A critical evaluation of loss aversion as the determinate of effort in compensation framing

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Abstract: A robust finding in managerial accounting research is that participants prefer economically equivalent contracts framed as bonuses to penalties. Another finding is that participants put forth more effort when facing penalty contracts than equivalent bonus contracts. Both results are commonly described as due to loss aversion, an integral portion of Prospect Theory. We test whether loss aversion is correlated with higher effort in an experiment with two parts. In the first part, we elicit individual participants' loss aversion using two measures. In the second part of the experiment, participants choose costly efforts to increase the likelihood of high versus low state-contingent payoffs framed as bonuses or penalties. We find significant differences in the effort chosen between treatments: participants put in significantly more effort when facing penalty contracts. However, we find no evidence that the degree of loss aversion from either measure correlates with effort choices as predicted by Prospect Theory. We find that only a quarter of participants are consistent with the Prospect Theory, and for those, we see little evidence of the commonly cited features of loss aversion. While the most cited reason for framing incentives changing participant behavior is loss aversion, our results suggest that this reason is falsified. While the results from prior studies are replicable, the untested underlying mechanism is not loss aversion.

Keywords: contract framing, loss-aversion, bonus, penalty, utility preference, model selection

Introduction

Research in managerial accounting and economics has examined effort exerted by workers working under economically equivalent contracts framed as either bonuses or penalties. For example, imagine the worker could earn one of two payoffs, high and low. One could frame the contract as a bonus if the worker is initially paid the low amount, but if a desired outcome is achieved, then total compensation increases to the high amount. Likewise, one could frame the contract as a penalty if the worker is initially paid the high amount, but if a desired outcome is not achieved, total compensation is decreased to the low amount. Prior research frequently finds that workers exert more effort when facing a penalty contract than when facing a bonus contract. The reason commonly cited is loss aversion stemming from Prospect Theory (Kahneman and Tversky 1979) or Cumulative Prospect Theory (Kahneman and Tversky 1992; CPT hereafter), which posit that disutility from losses "looms larger" than utility from gains. Consequently, the consensus explanation for the difference in effort across contract frames is that the worker is willing to put forth more effort to avoid the penalty than they are to achieve the bonus. Surprisingly missing from the literature are (a) a test of the implicit assumption that CPT is empirically descriptive of the behavior of workers, (b) any rigorous measurement of workers' loss aversion, and (c) an attempt to determine if individual workers' loss aversion is positively correlated with effort in penalty contract settings. This paper seeks to remedy those omissions.

Testing the assumed mechanism driving differential effort across contract frames should be of interest to not only academic researchers, but also to managers and regulators. Academic researchers should be cautious about basing policy recommendations for contracts and control systems on uncritical acceptance of loss aversion. While Prospect Theory is an appealing normative theory in that it seemingly explains stylized behaviors, the questions of whether agents make choices consistent with it or whether it is predictive in effort-based settings are empirical ones. Managers and regulators should clearly prefer to receive policy recommendations based on sound theoretical arguments since implementing new contracts, controls, and policies is expensive. Further, if such instruments are unsuccessful, their failure entails substantial opportunity costs.

To address our research agenda, we conduct a multi-stage, incentivized experiment. We first ask participants to make choices over 96 lottery pairs which allows us to estimate latent loss aversion at the individual level as per Harrison and Swarthout (2023). Additionally, we elicit an alternative measure of loss aversion (Gächter et al., 2022). After answering some demographic questions, participants are randomly assigned (between subjects) to either a bonus contract or an economically equivalent penalty contract and asked to provide effort in a task adapted from Hannan et al. (2005).

This design allows us to answer the following questions. First, we are able to determine whether participants working under a penalty contract exert more effort than participants working under a bonus contract, consistent with the results of prior literature. Second, we are able to make assertions about what proportion of our participants make choices consistent with CPT as opposed to two alternative utility models (expected utility theory and rank-dependent utility theory). Third, we test whether higher estimated loss aversion results in higher effort provision in the penalty setting. Relatedly, we are able to test the relationship between loss aversion and effort provision for participants working under the *bonus* contract. This is an important falsification test because, assuming that loss aversion as captured by CPT is responsible for the differential effort provision effect across contract frames, then, *ceteris paribus*, variance in loss aversion should be irrelevant when predicting effort provision in the bonus setting (Tversky and Kahneman, 1992). Fourth, we are able to test whether there is a correlation between the maximum likelihood method of estimating loss aversion under CPT and the simpler measure proposed by Gächter, Johnson, and Herrmann (2022). Further, we are able to test whether variance in the Gächter et al measure correlates with effort provision in the penalty condition.

We recruit 160 international participants via Prolific to complete our experimental instrument. We find greater effort when participants faced penalty contracts, consistent with Hannan et al. (2005) and a host of other studies. After determining which utility model (EUT, RDU, or CPT) best describes each participant's lottery choices, we find that the difference in effort provision across contract frames is indeed driven by those participants who are best described by CPT but that these individuals represent only one-fourth of our total participant pool. However, the actual degree of utility loss aversion, using either measure, has no explanatory power in predicting effort in penalty settings. That is, while utility loss aversion may explain some participants' choices in lotteries, it does not explain behavior in our effort settings.

We believe that our study makes the following contributions to the literature. First, we provide, to our knowledge, the first rigorous test of the received assumption that (utility) loss aversion is the cause of the empirical finding that more effort is exerted by agents working under penalty contracts as opposed to economically equivalent bonus contracts. Our results suggest that this effect is driven by the relatively small proportion of agents who exhibit behavior consistent with CPT. For the majority of the participants whose choices are better characterized by either expected utility theory (EUT) or rank-dependent utility (RDU), we find no difference in effort provision between the two contract frames. Taken together, these results offer at least two important contributions. First, these results suggest an explanation for the inconsistent conclusions of prior studies, some of which find a contract framing-driven difference in effort and some of which do not (Ferraro and Tracy 2022). Second, our results offer a strong caveat to practitioners seeking to increase effort provision from their employees via contract design. Specifically, the consensus conclusion from prior accounting research is that penalty contracts induce more effort from agents. If practitioners take this advice at face value, they should implement penalty contracts in those situations where high effort provision is most critical. However, our results offer a warning that, depending on the characteristics of the firm's workforce (i.e. whether they behave more consistently with EUT or RDU as opposed to CPT), implementing a penalty contract may not result in more effort. Indeed, our results may help to explain the ongoing academic question of why penalty contracts are so infrequently observed in practice when they are presumed to induce more effort from agents.

Second, we provide empirical evidence regarding the correlation (or lack thereof) between individual-level maximum likelihood estimation of CPT loss aversion and the simpler measure proposed by Gächter et al. (2022). While the Gächter et al. measure is unarguably easier to implement, our results suggest that it holds little descriptive power for participants' behavior, especially in the kind of highly contextualized instruments that are common in managerial accounting experiments.

Finally, while it is integral to our ability to present the current research, we provide what we hope will be a useful review of three popular utility models and their primary elements and explicate the differences between them.

Background and Hypothesis

Contract Framing Literature

Accounting researchers have studied the effects of incentive frames on agents' behavior for about 30 years. Neo-classical economic theory, which relies on expected utility theory, predicts that describing equivalent incentives in bonus or penalty terms should not affect agents' behavior. In what is arguably the first contract framing paper in accounting, Luft (1994) explores the notion that agents prefer to work under bonus contracts rather than economically equivalent penalty contracts. Participants in Luft's experiment were provided with a multiple price list and, for each choice, asked to state their preference between a (single) flat rate contract and a (varying) performance-contingent contract, framed as either a bonus or a penalty. The results demonstrated a dislike of economically equivalent contracts framed as bonuses compared to penalties in that participants required higher expected payoffs to select the penalty contract. Critically, the development of the hypothesis that predicted this result of penalty aversion relied on prospect theory (Kahneman and Tversky 1979) as the presumed utility model.[1]

In an extension of Luft (1994), Hannan, Hoffman, and Moser (2005) posited that if loss aversion were the underlying reason driving contract preferences, then it would follow that participants or workers facing penalty contracts would exert more costly effort than those

[1] Luft (1994) uses the term "penalty aversion" not use the term "loss aversion". Our reading suggests that penalty aversion is aversion to the penalty contract, regardless of the exact cause of the dispreference. However, as prospect theory is specifically discussed in the hypothesis development of the study, one could make the case that penalty aversion and loss aversion are equivalent since the former follows directly as result of the latter.

facing bonus contracts. Results of the study were consistent with this prediction and they were also able to replicate Luft's results that bonus contracts are perceived as fairer than penalty contracts. While a construct used in Hannan et al (2005) to predict the difference in effort provision was "expected disappointment," this construct is rooted in loss aversion stemming from prospect theory as the received utility model.

Building from these two papers, higher effort provision in penalty contracts, relative to bonus contracts, has been reported in laboratory settings (e.g., Armantier and Boly, 2015; Burke et al., 2023; Christ et al., 2012; Church et al., 2008; Imas et al., 2017), field experiments (e.g., Fryer et al., 2012; Hong et al., 2015; Hossain and List, 2012), archival studies (e.g., Van der Stede et al., 2020), and in settings where information was being sought instead of pecuniary rewards (Litovsky et al., 2022). Overwhelmingly, loss aversion is the presumed explanation for the difference in effort provision. However, these papers neither question whether prospect theory has descriptive validity for the agents they are generalizing to nor, in the case of the laboratory experiments, explicitly elicit participants' degree of loss aversion.

Utility Models

While prospect theory is one candidate for participants behavior, there are several alternatives. Indeed, there is compelling evidence that prospect theory has little empirical validity in describing the behavior of incentivized laboratory participants (Harrison and Rutström, 2008). While a comprehensive review is outside the scope of our research question, to provide sufficient background for our estimation procedures (described later) we discuss three commonly referenced utility models in this section.

Expected Utility Theory (EUT)

At the cornerstone of modern microeconomic theory lies expected utility theory (Von Neumann and Morgenstern, 1947, 2007). While one could assume a variety of functional forms, we will assume that an agent has preferences over pecuniary income which exhibit constant relative risk aversion (CRRA), with the following utility function

$$U(x) = x^{1-r}/1-r. \tag{1}$$

where $x > 0$ is income and r is the risk parameter. By L'Hospital's rule $U(x) = \ln(x)$ when $r = 1$. When $r > 0$ the agent is described as risk averse, when $r = 0$, risk neutral, and when $r < 0$ risk loving (or risk affine). For clarity, when we say "risk averse" we are explicitly describing an individual whose risk preferences are such that their certainty equivalent from a given uncertain outcome is less than the expected value of that outcome.

When the agent evaluates a lottery in which there are $J > 1$ possible prizes, x_j , for $j = 1, \dots, J$, each with known probability $p(x_j)$, then the expected utility of lottery i is the probability weighted utility of each outcome

$$EU_i = \sum_{j=1}^{J} \left(p(x_j) \times U(x_j)\right). \tag{2}$$

As a result, with CRRA there is only parameter, risk r, that characterizes an agent whose choices are described by EUT.

Rank Dependent Utility (RDU)

Quiggin (1982) proposes a more general utility model called rank dependent utility. RDU maintains the notion of different risk attitudes (e.g. risk aversion) like EUT but allows for the possibility that the weight the agent places on the probabilities of outcomes for decision making need not be the objective probabilities of the outcomes. For example, perhaps an agent views the probability of heads obtaining on a fair coin flip to be 40% rather than the objective 50% probability. Instead of the expected utility in equation (2), the expected utility of lottery i under RDU is

$$RDU_i = \sum_{j=1}^{J} \left(w_j \times U(x_j)\right), \tag{3}$$

where $w_j = \omega(p_j)$ when $j = J$, and $w_j = \omega(p_1 + \cdots + p_j) - \omega(p_{j+1} + \cdots + p_j)$ for $j = 1, \ldots, J-1$, where ranking of outcomes is from best to worst (i.e., $x_{j-1} > x_j$). We maintain the functional form of the utility function $U(x_j)$ as the CRRA function described in equation (1).

There are various choices we can use for the weighting function, including a simple power function and an inverse S-shaped function effectively exhibiting overweighting for small probabilities and underweighting for larger probabilities as in Tversky and Kahneman (1992):[2]

$$\omega(p) = \frac{p^\gamma}{\left(p^\gamma + (1-p)^\gamma\right)^{1/\gamma}}. \tag{4}$$

This weighting function is defined for $0 \leq p \leq 1$. When $\gamma = 1$ the function is the identity $\omega(p) = p$ as in EUT. When $\gamma < 1$, the function exhibits pessimism for small p, and optimism for large p. When $\gamma > 1$, the function exhibits optimism for small p, and pessimism for large p.

[2] The terms "optimism" and "pessimism" are often used. When discussing outcomes in the loss domain in prospect theory and, more generally, when more than two possible outcomes exist, this terminology can be confusing. Consequently, we will use the term "overweighting" to describe a situation in which an agent assigns greater decision weight than the objective probability of an outcome. We will use "underweighting" in a complementary manner.

Assuming the CRRA utility function shown in (1) and the probability weighting shown in (4), an agent's choices under RDU are characterized by two parameters, one pertaining to their utility risk preferences r , and one describing their probability weighting, γ.

