Waterfall illusion in risky choice – exposure to outcome-irrelevant gambles affects subsequent valuation of risky gambles

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Based on recent discoveries in economics, neuroscience, and psychology, we hypothesize that pure exposure to high-payoff or low-payoff gambles can change people's subsequent reported valuations of gambles and confirm this hypothesis in a laboratory experiment. In particular, the same participants within the same experimental session provide higher valuations for the same gambles after they have been exposed to low-payoff gambles compared to after they have been exposed to high-payoff gambles. These results are consistent with the current understanding of how the nervous system encodes payoffs and imply that even brief experiences that do not change wealth can impact an individual's reported valuations of risky options.

JEL Classification: D90

Keywords: decision-making, risk attitude, neuroeconomics, normalization

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Most of the important decisions we make daily rely on our attitudes towards risky prospects. Many of the currently used models in macro- and microeconomics still assume that inconsequential exposure to high-value or low-value payoffs does not affect the utility of risky prospects. In this paper, we challenge this assumption. In recent decades, researchers from many disciplines observed that perception and choice changes depending on the context and hence decision scientists argued that utility function should be reference-dependent; a phenomenon first pioneered in Prospect Theory (Kahneman & Tversky, 1979) and further developed by Köszegi & Rabin (2006). The key development in this literature has been that the reference point is dynamic, adaptive, and expectations-based (Abeler et al., 2011; Baucells & Villasís, 2010; Card & Dahl, 2011; Ericson & Fuster, 2011; Ericson & Fuster, 2014; Rosato & Tymula, 2019 to name some examples). As the literature has predominantly focused on reference point that is created by the current choice set and/or is forward-looking, whether prior inconsequential exposure to payoffs affects the utility of gambles is still an open question.

Even though the focus in the economic literature has been predominantly on the context created by current and forward-looking reference points, there is substantial evidence from both neuroscience and economics that past experience shapes our future perception and choices. Our sensory perception is constantly influenced by previously experienced sensory stimuli. To give an example, imagine that you are in your basement at night with the lights switched on. If suddenly the lights switch off, you will be immediately "blinded" and unable to tell objects in that room apart. This blindness is, however, temporal. With time, even though the objective brightness does not change, your perception will adjust, and you will be able to navigate your dark basement even with the lights out. Other well-known examples of such sensory temporal dependencies include waterfall illusion (hence the title of our paper) or motion aftereffect (anybody who suddenly stopped their treadmill will be aware of the embarrassment it can cause). Such temporal dependencies have been documented in all of the sensory systems (see Ohzawa et al. (1985) for an early account that includes brain activity measurement) and the neural computations that lead to them are now well-understood (Carandini & Heeger, 2012).

In the decision-making domain, prior consequential experiences have also been shown to influence subsequent choice under risk. For example, stark differences in the attitudes towards risk based on socioeconomic status have been traditionally explained by the wealth accumulated to date. Prior exposure to economic crisis (Malmendier & Nagel, 2011; Nishiyama, 2006), natural disasters and violence (Callen et al., 2014; Brown et al., 2019; Jakiela & Ozier, 2019) has been shown to affect future attitudes towards risk. Investors perceive earnings today as more impressive if yesterday's earnings were worse than expected and less impressive if yesterday's earnings were better than expected (Hartzmark & Shue, 2018) and priming investors with a boom increases their risk tolerance (Cohn et al., 2015). Mengel et al. (2016) demonstrated that participants who have been exposed to imperfect information about uncertain gambles become more risk-averse in the subsequent decisions (see also Ma & Schipper (2017)). Brooks & Sokol-Hessner (2020) found that larger recent payoff-relevant outcomes negatively influence subsequent risk-taking. Overall, there exists literature suggesting that reference point is indeed backward-looking (Baucells et al., 2011) and that past experiences can affect behaviors (Baucells et al., 2011; Genesove & Mayer, 2001; Hastings & Shapiro, 2013; Odean, 1998; Strahilevitz & Loewenstein, 1998). However, only a few studies have tried to understand the temporal effect of sequentially presented payoffs on the subsequent utility of gambles from the perspective of dynamic, backward-looking reference points (Stewart et al., 2003). Moreover, the related empirical literature has either investigated the formation of the reference point (Baucells et al., 2011), examined the effect of payoff history on decisions not involving risk (Khaw, Glimcher, & Louie, 2017), studied the effect of past wealth-changing outcomes on the utility of gambles without explicitly noting the impact of the reference point (Malmendier & Nagel, 2011), or did not control for wealth effects or rational expectations about future payments (Brooks & Sokol-Hessner, 2020; Ma & Schipper, 2017; Mengel et al., 2016). Therefore, whether exposure to inconsequential payoffs that does not change an individual's wealth or health, affects the subsequent utility of risky prospects remains unclear.

Theoretically, the effect of exposure to inconsequential payoffs on risk attitudes remains unclear because most of the choice models were not designed to account for such dependency. Traditional economic theory does not have the capacity to capture such effects. When utility is defined only over terminal wealth or over received payoffs, inconsequential experiences do not shape preferences and do not affect choice. More recently, reference-dependent theories could in principle predict that inconsequential exposure will influence choice by assuming that it affects the reference point. We could imagine that exposure to high or low payoffs, even if these payoffs are not received, shapes expectations about future payoffs and that these expectations serve as a reference point that the actual future payoffs are compared to. Using the classical framing of Prospect Theory value function,[1] we would predict that when a gamble is evaluated relative to a reference point that is lower (higher) than this gamble's payoffs, then the individual is risk-

[1] To streamline the argument, we make a simplifying assumption of no probability weighting.

averse (seeking). More generally gamble valuations could change even if the reference point adjusts more subtly and does not change the perception of the gamble as a gain or a loss. In such cases, increases in reference point could either increase, decrease, or have no effect on risk taking, depending on the modelling assumptions about the utility function and the reference point formation.[2]

Relevant to our enquiry, empirical research in neuroeconomics revealed that the neural computations underlying sensory experiences (such as perception of brightness) and valuation share their contextual properties (Bujold et al., 2021; Louie et al., 2013; Padoa-Schioppa, 2009; Yamada et al., 2018) which inspired a new wave of theoretical modelling (Glimcher & Tymula, 2020; Padoa-Schioppa & Rustichini, 2014; Robson et al., 2021; Woodford, 2012). For our research question, the most important finding has been that the utility-like signal in the brain depends on the statistics of previous trials (Louie et al., 2014; Padoa-Schioppa, 2009; Zimmermann et al., 2018) and more specifically that the brain activity is suppressed after experiencing higher payoffs. Combined with the evidence that the activity in specific brain regions robustly correlates with utility functions estimated from behavior (see Bartra et al. (2010) for a meta-analysis) and with inferred or stated valuations (Gross et al., 2014; Levy et al., 2011; Smith et al., 2014), this indirectly implies that past payoff exposure should influence future valuations. Specifically, we would predict that exposure to high-value rewards decreases the valuations of subsequently seen monetary gambles (because of the suppression of firing rates). This is the prediction that we will test behaviorally in this paper. It is notable that it contrasts with the framing prediction of Prospect Theory.

In this paper, we fill the gap in the literature on reference-dependent preferences, by experimentally testing whether we can change people's reported valuations of gambles by manipulating their prior exposure to gambles with either high- or low-value payoffs. Our innovation is that this exposure is inconsequential and uninformative about future payoff statistics. If such exposure creates similar "illusions" in risky decision-making as it does in sensory perception, this has substantial consequences for economic decisions about health and well-being, employment, finances, daily grocery shopping, and other aspects of our everyday lives.

We find that after being exposed for only a couple of minutes to high-payoff gambles, study participants provided lower valuations of identical gambles than after exposure to low-payoff gambles. What is

[2] For example, individuals with a linear utility function, for example $u=x-r$ where x is the reward and r is the reference point, would not change their risk attitude when reference point changes. Other non-liner utility specifications could predict both increase and decrease risk taking.

remarkable is that this change in reported valuations occurred within individuals and in the timeframe of one experimental session. Moreover, this effect on reported valuations occurs even though our experimental manipulation is pure exposure without actual consumption or accumulation of payoffs and hence does not affect an individual's wealth and rational wealth expectations.

The most related study to ours is by Khaw et al. (2017). They found that the current monetary valuations of popular snacks move inversely with the average valuations of previously observed snacks. Whether these results extend to risky choice is not obvious ex-ante and a timely question given the recent empirical evidence and theoretical discussion on differences between risky and riskless utility (Abdellaoui et al., 2013; Andreoni & Sprenger, 2012b; Cheung, 2015; Chung et al., 2019).

Finally, our paper also contributes to the substantial literature on the malleability of preferences. Some of this literature focused on differences in preferences across domains (Blais & Weber, 2006; Dohmen et al., 2011; Levy & Glimcher, 2011) while other papers focused on the stability of risk preferences elicited in the same domain but at different points in time (Zeisberger, Vrecko, & Langer, 2012). Our paper sheds light on the origins of the temporal variation in individual risk preferences.

