A Comprehensive Analysis of the Subproportionality and Risk-Tolerance/Risk-Aversion Properties

PRE-ANALYSIS PLAN

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1 MOTIVATION

Decision-making under uncertainty is of core interest to economists. An understanding of individual risk attitudes is necessary to analyze and predict choices ranging from insurance purchases and investments to migration decisions and political engagement. The standard economic model of expected utility (EU) formulates such decisions as being determined by the mathematical expectation of utility outcomes: For a lottery $X \equiv (x_1, q_1; x_2, q_2; ...; x_N, q_N)$, where $\{x_1, x_2, ..., x_N\}$ are potential outcomes and $\{q_1, q_2, ..., q_N\}$ are the associated probabilities, the expected utility is given by

$$EU(X) = \sum_{i=1}^{N} q_i u(x_i).$$

A key feature of the EU formulation is that the expected utility is linear in probabilities. However, this feature has been contradicted by experimental evidence (as we discuss more below). Motivated by such evidence, several non-EU models have been proposed that relax linearity in probabilities by instead assuming a nonlinear probability weighting function—perhaps the most prominent examples are original prospect theory (OPT) from Kahneman and Tversky (1979) and cumulative prospect theory (CPT) from Tversky and Kahneman (1992)(collectively PT). In this project, we conduct a more comprehensive experimental assessment of some of the key properties that motivate existing models of probability weighting.

To avoid concerns about whether to apply rank dependence (the main difference between OPT and CPT), or whether the number of outcomes in a lottery might have a separate impact on decisions (as suggested by Puri (2025)), we focus on a narrow domain in which OPT and CPT are identical and in which PT is thought to perform well: comparisons between binary lotteries that yield some amount x with probability q and zero otherwise, which we denote by (x, q). For this domain, under PT lotteries are evaluated according to a functional that takes the form

$$U(x, q) = \pi(q)u(x).$$

In this formulation, the function u is a utility or value function defined over outcomes, where the formulation normalizes $u(0) = 0$. The function π is a probability weighting function that transforms the probability q into a decision weight $\pi(q)$ with restrictions that $\pi(\cdot)$ is monotonic with $\pi(0) = 0$ and $\pi(1) = 1$.

Based on experimental evidence, the literature has posited two regularities that govern the shape of the probability weighting function. The first posited regularity is *subproportionality*: if for some $x > 0$, $y > x$, $p \in (0, 1)$, and $r \in (0, 1]$ a person has $(x, r) \sim (y, pr)$, then for any $r' \in (0, r)$ the person will have $(x, r') \prec (y, pr')$ (and for any $r' \in (r, 1]$ the person will have $(x, r') \succ (y, pr')$). In words, when comparing a smaller amount that is more likely to a larger amount that is less likely, scaling the probabilities proportionally downward makes a person more risk tolerant and thus more likely to choose the larger, less-likely amount. Given the structure of the probability weighting model, this regularity implies that the function π has the property that $\pi(pr)/\pi(r)$ gets larger as r gets smaller.

The second regularity is that, when people provide certainty equivalents for binary lotteries, they exhibit *risk tolerance for small probabilities and risk aversion for large probabilities*. This regularity is more self-explanatory, and translates (under an assumption of a linear utility function) to the function π having the property that $\pi(q) > q$ for small q, whereas $\pi(q) < q$ for large q.

The combination of these two regularities along with an assumption of continuity at $q = 0$ and $q = 1$ suggests a probability weighting function that is inverse-S shaped—specifically, that is initially concave and then convex with $\pi(q) > q$ for small q and $\pi(q) < q$ for large q. Over the years, several inverse-S-shaped functional forms have been proposed (see, e.g., Figure 1 borrowed from Prelec (1998) Figure 1 for some specific examples).

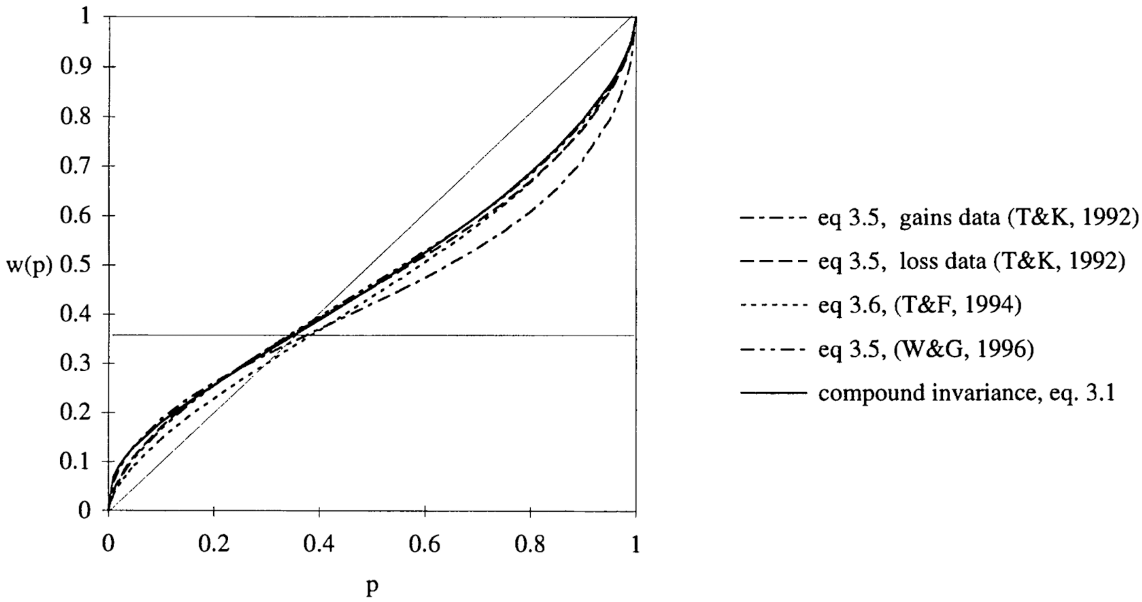


FIGURE 1.—The compound invariant form (solid line) and several empirical probability weighting functions. Estimates of the one-parameter equation (3.5) are taken from Tversky and Kahneman (1992) and Wu and Gonzalez (1996a); estimates of the two-parameter equation (3.6) are taken from Tversky and Fox (1994).

Figure 1: Figure 1 from Prelec (1998).

1.1 Existing Evidence, Its Limitations, and Motivation for Comprehensive Design

While the literature has often interpreted existing experimental evidence as providing broad support for these two regularities, when one takes a closer look, there are reasons to be cautious. In particular, the experimental foundation for these regularities relies on experiments covering a limited set of problems within the general class of problems that compare

$$(M, q_M)\ vs. (H, q_H),$$

yet the regularities are assumed to hold for all such problems (and more).

The origins of subproportionality are the hypothetical examples put forward by Allais (1953) for how individuals might violate the independence axiom—which is the axiom that delivers linearity in probabilities in the EU model. In his second example, he posits that a person might prefer $(\$1\text{ million}, 1)$ over $(\$5\text{ million}, 0.98)$, while the same person might also prefer ($5 million, 0.0098) over ($1 million, 0.01).[1] This example corresponds to a canonical "common ratio problem", a special case of the general class of problems noted above where individuals decide between

$$(M, 1) \ vs. \ (H, q_H),$$

and also decide between

$$(M, r) \ vs. \ (H, rq_H),$$

for some common ratio $r \in (0, 1)$. The "common ratio effect"—choosing $(M, 1)$ in the first comparison but (H, rq_H) in the second comparison—is one implication of subproportionality. Since Allais' original instantiation of the common ratio problem, there have been over 150 studies of such paired choice tasks (for a review see Blavatskyy et al. (2023)).

But subproportionality implies more than just the common ratio effect. Note that we can parameterize the problems above using parameters (p, r) where $q_H = pr$ and $q_M = r$. In other words, people compare

$$(M, r) \ vs. \ (H, pr).$$

With this notation, the subproportionality property relates to how behavior varies with r while holding p constant—specifically, it says that as we decrease r, the propensity to choose (H, pr) should increase. As described above, the vast majority of the experimental literature focuses on the special case of common ratio problems that compare two tasks with the same p, one with $r = 1$ and one with $r < 1$. But the subproportionality property implies we should see similar patterns when we compare two tasks with the same p, one with $r < 1$ and the other with $r' < r$. One of our goals is to collect experimental evidence on subproportionality for a much broader set of (p, r, r') combinations.[2]

For the risk-tolerance/risk-aversion property, a number of experiments have confirmed a feature originally seen in Preston and Baratta (1948) that when people value binary lotteries that yield some amount $\$X$ with probability q and zero otherwise, people tend to exhibit risk tolerance for smaller q and risk aversion for larger q. In other words, if we let $CE(X, q)$ denote

[1] Allais' first example is the more commonly known "Allais paradox", often referred to as the "common consequence problem". We do not discuss it here because it involves a three-outcome lottery and thus is outside our simpler domain of comparisons between binary lotteries (and note that rank dependence or preferences for simplicity could impact common consequence problems).

[2] Even within the class of CRE problems, McGranaghan et al. (2024b) documents that there is limited coverage of the parameter space, and that paper provides some broader coverage of the CRE space.

the certainty equivalent for the lottery (X, q), that is,

$$(CE(X, q), 1) \sim (X, q),$$

then $CE(X, q) > qX$ when q is low and $CE(X, q) < qX$ when q is high. Kahneman and Tversky (1979) discuss this property, and it appears pretty reliably in many experiments over the years.

Using our (p, r) parameterization of problems, the risk-tolerance/risk-aversion property relates to how behavior varies with p while holding $r = 1$. When investigated in conjunction with subproportionality, it seems natural to investigate this same comparative static for values of $r < 1$ because different models of risk preferences make different predictions for this comparative static (as we describe in Section 2). A second goal of this study is to collect experimental evidence on how behavior depends on p holding r constant for a broad set of r. We are not aware of prior experiments that investigate this comparative static.

1.2 Using Valuations

As described above, prior evidence on subproportionality (virtually always on the CRE) has been conducted primarily using paired choice tasks, whereas prior evidence on the risk-tolerance/risk-aversion pattern has been conducted primarily using CE's for binary lotteries. In this project, we will collect *m-valuations* for a variety of (p, r) combinations. Specifically, for a fixed H, we elicit $m(p, r)$ such that

$$(m(p, r), r) \sim (H, pr).$$

When $r = 1$, an m-valuation is equivalent to a certainty equivalent—that is, $m(p, 1) = CE(H, p)$. Hence, our m-valuations include the usual type of data for assessing the risk-tolerance/risk-aversion property, and moreover permit us to investigate the impact of changing p while holding r constant for values of r smaller than 1.

For investigating subproportionality, comparing valuations instead of comparing choices has the advantage of solving an important inference problem. McGranaghan et al. (2024a) highlight the inferential challenges associated with using paired choice tasks to test EU relative to alternative models. If choice noise differentially impacts the two tasks, then the researcher cannot tell how much of any difference in choice probabilities derives from changing preferences (i.e., subproportionality) and how much derives from the changing impact of noise. They further demonstrate how, under the same assumptions about choice noise where paired choice tasks yield problematic inference, paired valuation tasks can yield unbiased inference.

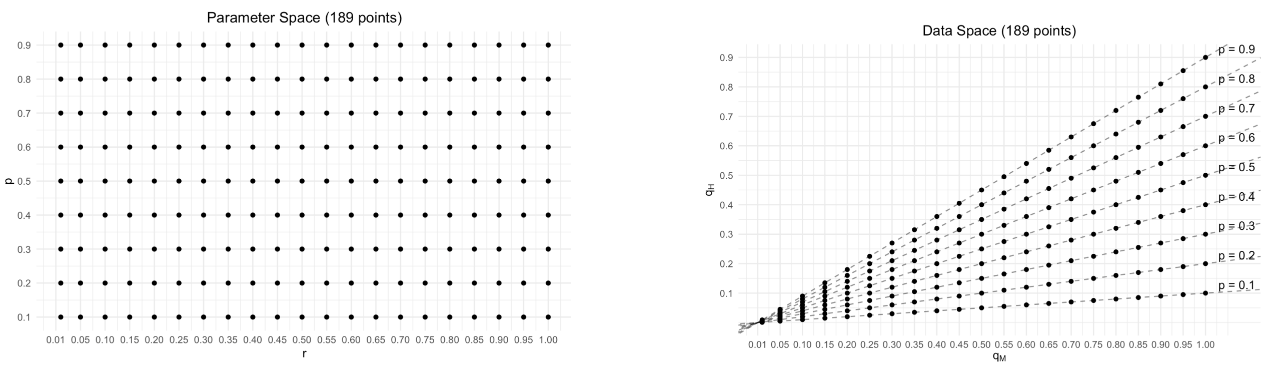
Moreover, m-valuations permit a more direct test of the subproportionality feature. In particular, the subproportionality feature implies that, holding p constant, $m(p, r)$ should increase as r declines. Hence, instead of merely studying pairs of valuation tasks, we can study the overall pattern of of how $m(p, r)$ varies with r for different fixed values of p.

1.3 A Comprehensive Design

This project seeks to provide a common and comprehensive evidence base to understand the nature of the subproportionality property and the risk-tolerance/risk-aversion property, and to assess existing models in light of this more comprehensive evidence base. To do so, we shall collect m-valuations for a comprehensive set of (p, r) combinations.

One can visualize our design in two ways. First, using the (p, r) parameterization, we elicit m-valuations for nine values of p and 21 values of r, as depicted in panel A of Figure 2. Panel A clearly illustrates our two main comparative statics: (i) the subproportionality investigation involves assessing the impact of changes in r while holding p constant; and (ii) the risk-tolerance/risk-aversion investigation involves assessing the impact of changes in p while holding r constant.

Alternatively, using (q_M, q_H) notation, where $q_M = r$ and $q_H = pr$, one can visualize our design as depicted in panel B of Figure 2. In this panel, each p defines a ray from the origin, and thus the subproportionality investigation involves assessing the impact of moving along one of these rays. In contrast, each r defines a vertical column, and thus the risk-tolerance/risk-aversion investigation involves assessing the impact of moving down a column.



