the risky alternative drops below 50%, this should considerably reduce and possibly even reverse the approach effect. This was examined in Studies 3 and 4.

Study 1a. Replication in Amazon Mechanical Turk

We first replicated the study of Yechiam and Hochman (2013a) using the environment of Amazon Mechanical Turk (MTurk). We thus focused on Problem 1 in Table 1, in which a minor loss (of -1 in the Loss condition), or a minor gain (of +1 in the Gain condition), is produced by a risky but advantageous alternative. The Gain/Loss condition was manipulated between subjects. Following Yechiam and Hochman (2013a) the gain and loss schemes were administered under two additional between-subjects conditions: decisions from experience and from description.

Method

Participants. Overall 424 Amazon MTurk participants were recruited for the study, 202 for the decisions from experience condition (96 females, average age = 39.2) and an additional 222 for the decisions from description condition (93 females, average age = 34.9). The participants provided informed consent statements, and all studies were ethically approved by the Ethics Committee for Behavioral Studies at the Interdisciplinary Center (IDC) at Herzliya. An attention check was included (Oppenheimer, Meyvis, & Davidenko, 1995), as described below. Those who failed the attention check were not allowed to participate.[4] Participants in the decisions from experience condition received $0.50 and an additional amount contingent on their decisions (as specified below). Participants in the decisions from description condition received a fixed amount of $2.

Measures and apparatus. In the decisions from experience condition the task involved making 100 repeated selections between two options presented as virtual buttons. Participants received no information about the payoff distributions or the number of trials they would encounter. The two options were labeled “Option A” and “Option B”

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[4] Across the Mturk studies, approximately 33% of those initiating the study failed the attention test. Additionally, 6% took the study twice (or more) and their data was excluded from the analyses.

(see Appendix A). The allocation of the safe and risky alternatives (S and R) to the two options (A and B) was randomly determined for each participant, but was kept constant throughout the 100 trials. After selecting an option the outcomes of the selected and unselected options were shown simultaneously for one second. Additionally, an accumulating payoff counter, which was displayed constantly, was updated based on the outcome of the selected option.

In the decisions from description condition the task involved a single choice between lotteries which were described on the screen (see Appendix A). Using radio buttons participants selected their preferred option and pressed a button to complete the experiment. As in Yechiam and Hochman (2013a), they did not receive payoffs contingent on their choice, but instead received a fixed amount. The choice outcomes in both the decisions from experience and decisions from description conditions were those of Problem 1 in Table 1, as in Yechiam and Hochman (2013a).

The allocation of participants to the Gain and Loss conditions was randomly determined. In the decisions from experience condition 97 participants were randomly allocated to the Gain condition and 105 to the Loss condition. In the decisions from description condition, 116 participants were allocated to the Gain condition and 106 to the Loss condition.

Procedure. After completing an informed consent statement, participants were asked to provide demographic details (age, gender) and press “continue” in order to move to the task instructions (a large font “continue” label was presented at the bottom of the screen). The instructions in all conditions were as in Yechiam and Hochman (2013a) with the magnitude of the fixed rewards and the point-to-money conversion rate being slightly modified. Briefly, in the decisions from experience condition participants were notified that on top of their basic payoff ($0.50), they would additionally be paid based on the total amount of points earned during the task, converted at a rate of $0.25 per 1000 points. They were further informed that their task was to earn as many points as possible by selecting from the available options. Participants were notified that they would select from the options a predetermined number of times and that they would receive feedback about the outcome they obtained (i.e., the outcome of the option they selected) as well as about the outcome they would have obtained had they selected the other option. In the decisions from description condition participants were simply asked to select between the two choice options.

At the end of the instructions it was indicated that in order to start the task participants should click an invisible box on the top left part of the screen rather than press the “continue” label (which was presented as previously at the bottom of the screen). This was used to screen out inattentive individuals before the study began (Oppenheimer et al., 1995). In both conditions, after participants finished the task they were informed of their earnings and thanked for their time.

Results

Experience condition. The left panel of Figure 2 shows the results for the decisions from experience condition. In line with our prediction the proportion of choices from the risky option (P(R)) appears higher when this alternative produced a small loss than when it produced a small gain, a difference that became distinct as the participants gained experience. We examined the significance of these observations using a repeated measures analysis of variance (ANOVA) with trial block (10 blocks of 10 trials) as a within subject factor and condition (Gain vs. Loss) as a between subject factor. The results indicated no main effect of condition, $F(1,200) = 0.44$, $p = .51$, $\eta^2 = .002$. Importantly, however, there was a significant interaction between condition and trial block, with P(R) increasing to a greater extent over trials in the Loss condition, $F(9,200) = 2.53$, $p = .009$, $\eta^2 = .11$.

Post-hoc tests of the first 10 trials showed that P(R) in the Loss condition ($M = .51$, $CI_{95\%}[.46, .56]$) was significantly smaller than in the Gain condition ($M = .59$, $CI_{95\%}[.54, .63]$), $t(200) = 2.28$, $p = .02$). In contrast, P(R) in the Loss condition ($M = .88$, $CI_{95\%}[.83, .92]$) was significantly higher than in the Gain condition ($M = .79$, $CI_{95\%}[.75, .84]$), $t(200) = 2.52$, $p = .01$) in the final 10 trials. Thus, the approach response to losses in the decisions from experience paradigm only emerged following repeated experience, supplanting an initial avoidance effect (in comparison to the Gain condition). We also carried out an analysis of choices contingent on the previous trial outcome (see Appendix B), with the results showing increased sensitivity to a previous trial's outcome in the Loss condition.

Description condition. As noted above, if the approach response to losses requires experience it should not emerge in decisions from description. In this setting we find that in the Gain condition 70% of the participants selected option R compared to 68% in the Loss condition: Though this did not amount to a significant effect, $\chi^2(1) = 0.08$, $p = .78$; log linear model $z(1) = 0.27$, $p = .79$. The findings therefore suggest that the approach response to losses was present in decisions from experience but not in decisions from description.

Study 1b: Effect of outcome size

To verify that the effect found in decisions from experience in Study 1a was driven by increased investment of cognitive resources with losses, and was not merely due to increased risk taking, we examined Problem 6, in which there is a smaller difference between the options expected values, as follows:

Problem	Condition	Option S	Option R (equal odds)
6.	Gain	35	1 or 100
	Loss	35	-1 or 100

Based on the simulation results described above (see Figure 1), we predicted that owing to the reduced expected value difference between options in Problem 6, the approach effect of losses would be diminished.

Method

Participants. One-hundred and eighty-three new participants were recruited from MTurk (85 females, average age = 35.1). An attention check was included as in Study 1a and participants received $0.50 and an additional amount contingent on their decisions as in Study 1a.

Design, apparatus, and procedure. The layout of the task was identical to the decisions from experience condition of Study 1a, though the options consisted of those in Problem 6. As in Study 1a the allocation of participants to the Gain (N = 86) and Loss (N = 97) conditions was random.

