Chapman University Digital Commons

ESI Working Papers

Economic Science Institute

9-14-2024

A Critical Evaluation of Loss Aversion as the Determinate of Effort in Compensation Framing

Timothy W. Shields

James Wilhelm

Follow this and additional works at: https://digitalcommons.chapman.edu/esi_working_papers

Part of the Econometrics Commons, Economic Theory Commons, and the Other Economics Commons

A Critical Evaluation of Loss Aversion as the Determinate of Effort in Compensation Framing

Comments
ESI Working Paper 24-14

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

Timothy Shields
Associate Professor
Argyros College of Business and Economics
Economic Science Institute
shields@chapman.edu

James Wilhelm
Assistant Professor
Argyros College of Business and Economics
Economic Science Institute
jwilhelm@chapman.edu

14 September 2024

Preliminary and Incomplete

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

14 September 2024

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 either measure's degree of loss aversion 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

1 Introduction

Research in managerial accounting and economics has examined the relative amount of effort exerted by agents who face economically equivalent contracts framed as either bonuses or penalties. Such contracts are structured in the following way. Imagine an agent is provided with a contract under which they could earn one of two payoffs, high or low. Framed as a bonus, the contract initially pays the agent the low amount, but should a desired outcome be achieved, then their total compensation is increased to the high amount. Alternatively, the firm could frame the contract as a penalty by initially paying the agent the high amount, but then reducing their compensation to the low amount should the desired outcome not be achieved. Prior research frequently (but not universally) finds that agents facing a penalty contract exert more effort than those facing a bonus contract (Hannan, Hoffman, and Moser 2005; Tracy and Ferraro 2022). The reason commonly cited for this finding is that agents are loss-averse, consistent with prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992), and are therefore willing to exert more effort to avoid the disutility from incurring a penalty than they are to provide effort toward earning a bonus. Surprisingly missing from this stream of literature are (a) an attempt to show whether prospect theory is empirically descriptive of agents' decisions under risk, (b) a rigorous measurement of agents' loss aversion which incorporates the full prospect theory model, and (c) an attempt to show that the degree of agents' loss aversion is positively correlated with agent effort under penalty contracts. This paper seeks to provide empirical evidence regarding these three points.

As noted above, prior research provides evidence that agents faced with a penalty contract exert more effort than do those faced with an economically equivalent bonus contract and that this is due to agent loss aversion (e.g., Armantier and Boly 2015; Burke, Towry, Young, and Zureich 2023; Church, Libby, and Zhang 2008; Frederickson and Waller 2005; Fryer, Levitt, List, and Sadoff 2012; Gonzalez, Hoffman, and Moser 2019; Imas, Sadoff, and Samek 2017; Van der Stede, Wu, and Wu 2020). The most frequently cited utility model that incorporates loss aversion is prospect theory (Kahneman and Tversky 1979, Tversky and Kahneman 1992). Indeed, a great many of the aforementioned studies that study contract framing effects explicitly reference loss aversion or prospect theory. Loss aversion, one of the three integral elements of prospect theory, posits that the disutility individuals experience from a loss is greater than the utility they experience from an equivalent size gain. This suggests that because "losses loom larger than gains" agents will work harder to prevent losses than they will to obtain gains. It is important to recognize that this line of logic relies implicitly on the representative agent assumption. Specifically, researchers assume that every agent is adequately described by the behavior of a single "representative" individual and that, in this context, this individual's choices are best described by prospect theory. However, evidence in economics suggests that there is substantial heterogeneity across individuals as to whether their choices are best described by prospect theory or some alternative utility model (e.g. expected utility theory, rank dependent utility, disappointment aversion, etc.) (Harrison and Rutström 2009; Harrison and Swarthout 2023). Critically, loss aversion is not an element in these other utility models. Consequently, if a sizeable proportion of agents are not "prospect theory users," then one is faced with the question of whether the empirical regularity in the literature showing greater effort provision under penalty contracts is driven only by a subset of agents who are, indeed, loss averse or if there is another mechanism that accounts for the differential effort provision.

If we set aside the question of which utility model is most empirically descriptive and take as given that loss aversion from prospect theory is the reason for greater effort provision under penalty contracts, then there are some direct empirical results that are implied by that conclusion. First, it should be the case that when working under a penalty contract, those individuals who are more loss averse should provide more effort than those who are less loss averse. Stated differently, there should be a positive correlation between individual-level loss aversion measures and individual effort. Second, it should be the case that when working under a bonus contract, loss aversion should be uncorrelated with effort. This is because all the outcomes under a bonus contract are (weakly) in the gain frame and, in the gain frame, loss aversion has no impact on utility. Taken together, these two questions provide a strong falsification test of the consensus reached in prior contract framing literature.

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 utility function parameters, including loss aversion, at the individual level as per Harrison and Swarthout (2023). Additionally, we elicit an alternative measure of loss aversion (Gächter, Johnson, and Herrmann 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).

We first find that, consistent with the consensus in the literature, participants provided more effort when facing a penalty contract. After determining which of three commonly cited utility models best describes each participant's lottery choices, we find two important results. First, only one-fourth of our participant pool is best described by prospect theory. The choices of the remaining three-quarters of the participants are more consistent with either expected utility theory (roughly half of all participants) or rank-dependent utility (roughly one-fourth of all participants). Second, we find that the difference in effort provision across contract frames is indeed driven by those individuals whose choices are best described by prospect theory. We find no evidence of differential effort provision across contract frames for those participants whose choices are better described by a non-prospect theory model.

We next focus on only those individuals who are "prospect theory users." Contrary to the expected results, we find that the degree of utility loss aversion has no explanatory power in predicting effort provision in the penalty condition. This is true irrespective of which measure of loss aversion is used. Stated differently, while utility loss aversion may explain the lottery choices of a subset of our participants, it does not explain effort provision choices in our setting.

We believe that our study makes the following contributions. First, we provide, to our knowledge, the first test, based on a full-model estimation of the parameters of prospect theory, 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 compared 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 prospect theory. 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 (Tracy and Ferraro 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 compel agents to work harder than bonus contracts. 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. which utility model best describes the behavior of their labor force), implementing a penalty contract may not result in more effort than a bonus contract. Indeed, our results may help to explain the ongoing academic question of why penalty contracts are so infrequently observed in practice despite the fact that 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 prospect theory loss aversion and the simpler measure proposed by Gächter, Johnson, and Herrmann (2022). While the Gächter et al. measure is unarguably easier to implement, our results suggest that it holds little descriptive power for participants' behavior, particularly in the highly contextualized instruments 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 commonly cited utility models and their primary elements and explicate the differences between them.

2 Background and Theory

2.1 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 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. For each choice, participants in Luft's experiment were given a multiple price list and 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 facing bonus contracts. The 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.

At approximately the same time, Frederickson and Waller (2005) examined the role of risk aversion in a principal-agent setting where either bonus or penalty contracts were used across conditions. Principals determine the contingent pay for contracts (e.g., bonus or penalty amount), and agents decide to accept the contract and receive a fixed amount. They found the acceptance point (at which participants tended to accept the contract) was greater for the penalty than for the bonus condition. This result is consistent with agent participants being loss averse and participant principals anticipating loss aversion.

Accounting experimental research subsequently explicitly cited loss aversion via prospect theory as the underlying mechanism resulting in higher effort provision in penalty contracts relative to bonus contracts (e.g., Burke et al., 2023; Christ et al., 2012; Church et al., 2008; Gonzalez et al., 2019). This is also true with field experiments, case studies, and other laboratory research (e.g., Armantier and Boly, 2015; Fryer et al., 2012; Hong et al., 2015; Imas et al., 2017; Litovsky et al., 2022; Van der Stede et al., 2020). 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.

Our study is closer to Brink and Rankin (2013) in that they also measure individual's loss aversion. Brink and Rankin use an elicitation technique over mixed gambles (with both a loss and gain) similar to (Gächter et al. 2022), except that instead of giving the participant the option to play the gamble or not, in Brink and Rankin the alternative option is a gamble with equally likely outcomes of a $1 gain and a $1 loss. In their experiment, participants chose contracts, like in Luft (1994), but did not have to put forth effort under the chosen contract. While Brink and Rankin can speak to the correlation of the loss aversion measure and the preference over contracts, they cannot speak to the effort put forth.

[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.

2.2 Utility Models

One of the stated goals of this study is to investigate whether prospect theory is empirically descriptive of the choices made by agents. To that end, in this section, we present a brief description of not only prospect theory but also of the two alternate models we consider.

Before we begin the descriptions, there are several definitions and assumptions that are common to all three models. First, all the decisions discussed in this paper are taken under risk. By this we explicitly mean that the agent faces a lottery (or gamble) in which there are some number of possible monetary outcomes, each of which has an objective probability of occurring. The number of outcomes, their values, and the associated probabilities are all commonly known. The models we describe can potentially be used to address decisions under uncertainty or ambiguity, but we restrict all of the discussions in this paper to decisions taken under risk.

Second, the only arguments admitted to the utility models described in this paper are utility from money and disutility from effort. As a consequence, any other-regarding preferences (e.g. honesty, distributional fairness, etc.) are assumed to be irrelevant to the decisions made by the agents we discuss. While prior research has clearly established that other-regarding preferences exist and, indeed, could be included in any of the utility models described below, we leave to other courageous researchers the task of investigating how such preferences should be modeled and estimated.

Finally, we assume additive separability between elements of the utility function and source independence. By the former we mean that there are no interactions between elements of the utility function (e.g. pecuniary utility is not impacted by the disutility from effort except to the extent that effort may impact the probabilities of the pecuniary outcomes). By the latter we mean that the choices agents make in one task (e.g. choosing between lotteries) are assumed to be driven by the same utility function driving the choices they make for every other task (e.g. choosing how much effort to provide in a job setting).

2.2.1 Expected Utility Theory (EUT)

At the cornerstone of modern microeconomic theory lies expected utility theory (Von Neumann and Morgenstern 2007). EUT posits that an agent that faces a lottery with $J \geq 1$ outcomes (sometimes called prizes), each with a known probability, has expected utility from that lottery equal to a weighted average of the outcomes where the weights are determined by the objective probabilities of those outcomes. Mathematically, the expected utility for a given lottery is

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

where $U(x_j)$ is the utility from outcome j, and $p(x_j)$ is the probability that outcome j will occur.

A wide variety of functional forms could be used for $U(x)$, and we will specify exactly the functions used for our estimations below. However, it is useful to group potential functions into three broad classes – linear functions, concave functions, and convex functions. When a linear function is specified, agents are described as risk neutral. By this we explicitly mean that they are indifferent between taking a lottery and receiving the expected value of that lottery for certain.[2] If the utility function is concave, the agent's utility from the expected value of the lottery is greater than the expected utility from the lottery and the agent is described as risk averse. This implies the agent would accept an amount for certain (the certainty equivalent) that is less than the expected value of the lottery in order to avoid taking on the risk. Conversely, if the utility function is convex, the agent is said to be risk affine (or risk seeking) and would prefer to take the lottery over the expected value of the lottery for certain.[3]

At this juncture, it is critical to highlight that the argument that enters the utility function is the <u>entire</u> wealth of the agent. For example, when a lottery is specified as a (fair) coin flip to either earn or pay $5 (i.e. 50% of receiving $5, 50% of paying $5), the arguments to the utility function are the agent's starting wealth position plus five dollars and the agent's starting wealth position less five dollars. The EUT utility function is not defined for values less than zero.

