Absolute and relative stability of loss aversion across contexts

Mikhail S. Spektor[1,2*], David Kellen[3*], Jörg Rieskamp[4], and Karl Christoph Klauer[5]
[1]University of Warwick
[2]Universitat Pompeu Fabra
[3]Syracuse University
[4]University of Basel
[5]University of Freiburg

Individuals' decisions under risk tend to be in line with the notion that "*losses loom larger than gains*". This *loss aversion* in decision making is commonly understood as a stable individual preference that is manifested across different contexts. The presumed stability and generality, which underlies the prominence of loss aversion in the literature at large, has been recently questioned by studies reporting how loss aversion can disappear, and even reverse, as a function of the choice context. The present study investigated whether loss aversion reflects a trait-like attitude of avoiding losses or rather individuals' adaptability to different contexts. We report three experiments investigating the within-subject context sensitivity of loss aversion in a two-alternative forced-choice task. Our results show that the choice context can shift people's loss aversion, though somewhat inconsistently. Moreover, individual estimates of loss aversion are shown to have a considerable degree of stability. Altogether, these results indicate that even though the absolute value of loss aversion can be affected by external factors such as the choice context, estimates of people's loss aversion still capture the relative dispositions towards gains and losses across individuals.

Keywords: loss aversion, risky choice, prospect theory, context effects, computational modeling

Public significance statement

Loss aversion is a core feature of prospect theory, and is widely relied upon by researchers and practitioners when characterizing the causes behind real-world phenomena; for example, why people generally dislike stocks despite them having higher returns than risk-free bonds. The present work shows systematic changes in loss aversion across contexts, alongside stable individual differences. These results legitimize the comparison of people's loss aversion relative to one another, while undermining the comparability of estimates to different contexts.

There are only a few theoretical concepts in the social and decision sciences that are as prominent as *loss aversion*, a core component of prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Loss aversion establishes how the displeasure of a loss of any magnitude weighs heavier than the pleasure of an equally large gain or, in other words: '*losses loom larger than gains*' (Kahneman & Tversky, 1979, p. 279). This status of loss aversion in the literature at large can be attributed to its intuitive appeal and explanatory power, both in the lab (Camerer, 2005) and in the wild (Barberis et al., 2001; Benartzi & Thaler, 1995; Camerer, 2000; DellaVigna, 2009; Odean, 1998). More recently, researchers have attempted to uncover correlates of loss aversion (Boyce et al., 2016; Kellen et al., 2016; Sokol-Hessner et al., 2009) as well as its neural foundations (Botvinik-Nezer et al., 2020; Canessa et al., 2013; De Martino et al., 2010; Tom et al., 2007). These efforts presuppose — explicitly or implicitly — that loss aversion is a relatively stable individual characteristic, an assumption that is corroborated by reports of sizeable test–retest correlations (Glöckner & Pachur, 2012; Rakow et al., 2020; Scheibehenne & Pachur, 2015).

Empirical investigations of loss aversion, in which individuals are typically asked to make choices between different options that involve potential losses as well as gains, find that the impact that losses have on choices is about twice as large as that of equivalent gains (e.g., Abdellaoui et al., 2007; Barberis et al., 2001; Booij et al., 2010; see Brown et al., 2022, for a recent meta-analysis). Although the empirical merit of loss aversion has been criticized by several authors challenging prospect theory (Birnbaum, 2008; Gal & Rucker, 2018; Hofmeyr & Kincaid, 2019), the notion that there is some stable individual-level relation between gains and losses has either been left out of the discussion or given only very limited attention (for notable exceptions, see Brooks & Zank, 2005; Chechile & Cooke, 1997; Ert & Erev, 2013).

This situation drastically changed with the recent work of Walasek and Stewart (2015), who claimed that one can easily make loss aversion disappear or even reverse by simply manipulating the decision context, specifically, by varying the relative rank of gains and losses within the outcome distributions encountered by people in the experiments that they take part in. Walasek and Stewart reported that the very same loss outcome is evaluated more/less favorably if it is among the lower/higher losses encountered in the course of the experiment.[1]. Such behavior would cast serious doubts on the possibility of drawing any general conclusions about loss aversion at the individual level: people found among the most loss averse in a study might simply be those that most dramatically adjusted their preferences to the present context. Under different circumstances, the very same people might have turned out to be among the *least* loss averse. Walasek and Stewart's conclusions also open the door to a reinterpretation of the relationship between loss aversion and a number of empirical correlates: For example, the levels of activity in the brain regions identified by Tom et al. (2007) as associated with loss aversion might in fact be tracking the decision-maker's adaptation to the choice context in which they are operating. Last but not least, their report of context sensitivity also raises concerns over the merit of policies designed around the idea of loss aversion as a vehicle to promote or discourage certain behaviors (e.g., encouraging smoking cessation; Halpern et al., 2015).

As compelling as Walasek and Stewart's (2015) original report might be, there are a number of issues that call for further scrutiny. First, their studies relied on *between-subject* designs that are unable to shed light on the question of relative individual stability. Second, there are concerns with the *accept/reject task* that they adopted. In each choice trial, participants were shown a single mixed lottery with two equiprobable outcomes, one of which was a gain and the other a loss. Participants were then asked to state whether they would like to play the lottery or instead reject playing it in favor of the status quo. It turns out that it is quite difficult to obtain reliable estimates of loss aversion based on accept/reject judgments (see Walasek & Stewart, 2021).

A number of additional concerns were raised in a recent critique by André and de Langhe (2021b). They argued that the comparisons of loss aversion reported by Walasek and Stewart (2015) are invalid given that the compared estimates are obtained from different sets of lottery problems. According to André and de Langhe, this constitutes a violation of *measurement invariance* that can produce spurious differences in loss aversion. As a proof of concept, André and de Langhe considered a number of scenarios where choices were simulated from models different from the one used by Walasek and Stewart to estimate loss aversion. While none of these models assumed any change in the underlying representations of gains and losses across conditions — nor assumed loss aversion for that matter — the estimates obtained from these simulated choices nevertheless repli-

Mikhail Spektor, Department of Psychology, University of Warwick, and Department of Economics and Business, Universitat Pompeu Fabra. David Kellen, Department of Psychology, Syracuse University. Jörg Rieskamp, Department of Psychology, University of Basel. Karl Christoph Klauer, Department of Psychology, University of Freiburg.

David Kellen and Mikhail Spektor contributed equally to this manuscript. The authors thank Lukasz Walasek for helpful discussions and Nathaniel Phillips for blinding the data of Experiment 3. All data and analysis scripts are available on the Open Science Framework: https://osf.io/28qzs/.

Mikhail Spektor gratefully acknowledges financial support from the Spanish State Research Agency (AEI) through the Severo Ochoa Programme for Centres of Excellence in R&D (CEX2019–000915–S), the Spanish Ministry of Economic Affairs and Digital Transformation (MINECO) through the Juan de la Cierva fellowship (FJC2019–040970–I), the Spanish Ministry of Science and Innovation (MICINN; project PID2019–105249GB–I00), and the BBVA Foundation (project G999088Q). David Kellen's work was supported by the National Science Foundation (NSF CAREER Award, ID 2145308). Jörg Rieskamp's work was supported by the Swiss National Science Foundation (SNSF–Sinergia, CRSII5_177277).

Author Contributions Statement. **Mikhail Spektor**: Conceptualization, Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Validation; Visualization; Writing – original draft; Writing – review & editing. **David Kellen**: Conceptualization, Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Validation; Visualization; Writing – original draft; Writing – review & editing. **Jörg Rieskamp**: Funding acquisition; Resources; Writing - original draft; Writing - review & editing. **Christoph Klauer**: Funding acquisition, Resources, Writing - original draft; Writing - review & editing.

Correspondence can be sent to Mikhail Spektor (mikhail@spektor.ch) or David Kellen (davekellen@gmail.com).

[1]The general idea that people's evaluations might depend on distributional properties of stimuli was introduced in the seminal work by Parducci (1965)

cated Walasek and Stewart's original findings.[2] However, André and de Langhe also show that, even when measurement invariance is satisfied, there are ways to engage with the accept–reject task that can lead to spurious differences in measured loss aversion. For instance, they can emerge in a scenario where individuals attempt to track their history of accepted lotteries, which they regulate throughout the course of the experiment.

The goal of the present work is to appraise the stability of loss aversion while directly addressing the aforementioned issues. We present a number of choice experiments in which we implemented a *within-subject* manipulation of gain- and loss- outcome ranges, allowing us to assess the degree to which the individual differences found in loss aversion estimates are stable across contexts. Moreover, the reported experiments rely on a *two-alternative forced choice task*: in each trial, participants were requested to select which of two lotteries they preferred. A main advantage of this task, which is widely used by decision-making researchers, are its desirable psychometric properties (e.g., in terms of parameter estimability; Broomell & Bhatia, 2014; Nilsson et al., 2011), which happen to be absent in its accept/reject counterpart (see Walasek & Stewart, 2021). Additionally, it has the benefit of being immune to the task-engagement issue identified by André and de Langhe (2021b): Whereas the accept/reject task can invite comparisons between the present lottery and the history of previously accepted/rejected lotteries, the two-alternative forced-choice task, in which people choose one lottery *over another*, manages to narrow the focus to the pair being compared; strategies aiming at maintaining a specific rate of lottery acceptances or rejections are not feasible in this context.

Lastly, our studies rely on a number of shared lottery problems that can be used to estimate and compare loss aversion, without raising concerns with measurement invariance or estimation bias. This possibility will be exploited later on to establish the robustness of the results obtained when estimating loss aversion using overlapping but distinct sets of lottery problems.

Experiment 1

Experiment 1 aims to establish the main phenomenon of interest, a change in loss aversion while adopting an experimental design that is as close as possible to the original study by Walasek and Stewart (2015). Specifically, we adopted the same distributions of outcomes used in their Experiment 3 (the in-person lab experiment). In contrast with their original design, we used a within-subjects manipulation of choice context, such that each participant encountered the outcome distributions designed to elicit both loss-averse behavior and the polar opposite.

Measuring loss aversion

Our evaluations of loss aversion relied on its parametric and behavioral definitions. For the parametric definition, we relied on a (streamlined) version of prospect theory (Kahneman & Tversky, 1979). Here, the subjective utility (U) of the lottery $A = \left(\begin{smallmatrix} a_1 & a_2 \\ .50 & .50 \end{smallmatrix}\right)$ that yields two outcomes, a_1 and a_2, with equal probabilities is given by $U(A) = w(.50)\times(v(a_1)+v(a_2))$. In two-alternative forced-choice tasks, $w(.50)$ is a constant and can be set to 1 without loss of generality. The model includes a value function $v(x) = x^\alpha$ for $x \geq 0$, $v(x) = -\lambda|x|^\alpha$ for $x < 0$, with parameter α capturing the decision maker's sensitivity to outcomes and parameter λ capturing loss aversion. Individuals are considered to be *loss averse* whenever their estimated $\lambda > 1$. Individuals with estimates of $\lambda = 1$ or below 1 are referred to as being *loss neutral* or *gain seeking*, respectively. Lottery valuations, in this case of lotteries A and B, are then transformed into choice probabilities by virtue of a sigmoid choice function:

$$Pr(A) = \frac{1}{1 + e^{-\theta\times\left(U(A)-U(B)\right)}},$$

where $\theta \geq 0$ corresponds to the choice sensitivity of the logistic choice rule. Individual λ estimates were obtained from a hierarchical-Bayesian application of this prospect theory model. Additional modeling details are provided in section A.

As an alternative to λ's *parametric* definition, we also relied on a purely *behavioral* definition of loss aversion (Brooks & Zank, 2005). Consider the two lotteries $A = \left(\begin{smallmatrix} x & -x \\ .50 & .50 \end{smallmatrix}\right)$ and $B = \left(\begin{smallmatrix} y & -y \\ .50 & .50 \end{smallmatrix}\right)$, with outcomes $x \geq y \geq 0$. Although both options have the same expected value, A is riskier than B by virtue of yielding more extreme gain/loss outcomes. Gain seeking and loss averse individuals are expected to prefer lotteries A and B, respectively. For these individuals, the proportion of riskier options chosen in this kind of lottery pair, the mean-preserving pair, can be used to track their relative attitudes towards gains and losses (for relevant discussions, see Brooks & Zank, 2005). This measure of loss aversion is based on each participant's proportion of riskier choices in mean-preserving pairs.