(a) (p, r) parameter space

(b) (q_M, q_H) parameter space, where $q_M = r$ and $q_H = pr$

Figure 2: Parameter space representations.

2 MEASURES AND LINKS TO UNDERLYING THEORIES

2.1 Measures and Comparative Statics

In our experiment, for a fixed H, we elicit *m-valuations* for a variety of (p, r) combinations. Specifically, we elicit $m(p, r)$ such that

$$(m(p, r), r) \sim (H, pr).$$

While we sometimes analyze $m(p, r)$ directly, we more often analyze the implied risk premium. A risk premium would typically be measured in terms of the expected value that a person is giving up to reduce risk, which here would be $prH - rm(p, r)$. In order to put this on the same scale as our response variable, we consider a *normalized risk premium*

$$RP(p, r) \equiv pH - m(p, r).$$

Our main analysis will focus on three types of results.

(1) First, we will do a simple characterization of when people are risk-averse versus risk-tolerant as a function of (p, r). In other words, we assess when $RP(p, r)$ is positive (meaning people are risk-averse) or negative (meaning people are risk-tolerant).

(2) Second, we study the impact on $RP(p, r)$ of changing r while holding p constant. This comparative static permits a model-free test of subproportionality. In particular, for a given (p, r), $m(p, r)$ is such that $(m(p, r), r) \sim (H, pr)$. If we then consider some $r' < r$, subproportionality implies $(m(p, r), r') \prec (H, pr')$, which in turn implies $m(p, r') > m(p, r)$. In other words, global subproportionality would imply that $m(p, r)$ is globally decreasing in r. In contrast, global superproportionality would imply that $m(p, r)$ is globally increasing in r. And of course people could be locally subproportional in some portions of the parameter space and locally superproportional in other regions of the parameter space.

Note that it will often be useful to focus on the risk premium $RP(p, r)$ instead of $m(p, r)$. Because $RP(p, r) \equiv pH - m(p, r)$ and because pH is independent of r, the implications for the risk premium are just reversed—e.g., global subproportionality implies that $RP(p, r)$ is increasing in r, that is, as we increase r the person becomes more risk-averse.

(3) Third, we study the impact on $RP(p, r)$ of changing p while holding r constant. When $r = 1$, this comparative static is the one usually studied to provide evidence of risk tolerance for small probabilities and risk aversion for large probabilities. Here, we propose to also conduct

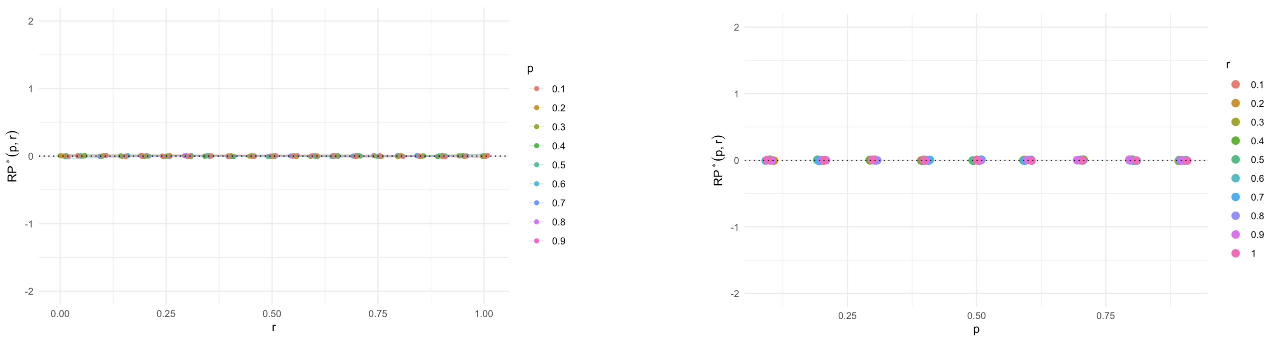
this comparative static for $r < 1$, because different models of risk preferences make different predictions for this comparative static, as we discuss below.

2.2 Links to Underlying Theories

We next describe the predictions of different models of risk preferences for our measures and comparative statics. Note that, whereas above we use $m(p, r)$ and $RP(p, r)$ to denote empirical objects, in this subsection we use $m^*(p, r)$ and $RP^*(p, r)$ to denote theoretical predictions.

2.2.1 Risk Neutrality

As a benchmark, note that a risk-neutral person who maximizes expected value would have $m^*(p, r) = pH$ and thus $RP^*(p, r) = 0$ for all (p, r), as illustrated in Figure 3b.



(a) $RP^*(p, r)$ as a function of r (b) $RP^*(p, r)$ as a function of p

Figure 3: EU Predictions with linear utility function (risk neutrality): $u(x) = x$.

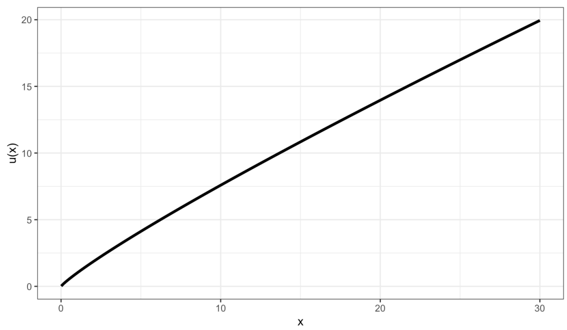
2.2.2 Expected Utility with Risk Aversion

Economists typically assume that people obey expected utility (EU) with risk aversion (i.e., with a concave utility function). If so, then people would have $RP^*(p, r) > 0$ for all (p, r). More interesting, EU with risk aversion implies specific patterns for our two main comparative statics.

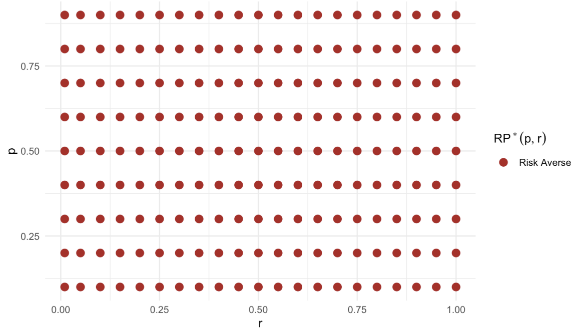
First, EU in general (i.e., for any utility function, not just a concave one) implies that, holding p constant, changes in r should have no impact on $RP^*(p, r)$. Again, this is why prior evidence on subproportionality is evidence against EU.

Second, EU with risk aversion implies that, holding r constant, $RP^*(p, r)$ should have an inverse-U shape with respect to changes in p. More precisely, at $p = 1$, $RP^*(p, r) = 0$, and as we decrease p, initially the risk premium increases, reaches a maximum, and then converges back to 0 as p approaches 0.

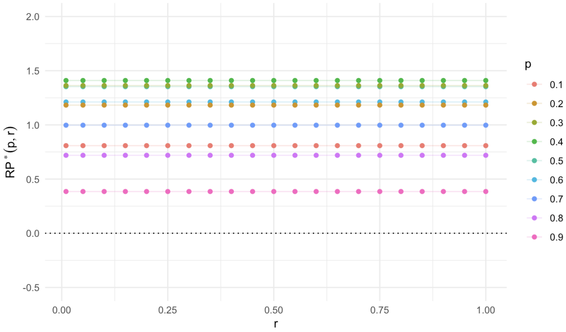
These features are illustrated in Figure 4.[3]



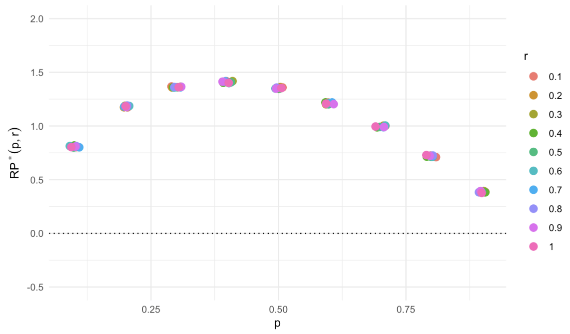
(a) Utility Function: $u = x^{\alpha}$, $\alpha = 0.88$



(b) r vs. p



(c) $RP*(p, r)$ as a function of r



(d) $RP*(p, r)$ as a function of p

Figure 4: EU Predictions with Risk Aversion

2.2.3 Probability Weighting

Our analysis is in large part motivated by existing evidence that is typically interpreted in terms of probability weighting. While probability weighting is just one aspect of prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), to highlight the implications of probability weighting, it is useful to develop predictions of a model of probability weighting and linear utility.

Suppose a person evaluates lottery (X, q) as $\pi(q)X$, where π is a probability weighting function. Several functional forms have been suggested in the literature. Most have an inverse-S shape wherein π is initially concave and then convex, with $\pi(q) > q$ for small q and $\pi(q) < q$

[3] Note that, for our domain, prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) with a linear weighting probability weighting function and a concave utility function over gains is equivalent to EU with risk aversion, and thus shares these predictions.

for large q, as depicted in panel (a) of Figure 5. Below, we refer to two functional forms, the versions suggested by Tversky and Kahneman (1992) and by Prelec (1998).

Under probability weighting, the indifference valuation $m^*(p,r)$ is given by

$$\pi(r)m^*(p,r) = \pi(pr)H \qquad \Longleftrightarrow \qquad m^*(p,r) = \frac{\pi(pr)}{\pi(r)}H.$$

Hence, the normalized risk premium is given by

$$RP^*(p,r) = pH - \frac{\pi(pr)}{\pi(r)}H = \left(p - \frac{\pi(pr)}{\pi(r)}\right)H.$$

First, consider the predictions of probability weighting for when we should observe risk aversion versus risk tolerance. Note that

$$RP^*(p,r) > 0 \qquad \Longleftrightarrow \qquad p > \frac{\pi(pr)}{\pi(r)} \qquad \Longleftrightarrow \qquad \frac{\pi(r)}{r} > \frac{\pi(pr)}{pr}.$$

Note that, for any $q \in (0,1]$, $\frac{\pi(q)}{q}$ is the slope of the line segment between the origin and the point $(q, \pi(q))$, or equivalently it is the average slope of $\pi(q)$ between $\pi(0)$ and $\pi(q)$. Given an inverse-S-shaped probability weighting function as in panel (a) of Figure 5, $\frac{\pi(q)}{q}$ starts large, decreases with q up to some $\bar{q}$, and then increases with q up to $q = 1$. In addition, $lim_{q\to 0}\frac{\pi(q)}{q} > \frac{\pi(1)}{1}$.

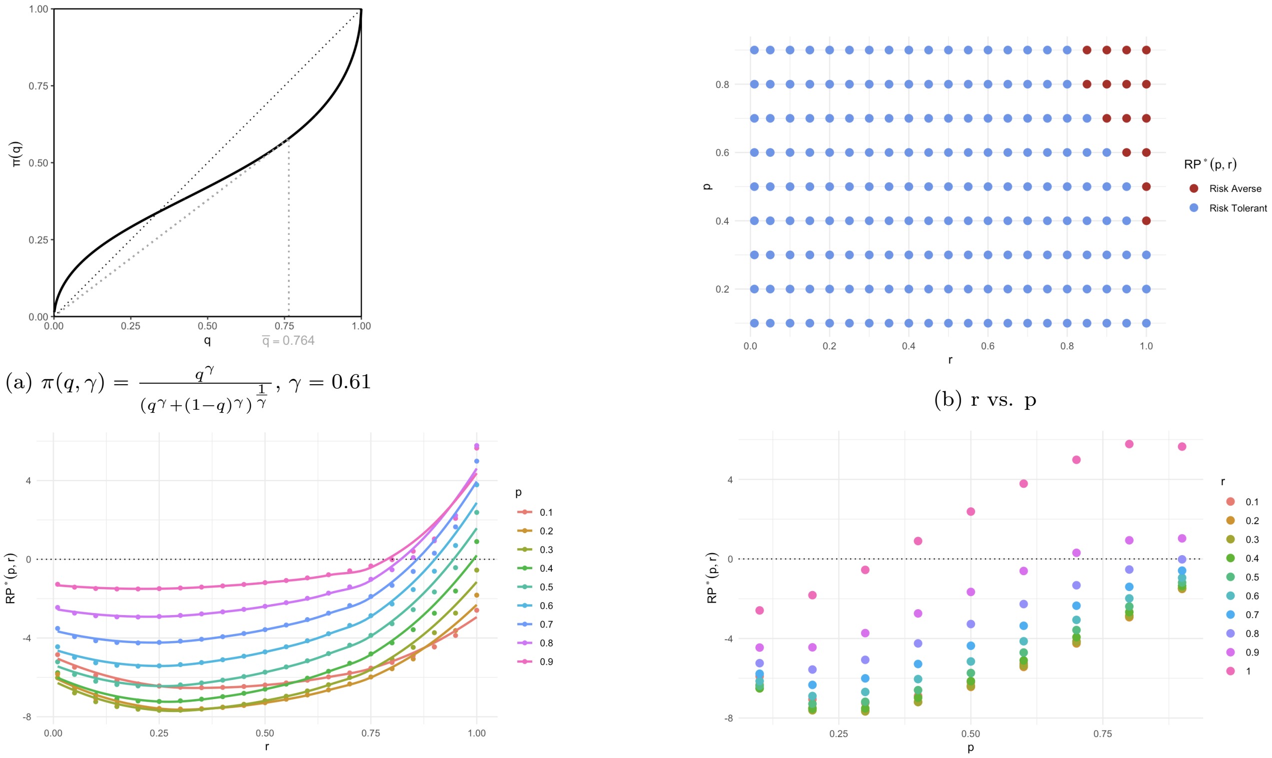
Given this structure of π, the model predicts risk aversion only if $r > \bar{q}$ and p is sufficiently close to 1; otherwise, the model predicts risk tolerance. This pattern is illustrated in panel (b) of Figure 5.