Cumulative Prospect Theory (CPT)

Prospect theory was introduced in Kahneman and Tversky (1979). The "original" prospect theory formulation includes three critical deviations from EUT. First, agents are theorized to make decisions over deviations from a reference point rather than final wealth states. This implies what is known as "sign-dependence." Specifically, increases in wealth relative to the reference point are termed gains and decreases in wealth relative to the reference point are termed losses. Second, subjective probability weighting, similar to RDU, is allowed in both the gain and loss domains.[3] Third, disutility from a loss of a given size is greater than the utility from an equivalent size gain. This is the often-cited loss aversion of the theory. In an update to the model, cumulative prospect theory was introduced in Tversky and Kahneman (1992) which incorporates rank-dependence from RDU.

As with the previous two models, there are many choices that can be made in terms of functional forms for each of the elements of CPT. We follow Tversky and Kahneman (1992) and use the CRRA utility function described in equation (1). Because there are two domains in CPT, one must split the utility function into separate parts for the gain and loss domains, which may exhibit different curvatures. Specifically, income less the reference point enters utility in the following manner

$$U(m) = \begin{cases} m^{1-\alpha}/1-\alpha\,, & \text{when } m \geq 0 \\ -\lambda[-m^{1-\beta}/1-\beta]\,, & \text{when } m < 0 \end{cases} \tag{5}$$

where m is the value of the proposition (i.e. deviation from reference point) and λ is the loss aversion parameter, which describes the amount by which disutility from a loss exceeds the utility from a gain of the equivalent magnitude.

As with RDU, there are many options for weighting functions. We will use equation (4), but altered to accommodate the different domains in prospect theory:

$$\omega(p) = \begin{cases} \,, & \text{when } m \geq 0 \\ \dfrac{p^{\gamma_L}}{\left(p^{\gamma_L} + (1-p)^{\gamma_L}\right)^{1/\gamma_L}}\,, & \text{when } m < 0 \end{cases} \tag{6}$$

[3] It is worth noting that there can be a difference between a gain/loss domain and a gain/loss frame. A prospect that increases (decreases) wealth compared to the reference point yields an outcome in the gain (loss) domain. This is potentially as opposed to a prospect that is *framed* as a gain or loss, but which may not yield a final wealth state that is in the framed domain. This most frequently occurs when the agent's reference point is different from the theorist or experimenter's presumed reference point. In this paper we will use the term gain/loss frame.

The above formulation allows agents to exhibit different probability weighting not only over small and large probabilities, but over the same underlying probability when the outcome is the gain domain as opposed to in the loss domain.

The decision for a CPT agent depends on the expected value as in EUT and RDU, but since income is perceived relative to a reference point, income x is replaced with m, income net of the reference point. Consequently, using the utility from equation (5) and the weighting function from equation (6) yields the following expected utility:

$$CPT_i = \sum_{j=1}^{J} \left(w_j \times U(m_j) \right). \tag{7}$$

Under the functional form assumptions above, an agent's value function characterized under CPT has two curvature parameters, α and β, a loss parameter λ, and two weighting parameters, γ_H, and γ_L, for a total of five parameters to characterize the agent.

Comments on utility functions and loss aversion

It is critical to understand how the three models discussed relate to one another. When an RDU agent has weighting parameters $\gamma = 1$, the agent's utility reduces to EUT. That is, since EUT is a special case of RDU, EUT is nested in RDU. However, neither EUT nor RDU are special cases of CPT. Further, the three models are not defined over the same outcomes. Specifically, EUT and RDU are defined over wealth amounts which can never be less than zero. CPT is defined over prospects which are changes from some reference wealth state. The concept of a reference point is not defined in either EUT or RDU so even if the loss aversion parameter λ equals one, and the curvatures α and β equal each other CPT is still not a more general form of EUT or RDU. This relationship between utility functions will be particularly germane when comparing non-nested models fit at participant and representative agent levels.

Of the models discussed, only CPT incorporates loss aversion. However, for any starting income x, all three models can exhibit the property that a reduction to income $x - m$ reduces utility more than an increase to income $x + m$ increases utility. This is the case when $r > 0$ for EUT or RDU, and when $\alpha > 0$ for CPT. This is a familiar result of decreasing marginal utility due to risk aversion and casually consistent with the description, "losses loom larger than gains." However, risk aversion alone cannot explain an aversion to economically equivalent contracts framed as gains or losses (as in Hannan et al., 2005). If the agent is paid some amount H for the preferred outcome and L for the non-preferred outcome, where $H > L > 0$, then framing the contract as contract as a base rate of H (L) and penalty (reward) of $H - L$ result in the same utility under either EUT or RDU. Only CPT with a reference point can predict different utility; risk aversion alone cannot. As emphasized above, much of the literature in accounting assumes that Prospect Theory is the "correct" model, and that loss aversion is the key element of the model that drives observed behavior.

Clearly, the three models considered are not exhaustive. For example, Dual Theory (Yaari, 1987), Gul's Disappointment Aversion model (Gul, 1991), Maximin (Savage, 1951), and others. However, these are (a) more exotic and (b) do not have loss aversion and/or subjective probability weighting as integral components.[4] Importantly, models incorporating social preferences involving others' utility are irrelevant to our experimental tasks because each participant's payoff is due solely to their own actions (i.e. there are no "others" for other-regarding preferences to impact). Examples include (i) a utilitarian concern for efficiency or otherwise maximizing the sum of surplus to be shared (e.g Hannan et al., 2005), (ii) an egalitarian concern for equal outcomes (minimizing the differences in payoffs between agents), and (iii) a Rawlsian concern (e.g., Charness and Rabin, 2005; Rawls, 1971) for aiding the agent who is 'worst off' (maximizing the minimum payoff across agents).

Utility Model Elicitation

It is one thing to posit peoples' preferences and construct a utility function accordingly. It is an exercise in logic. It is an entirely different exercise to estimate the theorized utility and find its parameters using observed behavior. In this application, we will treat the models 'as-if' participants are using them but allowing for behavioral errors. Second, when we elicit and report model parameters over all participants, estimates of parameters may be skewed. For example, if everyone is assumed to be a CPT user, but there are, in fact, EUT users mixed into the sample of participants, estimates of lambda (the loss aversion parameter) will be artificially lower than the true population parameters. For this reason, we estimate the models for each participant to test our hypotheses.

The overall process is (i) construct an index of the difference in expected utility between the two lotteries in a pair as per the utility function, (ii) construct a probabilistic link function between the index and hypothetical choices, (iii) construct a conditional log-likelihood model using the index and observed choices, and (iv) use maximum likelihood routines to find parameters of the posited utility function. Thereafter, we can use statistical tests to find which model best fits (a) a representative agent using all participants' choices, and (b) which model best fits each individual participant using only that participant's choices.

Hypotheses

While our effort task is not identical to Hannan, Hoffman, and Moser (2005), we propose that participants facing penalty contracts will provide more effort, on average, than those facing bonus contracts. This proposition is irrespective of participants' utility functions.

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[4] Yaari's Dual Theory is essentially a special case of rank-dependent utility in which utility is assumed to be linear, but agents may place subjective weights on probabilities for decision-making purposes.

P1: More effort should be provided by those who face a penalty contract than those who face an economically equivalent bonus contract.

While the proposition replicates prior work, it is not without tension. De Quidt et al. (2017) do not find significant differences in effort between bonus and penalty frames. Apostolova-Mihaylova et al. (2015) assign different sections of the same undergraduate class into conditions where (i) students traditionally accumulate points throughout the semester versus (ii) students begin with full marks and lose points as the semester progresses. They find no significant differences in final scores. Tracy and Ferraro (2022) have participants work under both economically equivalent bonus and penalty contracts and then allow them to choose between contracts for the last round. They find that the increased effort is only detectable in the subgroup of workers who preferred the penalty contracts.

Tracy and Ferraro (2022) also include a meta-analysis of experiments that examine the effort between economically equivalent bonus and penalty contracts. Five of the 26 laboratory and field experiments do not report significantly higher effort for penalty contracts.

Despite the tension, most of the cited research that finds an increase in effort for bonus relative to penalty contracts cites loss-aversion and/or Prospect Theory. If that is true, then we should find:

H1: If loss aversion drives the difference in effort provision, then participants who are CPT users will provide more effort, on average, than non-Prospect Theory users when faced with a penalty contract. This difference should not be observed under bonus contracts

Experimental Design

Experimental tasks

Participants participated in an online incentivized experiment documented in Appendix A. The experiment consisted of four parts. All payments are in US currency. The sequence of the experiment is illustrated in Figure 1. Below, we summarize the experimental tasks and discuss various design choices.

1. After consenting, participants answered nine trivia questions. If the participant answered five or more of the questions correctly, they earned $7. This amount covered the largest loss on the lottery tasks, assuring that income would be weakly positive. This also provided an endowment 'earned' so there was "something to lose" in the following lottery tasks, in contrast to an endowment perceived as 'pennies from heaven." The trivia questions were tested using approximately 100 anonymous undergraduate students in the authors' classes, and over 95% answered five or more correctly using a paper elicitation. All the study's online participants earned $7 for this part.

2. Participants chose between a right and left lottery for 96 pairs presented in random order. We used scaled lottery values from Harrison and Swarhout (2023), where some lottery pairs were gains, losses, and mixed (see Table 1). Assuming the participant used CPT, we could measure curvatures in the gain and loss domains and infer the loss aversion parameter. See Figure 2 for examples of what the participants saw. These choices allow us to ascertain if the participant was loss-averse and, if so, the degree of the loss aversion parameters.
3. Participants answered typical demographic questions, including age, gender, and education level. Also included was an alternative loss aversion measure akin to the lottery task of Gächter et al. (2022). Each lottery specified a 50% probability of winning \$2.50 and a 50% probability of losing money that varied across lotteries from \$0.50 to \$3.00 in \$0.50 increments. Participants could accept or reject to play each lottery. The loss aversion measure is based on the number of lotteries a participant chooses to play.
4. Participants chose to exert costly effort in a task inspired by Hannan, Hoffman, and Moser (2005). Participants were randomly assigned to a Bonus or economically equivalent Penalty condition. The bonus contract paid a salary of \$7 plus a bonus of \$7 if the target (high) outcome was achieved, while the penalty contract paid a salary of \$14 with a \$7 penalty if the target (high) outcome was not achieved. Participants assigned to either condition were unaware that the alternative condition existed. There was a 10% chance the high outcome would occur, but participants could exert costly effort to increase the chance up to 90% incrementally. Consequently, the outcome was stochastic for all levels of effort. We depart from Hannan et al. (2005) in that (i) costs are non-linear, and (ii) effort is quasi-continuous rather than in increments of five. The cost of effort e was $c(e) = \mathrm{Exp}[\lambda((\frac{e-10}{\alpha})^{\alpha})] - 1$, where chosen effort $e \in \{10,11,12,\dots,89,90\}$. The parameters $\lambda \cong 0.003977$ and $\alpha = 1.6$, resulting in a cost of minimum effort of \$0 and a maximum effort of \$7, as illustrated in Figure 3. While the cost function is strictly increasing, rounding to the penny results in equivalent cost for different levels of effort at the start of the convex function. We implemented the function $\max\{c(e), (e-10)/100\}$ to guarantee unique costs for all levels of effort despite rounding. We asked participants to (i) rate the fairness of the performance-based portion of their contract and (ii) how disappointed they would be if the target outcome were not achieved. Both questions used a 13-point Likert scale and were asked before disclosing the realized outcome.

Procedures

Participants were recruited from Prolific. Recruits were offered US \$5 to complete the estimated 30-minute study plus a bonus of as little as \$0.00 or as much as US \$30.50. We required computer use; those using mobile devices were automatically rejected. Only online workers with over a 99 percent approval rating, who completed at least ten prior tasks on Prolific, were at least 19 years old, and reported English as their primary language could see the posting. Potential participants had to pass two robot checks and consent before starting the abovementioned tasks.

We told participants their trivia scores immediately after the trivia questions for the reasons previously mentioned. Payments consisted of one randomly selected lottery was played out, along with one randomly selected option in the Gächter et al. (2022) alternative loss-aversion task, along with the costly effort task. Feedback on these outcomes, and the resulting payment, was withheld until after all tasks were completed.

Methodology

To access the likelihood of participants' observed choices, conditional upon one of the three utility models, we build a link function as in Harrison and Swarhout (2023). Participants in our lottery task chose between a left and right lottery of 96 pairs.

The index

$$\nabla EU = EU_R - EU_L \tag{8}$$

is calculated from the expected value of the right and left lotteries seen by participants. The form of the expected value depends upon whether their utility is EUT as per equation (2), RDU as per equation (3), or CPT as per equation (7).

The index is linked to observed choices using a probit-like function that allows for behavioral errors. This function takes any real argument from negative to positive infinity and maps it to a number between zero and one. Specifically,

$$\text{prob(choose Right lottery)} = \Phi(\nabla EU/\mu) \tag{9}$$

where Φ is the cumulative density function of the standard normal distribution and $\mu \geq 0$ is a structural noise parameter due to Fechner (1860). The index per equation (8) is linked to participant choices by specifying that the right lottery is chosen when equation (9) exceeds one-half.