Method

Participants and procedure

Forty participants (22 female, 16 male, age: 18–43, $M = 24.39$, $SD = 4.71$)[3] completed a total of 352 choice trials, divided across two counterbalanced blocks that corresponded

[2] André and de Langhe's (2021b) critique also discussed whether decision by sampling (Stewart et al., 2006) is an adequate theory to explain the results, an issue that is of little import for the present study.

[3] Due to technical problems, the demographic data from two participants were lost. The demographic questionnaire was delivered

to a condition designed to elicit loss-averse behavior (the loss-aversion condition or LAC) and one that is designed to elicit gain-seeking behavior (the gain-seeking condition or GSC). On each trial, two binary lotteries with equiprobable outcomes were presented side by side (see Figure 1). A choice was made by clicking on one of the two boxes below the outcomes and then confirming their choice by clicking on a box in the middle of the screen. Participants had the opportunity to make two self-paced breaks during each block, as well as a break of at least 60 seconds between the two blocks. Between blocks, participants were explicitly told that the upcoming block and the lotteries presented therein were completely independent from the previous one. After both blocks were completed, one trial from each block was randomly drawn and the participant's chosen lottery was played out (participants were informed of this incentive structure at the beginning of the experiment). A fraction of the resulting outcomes was added to or subtracted from the show-up fee of CHF 20, yielding a final payoff that ranged from CHF 12.50 to CHF 27.50. Explicit ethical approval was obtained from the Institutional Review Board of the Department of Psychology, University of Basel (`IRB ID 017-15-2`).

Transparency and openness

The anonymized data from all three experiments and the analysis scripts are available on the Open Science Framework: https://osf.io/28qzs/. The hypotheses of Experiment 3 were pre-registered and the data were blinded prior to the main analyses (see https://osf.io/7kcds/).

Design

In the LAC, losses were uniformly distributed from -5 to -20 in steps of 1 and gains from 10 to 40 in steps of 2. Each gain/loss occurred 22 times, for a total of 176 trials. The trials in this condition were randomly generated to fulfill the following conditions. A majority of the trials (142 trials) were those in which both lotteries had the same expected value: 102 trials were comprised of mixed lotteries (e.g., $\begin{pmatrix} 26 & -6 \\ .50 & .50 \end{pmatrix}$ vs. $\begin{pmatrix} 36 & -16 \\ .50 & .50 \end{pmatrix}$), eight of which were mean-preserving pairs included in both conditions (e.g., $\begin{pmatrix} 10 & -10 \\ .50 & .50 \end{pmatrix}$ vs. $\begin{pmatrix} 14 & -14 \\ .50 & .50 \end{pmatrix}$), and an additional set of 40 trials were comprised of pairs of gain-only (e.g., $\begin{pmatrix} 34 & 16 \\ .50 & .50 \end{pmatrix}$ vs. $\begin{pmatrix} 40 & 10 \\ .50 & .50 \end{pmatrix}$) and loss-only lotteries (e.g., $\begin{pmatrix} -8 & -15 \\ .50 & .50 \end{pmatrix}$ vs. $\begin{pmatrix} -12 & -11 \\ .50 & .50 \end{pmatrix}$). There were outcomes left that could not be combined to have the same expected value, so the remaining 34 trials were randomly generated from those outcomes in order to achieve uniform outcome distributions (e.g., $\begin{pmatrix} 38 & -19 \\ .50 & .50 \end{pmatrix}$ vs. $\begin{pmatrix} 22 & -12 \\ .50 & .50 \end{pmatrix}$). The GSC trials were a mirrored version of the LAC trials (i.e., all signs flipped). A complete list of trials can be found on OSF: https://osf.io/nfpy8

Results

In terms of behavioral loss aversion, the analysis of the mean-preserving pairs that were common across conditions (as is standard in tests of contextual adaptability; e.g., Frydman & Jin, 2022) revealed a main effect of experimental condition: individuals in the condition designed to elicit loss aversion (LAC) were less likely (M = .394, SD = .410) to choose the riskier of the two options than in the condition (GSC) designed to elicit gain-seeking preferences (M = .497, SD = .395), with $t(39) = 2.037$, $p = .048$, and $d_z = 0.322$ (95% CI: [0.002, 0.638]).

However, a closer inspection of choice proportions revealed that this main effect was overshadowed by a larger effect of *starting condition*: Individuals who encountered the LAC first chose the riskier of the two options in only 27.5% (SD = 29.6%) of the cases across both conditions, whereas individuals who started with the GSC chose the riskier option in 61.6% (SD = 36.2%) of the cases. This large difference ($d = 1.030$, 95% CI: [0.363, 1.686]) was mainly driven by the apparent rigidity of the participants when transitioning from the first to the second experimental condition: Individuals starting in the LAC chose the riskier option in the LAC in 21% of the cases, going up to 34% in the GSC. In contrast, individuals who started in the GSC began by choosing the riskier option 66% of the cases, a rate that reduced slightly to 57% in the subsequent LAC (see Figure 2A). This pattern of results holds when extending the analysis to all choices between two options with equal expected values (see Figure 2B).

The λ estimates obtained from the hierarchical-Bayesian application of the prospect theory model, reported in Table 1, corroborate these first results: people who started with the LAC were, on average, loss averse (M_λ = 1.606, 95% highest-density interval [HDI]: [1.049, 2.243]) and people who started with the GSC were, on average, gain seeking or neutral (M_λ = 0.737, 95% HDI: [0.475, 1.088]). When moving from this first choice context to the second, we observed changes in the expected direction: the average λ decreased to 1.100 in the GSC, whereas it increased to 0.923 in the LAC. However, the uncertainty surrounding these averages prevents us from taking any of these estimate shifts with confidence. For context, note that individual-level parameters were strongly correlated across conditions, which is indicative of stable individual differences (see Table 1; for more detailed results on parameter correlations, see Table A1).[4]

in German for which the word 'Geschlecht' means both 'sex' and 'gender'. Participants were asked to choose between 'weiblich' (female), 'männlich' (male), and 'keine Angabe' (prefer not to disclose).

[4]An inspection of the model's posterior-predictive distribution indicates that it succeeded in providing a good account of individuals' choices. This success extends to all three experiments reported here.

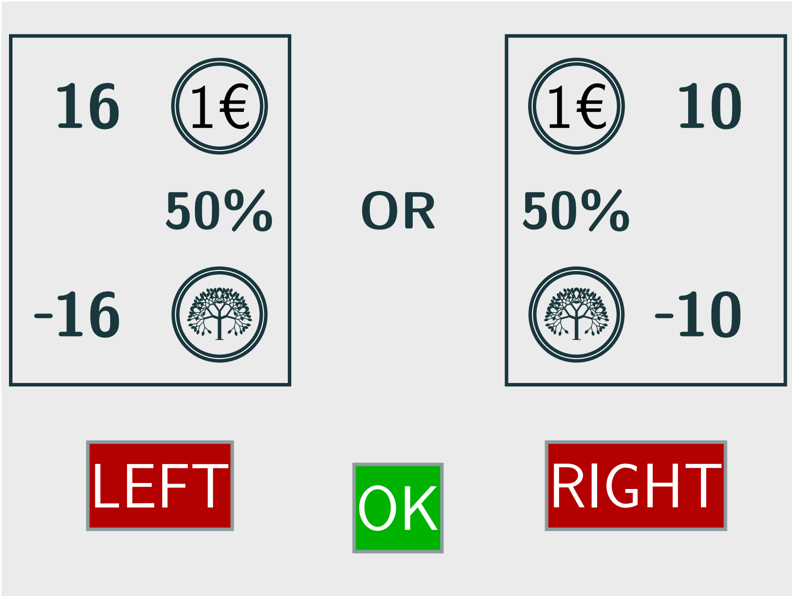

Figure 1

Depiction of a choice trial in Experiment 1. A similar layout was used in the other experiments as well.

Trials used	Starting condition	Condition	Mean	Difference	Correlation
All	GSC	GSC	0.74 [0.48, 1.09]	0.26 [-0.56, 1.31]	.46 [.19, .72]
		LAC	0.92 [0.20, 2.11]		
	LAC	LAC	1.61 [1.05, 2.24]	-0.43 [-1.53, 0.77]	
		GSC	1.10 [0.25, 2.40]		
Shared (5% of total)	GSC	GSC	0.52 [0.14, 1.07]	0.22 [-0.63, 1.29]	.62 [.28, .86]
		LAC	0.71 [0.15, 1.75]		
	LAC	LAC	1.61 [0.86, 2.86]	-0.43 [-1.77, 0.94]	
		GSC	1.14 [0.27, 2.40]		

Table 1

Experiment 1: Group-level parameter estimates of λ and correlation between individual LAC and GSC λ estimates. The values in brackets correspond to Bayesian highest-density 95% intervals.

Discussion

Experiment 1 evaluated whether people's loss aversion is sensitive to the distribution of gains and losses encountered in a decision-making context. Specifically, it focused on two-alternative forced choices and the question whether changes in loss aversion can be observed in a within-subjects design in a single experimental session. We found that individuals attached a higher decision weight to losses if most of the lotteries they encountered were favorable than if most of the encountered lotteries were unfavorable. However, these results were limited to the first experimental block encountered by the participants. Participants' choices for common lottery pairs, as well as their prospect theory parameters, were pretty much the same across blocks.

The stability of individual choice behavior across the two choice contexts is likely due to the fact that they were encountered by the participants in the same experimental session. Inspecting the aggregate choice proportions reported in Figure 2B, it becomes evident that the propensity to choose riskier options picked up right where it left off at the end of the first block. Although choice behavior appeared to slowly adapt to the distribution of outcomes (as predicted by decision by sampling; Stewart et al., 2006), it did not manage to overcome the primacy effect of the first condition. Such carryover effects across conditions within a single experimental session have been reported in other settings before (Schneider et al., 2016), an issue we will address in our other

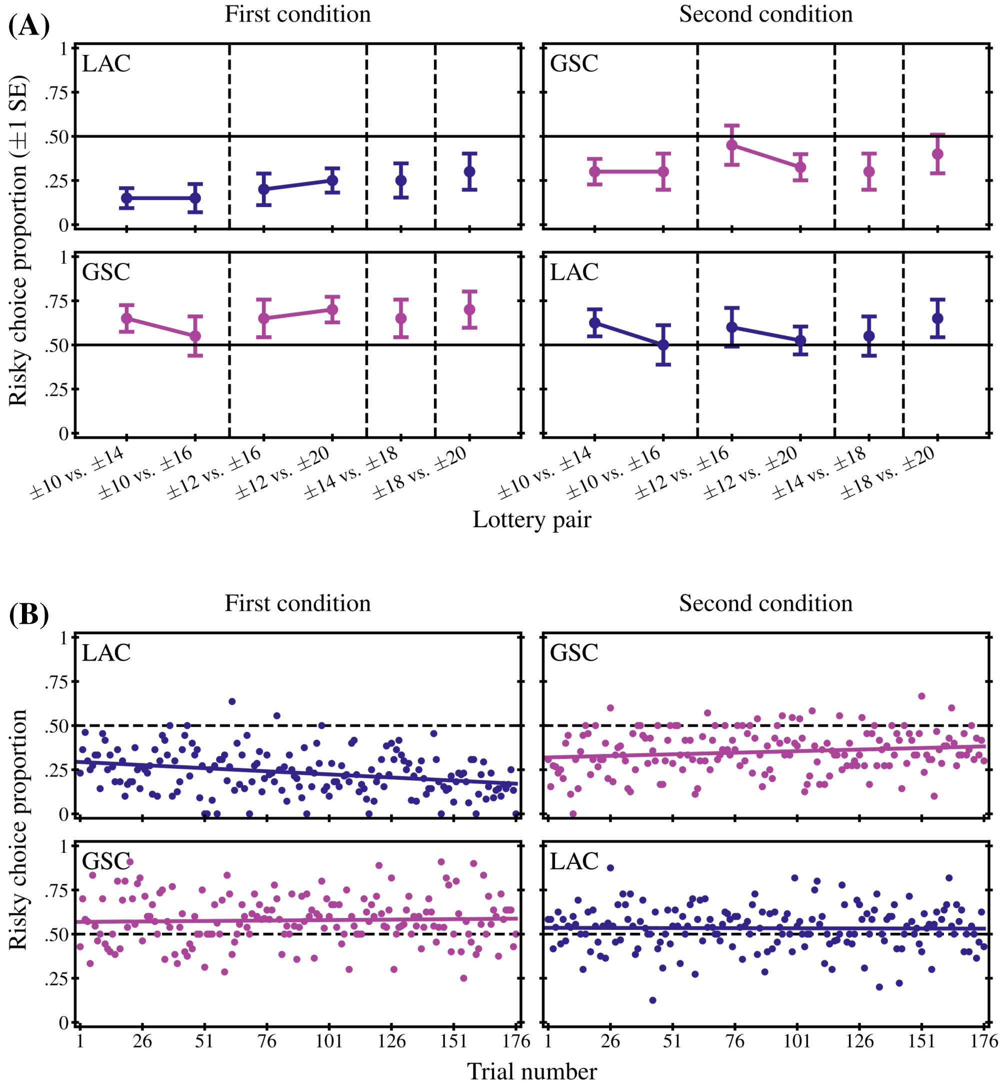

Figure 2

Behavioral results in Experiment 1 as a function of condition and starting condition. Panel A depicts choice proportions of the riskier option in mean-preserving spreads (e.g., ±10 *vs.* ±14 *contains a lottery that either wins or loses $ 10 with equal probabilities and one that either wins or loses $ 14 with equal probabilities). Panel B shows aggregated choice proportions of the riskier option among two options with equal expected values. Solid lines depict the fit of simple linear regressions. In both panels, choice proportions below 50% reflect loss aversion, those above 50% gain seeking. LAC = loss aversion condition. GSC = gain seeking condition.*

experiments.

