TI 2022-046/I
Tinbergen Institute Discussion Paper

Impulsiveness moderates the effects of exogenous attention on the sensitivity to gains and losses in risky lotteries

Alejandro Hirmas[1,2]
Jan Engelmann[1,2]

1 University of Amsterdam, Center for Experimental Economics and political Decision making (CREED)

2 Tinbergen Institute

Tinbergen Institute is the graduate school and research institute in economics of Erasmus University Rotterdam, the University of Amsterdam and Vrije Universiteit Amsterdam.

Contact: discussionpapers@tinbergen.nl

More TI discussion papers can be downloaded at https://www.tinbergen.nl

Tinbergen Institute has two locations:

Tinbergen Institute Amsterdam
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 598 4580

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900

Impulsiveness moderates the effects of exogenous attention on the sensitivity to gains and losses in risky lotteries *

Alejandro Hirmas[1] and Jan Engelmann[1]

[1]University of Amsterdam, Center for Experimental Economics and political Decision making (CREED) and Tinbergen Institute

July 18, 2022

Abstract

Does attention have a causal impact on risky decisions? We address this question in a preregistered experiment in which participants accept or reject a series of mixed gambles while exogenously varying how information can be sampled. Specifically, in each trial participants observe the outcomes of a mixed-gamble with gains and losses presented sequentially. To isolate the causal role of attention on the decision process, we manipulate for how long each outcome is presented before showing the next one. Our results partially confirm our preregistered hypotheses that longer exposure to an outcome increases its weight on the decision. We find specific effects in the domain of losses, but not gains. A longer presentation duration of losses leads to increased sensitivity for losses, such that lotteries with higher losses are rejected more often when losses are presented for longer. To our surprise, when gains are presented for longer, the participants show increased sensitivity to both gain and loss values in their decision. Further analyses show that specifically participants with higher impulsiveness become more sensitive to outcome values when gains are presented for longer. Attentional impulsiveness is the strongest driver of this effect. Jointly, these results support the notion that attention has a causal impact on risky choice. Moreover, our results underline the moderating role of impulsiveness on the relationship between attention and choice.

Keywords: Attention, Impulsiveness, Loss Aversion, Random Utility Models.

JEL Codes: D81, D83, D87, D91.

*We thank our MSc. student Evgeny Vasilets for his help programming the experiment.

1 Introduction

Attention is an important cognitive process that assists decision-making. Across the disciplines of behavioral economics, cognitive psychology and neuroeconomics studies have repeatedly shown that attention can have a causal impact on preferences, including time (Fisher, 2021), social (Ghaffari and Fiedler, 2018; Amasino et al., 2019) and taste preferences (Shimojo et al., 2003; Armel et al., 2008; Chandon et al., 2009; Reutskaja et al., 2011), as well as risk- and loss aversion (Pachur et al., 2018; Engelmann et al., 2021). A common experimental approach of earlier studies aiming to demonstrate the causal effects of attention on choice was to increase or decrease the relative salience of decision attributes, for instance by changing their position, size and color (See Orquin and Mueller Loose, 2013, for a full review). Altering attribute salience has been shown to influence the decision process by changing how participants deploy their attention to attributes (e.g., Amasino et al., 2021). Jointly, this work has supported the development of theories that model the mechanism of how salience and bottom-up control of attention can affect the decision process, such as the attentional drift diffusion model (Krajbich et al., 2010, 2012), and salience-based utility models (Bordalo et al., 2012, 2013).

Parallelly, another salience-driven manipulation of attention has been controlling for how long decision-relevant information is available for participants. If attention has a causal impact on the processing of information, then by reducing or increasing the time spent looking at a stimulus one can affect the relevance of said stimulus in the decision process (Armel et al., 2008). By inducing participants to look at information for a specific amount of time, the observed impact on choice comes from exogenously driven changes in attention, which are causal (e.g., Ghaffari and Fiedler, 2018; Amasino et al., 2019, 2021; Fisher, 2021). A prominent example of this approach by Ghaffari and Fiedler (2018) investigates how attention can affect prosocial behavior. In their paradigm, participants are shown two options, in which one displays prosocial behavior. In a first study, participants freely observe two options and then make a decision while the timing of their attentional focus is recorded using eye-tracking. Their second study uses the visual patterns from the first study to attempt to replicate behavior. Specifically, they display to a new participant the two options using the order and timing of fixations to the different choice options from a previous participant. Their results show that even when the patterns of presentation are exogenously determined, there is a significant role of attention in the decision process.

The current study applies a similar exogenous manipulation of attention to the domain of risky choice, by manipulating for how long choice alternatives are presented, but leaving the frequency with which an alternative was presented largely in the control of the participant. Specifically, we use the data from our previous study, Engelmann et al. (2021), in which our participants were asked to evaluate the same mixed lotteries presented in the current study. In that study, we assessed the attentional focus of participants using eye-tracking and found that between- and within-subject variations in attention could significantly explain the differences in decision weights allocated to different outcomes. Our results suggested that between-subject variations in attention were driven by goal-oriented attention that reflects the choice strategy of the subject and is akin to top-down control of attention, while within-subject variations in attention were driven by stimuli-oriented attention that is captured by the saliency of choice options and is akin to bottom-up attention. For both types of attention, we found that longer fixation times on gains led to enhanced sensitivity towards gain values, while longer fixation times on losses led to enhanced sensitivity towards loss values. These results agree with prior findings and closely follow the model predictions (e.g., Armel et al., 2008; Krajbich et al., 2010).

In the current study, we aim to assess the extent to which attention can causally affect choice by exogenously inducing participants to look at one outcome for an extended period compared to another. Participants then decide to accept or reject a series of risky lotteries. The outcomes of each lottery are equally likely, and each mixed lottery presents both gains and losses that vary in magnitude. We implemented two elements in our experimental design that enhance the ecological validity of our experiment. First, we used the eye-tracking data from our prior study to compute the average fixation times for each attribute of the mixed lotteries (gains / losses) when subjects decided whether to accept or reject these lotteries (see also Ghaffari and Fiedler (2018). Second, while the sequence and timing of outcome presentations was under experimental control, participants were allowed to observe this sequence potentially multiple times until they made a choice (but within a given time limit). This allowed participants to reach their natural decision threshold before committing to a decision.

Our results show that longer presentation durations have a different impact for gains compared to losses. In accordance with our preregistered hypotheses, we that that in the domain of losses, longer presentation durations lead to increased sensitivity specifically to losses, such that lotteries with higher losses are rejected more often when losses are presented for longer. On the other hand, when participants are presented with gains for longer, the sensitivity for both gains *and* losses increase. Hence, participants are more likely to reject lotteries with higher loss values and, at the same time, more likely to accept lotteries with higher gain values. This result is moderated by the level of impulsiveness of the decision-maker, which we measured via the well-established BIS-11 scale (Patton et al., 1995). We find that the results of increased presentation durations for gains are mostly driven by impulsive participants. Finally, we find that the increase in sensitivity to both gains and losses qualitatively decreases the degree of loss aversion.

Our study contributes to the literature not only by replicating prior results demonstrating a causal impact of attention on decisions (Armel et al., 2008; Ghaffari and Fiedler, 2018; Pachur et al., 2018), but also by using a careful experimental approach that extends the ecological validity of prior research. Specifically, we model the presentation durations of the stimuli based on the average focus times participants exhibited with the same lotteries in a prior study. Moreover, we allow participants to choose when to terminate the decision process and thereby to reach their natural decision threshold. We measure the total duration of the decision process and control for its effects in our regression models. Finally, we measure and analyze the moderating role of choice-relevant individual differences on the relationship between attention and choice. This approach provides novel results on the mechanism of how attention can influence the decision process. Specifically, we show that the effect of longer exposure to the information can increase outcome value sensitivity, and, that decision-makers with a specific personality profile (i.e., impulsive) can be positively affected by exogenous shifts in attention.

2 Methods and Procedures

2.1 Participants

We recruited 222 participants from Prolific to take part in our experiment. As preregistered[1], participants who failed the attention checks (missed or incorrect response) were excluded from further analyses. We excluded 18 participants, leading to a final sample of 204 participants (34.3% Female, avg. age 27.97), consistent with the amount aimed for in our preregistration (200 participants). The majority of the participants come from Continental Europe (65.7%) and the United Kingdom (27.84%). All procedures were approved by the ethics committee of Economics and Business (EBES), University of Amsterdam.

2.2 Materials

The experiment was programmed using the web-based software oTree. Since our experiment relies heavily on how participants perceive visual stimuli, we programmed most of the experiment using a combination of html, JavaScript and CSS[2]. Participation from smartphones and tablets was blocked to ensure that visual stimuli were presented on a sufficiently large screen (i.e., on desktop and laptop computers). Moreover, we asked participants to turn on their Fullscreen mode to minimize distraction.

[1] See preregistration here `https://osf.io/fgdvw/?view_only=b9ed94f073804e328748b12ac02a6d4f`

[2] Code available here: `https://github.com/janohirmas/RA_experiment`

2.3 Procedure

Participants could access our experiment from the online platform Prolific. First, participants provided their informed consent, followed by instructions that informed them of the experimental goals and the sequence of the experiment. The main task consisted of a series of decisions involving risk. On each trial, participants chose to accept or reject mixed gambles with two equally likely outcomes, a positive (gain) and a negative (loss) one. To frame the outcomes as gains and losses, we carefully explained to the participants that they were provided with an initial endowment, which can increase or decrease depending on participants' choices. This initial endowment was furthermore provided to avoid the house money effect (Thaler and Johnson, 1990).

The main goal of our experiment was to evaluate the impact of exogenous shifts in attention on decisions involving risk. Exogenous attention was manipulated by changing presentation durations to gains and losses, such that longer presentation durations were expected to lead to increased decision weights for the information that participants focused on for longer. To this end, each trial consisted of a sequence of events (shown in Figure 1), in which the gain and loss parts of the mixed lottery were presented in alternation, each for a predetermined period of time. The order in which the outcomes were presented was randomized in each trial. The presentation duration to one outcome before switching to the other varied between trials and outcomes over three possible lengths of 400ms, 600ms or 800ms. These values were based on a reanalysis of the data from Engelmann et al. (2021), with 400ms reflecting the (rounded) median fixation time in our previous experiment plus the median saccade time, while 600ms is equivalent to the (rounded) 75th percentile of the same measure. Additionally, to explore the potential non-linearity of the effects, we considered 800ms as it is double the increment from the median to the 75th percentile durations.

Importantly, to study the interactive effects between exogenous attention and outcome valence, we crossed the presentation duration for gains and losses, such that in some trials, losses were presented longer than gains, while in others, gains were presented longer than losses. This led to the five treatment conditions shown in Table 1 (left). The order of gains and losses were randomized, such that, for each presentation duration, on about half the trials gains were shown first, while on the other half, losses were shown first. The participants observed each outcome at least once before making a decision, but were able to continue watching the outcome sequence multiple times until a maximum trial length of 6 seconds was reached. Subjects were informed that if they did not choose any outcome within the 6-second period and that trial was randomly selected for payment, they would receive the worst possible outcome (i.e., the loss amount on that trial). Subjects could communicate their decision by pressing the 'up' key to accept, or

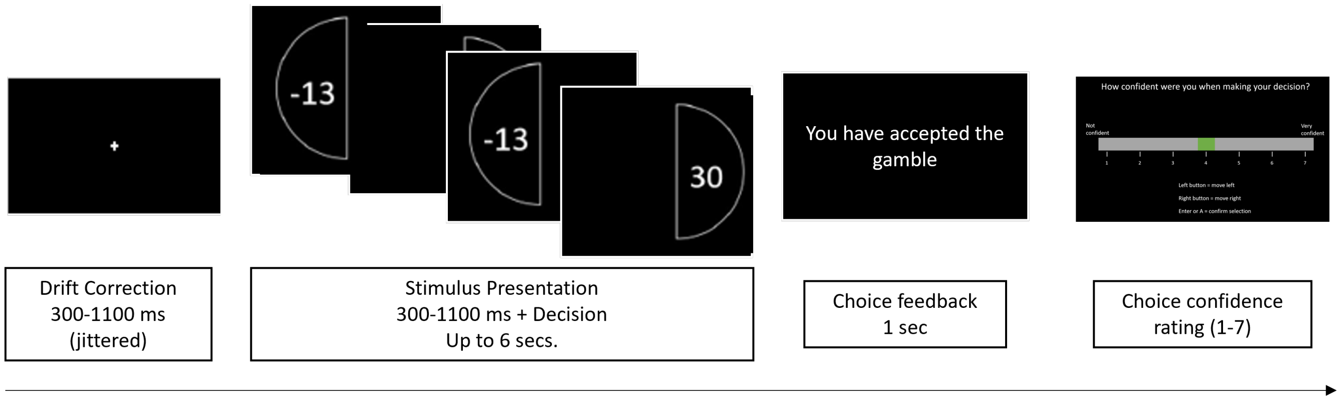


Figure 1: Example of a trial

Outline and sequence of a decision trial. First, participants observe a fixation cross for a jittered duration (300-1100ms). Then the outcomes of the lottery are presented sequentially. The presentation duration of an outcome before changing to the other, as well as whether the first outcome is a gain or a loss varies over trials (See Table 1). Participants decided to accept or reject the gamble within 6 seconds. When they decide or the time runs out, they receive a confirmation of their choice. Finally, we ask them to describe how confident they feel they made the right decision.

