Supplementary Materials for:

Prospective Outcome Bias:

Incurring (Unnecessary) Costs to Achieve Outcomes That Are Already Likely

Joshua Lewis
University of Pennsylvania

Joseph P. Simmons
University of Pennsylvania

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Online Supplement 1: Exclusions, Attrition, and Reported Sample Sizes

Table S1 provides an overview of the preregistered exclusion rules, attrition, and reported sample sizes for Studies 1-9 & S1. The comprehension check and attention check questions are described in Online Supplement 6.

Table S1. Total responses, attrition, preregistered exclusions, and reported sample sizes.

Study	Target Sample Size	Total responses	Attrition: Dropped out before the first question in the survey[1,2]	Attrition: Shared an MTurk ID, lab ID, or IP address with a previous response	Attrition: Automatically excluded for failing an attention check	Attrition: Dropped out after the first attention / comprehension check but before providing any DV	Attrition: Manually excluded for failing / not attempting a comprehension check	Attrition: Observations (participants) excluded due to insufficient motivation to win the prize[3]	Observations (participants) used in the main analysis
1	500	669	41	67	96	16	46	NA	403 (403)
2	200	193	3	0	NA	0	27	1,183 (5)	1,262 (158)
3	200	134	0	0	NA	0	30	832 (1)	728 (103)
4	400	442	35	15	NA	NA	NA	NA	7,781 (392)
5	500	987	189	105	271	0	NA	NA	3,369 (422)
6	150	212	2	2	NA	0	24	1,234 (3)	1,526 (181)
7	200	159	3	3	NA	1	2	1,276 (10)	1,724 (140)
8	400	691	58	64	195	1	NA	NA	2,195 (373)[4]
9	150	146	3	2	NA	0	27	NA	1,824 (114)
S1	1,000	1,382	84	152	225	21	87	NA	813 (813)

Note. All manual exclusions (from shared Laboratory ID, MTurk ID, or IP Addresses or from incorrect or missing responses to comprehension check questions) were applied as preregistered. For each MTurk study (Studies 1, 4, 5, 8, and S1), we entered the target sample size into the MTurk HIT, and so deviations of the total responses from the target sample size were due to MTurk software and outside of our control. For each laboratory study (Studies 2, 3, 6, 7, and 9), the laboratory recruited as many participants as it could in a week-long laboratory session, expecting to end up with the reported target sample size. Deviations of the total responses from the target sample size were due to the laboratory's recruitment policies and outside of our control.

[1] The first question in the survey was an attention check in Studies 1, 5, 8, and S1, a comprehension check in Studies 2, 3, 6, 7, and 9, and the first willingness to pay judgment in Study 4.

[2] These figures include participants who were automatically screened out of the surveys due to participation in previous studies.

[3] *Observations* for a given prize and a given participant are excluded only if that participant was insufficiently motivated to win that particular prize. *Participants* are excluded only if they were insufficiently motivated by every single prize for which they provided an observation.

[4] 2,195 refers to the number of observations included in the reported analysis in the Results and Discussion section of Study 8. There were 2,194 observation in the preregistered analysis for Study 8 that was reported in Online Supplement 5, because for one scenario, one participant completed the two questions required for the reported predictor variable but not the four questions required for the preregistered predictor variable.

Online Supplement 2: Study S1

In the Introduction, we argued that outcome bias applies much more to *costly* decisions that are intended to *improve* one's chances of success (e.g., buying extra raffle tickets to improve one's chances of winning a prize) than to *costless* decisions that merely *affect* one's chances of success but are *not* intended to improve them (e.g., declining to buy extra raffle tickets, or even selling existing tickets). The distinction between initially costly decisions (which are more affected by outcome bias) and initially costless decisions (which are less affected by outcome bias) is important because it explains why, when their chances of success are already high, people find the decision to invest resources to further increase those chances more appealing relative to the decision *not* to invest.

To test this distinction empirically, we conducted Study S1 in which we compared outcome bias for a costly decision to *increase* a win probability with outcome bias for a compensated decision to *reduce* a win probability. Specifically, Study S1 followed the exact same procedure as Study 1, with one important exception. In addition to manipulating whether the participant won or lost the raffle, we also manipulated whether the participant *bought* additional tickets or *sold* existing tickets. As in Study 1, we predicted that people would more positively evaluate an inconsequential (but costly) decision to increase win probabilities (i.e., by buying extra raffle tickets) that was followed by a *win* than an inconsequential (but costly) decision to increase win probabilities that was followed by a *failure* to win. However, we also predicted that this effect would be smaller for an inconsequential (but compensated) decision to *reduce* win probabilities (i.e., by selling existing raffle tickets).

Method

Participants. We recruited participants from Amazon's Mechanical Turk (MTurk). Participants received $0.30 for completing the study. We decided in advance to collect data from 1,000 participants. In the event of multiple responses from a single MTurk ID or IP address, we preregistered to include the original response only, resulting in 152 exclusions,[1] and a final sample of 900 participants (mean age = 39.1, 53.8% female).

Procedure. Our procedure was identical to that of Study 1, except for one major change. We added a sell condition to the design, in which instead of buying 10 extra raffle tickets, the participants were asked to imagine *selling* 10 of their existing raffle tickets. Thus, we randomly assigned participants to one cell in a 2 (outcome: win vs. lose) by 2 (decision: sell vs. buy) between-subjects design.

For the win [lose] condition, the new sell condition scenario read as follows (with wording unique to the sell condition in **bold**).

> *Imagine that you participate in a raffle for a $200 Amazon gift card. The winning raffle ticket will be randomly drawn from 100 raffle tickets, numbered 1 through 100. Imagine that you originally were given numbers* ***1-70 [1-40]****, and that somebody offers you the chance to* ***sell*** *10* ***of your*** *numbers (61-70 [31-40]) for $10. Imagine that you* ***sell*** *these 10 numbers for $10.*
>
> *The winning number turns out to be 50. As a result, you win [lose] the $200 gift card, and you would [would not] have won regardless of whether you decided to* ***sell*** *10* ***of your*** *tickets for $10.*

[1] There were a large number of duplicate responses because many participants could not answer the attention check question on their first attempt and so attempted the survey again. As preregistered, we excluded all such participants from our main analysis.

How good a decision was it to ***sell*** *10* ***of your*** *tickets, numbered 61-70 [31-40]?*

In the buy condition, the scenario and wording were identical, except for that the participant was asked to imagine starting without the raffle tickets that could be sold in the sell condition, and had to decide whether to buy those extra tickets. For the win [lose] condition, this buy condition scenario reads as follows (with wording specific to the buy condition in bold).

> *Imagine that you participate in a raffle for a $200 Amazon gift card. The winning raffle ticket will be randomly drawn from 100 raffle tickets, numbered 1 through 100. Imagine that you originally were given numbers* ***1-60 [1-30]****, and that somebody offers you the chance to* ***buy*** *10* ***extra*** *numbers 61-70 [31-40] for $10. Imagine that you* ***buy*** *these 10 numbers for $10.*
>
> *The winning number turns out to be 50. As a result, you win [lose] the $200 gift card, and you would [would not] have won regardless of whether you decided to* ***buy*** *10* ***extra*** *tickets for $10.*
>
> *How good a decision was it to* ***buy*** *10* ***extra*** *tickets, numbered 61-70 [31-40]?*

As in Study 1, all participants evaluated the decision to buy or sell the extra raffle tickets on a 7-point scale ranging from 1 = "Extremely bad" to 7 = "Extremely good." This measure was our dependent variable.

Results and Discussion

As in Study 1, we preregistered to exclude participants who answered either of the two comprehension checks incorrectly (see Online Supplement 6 for details). We excluded 37 participants from the "win" / "buy" cell of the design, 16 participants from the "win" / "sell" cell of the design, 15 participants from the "lose" / "buy" cell of the design, and 19 participants from the "lose" / "sell" cell of the design. This left us with 813 participants for our main analysis, 193 participants in the “win” / “buy” cell of the design, 207 participants from the “win” / “sell” cell of the design, 212 participants from the “lose” / “buy” cell of the design, and 201 participants from the “lose” / “sell” cell of the design. The statistical significance of our results does not change if we include all participants.

As in Study 1, we expected participants to evaluate the inconsequential (but costly) decision to buy additional raffle tickets more favorably when the decision was followed by a good outcome than when it was followed by a bad outcome. However, we predicted that this effect would be attenuated in the sell condition, in which the inconsequential decision being evaluated was not an investment intended to improve chances of winning the raffle, but rather a decision intended to yield an immediate benefit at the expense of the chances of winning the raffle. To test this hypothesis, we conducted a 2-way ANOVA on the participants’ decision ratings with the outcome (win vs. lose) and decision (buy vs. sell) as factors. Consistent with our hypothesis, we found a significant interaction, $F(1, 809) = 33.06$, $p < .001$. Unpacking this interaction, participants in the buy condition evaluated the decision to buy inconsequential extra tickets more favorably in the win condition ($M = 4.51$) than in the lose condition ($M = 3.59$), $t(403) = 5.39$, $p < .001$. However, while we only predicted an attenuated interaction, we found a significant reversal in the sell condition: participants in the sell condition rated the decision to sell *less* favorably in the win condition ($M = 5.27$) than in the lose condition ($M = 5.74$), $t(406) = -2.75$, $p = .006$. This result thus lends even stronger support than anticipated for the notion that prospective outcome bias leads to a greater tendency to increase high win probabilities than low win probabilities. In addition, it also demonstrates an important caveat to the outcome bias literature: Outcome bias applies primarily to costly decisions intended to *improve* the chances of the preferred outcome, not to compensated decisions made *at the expense of* the chances of the preferred outcome.

Online Supplement 3: Study 3 Full Write-Up

In Study 2, we found that people were more likely to incur costs to increase high rather than low win probabilities. In Study 3, we test whether our effects also apply to decisions to *maintain* win probabilities (at the expense of forgoing a possible bonus payment) rather than to *increase* win probabilities (at the expense of exerting effort). Prospective outcome bias predicts that people expect to be happier with a (costly) decision to maintain their initial chances of success when their initial chances of success are high than when they are low. Thus, people should be more inclined to refuse a benefit when it would come at the expense of reducing high rather than low chances of success. We tested this prediction in Study 3, in which participants made incentive compatible decisions about whether to accept bonus payments at the expense of reduced chances of winning various prizes.

Method

Participants. Participants were paid $10 for an hour-long laboratory session in a northeastern university, and this study was a 15-minute part of this session. We preregistered to collect data from participants in a week-long series of lab sessions, aiming to get 200 participants in total. We also preregistered to include only the original response of any participant who completed the study more than once, but none of them did. After all preregistered exclusions, including some described below, our final sample comprised 103 participants (mean age = 25.7, 68.9% female).

Design. For each of 15 prizes, participants decided whether to accept a bonus payment that would be paid at the expense of a reduced win probability. For each prize (and, thus, within-subjects), the survey software randomly determined whether the potential win probabilities would be low (i.e., below 50%) or high (i.e., above 50%). Table S2 lists the 15 prizes, along with the win probabilities associated with each prize, and the bonus payment that participants were offered at the expense of a reduced win probability for that prize. For example, the first row of Table S2 shows that, on one trial, participants were asked whether they would be willing to accept a $0.50 bonus payment at the expense of reducing their probability of winning a $5 Amazon gift card either from 16% to 7% (low probabilities condition) or from 93% to 84% (high probabilities condition). The last row of Table S2 shows that, on a different trial, participants were asked whether they would be willing to accept a $0.25 bonus payment at the expense of reducing their probability of winning post-its either from 23% to 7% or from 93% to 77%.

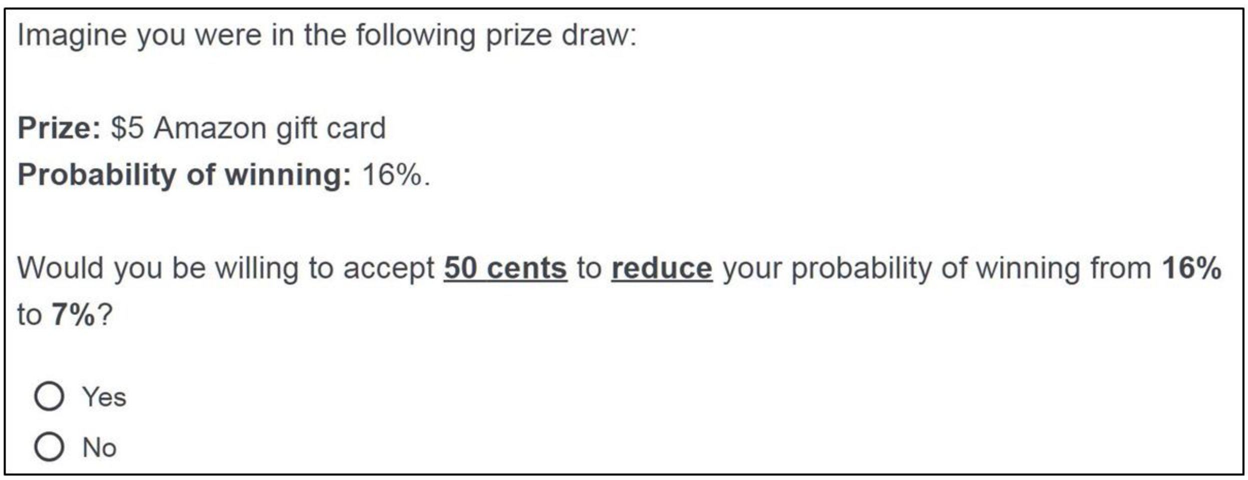
Table S2. Study 3 stimuli.

Prize	Payment offered in return for reduced win probability (cents)	Possible reduction in win probability	
		Low probabilities	**High probabilities**
Amazon $5 gift card	50	From 16% to 7%	From 93% to 84%
Starbucks $5 gift card	50	From 13% to 4%	From 96% to 87%
Dunkin' Donuts $5 gift card	50	From 15% to 4%	From 96% to 85%
Pack of Oreos	25	From 13% to 6%	From 94% to 87%
Granola bar	25	From 14% to 4%	From 96% to 86%
CVS $5 gift card	50	From 15% to 6%	From 94% to 85%
Flashlight	25	From 15% to 8%	From 92% to 85%
Mini-bag of M&Ms	25	From 9% to 4%	From 96% to 91%
4 Hershey's kisses	25	From 13% to 9%	From 91% to 87%
Notebook	25	From 11% to 5%	From 95% to 89%
McDonald's $5 gift card	50	From 21% to 8%	From 92% to 79%
Bottle of coke	25	From 18% to 6%	From 94% to 82%
Highlighter	25	From 18% to 4%	From 96% to 82%
Pen	25	From 21% to 6%	From 94% to 79%
Post-its	25	From 23% to 7%	From 93% to 77%

Procedure. At the beginning of the survey, we explained to participants that they would be asked to decide whether to accept various bonus payments at the expense of reducing their chances of winning each of the 15 prizes. As in Study 2, to ensure that participants took their decisions seriously, we truthfully told them that we would randomly select one of these 15 prize draws to conduct for real, and we displayed a selection of the prizes on a table at the front of the room. Participants then answered two comprehension questions about these instructions, paralleling those of Study 2. On the next page they rated their motivation to win each of the 15 prizes, again following Study 2.