The idea of behavioral errors is incorporated statistically by an assumption that the probability of choosing the lottery with a higher expected value is not one. Without errors, equation (9) would be zero when the arguments are less than zero, one when the arguments are greater than zero, and anything in the unit interval when the expected values of the right and left lotteries are equal. The noise parameter μ allows us to estimate the behavioral errors. As μ goes to zero, the choice is described above, where the lottery with greater expected value is always chosen. When μ is one, the probability of choosing the right lottery is given by the ratio of the expected value of the right lottery to the sum of both lotteries' expected values. As μ gets larger, choices become noisier, and if μ is big enough, choices appear random.

Given the utility model, and the link function using the normal CDF with the Fechner error term in equation (9), the log-likelihood of a participant's Y observed choices in N lottery pairs is

$$\ln L(\boldsymbol{\theta}, \mu: \boldsymbol{Y}) = \sum_{i}^{N} (\ln[\Phi(\nabla EU/\mu) \times I_i] + \ln[(1 - \Phi(\nabla EU/\mu)) \times (1 - I_i)]) \tag{10}$$

where θ is an array of the parameters in the utility function (e.g., EUT, RDU, or CPT), and the indicator variable I_i is 1 if the participant selected the right lottery in the indexed lottery choice $y_i \in Y$.

The log-likelihood of all S participants' choices for given utility model is

$$\ln L(\boldsymbol{\theta}, \mu: \boldsymbol{Z}) = \sum_{s}^{S} \ln L(\boldsymbol{\theta}, \mu: \boldsymbol{Y}_s) \tag{11}$$

Where Z is a matrix where each of the $s \in S$ rows in an array of length N with the choices of participant (i.e., Y from eq. (10)), indexed by s.

A non-trivial concern when performing structural estimations of CPT is how to define the loss aversion parameter, lambda. Prior literature has offered several suggestions for how to define lambda, a summary of which is presented in Abdellaoui, Bleichrodt, and Paraschiv (2007, see Table 1).

Which definition should be chosen? The two most plausible choices seem to be either Kahneman and Tversky's (1992) definition or that suggested by Köbberling and Wakker (2005).[5] Kahneman and Tversky (1992) implicitly define lambda as:

$$\lambda = \frac{-U(-\$1)}{U(\$1)} \tag{12}$$

Note that the exact amount of the wealth change is not critical, rather the "unit" is some small difference between two wealth states. We use $1.25 as our "unit" to avoid issues with lambda being a constant if power utility, instead of CRRA, is used in our estimations. Köbberling and Wakker (2005) define lambda as:

$$\lambda = \frac{U'_-}{U'_+} \tag{13}$$

i.e. the ratio of the derivative of the utility function at the reference point taken from the left to the derivative taken from the right.

Both definitions have drawbacks. Köbberling and Wakker make the point that if the Kahneman and Tversky definition is used, then one needs to perform a "readjustment after inflation or a change in currency." (Köbberling and Wakker 2005, pg 125). On the other hand, Wakker (2010)makes the point that if the Köbberling and Wakker measure is used, then the parameter of loss aversion applicable to every possible change in wealth is being

[5] While not listed in Abdellaoui et al.'s (2007) Table 1, Köbberling and Wakker (2005) is discussed in the text. It is equivalent to the measure suggested in Booij and van de Kuilen (2009), which is tabulated.

driven by the curvature of the utility function very close to the reference point. This implies that the degree of utility loss aversion for a very small loss is the same as it is for an enormous loss (Harrison and Swarthout, 2023).

Ultimately, we choose to emulate Harrison and Swarthout's (2023) definition of lambda by using the Kahneman and Tversky (1992). Harrison and Swarthout's argument is that the majority of the literature uses the definition in Kahneman and Tversky (1992), even if only implicitly (e.g. studies that use CPT as the received utility model but make no attempt to estimate its parameters). We find this argument compelling enough to warrant following their lead, particularly since this study's primary motivation is to comment on previous accounting research that implicitly uses the Kahneman and Tversky (1992) definition of lambda (e.g. Hannan et al., 2005).

Results

Participants' demographical information for each condition is listed in Table 2. We find no significant differences in any variable across conditions. Participants earned, on average, \$17.06 (SEM \$0.59) and \$18.05 (SEM \$0.49) in the Bonus and Penalty conditions, respectively. There is no significant difference in payments between treatments.

Model Parameter Estimates

We estimate EUT, RDU, and CPT over all participants to generate a characterization of a representative participant. As previously discussed, this assumes homogenous preferences but allows us to illustrate overall results and determine which of the three candidate models best fits the observed participant behavior.

Models using all participants

Table 3 reports the maximum likelihood estimates for each model using the 160 participants' 96 choices, where the errors are clustered at the participant level. Using the model with the least parameters, EUT, we see that the representative participant is risk averse as $r > 0$. We can reject for EUT the risk parameter r is zero ($\chi^2(1)$ = 129.28, p < 0.001). The utility function is plotted over values possible in Figure 4.[6] We can also reject that participants are choosing without any behavioral error conditional upon being EUT users, as the noise parameter μ is significantly different from zero ($\chi^2(1)$ = 681.08, p < 0.001). This allows for a descriptive benchmark to compare other models, where the risk aversion can be decomposed differently through the weighting function and/or other parameters.

[6] Since all participants earned the maximum income from the trivia quiz, the support is zero to fourteen for income.

Examining the fit results from the RDU fitted model, we see evidence of pessimism for probabilities approximately above 30 percent, as shown in Figure 5. We can reject that there is no probability weighting, i.e. $\gamma = 1$ ($\chi^2(2)$ = 341.66, p < 0.001). Given the pessimism, we find the RDU risk parameter insignificant from zero, which would be risk neutral, *ceteris paribus.* Given the risk premium overall from EUT, there is a linear utility function so that the net effect of probability pessimism generates the level of risk aversion in the expected value shown in EUT. The noise parameter is significantly larger, indicative of higher behavioral errors ($\chi^2(1)$ = 113.67, p < 0.002). Overall, RDU fits behavior significantly better than EUT ($\chi^2(1)$ = 265.39, p < 0.001).[7]

Examining the fit results from the CPT model, we again see curvature in the gain domain (see Figure 8), akin to the risk we saw in EUT. The curvature parameter α is significantly positive ($\chi^2(2)$ = 30.10, p < 0.001). Furthermore, we find significant evidence of pessimism for probabilities in the gain domain (see Figure 9) as in RDU. However, in the loss domain we cannot reject that utility is linear with no curvature, as β is not significantly different from zero. Likewise, pessimism in the loss domain is subdued compared to the gain domain, where we see the fitted weighting function closer to the 45-degree line for losses in Figure 9. However, we do find the loss aversion parameter λ significantly different from 1 ($\chi^2(2)$ = 10.95, p < 0.001).

Because neither EUT nor RDU is nested within CPT, we cannot use the chi-squared test as we did when comparing RDU fit to EUT. We identify two alternative tests: the Vuong test and the Clarke test (Clarke, 2007; Vuong, 1989).[8] The Vuong test requires the ratio of participants' log-likelihoods from each model to be Gaussian, while the Clarke test is non-parametric. Examining the distributions of likelihood ratios for CPT/RDU and CPT/EUT that form the basis of the Vuong test, we can reject that the distributions are normally distributed. As such, we use the Clarke test.

The Clarke test compares the log-likelihood from CPT to the maximum of the log-likelihood from EUT or RDU. A dummy variable for each participant is one if CPT is larger, and zero otherwise. Using the binomial test, one calculates the probability of the sum of dummies, given the count of observations, for a probability of a dummy equaling one is one-half. We find approximately 87% of participants had a dummy value of one, and the Clarke test statistic is highly significant (p < .0001).

Overall, the fit on a model using all participants is best when using CPT, and the fit of RDU is better than that of EUT.

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[7] For nested models, the significant test is a chi-squared test statistic equal to the difference in log-likelihoods with the difference in parameters degrees of freedom.

[8] One might also use the Bayesian Information Criteria (BIC), as it allows comparisons of fit non-nested models and punishes for additional parameters. The results are comparable.

Designating the best model for individual participants

When typing individuals (such as EUT, RDU, or CPT), we can use the chi-squared test to compare the fit of RDU to EUT, assuming both models converged at an individual level. If there is a significant increase in fit at the 5 percent level and we could reject that the individual's weighting function was not the identity function at the 5 percent level, then RDU fits better than EUT. Of the participants for whom the EUT model converged, RDU was a better fit for 30%. The distribution of p-values from the Clarke test is shown on Figure 7, with one p-value for each participant where both EUT and RDU converged.

We use the Clarke test when comparing CPT to the best-fitting model of EUT vs RDU. First, we create a 'hit' measure for each of a participant's choices. A hit is dummy variable that is one if (i) probability of choosing the right lottery per equation (9) is greater than or equal to 50% and the participant choose the right lottery or (ii) if the probability is less 50% and the participant choose the left lottery. As before, using the Clarke test requires both models to converge at the individual level. The results of the Clarke test statistics are shown on Figure 10. If the Clarke test is less than or equal to 5 percent level, and the number of hits from CPT are greater than both the hits from EUT and from RDU, and we can reject that the individual's CPT utility had no 'kink' at the reference point (i.e., $\alpha = -\beta$) at the 5 percent level, we classify the participant as a CPT user. The results, shown in Figure 11, are inconsistent with the representative participant exercise: more participants are EUT users than CPT users than RDU users. The number of participants classified as CPT is insignificant from the number classified as RDU.

Test of P1: Is There More Effort in the Penalty than the Bonus Contract? Yes.

Results for the effort task are shown in Table 4. Participant's effort differed between conditions, with significantly more effort put forth in the Penalty condition (71.96 out of maximum of 90) than in the Bonus condition (64.46). We can reject that effort is normally distributed using the Shapiro–Wilk W test, so use Wilcoxon rank-sum test to measure significance (Z = -2.627, p = 0.0086). This replicates the findings of Hannan et al. (2005). Higher effort led to a higher occurrence of the target (good) state (Z = 2.04), p = 0.0413).

Like Hannan et al., we asked participants about the fairness of the contingent portion of the contract, and how disappointed they would be if the target state was not realized. We find no significant difference in these questions across conditions. Because effort is not normally distributed, we use general linear models and regress the condition (contract type), disappointment, and fairness upon effort. We only find significance on the contract type (non-tabulated). We used nested model statistics to test whether the fit of the model significantly increased if we added participants' disappointment and/or fairness: it did not (non-tabulated).

Tests of H1: Do CPT participants provide more effort, on average, than non-Prospect Theory users when faced with a penalty contract? Marginally.

We report the effort in each condition by type in Table 5. We test whether those participants typed as CPT users exert more effort (M = 76.48, SEM = 2.65) than non-CPT users (M = 60.71, SEM = 6.18, nontabulated) when facing a penalty contract using the Wilcoxon rank-sum test. The increase is marginal (z = 1.728, p = 0.084). The difference is insignificant using the Wilcoxon rank-sum test when facing the bonus contract, where CPT users averaged lower effort (M = 60.71, SEM = 6.18) than non-CPT users (M = 65.26, SEM = 2.39, nontabulated). However, we find a significant difference using the Wilcoxon rank-sum test in effort by CPT users facing the bonus contract versus the penalty contract (z = 2.203, p = 0.027), but effort between conditions is insignificant for either EUT or RDU users. This suggests that the increase in effort found in P1 is driven by the CPT types, which make up approximately one-fourth of the population.

Exploring the relationship between individuals' loss aversion and effort

To examine the degree of loss-aversion on effort we use GLM regressions reported on Table 6. We use the Gächter measure in equation (2). The coefficient on the loss-aversion measure is insignificant, and the interaction between the measure and the penalty contract is insignificant. The sum of the interaction and the measure is positive, but marginally significant ($\chi^2(2)$ = 3.73, p = 0.054).

Given that we find support for our hypothesis, do we find that the degree of loss aversion can be used to predict effort when facing penalty contracts, but is irrelevant when facing bonus contracts? Using the individual participant fitted CPT model loss-aversion measure λ, as per equation (3), shown on Table 6, yields interesting results. The coefficient on the loss-aversion measure is significantly negative. However, the coefficient on interaction between the penalty contract is positively significant, bringing the sum of the coefficients to approximately zero, yet marginally significant ($\chi^2(2)$ = 3.24, p = 0.072). This suggests that participants with higher loss-aversion put forth less effort when facing a bonus contract, despite that as per Prospect Theory, loss aversion should not make a difference in the gain domain. When facing a penalty contract, a participant's loss-aversion does not predict effort, despite per CPT it should. In summary, loss aversion has a negative effect on bonus contracts and no effect on penalty contracts.

We plot the loss-aversion measure and effort to graphically represent the observed behavior. Each marker represents an individual participant in Figure 12 using the Gächter measure and in Figure 13 using the fitted CPT model. We relax the assumption of a linear relationship and show the 95 percent confidence interval for a quadratic relationship between effort and the corresponding measure. In both figures, the confidence intervals overlap for much of the support for the measure.

Conclusion

In the paper we examine if loss aversion is the latent mechanism driving increased effort in economically equivalent contracts framed as penalties than when framed as bonus. While we do find that participants typed as using Prospect theory (CPT) do exert more effort when facing penalty contracts compared to bonus contracts, this is not the case for participants typed as using traditional expected utility (EUT) or rank dependent utility (RDU). Furthermore, approximately half of participants are best predicted by EUT, compared to a fourth by CPT. We measure loss aversion using two different measures the participant level but find neither is correlated with increased effort.