Treatment conditions (Gain PD, Loss PD)		Outcome Ranges	
Equal	(400ms,400ms)		
Loss Longer	(400ms,600ms)	Low Loss	(-10 to -19)
Loss Double	(400ms,800ms)	High Loss	(-20 to -29)
Gain Longer	(600ms,400ms)	Low Gain	(20 to 29)
Gain Double	(800ms,400ms)	High Gain	(30 to 39)

Table 1: Treatment conditions and outcomes

The tables above show the treatment conditions and outcome ranges for the lotteries. The left table shows the presentation duration to one outcome before switching to the other. Every participant observed 8 trials with each of these presentation-duration combinations. In each trial, the observed outcomes were drawn from one of the ranges on the right panel. For each condition, subjects observed twice the following combinations: Low gain × Low loss, Low gain × High Loss, High gain × Low Loss, High gain × High Loss. Therefore, participants made a total of 40 decisions each.

the 'down' key to reject the lottery.

The gains and losses were presented in experimental currency units (ECUs), where 40 ECUs were equivalent to one pound. The gains ranged from 20 to 40 ECUs, while losses ranged from -10 to -30 ECUs. The outcome values were pseudo-randomized to ensure that the gains and losses were uncorrelated at a participant level. Within each treatment condition, the potential outcomes were randomly drawn from the values in Table 1 (right). Additionally, participants were presented with four 'catch trials' in which one of the potential outcomes would take its largest value possible and the other the value of zero (lotteries showed either 0 vs. 40 ECUs or 0 vs. -30 ECUs), and therefore served as additional attention checks throughout the experiment[3]. In total, participants completed 40 trials plus three practice trials and four catch trials. The order of all trials after practicing was randomized.

After finishing all the decisions, participants completed a demographics survey and the Barratt Impulsiveness Scale (BIS-11; Patton et al., 1995), which has been shown to moderate decisions under risk (e.g., Capra et al., 2013; Engelmann et al., 2019). This questionnaire is composed of 30 items, which are classified into three major impulsiveness factors including attentional (capacity of focusing), motor (acting without thinking) and non-planning (being forward-looking). The final survey included one attention check that asked participants to state one specific answer ('Please indicate "Often" in this question.'). Participants who failed to respond 'often' in this question were excluded from the analysis.

2.4 Theoretical framework and empirical strategy

We use the framework of random utility to model the stochastic process driving the decision (McFadden, 1973; Webb, 2019). Let us consider a population of subjects J (indexed by j=1,2...,N) that make a series of similar decisions indexed by $t \in \{1, 2, 3...T\}$. In our context, the decision consists of evaluating a mixed gamble with two equally likely outcomes, a gain G and a loss L. Depending on these values, participants can choose to accept or reject the gamble. Under Random Utility models (RUM) the agents choose the option that grants them a higher expected utility (i.e., subjective measure of value). Nonetheless, RUM assumes that agents do not observe/calculate the exact utility granted by the options due to perception errors, lack of information or unobserved variations in taste. In our experiment, participants have limited time to both sample the available information and make a decision. Hence, agents can suffer from perception biases due to time constraints.

Due to these perception biases, the decision process becomes stochastic (McFadden, 1973). Thus, different choices with the same information can differ from one another. Moreover, decisions can be influenced by the context in which they were made. In our experiment, we manipulate two contextual factors, the relative length of exposure to the information relevant for the decision (longer, equal, shorter). Let us consider that the agents' decisions can take place in a set of different contexts C, where $c \in C$ describes all the contextual factors that affect choice. Conditional on the decision context c, the probability

[3]Participants with two or more mistakes in these catch trials were excluded (See Participants section).

that an agent i chooses to accept the gamble with gains G and losses L is defined by the following equations:

$$P(Accept|c, G, L, i) = P(u_i(G, L|c) > 0) = (1 + \exp(SV_{c,i}(G, L)))^{-1} \tag{1}$$

$$SV_{c,i}(G, L) = \omega_{G,c}G + \omega_{L,c}L + \alpha_{c,i} \tag{2}$$

Where $\omega_{s,c}$ is the decision weight allocated to the attribute $s \in \{G, L\}$ in context c and $\alpha_{c,i}$ can be interpreted as the value of gambling relative to not gambling for a given agent i in context c. We represent subjective value (SV) as a linear weighted function of the different potential outcomes. We allow G and L to be weighted differently to account for potential loss aversion (Kahneman and Tversky, 1979; Engelmann et al., 2021) and other potential factors that might influence outcomes depending on their valence.

The stochastic nature of RUMs is driven by the perceptual errors that distort the subjective valuations of the agents' options. The parameters in our logistic model in equation (2) are influenced by the variance of this perceptual error (Fechner error; Fechner, 1966; Andersen et al., 2010). A larger variance of the error (i.e., more randomness in the agents' decisions) will decrease the scale of all the parameters. This implies that contextual changes do not only affect the parameters $\omega_{G,c}$ and $\omega_{L,c}$ due to changes in relative importance, but also due to changes in sensitivity to outcome values. Agents that are more sensitive to outcome values, will be less affected by the perceptual biases and thus, their choices will become more consistent. Our representation of the decision weights will therefore capture the effect of contextual factors on both the relative and absolute sensitivity towards the outcome values.

We use a conditional logit regression to estimate these models (Chamberlain, 1980). These models absorb group-relevant fixed effects (i.e. $\alpha_{c,i}$) to be able to consistently estimate the slopes of the different covariates (i.e. $\omega_{G,c}$ and $\omega_{L,c}$). The observations are grouped at an individual plus condition level. We consider different combinations of contextual factors (c) that can affect the decision process. For this purpose, we estimate the following three models that differ on how exactly contextual factors c were modeled:

- Model 1. Attention is modeled as the exact duration for which {Gains, Losses} were presented as follows: {(800,400),(600,400),(400,400),(400,600),(400,800)}
- Model 2. Attention is modeled as a dummy variable reflecting relatively longer or equal presentation durations: {Loss Longer, Equal, Gain Longer}
- Model 3. Attention is not modeled. This model serves as a baseline: {None}

Additionally, we expect that the effect of these contextual factors will change across individuals. Namely, we expect that distracted or impulsive participants will be more likely to be affected by these factors. We use the BIS-11 scale to rank participants by their degree of impulsiveness. Using the aggregate measure of impulsiveness (average of three sub-scales), we classify individuals as impulsive and non-impulsive via a median split. Then, we proceed to estimate models M1-M3 and include the impulsiveness classification as a moderator. The models that include the impulsiveness classification will be indexed by an i in the end (e.g. M2i : $\{$ Loss Longer, Equal, Gain Longer$\}\times\{$Impulsive, Non-impulsive$\}$).

3 Results

We first perform manipulation checks to evaluate the effectiveness of our experimental design. Then, we present the results of the different treatment conditions on the decision weights for the outcomes (losses and gains). The presented results come from the conditional logit estimations of the models presented in section 2, clustering at the individual and condition levels specific to the model specification.

Before we proceed to summarize our results, we need to clarify the use of two terms that will be discussed in length throughout the rest of the paper. First, we refer to the presentation duration of an outcome before the other outcome appears on the screen as treatment-based presentation duration (treatment PD). Secondly, when we refer to the total time that an outcome was displayed on the screen, which depends in part on the participants' choice of when to submit a decision, we will refer to it as total presentation duration (total PD).

3.1 Effectiveness of the treatments / Manipulation Checks

Our experimental manipulation was designed to exogenously manipulate for how long participants focus on specific outcomes (gains vs. losses). Under the assumption that participants are looking at the screen, which is reasonable because participants' payouts depend on their decisions, we manipulate two factors that can affect which outcome was observed for longer. First, our treatment conditions exogenously change the treatment-based presentation duration (treatment PD from now on) of the given outcomes. Longer treatment PDs aimed to increase the time spent looking at said outcome. However, since participants were given a six-second period to decide and therefore had the opportunity to inspect each outcome multiple times until they communicated their decision via button press, this is not necessarily the case. A second factor that can affect the length of time an item is looked at is the presentation order. By presenting one outcome first, it is possible that the first outcome is also looked at for longer depending on when the participant terminates the trial. Due to the interaction of these two effects, in some of our treatment conditions (i.e., treatment PDs of 600ms) it is possible that the non-treated outcome is presented for longer. Nonetheless, when the treated outcome is presented second with 600ms, we still find that most of the cases (65.2% for longer losses and 64.7% for longer gains) the treated outcome has a longer total PD[4].

A second and related concern about our experimental design is that participants can decide to shift their attention towards one outcome over the other (i.e., they exert top-down control of attention). One way to exert such top-down attention is to simply repeat the trial sequence and continue observing the different outcomes, thereby enforcing desired total presentation durations for one outcome over the other. Participants might choose to adopt this strategy particularly under conditions of high stakes. For instance, if participants exert top-down attentional control on higher gains, we should observe increased total PDs as gains increase. Our experimental design enables us to estimate whether this is indeed the case. Appendix Figure 7 shows the estimated proportion of total PD for losses relative to gains (ratio of total PD on losses over total time) for different combinations of outcome values. The effects shown in the figures already control for the treatment conditions and presentation order. The largest significant difference in proportion of total PD for losses that is due to a change in the outcome values (and thereby related to top-down attention) is less than 2%. These effects are an order of magnitude smaller when contrasted with the proportion of total PD for losses in the whole dataset that ranges between 20% and 80%. Therefore, in case there is any top-down control of attention, the effects would be negligible.

3.2 Effects of treatment presentation duration

Figure 2 presents the effects of the changes in treatment presentation duration (PD) on the decision weights ($\omega_{s,c}$ for attribute s under condition c). The presented results come from the estimations for models 1 and 2 shown in Table 2. All treatment effects represent the difference in decision weights between a specific treatment condition and the baseline condition with equal treatment PDs for both outcomes (400ms). Model 1 shows the effects of each treatment condition separated by their exact duration. Model 2 results reflect the pooled effects of the treatment conditions such that we evaluate the effect of longer treatment PDs without considering the exact length of the increase, but separately for gains and losses. These effects combine both conditions where the given outcome is presented for longer (600ms vs 400ms and 800ms vs. 400ms). First, we inspect the baseline decision weights in the equal condition, that is in the absence of any attentional manipulations. Both models yield similar results regarding the decision weights of the gain and loss values in the equal condition. Based on the results of model 1, the decision weights in the equal condition for gains (b(gains) = .238, p-val<0.001, model 1) are lower relative to losses (b(losses) = .294, p-val<0.001, model 1). These differences are significant in both models as well (Chi(1)=10.59, p-value=.001, model 1), reflecting the presence of loss aversion in the equal treatment condition.

