What Do We Really Know About Risk Preferences for Binary Lotteries?

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Online Appendix

Table of Contents

A Additional Design Details (for Section 2) 2

B Additional Aggregate-Level Tables and Figures (for Section 3) 4

C Data Quality 8
- C.1 Assessment of Data Quality 8
- C.2 Robustness I: High-Quality Subsample 9
- C.3 Robustness II: Subsample Based on Quiz Questions 12

D Additional Details for Model Implications (for Section 4) 15
- D.1 Model-Implied Risk-Premium Maps for PT, PPW, and SSV 15
- D.2 Details of the Upside Potential (UP) Model 19

E Additional Estimation Details (for Section 5) 21

F Additional Individual-Level Tables and Figures (for Section 6) 31

G Experiment Instructions Screenshots 35

A Additional Design Details (for Section 2)

As described in Section 2, we collect 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 valuations for 25 different (p, r) combinations. Here is the algorithm used to select those 25 different (p, r) combinations:

1. 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.

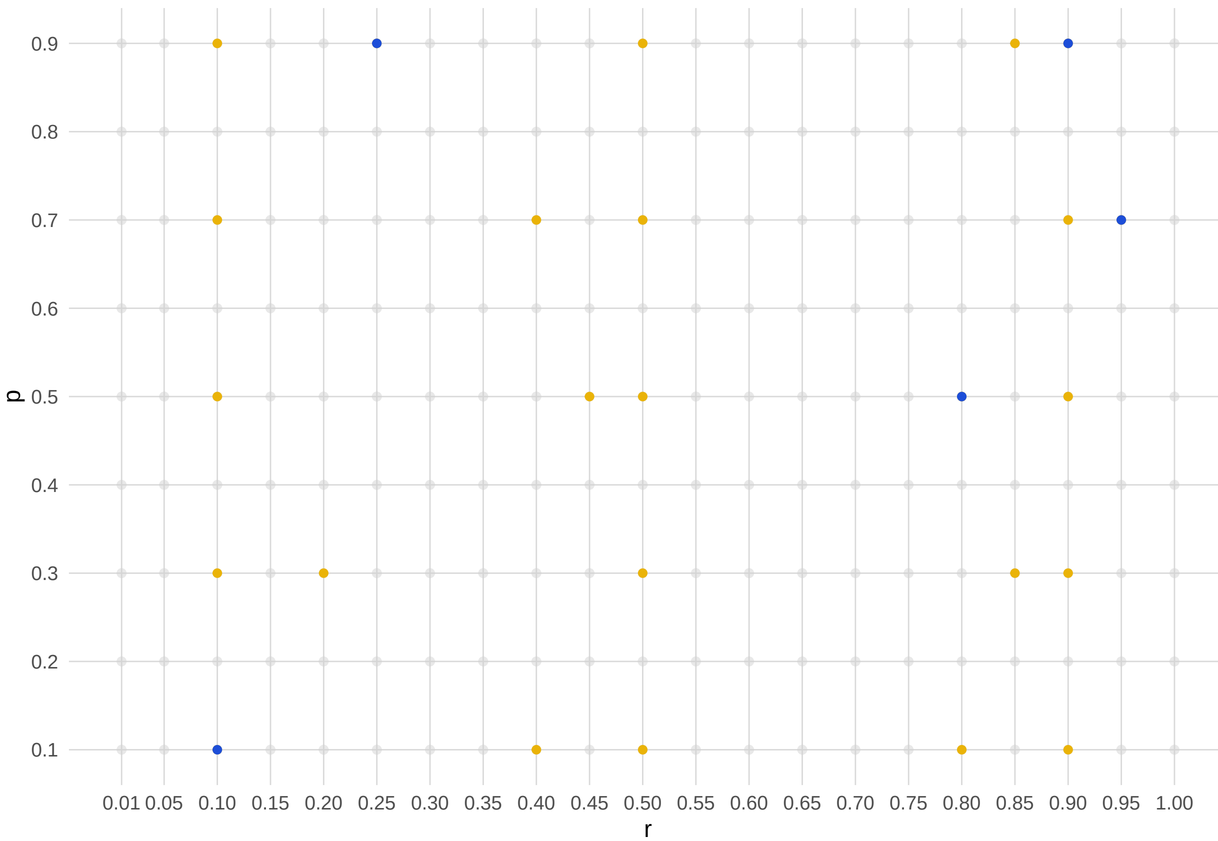
2. Select 5 values of r for each of those p: We divide the 21 values of r into three groups: the bottom 7, the middle 7, and the top 7. We then select one randomly from each group, and use these three r values for all five values of p. Next, we divide the remaining 18 values into two groups: the 9 smaller 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 $RP_i(p, r)$ 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 $RP_i(p, r)$ depends on p while holding r constant.