Next, consider the predictions for how $RP^*(p,r)$ varies with r while holding p constant, that is, the subproportionality test. Given that $m^*(p,r) = \frac{\pi(pr)}{\pi(r)}H$, local subproportionality holds if the probability weighting function π is such that $\frac{\pi(pr)}{\pi(r)}$ gets larger as r gets smaller, whereas local superproportionality holds if $\frac{\pi(pr)}{\pi(r)}$ gets smaller as r gets smaller. It turns out that local sub- versus superproportionality differs for some of the prominent functional forms in the literature. For instance, the Prelec (1998) functional form exhibits global subproportionality (which is an axiom in his analysis). In contrast, the Tversky and Kahneman (1992) functional form exhibits local subproportionality for r close to 1, but regions of local superproportionality for r small, as illustrated in panel (c) of Figure 5. Note, however, that for each p, $RP(p,1) > RP^*(p,r)$ for all r, and thus the Tversky and Kahneman (1992) functional form predicts the classic common ratio effect.

Finally, consider the predictions for how $RP^*(p,r)$ varies with p while holding r constant. Note that

$$\frac{d[RP^*(p,r)]}{dp} = \left(1 - \frac{r\pi'(pr)}{\pi(r)}\right) H > 0 \qquad \Longleftrightarrow \qquad \frac{\pi(r)}{r} > \pi'(pr)$$

Hence, for an inverse-S-shaped $\pi(q)$, if $r < \bar{q}$ then $RP^*(p,r)$ is U-shaped. In contrast, for $r > \bar{q}$, as p declines, the risk premium initially increases and then decreases, and eventually becomes U-shaped once it becomes negative. These patterns are illustrated in panel (d) of Figure 5.



(a) $\pi(q,\gamma) = \frac{q^\gamma}{(q^\gamma+(1-q)^\gamma)^{\frac{1}{\gamma}}}$, $\gamma = 0.61$

(b) r vs. p

(c) $RP^*(p,r)$ as a function of r

(d) $RP^*(p,r)$ as a function of p

Figure 5: PT Predictions with Median Parameter Estimate for π from Tversky and Kahneman (1992), and linear utility function.

2.2.4 Probability Weighting with a Concave Value Function

In most applications of prospect theory applied to binary lotteries, an inverse-S-shaped probability weighting function is combined with a concave value function. If so, then the predictions would reflect a combination of the predictions of the previous two subsections. Concavity of utility will tend to expand the region of risk aversion in Figure 5 panel (b) and increase the level of $RP^*(p, r)$ in panels (c) and (d).

2.2.5 Upside Potential

As we describe more in Section 4, in pilot data (with a slightly different design—see Section 3) we observe a particular pattern: there seems to exist a p' such that for all r we observe risk aversion ($RP(p, r) > 0$) for $p > p'$ and risk tolerance ($RP(p, r) < 0$) for $p < p'$. This pattern is inconsistent with EU with risk aversion and with typical functional forms for probability weighting. However, it turns out that it can be consistent with the model of upside potential proposed by McGranaghan et al. (2024b). Because this pattern might arise in our actual data, we also delineate the predictions of this model here.

According to upside potential, a person evaluates lottery (X, q) as $qX + q^2\kappa(X)$, where κ is an upside-potential function assumed to be monotonically increasing. Hence, the indifference valuation $m^*(p, r)$ is given by

$$rm^*(p, r) + r^2\kappa(m^*(p, r)) = prH + (pr)^2\kappa(H) \tag{2.1}$$

Note that

$$\kappa(pH) > p^2\kappa(H) \qquad \Longleftrightarrow \qquad r(pH) + r^2\kappa(pH) > prH + (pr)^2\kappa(H).$$

Given that $rm + r^2\kappa(m)$ is increasing in m, it follows that $m^*(p, r) < pH$ and thus $RP^*(p, r) > 0$. Analogously, $\kappa(pH) < p^2\kappa(H)$ implies $m^*(p, r) > pH$ and thus $RP^*(p, r) < 0$. In other words, whether a person exhibits risk aversion or risk tolerance for a particular (p, r, H) combination depends on how their $\kappa(pH)$ compares to their $p^2\kappa(H)$. Note that r does not impact this condition, and thus a first implication of upside potential is that the sign of $RP^*(p, r)$ should be unchanged as we vary r.

Using their data, McGranaghan et al. (2024b) estimate an S-shaped κ function, and they further demonstrate how an S-shaped κ function might naturally generate the existence of a $\bar{p}$ such that $\kappa(pH) < p^2\kappa(H)$ for $p < \bar{p}$ and $\kappa(pH) > p^2\kappa(H)$ for $p > \bar{p}$. To see this, note that for any $z \in (0, H)$, if $\kappa(z) > \left(\frac{z}{H}\right)^2 \kappa(H)$, then $\kappa(pH) > p^2\kappa(H)$ for $p = \frac{z}{H}$, and if $\kappa(z) < \left(\frac{z}{H}\right)^2 \kappa(H)$, then $\kappa(pH) < p^2\kappa(H)$ for $p = \frac{z}{H}$. Panel (a) of Figure 6 illustrates how an S-shaped κ function can naturally generate a unique $\bar{z}$ such that $\kappa(z) < \left(\frac{z}{H}\right)^2 \kappa(H)$ for $z < \bar{z}$ and $\kappa(z) > \left(\frac{z}{H}\right)^2 \kappa(H)$ for $z > \bar{z}$. Defining $\bar{p} \equiv \frac{\bar{z}}{H}$, it follows that $\kappa(pH) < p^2\kappa(H)$ for $p < \bar{p}$

and $\kappa(pH) > p^2\kappa(H)$ for $p > \bar{p}$.

Panel (b) of Figure 6 illustrates how such a κ function would imply that the person is risk-averse ($RP^*(p,r) > 0$) for any $p > \bar{p}$ and risk-tolerant ($RP^*(p,r) < 0$) for any $p < \bar{p}$ (regardless of r).

Next, consider the predictions for how $RP^*(p,r)$ varies with r while holding p constant, that is, the subproportionality test. Totally differentiating equation 2.1 with respect to r yields

$$m^*(p,r) + 2r\kappa(m^*(p,r)) + \left[r + r^2\kappa'(m^*(p,r))\right]\frac{\partial m^*(p,r)}{\partial r} = pH + 2rp^2\kappa(H)$$

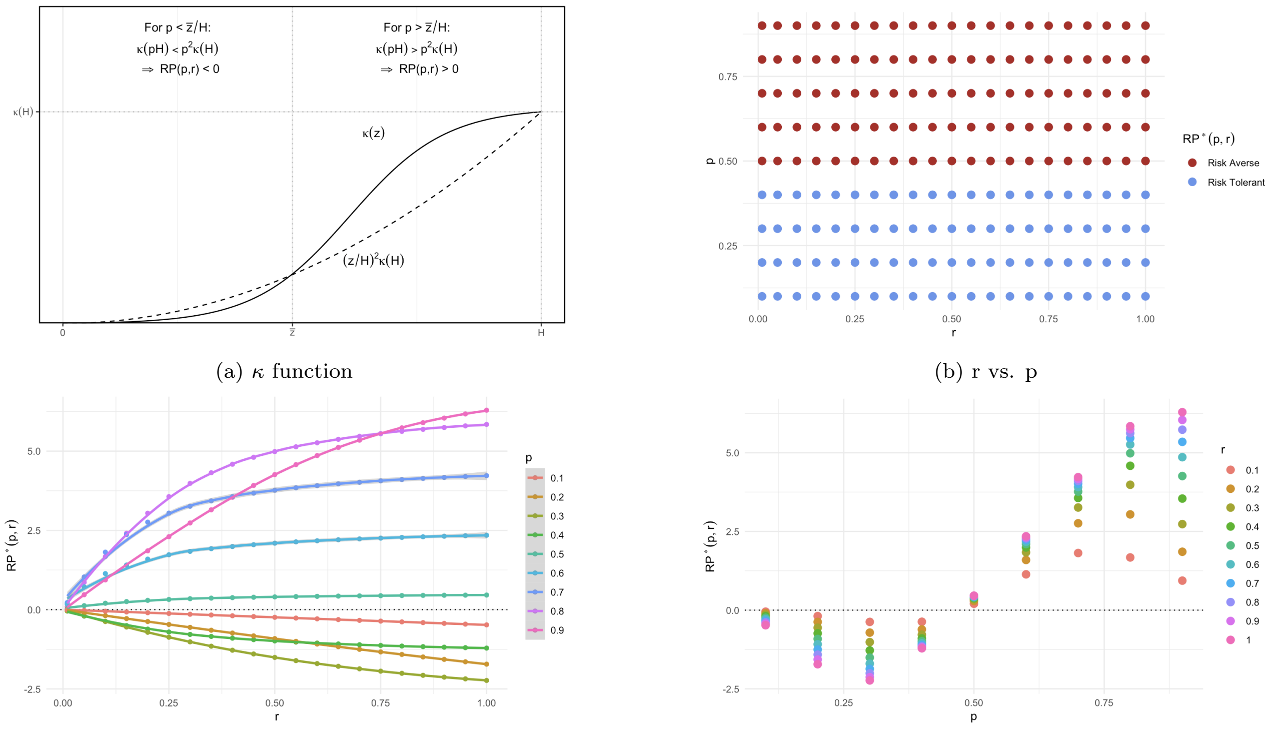
or

$$\frac{\partial m^*(p,r)}{\partial r} = \frac{(pH - m^*(p,r)) - 2r(\kappa(m^*(p,r)) - p^2\kappa(H))}{r + r^2\kappa'(m^*(p,r))}$$

Whenever $RP^*(p,r) > 0$ and thus $pH > m^*(p,r)$ (since $RP^*(p,r) = pH - m^*(p,r)$), equation 2.1 implies $pH - m^*(p,r) = r(\kappa(m^*(p,r)) - p^2\kappa(H)) > 0$, and thus $\frac{\partial m^*(p,r)}{\partial r} < 0$. An analogous argument yields that $RP^*(p,r) < 0$ implies $\frac{\partial m^*(p,r)}{\partial r} > 0$.

Hence, upside potential makes the following combined prediction: For any p such that $\kappa(pH) > p^2\kappa(H)$, the person will be risk-averse ($RP^*(p,r) > 0$) and globally subproportional (smaller r implies smaller risk aversion); and for any p such that $\kappa(pH) < p^2\kappa(H)$, the person will be risk-tolerant ($RP^*(p,r) < 0$) and globally superproportional (smaller r implies smaller risk tolerance). Finally, if an S-shaped κ function generates a $\bar{z}$ and thus a $\bar{p} \equiv \frac{\bar{z}}{H}$, as in panel (a) of Figure 6, then the former holds for $p > \bar{p}$ while the latter holds for $p < \bar{p}$. Panel (c) of Figure 6 illustrates that case.

Finally, consider the predictions for how $RP^*(p,r)$ varies with p while holding r constant. Here, the predictions of upside potential are less clear. However, for the case where an S-shaped κ function generates a $\bar{p}$ as in panel (a) of Figure 6, we know that $RP^*(p,r)$ must transition from being positive to negative as p crosses $\bar{p}$, although it need not be monotonic on either side. Panel (d) of Figure 6 illustrates predictions associated with the specific κ function from panel (a).



(a) κ function

(b) r vs. p

(c) $RP^*(p,r)$ as a function of r

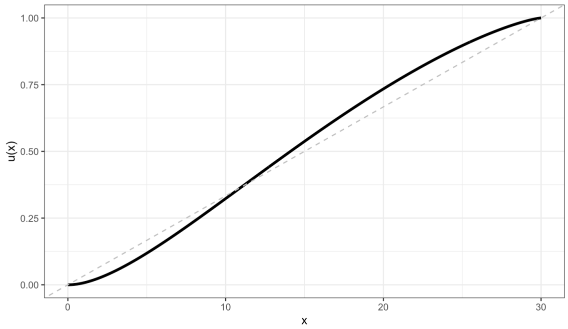
(d) $RP^*(p,r)$ as a function of p

Figure 6: Upside Potential Predictions

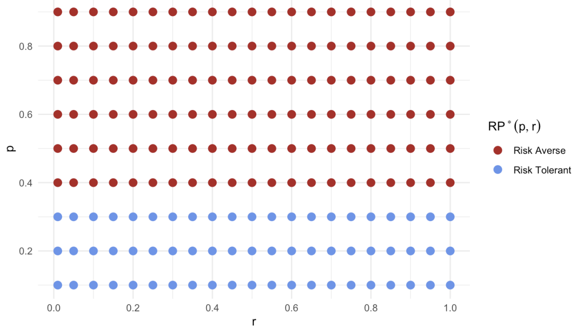
2.2.6 EU with an S-Shaped Utility Function (or PT with an S-Shaped Value Function)

Again, in pilot data we observe a pattern of risk aversion ($RP(p,r) > 0$) for $p > p'$ and risk tolerance ($RP(p,r) < 0$) for $p < p'$ for some $p' \in (0,1)$. The key part of upside potential that explains this pattern is having an S-shaped κ function. Of course, one could also explain this pattern under EU with an S-shaped utility function (or under prospect theory with linear weighting and an S-shaped value function, which for binary lotteries is equivalent to EU with an S-shaped utility function).

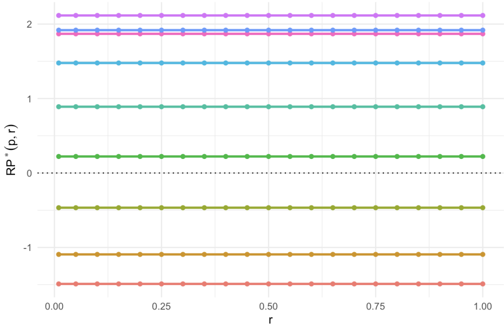
Figure 7 illustrates this possibility. Panel (a) depicts an S-shaped utility function that has a unique $\bar{x} \in (0,H)$ such that $u(x) = \frac{\bar{x}}{H}u(H)$. Letting $\bar{p} \equiv \frac{\bar{x}}{H}$, it follows that $u(x) < pu(H)$ for $p < \bar{p}$ and $u(x) > pu(H)$ for $p > \bar{p}$. Panels (b) and (d) of Figure 7 depict patterns analogous to those under upside potential. However, panel (c) of Figure 7 illustrates the key difference relative to upside potential, because EU for any utility function implies no sub- or superproportionality, that is, that $RP^*(p,r)$ is independent of r.