2.2.2 Rank-Dependent Utility (RDU)

Quiggin (1982) developed a more general conception of EUT known as rank-dependent utility. The primary innovation over EUT is that RDU allows for the possibility that the weight an agent places on the probabilities of outcomes for decision-making purposes is different from the objective probabilities of those outcomes. For example, perhaps an agent assesses the probability of a fair coin flip landing heads as 40% rather than the objective 50% probability. Consequently, instead of expected utility conforming to equation (1), the expected utility for a given lottery is

$$RDEU_i = \sum_{j=1}^{J} \left[w_j \times U(x_j) \right] \tag{2}$$

where $w_j = \omega(p_j)$ when $j = J$ and $w_j = \omega(p_j + \cdots + p_J) - \omega(p_{j+1} + \cdots p_J)$ for *j = 1, 2, ... J-1*, where the J outcomes are ranked from best to worst (i.e. $x_{j-1} > x_j$). As in EUT, a variety of functional forms could be chosen for $U(x)$, and the shape of the function has the same implications for the risk attitudes of the agent.

In addition to utility risk aversion, a consequence of probability weighting is that agents may exhibit probabilistic risk aversion or affinity. In the same way that curvature of the utility function leads to a certainty equivalent that is different than the expected value of the lottery, resulting in either risk aversion or risk affinity, probability weighting can lead to "as-if" risk aversion/affinity. This is perhaps best explained with an example.

---

[2] The expected value of a lottery is simply a linear combination of the probabilities of each outcome and their dollar payoff.

[3] This also implies that the agent's certainty equivalent for that lottery is greater than the expected value of the lottery. In other words, the agent would need to be paid, for certain, an amount greater than the lottery's expected value in order to *not* take the risk.

Assume an agent faces a lottery that pays $20 if a flipped fair coin comes up heads and $0 if the coin comes up tails. Further, assume that the agent is risk neutral over utility – i.e. they have a linear utility function of the form $U(x) = x$. Finally, the agent's probability weighting function takes the form $\mathrm{w_j} = \mathrm{p_j^2}$. The decision weight the agent places on heads is 25% and the decision weight placed on tails is 75%.[4] Consequently, their rank-dependent expected utility for this lottery is 5, leading to a certainty equivalent of $5. The expected value of the lottery is $10. Since the agent's certainty equivalent is less than the expected value of the lottery, we would classify the agent as risk averse, despite the fact that their utility function is linear (i.e. they are *utility* risk neutral). Likewise, if the probability weighting function had been concave, the agent would have been utility risk neutral and probabilistically risk affine.

Importantly, EUT is a special case of RDU. Specifically, when an agent engages in no probability weighting – i.e. they use the objective probabilities as their decision weights for outcomes (i.e. $w_j = p_j$) – then RDU collapses to the EUT specification. Further, the arguments for RDU are again total wealth amounts and the model is not defined for values less than zero.

2.2.3 Prospect Theory (PT) and 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 over 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 for in both the gain and loss domains.[5] Third, disutility from a loss of a given size is greater than the utility from an equivalent size gain. This comprises the often-cited loss aversion element 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, primarily to deal with technical issues regarding first-order stochastically dominated choices being possible under the first formulation of prospect theory. Because cumulative prospect theory is the more mathematically complete model of the two, hereafter we will use the term "prospect theory" to denote cumulative prospect theory.

---

[4] The calculation of the decision weights is as follows. Prizes are first ranked from best to worst (i.e. $20, $0). The probability weighting function is applied to the *cumulative* probability of the prizes in rank order. The probability weight of the best prize is therefore $w_{\$20} = 0.50^2 = 0.25$. Similarly, the probability weight of the second prize is $w_{\$0} = 1.00^2 = 1.00$. Decision weights are then calculated as the marginal probability weights between a given prize and the next best prize. In this case, since there are only two prizes, the decision weight on the $20 outcome (heads) is 0.25 and the decision weight on the $0 outcome (tails) is 1.00 – 0.25 = 0.75.

[5] 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.

Expected prospect theory utility is given by

$$PEU_i = \sum_{j=1}^{J} \left[w_j \times U(m_j) \right] \tag{3}$$

where w_j is a probability weighting function as in RDU and m_j is the change in wealth relative to the reference point (which is often assumed to be a $0 change in wealth but need not be; see for example Armantier and Boly 2015, and Van der Stede et al. 2020). Sign dependence is incorporated in the utility function by defining $U(m_j)$ as

$$U(m_j) = \begin{cases} U(m_j), & when\ m \geq 0 \\ -\lambda\, U(-m_j), & when\ m < 0 \end{cases} \tag{4}$$

where λ is the loss aversion parameter that describes how much more disutility the agent suffers from a loss relative to the utility they experience from an equal size gain.

Two additional points regarding CPT must be highlighted. First, because probability weighting is a factor in CPT, probabilistic risk attitudes are possible just as in RDU. Similarly, probabilistic loss aversion can be observed (Schmidt and Zank 2009). Broadly, this can happen when more weight is placed on losses than on gains. A somewhat contrived example occurs when there is no probability weighting in the gain frame and convex probability weighting in the loss frame (i.e. overweighting of the largest losses; see Harrison and Swarthout (2023) for additional discussion). As with probabilistic risk aversion, this means that individuals may display *utility* loss neutrality (i.e. $\lambda = 1$) but display probabilistic loss aversion.

Second, CPT is not a more general formulation of either RDU or EUT. As stated above, EUT is nested in RDU, but even if λ is equal to one, RDU is not nested in CPT. Critically, EUT and RDU are defined over wealth states, but CPT is defined over gains and losses. Of the models discussed, CPT is the only one that incorporates loss aversion. It is possible for any of the models to exhibit the property that a decrease in wealth from x to $x - m$ decreases utility more than an increase in wealth from x to $x + m$. This will be the case for any concave function in the gain frame, consistent with decreasing marginal utility due to utility risk aversion. However, risk aversion alone cannot explain an aversion to economically equivalent contracts framed as losses rather than as gains as in Hannan, Hoffman, and Moser (2005). For this reason, as emphasized above, much of the contract framing literature implicitly assumes that prospect theory is the "correct" utility model when loss aversion is advanced as the explanation for the observed differential effort across contract frames.

Clearly, the three models discussed are not exhaustive. A variety of other models, such as dual theory (Yaari 1987), Gul's disappointment aversion model (Gul 1991), maximin (Savage 1951), and others, exist. However, these are (a) more exotic, (b) do not have loss aversion and/or subjective probability weighting as integral components, and (c) have been shown by prior research to be empirically descriptive of a relative paucity of agents (Harrison and Rutström

2009; Harrison and Swarthout 2023).[6] As noted above, 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 of such models include (a) a utilitarian concern for efficiency or otherwise maximizing the sum of surplus to be shared (e.g. Hannan et al., 2005), (b) an egalitarian concern for equal outcomes (i.e. minimizing the differences in payoffs between agents), and (c) a Rawlsian concern for aiding the agent who is 'worst off' (i.e. maximizing the minimum payoff from among all agents) (e.g., Charness and Rabin, 2005; Rawls, 1971).

3 Predictions and Research Questions

As discussed above, the majority of the contract framing literature finds that agents working under a penalty contract exert more effort than those agents working under an economically equivalent bonus contract. Consequently, we make the following proposition, consistent with prior findings. Note that this proposition is made irrespective of which utility model best describes choices at the individual level.

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

While the proposition is a replication of 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 to one of two conditions. In one condition, students accumulate points throughout the semester in the traditional fashion. In the other condition, students begin with full marks and lose points as the semester progresses. The researchers find no significant differences in final scores, suggesting that, on average, effort was equal across "contract" frames. Tracy and Ferraro (2022) present evidence both consistent with and contrary to our proposition. They include a meta-analysis of experiments that examine the effort between economically equivalent bonus and penalty contracts. Only five of the twenty-six laboratory and field experiments do <u>not</u> report significantly higher effort for penalty contracts. However, they also conduct an experiment in which participants work under both economically equivalent bonus and penalty contracts but then choose their contracts for the last round. The researchers find that increased effort is only detectable in the subgroup of workers who selected the penalty contracts.

Presuming that, on average, more effort is observed from agents working under a penalty contract, we turn our attention to exploring the consensus cause for this phenomenon, namely that loss aversion stemming from prospect theory impels agents to exert more effort to avoid a penalty than to earn an equivalent sized gain. For this explanation to be correct, agents must exhibit loss aversion, implying that their choices must best be described by prospect theory rather than either EUT or RDU. However, we are reluctant to hypothesize that *all* agents behave consistently with prospect theory, particularly since prior research has repeatedly shown that

[6] 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.

there is a mix of types when it comes to utility models (Harrison and Rutström 2009; Harrison and Swarthout 2023; Harrison and Ng 2016). Further, there does not appear to be a normative benchmark for the proportions of individuals in the overall population that behave consistently with each of the models. Indeed, the studies of which we are aware that perform the kind of estimation of latent utility models that we are relying on are conducted in laboratories with students and the proportions observed in those samples may or may not be representative of the mix of utility models found in the broader population. As a result of these factors, we pose the following research question:

RQ: What proportion of agents are best described by EUT, what proportion are best described by RDU, and what proportion are best described by CPT?

Several predictions are implied by the explanation that loss aversion drives differential effort across contract frames. First, only those agents that are loss averse (i.e. whose choices are best described by CPT) should exert more effort under penalty contracts than under economically equivalent bonus contracts. For the agents that are not loss averse, the disutility from incurring the penalty is not larger than the utility from attaining the same size bonus. These individuals should therefore be willing to exert approximately the same effort under both bonus and penalty contracts.

H1a: Those agents whose choices are best described by CPT will exert more effort under a penalty contract than under an economically equivalent bonus contract.

H1b (null): Those agents whose choices are best described by either RDU or EUT will exert the same amount of effort under a penalty contract as they do under an economically equivalent bonus contract.

Second, agents who are "prospect theory types" and agents who are "non-prospect theory types" should be willing to exert approximately the same amount of effort under bonus contracts. Loss aversion has no impact on utility in the gain frame, which is where all the payouts in a bonus contract exist. Consequently, loss aversion should have no impact on effort provision choices under bonus contracts.

H2 (null): Those agents whose choices are best described by CPT will exert the same amount of effort under a bonus contract as those agents whose choices are best described by either RDU or EUT.

Finally, if loss aversion is driving differential effort provision, then it follows that, when working under a penalty contract, those agents who are more loss averse incur greater disutility from incurring the penalty than those agents that are less loss averse. As a result, those who are more loss averse should be willing to exert more effort under a penalty contract than those who are less loss averse, which is encapsulated in the following hypothesis.

