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Why do people reject mixed gambles?

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Abstract

Decision makers often reject mixed gambles offering equal probabilities of a larger gain and a smaller loss. This important behavioral pattern is generally seen as evidence for loss aversion, a psychological mechanism according to which losses are given higher utility weights than gains. In this paper we consider an alternate mechanism capable of generating high rejection rates: A predecisional bias towards rejection without the calculation of utility. We use a drift diffusion model of decision making to simultaneously specify and test for the effects of these two psychological mechanisms in a gambling task. Our results indicate that high rejection rates for mixed gambles result from multiple different psychological mechanisms, and that a predecisional bias applied prior to the computation of utility (rather than loss aversion) is the primary determinant of this important behavioral tendency.

Keywords: drift diffusion model; risky choice; predecisional bias; loss aversion

Introduction

Consider a gamble that offers you a gain of $11 if a coin toss lands heads, and a loss of $10 if it lands tails. Would you accept or reject this gamble? Most people choose to reject similar positive expected value mixed gambles (gambles that offer both a possibility of a gain and a possibility of a loss; Kahneman & Tversky, 1979; Samuelson, 1960), suggesting an aversion to risk. Yet risk aversion for such small monetary payoffs cannot be easily explained by conventional applications of expected utility theory. Such models predict that anyone who rejects a 50-50 gamble between a gain of $11 and a loss of $10, displays such a strong degree of risk aversion, so as to also reject a 50-50 gamble involving a loss of $100 (regardless of the magnitude of the corresponding gain; Rabin, 2000).

This (clearly unreasonable) prediction presents compelling evidence against expected utility theory, and indicates that additional psychological mechanisms need to be incorporated into models of risky choice in order to account for high rejection rates in mixed gambles (Rabin, 2000). The psychological mechanism that is widely considered to be responsible for these high rejection rates is loss aversion, which states that losses have a greater impact on utility than gains (Kahneman & Tversky, 1979; Kőszegi & Rabin, 2007; Rabin & Thaler, 2001). For example, in the mixed gamble presented at the start of this paper, loss aversion predicts that individuals experience more negative utility from the $10 loss than positive utility from the $11 gain. Thus the gamble, despite having a positive expected value, appears unattractive, and is rejected.

If loss aversion is the only mechanism responsible for the rejection of mixed gambles, an individual's degree of loss aversion can be estimated by observing how likely he or she is to accept or reject such gambles. This measure can then be used to relate loss aversion to various psychological, clinical, and neurobiological variables. Following this logic, researchers have argued that loss aversion plays an important role in irrational financial decision making, problem gambling, suicidal decision making, and incorrect affective forecasting (Hadlaczky et al., 2018; Kermer, Driver-Linn, Wilson, & Gilbert, 2006; Lorains et al., 2014; Takeuchi et al., 2015); in explaining differences in risky decision making between decision contexts (Polman, 2012; Schulreich, Gerhardt, & Heekeren, 2016; Vermeer, Boksem, & Sanfey, 2014) and between individuals with varying psychological traits, demographic profiles, and life experiences (Barkley-Levenson & Galvan, 2014; Bibby & Ferguson, 2011; Pighin, Bonini, Savadori, Hadjichristidis, & Schena, 2014; Sokol-Hessner, Hartley, Hamilton, & Phelps, 2015a); and in determining physiological and neural responses to risky prospects (Canessa et al., 2017; De Martino, Camerer, & Adolphs, 2010; Gelskov, Henningsson, Madsen, Siebner, & Ramsøy, 2015; Lazzaro, Rutledge, Burghart, & Glimcher, 2016; Markett, Heeren, Montag, Weber, & Reuter, 2016; Sokol-Hessner, Lackovic, Tobe, Camerer, Leventhal, et al., 2015b; Tom, Fox, Trepel, & Poldrack, 2007). An influential example of this approach is presented in Tom et al. (2007): In this paper, neural activity is correlated with loss aversion, measured using gamble rejection rates, and is used to identify brain regions that encode loss aversion in risky choices involving mixed gambles.

