

Framing, Perception, and Previous Outcome Heuristic:

Evidence from Two-stage Lotteries

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A thesis presented for the degree of
Bachelor of Arts

Economics Department
Columbia University
April, 2019

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Abstract

There has been a long ongoing debate about reference dependent preferences and the framing effect. Kahneman and Tversky (1979) were among the first ones to theorize it with their famous Prospect Theory. However, more recently economists started looking at perception effects that could explain the same preference reversal patterns, but instead of non-expected utility maximization, they attribute those effects to noisy encoding (Li, Khaw, and Woodford, 2017). In our paper, we analyze how exactly reference dependence and framing effects interact with perception. We observed that framing did not affect subjects' risk preferences but helped them to make more *accurate* decisions, suggesting that *Mixed* condition reduced noise in perception of expected value differences. At the same time, we found that emphasizing previous outcomes relative to a reference point led some subjects to heuristic decision making, which in turn increased risk-seeking behavior after immediate losses. In the end, we suggest a model that could incorporate both the framing and previous outcome effects, dependent on two distinct individual objective functions.

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¹I am deeply humbled by all the support that people showed me throughout this year. I want to thank my adviser Prof. Michael Woodford for sparking my interest in this fascinating field of human behavior and encouragement to always make a step ahead of my limits. In addition, this work would not have been possible without insights from Prof. Michael Best and Prof. Mark Dean, honors seminar students, and members of Cognition & Decision lab (in particular, Silvio Ravaioli, Oskar Zorilla, Arthur Prat-Carrabin, and Xi Zhi Lim). Finally, I could not be more grateful for my family in Lithuania and friends around the world, who were always there in both joyful and challenging moments throughout my undergraduate years abroad.

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1 Introduction

Individual decisions are never independent from the circumstances they are being made in. At every moment, we are affected by past events as well expectations about the future, instead of focusing on present information alone. It is indeed a natural cognitive process, given that choices in real life are most of the time highly complex and require judgements based on previous experience as well as inference about their consequences. However, sometimes this evolutionary trait works against our best interest, when a task at hand requires an analytical decision in isolation from any contextual influences. Behavioral scientists analyze inconsistencies in human behavior that arise from subjective representation of reality and generally call them *cognitive biases*. These biases are particularly relevant to decision making in economics and thus have been studied thoroughly and incorporated into numerous economic theories ever since the 1950s.

In economics, behavioral biases primarily raise questions about the definition of *rationality* formalized by von Neuman and Morgenstern in their 1944 book *Games and Economic Behaviour* and the standard expected utility maximization (EUM) framework (Bernoulli, 1738). Empirical studies have shown systematic preference reversals that violate the axioms of *transitivity* (decoy effects), *independence* (Allais' paradox) or *invariance* (Asian disease paradox). Usually, those biases are invoked by affecting people's perception of the task, for example, changing the question description, providing redundant information or manipulating their attention in some other way. Let's consider a simple choice, described by Kahneman and Tversky in their article *The Framing of Decisions and the Psychology of Choice* (1981). Suppose, that a disease is predicted to kill 600 people, but they have a choice to implement one of the two prevention programs and lower the number of deaths. One of them will save a third of the population with certainty and the other could either save everyone or no one with probabilities of one third and two thirds respectively. Both programs are expected to save 200 out of 600 people on average, yet, they differ in the amount of riskiness involved. A different frame was used in two surveys with the goal of estimating an effect of different choice representation.

Questionnaire 1

Program A : 200 people will be saved

Program B : there is a $1/3$ probability that 600 people will be saved and
a $2/3$ probability that no people will be saved

Questionnaire 2

Program A : 400 people will die

Program B : there is a $1/3$ probability that nobody will die and
a $2/3$ probability that 600 people will die

The framing effect was substantial. In Questionnaire 1, 72% of respondents preferred *Program A* (safe choice), while in Questionnaire 2, 78% of respondents preferred *Program D* (risky choice). We could conclude that people have different preferences over someone *living* and someone *not dying*, which means exactly the same thing! Kahneman and Tversky suggested that the use of words "save" and "die" put emphasis on positive and negative effects of the programs. They generalized an idea that under uncertainty individuals will be risk seeking when they face potential losses, but risk averse when they face potential gains, and called it the Prospect theory (1979). It argues that people estimate prospects relative to a neutral point of reference and due to a different shape of utility functions in loss and gain domains, they will indeed exhibit a similar preference reversal as in the example above. Hundreds of studies found similar patterns both in experimental setting and in the wild (Camerer, 1998) and the prospect theory remains one of the best explanations of human behavior under risk to this day (Barberis, 2013).

However, with a development of better experimental technologies, researchers started to find contradicting evidence to absolute loss aversion (Ert and Erev, 2013) and gain better understanding of the causes of the reflection effect, such as asymmetric attention allocation (Pachur et al., 2018). In the light of these recent developments, we created an experiment to test the effect of losses in two different frames, while controlling for overall risk seekingness and attentiveness to the outcomes at the individual level. *Gain* and *Mixed* frames were used to measure the effect of negative numeric representation, yet more importantly, red and green colors were used to emphasize losses and gains in both frames. Therefore, we can account for the effects of previous outcome and framing separately. The experiment design was similar to Thaler and Johnson (1990), which produced particularly interesting insights in how framing interacts with prior losses and gains, yet a lot of questions left unanswered due to a lack of consistency between them. To quote their conclusion, *Perhaps the most important conclusion to be reached from this research is that making generalizations about risk-taking preferences is difficult* (Thaler and Johnson, 1990). Our study achieved two important results on this issue: framing systematically increased subjects' sensitivity to expected value differences but did not lead to shifts in overall risk preferences; at the same time prior losses significantly increased risk seekingness independent of the frame, which we attribute to individual characteristics such as numeracy and heuristic decision making. We conclude that ignoring differences in individual behavior can lead to false interpretations of the pooled data.

This paper will present the experiment results from a few different theoretical points of view such as loss aversion, break-even effect, noisy representation, and heuristic decision making, with the goal of providing insights on these conceptually conflicting theories. In the end, we propose a model, which reconciles features of multiple theories and fits our results sufficiently well.

2 Relevant topics in literature

2.1 Reference dependent preferences

2.1.1 Framing effect and loss aversion

Rabin (2000) provides a rigorous proof that if a person turns down a 50-50 gamble between losing \$100 and gaining \$125, she would be risk-averse to the extent of turning down *any* gamble that offered a 50% chance of losing more than \$600, given a continuous CARA utility function. Such extreme risk aversion, frequently observed in experiments with modest-stakes payoffs, has since gained a name of Rabin’s paradox. This logical inconsistency in normative expected utility theory predictions and other cognitive biases mentioned earlier led behavioral economists to thinking about *reference dependent* preferences. It is plausible, that people perceive outcomes as deviations from some point of reference instead of changes in final level of wealth. For example, if someone expects their annual bonus to be \$10,000, but only receives \$5,000, this outcome could actually feel like a *loss* relative to the reference point of \$10,000 and cause disutility, even though their total wealth increased. Similarly, if one had to pay \$1000 in taxes but received an unexpected \$500 deduction, the entire transaction could feel like a win.

In the experimental setting, a person might ignore her overall wealth level and make decisions that seem to be advantageous locally around some reference point, while the reference point itself can shift from task to task. That would explain why subjects’ responses change based on the question framing or show extreme sensitivity to small changes in low-stakes prospects, which have negligible influence on their lifetime wealth. Even though some economists provided alternative models that are reference-independent i.e. disappointment aversion (Gul 1991) or probability weighting (Neilson 2001) to account for the EUM violations mentioned above, reference-dependent utility remains widely accepted as the most consistent one (Bleichrodt et al. 2018).

Kahneman and Tversky’s prospect theory (1979) is among the earliest and definitely most influential frameworks of reference dependent preferences. Authors propose a value function of the following form²:

$$v(x) = \begin{cases} x^\alpha, & \text{if } x \geq 0 \\ -\lambda(-x)^\alpha, & \text{if } x < 0 \end{cases} \quad (1)$$
$$x = W - r, \alpha \leq 1, \lambda \geq 1$$

This and other similar parametrizations (Maggi, 2004) produce an S-shaped utility function that has a few key characteristics:

- v is convex for $x < 0$ and concave for $x > 0$ - reflection effect

²An equally important part of the prospect theory is probability weighing function and thus the utility function would be $u(x) = \int v(x)\pi(p(x))dx$. However, $\pi(\cdot)$ will not be used in this paper.

- $v''(x) < 0, \forall x > 0$ and $v''(x) > 0, \forall x < 0$ - diminishing sensitivity for both losses and gains
- v is steeper in the loss domain ($v(x) < -v(-x), \forall x > 0$) - loss aversion

Those characteristics have become fundamental in explaining multiple cognitive biases, such as reflection effect, disposition effect, and loss aversion. $v(x)$ indicates that subjects will evaluate the final payoff W relative to a neutral reference wealth r , which explains high sensitivity to expected value differences between prospects despite their low impact on one's lifetime wealth. In addition, the s-shaped curve predicts risk-averse behavior in the domain of gains and risk-seeking in the domain of losses. Finally, with the prospect theory, Kahneman and Tversky formalized *loss aversion*, a tendency that losses have a stronger impact compared to the gains of the same size.

Prospect theory exhibits two features that are particularly relevant to our experiment. First, it implies that if a person is facing a safe option C and a uniform lottery G that involves both losses and gains (*Mixed* condition), their choice will depend on the sign of C . If $C > 0$ then $C \succeq G$ and vice versa. However, if the same expected value gamble did not involve losses (*Gain* condition) and $C \geq 0$, subjects should be overall *less* risk averse than before (Thaler et al., 1997).

At the same time, prospect theory suggests if a prior loss is not integrated into the reference point, it will lead to more risk-seekingness³. However, it does not aim to provide any insights as of how subjects *set* their reference points. Therefore, one of the ways to test reference dependence and loss aversion is by imposing different frames in order to manipulate people's reference wealth. Some of previously tested reference points in the literature are *status-quo* (Kahneman et al., 1991), *expected choice* (Koszegi and Rabin, 2007), *lagged wealth* (Thaler and Jonhson, 1990), and *performance target* (Sullivan and Kida, 1995).

2.1.2 Previous outcome effect

Analyzing the effect of prior gains or losses on risk-taking can be a good tool to test loss aversion and reference dependence. If people evaluated prospects only as marginal changes from a status-quo wealth, previous outcomes would have no influence on risk-taking. If instead prior outcomes do influence subjects' behavior, we could analyze whether it follows predictions of the prospect theory utility function. Empirical evidence suggests that individuals indeed do not immediately integrate past outcomes into their reference wealth, which leads to shifts in behavior and biases such as "disposition" (Barberis and Xiong, 2009; Weber and Camerer, 1998) or "end-of-the-day" effects (Ali, 1977). Looking through the lens of reference dependent preferences, it can be argued

³It must be the case that *if a risky prospect $(x, p; -y, 1 - p)$ is just acceptable, then $(x - z, p; -y - z, 1 - p)$ is preferred over $(-z)$ for $x, y, z > 0$, with $x > z$* (Kahneman and Tversky, 1979)

that subjects do not actively update their reference point and evaluate options relative to a predetermined one.

Thaler and Johnson (1990) came up with an effective experiment design to capture both the framing and previous outcome effects at once. In their experiment, they asked subjects to choose between safe and risky prospects of the same expected value following a prior gain or loss in two formats: one-stage and two-stage versions. In two-stage version, the subject first received some initial wealth between $-\$7.50$ and $\$15$ and was then asked to choose between adding another safe or risky amount. In one-stage version, the initial outcome was not announced separately, but instead added to both prospects. The results did not strictly match the prospect theory predictions. For instance, 33% more subjects chose the risky gamble when it was presented in two-stage format following a $\$15$ gain, but 37% more subjects chose the gamble when it was presented in one-stage format following a $-\$7.50$ loss (Figure 1). In other words, a mixed gamble caused more risk-seekingness compared to a gains-only gamble, which is opposite of what the prospect theory would imply, but increased risk-aversion when compared to a loss-only version, satisfying the rules of loss aversion. In another situation, neither prior losses nor gains had any effect when the risky option involved a $\$0$ bound in either frame.

It is clear, that framing did not shift preferences in a predictable manner implied by loss aversion and its effect was also dependent on the previous outcome and the absolute magnitude of the payoffs. The authors suggest an explanation with a modified version of *hedonic editing rules* (Thaler, 1985), which allow subjects to react differently to previous outcomes depending on their sign and magnitude (i.e. segregate gains, but integrate losses; cancel small losses with larger gains). However, researchers agreed that the exact decision process conditioned on prior outcomes was unclear and that there were special cases that could not be explained neither by prospect theory nor by suggested quasi-hedonic editing rules.

From our point of view, Thaler and Johnson (1990) experimental design raises a question about the role of perception in risky choices. Arguably, comparing the two prospects in integrated and not integrated representation could be perceived as a fundamentally different task, in particular with regards to their complexity. Therefore, it is possible that framing and previous outcome do not necessarily alter one's preferences but rather influence subjects' perception of the prospects and ability to take the *most preferred option* more accurately.

TABLE 4
Experiment 4

Initial Outcome	Two-Stage Gambles Choices		Percent Risk Seeking		One-Stage Gambles Choices	
	Payoff	Prob.	N = 95	N = 111	Payoff	Prob.
1. +\$15	\$0	1	77	44	\$15	1
	\$4.50	0.5			\$19.50	0.5
	-\$4.50	0.5			\$10.50	0.5
4. -\$7.50	\$0	1	40	77	-\$7.50	1
	\$2.25	0.5			-\$5.25	0.5
	-\$2.25	0.5			-\$9.75	0.5

Figure 1: Previous outcome and framing effect combined.