2. Experimental Design

141 participants (68 females, mean age 22.69, standard deviation 4.22) recruited via the University of Sydney's ORSEE (Greiner, 2004) participated in the experiment. In our within-subject design, with 141 participants, assuming alpha=0.05 and power=0.80, effect sizes of 0.21 or more can be detected. Throughout the paper, we calculate effect sizes as the absolute value of the difference of means divided by the standard deviation. The data was collected over 15 sessions from August 2018 to April 2021 using the zTree software (Fischbacher, 2007). Each session lasted for approximately 90 minutes. Complete instructions for the task are included in Appendix A. The instructions were read aloud by the experimenter and shown on the computer screens. After the instructions were read, participants were asked to answer comprehension questions (Appendix B) to ensure that they understood the payment mechanism before they completed the task. After the task, participants completed a questionnaire with questions about demographics and the task (Appendix C), and then they collected payment.

2.1 The Task

The experimental task consisted of three valuation Test Blocks and two interweaving High and Low Adaptation Blocks that aimed to shift participants' reference points higher and lower respectively (Figure 1). The order in which High and Low Adaptation Blocks occurred was randomized between subjects. 65 participants completed the task in the "Test-High-Test-Low-Test" sequence (High-Low order) and 76 in the "Test-Low-Test-High-Test" sequence (Low-High order). These two sequences are pooled together for most of the analysis. The within-subject design allowed us to control for heterogeneity in individual valuations not related to the experimental treatment. We ran two variants of this general design with slight changes implemented after the first 6 sessions (66 participants).

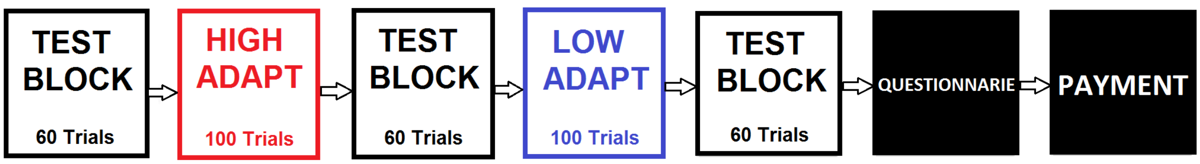

Figure 1. Timeline of the experiment (version 1). In version 2, there were 30 trials in Test Blocks and 80 trials in Adaptation Blocks.

2.2 Test blocks: valuation trials

Each Test Block comprised of valuation trials where participants gave valuations for 30 distinct 50-50 binary gambles, each appearing in an order randomized independently for each participant. The 30 gambles could be classified into three different types: low-value (with \$2.50-\$7.25 payoffs), medium-value (with \$10-\$29 payoffs), and high-value (with \$20-\$58 payoffs). The low-value and high-value gambles were created by multiplying the payoffs of the medium-value gambles by a common factor (0.25 and 2 respectively). All gambles used are listed in Appendix D, Table D1. In the first six sessions, each gamble was repeated twice for a total of 60 trials in each Test Block. This repetition allowed us to check the consistency of valuations within a block. In the remaining sessions, to shorten the duration of the experiment, we asked for a valuation of each gamble only once resulting in a total of 30 trials in each Test Block.

An example of a valuation trial is shown in Figure 2A. Participants reported valuations by clicking on the slider and confirmed their valuation with a single mouse click. The slider bar had dollar amounts on it and the dollar amount represented by the current slider position was indicated above the slider (\$1–\$60, in \$0.25 increments). At the beginning of each trial, to avoid any anchoring effects, the slider was reset to empty meaning that no valuation was indicated until a participant clicked on the slider.

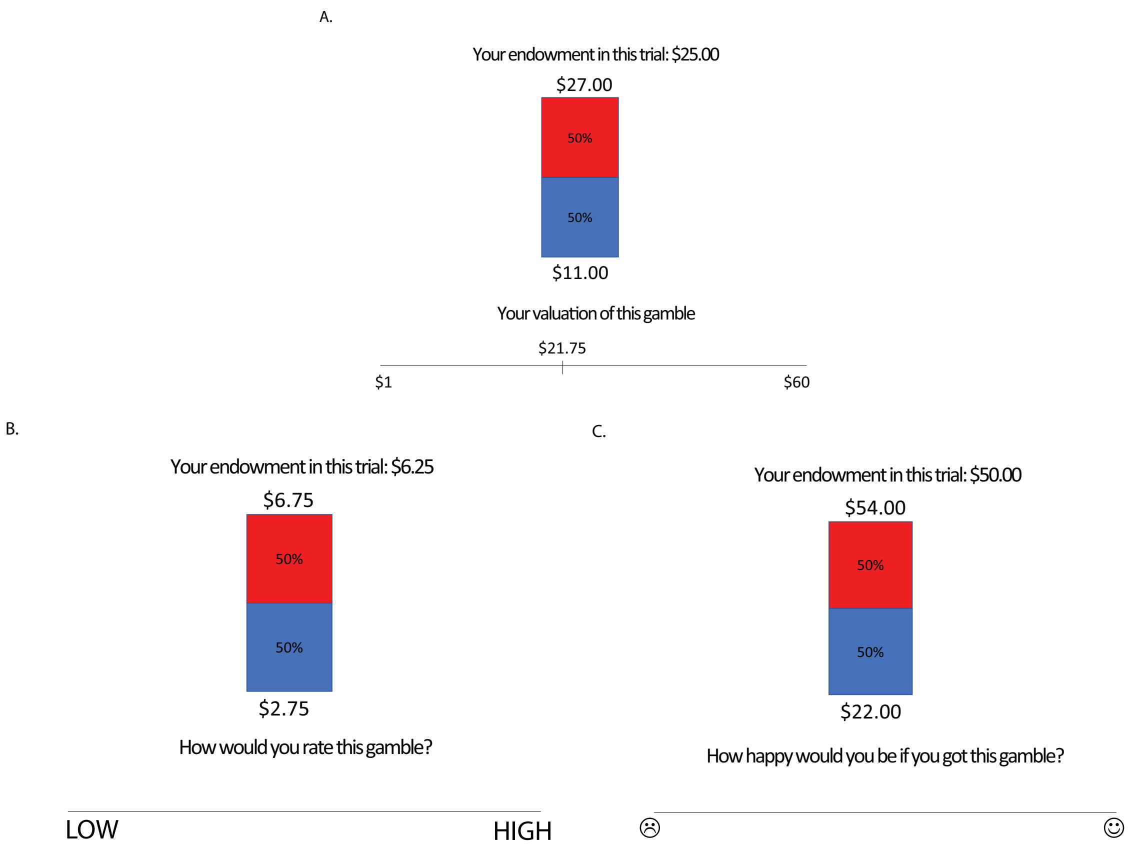

Figure 2. Examples of A: Test Block valuation trial, B: adaptation rating trial with low-value gamble in experiment version 2, and C: adaptation rating trial with high-value gamble in experiment version 1.

2.3 Test block payment

To ensure incentivized valuations, we used a Becker-DeGroot-Marschak procedure (Becker, DeGroot, & Marschak, 1963, hereafter BDM),[3] and to comply with ethical standards, participants were endowed with an amount of money for every trial. This endowment was equal to $6.25 for low-value, $25 for medium-value, and $50 for high-value gambles, all multiples of one another just as the lottery payoffs. The information about the current trial's endowment was displayed at the top of the screen (see Figure 2). This is identical in all test blocks.

Participants' payment was determined by their valuation of a gamble in one randomly selected valuation trial and a price for that gamble that was randomly selected by a computer. Any price between the

[3] Although not incentive-compatible for all non-expected utility preferences, no universally acceptable alternative to BDM exists to elicit valuations.

minimum and the maximum gamble payoff, in \$0.25 increments, was equally likely to be selected. If a participant's valuation was below the price, they received the payment trial's endowment. If the participant's valuation was higher than the price, they received the payment trial's endowment, paid the price, and played the gamble by drawing a chip out of a bag with 50 red and 50 blue chips to determine the gamble earnings. Participants made on average \$27.66.

2.4 Adaptation Blocks: rating trials

The goal of the Adaptation Blocks was to change participants' reference points without changing their current wealth or the rational expectations of their earnings from the experiment. Therefore, the rating trials had no impact on individuals' earnings from the experiment and this was made clear to participants at the start of the experiment. The adaptation trials also did not change the range of payoffs experienced so far which was established in the first Test Block.