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

Figure A.1 shows a simulation of this selection process, where the yellow dots represent valuations that are elicited once, and the blue dots represent valuations that are elicited twice.

Figure A.1: Simulated Selection of Parameters for One Subject



Notes: Figure depicts simulated selection of parameters for one subject. In this simulation, the five selected values for p are $p \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$, and the three values of r that are selected to be used for all p are $r \in \{0.10, 0.50, 0.90\}$. For each p, two additional values of r are chosen independent of what is chosen for other p. Yellow dots represent valuations elicited once, and blue dots represent valuations elicited twice.

B Additional Aggregate-Level Tables and Figures (for Section 3)

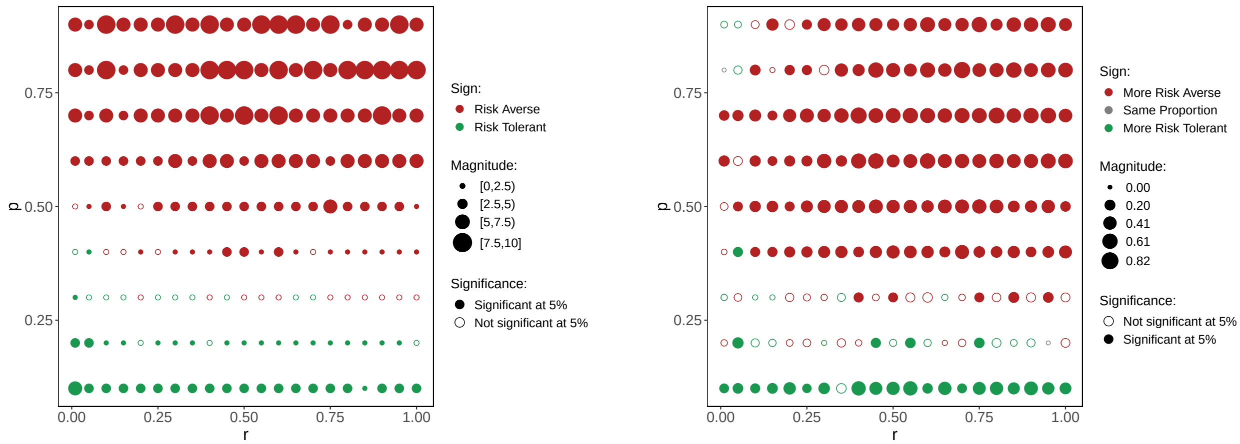
Table B.1 reports the mean valuation $m(p, r)$ for each of the 189 combinations of (p, r). Overall, we collect 24,000 valuations, and thus each of these is based on roughly 127 observations. In parentheses below each mean, we report standard errors clustered at the participant level (the clustering is needed for instances where one subject contributes two $m_i(p, r)$ for the same (p, r) due to repeats).

Table B.2 reports the mean normalized risk premium $RP(p, r)$ for each of the 189 combinations of (p, r), where again each of these is based on roughly 127 observations. Again, in parentheses below each mean, we report standard errors clustered at the participant level. Note that because $RP(p, r) \equiv pH - m(p, r)$, each entry in Table B.2 is equal to pH minus the corresponding entry in Table B.1. Moreover, for each (p, r) combination, the standard errors are the same in Tables B.1 and B.2.

Figure B.1 provides a summary of the aggregate-level results on risk aversion versus risk tolerance by (p, r). In both panels, each point corresponds to a (p, r) combination and is based on roughly 127 observations. Panel (a) reproduces Figure 1 from Section 3; we repeat it here to facilitate a side-by-side comparison with panel (b). It presents the mean normalized risk premia $RP(p, r)$—this panel provides a visual depiction of the entries in Table B.2 and also indicates when those entries are statistically different from zero. In panel (a), color corresponds to sign of mean $RP(p, r)$, with red indicating risk aversion and green indicating risk tolerance; size corresponds to magnitude of deviation from risk neutrality; and filled points correspond to locations where H_0 : mean $RP(p, r) = 0$ is rejected at the 5% level based on a two-sided z-test using a participant-clustered standard error.