2.2 Perceptual influences

2.2.1 Numerical cognition

Neuroscientists have been increasingly interested in the mental processing of mathematical problems (Dehaene et al., 1996). Studies have shown that human brain creates associations between the task (i.e. to choose a larger or smaller number) and the magnitude of the numerals (Dehaene et al., 1993), hence displaying so-called semantic congruity and SNARC (spatial-numerical association of response codes) phenomena. Moreover, research reveals a reversed pattern with negative numerals.

Shaki and Petrusic (2005) found a polarity-based semantic congruity effect: participants' responses to positive numbers were faster when the instructions were to "select larger" than when the instructions were to "select smaller". In contrast, responses to negative numbers were faster when the instructions were to "select smaller" than when they were to "select larger" (Zhang and You, 2012).

Surprisingly, there is significantly less literature exploring the encoding of negative numbers, though there is an agreement that generally "negative numbers are processed less automatically than positive numbers" (Zhang and You, 2012). This evidence suggests, that economic decision making will also be influenced by the underlying cognitive processes and thus could be the source of preference reversals attributed to loss aversion.

A related alternative to loss aversion in behavioral economics has been proposed by Yechiam and Hochman (2011) - *loss attention*. Their experiments found that tasks that involved losses did not increase risk-aversion but rather made subjects attentive, hence

leading to a better performance on side tasks. In a different context, researchers pointed out that loss aversion itself can be caused by selective allocation of attention (Pachur et al., 2018).

Economists Ert and Erev (2013) conducted a thorough analysis of the impact of visual representation of prospects in risky choices in their paper *On the descriptive value of loss aversion in decisions under risk: Six clarifications*. They examined various manipulations of choice framing in order to answer the question whether loss aversion is a universal phenomenon as suggest by prospect theory or whether it is only created under certain visual and semantic conditions. In other words, the authors explored whether all frames produces a consistent and equally strong "framing effect".

The most insightful results were related to the nominal magnitude of the options in mixed and gain conditions. In the mixed condition, subjects took the risky option less often when the nominal payoffs were high, signifying that loss aversion is only activated by prospects that appear to be large⁴. However, in the gain condition, subjects instead risked *more* when the nominal magnitude was larger (Figure 2). Another important effect of framing was identified in the task that varied the expected value differences between safe and risky prospects, which will be particular relevant when discussing our experiment results. Authors found increasingly more risk-seekingness in the *Mixed* frame compared to *Gain*, for the gambles with positive expected value.

At the same time, studies that used fMRI scans showed that choosing a safe gain generally required less cognitive effort than choosing a risky gain, yet choosing a safe loss required equal cognitive effort as choosing a risky loss (Gonzalez et al., 2004). This could be a compelling explanation of why we observe more risk aversion after gains than after losses. It would signify that loss aversion bias does not come from risk preferences but instead from differences in mental processing.

Li, Khaw, and Woodford (2018) incorporate the importance of perception in risky choices with a model of *noisy encoding*. They use a psychophysics approach and consider risky decisions to be of a similar nature as other sensory stimuli detection problems (i.e. luminosity, sound signal, weight judgement tasks). In this case, authors consider a *signal* to be the difference of logarithms of prospect values, $\log(G/C)$, where prospects themselves are noisy representations of actual nominal values. In that case, the value difference will be perceived imprecisely and thus the probability of correctly choosing a more rationally advantageous prospect will depend not only on the signal strength but also on the prior distributions of prospects.

If looked at Ert and Erev's task from noisy encoding perspective, a constant that

⁴Indeed, mainly high nominal payoffs (\$50-2000) were used in all foundational experiments by Kahneman and Tversky (1979, 1981, 1986, 1992) when developing the prospect theory. Multiple other studies confirmed the same pattern: strong loss aversion with high nominal payoffs (Booij et al., 2010; Abdellaoui et al., 2007), but weak or none with the low ones (Andersen et al., 2010; Harrison and Rutström, 2009), presented in Ert and Erev (2013), Table 8.

Table 4: Examination of relative loss aversion in decisions under risk with low nominal payoffs (Sheqels) and high nominal payoffs (Agoras; 1 Sheqel = 100 Agoras)

Evidence for loss aversion	P(Risk)	No evidence for loss aversion	P(Risk)
Abstract investment decisions with high nominal payoffs Task: one-shot binary choice		Abstract investment decisions with low nominal payoffs Task: one-shot binary choice	
Mixed problem with high nominal payoff: Please choose between:	38%	Mixed problem with low nominal payoff: Please choose between:	51%
1. 500 Agoras with certainty 2. 1500 Agoras with probability of 0.5 -500 Agoras otherwise (p=0.5)		1. 5 Sheqels with certainty 2. 15 Sheqels with probability of 0.5 -5 Sheqels otherwise (p=0.5)	
Gain problem with high nominal payoff: Please choose between:	54%	Gain problem with low nominal payoff: Please choose between:	31%
1. 4000 Agoras with certainty 2. 5000 Agoras with probability of 0.5 3000 Agoras otherwise (p=0.5)		1. 40 Sheqels with certainty 2. 50 Sheqels with probability of 0.5 30 Sheqels otherwise (p=0.5)	

Figure 2: Loss aversion dependence on the magnitude of nominal payoffs.

is added to both prospects (Gain condition) automatically reduces the signal strength⁵. Similarly, in Thaler and Johnson (1990) experiment, both the safe prospect and gamble bounds had much smaller variance in the two-stage frame than those in the one-stage frame⁶, therefore, in repeated decisions the noise in perception of prior distributions of each prospect would be lower as well. Both a stronger signal and lower prior noise mean that in similar tasks as described above, the *Mixed* frame could be considered as being less *complex* from the perceptual perspective and thus lead to a more *consistent* performance.

2.2.2 Individual characteristics and heuristics

Given the evidence that risk behavior is subject to perceptual context, it is necessary to take into account individual characteristics such as numeracy and attentiveness that could determine how much one would be affected by those visual influences.

Since the early days of behavioral economics one of the main criticisms against robustness of systematic violations of EUM axioms in lab settings have been the lack of incentives, therefore, they would not occur under serious deliberation and higher attentiveness (an issue addressed by Kahneman and Tversky (1986)). In other words, subjects might not put enough effort to perform perfectly rationally given low-stake choices and thus resort to choice criteria that require less mental effort, known as heuristics. One of the possible shortcuts could be to never accept a sure loss, known as loss avoidance

⁵For the same absolute value difference, adding a positive constant will strictly decrease the ratio of logarithms, $\log(G/C) < \log((G+a)/(C+a)), \forall G, C, a > 0$. I.e. $\log(10/5) \approx 0.7$ and $\log(15/10) \approx 0.4$.

⁶For example, $var(C) = 5.9$ in the two-stage frame and $var(C) = 93.3$ in the one-stage frame, where C is the safe amount. That is determined by the fact that the variance of the prospects is independent from the variance of the previous outcome in the former but not in the latter case.

heuristic (Ert and Erev, 2007). Therefore, in sequential gambles some individuals might make their choices based entirely on the prior outcome, irrespective of the expected value differences. This could be particularly prevalent among individuals with lower numeric abilities, since to them a rational decision appears relatively more costly, hence making heuristic approach more appealing.

Multiple studies confirm the relationship between cognitive biases and individual characteristics. For example, in financial markets, loss aversion was found to affect individual investors but not professional traders, suggesting that experience and relevant skills indeed reduce the effects of behavioral biases (Locke and Mann, 2005). Similarly, a framing effect was found to significantly affect subjects with low numeric skills, but not those with high, in a replication of *disease paradox* among hospital patients (Peters, Hart, and Fraenkal, 2011). Finally, perceptual factors can lead to distinct decision strategies employed by some subjects, but not the others, hence resulting in heterogeneous behavioral patterns between different individuals (Reeck, Wall, and Johnson, 2017).

Cognitive processes in risky decisions as well as individual characteristics have been largely ignored in the early developments in behavioral economics due to technological limitations. Most of the initial studies of decisions under risk were designed as one-shot binary choice problems of a static form. However, the majority of recent results emphasize the importance of individual level analysis in order to prevent false conclusions when considering average effects alone. Therefore, our study will aim to address these two majors concerns related to perception and individual biases as well.

3 Experiment design

The experiment was run at Columbia Business School Behavioral Research Lab. A total of 53 participants completed the experiment, which lasted 15-25 minutes and had the average payment of \$6.9. The study was advertised as a gambling decisions game that paid a flat \$5 show-up fee and a performance based premium of \$0-3. Each participant on average completed 26 rounds (15-25-30, depending on a session) of each of the two treatment conditions named Version 1 and 2 (*V1* and *V2* henceforth), which were comparable to *Gain* and *Mixed* frames in the existing literature. The order of treatments was assigned randomly and all subjects finished the study in its entirety. At the beginning of each version, frame-specific instructions were shown, followed by three practice rounds in order to make participants familiar with the task and its frame. All amounts throughout the game were displayed in dollars. In the instructions, subjects were informed that a payoff from one randomly selected round will become their final reward, hence making all rounds equally important.

The experiment design and code are original, based on similar experiments in existing literature on loss aversion (Thaler and Johnson, 1990; Ert and Erev, 2013). The user

interface and back-end program was built using *Otree* (Daniel Li Chen, Martin Walter Schonger, and Chris Wickens, 2014) and was deployed on the server using *Heroku* application. No technical issues were encountered throughout the experiment sessions and no collected data was removed from the sample. A pilot session was run with honors seminar students. Even though their behavior was more risk neutral, the framing and previous outcome effects were of the same direction as in the final sample. The pilot data was not included in the analysis due to official IRB procedures and some modifications in the design.

3.1 General structure and main variables

A 2-stage structure was chosen in order to control for individual risk preferences and estimate the impact of previous outcomes as well as the framing effect *conditional* on subjects' types in terms of their overall risk-seekingness and performance. A game tree in Figure 3 represents the structure of one round.

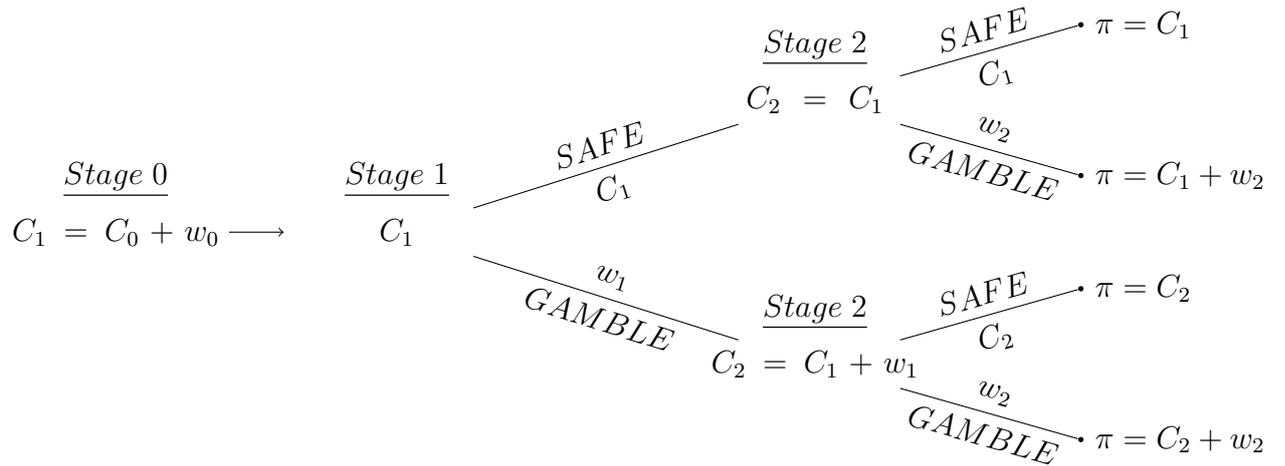


Figure 3: One round structure in a game tree form

$$decision = \begin{cases} GAMBLE (D = 1), & \text{if } E[u(G)] > u(C) \\ SAFE (D = 0), & \text{otherwise} \end{cases} \quad (2)$$

A strictly dominant strategy in both rounds with exponential utility function

The task was to choose between **SAFE** (C) and **GAMBLE** (G) options in two consecutive stages with the goal of maximizing the final payoff, π , in each round. Subjects were told that a new gamble in Stage 2 would be generated independently from their choice in Stage 1. Therefore, despite a compound structure of the task, a rational (EUM) decision

must have been made in isolation and should have been independent of the prior outcome or previous decision *per se*⁷ for any exponential utility function⁸.

$$\begin{aligned} w_o &\sim U[-0.6, 0.6], w_o \neq 0 \\ w_1 &\sim U[-k_{min}, k_{max}], \text{ where } k_{min} \sim U[0.3, 0.8], k_{max} \sim U[0.3, 1.0] \\ w_2 &\sim U[-k_{min}, k_{max}], \text{ where } k_{min} \sim U[0.4, 1.1], k_{max} \sim U[0.4, 1.2] \end{aligned}$$

Prior to each round, the certain prospect for Stage 1 was generated from a uniform distribution, $C_1 \sim U[5.9, 7.1]$, $C \neq 6.5$ ⁹. Subjects could then either take C_1 (SAFE) or enter a lottery (GAMBLE) and win a new amount. The risky option was a uniformly distributed gamble, presented to the participants as "a lottery that would give any amount between \$LB and \$UB with equal probability". The lottery bounds were generated independently from one another, thus allowing for positive and negative expected value differences between the two prospects. The safe amount was always within the lottery interval with at least a \$0.30 distance from either end, $C \pm 0.3 \in [LB, UB]$. We denote the distance between the gamble bounds and the certain amount as k_{min} k_{max} . The expected gains from taking the risky choice will be denoted $EV[G] = E[G] - C$, where $E[G] = \frac{LB+UB}{2}$. This variable¹⁰ should be the only relevant choice criterion for a risk neutral individual. The outcome of Stage 1 will result from an individual decision and will become the certain amount in Stage 2 problem ($C_2|SAFE = C_1$ and $C_2|GAMBLE = C_1 + w_1$). The choice in Stage 2 is equivalent as in Stage 1. The subjects can either take the certain amount and end the round or enter a new lottery, whose bounds k_{min} and k_{max} were generated anew, independently from the previous decision. The final payoff for the round is the outcome of Stage 2. After the round is over, subjects were shown their final outcome ("Round Results") and then the list of all previous payoffs ("Results Summary"). Finally, the player has to select "Start a new round" and begin the next round with Stage 1 again.