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Appendix

A. Research Instrument

The Prolific instrument is included as a separate document.

Figures

Recruitment

Screening for bots and informed consent

⬇

Part 1: Trivia Questions

Nine questions and results

⬇

Part 2: 96 Pairs of Lotteries

Random presentation of 96 lottery pairs

⬇

Part 3: Demographics, Alternative Loss Aversion Measure, attention check

Race, education, employment status, household income, age, and gender

Alternative loss aversion measure

Attention check

⬇

Part 4: Costly Effort Choice

Participants randomly assigned a bonus or penalty contract

Participants make costly effort choice

Participants assess fairness and disappointment of contracts

⬇

Payment and Feedback on parts 2-4

Payment based on

i. trivia answers,
ii. lottery results,
iii. alternative loss aversion task,
iv. and effort choice

Figure 1: Sequence of experimental tasks for recruited online workers

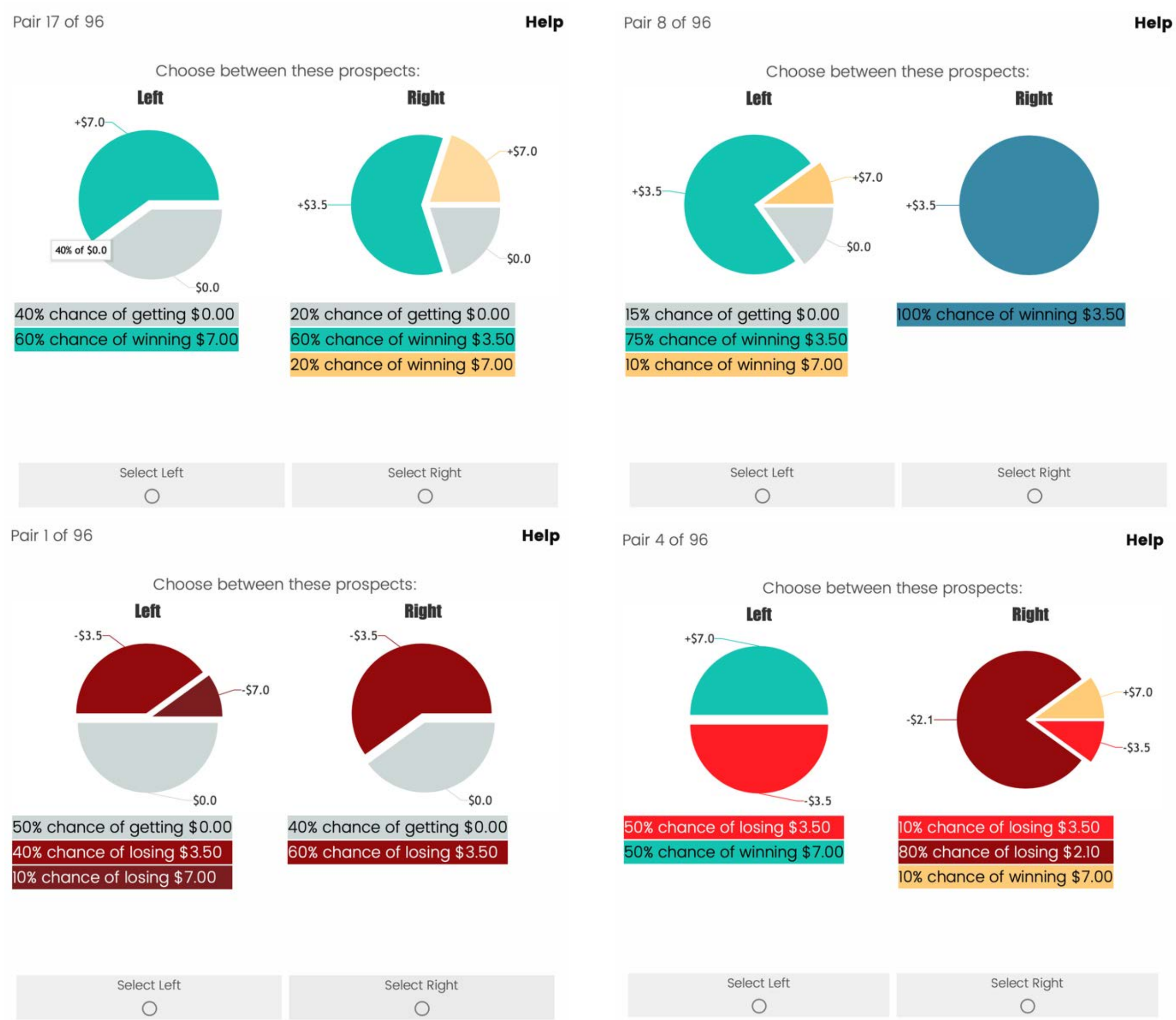


Figure 2: Examples of lottery tasks as seen by participants

From left to right, top to bottom, examples of lotteries in the gain domain, with riskless options, in the loss domain, and mixed domains.

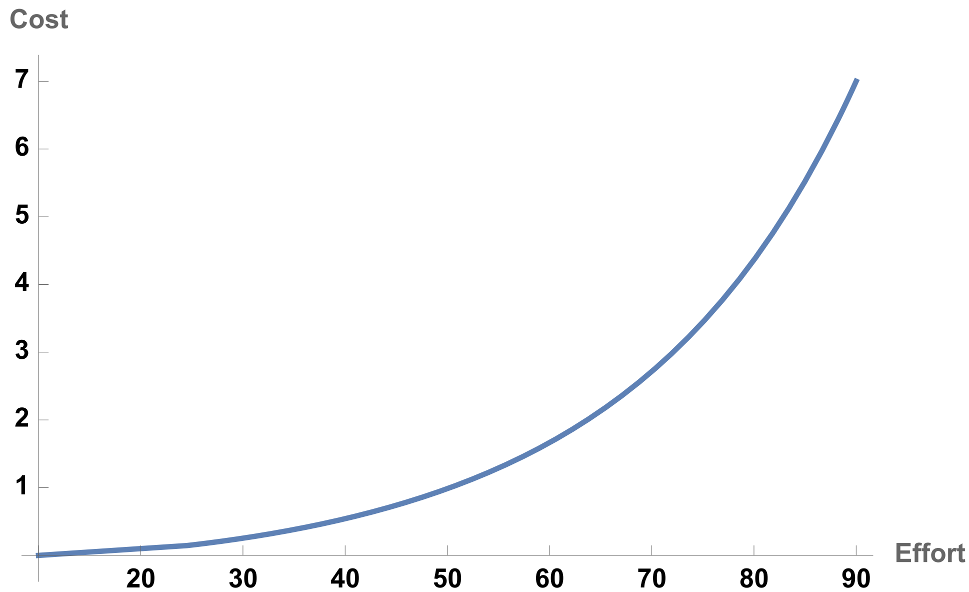


Figure 3: Cost of effort for both Bonus and Penalty conditions

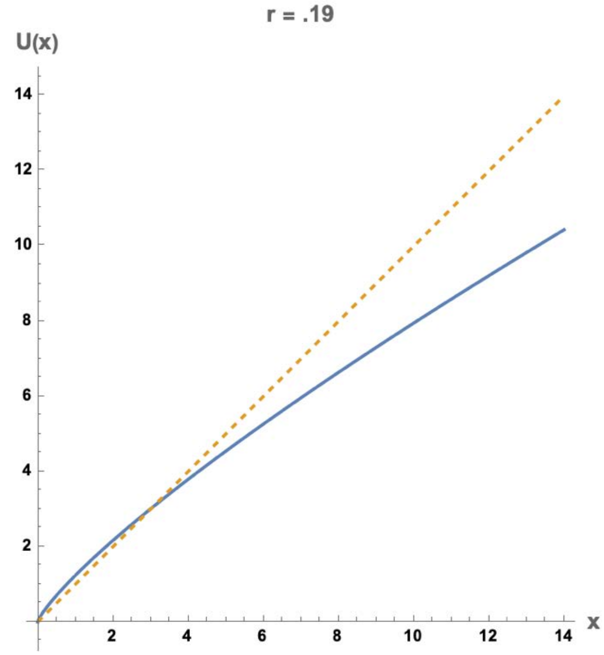


Figure 4: Utility function for EUT given fitted parameters over all participants

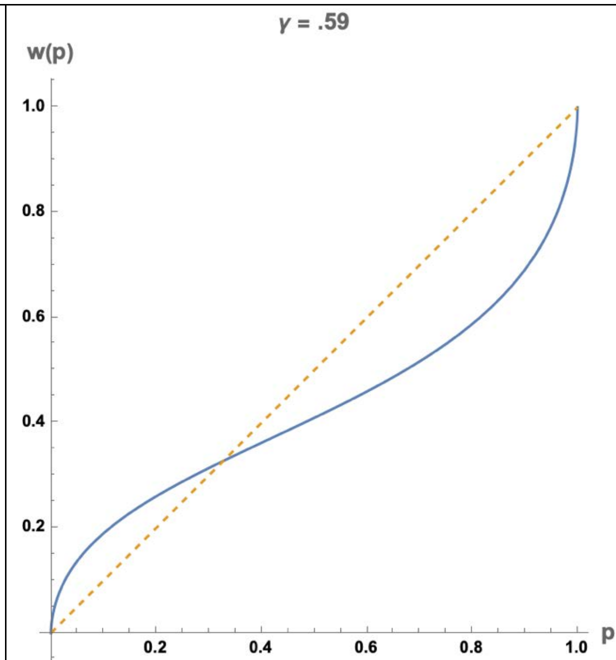


Figure 5: Probability weighting function for RDU given fitted parameters for all participants

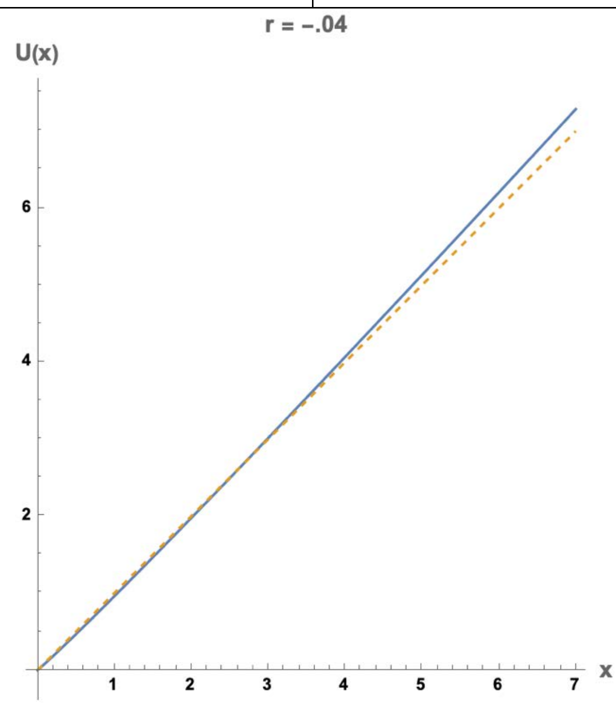


Figure 6: Utility function for RDU given fitted parameters using all participants

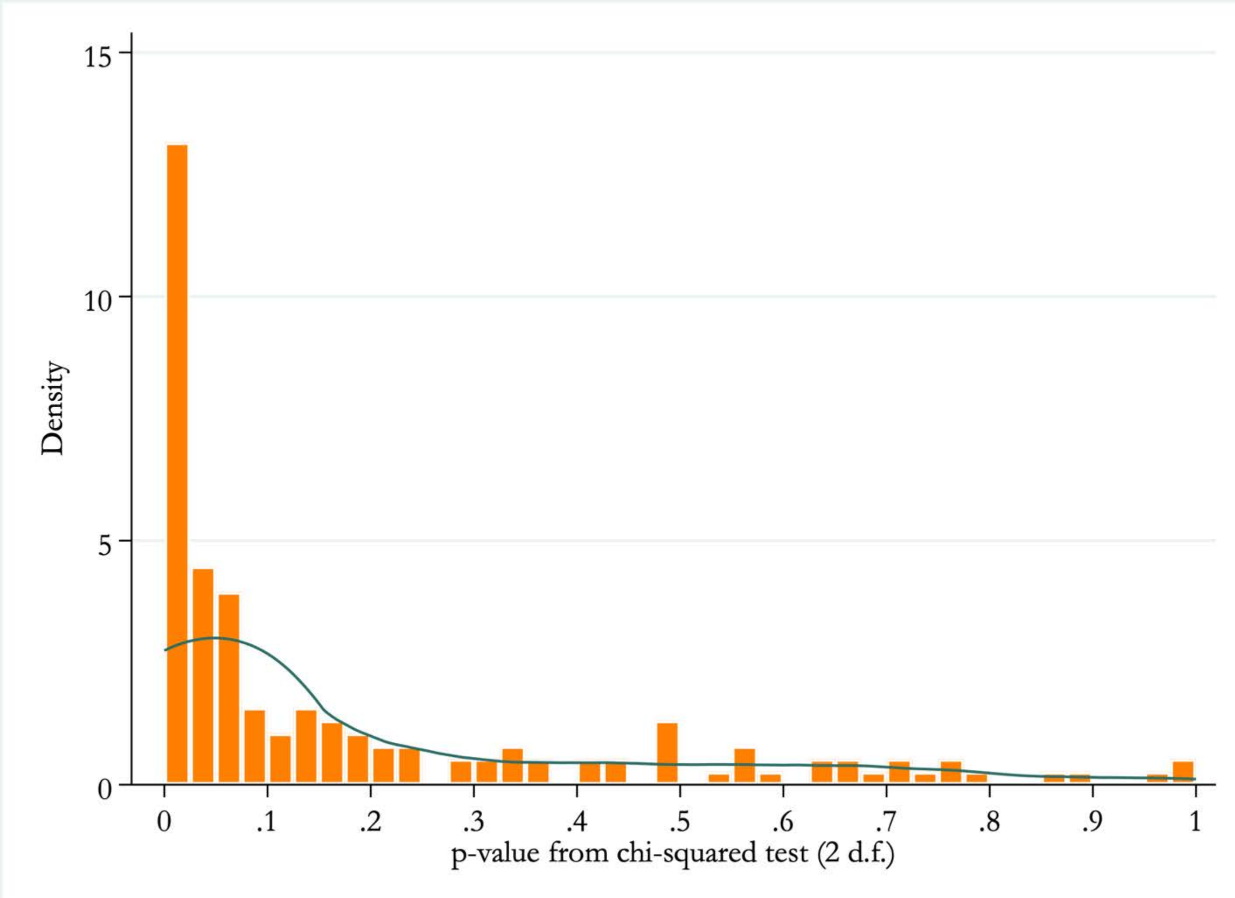


Figure 7: Histogram of p-values of test to reject EUT in favor of RDU

Note: N = 152, one p-value per participant. The Epanechnikov kernel density estimate is plotted over the histogram.