H3: For those agents facing a penalty contract and whose choices are best described by CPT, agents who are relatively more loss averse exert more effort than those agents who are relatively less loss averse.

4 Method

This section has two purposes. First, it describes the experiment we conducted to explore our predictions and research question, explains the procedures we implemented, and discusses some of our experimental design choices. Second, it provides an explanation of the maximum likelihood estimation (MLE) procedure used to generate parameter estimates for the utility models described above and provides explicit functional forms for our estimations.

4.1 Instrument

We designed and implemented a 1x2 online experiment in which the contract frame the agent works under in the second half of the experiment is manipulated at two levels, *Bonus* and *Penalty*. The experimental materials can be found in Appendix A. Necessary IRB approval was obtained from the authors' institution prior to the implementation of the experiment. The sequence of the experiment is illustrated in Figure 1, and we summarize the experimental tasks and discuss various design choices below. All referenced payments were stated and paid in terms of US dollars.

After consenting to participate in the experiment, participants were asked to answer nine trivia questions. If the participant answered five or more of the questions correctly, they earned \$7. This corresponded to the largest possible loss on the forthcoming lottery tasks, assuring that income over the entire experiment would be weakly positive. 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.

Once the results of the trivia task were revealed to the participant, they were then presented with 96 pairs of lotteries and asked to choose either the lefthand or righthand lottery from each pair. Each lottery consisted of between one and three prizes and included the objective probability of each prize. To construct the lottery pairs, we used the lotteries presented in Harrison and Swarthout (2023) with the sole modification that the lottery prize amounts were scaled. Among the lotteries were pairs containing two gains (64), pairs containing two losses (16), and pairs containing some mix of both (known as "mixed frame lotteries", 16 of these lotteries were included). Consult Table 1 for a listing of all lottery values and Figure 2 for an example of a typical lottery that was presented to the participants. Participants were informed before making their choices that one lottery would be selected at random, the lottery they chose from that pair would be played out, and they would be paid according to the outcome.

After completing their lottery choices, participants answered typical demographic questions including age, gender, and education level. Along with the demographic questions, an alternative loss aversion measure was presented, akin to the lottery task in Gächeter et al (2022). The participant was presented with six lotteries which each comprised a 50% probability of winning \$2.50 and a 50% probability of losing some amount that varied from lottery to lottery. The loss amounts ranged from \$0.50 to \$3.00 in \$0.50 increments. For each lottery, participants made the choice to make the coin flip or not make the coin flip. Each choice was made independently (i.e. if the participant chose not to flip the coin for the \$0.50 loss lottery, this had no impact on their choice menu for any of the remaining five lotteries). The fewer coin flips the participant chose to engage in, the greater their loss aversion.

In the third phase of the experiment, which was adapted from the task found in Hannan et al. (2005), participants were randomly assigned (between subjects) to either the *Bonus* or *Penalty* condition and asked to take the role of a salesperson at a hypothetical retail business. They were informed that their job was to sell the firm's only product. Their compensation contract had two parts. The first part took the form of a guaranteed salary of $7.00. The second part was performance-contingent. If the participant reached the (unspecified) sales goal that their manager had set, they would earn an additional $7.00. If the sales target was not reached, they would receive no additional compensation. In the *Bonus* condition, participants were told that their performance-contingent compensation started at $0 and would be increased to $7.00 if they reached the sales target. In the economically equivalent *Penalty* condition, participants were informed that their performance-contingent compensation started at $7.00 and if they failed to reach the sales target, it would be reduced to $0. Participants in either condition had no knowledge of the existence of any other conditions.

Once the participant was informed of the details of their compensation contract, it was explained that while there were factors that influenced sales volume which were beyond the participant's control, their effort was positively correlated with the probability that the sales target would be reached. Participants were then asked to select an amount of costly effort to exert on a slider with endpoints of 10% and 90% corresponding to the minimum and maximum likelihood, respectively, of achieving the sales target. Critically, the outcome (i.e. whether or not the sales target was reached) was stochastic at all levels of effort, including the minimum and maximum. While this task is adapted from Hannan et al. (2005), we importantly depart from their instrument in that our costs are (i) non-linear and (ii) effort is quasi-continuous (rather than in increments of five). Cost of effort was given by the function

$$c(e) = exp\left[\delta \times \left(\frac{e-10}{\psi}\right)^{\psi}\right] - 1 \tag{5}$$

where $e \in \{10,11,12, \dots, 89,90\}$ is the amount of effort chosen by the participant. The parameters $\delta \cong 0.003977$ and $\psi = 1.6$ were chosen to result in a cost of minimum effort of $0 and a cost of maximum effort of $7.00. A graphical representation of the cost function is provided in Figure 3. While the cost function is strictly increasing, rounding to the penny results in costs that are invariant to effort at the lowest levels of chosen effort. To rectify this issue, we implemented the function $max\{c(e),\ (e-10/100)\}$ to guarantee unique costs for all levels of effort despite rounding. Participants were able to see the cost of effort at each level in real time and were asked to confirm their choice before submitting it. The cost of effort was deducted from the participant's final payoff total.

After participants made an effort choice, they were asked two process measure questions. The first asked them to rate the fairness of the performance-contingent portion of their contract. The second asked them how disappointed they would be if the sales target were not reached. Both questions were on a 13-point Likert scale. These questions were asked before disclosing whether or not the sales target had been achieved.

To round out the experiment, procedures related to the participant's payout were performed. The computer selected a lottery pair from phase two of the experiment and played out the lottery the participant had selected from that pair. Next, one of the six Gächter et al. (2022) lotteries was selected at random by the computer and a coin flip was performed if the participant had chosen to flip the coin in that lottery. Finally, the computer determined whether the participant had reached the sales target based on their effort and the result of a random number between 0 and 100 (if the number was less than or equal to their effort, the sales target was reached). All elements of the participant's payoff were summed, the participant was informed of this amount and then dismissed.

4.2 Recruitment Procedures

Participants were recruited from Prolific. Recruits were offered \$5.00 to complete the estimated 30-minute study plus a bonus of as little as \$0.00 or as much as \$30.50. Computer use was required; those using mobile devices were automatically rejected. Only Prolific workers with over a 99 percent approval rating, who had 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 provide consent before starting the abovementioned tasks.

Of the 175 individuals who signed up to complete our instrument, all passed the first robot check (which consisted of correctly identifying the shapes and colors of two objects in a picture – e.g. a black square and a blue triangle). Three individuals failed the second robot check, which required the participant to perform a simple arithmetic calculation described in a non-standard font (e.g., "What is three times two?" printed using combinations of fonts utilizing non-alphabetic characters such as the number five for 's', or the null set symbol for 'o'). An additional twelve individuals chose not to consent to participate in the research leaving 160 individuals that comprise our sample.

4.3 Maximum Likelihood Estimations (MLE) Procedure and Functional Forms

4.3.1 MLE Procedure

In order to estimate participants' latent characteristics, we use the maximum likelihood estimation procedure detailed in Harrison and Swarthout (2023), which is briefly described in this section.

The logic of the MLE process starts with the assumption of one of the three utility models we estimate – EUT, RDU, or CPT. Recall from the information above that each participant was presented with 96 binary lottery choices. For each lottery pair, we construct the following index that gives the difference in utility between the righthand lottery and the lefthand lottery

$$\nabla EU = \frac{EU_R - EU_L}{\mu} \tag{6}$$

where EU_R is the expected utility of the righthand lottery and EU_L is the expected utility of the lefthand lottery. The parameter $\mu \geq 0$ is a structural noise parameter as in Fechner (1860), discussed in more detail below.

Next, a function, referred to as a "link function", is chosen that transforms the difference in utility from Eq. 6 (which is theoretically unbounded) to a probability that the right lottery is chosen (i.e. a number between zero and one). It might seem intuitive to simply choose a binary function that assigns 100% probability of choosing the right lottery when the utility of the right lottery is higher and 0% probability when the utility of the left lottery is higher. However, this is "unforgiving" in the sense that as the difference in utility between the two lotteries gets arbitrarily small, individuals may have a difficult time determining which lottery is the better choice. Instead, we choose the standard normal distribution function as our link function. Notably, when the difference in expected utility of the two lotteries is zero, the probability that the right lottery is chosen is 50% which is normatively attractive as we would expect the agent to be indifferent between the lotteries and resort to a "coin flip." Similarly, as the difference in utility between the lotteries grows, the probability that the lottery that represents greater utility is chosen approaches one.

The Fechner error (μ) from Eq. 6 allows us to account for the possibility of systematic behavioral errors at the level of the individual. Essentially, μ measures the "consistency" of the individual's choices. As this parameter goes to zero, the individual always chooses the lottery with the highest utility – i.e. there is no noise in their choices. By contrast, as μ gets larger, the individual's choices are noisier until, if μ is large enough, the individual's choices appear random.

To estimate an individual's latent utility function, an initial candidate set of parameters for the assumed utility model (e.g. EUT, RDU, or CPT) is chosen. A log-likelihood value is then calculated from the chosen parameters and the individual's 96 choices as

$$ln\, L(\boldsymbol{\theta}, \mu \colon \boldsymbol{Y}) = \sum_{i}^{N} \left(ln\, [\Phi(\nabla EU) \times I_i] + ln\big[\big(1 - \Phi(\nabla EU)\big) \times (1 - I_i)\big]\right) \tag{7}$$

where $\boldsymbol{\theta}$ is an array of the parameters of the utility model being estimated (see section 4.3.2 for a review of the parameters associated with each model), $\Phi(\nabla EU)$ is output of the link function (i.e. the probability that the right lottery is chosen), and I_i takes a value of one if the participant chose the righthand lottery in choice $y_i \in \boldsymbol{Y}$ and zero if the lefthand lottery was chosen.

Log likelihood values are iteratively calculated over a range of candidate values until a maximum log likelihood value is determined. The parameters that lead to the maximum log likelihood value are reported as the estimated model parameters for that individual.

4.3.2 Functional Forms for Utility Function Estimations

As discussed in Section 2.2, the utility models we estimate have general properties, but a wide array of specific functional forms can be chosen for the utility functions, probability weighting functions, and definition of loss aversion. This section provides the precise functional forms we use for each of these elements and provides some discussion of the choices.

We assume that agents have preferences over pecuniary income which exhibit constant relative risk aversion (CRRA) and which take the following functional form

$$U(x) = \frac{x^{1-r}}{1-r} \tag{8}$$

where x is the agent's wealth and r characterizes the agent's risk attitudes. When $r > 0$, the agent is described as risk averse. When $r = 0$, the agent is risk neutral, and when $r < 0$, the agent is described as risk loving (or risk affine). When $r = 1$, $U(x) = ln(x)$, by L'Hopital's rule. This functional form is used for all three utility models. Recall that, for CPT, x (the agent's wealth) is replaced by m (the gain or loss the agent experiences relative to the reference point of a $0 change in wealth).