Notation $S1$ and $S2$ will be used to specify the stage, while $S2$ after SAFE and GAMBLE ($S2|S$ and $S2|G$) will signify which path was chosen in Stage 1.

⁷Prior outcomes could affect the decision only by shifting the certain amount along the curve. However, it would have to be consistent at the individual level throughout the experiment, i.e. when facing the exact same safe amount C_t and lottery G_t , their position relative to the previously owned amount C_{t-1} should not reverse the risk preferences. In our analysis, we will indeed relax this assumption with models of reference-dependent preferences.

⁸ $u(c) = (1 - e^{-ac})/a$, $\forall a \neq 0$ and $u(c) = c$ if $a = 0$

⁹All amounts throughout the task were rounded to nearest \$0.10

¹⁰ $EV[G]$ has a slightly asymmetric triangular distribution with $\mathbb{E}(EV[G]) > 0$, though not significantly different from 0. This was done in order to obtain more Stage 2 observations on the GAMBLE path. Note that this upwards bias would not compromise our findings, because it was consistent across treatments as well as independent from previous outcome and choice.

¹¹Mistake is defined as a choice that was disadvantageous in terms of its expected value. It will be specified and discussed in later sections.

Table 1: Variables summary by Version and Stage

Variable / Stage	Version 1		Version 2	
	S1	S2	S1	S2
C	6.49 (0.47)	6.58 (0.54)	6.5 (0.47)	6.61 (0.54)
E[G]	6.58 (0.49)	6.61 (0.56)	6.6 (0.49)	6.64 (0.55)
EV[G]	0.09 (0.16)	0.02 (0.15)	0.09 (0.15)	0.03 (0.15)
$k_{min} + k_{max}$	1.23 (0.24)	1.55 (0.31)	1.24 (0.25)	1.56 (0.32)
Stage payoff	6.58 (0.54)	6.61 (0.66)	6.61 (0.54)	6.65 (0.64)
% GAMBLES	0.61 (0.01)	0.58 (0.01)	0.61 (0.01)	0.53 (0.01)
Mistakes ¹¹	0.31 (0.01)	0.32 (0.01)	0.23 (0.01)	0.3 (0.01)
Response Time	5.03 (3.85)	4.26 (3.27)	3.11 (2.21)	2.71 (1.81)
N	1385	1385	1390	1390

Table 2: Both versions were identical in terms of variable generation. Stage 1 had a slight upward bias in risky prospect bounds, while Stage 2 had a slightly larger spread, although the differences were not significant. The only outstanding differences are *Response Times* across the versions and the lower percentage of mistakes in V2 S1, which will be discussed in detail later on.

3.2 Two frames

The two treatments, Version 1 and 2, differed in a visual presentation of the risky option in order to test the framing and previous outcome effects. In Version 1, both the certain and risky prospects were displayed as potential final payoffs, whereas in Version 2, the certain amount was subtracted from the gamble bounds in order to emphasize the potential deviation from the safe prospect. Even though the two versions were similar to *Gain* and *Mixed* conditions, we decided to create a sensation of losses in the *Gain* version as well and verify whether we can obtain equal loss aversion in both treatments. This was implemented by explicitly using an anchor value of \$6.50, which was the average expected payoff, and showing all amounts in green and red colors depending on their position relative to the anchor. In this way, both safe and risky prospects below 6.50 could feel as losses and thus cause loss aversion. Meanwhile, the certain amount in Version 2 was always black in order to make the safe option to feel *neutral* and only highlight potential losses from taking the risky option. With this framing, we hoped to impose comparable reference points and analyze the relationship between the previous outcome effect and visual display of the prospects.

$$G \sim U[LB, UB] \text{ is displayed as } G \sim U[C - k_{min}, C + k_{max}] \quad (3)$$

Version 1

$$G \sim U[LB, UB] \text{ is displayed as } G \sim U[-k_{min}, +k_{max}] \quad (4)$$

Version 2

In addition, the two versions differed significantly in terms of signal strength, $EV[G]$ and noisiness in prior distributions of the risky prospect, as discussed in the models of *noisy encoding* earlier. In other words, calculating the expected value of the lottery and comparing it to the safe option could be easier in *V2*, where the certain amount is already subtracted from the gamble bounds¹².

¹²This would be true, if subjects considered the reference point of 0 in Version 1, but safe amount in Version 2

Stage 1 display in two versions

Stage 1

You start the round with **\$6.50**.

Choose between the two options:

Option "Safe":

Take **\$6.70** with certainty and move on to Stage 2.

Option "Gamble":

Enter the lottery to draw a new amount in between **\$6.20** and **\$7.30** and move on to Stage 2.

Select the Option

Version 1, Stage 1

Stage 1

You start the round with:

\$6.40

Choose between the two options:

Option "Safe":

Do not gamble and move on to Stage 2.

Option "Gamble":

Enter the lottery to add any amount in between **-\$0.40** and **\$0.90** and move on to Stage 2.

Select the Option

Version 2, Stage 1

Stage 2 display in two versions

Stage 2

You chose to **gamble** in Stage 1.

You gambled between \$6.20 and \$7.30 and the outcome of the lottery was:

[**\$6.20** , **\$7.30**]
\$6.70

Your new options are:

Option "Safe":

Keep **\$6.70** with certainty and end the round.

Option "Gamble":

Enter the lottery to draw a new amount in between **\$5.80** and **\$7.20** and end the round.

Select the Option

Version 1, Stage 2

Stage 2

You chose to **gamble** in Stage 1.

You gambled between **-\$0.40** and **\$0.90** and you **gained**:

\$0.50

Your current payoff is $\$6.40 + \$0.50 = \$6.90$

Your new options are:

Option "Safe":

Do not gamble and end the round.

Option "Gamble":

Enter the lottery to add any amount in between **-\$0.70** and **\$0.60** and end the round.

Select the Option

Version 2, Stage 2

4 Motivating results

At first, it is helpful to look at experiment results graphically to explore the main trends. Therefore, in this section we present visual evidence that illustrate our main findings, framing and prior outcome effects, as well as their dependence on subjects' decision in Stage 1.

4.1 Framing Effect

Prospect theory predicts a higher risk aversion in the Mixed frame compared to the Gain one. However, Ert and Erev (2013) showed that Gain condition caused more risk aversion for positive expected value gambles. Our results support their findings and reveal an even more consistent pattern - Version 2 significantly increased subjects' sensitivity to expected value differences, therefore, leading to opposite shifts in risk taking depending on whether the gamble was favorable or not. The results suggest that framing was more important in terms of reducing the *noise* in signal ($EV[G]$) rather than changing individual risk preferences. However, a noisier representation did not lead to a higher risk aversion as predicted by Khaw, Li, and Woodford (2017).

4.2 Reference Dependence and Previous Outcome Effect

Our second hypothesis was related to the effect of previous outcomes. CARA utility would indeed predict an increasing risk aversion with the size of a safe option. However, the results provide strong evidence for reference dependence preferences rather than first order (local) risk aversion. Therefore, based on prospect theory value function, if subjects do not immediately update their reference wealth (do not integrate prior outcomes), they will be more risk seeking after losses than after prior gains. Two-stage gambles not only gave us insights of how individuals updated their reference points, but also revealed that the effect of prior outcomes was strongly dependent on the *types* of people, which will be discussed in the last section.

% GAMBLE based on $EV[G] = E[G] - C$, pooled data

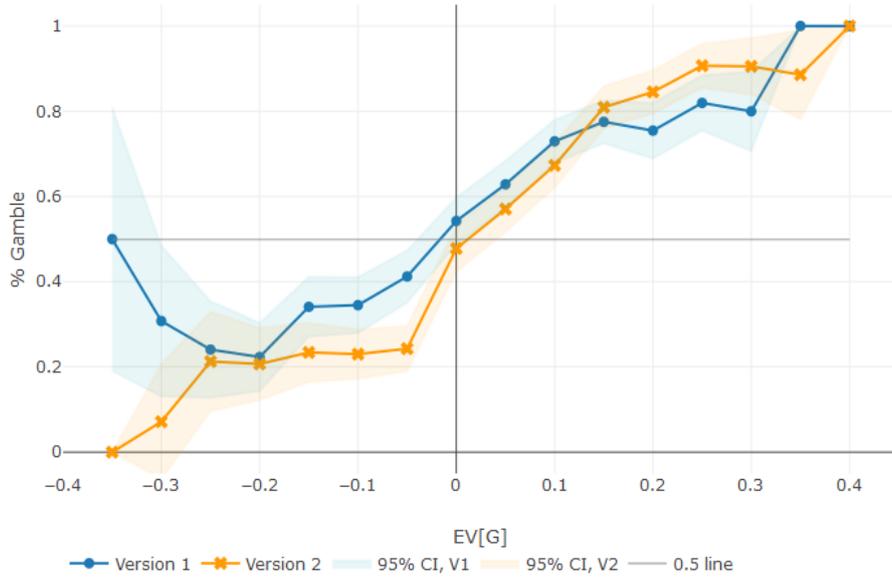
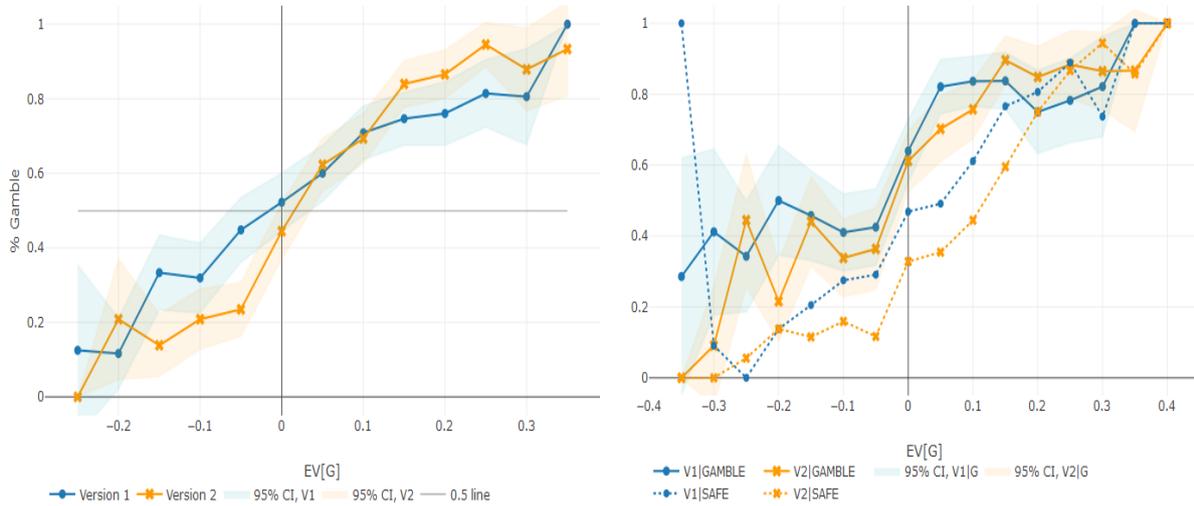


Figure 4: Framing led to a higher risk aversion as well as an increased sensitivity to expected value differences, thus leading to a more risk neutral behavior in V2. It suggests that framing also reduced *noise*. A particular asymmetry is visible in Version 2 on the left and right from 0. It seems that % of GAMBLE was constant among people who took unfavorable gambles, but increasing with $EV[G]$ among those who took favorable ones.

% GAMBLE based on $EV[G] = E[G] - C$



Stage 1

Stage 2 after SAFE and GAMBLE

Figure 5: No significant difference in risk aversion was observed in $S1$ and $S2|G$. In Stage 2, framing had a distinct effect on those who took safe and risky options in Stage 1. Version 2 indeed increased risk aversion for all levels of $EV[G]$, but did not change sensitivity after SAFE. Meanwhile, it did not change risk aversion and only slightly increased sensitivity to $EV[G]$ after GAMBLE. Therefore, we have a 10% higher gap between $S2|S$ and $S2|G$ in V2 compared to V1.

