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# The consistency of visual attention to losses and loss sensitivity across valuation and choice

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**Abstract**

Sensitivity to losses has been found to vary greatly across individuals. One explanation for this variability is that for some losses garner more visual attention and are subsequently given more weight in decision making processes. In three studies we examined whether biases in visual attention towards potential losses during valuation and choice were related to loss-sensitivity, as well as the valuations provided and the choices made. In all studies we find a positive relationship between estimated loss-sensitivity and attention to losses for valuation, with increased attention to losses predicting decreased valuations. For choices, however, there was no robust relationship between attention and loss-sensitivity or the choices made. In addition, preferences were not strongly consistent across tasks (i.e., valuations and choices did not robustly align), nor was the distribution of attention robustly related across tasks. Study 3 involved testing across separate sessions and found significant consistency in loss-sensitivity and attention to losses across sessions for both choice and valuation. In sum, it appears that loss-sensitivity varies across individuals, is differentially related to attention across tasks, and shows some consistency across time. Attention to losses also shows consistency across time, and its relationship with valuations appears much more robust than with choices; patterns of results which add to research suggesting that different cognitive processes underlie valuations and choices.

Keywords: eye-tracking; valuation; choice; loss aversion; attention; preference consistency.

Loss aversion is the tendency for individuals to overweight losses (i.e. show increased sensitivity to losses relative to gains; Kahneman & Tversky, 1979). For decades this phenomenon of increased loss-sensitivity was proposed to be robust, with research suggesting that the weight given to a loss (often formalized by the parameter λ) during decision making processes was about double the weight given to gains (Tverksy & Kahneman, 1992). Over the years this increased weighting of losses has been shown to be less robust than previously thought. Specifically, many studies have failed to find strong loss aversion on the aggregate level (see review in Yechiam & Hochman, 2013). One explanation for this discrepancy in loss-sensitivity across studies is that loss-sensitivity varies on the level of the individual and perhaps across cultures (Weber & Hsee, 1998). As such, some studies are likely to find loss aversion on average while others will not due simply to random variation in participant samples. Such an explanation seems reasonable given that studies assessing loss-sensitivity on the level of the individual have found considerable variability across individuals (Gächter, Johnson, Herrmann, 2007; Pachur, Hanoch, & Gummerum, 2010).

A plausible contributor to this individual level variability in loss-sensitivity is how decision information is searched out and attended to. Specifically, from an evidence accumulation (drift-diffusion) perspective the more attention a given attribute receives during the decision-making process the more weight it is given (Busemeyer & Townsend, 1993; Usher & McClelland, 2001). In support of these predictions eye-tracking research has shown that attractive options which receive more visual attention (are fixated longer) are selected more frequently (Ashby, Dickert, Jekel, & Glöckner, 2016; Krajbich, Armel, & Rangel, 2011; Krajbich & Rangel, 2010; Shimojo et al., 2004); less frequently if options are unattractive (Armel, Beaumel, & Rangel, 2008). Similarly, in valuations there is a consistent finding that if lower value attributes (e.g., the magnitude and probability of a lower payout) receive a greater proportion of visual attention than higher value attributes, subjective monetary valuations are lower (Ashby, Dickert, & Glöckner, 2012; Ashby, Walasek, & Glöckner, 2015). Thus, one possible contributor to loss-sensitivity is the degree to which individuals' attention is biased towards losses.

In other words, the more a potential loss is focused on (fixated) relative to a potential gain the more weight we should expect it to be given in the decision-making process. This seems to be the case for the disparity seen between buyers' and sellers' behavior (i.e., the endowment effect), where sellers are proposed to feel a loss when parting with a good and are therefore reluctant to part with it (Kahneman, Knetsch, & Thaler, 1990; Thaler, 1980). Specifically, this endowment effect has been shown to be partially explained by differences in attention to negative attributes (Ashby et al., 2012, 2015), the order in which negative aspects of making a transaction are retrieved (Johnson, Haubl, & Keinan, 2007), and the magnitude of the outcome search is terminated on (Pachur & Scheibehenne, 2012). Note that our usage of the term attention in the current context pertains only to (directed) visual attention. There is also arousal or engagement which has less granular temporal dynamics (i.e., longer decay) and might also be considered a facet of general attentional processes. For instance, it has been shown that the presence of potential losses is related to increases in heart rate and pupil diameter (Hochman & Yechiam, 2011; Yechiam, Retzer, Telpaz, & Hochman, 2015), physiological changes which were not associated with observed loss-sensitivity.

In the current investigations we aimed to examine whether there is a relationship between how losses are visually attended to and loss-sensitivity. To achieve this, we examine valuations of (i.e., subjective estimations of monetary worth), and choices between, risky prospects (gambles) containing potential gains and losses. This allows us to estimate loss-sensitivity on the level of the individual across decision formats. We test the hypothesis that individual differences in the distribution of visual attention (i.e., the proportion of attention to an options positive and negative attributes) are related to loss-sensitivity. Specifically, we predict that increases in the proportion of visual attention (operationalized as fixation durations; Just & Carpenter, 1984) directed towards losses will be related to increases in loss-sensitivity.

Our methodologies also allow us to make a novel comparison of the distribution and impact of visual attention across valuation and choice within the same individual where there is evidence that the two may not align. For example, a disconnect between visual attention to attributes in choice was reported by Stewart, Frouke, and Matthews (2016), but found in valuations by Ashby et. al. (2012, 2015). In addition, it has long been known that choices and valuations do not always align (e.g., Lichtenstein & Slovic, 1971, 1973). Thus, while valuation and choice are sometimes considered to rely on similar cognitive processes (Grabenhorst & Rolls, 2011), they may involve different procedural elements, such as different reference points (Knetsch, 2007) and different levels of effort, with more cognitive effort being invested in valuations (e.g., Ofek, Yildiz, & Haruvy, 2002).

It is important to note that the current studies do not aim to, and are therefore not designed to, assess a causal relationship between attention and loss-sensitivity or behavior. That is, we make no claims as to whether attention itself drives loss-sensitivity and behavior, or whether the distribution of attention simply reflects individual (or temporal) differences in sensitivity to losses. Instead, our aim is to take the first step in assessing whether there is a relationship between how attention is distributed and loss-sensitivity, which will provide novel and needed insight into the cognitive processes related to loss-sensitivity and human behavior.

## Study 1

## Method

### Participants.

Eighty participants ($M_{age}$ = 24.96; 28% female) were recruited from a universities human subjects pool and took part in the study for 20 NIS plus monetary incentives as outlined below. We aimed for 80 participants to provide sufficient power to detect strong relationships between loss-sensitivity and attention[1]. Eye-tracking data for four participants during valuations and two participants during choice were not recorded due to experimenter error (i.e., a failure to press record on the eye-tracking software). These participants' behavioral responses are excluded from all analyses.

**Equipment.**

We used an Eye Tribe eye-tracker with an average sampling rate of approximately 35 Hz and a calibration threshold of less than 1° of visual angle error. The experiment was conducted using Presentation® (Version 18.1, www.neurobs.com) and stimuli were presented on an LCD monitor with a resolution of 1600 by 1200 and a display area of 41 by 30cm. Participants were seated approximately 60 cm from the monitor and a chinrest was employed to reduce head movement.

**Stimuli.**

The stimuli consisted of the 14 gambles presented in *Table 1*. Stimuli (i.e., each outcome or probability) occupied approximately 1.83° by 0.59° of visual angle; see *Figure 1* for a screen shot of a valuation (left panel) and a choice trial (right panel). The location of each attribute (negative and positive outcomes and probabilities) was counterbalanced across participants and decision formats, though fixed within each decision format (e.g., outcomes and probabilities always appeared in the same locations for a participant during valuation).

*Table 1*. The positive and negative outcomes – in NIS (1 NIS ≈ $0.25) - associated with each gamble as well as their probabilities of occurrence, sorted by expected values (EV) in Study 1. The mean

[1] A samples size of 80 participants was estimated to provided high power ($1-\beta = .99$) to detect a large effect (.50) and moderate power ($1-\beta = .79$) to detect a medium effect (.30) as assessed using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007).

valuation and the proportion of participants selecting to play the gamble rather than take a certain outcome of 0 NIS during choice (Acceptance Rate).

| **Positive Outcome** | **Positive Probability** | **Negative Outcome** | **Negative Probability** | **EV** | **Valuation** | **Acceptance Rate** |
|---|---|---|---|---|---|---|
| 40 | 10% | -40 | 90% | -32 | -24.61 | 4.05% |
| 25 | 50% | -75 | 50% | -25 | -22.71 | 8% |
| 40 | 20% | -40 | 80% | -24 | -17.72 | 6.58% |
| 40 | 30% | -40 | 70% | -16 | -12.95 | 13.33% |
| 25 | 50% | -50 | 50% | -12.5 | -9.64 | 13.33% |
| 40 | 40% | -40 | 60% | -8 | -6.03 | 18.67% |
| 40 | 50% | -40 | 50% | 0 | 2.81 | 46.67% |
| 25 | 50% | -25 | 50% | 0 | 1.02 | 42.67% |
| 40 | 60% | -40 | 40% | 8 | 11.18 | 69.33% |
| 50 | 50% | -25 | 50% | 12.5 | 12.07 | 80% |
| 40 | 70% | -40 | 30% | 16 | 17.76 | 78.95% |
| 40 | 80% | -40 | 20% | 24 | 23.61 | 89.33% |
| 75 | 50% | -25 | 50% | 25 | 29.58 | 84% |
| 40 | 90% | -40 | 10% | 32 | 27.95 | 97.29% |
| *Mean* | | | | 0 | 2.38 | 46.67% |

*Note:* Valuations and acceptance rates only include observations used in the primary analyses.

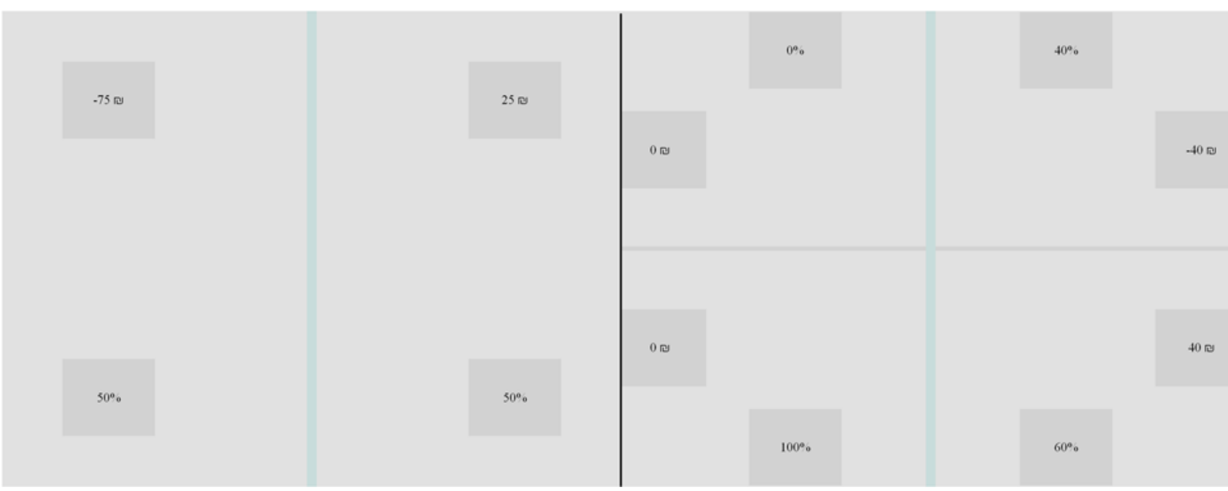


*Figure 1*. Screenshot of a Valuation (left panel) and Choice trial (right panel). Shaded areas around attributes (i.e., outcomes and probabilities) represent the areas of interest used in analysis and were

not visible to participants. In Study 2 the 0 outcome option was represented as a 0 at the center of its respective quadrant (e.g., the left quadrant in the choice trial shown above).

**Procedure.**

Participants were calibrated to the eye-tracker and then either provided monetary valuations of the gambles presented in *Table 1* or chose between these gambles and 0.00 NIS with certainty (see right panel of *Figure 1*). The order of valuations and choices was counterbalanced across participants and the gambles were presented in randomized order for each participant in each decision format. Between the two tasks two paper-and-pencil questionnaires (Holt & Laury, 2002; Watson, Clark, & Tellegen, 1988) were included as fillers to reduce the potential for order effects and participants could take a short break if they wished. Participants were then recalibrated to the eye-tracker and made valuations or choices depending on the format they had previously made decisions in (i.e., if the first task was valuation the second was choice).

