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An examination of the myopic loss aversion hypothesis

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LOSS ATTENTION AND THE EQUITY PREMIUM PUZZLE: AN EXAMINATION OF THE MYOPIC LOSS AVERSION HYPOTHESIS

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Myopic loss aversion is the assumption that because investors frequently check their portfolios and are loss averse, they under-invest in financial assets producing short term losses that are advantageous in the long run. This notion is inconsistent with findings indicating that losses increase exploitation based on the experienced payoff structure. To clarify this gap, we conducted two studies using Thaler et al.'s (1997) original paradigm for supporting the notion of myopic loss aversion. The findings indicate that avoidance of a risky alternative producing losses only emerged when the risky option was experienced as disadvantageous and with partial information (no foregone payoffs). These findings are inconsistent with myopic loss aversion, and suggest that the response to risky options producing losses is driven by increased exploitation based on past experience – leading to a hot stove effect, as well as a more general diminishing sensitivity to zero.

Keywords: Loss aversion, loss attention, equity premium paradox, myopia

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1. INTRODUCTION

The construct of myopic loss aversion was originally proposed as an explanation for the so called the "equity premium puzzle" (Grossman and Shiller, 1981; Shiller, 1982; Mehra and Prescott, 1985; Siegel and Thaler, 1997), the finding that from the beginning of the past century and until 2006 (Dimson, Marsh, and Staunton, 2008), observed 10-year returns on major stock indices in various countries (such as US, UK, Germany, and Japan) were much higher than returns on government bonds. This suggests that for over a century the public had invested too much in bonds and too little in stocks. Myopic loss aversion explains this pattern as being due to two basic regularities (Benartzi and Thaler, 1995): First, investors are assumed to be loss averse, namely they overweight losses compared to equivalent gains (Kahneman & Tversky, 1979). Secondly, they are assumed to frequently check their portfolio returns. Consequentially, when risky investments (such as stocks) incur frequent losses, this induces risk aversion even though the investment may be advantageous in the long run. The role of losses in the avoidance of risky and advantageous alternatives has been supported in a lab experiment by Thaler, Tversky, Kahneman, and Schwartz (1997) in which participants avoided a highly advantageous risky alternative when it incurred losses, though they did not avoid an equally risky alternative that did not produce losses.

The myopic loss aversion account seems, however, to be inconsistent with a recent line of studies showing that losses increase selection from alternatives that are experienced as advantageous on average (Yechiam and Hochman, 2013a, b; Yechiam, Ashby, and Hochman, in press) and those that are better on the long run (Pang, Otto, and Worthy, 2015). These findings have been explained by the positive effect of losses on task attention – known as loss attention – which supposedly increases individuals' sensitivity to the experienced payoff structure (Yechiam and Hochman, 2013a, b). The main goal of the current study is to clarify the gap between the myopic loss aversion and loss attention accounts by examining their predictive power in the original task used by Thaler et al. (1997) to confirm the former construct.

Our proposed explanation for the apparent inconsistency is that experiments using Thaler et al.'s (1997) paradigm typically showed profits only or mostly for the selected investments. This implies that exploitative choices are likely to result in risk aversion owing to insufficient sampling of the risky option (Denrell and March, 2001). Therefore, there are two possible reasons for avoiding risky alternatives in this paradigm: myopic loss aversion, and reduced sampling owing to increased exploitative choices with losses. In order to evaluate these two potential explanations we examined a task version where decision makers get complete and unbiased information from all available choice alternatives.

1.1.Thaler et al.'s experiment

To evaluate their argument that under-investment in stocks is driven specifically by loss aversion, and not only by risk aversion (e.g., sensitivity to high variance), Thaler et al. (1997) conducted a lab experiment in which an investment-like task was administered in a loss and no-loss condition. The task involved making choices between two alternatives presented as funds, S (safe) and R (risky), as shown in Table 1.[2] In each round participants decided how much to invest in the two funds and were given feedback

[2] Participants were not given any information about these alternatives other than the fact that they represent investment opportunities; and the notations S and R are used for explanatory purposes.

regarding the returns on their investment. In the loss condition, the returns for R were drawn from a normal distribution with an average of 1% and a standard deviation of 3.54%; the returns for S were drawn from a normal distribution with an average of 0.25% and a standard deviation of 0.177%, and the distribution of S was further truncated above 0. In the gain condition all payoffs were increased by 10% so that no losses were possible. The experiment included 400 trials with feedback and an additional single binding decision for the remaining 400 trials. Thaler et al.'s (1997) findings indicated that in the loss condition, decision makers showed a preference for alternative S over R, with about 57% of their funds being allocated to S across trials. This behavioral pattern emerged even though the expected value of R was approximately four times that of S. Furthermore, in the gain condition individuals learned to select R (with only 34% of their funds being allocated to S), suggesting that avoidance of the advantageous risky alternative only emerged when it produced losses, thus reinforcing Thaler et al.'s (1997) explanation based on myopic loss aversion. These finding were replicated in several other studies which used discrete choices instead of allocation decisions, and tokens instead of percentages (Barron and Erev, 2003; Erev, Ert, and Yechiam, 2008; Yechiam and Busemeyer, 2008; though not by Shavitt, Rosenboim, and Cohen, 2013). Additionally, Thaler et al. (1997) and Gneezy and Potters (1997) found that presenting outcomes pooled across investment periods (wide bracketing) eliminated risk aversion in the loss condition, This was also argued to support the notion of myopic loss aversion since the pooled returns reduce the likelihood of losing.