Results

The right panel of Figure 2 shows the proportion of choices from the risky option in Study 1b. It appears that the approach response to losses was somewhat smaller than in Study 1a. Performing a repeated measures ANOVA as in Study 1a we find no significant effect of Gain/Loss condition, $F(1,181) = 0.24$, $p = .63$, $\eta^2 = .001$. Also, counter to Study 1a the interaction between condition and trial was not significant, $F(9,173) = 0.40$, $p = .94$, $\eta^2 = .002$.[5]

The fact that in Study 1a we find a significant approach effect of losses whereas in Study 1b – where the risky alternative was not as advantageous – we do not find it, suggests that the approach response to minor losses is not simply due to increased risk taking with losses. Rather, the effect seems to be contingent on the advantageousness of the alternative producing losses. As predicted in Figure 1, the approach response was eliminated when differences in the expected value of the options were reduced.

Study 2: Effect of probability

We next examined whether the approach effect of losses recorded in Study 1a is robust to the probability of the risky alternative's positive outcomes. Two versions of Problem 1 were constructed in which the high outcome of 200 was obtained with either 60% chance or 40% chance. These theoretical (or population) probabilities resulted in a distribution of actual frequencies ranging from 29% to 75% to get the high outcome for different individuals (this refers to the rate of the high outcomes on all trials, whether the risky

[5]We also examined whether the effect was significant in the final block of 10 trials as in Study 1a. Counter to Study 1a we find no significant differences, $t(181) = .97$, $p = .34$.

alternative was selected or not). We evaluated the effect of different theoretical probabilities as well as actual frequencies of high and low payoffs on the approach response to losses. In line with Figure 1, we expected a stronger approach response with higher probabilities/frequencies because this increases the expected value gap between the advantageous risky alternative and its safer counterpart.

Method

Participants. We recruited 782 participants from MTurk (389 females, average age = 39.0). An attention check was included as in Study 1a. Participants received $0.50 and an additional amount contingent on their decisions as in Study 1a.

Design, apparatus, and procedure. The layout of the task was identical to the decisions from experience condition of Study 1a, with the following differences: First, the probability of getting the high and low outcome was manipulated, as noted above: Two versions of Problem 1 were used in which the theoretical probability of getting 200 was either 60% or 40%, and the corresponding probability of getting 1 or -1 was either 40% or 60%, respectively. The participants were randomly divided into these two conditions (N = 399, 383, respectively). Secondly, in order to investigate the robustness of the findings of Study 1a to situations where the safe alternative does not produce a constant payoff, we added a noise factor to the safe outcome: a random number ranging from -5 to 5 was added/subtracted on each trial from the 35 payoff.

Results

The left panel of Figure 3 shows the proportion of choices from the risky option in the two conditions. A visual examination of the figure suggests that the approach response to losses was somewhat stronger when the likelihood of the high option was 60% compared to 40%. In order to examine the effect statistically, we conducted a repeated measures ANCOVA with trial block (10 blocks of 10 trials) as a within subject factor, Gain/Loss condition and theoretical probability condition (60% versus 40% of getting the high gain) as between subject factors, and with the absolute disparity of the actual frequency from the population probability as a covariate. Interactions with the covariate were included in the analysis as recommended in Yzerbyt, Muller, and Judd (2004). The results showed a close to significant main effect of Gain/Loss condition in the expected direction, $F(1, 774) = 3.50$; $p = .062$; and importantly a significant interaction between the Gain/Loss condition, the theoretical probability condition, and trial block, $F(9, 766) = 2.77$, $p = .003$.

An examination of the effect of actual frequencies on the difference between conditions appears in Figure 3 right panel. The figure illustrates that the effect of probability is different from that postulated: The difference between the Gain and Loss conditions peaks for equiprobable gains and losses and diminishes for more extreme probabilities (though the effect only reverses for the lowest probability as predicted in Figure 1). Thus, it appears that asymmetric probabilities of gaining and losing mask the approach effect of losses. To examine this effect, we conducted an ANCOVA co-varying for the distance of the frequency from 50% (marking the extent of its extremity), instead of the distance from the theoretical probability of the two conditions. The results showed that controlling for the extremity of the frequency, the main effect of Gain/Loss condition was significant, $F(1, 774) = 5.42$, $p = .02$, while the interaction between the Gain/Loss condition, theoretical probability condition, and trial block, was not significant, $F(1, 774) = 0.43$, $p = .092$. Also, the interaction of the Gain/Loss condition with the extremity of the frequency did not reach significance, $F(1,774) = 2.75$, $p = .10$. It seems, therefore, that the approach effect is replicable, but high probabilities of getting the favorable outcome do not increase the effect. The possible reasons for this are further discussed below.

Study 3. Decisions From Experience Without Forced Experience

In Study 3 we examined whether the approach response to losses is contingent on forced experience with the advantageous option producing losses. In the decisions from experience condition of Study 1a, as in Yechiam and Hochman (2013a), even if individuals did not select the risky option they still experienced it vicariously because the feedback on each trial included both obtained and foregone payoffs (i.e., outcomes for both the selected and unselected options were shown following each choice). In the present study we employed the same problems used in Study 1a and 1b, but provided feedback for the selected option only. As such, participants only saw the outcomes of their choices and therefore did not learn about the outcomes of the risky option if they did not choose it. If the approach effect of losses requires ample experience with the alternative producing losses (as suggested at the outset), then without forced experience it should be reduced.

Method

Participants. The study included 190 new participants recruited from MTurk (102 female, average age = 39.1). As in the previous studies an attention check was included and participants who failed the check were not allowed to participate. Participants received \$0.50 and an additional amount contingent on their decisions as in the previous studies.

Design, apparatus, and procedure. The experimental set up was the same as in the previous studies. As previously, the allocation of participants to the two decision problems and the Gain and Loss conditions was randomly determined: In Problem 1, 46 participants were allocated to the Gain condition and 54 to the Loss condition. In Problem 6, 46 participants were allocated to the Gain condition and 44 to the Loss condition.

The only difference from Study 1a and 1b was that the feedback on each trial included the payoff for the chosen option only (i.e., no foregone outcome feedback was provided). The instructions of Study 1a and 1b were changed accordingly: Participants were told that upon making a choice they would only see the payoff from the option they selected.

Results

Figure 4 shows the proportion of choices from the risky option (P(R)) in the four experimental conditions. As can be seen, the pattern of results is somewhat different from that observed in Study 1. There was no increase in P(R) in the Loss condition in either problem and in any stage of the experiment. Instead, in both problems losses appeared to reduce choices from R. We examined the significance of the difference between the Gain and Loss conditions using a repeated measures ANOVA with trial block (10 blocks of 10 trials) as a within subject factor and choice problem (1 or 5) and condition (Gain vs. Loss) as between subject factors. The results revealed a main effect of choice problem, with higher P(R) in Problem 1 than in Problem 6, $F(1,186) = 11.74$, $p = .001$, $\eta^2 = .06$. Additionally, there was a main effect of condition, $F(1,186) = 5.77$, $p = .006$, $\eta^2 = .04$, in line with the lower P(R) in the Loss condition. None of the interactions reached significance: for the interaction of trial block by condition, $F(9,178) = 1.79$, $p = .07$, $\eta^2 = .08$ and for the remaining interactions, $F < 1.78$ and $p > .18$.