Participants then made their decisions, which were presented one at a time on the computer screen and in a random order. For each decision, we informed participants of the prize, what their baseline probability of winning would be, and what their reduced probability of winning would be if they accepted the possible bonus payment. Figure S1 shows an example of what participants saw on the Amazon gift card trial.

After they made their decisions, the survey randomly selected one of the prize draws to conduct for real, and informed participants of which prize draw had been selected. Participants who earned payments and/or prizes received those at the end of the session, in a manner similar to what was described in Study 2.



Imagine you were in the following prize draw:

Prize: $5 Amazon gift card
Probability of winning: 16%.

Would you be willing to accept **50 cents** to **reduce** your probability of winning from **16%** to **7%**?

- Yes
- No

Fig. S1. Screenshot of the low probabilities condition for the Amazon gift card trial in Study 3.

Results and Discussion

As in Study 2, we preregistered to exclude all decisions from any participant who failed the first comprehension question on their first attempt, and to exclude decisions about prizes for which participants rated their motivation to win at less than a 4 (“Neutral”) on a 7-point scale (1 =

“Extremely unmotivated” to 7 = “Extremely motivated”). This left us with 103 participants and 728 observations for our main analysis.

Each participant provided up to 15 observations of the dependent variable, one for each prize for which they rated their motivation to win as at least “Neutral.” Our key dependent variable captured whether, for each prize, the participant declined the bonus payment to maintain the win probability (1 = decline; 0 = accept). To test the hypothesis that participants would be more likely to decline a bonus payment to maintain high win probabilities than low win probabilities, we used a logit model to regress the dependent variable on a high probabilities condition dummy variable (1 = high probabilities condition; 0 = low probabilities condition). We included fixed effects for each prize, and we clustered standard errors by participant.

Figure S2 displays the results. Consistent with prospective outcome bias, we found that participants were more likely to decline bonus payments that would have reduced high win probabilities than bonus payments that would have reduced low win probabilities, $b = .80$, clustered $SE = .28$, $p = .004$, $OR = 2.22$ (95% CI: 1.29, 3.81).

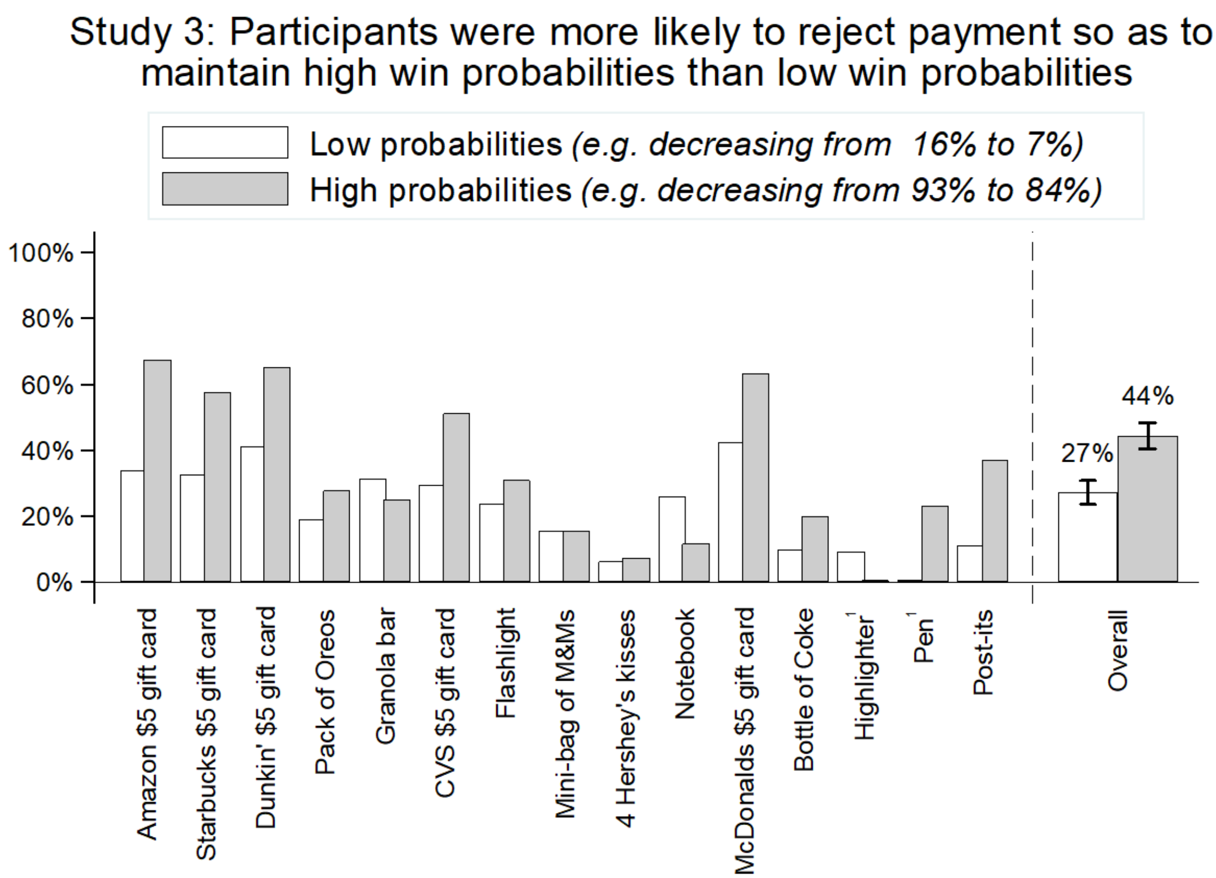


Fig. S2. Percentage of the time participants rejected a bonus payment in order to maintain the probability of winning a prize, as a function of whether the win probability was high or low (manipulated within-subjects and across prizes). Bars to the left of the dotted line show the results for each prize (i.e., between-subjects results) and bars to the right show results collapsed across prizes (i.e., within-subjects results). Error bars to the right of the dotted line depict ± 1 clustered standard error.

[1] 0% of participants decided to reject a bonus payment in order to maintain either high probabilities of winning a highlighter or low probabilities of winning a pen.

Online Supplement 4: Study 4 Full Write-Up

In Studies 2 and 3, we found that people are more willing to increase/maintain high win probabilities than low win probabilities. In Study 4, we sought to further establish the generalizability of this effect, this time by more systematically sampling from the full range of probabilities. In this study, we asked participants to indicate their (hypothetical) willingness to pay to increase win probabilities for various prizes from X% to Y%, where X% and Y% were both randomly sampled from either the low end of the probability distribution (i.e., less than or equal to 50%) or the high end of the probability distribution (i.e., greater than or equal to 50%; Wells & Windschitl, 1999). In addition to helping to establish the generalizability of the effect, this design allowed us to examine whether people's greater motivation to increase high win probabilities than low win probabilities varied according to the extremity of the potential probabilities and/or the size of the potential probability increase.

Method

Participants. We recruited participants from Amazon's Mechanical Turk (MTurk). Participants received $1.00 for completing the study. We decided in advance to collect data from 400 participants. In the event of multiple responses from a single MTurk ID or IP address, we preregistered to include the original response only, resulting in 15 exclusions, and a final sample of 392 participants (mean age = 35.4, 43.8% female).

Design. Participants made hypothetical decisions about how much they would pay to increase their chances of winning each of 20 prizes (e.g., an iPhone X) from a baseline probability to an increased probability.[2] For each prize (and, thus, within-subjects), the survey software randomly

[2] The 20 prizes were: an iPhone, a mountain bike, a trip to Paris, a $500 Amazon gift card, a mattress, a spa retreat, a MacBook, a 5-year Netflix subscription, an iPad, a widescreen TV, a digital camera, a sofa, a leather office chair, a gold-plated wrist watch, an Amazon Fire Kindle, a $500 eBay gift card, a $600 BestBuy gift card, an $800 Macy's gift card, a $500 Walmart gift card, and a $300 American Express gift card.

determined whether the potential win probabilities would be low (i.e., less than or equal to 50%) or high (i.e., greater than or equal to 50%). In the low probabilities condition, we sampled two probabilities from a uniform distribution between 0.01% and 50.00% (displayed to the nearest 2 decimal places). The lower of these two probabilities was assigned to be the baseline probability, and the higher of the two probabilities was assigned to be the increased probability. For the high probabilities condition, we determined the probabilities in the same way, but instead sampled from a uniform distribution between 50.00% and 99.99%.

Procedure. At the beginning of the survey, we briefly described the task to participants, and then, on the next page, participants began making their decisions. The questions were presented on the screen one at a time, in a random order. For each decision, participants learned what the prize was, as well as the baseline win probability and the potential increased win probability. For example, for a baseline probability of 1.24% and an increased probability of 10.02%, they would answer the question, "How much (in dollars) would you be willing to pay to increase your probability of winning from 1.24% to 10.02%?" At the end of the survey, participants entered their demographic information.[3]

[3]After participants had made all of their decisions but before providing their demographic information, we asked an additional question to participants who had indicated a greater average willingness to pay to increase their win probability in the high probabilities condition than in the low probabilities condition. Specifically, we told them, *"On average, you were willing to pay more to increase probabilities when the original probability was above 50%, compared to when it was below 50%. Please explain whether you think this was just a fluke, or whether it reflects a genuine preference for trying to increase high probabilities over low probabilities. If it reflects a genuine preference, please explain why you are more willing to pay to increase high probabilities than low probabilities."* Participants could then answer in a textbox. Although we did not systematically analyze these responses, perusing them helped us in the development of our prospective outcome bias account. All of participants' responses are available in the posted data file.

Results and Discussion

We designed our analyses both to test whether people indicate a greater willingness to pay to improve already favorable win probabilities, and also to explore under which circumstances this result would be strongest.

Because willingness-to-pay responses often contain outliers, we preregistered to run analyses using two transformations of the dependent variable that are designed to lessen the influence of outliers. Specifically, we analyzed both a winsorized willingness-to-pay dependent variable and a rank willingness-to-pay dependent variable. We report the analyses with the winsorized dependent variable in this section and in Table S3, and we depict results with this dependent variable in Figure S3. We learned after submitting the preregistration that rank transforming a dependent variable can lead to inflated false positive rates for interaction effects (Blair, Sawilowsky, & Higgins, 1987), so we report these analyses in Online Supplement 7 only. However, the results are the same using either dependent variable, except for in one instance described below. To ensure that our analysis of winsorized willingness to pays would be robust to outliers, we generated this dependent variable in three steps. First, we determined the highest willingness to pay indicated by each participant. Second, we calculated the 95^{th} percentile of these highest willingness to pay responses. Third, we winsorized all of the raw willingness to pays at this level. In our data, we found that exactly 95% of participants reported a maximum willingness to pay that was less than or equal to \$500. Thus, for our analysis, we set all values greater than \$500 as equal to \$500.

Each participant provided up to 20 observations, one for each of their willingness to pay judgments. Following our preregistration, we regressed their willingness to pay on (1) a high probabilities condition contrast-coded variable (-0.5 = low probabilities condition; 0.5 = high probabilities condition), (2) the extremity of the probabilities, computed as the absolute difference between the most extreme potential win probability and 50% (mean-centered), (3) the extent of the potential probability increase, computed as the absolute difference between the two potential win probabilities (mean-centered), (4) the order in which the item was answered (mean-centered), and (5-7) the interaction of the win probabilities condition (1) with each of the other three variables (2)-(4).

Table S3 details the regression results for winsorized willingness to pay. Replicating our effect from previous studies, we found that participants indicated a greater willingness to pay to increase high win probabilities than low win probabilities, $b = 18.13$, clustered $SE = 1.44$, $p < .001$. Additionally, we found that this effect was larger when the win probabilities were more extreme, $b = .81$, clustered $SE = .09$, $p < .001$ (see Figure S3). This result indicates that people are least inclined to pay to improve their chances of success when they are extremely unlikely to be happy with their decision (because success is extremely unlikely), and that they are most inclined to pay to improve their chances of success when they are extremely likely to be happy with their decision (because success is extremely likely). Thus, this result is consistent with prospective outcome bias. In general, when potential win probabilities are higher, prospective outcome bias predicts people will be willing to invest more; and the results shown in Figure S3 support this hypothesis.

Finally, we also found that the effect of higher win probabilities on willingness to pay was greater when the extent of the potential probability increase was also greater, $b = .32$, clustered $SE = .10$, $p = .002$.[4] We speculate that this result arises because people may be unwilling to invest to attain an extremely small improvement in the expected value of a lottery regardless of their final win probability.

[4] For mechanical reasons related to the problems with interpreting interactions with rank-transformed dependent variables (Blair et al., 1987), this interaction is significant in the *opposite direction* for the rank dependent variable. We discuss this reversal in more detail in Online Supplement 7.

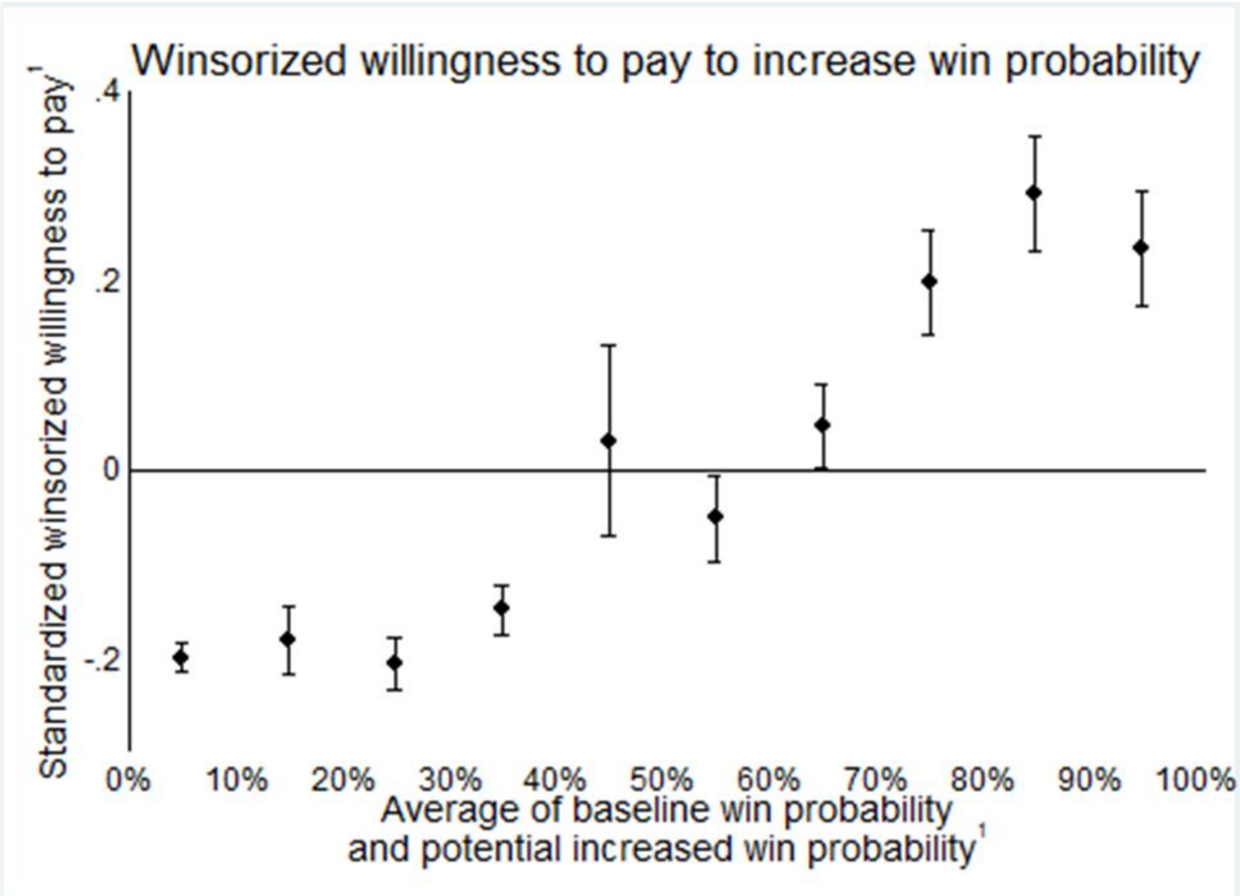


Fig. S3. Participants' average winsorized willingness to pay (WTP) to increase probabilities of winning prizes, as a function of the average of the potential win probabilities, controlling for the size of the probability increase. Each participant provided 20 observations, one for each of 20 prizes. Error bars depict ± 1 clustered standard error.