Erev et al. (2008) noted that the distribution of payoffs in Thaler et al.'s (1997) experiment was highly skewed, and accordingly high diminishing sensitivity to the distance zero (i.e., diminishing returns; Bernoulli, 1738/1954; Kahneman and Tversky, 1979) might also result in risk aversion in the loss condition because the relatively lower losses are discounted less than the higher gains. Nevertheless, the fact that participants avoided an alternative producing frequent losses yielding four times the amount of profit than its safer counterpart is striking, especially in light of recent claims that losses facilitate sensitivity to the experienced choice outcomes (Yechiam and Hochman, 2013a,b).

We examined a novel explanation which clarifies this gap: In Thaler et al.'s (1997) experiment the distribution of potential payoffs was not provided to the participants, and they had to learn about the risks and returns of the two alternatives through experience. After making a choice, participants were given graphical information regarding the returns of each option, and a point estimate of their portfolio returns. However, they were not given information on alternative (foregone) returns that would have resulted from different portfolios. More so, in Barron and Erev (2003), Erev et al. (2008), and Yechiam and Busemeyer's (2008) replications, participants made discrete choices between options and only received payoff feedback from the selected choice option. Accordingly, participants may have been misled by initial trials in which the experienced mean value of the risky option was lower than that of the safe option. Specifically, the hot stove effect (Denrell and March, 2001) is a phenomenon whereby individuals under-sample risky alternatives when their payoffs are experienced as relatively low, leading to avoidance of these alternatives. Additionally, it was recently proposed that because losses increase exploitative choices based on past experience, they facilitate the hot stove effect (Yechiam et al., in press). Hence, losses could bias the sampling of risky alternatives experienced as disadvantageous, thereby exacerbating subsequent risk aversion even though the risky alternative might be advantageous in the long run.

1.2. A Model and Current Studies

We juxtaposed these accounts into opposing predictions for the effect of getting full information on possible outcomes in a given investment period, namely both obtained and foregone payoffs. Under myopic loss aversion this should have no effect on the pattern of extreme risk aversion with losses because it is driven by a bias in the utility function. However, if the effect of losses is driven by increased exploitation and hot stove effect, extreme risk aversion should not emerge in a loss condition with full information, because this condition eliminates the hot stove effect (i.e., participants do not get biased feedback from the risky option).

Formally, the notion that losses increase exploitation can be captured by a simple softmax choice rule (Luce, 1959; Daw et al., 2006) with higher choice sensitivity for tasks with losses than for tasks with no losses (see Yechiam et al., in press). In the simple case of discrete choices between options, the probability of selecting alternatives is assumed to be a function of their expectancies, representing the outcomes predicted upon selecting them, and random noise:

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

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. The Parameter θ controls the sensitivity of the choice probabilities to the expectancies. θ of zero implies random choice, and as θ increases participants make choices that are more consistent with the expectancies. If losses increase exploitation based on the available outcomes, then θ is higher for tasks with losses than for tasks with no losses ($\theta_{Loss} > \theta_{Gain}$).

We conducted a simulation based on this notion by approximating 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 $x = 0$; $sgn(x) = 1$ if $x > 1$) and by its adjusted absolute magnitude, where α is the degree of the utility function's concavity/convexity, (following Kahneman and Tversky, 1979; Ahn et al., 2008; Erev et al., 2008). The three parameters of the model are therefore θ_{Loss} , θ_{Gain} , and α. We used the estimated values of θ in Yechiam et al. (in press), based on a dataset of 1,417 Amazon Mechanical Turk (Mturk) participants. These estimated parameters were $\theta_{Gain} = 0.052$ and $\theta_{Loss} = 0.095$. Additionally, as the nominal payoffs in Yechiam et al. (in press) were smaller than in Thaler et al.'s (1997) paradigm we examined α values ranging from 0.5 to 0.9 (to account for varying diminishing sensitivity to zero for higher payoffs). The results of the simulation are shown in Figure 1. It indicates that given full information, the tendency to exhibit risk aversion for alternatives producing losses should disappear and potentially even reverse if one assumes weak diminishing sensitivity to zero.

In Study 1 we replicated the discrete choice version of Thaler et al.'s (1997) experiment, studied by Erev et al. (2008) and others, and evaluated whether getting full information from both alternatives changes the effect of losses on risk aversion. We also examined trial to trial choices in the original partial-information condition to test the hot stove account. In Study 2 we re-examined the effect of full information in a condition with lower nominal values. This reduces the psychological tendency to exhibit diminishing sensitivity to zero (Erev et al., 2008).

2. STUDY 1: FEEDBACK FROM OBTAINED AND FOREGONE PAYOFFS

Can the laboratory instantiation of the equity premium puzzle be eliminated if participants get unbiased experience from the safe and risky options, namely payoff information from both alternatives regardless of one's choices? If a key determinant of risk aversion with losses is increased exploitation and hot stove effect, then complete and unbiased information from the available choice alternatives should eliminate risk aversion in the loss condition of Thaler et al. (1997). Conversely, under myopic loss aversion, extreme risk aversion with losses should be replicated even with full information because it is driven by individuals' biased utility functions. We therefore compared a version of Thaler et al.'s (1997) experiment where participants get only partial information from the selected choice alternative (e.g., as in Barron and Erev, 2003; Erev et al., 2008) to a new condition where full information from the selected as well as unselected alternatives is presented. The study was run in a two (gain/loss) by two (partial vs. full information) between-subjects design. The research was approved by the Herzliya Interdisciplinary Center (IDC) Ethics Committee for Behavioral Studies.