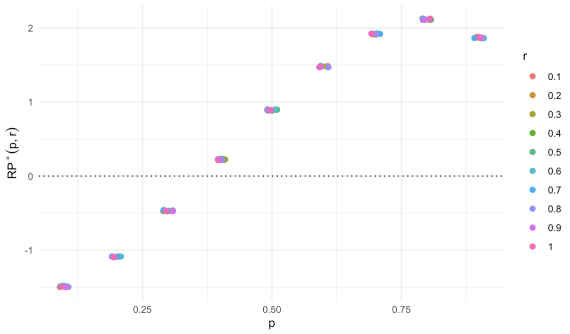
(a) $u(x) = \exp\left(-\beta\left(-\ln\left(\frac{x}{H}\right)\right)^{\alpha}\right)$ where $\alpha = 1.3$ and $\beta = 1$



(b) r vs. p



(c) $RP*(p, r)$ as a function of r



(d) $RP*(p, r)$ as a function of p

Figure 7: EU Predictions with inverse s shaped utility function.

3 EXPERIMENTAL DESIGN

We collect m-valuations for 189 different (p, r) combinations, specifically, by considering nine values of p and 21 values of r. Each subject provides m-valuations for 25 different (p, r) combinations, with five of those collected twice. Thus, each subject provides a total of 30 m-valuations. The algorithm used to generate the set of (p, r) for each subject is described in Section 3.2.

The experiment begins with an instruction phase where participants go through practice tasks, followed by comprehension and attention checks. They then complete their 30 m-valuations, with breaks occurring after tasks 4, 8, 16, 20, 24, and 28, during which they search for a camouflaged animal in a picture. After completing all valuations, participants answer two quiz questions, which allow us to assess their understanding. Finally, we determine whether they qualify for a bonus payment; if they do, we calculate the amount and inform them, and if not, we notify them that they will receive only the participation fee.

3.1 Valuation Tasks

For a fixed $H = \$30$, for a specific (p, r), we elicit the valuation m such that

$$(m, r) \sim (\$30, pr)$$

To elicit this m, we will use multiple-price lists with the following structure:

Valuation Task:

Option A		**Option B**
pr chance of \$30 $1 - pr$ chance of \$0	OR	r chance of \$0 $1 - r$ chance of \$0
pr chance of \$30 $1 - pr$ chance of \$0	OR	r chance of \$0.50 $1 - r$ chance of \$0
pr chance of \$30 $1 - pr$ chance of \$0	OR	r chance of \$1.50 $1 - r$ chance of \$0
...	...	...
pr chance of \$30 $1 - pr$ chance of \$0	OR	r chance of \$29.50 $1 - r$ chance of \$0
pr chance of \$30 $1 - pr$ chance of \$0	OR	r chance of \$30 $1 - r$ chance of \$0

Each valuation task requires participants to select an option for each row. To simplify the process, they only need to click twice: once for Option A and once for Option B. Clicking on Option A in a particular row automatically populates all rows above it with Option A, while clicking on Option B populates all rows below it with Option B. Participants can adjust their selections as many times as they wish, but all rows must be populated before they can submit a list. This interface ensures that there is always a single switch from Option A to Option B. The participant's valuation, $m(p, r)$, is coded to be the midpoint between the Option B positive outcomes of the last row where Option B is not chosen and the first row where it is chosen.

Note that we have structured the multiple price list such that censored observations—that is, choosing Option B in the first row (and thus Option B in all rows) or Option A in the last row (and thus Option A in all rows)—reflect violations of first-order stochastic dominance. Such observations would seem to be an indicator of low data quality, and indeed we shall use them as such (see Section 4.1). But we will often want to present results using all the data; for such analyses, we code $m(p, r) = 30.50$ if a subject selects Option A in all rows, and we code $m(p, r) = -0.50$ if a subject selects Option B in all rows.

While our primary analysis will use $m(p, r)$ as coded above, additional robustness analyses will be presented that account for the interval nature of the data by using interval regressions.

3.2 Task Selection

Again, we collect m-valuations for 189 different (p, r) combinations, specifically, by considering nine values of p and 21 values of r:

$$p \in \{0, 1, 0.2, 0.3, ..., 0.9\} \qquad \text{and} \qquad r \in \{0.01, 0.05, 0.10, 0.15, ..., 0.95, 1\}$$

Each subject provides m-valuations for 25 different (p, r) combinations, selected using the following algorithm:

1. We first select 5 values of p: We divide the 9 values of p into three groups: the bottom 3, the middle 3, and the top 3. We then select one randomly from each group. Next, we divide the remaining 6 values into two groups: the 3 smaller and the 3 larger ones. We then select one randomly from each group.

2. We next choose 5 values of r for each of those p: We divide the 21 values of r into three groups: the bottom 7, the middle 7, and the top 7. We then select one randomly from each group, and use these three r values for all five values of p. Next, we divide the remaining 18 values into two groups: the 9 smaller and the 9 larger ones. For each value of p independently, we choose another 2 values of r, one from each of these groups.

With this algorithm, each subject will face five p values, and for each of these p values they will face five r values—thus permitting variation at the individual level to investigate how $m(p, r)$ depends on r while holding p constant. Analogously, each subject will face three r values for which they also face all five p values—thus permitting variation at the individual level to investigate how $m(p, r)$ depends on p while holding r constant.

Of the 25 m-valuations described above, five are collected twice. These are selected randomly without replacement. Thus, each subject provides a total of 30 m-valuations. These 30 tasks are presented in random order subject to the constraint that two elicitations of the same m-valuation cannot occur within three tasks of each other.

Figure 8 shows a simulation of this selection process, where the red dots represent valuations that are elicited once, and the blue dots represent valuations that are elicited twice.

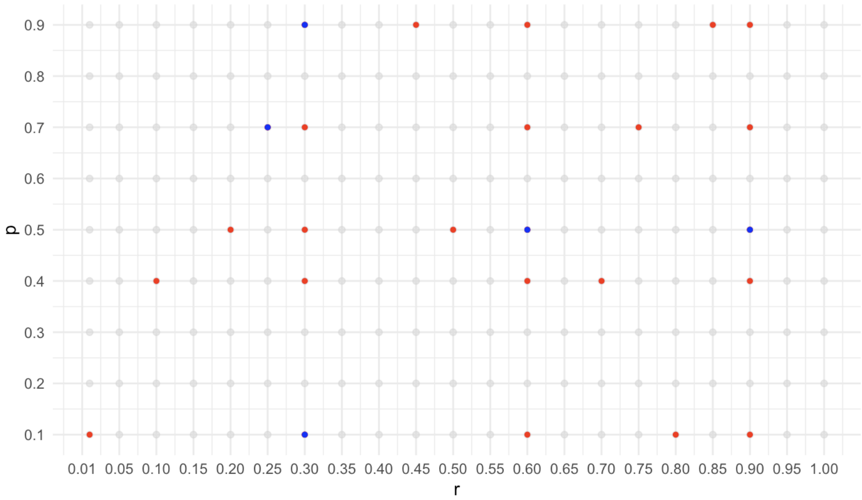


Figure 8: Simulated selection of parameters for one subject (red dots represent valuations elicited once, blue dots represent valuations elicited twice

3.3 Sample Size and Power

We propose to conduct our study with 800 total subjects. Deploying this selection process outlined above for 800 subjects, provides adequate coverage of our (p, r) space with approximately 105 observations per (p, r) combination. We show this with a simulation in Figure 9. Checking the distribution of observations across (p, r) combinations, it appears close to uniform as expected.

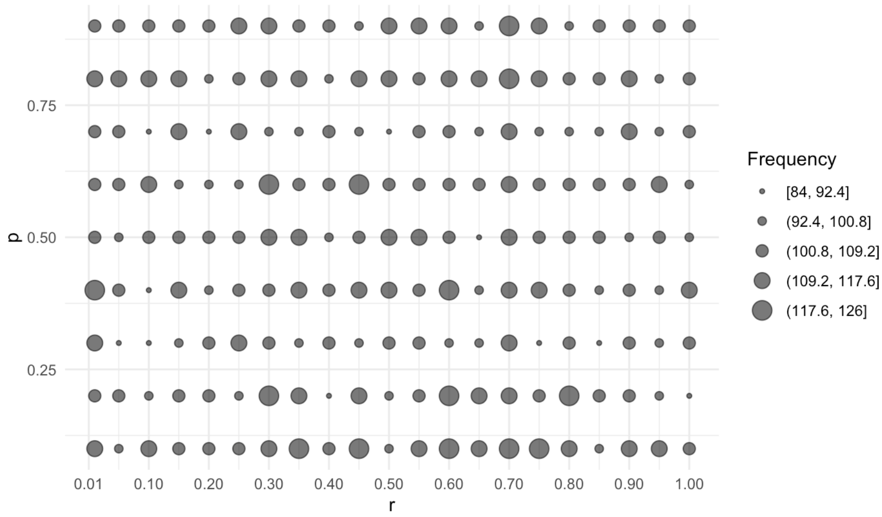


Figure 9: Simulated selection of parameters for 800 subjects.

Within our pilot data, we found that elicitations of $m(p, r)$ generally had standard deviations on the order of \$7. Our objective of collecting approximately 100 observations for each (p, r), therefore, permits the detection of $RP(p, r) \equiv m(p, r) - pH$ of around \$2 with 80% power in a single mean test. Similarly, group sizes of approximately 100 permits detection of differences, $m(p, r) - m(p', r')$, of around \$2.75 with 80% power in a test of equal means. Examination of subproportionality and risk-tolerance/risk-aversion implicate both types of comparisons.

3.4 Recruitment and Payment

Our study will be conducted on the online platform Prolific.com. Subjects will be restricted to be from the United States or Western Europe, have completed at least high school education, be substantially experienced with the Prolific platform, and have high prior approval rating. We also exclude all subjects who participated in the pilot for this experiment.

All participants who complete the study receive a \$5 participation fee, and one in five is randomly selected for a bonus payment. If chosen, either a valuation task or a quiz question is randomly selected. If a valuation task is chosen, a random row from that task is drawn, and the lottery selected in that row is played and paid accordingly. If a quiz question is selected, participants receive \$5 for a correct answer and \$0 otherwise. The comprehension question and attention check do not qualify for the bonus payment, as participants must answer them correctly to proceed in the experiment.

4 ANALYSIS

We propose to analyze the data at both the aggregate and individual level. To illustrate our approach, we conduct our proposed analytical steps on pilot data collected in the Fall of 2024. The pilot was conducted with 561 subjects, 250 of which completed 30 valuations and 311 of which completed 34 valuations, yielding a total of 18,074 observations. The algorithm used in the pilot to generate questions for each subject was somewhat different than the algorithm described in Section 3 that we will use for our primary data. As a result, the pilot data are not ideal for assessing the main comparative statics that we describe in Section 2. Nonetheless, they provide an initial sense of what we might find.

The analysis outlined in this section is what we consider our primary analysis.

4.1 Data Quality

We will begin our analysis by examining data quality. Our general plan is: (i) We will conduct the five data checks below to obtain an overall assessment of the quality of the data using the benchmarks that we describe below. (ii) Assuming the overall assessment of the data looks reasonable, we will conduct our primary analysis on the entire dataset. (iii) As a robustness check, we will re-run our primary analysis on a subsample selected to be more likely to be high-quality data, where the selection criteria are described at the end of this subsection.

If the overall assessment of the data looks problematic relative to the benchmarks described below, we will check to see whether at least 60% of the data are high-quality according to the selection criteria described below. If they are, we will conduct our primary analysis on the subsample of high-quality data. However, we will still report in an appendix results from conducting our primary analysis on the entire dataset.

For our overall assessment of data quality, we will conduct the following five checks:

1. What proportion of valuation observations are censored by the multiple-price list, indicating violations of first-order stochastic dominance?

   Given the structure of our multiple price lists, censored observations—that is, choosing Option B in the first row (and thus Option B in all rows) or Option A in the last row (and thus Option A in all rows)—reflect violations of first-order stochastic dominance. Such observations would seem to be an indicator of low data quality.

   We will assess this one in two ways. First, we will check what proportion of all observations are censored. Second, we will check how many subjects have a large proportion of their observations censored.

In our pilot data, 10% of all observations are censored; we consider this a reasonable benchmark for satisfactory data quality on this dimension, and will judge our final data set against this benchmark. Second, Figure 10 presents for our pilot data a histogram of the proportion of censored observations per subject. We shall take a proportion larger than 40% to be a signal of low data quality, which in the pilot data includes roughly 7% of subjects; we consider 5-10% of subjects failing this criterion to be a reasonable benchmark for satisfactory data quality on this dimension, and will judge our final data set against this benchmark.