Thus, the results indicate that the approach response we observed in Study 1a did not emerge without forced experience. In addition, we observed a considerable avoidance response to losses in both choice problems. To further understand the reasons for this avoidance effect we divided the dataset into two subsets of trials (as in Study 1): Trials where the actual expected value of the risky alternative (based on the obtained outcomes) was larger than that of the safe alternative (R > S) and trials where the expected value of the risky alternative was smaller than that of the safe alternative (S > R). On average, S > R in 17% of the trials in Problem 1 (11% in the Gain condition and 23% in the Loss condition) and in 28% of the trials in Problem 6 (18% in the Gain condition and 38% in the Loss condition). Figure 5 presents the differences between conditions in these two subsets of trials. As can be seen, across choice problems no consistent difference between conditions was found for trials in which R > S. By contrast, there were considerably more S choices in the Loss condition implying an avoidance effect in trials where S > R. Because different trials are included for each participant we examined the aggregate choices across trials using an analysis of variance with Gain/Loss condition and choice problem as independent variables. The results for the subset of trials where S > R indicated a significant main effect of Gain/Loss condition, $F(1, 96) = 6.04$, $p = .02$, $\eta^2 = .06$, with lower P(R) in the Loss than in the Gain condition. There was no significant interaction between condition and choice problem, $F(1, 96) = 0.65$, $p = .42$, $\eta^2 = .01$. By contrast, for the subset of trials where R > S there was no main effect of condition ($F(1, 159) = 0.31$, $p = .58$, $\eta^2 = .002$; and no interaction between condition and choice problem, $F(1, 159) = 2.17$, $p = .14$, $\eta^2 = .01$. Furthermore, as noted above, losses were also associated with an increase in the proportion of trials where S > R. This increase was significant, $F(1, 186) = 10.73$, $p = .001$, $\eta^2 = .06$, and did not interact with the choice problem, $F(1, 186) = 0.61$, $p = .44$, $\eta^2 = .003$.[6]

This pattern of results indicates that the avoidance effect of losses that we observed is not merely due to loss aversion (or loss avoidance). It is instead a product of an increased tendency to avoid a risky alternative in the specific case where its experienced expected value is smaller than that of the safe alternative. In other words, it represents an accentuated hot stove effect (Denrell & March, 2001) with losses. Thus, the avoidance effect in this setting seems to also be driven by a positive effect of losses on the sensitivity to experienced outcomes because losses facilitated the avoidance of the risky alternative only when doing so was advantageous based on the participants' experience.

[6] This clarifies what might be seem as a discrepancy between Figures 4 and 5. In the last blocks of trials presented in Figure 4 there were more choices from R in the Gain than in the Loss condition whereas for trials with R > S there were more choices from R in the Loss condition; and for trials with S > R choice proportions were about equal in the two conditions. However, because in the Loss condition there were fewer trials with R > S, across trials losses were nevertheless conducive to fewer R choices.

Study 4: Decisions From Experience With Initial Forced Experience

The notion that the approach effect of losses requires experience with the alternative producing losses implies that if participants experience the two alternatives in an unbiased fashion this can produce an approach effect, even with no foregone payoffs. To evaluate this prediction, we examined a condition where participants were forced to experience the alternative producing losses in the beginning of the task. Initial forced experience was implemented by having the participants make 10 choices from each of the two alternatives (options S and R) in the first 20 trials.

Method

Participants. The study included 60 participants, all undergraduates at the Technion – Israel Institute of Technology (30 female, average age = 25.0). Participants received NIS 20 and an additional amount contingent on their decisions as in the previous studies.

Design, apparatus, and procedure. The experimental task was similar to Study 3's Problem 1 condition. The main difference was that in the first 20 trials participants had to make 10 choices from each of the two alternatives. The instructions began as in Study 3 and followed by informing participants that the experiment will involve two stages (A and B): in Stage A they are requested to select 10 times from each button (in any order they want) while Stage B involves free choices between buttons.

A letter "A" or "B" was presented at the top of the screen marking the respective stage of the experiment. In the first 20 trials involving forced choices (Stage A), the task included two progress bars presenting the total number of times that each of the two alternatives was selected. If a participant selected an alternative more than 10 times, pressing the button resulted in a message box stating that "In this stage, each of the two alternatives needs to be selected 10 times" and no outcome information was provided. After 20 trials, the progress bar was removed and participants completed the remaining 80 trials with no foregone payoffs (Stage B). The allocation of participants to the Gain and Loss conditions was randomly determined (30 participants allocated to each condition).

Payoffs in the initial 10 choices from R were randomly drawn from the alternative's payoff distribution. However, we did make sure that participants will obtain the positive outcome at least once, and this was used as an inclusion criterion (a single participant was excluded). For all participants, the mean expected value of the risky alternative for the 10 forced choices was higher than that of the safe alternative.

Results

Figure 6 presents the proportion of choices from the risky option (P(R)) in the two experimental conditions. The figure suggests a robust approach response with losses in the 80 trials involving free choices. We examined the significance of the differences using a repeated measures ANOVA with trial block (8 blocks of 10 trials) as a within subject factor and condition (Gain vs. Loss) as between subject factors. The results indicated a significant main effect of Gain/Loss condition, $F(1, 58) = 4.67$, $p = .03$, $\eta^2 = .08$, and no interaction effect of block by condition, $F(7, 52) = 0.84$, $p = .56$, $\eta^2 = .10$). Thus, it appears that direct unbiased experience with losses, and not only vicarious experience, provides sufficient conditions for the emergence of the approach effect of losses.[7]

Study 5: Decisions From Description

We next re-examined the decisions from description paradigm and evaluated two potential reasons for the absence of an approach response to losses in this paradigm. The first explanation is that MTurk participants might exhibit greater loss avoidance than student populations (see e.g., Wolfson & Bartkus, 2013), which could explain why Study 1a failed to replicate the results of Yechiam and Hochman (2013a). The second explanation is that the approach response to losses is sensitive to experience and thus not robust with mere description. In Study 5 we therefore re-ran the decisions from description condition of Yechiam and Hochman (2013a) using the same population as in the original study – students – and with the exact same experimental protocol (i.e., a direct replication).

Contrary to the decisions from experience condition, in the decisions from description conditions of Yechiam and Hochman (2013a) and Study 1a choices were not incentivized, which might have increased noise in the latter condition (Hertwig & Ortmann, 2001). We therefore added a condition where participants making decisions from description were incentivized based on their choices.

[7] We also ran another lab experiment replicating Study 4 with no forced experience. This involved 60 participants recruited as above (30 males and 30 females). Differences between conditions were smaller (Loss (M = .66, $CI_{95\%}$[.54, .78]), Gain (M = .60, $CI_{95\%}$[.50, .69]), with no significant difference between the Gain and Loss conditions, $F(1, 58) = 0.69$, $p = .41$, $\eta^2 = .01$; or an interaction effect of block by condition, $F(7, 52) = 0.86$, $p = .54$, $\eta^2 = .10$).

Method

Participants. Two-hundred and ninety-four participants (62 females, average age = 32.4) drawn from the participant recruitment pool at the Interdisciplinary Center (IDC) at Herzliya took part in the study. Out of these participants, 162 took part in the non-incentivized condition and 132 in the incentivized condition. The experiment was advertised by an email message. Ten participants in the non-incentivized condition were randomly selected for a NIS 50 voucher for a popular bookstore, and ten participants in the incentivized condition were randomly selected and were paid based on their decision.