The experimental participants were 702 MTurkers (341 females, 349 males, 2 not identified) who responded to ads asking for participation in a paid experimental study. Participants' ages ranged between 18 and 72, with a mean age of 37.2 (SE = 0.47). We restricted participation to individuals who were USA residents and had a 95% approval rate of previous works submitted to MTurk. This is consistent with the recommendation of Peer, Vosgerau, and Acquisti (2014), who found the 95% approval rate criterion to be as effective as traditional attention-check procedures. Each participant was randomly allocated to one of four experimental conditions. By this random allocation, 176 participants were assigned to the loss partial-information condition and 178 to the loss full-information condition; 186 participants were assigned to the gain partial-information condition, and 162 to the gain full-information condition.[3] All participants received a fixed fee of $1.5 as well as an additional amount based on their performance as noted below.

The decision problem was presented as an investment game in which participants repeatedly choose between two options by pressing a button. This choice was repeated during 100 trials. Following each choice the selected button's outcome was presented based on a draw from the relevant distribution (see Table 1 top rows), as was the trial number and the accumulating payoff (this is consistent with an investment setting in

[3] We only included participants who completed all 100 trials. The rate of drop-outs was 2.6%, and was about equal in the gain and loss conditions (11 vs. 8 participants, respectively).

which outcomes accumulate over time). As in Thaler et al. (1997), participants did not receive a description concerning the payoff distributions, but rather had to base their decisions on the feedback they received from previous choices. Points were converted to cash at the end of the experiment at a rate of 0.1 cent per $1,000 earned.

In the partial-information condition participants only saw the outcomes from the selected alternative (as in Barron and Erev, 2003; Erev et al., 2008). In the full-information condition upon selecting one of the options, outcomes from the unselected option were presented as well. Additionally, the task was implemented in three versions to examine the robustness of the findings. In the first version (n = 200) losses were identified by a minus sign (no-color version), similarly to Erev et al. (2008). The second version (n = 200) identified gains and losses by a label ("gain", "loss") as well as a color code: green for gains, red for losses (color version), as in Shavitt et al. (2013). The third version (n = 300) did not give complete information about the conversion rate, but only presented the possible range of final payoffs (no conversion rate version). It was otherwise similar to the color version. This last version followed the design of Thaler et al. (1997), who argued that explicit conversion rates may encourage participants to consider the very small gains and losses that occur on each individual trial. The Appendix section includes the instructions in each of the three versions as well as screenshots from the different conditions (see Figure A1). The experiment was programmed using the oTree platform (Chen, Schonger, and Wickens, 2015).

2.1. Results

Figure 2 presents the rate of R selections (P(R)) in each condition. The pattern of results in the partial-information condition was similar to that found in Thaler et al. (1997) and subsequent replications. In this condition participants exhibited a tendency to avoid the risky alternative in the loss condition (P(R) = 0.29) and a much lower tendency to do so in the gain condition (P(R) = 0.47). However, in the full-information condition participants did not seem to avoid the risky alternative in the loss condition (P(R) = 0.49; one sample t-test t(171) = 0.74, p = .46), and had a slight tendency to prefer it in the gain condition (P(R) = 0.59). Importantly, compared to the partial-information condition the difference between the gain and loss conditions in the full-information condition was smaller by about 40% ($P(R)_{Loss\ -Gain}$ = 0.11 in the full-information condition compared to 0.18 in partial-information condition). Also the effect of full information was more prominent in the loss than in the gain condition ($P(R)_{Full-\ Partial}$ = 0.20 in the loss compared to 0.13 in the gain condition). To statistically compare the different conditions, we used analysis of variance (ANOVA) with gain/loss and partial/full information conditions as independent variables, and P(R) as the dependent variable. Because some of the conditions had skewed data and the variances across all four conditions were unequal (Levene F(3) = 53.09, p < .001), we logit-transformed the data. The results, shown also in Table 2 (Model 1), indicated a significant difference between the gain and loss conditions (F(1,698) = 45.80, p < .001) as would be predicted by myopic loss aversion. Additionally, there was a significant interaction between the partiality of the information and the gain/loss condition (F(1,698) = 8.81, p = .003). This interaction effect implies that some of the effect of losses is washed away with full information, consistent with idea that losses increase exploitation and the hot stove effect.

Separate learning curves for the three task versions appear in supplementary Figure S1. As indicated in Table 2 (Model 2), entering task version as an additional independent factor in the ANOVA replicates the aforementioned main and interaction effects while indicating no three-way interaction with task version.

We also examined whether differences between conditions were affected by experience, by conducting a repeated-measures ANOVA with trial block (of 20 trials) as an additional within-subject factor. The results showed a significant effect of trial block ($F(4,695) = 3.53$, $p = .007$), reflecting a general tendency to avoid risk with trial experience. The interaction of trial block by gain/loss condition was also significant ($F(4,695) = 6.63$, $p < .001$) denoting an increase in the difference between the gain and loss conditions with accumulating experience. Also, the three-way interaction between the partiality of the information, the gain/loss condition, and trial block was significant, F(4,695 = 2.87, p = .02). The two and three-way interactions illustrate that while differences between the gain and loss conditions increased with experience, the full-information condition partially buffered this effect.