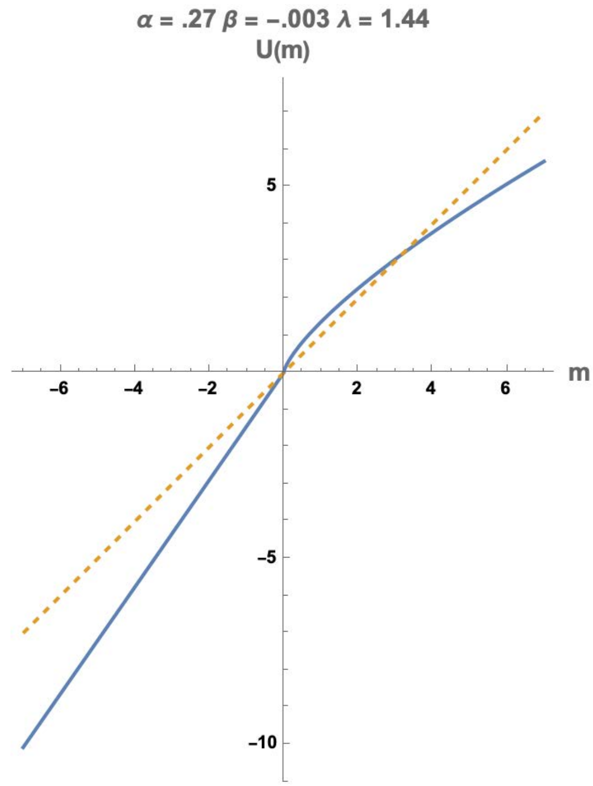


Figure 8: Utility function for CPT given fitted parameters using all participants

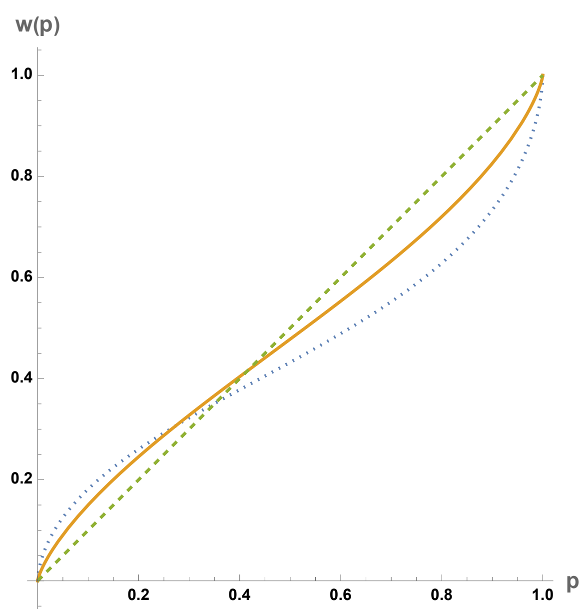


Figure 9: Probability weighting functions for CPT gains and losses given fitted parameters for all participants

Note: The dotted blue line is for gains, and the solid orange line is for losses

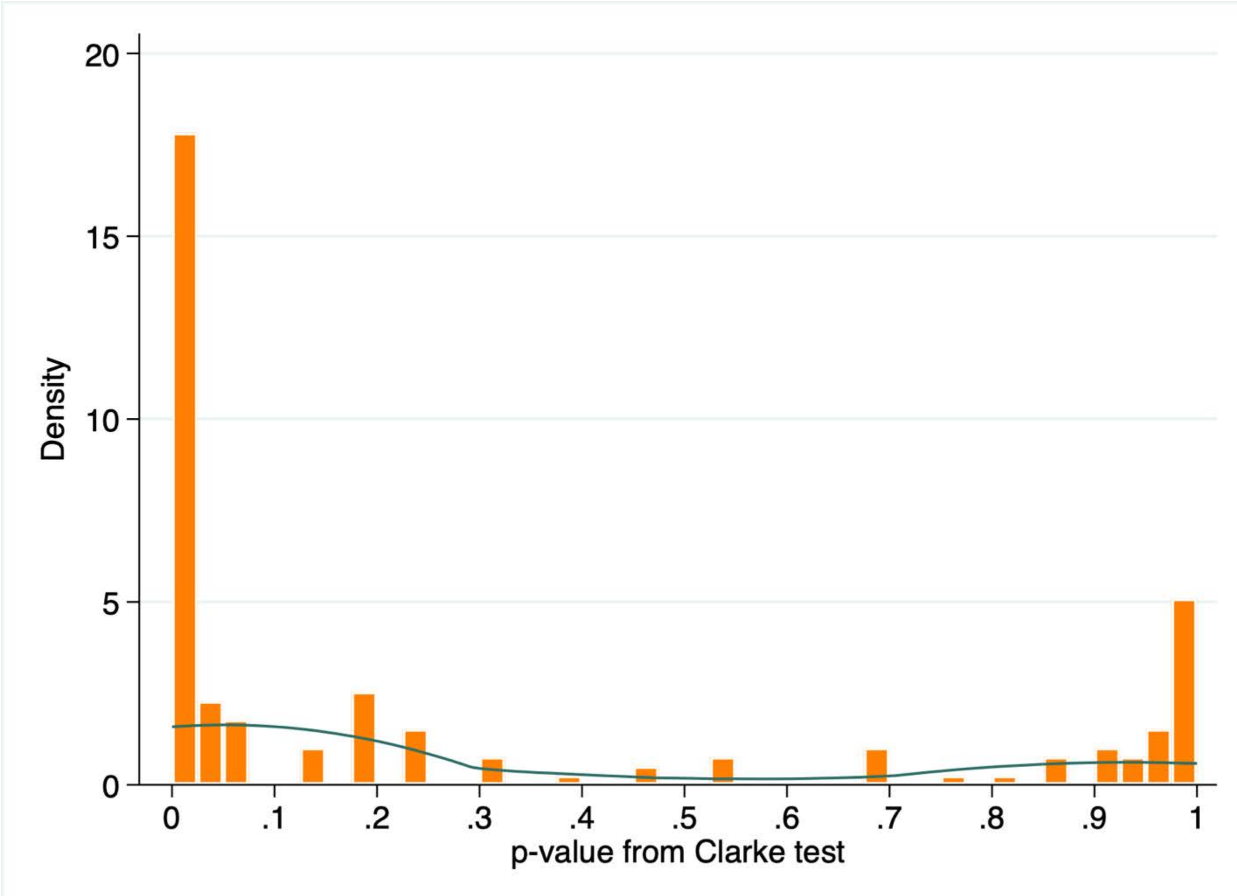


Figure 10: Histogram of p-values of test to reject best fitting nested model in favor of CPT

Note: N = 157, one p-value per participant. The Epanechnikov kernel density estimate is plotted over the histogram.

