Loss-aversion or loss-attention:
The impact of losses on cognitive performance

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Losses were found to improve cognitive performance, and this has been commonly explained by increased weighting of losses compared to gains (i.e., loss aversion). We examine whether effects of losses on performance could be modulated by two alternative processes: an attentional effect leading to increased sensitivity to task incentives; and a contrast-related effect. Empirical data from five studies show that losses improve performance even when the enhanced performance runs counter to the predictions of loss aversion. In Study 1 to 3 we show that in various settings, when an advantageous option produces large gains and small losses, participants select this alternative at a higher rate than when it does not produce losses. Consistent with the joint influence of attention and contrast-related processes, this effect is smaller when a disadvantageous alternative produces the losses. In Studies 4 and 5 we find a positive effect on performance even with no contrast effects (when a similar loss is added to all alternatives). These findings indicate that both attention and contrast-based processes are implicated in the effect of losses on performance, and that a positive effect of losses on performance is not tantamount to loss aversion.

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1. Introduction

Although they come in different shapes and flavors (e.g., taxes, deductions, payments), losses are inherent in many of the decisions we make. In this study, we examine how losses affect the execution of these decisions and their resulting effect on cognitive performance. In tasks ranging from simple economic decisions to metaperceptions, previous studies have generally shown positive effects of losses on performance (e.g., Costantini & Hoving, 1973; Denes-Raj & Epstein, 1994; Bereby-Meyer & Erev, 1998; Dawson, Gilovich, & Regan, 2002; Haruvy & Erev 2002; Maddox, Baldwin, & Markman, 2006; Yechiam & Ert, 2007; Pope & Schweitzer, 2011; Saguy & Kteily, 2011). For example, in an early study Costantini and Hoving (1973) found that the development of response inhibition among second graders was faster when tokens were removed upon making errors, than when tokens were added for successes. Maddox, Baldwin, and Markman (2006) found similar results for the performance of adults in a complex categorization task (see Yechiam & Hochman, in press). An independent line of research examined performance in decision tasks (e.g., Denes-Raj & Epstein, 1994; Bereby-Meyer & Erev, 1998). Bereby-Meyer and Erev (1998) coined the term the “successful loser” effect to denote the positive effect of losses on decision performance. For instance, in Haruvy and Erev (2002), adult participants were required to repeatedly select between two choice alternatives. In the Loss condition, one alternative produced -10 tokens and the other -11 tokens (with certainty). In the Gain condition, these same tokens were presented as gains: one alternative produced 10 tokens and the other 11 tokens. Even in this very simple task, participants converged much faster to the better choice in the condition where payoffs were presented as losses.

On the other hand, some studies (e.g., Thaler, Tversky, Kahneman, & Schwartz, 1997; Slovic, Finucane, Peters, & MacGregor, 2002) have demonstrated a reverse effect of losses. These studies also focused on decision performance. For example, Slovic et al. (2002) gave participants a choice between a sure outcome (of $2 or $4) and a lower expected value gamble. In the Gain condition, the gamble produced a 7/36 chance to win $9, and $0 otherwise. In the Loss condition, the gamble produced an additional loss of 5 cents with 29/36 chance. Paradoxically, more choices were made from the disadvantageous gamble in the condition where it included a loss. Thus, losses appeared to have "confused" participants into selecting the disadvantageous gamble.

Our goal in the current study is to contrast the predictions of different process models accounting for the effect of losses on cognitive performance. The most well known explanation for the effect of losses on performance is that performers are driven to avoid potential losses implicated in failure because of loss aversion (Kahneman & Tversky, 1979), the notion that losses have greater subjective weight than equivalent gains. We examine whether positive effects of losses on performance could be driven by processes other than differences in weighting, especially the effect of losses on task attention (Taylor, 1991; Yechiam & Hochman, in press) and contrast-related effects (Slovic, Finucane, Peters, & MacGregor, 2002). For this purpose, we examine conditions where the positive effects of losses on performance implied by these processes are inconsistent with loss aversion. In addition, we examine whether understanding the relative influence of these different processes can shed light on the apparently contradictory findings concerning the effect of losses on performance noted above.

In most of the studies that have examined this issue, the (positive or negative) effect of losses on performance was primarily attributed to loss aversion (e.g., Thaler et al., 1997; Bereby-Meyer & Erev, 1998; Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Erev & Barron, 2005; Hossain & List, in press). For example, Haruvy and Erev's (2002) results can be explained by the fact that a loss of 11 tokens looms larger than a gain of 11. Consequentially, participants' tendency to avoid -11 was stronger than their tendency to approach 11 (under loss aversion the subjective difference between two losses is also larger than between two gains). Similarly, in Thaler et al.'s (1997) study of investment portfolios, participants invested little in a fund with a mean expected return of 1% which yielded occasional losses and instead preferred investing in a lower risk fund with a mean return of 0.25% in which returns were all positive. Thaler et al.

(1997) argued that the aversion to losses won over participants' desire to maximize their outcomes. The asymmetric effect of losses compared to gains is "deemed axiomatic in the most influential theories of human decision-making" (Hackenberg, 2009) and has been treated as the most likely explanation for the effect of losses on cognitive performance (e.g., Bereby-Meyer & Erev, 1998; Hackenberg, 2009; Pope & Schweitzer, 2011; Hossain & List, in press).

However, we recently proposed an alternative account (Yechiam & Hochman, in press) based on attentional processes. Our model suggests that losses increase the overall attention allocated to the situation, and the modulation of behavior by task payoffs.[1] Findings indeed show that losses trigger autonomic arousal, as evidenced by increased pupil diameter and heart rate following losses compared to respective gains (Satterthwaite et al., 2007; Löw, Lang, Smith, & Bradley, 2008; Hochman & Yechiam, 2011). These effects of losses on autonomic arousal were obtained even in the absence of loss aversion (Hochman & Yechiam, 2011; Hochman, Glöckner, & Yechiam, 2010). The mere increase in attention is well known to positively affect performance under restricted conditions, which include low initial (baseline) level of attention (i.e., the Yerkes-Dodson rule; Yerkes & Dodson, 1908; Watchel, 1967; Kahneman, 1973) and a requirement to encode rather than merely retrieve information (Craik, Govoni, Naveh-Benjamin, & Anderson, 1996).

The attention-based model of losses can be formally stated in a simple form using Luce's choice rule (Yechiam & Hochman, in press). Under Luce's rule the probability of selecting strategies is a function of their expectancies, representing the outcomes predicted upon selecting them, and random noise (Luce, 1959; see also Daw et al., 2006):

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

[1] Note that the proposed attention-based model is somewhat similar to the affective mapping account. The difference between them is that we posit that the attentional effect of losses is global, such that it enhances the contrasts between payoffs from the entire set of outcomes and not only for the alternative producing the losses.

Specifically, the probability (P) of selecting a strategy *j* is a function of the distance between its expectancy (E_j) and the expectancy of other available strategies, but it is also affected by random noise. The Parameter θ controls the sensitivity of the choice probabilities to the expectancies. As θ increases the likelihood of basing one's strategy on the expectancies increases. The attention-based account predicts that θ would be larger for tasks involving losses than for equivalent tasks with no losses. This argument can be directly contrasted with the assumption that the asymmetry between gains and losses is in the relative weight of gains and losses on the expectancies. The loss aversion account and the attention-based account do not necessarily imply completely different models. Rather, the two accounts differ in the component process assumed to be affected by losses. Under loss aversion this component involves the translation of objective outcomes into subjective valences. Under the attention-based account losses reduce random noise and increase the sensitivity of choices to the incentive structure of the task.

Note that while most of the findings reviewed above showing a positive effect of losses on performance (e.g., Bereby-Meyer & Erev, 1998; Haruvy and Erev, 2002; Hossain & List, in press) have been attributed to loss aversion, they could also be explained by an attentional effect of losses. These studies used a choice task involving a disadvantageous option producing losses, and in this case avoiding losses and paying attention to the task are both expected to result in more successful performance. The attentional model is inconsistent, however, with the findings of Thaler et al. (1997), who demonstrated that when losses were part of the advantageous option participants still avoided losses and chose disadvantageously. However, Thaler et al.'s (1997) research design was recently criticized as it confounded the availability of losses with the size the outcomes (see extensive review in Erev et al., 2008).