[4]See appendix section B for a more detailed explanation

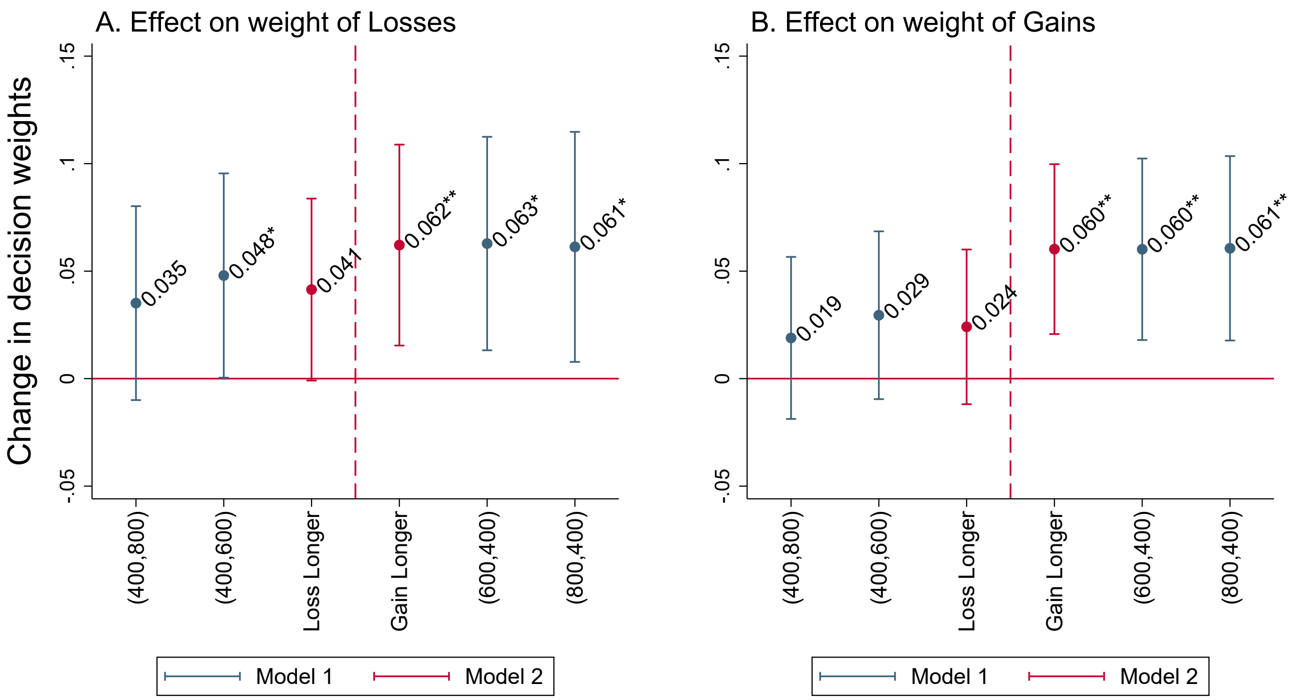


Figure 2: Treatment conditions and outcomes

The figures above display the effect of the treatment conditions on the decision weights for losses and gains respectively. These effects are relative to the decision weights in the Equal condition (400ms, 400ms), where both outcomes have equal PDs. Treatment conditions are described as (PD Gains, PD Losses) in ms. Error bars reflect the 95 % confidence interval. Conditions Loss Longer and Gain Longer show the pooled results of both conditions where the said outcome is presented for longer. Parameters estimated from models 1 and 2 are shown in table 2. Estimated values and significance are shown alongside markers. $*p < 0.05, **p < 0.01, ***p < 0.001$

First, we analyze the effect of longer treatment PDs for losses. Model 1 shows that when losses are presented for longer, there is no significant effect on the decision weights (delta b(loss)= 0.041, p-value=0.055; delta b(gains)= 0.024, p-value=0.190). Model 2, which differentiates between the two longer-exposure conditions (600ms, 800ms), shows that the increase is similar in value for both treatment conditions, but is only significant for the 600ms condition (delta b(loss)=0.048, p-value=0.048). We see no significant increase for the decision weights for gains when the losses are presented for longer.

Result 1. *Effects of the treatment presentation duration for losses on the decision weights are relatively weak and limited to one specific condition. A treatment PD of 600ms for losses increases the decision weight for losses.*

When we analyze the effects of longer presentations of gains, Model 1 shows a significant increase in the decision weights for both gains (delta b(gains)=0.062, p-value=.003) and losses (delta b(losses)=0.060, p-value=0.009). The effects are relatively similar for when the gains are presented for 600ms and 800ms (Model 2). This very stable and significant effect shows that participants increase their sensitivity to both lottery outcomes, gains and losses, when presented with the gains for relatively longer durations.

Result 2. *The decision weights for both gains and losses increase when gains are presented for relatively longer durations.*

Since the decision weight for losses is larger compared to the decision weight for gains in the equal condition, an equivalent increase of both weights should decrease the relative importance allocated to the losses. This result suggests that losses become relatively less relevant compared to gains when gains are presented for longer. Similarly, when the losses are presented longer (600ms), there is a significant increase in the weights for losses. We therefore analyze the impact of the treatment conditions on the relative importance of the outcomes by focusing on loss aversion defined as the ratio between the weights for losses and gains. Figure 3 shows the estimations for loss aversion in each treatment condition (using quadratic approximations for the standard errors). The results in Model 1 show an increase in loss aversion when losses are presented for longer, mirrored by a decrease when gains are presented for longer. It must be noted that these differences are non-significant ($\ln(\lambda_{LossLonger}/\lambda_{GainLonger}) = .0693$, p-value = 0.149), but their signs correspond to the evidence reported previously (Pachur et al., 2018; Engelmann et al., 2021). There are no obvious effects of the length of the treatment PD on loss aversion (Model 2).

3.3 Moderating effects of impulsiveness

Since our experimental design placed time constrains on participants' decisions, we expected that participants' impulsiveness might affect how sensitive they are to the treatment conditions. We measured

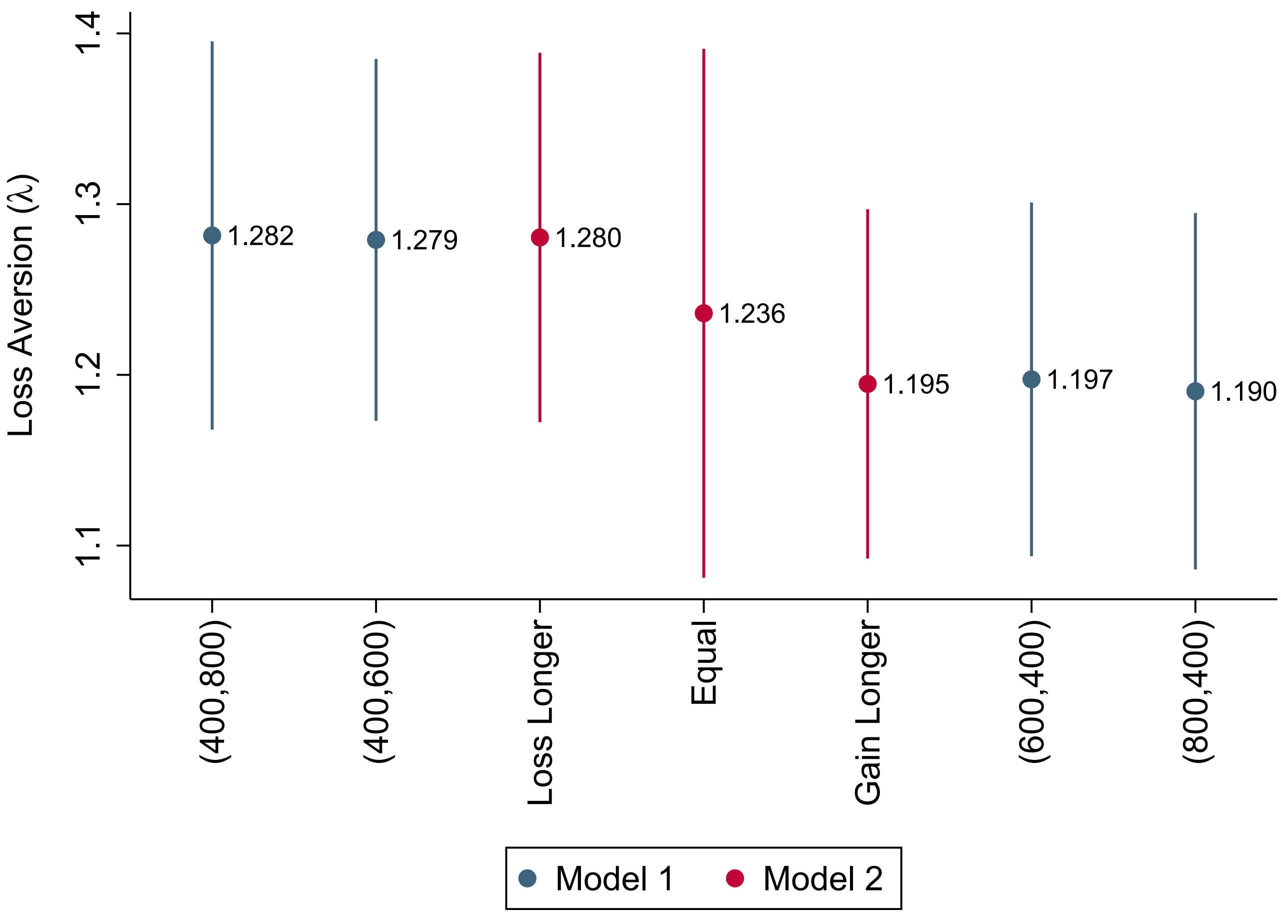


Figure 3: Loss aversions depending on treatment PD

The figure above shows the degrees of loss aversion (λ) estimated for the different treatment conditions. λ is calculated by estimating the ratio of the decision weights for losses relative to the gains. The differences between the treatment conditions are not significant ($\ln(\lambda_{LossLonger}/\lambda_{GainLonger}) = .0693$, p-value = 0.149). Parameters estimated from models 1 (circle) and 2 (diamond) from table 2. Errors bars reflect the 95 % CI.

impulsiveness using the general scale of the well-established BIS-11 (Patton et al., 1995). We consider impulsive participants as the ones having an overall score above the sample median. Table 3 shows the estimations for models 1i and 2i, which estimate models 1 and 2 conditional on whether the participant is classified as impulsive or not. When comparing the decision weights under the equal condition (both attributes with the same treatment PDs), impulsive participants show significantly lower decision weights for both gains and losses relative to non-impulsive participants (Δb(gain) = -0.112, p-val=0.020; Δb(loss) =-0.133, p-val=0.018; Model 1i). As expected, these results confirm that impulsive participants are less sensitive to outcome values (both for gains and losses).

Next, we compare the effects of different treatment PDs on the decision weights for impulsive compared to non-impulsive individuals. Figure 4 shows the effect of all treatment conditions conditional on whether participants are classified as impulsive or not. When participants are classified as non-impulsive, there is no significant treatment effect. For impulsive participants, the decision weights of both gains and losses increase with longer treatment PDs for gains (b(Gain) = .0943, p-val<0.001; b(Loss) = 0.0935, p-val=0.001, Model 1i). Longer treatment PDs for losses also significantly increase both weights, but to a lesser extent (b(Loss) = .057, p-val=0.030; b(Gain) = 0.045, p-val=0.042, Model 1i). When considering the exact length of the treatment PDs (Model 2i), the effects of longer losses become non-significant. The effects of longer treatment PDs for gains are similar for both durations of 600ms (b(Gain) = .091, p-val=0.004; b(Loss) = 0.084, p-val=0.016) and 800ms (b(Gain) = .0742, p-val=0.010; b(Loss) = 0.0694, p-val=0.031). Again, the scale and significance of these results suggest that the effects of longer presentations are stronger for gains than for losses.

Result 3. *The effects of treatment presentation durations on the decision weights are moderated by impulsiveness.*

Additionally, we analyze the treatment effects on the loss aversion for both groups. Figure 5 shows the degrees of loss aversion conditional on the treatment conditions and impulsiveness. In model 1i, none of the groups (impulsive and non-impulsive) show significant differences in their degree of loss aversion between treatment conditions. When separated by treatment PD length (Model 2i), we see that both groups present larger differences for the treatment PDs of 600ms compared to 800ms. While the qualitative trends follow the predicted direction (greater loss aversion with larger treatment PDs for losses, smaller loss aversion with larger treatment PDs for gain), none of these differences are significant.