Experiment 2

From Experiment 1, it became clear that the lotteries encountered in one experimental condition have an effect on behavior in subsequent blocks. This not only limits the ability to identify the effect of each condition on individual loss aversion separately, it also reduces the stability estimates of loss aversion to an estimate of reliability, because participants' estimated loss aversion did not change from one condition to the other. In response to these carryover effects, Experiment 2 varied choice contexts across different experimental sessions at least one week apart.

Method and Results

A total of 185 participants (87 male, 86 female, 2 other; age: 18–57, $M = 26.98$, $SD = 7.44$) were recruited through Prolific Academic and completed 49 choice trials in each of two experimental sessions, separated by at least one week.[5] At the end of the second session, one decision from each of the two sessions was randomly picked and a fraction of the chosen options' outcomes were added to or subtracted from the show-up fee of £1.50 per session, yielding a final payoff between £2.30 and £3.70. Explicit ethical approval was obtained from the Institutional Review Board of the Department of Psychology, Syracuse University (`IRB ID 16-253`). The lotteries were designed to maximize the number of symmetrical, common lotteries across the two conditions. We also reduced the total number of lottery pairs. The outcome ranges were between 6 and 32 or between 12 and 64, depending on the condition, with fifteen common lottery pairs. A complete list of lottery pairs can be found on OSF: https://osf.io/5kw68. All other aspects of the experiment were comparable to Experiment 1.

Once again, the analysis of the common mean-preserving pairs revealed an effect of choice context that (partially) carried over across experimental sessions: Individuals starting in the LAC were, on average, loss averse in the first condition, choosing the riskier option in 45% of the cases.[6] Their subsequent choices in the GSC indicated gain-seeking preferences, with the riskier option being chosen in 56% of the cases ($d_z = 0.299$, 95% CI: [0.089, 0.505]). In turn, individuals starting in the GSC manifested gain-seeking preferences in both conditions, choosing the riskier option in 68% and 66% of the cases in the GSC and the LAC, respectively (see Figure 3A). The same pattern of results holds when considering lottery pairs with equal expected value (see Figure 3B). Moreover, individual choice proportions were found to be correlated across contexts, such that the most/least loss-averse individuals, as determined by their choices in common mean-preserving pairs, tended be so in both conditions, $r(184) = .513$ (95% CI: [.399 .612]), $p < .001$.

These results were corroborated by the prospect theory estimates of λ: As reported in Table 2, participants who started with the LAC were, on average, slightly loss averse. These same participants became, on average, gain seeking in the subsequent GSC. In turn, participants who started with GSC were gain seeking across the two experimental sessions. Once again, we found individual estimates of λ to be strongly correlated across conditions (see also Table A2).

Discussion

Although Experiment 2 was partially successful in getting rid of carryover effects, we essentially replicated the results of Experiment 1: the first condition that individuals encountered had the strongest effect on loss aversion, with stable individual differences across conditions. The resilience of the carryover effects is quite surprising given that i) participants encountered a much smaller number of lotteries, ii) both sessions were at least one week apart, and iii) participants in online platforms typically complete multiple experiments per week, which should have made these sessions less memorable and, therefore, less impactful.

Experiment 3

So far, both experiments have provided evidence that a between-subject manipulation of the ranges of gains and losses encountered during an experiment affect individuals' propensity to engage in loss-averse or gain-seeking behavior. The effect of this experimental manipulation was somewhat larger in the first experiment, whereas the temporal separation of the two conditions was able to induce a change in loss aversion in one of the two starting conditions. Experiment 3 attempts to combine the desirable characteristics of the previous designs to assess the robustness of the results. Specifically, it was an in-person study with two sessions at least one week apart, with a greater number of lottery pairs per session.

Method and Results

A total of 57 participants (40 male, 16 female, 1 prefer not to disclose; age: 18–44, $M = 24.93$, $SD = 4.92$) were recruited from the participant pool of the Department of Psychology at the University of Freiburg for a lab-based study.[7] Each participant completed 360 choice trials in each of two experimental sessions that were separated by at least one week. At the end of the second session, one decision from each of the two sessions was randomly picked and a fraction of the chosen options' outcomes were added to or subtracted from the show-up fee of 8€ per session, yielding a final payoff between 10€ and 22€. The present study used only procedures that are exempt from formal ethical approval in Germany (where the data were collected) under the ethical guidelines of the Deutsche Gesellschaft für Psychologie [German Psychological Society]. The lotteries were designed to maximize the precision of parameter estimates of

[5] The demographics from 10 people were lost due to technical problems. All demographics were obtained directly from Prolific.

[6] Much like in the previous experiment, the effect of experimental condition (across both levels of starting condition) was significant and numerically smaller than that of starting condition (across both levels of experimental condition): individuals in the LAC were less likely to choose the riskier option ($M = .553$, $SD = .368$) than in the GSC ($M = .622$, $SD = .354$), $t(184) = 2.655$, $p = .009$, $d_z = 0.195$ [0.049, 0.340].

[7] The demographic questionnaire was delivered in German for which the word 'Geschlecht' means both 'sex' and 'gender'. Participants were asked to choose between 'weiblich' (female), 'männlich' (male), and 'keine Angabe' (prefer not to disclose).

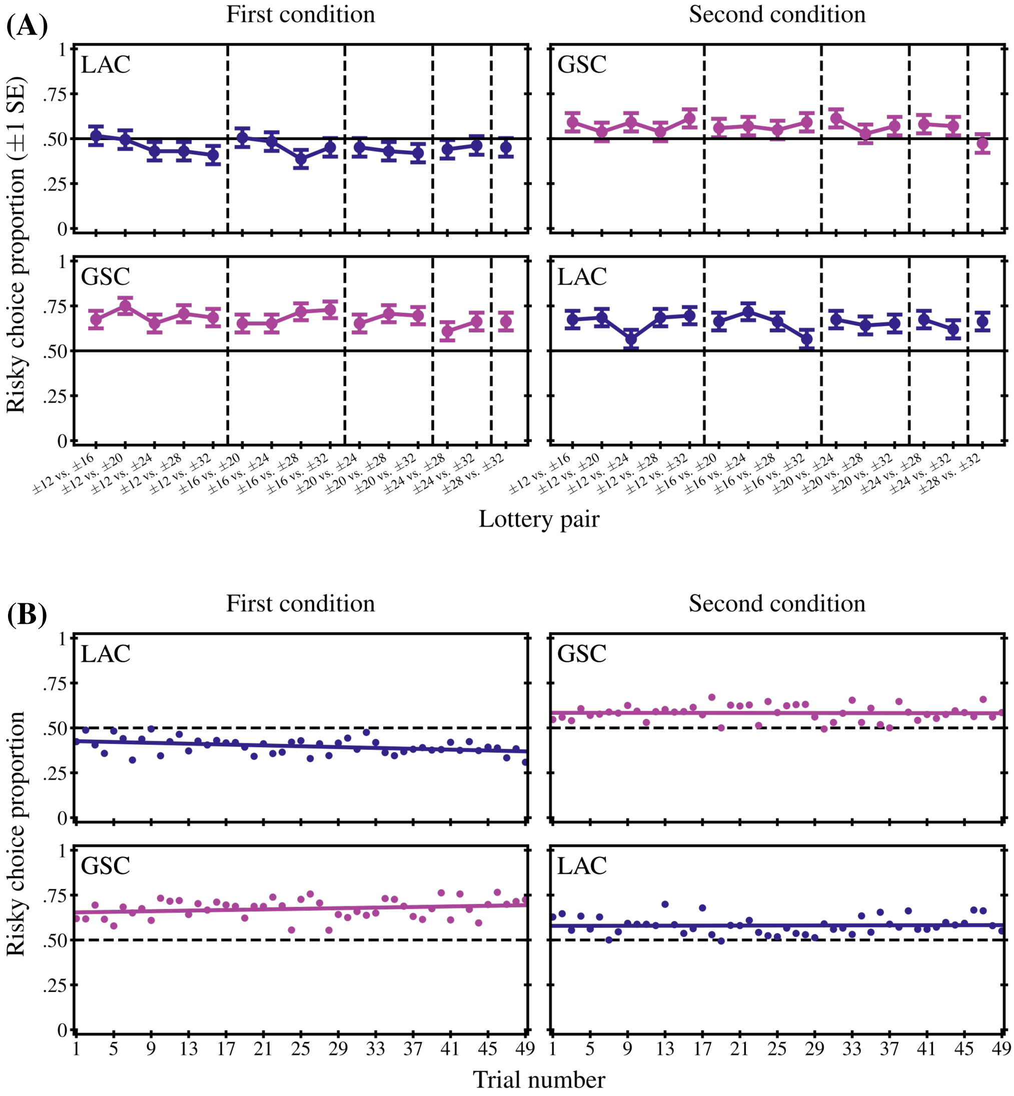

Figure 3

Behavioral results in Experiment 2 as a function of condition and starting condition. Panel A depicts choice proportions of the riskier option in mean-preserving spreads (e.g., ±10 vs. ±14 contains a lottery that either wins or loses \$ 10 with equal probabilities and one that either wins or loses \$ 14 with equal probabilities). Panel B shows aggregated choice proportions of the riskier option among two options with equal expected values. Solid lines depict the fit of simple linear regressions. In both panels, choice proportions below 50% reflect loss aversion, those above 50% gain seeking. LAC = loss aversion condition. GSC = gain seeking condition.

prospect theory. To achieve that, every condition was comprised of 180 unique trials (42 pure-gain, 42 pure-loss, and 96 mixed) that were repeated (in a newly randomized order) once in every experimental session, allowing a precise estimate of the choice-sensitivity parameter as well as of the curvature of the utility function.[8] All other aspects of the experiment were comparable to the previous two.

Looking at choices among the common mean-preserving pairs, we found that people who started in the LAC were not reliably less likely to choose the riskier mean-preserving spread (M = .315, SD = .315) than those who started in the GSC (M = .421, SD = .330), d = 0.329 95% CI: [-0.196, 0.851].[9] Similar to Experiment 2, only people who started

[8] A complete list of trials can be found on OSF: https://osf.io/7hc69.