% GAMBLE based on SAFE option, pooled data

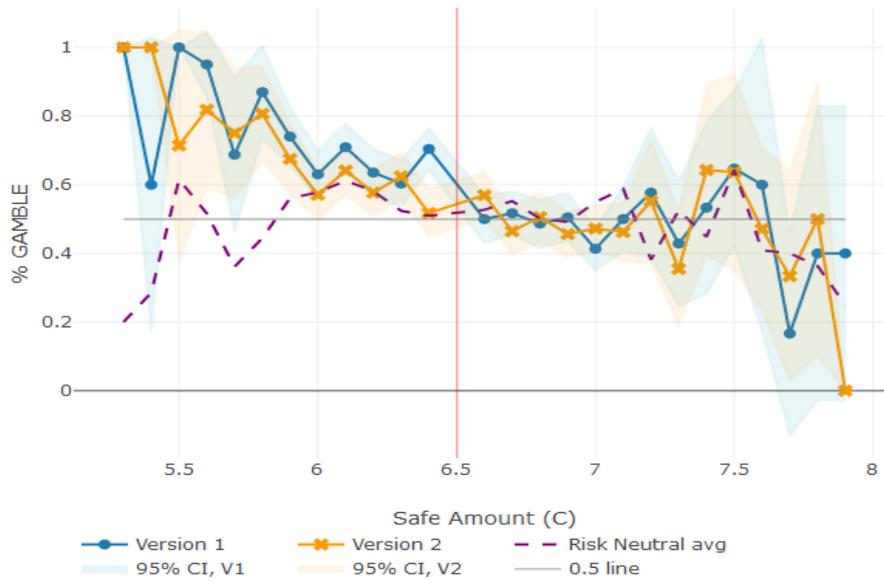


Figure 6: A clear asymmetry is observed to the left and right from the expected-value reference point (\$6.50). Subjects were *increasingly* more risk seeking in the loss domain, but gambled near risk neutrally on the gain domain.

% GAMBLE actual - % GAMBLE risk neutral



Stage 1

Stage 2 after SAFE and GAMBLE

Figure 7: In both stages subjects were more risk seeking after prior losses, suggesting underlying reference dependent preferences. However, reference dependence in Stage 2 was particularly strong for individuals who took the risky option, but insignificant for those who took the safe option in Stage 1. Therefore, the effect could be attributed to immediate prior outcome and one-period lagged reference point or to diverging decision criteria based on individual risk preferences.

5 Prospect theory model

Given the evidence for reference dependent preferences in the experiment data, we will use the prospect theory to estimate the effect of framing as well as incorporate the previous outcome effect by comparing status-quo and one-period lagged reference point models. As is the case in most behavioral experiments, we will allow for choice stochasticity.

5.1 Random utility maximization

If all the individuals were risk neutral, we should observe $D = 1$, if $E[G] > C$ and $D = 0$ otherwise. However, it is natural to assume that individuals have heterogeneous preferences towards risk even for low-stake gambles, while maintaining an increasing utility of wealth function. Then in the pooled data, we would expect the percentage of gambling choices to be an increasing function of the expected value difference between the risky and safe prospects. However, on the individual level, given a continuously differentiable utility of wealth, a risk-averse person should never gamble when $E[G] \leq C$, while a risk-seeker should always gamble when $E[G] \geq C$ (based on concave and convex utility functions respectively). Most experiments show that subject choices are not deterministic and involve a factor of randomness (Mosteller and Nogge, 1951). In our experiment, preference reversal was observed for all individuals, meaning that a subject changed their preferred choice when facing the exact same expected value difference problem. It could result from two factors: stochasticity in behavior or other parameters beyond the expected value difference, such as size of the safe option or gamble spread. We will choose a model of *random utility maximization* (Luce, 1959; Harless and Camerer, 1994) that take into account both ideas. It allows for an error factor and thus makes subjects' choices a *probabilistic* function of observable parameters. One of most common specifications in binary choice problems is the logistic function (Stott, 2006). In the following analysis, I will use logistic specification and obtain the optimal parameters based on prospect theory value function with *Maximum Likelihood Estimation* (MLE). A standard notation will be used, following *Hierarchical Maximum Likelihood Parameter Estimation for Cumulative Prospect Theory* (Murphy and Brincke, 2017).

Let us consider two prospects G and C . The subject will prefer one over the other with some probability (due to an error factor), based on the utility difference between the two ($u(G) - u(C)$) and a factor of sensitivity (γ). Denote a parameter vector θ (members of θ will be specified later) and a choice y_i ($y_i = 1$ if G is chosen, 0 otherwise) for the i -th lottery. A choice must come from a decision function that is dependent on the parameters (θ) and observed prospects (C and G). Then $D(\cdot)$ will denote a probability of G being chosen ($y_i = 1$):

$$D(y_i|\theta) = \begin{cases} p(G \succ C) & \text{if G is chosen } (y_i \text{ is } 1) \\ 1 - p(G \succ C) & \text{if C is chosen } (y_i \text{ is } 0) \end{cases} \quad (5)$$

$$p(G \succ C) = \frac{1}{1 + e^{-\gamma(u(C) - u(G))}}, \quad \gamma \geq 0 \quad (6)$$

Constructing the likelihood function and solving for the parameters that were most likely to generate the observed data will give us $\hat{\theta}_{MLE}$:

$$\mathcal{L}(\theta | y) = \prod_{i=1}^N p(G \succ C)^{y_i} (1 - p(G \succ C))^{1-y_i} \quad (7)$$

$$\hat{\theta}_{MLE} = \operatorname{argmax}_{\theta} \prod_{i=1}^N D(y_i | \theta) = \operatorname{argmax}_{\theta} \mathcal{L}(\theta | y) \quad (8)$$

In the two following subsections, I will use the model described above and compare the estimates between the versions with two specifications: a status-quo (safe option) reference point and a lagged expectations reference point¹³. Applying the prospect theory value function and logistic regression described above we will obtain a loss aversion parameter λ , a diminishing wealth sensitivity parameter α , and a sensitivity to utility difference γ .

5.2 Prospect theory estimation

5.2.1 Status-quo reference point

As discussed previously, a common way to evaluate risky gambles is to consider the reference point to be the safe amount that a subject can have with certainty, $r = C$. This specification assumes that previous outcomes have no effect as they are immediately integrated into the certain wealth level. Therefore, the safe option feels *neutral* and its utility is zero, $u(C | r) = u(C | C) = v(C - C) = v(0) = 0$ ¹⁴. The gamble is then evaluated in comparison to the safe amount as $u(G | C) = \int v(x - C)p(x)dx$. Remember, that in our experiment $G \sim U[C - k_{min}, C + k_{max}]$, which gives:

$$\begin{aligned} u(G | r) = u(G | C) &= \int_{C-k_{min}}^{C+k_{max}} v(x - C)p(x)dx = \int_{-k_{min}}^{k_{max}} v(x)p(x)dx = \\ &= \frac{1}{k_{min} + k_{max}} \left(\int_{-k_{min}}^0 \lambda(-x)^\alpha dx + \int_0^{k_{max}} x^\alpha dx \right) = \frac{-\lambda k_{min}^{\alpha+1} + k_{max}^{\alpha+1}}{(\alpha + 1)(k_{min} + k_{max})} \end{aligned} \quad (9)$$

Then $p(G \succ C) = \frac{1}{1 + e^{-\gamma(u(G))}}$. Solving for maximum likelihood estimates gives

¹³Parameters were also estimated with the reference point of 0, but that specification led to extremely imprecise estimates, which are reported in the appendix but will not be discussed in detail. This finding only supports the idea that subjects do not evaluate prospects in terms of their final payoffs

¹⁴ $v(\cdot)$ is the prospect theory value function as defined in the literature review section above.

$\hat{\theta}_{MLE} = \{\hat{\alpha}, \hat{\lambda}, \hat{\gamma}\}$. In Table 3, we report the estimates of each treatment version and stage separately. Standard errors were calculated based on *Cramér–Rao lower bound* theory¹⁵:

$$var(\hat{\theta}) \geq \frac{1}{I(\theta)}, \text{ where } I(\theta) = -E\left[\frac{\partial^2 \mathcal{L}(y; \theta)}{\partial \theta^2}\right] \quad (10)$$

	Version1				Version2		
	Pooled	Stage1	S2 C	S2 G	Stage1	S2 C	S2 G
α	0.22 (0.16)	-0.41 (0.36)	0.28 (0.6)	0.89 (0.5)	0.32 (0.31)	0.53 (0.48)	-0.12 (0.43)
λ	0.98 (0.02)	0.97 (0.03)	1.13 (0.09)	0.56 (0.09)	1.09 (0.05)	1.48 (0.18)	0.87 (0.06)
γ	4.89 (0.37)	2.71 (0.61)	5.34 (0.98)	6.16 (1.21)	6.49 (1.01)	6.23 (0.87)	5.36 (0.99)
N	5550	1385	540	845	1390	540	850
$R_{McFadden}^2$	0.15	0.11	0.15	0.09	0.23	0.2	0.16

Table 3: Prospect theory parameters when the reference point is the certain amount. $S2 | C$ and $S2 | G$ are the subsets depending on the choice in $S1$. Each column represents a separate regression. *Pooled* model takes into account the entire sample. Note that an equal number of people in $S2|S$ across the treatments was a coincidence, reminding once again that Version 2 did not lead to a higher risk aversion in Stage 1.

Comparing λ parameter in $V1$ and $V2$ shows that framing indeed increased loss aversion across both stages, which is consistent with previous literature. However, Gain and Mixed treatments seem to differ more in the other two parameters, α and γ . In our experiment, 85% of gamble bounds (k_{min}, k_{max}) were between 0.3 and 1, therefore, all prospects were close to the reference point and thus a lower α also means a higher sensitivity to prospect values. Combining α and γ , we can conclude that Version 2 made subjects much more sensitive to gamble bounds and utility difference between the prospects. At the same time, we see some unusual parameter estimates. For example, α is not significantly different from 0 in any stage, which leads to thinking that the status-quo reference point might ignore some other criteria in subjects' decision making and is not an accurate representation of the underlying choice process. In addition, λ is significantly lower than 1 in $S2|G$ in both treatments, which is the opposite of loss aversion and suggests that subjects put a smaller weight on the negative bound of the lottery, thus leading to overall higher risk seeking.

This specification fits Version 2 Stage 1 data the best where the previous outcome was felt the least from a visual perspective. This suggests that anchoring and previous outcome effect emphasized with colors indeed played an important role. At the same time,

¹⁵Standard errors are square root terms of the diagonal of the variance matrix, which gives an equivalent of White's consistent standard errors.

estimated parameters reveal strong contrasts in Stage 2 between individuals who took SAFE and GAMBLE options in Stage 1. It suggests that loss aversion either depends on overall individual risk preferences or, more likely, on other characteristics such as attentiveness, numeracy, and heuristics. Therefore, we first want to look at the prospect theory model that would take into account the effect of prior outcomes and then analyze alternative explanations for path dependent differences in Stage 2 behavior.

5.2.2 Lagged wealth reference point

We saw that the size of the safe option has a strong effect. Rather than considering the diminishing sensitivity of wealth, which makes the safe option increasingly more attractive, it is more reasonable to assume that this behavior comes from the fact that people do not immediately update their reference point. In other words, when people do not integrate previous outcomes, taking the safe option does not feel neutral anymore, but rather is perceived as taking a sure loss or a gain. We can incorporate this effect by considering that at the time of the decision, subject's reference point is a lagged level of wealth, i.e. a previously owned wealth level or a target value based on expectations.

In our experiment, \$6.50 was a strong anchor in Version 1 as the green and red colors were used to show payoffs' position relative to that value in both stages. However, in Version 2, this anchor should not have a direct effect, since the certain option was always displayed in black. Instead, in $V2$ the emphasis was put on the lottery outcome in $S2$ - green and red colors indicated a positive or negative outcome relative to the previously owned safe amount. Based on this design, we will consider two potential reference points: the anchor value, $r = 6.50$, and previous wealth, $r = C_{t-1}$. Note that the distinction between the two possible reference points only matters in Stage 2, because the expected initial wealth in Stage 1 was \$6.50 as well.¹⁶ Therefore, comparing those reference points after the risky option in Stage 2 will help us to determine, whether the anchoring or prior outcome effect had a stronger impact on people's behavior. Using the earlier notation, the deviation from the lagged reference point is denoted as W_p (previous winnings). Hence, in $S1$, $W_p = C_1 - 6.5$, while in $S2$, $W_p = C_2 - 6.5$ or $W_p = C_2 - C_1$ depending on the reference point. In general:

$$u(C | r) = v(C - r) = v(W_p)$$

$$u(G | r) = \int_{r+W_p-k_{min}}^{r+W_p+k_{max}} v(x - r)p(x)dx = \int_{W_p-k_{min}}^{W_p+k_{max}} v(x)p(x)dx \quad (11)$$

Solving the integral involves three different cases depending on the position of the

¹⁶Interestingly, neither cumulative, nor immediate payoffs from previous rounds had an effect on Stage 1 decision, which is something that other studies found to be an important factor in repeated choice problems.

bounds relative to 0, since by construction $W_p - k_{min}$ and $W_p + k_{max}$ can both be positive or negative as well as have opposite signs. Now $p(G \succ C) = \frac{1}{1+e^{-\gamma(u(G|r)-u(C|r))}}$. *MLE* will give the same vector of parameters $\hat{\theta}_{MLE} = \{\hat{\alpha}, \hat{\lambda}, \hat{\gamma}\}$ as earlier.