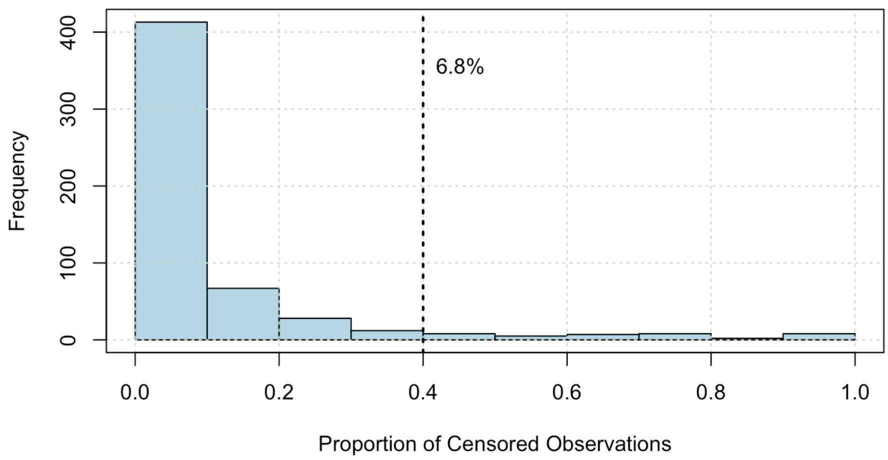


Figure 10: Proportion of censored observations per subject

2. What proportion of subjects exhibit little variation in their experimental responses, indicating a lack of attentiveness to the experimental parameters?

   For our pilot data, Figure 11 presents a histogram for the number of each subject's choices that differ from that subject's modal response. When this value is zero, a subject has no variation in their responses; roughly 1% of subjects in our pilot data have zero variation in their experimental responses.

   In our experiment, subjects respond to 30 questions. However, they come in five sets of five where EU would predict the same response within each set. In addition, subjects face five repeats. Given all this, we shall take subjects having fewer than 10 responses that differ from their modal response to be a signal of low data quality. In our pilot data, roughly 4% of subjects fail this criterion; we consider 5-10% of subjects failing this criterion to be a reasonable benchmark for satisfactory data quality on this dimension, and will judge our final data set against this benchmark.

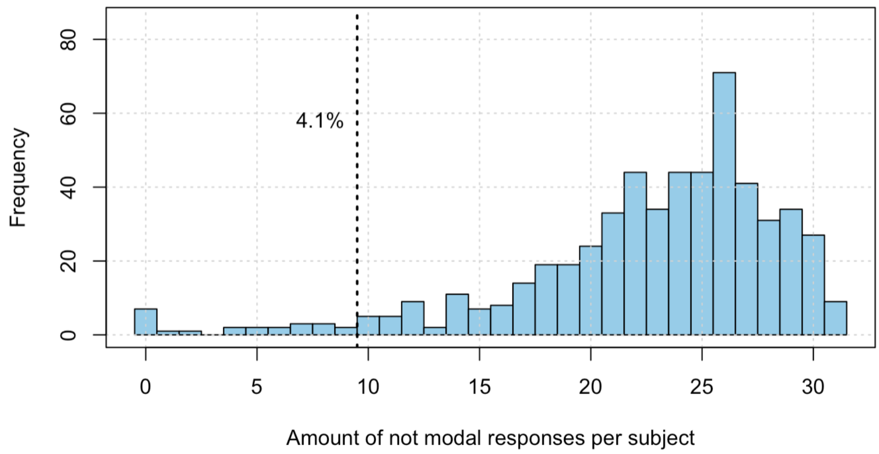


Figure 11: Histogram of number of observations that are not the modal responses per subject.

3. Using our (q_M, q_H) notation instead of our (p, r) notation, a person's valuation m should satisfy the indifference condition $(m, q_M) \sim (H, q_H)$. Hence, monotonicity in preferences require that a person's valuations be decreasing in q_M and increasing in q_H. Hence, for our third check, for each subject we regress m on q_H and q_M, and assess what proportion of subjects have an incorrect signs for these coefficients (i.e., they react in the wrong direction).

   We run these regressions in our pilot data; Figure 12 presents histograms for the two coefficients. It turns out that 3.6% of participants have the wrong sign for q_H, and 9.3% of participants have the wrong sign for q_M. We consider having only 5-10% of participants having the wrong sign for each coefficient to be a satisfactory indicator of data quality, and will judge our final data set against this benchmark.

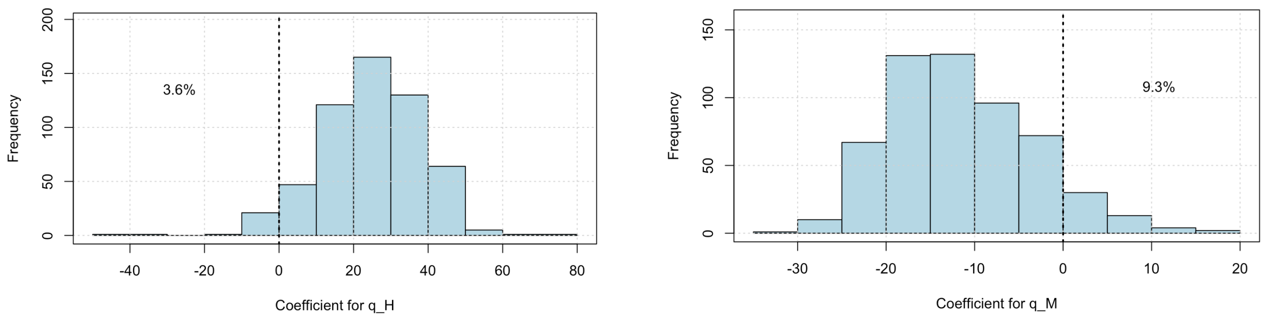


Figure 12: Histogram of the coefficients of individual regressions: $m \sim q_H + q_M$.

4. For each subject, our data contain multiple observations of the same valuations, separated by at least three other valuations. As another check, we will assess the correlation between multiple elicitations of the same valuation.

   Regressing repetitions of the same valuation on each other with (q_M, q_H) fixed effects and standard errors clustered at the individual level delivers a regression coefficient of 0.573 (s.e. = 0.025).[4] This highly significant relationship between multiple observations indicates that though noise plays a role (i.e., the coefficient is not one), valuations have a substantial preference component. Indeed, this value suggests that approximately 57% of the variability in valuations is derived from variability in preferences. We actually feel that this correlation in the pilot data is remarkably high; we feel that a correlation in the 0.2-0.3 range is a reasonable benchmark against which to judge our final data.

5. Do we suspect responses were given by a bot rather than a person?

   In our main study, we include a button to check that the responder is not a bot; any respondent who fails this check will not be permitted into the study. Beyond this, we do not have any specific checks planned on this dimension. However, we will record mouse-tracking data, and if we discover an accepted way to use such data to screen out potential bots, we may do some such screens as part of a more exploratory analysis.

Finally, we describe the selection criteria that we will use to create a subsample that seems more likely to contain high-quality data. The selection criteria will all be done at the subject level (i.e., each subject is either included or excluded) based on three of the checks above.

[4]Note that our labeling of a valuation and its "repeat" are done randomly, so a repeat might be seen first or second. Also note that, because it is natural to assume that the variance of a valuation and its repeat are the same, the regression coefficient can be interpreted as a correlation coefficient.

First, we will exclude all subjects whose proportion of censored observations is larger than 40%. Second, we will exclude all subjects who have fewer than ten observations that differ from their modal response. Third, we will exclude all subjects whose coefficient on q_H has the the wrong (i.e., a negative) sign when we regress m on q_H and q_M.

- Note: We will not apply a similar exclusion criterion for the coefficient on q_M because our data are less well designed to estimate that coefficient. Recall that our design creates random variation in p and r. Variation in p generates variation in q_H holding q_M constant, and thus provides exactly the type of variation we need to identify the coefficient on q_H. In contrast, variation in r generates positively correlated variation in both q_M and q_H, and thus is not ideal for identifying the coefficient on q_M (indeed, under EU variation is r is predicted not to change m). Combined p and r variation does permit some identification of the coefficient on q_M, and thus we feel comfortable using this coefficient as a part of our overall assessment of data quality. But we do not feel comfortable using this coefficient at the subject level to justify including versus excluding subjects.

In our pilot data, applying these three exclusion criteria would lead to 9.5% of subjects being excluded (53), which we view as reasonable for a robustness check:

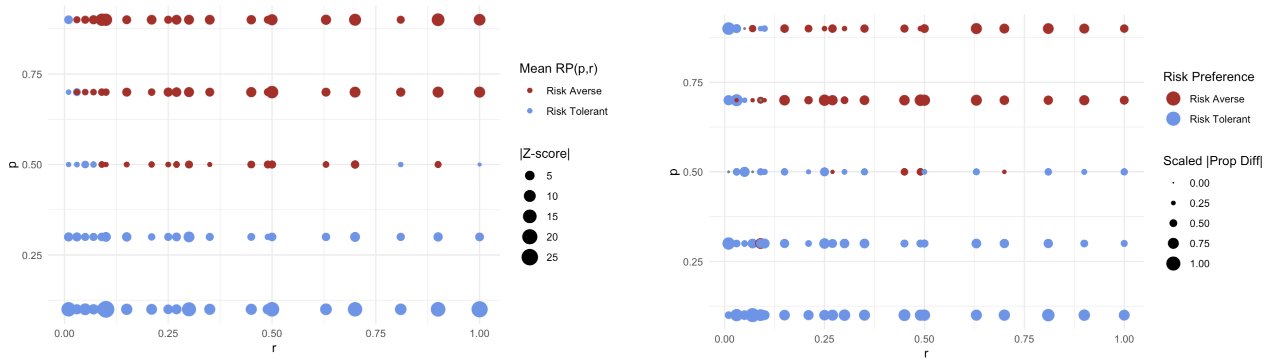
1. 39 subjects had more than 40% of their observations censored.
2. 23 subjects had fewer than ten observations that differ from their modal response.
3. 20 subjects had a negative sign in their coefficient of q_H.

Finally, while we will not use them in our overall data assessment or in our main subsample described above, responses to the two incentivized quiz questions will be used to conduct an additional robustness check. In particular, for whichever main analysis is selected according to the procedure above, we will re-run the analysis after excluding subjects who got both quiz questions incorrect, and we will report this analysis as an additional robustness check (most likely in an appendix).

4.2 Aggregate Analysis

Our aggregate analysis will begin by examining the three results outlined in Section 2.1 for both our primary analysis sample and our quality data sample following the protocols described above.

1. First, we will assess the locations of risk aversion and risk tolerance by classifying each (p, r) into the broad categories of "Risk Averse" and "Risk Tolerant". We do so by using either (i) the sample mean of $RP(p, r)$ or (ii) the proportion of $RP(p, r) > 0$ vs $RP(p, r) < 0$. The data will be presented with reference to the magnitude of the deviation from risk neutrality, either in terms of the z-score for the test against $RP(p, r) = 0$ or the difference in proportions. Panels (a) and (b) of Figure 13 present this classification conducted on our pilot data. Notable from our pilot data is that, by-and-large, risk aversion and risk tolerance appear to separate between different values of p, but are largely consistent within a p for each r.

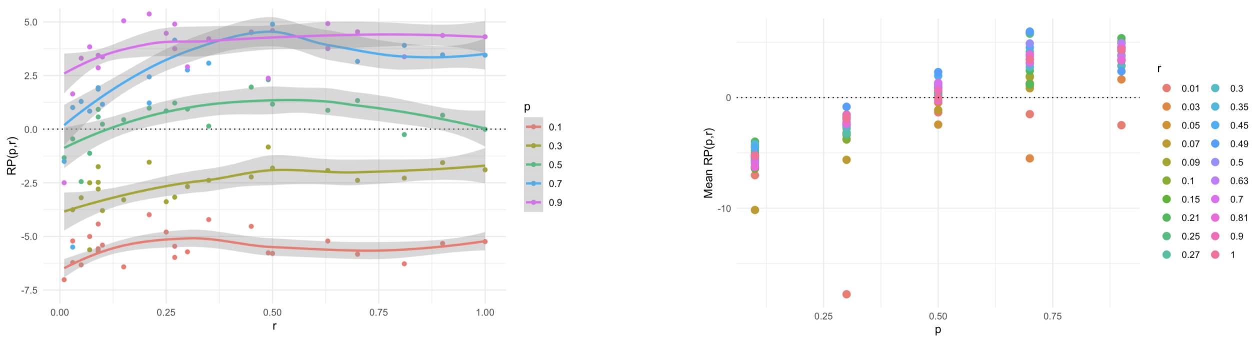


(a) Mean: Size by z-score

(b) Proportion: Size by difference in proportions.

Figure 13: Pilot Data: Risk Aversion, Risk Tolerance Classification

2. Second, we study the impact on $RP(p, r)$ of changing r while holding p constant. This comparative static permits a model-free test of subproportionality. Figure 14 panel (a) presents these data for our pilot study. Clear from the figure is that though risk premia are generally increasing with r, consistent with subproportionality, there are regions of decreasing and constant risk premia. To provide a comprehensive test for increasing or decreasing trends, we will conduct a non-parametric trend test for each p based on the aggregate data; a Kendall rank-correlation would be appropriate and the test statistic (the relative proportion of concordant vs. discordant pairs in the data) will be reported to summarize how increasing or decreasing the risk premia are for each p.



(a) r vs. $RP(p, r)$

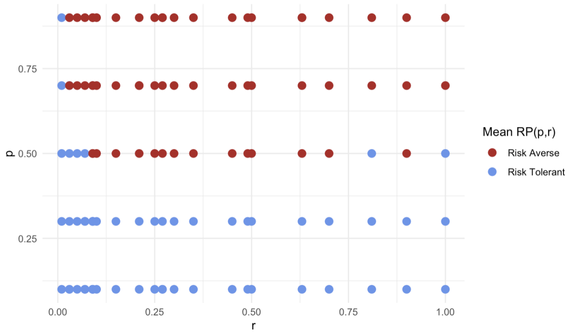
(b) p vs. $RP(p, r)$

Figure 14: Pilot Data: Subproportionality and Overweighting/Underweighting Tests

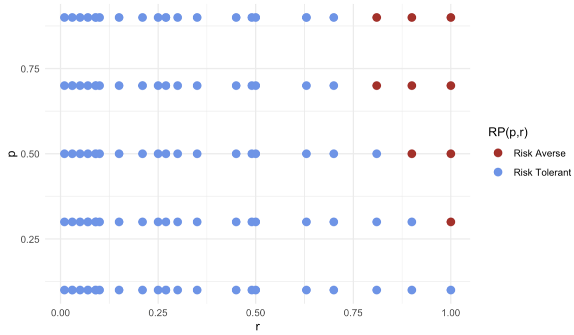
3. Third, we study the impact on $RP(p, r)$ of changing p while holding r constant. When $r = 1$ this comparative static corresponds to the standard test employed to study the risk-tolerance/risk-aversion pattern. Figure 14 panel (b) presents these data for our pilot study. It demonstrates that transition from risk tolerance to risk aversion for each p is largely consistent across values of r.