Participants were told that one decision from each decision format would be randomly selected and carried out. For valuations the Becker-DeGroot-Marschak (1964) method of incentivization was employed. Specifically, participants were told that they should indicate exactly what the gamble was worth to them. That is, they should indicate an amount that would make them indifferent between playing the gamble or gaining/losing the amount they indicated. A random number would then be drawn from a set of numbers ranging from the highest to the lowest payouts offered in the randomly selected gamble. If their valuation was less than the number drawn that amount would be added or subtracted from their earnings, while if the number drawn was less than their valuation the gamble would be played out and the outcome that occurred would be added or subtracted from their earnings. Note, that negative valuations indicate the most a participant would be *willing-to-pay* in order to abstain from playing a gamble. Participants were given as much time as they wished to look at each gambles attributes, and pressed the spacebar when they were ready to provide their valuation; gamble attributes were not visible when valuations were entered. Valuations started at 0.00 NIS and were adjusted by moving (pushing) a mouse up (down) to increase (decrease) their valuation in 0.01 NIS increments. Valuations were constrained such that a gamble's positive (negative) outcomes were the highest (lowest) value that could be entered.

For choices, participants were shown one of the gambles on one side of the screen and a gamble always paying out 0.00 NIS with 100% probability on the other (i.e., a certain zero option). After taking as much time as they wished to view the gambles participants clicked the left (right) mouse button to select the gamble on left (right)[2]. A random choice was then selected and carried out (i.e., receive 0 or the gamble was played out and the outcome that occurred was add/subtracted from their earnings). After both valuations and choices were made participants were informed of their earnings, paid, and thanked for their time.

**Pre-Processing of Eye-Tracking Data.**

We defined our areas of interest (AOIs) by adding a 2° visual angle boarder around each attribute in line with the specifications laid out in Orquin, Ashby, and Clarke (2016; see shaded areas in *Figure 1* which were not visible to participants). We then created fixations by summing consecutive gaze to one of the AOIs or to blank space. Eye-tracking data was then merged with the behavioral response data (i.e., choices and valuations); we removed eye-tracking data for periods where participants were indicating their valuations as we had no *a priori* predictions here. In addition, prior to analysis we removed all trials where at least one outcome and one probability in the gamble was not attended to as this signaled either a failure of the eye-tracker to assess participants' gaze or a

[2] We examined whether there was a bias to click the left mouse button since it is more frequently used (e.g., navigating in the Windows operating system used at the university). No significant bias for clicking left versus right was found in Study 1 (53% $CI_{95\%}$[.49, .57[; $t(75) = 1.51$, $p = .13$), Study 2 (50% $CI_{95\%}$[.47, .54; $t(88) = .06$, $p = .95$), or Study 3 (47% $CI_{95\%}$[.42, .51; $t(37) = -1.60$, $p = .12$).

general lack of attention to the task; more constrained (e.g., only retaining trials where all outcomes and probabilities were fixated) and more liberal analysis (e.g., including trials with only one type of attribute were fixated) led to similar patterns of results. Two participants in valuation and two in choice had less than five viable trials after data cleaning and were removed from analysis. The final data set included 1,013 observations from 74 participants for valuations (four participants removed due to failure to record eye-movements and two removed for having less than five viable trials) and 1,050 observations from 76 participants for choices (two participants removed due to failure to record eye-movements and two removed for having less than five viable trials).

**Estimating Sensitivity to Losses.**

We used a one-parameter model to capture loss-sensitivity. Specifically, we estimated the subjective value (*V*) of a given gamble (*g*) using Equation 1:

$$V_g = (PO_g \times PP_g) + (\lambda \times NO_g \times NP_g)$$
$$V_g = (PO_g * PP_g) + (\lambda * NO_g * NP_g)$$

$$V_g = (PO_g * PP_g) + (\lambda * NO_g * NP_g)$$
(1)

Where *PO* and *NO* represent the positive and negative outcome of a given *g* and *PP* and *NP* represent the positive and negative outcomes probabilities, respectively. λ is a parameter which is free to vary and captures sensitivity to losses: Increased loss-sensitivity is indicated for λs > 1, decreased loss-sensitivity for λs < 1, and equal sensitivity to gains and losses for λ = 1.

To find the best fitting parameter, we fit λ to each participant's valuations (Equation 2) and choices (Equation 3), separately, in STATA by maximizing the log-likelihood (*LL*) for each participant. We employed a complete grid search from 0 to 3 in .01 increments[3]. For estimations of

[3]Attempts to employ a variety of maximization algorithms rather than a grid search consistently led to failures to converge, perhaps due to the limited number of observations for each participant in each task.

decision probabilities we followed Ashby and Rakow (2015; for original work see Zeisberger, Vrecko, & Langer, 2012) for valuations (Equation 2) and Harrison (2008) for choices (Equation 3):

$$LL_{Valuations} = \sum \left( \ln \left( \phi \left( V_g, SV_g, \varepsilon \right) \right) \right) \quad LL_{valuations} = \sum \square \ln \left( \Phi \left( V_g, SV_g, \varepsilon \right) \right)$$

$$LL_{valuations} = \sum \left( \ln \left( \Phi \left( V_g, SV_g, \varepsilon \right) \right) \right) \tag{2}$$

For valuations the probability of $V_g$ was estimated under the assumption that $V$s are distributed around the subjective valuation ($SV$) of $g$ following a standard normal distribution density function ($\Phi$) with a mean equal to $SV_g$ and a standard deviation ($\varepsilon$) of 1.

$$LL_{Choices} = \sum \left( \ln \left( \phi \left( V_g \right) \right) \right) \text{ if } g \text{ is selected, else } \sum \left( \ln \left( \phi \left( -V_g \right) \right) \right) \tag{3}$$

For choices the probability of $V_g$ was estimated by linking $V_g$ to a standard cumulative normal distribution function ($\Phi$; a probit function) transforming $V_g$ to a value between 0 and 1.

We note that our fitting of $\lambda$ is liable to biased estimations due to violations of our stochasticity assumptions as well as general biases or randomness in response. As such we also estimated $\lambda$ following Tom, Fox, Trepel, and Poldrack (2007). This approach returned more extreme estimates (Study 3 returned similar estimates) and many participants $\lambda$ parameters could not be estimated in choice. Nevertheless, the results were fairly consistent with those that follow (see Online Supplementary Materials). Thus, while we urge caution in taking our estimated $\lambda$ as precise/unbiased estimates of loss-sensitivity, it does appear that the general patterns of results relating loss-sensitivity to attention are somewhat consistent across different estimation techniques.

## Results

**Behavioral Data.**

**Sensitivity to losses.** *Table 1* lists the average valuations and acceptance rates (choosing to play the gamble rather than take 0 with certainty) for each gamble and suggests that there is little evidence for increased sensitivity to losses on the aggregate: The mean valuation was greater than zero ($t(73) = 2.37$, $p = .02$) and the average acceptance was not significantly different than 50% ($t(75) = -1.61$, $p = .11$). Forty-nine percent of valuations were higher than the EVs while 39% of valuations were below a gamble's EV. Examining departures from EV on the level of the individual we find a great deal of variability: 19% of participants valuations were below the gambles EV at least half the time, while 46% of participants valuations were above the gambles EV greater than half the time. Thus, on the aggregate behavior was not in line with the predictions of loss aversion, though the variability found on the level of the individual suggests that loss-sensitivity was strong for some, while reversed (i.e., diminished loss-sensitivity) for others.

Participants did display sensitivity to the gambles' EVs. During choice most positive EV gambles were accepted and most negative EV gambles rejected (86% of choices were in line with an EV maximization decision strategy). About 3% of participants choices aligned with EV maximization less than 50% of the time, while for 26% of participants all of their choices aligned with such a strategy.

To get a clearer estimate of sensitivity to losses we fit λ to the data as described in the preceding section. We find the average (and median) λ to be significantly below 1 for valuations ($M = .87$ $CI_{95\%}[.78, .96]$; *Mdn.* = .94; $t(73) = -2.96$, $p = .004$) suggesting that participants showed diminished loss-sensitivity when providing their subjective values. However, for choices we find λ to be significantly larger than one ($M = 1.30$ $CI_{95\%}[1.13, 1.47]$; *Mdn.* = 1.09; $t(75) = 3.53$, $p < .001$) suggesting increased loss-sensitivity during choice. Nevertheless, there is a great deal of variability across participants with 32% (59%) showing increased (decreased) loss-sensitivity during valuation

(*Figure 2* left panel), while 55% (43%) showed increased (decreased) loss-sensitivity during choice (*Figure 2* middle panel).

**Consistency across valuation and choice.** To examine the degree to which valuation and choice aligned[4] we first created a variable coding whether a valuation for a particular gamble was greater than zero. If choice and valuation align, we should expect whenever a valuation is greater than zero for a particular gamble that a participant should accept it (play it) during choice, while if the valuation is less than zero the participant should reject it (take the certain zero gamble); valuations of zero do not allow for clear predictions to be made and are excluded from this analysis. Overall the level of valuation-choice consistency was 77%, significantly greater than what would be expected by chance (50%), $t(71) = 11.15$, $p < .0001$. Looking at consistency on the level of the individual we again find a great deal of variability with some participants (21%) showing 100% consistency, while others (8%) showed less than 50% consistency. Next we correlated the estimated λ parameters for valuation and choice (*Figure 2* right panel) and found a non-significant relationship, $r(71) = .10$, $p = .39$. An alternative way to examine consistency in loss-sensitivity across tasks, which should be less impacted by estimation error and noise, is to examine how many participants showed increased or decreased loss-sensitivity in both valuation and choice. We find that the rate of loss-sensitivity matching across tasks ($M = .54$; $CI_{95\%}[.42, .66]$) to be no different than would be expected by chance (50%), $t(71) = .70$, $p = .48$. Thus, while participant's valuations and choices align, loss-sensitivity did not seem to be particularly stable across decision formats.

[4] In all analysis investigating consistency we first matched each participants decisions for each gamble (and session in Study 3) and then aggregate across those matched decisions. Other methods of aggregation (e.g., averaging irrespective of matching) returned similar results.

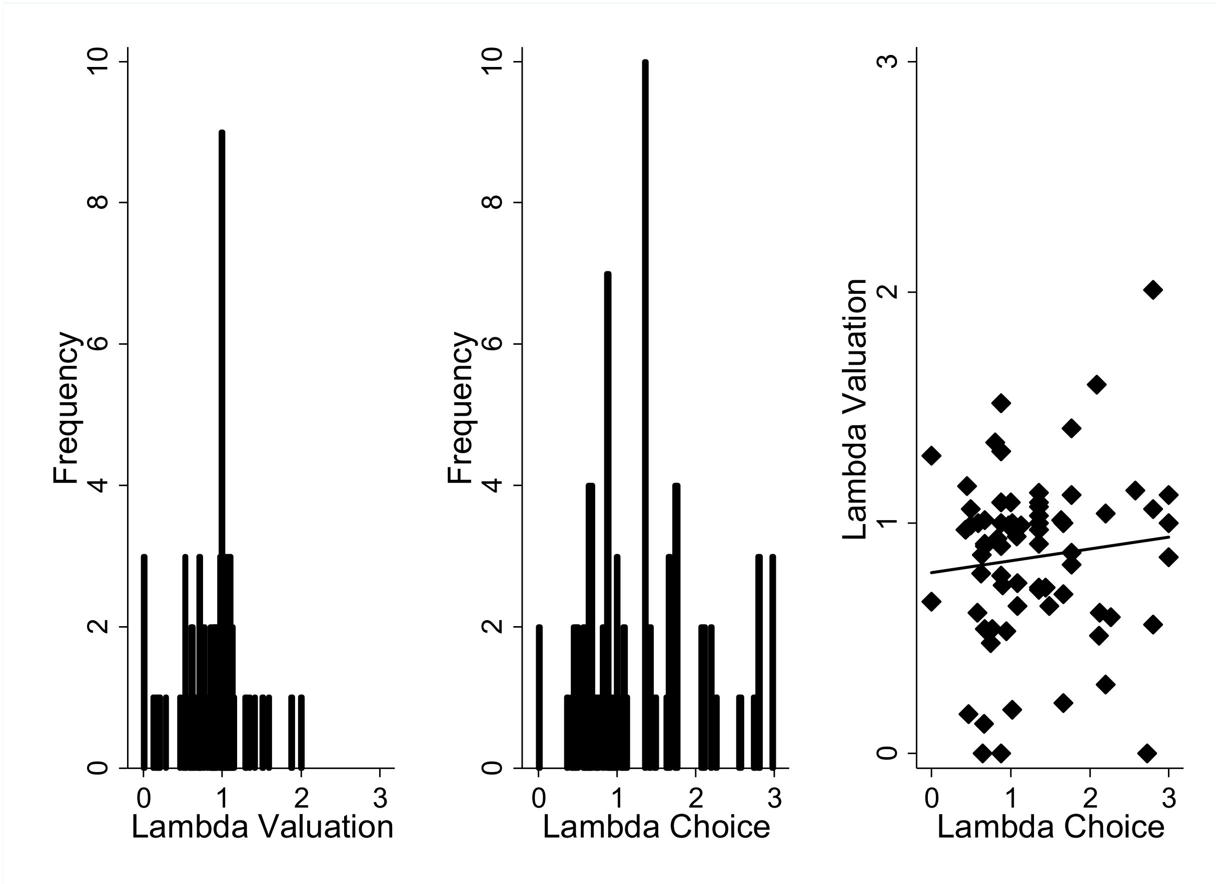


*Figure 2.* Histograms displaying the frequency (y-axis is the number of participants) of estimated λ (Lambda) parameters for valuation and choice (left and middle panel respectively) in Study 1. Scatterplot showing the relation between individual's λ parameters across valuation and choice (right panel); solid black line indicates the identity line.