Next, we examined to what extent choices in the *partial-information* condition were driven by a hot stove effect. For this purpose, we divided the trials into two types based on each individual's past experience: Those where the risky alternative was experienced as advantageous (S < R) and those where it was experienced as disadvantageous (S > R). The type for trial *t* was determined based on the mean outcome from each alternative in trials 1 to *t*-1. Trials where S = R were omitted, and owing to the normal distributions their rate was very small (0.0002). In the gain condition 22.6% of the trials were of the S > R type, compared to 39.8% in the loss condition, a significant difference ($t(360) = 4.53$, $p < .001$). Figure 2 bottom panel presents the rate of R selections in each trial type. The results indicate that the extreme risk aversion found in the partial-information loss condition was mostly due to trials in which the mean experienced value of the risky alternative was lower than that of the safe alternative. In these S > R trials, the risky alternative was selected only at a rate of 0.28; compared to 0.44 in trials where S < R. Given that the rate of S > R trial in the loss condition was about twice than in the gain condition, this explains the preponderance of risk aversion in this condition.

In summary, much of the risk aversion observed in the loss condition was due to trials in which the risky alternative was experienced as disadavntegous, with the full-information condition cutting the effect of losses on risk aversion by about 40%. This suggests the working of both a general effect of losses independent of an information bias, as well as an effect of losses that is contingent on partial information, consistent with the notion of increased exploitation and hot stove effect with losses. Importantly, the general effect (the main effect of losses across information condition) could be due to myopic loss aversion but also to diminishing sensitivity to zero. As shown on the left-most bar in Figure 1 a similar effect is predicted if one assumes high levels of diminishing sensitivity.

3. STUDY 2: FULL INFORMATION WITH LOWER NOMINAL VALUES

As in Study 1 full information only removed some 40% of the difference between the gain and loss conditions of Thaler et al.'s (1997) experiment, we aimed to examine the cause of the remaining disparity. Obviously, one candidate mechanism is myopic loss aversion, which if higher in the loss condition should lead to more risk aversion in this condition. Alternatively, though, it could be that the differences are driven by diminishing sensitivity to zero, as proposed by Erev et al. (2008). Under this latter explanation because of the high nominal values of token amounts and the fact that losses are smaller than gains in the loss condition, there is a relatively high discounting of the risky alternative's gains compared to its losses, which facilitates extreme risk aversion in the loss condition. To evaluate these possible explanations we examined a version of the experiment using smaller amounts (actually closer to the amounts used by Thaler et al., 1997) by dividing all nominal outcomes (i.e., token payoffs) by 100. We examined whether in this setting the difference between conditions would remain with full information – as posited by myopic loss aversion – or disappear completely as posited by the notion that losses increase exploitation and the hot stove effect.

The experimental participants were 201 MTurkers (109 females, 89 males, 3 not identified) who responded to ads regarding a paid study. Participants' ages ranged between 18 and 84, with a mean age of 36.2 (SE = 0.78). We again restricted participation to individuals who were USA residents and had a 95% MTurk approval rate. Each participant was randomly allocated to the gain and loss conditions. By this random allocation, 49 participants were assigned to the loss partial-information condition and 56 to the loss full-information condition, 51 were assigned to the gain partial-information condition, and 45 to gain the full-information condition.[4] All participants received a fixed fee of $1.5 as well as an additional amount based on their performance as noted below.

[4] As in Study 1, we only included participants who completed all 100 trials. The rate of drop-outs was 2.0%.

The experiment was identical to Study 1 no-color version with the following two exceptions: First, all nominal amounts (i.e., token amounts) were divided by 100 (see Table 1 bottom rows). Secondly, the conversion rate was 0.1 cent for each $10. Thus, in terms of actual monetary amounts the experiment was identical to Study 1 even though the nominal amounts were smaller. Complete instructions appear in the Appendix section.

3.1. Results

Figure 3 presents the rate of R selections in each condition. The pattern of results in the partial-information condition was similar to that found in Study 1, with more risk aversion in the loss condition (P(R) = 0.33) than in the gain condition (P(R) = 0.45) . In the full-information condition, however, the difference between the gain and loss conditions all but disappeared (Loss P(R) = 0.57, Gain P(R) = 0.59) with participants preferring the risky over the safe option in both conditions (Loss: $t(55) = 2.31$, $p = .02$; Gain: $t(44) = 2.42$, $p = .02$). The results of the ANOVA (conducted as in Study 2) showed a marginally significant main effect for the gain/loss condition, ($F(1,197) = 2.91$, $p = .09$), and importantly a significant interaction between the partiality of the information and the gain/loss condition ($F(1,197) = 3.97$, $p = .048$). Simple t-tests indicated that with partial information there was a significant difference between the gain and loss condition ($t(98) = 2.41$, $p = .02$) while with full information the difference between the gain and loss condition was not significant ($t(99) = 0.22$, $p = .82$).

We also examined whether these patterns were robust across trial blocks by conducting a repeated measures ANOVA as in Study 1. This time the results did not indicate a significant interaction between gain/loss condition and trial block ($F(4,194) = 1.50$, $p = .20$) as well as no significant three-way interaction with the partiality of the information ($F(4,194) = 0.33$, $p = .86$). Therefore, in this experiment with lower nominal payoffs there was no longer any difference in risk aversion between the gain and loss conditions, and in both condition there was a slight but significant tendency to prefer the risky alternative.

Finally, we also examined contingent choices in the partial-information condition. As indicated in the bottom panel of Figure 3, the pattern of contingent choices was generally similar to that found in Study 1, with avoidance of the risky alternative in the loss condition occurring mostly in trials where the risky alternative was experienced as disadvantageous (S > R trials). The slight tendency to avoid R in the loss condition for S < R was driven by a few participants who had very few trials of this type. For participants who had 5 or more S < R trials, the rate of risky selections approached 0.5 ($P(R) = 0.44$, one sample $t(40) = 1.42$, $p = .17$).