	<i>Version1</i>					<i>Version2</i>			
	$r = C_{t-1}$	$r = 6.50$			$r = C_1$	$r = 6.50$			$r = C_1$
	<i>Pooled</i>	Stage 1	S2, S	S2, G	S2, G	Stage 1	S2, S	S2, G	S2, G
α	0.78 (0.02)	0.75 (0.04)	0.98 (0.06)	0.68 (0.04)	0.74 (0.05)	0.87 (0.03)	0.99 (0.05)	0.82 (0.04)	0.75 (0.03)
λ	1.05 (0.04)	0.9 (0.13)	1.38 (0.21)	0.39 (0.09)	0.25 (0.08)	1.22 (0.12)	2.19 (0.29)	0.61 (0.09)	0.41 (0.08)
γ	6.53 (0.23)	5.87 (0.49)	5.72 (0.77)	8.33 (0.78)	7.9 (0.65)	8.16 (0.56)	5.33 (0.76)	9.01 (0.76)	9.68 (0.73)
N	5550	1385	540	845	845	1390	540	850	850
$R^2_{McF.}$	0.16	0.12	0.15	0.11	0.14	0.24	0.15	0.16	0.22

Table 4: Prospect theory parameters when the reference point is lagged level of wealth. Each column represents a separate regression.

First of all, we achieve a strong increase in efficiency for parameters α and γ . In this model, α is around 0.8 and has 8-10 times smaller standard errors, compared to the status-quo reference point. Its magnitude is consistent with previous literature and shows that subjects evaluate the wealth almost linearly. At the same time, we still observe a significantly higher loss aversion in *V2* than in *V1* across both stages, which confirms the idea that mixed condition increases loss aversion. Once again, the main difference in loss aversion is visible within each treatment's Stage 2, after safe and gamble paths. Firstly, λ is significantly lower than 1 in $S2 | G$ as previously. It could suggest that when a person is facing a mixed problem (the upper bound is above the lagged reference point), they will pay less attention to the lower bound, similarly as with status-quo r . Alternatively, in this model, it could also suggest that a certain amount that is below r will be weighted less than if it was above r . Either explanation leads to risk-seeking after losses. Secondly, in $S2 | C$ in Version 2, $\lambda = 2.19$, which shows the opposite - people who took the safe option which was below \$6.50 indeed risked *less* than those who were above \$6.50. This value of λ is also similar to Kahneman and Tversky's observed parameter in their original study and other following experiments. Moreover, the difference in λ between the two treatments is 0.81, which suggests that framing has a particularly strong effect on people who are overall more risk averse or more attentive, an idea that will be explored in later sections. Those reasons are good indicators that previous outcome had a significant effect on subjects' behavior, which in turn was asymmetric depending on the first stage decision.

Given that α parameters are similar across the versions, we can now more robustly compare the sensitivity to utility differences, γ . It remains larger in *V2* across all stages

except for $S2 | C$. In this situation the framing only increased loss aversion, thus, leading to lower percentage of gambling in *Mixed* condition, but had no effect on subjects' ability to make better decisions based on their preferences.

Finally, the model fit (R^2) has increased in both versions in $S2 | G$ and only decreased for Version 2 in $S2 | C$, which supports the evidence for previous outcome effect and different decision making criteria in the two subsets of $S2$. In addition, comparing the two reference points in $S2 | G$, we see that $r = C_{t-1}$ fits data better in both treatments, illustrating that anchoring was not as strong as immediate prior outcome. This reference point did relatively better in $V2$, given how the colors were used to emphasize the deviations from the previous certain amount instead of position relative to the anchor value.

Comparing the models of status-quo and lagged wealth reference point, we can conclude that previous outcomes were not integrated immediately and thus the options were evaluated relative to a lagged reference wealth. Furthermore, loss aversion parameters showed that people's decisions were definitely influenced by an asymmetric evaluation of gains and losses. High λ 's indicate risk-aversion in Stage 2 after the safe option, while low λ parameters in Stage 2 after gambling point to underestimation of losses, which led to a risk-seeking behavior. However, it is difficult to conclude whether this asymmetry *caused* such patterns or was instead just an illustration of other potential factors that could have influenced the results. Therefore, we will examine alternative explanations of framing and previous outcome beyond loss aversion.

6 Alternatives to prospect theory preferences

6.1 Breaking even and gambling with house money

Thaler and Johnson (1990) proposed another way in which previous outcomes shift gambling behavior - break-even and gambling with house money effects. Break-even is a behavioral pattern when a person who lost has a chance to make up for those losses by gambling again, while house-money phenomenon suggests that a person will gamble more after previous winnings when there is no risk of falling below their initial wealth. Although due to different reasons, both effects predict higher risk seeking in those specific cases. Empirical evidence supports the existence of such behavior in lab experiments (Thaler and Johnson, 1990) as well as in financial markets (Weber and Camerer, 1998; Huang and Chan, 2013).

These effects would be particularly relevant to our experiment, because most of the time (88.8%) subjects had a chance to potentially *make up* for previous losses by gambling again, while after previous gains, 23.8% of the time they were not risking to fall below the prior wealth. Anticipating a possibility of such effects due to a similar design as in

Thaler and Johnson’s (1990) experiment, we wanted to test them in a robust manner, hence included four special rounds with fixed conditions, played by all individuals in both treatments. Those rounds make up 15% of the sample¹⁷ (848 observations) and were not extreme outliers in any measure, therefore, subjects should not have noticed any difference. The four special conditions were placed randomly within each version, one in each quartile, to avoid any effect of timing.

Firstly, the four conditions differed in safe amount in Stage 1, while the risky prospect always had a fixed higher expected value in order to incentivize people to gamble. Secondly, the outcome of the lottery in Stage 1 was divided into two groups - a small loss or a large gain. This design allowed us to verify if the break-even and house-money effects played a role in Stage 1, measure the effect of gambling outcome, and compare the two in a controlled way.

$$C_0 = 6.50 \rightarrow C_1 = \left\{ \begin{array}{l} 5.30 \rightarrow G \sim U[-0.3, 0.9] \rightarrow W_p = +0.70 \\ 6.10 \rightarrow G \sim U[-0.3, 0.9] \rightarrow W_p = -0.10 \\ 6.70 \rightarrow G \sim U[-0.4, 1.1] \rightarrow W_p = +0.80 \\ 7.60 \rightarrow G \sim U[-0.4, 1.1] \rightarrow W_p = -0.10 \end{array} \right\} \rightarrow C_2 = 6.00$$

$$\left\{ \begin{array}{l} 6.10 \rightarrow G \sim U[-0.3, 0.9] \rightarrow W_p = -0.10 \\ 6.70 \rightarrow G \sim U[-0.4, 1.1] \rightarrow W_p = +0.80 \\ 7.60 \rightarrow G \sim U[-0.4, 1.1] \rightarrow W_p = -0.10 \end{array} \right\} \rightarrow C_2 = 7.50$$

Table 5: Stage 1 Special Rounds

Condition	SAFE	Version 1 ($N = 212$)			Version 2 ($N = 212$)		
		D	95% CI	95% CI	D	95% CI	95% CI
<i>sure loss</i>	$C = 5.3$	0.868	0.774	0.962	0.962	0.909	1.015
<i>break – even</i>	$C = 6.1$	0.868	0.774	0.962	0.925	0.851	0.998
<i>risky gain</i>	$C = 6.7$	0.774	0.657	0.890	0.887	0.799	0.975
<i>house – money</i>	$C = 7.6$	0.660	0.529	0.792	0.755	0.635	0.874

$EV[G] = 0.30$ when $C < 6.5$ and $EV[G] = 0.35$, when $C > 6.5$, in order to account for the magnitude of the safe option and make the expected value difference proportional to it ($EV[G]/\bar{C} \approx 0.05$). As a benchmark, $\mathbb{E}[EV[G] \mid EV[G] > 0] = 0.14$ and $\mathbb{E}[D \mid EV[G] > 0] = 0.74$ in the remaining sample without special rounds.

We can see that in Stage 1, a possibility to break even had no significant effect in either version. A more important factor was the size of the certain option. In both versions subjects were (almost) equally likely to gamble whether they started \$0.40 or \$1.20 below the initial expected wealth. In V1 we observe a sharper decrease between $C=6.1$ and $C=6.7$ due to anchoring effect. However, in both versions, the largest effect was a large initial gain. Comparing $C=6.7$ and $C=7.6$, subjects gambled 11.4% (13.2%) less in V1 (V2) given the higher safe amount, which is exactly the opposite of what gambling

¹⁷They were removed from the graphs in Motivating results section in order to maintain uniformity of underlying distributions, but not from the prospect theory model estimation.

with house money would predict. Finally, we see that given a positive $EV[G]$, much more subjects took the gamble in $V2$ than $V1$ across all conditions, hence, confirming a higher sensitivity to $EV[G]$ in the Mixed frame.

In Stage 2, we took a subset of subjects who chose to gamble in Stage 1 and received a fixed outcome, which resulted in equal C_2 . Since the second stage gamble bounds were not fixed, a linear probability model was used to estimate the prior outcome effect on gambling behavior through the average risk taking (δ_k) and sensitivity to the expected value difference (β_k) with a dummy variable T^k and its interaction with expected gambling gains. The same regression was run for $V1$ and $V2$ separately. Note that the number of observations differed across the versions and was relatively small in each condition (35-51), resulting in low statistical power, yet the general trends are evident and some were significant even with a such small sample.

$$Prob(D = 1) = \delta_k T_i^k + \beta_k T_i^k \times (E[G_i] - C_i) \quad (12)$$

Table 6: Stage 2 Special Rounds

<i>Estimate</i>	<i>SAFE</i>	Version 1 ($N = 168$)		Version 2 ($N = 187$)	
		$W_p < 0$	$W_p > 0$	$W_p < 0$	$W_p > 0$
δ_k	$C_2 = 6.00$	0.712 (0.065)	0.574 (0.072)	0.768 (0.069)	0.426 (0.061)
	$C_2 = 7.50$	0.698 (0.082)	0.516 (0.092)	0.746 (0.072)	0.310 (0.053)
β_k	$C_2 = 6.00$	1.311 (0.445)	1.093 (0.417)	0.786 (0.329)	1.570 (0.297)
	$C_2 = 7.50$	1.088 (0.517)	0.952 (0.495)	0.800 (0.414)	1.491 (0.267)

Note: whether a person lost 0.1 or gained 0.70 (0.80), their wealth position relative to 6.50 did not change. In other words, those who started below 6.50 and earned 0.70, did not break-even, and those who started above 6.50 and lost 0.1, did not fall below house-money category.

This analysis showed that the size of safe option had little effect on gambling behavior in Stage 2. Instead, the main differences are visible by comparing the coefficients *across* the columns, based on the previous outcome. It is clear, that the large gain reduced risk seekingness, independently of the level of the certain amount. This effect was statistically significant¹⁸ ($p < 0.001$) in $V2$ for both high and low safe options but not in $V1$ ($p = 0.14$ and $p = 0.15$ respectively). In addition, not only people became more risk averse overall after winning, but they also became more sensitive to expected gambling gains in $V2$

¹⁸F-test with HAC standard errors.

both when $C_2 = 6.00$ ($p = 0.07$) and $C_2 = 7.50$ ($p = 0.16$). Pooling the data for both versions, would have given more power to show the significance of previous outcome, yet it would have misrepresented its asymmetric effect across the treatments.

Four special rounds allowed us to rule out the possibility of break-even and house-money effects. It also provided evidence that risk seekingness did not change due to diminishing sensitivity of wealth (more attractive safe option) but rather due to the influence of immediate previous outcome. In addition, Stage 1 revealed an asymmetric effect of the magnitude of positive and negative previous outcomes. Finally, it showed that W_p had a stronger in $V2$ than in $V1$ after taking the lottery, hence confirming that more relevant reference points were $\$6.50$ in $V1$ and C_{t-1} in $V2$.

6.2 Noise reduction effect

6.2.1 Response time analysis

Prospect theory parameters revealed that *Mixed* condition led to a higher sensitivity to expected value differences that was independent from loss aversion parameters. Instead, we observed a heterogeneous risk and loss aversion based on subjects' choices in the first stage. As done in the loss attention theory, one could reason that losses lead to more attentiveness and thus higher performance by default. However, models of noisy representation attribute this effect to a more precise encoding of signals. We could analyze the response times in two treatment conditions, while controlling for previous outcomes and subjects' decisions.

	<i>Dependent variable:</i>		
	<i>Response Time (s)</i>		
	Stage 1	S2, SAFE	S2, GAMBLE
$V2$	-1.602*** (0.211)	-1.665*** (0.219)	-1.104*** (0.229)
$ E[G] - C $	-1.471*** (0.380)	-0.800 (0.489)	-1.136** (0.528)
D_t	-0.263** (0.126)	0.304* (0.175)	-0.293* (0.152)
$C_t - C_{t-1}$	-0.087 (0.088)		0.132 (0.164)
$\max\{G\} - \min\{G\}$	-0.036 (0.186)	-0.091 (0.147)	0.124 (0.169)
Individual effects	Yes	Yes	Yes
F Statistic	14.07***	14.71***	6.40***
Observations	2,731	1,070	1,674
R^2	0.161	0.197	0.094
Adjusted R^2	0.143	0.152	0.062

Note: Clustered SEs.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7: Response times

The regression illustrates a clear pattern that Version 2 reduced the response times by more than one second across all stages¹⁹. More importantly, we see that attention time depended on whether the subjects *were* to choose the safe or risky prospects. We can see that choosing a gamble took less time both in Stage 1 and in Stage 2 after already taking a gamble in *S1*. However, those who took the safe path in *S1*, instead spent *more* time before taking the risky option. We could attribute the the choice in Stage 2 to *inertia* (Khaw and Zorilla, 2019). Yet we have little explanation why subjects spent less time before taking the gambling in Stage 1, which is opposite of what the status-quo bias would predict. Finally, we see that prior outcome had no effect on attention at all. Therefore, we confirmed the idea of framing as a noise reducing phenomenon and rejected the loss attention hypothesis.