In contrast, panel (b) presents the proportion of observations with $RP_i(p, r) > 0$ minus the proportion with $RP_i(p, r) < 0$. Color corresponds to the sign of the difference, with red indicating risk aversion and green indicating risk tolerance; size corresponds to the absolute value of the difference; and filled points correspond to locations where the null hypothesis of equal proportions is rejected at the 5% level based on a two-sided sign test. We note that, unlike panel (a), this procedure does not naturally accommodate participant-level clustering, so the reported significance should be interpreted cautiously.

Figure B.1: Risk Aversion and Risk Tolerance by (p, r)



(a) Mean Normalized $RP(p, r)$

(b) Proportion Positive vs. Negative $RP_i(p, r)$

Notes: Both panels depict the extent of risk aversion versus risk tolerance for each of the 189 locations in the (p, r) parameter space, based on 24,000 total observations and thus roughly 127 for each (p, r). Panel (a) repeats Figure 1 and presents mean normalized risk premia $RP(p, r)$. Color corresponds to sign of mean $RP(p, r)$, with red indicating risk aversion and green indicating risk tolerance; size corresponds to magnitude of deviation from risk neutrality; and filled points correspond to locations where H_0 : mean $RP(p, r) = 0$ is rejected at the 5% level. Panel (b) presents the proportion of observations with $RP_i(p, r) > 0$ minus the proportion with $RP_i(p, r) < 0$. Color corresponds to the sign of the difference, with red indicating risk aversion and green indicating risk tolerance; size corresponds to the absolute value of the difference; and filled points correspond to locations where the null hypothesis of equal proportions is rejected at the 5% level. Tests in each panel are two-sided.

Table B.1: Mean Valuation $m(p, r)$ with Clustered Standard Error

r	p 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.01	8.69 (0.97)	8.58 (0.81)	11.44 (0.98)	13.61 (0.99)	14.98 (0.93)	13.41 (1.04)	15.88 (1.07)	18.23 (1.14)	20.46 (1.14)
0.05	7.61 (0.95)	10.10 (0.87)	9.20 (0.69)	13.93 (0.83)	13.48 (0.75)	15.20 (0.98)	16.57 (0.98)	19.98 (0.97)	22.39 (0.87)