On top of loss aversion and the attention-based model, a third account attributes the effect of losses to the specific case of selecting among gambles involving both losses and gains (Slovic et al., 2002). Specifically, according to this account, choice alternatives contrasting small losses with large gains appear more attractive. For example, norm theory (Kahneman & Miller, 1986) postulates that stimuli are evaluated compared to the norm of their class. Hence, without losses an alternative is presumably in the "gain" class and may be viewed as a mediocre instance relative to the set of all positive outcomes. The addition of a minor loss moves the outcome into a mixed loss-gain domain, and relative to members of the mixed outcomes class the same gain may seem like a more attractive instance. A related explanation made by Slovic et al. (2002) is that losses introduce an affective contrast between outcomes produced by a choice alternative, and if the loss is small enough this contrast can amplify the positive part of the gamble, thus increasing its overall attractiveness. Supporting this claim, Slovic et al. showed that a gamble producing 7/36 to win $9 is ranked higher when it also produces minimal losses. For conciseness, we shall refer to these accounts as contrast-based models.

Importantly, Slovic et al.'s (2002) findings imply that contrast-related effects of losses emerge even at the absence of loss aversion. In addition, losses in their study had a negative effect on performance, which can only be predicted by the contrast-based model and not by the attention-based model. This might suggest that contrast-related effects are stronger than attentional ones. Still, Slovic et al. (2002) only meant to demonstrate the contrast effect and did not prospectively evaluate the predictions of the contrast-based model with those implied by the attentional model or by loss aversion. Thus, while the three proposed accounts for the effect of losses seem plausible, to our knowledge no study has prospectively compared the predictions of loss aversion with those implied by the attentional and contrast-based models.

1.2. Comparing the different accounts

In five studies, we examine whether even in the absence of loss aversion, effects of losses on performance can be produced merely by attentional and contrast-related processes. Hence, our aim was not to test the existence of loss aversion but rather the stronger view that loss aversion is the exclusive driver of the effect of losses on performance. Since in many domains it is often difficult to set equal objective magnitudes for gains and losses, in the current studies we focused on simple decision making tasks. These kinds of tasks, which control for the probability and magnitude of gains and losses, allow rigorous comparisons concerning the weighting assigned to each component (Baumeister at al., 2001). We specifically investigated two main lines of contrasting predictions derived from these three accounts.

1). Adding minor losses to one of the choice alternatives. The first line of predictions refers to a situation where a minor loss is added to one of the alternatives. This is similar to what was done in Slovic et al. (2002) but they did not systematically vary the expected values of the two alternatives. By manipulating the relative expected values of the alternative to which a loss is added (see detailed example in Study 1), we can prospectively derive contrasting predictions implied by the three processes. Specifically, if participants are loss averse, then (all things being equal) they should avoid the alternative producing losses. Accordingly, the loss aversion account predicts that losses increase performance only when a disadvantageous alternative includes losses; since they lead to avoiding this alternative. By contrast, the attentional model predicts that losses improve decision performance regardless of whether they are added to the advantageous or disadvantageous alternative. According to this model, in both cases more attention is allocated to the task, resulting in responses that are more aligned with the incentive scheme. Finally, the contrast-based model predicts that only an advantageous alternative that includes a minor loss with a larger gain should lead to enhanced performance.

2) Adding similar losses to all alternatives. The second line of predictions refers to a situation where similar size losses are added all choice alternatives (which otherwise produce only gains). Both loss aversion and the contrast-based models predict that this should yield no unique effect of losses, as all alternatives incur the same loss and all gains are contrasted with the same loss. However, under the attentional model such an addition is expected to increase performance due to the mere increase in task attention.

To examine these contrasting predictions we conducted five studies. The studies are organized in accordance with the two sets of research questions. Studies 1 to 3 address the effect of minor losses produced by one of the choice alternatives, while studies 4 and 5 address the effect of similar losses produced by all alternatives. In both lines of studies we administered two types of tasks, experience-based tasks in which individuals actually obtain losses and description-based tasks where the likelihood and magnitude of potential losses are presented to the participants.

2. Adding minor losses to one of the choice alternatives

2.1 Study 1: The effect of minor losses in experience-based decisions

In this study we examined decision making in four conditions that disentangle the predictions of loss aversion, the attention-based model, and the contrast-based model. The choice problems and task conditions are presented in Table 1. In each choice problem there is an advantageous choice alternative, which has higher expected value, and is denoted as High-EV, and a disadvantageous choice alternative, denoted as Low-EV. In the "Advantageous-losing" problem (Problem 1), the High-EV alternative is the one that produces losses. Specifically, in the Loss condition it produces an equal chance to obtain either a large gain (200 tokens) or a minor loss (-1 token), while in the Gain condition it produces an equal chance to obtain the same large gain or a minor gain (+1 token).

A positive effect for losses in this setting is not predicted by loss aversion. Namely, under loss aversion people should perform worse in the Loss condition (i.e., select High-EV less) because they would avoid the possible loss produced by the advantageous alternative (this is also implied under the expected utility theory assumption of dominance).

In contrast, according to the attention-based model, losses increase the sensitivity to the different task payoffs. Therefore, since the loss is quite minor, it should enhance the ability to discriminate between alternatives Low-EV and High-EV, leading to more choices from High-EV in the Loss condition than in the Gain condition. Thus, under the attentional model, losses are assumed to have a positive effect on performance even where selecting advantageously leads to losses. A similar prediction is made by norm theory and affective mapping (i.e., contrast models). Because the loss introduces a contrast between the outcomes associated with the risky alternative, and the loss is much smaller compared to the gain, the (risky) High-EV alternative is expected to be more attractive with losses than with no losses. Thus, the Advantageous-losing problem alone does not disentangle the predictions of the attention-based and contrast-based accounts.

For this purpose we also added a “Disadvantageous-losing” problem, in which the same risky alternative is disadvantageous in terms of expected value (see Table 1). In this setting, under contrast-based models the risky alternative (Low-EV) is still expected to be more attractive in the Loss compared to the Gain condition, since it contrasts a large gain with a small loss. Therefore, losses are expected to impair performance. By contrast, under the attentional model, losses should result in fewer choices from the Low-EV alternative because they increase the sensitivity to the payoff structure. If both processes are evident then since they are assumed to work in opposite directions an interaction is expected. Namely, the positive effect of losses on performance should be higher in the “Advantageous-losing” problem than in the “Disadvantageous-losing” problem.

In Study 1 we examined these two problems using experience-based decision tasks in a form similar to that used by Haruvy and Erev (2002). In this type of task the participant is not provided with full descriptions of the outcome distributions, but rather has to learn them by making choices and receiving feedback (see review in Rakow & Newell, 2010). As repeated measures are provided for each performer in each choice problem this enhances statistical power for evaluations using quantitative models, which we present following our main analysis. The participants’ outcomes were generated by randomly sampling from the outcomes of Problems 1 and 2 (see Table 1) on each of 100 trials. In order to reduce the transparency of the task, a noise factor ranging from -5 to 5 (rounded to the closest integer) was randomly drawn on each trial and added to the constant outcome (35 or 135) in all conditions.

2.1.1. Method

Participants: One-hundred and twenty-two Technion students (63 males and 59 females) took part in the study after responding to ads asking for participation in a paid experimental study. Fifty-seven participants performed the Advantageous-losing problem and 65 performed the Disadvantageous-losing problem. All participants received a participation fee of NIS 20 as well as an additional amount based on their performance.

Measure and Apparatus: The experimental task involved making 100 repeated selections between choice options that appeared as virtual buttons. It was presented on 19-inch computer screens (button sizes were 0.7 ×1.4 inches). Button clicking was performed using a standard computer mouse. Upon pressing a button with the mouse, the image of the button changed to a "pressed" form. The two buttons were labeled only as A and B. The participants received no prior information about the payoff distributions or the number of trials. The allocation of alternatives Low-EV and High-EV to buttons A and B was randomized for each participant, but was kept constant throughout the 100 trials. Each choice was followed by a realization of the selected alternative, which was randomly drawn from the relevant distributions described above. Two types of feedback immediately followed each choice: (1) The basic payoff for the chosen and unchosen alternative,[2] which appeared on each button for two seconds, and (2) an accumulating payoff counter, which was displayed constantly. The dependent variable was the proportion of High-EV selections across trials.

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[2] Foregone payoffs were added in order to reduce noise due to early convergence to local optima (Denrell, 2007).