**Eye-Tracking Data.**

**Distribution of attention.** Turning to the eye-tracking data we examined the average amount of time positive and negative attributes were inspected (e.g., the total time participants fixated on the negative outcome and its probability)[5]. We created two variables indexing attentional

[5] We find no significant gaze bias towards the left or right side of the screen for valuations ($t(73) = -.10$, $p = .92$) or choices ($t(75) = .91$, $p = .37$) in Study 1 or Study 2 (valuation, $t(87) = -1.05$, $p = .29$;

biases. The first (Equation 4) is known as the Low-Gaze-Proportion (Ashby et al., 2012, 2015) and provides an index of the proportion of time attention is allocated to the negative attributes of a gamble (i.e., the negative outcome and its probability).

$$\text{LGP} = \frac{\text{Gaze Durationto Negative Attributes}}{\text{Gaze Durationto All Attributes}} \tag{4}$$

Values of LGP > .50 indicate that more attention was placed on negative attributes than positive ones, a LGP < .50 indicates more attention was placed on positive attributes, and a LGP = .50 indicates attention was equally distributed between negative and positive attributes. We find the average LGP to be significantly less than .50 for valuations ($M_{LGP\_Choice}$ = .47 $CI_{95\%}$ [.45, .49]; $t(73) = -2.25$, $p = .03$), but not for choices ($M_{LGP\_Choice}$ = .48 $CI_{95\%}$[.45, .50]; $t(75) = -1.86$, $p = .07$). We again find a great deal of variability on the level of the individual (*Figure 3* left and middle panels).

The next variable we created is the Side-Gaze-Proportion (Equation 5; essentially the $Base_A$ model in Ashby et al., 2016) for choices.

$$\text{SGP} = \frac{\text{Gaze Duration to Gamble}}{\text{Gaze Duration to Gamble and Certain Zero Option}} \tag{5}$$

SGP indexes the attentional bias, or lack thereof, to the gamble containing gains and losses relative to the certain zero gamble, with larger (smaller) values indicating more (less) attention to the gamble containing gains and losses. On average SGP ($M_{SGP}$ = .69 $CI_{95\%}$[.68, .71]) was significantly larger than .50 suggesting a general bias of attention towards the gamble containing gains and losses $t(75) = 21.69$, $p < .0001$; *Figure 3* right panel).

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choice, $t(88) = .89$, $p = .37$), while in Study 3 we find a bias for the right side of the screen for valuation ($t(41) = -2.47$, $p = .02$) and left side for choice, $t(37) = 4.72$ , $p < .001$.

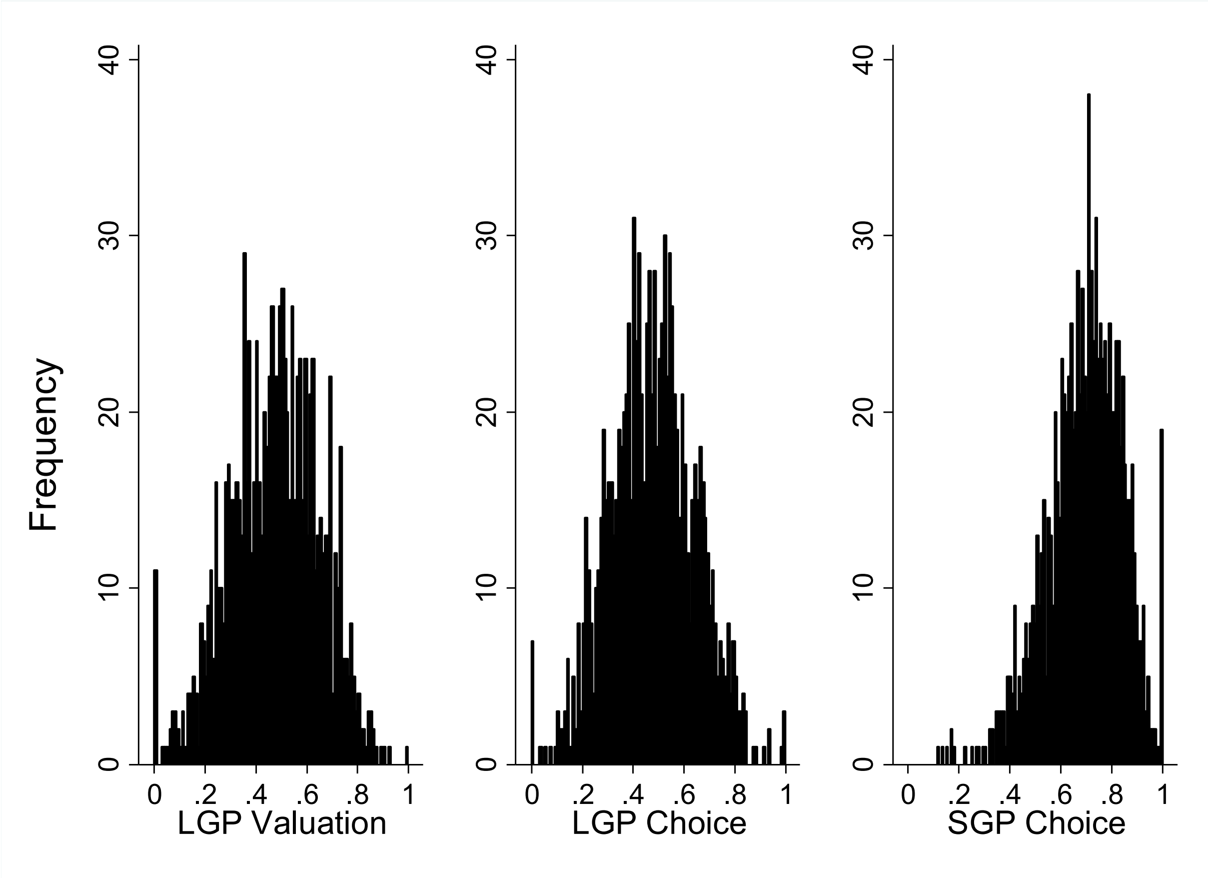


*Figure 3*. Histograms displaying the frequency (y-axis is the number of trials) of Low-Gaze-Proportions (LGP) for Valuation (left panel) and Choice (middle panel) and Side-Gaze-Proportion (SGP) for Choice (right panel) in Study 1.

**Consistency across valuation and choice.** Looking at the total amount of time a participant took before making a valuation or choice we find that valuations took significantly longer than choices on average, ($M_{RT\_Valuation}$ = 11.46 seconds $CI_{95\%}$[10, 12.92] vs. $M_{RT\_Choice}$ = 6.76 seconds $CI_{95\%}$[6.09, 7.462]), $t(71) = 7.08$, $p < .0001$. Nevertheless, participants who on average took more time during choice also took more time on average during valuation, $r(71) = .42$, $p = .002$.

Correlating participants' average LGP during valuation and choice we find the relationship to be non-significant, $r(71)= -.08$, $p = .51$. Examining whether average LGP was above/below .50

during both valuation and choice for each participant we find that participants' alignment across contexts (49%; $CI_{95\%}$[.45, .54]) was not significantly different than chance (50%), $t(71) = -.23$, $p = .82$. Thus, there appears to be little consistency in terms of how attention was allocated across tasks.

**Attention, Behavior, and Sensitivity to Losses.**

**Valuations.** In line with our core hypothesis we find a significant relation between a participant's average LGP and their estimated λ, with attention to negative attributes increasing as sensitivity to losses increased, $r$ (73) = .37, $p = .001$ (*Figure 4* left panel). To examine if biases in attention were predictive of valuations we performed a multi-level linear regression predicting valuations by LGP and EV, including a random effect of subject to account for repeated measurement and allowing slopes for EV and LGP to vary. Replicating previous studies showing a link between attention (LGP) and valuation (e.g., Ashby et al., 2015, 2016), we find LGP to be predictive, with increased attention to negative attributes relative to positive attributes predicting decreased valuations, $b = -10.41$ $CI_{95\%}$[-15.26, -5.56], $z = -4.21$, $p < .001$. EV was also found to be significant, with valuations increasing as EV increased, $b = .88$ $CI_{95\%}$[.78, .97], $z = 18.34$, $p < .001$.

**Choices.** While LGP was not significantly related to λ ($r(75) = -.12$, $p = .31$), SGP was ($r(75) = -.34$, $p = .002$) suggesting that individuals who showed increased loss-sensitivity shifted their attention away from the gamble containing potential losses (*Figure 4* middle and right panels' respectively). To see if choices were predicted by attentional biases we performed a multi-level logit regression predicting acceptance of the gamble (coded 1 for accept, 0 for reject) by LGP, SGP, and the gambles EV including a random effect of subject and allowing slopes to vary for LGP and SGP (inclusion of EV as a random slope led to failures to converge when either LGP or SGP were also free to vary); we included SGP as research has consistently shown that attentional biases to a particular option are strongly related to selection of that option (Ashby et al., 2016; Shimojo et al., 2003). LGP was not found to be a significant predictor suggesting that unlike valuations, choices were not as strongly influenced by a participant's focus on positive or negative attributes, *b* = -1.16 $CI_{95\%}$[-2.59, .28], *z* = -1.58, *p* = .11. SGP was a significant predictor with more attention to the gamble predicting an increased likelihood of selecting it, *b* = 1.94 $CI_{95\%}$[.41, 3.48], *z* = 2.49, *p* = .01. Additionally, as in valuations, EV was a significant predictor with there being an increased likelihood of the gamble being accepted as it's EV increased, *b* = .14 $CI_{95\%}$[.12, .16], *z* = 15.3, *p* < .001.

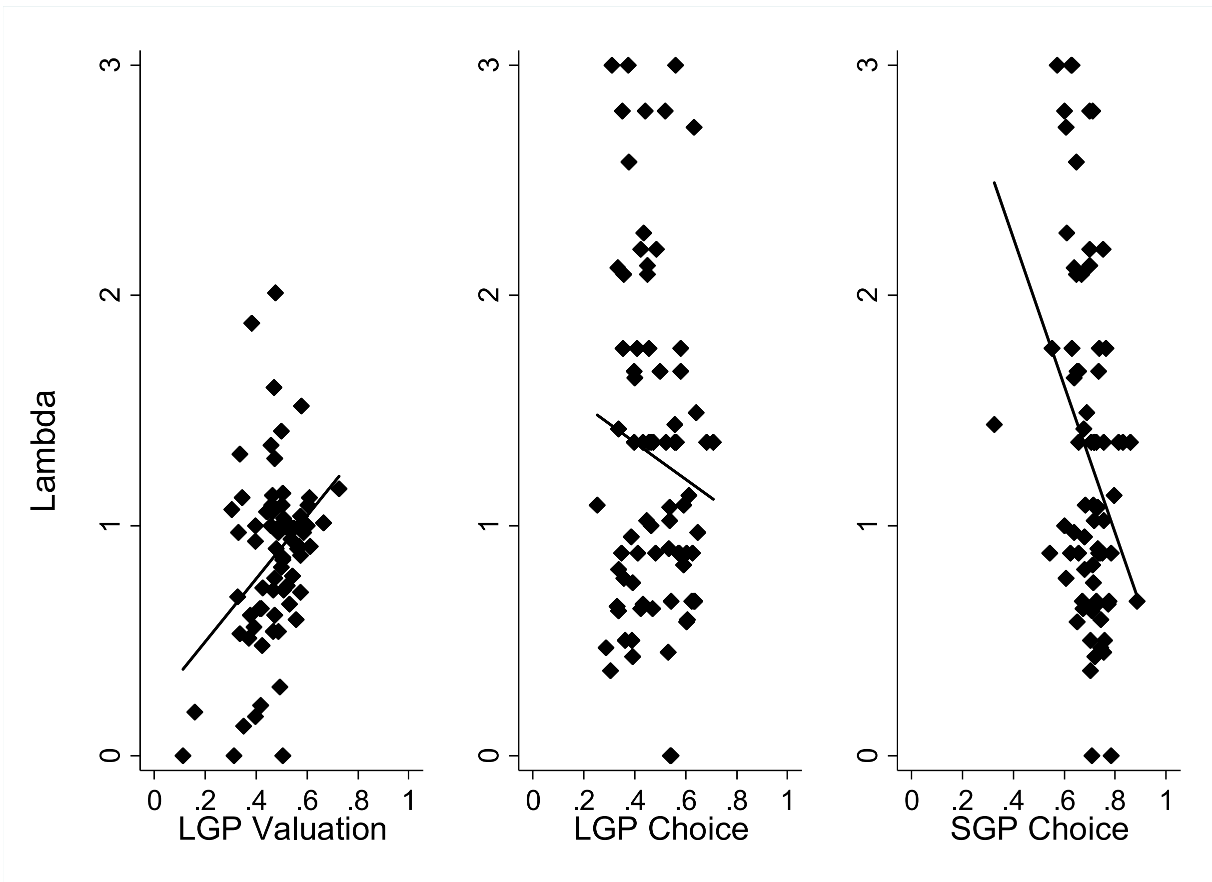


*Figure 4*. Scatter plots showing the relationship between a participants estimated λ (Lambda) and their averaged Low-Gaze-Proportion (LGP) in valuation (left panel), choice (middle panel), and the relation between λ and a participants averaged Side-Gaze-Proportion (SGP; right panel) in choice in Study 1; solid black lines indicate the identity lines.