[1]Both variables are adjusted to control for the size of the probability increase. Specifically, we divided the size of the probability increase into 50 groups, including probability increases of 0.00% - 0.99%, 1.00% - 1.99%, through to 49.00% - 49.99%. We calculated the means of both the x-axis variable and the y-axis variable within each of these groups and subtracted out these means to create the adjusted x-axis and y-axis variables. Thus, we display the relationship between the variables while controlling for the size of the probability increase.

Table S3. Study 4 OLS regression analysis.

Dependent variable	Winsorized willingness to pay
Independent variable	
high probabilities condition (-.5 = low; .5 = high)	18.13 (1.44)***
extremity of the probabilities[1]	0.24 (0.04)***
extent of the increase in win probability[2]	0.73 (0.06)***
randomized decision order[3]	-.09 (0.10)
high probabilities condition × extremity of the probabilities	0.81 (0.09)***
high probabilities condition × extent of the increase in win probability	0.32 (0.10)**
high probabilities condition × randomized decision order	-0.24 (0.17)
fixed effects for participant	Yes
fixed effects for prize	Yes
observations	7,781
R^2	0.49

Cluster-robust SEs are in parentheses. Cluster: participant.

*p < .05, **p < .01, *** p < .001

[1]Absolute difference between most extreme potential win probability (i.e. the baseline probability in the low probabilities condition and the potential increased probability in the high probabilities condition) from 50% (mean-centered).

[2]Absolute difference between baseline and potential increased win probabilities (mean-centered).

[3]The place of the item in the sequence in which the items were answered (e.g., 1st item answered = 1, 2nd item answered = 2, etc., then mean-centered).

Online Supplement 5: Study 5 Full Write-Up

Studies 2-4 demonstrated people's greater preference for increasing high chances of success over low chances of success in incentive-compatible laboratory settings and hypothetical online settings. In Study 5, we investigate the applicability of this finding to a variety of realistic, high stakes scenarios, including scenarios in which "success" constitutes obtaining positive outcomes and scenarios in which "success" constitutes avoiding negative outcomes.

Method

Participants. We recruited participants from Amazon's Mechanical Turk (MTurk). Participants received $1.50 for completing the study. We decided in advance to collect data from 500 participants. In the event of multiple responses from a single MTurk ID or IP address, we preregistered to include the original response only, resulting in 105 exclusions,[5] and a final sample of 422 participants (mean age = 36.9, 50.8% female).

Design. For each of 8 scenarios, participants indicated whether they would take action to improve their chances of success. For each scenario (and, thus, within-subjects), the survey software randomly determined whether the potential probabilities of success would be favorable or unfavorable.

To test whether the preference for increasing favorable over unfavorable chances of success generalizes to a wide variety of potential "successful" outcomes, we constructed four scenarios that were about "achieving success" and four scenarios that were about "avoiding failure." For example, in one "achieving success" scenario, participants were asked whether they would be willing to hire a more expensive lawyer in order to increase the probability of successfully suing

[5] The high number of duplicate responses owes to the fact that many participants could not answer the attention check on their first attempt and so attempted the survey again. As preregistered, we excluded all such participants from our main analysis.

either from 5% to 8% (unfavorable probabilities condition) or from 92% to 95% (favorable probabilities condition). In one “avoiding failure” scenario, participants were asked whether they would be willing to administer a painful treatment in order to reduce the probability of a patient fatality either from 96% to 91% (unfavorable probabilities condition, as the probability of successfully saving the patient’s life is low in these cases) or from 9% to 4% (favorable probabilities condition). For each scenario, the survey software randomly determined whether the probabilities would be favorable (i.e., above 50% in the “achieving success” scenarios or below 50% in the “avoiding failure” scenarios) or unfavorable (i.e., below 50% in the “achieving success” scenarios or above 50% in the “avoiding failure” scenarios). Table 2 in the main article provides a summary of each scenario.

Procedure. At the beginning of the survey, we explained the task to participants. Specifically, we told them that they would decide whether they would take certain actions in order to improve the chances of various outcomes. On the next page, participants were presented with an attention check question that they had to answer in a way that indicated that they understood this instruction. If they failed to answer correctly on their first attempt, the survey prevented them from continuing and we collected no further data from them. Participants then moved on to the main part of the survey, which presented them with the eight scenarios, one at a time and in a random order.

For each scenario, participants indicated which action they would take. For example, one “achieving success” scenario read as follows, with the unfavorable probabilities version in the main text and the favorable probabilities version in brackets:

> *Imagine your business start-up is looking for investment, which it needs to be a sustainable source of income for you. There is a big, local investment fund that currently has a 5% [88%] chance of making an investment. You could add a new service to your start-up,*

which you know would appeal to the investment fund, but doesn't fit in your current business plan. If you add this new service, there is instead a 12% [95%] chance that the investment fund will invest in your start-up.

Would you add the new service?

Participants chose their answer from two options: "Yes: Add the new service to increase the chance of getting the investment to 12% [95%]," and "No: Keep the start-up as it is now and accept a 5% [88%] chance of getting the investment."

One "avoiding failure" scenario read as follows, with the unfavorable probabilities version in the main text and the favorable probabilities version in brackets:

Imagine you are CEO of a small financial company, and your local government is considering new regulations that you think are deeply misguided, and could cost your company millions of dollars. Currently, there is around a 96% [19%] chance that these regulations are implemented. You could launch a lobbying campaign, which would reduce the chance to around 81% [4%]. However, this lobbying campaign would cost tens of thousands of dollars, and might come at a reputational cost.

Would you launch a lobbying campaign?

Participants chose their answer from two options: "Yes: Launch the campaign to reduce the chances that the misguided regulations are implemented to 81% [4%]," and "No: Forgo the campaign and accept a 96% [19%] chance that the misguided regulations are implemented."

At the end of the survey, participants entered their demographic information.

Results and Discussion

We hypothesized that people would be more likely to improve favorable chances of success than unfavorable chances of success. To test this hypothesis, we preregistered to use a binary dependent variable to indicate whether the participant reported that they would take a costly action to improve the chances of success (1 = yes; 0 = no). Thus, each participant provided up to 8 observations of the dependent variable, one for each scenario for which they made a judgment. Following our preregistration, we used a logit model to regress the dependent variable on a favorable probabilities condition dummy variable (coded as 1 for high success-probabilities in the "achieving success" scenarios and low failure-probabilities in the "avoiding failure" scenarios; coded as 0 for low success-probabilities in the "achieving success" scenarios and high failure-probabilities in the "avoiding failure" scenarios), and fixed effects for each scenario, clustering standard errors by participant.

Figure S4 displays the results. Consistent with prospective outcome bias, we found that people were indeed more likely to incur costs to improve favorable probabilities than unfavorable probabilities, $b = .39$, clustered $SE = .07$, $p < .001$, $OR = 1.48$ (95% CI: 1.29, 1.71). We also preregistered to run the same regression separately for the "achieving success" scenarios and the "avoiding failure" scenarios. The effect was significant for both the positive "achieving success" outcomes, $b = .34$, clustered $SE = .10$, $p < .001$, $OR = 1.40$ (95% CI: 1.16, 1.70), and for the negative "avoiding failure" outcomes, $b = .45$, clustered $SE = .10$, $p < .001$, $OR = 1.56$ (95% CI: 1.29, 1.90).

These results indicate that prospective outcome bias manifests for realistic, high-stakes scenarios. It also manifests whether or not people are striving to obtain positive outcomes or to avoid negative outcomes, and whether or not we frame the improvement in the chances of success as an increase in the probability of a positive outcome or a decrease in the probability of a negative outcome.

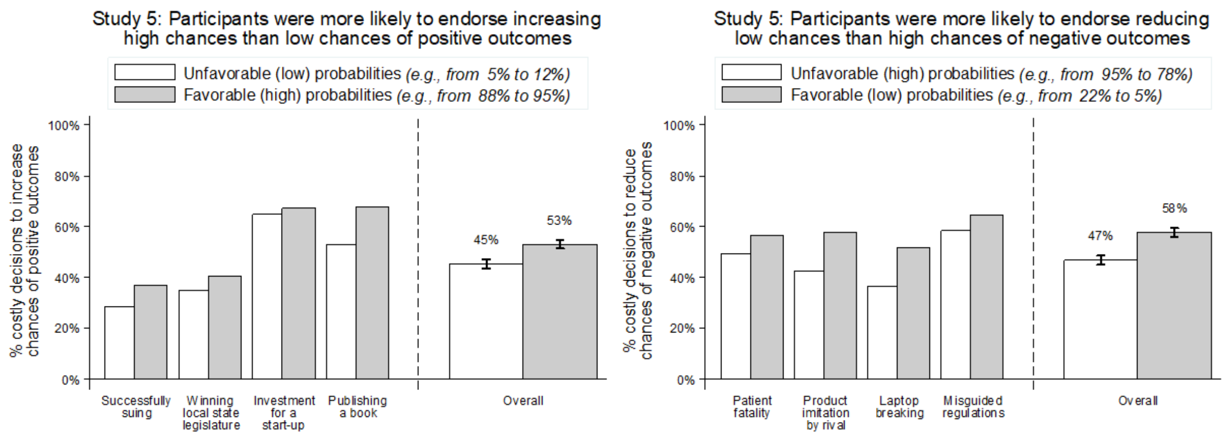


Fig. S4. Percentage of the time participants endorsed taking action to increase the probability of a positive outcome (left panel) or to decrease the probability of a negative outcome (right panel), as a function of whether the probabilities were favorable or unfavorable (manipulated within-subjects and across scenarios). Within each panel, bars to the left of the dotted line show the results for each scenario (i.e., between-subjects results) and bars to the right show results collapsed across the four scenarios to the left (i.e., within-subjects results). Error bars to the right of the dotted line depict ± 1 clustered standard error.

Online Supplement 6: Comprehension Checks and Attention Checks

Study 1, 5, 8, and S1: Attention Check Questions

In Studies 1, 5, 8, and S1, we asked participants an attention check question to confirm they had read the page on which we had briefly described the survey. In Studies 1 and S1, we asked, "What kind of judgment will you be making in this study?" In Study 1, participants had to select the response, "The quality of a decision to buy 10 raffle tickets." In Study S1, participants had to select the response, "The quality of a decision about 10 raffle tickets." In Studies 5 and 8, we asked, "What kind of hypothetical judgments will you be making in this study?" In Study 5, participants had to select the response, "Whether you would take an action to change the probability of an outcome." In Study 8, they had to select the response, "How likely you would be to take an action to change the probability of an outcome."

Participants had to select the correct answer to these attention check questions from a set of five answer choices. If they answered correctly, they could move on with the survey. If they answered incorrectly, they were ineligible to continue and we collected no further data from them.

Across Studies 1, 5, 8, and S1, 465 out of 561, 422 out of 693, 374 out of 569, and 921 out of 1,146 participants who attempted the attention check answered correctly.

Studies 1 and S1: Comprehension Check Questions

In Studies 1 and S1, after participants rated the decision in the raffle tickets scenario, we asked them two questions to ensure that they had properly understood it. First, for both studies, we asked, "In the scenario on the previous page, was the winning ticket one of your tickets?" Participants in the win condition had to select "Yes" and participants in the lose condition had to select "No." Second, both in Study 1 and in the buy condition of Study S1, we then asked, "In the scenario on the previous page, was the winning ticket one of the extra tickets that you bought for $10?" In the sell condition in Study S1, we instead asked this same question, except that we replaced the word “bought” with the word “sold.” Participants had to select the correct answer (i.e., “No”) to the relevant version of this comprehension check question from a set of three answer choices, “Yes,” “Maybe,” and “No.” All participants could continue with the survey after answering these questions. However, as preregistered, we manually excluded any participants who answered these questions incorrectly from our main analysis.

Across Studies 1 and S1, 414 out of 448 and 845 out of 900 participants who attempted the first comprehension check passed it, and 409 out of 448 participants and 824 out of 900 participants who attempted the second comprehension check passed it.

Studies 2, 3, 6, 7, and 9: Win Probability Increase/Decrease

In Studies 2, 3, 6, 7, and 9, we asked participants questions to ensure that they understood that they were about to make decisions that determined the level of their win probability in various prize draws, as opposed to decisions that determined whether they were entered into various prize draws at given win probabilities. Specifically, in Studies 2 and 6, we gave participants an example decision in which they started with a 45% probability of winning some ChapStick and had to decide whether they would be willing to type “ab” 50 times in order to increase their win probability from 45% to 55%. We asked participants, “If this prize draw was randomly selected to enter you into for real, what would your answer to this question mean for your probability of winning the prize?” Participants had to select the response, “If you answer "no," you have a 45% probability of winning. If you answer "yes," you will have a 55% probability of winning, and will have to type "ab" 50 times at the end of the survey.” In Study 3, we gave participants a different example decision in which they started with a 55% probability of winning some ChapStick and had to decide whether they would accept $0.50 at the expense of a reduction in their win probability from 55% to 45%. We asked participants the same question as in Studies 2 and 6, but participants in Study 3 had to select the response, “If you answer "no," you have a 55% probability of winning. If you answer "yes," you will have a 45% probability of winning, and will receive 50 cents at the end of the session.” In Study 7, we gave participants an example decision in which they started with a 45% probability of winning a notebook and had to decide how much they would be willing to pay in order to increase their win probability from 45% to 55%. We asked participants, “If this decision is randomly chosen to be enacted, what happens?” and participants had to select the response, “If your answer is at least as much as the the [sic] randomly determined potential bonus payment, you will be entered into the prize draw with a 55% chance of winning, instead of receiving the bonus. Otherwise, you will receive the bonus payment and be entered into the survey with a 45% chance of winning.” Finally, in Study 9, we gave participants a different example decision in which they started with a 45% probability of winning $1.50 and had to decide whether they would type “ab” 100 times to increase their win probability from 45% to 55%. We asked participants the same question as in Studies 2 and 4, but participants in Study 9 had to select the response, “If you answer "no," you have a 45% probability of winning. If you answer "yes," you will have a 55% probability of winning, and will have to type "ab" 100 times at the end of the survey.”

Participants had to select the correct answer to these comprehension check questions from a set of four answer choices. If they answered correctly, they could move on with the survey. If they answered incorrectly on their first attempt, the survey software showed them the instructions again and prevented them from moving onto the next page within 30 seconds. We then gave participants a second opportunity to answer the comprehension check, and if they answered incorrectly again, the survey software again showed them the instructions and prevented them from moving onto the next page within 30 seconds. All participants could then continue with the survey.