Procedure: Participants sat in cubicles divided by partitions (4-6 participants were tested at a time). The allocation to the Gain/Loss conditions was random. Due to this random mechanism for the Advantageous-losing problem, 29 students (55% male) were allocated to the Gain condition and 28 students (50% male) were allocated to the Loss condition. The participants performing the Disadvantageous-losing problem were likewise randomly allocated to the Gain condition (34 participants, 53% male) and Loss condition (31 students 48% male). There were no significant differences in age between conditions (the average age in all conditions was 25).

Participants in all conditions received the following written instructions: "In this experiment you will perform a decision making task. Your basic payoff is NIS 20. Additionally, you will earn NIS 1 for every 1,000 game points. In the presented window you will immediately see two buttons, A and B. Your task is to select between buttons by pressing them. You can press a button several times repeatedly (as much as you wish) or switch between buttons (as you wish). The payment for your selection will appear on the button you have chosen and under the two buttons. Also, in each trial you would be able to see the results from the unselected button on the button you did not press. Your accumulating payoff will appear at the bottom of the screen. Please notice: The outcome obtained after each selection is affected only by the last selection and not by your previous choices (there is no dependency between rounds)."

Three participants who performed the Advantageous-losing problem (two in the Gain and one in the Loss condition) selected the same button (i.e., choice alternative) throughout the entire 100 trials. Possibly, these individuals ignored the payoff structure all together, and they were thus excluded from the analysis.

2.1.2. Results

The participants' learning curves appear in Figure 1. In the Advantageous-losing problem, losses led to more selections from the advantageous alternative. As can be seen, starting from the second block of trials, the rate of selections from the High-EV option was higher in the Loss condition than in the Gain condition. In the Disadvantageous-losing problem, losses also led to more selections from the advantageous alternative, but the effect was weaker than in the Advantageous-losing problem.

Across trials, in the Advantageous-losing problem the average rate of High-EV selections in the Gain condition was 56.1% (SE = 3.3) while in the Loss condition it was 65.6% (SE = 2.8). In the Disadvantageous-losing problem the average rate of High-EV selections in the Gain condition was 62.0% (SE = 2.8) and in the Loss condition it was 67.9% (SE = 3.8). A repeated measures ANOVA was conducted with trial block (of 25 trials) as a within-subjects factor and choice problem (Advantageous-losing versus Disadvantageous-losing) and condition (Gain vs. Loss) as between-subjects factors. The analysis revealed a main effect of choice problem ($F(1,115) = 64.4$, $p < .001$) but not of condition ($F(1,115) = 0.30$, $p = .58$). Also, there was a significant interaction between the experimental condition and trial block ($F(3,345) = 2.65$, $p = .049$), denoting the emergence of a positive effect of losses on performance in later trials. Moreover, there was a significant interaction of choice problem and condition ($F(1,115) = 5.69$, $p = .02$), suggesting that the effect of losses on performance was highly contingent on the choice task, being more prominent in the Advantageous-losing problem.

Post-hoc tests showed that in the Advantageous-losing problem there was a significant difference between the Gain and Loss conditions ($F(1,55) = 4.75$, $p = .02$). In this choice problem, losses had a paradoxical effect of increasing the proportion of selections from the advantageous alternative producing losses. Examination of specific trial blocks showed that the effect of condition was significant only in blocks 3 and 4 ($F(1,55) = 5.45$, $p = .02$; $F(1,55) = 5.74$, $p = .02$, respectively), namely in the second half of the task. By contrast, the effect of losses in the Disadvantageous-losing problem was not significant ($F(1,60) = 1.57$, $p = .21$). The fact that the positive effect of losses on decision performance was smaller when the disadvantageous alternative included the contrast is consistent with the joint influence of attentional processes and contrast effects.

Our interpretation of this result is that in the Advantageous-losing problem contrast and attentional effect were working in the same direction. Thus, in this problem both processes contributed to enhancing the attractiveness of the advantageous alternative with losses, resulting in the observed reliable positive effect of losses on performance. By contrast, in the Disadvantageous-losing problem the contrast and attention-based effects of losses worked in opposite directions. Thus, in this problem the positive effect induced by attention was smaller.

The results of this experiment cannot be driven only by loss aversion, as in the Advantageous-losing problem participants behaved as if losses made the risky alternative more attractive. Still, we could not discard the option that because participants gave greater weight to losses, this resulted in other effects involved in learning (for instance, enhanced sensitivity to all payoffs, as implied by the attentional model). To examine this possibility further, we modeled the participants' trial to trial choices.

2.1.3. Quantitative modeling

An asymmetric effect of losses compared to gains can be expressed in changes in parameters reflecting different components of the basic reinforcement learning model. A general reinforcement learning paradigm introduced by Busemeyer and Myung (1998), called the Expectancy Valence (EV) model, can capture the possible effects of losses on these different components. This model includes the essential parameters of most plausible models of experiential tasks (see e.g., Erev & Roth, 1998; Camerer & Ho, 1999; Denrell, 2007; Worthy, Maddox, & Markman, 2008) and has been specifically validated in experience-based tasks (Yechiam & Busemeyer, 2005; 2008). Like other reinforcement learning models, it is composed of three rules reflecting the effect of different component processes: First, a utility function is used to represent the evaluation of outcomes experienced immediately after each choice. Second, a learning rule is used to form an expectancy for each alternative, which is a summary score for all past utilities produced by each alternative. Third, a choice rule selects the alternative based on the comparison of the expectancies.

Utility rule. The model assumes that losses and gains could be given different weights by individual decision makers. The utility for trial t is denoted $u(t)$, and is calculated as follows:

$$\text{If } x(t) < 0,\ \ u(t) = -w \cdot |x(t)|^{\gamma}, \qquad (2)$$
$$\text{If } x(t) > 0,\ \ u(t) = (2-w) \cdot x(t)^{\gamma},$$

The term $x(t)$ denotes the amount of money won or lost on trial t, w is a parameter that indicates the relative weight to losses versus gains, and γ is a parameter that determines the curvature of the utility function. Possible values of w were limited between 0 and 2 (where loss neutrality implies strict averaging of payoffs, namely $w = 1$).[3] The loss aversion model implies that w will be larger than 1, reflecting greater weight to losses than to gains. Note that for the small amounts of money used in the present experiment, $\gamma = 1$ was found to be sufficient (estimation of γ produced only minor improvements).

Learning rule. The term expectancy is used in reinforcement learning as a summary score of past utilities produced by each alternative. A delta learning rule was used for updating the expectancies (see Busemeyer & Myung, 1992; Sarin & Vahid, 1999). According to this learning rule, the expectancy $E_j(t)$ for each alternative j on each trial t is updated as follows:

$$E_j(t) = E_j(t-1) + \phi \cdot [u(t) - E_j(t-1)]\ , \qquad (3)$$

where j is a given choice alternative. Since foregone payoffs were administered, the expectancy was updated for both alternatives simultaneously, assuming equal weight to foregone and

[3] The upper-bound of 2 and the implication that loss neutrality is at $w = 1$ enables comparing a condition with losses and a condition with no loss, with no bias in the form of a constant multiplying the utilities, under the assumption of loss neutrality.

obtained payoffs (following Otto & Love, 2010; Yechiam & Rakow, 2011; Erev & Haruvy, in press). The learning rate (or recency) parameter ϕ describes the degree to which the expectancy reflects the influence of the most recent outcomes or more distant past experiences ($0 \leq \phi \leq 1$). The delta learning rule has been shown to have better fit at the individual level than several alternative models (see e.g., Yechiam & Ert, 2007; Worthy et al., 2008; Yechiam & Busemeyer, 2008). In this component as well one can assume an asymmetry resulting from losses, for instance greater recency in a condition with losses.

Choice rule. The probability of choosing an alternative is assumed to be a strength ratio of the expectancy of that alternative relative to all others, using Luce's rule (see equation 1 above), as follows:

$$\mathrm{P}[j,t+1] = \frac{e^{\theta \cdot E_j(t)}}{\sum_j e^{\theta \cdot E_j(t)}}\ , \quad \theta = 3^c - 1\ , \qquad (4)$$

The parameter θ controls the consistency of the choice probabilities and the expectancies. In our analysis, the final parameter θ was set to 3^c - 1, where $0 \leq c \leq 10$. A value of c between 0 and 10 enables examining the range between practically random choices (c = 0) and practically deterministic choices (c = 10). To make the model as simple as possible, the value of θ was kept independent of the trial number, as in Ahn et al. (2008). The attention-based model implies that the parameter θ would be higher in conditions with losses compared to conditions involving only gains.