However, loss aversion may not be the only mechanism responsible for the rejection of mixed gambles. Another possibility, one which we explore in the present paper, is that individuals exhibit a predecisional bias towards rejecting such gambles. Psychologically, this form of behavior may reflect a general preference for the status quo, whereby a decision to accept a lottery is regarded as a departure from one's status quo (Gal, 2006; W. Samuelson & Zeckhauser, 1988). We refer to this tendency as a *predecisional* bias to capture the intuition that individuals may be predisposed towards maintaining the status quo in mixed gamble tasks even *before* they have inspected and learnt about the monetary amounts that could be gained or lost. Although such a tendency could be overridden after monetary amounts are evaluated, we would nonetheless expect the predecisional bias to influence people's decisions and, in many settings, lead to a higher probability of rejection than acceptance. An important prediction of this account is that the effect of such a bias would be greatest early on in the decision, and would diminish as the decision maker deliberates about the money that could be gained or lost.

Although the predecisional bias mechanism provides a fairly intuitive explanation for high rejection rates in mixed gambles, it hasn't yet been formally compared against loss aversion, which remains the dominant explanation for this important behavioral phenomenon. The reason for this is that predecisional biases cannot be accommodated within the types of economic models used to specify loss aversion and predict risky choice. Typically, these models assume that choices depend entirely on *utility*, which itself is a product of the gains and losses offered by the gamble in consideration (e.g., Kahneman & Tversky, 1979). Thus there is no place for a mechanism that influences choice prior to the formation of utility.

There are, however, neurocomputational models of decision making that permit a more nuanced understanding of the deliberation process underpinning people's choices. One such model is the drift diffusion model (DDM), which assumes that individuals gradually accumulate evidence over the time course of the decision, with the decision being made when evidence reaches a threshold value (e.g., Bhatia, 2014; Dai & Busemeyer, 2014; Krajbich, Armel, & Rangel, 2010; Ratcliff, 1978). The evidence being accumulated depends on features of the choice alternatives, such as gains and losses, and subsequently on relative utilities. However, the start of this accumulation process can be biased towards a response (such as rejection), even before these utilities have been evaluated by the decision maker.

Mathematically, DDM implements a sequential probability ratio test, and with this interpretation, its predecisional bias can be seen as a biased prior. The DDM has also been shown to capture aspects of neural information processing, for which a predecisional bias corresponds to a bias in baseline firing rates (Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Gold & Shadlen, 2007). In either case, a predecisional bias in the DDM generates unique patterns in response times, and can be quantitatively estimated and differentiated from other DDM parameters (including those that govern the use of decision features like gains and losses) with a combination of choice and response time data (White & Poldrack, 2014). In prior work, psychologists and neuroscientists have used these estimates to compare predecisional biases against alternate decision mechanisms in a variety of perceptual, lexical, and motor choice tasks (Leite & Ratcliff, 2011; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012; A. Voss, Rothermund, & Voss, 2004; White & Poldrack, 2014). The goal of this paper is to use a similar methodology to establish the extent to which a predecisional bias can account for choices in the popular mixed gamble task.

As an example of this task, consider the decision to accept or reject a gamble i, offering a 50% chance of gaining G_i and a 50% chance of losing L_i. The utility for accepting the gamble in the presence of loss aversion is given by $U_i = G_i - \lambda \cdot L_i$ (as the probabilities of the gains and losses are identical, they can be ignored without any effect on model predictions). Here λ is the loss aversion parameter, where $\lambda > 1$ indicates the larger impact of loss than gains. Assuming that the utility for rejecting the gamble is 0, the decision maker will accept gamble i when $U_i > 0$, and reject the gamble when $U_i < 0$. Stochasticity in choice can be modelled with a logistic response function. With such specification, the magnitude of λ (the loss aversion parameter) can be estimated using a logistic regression: $A_i \sim \beta_G \cdot G_i - \beta_L \cdot L_i$. Here A_i is the participant's binary response to the i^{th} gamble (1 if Accept, 0 if Reject), and β_G and β_L are regression coefficients that yield $\lambda = \beta_L / \beta_G$. In practice, researchers often include an additive intercept (α) in the logistic regression: $A_i \sim \alpha + \beta_G \cdot G_i - \beta_L \cdot L_i$. Here the additive intercept corresponding to a fixed impact on utility favoring acceptance or rejection.