0.10	6.68 (0.82)	7.87 (0.67)	9.44 (0.75)	10.94 (0.75)	12.20 (0.84)	14.11 (0.87)	15.10 (0.91)	16.18 (1.06)	19.46 (1.02)
0.15	6.97 (0.84)	8.45 (0.83)	9.59 (0.66)	10.87 (0.73)	12.53 (0.76)	14.91 (0.76)	17.51 (0.74)	20.09 (0.83)	21.53 (0.79)
0.20	6.51 (0.66)	7.07 (0.69)	8.35 (0.52)	9.79 (0.74)	13.86 (0.69)	14.13 (0.77)	15.88 (0.84)	17.68 (0.92)	20.09 (0.93)
0.25	6.11 (0.70)	7.95 (0.70)	9.19 (0.62)	10.70 (0.86)	12.05 (0.64)	14.56 (0.70)	13.95 (0.81)	18.19 (0.88)	21.41 (0.89)
0.30	6.43 (0.70)	7.69 (0.64)	9.81 (0.68)	10.41 (0.73)	11.40 (0.63)	10.87 (0.66)	15.49 (0.70)	18.11 (0.91)	19.06 (0.88)
0.35	7.07 (0.80)	8.11 (0.65)	9.95 (0.71)	10.04 (0.78)	11.40 (0.66)	14.45 (0.78)	15.43 (0.81)	16.92 (0.88)	19.71 (0.92)
0.40	7.76 (0.81)	7.22 (0.68)	8.47 (0.63)	10.18 (0.63)	11.77 (0.60)	11.94 (0.65)	12.57 (0.78)	16.49 (0.92)	18.42 (0.84)
0.45	6.84 (0.70)	7.86 (0.68)	9.40 (0.71)	9.06 (0.67)	10.65 (0.70)	10.96 (0.73)	14.41 (0.62)	14.66 (0.74)	20.29 (0.77)
0.50	6.86 (0.56)	7.53 (0.58)	8.27 (0.60)	9.15 (0.57)	11.46 (0.65)	13.26 (0.77)	13.39 (0.72)	16.23 (0.79)	20.90 (0.76)
0.55	6.88 (0.72)	7.81 (0.69)	8.04 (0.59)	9.78 (0.56)	10.46 (0.70)	12.68 (0.76)	13.54 (0.66)	17.01 (0.77)	19.17 (0.79)
0.60	6.10 (0.62)	7.66 (0.63)	8.20 (0.58)	9.31 (0.60)	12.27 (0.63)	10.61 (0.68)	12.91 (0.78)	15.05 (0.77)	19.11 (0.82)
0.65	7.24 (0.64)	7.86 (0.72)	9.39 (0.57)	10.21 (0.63)	11.14 (0.62)	12.84 (0.72)	14.97 (0.73)	17.41 (0.73)	19.31 (0.78)
0.70	7.01 (0.68)	7.81 (0.61)	9.57 (0.63)	10.66 (0.72)	10.88 (0.59)	12.67 (0.71)	14.58 (0.68)	15.72 (0.75)	20.79 (0.72)
0.75	6.70 (0.68)	8.25 (0.65)	8.46 (0.63)	9.71 (0.67)	9.97 (0.64)	13.06 (0.71)	15.63 (0.79)	17.05 (0.63)	18.33 (0.73)
0.80	6.65 (0.73)	7.94 (0.66)	8.60 (0.63)	9.58 (0.67)	11.06 (0.63)	12.36 (0.74)	14.28 (0.71)	16.18 (0.75)	22.95 (0.66)
0.85	5.35 (0.46)	7.29 (0.50)	8.34 (0.58)	10.51 (0.65)	12.38 (0.57)	12.86 (0.61)	15.11 (0.64)	15.16 (0.66)	20.64 (0.66)
0.90	7.41 (0.73)	8.19 (0.71)	8.36 (0.64)	10.19 (0.70)	11.86 (0.80)	12.71 (0.70)	13.24 (0.73)	16.34 (0.81)	19.61 (0.77)
0.95	7.66 (0.72)	8.47 (0.84)	8.20 (0.60)	9.81 (0.65)	11.79 (0.76)	11.42 (0.71)	13.79 (0.87)	15.88 (0.83)	18.94 (0.94)
1.00	6.33 (0.79)	7.23 (0.87)	8.14 (0.69)	9.51 (0.70)	12.74 (0.71)	12.49 (0.65)	15.50 (0.95)	15.86 (0.91)	20.77 (0.78)