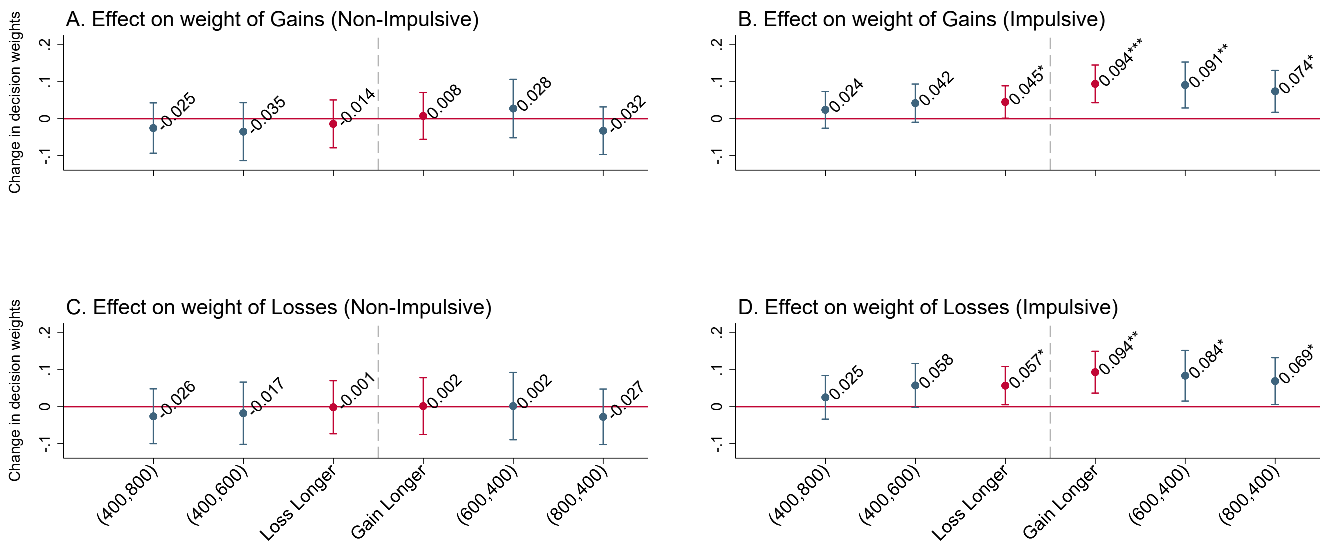


Figure 4: Decision weights depending on treatment PD and impulsiveness

The figures above display the effect of the treatment conditions on the decision weights conditional on the participant being classified as impulsive or non-impulsive. The first row shows the effects on the decision weights of gains, while the second row shows the effects on the decision weights of losses. The left column describes the treatment effects of non-impulsive participants and the right column for impulsive ones. These effects represent the difference in the decision weights relative to the Equal condition (400ms, 400ms) for that specific group (Impulsive or non-Impulsive). Treatment conditions are described as (treatment PD Gains, treatment PD Losses) in ms. The confidence intervals are at a 95% of confidence. Conditions Loss Longer and Gain Longer show the pooled results of both conditions where the said outcome is presented for longer. Parameters estimated from models 1i and 2i from table 3. Estimated values and significance are shown alongside markers. $*p < 0.05, **p < 0.01, ***p < 0.001$

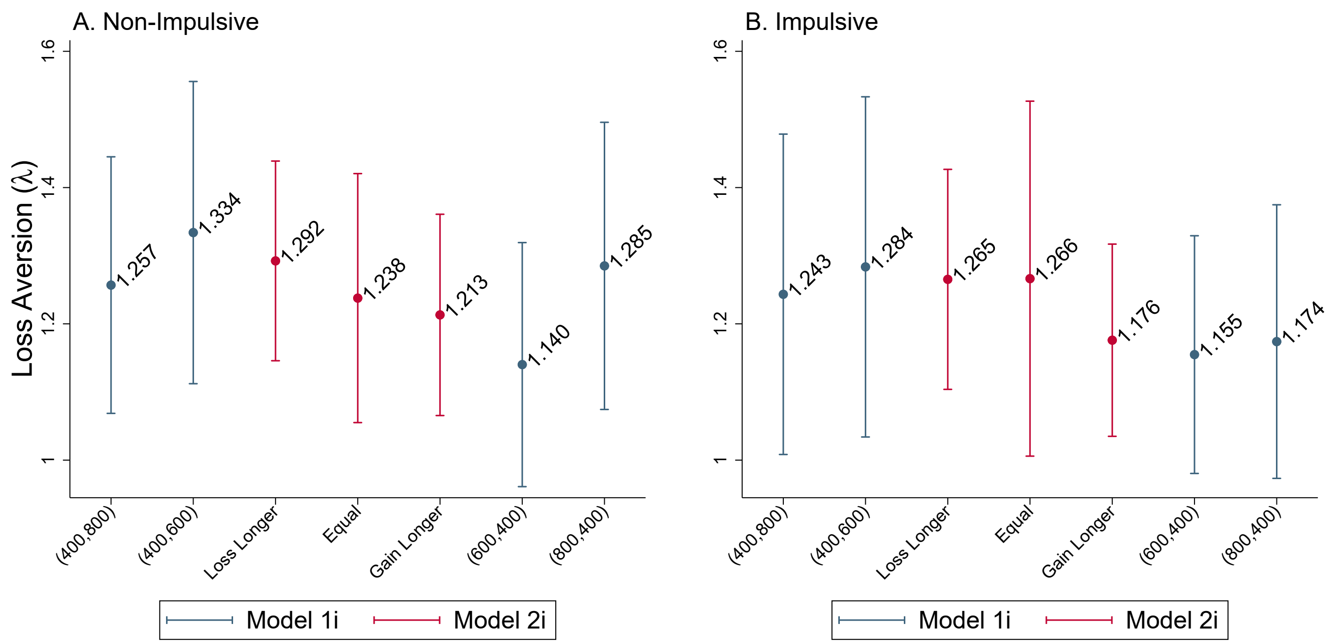


Figure 5: Loss aversions depending on treatment PD and impulsiveness

The figure above shows the degrees of loss aversion (λ) separately estimated for the different treatment conditions and for impulsive and non-impulsive participants. The left panel shows the Loss aversion parameters for non-impulsive participants, while the right panel shows the Loss aversion for the impulsive ones. The loss aversion is calculated by estimating the ratio of the decision weights for losses relative to the gains. The error bard reflect the 95% confidence interval. Conditions Loss Longer and Gain Longer show the pooled results of both conditions where the said outcome is presented for longer. Parameters estimated from models 1i and 2i from table 3.

4 Discussion

The purpose of our experiment was to identify the causal impact of attention on the decision process in the domain of risky choice. Based on prior literature, we formalized our expectation in preregistered hypotheses stating that by exogenously increasing the focus of attention on a specific decision attribute (gain and loss outcomes), the relevance of said attribute would be increased in the decision. Our results partially support this notion. Specifically, we find that lotteries with higher losses are rejected more often when losses are presented for longer. This effect is reflected by increased decision weights for losses when losses are presented for longer (see Figure 2), but only in the case of 600ms presentation durations. In the case of relatively longer presentation durations of gains (both 600ms and 800ms), we found that the decision weights for gains increase significantly, as predicted. However, we also find that decision weights for losses increase significantly (see Figure 2). This result is somewhat surprising, as it suggests that enhancing participants' focus on the positive outcomes will lead to more accurate decisions (due to increased sensitivity to both outcome values). In other words, when gains are presented for longer, participants are more likely to accept highly valued lotteries and reject lowly valued ones. In additional analyses, we also show that this result is moderated by the level of impulsiveness of the decision-maker, which we measured via the BIS-11 inventory (Patton et al., 1995). We find that the results of increased presentation durations for gains are mostly driven by impulsive participants. Finally, when considering the effect of presentation durations on loss aversion, which we computed as the ratio of estimated decision weights for gains relative to losses, we find a non-significant trend that suggests that longer exposure to gains decreases loss aversion, while longer exposure to losses increases loss aversion.

Many studies in the fields of neuroscience and cognitive psychology assess the link between the last fixated outcome and the decision. The last fixation has been shown to be a good predictor of choice (Krajbich et al., 2010; Krajbich and Smith, 2015; Ghaffari and Fiedler, 2018). We conducted an equivalent analysis on our dataset and find that, consistent with the predictions in the literature, acceptance rates increased by 4.4% ($p<0.001$) when the last presented outcome was a gain[5]. Given the presence of this effect in our data, it is important to test whether presentation order affects how gains and losses are weighted in the decision. Tables 7 and 8 show that alternative specifications with either first fixated outcome, or last fixated outcome do not significantly influence sensitivity to gains and losses. Moreover, since our paradigm only has two attributes to attend to, there is a strong correlation between which attribute was presented first and which one is viewed last. This suggests that the well-established connection between choice and the last fixation is not the driver of the results reported here.

[5]This result is based on a comparison between trials in which the gain was presented last compared to trials in which the loss was presented last.

An additional concern regarding the presentation order is that it might reduce the effectiveness of the attention manipulation. In section 3.1, we argue that the treatment conditions induce longer presentation times for the intended outcomes on the majority of trials. We also showed that the outcome that was presented first would be viewed for longer durations on average. When the targeted outcome had a presentation duration of 600ms and was not presented first, about one third of the trials showed longer durations for the non-targeted outcome. In order to account for the potential effects of this subset of trials on our results, we computed the actual total presentation duration that depends on when exactly a participant terminates a trial and reanalyzed our data. In the appendix section F we show the effects of effectively longer exposure to an outcome over the decision weights. We used a discrete variable that determines whether the gains or losses were available on the screen for more than 0, 100 and 200ms with respect to the other attribute. Our results show that only the effects of longer exposure to gains are still robust. Namely, longer exposure to gains increases the decision weights of both gains and losses (suggesting more consistency in the participants' choices). This increase in both weights also decreases the degree of loss aversion, although these differences are not significant.

Given the nature of our experiment, in which participants had to make repeated and fast-paced choices, we expected that the subjects' impulsiveness would have an impact on the participants propensity to be affected by our treatment conditions. Our results show that participants classified as impulsive are less sensitive to outcome values overall. Moreover, in the trials where an outcome was targeted with a longer treatment PD, we see that impulsive participants become more sensitive to all outcomes values. This effect was present when both losses and gains were presented for longer. For our initial estimations, we used the aggregate measure of impulsiveness from the BIS-11. This scale presents three different factors: Motor, Attentional and Non-planning impulsiveness. In order to probe whether one of these factors is the major driver of the effects, we repeated the analysis in section 3.4 using each subscale at a time instead of the aggregate scale. The results show that with any scale, longer treatment PDs for gains increase the consistency of the choice for impulsive participants. Moreover, the attentional factor of impulsiveness shows larger and more significant effects. Regarding the effects on loss aversion, non-impulsive participants show an increasing trend in loss aversion when the presentation duration of losses is longer (similar to the trend in Figure 5). These differences are significant when using the attention or non-planning impulsiveness subscale (p-value(attention)=0.0252; p-value(non-planning) = 0.0151), but are not significant for the motor subscale (p-value=0.3489). These results suggest that impulsiveness moderates the effects of attention on the sensitivity to outcome values; and affects the relative weighting of information in a limited manner (i.e., not for all subscales).

Finally, our results also show that the impact of increasing the presentation duration on the decision weights is not linear. We found stronger and larger effects when increasing the PD from 400ms to 600ms compared to the increases to 800ms. It is important to note that such non-linearities of causal attention will lead to distorted results in any model that uses dwelling times as a linear moderator. We originally intended to test for such linear effects of attention using the model by Engelmann et al. (2021), which linearly approximates top-down and bottom-up effects of attention by separating the eye-tracking data into average attention and trial-wise deviations of attention, respectively. We solve this here by treating presentation duration as categorical variables. The current results on causal attention, together with our previous results using eye-tracking (Engelmann et al., 2021), suggest that attention effects on decision weights are linear in experimental settings that allow participants to direct their attention freely, but that attention effects may become non-linear in experimental settings that control viewing times. This question is important for accurately modelling the effects of attention and requires systematic study in future research.