For RDU and CPT, a probability weighting function that transforms objective probabilities into decision weights must be selected. There are several popular functions that have been used, but we choose to use the function adopted by Tversky and Kahneman (1992), provided below.

$$\omega(p) = \frac{p^{\gamma}}{[p^{\gamma} + (1-p)^{\gamma}]^{1/\gamma}} \tag{9}$$

When performing estimates for CPT, we allow for different utility function curvatures in the gain and loss frames and for different probability weighting in the gain and loss frames. This means that in place of r in the utility function shown in Eq. 8, we estimate α in the gain frame and β in the loss frame for CPT. Additionally, we estimate γ_G in place of γ in Eq. 9 in the gain frame when performing CPT estimates and γ_L in the loss frame.

Akin to the selection of the functional forms for utility and probability weighting, there are choices with regard to how to define the loss aversion parameter, lambda, in CPT. A summary of these choices is presented in Table 1 of Abdellaoui, Bleichrodt, and Paraschiv (2007).

Of the definitions discussed in Abdellaoui et al (2007), the two most plausible choices seem to be either Tversky and Kahneman's (1992) definition or that suggested by Köbberling and Wakker (2005).[7] Tversky and Kahneman (1992) implicitly define lambda as:

$$\lambda = \frac{-U(-\$1)}{U(\$1)} \tag{10}$$

which is the ratio of the disutility of a loss of $1 to the utility of the gain of $1. It is important to note that the exact amount of the wealth change is not critical, rather the "unit" is some small deviation from the reference point. We use $1.25 as our "unit" to avoid issues when, in robustness checks, we estimate the abovementioned utility models using power utility rather than the function displayed in Eq. 8.

[7] 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.

The other alternative for estimating lambda is Köbberling and Wakker's (2005) definition given by

$$\lambda = \frac{U'_-}{U'_+} \tag{11}$$

This equation is the ratio of the derivative of the utility function at the reference point taken from the left to the derivative taken from the right. Effectively, this measure compares the curvature of the utility function in the loss frame to the curvature in the gain frame very close to the reference point.

Both definitions have drawbacks. Köbberling and Wakker make the point that if the Tversky and Kahneman 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 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 (2023) by using the definition of lambda found in Tversky and Kahneman (1992). Harrison and Swarthout's argument is that the majority of the literature uses the definition in Tversky and Kahneman (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 Tversky and Kahneman (1992) definition of lambda (e.g. Hannan et al., 2005).

For reference, the Table 2 below provides a complete list of all the parameters that make up each of the utility models that we estimate.

5 Results

Participants' demographic information for each condition is listed in Table 3. 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.

5.1 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.

5.1.1 Models using all participants

Table 4 reports the maximum likelihood estimates for each model using all 160 participants' 96 choices, where the errors are clustered at the participant level. Using the model with the fewest 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.[8] 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 risk aversion can be decomposed differently through the weighting function and/or other parameters.

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 this pessimism, we find that the RDU risk parameter is insignificant from zero, which would indicate utility risk neutrality, *ceteris paribus*. Given that the EUT estimations show a risk premium and the RDU estimations show linear utility, our results suggest that participants are, on average, utility risk neutral and probabilistically risk averse. 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 ($\chi^2(1) = 265.39$, $p < 0.001$).[9]

Examining the fit results from the CPT model, we again see curvature in the gain domain (see Figure 8), akin to the risk aversion 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 ($\chi^2(2) = 10.95$, $p < 0.001$) indicating the presence of utility loss aversion.

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).[10] 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.

---

[8] Since all participants earned the maximum income from the trivia quiz, the support is zero to fourteen for income.
[9] 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.
[10] 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.

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 of a model using all participants is best when using CPT, and the fit of RDU is better than that of EUT. This result suggests that, were we to use a single, representative agent to describe the behavior of all participants, that representative agent's choices would be best described by prospect theory.

5.1.2 Designating the best model for individual participants

Our research question seeks to determine the relative proportions of individuals whose choices are best described by EUT, by RDU, and by CPT. When typing individuals (as EUT, RDU, or CPT), the following two-step strategy is employed. In the first step, we determine whether the individual is better described by either EUT or RDU. In the second step, we determine whether that individual is better described by either the utility model from the first step (i.e. EUT or RDU) or CPT. If the individual is better described in the second step by CPT, they are labeled a CPT type. If they are better described in the second step by their first step utility model, then they are labeled either an EUT type or an RDU type, depending on which of the two models better described their choices in the first step.

To perform the first step of the typing process we 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 can reject that the individual's probability weighting function was not the identity function at the 5 percent level (i.e. they use objective probabilities as decision weights), then RDU describes that individual's choices better than EUT does. RDU was a better fit for 30% of the participants for whom the EUT model converged. The distribution of p-values from the Clarke test is shown in Figure 7, with one p-value for each participant for whom both EUT and RDU converged.

In the second step of the process, we use the Clarke test to compare CPT to the best-fitting model of either EUT or RDU from the first step. 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 (6) 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 in Figure 10. If the Clarke test is less than or equal to the 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 of our RQ, graphically shown in Figure 11, are inconsistent with the representative participant exercise. Specifically, 81 participants are classified as EUT types (≅51%), 38 participants are classified as RDU types (≅24%%), and 39 participants are classified as CPT types (≅24%) (see Table 5). There are significantly more EUT types than RDU types and significantly more EUT types than CPT types. Two participants (≅1%), one in each condition, did not converge for any model. The number of participants classified as CPT is insignificantly different from the number classified as RDU.

5.2 Tests of Predictions and Hypotheses

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

Results for the effort task are shown in Table 5. Participants' effort differed between conditions, with significantly more effort put forth on average in the *Penalty* condition (71.96 out of a maximum of 90) than in the *Bonus* condition (64.46). Since we can reject that effort is normally distributed using the Shapiro–Wilk W test, we use the Wilcoxon rank-sum test to measure significance (Z = -2.627, p = 0.009). This replicates the findings of Hannan et al. (2005). Also, higher effort led to a higher frequency of reaching the sales target (Z = 2.04), p = 0.041). We conclude that our proposition is supported. These results are robust to dropping the two participants who never converged.

Like Hannan et al. (2005), we asked participants about the fairness of the performance-contingent portion of the contract, and how disappointed they would be if the sales target 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 effort on the condition (contract type), disappointment, and fairness. We find significance only for the contract type variable (non-tabulated). Using nested model statistics, we find no evidence that the fit of the model significantly increases if we add participants' disappointment and/or fairness (non-tabulated).

5.2.2 Tests of H1: Do CPT participants provide more effort, on average, under penalty contracts relative to bonus contracts?

Our first hypothesis predicts that those participants who are identified as CPT types will provide more effort under a penalty contract than they will under a bonus contract. The effort provided in each condition by each type of participant can be found in Table 5. We find that those classified as CPT types exert significantly more effort in the *Penalty* condition than do those in the *Bonus* condition based on a Wilcoxon rank-sum test (76.48 effort vs. 60.71 effort; Z = 2.203, p = 0.027). This result is consistent with our H1.

The second half of our first hypothesis, H1b, posits that the difference in effort across contract frames should not be observed for those who are identified as non-CPT types (i.e. EUT or RDU). We find no difference in effort across *Bonus* and *Penalty* conditions for either EUT or RDU types, consistent with our expectations. While one should always regard conclusions based on the failure to reject a null hypothesis with skepticism, we feel that, taken together, the results of our H1a and H1b, suggest that differential effort provision across contract frames is driven only by those individuals best described by prospect theory.

5.2.3 Tests of H2: Do CPT participants provide more or less effort, on average, than non-Prospect Theory users when faced with a bonus contract?

Recall that our H2 makes the case that if loss aversion is driving the difference in effort provision across contract frames, then when a contract presents no possibility of a loss, then there should be no difference in effort provision. We therefore test whether those participants typed as CPT users exert more effort than non-CPT users in the *Bonus* condition. The difference in effort is insignificant using a Wilcoxon rank-sum test, consistent with our expectations ($Z = 0.629$, $p = 0.535$). Interestingly, while statistically insignificant, we do find that CPT types exert less effort ($M = 61.71$, $SEM = 6.18$), when faced with a bonus contract than non-CPT types ($M = 65.26$, $SEM = 2.39$, non-tabulated). This result supports our proposition that while more effort is exerted under a penalty contract, this additional effort is driven by only the CPT types, which make up a relative minority of our participants.

While not hypothesized, if loss aversion from prospect theory drives greater effort provision in the *Penalty* condition, then one would expect that CPT types, who are loss averse, should exert more effort than non-CPT types, who are, by definition, not loss averse. The results of a Wilcoxon rank-sum test show that CPT types exert marginally more effort ($M = 76.48$, $SEM = 2.65$) than non-CPT types ($M = 69.93$, $SEM = 2.34$, non-tabulated) when faced with a penalty contract ($Z = 1.728$, $p = 0.084$).

5.2.4 Tests of H3: Exploring the relationship between individuals' loss aversion and effort

As argued above, if loss aversion accounts for the greater provision of effort under penalty contracts, then we should expect to find that participants who are more loss averse should exert more effort than those who are less loss averse. To examine this relationship between the degree of loss-aversion and effort, we use the GLM regressions reported in *Table* 7 columns (2) – (4). In each regression, effort is regressed on the contract type (*Bonus* or *Penalty*; the indicator variable is one for the *Penalty* condition), a measure of loss aversion, and the interaction between the condition and the measure of loss aversion. We start by using the Gächter et al. (2022) measure in column (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 ($\chi^2(2) = 3.73$, $p = 0.054$). This suggests that the measure of loss aversion presented in Gächter et al. (2022) measure does not predict effort choices under the penalty contract in our effort task.

Next, we move to sing the individual participant fitted CPT model loss-aversion measure, λ. The regression tabulated in column (3) of *Table* 7 yields interesting results. The coefficient on the loss-aversion measure is significantly negative. However, the coefficient on the interaction between the penalty contract is significantly positive, 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 the fact that, per prospect theory, loss aversion should not make a difference in the gain frame. When facing a penalty contract, a participant's loss-aversion does not predict effort, contrary to the logic drawn from CPT. In summary, loss aversion has a negative effect on effort in bonus contracts and no effect on effort in penalty contracts when we consider all participants, irrespective of which utility model best describes their choices.

Importantly, the regressions just described are performed with *all* participants no matter which utility model they are associated with. This may well bias away from us finding the predicted result that loss aversion is correlated with effort in the penalty contract because, in essence, we are artificially injecting noise into our regressions. Specifically, those participants who are non-CPT types (i.e. are either EUT or RDU types) are, by definition, not loss averse. Consequently, their effort should be invariant to their estimated lambda values. As a result, we rerun the regression in Table 6, column (3) with only those participants identified as CPT types, whose measure of loss aversion is most likely to be correlated with their effort in order to address our H3.