Although commonly used to make inferences regarding the psychological and neural underpinnings of risky choice (Tom et al., 2007), the logistic model outlined above neglects the possibility that decision makers may be predisposed towards one of the choice options (acceptance or rejection) prior to evaluating the underlying utilities. To permit this possibility, we model the decision using a drift diffusion process, which is illustrated in Figure 1A. This model assumes that decision makers accumulate evidence in favor of accepting vs. rejecting the gamble over time, with a *drift rate* that relates the utility of the gamble to the accumulation process. To keep model specifications consistent with the static logistic model outlined above, we write the drift rate for a trial involving gamble i, as $v_i = \alpha + \beta_G \cdot G_i - \beta_L \cdot L_i$. Choices are made when the accumulated evidence reaches a positive threshold $+\theta$ (corresponding to acceptance) or a negative threshold $-\theta$ (corresponding to rejection). The magnitude of θ quantifies the amount of evidence required for reaching a decision. Mechanistically, this threshold captures the speed-accuracy tradeoff in decision making, with higher value of θ generating slower but more accurate choices.

In the DDM, the predecisional bias takes the form of a starting point $\gamma > 0$, that is closer to $+\theta$ (predisposing the decision maker towards accepting the gamble), or $\gamma < 0$, that is closer to $-\theta$ (predisposing the decision maker towards rejecting the gamble). When $\gamma = 0$, the preference accumulation process starts from a neutral state, and the choice probabilities generated by the DDM are identical to those predicted by the static logistic model introduced above. Allowing for the gradual accumulation of evidence prior to the decision enables the DDM to predict response times (RTs). The response time in a trial is assumed to be the time taken for the accumulating evidence to reach a decision threshold added to a fixed non-decisional time τ (which captures the time taken to perceive the stimuli, execute motor responses after the decision has been made, and so on).

The response times predicted by the DDM depend critically on the gamble that is offered on a given trial. Responses times on trials with extremely desirable or undesirable gambles (which generate large positive or negative drift rates) will be shorter, capturing the fact that easier decisions are made relatively quickly compared to more difficult decisions. Besides the influence of the specific gamble at hand, response times also depend on the predecisional bias. If there is a predecisional bias in favor of rejection ($\gamma < 0$), response times associated with rejection will tend to be shorter than those associated with acceptance, and correspondingly, the rejection rates in quicker choices will be higher than those in slower choices, controlling for the difficulty of the choice in consideration (see Figure 1A). Intuitively, the effects of the drift rate (i.e. the utilities used in evaluation) persist throughout the preference accumulation process; whereas the impact of a non-neutral starting point (predecisional bias) gets gradually washed out over time. Crucially, such a prediction cannot be made by the DDM in the absence of the predecisional bias (i.e. when $\gamma = 0$, and DDM choice probabilities mimic the standard logistic specification), indicating that the choice-RTs patterns can be used as a behavioral marker to infer the existence of a predecisional bias (White & Poldrack, 2014).

Methods

Our main experimental task incentivized accept-reject decisions for mixed gambles with a 50% chance of a gain and a 50% chance of a loss. We preregistered our study at OSF(https://osf.io/varx6/?view_only=b9b9f84bd9fc4a56b8df19ea02998fec). In addition to our preregistered study, we also conducted three additional non-incentivized studies (Experiments 1A-1C), which we do not report in the paper due to space limit. The main conclusions of Experiment 2 were replicated in those studies.

Experimental design

Participants. 49 participants were recruited from a paid participant pool at the University of Pennsylvania.

Procedures. Participants were instructed to accept or reject a sequence of 200 gambles, presented in four blocks of 50 gambles. Each gamble had two possible outcomes: A gain of some amount of tokens occurring with a 50% chance and a loss of some amount of tokens occurring with a 50% chance. The outcomes were displayed side by side, with positive/negative values indicating gains and losses (see Figure 1B). Participants pressed up or down arrow keys on a keyboard to indicate acceptance or rejection, with the specific key-response associations alternating across blocks to control for response biases favoring one of the keys. Choices and reaction times were recorded.