Across Studies 2, 3, 6, 7, and 9, 163 out of 190, 104 out of 134, 175 out of 208, 141 out of 152, and 114 out of 141 participants who attempted the comprehension check passed on their first attempt, and 21 out of the remaining 27 participants, 14 out of the remaining 30 participants, 17 out of the remaining 33 participants, 9 out of the remaining 11 participants, and 19 out of the remaining 27 participants passed on their second attempt.

Studies 2, 3, 6, 7, and 9: Random Selection of Implemented Prize Draw

In Studies 2, 3, 6, 7, and 9, to ensure that participants took their decisions seriously, we told them truthfully that we would randomly select one of their decisions to implement for real. In each of these studies, we asked participants a question to ensure that they understood this information. In Studies 2, 3, 6, 7, and 9, we asked "How is it determined which prize draw you will be entered into?" In Studies 2, 3, and 6, participants had to select the response "The survey randomly selects one of the 15 prize draws to enter you into," and in Study 9, participants had to select a similar response which referenced 16 rather than 15 total prize draws. In Study 7, we phrased the question slightly differently, asking "How is it determined which of your 30 decisions will be enacted?" and participants had to select the response "The survey randomly selects one of the 30 decisions to enact for real."

Participants had to select the correct answer to these comprehension check questions from a set of four answer choices. If they answered correctly, they could move on with the survey. If they answered incorrectly on their first attempt, the survey software showed them the instructions again and prevented them from moving onto the next page within 30 seconds. We then gave participants a second opportunity to answer the comprehension check, and if they answered incorrectly again, the survey software again showed them the instructions and prevented them from moving onto the next page within 30 seconds. All participants could then continue with the survey.

Across Studies 2, 3, 6, 7, and 9, 166 out of 190, 121 out of 134, 187 out of 208, 147 out of 152, and 120 out of 141 participants who attempted the comprehension check passed on their first attempt, and 23 out of the remaining 24 participants, 10 out of the remaining 13 participants, 19 out of the remaining 21 participants, 4 out of the remaining 5 participants, and 20 out of the remaining 21 participants passed on their second attempt.

Study 6: Finding Out Whether Effort Made a Difference

In Study 6, we asked participants a comprehension check question in which they had to confirm that they would find out whether their decision influenced the outcome of the prize draw. Specifically, we asked participants, "Will you find out how your decision about whether or not to type "ab" influences whether or not you win the prize?" and they had to select the response, "Yes, definitely."

Participants had to select the correct answer to this comprehension check question from a set of four answer choices. If they answered correctly, they could move on with the survey. If they answered incorrectly on their first attempt, the survey software showed them the instructions again and prevented them from moving onto the next page within 30 seconds. We then gave participants a second opportunity to answer the comprehension check, and if they answered incorrectly again, the survey software again showed them the instructions and prevented them from moving onto the next page within 30 seconds. All participants could then continue with the survey.

One hundred and thirty two out of 208 participants passed on their first attempt and 63 out of the remaining 76 participants passed on their second attempt.

Study 7: Prize Draw Entry

In Study 7, before participants indicated how much they would pay to enter prize draws at given probabilities, we asked participants a question to ensure that they understood that these decisions were about *entering* prize draws at given win probabilities as opposed to *increasing* their win probabilities. We gave participants an example decision in which they would be asked how much they would be willing to pay in order to enter a prize draw to win a notebook at a 50% win probability. We asked participants, “If this decision is randomly chosen to be enacted, what happens?” and participants had to select the response “If your answer is at least as much as the the [sic] randomly determined potential bonus payment, you will be entered into the prize draw with a 50% chance of winning, instead of receiving the bonus. Otherwise, you will receive the bonus payment.”

Participants had to select the correct answer to this comprehension check question from a set of four answer choices. If they answered correctly, they could move on with the survey. If they answered incorrectly on their first attempt, the survey software showed them the instructions again and prevented them from moving onto the next page within 30 seconds. We then gave participants a second opportunity to answer the comprehension check, and if they answered incorrectly again, the survey software again showed them the instructions and prevented them from moving onto the next page within 30 seconds. All participants could then continue with the survey.

One hundred and forty nine out of 152 participants passed on their first attempt and all 3 remaining participants passed on their second attempt.

Online Supplement 7: Preregistered OLS Regression Results for Studies 2, 3, 5, 6, & 9

Although we preregistered to use easier-to-interpret Ordinary Least Squares (OLS) regressions for analyses with binary dependent variables, we honored the review team's request to report the results of logistic regressions instead. However, the OLS analyses are valid in these instances because we use clustered standard errors (which deal with the potential for heteroscedasticity) and because the key tests are for binary independent variables that are uncorrelated with other predictors (Ai & Norton, 2003; Horrace & Oaxaca, 2006). Thus, all of the statistical tests with binary dependent variables that we reported have the same level of significance using either OLS or logistic regression. We report the preregistered OLS results in Table S4 below (using the exact same covariates as we used for the logistic regressions reported in the main article).

Table S4. Preregistered analyses in Studies 2, 3, 5, 6, & 9.

Study	Analysis	Result
2	Test of high (vs. low) probabilities condition	b = .25, clustered SE = .03, p < .001
3	Test of high (vs. low) probabilities condition	b = .16, clustered SE = .05, p = .004
5	Test of favorable (vs. unfavorable) probabilities condition for all scenarios	b = .09, clustered SE = .02, p < .001
5	Test of favorable (vs. unfavorable) probabilities condition for positive outcome scenarios	b = .08, clustered SE = .02, p < .001
5	Test of favorable (vs. unfavorable) probabilities condition for negative outcome scenarios	b = .11, clustered SE = .02, p < .001
6	Test of high (vs. low) probabilities condition	b = .12, clustered SE = .03, p < .001
9	Test of high (vs. low) probabilities condition	b = .13, clustered SE = .02, p < .001
9	Test of 5% (vs. 25%) probability increase condition	b = .20, clustered SE = .03, p < .001

Online Supplement 8: Interactions with Initial Motivation

When participants are more motivated by success, then a successful outcome should do more to justify the costs incurred to achieve it. Thus, prospective outcome bias predicts that the effect of greater willingness to improve higher win probabilities will increase with participants' initial motivation to win the prize. We found directional support for this prediction in all of the studies in which we collected an initial measure of motivation, and significant results in many of them. All these analyses are reported in Table S5 below. For binary dependent variables, we report both logistic regressions and OLS regressions because the sign and significance of interaction terms can be inconsistent across these two models (Ai & Norton, 2003). We thank the review team for suggesting these analyses.

Table S5. Interactions with initial motivation in Studies 2, 3, 6, & 7.

Study	DV	Interaction between initial motivation to win the prize and…	Logit	OLS
2	Binary	...high (vs. low) probabilities condition	b = .170, clustered SE = .058, p = .003 OR = 1.19 (95% CI: 1.06, 1.33)	b = .034, clustered SE = .008, p < .001
3	Binary	...high (vs. low) probabilities condition	b = .126, clustered SE = .078, p = .106 OR = 1.13 (95% CI: .97, 1.32)	b = .038, clustered SE = .012, p = .003
6	Binary	...high (vs. low) probabilities condition	b = .066, clustered SE = .058, p = .256 OR = 1.07 (95% CI: .95, 1.20)	b = .005, clustered SE = .006, p = .432
7	WTP	...high (vs. low) probabilities condition	N/A	b = 5.51, clustered SE = 2.86, p = .056
7	WTP	...increase (vs. separate) condition	N/A	b = 13.18, clustered SE = 3.78, p < .001
7	WTP	...high (vs. low) probabilities condition and increase (vs. separate) condition	N/A	b = 10.01, clustered SE = 4.58, p = .031

Online Supplement 9: Study 4 Additional Results and Discussion

For Study 4, we preregistered to run analyses with two separate dependent variables: a winsorized willingness-to-pay dependent variable and a rank willingness-to-pay dependent variable. We report the analyses with the winsorized dependent variable in the Results and Discussion section of Study 4 (Online Supplement 4), and the rank dependent variable in this section of the Online Supplement. Unfortunately, we learned after submitting the preregistration that rank transforming a dependent variable can lead to inflated false positive rates for interaction effects (Blair et al., 1987), so the interactions reported in this section should be interpreted cautiously. However, all of the results are the same using either dependent variable, except for in one instance that we mention below.

To generate the rank dependent variable, we rank transformed willingness to pay within each prize. So, for any prize, the lowest willingness to pay was ranked as 1, the second lowest willingness to pay was ranked as 2, and so on. When there were ties, all observations were given what would have been the average rank. For example, if three observations had the second lowest willingness to pay for a given prize, they would all have been ranked 3 (the average of 2, 3, and 4).

Each participant provided up to 20 observations, one for each of their willingness to pay judgments. Following our preregistration, we regressed participants' rank willingness to pay on the exact same covariates as we did for winsorized willingness to pay (listed in Table S3 in Online Supplement 4). Replicating our effect from previous studies (and the results with the winsorized dependent variable), we found that rank willingness to pay to increase high win probabilities was greater than rank willingness to pay to increase low win probabilities, b = 53.52, clustered SE =

2.60, $p < .001$. As with the winsorized dependent variable, we also found that this effect was larger when the win probabilities were more extreme, $b = 2.48$, clustered $SE = .20$, $p < .001$.

Finally, and in contrast to the equivalent interaction with the winsorized dependent variable, we found that the effect of higher win probabilities on rank willingness to pay was *smaller* when the extent of the potential probability increase was greater, $b = -.44$, clustered $SE = .20$, $p = .033$. This reversal with the rank dependent variable probably arises because, when willingness to pay is larger (as is the case for larger probability increases), the distribution of willingness to pay reports tends to be more dispersed, and so a greater *absolute* change in willingness to pay is required to influence the *rank* of willingness to pay. This result is thus consistent with the aforementioned difficulties in interpreting interactions with rank transformed dependent variables (Blair et al., 1987).

Online Supplement 10: Study 7 Analyses with Rank Dependent Variable

In Study 7, we also preregistered to test for the high probabilities × probability increase interaction using a rank dependent variable. Specifically, we ranked participants' (direct or implied) willingness to pay for the probability increase separately within the high probabilities condition and within the low probabilities condition. For example, if the two lowest observations in the low probabilities condition were $0.02 and $0.04, they would be assigned a rank of 1 and 2 respectively, and if the two lowest observations in the high probabilities condition were $0.05 and $0.10, they would also be assigned a rank of 1 and 2. The purpose of this rank dependent variable was to rule out an interaction that arises purely because of the effect of the probability increase condition being proportional to the level of willingness to pay (which differs across the high vs. low probabilities conditions). For example, imagine that people's willingness to pay to increase win probabilities tends to be twice as large in the probability increase condition as in the separate probabilities condition. Now, imagine that the lowest observation in the low probabilities condition and the lowest observation in the high probabilities conditions ($0.02 and $0.05 respectively) both arose in the *separate probabilities* condition, and the second lowest observations ($0.04 for the high probabilities condition and $0.10 for the low probabilities condition) both arose in the *probability increase* condition. In the low probabilities condition, the effect of the probability increase vs. the separate probabilities condition on willingness to pay would have a magnitude of $0.02 (= $0.04 – $0.02), whereas in the high probabilities condition, the effect would have a greater magnitude of $0.05 (= $0.10 – $0.05). However, in proportional terms, the effect would be a 100% increase (i.e. a doubling) in both cases. Thus, if the effect of the probability increase condition is proportional, then we could observe a high probabilities × probability increase interaction as a mechanical consequence of the effect of higher willingness to pay in the high probabilities condition than in the low probabilities condition.

In the above example, ranking the dependent variable separately within the high probabilities condition and within the low probabilities condition mitigates this problem, and would yield no interaction effect. To illustrate this point using the observations that we posited above, the effect of the probability increase condition vs. the separate probabilities condition on the *rank* dependent variable has a magnitude of a 1 (i.e. 2nd lowest observation – 1st lowest observation) in both the low probabilities condition (in which we posited $0.04 to be the second lowest observation and $0.02 to be the lowest observation) and also in the high probabilities condition (in which we posited $0.10 to be the second lowest observation and $0.05 to be the lowest observation). Thus, even if the effect of the probability increase condition is proportional, we would not necessarily observe an interaction between the probability increase condition and the high probabilities condition when using a rank dependent variable. However, when we tested for the interaction using this rank dependent variable in Study 7, it remained highly significant in the predicted direction, suggesting that a proportional effect of the probability increase condition cannot account for it, $b = 100.17$, clustered $SE = 19.82$, $p < .001$.

Unfortunately, we realized after submitting the preregistration that certain rank transformations can lead to inflated false positive rates when used with interactions (Blair et al., 1987). Nonetheless, the interaction in Study 7 is still too large to be explained by the effect of the probability increase condition being proportional. Specifically, winsorized willingness to pay to increase *high* win probabilities is 3.6 times larger in the probability increase condition vs. the separate probabilities condition, but winsorized willingness to pay to increase *low* win probabilities is just 2.2 times larger in the probability increase condition vs. the separate probabilities condition.

Moreover, the interaction is still highly significant and positive with a log-transformation of the dependent variable, $b = 1.13$, clustered $SE = .17$, $p < .001$.[6] This result shows that a proportional effect of the probability increase condition is insufficient to explain the interaction, because effects on the log transformed dependent variable represent proportional changes in willingness to pay.

[6] To log transform the dependent variable, we code any value that is lower than 1 as equal to 1 before taking the natural logarithm of the resulting quantity. This coding is necessary because the log function is undefined for values of 0 or lower, and in the separate probabilities condition, the dependent variable was sometimes negative due to a higher reported willingness to pay for the *unimproved* win probability than for the *improved* win probability.

Online Supplement 11: Study 8 Preregistered Analysis

In Study 8, as well as measuring outcome bias with respect to decisions to improve chances of success, we also measured outcome bias with respect to decisions *not* to improve chances of success. Although we preregistered to incorporate these questions into our overall measure of outcome bias, we later realized that doing so muddies the interpretation of this measure, making it less a measure of outcome bias and (potentially) more a measure of anticipated regret. The Results and Discussion section for Study 8 therefore describe analyses using only the measure of outcome bias with respect to decisions to *improve* chances of success. However, we report our preregistered analysis in this section of the Online Supplement. The result remains very highly significant in the predicted direction.

Recall that, in the Results and Discussion section of Study 8, we measured outcome bias by calculating the difference between the participants' rating of (1) how they would feel if they acted to improve their chances of success and achieved a successful outcome, and (2) the equivalent rating for if they acted and did *not* achieve a successful outcome. However, we preregistered to adjust this measure of outcome bias in order to control for outcome bias with respect to the decision *not* to act to improve chances of success. We measured outcome bias with respect to this alternative decision by calculating the difference between the participants' rating of (1) how they would feel if they did *not* act and nonetheless achieved a successful outcome, and (2) the equivalent rating for if they did *not* act and also did *not* achieve a successful outcome. The preregistered predictor variable was the difference between the measure of outcome bias for the decision to act and the measure of outcome bias for the decision *not* to act.