## Study 2

In Study 1 there was a high degree of outcome consistency (i.e., ± 40 for many of the outcomes), which may have influenced the results. For example, participants might have learned that an outcome of 40 was always paired with -40, learning which could reduce the number of fixations and fixation durations (Orquin, Bagger, & Loose, 2013). Study 2 was conducted to test the robustness and replicability of our initial findings with a new set of participants and gambles with less outcome consistency.

## Method

### Participants.

Power analysis based on the weakest significant correlation (i.e., between SGP and λ in choice; $r$ = -.34) central to our research main question (i.e., whether loss-sensitivity is related to attention) in Study 1 conducted using G*Power indicated 83 participants would be required to achieve 90% power to detect an effect; we ran seven additional participants to insure against data loss (e.g., from eye-tracker failure). Ninety ($M_{age}$ = 25.33; 36% female) new participants were recruited using the same university human subjects pool and received 20 NIS plus monetary incentives as in Study 1.

### Changes.

There were only two changes to the experimental design. First, we jittered the outcomes of the ± 40 gambles from Study 1 by randomly adding or subtracting small amounts from each outcome (see *Table 2*) to reduce outcome consistency. Second, during choice the certain zero outcome option was displayed simply as "0 ₪" and was presented at the center of the side (left or right) of the screen it was presented on. All other aspects were identical to Study 1.

*Table 2.* The positive and negative outcomes – in NIS (1 NIS ≈ \$0.25) - associated with each gamble as well as their probabilities of occurrence, sorted by expected values (EV) in Study 2. The mean valuation and the proportion of participants selecting to play the gamble rather than take a certain outcome of 0 NIS during choice (Acceptance Rate).

| Positive Outcome | Positive Probability | Negative Outcome | Negative Probability | EV | Valuation | Acceptance Rate |
|---|---|---|---|---|---|---|
| 41 | 10 | -45 | 90 | -36.4 | -22.17 | 16% |
| 23 | 50 | -73 | 50 | -25 | -19.89 | 18% |
| 39 | 20 | -38 | 80 | -22.6 | -13.6 | 18% |
| 43 | 30 | -40 | 70 | -15.1 | -7.66 | 21% |
| 27 | 50 | -52 | 50 | -12.5 | -13.45 | 20% |
| 41 | 40 | -38 | 60 | -6.4 | -4.3 | 26% |
| 41 | 50 | -41 | 50 | 0 | 5.16 | 38% |
| 25 | 50 | -25 | 50 | 0 | 3.54 | 46% |
| 37 | 60 | -39 | 40 | 6.6 | 10.66 | 44% |
| 49 | 50 | -24 | 50 | 12.5 | 17.89 | 71% |
| 38 | 70 | -35 | 30 | 16.1 | 19.19 | 80% |
| 76 | 50 | -26 | 50 | 25 | 28.78 | 78% |
| 43 | 80 | -40 | 20 | 26.4 | 24.37 | 83% |
| 44 | 90 | -45 | 10 | 35.1 | 30.65 | 85% |
| *Mean* | | | | .26 | 4.02 | 46% |

*Note:* Valuations and acceptance rates only include observations used in the primary analyses.

**Pre-Processing of Eye-Tracking Data.**

Two participants in valuation and one in choice had less than five viable trials after data cleaning and were removed from analysis. The final data set included 1,202 observations from 88 participants for valuations and 1,214 observations from 89 participants for choices.

## Results

**Behavioral Data.**

**Sensitivity to losses.** *Table 2* lists the average valuations and acceptance rates (choosing to play the gamble rather than take 0 with certainty) for each gamble. Roughly in line with Study 1 there appears to be minimal evidence of increased sensitivity to losses on the aggregate for valuation with the average valuation being greater than the average EV of .26 ($t(87) = 4.47$, $p < .0001$). In contrast, for choice the average acceptance was significantly lower than 50% ($t(88) = -2.36$, $p = .02$). Fifty-eight percent of valuations were higher than the gambles' EVs, 36% were below, and approximately 6% were equal to the gambles EV. Examining departures from EV on the level of the individual two participants never provided a valuation below a gamble's EV, while 22% of participants did so in at least half of their valuations. Thus, as in Study 1, aggregate behavior was not squarely in line with the predictions of loss aversion, and there was a degree of variability suggesting that loss-sensitivity was likely strong for some while absent for others.

Replicating Study 1 most choices were consistent with an EV maximization strategy (77%). In line with the variability seen in valuations, about 7% of participants never made an EV consistent choice, 19% always did, and 89% did at least half the time. These patterns hold when examining gambles where both the gain and loss had equal chances of occurring.

To get a clearer estimate of sensitivity to losses we fit λ to the data as described in the preceding section. Replicating Study 1 we find the average (and median) λ to be significantly below 1 for valuations ($M = .78$ $CI_{95\%}[.70, .86]$; *Mdn.* = .72; $t(87) = -5.45$, $p < .0001$) suggesting that participants showed decreased loss-sensitivity when providing their subjective values. As in Study 1 we the average λ was significantly larger than 1 ($M = 1.29$ $CI_{95\%}[1.13, 1.46]$; *Mdn.* = 1.14; $t(88) = 3.6$, $p = .0005$) for choices, suggesting increased sensitivity to losses during choice. Nevertheless, there was considerable variability across participants with 23% (76%) showing increased (decreased) loss-sensitivity during valuation (*Figure 5* left panel), while 58% (42%) showed increased (decreased) loss-sensitivity during choice (*Figure 5* middle panel).

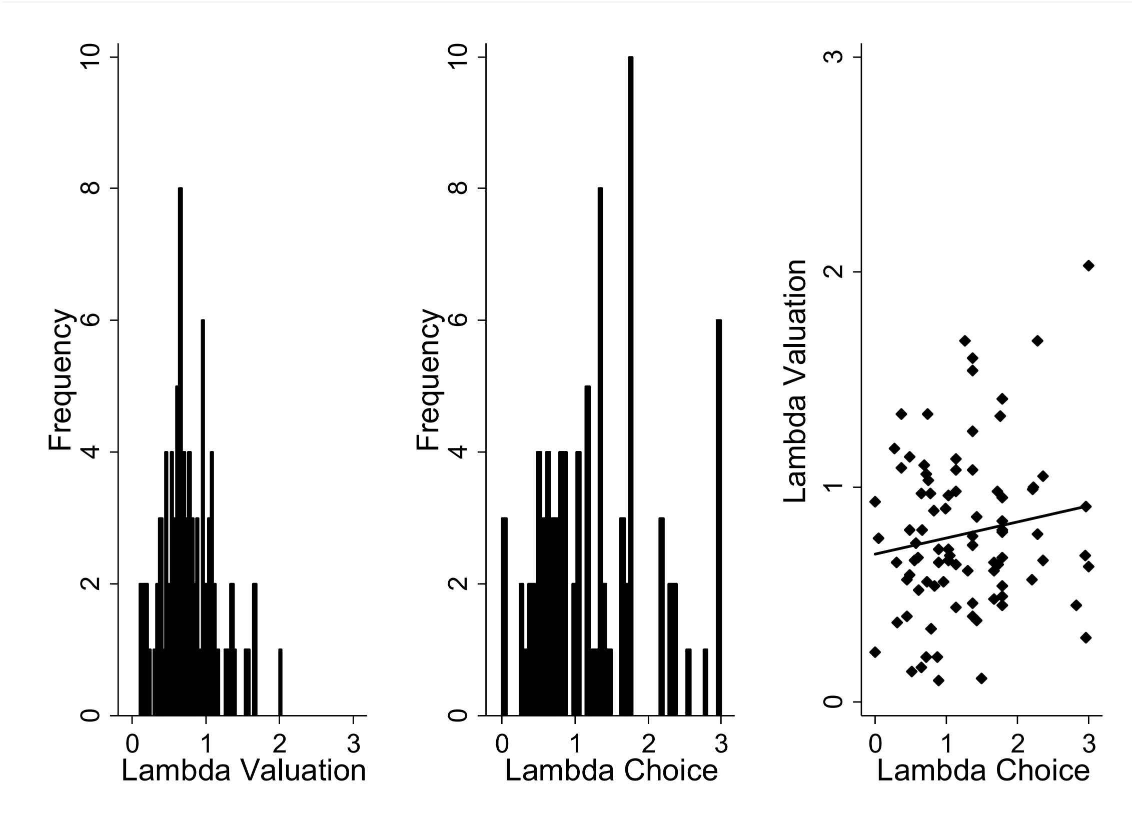


*Figure 5*. Histograms displaying the frequency (y-axis is the number of participants) of estimated λ (Lambda) parameters for valuation and choice (left and middle panel respectively) in Study 2. Scatterplot showing the relation between individual's λ parameters across valuation and choice (right panel); solid black line indicates the identity line.

**Consistency across valuation and choice.** As in Study 1 we examined the degree to which valuation and choice aligned (e.g., if a gamble was selected and participants gave it a valuation above 0). The level of valuation-choice consistency was 69%, significantly higher than 50%, $t(86) = 7.33$, $p < .001$. Looking at consistency on the level of the individual we again find some participants (8%) showed 100% consistency, while others (17%) showed less than 50% consistency. Next we correlated the estimated λ parameters for valuation and choice (*Figure 5* right panel) and found a non-significant relationship, $r(86) = .15$, $p = .17$. As in Study 1 we also examined how many participants showed increased or decreased loss-sensitivity in both valuation and choice. We find that the rate of loss-sensitivity matching across tasks ($M$ = .47; $CI_{95\%}$[.36, .58]) was no different than chance (50%), $t(86) = -.53$, $p = .59$. Thus, as in Study 1, estimated sensitivity to losses does not appear to reflect a strong relationship across tasks.

**Eye-Tracking Data.**

**Distribution of attention.** We again created the Low-Gaze-Proportion (LGP; Equation 4) for both valuations and choices. Replicating Study 1, the average LGP was significantly less than .50 for valuations ($M_{LGP\_Valuation}$ = .46 $CI_{95\%}$ [.45, .48]; $t(87) = -4.20$, $p = .0001$) and choices ($M_{LGP\_Choice}$ = .47 $CI_{95\%}$[.44, .49]; $t(88) = -2.24$, $p = .03$) suggesting participants showed a bias for looking at what they could win rather than lose. Again considerable variability on the level of the individual was observed (*Figure 6* left and middle panels).

Next, we created the Side-Gaze-Proportion (Equation 5) for choices. On average, SGP ($M_{SGP}$ = .92 $CI_{95\%}$[.89, .94]) was significantly larger than .50 suggesting a strong bias of attention towards the gamble containing gains and losses, $t(88) = 38.66$, $p < .0001$ (*Figure 6* right panel). Notably this bias was much larger than in Study 1, likely due to the simplification of the certain zero options presentation in the current study.