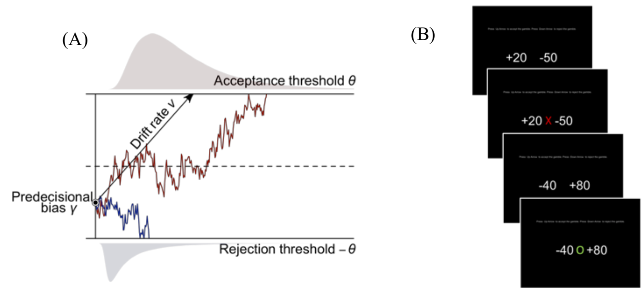

Figure 1 A: The drift diffusion model. B: Task presentation.

Each token was worth US$0.10, and participants began the experiment with an endowment of 100 tokens (US$10). Participants were informed that their choices in the experiment would determine their bonus payment, which they would receive on top of a fixed show-up fee of US$8. This was accomplished by selecting one of the gambles at random. If the participant rejected the gamble, the bonus payment would be 100 tokens (US$10). If the participant accepted the gamble, then they would flip a coin in front of the experimenter to play out the gamble. Their received token amount would be their initial endowment (100 tokens = US$10) plus or minus the gain or loss associated with the coin flip. Average total payments in the experiment were US$ 10.43 per participant.

Stimuli. The possible gain and loss values were taken from the set of {10, 20, 30, 40, 50, 60, 70, 80, 90, 100} tokens, or equivalently US$ {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}. With this stimuli set we were able to generate a total of 100 unique gambles. We counterbalanced the positions of the gain/loss outcomes across blocks, resulting in 200 total trials.

Model Fitting

The models were fit to choice and RT data using HDDM (Wiecki, Sofer, & Frank, 2013), a Python package for hierarchical Bayesian estimation of drift-diffusion models, using its default priors. To fit the models, 4 chains of 50,000 samples were generated, where the first 25,000 were burn-ins, and a thinning of 2 was applied.

Results

Overall, the average rejection probability across participants was 71.5%, with 79.6% of participants being more likely to reject than accept the gambles. These probabilities are significantly different to 50% which is the rate we would expect if choices were made by chance or if individuals did not display loss aversion or predecisional biases ($p < 0.001$ when compared to 50% using t-tests). On average, participants accepted the gambles only when the size of the gain exceed 1.75 times the size of the loss. This pattern of behavior can be explained by both the loss aversion and the predecisional bias mechanisms. According to a model with loss aversion but no predecisional bias, the probability of acceptance is greater than the probability of rejection only when the utility for the gamble exceeds 0, which happens only when the size of the gain exceeds the size of the loss by a large enough margin to counteract loss aversion. According to a model with a predecisional bias but no loss aversion, the probability of acceptance is greater than the probability of rejection only when the utility of the gamble is large enough to override the starting point bias favoring rejection. This happens only when the size of the gain exceeds the size of the loss by a large enough margin, giving a sufficiently positive utility.

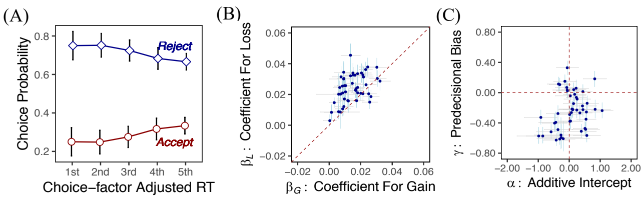

Figure 2. A: Choice-RT relationships. Error bars indicated 95% CI. B: Loss aversion in the DDM. C: Predecisional bias and additive intercept in the drift rate. Most participants have negative posterior means for predecisional bias (i.e., bias towards rejecting gambles). In panel B and C each dot represents a participant and the error bars indicate 95% posterior credible intervals for the parameters in the two figures.

We also found that rejections were quicker than acceptances. Overall, the average rejection decision took 1.30 seconds, whereas the average acceptance decision took 1.72 seconds (the difference is significant: $t(46) = 4.04, p < 0.001$). Additionally, 74.5% of participants took less time to reject than to accept. The RT distributions for acceptance and rejections are different from each other (Wilcoxon signed rank test: $V = 935, p < 0.001$).