The reason for using this more complicated predictor variable is that prospective outcome bias most strongly predicts a greater preference for acting to improve higher win probabilities in people who succumb to outcome bias for the decision to act to improve chances of success, but who do *not* succumb to outcome bias for the decision *not* to act to improve chances of success. To illustrate, imagine that somebody can improve their probability of winning a gift card by typing "ab" 100 times on a keyboard. If that somebody evaluates the decision *not* to type "ab" 100 times more positively when they nonetheless win the gift card than when they do not win the gift card, then at higher initial probabilities of winning the gift card, that person may anticipate feeling better about the decision to *refrain* from typing "ab" 100 times. Thus, because both the decision to type and the decision *not* to type would be likely to be evaluated more positively at high win probabilities than at low win probabilities, high win probabilities may not render this person more inclined to type. Instead, we would predict the greater preference for typing at high win probabilities over low win probabilities to be strongest in people who experience *greater* outcome bias for decisions to type relative to decisions *not* to type. In general, greater preference for acting to improve favorable chances of success over unfavorable chances of success should be strongest in people who exhibit greater outcome bias for decisions to act than for decisions not to act.

To test this prediction, we regressed our dependent variable on the preregistered predictor variable, including fixed effects for scenario and clustering standard errors by participant. As predicted, we found that when participants exhibited greater outcome bias for a decision to act relative to a decision *not* to act, they also reported themselves more likely to increase favorable vs. unfavorable probabilities of success, $b = .16$, clustered $SE = .03$, $p < .001$.

Online Supplement 12: Mathematical Derivation of Key Predictions

In this supplement, we derive our three key predictions from a simple model of willingness to pay that reflects prospective outcome bias.

For the purpose of deriving our predictions, we consider a gamble X that yields earnings x_i: either low earnings x_1 with probability $Pr(X = x_1)$ or high earnings x_2 with probability $Pr(X = x_2) = 1 - Pr(X = x_1)$. Without loss of generality, we can posit that:

$$x_2 > x_1 \qquad \textbf{Inequality 1}$$

The probabilities of these outcomes depend on whether an individual chooses to incur some positive cost c that meets a requirement r. If this cost meets or exceeds the requirement, then the gamble will yield the better outcome x_2 with a higher probability p_h, and the worse outcome x_1 with a lower probability $1 - p_h$. If the individual chooses to incur a cost of *less* than the requirement, then the gamble will yield the better outcome x_2 with a lower probability p_l, and the worse outcome x_1 with a higher probability $1 - p_l$. Formally, we can write this:

$$p_h \equiv Pr(X = x_2 | c \geq r) > Pr(X = x_2 | c < r) \equiv p_l$$

According to prospective outcome bias, the costs incurred to improve the chances of a superior outcome feel more justified and thus less painful as the value of the realized outcome increases. So, people's willingness to incur these costs will depend on the *improved* expected value of the outcome, as well as the possible *improvement* in this expected value. Thus, to derive our predictions, we assume that people are willing to incur a cost c that is a weighted average of:

1. The potential *improvement* in the expected value of the gamble (as measured by the difference between the potential probabilities multiplied by the difference between the values of the possible outcomes, $(p_h - p_l)(x_2 - x_1)$).

2. The potential *improved* expected value of the outcome (as measured by the improved probability of the superior outcome multiplied by the difference between the values of the possible outcomes, $p_h(x_2 - x_1)$).

Let w be the weight that the willingness-to-incur-costs function places on the potential improved expected value of the outcome, such that:

$$0 < w < 1$$

We define willingness to incur costs to improve the chances of the superior outcome as: [7]

$$c(p_h, p_l, x_1, x_2) \equiv (1 - w)(p_h - p_l)(x_2 - x_1) + wp_h(x_2 - x_1)$$

We will derive the key predictions of prospective outcome bias from this expression. Specifically, we will show that prospective outcome bias predicts:

1. A greater willingness to incur costs to improve high than low chances of success (e.g. winning a lottery).
2. That this greater willingness to incur costs to *improve* high than low probabilities of winning lotteries does *not* show up as forcefully in differences between the willingness to incur costs to *enter* separate lotteries at each potential win probability (which we demonstrate empirically in Study 7).
3. A greater willingness to incur costs for small improvements in the probability of winning large rewards than for large improvements in the probability of winning small rewards (which we demonstrate empirically in Study 9).

[7] This equation may seem to make some unlikely predictions, including that people will be willing to invest considerable amounts for tiny improvements in the expected value of a lottery. This issue can easily be resolved by defining w as a function of the improvement in the expected value of the lottery $(p_h - p_l)(x_2 - x_1)$ such that, as $(p_h - p_l)(x_2 - x_1) \to 0, w \to 0$. This adjustment does not affect any of the proofs, since the potential improvement in the expected value of the lottery is always fixed.

Prediction 1: *People are willing to incur greater costs to increase their likelihood of success when success is already likely.*

Proposition 1: People are willing to incur greater costs to improve the likelihood of a superior outcome when both of the potential probabilities of the superior outcome are greater (i.e. in a high probabilities scenario). That is, if we define ε as an arbitrarily small quantity (representing the amount by which both of the potential probabilities are greater in the high probabilities scenario vs. the low probabilities scenario) such that $\varepsilon > 0$, we propose that:

$$c(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - c(p_h, p_l, x_1, x_2) > 0$$

Proof of Proposition 1.

From the definition of $c(p_h, p_l, x_1, x_2)$:

$$c(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - c(p_h, p_l, x_1, x_2)$$

$$= [(1 - w)((p_h + \varepsilon) - (p_l + \varepsilon))(x_2 - x_1) + w(p_h + \varepsilon)(x_2 - x_1)]$$

$$- [(1 - w)(p_h - p_l)(x_2 - x_1) + wp_h(x_2 - x_1)]$$

The εs in "$(p_h + \varepsilon) - (p_l + \varepsilon)$" cancel out. Intuitively, "$(p_h + \varepsilon) - (p_l + \varepsilon)$" represents the potential improvement in the probability of success in the high probabilities scenario, which is equal to the potential improvement in the low probabilities scenario $p_h - p_l$ (i.e. the improvement without having added ε to each of the original probabilities). Therefore:

$$c(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - c(p_h, p_l, x_1, x_2)$$

$$= [(1 - w)(p_h - p_l)(x_2 - x_1) + w(p_h + \varepsilon)(x_2 - x_1)] -$$

$$[(1 - w)(p_h - p_l)(x_2 - x_1) + wp_h(x_2 - x_1)]$$

Note that the first term in each of the square brackets is the same. Intuitively, these terms represent the potential improvement in the expected value of the lottery, which is the same across the low probabilities and high probabilities scenarios. So, these terms cancel out, leaving us with:

$$c(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - c(p_h, p_l, x_1, x_2) = w(p_h + \varepsilon)(x_2 - x_1) - wp_h(x_2 - x_1)$$

$$= w[(p_h + \varepsilon)(x_2 - x_1) - p_h(x_2 - x_1)]$$

$$= w\varepsilon(x_2 - x_1)$$

In words, the difference in willingness to incur costs to improve the probability of the superior outcome by a given amount in the high probabilities scenario vs. the low probabilities scenario is represented by the weight on the improved expected value of the outcome (w), multiplied by the extent to which the high-scenario probabilities exceed the low-scenario probabilities (ε), multiplied by the difference between the values of the possible outcomes ($x_2 - x_1$).

It is easy to show that this expression is positive. From Inequality 1:

$$x_2 > x_1$$

$$\Rightarrow x_2 - x_1 > 0$$

Since $w > 0$ and $\varepsilon > 0$:

$$\Rightarrow c(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - c(p_h, p_l, x_1, x_2) = \mathrm{w}\varepsilon(x_2 - x_1) > 0$$

Thus, prospective outcome bias predicts that people are more willing to improve high than low chances of success.

■

Prediction 2: *People will be willing to incur relatively greater costs to increase high vs. low win probabilities than would be implied by their willingness to pay to enter lotteries at each of the separate possible win probabilities.*

Proposition 2: The effect of greater willingness to incur costs to improve the chances of the superior outcome in the high probabilities scenario than in the low probabilities scenario is *greater* than the imputed effect as measured by the difference between (1) people's separate willingness to incur costs to *enter* a lottery at the potential *improved* probability of the superior outcome and

(2) their willingness to incur costs to *enter* the lottery at the potential *unimproved* probability of the superior outcome. That is, if we define ε as an arbitrarily small quantity (representing the amount by which both of the potential probabilities are greater in the high probabilities scenario vs. the low probabilities scenario) such that $\varepsilon > 0$ and model willingness to incur costs to *enter* a lottery as willingness to incur costs to *improve the chance of winning a lottery from 0*, we propose that:

$$c(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - c(p_h, p_l, x_1, x_2)$$
$$> [c(p_h + \varepsilon, 0, x_1, x_2) - c(p_l + \varepsilon, 0, x_1, x_2)] - [c(p_h, 0, x_1, x_2) - c(p_l, 0, x_1, x_2)]$$

Proof of Proposition 2.

First, we can calculate the right hand side of the inequality by substituting the expressions for $c(p_h + \varepsilon, 0, x_1, x_2)$, $c(p_l + \varepsilon, 0, x_1, x_2)$, $c(p_h, 0, x_1, x_2)$, and $c(p_l, 0, x_1, x_2)$, which each represent willingness to incur costs to enter lotteries at different win probabilities (i.e. improve the win probability from 0%). Intuitively, since the improvement in the expected value of the lottery is the same as the expected value of the lottery itself, a weighted average of these two quantities is just equal to the expected value of this lottery. So, the expression for willingness to incur costs to enter a lottery with the *improved* win probability from the high probabilities scenario ($p_h + \varepsilon$) is:

$$c(p_h + \varepsilon, 0, x_1, x_2) = (1 - w)(p_h + \varepsilon - 0)(x_2 - x_1) + w\big(p_h + \varepsilon\big)(x_2 - x_1\big)$$
$$= \big(p_h + \varepsilon\big)(x_2 - x_1\big)$$

Similarly, the expression for willingness to incur costs to enter a lottery with the *unimproved* win probability from the high probabilities scenario ($p_l + \varepsilon$) is:

$$c(p_l + \varepsilon, 0, x_1, x_2) = (1 - w)(p_l + \varepsilon - 0)(x_2 - x_1) + w\big(p_l + \varepsilon\big)(x_2 - x_1\big)$$
$$= \big(p_l + \varepsilon\big)(x_2 - x_1\big)$$

The expression for willingness to incur costs to enter a lottery with the *improved* win probability from the low probabilities scenario (p_h) is:

$$c(p_h, 0, x_1, x_2) = (1 - w\ )(p_h - \ 0)(x_2 - x_1) + wp_h(x_2 - \ x_1)$$

$$= p_h(x_2 - \ x_1)$$

The expression for willingness to incur costs to enter a lottery with the *unimproved* win probability from the low probabilities scenario (p_l) is:

$$c(p_l, 0, x_1, x_2) = (1 - w\ )(p_l - \ 0)(x_2 - x_1) + wp_l(x_2 - \ x_1)$$

$$= p_l(x_2 - \ x_1)$$

So, in the high probabilities scenario, the difference between willingness to incur costs to enter a lottery with an *unimproved* win probability ($p_l + \varepsilon$) and a lottery with an improved win probability ($p_h + \varepsilon$) is given by:

$$c(p_h + \varepsilon, 0, x_1, x_2) - c(p_l + \varepsilon, 0, x_1, x_2) = \left(p_h + \varepsilon\right)(x_2 - \ x_1\big) - \big(p_l + \varepsilon)(x_2 - \ x_1\big)$$

$$= \big(p_h + \varepsilon - p_l - \varepsilon)(x_2 - \ x_1\big)$$

$$= (p_h - p_l)(x_2 - x_1)$$

And, in the low probabilities scenario, the difference between willingness to incur costs to enter a lottery with an *unimproved* win probability (p_l) and a lottery with an *improved* win probability (p_h) is given by:

$$c(p_h, 0, x_1, x_2) - c(p_l, 0, x_1, x_2) = p_h(x_2 - \ x_1) - p_l(x_2 - \ x_1) = (p_h - p_l)(x_2 - x_1)$$

Intuitively, since the difference in the expected value of the improved and unimproved version of the lottery is the same no matter whether both probabilities are higher by ε percentage points, the difference between the willingness to incur costs for the improved and unimproved version of the lottery is also the same in the high probabilities scenario as in the low probabilities scenario. Thus, the right hand side of the original inequality that we are trying to prove is equal to zero:

$$[c(p_h + \varepsilon, 0, x_1, x_2) - c(p_l + \varepsilon, 0, x_1, x_2)] - [c(p_h, 0, x_1, x_2) - c(p_l, 0, x_1, x_2)]$$

$$= (p_h - p_l)(x_2 - x_1) - (p_h - p_l)(x_2 - x_1) = 0$$

We already know from the proof of Proposition 1 that people are willing to incur greater costs to improve their chances of the superior outcome in the high probabilities scenario, that is:

$$c(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - c(p_h, p_l, x_1, x_2) > 0$$

So, substituting $[c(p_h + \varepsilon, 0, x_1, x_2) - c(p_l + \varepsilon, 0, x_1, x_2)] - [c(p_h, 0, x_1, x_2) - c(p_l, 0, x_1, x_2)]$ for 0 in the above inequality gives:

$$\Rightarrow c(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - c(p_h, p_l, x_1, x_2)$$

$$> [c(p_h + \varepsilon, 0, x_1, x_2) - c(p_l + \varepsilon, 0, x_1, x_2)] - [c(p_h, 0, x_1, x_2) - c(p_l, 0, x_1, x_2)]$$

Thus, prospective outcome bias predicts the result of Study 7 in the main article, which showed that people's tendency to pay more to increase a win probability from, say, 70% to 80% rather than from 20% to 30% does *not* show up as forcefully when you ask them how much they are willing to pay to enter each of the separate lotteries that have win probabilities of 20%, 30%, 70%, and 80%.

■

Prediction 3: *Holding the improvement in expected value constant, people will incur greater costs for small increases in the probability of large rewards than for large increases in the probability of small rewards.*

Proposition 3: Willingness to incur costs to improve the chances of a superior outcome increases as:

- the value of the superior outcome increases relative to the value of the inferior outcome, and

- the value of the *unimproved* probability of the superior outcome increases to hold constant the potential improvement in the expected value of the lottery.

That is, if we define ε as an arbitrarily small quantity (representing the amount by which the superior outcome is greater in the higher-stakes scenario) such that $\varepsilon > 0$ and define τ (the amount by which the *unimproved* probability of the superior outcome must increase in the higher-stakes scenario to hold constant the potential improvement in the expected value of the lottery) such that:

$$(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1) = (p_h - p_l)(x_2 - x_1) \qquad \textbf{Equation 1}$$

We propose that:

$$c(p_h, p_l + \tau, x_1, x_2 + \varepsilon) - c(p_h, p_l, x_1, x_2) > 0$$

Proof of Proposition 3.