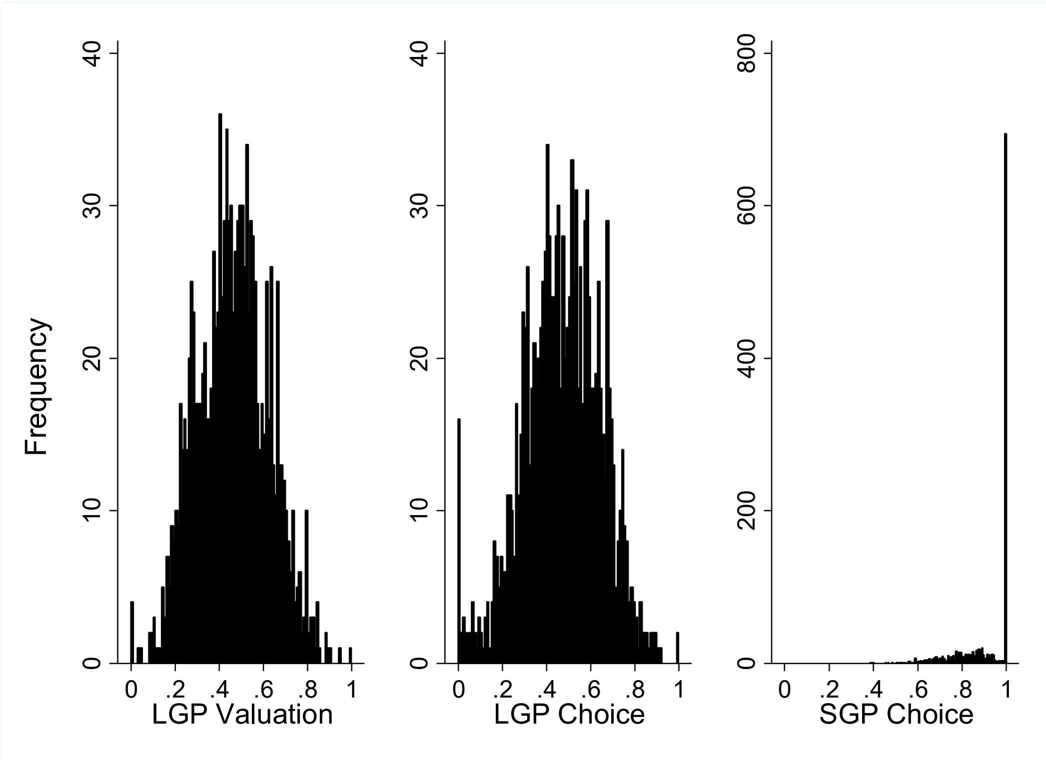


*Figure 6*. Histograms displaying the frequency (y-axis is the number of trials) of Low-Gaze-Proportions (LGP) for Valuation (left panel) and Choice (middle panel) and Side-Gaze-Proportion (SGP) for Choice (right panel) in Study 2.

**Consistency across valuation and choice.** As in Study 1 we find that valuations took significantly longer than choices on average, ($M_{RT\_Valuation}$ = 11.44 seconds $CI_{95\%}$[9.71, 13.17] vs. $M_{RT\_Choice}$ = 5.65 seconds $CI_{95\%}$[5.23, 6.06]), $t(86) = 7.37$, $p < .0001$. Nevertheless, participants who took more time during choice also took more time during valuation, $r\,(86) = .51$, $p < .0001$. Correlating participants' average LGP during valuation and choice we find the relationship to be non-significant as in Study 1, $r(86)= .11$, $p = .33$. Examining whether LGP was above/below .50 during both valuation and choice for each participant we find that participants' alignment across contexts (52%; $CI_{95\%}$[.48, .55]) was not significantly different than chance (50%), $t(86) = .88$, $p = .38$. Thus, as in Study 1, there was little consistency across decision formats for attentional allocation.

**Attention, Behavior, and Sensitivity to Losses.**

**Valuations.** Counter to our hypothesis and the results of Study 1 we do not find a significant relationship between a participant's average LGP and their estimated λ, $r\,(87) = .15, p = .16$. However, inspection of the left panel of *Figure 7* indicates a potential outlier (indicated by an "x"); this participant's average LGP value was more than three *SD*s from the group mean and was of high leverage value. Removal of this observation returns a significant relationship between LGP and estimated λ, replicating Study 1, $r\,(86) = .23, p = .04$. As in Study 1 we examined if biases in attention were predictive of valuations by performing a multi-level linear regression predicting valuations by LGP and EV, including a random effect of subject to control for repeated measurement and allowing slopes for EV and LGP to vary. Replicating Study 1, we find LGP to be predictive with increased attention to negative attributes relative to positive attributes being associated with decreased valuations, $b = -15.42$ $CI_{95\%}[-21.49, -9.34]$, $z = -4.97, p < .001$. EV was also a significant positive predictor, $b = .79$ $CI_{95\%}[.70, .89]$, $z = 16.68, p < .001$.

**Choices.** As in Study 1 LGP was not related to λ ($r(88) = -.04, p = .68$). In contrast to Study 1 SGP was not found to be significantly related to λ, $r(88) = .-.11, p = .30$ (*Figure 7* middle and right panels' respectively). To see if choices were predicted by attentional biases we performed a multi-level logit regression predicting acceptance of the gamble (coded 1 for accept, 0 for reject) by LGP, SGP, and the gambles EV including a random effect of subject and allowing slopes to vary for LGP and SGP: As in Study 1 inclusion of EV led to failures to converge. Replicating Study 1 LGP was not found to be a significant predictor, $b = -.59$ $CI_{95\%}[-1.53, .36]$, $z = -1.22, p = .22$. SGP was a significant predictor, $b = 2.94$ $CI_{95\%}[1.29, 4.59]$, $z = 3.49, p < .001$, indicating that participants who spent more time looking at the gamble were more likely to choose it as in Study 1. EV was a significant positive predictor, $b = .07$ $CI_{95\%}[.06, .07]$, $z = 15.30, p < .001$.

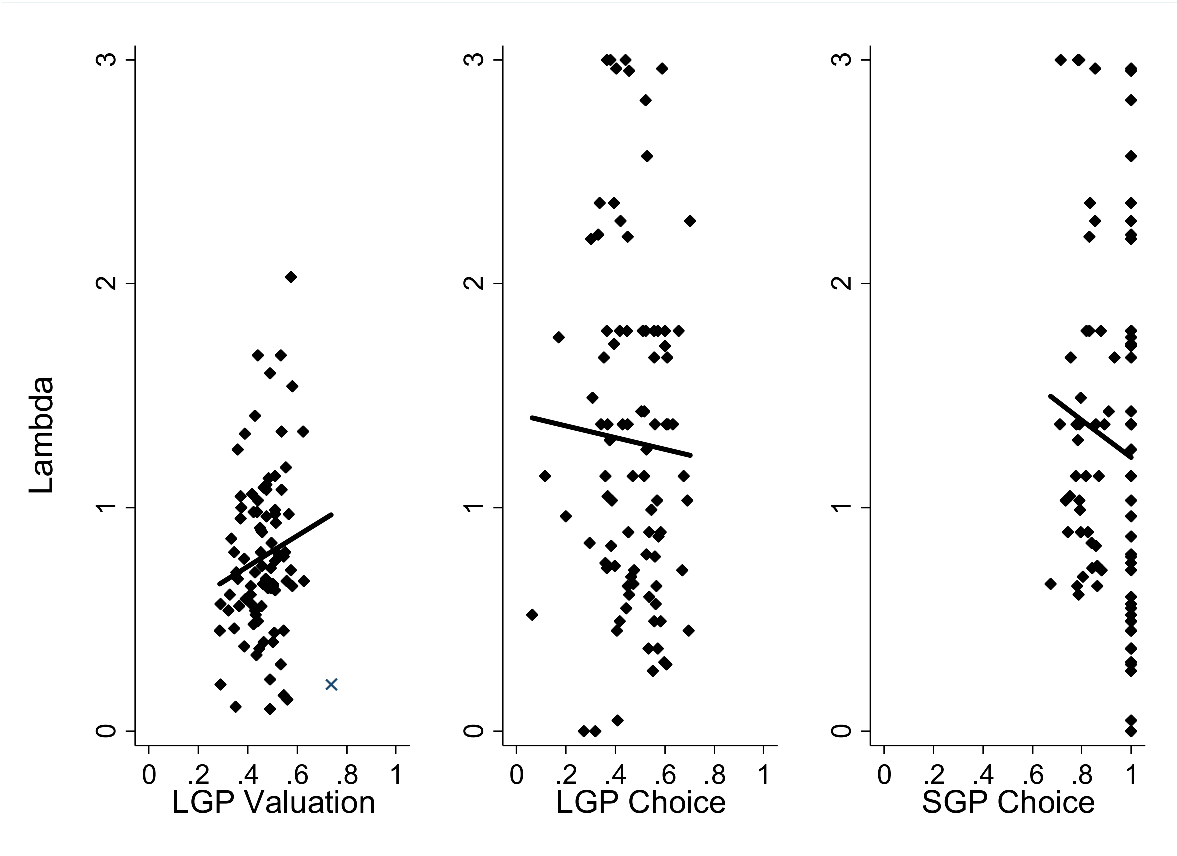


*Figure 7*. Scatter plots showing the relationship between a participants estimated λ (Lambda) and their averaged Low-Gaze-Proportion (LGP) in valuation (left panel), choice (middle panel), and the relation between λ and a participants averaged Side-Gaze-Proportion (SGP; right panel) in choice in Study 2; solid black lines indicate the identity lines and x indicates an outlier.

## Study 3

In Studies 1 and 2 the number of decisions made was small, far less than typically used to estimate parameters such as loss aversion (e.g., Glockner & Pachur, 2012; Rieskamp, 2008), and the outcomes and probabilities encountered were greatly constrained (e.g., constrained outcome and probability ranges have been shown to effect estimates of loss sensitivity; Walasek & Stewart, 2015). These aspects may have led to the challenges faced in fitting full mixed effects regression models (e.g., we could not include all predictors as random slopes in analyses involving choice) and to issues in fitting λ (see for example the Online Supplementary Materials). In addition, participants encountered each condition only once, which allowed us to investigate the relationship of attentional bias and loss sensitivity across conditions, but not their consistency within an individual decision maker across time (i.e., are attentional distribution and loss sensitivity consistent across time). To address these shortcomings Study 3 increased the number and variability of decisions in each condition, and participants went through the tasks twice with experimental sessions separated by at least one week.

## Method

### Participants.

Forty-two ($M_{age}$ = 25.04; 64% female) new participants were recruited using the same university human subjects pool as in Studies 1 and 2 and received 30 NIS plus monetary incentives: One valuation and one choice from each session were selected at random and incentivized.

### Changes.

Two changes were made to the methods of Study 2. First, 80 gambles were included (see *Table A1* in the Appendix): Twenty-eight were those employed in Studies 1 and 2, eight were drawn from those used (outcomes halved) by Glockner and Pachur (2012; adapted from Gachter, Johnson, & Herrman, 2007), and 44 were randomly generated similar to Rieskamp (2008; losses randomly drawn from -5 to -95, gains from 5 to 95, and the probability of loss from 10% to 90%). Second, participants attended two sessions (separated by at least seven days). In each session they encountered all gambles in both conditions (encountered in random order) and their eye-movements were recorded.

### Pre-Processing of Eye-Tracking Data.

Four participants in choice had less than five viable trials (in each session) after data cleaning and were removed from analysis. The final data set included 5,879 observations from 42 participants for valuations and 5,787 observations from 38 participants for choices.

## Results

### Behavioral Data.

**Sensitivity to losses.** *Table A1* in the appendix lists the average valuations and acceptance rates (choosing to play the gamble rather than take 0 with certainty) for each gamble. As in the previous studies there appears to be minimal evidence of increased sensitivity to losses on the aggregate for valuation with the mean valuation being greater than the average EV of 1.93 ($t(41) = 4.03$, $p = .0002$). In line with Study 2 the average acceptance was significantly lower than 50% ($t(37) = -2.13$, $p = .04$). Fifty-two percent of valuations were higher than, 39% lower than, and 9% equal to the gambles EVs. Only 10% of participants provided valuations below the gambles EV in at least half of their valuations, though all participants provided at least 1 valuation below a gambles EV Thus, as in the previous studies aggregate behavior was not in line with the predictions of loss aversion, and there was a degree of variability suggesting that loss-sensitivity varied across participants. Replicating the previous studies most choices were in line with an EV maximization strategy (87%). The rate of optimal choice varied from 51% to 99% across participants.

To get a clearer estimate of sensitivity to losses we fit λ to the data as in the previous studies. We find the average (and median) λ to be significantly below 1 for valuations ($M = .86$ $CI_{95\%}$[.79, .83]; *Mdn.* = .93; $t(41) = -3.96$, $p = .0003$) suggesting that participants showed decreased loss-sensitivity when providing their subjective values, in line with the previous studies. Replicating the previous studies the average λ was significantly larger than 1 ($M = 1.26$ $CI_{95\%}$[1.09, 1.44]; *Mdn.* = 1.19; $t(37) = 3.08$, $p = .004$) for choices, suggesting increased sensitivity to losses during choice. Nevertheless, there was considerable variability across participants with 24% (76%) showing increased (decreased) loss-sensitivity during valuation (*Figure 8* left panel), while 68% (29%) showed increased (decreased) loss-sensitivity during choice (*Figure 8* middle panel).