6.2.2 Individual behavior

We wanted to see how framing affected subjects on an individual level. Figure 8 shows each individual’s gambling percentage less how much a risk neutral person would have gambled in their place. The same calculation was done in both versions and plotted against each other in order to compare whether Version 2 caused more risk aversion at least to some individuals. First, we see that the sample contains both risk-averse and risk-seeking populations in both versions - no quadrant is empty. Even though more individuals (58%) were strictly below the 45-degree line, the intercept of a fitted line was -0.032 and was not significantly different from 0 ($p = 0.144$). This finding contradicts loss aversion theory on a pooled level, but suggests that for the majority of individuals, Mixed frame increased risk aversion at least to some extent. This graph also shows that individuals were not more risk averse as a result of nosier representation in *V1* as suggested by the perceptual bias theory of risk aversion. The slope of a fitted line was 0.738 and was not significantly different from 1 ($p = 0.079$). Yet its direction shows that framing had a stronger effect in reducing gambling percentage for those who were more risk seeking in Version 1.

At the same time, it is clear that framing positively increased subjects’ sensitivity to expected value of the gamble, which can be seen in Figure 9. The average sensitivity coefficient after controlling for individual fixed effects was 1.12 ($p < 0.001$) in *V1* and was 0.409 *higher* in *V2* ($p = 0.011$). On the individual level, sensitivity in *V2* was higher for 37 (70%) individuals out of which, 11 were significant at 5% level ($t > 2$). In addition, we see a pattern that framing was particularly helpful for subjects who had low sensitivity in Version 1. The fitted line slope was -0.36 ($p < 0.001$) and the intercept 0.80 ($p < 0.001$). In other words, framing did not matter to individuals who were performing close to risk neutral in both versions, but was particularly helpful for those who were not behaving as

¹⁹As mentioned earlier, $\overline{RT} = 5.03$ (4.26) in *V1* and $\overline{RT} = 3.11$ (2.71) in *V2* for Stage 1 (Stage 2).

risk neutrally in Version 1. This analysis showed that even at the individual level framing reduced noise in $EV[G]$ perception. At the same time, noise reduction by framing was not significant to those who had more acute perception of expected value differences to begin with.

% GAMBLE actual - % GAMBLE risk neutral on the individual level

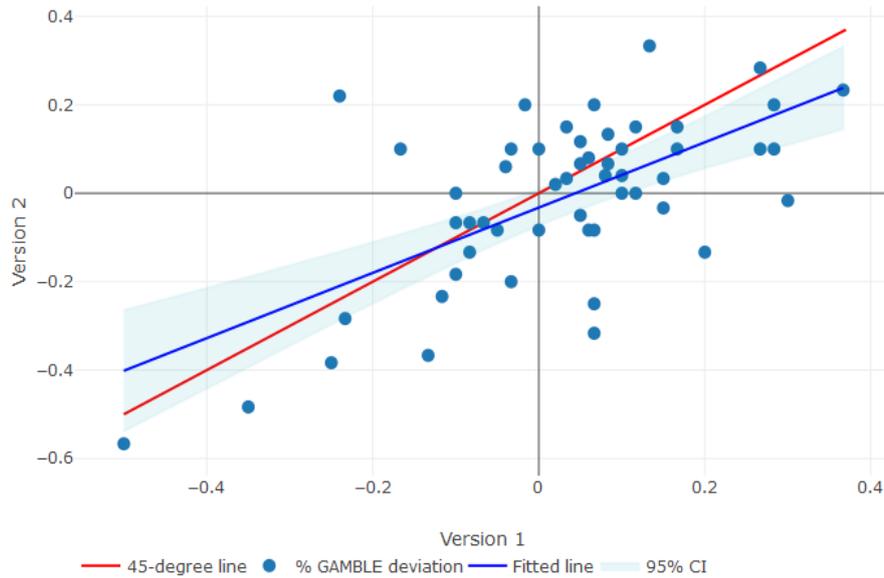


Figure 8: Framing effect on individual risk preferences

Individual coefficients of sensitivity to $EV[G]$ and their significance

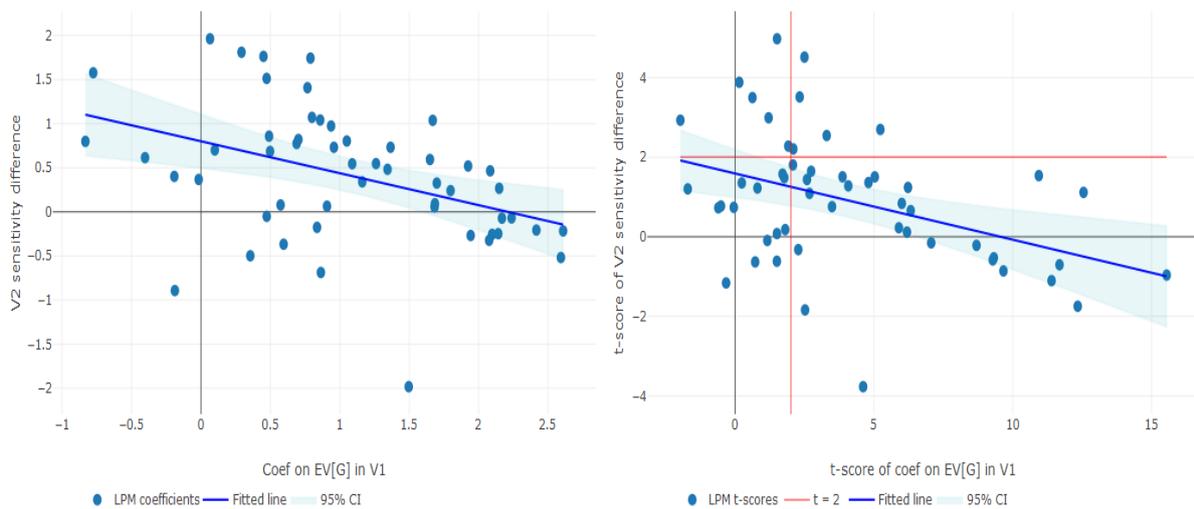


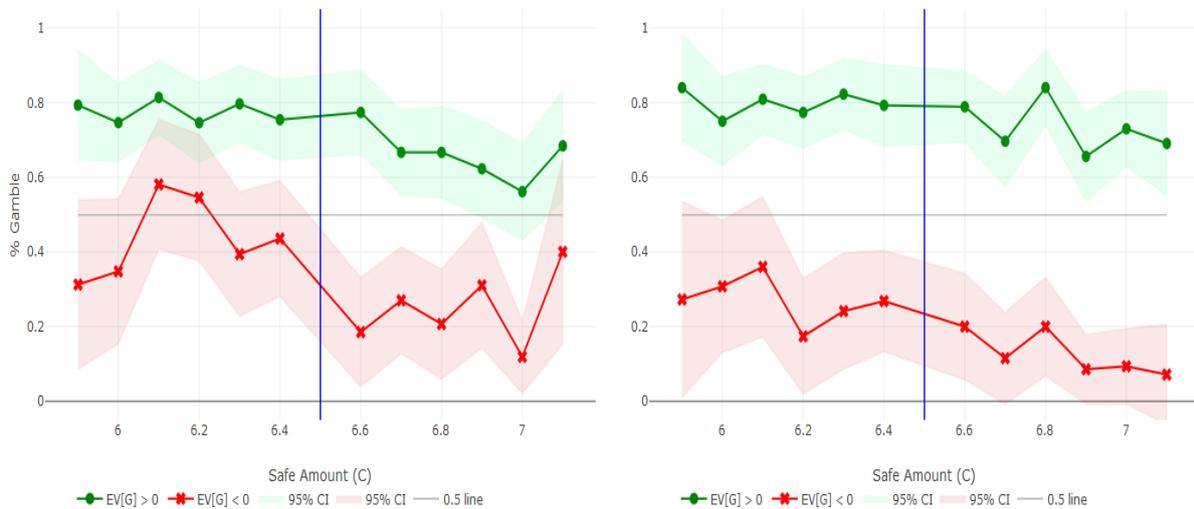
Figure 9: Framing effect on individual sensitivity to expected values

7 Heuristic decision making

Existing literature and our previous analyses provide evidence that framing and previous outcomes have distinct influence on different *types* of people based on their attention or numeracy. Given diverging *S2* results depending on the decision in *S1*, it is reasonable to think that they could have an asymmetric impact on *risk averse* and *risk seeking* people. At the same time, people can differ in their cognitive abilities. Therefore, we will add a *mistake* variable as a proxy for subjects' accuracy to see whether we can explain the differences in behavior due to the personal traits, which are distinct from risk preferences. In the end, we offer a thought experiment to provide insights on how previous outcome and framing effects could interact based on normative and heuristic choice criteria.

7.1 Risk seekers or mistake makers?

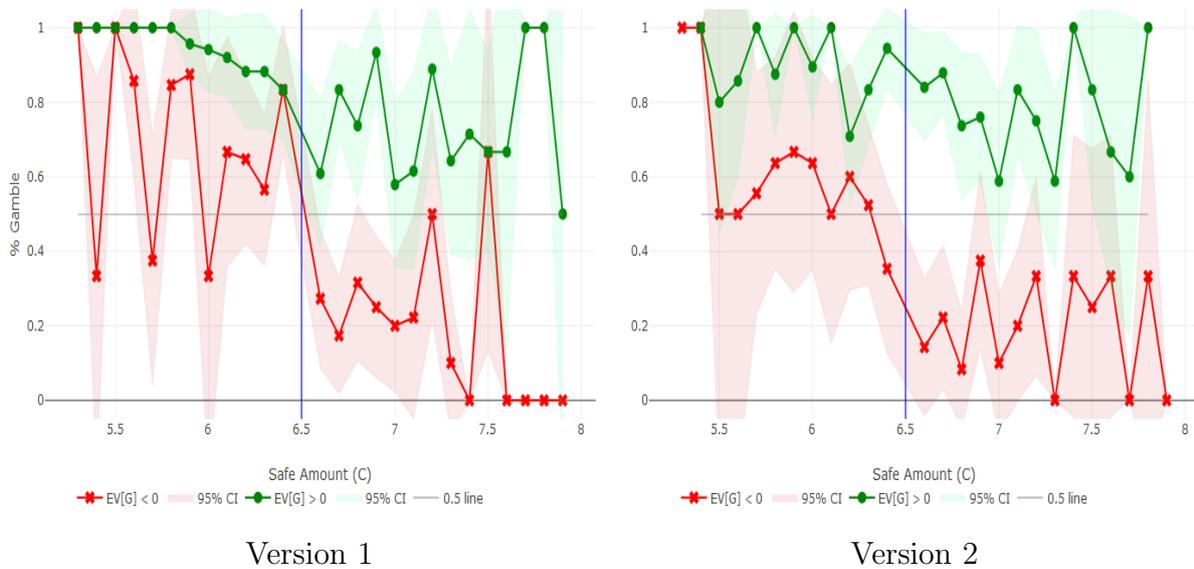
Figure 10: % GAMBLE in favorable and unfavorable lotteries, Stage 1



Dividing the sample based on the risk prospect's expected value sign was one of the most insightful findings of the study.²⁰ As seen in Figures 7 and 8, the size of the safe amount had a much stronger influence on individuals who chose to gamble when the lottery was disadvantageous. If we look at *V1 S1*, the anchor value shifted the gambling percentage by 25% from 0.44 (SE=0.08) to 0.19 (SE=0.07) when safe option increased from \$6.40 to \$6.60 on the negative $EV[G]$ line. However, it had no effect among those who took an advantageous gamble around the same point. Furthermore, gambling probability increased with a higher initial loss in the *red* subset but did not change with wealth levels above \$6.50, meanwhile in the *green* subset, the effect was

²⁰The average $EV[G]$ value for advantageous (disadvantageous) gambles was 0.144 (-0.124). $EV[G]$ was completely independent from the safe amount, $r = -0.01$, $p = 0.43$ ($r = 0.00$, $p = 0.72$) in the same subsets respectively.

Figure 11: % GAMBLE in favorable and unfavorable lotteries, Stage 2 after gambling



opposite - higher C affected gambling behavior only for values above \$6.50. Overall, the gambling percentage decreased by 12% and 22% on green and red lines respectively depending on the position relative to \$6.50. In Stage 1 of Version 2 the effect was overall less significant because the anchor value was not emphasized with colors. However, a starting wealth still significantly shifted the gambling probability and more so for those on the red line than on the green one (-14% and -8%) respectively.

The same pattern was even more prevalent in Stage 2 for those who took the risky option, but was insignificant for those who took the safe one. In Version 1, comparing the two points around \$6.50, the percentage of gambling shifted from 0.833 (SE=0.08) to 0.272 (SE=0.09) on the red line and 0.833 (SE=0.06) to 0.608(SE=0.10) on the green one. More importantly, the lottery outcome was strongly influential in Version 2 as well, which was achieved by using red and green colors relative to their wealth before gambling.