Although the observed response time pattern appears consistent with those generated by a predecisional bias favoring rejection, they do not control for choice factors (gains and losses) of the gamble, and thus can also be generated by a DDM model without this bias. More specifically, it is possible that trials on which gambles are rejected involve highly undesirable gambles (and therefore quicker response times), whereas trials on which gambles are accepted involve only moderately desirable gambles (and thus slower response times). To address this issue, Figure 2A shows these choice-RTs patterns, with RTs adjusted for choice factors. These adjusted RTs are residuals from participant-level regressions, in which log RTs are regressed on gain values and loss values of the mixed gambles for each participant. With choice factors controlled for, we observe a negative relationship between choice probability and response time for rejection decisions, and a positive relationship between choice probability and response time for acceptance decisions, showing that decision makers are quicker to reject and slower to accept. This is a novel behavioral pattern that suggests that our participants displayed a predecisional bias favoring rejection. Importantly, this pattern cannot be generated by a DDM model with only loss aversion and no predecisional bias (or by the standard logistic specification of the loss aversion mechanism).

A more rigorous comparison of the loss aversion and predecisional bias mechanisms requires quantitative model fitting. We did so using hierarchical Bayesian techniques applied to choice and RT data. This approach allows for three flexible parameters for the drift rate (α, β_L and β_G) as well as a flexible starting point bias (γ), threshold (θ) and non-response time (τ). Thus this model can simultaneously display both loss aversion and a predecisional bias. We also allowed the threshold (θ) to be dependent on the monetary loss, in order to capture the effect of losses on attention (as specified in our preregistration plan; Yechiam & Hochman, 2013).

Overall, we observe best-fit parameter values such that $\beta_L > \beta_G$ for 85.7% participants, with 57.1% of participants having a 95% credible interval for $\beta_L - \beta_G$ that is strictly positive. The posterior mean of $\lambda = \frac{\beta_L}{\beta_G}$ averaged across our participants is 2.11 ($SD = 1.35$). We also observe a negative posterior mean of γ for 77.6% participants (significant for 69.4% of participants as indicated by 95% credible intervals). The averaged participant-level posterior mean of γ is -0.24 ($SD = 0.25$) across all participants. Finally, we observe a negative posterior mean of α for only 40.8% participants (significant for 12.2% of participants as indicated by 95% credible intervals), with a mean value of $\alpha = 0.05$ ($SD = 0.45$) across our participants. This analysis indicates that most participants display loss aversion and predecisional biases favoring rejection, but do not display any systematic additive intercepts in the drift rate. The posterior means for participant-level parameters are shown in Figures 2B and 2C.

To better understand the descriptive power of the predecisional bias, and to compare it against the descriptive power of loss aversion, we also fit three restricted variants of the DDM. The first constrained model set $\beta_L = \beta_G$ (eliminating loss aversion while permitting flexible values of γ, as well as other DDM parameters). The second set $\gamma = 0$ (eliminating the predecisional bias while permitting flexible values of β_L and β_G, as well as other DDM parameters). The third constrained model is a baseline model that set both $\beta_L = \beta_G$ and $\gamma = 0$ (but permitted flexible values for the remaining DDM parameters). We compared the relative fits of these three constrained models against each other, and against the full model. The model comparisons were performed using the deviance information criterion (DIC; Spiegelhalter, Best, Carlin, & van der Linde, 2002), which measures model fits while penalizing model complexity to avoid over-fitting. Smaller DICs indicate better model performance. This measure revealed that despite having more parameters than the remaining models, the full model ($DIC = 16{,}871$) generated the best fit to the observed data (indicated by DIC differences between this model and the remaining models, which we denote as ΔDIC). Conversely, despite having fewer parameter than the other models, the baseline model generated the worst fit to the observed data ($DIC = 18{,}456$, $\Delta\mathrm{DIC} = 1{,}586$). This indicates that loss aversion and predecisional biases are useful for describing behavior in our experiment. However, out of the two constrained models, the one that set $\beta_L = \beta_G$ ($DIC = 17{,}332$, $\Delta\mathrm{DIC} = 461$) yielded much better fits than the one that set $\gamma = 0$ ($DIC = 17{,}979$, $\Delta\mathrm{DIC} = 1{,}108$), indicating that the predecisional bias plays a more important role than loss aversion.