Each Adaptation Block comprised of rating trials in which participants rated the lotteries on display. In the first six sessions, following Khaw et al. (2017), there were 100 rating trials in each Adaptation Block in which participants were asked to rate how happy they would be if they got the displayed gamble. In the remaining sessions, there were 80 rating trials in each Adaptation Block in which participants were asked to rate the gamble on a LOW to HIGH scale.[4] Participants clicked on a slider bar with happy or sad face icons (LOW or HIGH written) on each end of the slider. Just as in the valuation trials, the slider recorded the ratings on a scale from 0 to 60. However, in rating trials when participants selected their rating, we would not show them what number this rating corresponded to on our slider bar. The slider, therefore, had no numeric or monetary value meaning. We did this to make sure that participants do not confuse these trials with the payoff-relevant valuation trials. The icons at the end of the slider were flipped on every trial (randomly) to avoid potential motor adaptation effects. Figure 2B (3C) shows an example rating trial where a participant was exposed to a low-value (high-value) gamble. In the High (Low) Adaptation Block, participants were shown only the ten high-value (low-value) gambles (see Table D1 for the list of the gambles). Each of them appeared in a randomized order and ten times in the first six sessions and eight

[4] We added this modification based on referees' suggestion to eliminate happiness manipulation from our design. Happiness has been shown previously to affect risk attitudes (Isen & Patrick (1983) present an early account of such effect). We reduced the number of adaptation trials to shorten the duration of the experiment.

times in the remaining sessions. Importantly, the adaptation trials were hypothetical to not affect wealth or rational expectations of earnings.

3. Results

3.1 Preliminary results: valuation trials

Preliminary aggregate analysis of participants' decisions indicates that they understood and paid attention to the task. Participants increased their valuation of gambles by \$0.75 for each \$1 increase in the gamble's expected value (EV) (Appendix D, Table D2). Even though participants completed many trials in this study, their sensitivity to the expected value of the gamble remained the same through Test Blocks 1-3 and there was no time trend in their valuations (Table D2).[5] Figure 3A plots the average valuations for the gambles against EV across all Test Blocks. Consistent with the regression analysis, participants' valuation increased as the gamble payoffs increased but by less than \$1 for a \$1 increase in the gamble's expected value. Using data from the first six sessions in which participants provided a valuation for each gamble twice within a Test Block, we find these valuations to be highly correlated ($r = 0.92$, $p=0.00$, Figure 3B), indicating very high consistency in participants' valuations. A median participant answered 18 out of 20 comprehension questions correctly. Less than 3.55% of the participants answered less than half of the comprehension questions correctly. After answering comprehension questions, all participants were provided feedback that would further increase their understanding.

In a small fraction of trials (8.39%), participants submitted valuations that exceeded the gamble's higher payoff, and in an additional 0.96% of the trials, they submitted valuations equal to the higher payoff of the gamble. In 23.35% of the trials, participants submitted valuations smaller than the lower payoff of the gamble, and in an additional 5.90% of the trials submitted valuations equal to the lower payoff of the gamble. This fraction of first-order stochastic dominance (FOSD) violations is similar to previous estimates (Charness & Karni, 2007; Tymula et al., 2013). To understand the distribution of FOSD violations across participants, for each participant we calculated their FOSD score equal to the proportion of valuation trials in which the participant violated FOSD or equivalently those that submitted a valuation that was smaller than or equal to the lower lottery payoff or higher than or equal to the higher lottery payoff. Figure 3C presents the distribution of FOSD violations. To make sure that our results are not

[5] Throughout, we use a random effects model following the Hausman-Wu and the Breusch-Pagan Lagrange Multiplier (LM) test (χ^2=0.00, p-value=1.00) and LM test (χ^2=1.1e+05, p-value=0.00).

driven by participants who violate FOSD, throughout the results section, we check the robustness of our findings by repeating the analysis while excluding the 48 participants who violated FOSD on more than half of the valuation trials. With some abuse of terminology, we refer to this restricted sample as the rational sample.

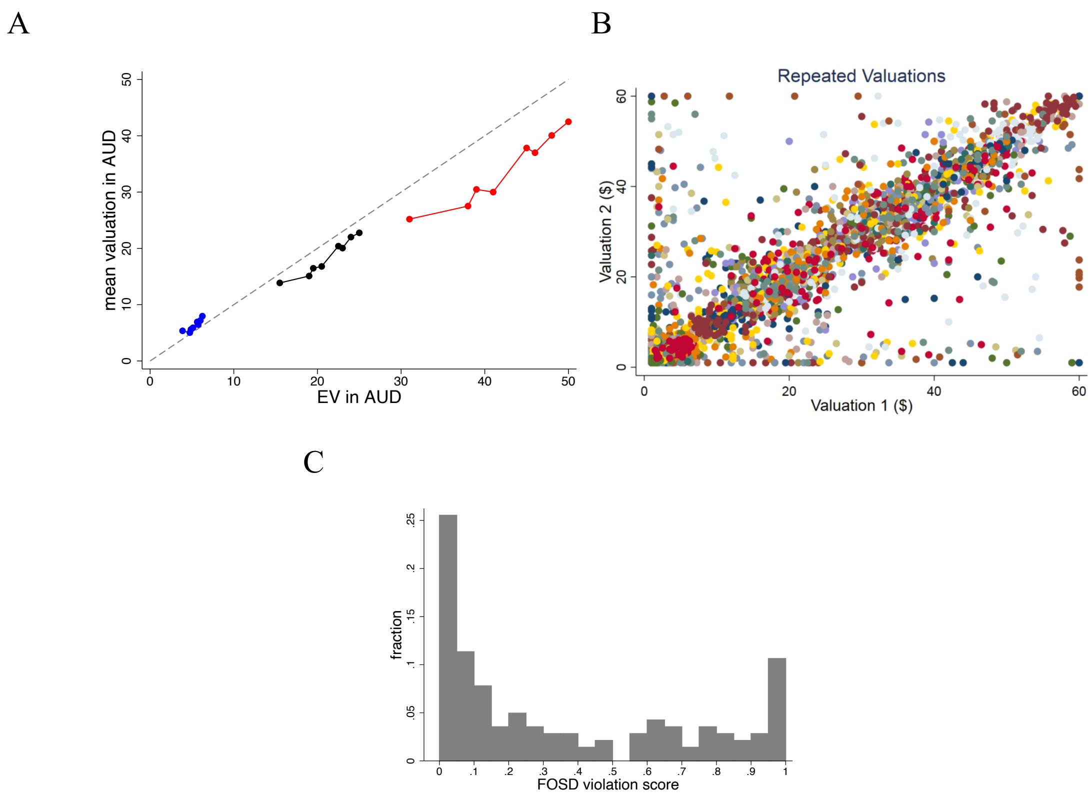

Figure 3. Consistency with economic principles. A: Relationship between the mean valuation of a gamble and gamble expected value (EV) is positive, B: Bid-rebid consistency within a Test Block is high, C: Prevalence of the first-order stochastically dominated valuations across individuals.

3.2 Preliminary results: rating trials

Although not incentivized, ratings were significantly lower in Low Adaptation Blocks than in High Adaptation Blocks (22.29 and 33.03 respectively, $p<0.001$),[6] suggesting that participants paid attention to this part of the task as well.

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[6] To test the significance, for each individual we calculated two numbers: the average ranking of the gambles in the High and in the Low Adaptation Blocks. We then compared these using a paired t-test.

3.3 Main results: Effect of adaptation on valuations

Comparing the difference in valuations between post-High Adaptation and post-Low Adaptation Blocks[7], we found that participants submitted higher valuations after completing Low Adaptation Blocks than after completing High Adaptation Blocks ($19.50 vs $19.27, Figure 4). To test the significance of the effect, for each participant we calculated their average gamble valuation, separately for after they were adapted to high and to low gambles. This gives us two observations per individual. Using a paired t-test, we find the difference to be significant (one-sided p=0.0410). With the average difference in valuations of $0.23 and the standard deviation of 1.56, this is a small effect size of 0.18. Focusing on the rational sample, the difference in valuations increases to $0.29 ($20.70 versus $20.41, one-sided p=0.0069) and the standard deviation decreases to 1.09, resulting in a small-to-medium effect size of 0.27. We stress that this adaptation of valuations occurs even though these are the same participants (within-subject design) providing valuations for the same gambles within the same experimental session while their wealth remains unchanged.

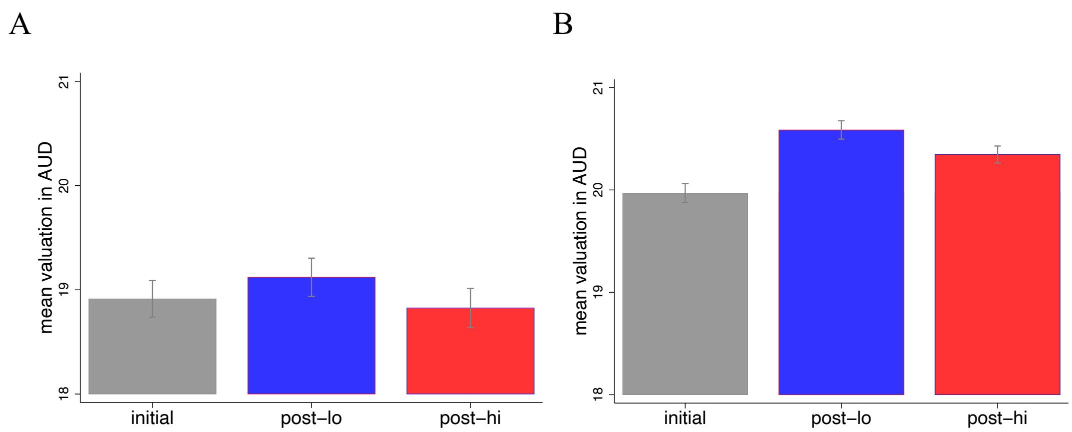

Figure 4. Aggregate mean gamble valuations in Test Block 1 (gray), post-High Adaptation (red), and post-Low Adaptation (blue) Blocks. The error bars are 95% confidence intervals. A: all data, B: data from rational participants only.