4. MODELING OF CURRENT DATASETS

We examined whether estimating the model shown in equations 1 and 2 on the current datasets would reproduce the increased choice sensitivity in the loss task, as found previously in simpler tasks with two possible outcomes (e.g., Yechiam and Hochman, 2013a; Yechiam et al., in press). 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 utility function's concavity/convexity. Parameter estimation was conducted only for the full-information conditions based on the nominal payoffs. Following previous experimental literature (e.g., Ahn et al., 2008; Erev et al., 2008; Yechiam et al., in press) the estimated value of α was constrained between 0 and 5 and the estimated value of θ_{Loss} and θ_{Gain} was bounded between 0 and 1. Optimization was conducted using an evolutionary algorithm (Coello, Lamont, and 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 results of the estimation procedure indicated a mean RMSD of 0.042, and the estimated parameters were θ_{Gain} = 0.38, θ_{Loss} = 2.72, and α = 0.54. Thus, the model reproduces the postulated asymmetry of higher choice sensitivity in the loss condition than in the gain condition. It also shows a considerable rate of diminishing sensitivity which explains why in Study 1 full information did not completely eliminate the difference in risk aversion between the gain and loss conditions. The model predictions are presented in Supplementary Figure S2. It captures the general pattern of increased risk taking in Study 2 compared to Study 1 (which is presumably driven by lower diminishing sensitivity to zero in Study 2) and the absence of a difference between the gain and loss condition in Study 2. It somewhat underpredicts the difference between conditions in Study 1.

5. REPLICATION WITH STUDENT PARTICIPANTS

One might argue that the finding that participants did not avoid the risky option in the full-information loss condition may be limited to Mturk participants, and that differences from previous experiments (e.g., Thaler et al., 1997; Erev et al., 2008) might be driven by the fact that they used student participants. To verify this we ran a re-ran the full information loss condition of Study 1 (no color version) in a sample of 33 Technion undergraduate students (16 males). Their fixed fee was NIS 25 (NIS 1 = $4.3) and the conversion rate of token to money was NIS 0.1 per 1,000 points. The participants' mean P(R) was 0.62 (SE = 0.042), significantly above 0.5 ($t(32) = 2.76$. $p = .01$). The participants' learning curve, presented in Supplementary Figure S3, indicated that the tendency to take risk did not decrease with experience. Thus, student participants as well did not seem to avoid the highly advantageous but loss-producing risky alternative when provided with full information.

6. GENERAL DISCUSSION

The notion of myopic loss aversion suggests that losses induce myopia because of a biased utility function for gains and losses. The current studies indicate that this supposedly myopic response in the face of losses is not robust, challenging the idea of myopic loss aversion. First of all, in both Study 1 and 2 we find that the avoidance response for a risky alternative producing losses in Thaler et al.'s (1997) paradigm was mostly driven by trials in which the risky alternative was experienced as disadvantageous, suggesting that participants' behavioral response to losses was in fact sensitive to the experienced choice outcomes. Secondly, in both studies in a condition with full information, where participants received both obtained and foregone payoffs, they did not avoid the risky alternative producing losses. In Study 1, this full-information condition also decreased differences in risk taking between the loss and gain conditions by about 40%. In Study 2, using lower nominal payoffs, differences between the gain and loss conditions of the task were virtually eliminated.

These findings can be explained based on two basic regularities. First, losses increase exploitation based on experienced outcomes, and facilitate the hot stove effect (as proposed by Yechiam et al., in press). Because the hot stove effect does not emerge with full information, this explains why full information reduced the effect of losses on risk aversion in Studies 1 and 2. The second regularity is diminishing sensitivity to the distance from zero. Erev et al. (2008) demonstrated greater diminishing sensitivity for amounts presented as larger numbers irrespectively of their actual money worth (i.e. greater discounting rates as a function of the size of token amounts). This explains why even with full information, there was still a difference between the gain and loss conditions in Study 1, with more risk aversion in the latter condition; and why this difference all but disappeared in Study 2 which used lower nominal payoffs.

An alternative explanation for the difference between the results of Study 1 and 2 is aversion to large losses, which may be triggered in a condition where a loss is presented as a nominally high number. According to this explanation, the reason there was as effect of losses on risk taking with full information in Study 1 is because individuals tended to avoid large token losses, a tendency which was eliminated in Study 2 where token losses were lower. This explanation is consistent with the literature in decisions from description showing that loss aversion mostly emerges for high monetary losses (see Ert and Erev, 2013; Malul, Rosenboim, and Shavit, 2013; Yechiam and Hochman, 2013a; Yechiam, 2018; Gal and Rucker, in press). However, this explanation is inconsistent with prior studies of decisions from experience, indicating that even with very high token amounts, loss aversion does not emerge in these types of decisions (e.g., Erev et al., 2008; and see review in Yechiam and Hochman, 2013a). For instance, in Erev et al.'s (2008) study of decisions from experience participants did not avoid lotteries producing 1,000 or -1,000 tokens with equal chances. This suggests that the current results are not driven by avoidance of high nominal losses though further studies should verify this.[5]

One could additionally argue that ceteris paribus, if losses increase the sensitivity to experienced choice outcomes there should have been more choices from the advantageous risky alternative in the loss condition than in the gain condition. This obviously did not materialize in the current studies. Still, the absence of a positive effect of losses on maximization can be explained by the positive skewness of the outcome distribution of the risky alternative in Thaler et al.'s (1997) paradigm, which likely reduced its attractiveness owing to diminishing sensitivity to zero (as demonstrated in Figure 1; and see also Erev et al., 2008; Walasek and Stewart, 2015). In tasks with non-skewed payoff distributions, losses were found to increase the rate of choices from advantageous risky alternatives (see Yechiam and Hochman, 2013a; Yechiam et al., in press).