Design, apparatus, and procedure. Participants were presented with a Qualtrics web-based questionnaire showing the lotteries of Problem 1 (see Table 1) either in the Gain or Loss condition (for example, the Gain condition item appears in Appendix A). The allocation of participants to the Gain and Loss conditions was random. In the non-incentivized condition, 79 students were randomly allocated to the Gain condition and 83 to the Loss condition. In the incentivized condition, 68 students were randomly allocated to the Gain condition and 64 to the Loss condition. In the non-incentivized condition participants were informed before taking part in the experiment that “ten participants completing this question will win a NIS 50 book voucher”. For the incentivized condition participants were told at this stage that “ten participants completing this question will get a monetary amount drawn from whichever choice option they select”.

Results

In the non-incentivized condition 53% of the participants chose alternative R in the Gain condition compared to 49% in the Loss condition. In the incentivized condition

77% of the participants chose alternative R in the Gain condition and 69% selected it in the Loss condition. Thus, in both the incentivized and non-incentivized settings losses reduced choices of the advantageous risky option. To simultaneously examine the effect of the two factors of incentivization and Gain/Loss condition, we conducted a log-linear analysis. Incentivization positively affected risky selections, $z(1) = 3.32$, $p = .001$, while condition had no significant effect, $Z(1) = 1.37$, $p = .17$. For the saturated model, the interaction between the effect of condition and incentivization was not significant as well, $Z(1) = 0.65$, $p = .52$.

Modeling of Current datasets

The data was modeled using the exact same approach as above. To recall, this model has three parameters: θ_{Loss} and θ_{Gain}, denoting the relative choice sensitivity in the Loss and Gain condition and α, which denotes the degree of diminishing marginal utility (i.e., concavity of the utility function). Parameter estimation was conducted only for the decisions from experience conditions. The model was based on the actual mean frequencies of gains and losses in the different experiments. In Study 1 and 2, which had full information from both obtained and foregone payoffs, these frequencies converged on average to the theoretical probabilities. In Study 3 and 4 because of the hot stove effect the mean frequencies of obtaining the high outcomes were lower than those in the distribution from which they were sampled (Study 3 Problem 1: Loss p(200) = 0.394, Gain p(200) = 0.461; Study 3 Problem 6: Loss p(200) = 0.379, Gain p(200) = 0.460; Study 4: Loss p(200) = 0.461, Gain p(200) = 0.468). The results of the estimation procedure indicate that model RMSD was 0.081 and the estimated parameters were θ_{Gain}

= 0.052, θ_{Loss} = 0.095, and α = 0.86. Thus, we recover the increased choice sensitivity in the Loss condition across studies.[8] Figure 7 shows the model predictions and mean proportion of risky selections in each study. As can be seen, the model captures the main qualitative results. Naturally, though, this simulation is a simplified one, and does not account for learning related effects (it is conditional on the observed frequencies which in Study 3 and 4 were affected by the participants' choices).

General Discussion

Our findings indicated that embedding a small loss in the outcomes of a risky alternative increased its attractiveness over the long run, consistent with previous studies showing an approach response to losses (e.g., Yechiam & Hochman, 2013a). The current studies delineate the boundary conditions for this effect: The approach response only emerged when participants had ample direct or vicarious experience with the alternative producing losses. The importance of experience is also evidenced by the absence of an approach effect of losses in one-shot decisions from description (in Studies 1, 4). Additionally, the approach response only occurred when the risky option was highly advantageous in terms of the size of its outcomes relative to the safe option.

Furthermore, in Study 1 there was an initial avoidance response to losses in the first 10 trials (in which losses reduced choices from the risky alternative), which was supplanted with an approach response following experience. The avoidance response was even more apparent in Study 3, where experience with the risky alternative was limited.

[8] A comparison of the modeling results to the initial simulation suggests that the choice sensitivity of the mostly M-turk participants in the current study was smaller than in previous studies which involved student participants (e.g., Yechiam & Hochman, 2013b).

At first glance, this pattern of results seems to support a general tendency to shy away from losses in the absence of experience, for instance due to loss aversion (Kahneman & Tversky, 1979) or loss avoidance (Payne et al., 1980). However, a closer look shows that the avoidance response emerged only in trials in which the risky alternative producing losses had an experienced expected value below that of the safe alternative. This suggests that even in trials in which participants seemed to avoid losses, they did so only when the alternative associated with losses was experienced as disadvantageous. Thus, the avoidance response we observed was most likely the result of a subtler process whereby losses increase the rejection of lower value risky options. In other words, losses increased the hot stove effect (Denrell & March, 1992), namely avoidance of a risky alternative based on sensitivity to its initial disadvantageous outcome. Behaving consistently with the hot stove effect is "correct" in terms of the information one has but it can lead to an inappropriate long-term strategy due to insufficient exploration of the alternative's long-term value (Denrell & March, 1992).

The main findings were generally in line with the prediction of a model assuming that individuals' choices are more sensitive to the options' experienced utility in task involving losses than in tasks that do not involve losses (and assuming a concave utility function). This model explains on the one hand the approach effect, and on the other the avoidance effect as a tendency to shy away from the alternative which is theoretically advantageous but is experienced as disadvantageous owing to the hot-stove effect. The model does not, however, capture the weak non-linear effect of probability recorded in Study 2, i.e., the finding that the approach effect was highest for moderate probabilities. One possible reason for this is a ceiling effect in the case of high probabilities of getting a positive outcome in Problem 1. Alternatively, additional factors, such as the underweighting of rare events in decisions from experience (see Erev & Haruvy, 2015) may mask the approach effect of losses. Our modeling approach also does not capture trial to trial contingencies, for example our findings that losses increase the sensitivity to recent outcomes from an advantageous alternative (see Appendix B). Also, the current modeling approach does not capture individual differences; addressing this seems a fascinating topic for further studies.

Both our behavioral and modeling findings suggest that losses increase exploitative behavior. This can lead to expected value maximization when there is a clear advantageous alternative, and when the information obtained with experience is not biased. Increased exploitative behavior with losses can also increase the convergence to a local optimum (the hot stove effect). These findings may seem at odds with the literature suggesting that losses increase exploration (e.g., Lejarraga & Hertwig, 2017). Note, however, that the previous literature demonstrating an increased effect of losses on exploration mostly compared tasks in the loss domain (or with mixed gains and losses) to tasks in the gain domain: it could be that what drives people to exploration in a loss (or mixed) domain is simply the considerably reduced mean payoff (this is also implied by the softmax model, e.g., Equation 1).

Limitations of the current study include our usage of an MTurk environment in several of the studies. For example, our findings that the approach response was rather small and only emerged during the second half of the task in Study 1a could be due to the particular sensitivity of MTurk participants to negative outcomes (see Wolfson & Bartkus, 2013). In Yechiam and Hochman (2013a) and Yechiam et al. (2015) a more considerable approach response was observed with student participants in a condition involving obtained and foregone payoffs. Nevertheless, the fact that the approach response to losses was found in a more diverse and relatively uncontrolled setting (i.e., performing the task at home) attests to the robustness of the effect. Another limitation is that we did not examine repeated decisions from description. In future studies it would be interesting to test whether the approach effect of losses in decisions from experience is robust to the presentation of descriptions, as found for other aspects in which decisions from experience diverge from normative prescriptions (e.g., Jessup, Bishara, & Busemeyer, 2008).