Table B.2: Mean Normalized Risk Premium $RP(p, r)$ with Clustered Standard Error

r	p								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.01	-5.69 (0.97)	-2.58 (0.81)	-2.44 (0.98)	-1.61 (0.99)	0.02 (0.93)	4.59 (1.04)	5.12 (1.07)	5.77 (1.14)	6.54 (1.14)
0.05	-4.61 (0.95)	-4.10 (0.87)	-0.20 (0.69)	-1.93 (0.83)	1.52 (0.75)	2.80 (0.98)	4.43 (0.98)	4.02 (0.97)	4.61 (0.87)
0.10	-3.68 (0.82)	-1.87 (0.67)	-0.44 (0.75)	1.06 (0.75)	2.80 (0.84)	3.89 (0.87)	5.90 (0.91)	7.82 (1.06)	7.54 (1.02)
0.15	-3.97 (0.84)	-2.45 (0.83)	-0.59 (0.66)	1.13 (0.73)	2.47 (0.76)	3.09 (0.76)	3.49 (0.74)	3.91 (0.83)	5.47 (0.79)
0.20	-3.51 (0.66)	-1.07 (0.69)	0.65 (0.52)	2.21 (0.74)	1.14 (0.69)	3.87 (0.77)	5.12 (0.84)	6.32 (0.92)	6.91 (0.93)
0.25	-3.11 (0.70)	-1.95 (0.70)	-0.19 (0.62)	1.30 (0.86)	2.95 (0.64)	3.44 (0.70)	7.05 (0.81)	5.81 (0.88)	5.59 (0.89)
0.30	-3.43 (0.70)	-1.69 (0.64)	-0.81 (0.68)	1.59 (0.73)	3.60 (0.63)	7.13 (0.66)	5.51 (0.70)	5.89 (0.91)	7.94 (0.88)
0.35	-4.07 (0.80)	-2.11 (0.65)	-0.95 (0.71)	1.96 (0.78)	3.60 (0.66)	3.55 (0.78)	5.57 (0.81)	7.08 (0.88)	7.29 (0.92)
0.40	-4.76 (0.81)	-1.22 (0.68)	0.53 (0.63)	1.82 (0.63)	3.23 (0.60)	6.06 (0.65)	8.43 (0.78)	7.51 (0.92)	8.58 (0.84)
0.45	-3.84 (0.70)	-1.86 (0.68)	-0.40 (0.71)	2.94 (0.67)	4.35 (0.70)	7.04 (0.73)	6.59 (0.62)	9.34 (0.74)	6.71 (0.77)
0.50	-3.86 (0.56)	-1.53 (0.58)	0.73 (0.60)	2.85 (0.57)	3.54 (0.65)	4.74 (0.77)	7.61 (0.72)	7.77 (0.79)	6.10 (0.76)
0.55	-3.88 (0.72)	-1.81 (0.69)	0.96 (0.59)	2.22 (0.56)	4.54 (0.70)	5.32 (0.76)	7.46 (0.66)	6.99 (0.77)	7.83 (0.79)
0.60	-3.10 (0.62)	-1.66 (0.63)	0.80 (0.58)	2.69 (0.60)	2.73 (0.63)	7.39 (0.68)	8.09 (0.78)	8.95 (0.77)	7.89 (0.82)
0.65	-4.24 (0.64)	-1.86 (0.72)	-0.39 (0.57)	1.79 (0.63)	3.86 (0.62)	5.16 (0.72)	6.03 (0.73)	6.59 (0.73)	7.69 (0.78)
0.70	-4.01 (0.68)	-1.81 (0.61)	-0.57 (0.63)	1.34 (0.72)	4.12 (0.59)	5.33 (0.71)	6.42 (0.68)	8.28 (0.75)	6.21 (0.72)
0.75	-3.70 (0.68)	-2.25 (0.65)	0.54 (0.63)	2.29 (0.67)	5.03 (0.64)	4.94 (0.71)	5.37 (0.79)	6.95 (0.63)	8.67 (0.73)
0.80	-3.65 (0.73)	-1.94 (0.66)	0.40 (0.63)	2.42 (0.67)	3.94 (0.63)	5.64 (0.74)	6.72 (0.71)	7.82 (0.75)	4.05 (0.66)
0.85	-2.35 (0.46)	-1.29 (0.50)	0.66 (0.58)	1.49 (0.65)	2.62 (0.57)	5.14 (0.61)	5.89 (0.64)	8.84 (0.66)	6.36 (0.66)
0.90	-4.41 (0.73)	-2.19 (0.71)	0.63 (0.64)	1.81 (0.70)	3.14 (0.80)	5.29 (0.70)	7.76 (0.73)	7.66 (0.81)	7.39 (0.77)
0.95	-4.66 (0.72)	-2.47 (0.84)	0.80 (0.60)	2.19 (0.65)	3.21 (0.76)	6.58 (0.71)	7.21 (0.87)	8.13 (0.83)	8.06 (0.94)
1.00	-3.33 (0.79)	-1.23 (0.87)	0.86 (0.69)	2.49 (0.70)	2.26 (0.71)	5.51 (0.65)	5.50 (0.95)	8.14 (0.91)	6.23 (0.78)

C Data Quality

C.1 Assessment of Data Quality

Our pre-analysis plan outlined five data checks and thresholds for evaluating data quality. Our data met all thresholds outlined in the pre-analysis plan for data quality and so we proceed by analyzing the entire data set. We describe the five checks below.

First, we checked for observations that are censored at the boundaries of our price lists, which would reflect violations of dominance; in our data, only 4.4% of all observations are censored, and only 2.9% of subjects have more than 40% of their observations censored.

Second, we checked for participants with little or no variation across their 30 valuations, which would make no sense for someone who was attending to the experiment; in our data, only 1% of subjects have no variation in their responses, and only 5% of subjects have fewer than 10 responses different from their modal response.