[9] The global analysis across starting conditions showed that

Trials used	Starting condition	Condition	Mean	Difference	Correlation
All	GSC	GSC	0.75 [0.64, 0.84]	0.07 [-0.10, 0.24]	.60 [.46, .74]
		LAC	0.82 [0.67, 0.98]		
	LAC	LAC	1.17 [1.03, 1.30]	-0.29 [-0.47, -0.10]	
		GSC	0.88 [0.72, 1.06]		
Shared (31% of total)	GSC	GSC	0.50 [0.21, 0.94]	0.10 [-0.45, 0.61]	.65 [.49, .81]
		LAC	0.61 [0.25, 0.99]		
	LAC	LAC	1.29 [0.85, 2.23]	-0.60 [-1.44, 0.06]	
		GSC	0.67 [0.28, 1.06]		

Table 2

Experiment 2: Group-level parameter estimates of λ and correlation between individual LAC and GSC λ estimates. The values in brackets correspond to Bayesian highest-density 95% intervals.

with the LAC were more likely to choose the riskier mean-preserving spreads in the second session than in the first condition, increasing from 28.1% to 34.9%, $d_z = 0.411$, 95% CI: [0.028, 0.773]. In turn, people starting with the GSC largely maintained their propensity to choose riskier options, with choice proportions not substantially decreasing from 43.7% in the first session to 40.5% in the second, $d_z = 0.199$, 95% CI: [-0.188, 0.574] (see Figure 4A). These patterns of results can be seen in a larger set of lotteries as well (Figure 4B). Once again, individual risky-choice proportions were strongly correlated across conditions ($r(56) = .875$ [.796, .925], $p < .001$).

The λ estimates tell a slightly different story: As reported in Table 3, while the point parameter estimates suggest a slight decrease from the LAC ($M(\lambda_{\text{LAC}}) = 1.712$) to the GSC ($M(\lambda_{\text{GSC}}) = 1.095$) when participants started in the LAC, their low precision renders this difference inconclusive. In fact, none of the mean λ estimates was reliably above or below 1. This low precision is quite surprising in light of the previous findings, the larger number of lottery pairs, as well as the concurrent observation that the individual λ estimates are strongly correlated across conditions (see also Table A3).

Discussion

The success of combining desirable experimental-design features from the two previous iterations proved to be modest. Although we no longer found carryover effects across conditions, the uncertainty surrounding the parameter estimates in each condition was so high that we were no longer able to derive any group-level conclusions with confidence. One possible explanation is that this uncertainty reflects the deleterious effects of using large number of lottery pairs (for an example and discussion, see Loomes, 2014). However, we do not see how this explanation can be squared with the strong individual differences found across conditions, with correlations of .88 and .92 for behavioral and parametric estimates, respectively. It is clear that participants were not merely guessing in reaction to a demanding task.

A Focused Analysis of Shared Lottery Problems

Up to this point, our analyses have considered all of the lottery problems encountered in both conditions. One concern with this practice is that the loss-aversion estimates obtained are not commensurate due to a violation of 'measurement invariance' (André & de Langhe, 2021b), according to which parameter comparisons are only valid if the stimuli used to obtain their estimates were identical. The purpose of this section is to further elaborate on this issue and to address it directly by conducting a focused analysis that only considers shared trials.

The notion of measurement invariance stems from the psychometric literature, where test items are characterized in terms of how they load onto a number of latent factors (Meredith, 1993). Comparisons that rely on different test items need to ensure that they have the same factor loadings, otherwise commensurability is compromised. One way to try to establish measurement invariance is to rely on the exact same test items.[10] However, when it comes to the specific case of estimating loss aversion by means of prospect theory, the problem faced is arguably different: The relevance of lottery problems involving gains and losses, when it comes

people in the LAC were less likely to choose the riksier mean-preserving spreads ($M = .340$, $SD = .327$) than in the GSC ($M = .391$, $SD = .341$), $t(56) = 2.314$, $p = .024$, $d = 0.307$ (95% CI: [0.039, 0.571]). While this effect is of similar magnitude as that of starting condition, this analysis has higher statistical power as it is a within-subject analysis.

[10]Measurement invariance is never guaranteed though. For example, it can be violated if different groups of individuals engage with the items differently, leading to different factor loadings. Similarly, it can also be violated if the same individuals engage with the items differently across contexts.

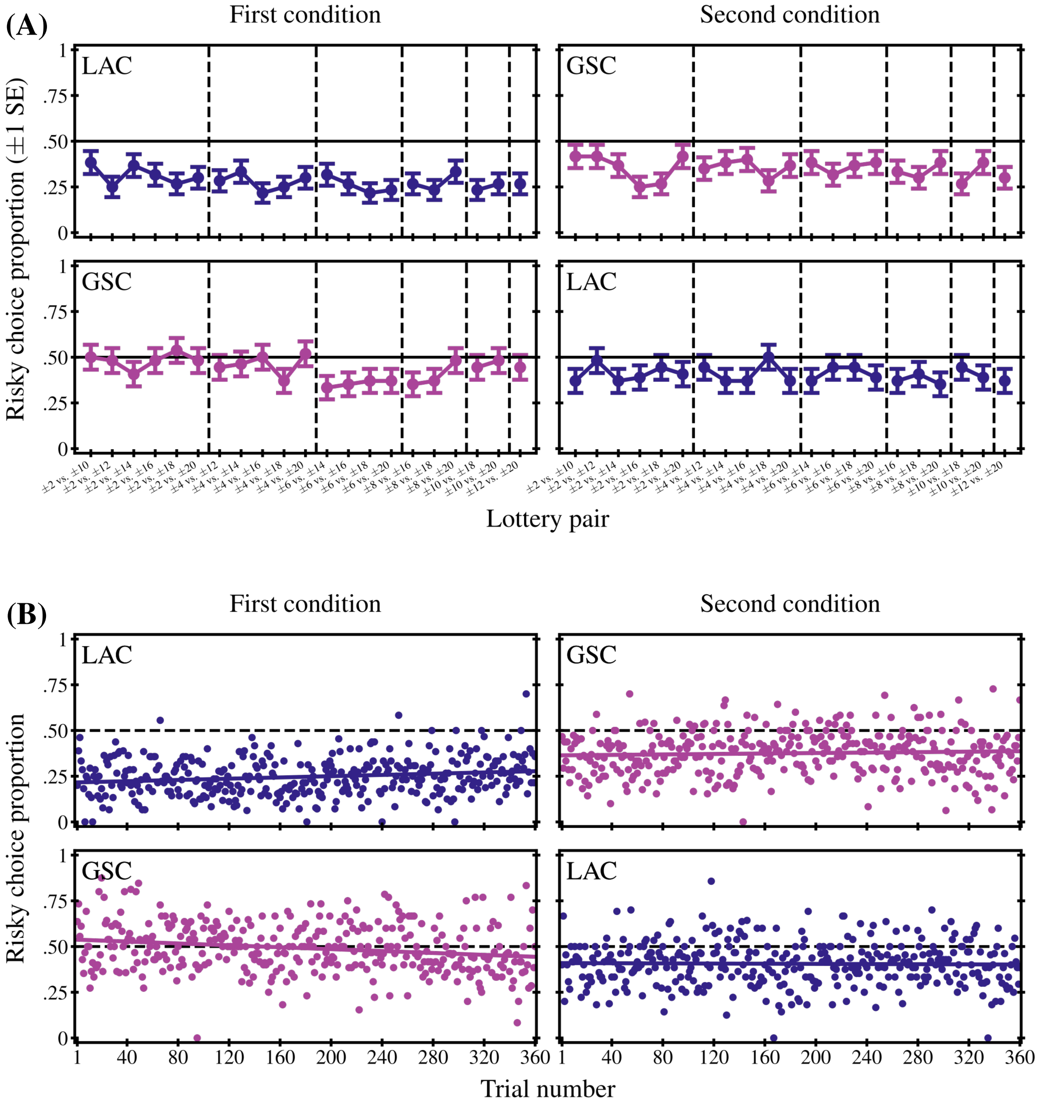

Figure 4

Behavioral results in Experiment 3 as a function of condition and starting condition. Panel A depicts choice proportions of the riskier option in mean-preserving spreads (e.g., ±10 vs. ±14 contains a lottery that either wins or loses $ 10 with equal probabilities and one that either wins or loses $ 14 with equal probabilities). Panel B shows aggregated choice proportions of the riskier option among two options with equal expected values. Solid lines depict the fit of simple linear regressions. In both panels, choice proportions below 50% reflect loss aversion, those above 50% gain seeking. LAC = loss aversion condition. GSC = gain seeking condition.

to the question of loss aversion, is not a to-be-determined empirical matter — this relevance is established *a priori* by the theory itself and the model instantiating it (Batchelder, 1998). The way in which the gain and loss outcomes in a lottery speak to loss aversion is formalized by the way in which the latter is operationalized into the model. That being said, there is some degree of ambiguity given that prospect theory is realized by a family of models with varying parametric forms (see, e.g., Stott, 2006).

Even if we take for granted that prospect theory provides an adequate characterization of people's choices, it is likely that the parametric model used to estimate λ is misspecified to some extent, and thereby vulnerable to distortions, especially so when said estimates rely on different subsets of lottery problems (Stewart et al., 2019). André and de Langhe (2021b) provide an illustrative example in which

Trials used	Starting condition	Condition	Mean	Difference	Correlation
All	GSC	GSC	0.84 [0.32, 1.96]	0.04 [-1.02, 1.65]	.92 [.82, .99]
		LAC	0.83 [0.16, 2.19]		
	LAC	LAC	1.71 [0.92, 2.56]	-0.59 [-1.36, 0.28]	
		GSC	1.10 [0.36, 2.01]		
Shared (36% of total)	GSC	GSC	0.67 [0.16, 2.02]	0.06 [-1.30, 1.30]	.90 [.76, .99]
		LAC	0.75 [0.16, 1.88]		
	LAC	LAC	1.17 [0.22, 2.61]	-0.42 [-1.96, 1.32]	
		GSC	0.74 [0.14, 1.99]		

Table 3

Experiment 3: Group-level parameter estimates of λ and correlation between individual LAC and GSC λ estimates. The values in brackets correspond to Bayesian highest-density 95% intervals.

accept/reject choices regarding GSC and LAC lotteries are governed by a prospect theory model assuming a logarithmic value function (concave/convex for gains/losses) without loss aversion (i.e., $\lambda = 1$). Fitting these choices with Walasek and Stewart's (2015) model, which assumes a *linear* value function and estimates loss aversion, results in spurious differences in λ across conditions, with λ taking on values smaller/larger than 1 for GSC/LAC lotteries.

To address the concern that a violation of measurement invariance is the main driver of our results, we refitted our prospect theory model on the subset of lottery problems that were shared across both conditions. The results obtained, which can be found in the bottom halves of Tables 1 to 3, are very similar to the outcomes of our original analyses; The only noteworthy difference between these two analyses lies in the precision of the parameter estimates, something that is to be expected if the estimation is based on just 5%–36% of the original data. Importantly, the robust positive correlations for λ across conditions corroborate the considerable degree of stability of individual differences (see also Tables A1–A3).

A Non-Parametric Take

To better understand the choice behavior underlying the estimated differences in loss aversion, we also conducted an additional non-parametric analysis of loss aversion. Assuming that the curvature of the utility function is identical for gains and losses, it is possible to derive general qualitative predictions that hold under all parametric assumptions of prospect theory. These predictions are closely related to the behavioral definition of loss aversion as introduced by Brooks and Zank (2005) and used for the behavioral analyses reported here. This analysis extends it to the complete set of mean-preserving spreads.

We rely on the data of the first condition of Experiment 2, as it had the clearest effect of the experimental condition. If individuals are loss averse, then the probabilities of choosing the riskier option $P(R)$ for the fifteen lottery pairs displayed in Figure 3A and indexed in Table 4 must satisfy the following system of inequalities:

$$\begin{aligned}
\tfrac{1}{2} &\geq P(R_{1,1}) \geq P(R_{1,2}) \geq P(R_{1,3}) \geq P(R_{1,4}) \geq P(R_{1,5}),\\
\tfrac{1}{2} &\geq P(R_{2,1}) \geq P(R_{2,2}) \geq P(R_{2,3}) \geq P(R_{2,4}),\\
\tfrac{1}{2} &\geq P(R_{3,1}) \geq P(R_{3,2}) \geq P(R_{3,3}),\\
\tfrac{1}{2} &\geq P(R_{4,1}) \geq P(R_{4,2}),\\
P(R_{2,1}) &\geq P(R_{1,2}),\\
P(R_{2,2}) &\geq P(R_{1,3}),\\
P(R_{4,1}) &\geq P(R_{3,2}) \geq P(R_{2,3}) \geq P(R_{1,4}),\\
P(R_{5,1}) &\geq P(R_{4,2}) \geq P(R_{3,3}) \geq P(R_{2,4}) \geq P(R_{1,5}).
\end{aligned} \tag{1}$$

In contrast, if individuals are gain seeking, then a mirrored system of inequalities is expected to hold (replace all $\geq$ with $\leq$). It is important to point out that both systems of inequalities impose severe constraints. To see this, consider the space of all possible choice probabilities, which in this case can be represented as a 15-dimensional hypercube with a volume of 1. The probabilities satisfying the inequalities occupy less than *one-hundred billionth* of said volume. Therefore, if people do not strictly choose in line with the predictions of loss-averse or gain-seeking behavior as established by prospect theory, it is extremely unlikely that these inequalities will hold. In spite of this, the choice data obtained in the GSC and LAC of the GSC- and LAC-first groups in Experiment 2 are in line with the systems of inequalities associated with gain-seeking and loss-averse preferences, respectively (largest $G^2 = 2.692$, with smallest *strictest* $p = .050$).[11] Not surprisingly, they were also found to be at odds with the in-

[11]For order-constrained null hypotheses, the G^2 statistic follows

equalities associated with the opposite preferences (smallest $G^2 = 20.475$, $p < .001$).