Although our quantitative fits do provide strong evidence in favor of the predecisional bias mechanism, using such fits as a single piece of evidence for theory testing is problematic (Roberts & Pashler, 2000). Ideally, we should also compare our models in terms of their ability to account for a qualitative behavioral marker, in this case, the finding that rejection rates are higher for trials with shorter RTs compared to trials with longer RTs (Figure 2A, and solid blue lines in Figures 3A-D). As discussed above, this pattern is consistent with the effect of a predecisional bias towards rejecting mixed gambles. A model without such a bias cannot account for RT differences between acceptance and rejection, controlling for choice factors. To establish this more rigorously, we used simulated data from the best-fitting full and constrained models. In line with our intuition, we found that the choice-RT relationship can be captured by the best-fit full model (Figure 3A), as well as by the best-fit constrained model with flexible predecisional bias but no loss aversion (Figure 3B). However, both the best-fit model with loss aversion but no predecisional bias (Figure 3C) and the best-fit baseline model (Figure 3D) fail to capture this relationship. This finding provides one explanation for why the predecisional bias plays a more important role than loss aversion in our quantitative model fits.

In our final analysis we tested the relationship between individual-level model parameters and observed heterogeneity in participant behavior. For this purpose, we correlated best-fitting participant-level estimates of loss aversion ($\lambda = \beta_L/\beta_G$) and predecisional bias (γ) with average participant-level rejection rates. The Pearson correlation between acceptance rates and the predecisional bias is 0.91 ($t(47) = 14.79, p < 0.001$; $Spearman\ Corr = 0.92, p < 0.001$); whereas the correlation between acceptance rates and loss aversion is -0.25 ($t(47) = 1.78, p = 0.08$; $Spearman\ Corr = -0.43, p = 0.002$). These correlations are displayed in Figures 3E and 3F. From the perspective of describing participant heterogeneity, the predecisional bias is clearly the more important psychological mechanism.

Did the participants develop the predecisional bias over the course of the experiment, or did they already have a predecisional bias for gamble choices based on previous life experiences? To test this, we examined the choice-RT relationship (the behavioral marker for predecisional biases) in the first 25 trials of the experiment (first half of the first block). As Figure 3G shows participants were quicker to reject gambles than accept gambles when choice factors are controlled for. In other words, participant already had a predecisional tendency to reject gambles, even when they had limited knowledge regarding the gain and loss value distributions involved in the experiment.

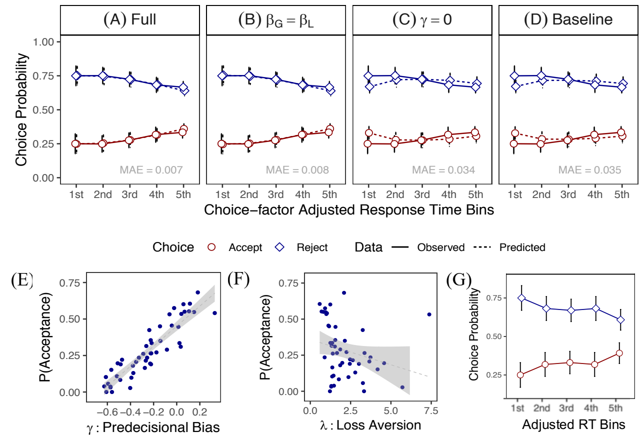

Figure 3. A-D: Choice-RT relationships for observed data (solid lines) and model simulated data (dashed lines). Rejection rates are higher in quicker trials compared to slower trials, controlling for choice factors (gain and loss values). This pattern can only be generated by models that permit a predecisional bias (panels A and B). MAE: Mean absolute error. E-F: Relationships between the DDM mechanisms and acceptance rates. Each dot represents a participant. The predecisional bias is more strongly correlated with the observed choice outcomes, compared to loss aversion. G: Choice-RT relationship for observed data in the first 25 trials of the experiment.