From the definition of $c(p_h, p_l, x_1, x_2)$:

$$c(p_h, p_l + \tau, x_1, x_2 + \varepsilon) - c(p_h, p_l, x_1, x_2)$$

$$= [(1 - w)(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1) + wp_h(x_2 + \varepsilon - x_1)]$$

$$- [(1 - w)(p_h - p_l)(x_2 - x_1) + wp_h(x_2 - x_1)]$$

We can factorize the expression on the right hand side by $(1 - w)$ and w, so the first term multiplies $1 - w$ by the difference between the *improvements* in the expected values of the lotteries across the two scenarios, and the second term multiplies w by the difference between the *final improved* expected values of the lotteries across the two scenarios:

$$c(p_h, p_l + \tau, x_1, x_2 + \varepsilon) - c(p_h, p_l, x_1, x_2)$$

$$= (1 - w)[(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1) - (p_h - p_l)(x_2 - x_1)]$$

$$+ w[p_h(x_2 + \varepsilon - x_1) - p_h(x_2 - x_1)]$$

From Equation 1 (that is, the assumption that the improvement in the expected value is equal in the two scenarios), the first term in the above equation equals 0:

$$(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1) - (p_h - p_l)(x_2 - x_1) = 0$$

$$\Rightarrow (1 - w)[(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1) - (p_h - p_l)(x_2 - x_1)]$$

$$+w[p_h(x_2 + \varepsilon - x_1) - p_h(x_2 - x_1)]$$

$$= w[p_h(x_2 + \varepsilon - x_1) - p_h(x_2 - x_1)]$$

So, the difference between willingness to incur costs in the two scenarios depends on the difference between the improved expected values of the lottery across the two scenarios (with the improved expected value being greater in the case where the superior outcome is of higher value). Specifically, the expression simplifies to be the weight on the improved expected value of the lotteries (w), multiplied by the improved win probability (p_h), multiplied by the difference in the value of the superior outcome across the two scenarios (ε):

$$c(p_h, p_l + \tau, x_1, x_2 + \varepsilon) - c(p_h, p_l, x_1, x_2) = wp_h\varepsilon$$

As $w > 0$, $p_h > 0$, and $\varepsilon > 0$, this expression for the difference between people's willingness to incur costs to slightly increase chances of higher-stakes rewards vs. people's willingness to incur costs to substantially improve chances of lower-stakes rewards is positive.

$$c(p_h, p_l + \tau, x_1, x_2 + \varepsilon) - c(p_h, p_l, x_1, x_2) = wp_h\varepsilon > 0$$

Thus, prospective outcome bias predicts the result of Study 9 in the main article, that for a given expected value of the improvement, people are more willing to slightly improve their chances of larger rewards than to substantially improve their chances of small rewards.

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Online Supplement 13: Mathematical Derivation of the Predictions of Loss Aversion

Intuition for the Predictions of Loss Aversion

In our studies, we repeatedly find that people are more motivated to increase higher vs. lower chances of success. Could this be explained by loss aversion, the tendency for people to weigh losses more than gains (Kahneman & Tversky, 1979)?

For loss aversion to explain this result, it needs to make two assumptions. First, in the absence of a successful outcome, people consider the costs incurred to improve their chances of success to be a "loss." Second, in the event of a successful outcome, these costs are integrated with the success and therefore perceived as a reduction in a gain rather than as a loss. Given these assumptions, a loss averse participant would be more inclined to incur costs to improve high probabilities of success (when the costs are likely to be perceived as a reduction in the gain from a successful outcome) than low probabilities of success (when the costs are likely to be perceived as a loss).

Although this account could potentially explain the findings from Studies 2-6, it cannot predict the results of Studies 7 and 9.

In Study 7, we found that greater sensitivity to higher probabilities shows up more forcefully in people's willingness to *improve* their win probabilities than in differences between people's willingness to pay to enter *separate* lotteries. However, loss aversion predicts at least as strong an effect for separate lotteries. To understand this prediction, consider that somebody who incurs costs to enter separate lotteries with either a 10% or a 20% win probability is much more likely to experience a "loss" than somebody who incurs costs to enter separate lotteries with either an 80% or a 90% win probability. If incurred costs are more likely to be losses, then because losses loom larger than gains, people will be more sensitive to differences between the costs required to enter different lotteries. Thus, the difference between how much they are willing to pay to enter a 10% vs. a 20% lottery (when the payment will probably be a loss) will be much smaller than the difference between how much they are willing to pay to enter a 80% vs. a 90% lottery (when the payment will probably be a reduction in the gain from winning the lottery).

In Study 9, we find that people prefer small increases in the probability of large rewards (e.g., a 5% improvement from 85% to 90% in their chances of winning $100) to large increases in the probability of small rewards (e.g., a 25% improvement from 65% to 90% in their chances of winning $10). However, so long as the *improved* win probability is the same in both cases, loss aversion predicts that costs incurred to increase the win probability in either scenario should be equally likely to be coded as a "loss." Thus, in contrast to both the result of Study 9 and the prediction of prospective outcome bias, loss aversion predicts that people will be willing to incur the same level of costs for both small increases in the probability of large rewards and large increases in the probability of small rewards.

Mathematically Deriving the Predictions of Loss Aversion

To derive the predictions of loss aversion and specify how they differ from those of prospective outcome bias, we use the same framework as in Online Supplement 10. Specifically, we consider a gamble X that yields earnings x_i: either low earnings x_1 with probability $Pr(X = x_1)$ or high earnings x_2 with probability $Pr(X = x_2) = 1 - Pr(X = x_1)$. Without loss of generality, we can posit that:

$$x_2 > x_1 \qquad \textbf{Inequality 1}$$

The probabilities of these outcomes depend on whether an individual chooses to incur some positive cost c that meets a requirement r. If this cost meets or exceeds the requirement, then the gamble will yield the better outcome x_2 with a higher probability p_h, and the worse outcome x_1

with a lower probability $1 - p_h$. If the individual chooses to incur a cost of *less* than the requirement, then the gamble will yield the better outcome x_2 with a lower probability p_l, and the worse outcome x_1 with a higher probability $1 - p_l$. Formally, we can write this:

$$p_h \equiv Pr(X = x_2|c \geq r) > Pr(X = x_2|c < r) \equiv p_l$$

For simplicity, we will derive the predictions of loss aversion from a value function that is linear in both the domain of losses and in the domain of gains. We will assume that the inferior outcome x_1 is the reference point, and so any cost incurred to increase the chances of attaining the superior outcome x_2 are coded as a loss if the *inferior* outcome is attained, but as a reduction of a gain if the *superior* outcome is attained. If we define λ as a constant such that $\lambda > 1$, and assume that the cost incurred to improve the chances of the superior outcome is always lower than the difference between the values of the superior and inferior outcomes ($x_2 - x_1 - c > 0$) we can write a loss averse value function as follows:

$$v(X, c) \equiv \begin{cases} x_2 - x_1 - c & \text{if } X = x_2 \\ -\lambda c & \text{if } X = x_1 \end{cases}$$

To analyze motivation to increase the probability of the superior outcome, we will derive an expression for the level of the requirement for the improved probability r^* at which people are indifferent between meeting it ($c = r^*$) and incurring no cost at all ($c = 0$). In other words, r^* is the maximum cost that people would be prepared to pay to improve the probability of the superior outcome.

To generate this expression, we start with expected utility given that an individual decides to incur no cost, so $c = 0$.[8] This expected utility is given by a weighted average of (1) what utility

[8] Trivially, given that the incurred cost is less than the requirement, people are best off if they incur no cost at all. Similarly, given that the incurred cost is at least as great as the requirement, people are best off if they incur a cost exactly equal to the requirement. Thus, we consider only these two cases.

would be given that the gamble yields the superior outcome ($v(x_2, 0)$) weighted by the probability of this superior outcome given that no cost incurred (p_l); and (2) what utility would be given that the gamble yields the inferior outcome ($v(x_1, 0)$) weighted by the probability of the inferior outcome given that no cost incurred ($1 - p_l$):

$$E(v(X, c)|c = 0) \ = \ p_l v(x_2, 0) \ + \ (1 - p_l)v(x_1, 0)$$

Now, because:

$$v(x_2, 0) = x_2 - x_1 - 0 = x_2 - x_1$$

And:

$$v(x_1, 0) = -\lambda \times 0 = 0$$

Expected utility given that no cost is incurred can be written:

$$E(v(X, c)|c = 0) = \ p_l(x_2 - x_1) \ + \ (1 - p_l)(0)$$

Equation 1

$$= p_l(x_2 - x_1)$$

Intuitively, the above expression for expected utility (when no cost is incurred) is simply the size of the potential gain ($x_2 - x_1$) multiplied by the (unimproved) probability of that gain (p_l).

Next, we consider expected utility when people incur the costs required to improve the probability of the superior outcome, so $c = r$. This expected utility is given by a similar weighted average:

$$E[v(X, c)|c = r]$$

$$= p_h \, v(x_2, r) + (1 - p_h)v(x_1, r)$$

Now, because:

$$v(x_2, r) = x_2 - x_1 - r$$

And:

$$v(x_1, r) = -\lambda r$$

Expected utility when people incur the costs required to improve the probability of the better outcome can be written:

$$E[v(X,c)|c=r] = p_h(x_2 - x_1 - r) + (1 - p_h)(-\lambda r)$$ **Equation 2**

Intuitively, the above expression for expected utility (when the required cost is incurred) is simply the sum of:

1. The utility in the gain domain $(x_2 - x_1 - r)$ multiplied by the (improved) probability of the superior outcome (p_h), and
2. The negative utility in the loss domain (given by the cost incurred (r) multiplied by the loss-aversion parameter (λ)) multiplied by the probability of the inferior outcome $(1 - p_h)$.

To measure people's willingness to incur costs to improve the gamble, we want to solve for the highest cost requirement r^* that makes people indifferent between incurring the required amount of cost to improve the probability of the better outcome and incurring zero costs. To do this, we equate expected utility given that the cost r^* is incurred with expected utility given that zero cost is incurred:

$$E(v(X,c)|\ c = r^*) - E(v(X,c)|c=0) = 0$$

We then substitute for the respective expected utilities (Equations 1 and 2):

$$E(v(x_i,c)|\ c = r^*) - E(v(x_i,c)|c\ =\ 0)$$

$$= [p_h(x_2 - x_1 - r^*) + (1 - p_h)(-\lambda r^*)] - [p_l(x_2 - x_1)] = 0$$

We can then rearrange this expression to solve for r^*:

$$[p_h(x_2 - x_1 - r^*) + (1 - p_h)(-\lambda r^*)] - [p_l(x_2 - x_1)] = 0$$

$$\Rightarrow p_h r^* + (1 - p_h)\lambda r^* = p_h(x_2 - x_1) - p_l(x_2 - x_1) = (p_h - p_l)(x_2 - x_1)$$

$$\Rightarrow r^* = \frac{(p_h\ -\ p_l)(x_2\ -\ x_1)}{p_h + (1 - p_h)\lambda}$$ **Equation 3**

Thus, Equation 3 can be thought of as an expression for the willingness to incur costs to improve the gamble, and has an intuitive interpretation. Specifically, the numerator represents the increase in the expected value of the gamble from the improvement in the probability of the superior outcome and the denominator represents the expected psychological impact of each unit of cost incurred as a function of the loss aversion parameter (λ) and the probability of the incurred cost being coded as a loss ($1 - p_h$).

We will define the loss-averse willingness-to-incur-costs function as equal to the expression in Equation 3:

$$\Rightarrow r^*(p_h, p_l, x_1, x_2) \equiv \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda}$$

Below, we will use this function to prove that:

1. Like prospective outcome bias, this form of loss aversion *can* predict a greater willingness to incur costs to improve high vs. low chances of success (e.g. winning a lottery).
2. Unlike prospective outcome bias, it also predicts that the greater willingness to incur costs to *improve* high than low probabilities of winning lotteries shows up more forcefully in differences between the willingness to incur costs to *enter* separate lotteries at each potential win probability (and so predicts the *opposite* of the result of Study 7).
3. Unlike prospective outcomes bias, it *cannot* predict a greater willingness to incur costs to improve the probability of winning large rewards by small amounts than small rewards by large amounts (and so fails to predict the result of Study 9).

<u>Loss-Aversion Prediction 1:</u> *People are willing to incur greater costs to increase their likelihood of success when success is already likely.*

Proposition 1: People are willing to incur greater costs to improve the likelihood of a superior outcome when both of the potential probabilities of the superior outcome are greater. That is, if we define ε as an arbitrarily small quantity (representing the amount by which both of the potential probabilities are greater in the high probabilities scenario vs. the low probabilities scenario) such that $\varepsilon > 0$, we propose that:

$$r^*(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2) > 0$$

Proof of Proposition 1.

From the definition of $r^*(p_h, p_l, x_1, x_2)$:

$$r^*(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$

$$= \frac{((p_h + \varepsilon) - (p_l + \varepsilon))(x_2 - x_1)}{(p_h + \varepsilon) + (1 - (p_h + \varepsilon))\lambda} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda}$$

The εs in "$(p_h + \varepsilon) - (p_l + \varepsilon)$" cancel out. Intuitively, "$(p_h + \varepsilon) - (p_l + \varepsilon)$" represents the potential improvement in the probability of success in the high probabilities scenario – which is equal to the potential improvement in the low probabilities scenario, $p_h - p_l$ (i.e. the improvement without having added ε to each of the original probabilities). Therefore:

$$= \frac{(p_h - p_l)(x_2 - x_1)}{(p_h + \varepsilon) + (1 - (p_h + \varepsilon))\lambda} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda}$$

$$= \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda + \varepsilon(1 - \lambda)} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda}$$

Equation 4

$$= r^*(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$

Intuitively, since the denominators represent the expected psychological impact of each unit of cost incurred, we would predict these denominators to be smaller in the high probabilities scenario when the cost is *less* likely to be perceived as a loss (i.e. the case represented by the denominator of the term $\frac{(p_h - p_l)(x_2 - x_1)}{(p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)}$ in Equation 4). If indeed the expected psychological impact of each unit of cost is smaller in the high probabilities scenario, we would expect people to be willing to incur greater costs in this scenario. To prove this, we need to show that the denominator of the left term $\frac{(p_h - p_l)(x_2 - x_1)}{(p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)}$ in Equation 4 is lower than the denominator of the term $\frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda}$. We will now derive this inequality from the premises that we have already stated.

Because $\lambda > 1$ (loss aversion):

$$1 < \lambda$$

$$\Rightarrow 1 - \lambda < 0$$

Because $\varepsilon > 0$:

$$\Rightarrow \varepsilon(1 - \lambda) < 0$$

Adding $p_h + (1 - p_h)\lambda$ to both sides of the inequality yields the desired inequality:

$$\Rightarrow p_h + (1 - p_h)\lambda + \varepsilon(1 - \lambda) < p_h + (1 - p_h)\lambda \qquad \textbf{Inequality 2}$$

Now we will use this inequality to show that people's willingness to incur costs to improve the probability of the superior outcome is greater in the high probabilities scenario.

Because $p_h > p_l$, and $x_2 > x_1$:

$$p_h - p_l > 0$$

$$\Rightarrow (p_h - p_l)(x_2 - x_1) > 0$$

Therefore, dividing both sides of Inequality 2 by $(p_h - p_l)(x_2 - x_1)$ does *not* flip the inequality sign and yields the new inequality:

$$\Rightarrow \frac{p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)}{(p_h - p_l)(x_2 - x_1)} < \frac{p_h + (1-p_h)\lambda}{(p_h - p_l)(x_2 - x_1)}$$

We can flip the denominators and the numerators in the above inequality (and flip the inequality sign accordingly) and then rearrange into a new inequality that compares the expression in Equation 4 to 0:

$$\Rightarrow \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)} > \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda}$$

$$\Rightarrow \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda} > 0$$

Using Equation 4 to substitute for the left hand side of the above inequality completes the proof:

$$\Rightarrow r^*(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2) > 0$$

Thus, as with prospective outcome bias, loss aversion predicts that people are more willing to improve high than low chances of success.