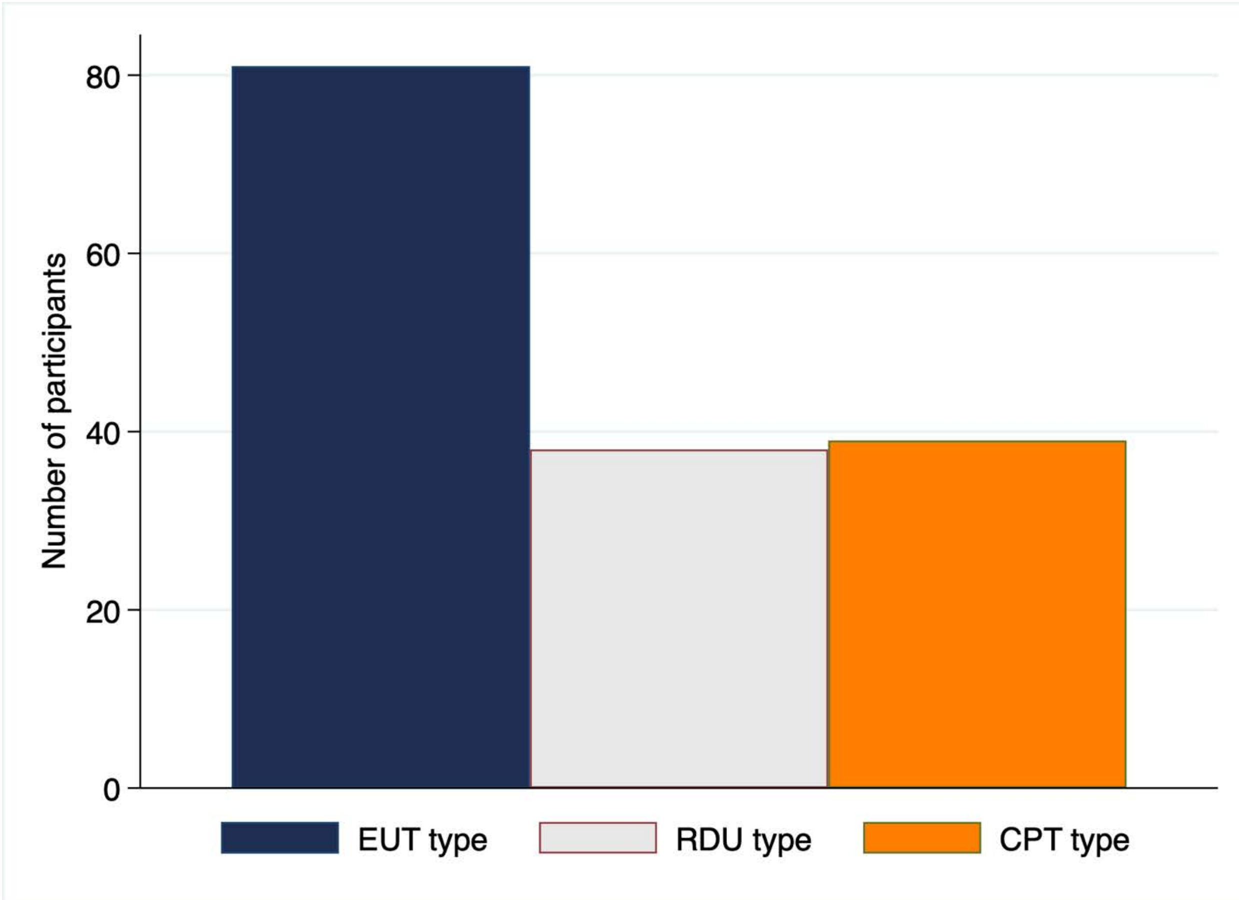


Figure 11: Count of participants typed as EUT, RDU, or CPT types

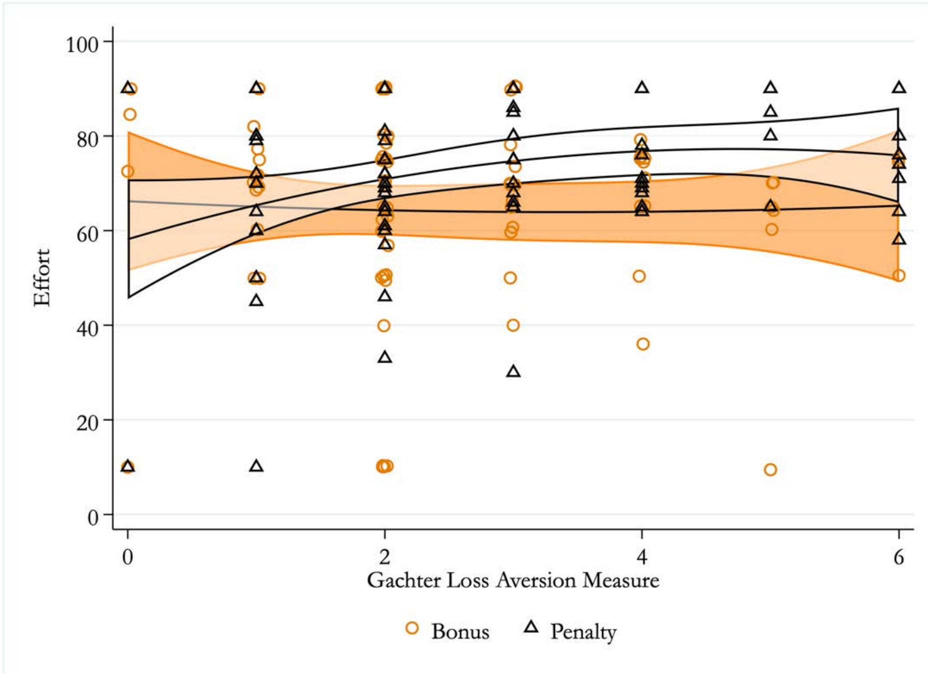


Figure 12: Scatterplot of effort and loss aversion - Gächter

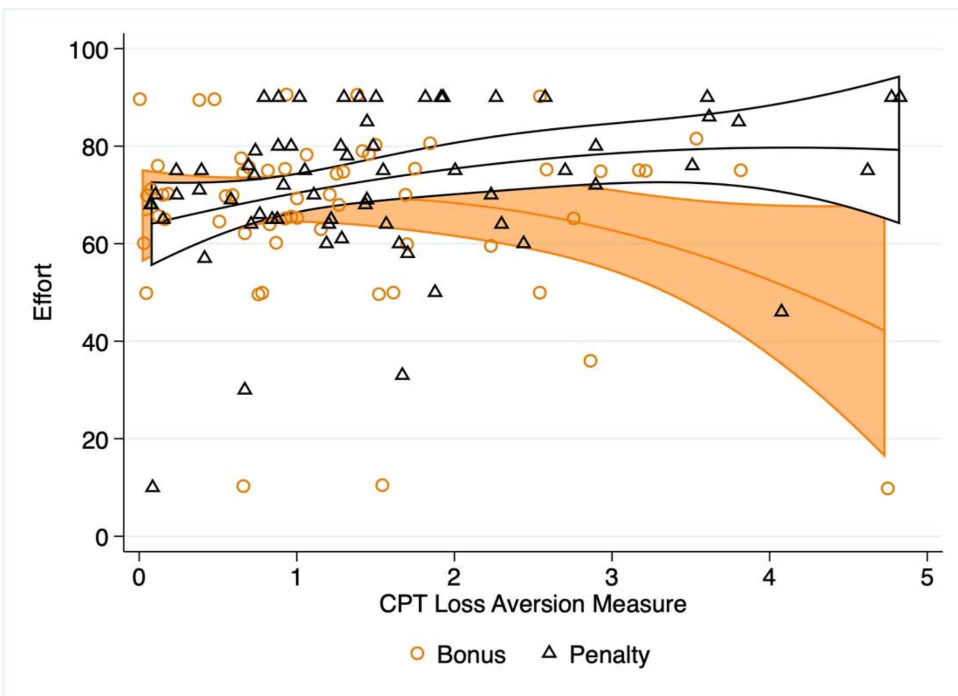


Figure 13: Scatterplot of effort and loss aversion – CPT

Note: 95% confidence interval based on quadratic regression

Tables

Table 1: Battery of 96 Lottery Tasks in Choices

	Left Lottery						Right Lottery					
	Outcome 1		Outcome 2		Outcome 3		Outcome 1		Outcome 2		Outcome 3	
Pair	**Payoff**	**Probability**	**Payoff**	**Probability**	**Payoff**	**Probability**	**Payoff**	**Probability**	**Payoff**	**Probability**	**Payoff**	**Probability**
1	$0.0	70%	$7.0	30%			$0.0	60%	$3.5	25%	$7.0	15%
2	$0.0	70%	$7.0	30%			$0.0	50%	$3.5	40%	$7.0	10%
3	$0.0	60%	$7.0	40%			$0.0	50%	$3.5	30%	$7.0	20%
4	$0.0	55%	$7.0	45%			$0.0	50%	$3.5	20%	$7.0	30%
5	$0.0	40%	$7.0	60%			$0.0	20%	$3.5	60%	$7.0	20%
6	$0.0	60%	$7.0	40%			$0.0	15%	$3.5	75%	$7.0	10%
7	$0.0	30%	$7.0	70%			$0.0	15%	$3.5	25%	$7.0	60%
8	$0.0	50%	$7.0	50%			$0.0	10%	$3.5	80%	$7.0	10%
9	$0.0	40%	$7.0	60%			$0.0	10%	$3.5	75%	$7.0	15%
10	$0.0	25%	$7.0	75%			$0.0	10%	$3.5	60%	$7.0	30%
11	$0.0	90%	$7.0	10%			$0.0	80%	$3.5	20%		
12	$0.0	90%	$7.0	10%			$0.0	75%	$3.5	25%		
13	$0.0	85%	$7.0	15%			$0.0	75%	$3.5	25%		
14	$0.0	80%	$7.0	20%			$0.0	70%	$3.5	30%		
15	$0.0	70%	$7.0	30%			$0.0	60%	$3.5	40%		
16	$0.0	60%	$3.5	25%	$7.0	15%	$0.0	50%	$3.5	50%		
17	$0.0	70%	$7.0	30%			$0.0	50%	$3.5	50%		
18	$0.0	50%	$3.5	40%	$7.0	10%	$0.0	40%	$3.5	60%		
19	$0.0	50%	$3.5	30%	$7.0	20%	$0.0	40%	$3.5	60%		
20	$0.0	50%	$3.5	20%	$7.0	30%	$0.0	40%	$3.5	60%		
21	$0.0	70%	$7.0	30%			$0.0	40%	$3.5	60%		
22	$0.0	60%	$7.0	40%			$0.0	40%	$3.5	60%		
23	$0.0	55%	$7.0	45%			$0.0	40%	$3.5	60%		
24	$0.0	20%	$3.5	60%	$7.0	20%	$0.0	10%	$3.5	90%		
25	$0.0	40%	$7.0	60%			$0.0	10%	$3.5	90%		
26	$0.0	15%	$3.5	75%	$7.0	10%	$3.5	100%				
27	$0.0	10%	$3.5	80%	$7.0	10%	$3.5	100%				

	Left Lottery						Right Lottery					
	Outcome 1		Outcome 2		Outcome 3		Outcome 1		Outcome 2		Outcome 3	
Pair	Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability
28	$0.0	10%	$3.5	75%	$7.0	15%	$f3.5	100%				
29	$0.0	10%	$3.5	60%	$7.0	30%	$3.5	100%				
30	$0.0	60%	$7.0	40%			$3.5	100%				
31	$0.0	50%	$7.0	50%			$3.5	100%				
32	$0.0	40%	$7.0	60%			$3.5	100%				
33	$0.0	25%	$7.0	75%			$3.5	100%				
34	$0.0	15%	$3.5	25%	$7.0	60%	$3.5	50%	$7.0	50%		
35	$0.0	30%	$7.0	70%			$3.5	50%	$7.0	50%		
36	$0.0	10%	$7.0	90%			$3.5	40%	$7.0	60%		
37	$0.0	10%	$7.0	90%			$3.5	30%	$7.0	70%		
38	$0.0	15%	$7.0	85%			$3.5	25%	$7.0	75%		
39	$0.0	10%	$7.0	90%			$3.5	25%	$7.0	75%		
40	$0.0	10%	$7.0	90%			$3.5	20%	$7.0	80%		
41	$0.0	70%	($7.0)	30%			$0.0	50%	($3.5)	40%	($7.0)	10%
42	$0.0	55%	($7.0)	45%			$0.0	50%	($3.5)	20%	($7.0)	30%
43	$0.0	50%	($7.0)	50%			$0.0	10%	($3.5)	80%	($7.0)	10%
44	$0.0	25%	($7.0)	75%			$0.0	10%	($3.5)	60%	($7.0)	30%
45	$0.0	90%	($7.0)	10%			$0.0	80%	($3.5)	20%		
46	$0.0	70%	($7.0)	30%			$0.0	60%	($3.5)	40%		
47	$0.0	50%	($3.5)	40%	($7.0)	10%	$0.0	40%	($3.5)	60%		
48	$0.0	50%	($3.5)	20%	($7.0)	30%	$0.0	40%	($3.5)	60%		
49	$0.0	70%	($7.0)	30%			$0.0	40%	($3.5)	60%		
50	$0.0	55%	($7.0)	45%			$0.0	40%	($3.5)	60%		
51	$0.0	10%	($3.5)	80%	($7.0)	10%	($3.5)	100%				
52	$0.0	10%	($3.5)	60%	($7.0)	30%	($3.5)	100%				
53	$0.0	50%	($7.0)	50%			($3.5)	100%				
54	$0.0	25%	($7.0)	75%			($3.5)	100%				
55	$0.0	10%	($7.0)	90%			($3.5)	40%	($7.0)	60%		
56	$0.0	10%	($7.0)	90%			($3.5)	20%	($7.0)	80%		
57	($3.5)	70%	$7.0	30%			($3.5)	50%	($2.1)	40%	$7.0	10%
58	($3.5)	55%	$7.0	45%			($3.5)	50%	($2.1)	20%	$7.0	30%
59	($3.5)	50%	$7.0	50%			($3.5)	10%	($2.1)	80%	$7.0	10%
60	($3.5)	25%	$7.0	75%			($3.5)	10%	($2.1)	60%	$7.0	30%

	Left Lottery						Right Lottery					
	Outcome 1		Outcome 2		Outcome 3		Outcome 1		Outcome 2		Outcome 3	
Pair	Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability
61	($3.5)	90%	$7.0	10%			($3.5)	80%	($2.1)	20%		
62	($3.5)	70%	$7.0	30%			($3.5)	60%	($2.1)	40%		
63	($3.5)	50%	($2.1)	40%	$7.0	10%	($3.5)	40%	($2.1)	60%		
64	($3.5)	50%	($2.1)	20%	$7.0	30%	($3.5)	40%	($2.1)	60%		
65	($3.5)	70%	$7.0	30%			($3.5)	40%	($2.1)	60%		
66	($3.5)	55%	$7.0	45%			($3.5)	40%	($2.1)	60%		
67	($3.5)	10%	$7.0	90%			($2.1)	40%	$7.0	60%		
68	($3.5)	10%	$7.0	90%			($2.1)	20%	$7.0	80%		
69	($3.5)	10%	($2.1)	80%	$7.0	10%	($2.1)	100%				
70	($3.5)	10%	($2.1)	60%	$7.0	30%	($2.1)	100%				
71	($3.5)	50%	$7.0	50%			($2.1)	100%				
72	($3.5)	25%	$7.0	75%			($2.1)	100%				
73	$1.0	30%	$6.0	70%			$1.0	15%	$2.0	25%	$6.0	60%
74	$1.0	60%	$6.0	40%			$1.0	15%	$2.0	75%	$6.0	10%
75	$1.0	15%	$2.0	25%	$6.0	60%	$2.0	50%	$6.0	50%		
76	$1.0	15%	$2.0	75%	$6.0	10%	$2.0	100%				
77	$1.0	15%	$6.0	85%			$2.0	25%	$6.0	75%		
78	$1.0	90%	$6.0	10%			$1.0	75%	$2.0	25%		
79	$1.0	30%	$6.0	70%			$2.0	50%	$6.0	50%		
80	$1.0	60%	$6.0	40%			$2.0	100%				
81	$0.5	70%	$5.5	30%			$0.5	60%	$2.5	25%	$5.5	15%
82	$0.5	40%	$5.5	60%			$0.5	10%	$2.5	75%	$5.5	15%
83	$0.5	85%	$5.5	15%			$0.5	75%	$2.5	25%		
84	$0.5	60%	$2.5	25%	$5.5	15%	$0.5	50%	$2.5	50%		
85	$0.5	70%	$5.5	30%			$0.5	50%	$2.5	50%		
86	$0.5	10%	$5.5	90%			$2.5	25%	$5.5	75%		
87	$0.5	10%	$2.5	75%	$5.5	15%	$2.5	100%				
88	$0.5	40%	$5.5	60%			$2.5	100%				
89	$1.5	60%	$4.5	40%			$1.5	50%	$3.0	30%	$4.5	20%
90	$1.5	40%	$4.5	60%			$1.5	20%	$3.0	60%	$4.5	20%
91	$1.5	80%	$4.5	20%			$1.5	70%	$3.0	30%		
92	$1.5	50%	$3.0	30%	$4.5	20%	$1.5	40%	$3.0	60%		
93	$1.5	60%	$4.5	40%			$1.5	40%	$3.0	60%		

	Left Lottery						Right Lottery					
	Outcome 1		Outcome 2		Outcome 3		Outcome 1		Outcome 2		Outcome 3	
Pair	**Payoff**	**Probability**	**Payoff**	**Probability**	**Payoff**	**Probability**	**Payoff**	**Probability**	**Payoff**	**Probability**	**Payoff**	**Probability**
94	$1.5	20%	$3.0	60%	$4.5	20%	$1.5	10%	$3.0	90%		
95	$1.5	40%	$4.5	60%			$1.5	10%	$3.0	90%		
96	$1.5	10%	$4.5	90%			$3.0	30%	$4.5	70%		