5 Conclusions

We conducted an experiment that assessed the causal impact of attention on the decision processes in the context of risky mixed lotteries. Participants decided whether to accept or reject a lottery involving positive and negative outcomes that could occur with equal probabilities. The lottery attributes were presented in alternation and potentially multiple times for a short span of time. To causally manipulate attention, we varied the duration for which participants could observe a lottery attribute before the other attribute was displayed. Our results show that exogenously increasing the presentation duration to a loss outcome only subtly changes how losses are weighted in the decision. When it comes to gains, however, we find that increased exposure time to gains increases the sensitivity to all lottery attributes, that is to both gains and losses.

It is noteworthy that the attentional effect of gains to increase outcome sensitivity was mostly driven by impulsive participants. Impulsive participants showed decreased decision weights for all outcomes at baseline, but significantly increased decision weights for all outcomes when any of the outcomes were presented for longer. The effects of presenting gains for longer were robust to the different measures of impulsivity, but the attentional factor of impulsiveness showed the strongest effects. This result suggests that by inducing impulsive participants to pay more attention to the information necessary for their decisions can in fact improve their decisions. Our results suggest that a good starting point for future research aiming to develop interventions for the many risk-related decision-making problems faced by impulsive individuals is to investigate the presence of attentional distortions due to impulsiveness. (e.g., Lauriola et al., 2014; Wittmann and Paulus, 2008).

Finally, it is important to note that some of our results could be called exploratory, as we did not foresee the overall increase in decision weights (for both outcomes simultaneously) due to our treatments. Nonetheless, tests of our preregistered hypotheses in combination with our preregistered experimental design, yielded repeated and robust results of exogenous manipulations of attention on risky choice. Further exploration of the moderators of the effects of exogenous attention on choice is needed to further strengthen the current results. One strong candidate suggested by the current research is impulsiveness.

References

Amasino, D., Pace, D., and van der Weele, J. J. (2021). Fair Shares and Selective Attention.

Amasino, D. R., Sullivan, N. J., Kranton, R. E., and Huettel, S. A. (2019). Amount and time exert independent influences on intertemporal choice. *Nature Human Behaviour*, 3(4):383–392.

Andersen, S., Harrison, G. W., Lau, M. I., and Rutström, E. E. (2010). Behavioral econometrics for psychologists. *Journal of Economic Psychology*, 31(4):553–576.

Armel, K. C., Beaumel, A., and Rangel, A. (2008). Biasing simple choices by manipulating relative visual attention. *Judgment and Decision making*, 3(5):396–403.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly Journal of Economics*, 127(3):1243–1285.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2013). Salience and consumer choice. *Journal of Political Economy*, 121(5):803–843.

Capra, C. M., Jiang, B., Engelmann, J. B., and Berns, G. S. (2013). Can personality type explain heterogeneity in probability distortions? *Journal of neuroscience, psychology, and economics*, 6(3):151.

Chamberlain, G. (1980). Analysis of covariance with qualitative data, the review of economic studies, vo1. 47, no. 1ij f. *Econometrics Issue*, 1.

Chandon, P., Hutchinson, J. W., Bradlow, E. T., and Young, S. H. (2009). Does in-store marketing work? Effects of the number and position of shelf facings on brand attention and evaluation at the point of purchase. *Journal of marketing*, 73(6):1–17.

Engelmann, J. B., Hirmas, A., and Van der Weele, J. J. (2021). Top Down or Bottom Up? Disentangling the Channels of Attention in Risky Choice by Jan Engelmann, Alejandro Hirmas , Joel J. van der Weele :: SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3834381.

Engelmann, J. B., Schmid, B., De Dreu, C. K. W., Chumbley, J., and Fehr, E. (2019). On the psychology and economics of antisocial personality. *Proceedings of the National Academy of Sciences*, 116(26):12781–12786.

Fechner, G. (1966). *Elements of Psychophysics*, volume I. New York.

Fisher, G. (2021). Intertemporal Choices Are Causally Influenced by Fluctuations in Visual Attention. *Management Science*.

Ghaffari, M. and Fiedler, S. (2018). The Power of Attention: Using Eye Gaze to Predict Other-Regarding and Moral Choices. *Psychological Science*, 29(11):1878–1889.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrics, 47, 263-291. *Econometrica*.

Krajbich, I., Armel, C., and Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, 13(10):1292.

Krajbich, I., Lu, D., Camerer, C., and Rangel, A. (2012). The attentional drift-diffusion model extends to simple purchasing decisions. *Frontiers in Psychology*, 3:193.

Krajbich, I. and Smith, S. M. (2015). Modeling eye movements and response times in consumer choice. *Journal of agricultural & food industrial organization*, 13(1):55–72.

Lauriola, M., Panno, A., Levin, I. P., and Lejuez, C. W. (2014). Individual Differences in Risky Decision Making: A Meta-analysis of Sensation Seeking and Impulsivity with the Balloon Analogue Risk Task. *Journal of Behavioral Decision Making*, 27(1):20–36.

McFadden, D. (1973). *Conditional Logit Analysis of Qualitative Choice Behavior*. Institute of Urban and Regional Development, University of California ....

Orquin, J. L. and Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, 144(1):190–206.

Pachur, T., Schulte-Mecklenbeck, M., Murphy, R. O., and Hertwig, R. (2018). Prospect theory reflects selective allocation of attention. *Journal of Experimental Psychology: General*, 147(2):147–169.

Patton, J. H., Stanford, M. S., and Barratt, E. S. (1995). Factor structure of the Barratt impulsiveness scale. *Journal of clinical psychology*, 51(6):768–774.

Reutskaja, E., Nagel, R., Camerer, C. F., and Rangel, A. (2011). Search Dynamics in Consumer Choice under Time Pressure: An Eye-Tracking Study. *American Economic Review*, 101(2):900–926.

Shimojo, S., Simion, C., Shimojo, E., and Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience*, 6(12):1317–1322.

Thaler, R. H. and Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management science*, 36(6):643–660.

Webb, R. (2019). The (neural) dynamics of stochastic choice. *Management Science*, 65(1):230–255.

Wittmann, M. and Paulus, M. P. (2008). Decision making, impulsivity and time perception. *Trends in Cognitive Sciences*, 12(1):7–12.

A Instructions

Welcome! You are participating in a study funded by the University of Amsterdam. In this study you will have to make a series of decisions about risk. Depending on your answers you can get a bonus payment

- **Expected duration:** The overall study should last about 20 minutes.
- **Requirements:** You need to be 18 or older and be able to speak and read English.
- **Risks and Benefits:** There are no expected risks associated with the participation in this study. Your decisions will affect how much you earn in the end. Aside from the participation fee, you can obtain a bonus payment depending on your decisions. This bonus can go up to 2 pounds.
- **Confidentiality:** Your decisions and identity will not be revealed to anyone. Moreover, you will be assigned to an identification number and all your decisions will be registered as such. No one will be able to link your decisions to you.
- **Voluntary Participation:** Your participation in this study is voluntary. You can decide to stop your participation at any time throughout the experiment, but you cannot earn the additional bonus if you do not finish the experiment. You do not need any reason to withdraw from the study.
- **Questions:** If you have any questions about the experiment, please write to the researcher Alejandro Hirmas at a.hirmas@uva.nl

☒ I agree to the conditions and want to participate in the study.

Continue

Thank you for participating in our experiment on how people react to different decision situations. The overall duration of the study should be about 20-25 minutes. This experiment uses Experimental Currency Units (ECU). Each ECU is equivalent to 2.5p (0.025 Pounds). You have received an initial Bonus Payment of 40 ECUs. This amount can *increase (or decrease)* depending on your decisions of this experiment. This bonus payment is additional to your participation fee.

In this study, you will be shown 44 different lotteries and will be asked to make decisions about whether you wish to accept each lottery or not. The lotteries, that you will see, offer a *positive* (*Gain*) and a *negative* (*Loss*) outcome with equal probability (fifty-fifty, same as a coin toss). *Gain* and *Loss* amounts will change for each new decision situation, so consider each lottery carefully before you make a decision. At the end of the experiment, one of the 44 lotteries will be selected at random.

If you **reject** the selected lottery, nothing will happen. If you **accept** it, one of the outcomes will be played out via a virtual coin flip. If the good state occurs (e.g., heads), the *Gains* will be *added* to your initial bonus payment. If the bad state occurs (e.g., tails), the *Losses* may be *subtracted* from your bonus payment. Therefore, your decisions in the experiment together with the outcome of the coin flip will determine your bonus payment.

For example:

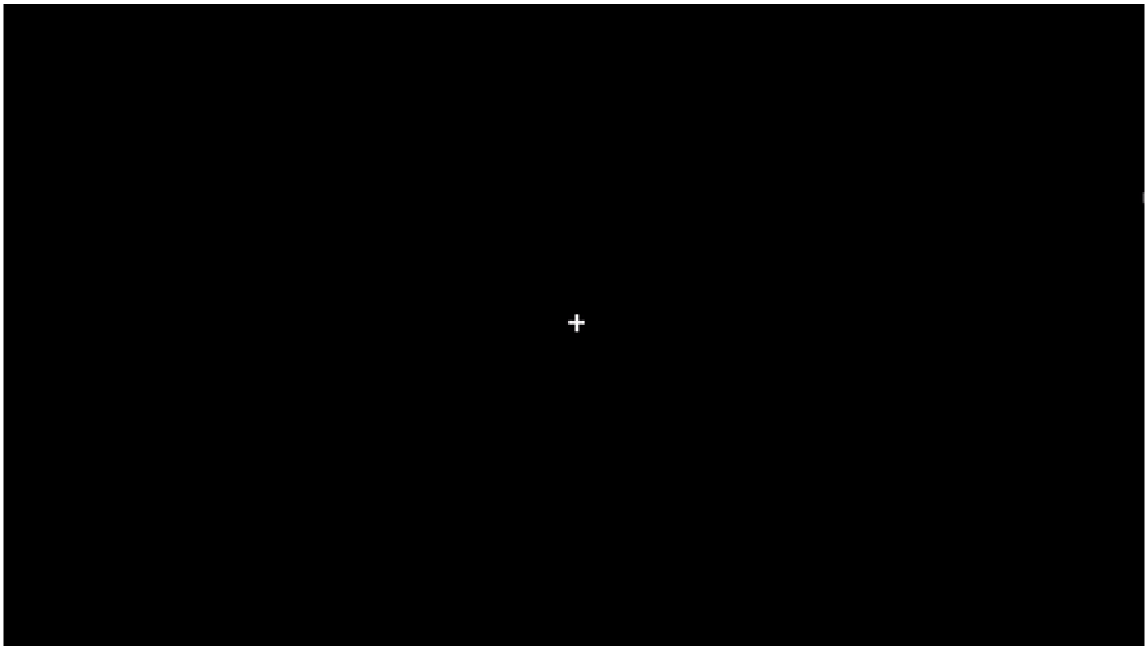
Let's say in the selected lottery (one of the 44), the possible outcomes are 32 (heads) and -20 (tails).

If you decide to **reject**, then, your bonus payment will remain unchanged.