However, these results would also be consistent with the hypothesis that there is no real difference in terms of risky-choice probabilities beyond being above/below 50% (e.g., André & de Langhe, 2021b). One way to evaluate this hypothesis while sidestepping the challenges associated with order-constrained inference (e.g., Davis-Stober, 2009; Heck & Davis-Stober, 2019; Sarafoglou et al., 2021) is to sample choice probabilities from the posterior distributions and check the proportions that conform to a weaker version of the aforementioned inequalities that omit the $\frac{1}{2}$ terms (in red).[12] The ratio of these proportions is expected to be 1 if choice probabilities are roughly the same across the board (i.e., mirrored opposite patterns are equally likely to be sampled). In the GSC of the GSC-first group, the ratio (corresponding to a Bayes factor; see Karabatsos, 2005) was 230, indicating much greater chances of sampling gain-seeking preferences from the posterior distributions. In contrast, in the LAC of the LAC-first group, loss-averse preferences were 780 times more probable.

Taken together, the non-parametric analyses corroborate the λ estimates obtained across conditions, and speak to the adequacy of the parametric prospect theory model adopted throughout this work.

General Discussion

The goal of the present work was to rigorously explore the context dependency of loss aversion originally reported by Walasek and Stewart (2015) using a two-alternative forced-choice task alongside a within-subject manipulation of the outcome distributions (i.e., the choice contexts). This approach has a number of advantages: i) it allows one to estimate prospect theory's parameter, in particular the loss aversion parameter λ, with a higher precision (Broomell & Bhatia, 2014; Walasek & Stewart, 2021), ii) it enables the estimation of behavioral loss aversion (Brooks & Zank, 2005), iii) it sidesteps existing concerns regarding the type of evaluation driving choices (André & de Langhe, 2021a, 2021b), and iv) it permits the assessment of individual differences and their relative stability.

Across three experiments, we found loss-aversion estimates — behavioral and parametric — to shift as a function of outcome distributions, vindicating Walasek and Stewart's (2015) original report. However, a much more complex picture emerged than the one painted in the literature so far: First, we found that individual differences were quite stable. That is, people's relative weighting of gains and losses tended to be preserved across choice contexts, even when there was an overall shift in loss aversion.[13] We also found the influence of context on loss aversion to be rather small, at least after the first outcome distribution was encountered. Surprisingly, this carryover effect persevered even when the different choice contexts were encountered at least a week apart. The effect of outcome distribution in people's choices appears to be quite difficult to override.

One of the limitations of Walasek and Stewart's (2015) study was its vulnerability to model misspecification. The model used to estimate loss aversion assumed that a) subjective values are well described by a linear value function, and b) that each accept/reject judgment is based on an independent evaluation of a single lottery. Not only can either assumption fail under plausible assumptions, such a failure can easily result in spurious changes in loss aversion across conditions. The examples reported by André and de Langhe (2021a, 2021b) showed how either a model with a curved non-linear value function or a mental accounting of advantageous lotteries can replicate the results reported by Walasek and Stewart (2015). Fortunately, both alternative accounts are directly addressed in our study. On one hand, we were able to estimate λ while allowing the value function to be curvilinear. On the other, our reliance on paired comparisons rendered the accounting of past choices as the decision-making process impossible.

Auxiliary assumptions aside, there is the more general question of whether prospect theory provides a valid account of human choices, and therefore of the differences observed across conditions. Fortunately, the status of our main results does not depend on the validity of prospect theory; They will hold even if the results are to be explained in terms of a change in attention exchange (e.g., Birnbaum, 2008), outcome-ratio evaluations (e.g., De Langhe & Puntoni, 2015), or a shift in risk preferences that is not based on utility functions (e.g., Coombs & Pruitt, 1960; Lopes, 1981). For example, according to the risk-as-variance perspective of expected-utility theory, people's choices in mean-preserving pairs reflect their general risk attitudes rather than their loss aversion. The important point is that, regardless of the exact processes leading to a decision, they are shown to be sen-

a mixture of χ^2 distributions. The strictest sampling distribution corresponds to a equal-weight mixture of two χ^2 distributions with zero and one degree of freedom (for an overview, see Davis-Stober, 2009).

[12] For each binomial distribution of choices, we assumed a Dirichlet prior with concentration parameter $\boldsymbol{\alpha} = (1, 1)$. This (arguably non-informative) distribution establishes that any value of $P(R)$ is equally likely a priori. For k risky choices over n observations, the posterior distribution of $P(R)$ corresponds to a Dirichlet distribution with parameter $\boldsymbol{\alpha} = (k + 1, n - k + 1)$.

[13] Compared to similar studies investigating the relative stability of loss aversion (e.g., Glöckner & Pachur, 2012), our estimates were substantially higher, particularly so in Experiment 3. This difference is likely due to our streamlined experimental design: All lotteries in our experiments had two outcomes with 50% probability of occurrence each. An advantage of this design is that it keeps the complexity of lotteries constant, not allowing it to play a confounding role (Kellen et al., 2017; Zilker et al., 2020).

Index	Lottery Pair (S vs. R)	GSC–GSC: $P(R)$	LAC–LAC: $P(R)$
1, 1	±12 vs. ±16	.67	.52
1, 2	±12 vs. ±20	.75	.49
1, 3	±12 vs. ±24	.65	.43
1, 4	±12 vs. ±28	.71	.43
1, 5	±12 vs. ±32	.68	.41
2, 1	±16 vs. ±20	.65	.51
2, 2	±16 vs. ±24	.65	.48
2, 3	±16 vs. ±28	.72	.39
2, 4	±16 vs. ±32	.73	.45
3, 1	±20 vs. ±24	.65	.45
3, 2	±20 vs. ±28	.71	.43
3, 3	±20 vs. ±32	.70	.42
4, 1	±24 vs. ±28	.61	.44
4, 2	±24 vs. ±32	.66	.46
5, 1	±28 vs. ±32	.66	.45

Table 4

Choice proportions in mean-preserving spreads in Experiment 2. The 'Index' column refers to the subscripts in the inequalities in Equation 1. The lottery pairs and choice proportions refer to those reported in Figure 3. S is always the safer of the two options, while R is the riskier. Choice proportions P(R) of the riskier option below 50% reflect loss aversion, whereas those above 50% indicate gain-seeking preferences. LAC = loss aversion condition. GSC = gain seeking condition.

sitive to the context in which they take place. Appraising the empirical merit of different theoretical accounts such as the ones described above is beyond the scope of the present work, as that would require the deployment of tailored experimental studies.

That being said, our results, in conjunction with previous research on this topic (Walasek & Stewart, 2015, 2019), highlight the need for theoretical accounts that incorporate context dependencies. For example, Parducci's (1965) range–frequency theory assumes that the evaluation of different attributes such as gains and losses depends on the context in which they occur (e.g., their ranges) while still maintaining the ability to identify context-free representations of stimuli (Birnbaum, 1974). More recently, Stewart et al. (2006) proposed a conceptually similar approach entitled *decision by sampling*, according to which preferences are constructed by means of a memory-retrieval process. In a nutshell, a sample from memory is drawn and the decision maker compares each sample with the options' attributes in a binary manner (better/worse?). These comparisons allow the decision maker to establish how these attributes rank, ranks that are then used to form preferences. According to these two theoretical accounts, participants should be loss averse and gain seeking in the LAC and GSC, respectively: For example, in a LAC where gains go up to $40 and losses down to -$20, a gain of $12 is not perceived as extreme as a loss $12. The opposite scenario occurs in a GSC where gains go up to $20 and losses down to $40. However, they fail to provide an adequate dynamic account: A visual inspection of how preferences develop throughout the experimental blocks/sessions (see Figure 2, Figure 3, and Figure 4) shows that the effects of context are already present in the earliest choice trials, barely changing later on (see also Alempaki et al., 2019; Zhao et al., 2020).

The joint occurrence of a high degree of inter-individual stability of loss aversion and the main effect of context is best understood within the framework of latent state–trait theory (e.g., Steyer et al., 1999). The stability reflects a high contribution of a trait-like disposition that would correspond to 'loss aversion'. This disposition is manifested across contexts, whereas the state influence is best described in terms of a main effect (i.e., it affects all individuals to the same extent). As an alternative perspective, choices could be understood as being governed by two independent processes, one of which is the overall tendency to trade off gains and losses, the other being a situation-specific effect of context that, in light of the high stability across contexts, is of smaller magnitude than the general tendency.

However, the observed order effects make it difficult to quantify and make sense of the exact nature of the contextual/state influence, such that further work exploring its impact is needed. A consistent finding across our experiments was that people's attitudes towards losses were almost unaffected by the LAC if they first encountered the GSC, even if both conditions were separated by more than a week. It is likely that the GSC, containing mostly highly disadvantageous lotteries with negative expected values, is uncommon in behavioral research such that it exerts a long-lasting shift in strategies adopted by decision makers. While further research is needed, such asymmetrical influences of experimental conditions might explain the fragility of loss aversion reported in recent studies (Chapman et al., 2022; Walasek et al., 2018).

The study of context dependencies is likely to shed light over ongoing debates on the neural processes involved in preferential choice: De Martino et al. (2010) reported a positive relationship between activity in the amygdala and loss aversion, whereas no such relationship was found by Tom et al. (2007). De Martino et al. attributed this discrepancy in part to differences in lottery favorableness (see also Canessa et al., 2013), an account that is corroborated by the present results. It is possible that the contributions of different neural structures and their associated functions can vary across contexts.

The concept of 'context' and its limits also deserves further scrutiny. In the present work, we treated different blocks of choice trials or experimental sessions as distinct contexts. However, there are good reasons to adopt a more fine-grained understanding that discriminates between different types of choice trials (for recent examples, see Davis-Stober & Brown, 2013; Kellen et al., 2017). One notable example is the work by Chechile and Cooke (1997), who demonstrated systematic shifts in the relative weighting of gains and losses across different type of lottery pairs. In their study, participants engaged in a *probability-matching task* in which individuals matched a reference lottery $R = \begin{pmatrix} \$50 & -\$50 \\ p & 1-p \end{pmatrix}$ with a comparison lottery $C = \begin{pmatrix} \$y & -\$z \\ q & 1-q \end{pmatrix}$ by setting its probability q. Chechile and Cooke found that when R was unfavorable (e.g., $p = .10$), individuals tended to be gain seeking, overweighting gains relative to losses (i.e., $\lambda < 1$). In contrast, when R was favorable (i.e., $p = .90$) they tended to be loss averse, overweighting losses relative to gains (i.e., $\lambda > 1$). Follow-up work refined the original methodology (Chechile & Butler, 2000, 2003; Chechile & Luce, 1999) but the take-home message is the same: The subjective representation of outcomes is context dependent, varying as a function of the favorableness of the reference lottery. Future work should attempt to reconcile these results with Walasek and Stewart's and the present ones.

Constraints on Generality

The present work relied on choices made by college students (Exps. 1 and 3) and a more representative sample of the general English-speaking population (Exp. 2) regarding hypothetical (but incentivized) monetary outcomes. Given that these characteristics are shared by a very large segment of work in psychology, experimental economics, and cognitive neuroscience, we see little reason to expect the results reported here to not generalize to them. With the prominence and importance of loss aversion as a theoretical concept, further research is needed to establish how people's behavior is affected by context dependencies '*in the wild*'.