Using regression analysis (Table 1) we further confirm that gamble valuations are lower after adaptation to high-value gambles. Furthermore, within a block, we see that the previous gamble EV has a further negative effect on the current valuation although it is not significant (Table 1).

[7] Since participants' payoff history (reference point) before they completed Test Block 1 is unknown, we cannot credibly interpret changes in valuations between Test Block 1 and Test Block 2.

Table 1. Random effects regressions with gamble valuation as a dependent variable. *post-hi* is a binary variable equal to 1 in a Test Block that follows the High Adaptation Block and 0 for Test Block that follows Low Adaptation Block; *L.EV* is the expected value of the gamble in the previous trial. Models (1)-(2) are estimated using the whole sample and models (3)-(4) are estimated using the rational sample.

	all sample		rational sample	
	(1)	(2)	(3)	(4)
post-hi	-0.2936*	-0.2828*	-0.2401*	-0.2228*
	(0.1367)	(0.1418)	(0.1134)	(0.1125)
EV	0.7551***	0.7554***	0.8927***	0.8927***
	(0.0315)	(0.0316)	(0.0137)	(0.0138)
L.EV		-0.0035		-0.0026
		(0.0055)		(0.0032)
constant	2.5488***	2.5757***	0.6076**	0.6477**
	(0.6295)	(0.6322)	(0.2131)	(0.2381)
N	12420	12138	7860	7674

Standard errors clustered on participant in parentheses
+ p<0.1, *p<0.05, ** p<0.01, *** p<0.001

On the individual level, there is some heterogeneity. Over half (81 out of 141) of the participants submitted higher valuations (on average by $1.03) after being exposed to low-value gambles. 56 participants lowered their valuations (on average by $0.90) after adaptation to low-value gambles. Only four participants' valuations did not change.

3.4. Additional results

3.4.1 Block order

One aspect of the study design that could have influenced our results is the order in which Adaptation Blocks occurred. Our participants were randomly assigned to one of two sequences: "Test-High-Test-Low-Test" (High-Low order) or "Test-Low-Test-High-Test" (Low-High order). In Test Block 1, participants were already exposed to the full range of payoffs used in the study, so the order of the adaptation blocks did not alter the range of the payoffs that participants could expect from the study. Nevertheless, the order of Adaptation Blocks could still in principle influence the effect of adaptation. In Figure 5, we plot the mean valuations of the rational participants in our study in each Test Block, separately for participants in Low-High order (solid line) and High-Low order (dashed line). Red (blue) dots indicate valuations made after adaptation to high (low)-value payoffs. The first thing to notice is that in both orders, red dots are below the blue dots meaning that the valuations after High Adaptation Block are lower than after Low Adaptation Block (p=0.024 in Low-High order and p=0.070 in High-Low order). The interaction term *post-hi*High-Low* in the regression analysis is not significant (Table 2), further supporting that the result is independent of the order of the Adaptation Blocks.

Table 2. Random effects regressions with gamble valuation as a dependent variable. *post-hi* is a binary variable equal to 1 (0) in a Test Block that follows the High (Low) Adaptation Block. *L.EV* is the gamble expected value in the previous trial. *happy* equals one if the subject used happiness rating and 0 otherwise. *post-hi*happy* is the interaction of *happy* and *post-hi. High-Low* is an indicator variable for High-Low order. Models (1)-(2) are estimated using the whole sample and models (3)-(4) are estimated using the rational sample.

	all sample		rational sample	
	(1)	(2)	(3)	(4)
post-hi	-0.0569	-0.4104+	-0.3911*	-0.2496
	(0.1834)	(0.2297)	(0.1560)	(0.1683)
EV	0.7551***	0.7551***	0.8927***	0.8927***
	(0.0315)	(0.0315)	(0.0137)	(0.0137)
*post-hi*happy*	-0.3711		0.2601	
	(0.2612)		(0.2219)	
happy	-2.2231+		-0.6621	
	(1.1977)		(0.6060)	
*post-hi*High-Low*		0.2418		0.0172
		(0.2680)		(0.2278)
High-Low		0.0017		-1.1454*
		(1.1823)		(0.5476)
constant	3.5641***	2.5506***	0.9035*	1.2002**
	(0.9590)	(0.7750)	(0.3972)	(0.3965)
N	12420	12420	7860	7860

Standard errors clustered on participant in parentheses
+ p<0.1, *p<0.05, ** p<0.01, *** p<0.001

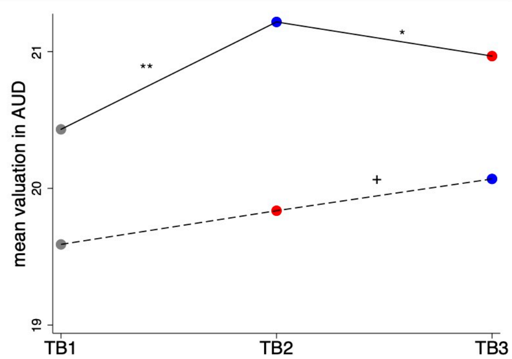

Figure 5. Aggregate mean valuations of rational participants in High-Low order (dashed line, 48 participants) and Low-High order (solid line, 45 participants). Red (blue) markers indicate valuations made after adaptation to high (low)-value payoffs.

We are cautious in making comparisons with the initial Test Block due to the lack of control over participants' initial reference points. However, consistent with the results so far after being exposed to low-value payoffs, participants in Low-High order increase their valuations in the second Test Block relative to the first Test Block. This is what we would expect if participants lowered their payoff expectations after the Low Adaptation Block. In the High-Low order, the change in valuations between the first and second Test Block is not significant suggesting that the High Adaptation Block did not change participants' initial reference points.

Overall, the valuations in the Hi-Low order are lower throughout all Test Blocks. This must be due to chance because these differences appear already in the first Test Block.

Finally, separately for each participant, we calculated the valuation difference between the average valuation of a gamble in Test block 3 and Test block 2. Because the participants were randomly allocated to High-Low or Low-High adaptation order, this procedure divides participants into two types: participants with the post-low valuation differences and participants with the post-high valuation differences, respectively. As shown in Figure 6 and consistent with the previous analysis, the post-low difference is significantly positive ($0.12, one-sided p=0.09) while the post-high difference is significantly negative (-$0.32, one-sided p=0.007). As previously presented, in the rational sample, the results are stronger: the post-low difference is significantly positive ($0.23, one-sided p=0.003) while the post-high difference is significantly negative (-$0.34, one-sided p=0.004).

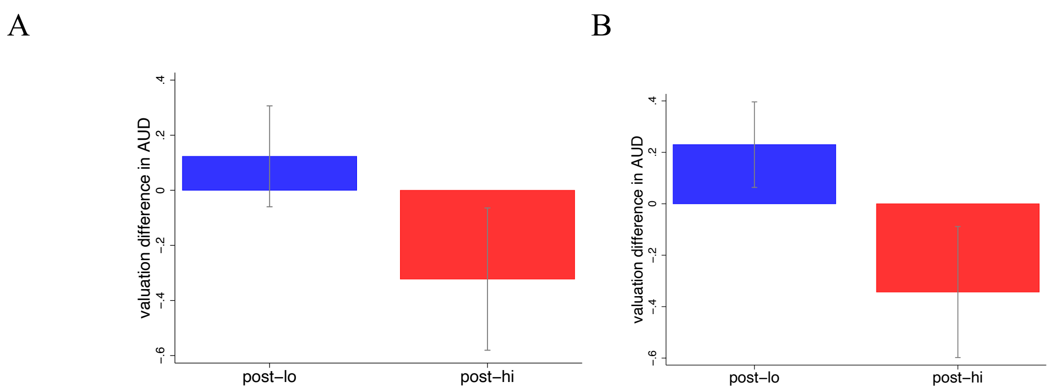

Figure 6. Mean valuation deviations between Test Block 3 and Test Block 2 for participants in the High-Low (blue) and Low-High (red) order. Error bars are 95% confidence intervals. A: All data B: data from rational participants only.