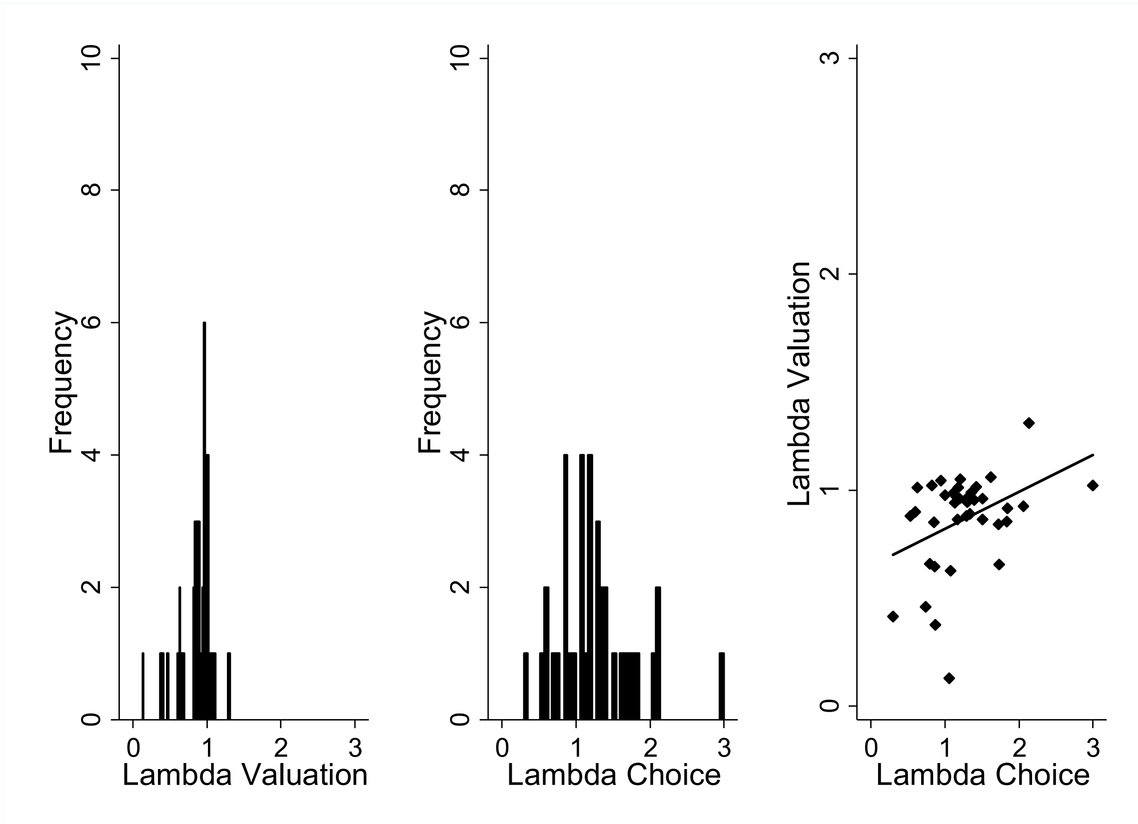


*Figure 8*. Histograms displaying the frequency (y-axis is the number of participants) of estimated λ (Lambda) parameters for valuation and choice (left and middle panel respectively) in Study 3. Scatterplot showing the relation between individuals' λ parameters across valuation and choice (right panel); solid black line indicates the identity line.

**Consistency across valuation and choice.** The level of valuation-choice consistency was 82%, significantly higher than 50%, $t(37) = 14.07$, $p < .0001$. Looking at consistency on the level of the individual we again find a great deal of variability with the rate of consistency ranging from 36% to 97%. Next we correlated the estimated λ parameters for valuation and choice (*Figure 8* right panel) and in contrast to the previous studies found a significant positive relationship, $r(37) = .39$, $p = .02$. We also examined how many participants showed both increased or decreased loss-sensitivity in both valuation and choice. As in the previous studies we find the rate of loss-sensitivity matching across tasks ($M = .42$; $CI_{95\%}[.29, .55]$) was no different than chance (50%), $t(37) = -1.23$, $p = .22$. Thus, while there is a significant correlation between λ in choice and valuation, the level of consistency does not appear particularly robust.

**Consistency Across Sessions.** The current study allowed us to examine the degree of consistency across sessions. To see how similar valuations were across sessions we correlated participants' average valuation in the first and second sessions and find a significant positive correlation ($r(41) = .66$, $p < .0001$) indicating some consistency in valuations across sessions (*Figure 9* upper left panel): Performing correlations for each participant across sessions all but two participants showed significant positive correlations with *r*'s ranging from .44 to .99. To see how consistent preferences were across choice we correlated participants' average rate of acceptance in the first and second sessions. As with valuations, we find a significant positive correlation (*Figure 9* upper right panel) again indicating some consistency across sessions, $r(37) = .48$, $p = .002$. Consistency across sessions on the level of the individual ranged from 54% to 100%, with 76% of participant showing consistency rates greater than 75%. Lastly, to examine the degree of consistency in loss sensitivity across sessions we correlated participants estimated λ's across sessions separately for valuation and choice. For valuation we find a positive correlation (*Figure 9* bottom left panel) in loss sensitivity on the level of the individual, indicating consistency of individual differences in this parameter, $r(41) = .57$, $p = .0001$. For choice we find a smaller but significant positive correlation (*Figure 9* bottom right panel) again suggesting some consistency in loss sensitivity on the level of the individual, $r(37) = .34$, $p = .04$.

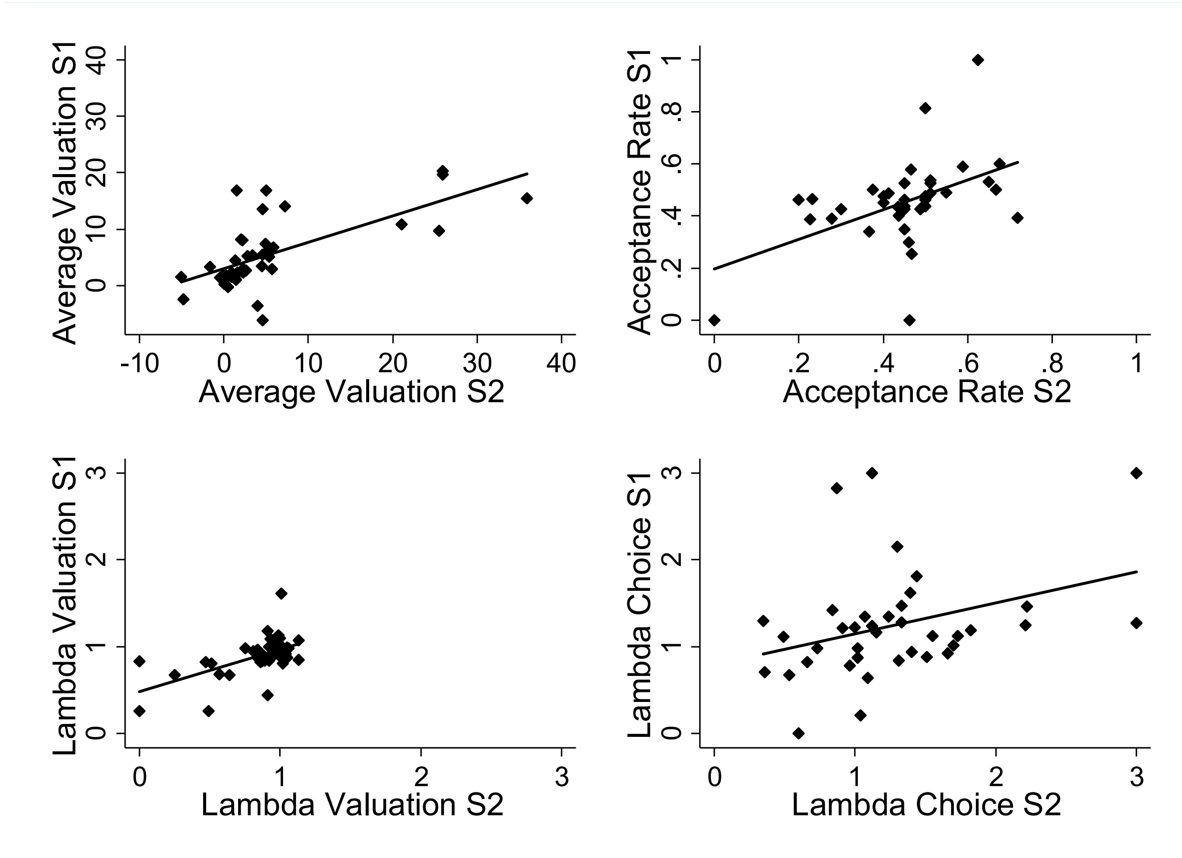


*Figure 9*. Scatter points showing the consistency of participants' behavior across sessions in Study 3. Scatter plots displaying the relationship between participants' averaged valuations across the first (S1) and second sessions (S2) in the top left panel, averaged acceptance rates across S1 and S2 in the top right panel, estimated λ (Lambda) parameters for valuations across S1 and S2 in the bottom left panel, and estimated λ parameters for choices across S1 and S2 in the bottom right panel; solid black line indicates the identity line.

**Eye-Tracking Data.**

**Distribution of attention.** As in Studies 1 and 2 we calculated the Low-Gaze-Proportion (LGP; Equation 4) for both valuations and choices. As in the previous studies the average LGP was significantly less than .50 for valuations ($M_{LGP\_Valuation}$ = .47 $CI_{95\%}$ [.44, .49]; $t(41) = -2.18$, $p = .04$)

suggesting participants showed a bias for looking at what they could win. Counter to previous studies we find no significant difference from .50 for choices ($M_{LGP\_Choice}$ = .48 $CI_{95\%}$[.45, .51]; $t(37) = -1.36$, $p = .18$). As in the previous studies considerable variability was observed (*Figure 10* left and middle panels). Next, we calculated the Side-Gaze-Proportion (SGP; Equation 5) and find it to be significantly larger ($M_{SGP}$ = .81 $CI_{95\%}$[.79, .84]) than .50 suggesting a strong bias of attention towards the gamble in line with Study 2, $t(37) = 24.47$, $p < .0001$ (*Figure 10* right panel).

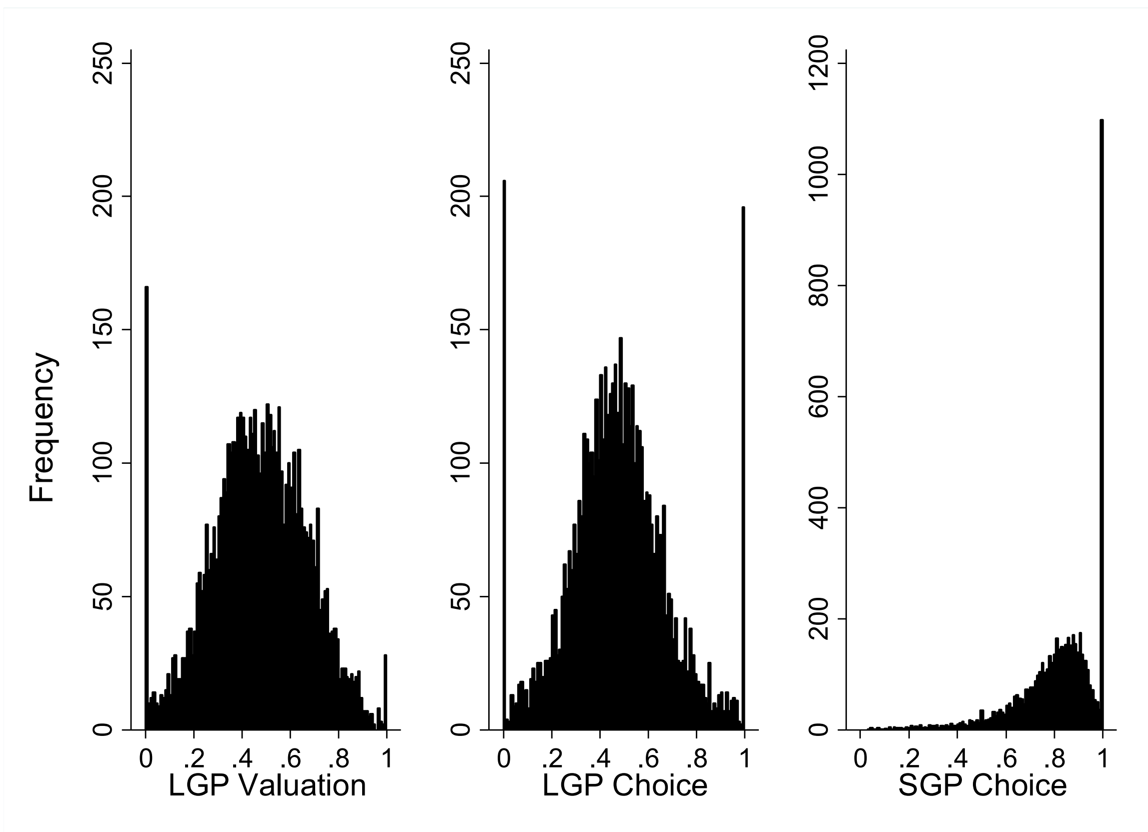


*Figure 10.* Histograms displaying the frequency (y-axis is the number of trials) of Low-Gaze-Proportions (LGP) for Valuation (left panel) and Choice (middle panel) and Side-Gaze-Proportion (SGP) for Choice (right panel) in Study 3.