Notable from our pilot data is that by-and-large risk aversion and risk tolerance appear to separate between different values of p: lower values of p are associated with risk tolerance while higher values of p are associated with risk aversion. When $r = 1$ these data accord with the classic findings from the PT literature on the risk-tolerance/risk-aversion pattern, but elsewhere the data are markedly dissimilar from PT's predictions. Instead, the pilot data are largely consistent with predictions of upside potential which predicts consistent patterns of either risk aversion or risk tolerance for each p.

If the final study data emerge in a similar manner, we will explore the relative model fit of prospect theory and upside potential on the aggregate data. First, we will ask what is the classification error obtained by classifying every observation for each p as risk averse or risk tolerant according to its most frequent observation. Second, we will ask if there is a p that separates risk aversion from risk tolerance in the data (as there is in our upside potential simulations) and the minimal classification error obtained from classifying all points on each side according to their most frequent observation. In our pilot data both exercises yield around 8% misclassification. In contrast, classifying points based on PT estimates in-sample yields misclassification of 46% (as we see in Figure 15).



(a) Aggregate data classification



(b) In-Sample Prospect Theory Predictions

Figure 15: Pilot data vs. CPT fitted to data

4.3 Heterogeneity Analysis

The aggregate analysis largely considers behavior without attention to individual heterogeneity. We forecast studying heterogeneity in two ways.

1. If the aggregate data are similar to our pilot data and indicate general separation into regions of risk aversion for high p and risk tolerance for low p, we will examine the heterogeneity of responses within each p. One simple way to examine this to take each p in the data, and subject-by-subject calculate the proportion of risk averse minus the proportion risk tolerant observations. Figure 16 conducts this analysis on our pilot data. The data at the individual level echo that of the aggregate level, with risk tolerance (negative observations) dominating for low p and risk aversion (positive observations) dominating for high p. Also note that, for each p, roughly half of the individuals exhibit exclusively risk tolerant (-1) or risk averse (+1) observations.

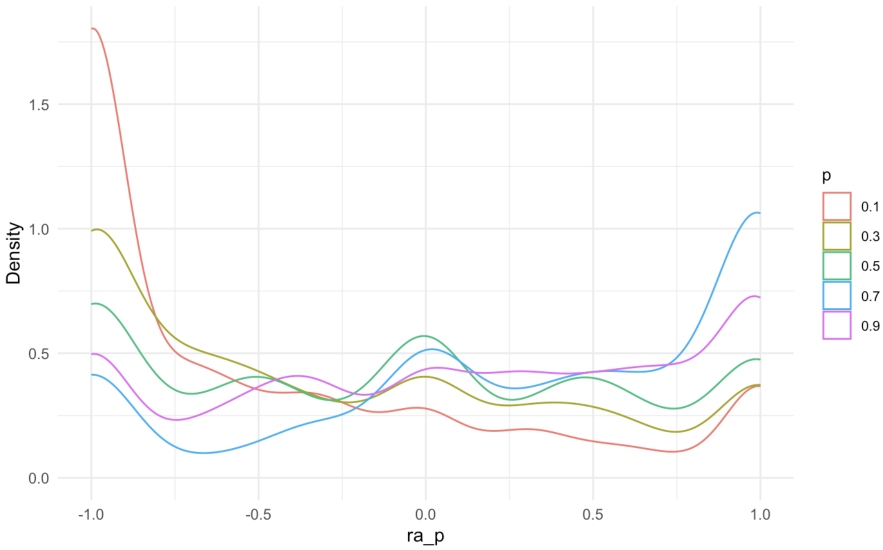


Figure 16: Heterogeneity of Risk Tolerance and Risk Aversion Across p

2. If the aggregate data indicate evidence of sub- or super-proportionality with respect to r for different values of p, then we will examine heterogeneity in sub- or super-proportionality. Our design delivers 5 values of p each with 5 different r values. For these 5 values of p we will calculate Kendall's τ as a non-parametric measure of trend. We will then investigate whether these data are similarly organized as the aggregate data Figure 17 presents an example of such an exercise showing the densities of Kendall's τ for values of p in our pilot data. For intermediate values of p, Kendall's tau is centered close to zero, while for low $p = 0.1$, its central tendency is negative and for high $p = 0.9$ its central tendency is positive.

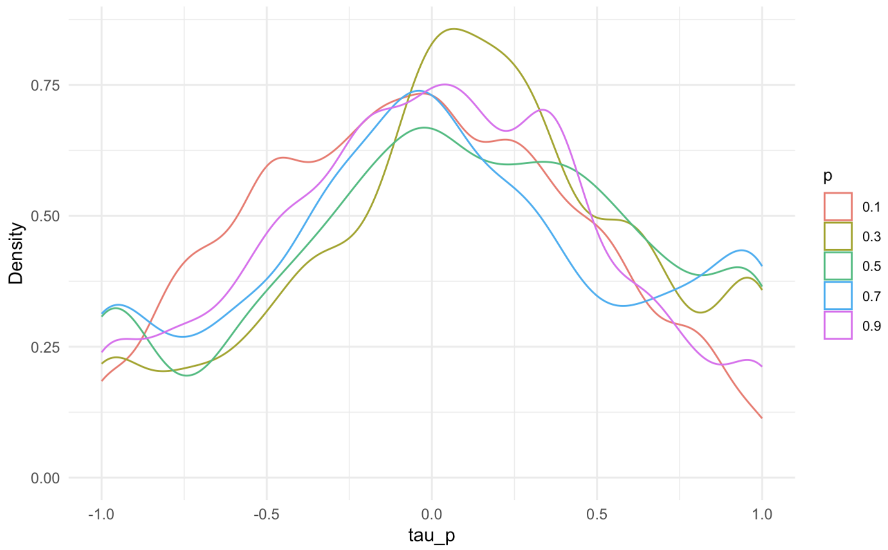


Figure 17: Individual Kendall's τ by p

The heterogeneity analysis will provide evidence on the robustness and generality of any aggregate findings.

4.4 Individual Analysis

If the aggregate data emerges in a similar fashion to our pilot data and indicates consistency with upside potential, we forecast two further individual analyses.

1. If the aggregate data indicate that there exist some value of p' such for $p > p'$ risk aversion obtains, and for $p < p'$ risk tolerance obtains, then we will conduct the classification approach described earlier at the individual level. Specifically, each subject will be classified based on best fit into one of the following four categories: (i) there exists a p' (allowed to be subject-specific) such that the person is risk-averse for $p > p'$ and risk-tolerant for $p < p'$, (ii) there exists a p' (allowed to be subject-specific) such that the person is risk-tolerant for $p > p'$ and risk-averse for $p < p'$, (iii) the person is risk-averse for all p, or (iv) the person is risk-tolerant for all p.[5] Note that category (i) corresponds to what we observe at the aggregate level; this analysis will reveal whether the average data patterns are driven by aggregating different consistent preferences (e.g., always risk-averse and always risk-tolerant).

[5] The description of this classification is in Appendix A

Figure 18 presents this analysis on our pilot data, for which $p \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$, and thus for categories (i) and (ii) we can limit attention to $p' \in \{0.2, 0.4, 0.6, 0.8\}$. We also use $p = 0$ to denote category (iii) and $p = 1$ to denote category (iv). While there does exist individuals whose behavior can best be described as always risk averse or always risk tolerant (around 45% of observations), the rest are best described by changing risk tolerance and overwhelmingly as exhibiting risk tolerance for low p and risk aversion for high p. This sort of classification is surprisingly accurate at the individual level, misclassifying on average only around 20% of observations per subject in our pilot data.

To further explore individual behavior, we will contrast the classification error obtained from the above methodology with that obtained in-sample from fitting standard PT to the data at the individual level.

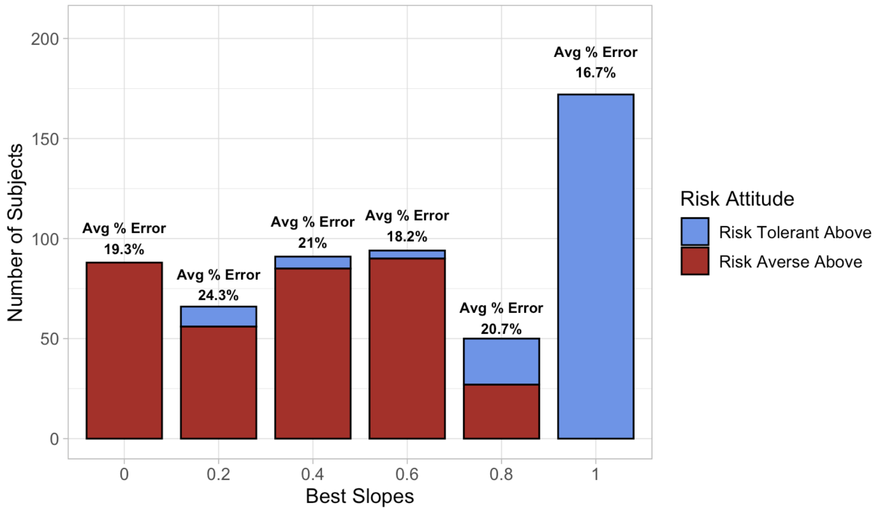


Figure 18: Histogram of best slopes to classify risk patterns.

2. If the aggregate data suggest different regions of sub- and super-proportionality for different values of p, then we we will examine whether at the individual-level there is a tendency to move from risk premia that increase with r to risk premia that decrease with r as we move across p. Following similar logic to that described above, each subject will be classified based on best fit into one of the following four categories: (i) there exists a p' (allowed to be subject-specific) such that the person's risk premium increases with r for $p > p'$ and decreases with r for $p < p'$, (ii) there exists a p' (allowed to be subject-specific) such that the person's risk premium decreases with r for $p > p'$ and

increases with r for $p < p'$, (iii) the person's risk premium increases with r for all p, or (iv) the person's risk premium decreases with r for all p.[6]

Figure 19 provides the product of such a classification exercise conducted at the individual level in our pilot data. Around 40% of subjects are best classified as consistently having risk premia that increase with r (red) or consistently having risk premia that decrease with r (blue). Among the subjects who alter their behavioral patterns as p changes, moving from risk premia that increase with r for large p to risk premia that decrease with r for low p is more frequent than the opposite (32.3 % vs. 28.3 %).

In terms of classification errors, in the final dataset, there will be five valuations for each value of p, and thus the trend for a given p is determined from 10 pairs of valuations. Since each subject provides valuations for five p values, in total this classification exercise will be based on 50 pairs of valuations. The pilot data are organized somewhat differently and there is variation across subjects in the number of pairs of observations that feed into this classification. The average misclassified pairs per subject in the pilot data is somewhat high, 38.5%.

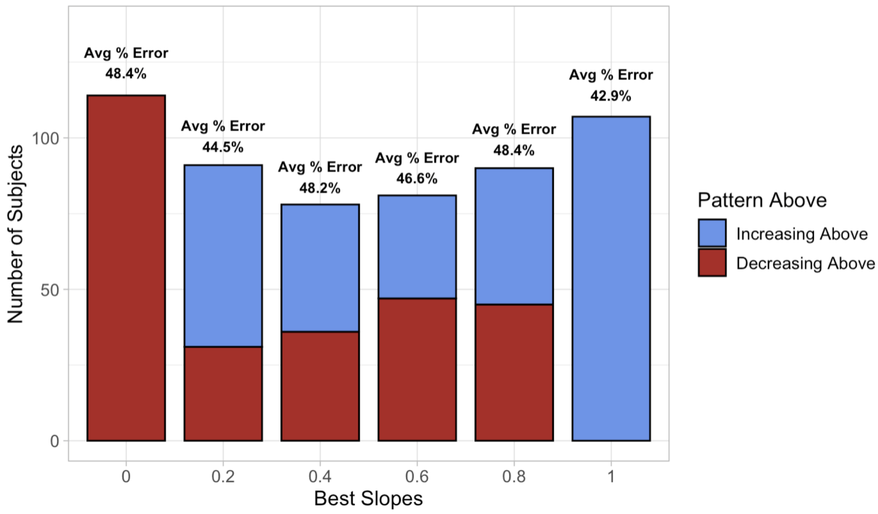


Figure 19: Histogram of best slopes to classify different regions of sub- and super-proportioanlity.

[6]The description of this classification is in Appendix B

5 POTENTIAL STRUCTURAL ANALYSIS FOR UPSIDE POTENTIAL

Given our pilot data's support for the upside potential model and prior estimations thereof (McGranaghan et al., 2024b), we may follow up the above analysis with structural estimation of upside potential. This structural analysis will yield information on the shape of κ that can be compared to the estimates of (McGranaghan et al., 2024b). The in-sample fit of these estimates can be contrasted with those derived from similarly parameterized PT models. This analysis is considered secondary and will be dependent on whether the aggregate data are suggestive of upside potential.

6 CONCLUSION

The present study focuses on constructing a more comprehensive empirical foundation for the study of subproportionality and the risk-tolerance/risk-aversion pattern. The analysis outlined above will be conducted after data collection, which is planned for Spring 2025. This document will be posted before data collection.

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APPENDIX

A Risk Aversion and Risk Tolerance by p at Individual-Level

If the aggregate data indicate that there exist some value of p' such for $p > p'$ risk aversion obtains while for $p < p'$ risk tolerance obtains, then we will conduct a classification approach at the individual level. Specifically, each subject will be classified based on best fit into one of the following four categories: (i) there exists a p' (allowed to be subject-specific) such that the person is risk-averse for $p > p'$ and risk-tolerant for $p < p'$, (ii) there exists a p' (allowed to be subject-specific) such that the person is risk-tolerant for $p > p'$ and risk-averse for $p < p'$, (iii) the person is risk-averse for all p, or (iv) the person is risk-tolerant for all p.