3.4.2 Rating trials – slider versions

Another aspect of the study that could influence the results are the variations in sliders during the adaptation trials. 66 of the participants were asked "How happy would you be if you got this gamble?" and used a slider with happy and unhappy face icons at its edges to indicate their response. It is possible that this question put participants in a good mood in the High Adaptation Block in which they generally click closer to the happy face icon, and this could, in turn, alter their risk attitude. If this was the case, given that the previous literature (for example Bassi, Colacito, & Fulghieri, 2013; Isen & Patrick, 1983) has shown that a good mood promotes risk-taking, we would expect participants to submit higher valuations of risky gambles after adaptation to high-value gambles. We observe the opposite. Furthermore, regression analysis reveals that participants who used different slider types did not respond differently to adaptation (the insignificant coefficient on *post-hi*happy* in Table 2). Also, the general effect of adaptation in the rational sample remains significant when we control for the mode of adaptation. Therefore, we conclude that our results are unlikely to be explained by the manipulation of happiness or mood.[8]

3.4.3 Simple neuroeconomics model

Given that our inquiry was inspired by theoretical models of sensory perception, we next asked whether it is plausible that divisive normalization, a canonical model of brain activity (Carandini & Heeger, 2012),

[8] This conclusion is not definite because as a referee pointed out it is possible that being show a lottery with (relatively lower outcomes after being exposed to high-value lotteries creates a bad mood/sadness.

which has recently gained interest in decision sciences (Glimcher & Tymula, 2020; Khaw et al., 2017; Landry & Webb, 2021; Louie et al., 2013; Zimmermann et al., 2018) could explain our data. The model defines the subjective valuation of an alternative x in a trial t as $v_t(x) = k\frac{\bar{x}}{\bar{x}+M_t}$, where $\bar{x}$ is a participant-specific objective value of the gamble and k is an individual-specific scaling parameter. In sensory neuroscience, $\bar{x}$ is taken to be the objective intensity of the stimulus (for example its brightness or contrast level). We approximate $\bar{x}$ with the average of participant's valuations of a gamble over all Test Blocks. The temporal adaptation of valuations is governed by a reference point, M_t, that is determined by past payoff exposure. Notice that in this model, consistent with our empirical findings, valuations decline after reference point increases. For this demonstration, we assume that the reference point is the average of the gamble's values over the past 59 trials ($M_t = \frac{1}{59}\sum_{\tau=t-59}^{\tau=t-1} \bar{x}_\tau$). We chose this period based on the results in Khaw et al. (2017). Figures 7A and 7B illustrate how this historical average fluctuates throughout the experiment. In the Low Adaptation Blocks (gray) it falls and in High Adaptation Blocks (black) it increases. In the Test Blocks that follow High Adaptation Blocks (red) this average falls and the opposite happens in the Test Blocks that follow Low Adaptation Blocks (blue). We found that the correlation between the valuations predicted by our model and actual valuations (in Test Blocks 2 and 3) is significant and strong (Pearson's correlation = 0.819, $p<0.001$, see Figure 7C) and the model captures 86.38% of the variation in valuations.

One caveat is that our simple normalization model does not consider the heterogeneity in participants' risk attitudes. It is possible that extensions that incorporate such heterogeneity would further increase the model's predictive power. Another caveat is that we assumed that the divisive normalization equation which was designed to capture brain activity translates linearly into valuations. The assumption that the higher the neural response to a payoff, the higher the monetary valuation of this payoff is intuitive and supported by neuroscientific evidence that has shown that firing rates predict valuations (Gross et al., 2014; Levy et al., 2011; Plassmann et al., 2007; Smith et al., 2014) but our assumption that the mapping of firing rates to valuations is not just monotonic but also linear may be a simplification. We hope that these results and the open questions that they pose will inspire future rigorous theoretical work in this area.

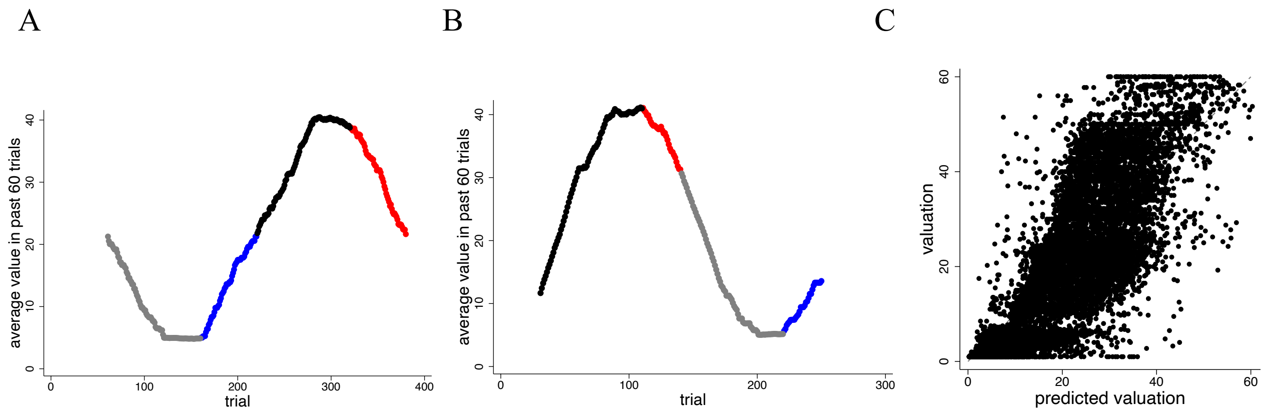

Figure 7. A-B: Historical average of the gamble values in A: Low-High order in version 1 of the experiment and B: in the High-Low order in version 2 of the experiment. Gray and black indicate the values in Low and High Adaptation Blocks respectively. Blue and red indicate the values in post-lo and post-hi Test Blocks. C: Relationship between participant's valuations and valuations predicted by the normalization model.

3.4.4 Effect of adaptation on ratings

Although the ratings in adaptation trials were not incentivized, we see evidence of similar normalization in participants' behavior in this part of the experiment. First, we see that ratings are negatively influenced by the expected value of the previously rated gamble (Table 3, model (1)). Second, if participants' reference points are indeed backward-looking, we would expect that within the Low Adaptation Block, the reference point decreases as the trials go by (see Figure 7A and 7B) and therefore the ratings should increase with each trial. In the High Adaptation Block, the effect should be the opposite. In Table 3 models (2) and (3), we provide evidence consistent with this conjecture. It is noteworthy that similar mechanism seems to occur in consequential valuation of risky gambles as well as their inconsequential (happiness) ratings.

Table 3. Random effects regressions with the hypothetical gamble rating as a dependent variable. *L.EV* is the expected value of the gamble in the previous trial; *trial* is the trial number within the block; *high adaptation* is an indicator variable for High Adaptation Block.

	all data	Low Adaptation	High Adaptation
	(1)	(2)	(3)
EV	0.4709***	3.1082***	0.6163***
	(0.0431)	(0.4755)	(0.0727)
L.EV	-0.1634***		
	(0.0418)		
trial	0.0096	0.0374**	-0.0184*
	(0.0073)	(0.0118)	(0.0088)
constant	20.0436***	4.4791+	8.2852*
	(1.1915)	(2.6150)	(3.3449)
N	24918	12600	12600

Standard errors clustered on participant in parentheses
+ p<0.1, *p<0.05, ** p<0.01, *** p<0.001

4. Discussion

Our results reveal that individuals' valuations of identical gambles are on average lower (higher) after exposure to payoff-irrelevant gambles with high (low) payoffs. Importantly, the effect occurs within participants without altering their wealth and "rational" payoff expectations because our treatment exposure to high-payoff and low-payoff gambles had no consequences for the earnings from the experiment and was not informative about future earning prospects. The effect is observed even though participants merely viewed the adaptation gambles and these gambles were never realized or played. If such normalization of value is a general phenomenon that occurs also outside laboratory conditions (just as it does in our senses), it will imply that human valuation and risk-taking is not a fixed parameter but rather fluctuates on a minute-to-minute basis adjusting to our changing conditions.

There now exist several models inspired by psychophysical perception. Arising from common principles, these models often make similar predictions. While our goal is to generally test for value normalization in a novel setting rather than to distinguish between these models, we find it worthwhile to discuss our findings in the context of the divisive, range, frequency, and variance normalization approaches.

In the divisive normalization model (see section 3.4.3), the neural signal corresponding to valuation is divisively normalized by the reference point determined by the payoffs observed in the past. An increase in the reference point lowers the firing rate which corresponds to a lower valuation of a payoff. Although we do not measure the firing rates, our results are consistent with this prediction. Khaw et al. (2017) found similar effect in a study where participants provided their valuations of snacks in riskless conditions. Taken together, these studies suggest that the payoff-adaptation effect that we observe here is a general phenomenon for choices involving riskless as well as risky options.

Under a simple range-normalization model (e.g. Kontek & Lewandowski, 2018), the utility of the gambles could be affected by prior exposure to payoffs if such exposure changes the range of the payoffs experienced so far. To control for range normalization, our treatment exposure to high- and low-value gambles never changes the range of payoffs experienced so far in the experiment because the initial block of decisions already includes all possible lotteries that will be later seen in the study. We, therefore, conclude that range normalization alone cannot account for the findings in our study.