We find similar results to those discussed for all participants. Namely, higher loss aversion is correlated with less effort in the bonus contract, but is irrelevant in predicting effort in the penalty contract. In other words, even for just the CPT types, loss aversion does not appear to be correlated with effort provision, contrary to our predictions in H3.

Likewise, the above results of the regression in *Table* 7, column (2) are robust to using only CPT types. The results of all regressions are robust to dropping participants who failed the attention check in part 3 of the experiment.

To further explore any relationship between effort and our loss aversion measures, we provide two scatterplots between the loss-aversion measure and effort to graphically represent the observed behavior. The scatterplot presented in Figure 12 is based on the Gächter et al (2022) measure and the scatterplot in Figure 13 is based on the prospect theory estimates of lambda. In both figures, each marker represents an individual participant. We find the Gächter et al. (2022) measure and the prospect theory estimate of lambda are negatively correlated but insignificantly (r = -0.134, p = 0.108, N = 144). This is also the case when only examining CPT types (r = -0.273, p = 0.099, N = 39).

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. These scatterplots support the interpretations of the regressions just discussed. The Gächter et al (2022) measure does not seem to predict effort provision either condition. The prospect theory measure of loss aversion, lambda, appears to have no predictive power for effort in the *Penalty* condition, but does seem to show that those with higher levels of loss aversion provide *less* effort in the bonus condition.

6 Conclusion

In this paper we examine whether loss aversion is the latent mechanism driving differential effort provision across contract frames, as suggested by prior literature. Overall, we find that those participants faced with a penalty contract exert more effort than those participants faced with an economically equivalent bonus contract, consistent with the most common finding in the literature. However, this greater provision of effort is driven only by the subset of participants whose choices are best described by prospect theory. Furthermore, these participants represent only a quarter of our sample. For the majority of participants whose choices are better described by either expected utility theory or rank dependent utility theory, no difference in effort between contract frames is observed. Further, we can find no evidence that the degree of loss aversion (regardless of which of our two measures is used) is correlated with the amount of effort provision, even for only those participants who behave consistent with prospect theory.

We believe that our results yield at least two broad conclusions. First, the representative agent model is inappropriate for research in this setting. We find large numbers of participants who behave consistently with each of the utility models discussed in this paper. Consequently, the assumption that all agents behave consistently with a specific utility model is, particularly one that exhibits characteristics that differ markedly from other utility models (e.g. loss aversion), should be treated with skepticism. Indeed, if our sample of agents is representative of the proportions seen in the broader population, if one needed to make a representative agent assumption, then the best assumption to make is that all agents behave consistent with expected utility theory rather than prospect theory.

This conclusion has strong implications for contract implementation in firms. Given that approximately three-quarters of our participants are identified as non-CPT types and provide no differential effort across contract frames, firms should be wary of expecting that implementing a penalty contract will necessarily yield more effort than implementing an economically equivalent bonus contract.

Second, we feel that our results provide some important nuance to prior findings. While greater effort under penalty contracts has been an often-replicated finding, the assumption has been that this is driven by more effort exertion in the penalty frame relative to some benchmark in the gain frame. Our results suggest that it may instead be the case that agents exert less effort in the gain frame relative to some benchmark in the penalty frame. Put differently, it appears that agents who behave consistent with prospect theory may require the disutility from the penalty contract to motivate them into putting forth even relatively minimal levels of effort. This would be consistent with the results presented in (Tracy and Ferraro 2022) in which the only participants who exhibit increased effort under penalty contracts are those who selected such contracts. It may be that these participants were aware that they were unlikely to be motivated to exert enough effort to obtain the required outcome by a bonus contract and chose the penalty contract as a self-commitment mechanism. This is similar in spirit to the arguments advanced in (De Quidt 2018), although he finds no evidence of such a mechanism at play in his study. Further research is likely warranted on this phenomenon.

7 References

Abdellaoui, M., H. Bleichrodt, and C. Paraschiv. 2007. Loss Aversion Under Prospect Theory: A Parameter-Free Measurement. *Management Science* 53 (10): 1659–1674.

Apostolova-Mihaylova, M., W. Cooper, G. Hoyt, and E. C. Marshall. 2015. Heterogeneous gender effects under loss aversion in the economics classroom: A field experiment. *Southern Economic Journal* 81 (4): 980–994.

Armantier, O., and A. Boly. 2015. Framing of Incentives and Effort Provision. *International Economic Review* 56 (3): 917–938.

Booij, A. S., and G. Van De Kuilen. 2009. A parameter-free analysis of the utility of money for the general population under prospect theory. *Journal of Economic Psychology* 30 (4): 651–666.

Brink, A. G., and F. W. Rankin. 2013. The Effects of Risk Preference and Loss Aversion on Individual Behavior under Bonus, Penalty, and Combined Contract Frames. *Behavioral Research in Accounting* 25 (2): 145–170.

Burke, J., K. L. Towry, D. Young, and J. Zureich. 2023. Ambiguous Sticks and Carrots: The Effect of Contract Framing and Payoff Ambiguity on Employee Effort. *The Accounting Review* 98 (1): 139–162.

Charness, G., and M. Rabin. 2005. Expressed preferences and behavior in experimental games. *Games and Economic Behavior* 53 (2): 151–169.

Charness, G., L. Rigotti, and A. Rustichini. 2016. Social surplus determines cooperation rates in the one-shot Prisoner's Dilemma. *Games and Economic Behavior* 100: 113–124.

Christ, M. H., K. L. Sedatole, and K. T. C. Accounting. 2012. Sticks and Carrots: The Effect of Contract Frame on Effort in Incomplete Contracts. *The Accounting Review* 87 (6): 1913–1938.

Church, B. K., T. Libby, and P. Zhang. 2008. Contracting Frame and Individual Behavior: Experimental Evidence. *Journal of Management Accounting Research* 20 (1): 153–168.

Clarke, K. A. 2007. A Simple Distribution-Free Test for Nonnested Model Selection. *Political Analysis* 15 (3): 347–363.

De Quidt, J. 2018. Your Loss Is My Gain: A Recruitment Experiment with Framed Incentives. *Journal of the European Economic Association* 16 (2): 522–559.

De Quidt, J., F. Fallucchi, F. Kölle, D. Nosenzo, and S. Quercia. 2017. Bonus versus penalty: How robust are the effects of contract framing? *Journal of the Economic Science Association* 3 (2): 174–182.

Fechner, G. 1860. *Elements of Psychophysics*. Vol. 1. New York: Holt, Rinehart and Winston.

Frederickson, J. R., and W. Waller. 2005. Carrot or Stick? Contract Frame and Use of Decision-Influencing Information in a Principal-Agent Setting. *Journal of Accounting Research* 43 (5): 709–733.

Fryer, R., S. Levitt, J. List, and S. Sadoff. 2012. *Enhancing the Efficacy of Teacher Incentives through Loss Aversion: A Field Experiment*. Cambridge, MA: National Bureau of Economic Research.

Gächter, S., E. J. Johnson, and A. Herrmann. 2022. Individual-level loss aversion in riskless and risky choices. *Theory and Decision* 92 (3–4): 599–624.

Gonzalez, G. C., V. B. Hoffman, and D. V. Moser. 2019. Do Effort Differences between Bonus and Penalty Contracts Persist in Labor Markets? *The Accounting Review* 95 (3): 205–222.

Gul, F. 1991. A Theory of Disappointment Aversion. *Econometrica* 59 (3): 667.

Hannan, R. L., V. B. Hoffman, and D. V. Moser. 2005. Bonus versus Penalty: Does Contract Frame Affect Employee Effort? *Experimental Business Research*: 151–169.

Harrison, G., and J. M. Ng. 2016. Evaluating the expected welfare gain from insurance. *The Journal of Risk and Insurance* 83 (1): 91–120.

Harrison, G., and E. E. Rutström. 2009. Expected utility theory and prospect theory: one wedding and a decent funeral. *Experimental Economics* 12: 133–158.

Harrison, G. W., and J. T. Swarthout. 2023. Cumulative Prospect Theory in the Laboratory: A Reconsideration. In *Research in Experimental Economics*, edited by G. W. Harrison and D. Ross, 107–192. Emerald Publishing Limited.

Hong, F., T. Hossain, and J. A. List. 2015. Framing manipulations in contests: A natural field experiment. *Journal of Economic Behavior & Organization* 118: 372–382.

Imas, A., S. Sadoff, and A. Samek. 2017. Do People Anticipate Loss Aversion? *Management Science* 63 (5): 1271–1284.

Kahneman, D., and A. Tversky. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica* 47 (2): 263–291.

Köbberling, V., and P. P. Wakker. 2005. An index of loss aversion. *Journal of Economic Theory* 122 (1): 119–131.

Litovsky, Y., G. Loewenstein, S. Horn, and C. Y. Olivola. 2022. Loss aversion, the endowment effect, and gain-loss framing shape preferences for noninstrumental information. *Proceedings of the National Academy of Sciences* 119 (34): e2202700119.

Quiggin, J. 1982. A theory of anticipated utility. *Journal of Economic Behavior & Organization* 3 (4): 323–343.

Rawls, J. 1971. *A theory of justice*. United States of America: Harvard University Press.

Savage, L. J. 1951. The Theory of Statistical Decision. *Journal of the American Statistical Association* 46 (253): 55–67.

Schmidt, U., and H. Zank. 2009. A simple model of cumulative prospect theory. *Journal of Mathematical Economics* 45 (3–4): 308–319.

Tracy, J., and P. Ferraro. 2022. A reassessment of the potential for loss-framed incentive contracts to increase productivity (published version). *Experimental Economics* 21.

Tversky, A., and D. Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5 (4): 297–323.

Van der Stede, W. A., A. Wu, and S. Y.-C. Wu. 2020. An Empirical Analysis of Employee Responses to Bonuses and Penalties. *The Accounting Review* 95 (6): 395–412.

Von Neumann, J., and O. Morgenstern. 2007. *Theory of games and economic behavior*. 60. anniversary ed., 4. printing, and 1. paperback printing. A Princeton classic edition. Princeton, NJ: Princeton University Press.

Vuong, Q. H. 1989. Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses. *Econometrica* 57 (2): 307.

Wakker, P. P. 2010. *Prospect theory: for risk and ambiguity*. Cambridge ; New York: Cambridge University Press.

Yaari, M. E. 1987. The Dual Theory of Choice under Risk. *Econometrica* 55 (1): 95.

8 Appendix

8.1 <u>Research Instrument</u>

The Prolific instrument is included as a separate document.

9 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.