■

Loss-Aversion Prediction 2: *Unlike prospective outcome bias, loss aversion predicts that people will be willing to incur relatively smaller costs to increase high vs. low win probabilities than would be implied by their willingness to pay to enter lotteries at each of the separate possible win probabilities.*

Proposition 2: *According to loss-aversion*, the effect of greater willingness to incur costs to improve the chances of the superior outcome in the high probabilities scenario than in the low probabilities scenario should be *smaller* than the imputed effect as measured by the difference between (1) people's separate willingness to incur costs to *enter* a lottery at the potential *improved* probability of the superior outcome and (2) their willingness to incur costs to *enter* the lottery at the potential *unimproved* probability of the superior outcome. That is, if we define ε as an arbitrarily small quantity (representing the amount by which both of the potential probabilities are greater in the high probabilities scenario vs. the low probabilities scenario) such that $\varepsilon > 0$ and model willingness to incur costs to *enter* a lottery as willingness to incur costs to *improve the chance of winning a lottery from 0*, we propose that:

$$r^*(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$
$$< [r^*(p_h + \varepsilon, 0, x_1, x_2) - r^*(p_l + \varepsilon, 0, x_1, x_2)] - [r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)]$$

Proof of Proposition 2.

First, we can calculate the right hand side of the inequality by calculating the expressions for $r^*(p_h + \varepsilon, 0, x_1, x_2)$, $r^*(p_l + \varepsilon, 0, x_1, x_2)$, $r^*(p_h, 0, x_1, x_2)$, and $r^*(p_l, 0, x_1, x_2)$, which each represent willingness to incur costs to enter lotteries at different win probabilities (i.e. improve the win probability from 0%). This side of the inequality represents the effect of the high probabilities vs. low probabilities scenario on *imputed* willingness to improve the probability (as measured by willingness to incur costs to enter separate lotteries). From the definition of the function r^*:

$$[r^*(p_h + \varepsilon, 0, x_1, x_2) - r^*(p_l + \varepsilon, 0, x_1, x_2)] - [r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)]$$
$$= \left[\frac{(p_h + \varepsilon - 0)(x_2 - x_1)}{p_h + \varepsilon + (1 - (p_h + \varepsilon))\lambda} - \frac{(p_l + \varepsilon - 0)(x_2 - x_1)}{p_l + \varepsilon + (1 - (p_l + \varepsilon))\lambda}\right]$$
$$- \left[\frac{(p_h - 0)(x_2 - x_1)}{p_h + (1 - p_h)\lambda} - \frac{(p_l - 0)(x_2 - x_1)}{p_l + (1 - p_l)\lambda}\right]$$

So removing the “0”s, we get the following equation:

$$[r^*(p_h + \varepsilon, 0, x_1, x_2) - r^*(p_l + \varepsilon, 0, x_1, x_2)] - [r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)]$$
$$= \left[\frac{(p_h + \varepsilon)(x_2 - x_1)}{p_h + (1 - p_h)\lambda + \varepsilon(1 - \lambda)} - \frac{(p_l + \varepsilon)(x_2 - x_1)}{p_l + (1 - p_l)\lambda + \varepsilon(1 - \lambda)}\right] \qquad \textbf{Equation 5}$$
$$- \left[\frac{p_h(x_2 - x_1)}{p_h + (1 - p_h)\lambda} - \frac{p_l(x_2 - x_1)}{p_l + (1 - p_l)\lambda}\right]$$

We can use Equation 4 (restated immediately below) as an expression for the left hand side of Proposition 2, which represents the effect of the high probabilities vs. low probabilities scenario on *actual* willingness to incur costs to improve the probability:

$$r^*(p_h+\varepsilon, p_l+\varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$

$$= \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda}$$

Subtracting Equation 5 from Equation 4 yields a new equation, representing how much greater the effect of the high probabilities vs. low probabilities scenario is on *actual* vs. *imputed* willingness to pay to improve the probability:

$$r^*(p_h+\varepsilon, p_l+\varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$

$$-\big[[r^*(p_h+\varepsilon, 0, x_1, x_2) - r^*(p_l+\varepsilon, 0, x_1, x_2)] - [r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)]\big]$$

$$= \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1-p_h)\lambda}$$

$$-\left[\left[\frac{(p_h + \varepsilon)(x_2 - x_1)}{p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)} - \frac{(p_l + \varepsilon)(x_2 - x_1)}{p_l + (1-p_l)\lambda + \varepsilon(1-\lambda)}\right]\right.$$

$$\left. - \left[\frac{p_h(x_2 - x_1)}{p_h + (1-p_h)\lambda} - \frac{p_l(x_2 - x_1)}{p_l + (1-p_l)\lambda}\right]\right]$$

Let us simplify the notation by defining the four dominators in the above equation thus:

$$d(p_h, \varepsilon) \equiv p_h + (1-p_h)\lambda + \varepsilon(1-\lambda)$$

$$d(p_l, \varepsilon) \equiv p_l + (1-p_l)\lambda + \varepsilon(1-\lambda)$$

$$d(p_h, 0) \equiv p_h + (1-p_h)\lambda$$

$$d(p_l, 0) \equiv p_l + (1-p_l)\lambda$$

Substituting in this notation, we have:

$$r^*(p_h+\varepsilon, p_l+\varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$

$$-\big[[r^*(p_h+\varepsilon,0,x_1,x_2)-r^*(p_l+\varepsilon,0,x_1,x_2)]-[r^*(p_h,0,x_1,x_2)-r^*(p_l,0,x_1,x_2)]\big]$$

$$=\frac{(p_h\ -p_l)(x_2-\ x_1)}{d(p_h,\varepsilon)}-\frac{(p_h\ -p_l)(x_2-\ x_1)}{d(p_h,0)} \qquad \textbf{Equation 6}$$

$$-\left[\left[\frac{(p_h\ +\varepsilon)(x_2-\ x_1)}{d(p_h,\varepsilon)}-\frac{(p_l\ +\varepsilon)(x_2-\ x_1)}{d(p_l,\varepsilon)}\right]-\left[\frac{p_h(x_2-\ x_1)}{d(p_h,0)}-\frac{p_l(x_2-\ x_1)}{d(p_l,0)}\right]\right]$$

At this point, within both the high and low probabilities scenarios, let us note the similarity between (1) the expressions for actual willingness to improve chances of the superior outcomes (i.e. the first term and the second term in the right hand side of Equation 6) and (2) the expressions for the *imputed* willingness to improve chances of the superior outcome (i.e. the expression in the first set of smaller square brackets and the expression in the second set of smaller square brackets in the right hand side of Equation 6). Specifically, in the high probabilities scenario, the expressions are:

$$r^*(p_h+\varepsilon,p_l+\varepsilon,x_1,x_2)=\frac{(p_h\ -p_l)(x_2-\ x_1)}{d(p_h,\varepsilon)}$$

$$r^*(p_h+\varepsilon,0,x_1,x_2)-r^*(p_l+\varepsilon,0,x_1,x_2)=\frac{(p_h\ +\varepsilon)(x_2-\ x_1)}{d(p_h,\varepsilon)}-\frac{(p_l\ +\varepsilon)(x_2-\ x_1)}{d(p_l,\varepsilon)}$$

These two expressions would be identical (and, since they have different signs in the equation, would cancel out) if the denominator of the second term of the expression for $r^*(p_h+\varepsilon,0,x_1,x_2)-r^*(p_l+\varepsilon,0,x_1,x_2)$ was $d(p_h,\varepsilon)$ instead of $d(p_l,\varepsilon)$. However, this denominator represents the expected impact of each unit of cost incurred from entering the *unimproved* lottery, as opposed to the *improved* lottery. Thus, this denominator is a little higher than it would be if the two expressions were equivalent.

We see a similar relationship between the corresponding expressions in the low probabilities scenario.

$$r^*(p_h,p_l,x_1,x_2)=\frac{(p_h\ -p_l)(x_2-\ x_1)}{d(p_h,0)}$$

$$r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2) = \frac{p_h(x_2 - x_1)}{d(p_h, 0)} - \frac{p_l(x_2 - x_1)}{d(p_l, 0)}$$

Specifically, these two expressions would be identical (and thus cancel out) if the denominator of the second term of the expression for $r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)$ was $d(p_h, 0)$ instead of $d(p_l, 0)$. However, as in the high probabilities scenario, this denominator represents the expected impact of each unit of cost incurred from entering the *unimproved* lottery, as opposed to the *improved* lottery. Thus, again, this denominator is a little higher than it would be if the two expressions were equivalent.

Now, the higher denominator in the second (subtracted) terms of the expressions for $r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)$ and for $r^*(p_h + \varepsilon, 0, x_1, x_2) - r^*(p_l + \varepsilon, 0, x_1, x_2)$ will mean that those subtracted terms are smaller (and therefore the overall expressions are greater) than if these expressions were equivalent to $r^*(p_h, p_l, x_1, x_2)$ and $r^*(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2)$. Importantly, this effect will be greater in the high probabilities scenario. This is for two reasons:

1. The numerator for the term $\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)}$ (which represents the *relatively high* expected value of the unimproved lottery in the high probabilities scenario) is greater than the numerator for the term $\frac{p_l(x_2 - x_1)}{d(p_l, 0)}$ (which represents the *relatively low* expected value of the unimproved lottery in the low probabilities scenario). Thus, due to the larger numerator, a given proportional difference in the respective denominator has a larger impact in the high probabilities scenario.

2. The denominator of the term $\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)}$ (which represents the *relatively low* expected psychological impact of each unit of cost from entering the unimproved lottery in the high probabilities scenario) is lower than the denominator of the term $\frac{p_l(x_2 - x_1)}{d(p_l, 0)}$ (which

represents the *relatively high* expected psychological impact of each unit of cost from entering the unimproved lottery in the low probabilities scenario). Since (1) a given absolute change in a denominator has a bigger proportional impact when that denominator is smaller and (2) the denominator is smaller in the high probabilities scenario than in the low probabilities scenario, we can infer that the impact of the higher denominator (on a given numerator) is greater in the high probabilities scenario.

To show this mathematically requires a little more algebra. First, let us restate Equation 6:

$$r^*(p_h+\varepsilon, p_l+\varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$

$$-\big[[r^*(p_h+\varepsilon, 0, x_1, x_2) - r^*(p_l+\varepsilon, 0, x_1, x_2)] - [r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)]\big]$$

$$= \frac{(p_h - p_l)(x_2 - x_1)}{d(p_h, \varepsilon)} - \frac{(p_h - p_l)(x_2 - x_1)}{d(p_h, 0)}$$

$$-\left[\left[\frac{(p_h + \varepsilon)(x_2 - x_1)}{d(p_h, \varepsilon)} - \frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)}\right] - \left[\frac{p_h(x_2 - x_1)}{d(p_h, 0)} - \frac{p_l(x_2 - x_1)}{d(p_l, 0)}\right]\right]$$

If the denominators in the expression in the large square brackets $d(p_l, \varepsilon)$ and $d(p_l, 0)$ were instead equal to $d(p_h, \varepsilon)$ and $d(p_h, 0)$, then the whole expression would cancel out to be equal to zero. Thus, the whole expression can be simplified to be the difference between the two terms with denominators $d(p_l, \varepsilon)$ and $d(p_l, 0)$ and similar terms with denominators $d(p_l, \varepsilon)$ and $d(p_l, 0)$, respectively. To show this, let us add and subtract $\frac{(p_l+\varepsilon)(x_2-x_1)}{d(p_h,\varepsilon)}$ from the terms in the first set of square brackets and also add and subtract $\frac{(p_l)(x_2-x_1)}{d(p_h,0)}$ from the terms in the second set of square brackets (with these terms highlighted yellow in the below equation only):

$$r^*(p_h+\varepsilon, p_l+\varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$

$$-\big[[r^*(p_h+\varepsilon, 0, x_1, x_2) - r^*(p_l+\varepsilon, 0, x_1, x_2)] - [r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)]\big]$$

$$= \frac{(p_h - p_l)(x_2 - x_1)}{d(p_h + \varepsilon)} - \frac{(p_h - p_l)(x_2 - x_1)}{d(p_h, 0)}$$

$$- \left[\left[\frac{(p_h + \varepsilon)(x_2 - x_1)}{d(p_h, \varepsilon)} - \left(\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_h, \varepsilon)}\right)\right.\right.$$

$$\left. - \left(\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)} - \left(\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_h, \varepsilon)}\right)\right)\right]$$

$$\left. - \left[\frac{p_h(x_2 - x_1)}{d(p_h, 0)} - \left(\frac{p_l(x_2 - x_1)}{d(p_h, 0)}\right) - \left(\frac{p_l(x_2 - x_1)}{d(p_l, 0)} - \left(\frac{p_l(x_2 - x_1)}{d(p_h, 0)}\right)\right)\right]\right]$$

Now, subtracting the second terms from the first terms in each set of square brackets yields:

$$= \frac{(p_h - p_l)(x_2 - x_1)}{d(p_h, \varepsilon)} - \frac{(p_h - p_l)(x_2 - x_1)}{d(p_h, 0)}$$

$$- \left[\left[\frac{(p_h - p_l)(x_2 - x_1)}{d(p_h, \varepsilon)} - \left(\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)} - \frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_h, \varepsilon)}\right)\right]\right.$$

$$\left. - \left[\frac{(p_h - p_l)(x_2 - x_1)}{d(p_h, 0)} - \left(\frac{p_l(x_2 - x_1)}{d(p_l, 0)} - \frac{p_l(x_2 - x_1)}{d(p_h, 0)}\right)\right]\right]$$

Because the terms $\frac{(p_h - p_l)(x_2 - x_1)}{d(p_h + \varepsilon)}$ and $\frac{(p_h - p_l)(x_2 - x_1)}{d(p_h)}$ now cancel out, we can write the expression:

$$= - \left[\left[- \left(\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)} - \frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_h, \varepsilon)}\right)\right] - \left[- \left(\frac{p_l(x_2 - x_1)}{d(p_l, 0)} - \frac{p_l(x_2 - x_1)}{d(p_h, 0)}\right)\right]\right]$$

$$= \left(\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)} - \frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_h, \varepsilon)}\right) - \left(\frac{p_l(x_2 - x_1)}{d(p_l, 0)} - \frac{p_l(x_2 - x_1)}{d(p_h, 0)}\right)$$

Our task is to show mathematically that this expression is less than 0. It is easiest to do this by reorganizing the expression into two sets of terms that reflect respectively the two intuitive reasons for why, relative to *actual* willingness to incur costs to improve lotteries, *imputed* willingness to incur costs is greater in the high probabilities scenario vs. the low probabilities scenario.