The frequency normalization, such as in Stewart et al. (2015) posits that the utility of an alternative is determined by its rank within the distribution. Given that the rank of the gamble in a negatively skewed distribution will be lower than in a positively skewed distribution (keeping range constant), if one is willing to assume that such rank corresponds to reported valuation, the model also predicts lower valuation after being exposed to high-payoff gambles. Stewart et al. (2015) found that people choosing between two binary lotteries in negatively skewed distributions are risk-seeking and in positively skewed distributions are risk-averse. This finding highlights the possibility that even though participants in our study after exposure to high payoffs value gambles less, this does not immediately imply that they will be more risk-averse when choosing between the gambles. Related to our work, Stewart et al. (2003) conducted two experiments (experiment 3 and experiment 5) where they tested whether preceding trials affect current, hypothetical valuations of gambles and hypothetical choices between gambles. They found no effects. There are some differences between ours and their experiments that can explain the difference in findings. In their experiment, both the probabilities and amounts were manipulated while in our experiment only amounts are changed. It is therefore possible that in their experiment the normalization of value and normalization of probability canceled each other out in the observed choice. Another difference is that Stewart et al. (2003) only test for the effect of one previous trial and we, on the other hand, created adaptation through a much longer exposure. This second explanation is consistent with our data. In Table

2, we show that also in our design the expected value of the gamble in the previous trial did not significantly affect the current valuation. However, when adaptation to low- or high-value gambles was over a prolonged period, the valuations of subsequently presented gambles were affected.

Finally, Payzan-LeNestour et al. (2020) present a model of variance adaptation and evidence consistent with this theory in financial markets and in the lab (Payzan-LeNestour, Balleine, Berrada, & Pearson, 2016). The prediction of the model, supported by the evidence, is that perceived variance is decreased after prolonged exposure to high variance and increased after exposure to low variance. In our study, High Adaptation Blocks not only constituted of gambles with higher payoffs but also with higher variance meaning that both value normalization and variance adaptation could be affecting participants in our study. The variance adaptation model predicts that after High Adaptation Blocks (which had higher payoffs but also higher variance), participants' perceived variance decreases. Given that most people dislike variance, this implies that after High Adaptation Blocks, if value normalization plays no role, participants should provide higher gamble valuations which is in contradiction to our findings. We, therefore, speculate that if we kept the variance in Low and High Adaptation Blocks constant, we would see a stronger effect of adaptation on subsequent valuations.

It is natural to ask why value normalization occurs. Wouldn't we be better off if we perceived payoffs objectively and always valued identical gambles the same? Recent literature suggests that the answer to this question is no. Given the limitations of our nervous system, we are better off representing the values of the payoffs in context. Realizing the constraints of the nervous system (limited number of neurons bounded biophysically by the maximum rate at which they can produce action potentials), economists argued that an organism that wants to maximize choice efficiency but faces constraints in the encoding of the utility/value should dynamically adapt this utility/value to the past and current properties of the environment (Frydman & Jin, 2019; Glimcher & Tymula, 2020; Rayo & Becker, 2007; Robson et al., 2021; Steverson, Brandenburger, & Glimcher, 2019; Woodford, 2012).

Presently, there is ample evidence (dating as far back as Ohzawa et al., 1985) that neurons encoding sensory stimuli and emerging evidence that neurons encoding value (Bujold et al., 2021; Louie et al., 2013; Padoa-Schioppa, 2009; Tremblay & Schultz, 1999; Yamada et al., 2018; Zimmermann et al., 2018) indeed dynamically adjust their firing rates to the properties of the environment. The functional forms that guide this adjustment have been described and studied (Carandini & Heeger, 2012). Such adaptive coding of payoffs would result precisely in the effects that we observe in the experiment.

A related study to ours in the risk-taking domain is Cohn et al. (2015) who study the effect of boom/bust exposure on subsequent willingness to invest in a risky asset. The participants watch an animation of a boom or a bust in the financial market and then write about their investment strategy under such market conditions. Participants primed with a boost invested more in the Gneezy & Potters (1997) investment task. Our participants at the surface seemed to do the opposite — after being exposed to high payoffs, they valued gambles less. However, our paper and Khaw et al. (2017) provide evidence that the valuation of both risky and riskless payoffs lowers after adaptation to high payoffs. Therefore, it is possible that even our participants would appear more risk-taking if we asked them to select from a range of investment strategies following adaptation to high payoffs if the valuations of safer options reduced more than the valuations of riskier options. In our adaptation procedure, we intentionally avoided a specific context (such as stock market) and instead opted for generic risky scenarios to increase the generality of the result.

Our finding that the valuation of gambles is adaptive and that pure exposure (without consumption) to payoffs of different magnitude affects the valuation of risky prospects may have important policy and social implications; because these are believed to have lifelong associations with health outcomes and well-being, wages, promotion opportunities, career path, and financial decisions of individuals. The exposure to payoff magnitudes in the real world differs significantly across individuals according to measurable criteria such as socioeconomic status and in some societies, gender. Adaptive reference points may therefore provide insights into social issues beyond experimental context such as understanding some of the observed differences in risky behaviors among different groups of people (e.g. characterized by age, culture, gender, geography). Moreover, the magnitudes of payoffs that we are exposed to change throughout the day which may affect our decisions at the workplace and at home. Further research on the difference between adaptations through pure exposure versus real consumption, as well as examining the adaptation effect in the loss domain would provide invaluable additional insights.

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Appendix A Instructions

Opening Instructions

Thank you for participating in today’s experiment with the School of Economics! This experiment will run for approximately 90 minutes. Please do not communicate with other participants until you finish the study and leave the room. If you have a question, raise your hand and we will gladly help you.

The study is strictly anonymous. Your identity and decisions will not be revealed to others and the identity and decisions of others will not be revealed to you.

The study consists of the following parts:

1) Instructions
2) Decision-making task
3) Questionnaire about you and the study
4) Payment and good-bye!

Your earnings

Your earnings will depend on **one** randomly selected decision that you made in the experiment. Each of your decisions has equal chance to be selected for payment.

Please follow the instructions carefully to learn how you can earn money. You will receive your earnings in cash at the conclusion of the experiment. Only you and the experimenter will know how much you earned.

What do I have to do?

In the experiment we will ask you to tell us how much you value or how much you like different gambles. There are two types of trials: valuation and rating trials.

In valuation trials, we will ask you how much you value a gamble that is currently on offer. These gambles change from trial to trial. Below is an example of how this information will be presented to you:

At the top of the screen is the “endowment” in this trial. In this example, it is $15. If this trial gets picked for payment, the “endowment” is added to your earnings from this study. Below is a gamble: in this example, it is 50% chance of receiving $25 and 50% chance of receiving $11.

Your task is to move the slider to a dollar amount that is equal to how much this gamble is worth to you. To decide that amount, you may want to think what amount of money for sure would make it really hard for you to choose between this gamble and that sure amount.
Move the slider until it displays how much the gamble is worth to you. The amount corresponding to the current slider position appears on the top in blue. You may choose any amount between $1 and $60, in $0.25 increments. You may change your valuation by clicking at a different position on the slider. Once you made your decision, press confirm. After you press confirm, you move to the next trial and you will not be allowed to go back and change your decision. Please choose carefully, as each of the decisions that you make has equal chance to be selected for payment. There are **no wrong decisions** in this experiment, we simply ask for your valuations.

What do I have to do?

In rating trials: we ask you to rate how happy you would be if you got the currently displayed gamble. Here, you will see a slider with a happy face on one side and an unhappy face on the other[9]. Please click on the corresponding position on the slider to indicate happiness. Once you make a decision, press confirm. After you press confirm, you move to the next trial and you will not be allowed to go back and change your decision. There are **no wrong decisions** in this experiment.
Please beware the sides which the happy and unhappy faces appear may **alternate** from trial to trial.[10]

How is my payment determined?

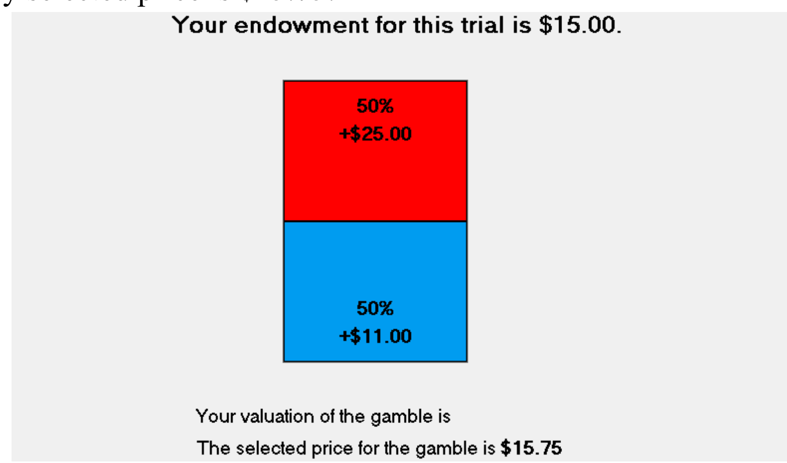
Your payment depends on one randomly selected valuation trial. Suppose that the computer randomly selected this trial:

[9] In version 2 of the experiment, this text was replaced with "we ask you to rate the currently displayed gamble. Here, you will see a slider with “LOW” on one side and “HIGH” on the other”

[10] In version 2 of the experiment, this text was replaced with “Please beware the sides which HIGH and LOW appear may alternate from trial to trial.