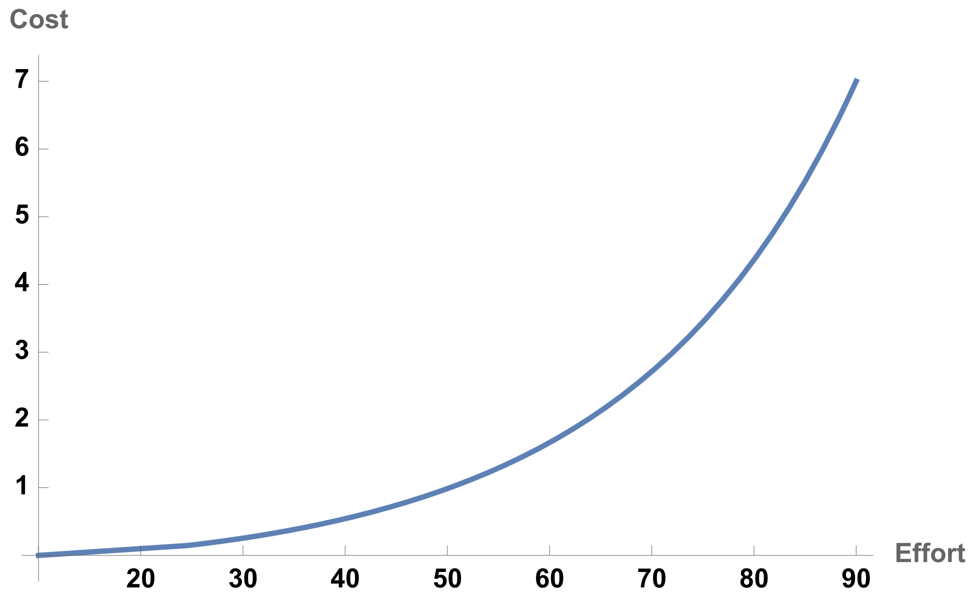


Figure 3: Cost of effort for both Bonus and Penalty conditions

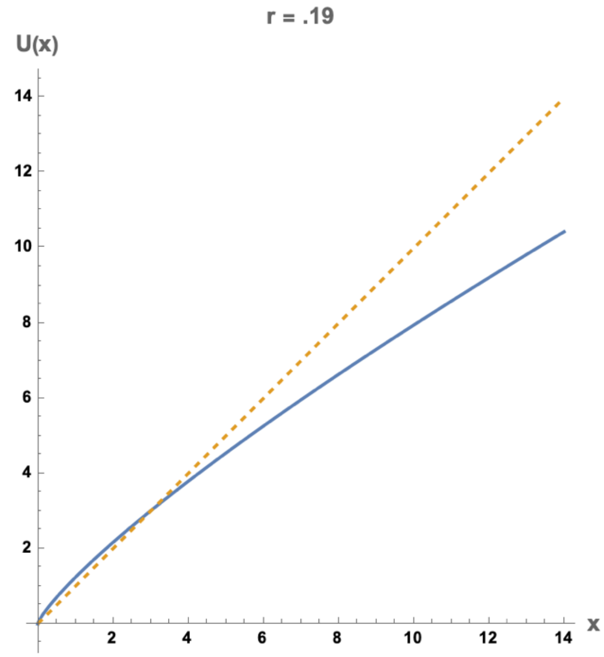


Figure 4: Utility function for EUT given fitted parameters over all participants

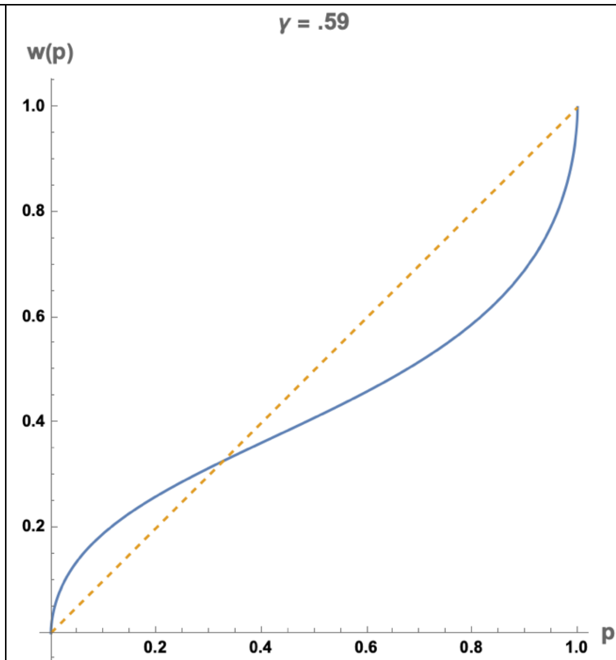


Figure 5: Probability weighting function for RDU given fitted parameters for all participants

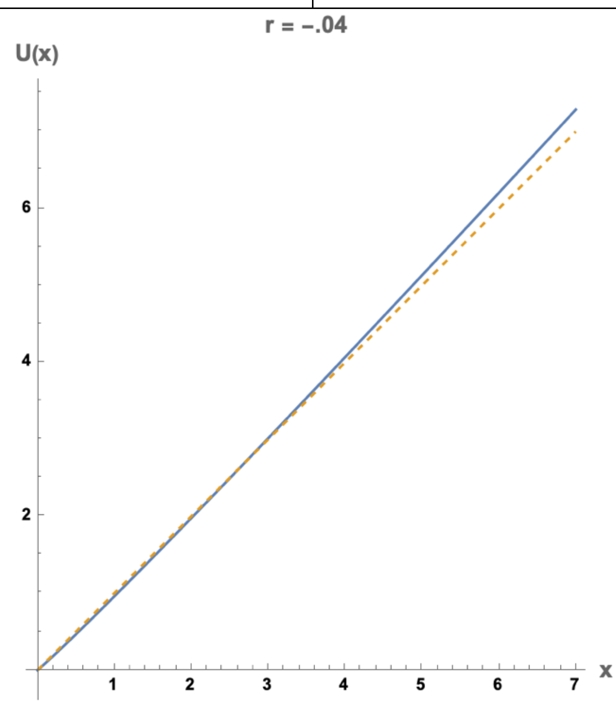


Figure 6: Utility function for RDU given fitted parameters using all participants

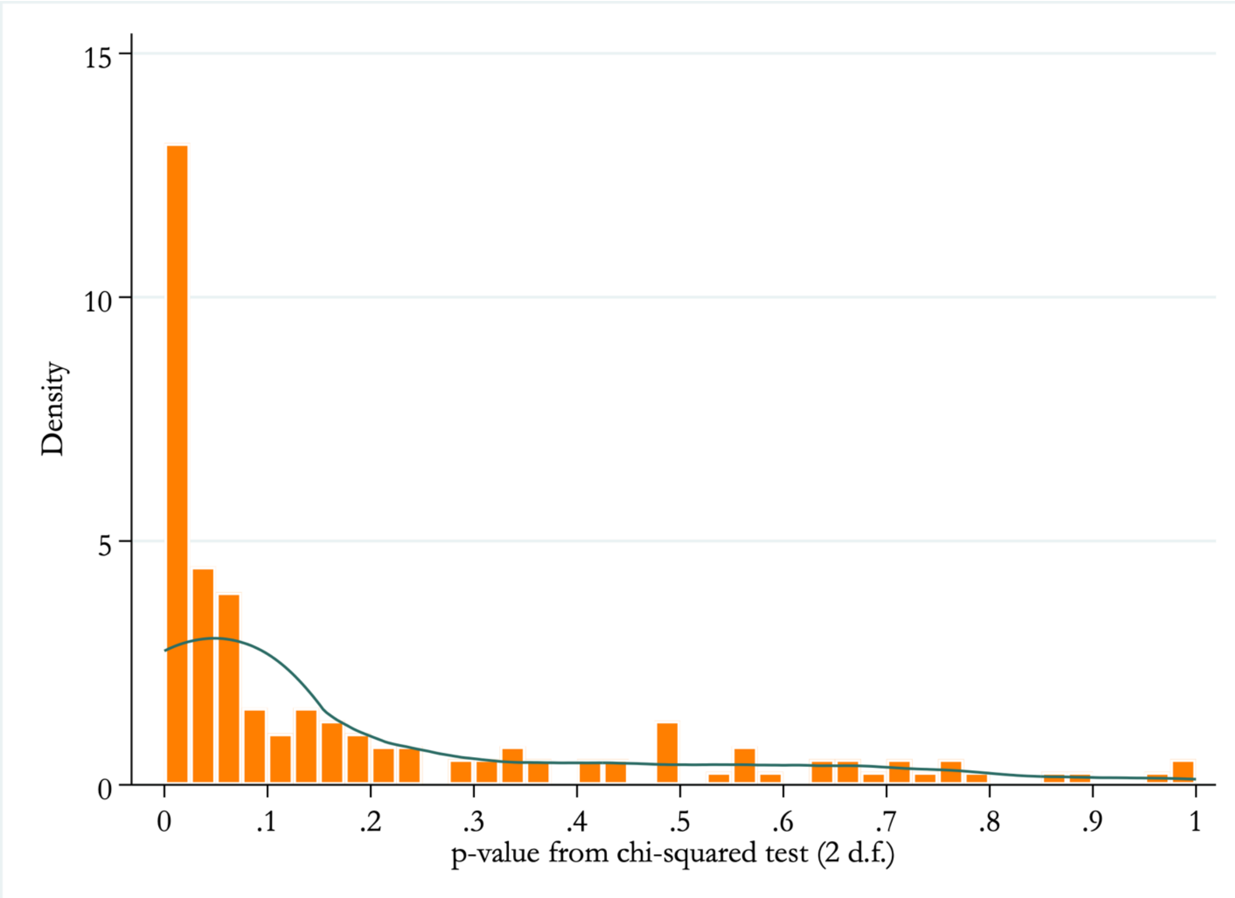


Figure 7: Histogram of p-values of test to reject EUT in favor of RDU

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

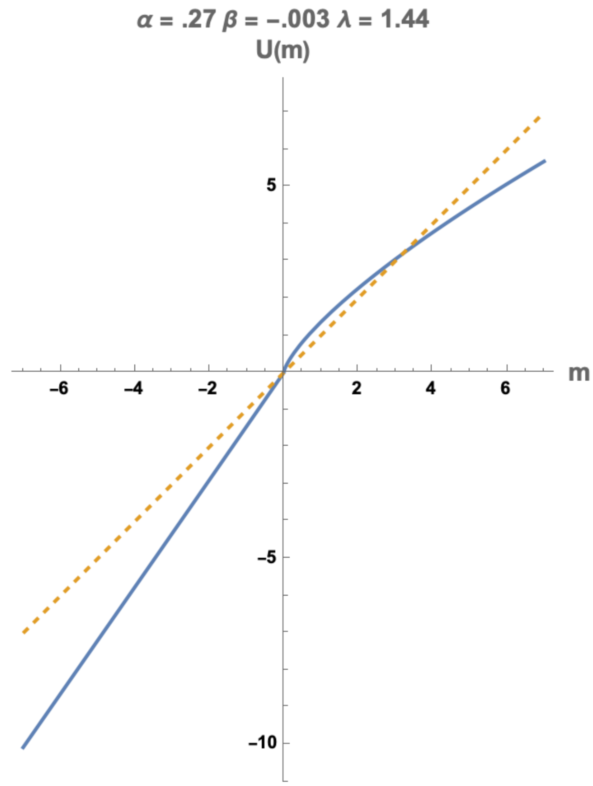


Figure 8: Utility function for CPT given fitted parameters using all participants