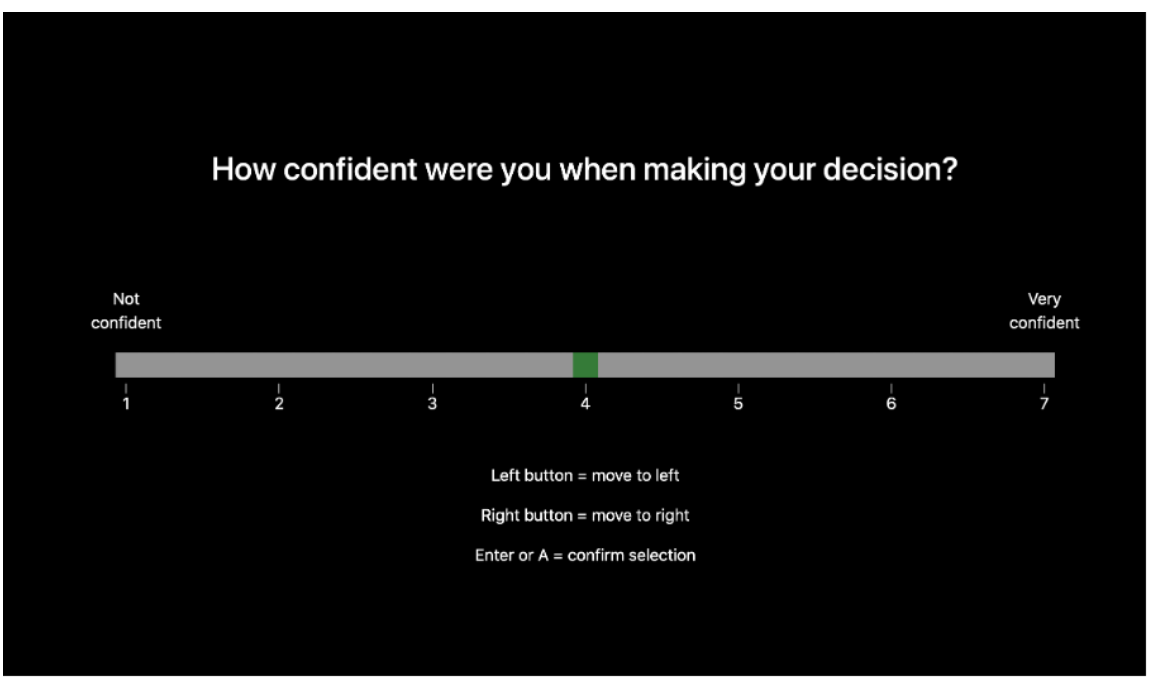
If you decide to **accept**, then a random outcome is determined.

- If the random outcome is heads, you *add* 32 to your bonus payment.
- If the random outcome is tails, you *subtract* 20 to your bonus payment.

In each decision situation, the presentation of the lottery goes as follows. First, you will see a cross in the middle. Then, the outcomes (*Gain* and *Loss*) will appear on the screen in alternation (similar to the black screen below). If you wish to **accept** the lottery, then press the upwards key (↑). In case you want to **reject**, press the downward key (↓). Once you have made your decision, it will be notified on the screen. You have a maximum of 6 seconds (starting after the cross appeared) to make your decision, so you need to press the key you decided before these 6 seconds. In case you don't answer within 6 seconds, we will ask you to answer faster, and if that decision situation gets selected in the end, you will get the *negative* outcome for certain.



After each decision situation, you will be informed about your decision. Next, we will ask you about your confidence in your decision. You will be presented with a scale that goes from 1 to 7 (See picture below). The scale will have a marker (green bar). You can move the marker to the left by pressing the left key (←) and you can move it to the right by pressing right key (→). Once you have placed the marker in the confidence level you want to select, then you need to press the Enter key or the letter A to accept. After you have selected your confidence level, the next trial will begin.



Questions

Now we will ask you a couple of questions regarding the instructions to see that everything is clear. After you answer these questions correctly, we will show you 3 practice trials for you to get used to making decisions in the current experiment. The lottery that will be selected will not come from these trials, these are simply there for you to try out how to make decisions in this experiment.

After you completed the practice trials, we will notify you and the actual experiment will start, with decisions that can count towards your final payout. After you finish all the decisions, a short survey will be presented. Once you finish the survey, one of the lotteries will be selected and your bonus payment will be calculated.

How many decisions are you going to make (without counting the practice trials)?

How many outcomes will be selected for payment?

To accept a lottery, you need to press:

Can the lottery, selected in the end, come from the first 3 trials?

B Manipulation Check: Manipulating exogenous attention in the context of free choice worked

The total presentation duration (PD) of an outcome, depended on two factors. First, the treatment conditions increased the treatment PD for a given outcome. Longer treatment PDs implied longer total PDs as well. The second factor that affects total PDs is the presentation order. If an outcome was presented first, the total PD was longer in expectation. Potentially, if the treated outcome (i.e. the outcome presented for the longer duration specified via the treatment PD) was presented second, these two effects could interact. Let us imagine that the target outcome (longer treatment PD of 600ms) is presented second. If the participant makes their decision right after seeing the first non-target outcome for the second time, then the total PD of the target outcome will be less than the non-target total PD. Note that this is not possible in the 800ms conditions, since the treatment PD of the non-target outcome was always 400ms. Therefore, even if the participant observes an extra repetition of the non-target outcome, the total PD of the non-target will never be larger than the target's total PD. In an initial set of analyses, we therefore tested whether our treatments indeed led to the desired total PDs.

Figure 6 shows a violin plot that reflects the percentage of time that Losses appear on the screen, conditional on the treatment conditions (Loss Longer / Gain Longer) and presentation order (Loss first / Gain first). Panel A displays the distribution for when the losses are presented first, while panel B shows the distribution for when gains are shown first. As expected, we find that the treatments are most effective when the outcome has longer treatment PDs and is presented first. Nonetheless, in the cases with longer treatment PDs for losses and when gains were presented first, our treatment was effective (i.e., loss total PDs were relatively longer) in 65.2% of the cases. In the cases with longer treatment PDs for gains and when losses were presented first, we see that 64.7% of the total PDs were longer for gains. In the equal condition, the outcome that is presented first was seen for an equal or longer amount of time. Hence, we conclude that on average the treatments are effective in inducing longer focus times. It must be noted, however, that we model the intention to treat.

C Manipulation Check: Attribute values do not affect relative allocation of time between attributes

Figure 7 describes the proportion of time focusing on the Losses (Vertical axis) depending on the attribute's values (Horizontal axis). Panel A shows the expected proportion of total PD for losses as a function of Loss amount. The three plotted lines represent the values conditional on the gains taking the minimum (20),

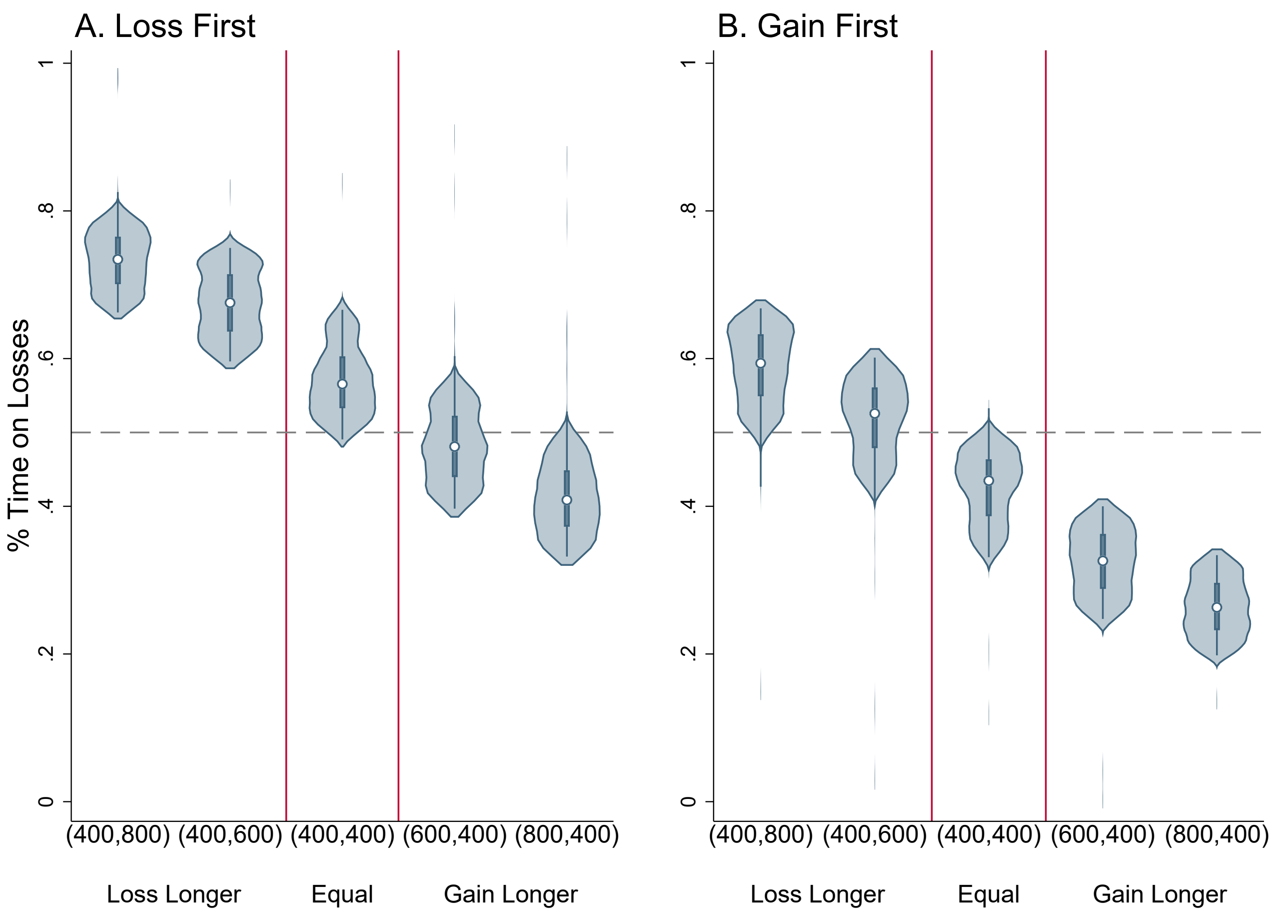


Figure 6: Proportion of time on Losses by treatment conditions

average (30) or maximum value (40) throughout the experiment. Similarly, Panel B shows the expected proportion of total PD for losses as a function of Gain amount. The three plotted lines represent the conditional values for the minimum (10), average (20) and maximum loss values (30).

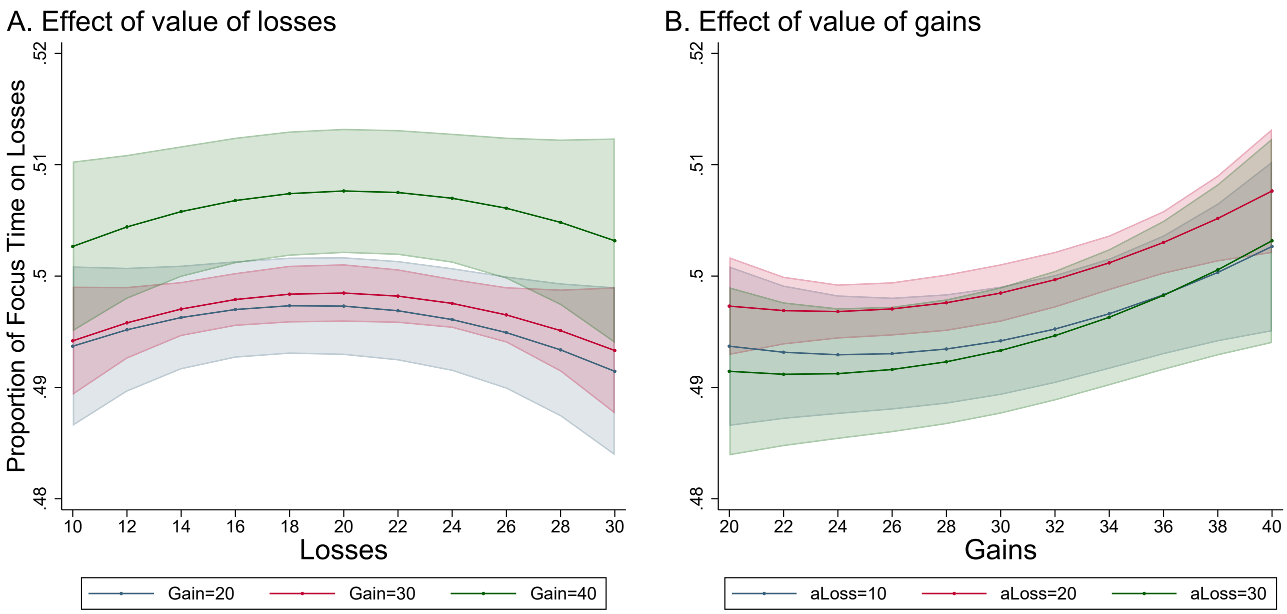
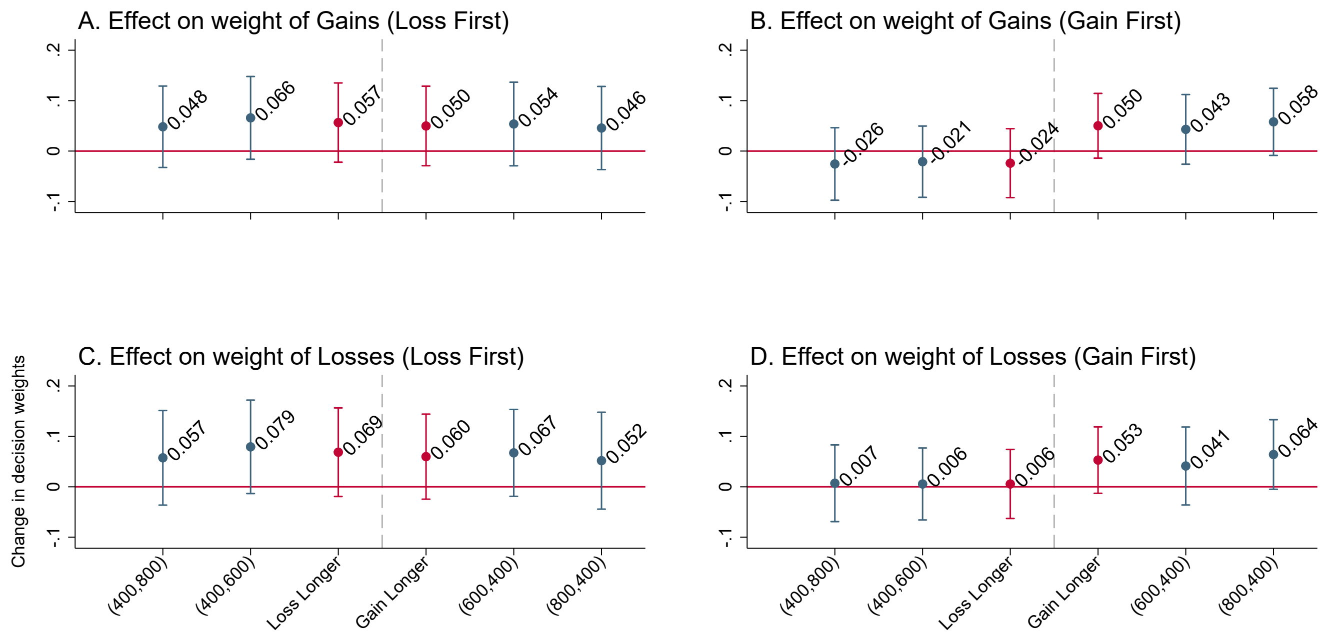