Next the computer randomly determines the **"price"** of the selected gamble by drawing an amount between the minimum and the maximum possible payoff. In this example, it picks a number between $11 and $25 (inclusive). The numbers between $11 and $25, in increments of $0.25, are all equally likely to be picked.
Click next to see the randomly selected price.

How is my payment determined?
Suppose the randomly selected price is $15.75:



Scenario 1
If your valuation of the gamble is **lower than** the randomly selected price ($15.75), you keep your endowment on that trial ($15) but **DO NOT** get the gamble. Since **the gamble price is above your valuation**, you don't get the gamble.

Payment=endowment=$15

Notice: if you enter a valuation lower than $11 (below the lower payoff of the gamble), you never get the gamble. Since the randomly selected price will always be higher or equal to the lower payoff of the gamble, $11 in this example.

Scenario 2

If your valuation of the gamble is **higher than** the randomly selected price ($15.75), you get the gamble and have to pay us $15.75 for it. Since **the price of the gamble is below your valuation**, you get the gamble. You also keep your endowment.

Payment=endowment– price + gamble=$15 - $15.75 + gamble

Notice: if you enter a valuation higher than $25 (above the higher payoff of the gamble), you always get the gamble. Since the randomly selected price will always be lower or equal to the higher payoff of the gamble, $25 in this example.

Scenario 3

If your valuation of the gamble is **equal to** this price, the computer randomly decides whether you get the gamble or not.

FAQs

Question: Can I make more money by entering a dollar amount lower than my valuation of the gamble?

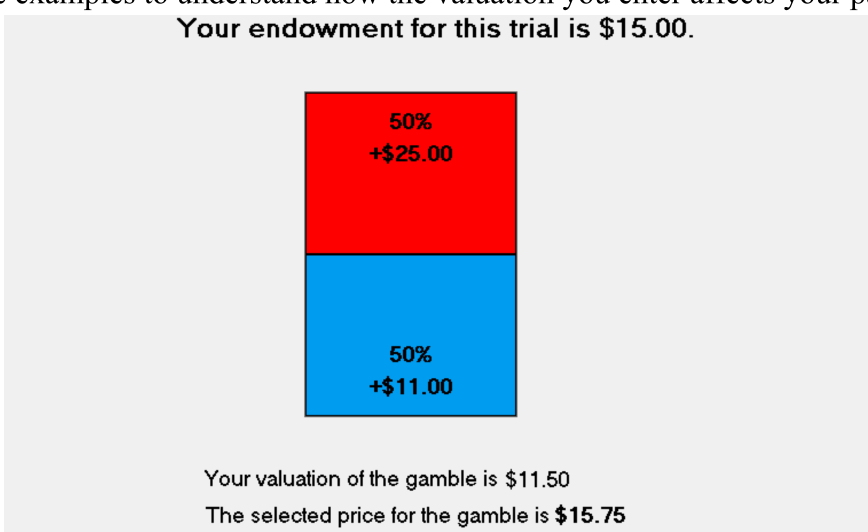
Answer: No. First of all, your valuation has no impact on the price of the gamble which is selected at random. Second, if you enter an amount that is lower than your valuation, it may happen that we draw a price that is below your valuation but not below the amount that you entered, in which case you do not get a gamble, but you would be better off getting the gamble.

Question: Can I make more money by entering a dollar amount higher than my valuation of the gamble?

Answer: No. First of all, your valuation has no impact on the price of the gamble which is selected at random. Second, if you enter an amount that is higher than your valuation, it may happen that we draw a price that is above your valuation but not above the amount that you entered, in which case you get a gamble, but would be better off not getting the gamble.

How is my payment determined?

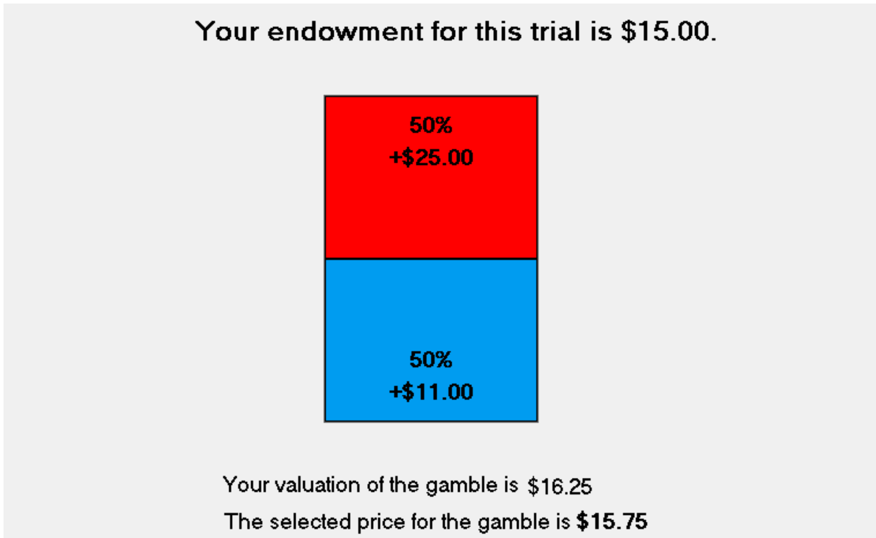
Let's look at some examples to understand how the valuation you enter affects your payment.



Suppose that you told us that the gamble is worth to you $11.50. It is worth to you less than the price ($11.50<$15.75), you are therefore unwilling to pay us $15.75 to get the gamble; so you **don't** get the gamble. Your payment is:

$15(endowment on the trial).

How is my payment determined?

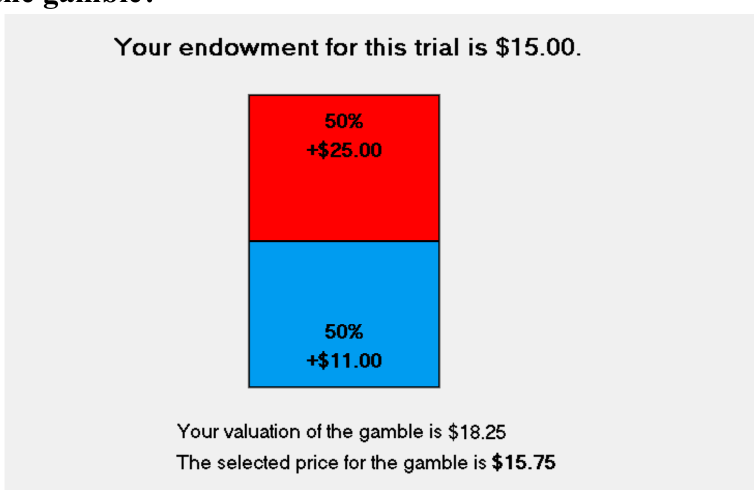


Suppose that you told us that the gamble is worth $16.25. It is worth to you more than the price ($16.25>$15.75), so you get the gamble and pay the price of $15.75. Your payment is:

$15(your endowment) - $15.75 + gamble.

IMPORTANT: The price of the gamble is drawn randomly from the amounts between the lowest and highest possible gamble outcome in $0.25 increments. You cannot affect this price with your valuation. Your valuation determines whether you get the gamble or not, but never the price.

How do I earn from the gamble?



Suppose that your valuation of the gamble is $18.25. Our randomly selected price ($15.75) is lower than your valuation, so you play the gamble to determine your exact earnings from this experiment. Specifically, you draw a chip from a bag that has 50 red and 50 blue chips. If you draw a red chip, your gamble payment will be $25. If you draw a blue chip, your gamble payment will be $11.