2.1.4. Implementation and results of the modeling analysis

The model was evaluated for its ability to predict 'one step ahead' choices on each trial in each of the experimental conditions. Specifically, the model parameters were estimated separately for each individual based on the fit of the prediction for trial t +1 to the actual choice, using log likelihood (LL) estimation. The parameter optimization process followed a robust combination of grid-search and simplex (Nelder & Mead, 1965) search methods (as detailed in Ahn et al., 2008). In the gain condition the weight to loss parameter was redundant, therefore it was not estimated (w = 1).

The fit of the EV model was compared to a baseline model assuming that the choices are generated by a statistical Bernoulli process (e.g., Busemeyer & Stout, 2002; Gureckis & Love, 2009). According to this model, for each participant there is a fixed probability of selecting each of the two alternatives, which is a free parameter of the model (since the task includes two choice options, only one free parameter is required). The difference between the EV and baseline model fits was corrected according to the Bayesian Information Criterion (BIC; Schwartz, 1978):

$$\mathrm{BIC} = -2\cdot[\, LL_{EV} - LL_{Baseline}] + k\cdot\ln(N)\ , \qquad (5)$$

where k equals the difference between the EV model and the baseline model in the number of parameters and N is the number of trials. Because this is a test of differences between models, positive BIC values denote an advantage for the EV model.

The full EV model was superior to the baseline model in the Loss condition (Advantageous-losing: BIC = 6.3; Disadvantageous-losing: BIC = 3.1) but not in the Gain condition (Advantageous-losing: BIC = -8.0; Disadvantageous-losing: BIC = -18.9). We therefore proceeded with caution to interpret the EV model's estimated parameters. Table 2 presents the mean estimated parameters in the four experimental conditions. The main results were as follows. First, no loss aversion was found in any of the two choice problems. The value of the w parameter in the Loss condition was close to 1 in both problems and it did not deviate significantly from 1.[4] Note that in the Loss condition the EV model was found to have adequate

[4] Similar findings of loss-neutral w values were obtained by Ahn et al. (2008) in their study of two experiential tasks with asymmetric expected values, as well as in other cognitive modeling analyses (e.g., Busemeyer & Stout, 2002; Yechiam & Busemeyer, 2005; Wetzels, Vandekerckhove, Tuerlinckx, & Wagenmakers, 2010).

fit compared to the baseline model; hence, we substantiated the argument that the positive effect of losses on performance emerged simultaneously with no loss aversion.

Additionally, the choice sensitivity parameter *c* was considerably higher in the Loss condition compared to the Gain condition. This effect was highly significant in both choice problems (Advantageous-losing: $t(55) = 2.49$, $p = .02$; Disadvantageous-losing: $t(60) = 4.51$, $p < .001$). In the Advantageous-losing problem losses also had an unexpected positive effect on the participants' learning rate, $t(55) = 2.40$, $p = .02$. Since the fit of the EV model in the Gain condition was poor, comparisons between parameter estimates in the Gain and Loss condition should be interpreted cautiously. Still, the pattern of results suggests that the overall sensitivity to the payoff structure and the learning rate were affected by losses.

2.2. Study 2: The effect of minor losses in description-based decisions

In the first study we focused on experienced losses. Under the attentional model of losses (Yechiam & Hochman, in press), positive effects of losses on performance should also emerge for *potential losses*, such as hypothetical losses in a gamble. By contrast, Slovic et al. (2002) showed that actually in one-shot hypothetical gambles losses had a negative effect on performance; which they interpreted as the result of a contrast effect. Hence, combining our results in Study 1 with Slovic et al.'s (2002) findings one might deduce that the attentional effects of losses are more prominent in experience-based decisions where participants actually obtain losses than in description-based decisions. To evaluate whether the attentional effect of losses is indeed different in decisions from description, we replicated Study 1 using one-shot gambles of the sort used by Kahneman and Tversky (1979) and Slovic et al. (2002).

As in Study 1, we examined whether we find larger effects of losses on performance when losses are produced by an advantageous alternative, consistent with joint effects of contrast and attention-based processes. We used the Advantageous-losing and Disadvantageous-losing problems with the exact payoffs described in Table 1.

2.2.1. Method

Participants: A survey was administered to 491 students (226 males and 263 females, two un-identified) drawn from the pool of experimental study participants at the Technion. From these participants, 268 performed the Advantageous-losing problem, and 100 participants performed the original Disadvantageous-losing problem (see Table 1), while 123 participants performed a slightly modified version of the Disadvantageous-losing problem, as indicated below. The experiment was advertised by an email. A reward of NIS 100 (at the time, about $30) was promised to six participants, selected by a raffle. Participation was done by following a link and entering the experiment's website. The participation rate was 73%.

Procedure: Participants were presented with a Qualtrics web-based questionnaire composed of a single choice problem either in the Gain or the Loss condition (for example, the Gain condition item in the Advantageous-losing problem appears in the appendix). The allocation of participants to the conditions was random. Due to this random mechanism for the Advantageous-Problem, 147 students (50% males) were allocated to the Gain condition and 121 (49% male) were allocated to the Loss condition. For the Disadvantageous-losing Problem, 42 students (52% male) were randomly allocated to the Gain condition and 58 students (52% male) to the Loss condition. There were no significant differences in age between conditions (the average age in all conditions was 25). Six participants were randomly drawn at the end of the experiment and were rewarded as promised.

2.2.2. Results

In the Advantageous-losing problem, the average proportion of selections from the High-EV option in the Gain condition was 56.4% (SE = 4.7), while in the Loss condition it increased to 68.6% (SE = 6.2). In the Disadvantageous-losing problem the average proportion of selections from the High-EV option in the Gain condition was 87.9% (SE = 4.0) while in the Loss condition it increased to 92.8% (SE = 4.3). The difference between the two choice problems was statistically significant ($\chi^2(1) = 27.08$, $p < .001$), with more choices from the High-EV option in the Disadvantageous-losing problem where the advantageous alternative was also the safe alternative. Across problems participants made more selections from the High-EV option in the Loss condition than in the Gain condition ($\chi^2(1) = 4.62$, $p = .02$). An analysis of each separate choice problem showed, however, that the positive effect of losses was statistically significant in the Disadvantageous-losing problem ($\chi^2(1) = 4.14$, $p = .04$) but not in the Advantageous-losing problem ($\chi^2(1) = 0.66$ $p = .42$).

Thus, in description-based decisions as well, we observed that the positive effect of losses on performance was task specific. The finding that the positive effect of losses on performance remained positive but diminished in the Disadvantageous-losing problem (where losses accompany the low-value gamble) suggests that while losses led to increased sensitivity to the task payoffs, they also induced a contrast-based effect. However, an alternative explanation for the results of this experiment is a ceiling effect, due to the participants being highly risk averse in the Disadvantageous-losing problem.

To further examine these two explanations we administered a version of the Disadvantageous-losing problem where the outcome from alternative High-EV was changed from 135 to 105. We expected that this would reduce the tendency to avoid the risky Low-EV option. This problem was administered in the same survey-based method as the previous two problems. One-hundred and twenty three participants (43 females and 79 males) were randomly allocated to the Gain and Loss conditions (n = 62, 61, respectively). The results replicated the small but non-significant positive effect of losses on performance. The average proportion of selections from the High-EV option in the Gain condition was 83.6% (SE = 4.1) and in the Loss condition it increased to 88.7% (SE = 4.8), but the difference was not significant ($\chi^2(1) = 0.67$, $p = .45$). This suggests that similarly to what we observed in experience-based tasks, the positive effects of losses on performance are more prominent in cases where they are produced by an advantageous alternative.

To summarize, when minor losses were produced by the advantageous alternative, they enhanced performance. This is consistent with both the attentional and contrast effects of losses. When minor losses were produced by a disadvantageous alternative, they had a much weaker positive effect on performance, presumably because the attention-based effects were counter-acted by the contrast-based effects.