Figure 7: Proportion of time on Losses by Gain/Loss values

D Moderating effects of presentation order

Figure 8 shows the effect of the treatment conditions on the decision weights conditional on which attribute was presented first. The first row shows the effects on the decision weights on gains, while the second row shows the effects on the decision weights on losses. The left column presents the treatment effects when losses are presented first and the right column when gains are presented first. These effects represent the difference in the decision weights with the Equal condition (400ms, 400ms) when the the corresponding attribute was presented first (losses left, gains right). Treatment conditions are described as (PD Gains, PD Losses) in ms. The confidence intervals are at a 95% of confidence. Conditions Loss Longer and Gain Longer show the pooled results of both conditions where the said outcome is presented for longer. Parameters estimated from models 3 and 4 from Table 7.



Estimated values and significance is shown alongside markers. * $p < 0.05$, **$p < 0.01$, *** $p < 0.001$

Figure 8: Proportion of time on Losses by Gain/Loss values

E Moderating effect of impulsiveness with different scales

The figures below display the effect of the treatment conditions on the decision weights conditional on the participant being classified as impulsive or non-impulsive. Each set of figures uses a different impulsiveness factor. In each set of figures, the first row shows the effects on the decision weights on gains, while the second row shows the effects on the decision weights on losses. The left column describes the treatment effects of non-impulsive participants and the right column for impulsive ones. These effects represent the difference in the decision weights with the Equal condition (400ms, 400ms) for that specific group (Impulsive or non-Impulsive). Treatment conditions are described as (PD Gains, PD Losses) in ms. The confidence intervals are at a 95% of confidence. Conditions Loss Longer and Gain Longer show the pooled results of both conditions where the said outcome is presented for longer. Parameters estimated from models 1i and 2i using the different impusliveness subscales. Results extracted from tables 4, 5 and 6.

F Results for effective treatment

Table 9 shows the effects of longer fixations when the treatments were effective. The variable $\Delta PD_X > Y ms$ is a dummy variable that takes the value of one if the treatment condition intended to increase the total Presentation Duration for attribute X and the total PD for outcome X was in fact longer than the alternative by at least Y ms. When gains are presented for effectively longer periods than the losses, we find similar

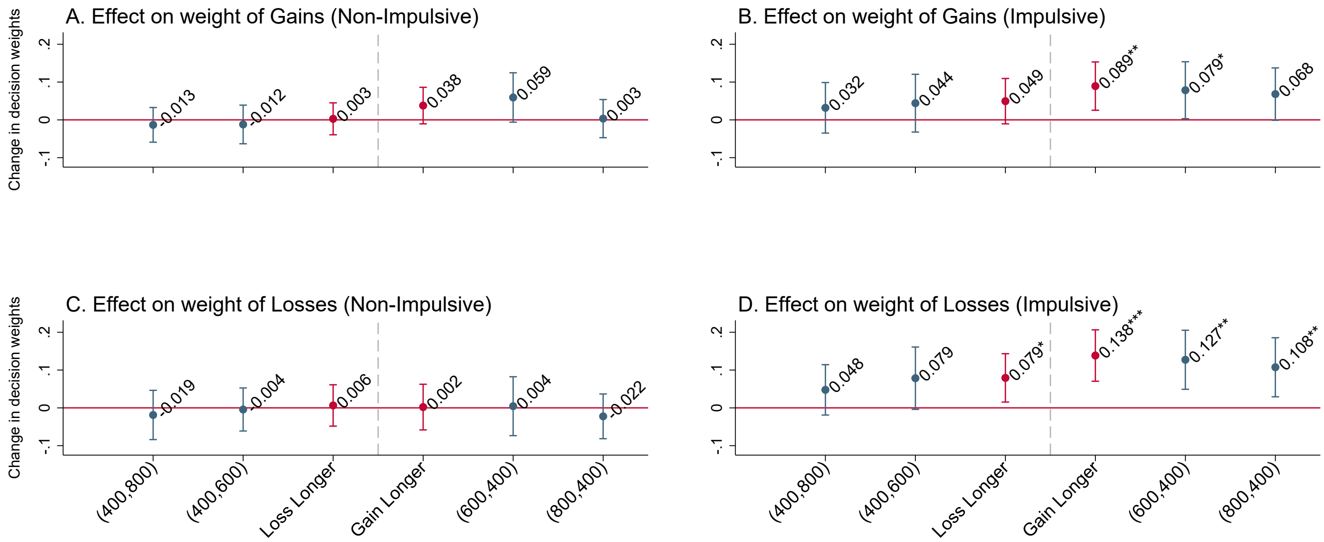


Figure 9: Moderating effect of BIS-11 attentional factor

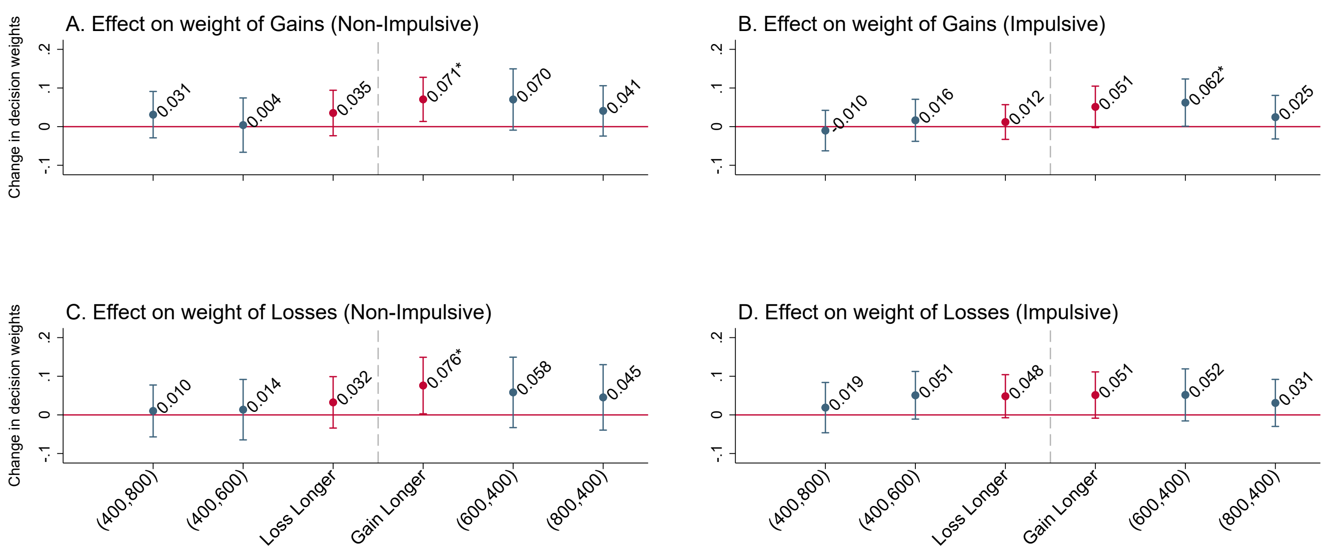


Figure 10: Moderating effect of BIS-11 motor factor

effects as in our main estimations. Namely, an increase in total presentation duration to gains increases the sensitivity to both gains and losses. The effects of longer presentation duration for losses become non-significant.

G Estimation Tables

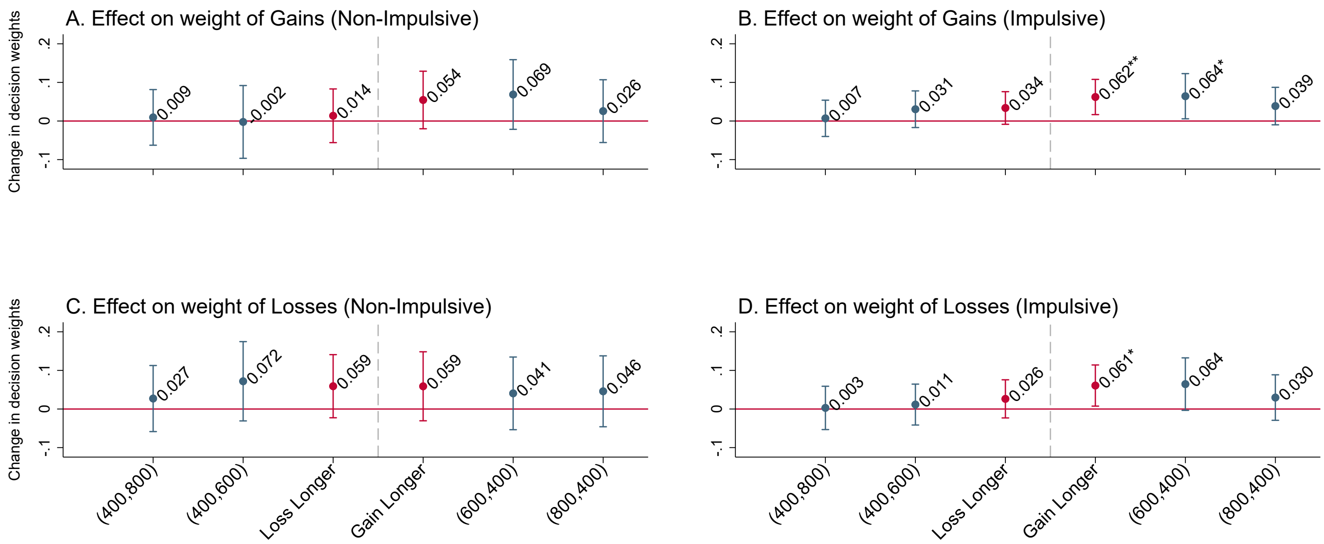


Figure 11: Moderating effect of BIS-11 non-planning factor

Table 2: Estimations of Decision Models

	Model 1		Model 2		Model 3	
Decision						
L	0.294***	(0.025)	0.294***	(0.025)	0.343***	(0.023)
Loss Longer × L			0.041	(0.022)		
(400,600) × L	0.048*	(0.024)				
(400,800) × L	0.035	(0.023)				
Gain Longer × L			0.062**	(0.024)		
(600,400) × L	0.063*	(0.025)				
(800,400) × L	0.061*	(0.027)				
G	0.238***	(0.021)	0.238***	(0.021)	0.276***	(0.020)
Loss Longer × G			0.024	(0.018)		
(400,600) × G	0.029	(0.020)				
(400,800) × G	0.019	(0.019)				
Gain Longer × G			0.060**	(0.020)		
(600,400) × G	0.060**	(0.022)				
(800,400) × G	0.061**	(0.022)				
Observations	7726		7726		7726	
AIC	3596.959		3589.730		4498.794	
BIC	3666.482		3631.444		4512.699	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Estimations of Decision Models by Impulsiveness (BIS-11)