Your total payments for the experiment:
If you draw a **red** chip:

\$15(endowment) - \$15.75(price) + \$25(gamble payment) = \$24.25

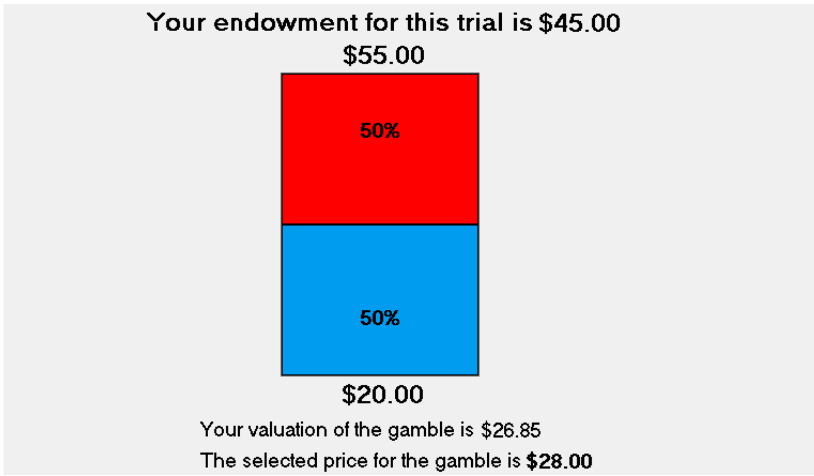
If you draw a **blue** chip:

\$15(endowment) - \$15.75(price) + \$11(gamble payment) = \$10.25

Appendix B Comprehension Questions

Practice Question 1

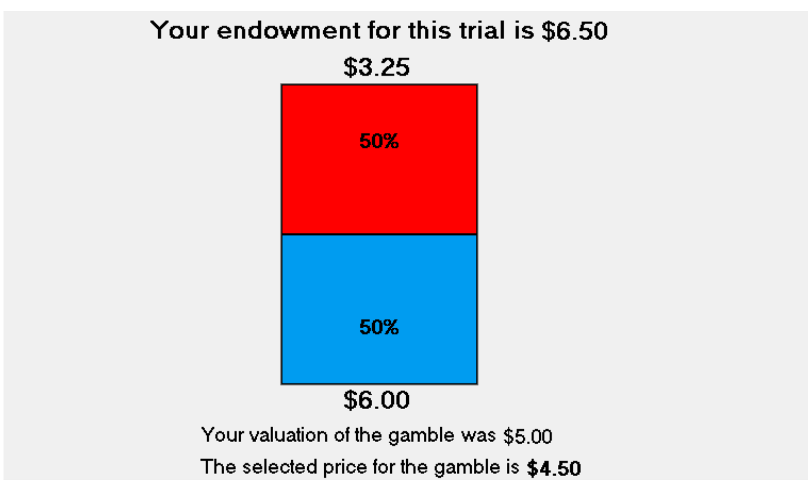
Suppose this trial is randomly selected for your payment. Answer all questions (TRUE/FALSE):



a) I don't get the gamble since $28>$26.85(price>my valuation).
b) I get the gamble since $28>$26.85(price>my valuation).
c) I lose $28, so my total payment is $17(endowment minus price).
d) My total and final payment is the endowment, which is $45.
e) I receive $26.85 since $28>$26.85(price>my valuation).
f) I will draw a chip out of a bag with 50 red and 50 blue chips to determine my payment. My total payment is either $55 if I draw a red chip or $20 if I draw a blue chip.
g) My total payment is calculated as my endowment+ gamble earnings– price, either $72($45 + $55 - $28) or $37($45 + $20 -28).

Practice Question 2

Suppose this trial is randomly selected for your payment. Answer all questions (TRUE/FALSE):

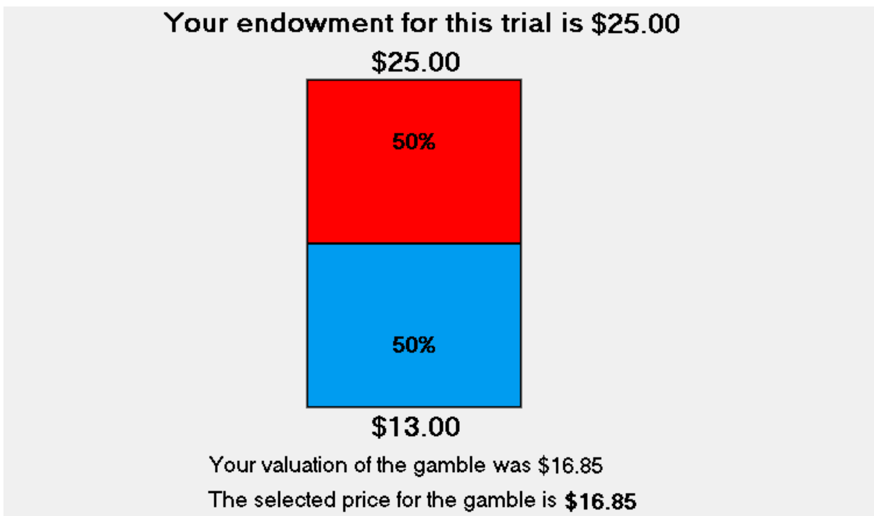


a) I don't get the gamble since $5>$4.50(my valuation>price).

b) I play the gamble and draw a chip out of a bag with 50 red and 50 blue chips. If I draw a red chip, I receive \$3.25 as my gamble earnings and if I draw a blue chip, I receive \$6 as my gamble earnings.
c) My final payment is either \$5.25(\$6.50 + \$3.25 -\$4.50) or \$8(\$6.50 + \$6 - \$4.50), depending on the colour of the chip I draw.
d) My total payment is the endowment, which is \$6.50.
e) I get the gamble since \$5>\$4.50 (my valuation> the price) and my total payment is \$6.50(endowment) + gamble - \$4.50 (price).
f) My total payment is \$11.50(\$6.50 + \$5), the sum of endowment and my valuation since my valuation is higher than the price of the gamble.

Practice Question 3

Suppose this trial is randomly selected for your payment. Answer all questions (TRUE/FALSE):



a) I don't get or play the gamble since my valuation equals the price.
b) I play the gamble since my valuation equals the price.
c) The computer randomly determines if I play the gamble or not play the gamble.
d) If the computer selected that I don't play the gamble, my payment is the endowment (\$25).
e) I pay the price of the gamble, so my payment is endowment minus the price or \$8.15(\$25-\$16.85).
f) My total payment is either \$25 or \$13 since I definitely play the gamble.
g) If I am randomly allocated to play the gamble, I draw a chip out of a bag with 50 red and 50 blue chips to determine my gamble earnings. My total payment is endowment (\$25)+ gamble earnings– price(\$16.85).

Appendix C Questionnaire

Page 1

(1) Age
(2) Gender
(3) Cultural/Ethnicity group
    (OCEANIAN)
    (NORTH-WEST EUROPEAN)
    (SOUTHERN/EASTERN EUROPEAN)
    (NORTH AFRICAN AND MIDDLE EASTERN)
    (SOUTH-EAST ASIAN)
    (NORTH-EAST ASIAN)
    (SOUTHERN/CENTRAL ASIAN)
    (PEOPLE OF THE AMERICAS)
    (SUB-SAHARAN AFRICAN)
    (Other)
(4) Are you an international or domestic student? (YES/NO)
(5) When do you expect to graduate?
(6) Are you currently employed? (YES/No)
    If YES, Please specify current annual earning.

Page 2

(7) How wealthy do you consider yourself?
    (Very Wealthy)
    (Wealthy)
    (Average)
    (Poor)
    (Very Poor)
(8) What annual salary package do you expect to receive in the first year after graduation?
(9) What annual salary package do you expect to receive after **5 Years from graduation?**
(10) What is your **weekly** budget for recreational activities and entertainment?
(11) What is your **weekly** budget for dining out or takeaway foods?
(12) What is your major/s at University?

Page 3

(1) What do you think the experiment is about?

Appendix D Supplementary Tables

Table D1. Low-, medium-, and high-value gambles used in the experiment. Low- (high-) value gambles were derived by multiplying payoffs of medium-value gambles by 0.25 (2). Each gamble pays either high payoff or low payoff with equal probability. Gambles were presented in an order randomized individually for each participant.

low value		medium value		high value	
high payoff	low payoff	high payoff	low payoff	high payoff	low payoff
$7.25	$3.00	$29.00	$12.00	$58.00	$24.00
$6.75	$2.75	$27.00	$11.00	$54.00	$22.00
$7.00	$2.50	$28.00	$10.00	$56.00	$20.00
$6.50	$3.25	$26.00	$13.00	$52.00	$26.00
$7.25	$5.25	$29.00	$21.00	$58.00	$42.00
$7.00	$4.50	$28.00	$18.00	$56.00	$36.00
$4.75	$3.00	$19.00	$12.00	$38.00	$24.00
$6.00	$3.75	$24.00	$15.00	$48.00	$30.00
$6.25	$5.00	$25.00	$20.00	$50.00	$40.00
$6.50	$5.50	$26.00	$22.00	$52.00	$44.00

Table D2. Random effects regression with valuations as the dependent variable regressed. *trial number* is the number of valuation trials completed so far and *trial number in block* is the number of trials completed in the current block. Models (1) and (5) include all data. Models (2), (3), and (4) include data only from Test Block 1, 2, and 3 respectively

	(1)	(2)	(3)	(4)	(5)
EV	0.7508***	0.7424***	0.7583***	0.7519***	0.7509***
	(0.0311)	(0.0355)	(0.0311)	(0.0327)	(0.0311)
trial number					-0.0022
					(0.0049)
trial number in block					-0.0004
					(0.0063)
constant	2.3943***	2.3727**	2.3823***	2.4095***	2.5460***
	(0.6407)	(0.7448)	(0.6450)	(0.6387)	(0.7720)
N	18630	6210	6210	6210	18630

Standard errors clustered on participant in parentheses
+ p<0.1, *p<0.05, ** p<0.01, *** p<0.001