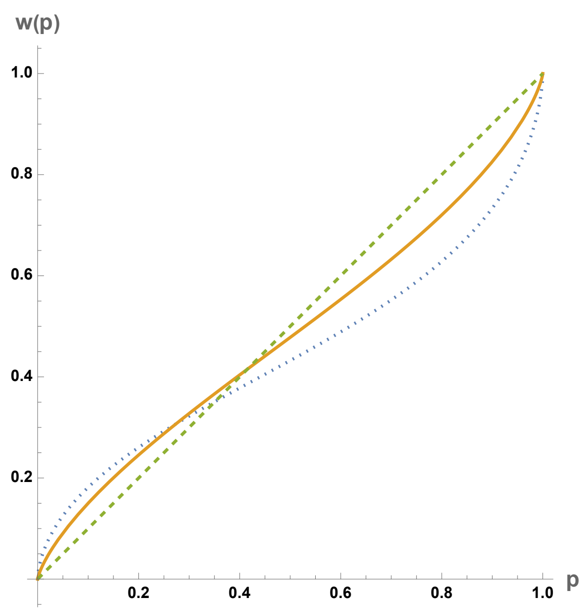


Figure 9: Probability weighting functions for CPT gains and losses given fitted parameters for all participants

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

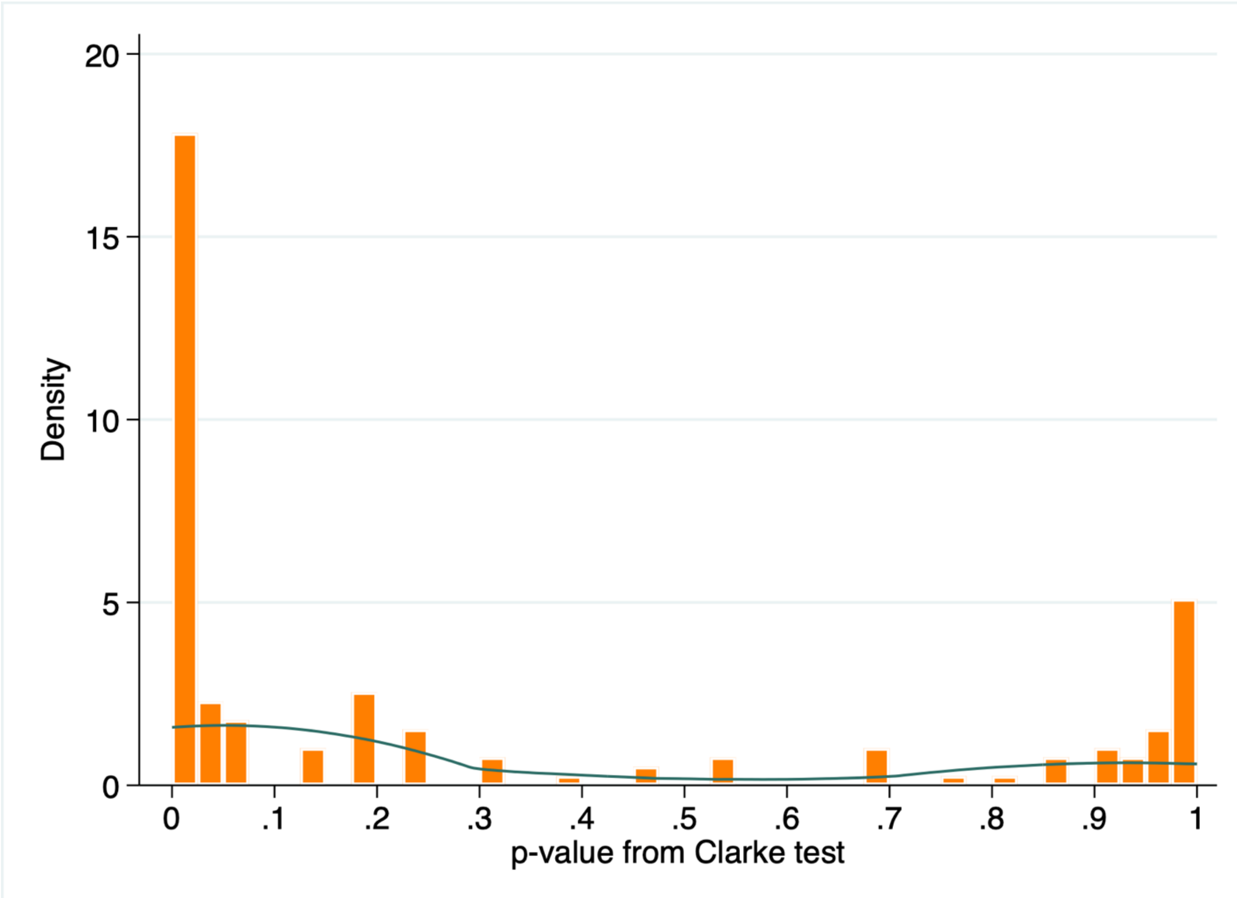


Figure 10: Histogram of p-values of test to reject best fitting nested model in favor of CPT

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

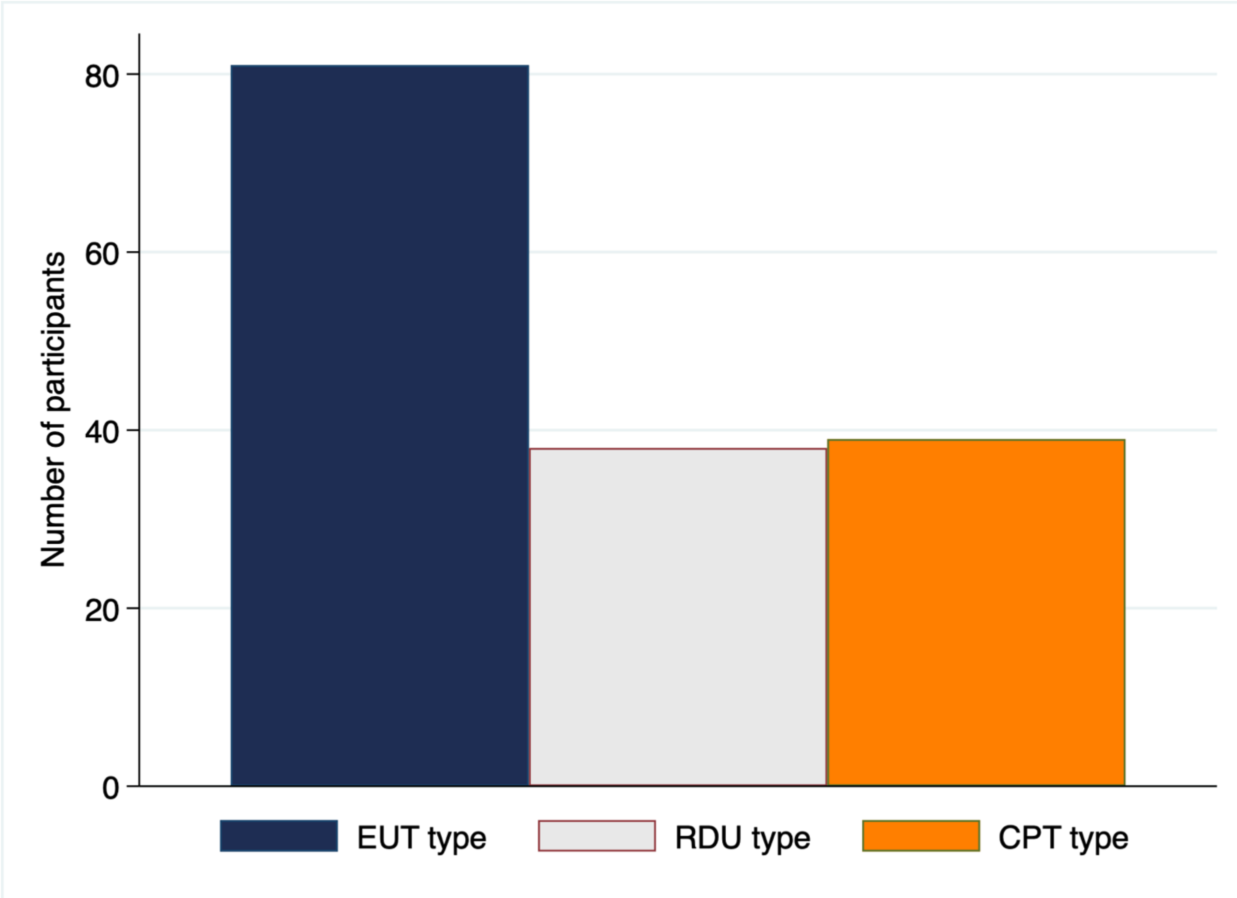


Figure 11: Count of participants typed as EUT, RDU, or CPT types

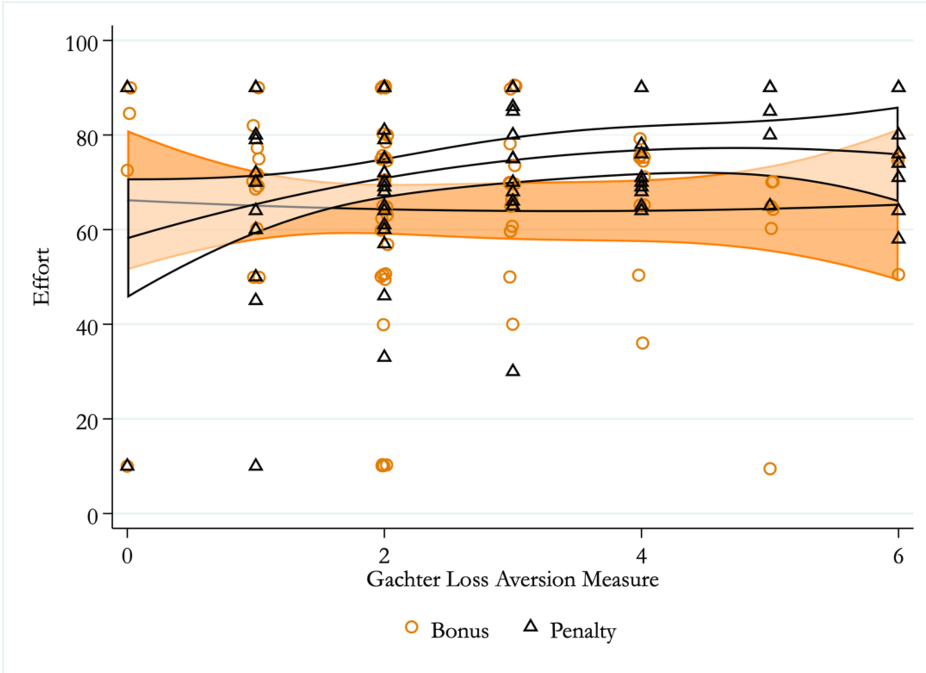


Figure 12: Scatterplot of effort and loss aversion using Gächter et al (2022) measures