2.3. Study 3: Replication using Slovic et al. (2002) settings

The finding of our previous study showed that when losses were part of a disadvantageous gamble, they had a weak and non-significant positive effect on performance. This finding is inconsistent with the results of Slovic et al. (2002) who found a negative effect of losses on performance in description-based decisions. There are multiple differences between the decision problems used in Study 2 and in Slovic et al.'s (2002) experiment. For example, our study involved 50:50 outcomes and Slovic et al. used small probability gains; our study was conducted in the lab whereas Slovic et al. administered the questionnaire to students on campus and in classes; and the payoffs were different. In order to better understand the discrepancy, we conducted an experiment using Slovic et al.'s (2002) settings. Participants performed one of two choice problems, which were administered with gains only and with the addition of a minor loss:

Problem 3: Similar-EV problem

Condition	Low-EV option	High-EV option
Gain	36 with probability 7/36 (EV = 7)	8 with certainty
Loss	36 with probability 7/36, -1 otherwise (EV = 6.03)	8 with certainty

Problem 4: Different-EV problem

Condition	Low-EV option	High-EV option
Gain	36 with probability 7/36 (EV = 7)	16 with certainty
Loss	36 with probability 7/36, -1 otherwise (EV = 6.03)	16 with certainty

In Slovic et al's (2002) study, there were two magnitudes for the minor loss (in different experiments) and we used the larger of the two. The only other difference between Problem 3 and 4 payoffs and the original payoffs used by Slovic et al. (2002) is that all outcomes were multiplied by four to reflect the current US dollar – Israeli Shekel conversion rate. Slovic et al. (2002) originally reported lower performance in the Loss condition for the Similar-EV problem. They also noted that the same results were obtained for the Different-EV problem, but did not present these findings.[5]

Alternatively, under the attention-based account when the expected values of the available options considerably differ, losses are actually expected to have a positive effect on performance. Hence, we predicted that in the Different-EV problem losses would lead to more choices from the High-EV option and enhance performance.

2.3.1. Method

Participants: The participants were 104 Technion students (62 males and 42 females). An experimenter approached participants on campus (as in Slovic et al., 2002) and asked them to volunteer to fill in a one-question survey. An equal number of participants were allocated to the four conditions of the study.

Measure and Apparatus: The task involved selecting between a single pair of options titled "Alternative A" and "Alternative B". The payoffs were presented in the same format as in Study

[5] They merely indicated that "a replication study with $4 as the alternative to the gamble produced similar results" (p. 403).

2. Payoffs were based either on the Similar-EV problem or the Different-EV problem (in the Gain condition or in the Loss condition).

Procedure: Participants were randomly allocated to the experimental conditions. For the Gain/Loss conditions the proportions of males to females were very similar (56% compares to 63% males, respectively). In the Similar-EV problem there were slightly more males than in the Different-EV problem (67% compared to 52%; $\chi^2(1) = 2.56$, p = .11). We therefore added an analysis controlling for gender when comparing the two choice problems.

2.3.2. Results

In the Similar-EV problem the average proportion of selections from the High-EV option was 76.9% (SE = 8.4) in the Gain condition, and it declined to 46.1% in the Loss condition ((SE = 10.1). This is very similar to the pattern found by Slovic et al. (2002), which is explained by the contrast-based model. In the Different-EV problem, however, losses had a reverse effect. The proportion of selections from the High-EV option (i.e., the safe option) in the Gain condition was 73.1% (SE = 8.8) while in the Loss condition it increased to 84.6%. Statistical analyses showed a marginally significant performance advantage for the Different-EV problem compared to the Similar-EV problem ($\chi^2(1) = 3.72$, p = .054).[6] Across choice problems, there was no effect for the Gain/Loss condition ($\chi^2(1) = 1.14$, p = .28) but a separate analysis of each problem showed that in the Similar-EV problem losses had a significant negative effect on performance ($\chi^2(1) = 5.20$, p = .02), while in the Different-EV problem they had a non-significant positive effect ($\chi^2(1) = 1.04$, p = .31).

Hence, our results in the Similar-EV problem replicate those found by Slovic et al. (2002). However, the results in the Different-EV problem are different: Introducing a pronounced

[6] Controlling for the slight gender differences between conditions replicated this result (F (1, 101) = 3.99, p = .05). The effect of the Gain/Loss condition in each individual choice problem was also replicated when controlling for gender.

expected value difference between choice options eliminated the negative effect of losses on performance. These findings are consistent with those of our previous experiments. In the Similar-EV problem, where the differences in expected value were minor, the attentional effect of losses presumably did not have any impact on performance. In this case, only the contrast effect impacted the participants' decisions, leading to impaired performance with losses. Conversely, in the Different-EV problem, where selecting the advantageous alternative led to a substantial performance advantage, the attentional effect of losses impacted performance in addition to the contrast effect. This led to the slight (non-significant) performance enhancement with losses.

3. Similar losses produced by all alternatives

3.1. Study 4: Similar losses produced by all alternatives in experience-based decisions

As noted in the introduction, another means of examining the different processes implicated in the effect of losses on performance, is to have the same or a similar loss incurred by all choice alternatives. Differently from the design of Studies 1-3 in which the contrast and attention based models have contrasting predictions, in this research design, the contrast model has no clear directional prediction, since all options are contrasted with the same loss. Similarly, loss aversion also does not predict an effect of losses on performance in this case. Hence, in this setting, only the attention-based model predicts a positive effect of losses on performance.

The task we designed had two types of choice trials:

Problem 5: Similar losses produced by all alternatives

Trial	Low-EV option	High-EV option
A	1 with probability 0.5, 200 otherwise (EV = 100.5)	1 with probability 0.3, 200 otherwise (EV = 140.3)
b	x with certainty	x with certainty

In each choice trial a random generator determined whether a trial would be of type a or b, and the participant chose between the High-EV and Low-EV options. In trials of type b the value of x was set to 5 in the Gain condition and -5 in the Loss condition. Hence, in trials of type b both alternatives produced the same outcome. Under the attention-based model, losses should enhance performance in this setting as they increase the sensitivity to payoff. On the other hand, under the contrast-based model, since the same contrast (between 200 and -5) is induced by losses in both choice options, they should have no effect. Similarly, under loss aversion since the same loss is sustained from both choice options, there should be no effect of losses on performance.

3.1.1. Method

Participants: Forty-Eight Technion students (24 males and 24 females) took part in the study after responding to ads asking for participation in a paid experimental study. The participants received a fixed fee of NIS 10 in addition to their performance-based stipend. Participants were randomly allocated to the Gain and Loss conditions (Gain condition: n = 24, Loss condition: n = 24).

Measure and Apparatus: The same lab settings were used as in Study 1. The experimental task involved making 200 repeated selections between choice options that appeared as virtual buttons. The layout of the experiment and the instructions were as in Study 1. The payoffs were as in Problem 5 above. The actual rate of type b trials was similar in the two conditions: 0.5008 in the Loss condition and 0.4990 in the Gain condition. The dependent variable was the proportion of selections from the High-EV option across trials. When analyzing the data the same number of trial blocks as in Study 1 was used (4 blocks), with each block having 50 trials.

Procedure: The same procedure was used as in Study 1. The proportion of males and females were set to 50% in both condition. Six participants made their choices from the very same choice alternative throughout the 200 trials. Possibly, these individuals ignored the payoff structure altogether. Indeed, their aggregated choice pattern was not much different from random choice, with 57% selections from High-EV throughout all choice trials. We therefore conducted the analysis without these participants. Interestingly, two of these participants were in the Loss condition and four in the Gain condition. This anecdotal information is consistent with the argument that participants pay more attention in the condition with losses.

3.1.2. Results

The participants' learning curves appear in Figure 2. The average rate of High-EV selections across all trials showed only a small advantage for the Loss condition over the Gain condition, with 68.7% compared 63.0% choices from High-EV. However, losses did seem to have a positive effect on performance at the very first block of trials. To examine the statistical significance of this pattern, the results were analyzed using a repeated measures ANOVA with trial block (of 50 trials) as a within-subjects factor and condition (Gain vs. Loss) as a between-subjects factor. The analysis showed that the main effect of condition was not significant ($F(1,40) = 0.60$, $p = .44$). However, the interaction between condition and trial block was significant ($F(3,46) = 5.06$, $p = .03$). Planned contrast tests showed that at the first block the difference between conditions was marginally significant in t-test ($t(40) = 1.81$, $p = .08$). In this block, in the Loss condition 63.5% of the choices were from the High-EV option compared to 50.1% in the Gain condition, with performance in the Loss but not in the Gain condition being significantly better than random choice (Loss: $t(21) = 2.37$, $p = .03$; Gain: $t(19) = 0.02$, $p = .98$). Thus, losses seemed to have accelerated learning in the first phases of the task even though they were incurred equally from all choice alternatives.