One of the explanations for such divergence could be that people who determine the shape of red and green lines differ in their *type*. For example, if the more numerate individuals did not take disadvantageous gambles, they would not be absent from the $EV[G] < 0$ sample (red lines). At the same time, if their attention was entirely focused on the expected value of the gamble, they would not be affected by previous outcomes, hence the green line would be less downwards sloping. We can test this idea by introducing a *mistake* variable, which will show whether a person made a risk neutral decision in the opposite stage and then verify if the previous outcome only affected those who took the unfavorable gambles. For this purpose, we used a linear probability model with individual fixed effects and three dummy variables - *mistake* (M), *decision* (D), and the sign of previous outcome (W^p). A subscript $-t$ indicates that the mistake or decision results from the choice in the *opposite* round. For example, $mistake_2 = 1$ means that a

subject did not choose risk neutrally in Stage 1. Similarly, $decision_1 = 1$ means that a subject will gamble in Stage 2 independently of their decision in Stage 1.

$$\begin{aligned}
 decision_t &= \begin{cases} 1, & \text{if } D_{-t} = \textit{GAMBLE} \\ 0, & \text{if } D_{-t} = \textit{SAFE} \end{cases} \\
 mistake_t &= \begin{cases} 1 & \text{if } D_{-t} = 1 \text{ and } EV[G_{-t}] \leq 0 \text{ or } D_{-t} = 0 \text{ and } EV[G_{-t}] > 0 \\ 0, & \textit{otherwise} \end{cases} \\
 W_t^p &= \begin{cases} 1, & \text{if } C_t < C_{t-1} \text{ } (C_2 < 6.50 \text{ in S2 after SAFE)} \\ 0, & \textit{otherwise} \end{cases}
 \end{aligned}$$

In Table 8, we estimate two specifications to account not only for average shifts in risk seeking behavior, but also for shifts in sensitivity to expected value of the gamble, which is the essential feature of previously defined subject types. In regression (A1), the coefficient on D means that those who *will* gamble in Stage 2, would also be 9% more likely to gamble in Stage 1, indicating and controlling for risk preferences within the population. In addition, an initial loss led to 12% higher gambling behavior, independent of a person's average risk seekingness or accuracy, represented by interaction terms. In Stage 2 regression (A2), the previous outcome was only significant to those who gambled in Stage 1, yet it was independent of *mistake* variable, which means that both the subjects who gambled in favorable and unfavorable lotteries were equally affected by its outcome. A -0.01 coefficient on D and 0.12 on $D \times M$ reveals that only those participants who entered the lottery when it was unfavorable, were affected by their previous *decision* and gambled again. Summing these coefficients gives an estimate that a person who took an unfavorable lottery in Stage 1 and lost, was 24% more likely to risk in Stage 2 again, compared to a person who did not take the same gamble.

More interesting findings were revealed in regressions (B1) and (B2), which confirm the idea that both risk seekers and "mistake makers" have much smaller sensitivity to the expected value of the lottery. Most importantly, a very high distance between coefficients on two interaction terms, $EV[G] \times W^p$ and $EV[G] \times W^p \times D$, indicates that those who started below \$6.50 and chose a favorable safe option, were *extremely* more sensitive to $EV[G]$ than those who took an unfavorable gamble and lost. These results allows us to conclude that in our experiment there were two distinct types of individuals - those who made their decisions based on the expected value of the gamble and those who primarily cared about the immediate previous outcome.

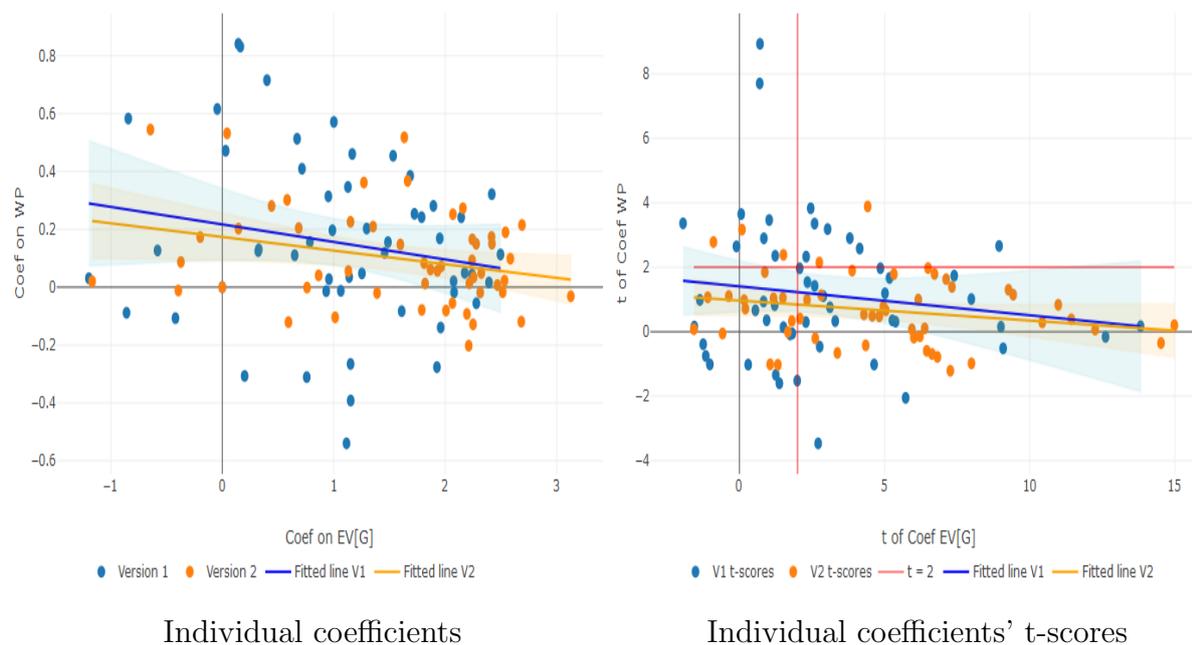
Table 8

	<i>Dependent variable:</i>			
	Prob(GAMBLE)			
	Stage 1 (A1)	Stage 2 (A2)	Stage 1 (B1)	Stage 2 (B2)
$EV[G]$	1.153*** (0.125)	1.192*** (0.129)	1.254*** (0.174)	1.452*** (0.154)
$V2$	-0.041 (0.032)	-0.047* (0.024)	-0.035 (0.032)	-0.044* (0.025)
$EV[G] \times V2$	0.491*** (0.126)	0.251* (0.130)	0.447*** (0.123)	0.261* (0.136)
W^p	0.119*** (0.037)	0.072 (0.059)	0.072* (0.039)	0.050 (0.056)
D	0.088*** (0.028)	-0.017 (0.031)	0.078*** (0.030)	-0.019 (0.031)
M	-0.062* (0.036)	-0.069** (0.029)	-0.019 (0.036)	-0.059** (0.030)
$W^p \times D$	-0.037 (0.033)	0.196*** (0.070)	0.046 (0.036)	0.234*** (0.069)
$W^p \times M$	0.011 (0.060)	0.063 (0.073)	0.009 (0.068)	0.075 (0.071)
$D \times M$	0.066 (0.056)	0.127** (0.049)	0.058 (0.064)	0.123** (0.050)
$W^p \times D \times M$	0.108 (0.079)	-0.060 (0.087)	0.104 (0.094)	-0.062 (0.089)
$EV[G] \times W^p$			0.493*** (0.171)	0.613*** (0.191)
$EV[G] \times D$			0.096 (0.146)	-0.045 (0.150)
$EV[G] \times M$			-0.426** (0.182)	-0.437* (0.226)
$EV[G] \times W^p \times D$			-0.857*** (0.207)	-1.178*** (0.224)
$EV[G] \times W^p \times M$			0.003 (0.314)	-0.375 (0.437)
$EV[G] \times D \times M$			0.048 (0.201)	-0.069 (0.329)
$EV[G] \times W^p \times D \times M$			-0.027 (0.351)	0.470 (0.592)
Fixed effects?	Yes	Yes	Yes	Yes
F Statistic	23.97***	54.82***	25.15***	59.94***
Observations	2,775	2,775	2,775	2,775
R ²	0.259	0.265	0.270	0.280
Adjusted R ²	0.242	0.249	0.252	0.261

Note: Clustered SEs

7.2 Framing combined with previous outcome - diverging heuristics

Sensitivity to normative and heuristic decision criteria coefficients in Stage 1



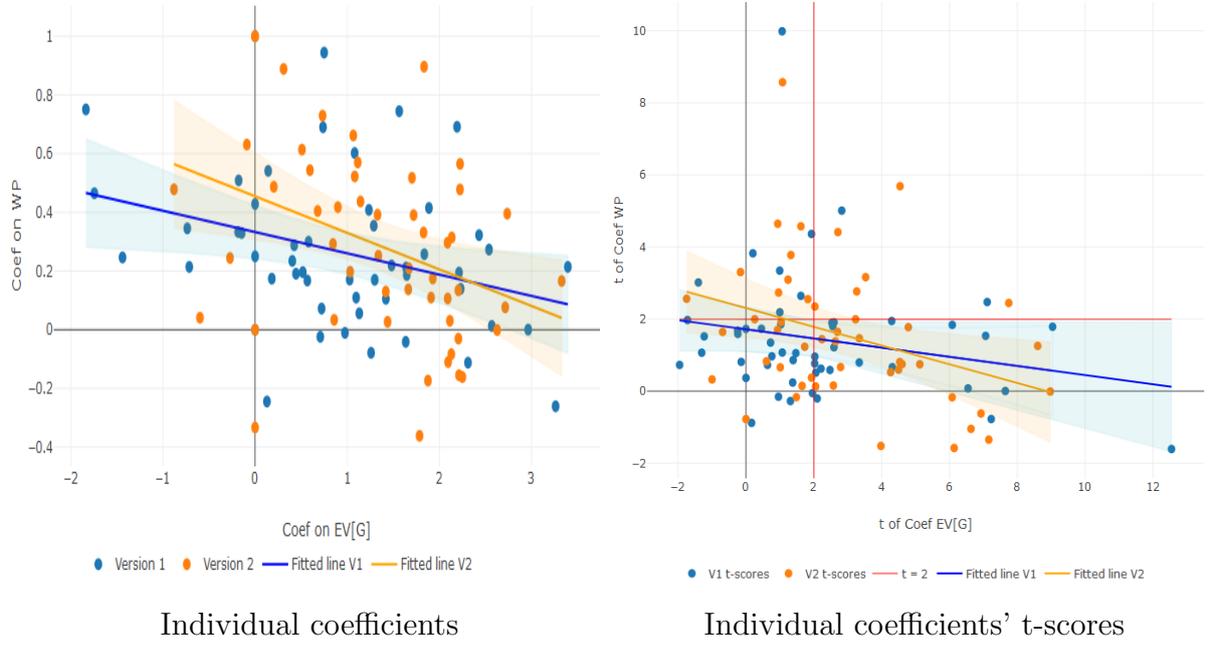
Individual coefficients

Individual coefficients' t-scores

Instead of calling a deviation from a risk neutral decision *mistake*, we will hypothesize that it could be caused by different choice heuristics. Therefore, what was observed as a mistake might be a perfectly rational decision if instead of maximizing the expected value, subjects made a choice based solely on the sign of previous outcome. At the individual level, we clearly see an inverse correlation between sensitivity to $EV[G]$ and WP . Indeed, we even found two subjects that made their decisions depending entirely on previous outcome, therefore they are not even present on the graph. Meanwhile, some other subjects behaved close to risk neutral and committed almost no "mistakes". We propose a thought experiment, which would allow to explain how framing effect and previous outcome interact with individual heuristics.

Suppose there are two types of people who have distinct decision criteria - Type A people are risk neutral and all they care about is the expected value differences, whereas, Type B people only care about the previous outcome (position relative to their reference point). Both types make exhibit stochastic behavior, thus, they can deviate from their optimal option due to some error.

Sensitivity to normative and heuristic decision criteria coefficients in Stage 2 | GAMBLE



Type A decision criterion:

$$D = \begin{cases} 1 & \text{with probability} = p, \text{ if } EV[G] > 0 \\ 0, & \text{otherwise} \end{cases}$$

Type B decision criterion:

$$D = \begin{cases} 1 & \text{with probability} = q, \text{ if } W^P < 0 \\ 0, & \text{otherwise} \end{cases}$$

Suppose that there are H number of individuals of Type A and L individuals of Type B, and $N = H + L$. Let's call the fraction of Type A individuals in the population $\theta = \frac{H}{N}$. In Stage 1, all subjects are equally likely to start above and below C_0 and to face a positive or negative expected value gambles. Therefore, we can obtain the conditional gambling probabilities for each of four cases:

		Previous outcome	
		$W^P < 0$	$W^P \geq 0$
Expected value	$EV[G] > 0$	$\theta p + (1 - \theta)q$	$\theta p + (1 - \theta)(1 - q)$
	$EV[G] \leq 0$	$\theta(1 - p) + (1 - \theta)q$	$\theta(1 - p) + (1 - \theta)(1 - q)$

Table 9: Conditional gambling probability in Stage 1.