Removing the large brackets and expanding by $(p_l + \varepsilon)$ we get:

$$= \frac{p_l(x_2 - x_1)}{d(p_l, \varepsilon)} + \frac{\varepsilon(x_2 - x_1)}{d(p_l, \varepsilon)} - \frac{p_l(x_2 - x_1)}{d(p_h, \varepsilon)} - \frac{\varepsilon(x_2 - x_1)}{d(p_h, \varepsilon)} - \frac{p_l(x_2 - x_1)}{d(p_l, 0)} + \frac{p_l(x_2 - x_1)}{d(p_h, 0)}$$

And reorganizing, we get:

$$r^*(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$ **Equation 7**

$$-\big[[r^*(p_h + \varepsilon, 0, x_1, x_2) - r^*(p_l + \varepsilon, 0, x_1, x_2)] - [r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)]\big]$$

$$= \left[\frac{\varepsilon(x_2 - x_1)}{d(p_l, \varepsilon)} - \frac{\varepsilon(x_2 - x_1)}{d(p_h, \varepsilon)}\right] + p_l(x_2 - x_1)\left[\left(\frac{1}{d(p_l, \varepsilon)} - \frac{1}{d(p_h, \varepsilon)}\right) - \left(\frac{1}{d(p_l, 0)} - \frac{1}{d(p_h, 0)}\right)\right]$$

Now, the terms in the first set of square brackets represent the first reason why, relative to *actual* willingness to incur costs to improve lotteries, *imputed* willingness to incur costs is greater in the high probabilities scenario vs. the low probabilities scenario. Specifically, recall that the numerator for the term $\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)}$ (which represents the *relatively high* expected value of the possible outcomes of entering the unimproved lottery in the high probabilities scenario) is greater than the numerator for the term $\frac{p_l(x_2 - x_1)}{d(p_l, 0)}$ (which represents the *relatively low* expected value of the possible outcomes of entering the unimproved lottery in the low probabilities scenario). The numerator of the terms in the first set of square brackets $\varepsilon(x_2 - x_1)$ reflects the difference between the respective numerators of the terms $\frac{(p_l + \varepsilon)(x_2 - x_1)}{d(p_l, \varepsilon)}$ and $\frac{p_l(x_2 - x_1)}{d(p_l, 0)}$. We will now show that the expression in the first set of square brackets on the right hand side of Equation 7 is negative, as a first step to proving that the *whole* expression on the right hand side of Equation 7 is negative.

First, because it is more likely for costs to be perceived as losses at unimproved win probabilities than improved win probabilities, it is easy to show that:[9]

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[9] Proving $d(p_l, \varepsilon) > d(p_h, \varepsilon)$ is left to the reader.

$$d(p_l,\varepsilon) > d(p_h,\varepsilon)$$

$$\Rightarrow \frac{1}{d(p_l,\varepsilon)} < \frac{1}{d(p_h,\varepsilon)}$$

In addition, as $x_2 > x_1$ and $\varepsilon > 0$:

$$\varepsilon(x_2 - x_1) > 0$$

So we can multiply both sides of the previous inequality $\frac{1}{d(p_l,\varepsilon)} < \frac{1}{d(p_h,\varepsilon)}$ by $\varepsilon(x_2 - x_1)$ without needing to flip the inequality sign:

$$\Rightarrow \frac{\varepsilon(x_2 - x_1)}{d(p_l,\varepsilon)} < \frac{\varepsilon(x_2 - x_1)}{d(p_h,\varepsilon)}$$

Inequality 3

$$\Rightarrow \frac{\varepsilon(x_2 - x_1)}{d(p_l,\varepsilon)} - \frac{\varepsilon(x_2 - x_1)}{d(p_h,\varepsilon)} < 0$$

So, the expression in the first pair of square brackets to the right of the equals sign in Equation 7 is negative. If we can show that $p_l(x_2 - x_1)\left[\left(\frac{1}{d(p_l,\varepsilon)} - \frac{1}{d(p_h,\varepsilon)}\right) - \left(\frac{1}{d(p_l,0)} - \frac{1}{d(p_h,0)}\right)\right] < 0$ as well, then we can easily complete the proof. This latter inequality captures the second intuitive reason why, relative to *actual* willingness to incur costs to improve lotteries, *imputed* willingness to incur costs is greater in the high probabilities scenario vs. the low probabilities scenario. Specifically, recall that the denominator of the term $\frac{(p_l+\varepsilon)(x_2 - x_1)}{d(p_l,\varepsilon)}$ (which represents the *relatively low* expected psychological impact of each unit of cost from entering the unimproved lottery in the high probabilities scenario) is lower than the denominator of the term $\frac{p_l(x_2 - x_1)}{d(p_l,0)}$ (which represents the *relatively high* expected psychological impact of each unit of cost from entering the unimproved lottery in the low probabilities scenario). Thus, a given absolute change in the denominators of these terms constitutes a bigger proportional change for the denominator in the high probabilities scenario, and thus, all things equal, causes a larger discrepancy between actual and imputed willingness to incur costs in the high probabilities scenario. This logic is captured in the expression $\left(\frac{1}{d(p_l,\varepsilon)} - \frac{1}{d(p_h,\varepsilon)}\right) - \left(\frac{1}{d(p_l,0)} - \frac{1}{d(p_h,0)}\right)$. We will now show that this expression is negative as the next step to proving that the whole expression in Equation 7 is negative.

This section of the proof is more convenient using the following notation:

$$\tau \equiv \varepsilon(1-\lambda)$$

$$a \equiv d(p_l, 0) \equiv p_l + (1-p_l)\lambda$$

$$b \equiv d(p_h, 0) \equiv p_h + (1-p_h)\lambda$$

Therefore, from the definition of $d(p_l, \varepsilon)$ and $d(p_h, \varepsilon)$:

$$d(p_l, \varepsilon) = a + \tau$$

$$d(p_h, \varepsilon) = b + \tau$$

Now, from the definitions of a, b, and τ:

$$a + b + \tau = [p_h + (1-p_h)\lambda] + [p_l + (1-p_l)\lambda] + [\varepsilon(1-\lambda)]$$

Equation 8

$$= \lambda(2 - (p_h + p_l + \varepsilon)) + p_h + p_l + \varepsilon$$

Since $1 > p_h + \varepsilon$ and $1 > p_l$ (as they represent probabilities):

$$2 > p_h + p_l + \varepsilon$$

$$\Rightarrow 2 - (p_h + p_l + \varepsilon) > 0$$

Since $\lambda > 1$ (as required by loss aversion):

$$\Rightarrow \lambda(2 - (p_h + p_l + \varepsilon)) > 0$$

And, since $p_h + p_l + \varepsilon > 0$ (as all three quantities are positive):

$$\Rightarrow \lambda(2 - (p_h + p_l + \varepsilon)) + p_h + p_l + \varepsilon > 0$$

Using Equation 8, we can substitute in $a + b + \tau$:

$$\Rightarrow a + b + \tau > 0$$

As $\lambda > 1$ (loss aversion) and $\varepsilon > 0$:

$$\tau \equiv \varepsilon(1-\lambda) < 0$$

$$\Rightarrow (a+b+\tau)\tau < 0$$

$$\Rightarrow a\tau + b\tau + \tau^2 < 0$$

Adding ab to both sides:

$$\Rightarrow ab + a\tau + b\tau + \tau^2 < ab$$

Factorizing:

$$\Rightarrow (a+\tau)(b+\tau) < ab$$

Because it is more likely for costs to be perceived as losses at unimproved win probabilities than at improved win probabilities, it is easy to show that $a \equiv d(p_l, 0) > d(p_h, 0) \equiv b$,[10] and so $a - b > 0$. So we can multiply both sides of the inequality by $a - b$ without flipping the inequality sign:

$$\Rightarrow (a+\tau)(b+\tau)(a-b) < ab(a-b)$$

As $a+\tau > 0$, $b+\tau > 0$, and $ab > 0$,[11] we can divide by each of these expressions without flipping the inequality sign:

$$\Rightarrow \frac{(a+\tau)(b+\tau)(a-b)}{(a+\tau)(b+\tau)ab} < \frac{ab(a-b)}{(a+\tau)(b+\tau)ab}$$

Cancelling common factors of the numerator and denominator of each fraction:

$$\Rightarrow \frac{(a-b)}{ab} = \frac{a}{ab} - \frac{b}{ab} < \frac{(a-b)}{(a+\tau)(b+\tau)}$$

Adding τ to both a and b in the numerator of the right hand side:

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[10] Proving $d(p_l, 0) > d(p_h, 0)$ is left to the reader.

[11] Proving $a+\tau > 0$ and $b+\tau > 0$ is left to the reader – but the proposition follows logically from all possible probabilities being between zero and one and follows intuitively from the fact that these sums both represent possible values of the expected psychological impact of incurring each unit of cost.

$$\Rightarrow \frac{a}{ab} - \frac{b}{ab} < \frac{a + (\tau) - (b + (\tau))}{(a+\ \tau)(b+\tau)} = \frac{a+\tau}{(a+\ \tau)(b+\tau)} - \frac{b+\tau}{(a+\ \tau)(b+\tau)}$$

Cancelling common factors (again) of the numerator and denominator of each fraction:

$$\Rightarrow \frac{1}{b} - \frac{1}{a} < \frac{1}{b+\tau} - \frac{1}{a+\tau}$$

$$\Rightarrow \frac{1}{a+\tau} - \frac{1}{b+\tau} - \left(\frac{1}{a} - \frac{1}{b}\right) < 0$$

Using the definitions of $a, b,$ and τ, we can substitute back $d(p_l, 0)$, $d(p_h, 0), d(p_l, \varepsilon)$, and $d(p_h, \varepsilon)$:

$$\Rightarrow \frac{1}{a+\tau} - \frac{1}{b+\tau} - \left(\frac{1}{a} - \frac{1}{b}\right) < 0$$

$$\Rightarrow \left(\frac{1}{d(p_l,\varepsilon)} - \frac{1}{d(p_h,\varepsilon)}\right) - \left(\frac{1}{d(p_l,0)} - \frac{1}{d(p_h,0)}\right) < 0$$

As $x_2 > x_1$ and $p_l > 0$:

$$p_l(x_2 - \ x_1) > 0$$

$$\Rightarrow p_l(x_2 - \ x_1)\left[\left(\frac{1}{d(p_l,\varepsilon)} - \frac{1}{d(p_h,\varepsilon)}\right) - \left(\frac{1}{d(p_l,0)} - \frac{1}{d(p_h,0)}\right)\right] < 0$$

So, the term with the second pair of square brackets to the right of the equals sign in Equation 7 is also negative. It is now easy to show that the whole expression is negative and complete the proof.

Adding $\frac{\varepsilon(x_2 - x_1)}{d(p_l,\varepsilon)} - \frac{\varepsilon(x_2 - x_1)}{d(p_h,\varepsilon)}$ to both sides of the inequality above:

$$\Rightarrow \frac{\varepsilon(x_2 - \ x_1)}{d(p_l,\varepsilon)} - \frac{\varepsilon(x_2 - \ x_1)}{d(p_h,\varepsilon)} + p_l(x_2 - \ x_1)\left[\left(\frac{1}{d(p_l,\varepsilon)} - \frac{1}{d(p_h,\varepsilon)}\right) - \left(\frac{1}{d(p_l,0)} - \frac{1}{d(p_h,0)}\right)\right]$$

$$< \frac{\varepsilon(x_2 - \ x_1)}{d(p_l,\varepsilon)} - \frac{\varepsilon(x_2 - \ x_1)}{d(p_h,\varepsilon)}$$

From Inequality 3:

$$\frac{\varepsilon(x_2 - x_1)}{d(p_l,\varepsilon)} - \frac{\varepsilon(x_2 - x_1)}{d(p_h,\varepsilon)} < 0$$

$$\Rightarrow \frac{\varepsilon(x_2 - x_1)}{d(p_l,\varepsilon)} - \frac{\varepsilon(x_2 - x_1)}{d(p_h,\varepsilon)} + p_l(x_2 - x_1)\left[\left(\frac{1}{d(p_l,\varepsilon)} - \frac{1}{d(p_h,\varepsilon)}\right) - \left(\frac{1}{d(p_l,0)} - \frac{1}{d(p_h,0)}\right)\right] < 0$$

Substituting in the left hand side of Equation 7 for the left hand side of the above inequality:

$$\Rightarrow r^*(p_h + \varepsilon, p_l + \varepsilon, x_1, x_2) - r^*(p_h, p_l, x_1, x_2)$$

$$-[r^*(p_h + \varepsilon, 0, x_1, x_2) - r^*(p_l + \varepsilon, 0, x_1, x_2)] - [r^*(p_h, 0, x_1, x_2) - r^*(p_l, 0, x_1, x_2)] < 0$$

So, Prospect Theory predicts the *opposite* of the result of Study 7 in the main article, which showed that people's tendency to pay more to increase a win probability from, say, 70% to 80% rather than from 20% to 30% does *not* show up as forcefully when you ask them how much they are willing to pay to enter each of the separate lotteries that have win probabilities of 20%, 30%, 70%, and 80%.

■

Loss-Aversion Prediction 3: *Unlike prospective outcome bias, loss aversion predicts that, holding the improvement in expected value constant, people will incur the same costs for small increases in the probability of large rewards as for large increases in the probability of small rewards.*

Proposition 3: *According to Prospect Theory*, willingness to incur costs to improve outcomes is *constant* as:

- the value of the superior outcome increases relative to the value of the inferior outcome, and
- the value of the *unimproved* probability of the superior outcome increases to hold constant the potential improvement in the expected value of the lottery.

That is, if we define ε as an arbitrarily small quantity (representing the amount by which the superior outcome is greater in the higher-stakes scenario) such that $\varepsilon > 0$, and define τ (the amount by which the *unimproved* probability of the superior outcome must be greater in the higher-stakes scenario to hold constant the potential improvement in the expected value of the lottery) such that:

$$(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1) = (p_h - p_l)(x_2 - x_1)$$

We propose that:

$$r^*(p_h, p_l + \tau, x_1, x_2 + \varepsilon) - r^*(p_h, p_l, x_1, x_2) = 0$$

Proof of Proposition 3.

From the definition of $r^*(p_h, p_l, x_1, x_2)$:

$$r^*(p_h, p_l + \tau, x_1, x_2 + \varepsilon) - r^*(p_h, p_l, x_1, x_2)$$

$$= \frac{(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1)}{p_h + (1 - p_h)\lambda} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda} \qquad \textbf{Equation 9}$$

Intuitively, willingness to incur costs to improve the lottery in both scenarios should be identical because:

1. The improvement in the expected value of the lottery is the same in both scenarios.
2. The expected psychological impact of each unit of cost incurred is also the same (because the potential improved probability is the same in both versions of the lottery).

To show this mathematically, we can substitute for $(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1)$ using Equation 9:

$$r^*(p_h, p_l + \tau, x_1, x_2 + \varepsilon) - r^*(p_h, p_l, x_1, x_2)$$

$$= \frac{(p_h - (p_l + \tau))(x_2 + \varepsilon - x_1)}{p_h + (1 - p_h)\lambda} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda}$$

$$= \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda} - \frac{(p_h - p_l)(x_2 - x_1)}{p_h + (1 - p_h)\lambda} = 0$$

So, loss aversion does *not* predict the result of Study 9 in the main article, that for a given expected value of the improvement, people are more willing to slightly improve their chances of larger rewards than to substantially improve their chances of smaller rewards.

■

References

Ai, C., & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, *80*(1), 123–129. https://doi.org/10.1016/S0165-1765(03)00032-6

Blair, R. C., Sawilowsky, S. S., & Higgins, J. J. (1987). Limitations of the rank transform statistic in tests for interactions. *Communications in Statistics - Simulation and Computation*, *16*(4), 1133–1145. https://doi.org/10.1080/03610918708812642

Horrace, W. C., & Oaxaca, R. L. (2006). Results on the bias and inconsistency of ordinary least squares for the linear probability model. *Economics Letters*, *90*(3), 321–327. https://doi.org/10.1016/j.econlet.2005.08.024

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Wells, G. L., & Windschitl, P. D. (1999). Stimulus Sampling and Social Psychological Experimentation. *Personality and Social Psychology Bulletin*, *25*(9), 1115–1125. https://doi.org/10.1177/01461672992512005