References

Abdellaoui, M., Bleichrodt, H., & Paraschiv, C. (2007). Loss aversion under prospect theory: A parameter-free measurement. *Management Science*, *53*(10), 1659–1674. https://doi.org/10.1287/mnsc.1070.0711

Alempaki, D., Canic, E., Mullett, T. L., Skylark, W. J., Starmer, C., Stewart, N., & Tufano, F. (2019). Reexamining how utility and weighting functions get their shapes: A quasi-adversarial collaboration providing a new interpretation. *Management Science*, *65*(10), 4841–4862. https://doi.org/10.1287/mnsc.2018.3170

André, Q., & de Langhe, B. (2021a). How (not) to test theory with data: Illustrations from Walasek, Mullett, and Stewart (2020). *Journal of Experimental Psychology: General*, *150*(12), 2671–2674. https://doi.org/10.1037/xge0001053

André, Q., & de Langhe, B. (2021b). No evidence for loss aversion disappearance and reversal in Walasek and Stewart (2015). *Journal of Experimental Psychology: General*, *150*(12), 2659–2665. https://doi.org/10.1037/xge0001052

Barberis, N., Huang, M., & Santos, T. (2001). Prospect theory and asset prices. *The Quarterly Journal of Economics*, *116*(1), 1–53. https://doi.org/10.1162/003355301556310

Batchelder, W. H. (1998). Cognitive psychometrics: Using multinomial processing tree models as measurement tools. In S. E. Embretson (Ed.), *Measuring psychological constructs: Advances in model-based approaches* (pp. 71–93). American Psychological Association.

Benartzi, S., & Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics*, *110*(1), 73–92. https://doi.org/10.2307/2118511

Birnbaum, M. H. (1974). Using contextual effects to derive psychophysical scales. *Perception & Psychophysics*, *15*(1), 89–96. https://doi.org/10.3758/BF03205834

Birnbaum, M. H. (2008). New paradoxes of risky decision making. *Psychological Review*, *115*(2), 463–501. https://doi.org/10.1037/0033-295X.115.2.463

Booij, A. S., van Praag, B. M. S., & van de Kuilen, G. (2010). A parametric analysis of prospect theory's functionals for the general population. *Theory and Decision*, *68*(1-2), 115–148. https://doi.org/10.1007/s11238-009-9144-4

Botvinik-Nezer, R., Holzmeister, F., Camerer, C. F., Dreber, A., Huber, J., Johannesson, M., Kirchler, M., Iwanir, R., Mumford, J. A., Adcock, R. A., Avesani, P., Baczkowski, B. M., Bajracharya, A., Bakst, L., Ball, S., Barilari, M., Bault, N., Beaton, D., Beitner, J., … Schonberg, T. (2020). Variability in the analysis of a single neuroimaging dataset by many teams. *Nature*, (November 2019). https://doi.org/10.1038/s41586-020-2314-9

Boyce, C. J., Wood, A. M., & Ferguson, E. (2016). Individual differences in loss aversion: Conscientiousness predicts how life satisfaction responds to losses versus gains in income. *Personality and Social Psychology Bulletin*, *42*(4), 471–484. https://doi.org/10.1177/0146167216634060

Brooks, P., & Zank, H. (2005). Loss averse behavior. *Journal of Risk and Uncertainty*, *31*(3), 301–325. https://doi.org/10.1007/s11166-005-5105-7

Broomell, S. B., & Bhatia, S. (2014). Parameter recovery for decision modeling using choice data. *Decision*, *1*(4), 252–274. https://doi.org/10.1037/dec0000020

Brown, A. L., Imai, T., Vieider, F. M., & Camerer, C. F. (2022). Meta-analysis of empirical estimates of loss aversion. *Journal of Economic Literature*. https://doi.org/10.1257/jel.20221698

Camerer, C. F. (2000). Prosect theory in the wild: Evidence from the field. In D. Kahneman & A. Tversky (Eds.), *Choices, values, and frames* (pp. 288–300). Cambridge University Press.

Camerer, C. F. (2005). Three cheers—psychological, theoretical, empirical—for loss aversion. *Journal of Marketing Research*, *42*(2), 129–133. https://doi.org/10.1509/jmkr.42.2.129.62286

Canessa, N., Crespi, C., Motterlini, M., Baud-Bovy, G., Chierchia, G., Pantaleo, G., Tettamanti, M., & Cappa, S. F. (2013). The functional and structural neural basis of individual differences in loss aversion. *Journal of Neuroscience*, *33*(36), 14307–14317. https://doi.org/10.1523/JNEUROSCI.0497-13.2013

Carpenter, B., Gelman, A., Hoffman, M. D., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M., Guo, J., Li, P., & Riddell, A. (2017). Stan: A probabilistic programming language. *Journal of Statistical Software*, *76*(1), 1–32. https://doi.org/10.18637/jss.v076.i01

Chapman, J., Snowberg, E., Wang, S., & Camerer, C. (2022, July). *Looming large or seeming small? Attitudes towards losses in a representative sample*, National Bureau of Economic Research. https://doi.org/10.3386/w30243

Chechile, R. A., & Butler, S. F. (2000). Is "generic utility theory" a suitable theory of choice behavior for gambles with mixed gains and losses? *Journal of Risk and Uncertainty*, *20*(2), 189–211. https://doi.org/10.1023/a:1007833125015

Chechile, R. A., & Butler, S. F. (2003). Reassessing the Testing of Generic Utility Models for Mixed Gambles. *Journal of Risk and Uncertainty*, *26*(1), 55–76. https://doi.org/10.1023/a:1022250307197

Chechile, R. A., & Cooke, A. D. J. (1997). An experimental test of a general class of utility models: Evidence for context dependency. *Journal of Risk and Uncertainty*, *14*(1), 75–93. https://doi.org/Doi10.1023/A:1007773804402

Chechile, R. A., & Luce, R. D. (1999). Reanalysis of the Chechile-Cooke experiment: Correcting for mismatched gambles. *Journal of Risk and Uncertainty*, *18*(3), 321–325. https://doi.org/Doi10.1023/A:1011156710779
240qq Times Cited:8 Cited References Count:9.

Coombs, C. H., & Pruitt, D. G. (1960). Components of risk in decision making: Probability and variance preferences. *Journal of Experimental Psychology*, *60*(5), 265–277. https://doi.org/10.1037/h0041444

Davis-Stober, C. P. (2009). Analysis of multinomial models under inequality constraints: Applications to measurement theory. *Journal of Mathematical Psychology*, *53*(1), 1–13.

Davis-Stober, C. P., & Brown, N. (2013). Evaluating decision maker "type" under p-additive utility representations. *Journal of Mathematical Psychology*, *57*(6), 320–328. https://doi.org/10.1016/j.jmp.2013.08.002

De Langhe, B., & Puntoni, S. (2015). Bang for the buck: Gain-loss ratio as a driver of judgment and choice. *Management Science*, *61*(5), 1137–1163. https://doi.org/10.1287/mnsc.2014.2045

De Martino, B., Camerer, C. F., & Adolphs, R. (2010). Amygdala damage eliminates monetary loss aversion. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(8), 3788–3792. https://doi.org/10.1073/pnas.0910230107

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, *47*(2), 315–372. https://doi.org/10.1257/jel.47.2.315

Ert, E., & Erev, I. (2013). On the descriptive value of loss aversion in decisions under risk: Six clarifications. *Judgment and Decision making*, *8*(3), 214–235.

Frydman, C., & Jin, L. J. (2022). Efficient coding and risky choice. *The Quarterly Journal of Economics*, *137*(1), 161–213. https://doi.org/10.1093/qje/qjab031

Gal, D., & Rucker, D. D. (2018). The loss of loss aversion: Will it loom larger than its gain? *Journal of Consumer Psychology*, *28*(3), 497–516. https://doi.org/10.1002/jcpy.1047

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). *Bayesian data analysis* (3rd ed.). CRC Press.

Glöckner, A., & Pachur, T. (2012). Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory. *Cognition*, *123*(1), 21–32. https://doi.org/10.1016/j.cognition.2011.12.002

Halpern, S. D., French, B., Small, D. S., Saulsgiver, K., Harhay, M. O., Audrain-McGovern, J., Loewenstein, G., Brennan, T. A., Asch, D. A., & Volpp, K. G. (2015). Randomized trial of four financial-incentive programs for smoking cessation. *New England Journal of Medicine*, *372*(22), 2108–2117. https://doi.org/10.1056/NEJMoa1414293

Heck, D. W., & Davis-Stober, C. P. (2019). Multinomial models with linear inequality constraints: Overview and improvements of computational methods for bayesian inference. *Journal of Mathematical Psychology*, *91*, 70–87.

Hofmeyr, A., & Kincaid, H. (2019). Prospect theory in the wild: how good is the nonexperimental evidence for prospect theory? *Journal of Economic Methodology*, *26*(1), 13–31. https://doi.org/10.1080/1350178X.2018.1561072

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–292. https://doi.org/10.2307/1914185

Karabatsos, G. (2005). The exchangeable multinomial model as an approach to testing deterministic axioms of choice and measurement. *Journal of Mathematical Psychology*, *49*(1), 51–69.

Kellen, D., Mata, R., & Davis-Stober, C. P. (2017). Individual classification of strong risk attitudes: An application across lottery types and age groups. *Psychonomic Bulletin & Review*, *24*(4), 1341–1349. https://doi.org/10.3758/s13423-016-1212-5

Kellen, D., Pachur, T., & Hertwig, R. (2016). How (in)variant are subjective representations of described and experienced risk and rewards? *Cognition*, *157*, 126–138. https://doi.org/10.1016/j.cognition.2016.08.020

Lewandowski, D., Kurowicka, D., & Joe, H. (2009). Generating random correlation matrices based on vines and extended onion method. *Journal of Multivariate Analysis*, *100*(9), 1989–2001. https://doi.org/10.1016/j.jmva.2009.04.008

Loomes, G. (2014). Quantitative tests of the perceived relative argument model: Reply to Guo and Regenwetter (2014). *Psychological Review*, *121*(4), 706–710.

Lopes, L. L. (1981). Decision making in the short run. *Journal of Experimental Psychology: Human Learning & Memory*, *7*(5), 377–385. https://doi.org/10.1037/0278-7393.7.5.377

Meredith, W. (1993). Measurement invariance, factor analysis and factorial invariance. *Psychometrika*, *58*(4), 525–543. https://doi.org/10.1007/BF02294825

Nilsson, H., Rieskamp, J., & Wagenmakers, E.-J. (2011). Hierarchical Bayesian parameter estimation for cumulative prospect theory. *Journal of Mathematical Psychology*, *55*(1), 84–93. https://doi.org/10.1016/j.jmp.2010.08.006

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance*, *53*(5), 1775–1798. https://doi.org/10.1111/0022-1082.00072

Parducci, A. (1965). Category judgment: A range-frequency model. *Psychological Review*, *72*(6), 407–418. https://doi.org/10.1037/h0022602

Rakow, T., Cheung, N. Y., & Restelli, C. (2020). Losing my loss aversion: The effects of current and past environment on the relative sensitivity to losses and gains. *Psychonomic Bulletin & Review*, *27*(6), 1333–1340. https://doi.org/10.3758/s13423-020-01775-y

Sarafoglou, A., Haaf, J. M., Ly, A., Gronau, Q. F., Wagenmakers, E.-J., & Marsman, M. (2021). Evaluating multinomial order restrictions with bridge sampling. *Psychological Methods*.

Scheibehenne, B., & Pachur, T. (2015). Using Bayesian hierarchical parameter estimation to assess the generalizability of cognitive models of choice. *Psychonomic Bulletin & Review*, *22*(2), 391–407. https://doi.org/10.3758/s13423-014-0684-4

Schneider, S., Kauffman, S., & Ranieri, A. (2016). The effects of surrounding positive and negative experiences on risk taking. *Judgment and Decision Making*, *11*(5), 424–440.