3.2. Study 5: Similar losses produced by all alternatives in description-based decisions

We also examined whether having a similar loss incurred from all choice alternatives might improve performance in description-based decisions. This condition was implemented in a somewhat more realistic tax-base scenario, where tax is deducted from the participant's gains. Three conditions were compared: No-Tax, Tax (a constant fraction paid back), and Bonus (a constant fraction added to the participant's tally). According to the attention-based model of losses, the implementation of the tax should facilitate performance (i.e., maximization), a pattern we labeled as the "tax-max effect". By contrast, contrast-based models do not have a direct prediction in this setting since the tax is imposed on all alternatives. Loss aversion actually implies a negative effect of losses on maximization because the tax imposes a larger loss on the higher expected-value alternative.

To validate the generality of the findings to different payoffs we used a battery of prospects developed by Holt and Laury (2002). The battery, presented in Table 3, was designed to incorporate a range of differences in expected value between prospects. Holt and Laury (2002) found a large incentive effect such that choices were better for real outcomes (from a randomly determined gamble) than for hypothetical ones. We examined whether presenting losses in the form of tax would have an effect in the same direction, even though taxes reduce the actual obtained outcomes.

3.2.1. Method

Participants: The participants were 105 Technion students (54 males and 51 females) who responded to ads asking for participation in a paid experimental study. They received a participation fee of NIS 10 as well as an additional amount based on their performance. Participants were randomly allocated into the three experimental conditions (No-Tax: n = 34, Tax: n = 38, Bonus: n = 33).

Measure and Apparatus: The task involved selecting between pairs of prospects. The outcomes and probabilities are described in Table 3. The order of the prospects was randomized for each participant. The items were presented in the exact phrasing shown in Table 3 with the addition of the word "chance" after the probability and the NIS symbol. For example, participants were presented with the following pair of items: "Alternative A: 0.1 chance to get ₪4.00, 0.9 chance to get ₪3.20, Alternative B: 0.1 chance to get ₪7.70, 0.9 chance to get ₪0.20" (the ₪ symbol denotes NIS). The selection between prospects was done by pressing the button labeled "Alternative A" or "Alternative B" positioned at the top of each prospect description. This basic task conforms almost exactly to the set of prospects presented by Holt and Laury (2002) with the exception that payoffs were in Israeli currency, and that all outcomes were multiplied by two. In the Tax condition below each pair of items the following text was added: "Please notice that 20% of your earnings will be paid as tax to the lab". In the Bonus condition this was changed to "Please notice that in addition you will get a bonus of 20% of your total payoff". The dependent variable was the proportion of selections from the alternative yielding the higher expected value, which will be referred to as the High-EV option (Option A in the first 4 rows of Table 3 and Option B in the last 5 rows).

Procedure: The same lab settings were used as in Study 1. The proportion of males and females was similar in each condition (50% males in the Tax and No-Tax condition and 48% in the Bonus condition). The participants were given the following written instructions: "In this study you will be asked to select between 10 pairs of gambles that you wish to play. Each gamble has two monetary consequences that are realized with different probabilities. The amounts and probabilities will be presented on screen. At the end of the experiment, one of the gambles will be randomly selected, and it will be played. The amount earned will be added to your overall payoff for this experiment." In the No-Tax condition this ended this part of the instruction. In the Tax condition an underlined text further indicated that "Please notice that 20% of your earnings will be paid as tax to the lab". In the Bonus condition this last sentence was converted to "Please notice that in addition you will get a bonus of 20% of your total payoff". These one-sentence messages were also presented at the bottom of the screen describing each pair of prospects (each message in its respective condition, as noted above). The instructions were followed by an easy example. The participants were then asked if they had any questions. They then selected between the pairs of prospects.

3.2.2. Results

The average proportions of selections appear in Figure 3. As indicated in the figure, the rate of selections from the High-EV option in the Tax condition was higher than in the other two conditions. A one-way analysis of variance showed that the difference between conditions was significant ($F(2,102) = 5.14$, $p < .01$). Scheffe contrast analyses indicated that the differences between the Tax condition and each of the other two conditions were significant (Tax, No-Tax: $p = .02$, Tax, Bonus: $p = .01$, one tailed).

Table 3 also shows the results for individual items from Holt and Laury's (2002) battery. As can be seen, across items there was an advantage to the Tax condition. Maximization rates in this condition were higher than in the Bonus or Control condition in 7 out of the 10 gambles. Maximization rates in the Bonus condition were higher than in the Control condition in only 4 out of the 10 gambles. Comparison of the Tax condition and the two other conditions using Student's t-test yielded significant results for three items (rows 2, 5, and 7 in Table 2; $p < .05$). By contrast, for the Bonus condition there was no significant advantage over the remaining two conditions in any of the studied gambles.

4. General discussion

The results of the current studies show that losses have unique effects on performance in decision tasks, which are not merely a symmetric mirror image of the effect of respective gains. However, the mechanism leading to these effects is not necessarily as simple as an increased weight of losses compared to gains. We examined two sets of new predictions concerning effect of losses on cognitive performance derived strictly by attention-based and contrast-based processes. Our findings confirm that effects of losses on performance can be predicted based on these processes, and that these effects may run counter to the predictions of loss aversion.

Adding minor losses to one of the choice alternatives. In Studies 1 and 2 we found that losses enhanced the selection of an advantageous choice option, even though this choice option was the only one that produced losses. The effect of losses in this condition, which was labeled as "Advantageous losing", could not be explained by loss aversion. Rather, it could be explained by either the attentional or contrast-based model. Formal modeling of trial to trial choices showed that indeed participants exhibited loss neutrality in this setting, and that losses increased the sensitivity to the entire set of incentives.

To further disentangle the predictions of the attentional and contrast-based models, we examined a "Disadvantageous losing" condition, in which losses are produced by a risky disadvantageous option. In this condition, under contrast models losses should promote the selection of the risky option, thereby impairing performance; while under the attention-based model losses should enhance performance. Our findings in this condition showed that losses still had a positive effect on performance in experience-based tasks and description-based tasks, though it was much weaker than in the "Advantageous losing" condition. This interaction suggests that both contrast and attention-based processes modulate the effect of losses on performance. When these processes both imply a positive effect of losses on performance, we find a larger effect than when they have counter-acting influences.

Our results also imply that when the contrast-related and attention-based effects of losses are in opposite direction, the attentional effect wins by a margin, as evidenced by the positive effect of losses on performance. This finding (obtained both in Study 1 and 2) appears to contradict those of Slovic et al. (2002). In order to examine this disparity we used Slovic et al.'s

(2002) specific design. We found that we replicated Slovic et al.'s (2002) results in the condition with almost no expected-value difference between the alternatives. Apparently, in the absence of a performance benefit to choosing either one of the alternatives, the contrast-related effect of losses moved decisions away from expected value maximization. However, in a second condition where the difference in expected values was substantial, we obtained a weak positive effect of losses on performance. This result, implied by the attention-based model, was consistent with those of Study 1 and 2.

The first three studies we conducted used very different settings: experience-based decisions with performance based compensation; description-based decisions with compensation based on a raffle; and description-based decisions with voluntary participation and involving a very different choice problem. Yet while this might well have impacted the data, in all three studies we obtained the same results: When alternatives differed in their expected value losses had a positive effect on performance, and this effect became significant (in Studies 1 and 2) when it was in the same direction as the contrast effect.

Similar losses produced by all alternatives. We also examined whether in the absence of contrast effects, losses would have a positive effect on decision performance, as implied by attention-based model. In study 4 we "planted" random trials where losses (or small gains) were emitted by both choice alternatives. As predicted by the attention-based model, the addition of small losses improved performance, though mostly in the first block of trials. It appears that losses helped participants to adjust quicker to the task demands. In Study 5 we examined a more realistic situation using a tax-based scenario where losses were incurred as a constant fraction of the participants' winnings. We found that taxes had a positive effect on maximization in a decision task, even though greater losses were sustained by making the right selection.