Discussion

The results presented above have a number of important implications for the study of risk preference. First, these results shed light on the psychological underpinnings of one of the most important behavioral findings pertaining to risk: The rejection of small scale 50-50 mixed gambles with positive expected values (Kahneman & Tversky, 1979; Samuelson, 1960). They show that this phenomenon is not just a product of loss aversion (i.e., higher weights attached to losses relative to gains), but is also due to a predecisional bias favoring the status quo. This bias generates a tendency to reject the gamble even before the gamble's payoffs are evaluated, and the effect of this bias is the strongest early on in the decision process. For this reason, the predecisional bias makes unique predictions regarding the relationship between response time and rejection probability. Our experiments provide novel evidence in support of these predictions, indicating that a model equipped with a predecisional bias is necessary to account for behavioral patterns in mixed gamble tasks.

We also used model fitting to evaluate the relative contributions of the loss aversion and predecisional bias mechanisms. Although both loss aversion and predecisional bias play a valuable quantitative role, a model with the predecisional bias but without loss aversion fits better than a model with loss aversion but without predecisional bias. A second test evaluating the predictive power of best fit model parameters shows that individual-level predecisional bias parameters correlate more strongly with individual-level rejection rates than do individual-level loss aversion parameters. These findings provide strong quantitative evidence that predecisional biases are the primary determinant of high rejection rates in mixed gamble tasks. In doing so they complement recent experimental results showing that loss aversion is not as good of a descriptor of choice behavior as has been previously assumed (Bhatia, 2017; Birnbaum, 2008; Erev, Ert, & Yechiam, 2008; Ert & Erev, 2013; Walasek & Stewart, 2015).

Our findings have important implications for how we interpret people's tendency to reject mixed gambles. A lot of prior work in psychology, economics, and neuroscience infers loss aversion through mixed gamble rejection rates, and subsequently uses this measure of loss aversion to explain the effect of social, cognitive, emotional, developmental, demographic, clinical, physiological, and neural variables on risky choice (e.g., Bibby & Ferguson, 2011; Canessa et al., 2017; Engelmann et al., 2015; Gelskov et al., 2015; Hadlaczky et al., 2018; Kermer et al., 2006; Lazzaro et al., 2016; Lorains et al., 2014; Markett et al., 2016; Pighin et al., 2014; Polman, 2012; Tom et al., 2007; Vermeer et al., 2014). Yet our results indicate that these explanations may be incorrect, and that these variables may be better understood in terms of predecisional bias tendencies. Thus, for example, the well-known finding that ventral striatum activity correlates with mixed gamble rejection rates (Tom et al., 2007) could be due to the relationship between brain activity and predecisional bias rather than the relationship between brain activity and loss aversion, as is commonly assumed. Additional research is needed to untangle these relationships, and future work should consider the possibility that gamble rejection rates, as well as the psychological and neurobiological correlates of high rejection rates, can be understood in terms of multiple different psychological mechanisms.

The tests presented in this paper rely critically on response time data: without this type of data, it would be impossible to identify and measure the predecisional bias. Our analysis uses the drift diffusion model to account for trends in response time data, and by doing so, illustrates the descriptive power of this popular neurocomputational theory (Ratcliff, 1978). The DDM has been previously used to model perceptual, lexical, motor phenomena, and the predecisional bias has been shown to be an important parameter in these low-level tasks (e.g., Forstmann, Ratcliff, & Wagenmakers, 2016; Mulder et al., 2012; Ratcliff et al., 2004; Ratcliff, Smith, Brown, & McKoon, 2016; White & Poldrack, 2014). Additionally, this bias has a theoretically compelling interpretation in terms of baseline firing rates in neural models and statistical priors in optimal sequential evaluation tasks (Bogacz et al., 2006; Gold & Shadlen, 2007). Recent work applying DDM and related models to preferential choice data has also shown that these models provide a powerful account of a variety of choice anomalies. We recommend that future research utilizes the DDM, alongside response time data, to obtain a more comprehensive understanding of the psychological and neurobiological determinants of risky choice.

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