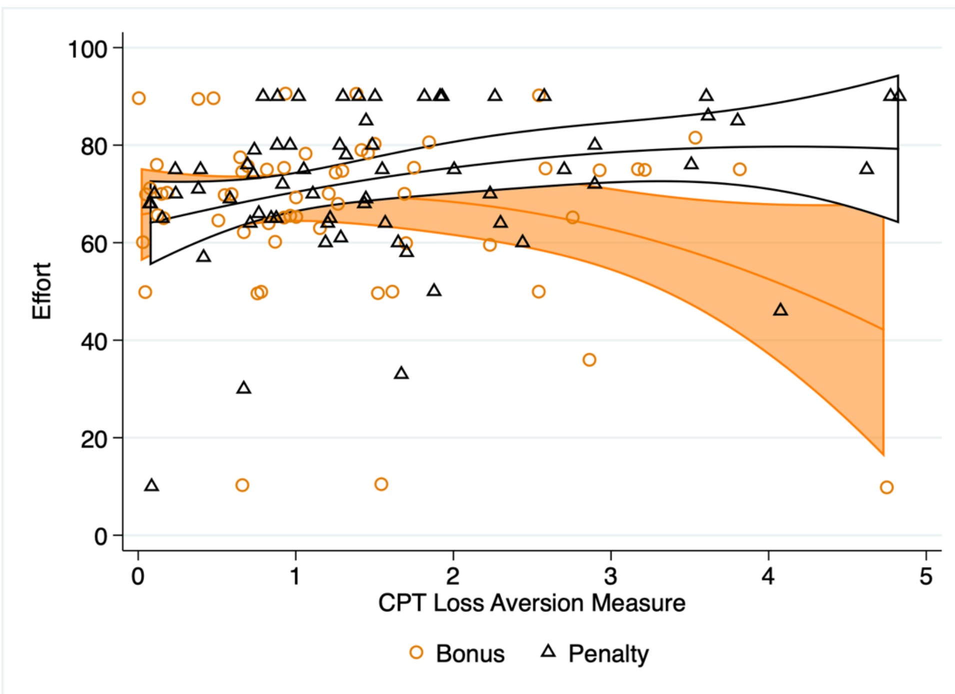


Figure 13: Scatterplot of effort and loss aversion using MLE CPT

Note: 95% confidence interval based on quadratic regression

10 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%				
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%				

	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**
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%
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%		

	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**
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%		
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: Parameters fit per type

	Risk Aversion: Gain Frame	Risk Aversion: Loss Frame	Probability Weighting: Gain Frame	Probability Weighting: Loss Frame	Loss Aversion
EUT	*r*	n/a	n/a	n/a	n/a
RDU	*r*	n/a	γ	n/a	n/a
CPT	α	β	γ_G	γ_L	λ

Table 3: 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	Bachelor of Arts
Penalty N = 80	37.8 (1.58)	52.5% (5.6%)	46.3% (5.6%)	Full-time	25-50K	Bachelor of Arts

Table 4: Estimates for EUT, RDU, and CPT Models using all 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 5: 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. The effort was chosen from [10,90], and fairness and disappointment questions were elicited using a 13-point Likert scale.

Table 6: Effort by utility type and condition

	Never converged	EUT type	RDU type	CPT type
Bonus condition	50.0	65.30	65.86	60.71
	n/a	(3.17)	(3.63)	(6.18)
	1	*43*	*22*	*14*
Penalty Condition	90.0	68.76	71.44	76.48
	n/a	(3.01)	(3.54)	(2.65)
	1	*38*	*16*	*25*

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

Table 7: 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]

- ○ A blue rectangle and black oval
- ○ A green cross and orange triangle
- ○ A red circle and green star
- ○ A yellow triangle and red circle
- ○ A black oval and blue cross
- ○ 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.]

- ○ Six
- ○ Five
- ○ Twelve
- ○ 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.

- ○ Yes, I agree to participate in this study
- ○ 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”?

- ◯ Disney+
- ◯ Amazon Prime
- ◯ Max
- ◯ Hulu

Who is credited with inventing the light bulb?

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

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

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

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

- ◯ Mike Pence
- ◯ Oprah Winfrey
- ◯ Elizabeth Warren
- ◯ 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.

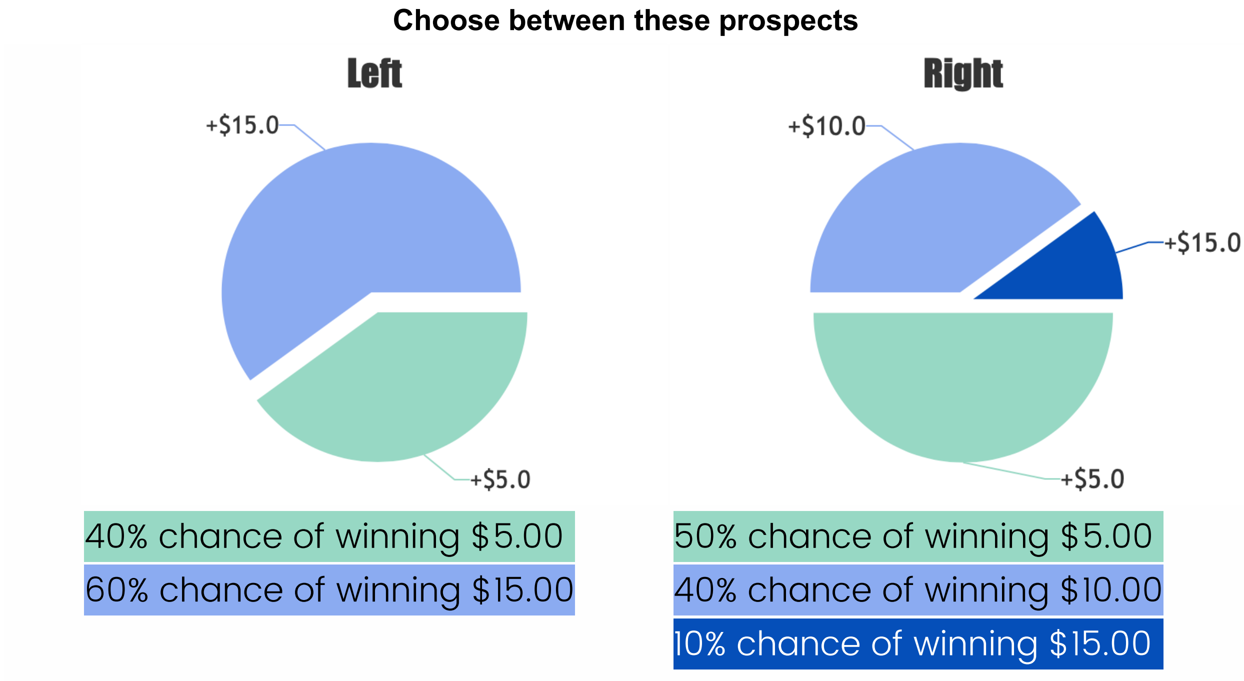
Display This Question:

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.

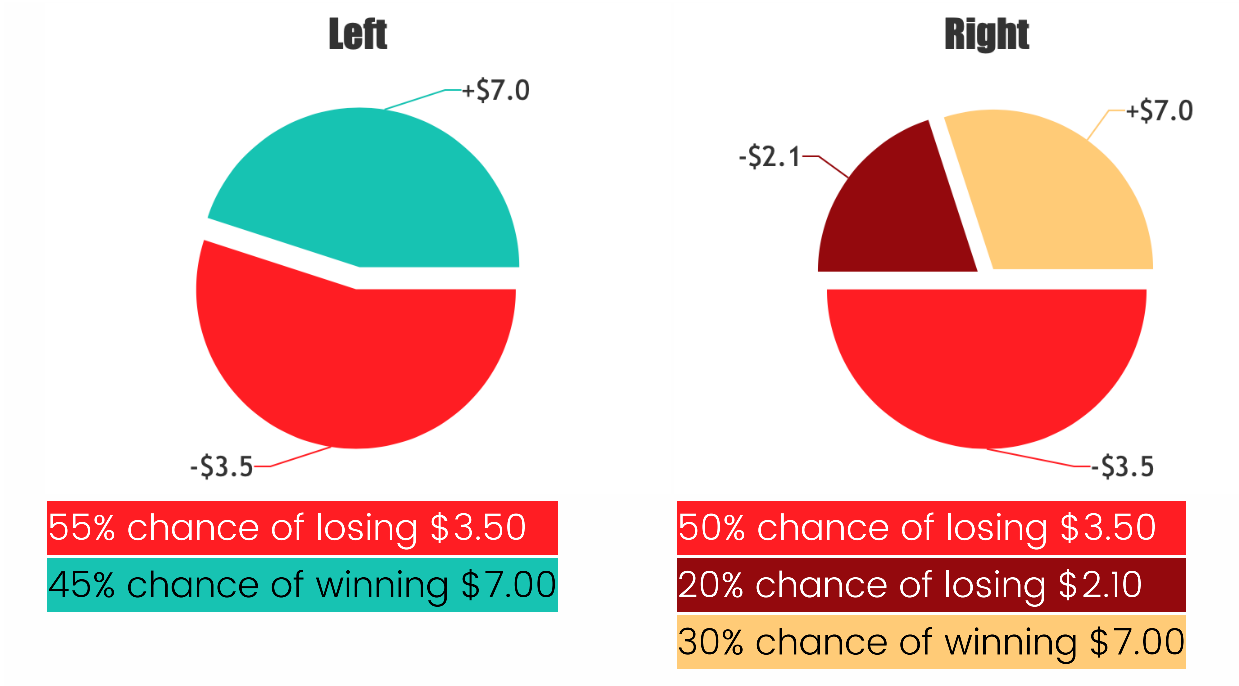
Starting on the next page, you can review the summary by hovering your mouse over the phrase **Help**.

Let's proceed to part 2.

Lottery Choices

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

Choose between these prospects:



○ Select Left ○ 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?

- ◯ Yes
- ◯ 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?

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

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

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

- ◯ Male
- ◯ Female
- ◯ Non-binary / third gender
- ◯ Prefer to self-describe
(____
- ◯ 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	○	○
lose $1.00 if heads, win $2.50 if tails	○	○
lose $1.50 if heads, win $2.50 if tails	○	○
lose $2.00 if heads, win $2.50 if tails	○	○
lose $2.50 if heads, win $2.50 if tails	○	○
lose $3.00 if heads, win $2.50 if tails	○	○

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

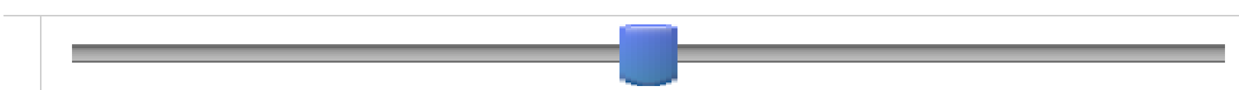
Recall your compensation package:

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 $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]
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.