5. Concluding remarks

Our experimental results suggest that the mechanisms leading to the unique effects of losses on cognitive performance should be re-evaluated. Indeed, as suggested by Novemsky and Kahneman (2005) "…a realistic theory of loss aversion is unlikely to be simple." (p. 126). The current findings are consistent with the theory that losses may be treated as signals of attention and not only as signals of avoidance. Our results thus complement previous findings showing that losses induce more controlled processing than comparable gains (Dunegan, 1993) and are associated with some of the physiological indices of attention (as reviewed in Yechiam and Hochman, in press). However, our findings also suggest that the contrast between losses and gains is an additional important factor that moderates the association between losses and performance.

A limitation of our experimental design is that we only examined relatively small nominal losses. Previously, Slovic et al. (2002) showed that contrast effects were lower as a function of the size of the loss. Possibly, larger losses may lead to loss aversion (cf. Abdellaoui, Bleichrodt, Paraschiv, 2007; Rabin & Weizsäcker, 2009). Note, however, that our goal in this paper was not to refute the existence of loss aversion but rather to refute two stronger arguments: 1) that loss aversion is the only explanation for the effect of losses on cognitive performance (e.g., Bereby-Meyer & Erev, 1998; Pope & Schweitzer, 2011), and 2) that the sensitivity to losses is a single primitive construct and whenever there are attentional effects of losses there is loss aversion and vice versa (e.g., Dunegan, 1993; Taylor, 1991). Our findings demonstrate that the attentional effect of losses is indeed distinct from loss aversion, and can lead to behavioral patterns that are contradictory to those implied by loss aversion.

In a broader sense, the non-specificity of the effect of losses to the stimuli that have produced the losses sheds light on a variety of social phenomena. Specifically, both the attention- and contrast-based models of losses imply that a negative feature may turn into an advantage when it draws attention to an overall positive nature of a person or a situation, but the attention-based model suggests that this is moderated by more global considerations. For example, experiments in Social Psychology using simulated interviews with job candidates have examined the effect of minor negative features on the candidates' evaluation. The results showed that when a generally favorable candidate had some minor negative occurrence (e.g., spilling his/her cup of coffee), this actually increased the candidate's positive evaluation (Nisbett & Bellows, 1977; Beauvois & Dubois, 1988). The attention-based model suggests, however, that the positive effect of losses in this setting is limited to an overall advantageous candidate, and should be reversed if a poor candidate presents slightly negative behavior. Under the joint influence of contrast and attention, the effect of losses is expected to diminish for poor candidates. A similar example in the field of marketing is the "blemishing effect", the finding that a weak negative feature in a particular product (e.g., a partially broken chocolate bar) improves its attractiveness (Ein-Gar, Shiv, & Tormala, 2012). Again, differing from the contrast-based account, the attention-based model implies that this finding is not general, and should emerge more strongly for products which most consumers recognize as attractive upon deliberation.

The tax-max effect we observed further suggests that the positive effect of weak negative features can be generalized to taxes. Anomalous effects of taxes on the value of products have been proposed for specific products, such as Veblen goods (high status products; e.g., Amaldoss & Jain, 2005). Our findings suggest that given a similar tax level and a tax-per-earning scheme, taxes also improve the selection of investment options and therefore increase preference for the most highly taxed option. We believe that this apparent paradox, which was demonstrated in simple gambles, emerges simply because taxes, like other forms of losses, have the effect of increasing attention to the task at hand.

Appendix: The experimental screen in Study 2 (Problem 1, Gain condition)

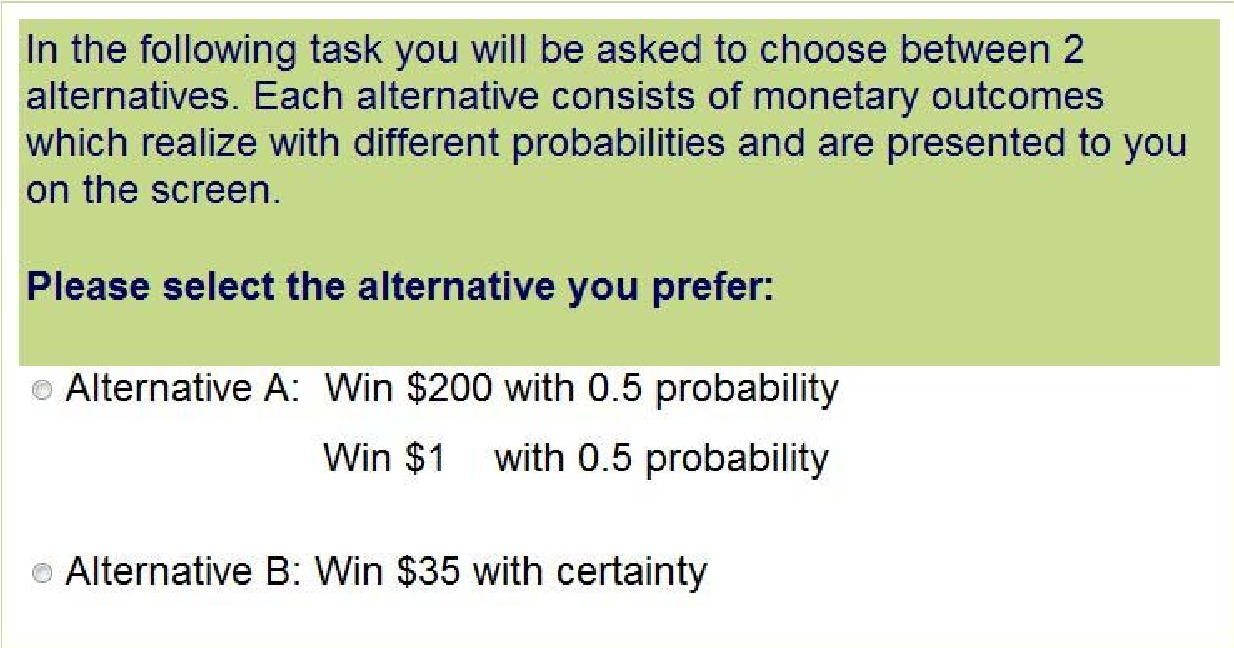

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Table 1: Outline of the choice problems used in Studies 1 and 2. The top table for each choice problem (Advantageous-losing and Disadvantageous-losing) presents the task payoffs in two conditions. Each condition (Loss versus Gain) involved choice between two alternatives (High-EV versus Low-EV; where EV denotes Expected Value). This table is followed by the behavioral predictions of loss aversion, the attentional model, and the contrast-based model. The predictions pertain to the mean choice P of a choice option in a specified condition. For example "P (High-EV, Loss)" refers to the predicted mean choice of the High-EV option in the Loss condition.

Problem 1: Advantageous -losing

Condition	Low-EV option	High-EV option
Loss	35 with certainty	-1 with probability 0.5, 200 otherwise (EV = 100.5)
Gain	35 with certainty	1 with probability 0.5, 200 otherwise (EV = 100.5)

Model	Predictions
Loss aversion	P (High-EV, Loss) < P (High-EV, Gain)
Attention	P (High-EV, Loss) > P (High-EV, Gain)
Contrast	P (High-EV, Loss) > P (High-EV, Gain)

Problem 2: Disadvantageous -losing

Condition	Low-EV option	High-EV option
Loss	-1 with probability 0.5, 200 otherwise (EV = 100.5)	135 with certainty
Gain	1 with probability 0.5, 200 otherwise (EV = 100.5)	135 with certainty

Model	Predictions
Loss aversion	P (High-EV, Loss) > P (High-EV, Gain)
Attention	P (High-EV, Loss) > P (High-EV, Gain)
Contrast	P (High-EV, Loss) < P (High-EV, Gain)

Table 2: Estimated parameters of the Expectancy Valence model for Study 1. Averages and standard errors (in parentheses) of the three model parameters: Weight to losses versus gains (*W*), recency (ϕ), and choice sensitivity (*c*).

		Parameter		
Problem	Condition	Loss weight (*W*)	Recency (ϕ)	Choice Sensitivity (*c*)
Adv. Losing	Gain	.	0.21 (0.07)	3.06 (0.83)
	Loss	1.08 (0.07)	0.46 (0.07)*	5.50 (0.50)*
Disadv. Losing	Gain	-	0.21 (0.05)	3.00 (0.65)
	Loss	1.05 (0.06)	0.23 (0.06)	6.40 (0.35)*

* $p < .05$ (comparison of the parameters in the Loss and Gain conditions in each of the two choice problems).