The current findings are consistent with accumulating empirical observations suggesting that people do not show loss aversion in decisions from experience (see review in Yechiam and Hochman, 2013a). Our studies indicate that what appears as myopic loss aversion in the paradigm of Thaler et al. (1997) is partly driven by an increased hot stove effect for losses, and partly by diminishing sensitivity to zero. These two factors can result in extreme risk aversion with partial information, creating a false impression that losses are strongly overweighted. However, this risk aversion for options

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[5] Moreover, even if participants were sensitive to high token losses in Study 1, this tendency was relatively weak, as it did not lead them to avoid the risky alternative in the full-information condition.

producing losses is largely eliminated with full information, inconsistently with the assumed robustness of myopic loss aversion.

7. IMPLICATIONS TO THE EQUITY PREMIUM PARADOX

The current findings suggest a novel psychological explanation for the equity premium puzzle that is quite different from the one proposed by Thaler et al. (1997). Our experimental findings indicate that individuals are highly sensitive to losses but not in the sense of giving them more subjective weight than gain; rather, losses lead to more sensitivity to the experienced payoffs, and a higher tendency to exploit the payoff information by selecting appropriate alternatives based on it. In the context of the equity premium puzzle this account predicts underinvestment in stocks when individuals a) frequently check their portfolio returns, b) check their own portfolio returns considerably more frequently than alternative portfolios with high stock allocations. In these conditions because stocks tend to produce short term returns that are lower than those of alternative investments individuals tend to display the hot hand effect, and because these outcomes include losses the hot hand effect intensifies. However, the hot stove effect should not be observed in a setting where individuals are frequently presented with returns from a variety of portfolios, even given frequent negative returns.

This account is consistent with the observed differences between investments of independent account holders (liquidity traders) and professional traders who manage multiple investment accounts (e.g., Shapira and Venezia, 2001; Garvey and Murphy, 2004; Guillemette, Martin, and Gibson, 2015). The latter are presumably more likely to be presented with returns from a variety of portfolios on a day to day basis, and should therefore be less likely to succumb to a hot stove effect. In line with this, it has been found that professional traders tend to make investments that are more diversified and somewhat more profitable than those of liquidity traders (Shapira and Venezia, 2001). Also, professional traders were found to make considerably more trades in stocks than liquidity traders (Garvey and Murphy, 2004; Guillemette et al., 2015; see also Kelly, 1995). The current findings suggest that differences between professional and unprofessional traders might be driven not only by expertise but also by different ways of obtaining feedback about portfolio returns.

It is important to stress that the present findings do not run against Thaler et al.'s (1997) and Gneezy and Potters' (1997) findings that pooling observed returns – a manipulation carrying the same financial effect as infrequently checking one's portfolio – decreases risk aversion. These findings have since been replicated both in the lab and in the real world. For example, using minute-by-minute trading observations from over 864,000 actual price realizations, Larson, List, and Metcalfe (2016) have found that professional traders who receive infrequent price information in their normal course of business invested 33% more in risky assets, yielding profits that were 53% higher, compared to traders receiving frequent price information. However, these findings do not necessitate the assumption of loss aversion (Bellemare, Krause, Kroger, and Zhang, 2005). Instead, they can be easily captured by the hot stove effect. Specifically, the hot stove effect is expected to diminish with the infrequency of information checks, owing to the law of large numbers. The effect of pooled returns could also be due to the lower risk implicated by having the returns averaged across investment periods, as noted by Samuelson (1963).

Also, the current findings do not rule out the possible role of myopia or delayed discounting in explaining the equity premium puzzle (Constantinides, 1990; Shavitt and Rosenboim, 2015). Myopic investing seems to be particularly pertinent given the tendency of stocks to out-profit bonds only following years of delay. However, our studies suggest that myopic investment is not facilitated by loss aversion. Consistent with this notion, while there is an extensive literature showing that myopia exists for a variety of payoff sizes (Soman et al., 2005), the literature on loss aversion for small to moderate outcomes is unreliable at best (see reviews by Yechiam and Hochman, 2013a; Gal and Rucker, in press).

APPENDIX: STUDY 2 INSTRUCTIONS AND SCREEN LAYOUT

"This is an investment game, in which you will have to choose between two investment options (the two options remain the same throughout the experiment). After each round, you will see the outcome for the option you chose (*Full-information condition:* and also for the option that you did not choose). In addition you will see the total reward you made until this round.

There are 100 rounds, and the duration of this game is 5-6 minutes. Your payment for participating in this game depends solely on the outcome of your choices in these rounds: if you will not pay attention - you may end up with no payment at all.

Your payment for participating in this experiment will include a fixed payoff of $1.5, as well as an the accumulating outcome of your investment choices, with a conversion rate such that your total payment for task performance will be:

Study 1 Color/No color versions: 0.1 cent for each $1000.

Study 1 No conversion rate version: between 0.01$ and 6$.

Study 2: 0.1 cent for each $10.

If your accumulating payoff will be negative – it will be deducted from your fixed payoff. If you will not finish the experiment all the way to the last round, you will not receive any payment."