Sokol-Hessner, P., Hsu, M., Curley, N. G., Delgado, M. R., Camerer, C. F., & Phelps, E. A. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(13), 5035–5040. https://doi.org/10.1073/pnas.0806761106

Spektor, M. S., Kellen, D., Rieskamp, J., & Klauer, K. C. (2023). *Absolute and relative stability of loss aversion across contexts [Data set]*. https://doi.org/10.17605/OSF.IO/28QZS

Stewart, N., Canic, E., & Mullett, T. L. (2019). *On the futility of estimating utility functions: Why the parameters we measure are wrong, and why they do not generalize*. https://doi.org/10.31234/osf.io/qt69m

Stewart, N., Chater, N., & Brown, G. D. A. (2006). Decision by sampling. *Cognitive Psychology*, *53*(1), 1–26. https://doi.org/10.1016/j.cogpsych.2005.10.003

Steyer, R., Schmitt, M., & Eid, M. (1999). Latent state-trait theory and research in personality and individual differences. *European Journal of Personality*, *13*(5), 389–408. https://doi.org/10.1002/(SICI)1099-0984(199909/10)13:5<389::AID-PER361>3.0.CO;2-A

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty*, *32*(2), 101–130. https://doi.org/10.1007/s11166-006-8289-6

Tom, S. M., Fox, C. R., Trepel, C., & Poldrack, R. A. (2007). The neural basis of loss aversion in decision-making under risk. *Science*, *315*(5811), 515–518. https://doi.org/10.1126/science.1134239

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. https://doi.org/10.1007/BF00122574

Walasek, L., Mullett, T. L., & Stewart, N. (2018). *A meta-analysis of loss aversion in risky contexts*. https://doi.org/10.2139/ssrn.3189088

Walasek, L., & Stewart, N. (2015). How to make loss aversion disappear and reverse: Tests of the decision by sampling origin of loss aversion. *Journal of Experimental Psychology: General*, *144*(1), 7–11. https://doi.org/10.1037/xge0000039

Walasek, L., & Stewart, N. (2019). Context-dependent sensitivity to losses: Range and skew manipulations. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *45*(6), 957–968. https://doi.org/10.1037/xlm0000629

Walasek, L., & Stewart, N. (2021). You cannot accurately estimate an individual's loss aversion using an accept–reject task. *Decision*, *8*(1), 2–15. https://doi.org/10.1037/dec0000141

Zhao, W. J., Walasek, L., & Bhatia, S. (2020). Psychological mechanisms of loss aversion: A drift-diffusion decomposition. *Cognitive Psychology*, *123*, 101331. https://doi.org/10.1016/j.cogpsych.2020.101331

Zilker, V., Hertwig, R., & Pachur, T. (2020). Age differences in risk attitude are shaped by option complexity. *Journal of Experimental Psychology: General*, *149*(9), 1644.

Appendix

Prospect theory model

The streamlined cumulative prospect theory (CPT) model was implemented within a hierarchical Bayesian framework. According to this model, the subjective valuation $V(A)$ of lottery A with the outcomes A_1 and A_2 is given by

$$V(A) = U(A_1) \times .50 + U(A_2) \times .50, \text{ where}$$
$$U(x) = \begin{cases} x^\alpha & \text{if} \quad x \geq 0 \\ -\lambda \times |x|^\alpha & \text{if} \quad x < 0. \end{cases}$$

Choices on each trial were given by a logit link function with choice-sensitivity parameter θ that governs the stochasticity of choices, such that choices become deterministic as $\lim_{\theta \to \infty}$ and completely random when $\theta = 0$.

Raw individual-level parameters were assumed to stem from a six-dimensional (α, λ, and θ for each of the two conditions) multivariate Gaussian distribution with a vector of means $\boldsymbol{\mu}$ and the variance–covariance matrix Σ. As priors, we used independent standard normal distributions for $\boldsymbol{\mu}$. Σ was decomposed into a correlation matrix Σ_r and a scaling vector $\boldsymbol{\zeta}$. For the correlation matrix Σ_r, we used the vague LKJ(3) prior (Lewandowski et al., 2009). For the scaling vector $\boldsymbol{\zeta}$, we used two independent half-Cauchy distributions with scaling parameters of 1.5. The *No-U-Turn* sampler as implemented in `Stan` (Carpenter et al., 2017) was used to obtain samples from the posterior distributions. The raw parameters were transformed to the $[0, \infty)$ scale using the softplus transformation $f(x) = \log(1 + e^x)$.

Posterior samples were obtained by running four chains in parallel for 15,000 samples each. The first 5,000 samples from each chain were discarded as warmup samples and the last 10,000 samples were thinned by a factor of 40, resulting in 250 posterior samples from each chain or 1,000 posterior samples in total. Convergence was confirmed using the $\hat{R}$ statistic (Gelman et al., 2013, p. 285) for each parameter separately, such that all $\hat{R} < 1.01$.

To assess the model's ability to (qualitatively and quantitatively) predict the phenomena observed in the data (often referred to as the model's "absolute fit"), we have simulated choices from the posterior parameter distribution in order to recreate the results figures reported in the main text using the model's predictions. The resulting figures (Figure A1, Figure A2, and Figure A3) reveal a very close match between the model predictions and the empirical choice proportions.

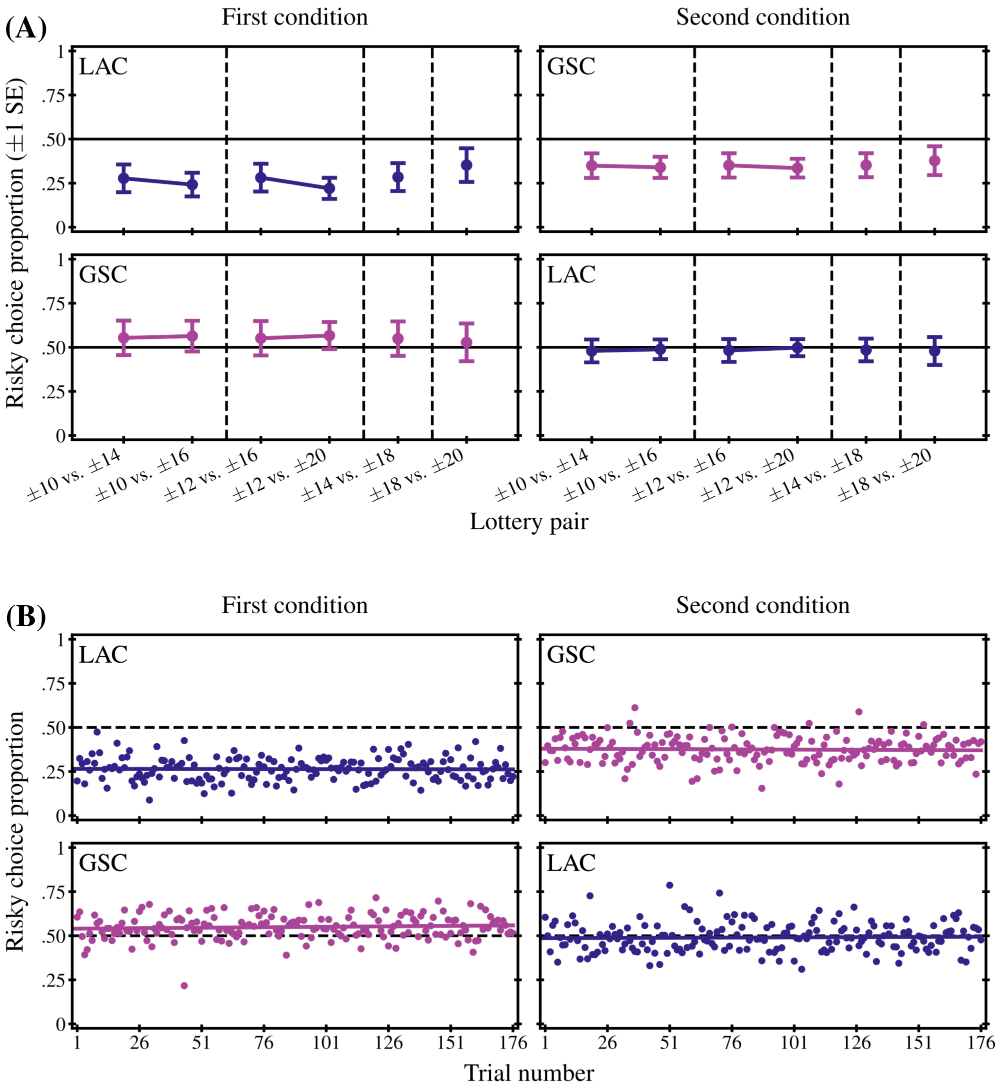

Figure A1

Posterior predictive simulations for Experiment 1 as a function of condition and starting condition. Panel A depicts the predicted choice proportions of the riskier option in mean-preserving spreads. Panel B shows expected choice proportions of the riskier option among two options with equal expected values and expected standardard errors. Solid lines depict the fit of simple linear regressions. In both panels, predicted choice proportions below 50% reflect loss aversion, those above 50% gain seeking. LAC = loss aversion condition. GSC = gain seeking condition.

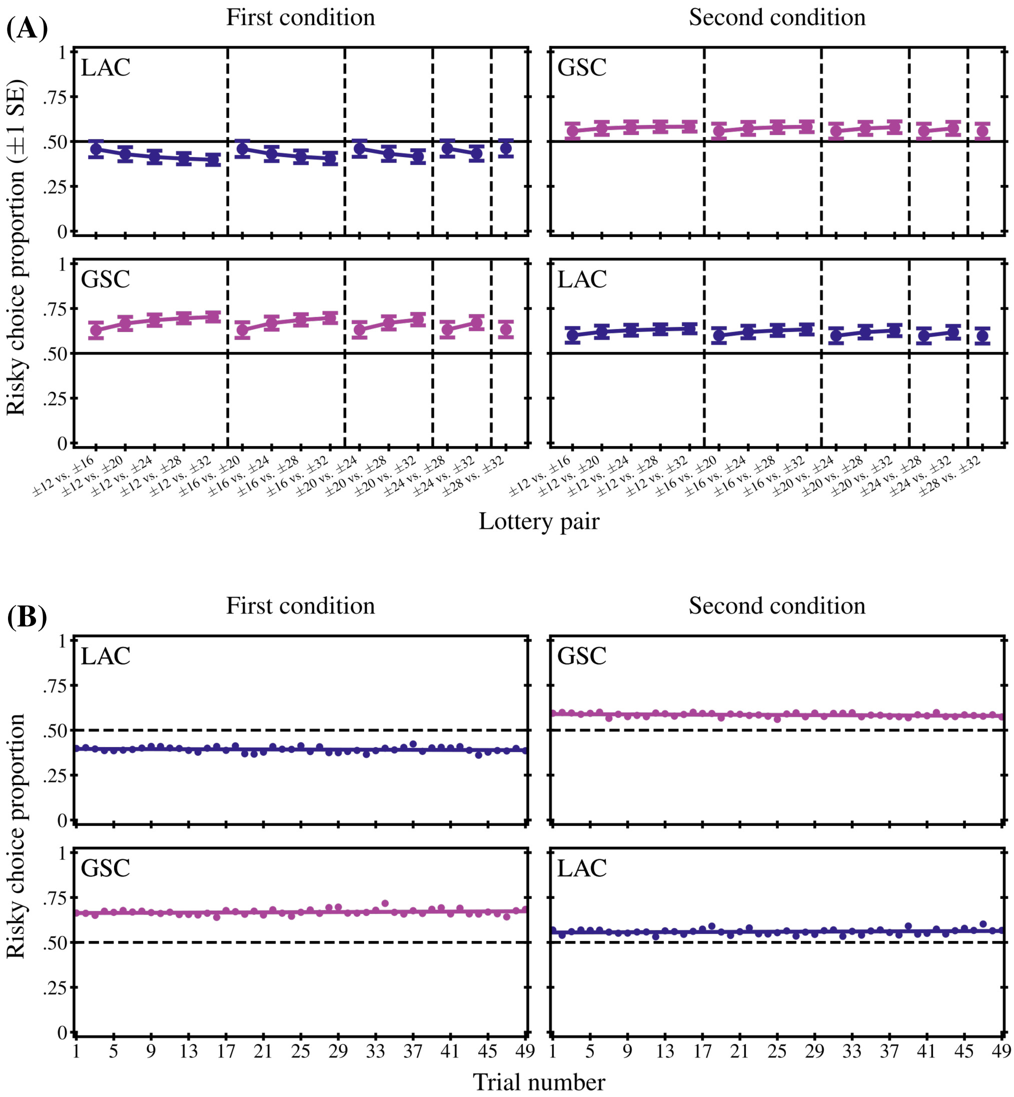

Figure A2

Posterior predictive simulations for Experiment 2 as a function of condition and starting condition. Panel A depicts the predicted choice proportions of the riskier option in mean-preserving spreads. Panel B shows expected choice proportions of the riskier option among two options with equal expected values and expected standardard errors. Solid lines depict the fit of simple linear regressions. In both panels, predicted choice proportions below 50% reflect loss aversion, those above 50% gain seeking. LAC = loss aversion condition. GSC = gain seeking condition.