To do so, we use the following algorithm (and note that this algorithm treats multiple elicitations of the same valuation as two independent observations):

1. **Define the Set of p' to Evaluate**

   In our pilot data, $p \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$, and thus for categories (i) and (ii) we can limit attention to $p' \in \{0.2, 0.4, 0.6, 0.8\}$. We also use $p = 0$ to denote category (iii) and $p = 1$ to denote category (iv).

   In our final data, $p \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$, and thus for categories (i) and (ii) we can limit attention to $p' \in \{0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85\}$. We again use $p = 0$ to denote category (iii) and $p = 1$ to denote category (iv).

2. **Check for Valid p'**

   A p' is considered valid if one of the following is true:

- The majority of observations are risk-averse for $p > p'$ and the majority of observations are risk-tolerant for $p < p'$ (in which case classify that p' as tentative category (i)); or
- The majority of observations are risk-tolerant for $p > p'$ and the majority of observations are risk-averse for $p < p'$ (in which case classify that p' as tentative category (ii)).

3. **Compute the Error for Each Valid** p'
   For each valid p', the error is calculated as the total number of misclassified points:
   - If that p' is classified as tentative category (i), the error is the sum of:
     - Risk-tolerant observations for $p > p'$, plus
     - Risk-averse observations for $p < p'$.
   - If that p' is classified as tentative category (ii), the error is the sum of:
     - Risk-averse observations for $p > p'$, plus
     - Risk-tolerant observations for $p < p'$.
4. **Choose the Best** p'
   Among all valid p' for that subject, choose the p' with the lowest classification error (there could be more than one; if so, select one at random).
5. **Handle Cases Where No Valid** p' **is Found**
   If no valid p' is found, then among all observations for that subject:
   - If the majority are risk-averse, select $p' = 0$ (category (iii)).
   - If the majority are risk-tolerant, select $p' = 1$ (category (iv)).
   - If there are an equal number of risk-tolerant and risk-averse observations, randomly select one of $p' = 0$ or $p' = 1$ to include in the results.

B Sub- vs. Superproportionality by p at Individual-Level

If the aggregate data suggest different regions of sub- and super-proportionality for different values of p, then we will conduct a classification approach at the individual level. Specifically, each subject will be classified based on best fit into one of the following four categories: (i) there exists a p' (allowed to be subject-specific) such that the person's risk premium increases with r for $p > p'$ and decreases with r for $p < p'$, (ii) there exists a p' (allowed to be subject-specific) such that the person's risk premium decreases with r for $p > p'$ and increases with r for $p < p'$, (iii) the person's risk premium increases with r for all p, or (iv) the person's risk premium decreases with r for all p.

To do so, we use the following algorithm (and note that this algorithm treats multiple elicitations of the same vaulation as two independent observations):

1. **Define the Set of p' to Evaluate**
   This step is identical to the classification approach in Appendix A.

2. **Perform Relevant Pairwise Comparisons**
   For each p where a subject has observations, order the n associated r values such that $r_1 < r_2 < ... < r_n$. Then compute for each (i, j) with $i < j$:

   - If $RP(p, r_i) < RP(p, r_j)$, then let $s(p; r_i, r_j) = +1$.
   - If $RP(p, r_i) > RP(p, r_j)$, then let $s(p; r_i, r_j) = -1$.
   - If $RP(p, r_i) = RP(p, r_j)$, then let $s(p; r_i, r_j) = 0$.

   Note: In the final dataset, we will have $n = 5$ for each p, and thus 10 pairwise comparisons for each p.

3. **Check Each p' for Validity**
   For each p', calculate:

   - $\text{AboveSum}(p') \equiv \sum_{p>p'} s(p; r_i, r_j)$
   - $\text{BelowSum}(p') \equiv \sum_{p<p'} s(p; r_i, r_j)$

   A p' is considered valid if one of the following is true:

   - $\text{AboveSum}(p') > 0$ and $\text{BelowSum}(p') < 0$ (in which case classify that p' as tentative category (i)); or
   - $\text{AboveSum}(p') < 0$ and $\text{BelowSum}(p') > 0$ (in which case classify that p' as tentative category (ii)).

   Note: If either $\text{AboveSum}(p') = 0$ or $\text{BelowSum}(p') = 0$, then p' is **not valid**.

4. **Compute the Error for Each Valid p'**

   For each valid p', the error is calculated as the total number of pairwise comparisons $s(p; r_i, r_j)$ that are inconsistent with the identified trend pattern:

   - If that p' is classified as tentative category (i), the error is the sum of:
     - The count of comparisons where $p > p'$ and $s(p; r_i, r_j) \leqslant 0$, plus
     - The count of comparisons where $p < p'$ and $s(p; r_i, r_j) \geqslant 0$.
   - If that p' is classified as tentative category (ii), the error is the sum of:
     - The count of comparisons where $p > p'$ and $s(p; r_i, r_j) \geqslant 0$, plus
     - The count of comparisons where $p < p'$ and $s(p; r_i, r_j) \leqslant 0$.

5. **Choose the Best p'**

   Among all valid p' for that subject, choose the p' with the lowest classification error (there could be more than one; if so, select one at random).

6. **Handle Cases Where No Valid p' is Found**

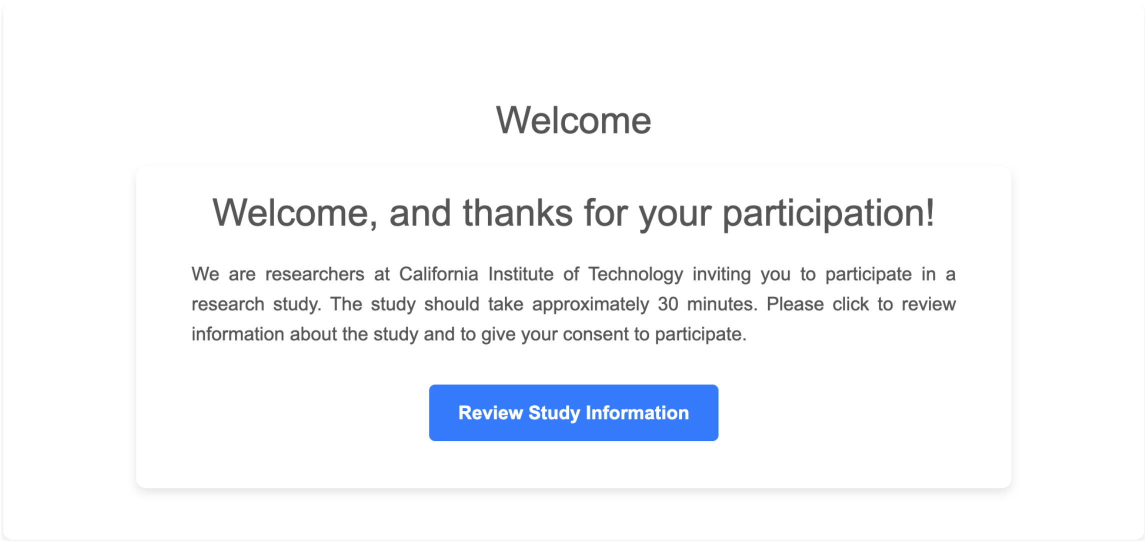
   If no valid p' is found, then calculate for that subject:

   - GlobalSum $\equiv \sum s(p; r_i, r_j)$

   Then:

   - If GlobalSum > 0, select $p' = 1$ (category (iii)).
   - If GlobalSum < 0, select $p' = 0$ (category (iv)).
   - If If GlobalSum $= 0$, randomly select one of $p' = 0$ or $p' = 1$ to include in the results.

C Experiment Instructions Screenshots



Consent

This is a consent form for research participation. It contains important information about this study and what to expect if you decide to participate.

Your participation is voluntary. Please consider the information carefully. If you decide to participate, please feel free to save or print a copy of this form.

Description: The experiment you are participating in today is part of a research study on decision making. The research study is designed to analyze individual behavior and preferences over risk. You will be asked to read several pages of instructions. Then you will be asked to make several choices that will determine the precise amount you will be paid.

Risks and Benefits: The risks involved in this study are not substantially different from participating in normal online activities. We cannot and do not guarantee or promise that you will receive any benefits from this study. Your participation may benefit society by improving our understanding of behavior. Your decision whether or not to participate in this study will not affect your relationship with Caltech.

Duration: Your participation in this experiment will take approximately as long as is indicated in the advertisement.

Payments: You will receive a fixed $5 completion payment for finishing the survey. One out of five subjects will be selected to receive additional payment based on their responses and pure chance. The average total payment for participation is $15 per hour, including the completion payment. All subjects will be paid. The minimum payment is the $5 completion payment.

Subjects' Rights: Your participation is voluntary and you have the right to discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled. The alternative is not to participate. You have the right to refuse to answer particular questions. The results of this research study may be presented at scientific or professional meetings or published in scientific journals. Your individual privacy will be maintained in all published and written data resulting from the study.

For Subjects Located In the European Economic Area: If you are in the European Economic Area (European Union, Iceland, Liechtenstein, and Norway) while you participate in the research study:

You have the right to request access, rectification or erasure of your personal information. You also have the right to object or restrict our processing of your personal information. Finally, you have the right to data portability, e.g., a copy of the data with your personal information. In order to make any such requests, please contact Tye Welch at gdpr@caltech.edu.

If you withdraw your consent to participate in this study, this will not affect the lawfulness of our collection, use and disclosure of your personal information, up to the point in time that you withdraw your consent. Even if you withdraw your consent, we may still use your data that has been anonymized or pseudonymized so that the data does not identify you, as permitted by applicable law for the purposes of: (a) the public interest, (b) scientific research, and (c) archiving in the public interest. Further, we will maintain your data in fully identifiable form if required by law.

You consent to the collection, use and disclosure of your personal information, which may include health and other sensitive personal information, for the purpose of carrying out the research study and confirming the accuracy of the study, with the lawful basis to comply with legal and regulatory requirements. You may withdraw your consent at any time, and we will stop processing (e.g., analyzing) your personal information, except as described above.

Please view Caltech's General Data Protection Regulation Notice at the following website: https://www.caltech.edu/general-data-protection-regulation-notice

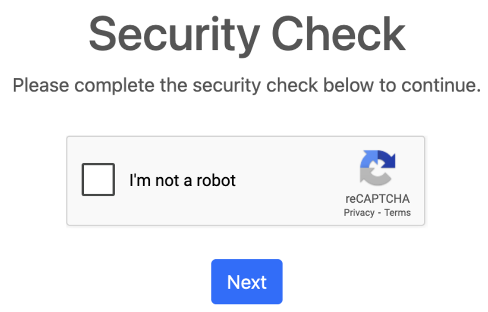
Contacts and Questions: For questions, concerns, or complaints about the study you may contact the Protocol Director, Camila Farres (e-mail– cfarresr@caltech.edu, Phone - (626) 563-7478) in the Division of Humanities and Social Sciences.

Independent Contact: If you are not satisfied with how this study is being conducted, or if you have any concerns, complaints, or general questions about the research or your rights as a participant, please contact the Caltech Institutional Review Board (IRB) to speak to someone independent of the research team at (626) 395-4699 or via email at irb@caltech.edu.

Note: All payments in this study are listed in US Dollars ($). If you are using a different local currency, it will be converted by Prolific from US Dollars to your currency at the current exchange rate.

Do you want to participate in this study?

○ Yes ○ No



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Please complete the security check below to continue.

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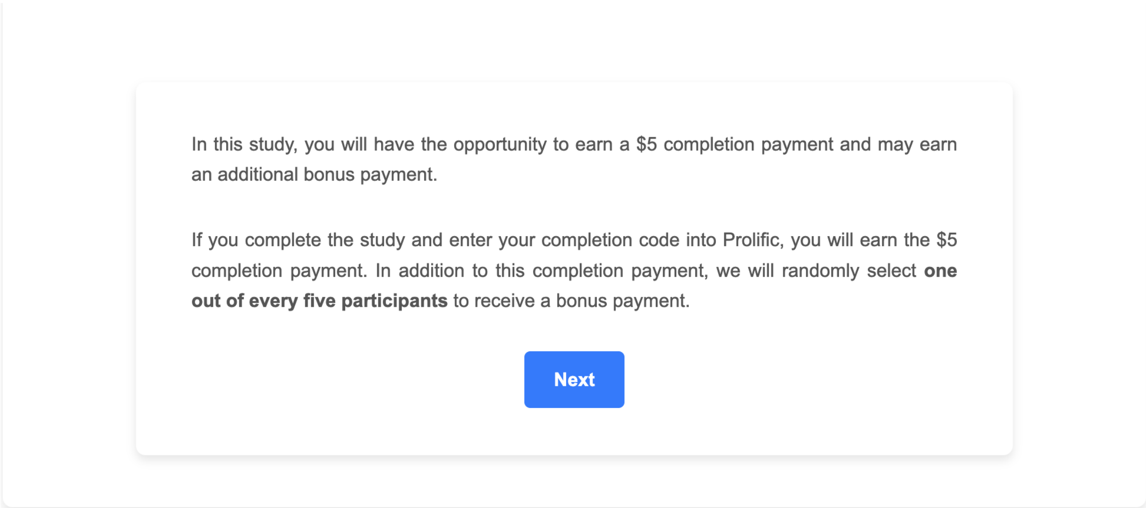


In this study, you will have the opportunity to earn a $5 completion payment and may earn an additional bonus payment.

If you complete the study and enter your completion code into Prolific, you will earn the $5 completion payment. In addition to this completion payment, we will randomly select **one out of every five participants** to receive a bonus payment.