Figure A1: Screenshots of two out of the four conditions in Study 1 (no-color version). Left panel: Partial information, loss condition. Right panel: Full information, gain condition. The order of the two options was randomly determined for each individual participant.

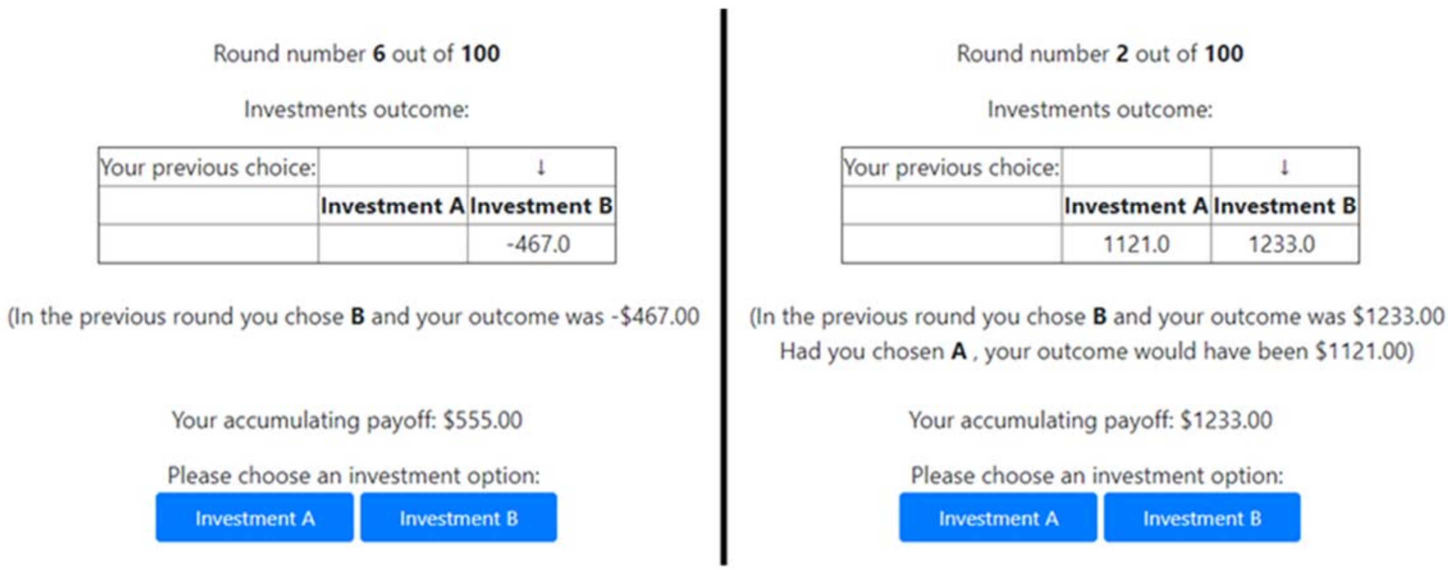

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Table 1: Incentive structure in the original task investigated by Thaler et al. (1997) as replicated by Erev et al. (2008). The task includes two alternative: S (Safe) and R (Risky). The first two rows denote the nominal payoffs used in Erev et al. (2008) and in Study 1. The next two rows denote the smaller nominal payoff (divided by 100) used in Study 2.

Choice problem			
Loss condition (Study 1)	S	A draw from a truncated (at zero) normal distribution with a mean of 25 and standard deviation of 17.7 (implied mean of 25.6)	TN~(25, 17.7, 0)
	R	A draw from a normal distribution with a mean of 100 and standard deviation of 354	N~(100, 354)
Gain condition (Study 1)	S	A draw from a truncated (at 1200) normal distribution with a mean of 1225 and standard deviation of 17.7 (implied mean of 1225.6)	TN~(1225, 17.7, 0)
	R	A draw from a normal distribution with a mean of 1300 and standard deviation of 354	N~(1300, 354)
Loss condition (Study 2)	S	A draw from a truncated (at zero) normal distribution with a mean of 0.25 and standard deviation of 0.177 (implied mean of 0.256)	TN~(0.25, 0.177, 0)
	R	A draw from a normal distribution with a mean of 1 and standard deviation of 3.54	N~(1, 3.54)
Gain condition (Study 2)	S	A draw from a truncated (at 12.0) normal distribution with a mean of 12.25 and standard deviation of 0.177 (implied mean of 12.256)	TN~(12.25, 0.177, 0)
	R	A draw from a normal distribution with a mean of 13.0 and standard deviation of 3.54	N~(13.0, 3.54)

Table 2: Analysis of variance results for Study 1. Model 1 includes the effect of gain/loss tasks and partial/full information conditions. Model 2 includes, in addition, the effect of task version. The statistics are η^2 measures of effect size (SS_B/SS_T).

	Model 1	Model 2
Gain/loss	0.06**	0.05**
Partial/full inf	0.08**	0.07**
Gain/loss × Partial/full inf	0.01**	0.009**
Version		0.004
Version × Gain/loss		0.0002
Version × Partial/full inf		0.006
Version × Gain/loss × Partial/full inf		0.003
Total model	0.14**	0.15**

** = p < .01

Figure 1: Simulated rate of R selections (P(R)) in a discrete choice version of Thaler et al.'s (1997) experiment with full information under the assumption that losses increase exploitation (θ_{Gain} = 0.052, θ_{Loss} = 0.095) and conditional on diminishing sensitivity to zero (α) ranging from 0.5 to 0.9.