Third, we checked for appropriate responsiveness to the probabilities. Specifically, we reorganized our data to define $q_M = r$, $q_H = pr$, and $\hat{m}_i(q_M, q_H)$ such that $(\hat{m}_i(q_M, q_H), q_M) \sim_i (H, q_H)$. With these objects, monotonicity implies that a person's $\hat{m}_i(q_M, q_H)$ should be decreasing in q_M and increasing in q_H. We regress $\hat{m}_i$ on q_M and q_H, and assess what proportion of subjects have incorrect signs for these coefficients (i.e., they react in the wrong direction). In our data, only 6.9% of participants have the wrong sign for q_H, and only 10.8% of participants have the wrong sign for q_M.[24]

Fourth, we evaluated whether there is excessive noise in responses. For each subject, our data contain multiple observations of the same valuations, separated by at least three other valuations. Using the formulation from the prior paragraph, we regress repetitions of the same valuation on each other with (q_M, q_H) fixed effects and standard errors clustered at the individual-level, and estimate a regression coefficient of 0.571 (s.e. = 0.022).[25] This highly significant relationship between repeated elicitations of the same valuation indicates that though noise plays a role (i.e., the coefficient is not one), valuations exhibit substantial regularities suggestive of a common preference component.

Finally, we included a check to ensure the participant was not a robot; anyone who failed this check was not permitted into the study.

[24] As discussed in our pre-analysis plan, our data are less well designed to estimate the q_M coefficient. Recall that our design creates random variation in p and r. Variation in p generates variation in $q_H = pr$ holding $q_M = r$ 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 $q_M = r$ and $q_H = pr$, and thus is not ideal for identifying the coefficient on q_M.

[25] Our labeling of a valuation and its "repeat" is done randomly, so a repeat might be seen first or second. 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.

C.2 Robustness I: High-Quality Subsample

In our pre-analysis plan, we specified that as long as our data looked reasonable in terms of the data-quality checks described in Section C.1, we would conduct our primary analysis on the entire dataset. In Section C.1, we concluded that the data do look reasonable, and thus our primary analysis in the main paper uses the entire dataset.

Our pre-analysis plan also specified that, even if we did our primary analysis using the entire dataset, as a robustness check we would re-do our main results using a high-quality subsample based on three criteria. These criteria were specified at the participant level, where a participant must pass all three criteria to be selected into our high-quality subsample. The three criteria are related to the checks on data quality reported in Section C.1. Applying these criteria, participants are selected out as follows:

1. Participants are excluded for excess censoring, specifically if more than 40% of their valuations are at the boundaries of our price lists. In our data, 23 participants (2.88%) fail this criterion.

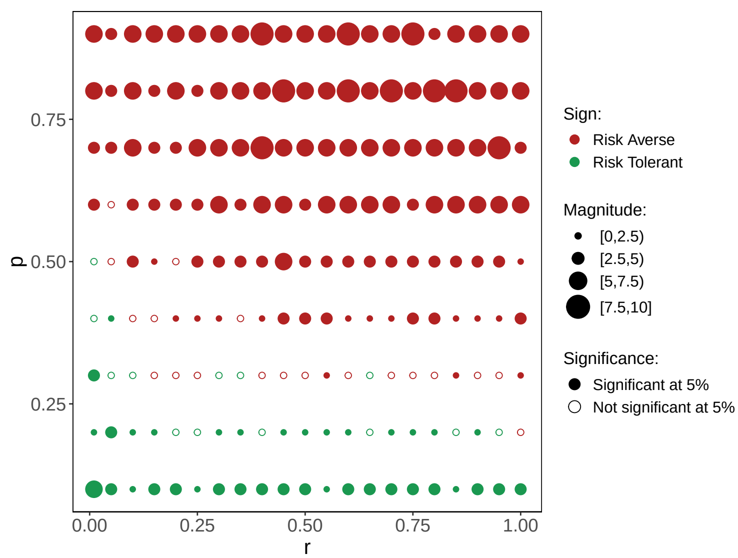
2. Participants are excluded for low within-subject variation, specifically if fewer than 10 of their valuations differ from their modal response. In our data, 40 participants (5%) fail this criterion.

3. Participants are excluded for failing monotonicity, specifically, if when running the participant-level regression described in Section C.1 of $\hat{m}(q_M, q_H)$ on q_M and q_H the sign of the coefficient on q_H is negative. In our data, 55 participants (6.88%) fail this criterion.

Combining all three criteria, in total 95 participants (11.88%) fail at least one criterion and are excluded, leaving 705 participants (88.12%) in our high-quality subsample.