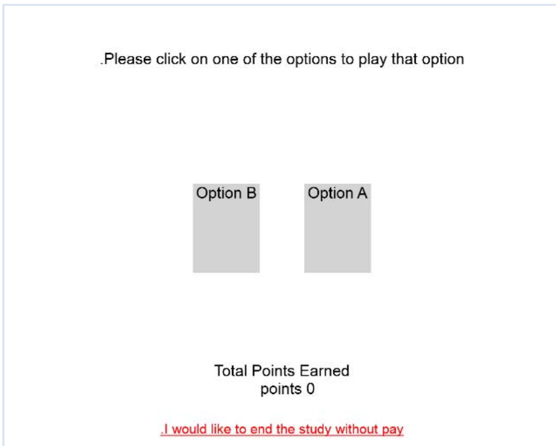
Conclusions

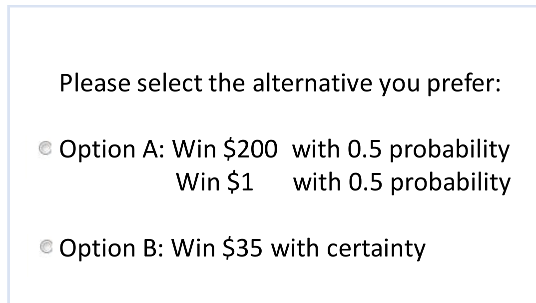
In summary, our findings suggest that in decisions from experience with no information about possible outcomes an initial experience with losses produced by a risky option leads to an immediate avoidance response. This effect is not ubiquitous, however, and emerges when the option producing losses is experienced as being disadvantageous. Nevertheless, it can prevent decision makers from fully exploring the option producing losses, impeding the ability to gain further experience and to assess this option's long-term value. By contrast, when the task provides experience in a compulsory and unbiased fashion either directly or vicariously, this leads to a paradoxical approach response: Individuals are more likely to select the risky option when it produces losses. This effect is also bounded and emerges for highly advantageous risky alternatives.

The current findings are consistent with a recent literature suggesting that the presentation of losses does not bias decision making processes, as assumed for instance in prospect theory (Kahneman & Tversky, 1979) but instead improves people's ability to make adaptive decisions based on the available information (e.g., Yechiam & Hochman, 2013a, b; Lejarraga & Hertwig, 2017). In this respect, our findings indicate that what may seem as a tendency of losses to promote shortsighted decisions, a regularity known as "myopic loss aversion" (Benartzi & Thaler, 1995), can be due the limitation of the available information in different stages of the decision problem and the inadequacy of locally optimal solutions. Additionally, our studies support the notion that the avoidance response to losses is not general (as assumed for instance under loss aversion) but occurs in particular contexts (Yechiam & Hochman, 2013b; Walasek & Stewart, 2015; Gal & Rucker, in press).

Appendix A: Experimental Tasks

Figure 1A. Illustration of the experimental tasks. Decisions from experience (left panel) and decisions from description (right panel).





Appendix B: Analysis of Contingent Decisions

Our main analysis in Study 1 focused on the selection of risky alternative in different trials irrespectively of the previous trial payout. We also examined the effect of losses on the likelihood of selecting a risky alternative contingent on a positive or a negative payoff in the previous trial. In this respect, in decisions from experience we typically see positive recency: a tendency to chase an alternative immediately following good outcomes and avoid it following bad outcomes (Barron & Yechiam, 2009), though there are cases were individuals show no recency, or even negative recency (i.e., a gambler's fallacy; Croson and Sundali, 2005; Jessup & O'Doherty, 2011). We examined whether consistent with the notion that losses increase the sensitivity to experienced payoffs (Yechiam & Hochman, 2013a, b) but also with a wrong assumption of non-independence between sequential outcomes, losses increase this recency effect.

This analysis focused on the decisions from experience conditions of Study 1a and 1b. Figure 2A presents the contingent responses following a high and low payoffs. A clear pattern seems to be unfolded for Study 1a (left panel of the figure): The participants exhibit positive recency which is higher in the Loss than in the Gain condition. To examine the statistical significance of the latter difference, we conducted an ANOVA with Gain/Loss condition as a between subject factor, the size of the outcome produced by the risky alternative on trial t (low, high) as a within subject factor, and the recency effect (i.e., the change in risky selection in trial t+1 consistent with the outcome in trial t: For high amount in trial t: $P(R)_{t+1}$ - $P(R)_t$; for low amount in trial t: $P(S)_{t+1}$ - $P(R)_t$) as the dependent variable. The results showed a significant effect of condition on the recency effect, $F(1, 200) = 4.27$, $p = .04$, consistent with the increased recency in the Loss condition, and no payoff size by condition interaction, $F(1, 200) = 0.22$, $p = .64$.

As indicated in Figure 2A (right panel), in Study 1b the participants appeared to exhibit only a slight tendency for higher recency in the Loss than in the Gain condition. An examination using ANOVA showed that the main effect of condition on recency was not significant, $F(1,181) = 0.02$, $p = .89$; and neither was the interaction of outcome size by condition, $F(1, 181) = 2.09$, $p = .15$. The increased sensitivity to the recent trial payoff found in Study 1a thus appears to be dependent on the risky option being highly advantageous, as it is not found in Study 1b.

Figure 2A: Contingent responses in Studies 1a and 1b. Proportions of selections from the risky alternative in trial t, t+1 and t+2 following a high (200) or low (1 or -1) payoff in trial t in the Gain and Loss conditions.