Table 3: The battery of prospects used in Study 5 (based on Holt and Laury, 2002). The two left most columns present the outcomes (in New Israeli Shekels, NIS). The next column shows the expected value difference between Option A and B. The right most columns present the data: mean proportion of selections from the High-EV option in the three experimental conditions (choice of A in the first four gambles and B in the last six).

			P(High-EV)		
Option A	Option B	EV (A-B)	No-Tax	Bonus	Tax
0.1 to get 4.00, 0.9 to get 3.20	0.1 to get 7.70, 0.9 to get 0.20	2.34	0.94	0.91	0.92
0.2 to get 4.00, 0.8 to get 3.20	0.2 to get 7.70, 0.8 to get 0.20	1.66	0.88	0.85	0.97
0.3 to get 4.00, 0.7 to get 3.20	0.3 to get 7.70, 0.7 to get 0.20	1.00	0.79	0.88	0.87
0.4 to get 4.00, 0.6 to get 3.20	0.4 to get 7.70, 0.6 to get 0.20	0.32	0.74	0.85	0.74
0.5 to get 4.00, 0.5 to get 3.20	0.5 to get 7.70, 0.5 to get 0.20	-0.36	0.24	0.21	0.58
0.6 to get 4.00, 0.4 to get 3.20	0.6 to get 7.70, 0.4 to get 0.20	-1.02	0.35	0.33	0.47
0.7 to get 4.00, 0.3 to get 3.20	0.7 to get 7.70, 0.3 to get 0.20	-1.70	0.59	0.67	0.82
0.8 to get 4.00, 0.2 to get 3.20	0.8 to get 7.70, 0.2 to get 0.20	-2.36	0.91	0.79	0.84
0.9 to get 4.00, 0.1 to get 3.20	0.9 to get 7.70, 0.1 to get 0.20	-3.02	0.91	0.88	0.92
1.0 to get 4.00 [0 to get 3.20]	1.0 to get 7.70, [0 to get 0.20]	-3.70	0.88	0.94	0.87

Figure 1. Study 1 Results: Average proportion of selections from the advantageous High-EV option in four blocks of 25 trials, in the Gain and Loss conditions. Top: Problem 1 (Advantageous losses). Bottom: Problem 2 (Disadvantageous losses).

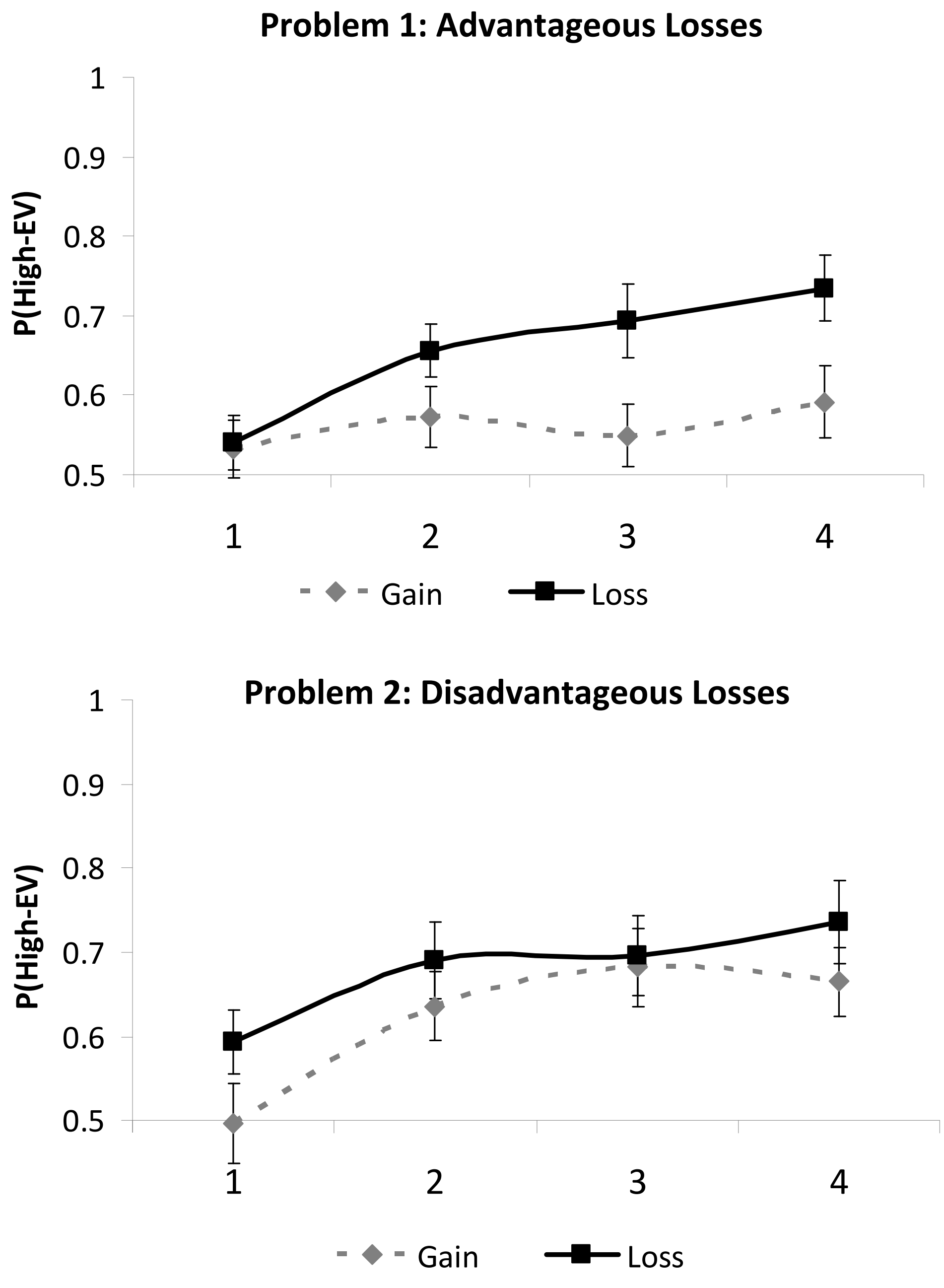

Figure 2: Study 4 results. Average proportion of selections from the advantageous High-EV option in four blocks of 50 trials, in the Gain and Loss condition.

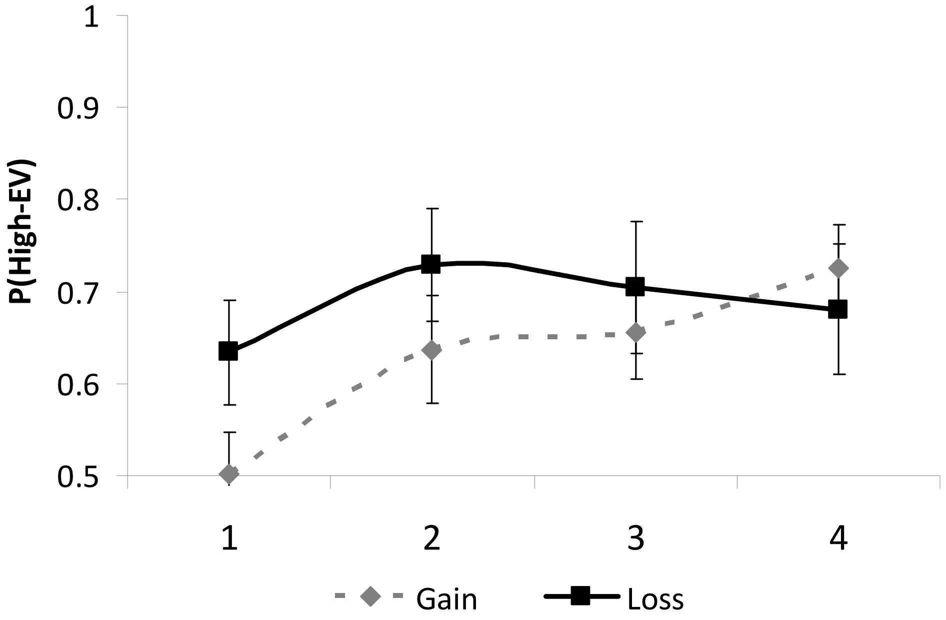

Figure 3. Comparison of the experimental conditions in Study 5: Average proportion of selections from the High-EV option in the No-Tax condition, Bonus condition, and Tax condition. The error bars denote the standard errors.