We can then obtain the distribution of individuals in Stage 2 after taking the safe and gamble options. After SAFE option, the share of Type A individuals will still be

equal, $\frac{H}{4}$ for both below and above C_0 , however, the share of Type B individuals will be $\frac{L}{2}(1-q)$ when $C < C_0$ and $\frac{L}{2}q$ when $C \geq C_0$. After GAMBLE option, the distribution of individuals will depend on the lottery outcome. Let's denote the probability that a person got an outcome of the same sign as expected, δ . Therefore, the probability that a person got an opposite outcome will be $1 - \delta$. This parameter will depend on the distribution of gamble bounds. We assume that δ is independent of a person's type. Therefore, the share of Type B individuals in each condition will be evenly distributed since their decision did not depend on the expected value of the gamble. However, a larger proportion of Type A individuals will receive a positive outcome since more of them took a favorable gamble. Moreover, we will allow some fraction γ of Type A people to switch to Type B after taking the gamble, given that the starting position in Stage 1 might not be as influential as the lottery outcome resulting from Stage 1 decision.

	$W^p < 0$	$W^p \geq 0$
$EV[G] > 0$	$\frac{\frac{1}{2}\theta p + (1-\theta)(1-q)q}{\frac{1}{2}\theta + (1-\theta)(1-q)}$	$\frac{\frac{1}{2}\theta p + (1-\theta)(1-q)q}{\frac{1}{2}\theta + (1-\theta)q}$
$EV[G] \leq 0$	$\frac{\frac{1}{2}\theta(1-p) + (1-\theta)(1-q)q}{\frac{1}{2}\theta + (1-\theta)(1-q)}$	$\frac{\frac{1}{2}\theta(1-p) + (1-\theta)(1-q)q}{\frac{1}{2}\theta + (1-\theta)q}$

Conditional gambling probability in Stage 2 after SAFE

	$W^p < 0$	$W^p \geq 0$
$EV[G] > 0$	$\frac{\theta(p(1-2\delta) + \delta)p + \frac{1}{2}(1-\theta)q}{\theta(p(1-2\delta) + \delta) + \frac{1}{2}(1-\theta)}$	$\frac{\theta(p(2\delta-1) + (1-\delta))p + \frac{1}{2}(1-\theta)(1-q)}{\theta(p(2\delta-1) + (1-\delta)) + \frac{1}{2}(1-\theta)}$
$EV[G] \leq 0$	$\frac{\theta(p(1-2\delta) + \delta)(1-p) + \frac{1}{2}(1-\theta)q}{\theta(p(1-2\delta) + \delta) + \frac{1}{2}(1-\theta)}$	$\frac{\theta(p(2\delta-1) + (1-\delta))(1-p) + \frac{1}{2}(1-\theta)(1-q)}{\theta(p(2\delta-1) + (1-\delta)) + \frac{1}{2}(1-\theta)}$

Conditional gambling probability in Stage 2 after GAMBLE (γ is omitted)

We can compare the actual results and see what parameters would fit the data well given this model. We find that this model can explain the general behavioral patterns quite accurately. In particular, it considers the previous outcome effect as a result of individual types, hence explaining, why the effect of losses would be more visible in a subset of choices where the expected value of risky prospect was negative. Furthermore, it shows why the effect of previous outcome is not as strong in $S2|S$ subset. For example, in Table 10, we see that after taking the safe option, $\Delta D = -0.10$ and $\Delta D = 0.03$ for those facing positive and negative expected value gambles respectively. Thus the effect of previous outcome is the opposite to that in $S1$ or $S2|G$! Finally, by considering framing

as a noise changing phenomenon, we could argue that it both increases the fraction of Type A people θ as well as their ability to take their most preferred decision p . However, we see that the model lacks one feature that definitely shifts the conditional proportions of risky options, which is subjects' overall risk-seekingness, which might or might not be endogenous to the person's type. In our sample, *mistake* and *decision* variables were not positively correlated ($r = -0.03, p = 0.03$), thus supporting more the idea of heuristic decision making rather than gambling by mistake due to low attentiveness.

	Stage 1			Stage 2 S			S2 G		
	$W^p < 0$	$W^p \geq 0$	ΔD	< 0	≥ 0	ΔD	< 0	≥ 0	ΔD
$EV[G] > 0$	0.77	0.66	-0.11	0.75	0.64	-0.10	0.92	0.72	-0.20
$EV[G] \leq 0$	0.48	0.32	-0.17	0.27	0.30	0.03	0.73	0.28	-0.44
$\theta = 0.7, p = 0.8, q = 0.8, \delta = 0.9, \gamma = 0$									
$EV[G] > 0$	0.80	0.62	-0.18	0.80	0.65	-0.15	0.80	0.57	-0.23
$EV[G] \leq 0$	0.38	0.20	-0.18	0.25	0.20	-0.05	0.54	0.20	-0.34

Table 10: Version 1 actual and predicted gambling percentages

	Stage 1			Stage 2 S			S2 G		
	$W^p < 0$	$W^p \geq 0$	ΔD	< 0	≥ 0	ΔD	< 0	≥ 0	ΔD
$EV[G] > 0$	0.79	0.73	-0.06	0.55	0.60	0.04	0.88	0.77	-0.11
$EV[G] \leq 0$	0.37	0.20	-0.17	0.19	0.16	-0.03	0.63	0.28	-0.35
$\theta = 0.8, p = 0.9, q = 0.8, \delta = 0.9, \gamma = 0.3$									
$EV[G] > 0$	0.88	0.76	-0.12	0.90	0.78	-0.11	0.84	0.63	-0.22
$EV[G] \leq 0$	0.24	0.12	-0.12	0.13	0.12	-0.02	0.51	0.14	-0.37

Table 11: Version 2 actual and predicted gambling percentages

	Stage 1			Stage 2 S			S2 G		
	$W^p < 0$	$W^p \geq 0$	ΔD	< 0	≥ 0	ΔD	< 0	≥ 0	ΔD
$EV[G] > 0$	-0.02	-0.07	-0.05	0.19	0.05	-0.15	0.04	-0.05	-0.09
$EV[G] \leq 0$	0.12	0.12	0.00	0.09	0.14	0.06	0.10	0.00	-0.10
$\Delta\theta = -0.1, \Delta p = -0.1, \Delta q = 0, \Delta\delta = 0, \Delta\gamma = 0.3$									
$EV[G] > 0$	-0.08	-0.14	-0.06	-0.10	-0.14	-0.04	-0.04	-0.05	-0.01
$EV[G] \leq 0$	0.14	0.08	-0.06	0.11	0.08	-0.03	0.03	0.06	0.03

Table 12: Gambling percentage difference $V1 - V2$ due to framing. Framing indeed led to risk aversion after the safe option, since that was the path in which prior outcome did not have an effect and the reference point was status-quo.

Framing effect in the pooled data - gambling difference between versions, $V1 - V2$

	$C < 6.50$	p	$C \geq 6.50$	p	$W^P < 0$	p	$W^P \geq 0$	p
$EV[G] > 0$	0.020	0.315	-0.043	0.056	-0.023	0.254	-0.061	0.013
$EV[G] < 0$	0.145	0.000	0.083	0.002	0.121	0.004	0.097	0.002
$EV[G] = 0$	0.057	0.305	0.099	0.054	0.003	0.965	0.117	0.043

Table 13: We can see that previous outcome and framing effects created a particular pattern, which is dependent on the individual types. Gain condition led to more risk-taking behavior only in the subset of unfavorable gambles. In contrary, for positive expected value gambles it increased risk-aversion. If we compare the framing effect depending on the safe option size, Gain condition increased risk seeking relatively more when the safe option was smaller. Colors signify that the gambling percentage difference between versions was significant at 5% level.

8 Conclusion

Our study compared conceptually different theories that address framing and previous outcome effects. First, we showed that framing had an effect on subjects' ability to make more preferred choices, independent of their risk preferences. Secondly, by emphasizing positive and negative outcomes with colors, we created a sensation of losses even in the gain condition. This allowed us to test whether the experience of losing caused loss aversion equally in both gain and mixed frames. At the same time, its differential between the two frames could signify a different processing of negative numerals. We found indeed that loss aversion was significantly higher in the mixed frame only after taking a safe option in Stage 1, suggesting heterogeneous framing effect with regards to subjects' risk preferences or attentiveness. Finally, we explained how previous outcome effect can occur not from the loss aversion, but rather as a result of previous outcome related heuristics.

This study could serve as an illustration of potential biases in behavioral research that occur due to limitations in experimental design, which do not allow to control for individual characteristics or other perceptual effects such as differences in task complexity. Further research is needed to explore interactions between framing, perception, and previous outcome effects, conditioned on heterogeneous population.

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9 Appendix

9.1 Experiment interface

Start page

Welcome to the Experiment!

You will play **2 different versions** of the game, each consisting of 3 practice and 30 real rounds. Each round will have 2 stages where you will have to make a decision between the "Safe" and "Gamble" options. Detailed information will be specified in each round.

At the end of each version you will see your final winnings for that game. Half of it will go towards your monetary payoff.

After completing both versions, the payment information will be shown on the screen.

The experiment should take around 25 min and both versions are equally long.

Next

Instructions, Version 1

Welcome to the experiment!

In this version, each round starts with \$6.50 and the chosen amounts do not accumulate.

Stage 1

In Stage 1, you will have the option to take the fixed amount or enter the lottery, which will instead give you a new amount from the specified interval. The outcome of Stage 1 will then carry on to Stage 2.

Stage 2

In Stage 2, you will have the option to keep the outcome from Stage 1 or enter another lottery, which will instead give you a new amount. Your choice will determine the final payoff of the round and you will start a new round.

Important

- Any amount within the lottery range is *equally likely*.
- The lottery offered in Stage 2 is *independent* of your choice in Stage 1.
- **Red** indicates that the amount is less than \$6.50, **green** that it is more than \$6.50.
- Only one round's outcome will be randomly selected and become your true monetary payment at the end.

The experiment consists of 15 rounds, but before that, you will have 3 practice rounds to familiarize yourself with the rules.

Please enter your SONA identification number.

Your SONA ID:

Start practice

Instructions, Version 2

Welcome to the experiment!

In this version, each round starts with a random amount between \$5.50 and \$7.50 and the winnings are cumulative.

Stage 1

In Stage 1, you will have the option to keep the given amount or enter the lottery and gain or lose additional money. The outcome of Stage 1 will then carry on to Stage 2.

Stage 2

In Stage 2, you will have the option to keep the outcome from Stage 1 or to enter another lottery and gain or lose some additional money. Your choice will determine the final payoff of the round and you will start a new round.

Important

- Any amount within the lottery range is *equally likely*.
- The lottery offered in Stage 2 is *independent* of your choice in Stage 1.
- In the lottery, **red** indicates that the amount is a loss, **green** that it is a gain.
- Only one round's outcome will be randomly selected and become your true monetary payment at the end.

The experiment consists of 15 rounds, but before that, you will have 3 practice rounds to familiarize yourself with the rules.

Please enter your SONA identification number.

Your SONA ID:

Start practice

Stage 1 display in two versions

Stage 1

You start the round with **\$6.50**.

Choose between the two options:

Option "Safe":

Take **\$6.90** with certainty and move on to Stage 2.

Option "Gamble":

Enter the lottery to draw a new amount in between **\$6.30** and **\$7.70** and move on to Stage 2.

Select the Option

Safe Gamble

Version 1, Stage 1

Stage 1

You start the round with:

\$6.10

Choose between the two options:

Option "Safe":

Do not gamble and move on to Stage 2.

Option "Gamble":

Enter the lottery to add any amount in between **-\$0.50** and **\$0.90** and move on to Stage 2.

Select the Option

Safe Gamble

Version 2, Stage 1

Stage 2 display in two versions

Stage 2

You chose to **gamble** in Stage 1.
You gambled between \$6.30 and \$7.70 and the outcome of the lottery was:

[**\$6.30** , **\$7.70**]
\$6.70

Your new options are:

Option "Safe":

Keep **\$6.70** with certainty and end the round.

Option "Gamble":

Enter the lottery to draw a new amount in between **\$6.10** and **\$7.30** and end the round.

Select the Option

Safe Gamble

Version 1, Stage 2

Stage 2

You chose to **gamble** in Stage 1.
You gambled between **-\$0.50** and **\$0.90** and you **gained**:

\$0.30

Your current payoff is $\$6.10 + \$0.30 = \$6.40$

Your new options are:

Option "Safe":

Do not gamble and end the round.

Option "Gamble":

Enter the lottery to add any amount in between **-\$1.10** and **\$1.00** and end the round.

Select the Option

Safe Gamble

Version 2, Stage 2

Outcome of Stage 2 - Round Results

Round Results

You chose to **gamble** in Stage 1 but **not** in Stage 2.
You kept the certain amount which was:

\$6.70

The final payoff for this round is \$6.70

Next

Version 1, Stage 2

Round Results

You chose to **gamble** in Stage 1 but **not** in Stage 2.
You kept the certain amount which was:

\$6.40

The final payoff for this round is \$6.40

Next

Version 2, Stage 2

Round Results, Version 1

Round Results

You chose to **gamble** in Stage 1 but **not** in Stage 2.
You kept the certain amount which was:

\$6.70

The final payoff for this round is \$6.70

Next

Round Results, Version 2

Round Results

You chose to **gamble** in Stage 1 but **not** in Stage 2.
You kept the certain amount which was:

\$6.40

The final payoff for this round is \$6.40

Next

Results Summary after each round

Results Summary

Round	Gamble and outcome
1	You gambled twice and earned \$6.10
2	You gambled once and earned \$5.80
3	You did not gamble and earned \$6.70
4	You did not gamble and earned \$6.30
5	You gambled once and earned \$6.10
6	You did not gamble and earned \$7.60
7	You gambled twice and earned \$6.00
8	You gambled twice and earned \$6.60
9	You did not gamble and earned \$6.80
10	You gambled once and earned \$6.70

New round