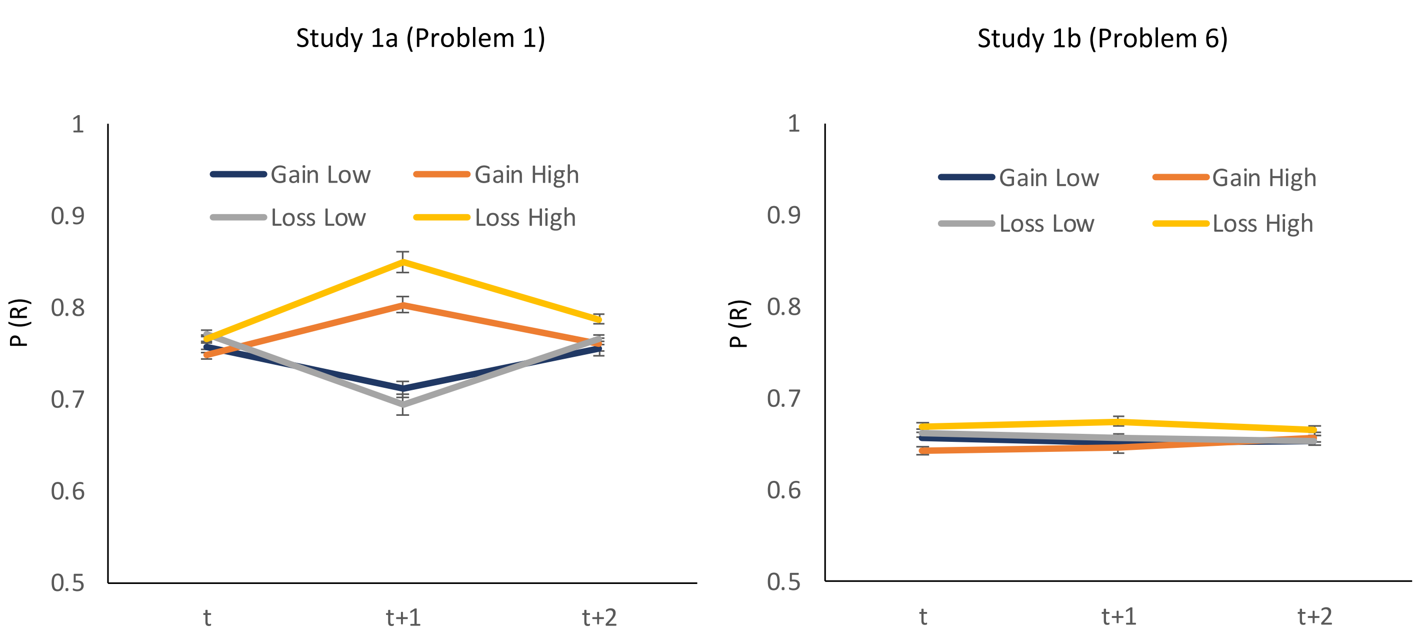


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Table 1: Findings from Yechiam and Hochman (2013a) (top panel), Yechiam et al. (2015) (middle panel), and Erev et al. (2017) (bottom panel). In the top and bottom panels rates of selections from the risky alternative (R) are shown separately for the decisions from experience and description.

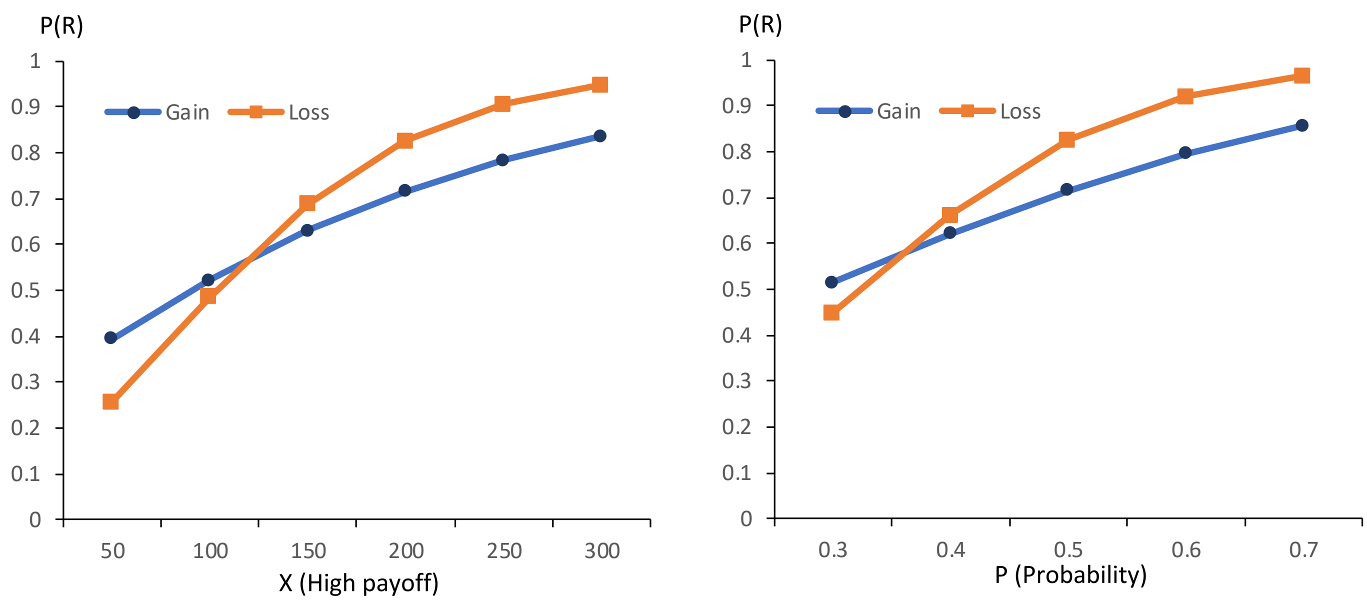
Problem	Condition	Option S	Option R (equal odds)	% R choices Experience	% R choices Description
1.	Gain	35	1 or 200	56.1%	56.4%
	Loss	35	-1 or 200	65.6% +	68.6% +
2	Gain	135	1 or 200	38.0%	12.1%
	Loss	135	-1 or 200	32.1%	7.8^%

Problem	Condition	Option S	Option R1 (equal odds)	Option R2 (equal odds)	% R1 choices Experience	% R2 choices Experience
3.	Gain	50	1 or 60	1 or 200	10.9%	65.2%
	Loss	50	-1 or 60	-1 or 200	5.7%	77.8% +
4	Gain	30	1 or 60	-	46.8%	
	Loss	30	-1 or 60	-	52.1%	

Problem	Condition	Option S (equal odds)	Option R (equal odds)	% R choices Experience	% R choices Description
5	Gain	7 or 1	1 or 50	85.0%	78.0%
	Loss	7 or 1	-1 or 50	81.5%	71.0%

+ = significant approach effect of losses ($p < .05$).

Figure 1. Model prediction for rates of R choices. A safe alternative (S) produces 35 and a risky alternative (R) produces x with a probability p or otherwise 1 in the Gain condition, and x or -1 in the Loss condition. Left panel: The abscissa denotes different values of x given p = 0.5. Right panel: The abscissa denotes different values of p given x = 200. The table below the graphs shows the implied expected value differences between S and R. The ordinate presents the projected rate of R choices based on the estimated parameters of the model.



EV(R) – EV(L)

Gain	-9.5	15.5	40.5	65.6	90.5	115.5
Loss	-10.5	14.5	39.5	64.5	89.5	114.5

EV(R) – EV(L)

25.7	45.6	65.5	85.4	105.3
24.3	44.4	64.4	84.6	104.7

Figure 2: Results of Study 1a (left panel) and study 1b (right panel). Proportions of selections from the risky alternative (P(R)) in decisions from experience, in the Gain and Loss conditions. Values on the abscissa correspond to blocks of 10 trials.