	Decision		Decision		Decision	
Decision						
L	0.376***	(0.048)	0.376***	(0.048)	0.389***	(0.040)
Impulsive × L	-0.133*	(0.056)	-0.133*	(0.056)	-0.0838	(0.049)
Loss Longer × L			-0.00133	(0.037)		
(400,600) × L	-0.0174	(0.043)				
(400,800) × L	-0.0258	(0.038)				
Gain Longer × L			0.00171	(0.039)		
(600,400) × L	0.00184	(0.047)				
(800,400) × L	-0.0273	(0.038)				
Impulsive × Loss Longer × L			0.0584	(0.045)		
Impulsive × (400,600) × L	0.0750	(0.053)				
Impulsive × (400,800) × L	0.0512	(0.048)				
Impulsive × Gain Longer × L			0.0918	(0.049)		
Impulsive × (600,400) × L	0.0821	(0.058)				
Impulsive × (800,400) × L	0.0967	(0.050)				
G	0.304***	(0.041)	0.304***	(0.041)	0.309***	(0.034)
Impulsive × G	-0.112*	(0.048)	-0.112*	(0.048)	-0.0609	(0.041)
Loss Longer × G			-0.0139	(0.033)		
(400,600) × G	-0.0350	(0.040)				
(400,800) × G	-0.0251	(0.035)				
Gain Longer × G			0.00759	(0.032)		
(600,400) × G	0.0276	(0.040)				
(800,400) × G	-0.0324	(0.033)				
Impulsive × Loss Longer × G			0.0592	(0.040)		
Impulsive × (400,600) × G	0.0773	(0.048)				
Impulsive × (400,800) × G	0.0492	(0.043)				
Impulsive × Gain Longer × G			0.0867*	(0.041)		
Impulsive × (600,400) × G	0.0636	(0.051)				
Impulsive × (800,400) × G	0.107*	(0.044)				
Observations	7512		7726		7726	
AIC	2939.3		3577.9		4478.9	
BIC	3077.8		3661.3		4506.7	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Estimations of Decision Models by Impulsiveness (BIS-11, Attention)

	Decision		Decision		Decision	
Decision						
L	0.321***	(0.039)	0.321***	(0.039)	0.334***	(0.034)
Impulsive × L	-0.0525	(0.051)	-0.0525	(0.051)	0.0217	(0.045)
Loss Longer × L			0.00644	(0.028)		
(400,600) × L	-0.00425	(0.029)				
(400,800) × L	-0.0188	(0.033)				
Gain Longer × L			0.00212	(0.031)		
(600,400) × L	0.00447	(0.040)				
(800,400) × L	-0.0224	(0.030)				
Impulsive × Loss Longer × L			0.0729	(0.043)		
Impulsive × (400,600) × L	0.0828	(0.051)				
Impulsive × (400,800) × L	0.0665	(0.048)				
Impulsive × Gain Longer × L			0.136**	(0.046)		
Impulsive × (600,400) × L	0.123*	(0.056)				
Impulsive × (800,400) × L	0.130**	(0.050)				
G	0.246***	(0.030)	0.246***	(0.030)	0.269***	(0.028)
Impulsive × G	-0.0154	(0.043)	-0.0154	(0.043)	0.0151	(0.038)
Loss Longer × G			0.00282	(0.022)		
(400,600) × G	-0.0120	(0.026)				
(400,800) × G	-0.0132	(0.023)				
Gain Longer × G			0.0378	(0.025)		
(600,400) × G	0.0592	(0.033)				
(800,400) × G	0.00334	(0.026)				
Impulsive × Loss Longer × G			0.0466	(0.037)		
Impulsive × (400,600) × G	0.0562	(0.047)				
Impulsive × (400,800) × G	0.0451	(0.041)				
Impulsive × Gain Longer × G			0.0515	(0.041)		
Impulsive × (600,400) × G	0.0193	(0.051)				
Impulsive × (800,400) × G	0.0649	(0.044)				
Observations	7512		7726		7726	
AIC	2952.2		3590.1		4501.2	
BIC	3090.6		3673.6		4529.0	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Estimations of Decision Models by Impulsiveness (BIS-11, Non-Planning)

	Decision		Decision		Decision	
Decision						
L	0.354***	(0.039)	0.354***	(0.039)	0.416***	(0.033)
Impulsive × L	-0.0982	(0.051)	-0.0982	(0.051)	-0.122**	(0.044)
Loss Longer × L			0.0591	(0.042)		
(400,600) × L	0.0719	(0.052)				
(400,800) × L	0.0271	(0.044)				
Gain Longer × L			0.0588	(0.046)		
(600,400) × L	0.0405	(0.048)				
(800,400) × L	0.0459	(0.047)				
Impulsive × Loss Longer × L			-0.0328	(0.049)		
Impulsive × (400,600) × L	-0.0604	(0.059)				
Impulsive × (400,800) × L	-0.0243	(0.052)				
Impulsive × Gain Longer × L			0.00194	(0.053)		
Impulsive × (600,400) × L	0.0240	(0.059)				
Impulsive × (800,400) × L	-0.0162	(0.056)				
G	0.303***	(0.035)	0.303***	(0.035)	0.341***	(0.028)
Impulsive × G	-0.110*	(0.044)	-0.110*	(0.044)	-0.110**	(0.038)
Loss Longer × G			0.0136	(0.035)		
(400,600) × G	-0.00241	(0.048)				
(400,800) × G	0.00938	(0.037)				
Gain Longer × G			0.0545	(0.038)		
(600,400) × G	0.0686	(0.046)				
(800,400) × G	0.0256	(0.041)				
Impulsive × Loss Longer × G			0.0202	(0.041)		
Impulsive × (400,600) × G	0.0329	(0.054)				
Impulsive × (400,800) × G	-0.00246	(0.044)				
Impulsive × Gain Longer × G			0.00770	(0.045)		
Impulsive × (600,400) × G	-0.00436	(0.055)				
Impulsive × (800,400) × G	0.0131	(0.048)				
Observations	7512		7726		7726	
AIC	2910.5		3553.8		4446.1	
BIC	3049.0		3637.2		4474.0	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Estimations of Decision Models by Impulsiveness (BIS-11, Motor)

	Decision		Decision		Decision	
Decision						
L	0.336***	(0.040)	0.336***	(0.040)	0.388***	(0.038)
Impulsive × L	-0.0795	(0.051)	-0.0795	(0.051)	-0.0858	(0.048)
Loss Longer × L			0.0324	(0.034)		
(400,600) × L	0.0135	(0.040)				
(400,800) × L	0.0102	(0.034)				
Gain Longer × L			0.0759*	(0.037)		
(600,400) × L	0.0582	(0.046)				
(800,400) × L	0.0453	(0.043)				
Impulsive × Loss Longer × L			0.0159	(0.044)		
Impulsive × (400,600) × L	0.0372	(0.051)				
Impulsive × (400,800) × L	0.00866	(0.048)				
Impulsive × Gain Longer × L			-0.0246	(0.048)		
Impulsive × (600,400) × L	-0.00648	(0.058)				
Impulsive × (800,400) × L	-0.0143	(0.053)				
G	0.268***	(0.032)	0.268***	(0.032)	0.314***	(0.032)
Impulsive × G	-0.0552	(0.043)	-0.0552	(0.043)	-0.0726	(0.040)
Loss Longer × G			0.0353	(0.030)		
(400,600) × G	0.00398	(0.036)				
(400,800) × G	0.0310	(0.031)				
Gain Longer × G			0.0705*	(0.029)		
(600,400) × G	0.0702	(0.040)				
(800,400) × G	0.0407	(0.033)				
Impulsive × Loss Longer × G			-0.0234	(0.038)		
Impulsive × (400,600) × G	0.0124	(0.045)				
Impulsive × (400,800) × G	-0.0412	(0.041)				
Impulsive × Gain Longer × G			-0.0194	(0.040)		
Impulsive × (600,400) × G	-0.00803	(0.051)				
Impulsive × (800,400) × G	-0.0162	(0.044)				
Observations	7512		7726		7726	
AIC	2939.3		3573.6		4474.7	
BIC	3077.8		3657.0		4502.6	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Estimations of Decision Models by Presentation Order (with Dummy for First viewed Outcome

	Model 2f		Model 3f	
Decision				
L	0.281***	(0.036)	0.347***	(0.026)
G. First × L	0.0208	(0.045)	-0.00734	(0.021)
Loss Longer × L	0.0686	(0.045)		
Gain Longer × L	0.0598	(0.043)		
Loss Longer × G. First × L	-0.0630	(0.062)		
Gain Longer × G. First × L	-0.00684	(0.054)		
G	0.226***	(0.032)	0.278***	(0.020)
G. First × G	0.0306	(0.044)	-0.00587	(0.020)
Loss Longer × G	0.0565	(0.040)		
Gain Longer × G	0.0498	(0.040)		
Loss Longer × G. First × G	-0.0806	(0.058)		
Gain Longer × G. First × G	0.000350	(0.054)		
Observations	7059		7643	
AIC	2670.7		3928.7	
BIC	2753.0		3956.4	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Estimations of Decision Models by Presentation Order (with Dummy for Last viewed Outcome)

	Model 2l		Model 3l	
L	0.322***	(0.046)	0.347***	(0.023)
Gain Last × L	-0.0136	(0.055)	-0.0230	(0.022)
Loss Longer × L	0.0258	(0.049)		
Gain Longer × L	0.0400	(0.050)		
Loss Longer × Gain Last × L	-0.0361	(0.076)		
Gain Longer × Gain Last × L	-0.00109	(0.060)		
G	0.240***	(0.035)	0.274***	(0.019)
Gain Last × G	0.0178	(0.047)	-0.0129	(0.021)
Loss Longer × G	0.0470	(0.036)		
Gain Longer × G	0.0280	(0.038)		
Loss Longer × Gain Last × G	-0.0874	(0.063)		
Gain Longer × Gain Last × G	0.00561	(0.057)		
Observations	7100		7100	
AIC	2678.4		2673.4	
BIC	2760.8		2700.8	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Estimations of Decision Models by Difference in total PD

	(1)		(2)		(3)	
L	0.301***	(0.025)	0.303***	(0.024)	0.306***	(0.023)
$(\Delta PD_L > 0ms) \times$ L	0.035	(0.020)				
$(\Delta PD_L > 100ms) \times$ L			0.033	(0.024)		
$(\Delta PD_L > 200ms) \times$ L					0.037	(0.026)
$(\Delta PD_G > 0ms) \times$ L	0.055*	(0.023)				
$(\Delta PD_G > 100ms) \times$ L			0.058*	(0.023)		
$(\Delta PD_G > 200ms) \times$ L					0.051*	(0.023)
G	0.243***	(0.022)	0.235***	(0.022)	0.242***	(0.021)
$(\Delta PD_L > 0ms) \times$ G	0.021	(0.018)				
$(\Delta PD_L > 100ms) \times$ G			0.032	(0.020)		
$(\Delta PD_L > 200ms) \times$ G					0.027	(0.021)
$(\Delta PD_G > 0ms) \times$ G	0.055**	(0.019)				
$(\Delta PD_G > 100ms) \times$ G			0.067***	(0.020)		
$(\Delta PD_G > 200ms) \times$ G					0.056**	(0.021)
Observations	7706		7708		7699	
AIC	3585.052		3572.186		3549.334	
BIC	3626.751		3613.887		3591.027	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$