**Consistency across valuation and choice.** Replicating the previous studies valuations took significantly longer than choices on average, ($M_{RT\_Valuation}$ = 10.13 seconds $CI_{95\%}$[7.99, 12.28] vs. $M_{RT\_Choice}$ = 3.55 seconds $CI_{95\%}$[3.19, 3.91]), $t(37) = 6.69$, $p < .0001$. Though as in the previous studies participants' decision times were positively correlated across tasks, $r\ (37) = .5$, $p = .001$. Correlating participants' average LGP during valuation and choice we find the relationship to be non-significant, $r(37) = .05$, $p = .77$. replicating the previous studies. Examining whether LGP was above/below .50 during both valuation and choice for each participant we find that participants' alignment across contexts (52%; $CI_{95\%}$[.39, .70]) was not significantly different than chance (50%), $t(37) = 1.41$, $p = .17$. As in Studies 1 and 2 there thus appears to be little consistency across decision formats in regards to attentional allocation.

**Consistency Across Sessions.** As with the behavioral responses we sought to examine the consistency in attentional distribution across sessions. We find a significant positive correlation in LGP across sessions for valuations (*Figure 11* left panel; $r(41) = .52$, $p = .0004$) and choices (*Figure 11* middle panel), $r(37) = .37$, $p = .02$. For SGP the relationship was found to be non-significant, $r(37) = .25$, $p = .14$. Therefore, LGP appears to show some stability within an individual (in the same task).

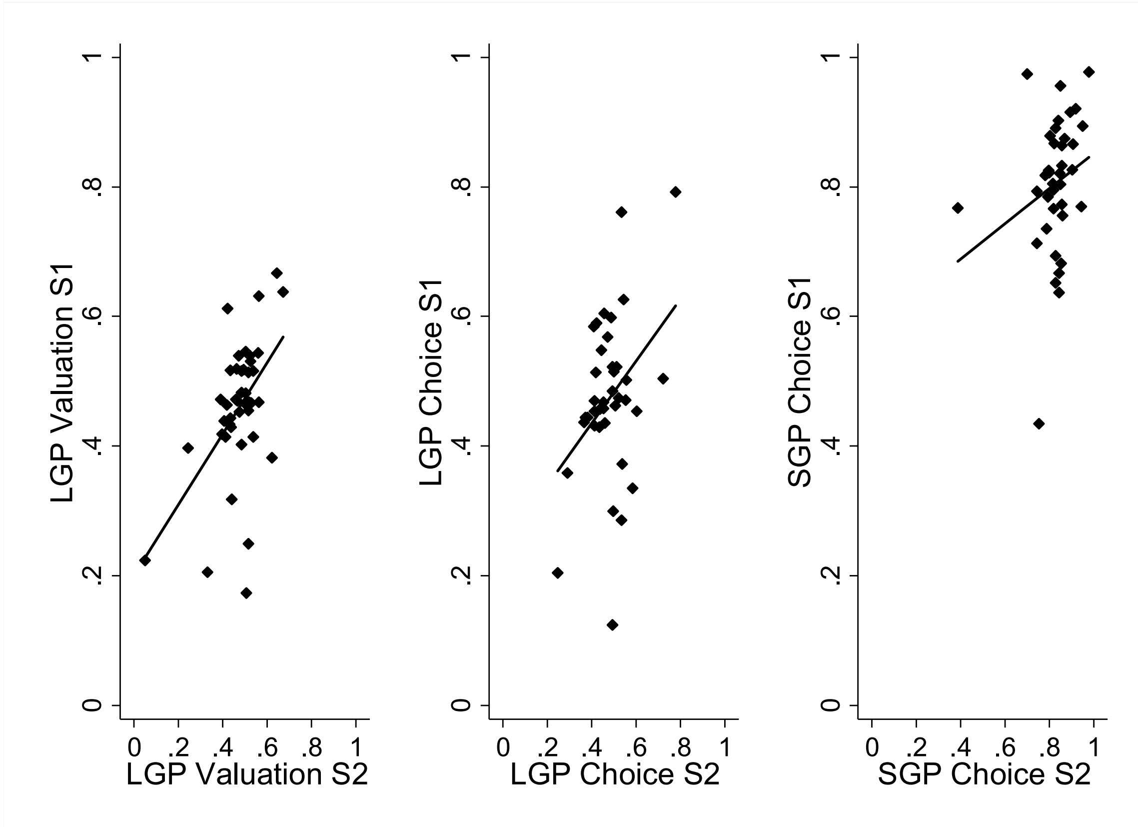


*Figure 11*. Scatter points showing the consistency of Low-Gaze-Proportion (LGP) and Side-Gaze-Proportion (SGP) across sessions in Study 3. The relationship between participants' averaged valuation LGP across the first (S1) and second sessions (S2) is presented in the left panel, averaged choice LGP across S1 and S2 in the middle panel, and averaged choice SGP across S1 and S2 in the right panel in Study 3; solid black line indicates the identity line.

**Attention, Behavior, and Sensitivity to Losses.**

**Valuations.** In line with our hypotheses and the results of Study 1 (and to an extent Study 2) we found a significant positive relationship (*Figure 12* left panel) between a participant's average LGP and their estimated λ, $r\,(41) = .68$, $p < .0001$. As in the previous studies we examined if biases in attention were predictive of valuations, performing a multi-level linear regression predicting valuations by LGP and EV, including a random effect of subject with sessions nested in subject and allowing slopes to vary. Replicating the previous studies, we find LGP to be predictive, with increased attention to negative attributes relative to positive attributes being associated with decreased valuations, $b$ = -16.96 $CI_{95\%}$[-21.42, -12.49], $z$ = -7.44, $p$ < .001. EV was also a significant positive predictor, $b$ = .96 $CI_{95\%}$[.89, 1.02], $z$ = 29.68, $p$ < .001.

**Choices.** As in the previous studies LGP was not related to λ ($r$(37) = .07, $p$ = .66). In line with Study 2 SGP was not found to be significantly related to λ either, $r$(37) = -.27, $p$ = .10 (*Figure 7* middle and right panels, respectively). Performing a multi-level logit regression predicting acceptance of the gamble (coded 1 for accept, 0 for reject) by LGP, SGP, and the gambles EV (including a random effect of subject with session nested in subject and allowing the slopes of LGP and SGP to vary)[6] we find counter to the previous studies that increased LGP was associated with decreased likelihood of selecting the gamble, $b$ = -1.06 $CI_{95\%}$[-1.65, .46], $z$ = -3.49, $p$ < .001. In line with the previous studies SGP was a significant positive predictor, with participants who spent more time looking at the gamble being more likely to select it, $b$ = 2.3 $CI_{95\%}$[1.59, 3.02], $z$ = 6.30, $p$ < .001. EV was a significant positive predictor, with participants being more likely to select gambles that provided higher EV, $b$ = .11 $CI_{95\%}$[.10, .11], $z$ = 34.86, $p$ < .001.

[6] As in Study 2, inclusion of a random slope for EV led to failures to converge.

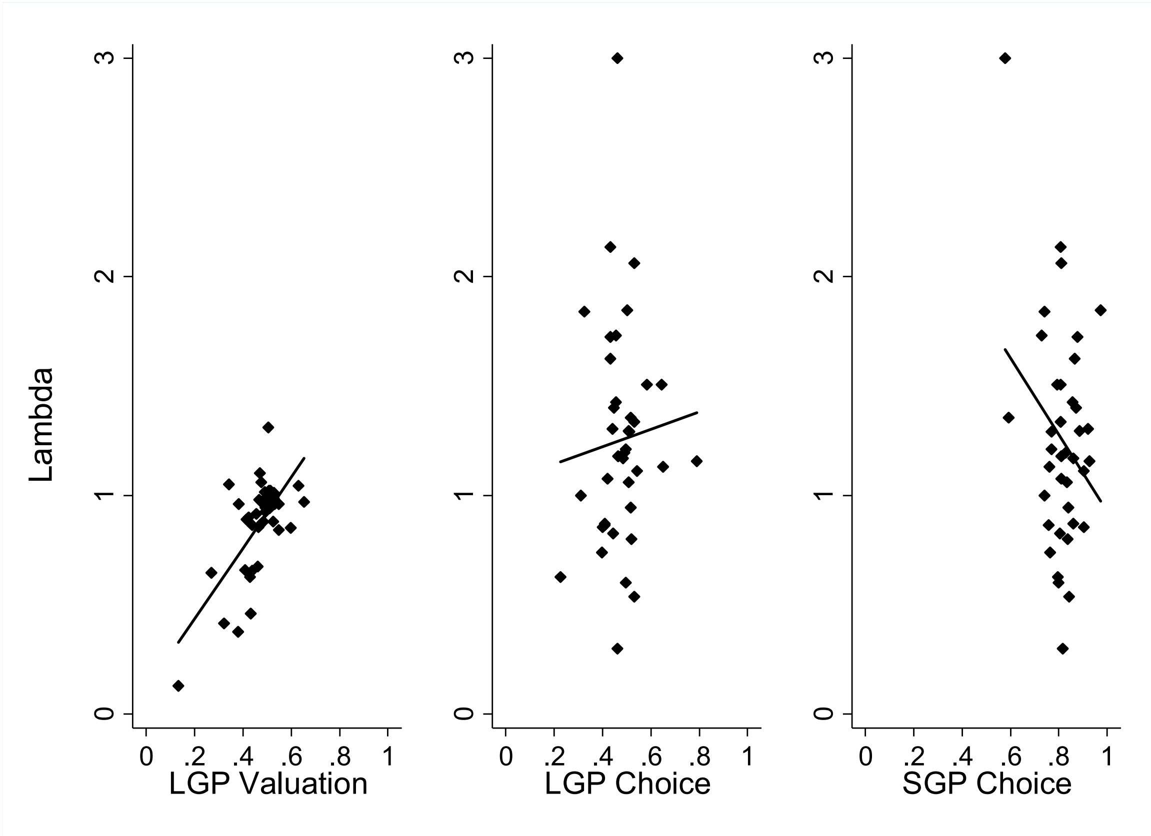


*Figure 12.* Scatter plots showing the relationship between participants' estimated λ (Lambda) and their averaged Low-Gaze-Proportion (LGP) in valuation (left panel), choice (middle panel), and the relation between λ and a participant's averaged Side-Gaze-Proportion (SGP; right panel) in choice in Study 3; solid black lines indicate the identity lines.

**Discussion**

In the current studies we examined the hypothesis that there would be a relationship between individual differences in loss-sensitivity and the distribution of visual attention during valuation and choice. In line with our predictions we find that participants who placed more attention on negative attributes (negative outcomes and their associated probabilities) than positive attributes during valuations showed increased loss-sensitivity and indicated lower valuations. In choice however, biases towards negative attributes were not significantly related to rejecting gambles containing potential losses in two out of three studies, nor were they related to individual differences in loss-sensitivity. Furthermore, there was no robust relationship between estimated loss-sensitivity across the two decision formats nor in the distribution of attention. Nevertheless, there was some level of consistency between subjective valuations and choices (i.e., the tendency to pick a gamble in choice trials was strongly associated with giving it a value above zero during valuation) and the direction of loss-sensitivity was also somewhat similar across the two tasks (i.e., having increased sensitivity to losses during choice and valuation). In addition, both attentional allocation and loss sensitivity showed a relationship across time within an individual for the same task, suggesting some consistency in how individuals allocate attention and weight losses in certain decision contexts.

Overall, the current study provides initial evidence that variation in loss-sensitivity is related to the distribution of attention in valuation, but not choice. However, it also suggests that on the level of the individual there is some similarity in loss-sensitivity between valuation and choice: The direction of loss-sensitivity (i.e., being more or less sensitive to losses) was s no different than chance in Study 1 and 2, and a significant relationship in loss sensitivity across tasks in Study 3. Thus, when it comes to loss-sensitivity there appears to be considerable variability across individual decision makers in line with the assertion that loss-sensitivity is in part an individual difference. Similarly, it is worth noting that we observed diminished sensitivity to losses for valuations in all studies, while we observed increased loss-sensitivity in choices in all studies. This suggests that very small differences in the format of how losses and gains are presented may tilt the average loss aversion parameter; it might also reflect imprecision in our estimation of loss-sensitivity (see below). By contrast, individual differences with respect to the relation between perceptual attention and behavioral loss aversion remained consistent across studies, suggesting when conceptualized as an individual difference (one's sensitivity to losses vs. gains compared to that of others in the population) loss aversion tends to be reliable: Inferences supported by the consistency found in loss sensitivity and attention to losses across time.