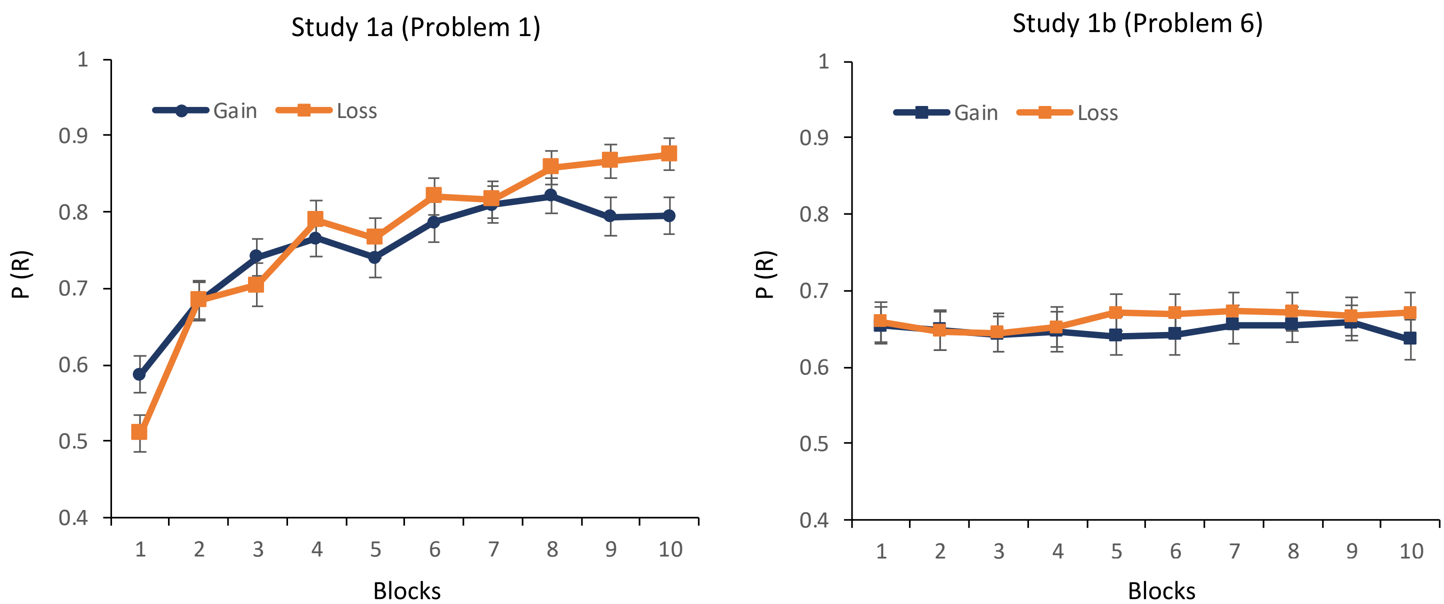
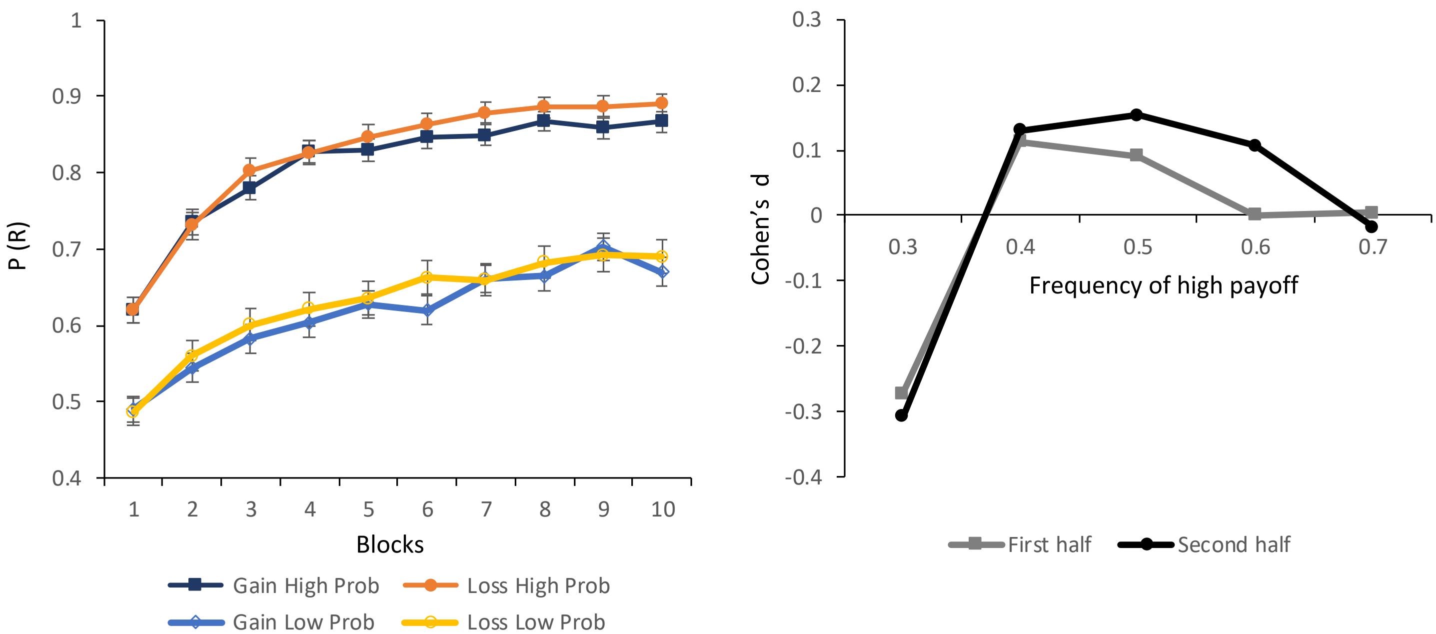


Figure 3: Results of Study 2. Left panel: Proportions of selections from the risky alternative (P(R)) in the Gain and Loss conditions and in the high and low probability conditions. Values on the abscissa correspond to blocks of 10 trials. Right panel: Differences between the Loss and Gain condition in units of standard deviation (Cohen's d's) as a function of actual frequency of the risky alternative's high outcome, in the first and second halves of the task.[9]



[9] Frequencies were discretized for the purpose of presentation at p ≈ .3 [p = .25 to .34], p ≈ .4 [p = .35 to .44], p ≈ .5 [p = .45 to .54], p ≈ .6 [p = .55 to .64], and p ≈ .7 [p = .65 to .74].

Figure 4: Results of Study 3 for Problem 1 (left panel) and Problem 6 (right panel). Proportions of selections from the risky alternative (P(R)) in decisions from experience with no foregone payoffs, in the Gain and Loss conditions. Values on the abscissa correspond to blocks of 10 trials.