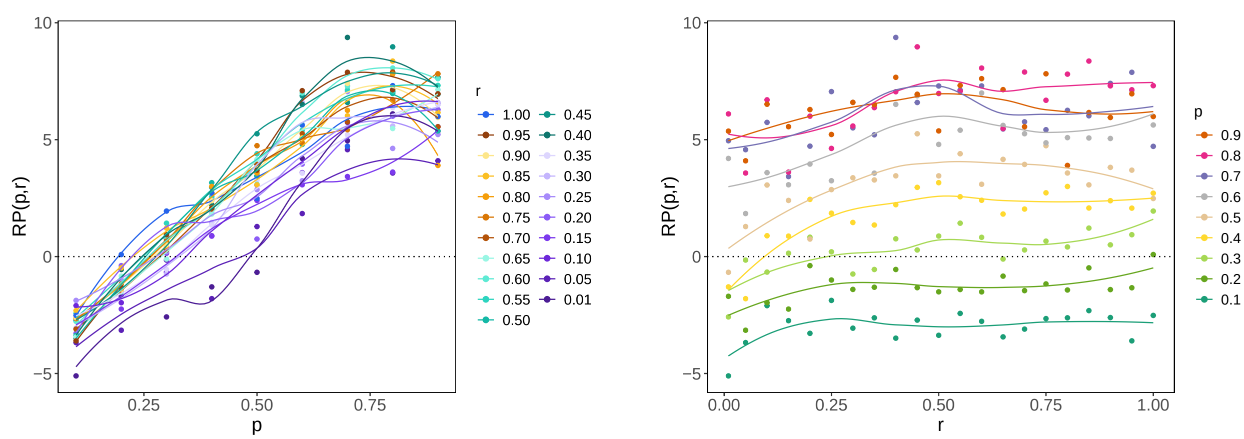
We take our main results to be our aggregate results in Figures 1 and 2 and Table 2. Appendix Figures C.1 and C.2 and Appendix Table C.1 replicate those results in the high-quality subsample. The main message is essentially unchanged—and in particular, Results 1 and 2 also emerge from the high-quality data.

Figure C.1: Mean Normalized Risk Premium $RP(p, r)$ by (p, r) (High-Quality Subsample)



Notes: Figure construction follows Figure 1. Figure presents mean normalized risk premium $RP(p, r)$ for each of the 189 (p, r) combinations. For each (p, r), $RP(p, r)$ is the mean of $RP_i(p, r)$ across all observations for that (p, r), including repeats. For each (p, r), color of circle captures sign of $RP(p, r)$, with red indicating risk aversion and green indicating risk tolerance, while size of circle captures the magnitude of $RP(p, r)$. Filled points correspond to (p, r) for which $H_0 : RP(p, r) = 0$ is rejected at the 5% level. Based on 21,150 observations from the 705 participants in our high-quality subsample, or roughly 112 observations for each circle.

Figure C.2: $RP(p, r)$ Variation Across p and r (High-Quality Subsample)



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

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

Notes: Figure construction follows Figure 2. Panel (a) presents mean normalized risk premium $RP(p, r)$ against p, showing a separate line for each value of r. Panel (b) plots $RP(p, r)$ against r, showing a separate line for each value of p. Lines in both panels correspond to LOESS fits. Based on 21,150 observations from the 705 participants in our high-quality subsample, or roughly 112 observations for each (p, r).

Table C.1: Parametric and Non-Parametric p and r Comparative Statics (High-Quality Subsample)