Table 2: Participant Demographics by Condition

Condition	Median Age (SEM)	Percent Male (SEM)	Percent Female (SEM)	Modal Employment Status	Modal Household Income	Modal Education
Bonus N = 80	38.8 (1.39)	46.3% (5.6%)	51.3% (5.6%)	Full-time	25-50K	Batchelor of Arts
Penalty N = 80	37.8 (1.58)	52.5% (5.6%)	46.3% (5.6%)	Full-time	25-50K	Batchelor of Arts

Table 3: Estimates for EUT, RDU, and CPT Models using participants

Parameter	Point Estimate	Standard Error	Z-score	p-value	95% CI	
EUT model (log-likelihood of -9,643.30)						
Risk r	0.19	0.017	11.4	<0.001	0.16	0.23
Noise μ	1.53	0.059	26.1	<0.001	1.42	1.65
RDU model (log-likelihood of -9,337.62)						
Risk r	-0.04	0.044	-1.0	0.343	-0.13	0.04
Weighting γ	0.59	0.022	26.4	<0.001	0.54	0.63
Noise μ	1.97	0.184	10.7	<0.001	1.61	2.33
CPT model (log-likelihood of -9,259.74)						
Curvature α	0.27	0.049	5.5	<0.001	0.17	0.36
Curvature β	0.00	0.038	-0.1	0.942	-0.08	0.07
Weighting γ_G	0.63	0.022	28.8	<0.001	0.59	0.68
Weighting γ_L	0.78	0.024	31.7	<0.001	0.73	0.82
Loss Aversion λ	1.44	0.134	10.8	<0.001	1.18	1.71
Noise μ	1.62	0.079	20.5	<0.001	1.46	1.77

Table 4: Effort, target outcome, fairness, and disappointment by condition

Condition	Effort	Target outcome achieved	Fairness	Disappointment
Bonus	64.46	0.61	7.34	9.65
	(2.24)	(0.05)	(0.33)	(0.34)
Penalty	71.97	0.76	6.59	10.07
	(1.83)	(0.05)	(0.32)	(0.30)

Note: Mean (Standard Error of the Mean) reported. Effort was chosen from [10,90], fairness and disappointment questions elicited using a 13-point Likert scale.

Table 5: Effort by utility type and condition

	EUT type	RDU type	CPT type	Total
Bonus condition	65.3	65.86	60.71	64.46
	(3.17)	(3.63)	(6.18)	(2.24)
	43	*22*	*14*	*80*
Penalty Condition	68.76	71.44	76.48	71.97
	(3.01)	(3.54)	(2.65)	(1.83)
	38	*16*	*25*	*80*

Note: Mean (Standard Error of the Mean) *N* reported

Table 6: GLM regression of effort examining loss aversion measures as determinants

	(1)	(2) Using Gächter	(3) Using Lamba, all types	(4) Using Lamba, CPT types
Intercept	64.46***	64.87***	67.91***	63.01***
	(28.89)	(12.96)	(32.63)	(9.96)
Penalty	7.513**	0.072	3.999	13.470
	(2.61)	(0.01)	(1.40)	(1.94)
Loss Aversion Measure		-0.156	-0.232*	-0.251***
		(0.10)	(2.17)	(3.93)
Penalty X Loss Aversion Measure		2.657	0.233*	0.251***
		(1.33)	(2.18)	(3.93)
N	160	160	144	39
AIC	1386.1	1386.3	1228.4	337.7
BIC	1392.3	1398.6	1240.2	344.3
Pseudo log-likelihood	-691.1	-689.1	-610.2	-164.8
χ^2 Statistic	6.789	16.25	17.95	98.93

Note: Z-score in parentheses. * p<0.05, ** p<0.01, *** p<0.001. In columns (1) and (2) we use all participants, in column (3) we use all participants where the CPT model converged at an individual level, and in column (4) we use all participants typed as CPT users.

Instrument

A pair of questions is being generated that will test your eligibility to complete this study. Participants who answer these questions incorrectly are NOT eligible, will be screened out immediately, and will NOT receive any payment.

Additionally, this experiment is not designed to work mobile devices. If you are using a mobile device, you will be screened out immediately and will NOT receive payment.

[One of six pictures randomly was presented, and participant was kicked out if the answer was incorrect]

- O A blue rectangle and black oval
- O A green cross and orange triangle
- O A red circle and green star
- O A yellow triangle and red circle
- O A black oval and blue cross
- O A pink square and purple star

[One of four randomly selected mathematic problems (i.e., what's two times three?) appeared in a picture, and the participant was kicked out if the answer was incorrect.]

- O Six
- O Five
- O Twelve
- O Ten

[Thereafter, the participant was kicked out if using a mobile device]

Consent

We invite you to participate in a research study by Timothy Shields and James Wilhelm, professors of Accounting at Chapman University. The purpose of the study is to better understand how individuals perform tasks.

If you agree to participate, we would like you to complete tasks that involve making decisions and solving problems. Afterward, you will be asked about yourself and about your views of the study. The study will take an average of 30 minutes to complete. Your bonus will be from $0.00 to $30.50 depending on your task performance and chance. At the end of the study, you will learn your task performance and the associated payment amount. You will only receive payment for completing the study in its entirety. There is minimal foreseeable risk associated with this study. All responses are anonymous.

Taking part in this research study is completely voluntary. If you do NOT wish to participate in this study, you can exit the study anytime. However, incomplete responses cannot be used for research and therefore, you will NOT receive payment.

If you have any questions about the study, please contact Timothy Shields: shields@chapman.edu. If you have any questions about your rights as a research participant, please contact the Human Subjects Office at Chapman University: (714) 628-2833, irb@chapman.edu.

Thank you very much for your consideration of this research study. Select the appropriate option below to indicate whether you agree to participate.

- O Yes, I agree to participate in this study
- O No, I do NOT agree to participate in this study

[If participants selected No, they were kicked out of the experiment]

Today’s experiment has four parts. In each part, you can win and, in some cases, lose money. Your compensation depends on your choices in all four parts and upon chance.

Part 1: Answer at least five out of nine trivia questions correctly and win $7.00, or else you receive $2.00. You will find out how much you won after answering all questions.

Part 2: You will see different pairs of prospects and choose which prospect to play. You can win, or lose, up to $7.00.

Part 3: In addition to some demographic questions, we will offer you the opportunity flip a computerized coin. If it lands tails, you win $2.50, but if it lands heads you will lose an amount up to $3.00. You may, instead, choose not to flip the coin.

Part 4: We want you to imagine you are working for a company and can earn a higher wage if you put forth costly effort. You can win up to $14.00 for this part.

After completing all four parts, you will be told the results of all parts and your bonus.

Let's proceed to the trivia questions.

[Part 1]

Now we will ask you to answer trivia questions. If you answer at least five of the nine questions correctly you will win $7.00 If not, you will earn $2.00.

On what streaming service can you watch “The Mandalorian”?

- O Disney+
- O Amazon Prime
- O Max
- O Hulu

Who is credited with inventing the light bulb?

- O Eli Whitney
- O Steve Jobs
- O Thomas Edison
- O Enrico Marconi

Which of the following movies takes place primarily in a prison?

- O Saving Private Ryan
- O Forrest Gump
- O The Shawshank Redemption
- O Good Will Hunting

Who is the current vice-president of the United States?

- O Mike Pence
- O Oprah Winfrey
- O Elizabeth Warren
- O Kamala Harris

Which of the following is a baseball team?

- Arizona Cardinals
- Boston Red Sox
- Milwaukee Bucks
- Chicago Blackhawks

Which of the following countries was a member of The Allies in World War II?

- Great Britain
- Switzerland
- Germany
- Japan

What is the capital of Ohio?

- Albany
- Baton Rouge
- Columbus
- Dover

Which of the following actors appeared in the TV show “Game of Thrones?”

- Anna Gun
- Evan Rachel Wood
- James Spader
- Peter Dinklage

Who is associated with the slogan, “Only You Can Prevent Wildfires?”

- Woodsy the Owl
- Smokey the Bear
- Clifford the Big Red Dog
- Toucan Sam

Display This Question:

If QuizPass > 4

Congratulations, you have answered at least five questions correctly so have earned $7.00.

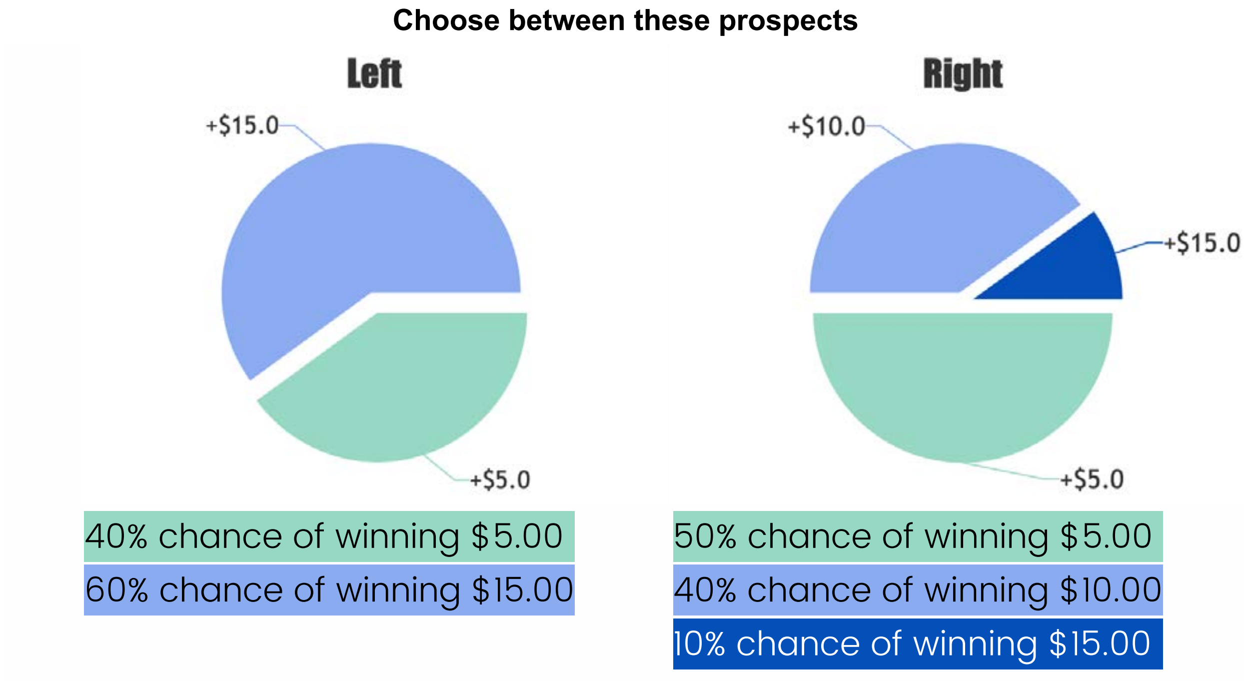
Display This Question:

If QuizPass < 5

You did not answer five questions correctly, so earned $2.00

[Part 2]

In part 2, you will be asked to make a series of choices between pairs of prospects. A pair of prospects looks like the following:



Each prospect displays two pieces of information.

First, a prospect shows between one and three prizes. In the example, the Left prospect has two prizes ($5 and $15) and the Right prospect has three prizes ($5, $10, and $15).

Second, each prospect shows the chance of winning each prize. The sizes of the colored areas indicate the chance of winning each prize. The exact chances are also listed below the prospect. In the example above, the sage green area in the Left prospect corresponds to 40% of the area in the circle. This shows that there's a 40% chance of winning the $5 prize. Similarly, the light blue area indicates that there is a 60% chance of winning the $15 prize.

Your task in this stage is to choose the prospect you would prefer to play from each of 96 pairs of prospects. At the end of the experiment, ONE of the pairs will be chosen at random by the computer and you will actually get to play the prospect you chose from that pair. Because you will actually be playing one of the prospects, you should think carefully about which prospect you prefer in each pair. Which prospect you choose is a matter of personal taste – there are no right or wrong choices.

Each pair of prospects will be presented on a separate screen. For each pair of prospects, you should indicate which you would prefer to play by clicking either "Right" or "Left" corresponding to the prospect you like better. Once you've made your choice, the next pair of prospects in the series will be presented to you.

When it is time to play a prospect at the end of the experiment, the computer will select a pair of prospects and then check to see which prospect in that pair you chose. It will then generate a number between 1 and 100. Each number between, and including, 1 and 100 is equally likely to be generated. The number generated by the computer will determine what prize you win from the prospect you chose.

Using the Right prospect in the example above, if the number generated by the computer is between 1 and 50, the prospect pays $5. If the number is between 51 and 90, the prospect pays $10, and if the number is between 91 and 100, the prospect pays $15.

[The text also below appeared as 'pop up' window during the lotteries]

Summary of Part 2 choices

- Each page will present two prospects. Your task is to choose one of the prospects from each pair.
- Each prospect has between one and three prizes, and each prize has a probability that it will be drawn. Some prospects will include prizes with negative amounts.
- At the end of this experiment, one pair of prospects will be chosen. The prospect you chose from that pair will be played out.
- The result of the prospect played will be added to, or subtracted from, the money you earned from the quiz.