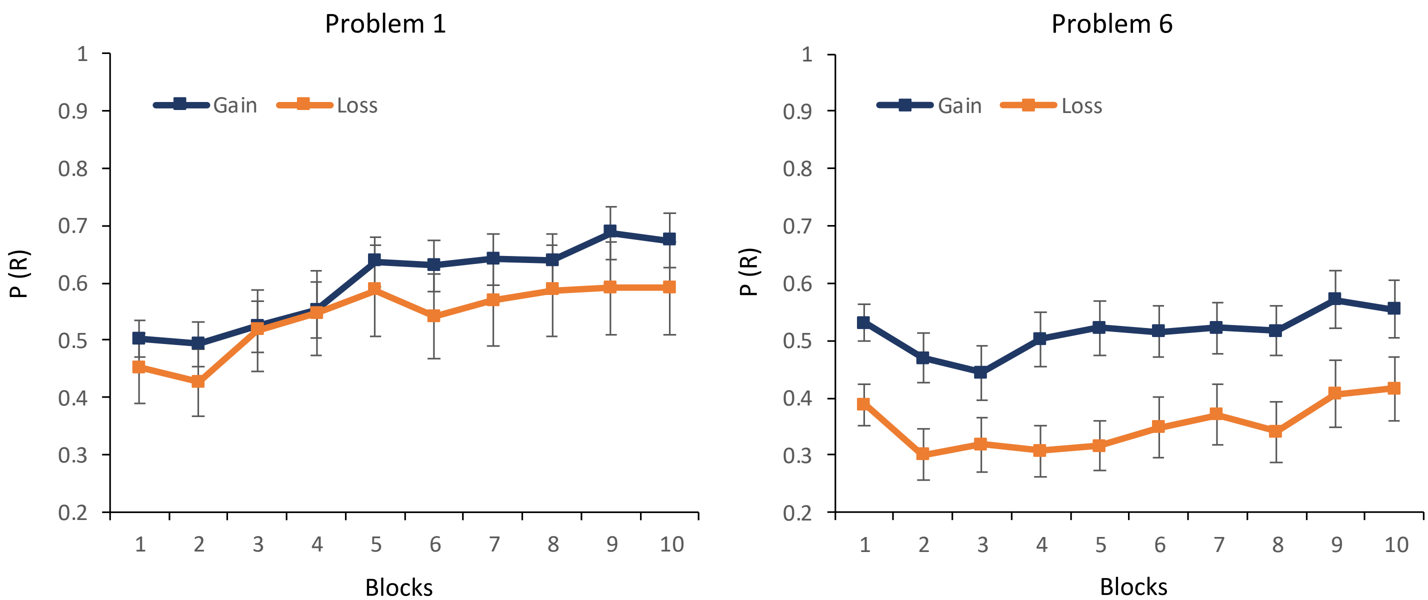


Figure 5: Results of Study 3 for two subsets of trials based on the experienced expected value for the risky (R) compared to the safe (S) alternative. The top panel presents the proportions of selections from the risky alternative in the Gain and Loss conditions on trials where the mean outcome from R was larger than from S (R > S); while the bottom panel includes trials where the mean outcome from R was smaller than from S (S > R). The left and right panels show choices in Problems 1 and 5, respectively. Values on the abscissa correspond to blocks of 10 trials.

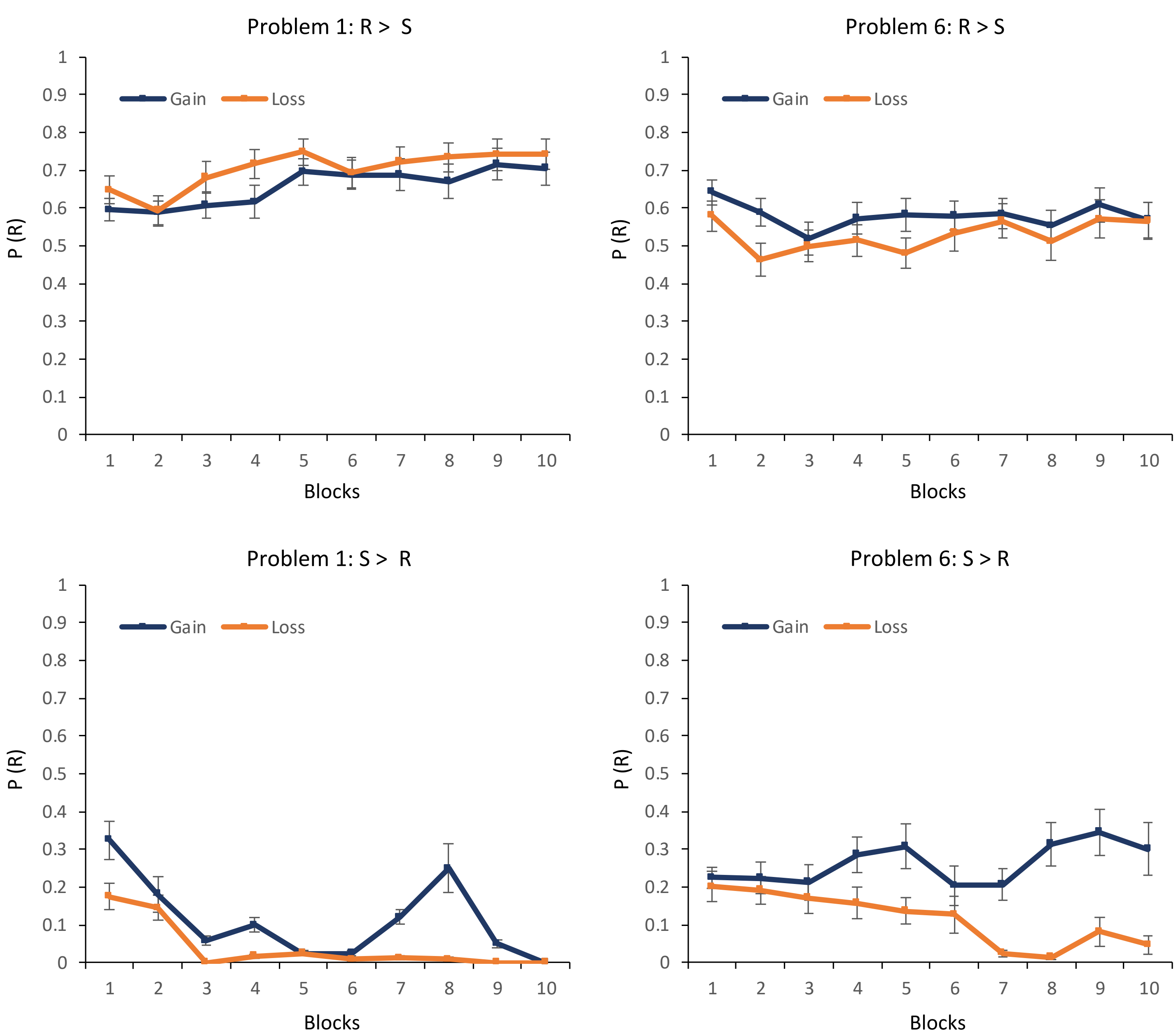


Figure 6: Results of Study 4. Proportions of selections from the risky alternative (P(R)) in the Gain and Loss conditions of Problem 1 in two initial 10-trials blocks of forced choice (10 forced selections from S and from R) and eight blocks of free choice. Values on the abscissa correspond to trial blocks.

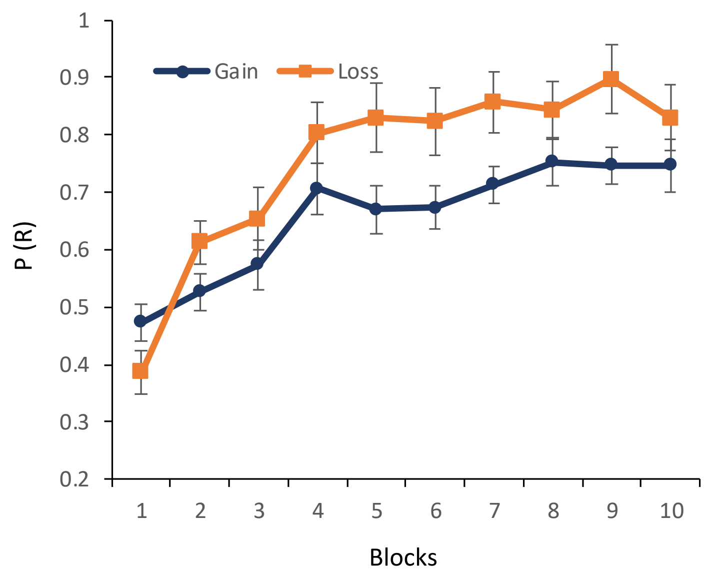


Figure 7: Predicted and actual proportions of selections from the risky alternative (P(R)) across trials in Studies 1 (experience condition), 2, 3, and 4.