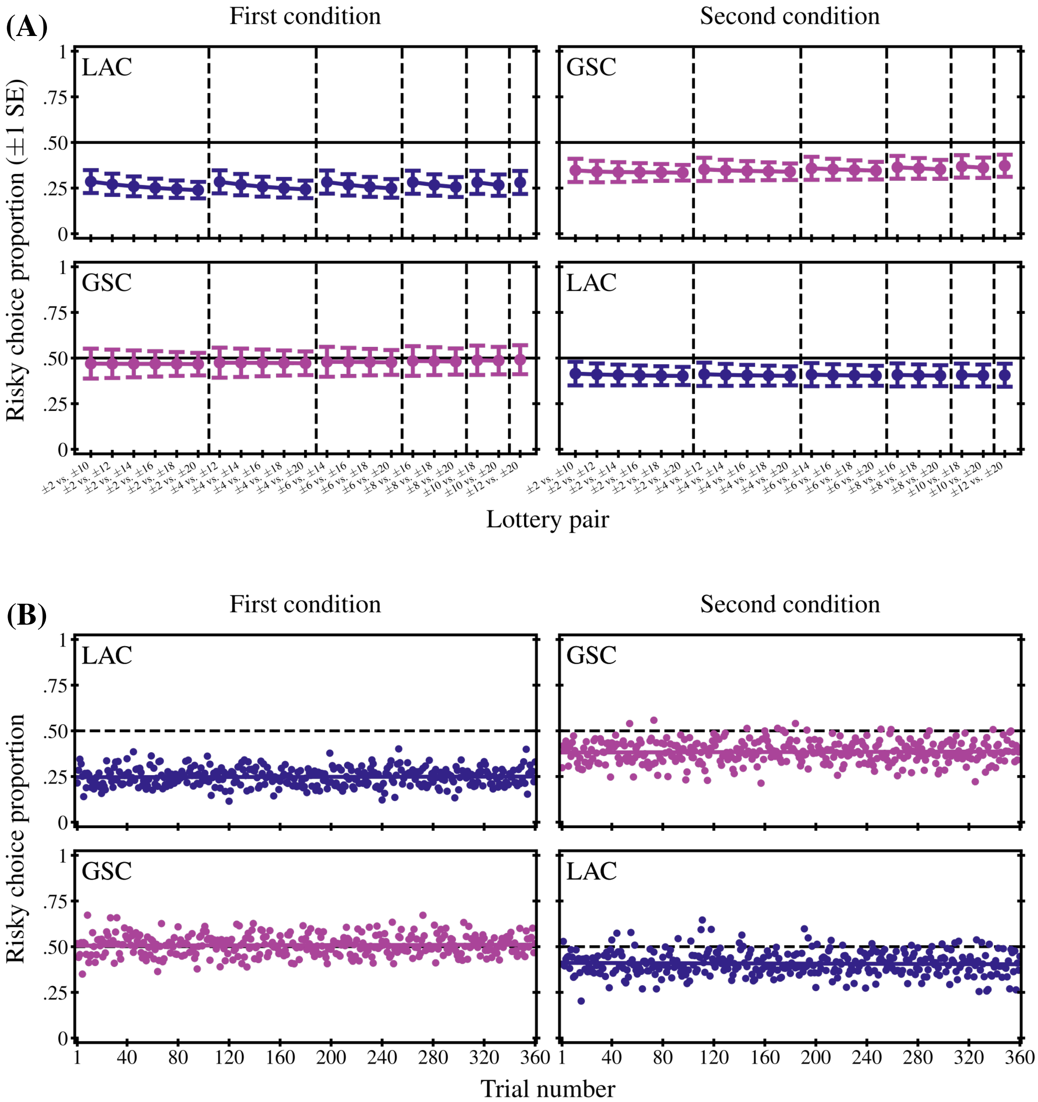

Figure A3

Posterior predictive simulations for Experiment 3 as a function of condition and starting condition. Panel A depicts the predicted choice proportions of the riskier option in mean-preserving spreads. Panel B shows expected choice proportions of the riskier option among two options with equal expected values and expected standardard errors. Solid lines depict the fit of simple linear regressions. In both panels, predicted choice proportions below 50% reflect loss aversion, those above 50% gain seeking. LAC = loss aversion condition. GSC = gain seeking condition.

All trials	θ_{GSC}	λ_{GSC}	α_{GSC}	θ_{LAC}	λ_{LAC}	α_{LAC}
θ_{GSC}		-.19	-.71	.76	-.24	-.44
λ_{GSC}	[-.47, .11]		.12	.05	.46	-.19
α_{GSC}	[-.89, -.53]	[-.20, .41]		-.47	.23	.49
θ_{LAC}	[.58, .91]	[-.23, .33]	[-.74, -.19]		-.05	-.57
λ_{LAC}	[-.49, .02]	[.19, .72]	[-.09, .52]	[-.35, .23]		-.30
α_{LAC}	[-.69, -.17]	[-.50, .09]	[.18, .75]	[-.80, -.33]	[-.56, .02]	
Shared trials	θ_{GSC}	λ_{GSC}	α_{GSC}	θ_{LAC}	λ_{LAC}	α_{LAC}
θ_{GSC}		-.03	-.04	.05	-.05	.14
λ_{GSC}	[-.54, .56]		-.08	.02	.62	-.04
α_{GSC}	[-.58, .55]	[-.64, .42]		.09	-.11	.20
θ_{LAC}	[-.56, .61]	[-.53, .56]	[-.46, .65]		-.02	-.03
λ_{LAC}	[-.61, .45]	[.28, .86]	[-.57, .39]	[-.62, .52]		-.11
α_{LAC}	[-.49, .67]	[-.52, .47]	[-.39, .69]	[-.61, .54]	[-.61, .37]	

Table A1

Parameter correlations across conditions obtained from a streamlined cumulative prospect theory model in Experiment 1, split by fits to all trials and shared trials, respectively. Upper triangular values show posterior means. Lower triangular values depict the 95% highest-density interval of the posterior. Grey shaded cells depict the correlations of the same parameters across the two conditions. GSC = gain-seeking condition. LAC = loss-aversion condition. θ = choice sensitivity of the logistic choice rule. λ = loss aversion coefficient. α = outcome sensitivity of the power-utility function.

All trials	θ_{GSC}	λ_{GSC}	α_{GSC}	θ_{LAC}	λ_{LAC}	α_{LAC}
θ_{GSC}		-.11	-.39	.30	-.03	.30
λ_{GSC}	[-.39, .12]		-.19	-.23	.60	-.12
α_{GSC}	[-.66, -.09]	[-.46, .08]		.28	-.18	-.07
θ_{LAC}	[.07, .51]	[-.44, -.02]	[.02, .55]		-.30	-.41
λ_{LAC}	[-.26, .20]	[.46, .74]	[-.43, .07]	[-.55, -.05]		-.11
α_{LAC}	[.00, .59]	[-.34, .12]	[-.40, .21]	[-.68, -.11]	[-.40, .14]	
Shared trials	θ_{GSC}	λ_{GSC}	α_{GSC}	θ_{LAC}	λ_{LAC}	α_{LAC}
θ_{GSC}		-.13	.00	.13	-.15	.22
λ_{GSC}	[-.61, .41]		-.14	-.16	.65	-.20
α_{GSC}	[-.57, .62]	[-.56, .32]		.20	-.19	.38
θ_{LAC}	[-.45, .68]	[-.62, .36]	[-.39, .69]		-.22	.00
λ_{LAC}	[-.58, .40]	[.49, .81]	[-.62, .27]	[-.75, .33]		-.43
α_{LAC}	[-.37, .71]	[-.53, .25]	[-.20, .81]	[-.55, .49]	[-.76, -.01]	

Table A2

Parameter correlations across conditions obtained from a streamlined cumulative prospect theory model in Experiment 2, split by fits to all trials and shared trials, respectively. Upper triangular values show posterior means. Lower triangular values depict the 95% highest-density interval of the posterior. Grey shaded cells depict the correlations of the same parameters across the two conditions. GSC = gain-seeking condition. LAC = loss-aversion condition. θ = choice sensitivity of the logistic choice rule. λ = loss aversion coefficient. α = outcome sensitivity of the power-utility function.

All trials	θ_{GSC}	λ_{GSC}	α_{GSC}	θ_{LAC}	λ_{LAC}	α_{LAC}
θ_{GSC}		-.10	-.57	.77	-.12	-.40
λ_{GSC}	[-.35, .17]		-.08	-.12	.92	.09
α_{GSC}	[-.75, -.34]	[-.35, .23]		-.28	-.02	.44
θ_{LAC}	[.62, .89]	[-.36, .12]	[-.54, -.01]		-.25	-.61
λ_{LAC}	[-.38, .13]	[.82, .99]	[-.28, .28]	[-.49, -.01]		.23
α_{LAC}	[-.65, -.13]	[-.16, .39]	[.20, .69]	[-.80, -.40]	[-.06, .49]	
Shared trials	θ_{GSC}	λ_{GSC}	α_{GSC}	θ_{LAC}	λ_{LAC}	α_{LAC}
θ_{GSC}		-.37	-.63	.81	-.32	-.40
λ_{GSC}	[-.61, -.10]		.27	-.18	.90	.03
α_{GSC}	[-.83, -.42]	[-.06, .57]		-.47	.21	.72
θ_{LAC}	[.65, .93]	[-.44, .09]	[-.73, -.22]		-.23	-.59
λ_{LAC}	[-.58, -.06]	[.76, .99]	[-.13, .51]	[-.49, .04]		.03
α_{LAC}	[-.69, -.09]	[-.26, .33]	[.49, .91]	[-.79, -.35]	[-.30, .31]	

Table A3

Parameter correlations across conditions obtained from a streamlined cumulative prospect theory model in Experiment 3, split by fits to all trials and shared trials, respectively. Upper triangular values show posterior means. Lower triangular values depict the 95% highest-density interval of the posterior. Grey shaded cells depict the correlations of the same parameters across the two conditions. GSC = gain-seeking condition. LAC = loss-aversion condition. θ = choice sensitivity of the logistic choice rule. λ = loss aversion coefficient. α = outcome sensitivity of the power-utility function.

Exp.	Start. cond.	Cond. no.	Condition	*M* (95% HDI)	M_{Δ} (95% HDI)
1	Aggregated	–	LAC	1.02 [0.89, 1.14]	0.04 [-0.13, 0.24]
			GSC	1.06 [0.91, 1.24]	
	GSC	1	GSC	1.10 [0.85, 1.41]	-0.21 [-0.53, 0.10]
		2	LAC	0.89 [0.72, 1.04]	
	LAC	1	LAC	1.08 [0.88, 1.30]	-0.08 [-0.31, 0.17]
		2	GSC	1.00 [0.83, 1.18]	
2	Aggregated	–	LAC	0.84 [0.78, 0.90]	0.11 [0.02, 0.20]
			GSC	0.95 [0.89, 1.01]	
	GSC	1	GSC	0.89 [0.79, 0.99]	-0.05 [-0.17, 0.08]
		2	LAC	0.84 [0.76, 0.92]	
	LAC	1	LAC	0.81 [0.73, 0.92]	0.18 [0.06, 0.29]
		2	GSC	0.98 [0.90, 1.06]	
3	Aggregated	–	LAC	1.04 [0.91, 1.18]	0.01 [-0.18, 0.22]
			GSC	1.05 [0.86, 1.27]	
	GSC	1	GSC	1.05 [0.80, 1.37]	-0.09 [-0.36, 0.21]
		2	LAC	0.97 [0.84, 1.13]	
	LAC	1	LAC	1.05 [0.84, 1.32]	-0.10 [-0.43, 0.18]
		2	GSC	0.95 [0.72, 1.23]	

Table A4

Group-level parameter estimates of the curvature of the utility function parameter, α, of a streamlined cumulative prospect theory model. Aggregated = across all starting conditions. GSC = gain-seeking condition. LAC = loss-aversion condition. HDI = Bayesian highest-density interval. Δ = difference between conditions.