Next

In this study, you will face 30 tasks followed by 2 quiz tasks. At the end of the study, if you are randomly selected to receive a bonus payment, then we will randomly select one of the 32 tasks, and we will determine your bonus payment based on your responses in this one randomly selected task.

Note: Each of the decisions you make today may determine your bonus payment. Therefore, it is in your best interest to answer every decision carefully and in a way that reflects what you'd truly prefer.

Next

Each task will involve several decisions between a lottery called Option A and a lottery called Option B. For each decision, all you have to do is decide whether you prefer Option A or Option B.

Your decisions in the first 30 tasks will be presented in a table in which each row represents a separate decision. In the example below, the decision in row 1 involves the choice between Option A (a 50% chance of receiving $30, 50% chance of receiving $0) and Option B (a 100% chance of **$0**). The decision in row 2 involves a choice between the same Option A, but now Option B gives a 100% chance of receiving **$0.50**. In row 3, Option B gives a 100% chance of receiving **$1.50**. In row 4, Option B gives a 100% chance of receiving **$2.50**, and so on .

Note that the only change from one row to the next is one number in Option B. In each successive row, the changing number will be larger than in the previous row. We will put the changing numbers in **bold** to help you see what changes. As you can see in the example below, the payment in Option B increases by $1 in each row (except for the first and last row that increase by $0.50) .

Option A will stay the same in each row of a given task.

OPTION A		OPTION B
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$0** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$0.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$1.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$2.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$3.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$4.50** 0% CHANCE OF $0

50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$5.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$6.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$7.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$8.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$9.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$10.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$11.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$12.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$13.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$14.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$15.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$16.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$17.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$18.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$19.50** 0% CHANCE OF $0

50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$20.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$21.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$22.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$23.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$24.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$25.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$26.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$27.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$28.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$29.50** 0% CHANCE OF $0
50% CHANCE OF $10 50% CHANCE OF $0	OR	100% CHANCE OF **$30** 0% CHANCE OF $0

Next

To give you an example of how these tasks work, consider the hypothetical task below. Option A gives a **100% chance of $10**. Option B gives a **100% chance** of a payment that varies from **$0 (in the first row)** to **$30 (in the last row)**.

In this hypothetical decision, if you prefer more money to less, you should prefer Option A for the first 11 rows. Starting from row 12 (**100% chance of $10.50**), you should prefer Option B.

To avoid having to make a selection in each row, you need only click two times: once for Option A and once for Option B. Once you click on Option A in a particular row, all rows above that row will populate to indicate that you choose Option A. Once you click a row in Option B, all rows below that row will populate to indicate that you choose Option B.

In the example below, you would click **"100% chance of $10"** in Option A in the 11th row (instead of "100% chance of $9.50"), and you would click **"100% chance of $10.50"** in Option B in the 12th row.

IMPORTANT: In order to progress, you have to make a selection for every row.

OPTION A		OPTION B
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$0** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$0.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$1.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$2.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$3.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$4.50** 0% CHANCE OF $0

100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$5.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$6.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$7.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$8.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$9.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$10.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$11.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$12.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$13.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$14.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$15.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$16.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$17.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$18.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$19.50** 0% CHANCE OF $0

100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$20.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$21.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$22.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$23.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$24.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$25.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$26.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$27.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$28.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$29.50** 0% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	100% CHANCE OF **$30** 0% CHANCE OF $0

Submit

To make sure you are comfortable with how the tables work, please complete the following **practice task**. Please try out how to select Option A in all rows, how to select Option B in all rows, and how to change your answer after selecting.

As in the main decisions, you will not be able to click to the next page until you have made a valid selection. To make a valid selection, you have to make a selection for every row. The submit button will not be activated until you make a selection in every row.

If the page is not letting you proceed, you have not made a selection in every row. Please make a selection in any unhighlighted rows to proceed.

OPTION A		OPTION B
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$0** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$0.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$1.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$2.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$3.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$4.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$5.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$6.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$7.50** 50% CHANCE OF $0

100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$8.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$9.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$10.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$11.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$12.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$13.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$14.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$15.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$16.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$17.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$18.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$19.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$20.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$21.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$22.50** 50% CHANCE OF $0

100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$23.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$24.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$25.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$26.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$27.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$28.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$29.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$30** 50% CHANCE OF $0

Submit

After you complete the 30 tasks and 2 quiz tasks, here is how we will determine your bonus payment.

First, the computer will randomly select a number between 1 and 5, with each number equally likely. If the number drawn is a 1, then you have been chosen to receive a possible bonus payment.

If you are chosen, then the computer will randomly select a number between 1 and 32, with each number equally likely. This determines which task will determine your payment.

If one of the 2 quiz tasks is selected, then you will receive $5 if your answer to that question is correct.

If one of the 30 tasks is selected, then we will randomly select a decision from that task (one of the rows) by drawing another random number, again with each row equally likely.

For example, imagine that you had filled out the table below as indicated, and imagine further that the decision-that-counts turned out to be the 15th row of this table (100% chance of $10 vs. 50% chance of $13.50, 50% chance of $0).

In this table, you chose Option A (100% chance of $10) over Option B (50% chance of $13.50, 50% chance of $0). In this case, you would receive a $10 bonus payment if you are one of the randomly selected participants who will receive a bonus payment.

If instead you had picked Option B, here's how we would determine your bonus payment. The computer would randomly generate a number between 1 and 100. Each number is equally likely. If the number comes up 1—50, we would pay you a $13.50 bonus payment. If the number comes up 51—100, we would pay you a $0 bonus payment.

Note, these bonus payments are in addition to your $5 completion payment.

OPTION A	OR	OPTION B
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$0** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$0.50** 50% CHANCE OF $0

100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$1.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$2.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$3.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$4.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$5.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$6.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$7.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$8.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$9.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$10.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$11.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$12.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$13.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$14.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$15.50** 50% CHANCE OF $0

100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$20.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$21.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$22.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$23.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$24.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$25.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$26.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$27.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$28.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$29.50** 50% CHANCE OF $0
100% CHANCE OF $10 0% CHANCE OF $0	OR	50% CHANCE OF **$30** 50% CHANCE OF $0

Next

Review Questions

Please answer the following review questions.

Next

Question 1: How will we determine your payment from this study?

- ○ You will receive a $5 completion payment.
- ○ You will receive a $5 completion payment, and 1 out of 5 participants will receive a bonus payment determined by their choices and random chance.
- ○ You will receive a $5 completion payment, and you are also guaranteed to receive a bonus payment determined by your choices and random chance.

Submit Answer

Question 2:
Imagine that you choose a lottery that gives a 50% chance of $10, 50% chance of $0. Just to make sure you're paying attention, please select the second answer option below. What would be your payment?

- ○ $10
- ○ $7
- ○ $0

Submit Answer

Start Study

Please click to proceed to the main tasks.

Next

Task 1 of 30

Please complete the table below. Note that the submit button will not be activated until you make a selection in every row.

OPTION A		OPTION B
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$0** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$0.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$1.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$2.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$3.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$4.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$5.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$6.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$7.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$8.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$9.50** 99% CHANCE OF $0

0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$10.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$11.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$12.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$13.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$14.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$15.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$16.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$17.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$18.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$19.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$20.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$21.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$22.50** 99% CHANCE OF $0

0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$23.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$24.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$25.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$26.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$27.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$28.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$29.50** 99% CHANCE OF $0
0.8% CHANCE OF $30 99.2% CHANCE OF $0	OR	1% CHANCE OF **$30** 99% CHANCE OF $0

Submit

Just for fun to take a little break: Can you spot the animal camouflaged below?
Please **click on the image** where you think the animal is.

Reveal

Task 30 of 30

Please complete the table below. Note that the submit button will not be activated until you make a selection in every row.

OPTION A		OPTION B
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$0** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$0.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$1.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$2.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$3.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$4.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$5.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$6.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$7.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$8.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$9.50** 10% CHANCE OF $0

63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$10.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$11.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$12.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$13.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$14.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$15.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$16.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$17.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$18.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$19.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$20.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$21.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$22.50** 10% CHANCE OF $0

63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$24.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$25.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$26.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$27.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$28.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$29.50** 10% CHANCE OF $0
63% CHANCE OF $30 37% CHANCE OF $0	OR	90% CHANCE OF **$30** 10% CHANCE OF $0

Submit

Before we finish, we have 2 Quiz Tasks for you to complete.

If you are randomly selected to receive a bonus payment, one of these quiz tasks could be chosen to determine your bonus payment. If you get the quiz task correct, you would receive a $5 bonus. If you get the quiz task incorrect, you would receive a $0 bonus.

Next

Quiz Task # 1

Imagine a person who values the lottery shown in Option A below at exactly $24. That is, he would rather have the lottery than any sure amount less than $24, but would rather have the sure amount for any amount greater than $24.

How would this person fill out the table below?

OPTION A		OPTION B
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$0.00** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$0.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$1.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$2.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$3.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$4.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$5.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$6.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$7.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$8.50** 0% CHANCE OF $0

75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$9.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$10.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$11.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$12.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$13.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$14.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$15.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$16.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$17.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$18.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$19.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$20.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$21.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$22.50** 0% CHANCE OF $0

75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$23.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$24.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$25.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$26.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$27.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$28.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$29.50** 0% CHANCE OF $0
75% CHANCE OF $10 25% CHANCE OF $0	OR	100% CHANCE OF **$30.00** 0% CHANCE OF $0

Submit

Quiz Task # 2

Imagine a person who values the lottery shown in Option A below at exactly the same level as the lottery with a 50% chance of $12 and a 50% chance of $0. That is, he would rather have Option A than any Option B lottery with a 50% chance of winning less than $12, but would rather have any Option B lottery with 50% chance of winning more than $12 than Option A.

How would this person fill out the list below?

OPTION A		OPTION B
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$0.00** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$0.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$1.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$2.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$3.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$4.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$5.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$6.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$7.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$8.50** 50% CHANCE OF $0

60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$9.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$10.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$11.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$12.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$13.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$14.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$15.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$16.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$17.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$18.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$19.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$20.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$21.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$22.50** 50% CHANCE OF $0

60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$23.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$24.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$25.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$26.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$27.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$28.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$29.50** 50% CHANCE OF $0
60% CHANCE OF $10 40% CHANCE OF $0	OR	50% CHANCE OF **$30.00** 50% CHANCE OF $0

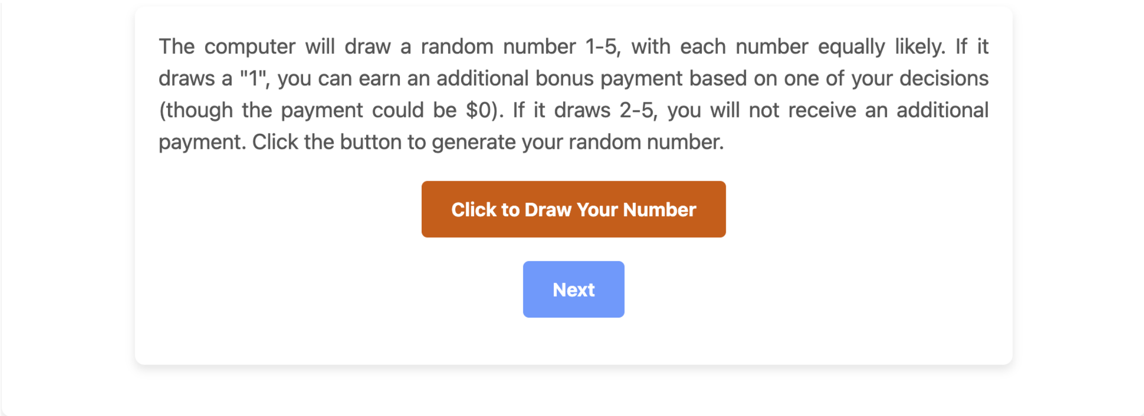
Submit

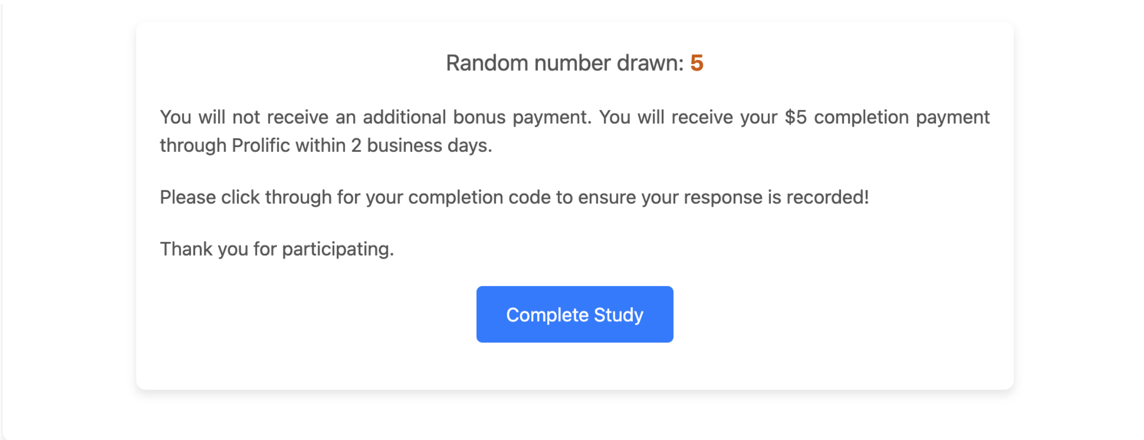
You're all finished!

Next

Did you experience any technical difficulties during this study? Is there anything else you think we should know about your experience and/or decisions?

Next


The computer will draw a random number 1-5, with each number equally likely. If it draws a "1", you can earn an additional bonus payment based on one of your decisions (though the payment could be $0). If it draws 2-5, you will not receive an additional payment. Click the button to generate your random number.
Click to Draw Your Number
Next


Random number drawn: 5
You will not receive an additional bonus payment. You will receive your $5 completion payment through Prolific within 2 business days.
Please click through for your completion code to ensure your response is recorded!
Thank you for participating.
Complete Study