Nevertheless, our estimations of loss-sensitivity were potentially biased to some extent, particularly in Studies 1 and 2 which did not include the extremely large sets of gambles frequently used to get precise estimates of loss-sensitivity (e.g., Reiskamp, 2008). Our motivation for running these shorter studies is based on the fact that attentional engagement has been shown to decrease substantially over the course of a task (Ashby & Rakow, 2016) and learning effects can influence the distribution of attention in similar tasks over time (Orquin et al., 2013). However, the results of Study 3 which employed a much larger set of gambles with more variety in outcomes and probabilities showed a similar distribution of loss sensitivity parameters, as well as corresponding changes in attention. Additionally, because we could not include all of our variables as random slopes in all our regression analysis involving choice it is possible that some of our findings regarding particular predictors effects are biased (Barr, Levy, Scheepers, & Tily, 2013). Future studies need to consider how much larger sets of gambles can be employed in the context of eye-tracking so that more precise estimates of loss-sensitivity might be gleaned and to allow for full mixed effect models.

Our findings regarding the absence of robust consistency in visual attention to losses during choice and valuation suggest that to an extent these decisions might reflect different cognitive processes. This is consistent with the finding that valuations are predicted by what attributes are focused on (Ashby et al., 2012, 2015), while choices appear to be less influenced by which attributes receive more attention (Stewart et al., 2016). By examining behavior across both formats for the same participants we provide clear evidence that choice and valuation are not very similar, and that such differences are not simply the result of variability in the populations from which they are drawn, or the peculiarities of the methodologies employed. Thus, the current investigation suggests that while behaviorally the two decision formats might seem to align the decision processes underlying them, at least in regards to how attention is distributed, give rise to substantial differences even within the same individual. An intriguing possibility is that choices and valuations are differentially affected by separate processing systems (Denes-Raj and Epstein, 1994; Kahneman & Frederick, 2002), with valuations being more affected by systems mediating deliberative and verbally mediated reasoning (see e.g., Ofek et al., 2007). Potentially, individual differences in the sensitivity of such systems to certain types of stimuli (e.g., losses) may differ, thereby accounting for the dissociation found across decision paradigms.

A question often pondered in research relating visual attention to behavior is which comes first: In our study did an individual's loss-sensitivity influence what attributes they looked at, or did some attributes capture more attention and influence the perception of potential losses? As we indicated in the introduction the current investigation cannot answer this question. There is evidence that valuation and choice are related to visual attention across many contexts (Ashby et al., 2012, 2015, 2016; Atalay et al., 2012; Glaholt & Reingold, 2011; Glaholt, Wu, & Reingold, 2009; Glöckner, Heinan, Raab, & Johnson, 2012; Krajbich et al., 2011), and that externally biasing visual attention (e.g., by manipulating viewing times) can impact choice and ratings of attractiveness (Armel et al., 2010; Shimojo et al., 2003). Our view is that the answer is likely more complex with both external and internal factors influencing loss-sensitivity. We suspect that while an individual might be predisposed to view losses with increased or decreased sensitivity (Pachur et al., 2010), variability in the decision to be made (Walasek & Stewart, 2015) likely plays a role as well. For example, while an individual might be naturally predisposed to be wary of losses, if potential gains capture greater attention then that individual might show some decrease in their loss-sensitivity. Thus, one area ripe for future research is to examine whether loss-sensitivity can be influenced by manipulating the direction of visual attention. Such a research endeavor will shed important insights into the stability of loss-sensitivity on the level of the individual as well as providing much needed clarification into whether attention can directly impact preferences, and if so to what degree.

In sum, the current investigation provides three important insights. First, our novel examination of loss-sensitivity suggests that there is a relationship between loss-sensitivity and the distribution of attention in valuations (i.e., a focus on the negative outcome) but such relation is not readily apparent in choices (i.e., avoidance of options containing losses). Second, we provide further support for the hypothesis that loss-sensitivity is indeed best conceptualized as an individual difference given the degree of variability we observe across participants, its consistency across time in the same task, and the absence of a clear central tendency. Lastly, we provide important clarity into what facets of visual attention matter for decisions involving valuation (i.e., how attention is distributed among attributes) and choice, as well as how they differ, and the degree to which it is stable across time.

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## Context of the Research

The current work marks a marriage between the first two authors primary research interests: Nathaniel is particularly interested in the role of individual differences in how information is attended (accumulated) and its impact on behavior. Eldad has spent much of his career highlighting issues with classical conceptualizations of loss aversion and the relationship between attentional processes and behavior. The idea for the research was born during conversations between Nathaniel and Eldad while Nathaniel was a post-doctoral researcher at the Technion – Israel Institute of Technology. The authors intend to follow up on the work by examining the directionality of the attention-behavior link: Can loss sensitivity be influenced by biases in attention.

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*Table A1*. The gambles used in Study 3, sorted by expected value (EV). The positive and negative outcomes – in NIS (1 NIS ≈ $0.25) - associated with each gamble as well as their probabilities of occurrence and the gamble's EV are presented on the left. The two rightmost columns indicate the mean valuation and the proportion of participants selecting to play the gamble rather than take a certain outcome of 0 NIS during choice (Acceptance Rate).

| Positive Outcome | Positive Probability | Negative Outcome | Negative Probability | EV | Valuation | Acceptance Rate |
|---|---|---|---|---|---|---|
| 5 | 0.24 | -85 | 0.76 | -63.4 | -11.08 | 1% |
| 31 | 0.25 | -92 | 0.75 | -61.25 | -29.36 | 5% |
| 38 | 0.31 | -90 | 0.69 | -50.32 | -32.36 | 7% |
| 74 | 0.17 | -68 | 0.83 | -43.86 | -15.69 | 11% |
| 58 | 0.3 | -86 | 0.7 | -42.8 | -6.06 | 4% |
| 19 | 0.39 | -82 | 0.61 | -42.61 | -18.42 | 5% |
| 74 | 0.15 | -57 | 0.85 | -37.35 | -19.00 | 10% |
| 41 | 0.1 | -45 | 0.9 | -36.4 | -15.89 | 7% |
| 60 | 0.28 | -71 | 0.72 | -34.32 | -25.43 | 5% |
| 65 | 0.25 | -65 | 0.75 | -32.5 | -10.75 | 7% |
| 40 | 0.1 | -40 | 0.9 | -32 | -25.74 | 7% |
| 39 | 0.41 | -79 | 0.59 | -30.62 | 8.60 | 13% |
| 23 | 0.27 | -47 | 0.73 | -28.1 | -58.02 | 4% |
| 63 | 0.05 | -32 | 0.95 | -27.25 | -32.90 | 8% |
| 23 | 0.5 | -73 | 0.5 | -25 | -16.09 | 10% |
| 25 | 0.5 | -75 | 0.5 | -25 | -17.00 | 4% |
| 40 | 0.2 | -40 | 0.8 | -24 | 2.83 | 7% |
| 43 | 0.49 | -88 | 0.51 | -23.81 | 3.95 | 4% |
| 39 | 0.2 | -38 | 0.8 | -22.6 | 7.42 | 5% |
| 32 | 0.39 | -52 | 0.61 | -19.24 | -3.77 | 8% |
| 9 | 0.42 | -35 | 0.58 | -16.52 | -51.95 | 4% |
| 40 | 0.3 | -40 | 0.7 | -16 | 18.82 | 3% |
| 43 | 0.3 | -40 | 0.7 | -15.1 | -3.93 | 6% |
| 16 | 0.14 | -19 | 0.86 | -14.1 | -9.42 | 7% |
| 59 | 0.35 | -53 | 0.65 | -13.8 | -27.55 | 9% |
| 25 | 0.5 | -50 | 0.5 | -12.5 | -17.24 | 14% |
| 27 | 0.5 | -52 | 0.5 | -12.5 | -4.17 | 11% |
| 25 | 0.5 | -50 | 0.5 | -12.5 | 13.61 | 17% |
| 70 | 0.19 | -30 | 0.81 | -11 | -31.94 | 11% |
| 59 | 0.48 | -75 | 0.52 | -10.68 | 18.74 | 15% |
| 40 | 0.4 | -40 | 0.6 | -8 | -8.19 | 10% |
| 46 | 0.18 | -18 | 0.82 | -6.48 | -9.23 | 15% |
| 41 | 0.4 | -38 | 0.6 | -6.4 | 16.99 | 12% |

| | | | | | | |
|---|---|---|---|---|---|---|
| 63 | 0.48 | -70 | 0.52 | -6.16 | -41.99 | 18% |
| 62 | 0.35 | -39 | 0.65 | -3.65 | -15.11 | 19% |
| 88 | 0.43 | -70 | 0.57 | -2.06 | -42.37 | 37% |
| 7 | 0.83 | -43 | 0.17 | -1.5 | -10.85 | 28% |
| 56 | 0.34 | -30 | 0.66 | -0.76 | 5.14 | 18% |
| 50 | 0.5 | -50 | 0.5 | 0 | 4.67 | 35% |
| 41 | 0.5 | -41 | 0.5 | 0 | 5.55 | 36% |
| 25 | 0.5 | -25 | 0.5 | 0 | -0.96 | 36% |
| 40 | 0.5 | -40 | 0.5 | 0 | -35.80 | 41% |
| 25 | 0.5 | -25 | 0.5 | 0 | 32.16 | 32% |
| 40 | 0.5 | -40 | 0.5 | 0 | 11.13 | 39% |
| 25 | 0.56 | -22 | 0.44 | 4.32 | -20.54 | 74% |
| 17 | 0.82 | -42 | 0.18 | 6.38 | -23.25 | 63% |
| 37 | 0.6 | -39 | 0.4 | 6.6 | 14.64 | 68% |
| 14 | 0.75 | -13 | 0.25 | 7.25 | 7.57 | 86% |
| 40 | 0.6 | -40 | 0.4 | 8 | -21.07 | 88% |
| 35 | 0.73 | -55 | 0.27 | 10.7 | 7.06 | 69% |
| 26 | 0.7 | -25 | 0.3 | 10.7 | 30.35 | 84% |
| 75 | 0.5 | -50 | 0.5 | 12.5 | 18.76 | 78% |
| 49 | 0.5 | -24 | 0.5 | 12.5 | 18.83 | 82% |
| 50 | 0.5 | -25 | 0.5 | 12.5 | 20.45 | 77% |
| 85 | 0.42 | -38 | 0.58 | 13.66 | 27.70 | 53% |
| 40 | 0.7 | -40 | 0.3 | 16 | 18.95 | 89% |
| 38 | 0.7 | -35 | 0.3 | 16.1 | -3.47 | 88% |
| 43 | 0.78 | -66 | 0.22 | 19.02 | -23.55 | 74% |
| 30 | 0.76 | -10 | 0.24 | 20.4 | -11.26 | 93% |
| 64 | 0.7 | -75 | 0.3 | 22.3 | 14.63 | 77% |
| 67 | 0.57 | -36 | 0.43 | 22.71 | 27.55 | 74% |
| 100 | 0.5 | -50 | 0.5 | 25 | 4.64 | 91% |
| 76 | 0.5 | -26 | 0.5 | 25 | 32.69 | 86% |
| 43 | 0.8 | -40 | 0.2 | 26.4 | 40.06 | 93% |
| 110 | 0.5 | -50 | 0.5 | 30 | 40.22 | 85% |
| 86 | 0.44 | -12 | 0.56 | 31.12 | 31.42 | 74% |
| 40 | 0.9 | -40 | 0.1 | 32 | 55.30 | 95% |
| 68 | 0.7 | -44 | 0.3 | 34.4 | 38.26 | 89% |
| 120 | 0.5 | -50 | 0.5 | 35 | 44.92 | 86% |
| 44 | 0.9 | -45 | 0.1 | 35.1 | 35.64 | 89% |
| 71 | 0.67 | -37 | 0.33 | 35.36 | 51.65 | 89% |
| 69 | 0.79 | -59 | 0.21 | 42.12 | 46.14 | 94% |
| 87 | 0.66 | -35 | 0.34 | 45.52 | 64.63 | 88% |
| 50 | 0.95 | -33 | 0.05 | 45.85 | 20.03 | 92% |
| 150 | 0.5 | -50 | 0.5 | 50 | 50.58 | 88% |
| 75 | 0.8 | -25 | 0.2 | 55 | 27.15 | 93% |
| 86 | 0.72 | -21 | 0.28 | 56.04 | 67.33 | 96% |
| 77 | 0.85 | -46 | 0.15 | 58.55 | 38.96 | 94% |
| 89 | 0.79 | -14 | 0.21 | 67.37 | 54.38 | 94% |
| 200 | 0.5 | -50 | 0.5 | 75 | 93.66 | 88% |

| | | | |
|---|---|---|---|
| *Mean* | 1.93 | 5.54 | 45% |

*Note:* Valuations and acceptance rates only include observations used in the primary analyses.