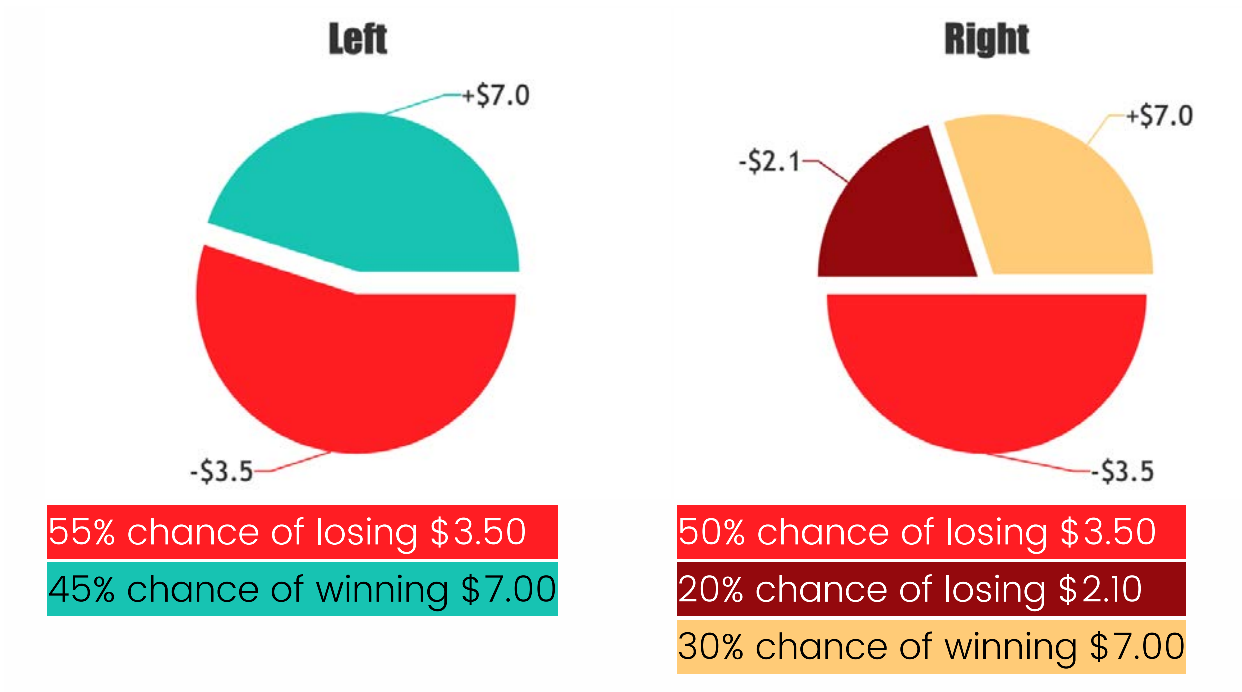
Starting on the next page, you can review the summary by hovering your mouse over the phrase **Help**.

Let's proceed to part 2.

Lottery Choices

Pair ${lm://CurrentLoopNumber} of 96 **Help**

Choose between these prospects:



O Select Left

O Select Right

[Pie charts based on Table X appeared here]
[Pressing the text 'help' above evoked the popup below]

Summary of Part 2 choices

- Each page will present two prospects. Your task is to choose one of the prospects from each pair.
- Each prospect has between one and three prizes, and each prize has a probability that it will be drawn. Some prospects will include prizes with negative amounts.
- At the end of this experiment, one pair of prospects will be chosen. The prospect you chose from that pair will be played out.
- The result of the prospect played will be added to, or subtracted from, the money you earned from the quiz.

[Part 3]

In part 3, we want you to answer some survey questions.

Are you of Spanish, Hispanic, or Latino origin?

- O Yes
- O No

Choose one or more races that you consider yourself to be.

- ☐ White or Caucasian
- ☐ Black or African American
- ☐ American Indian/Native American or Alaska Native
- ☐ Asian
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ Other
- ☐ Prefer not to say

What is the highest level of education you have completed?

- O Some high school or less
- O High school diploma or GED
- O Some college, but no degree
- O Associates or technical degree
- O Bachelor’s degree
- O Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.)
- O Prefer not to say

What best describes your employment status over the last three months?

- O Working full-time
- O Working part-time
- O Unemployed and looking for work
- O A homemaker or stay-at-home parent
- O Student
- O Retired
- O Other

What was your total household income before taxes during the past 12 months?

- Less than $25,000
- $25,000-$49,999
- $50,000-$74,999
- $75,000-$99,999
- $100,000-$149,999
- $150,000 or more
- Prefer not to say

How old are you?

- Under 18
- 18-24 years old
- 25-34 years old
- 35-44 years old
- 45-54 years old
- 55-64 years old
- 65+ years old

How do you describe yourself?

- O Male
- O Female
- O Non-binary / third gender
- O Prefer to self-describe
(____
- O Prefer not to say

[Alternative loss aversion measure]

In the following table, you will find a list of coin tosses with different payoffs. The payoffs differ in how much you lose if the coin turns up heads. The coin is fair such that the likelihood it will turn up heads is equal to the likelihood it will turn up tails.

For each row, you need to indicate whether you want to toss the coin or not. One of the six rows will be randomly selected by the roll of a computerized six-sided die. Once a row has been selected, your choice for that row will be implemented to determine your payoff.

If you chose NOT to flip the coin for the selected row, then you neither win nor lose any money. However, if you chose to flip for the computerized coin for the selected row, you will lose money if the coin lands heads, or win money if it lands tails.

	I do NOT want to flip	I want to flip
lose $0.50 if heads, win $2.50 if tails	O	O
lose $1.00 if heads, win $2.50 if tails	O	O
lose $1.50 if heads, win $2.50 if tails	O	O
lose $2.00 if heads, win $2.50 if tails	O	O
lose $2.50 if heads, win $2.50 if tails	O	O
lose $3.00 if heads, win $2.50 if tails	O	O

One more question before part 4.

Everyone has hobbies. Research has shown that a person's hobby influences his or her vocational aptitude. Hobbies that stimulate the frontal lobe will strongly influence vocational aptitude. To study this, we would like to ask you a question about your hobbies. Although we would like to ask you to tell us about your hobbies, we ask that you choose two hobbies that start with the letter B to show that you read carefully. Avoid clicking hobbies not corresponding to the above statement, like skiing, reading, swimming, or video gaming.

- ☐ Biking
- ☐ Fencing
- ☐ Skiing
- ☐ Writing
- ☐ Reading
- ☐ Video gaming
- ☐ Basketball
- ☐ Shopping
- ☐ Swimming
- ☐ Computing
- ☐ Football
- ☐ None of the above

[Part 4]

Display This Question:

If Treatment = Bonus

In this stage, imagine you are an employee at a sales firm, LA Gear. Your job is to sell the company's only product.

Your compensation package with LA Gear has two parts. For the first part, you receive a salary of $7.00 regardless of how many products you sell. The second part is performance-based and depends on how many products you sell. Your performance-based pay starts at $0.00. If you sell at least as many products as the sales target your manager sets for you, your performance-based pay is increased to $7.00.

Display This Question:

If Treatment = Penalty

In this stage, imagine you are an employee at a sales firm, LA Gear. Your job is to sell the company's only product.

Your compensation package with LA Gear has two parts. For the first part, you receive a salary of $7.00 regardless of how many products you sell. The second part is performance-based and depends on how many products you sell. Your performance-based pay starts at $7.00. If you do NOT sell at least as many products as the sales target your manager sets for you, your performance-based pay is decreased to $0.00.

[Remaining text shown for both treatments. This remaining text was also shown as a popup the participant selected help on the next page]

Obviously, how hard you work substantially impacts how many units of the product you sell. However, there are other factors, outside your control, that also influence how many units you sell. Demand for the company's product, the general state of the economy, and the prices at competing firms are all factors that could increase or decrease the number of units you sell, regardless of how hard you work.

Your task is to choose how much effort to provide in your job at LA Gear. You will choose effort by moving a slider whose endpoints are "Minimum Effort" and "Maximum Effort."

The effort is associated with (a) a chance of reaching the sales target your manager has set for you and (b) a cost in dollars. Choosing to provide more effort costs you more than providing less effort. However, the more effort you provide, the more likely you will reach the sales target and earn the larger performance-based pay.

On the next screen, as you adjust the effort slider, you will be shown the exact chance of reaching the sales target and the exact cost of effort. The screen will also remind you of the parts of your compensation, including what you will earn if you reach the sales target and what you will earn if you do not reach the sales target. You may adjust the slider as much as you like before deciding.

Once you are comfortable with your effort selection, click the button to proceed.

After you have made your effort choice, the computer will generate a number between 1 and 100. Each number between, and including, 1 and 100 is equally likely to be generated. The number generated by the computer and the amount of effort you chose will determine whether you reach the sales target. If the number the computer generates is less than or equal to the chance you reach the sales target, you will reach the sales target and earn the larger performance-based pay. If the number the computer generates is greater than the chance you reach the sales target, you will NOT reach the sales target and will instead earn the lower performance-based pay.

For example, assume there is a 60% chance the sales target is reached. If the computer generates a number between 1 and 60, the sales target will be reached. If the number is between 61 and 100, the sales target will NOT be reached.

Display This Question:

If Treatment = Bonus

Your compensation package with LA Gear has two parts. For the first part, you receive a salary of $7.00 regardless of how many products you sell. The second part is performance-based and depends on how many products you sell. Your performance-based pay starts at $0.00. If you sell at least as many products as the sales target your manager sets for you, your performance-based pay is increased to $7.00.

Display This Question:

If Treatment = Penalty

Your compensation package with LA Gear has two parts. For the first part, you receive a salary of $7.00 regardless of how many products you sell. The second part is performance-based and depends on how many products you sell. Your performance-based pay starts at $7.00. If you do NOT sell at least as many products as the sales target your manager sets for you, your performance-based pay is decreased to $0.00.

[For both treatments]

Help

Cost of providing effort: $0 *[Amount updated dynamically based on slider]*

Chance of meeting the sales target: 10% *[Percentage updated dynamically based on slider]*

	Minimum effort 10	Maximum effort 90
Click on scale and adjust slider left or right.		

[The vertical slider control was hidden until the participant clicked somewhere on the scale]

To complete part 4, you will be asked a series of questions to help us better understand the decisions you made in the previous parts. For each item, please select the answer that best answers the question or best characterizes your opinion. Click on the scale and move right or left to select your answer.

After you have completed the questions, the computer will select a pair of prospects from the first part of the experiment, play out the prospect you chose and show you the result. Once that has been completed, you will be informed of your final payoff and the experiment will be finished.

Display This Question:

If Treatment = Bonus

Recall your compensation package:

Your compensation package with LA Gear has two parts. For the first part, you receive a salary of $7.00 regardless of how many products you sell. The second part is performance-based and depends on how many products you sell. Your performance-based pay starts at $0.00. If you sell at least as many products as the sales target your manager sets for you, your performance-based pay is increased to $7.00.

Display This Question:

If Treatment = Penalty

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[For both treatments]
Please rate the fairness of the performance-based portion of your compensation package from LA Gear.

not fair at all						moderately fair					extremely fair	
1	2	3	4	5	6	7	8	9	10	11	12	13

How disappointed would feel if you did not reach your sales target so did not receive $7.00, but instead received $0.00 for the performance-based portion of the compensation?

not at all disappointed				moderately disappointed					extremely disappointed			
1	2	3	4	5	6	7	8	9	10	11	12	13

If you have any additional observations or comments that you think would be helpful to the researchers, please feel free to share your thoughts below. We very much appreciate your insight.

Your payoff from this experiment is composed of the following:

(1) Stage 1: On the trivia quiz, you answered ${gr://SC_23RQgR7j4Ff5hoq/Score} questions correctly and earned $${e://Field/WinningsQuiz}.

(2) Stage 2: The computer selected pair number ${e://Field/RandomLottery} from the list of prospects. In that pair, you chose the prospect that offered ${e://Field/LotteryChoiceDesc}. When that prospect was resolved by the computer, you ${e://Field/LotteryWinLost} $$e{ abs(round(${e://Field/WinningsLottery},2))}.

(3) Stage 3: The computer selected the coin toss in which you ${e://Field/FlipDesc}. You selected "${e://Field/ChoseToFlip}", and the coin landed ${e://Field/HeadsTailsDesc}. You ${e://Field/CoinWinLost} $$e{abs(round(${e://Field/WinningsCoin},2))} as a result.

(4) Stage 4: Based on your effort selection, there was a ${e://Field/Effort}% chance you would reach the sales target. This effort cost you $${e://Field/EffortCost}. The computer drew the number ${e://Field/Random100-Effort}, meaning you ${e://Field/EffortDidDidNot} reach the sales target. Your payoff from this stage was $${e://Field/WinningsEffort}.

Your total bonus earned from all four stages was $${e://Field/WinningsToPay}.

If you need to contact the authors, please denote your response ID #${e://Field/ResponseID} in your communication. After pressing the button below, you will return to Prolific.