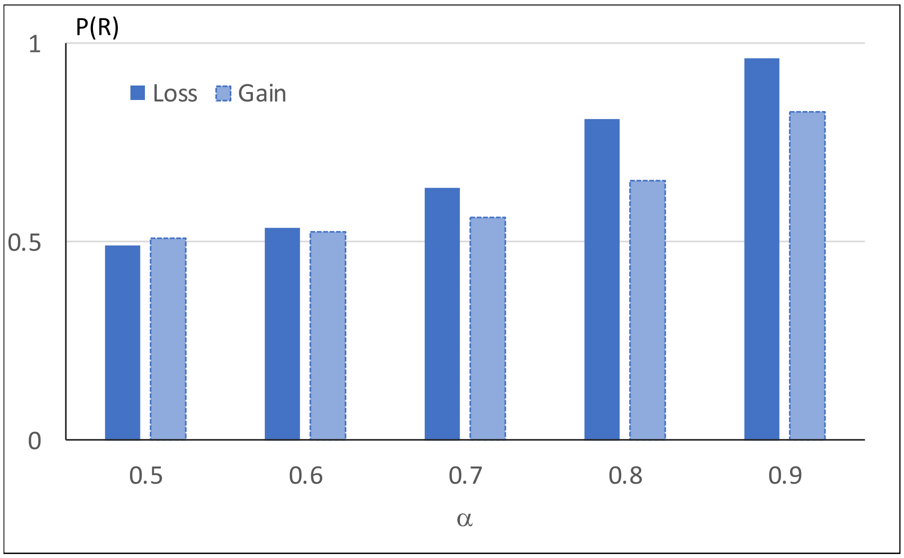

Figure 2: Learning rates and contingent choices in Study 1. Top: Proportions of R selections (P(R)) in the gain and loss conditions with partial and full information in five blocks of 20 trials. The partial and full information conditions are denoted by blue and green colors, respectively. Bottom: Proportions of selections from the risky alternative in the partial-information condition, by condition and trial type (S < R, S > R), across all trials.

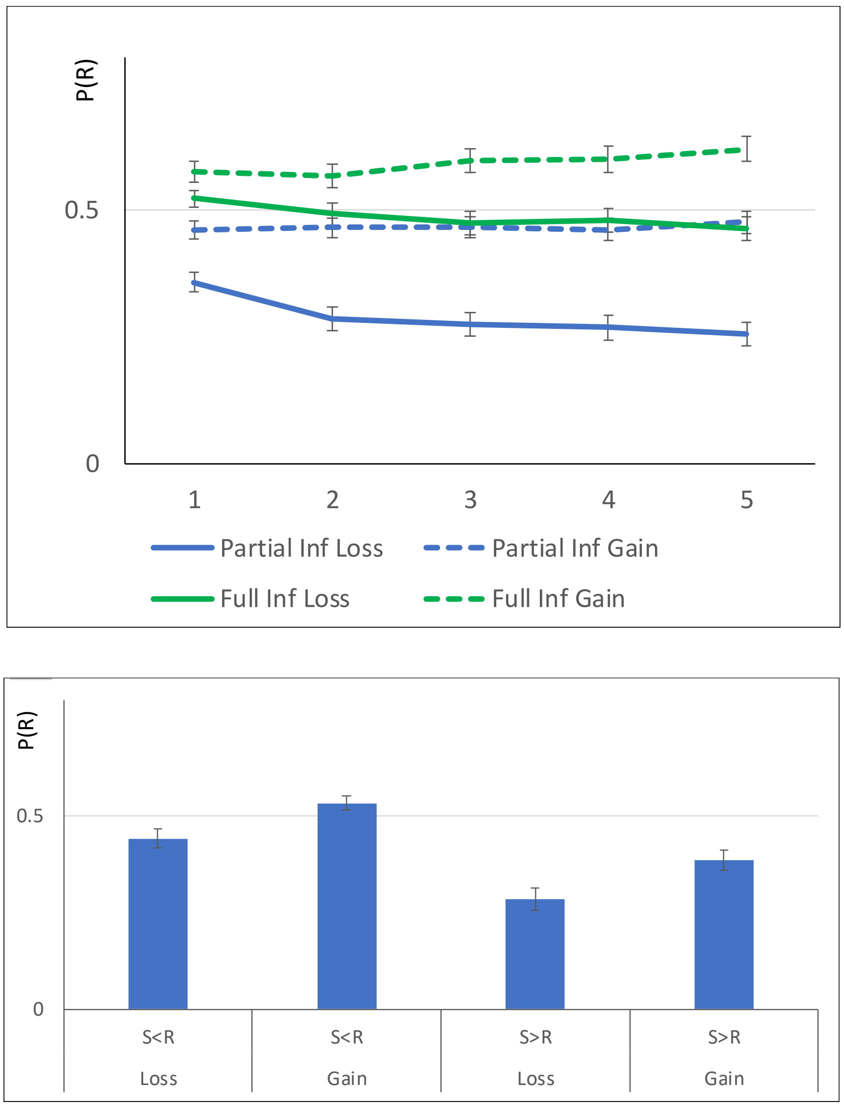

Figure 3: Learning rates and contingent choices in Study 2. Top: Proportions of R selections (P(R)) in the gain and loss conditions with partial and full information in five blocks of 20 trials. The partial and full information conditions are denoted by blue and green colors, respectively. Bottom: Proportions of selections from the risky alternative in the partial-information condition by condition and trial type (S < R, S > R), across all trials.