	p Comparative Statics When $\bar{r}=\bar{s}$			**r Comparative Statics When $\bar{p}=\bar{s}$**		
$\bar{s}$	β_p (SE)	τ_p^a (SE)	N	Slope β_r (SE)	τ_r^a (SE)	N
0.01	14.416 (1.312)	0.377 (0.046)	966			
0.05	10.579 (1.085)	0.258 (0.044)	975			
0.10	12.706 (1.041)	0.377 (0.042)	1005	0.552 (0.432)	-0.069 (0.021)	2228
0.15	9.807 (0.929)	0.316 (0.032)	1040			
0.20	11.122 (0.920)	0.280 (0.041)	1013	1.031 (0.417)	-0.022 (0.021)	2325
0.25	10.001 (0.853)	0.279 (0.038)	1088			
0.30	12.809 (0.917)	0.445 (0.039)	985	1.981 (0.424)	0.030 (0.021)	2466
0.35	12.178 (0.838)	0.419 (0.039)	967			
0.40	14.688 (0.792)	0.480 (0.039)	1006	2.843 (0.466)	0.073 (0.022)	2269
0.45	14.337 (0.799)	0.461 (0.033)	1001			
0.50	12.367 (0.776)	0.383 (0.038)	1067	2.471 (0.456)	0.083 (0.021)	2419
0.55	12.842 (0.766)	0.462 (0.037)	998			
0.60	14.573 (0.809)	0.507 (0.034)	949	2.665 (0.508)	0.076 (0.021)	2366
0.65	12.580 (0.763)	0.434 (0.034)	1081			
0.70	12.972 (0.771)	0.480 (0.032)	1073	1.591 (0.540)	0.041 (0.023)	2324
0.75	12.793 (0.746)	0.461 (0.037)	1026			
0.80	11.453 (0.775)	0.433 (0.035)	1001	2.917 (0.569)	0.141 (0.024)	2305
0.85	11.940 (0.698)	0.421 (0.033)	1099			
0.90	12.707 (0.819)	0.440 (0.035)	1013	0.786 (0.560)	0.077 (0.022)	2448
0.95	14.400 (0.880)	0.477 (0.034)	934			
1.00	10.220 (0.864)	0.327 (0.046)	863			
Total			21150			21150

Notes: Entries reflect separate comparative-static measures using observations from 705 participants in high-quality subsample. In each row, column (2) reports estimated coefficient β_p from regression specification in equation 3 using all observations in high-quality subsample with $\bar{r}=\bar{s}$ (number of observations N reported in column (3)); standard error reported in parentheses is clustered by participant using CR2. In each row, column (4) reports weighted mean τ_p^a of individual $\tau_{p,i}^a$ calculated from equation 5 using all individuals in high-quality subsample who saw at least two distinct values of p for $\bar{r}=\bar{s}$ (number of individuals m reported in column (5)); weight for individual i is $w_i = N_{p,i}/\sum_j N_{p,j}$; standard error in parentheses is corresponding weighted empirical standard error $\hat{\sigma}_w \cdot \sqrt{\sum_i w_i^2}$, where $\hat{\sigma}_w^2 = (1/(1-\sum_j w_j^2)\sum_i w_i(\hat{\tau}_{p,i}^a - \tau_p^a)^2$. Columns (6) and (7) are analogous to columns (2) and (3), reporting estimated coefficient β_r from regression specification in equation 4 using all observations in high-quality subsample with $\bar{p}=\bar{s}$. Columns (8) and (9) are analogous to columns (4) and (5), reporting calculated τ_r^a using all individuals in high-quality subsample who saw at least two distinct values of r for $\bar{p}=\bar{s}$.

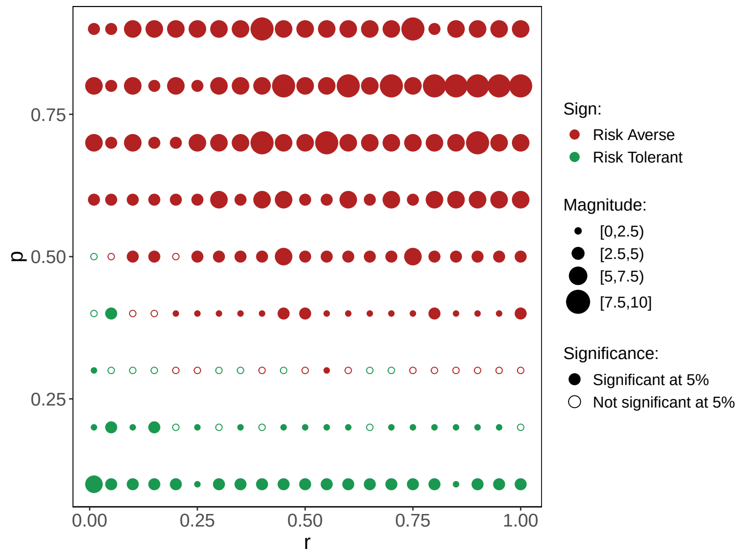
C.3 Robustness II: Subsample Based on Quiz Questions

Our experiment includes two incentivized quiz questions. In our pre-analysis plan, we specified that we would not use them in our overall data assessment, but that as an additional robustness check we would re-run our main analysis while restricting the data to participants who got at least one quiz question correct.

In our data, 696 participants (87%) got at least one quiz question correct (and 575 participants (71.9%) got both quiz questions correct).

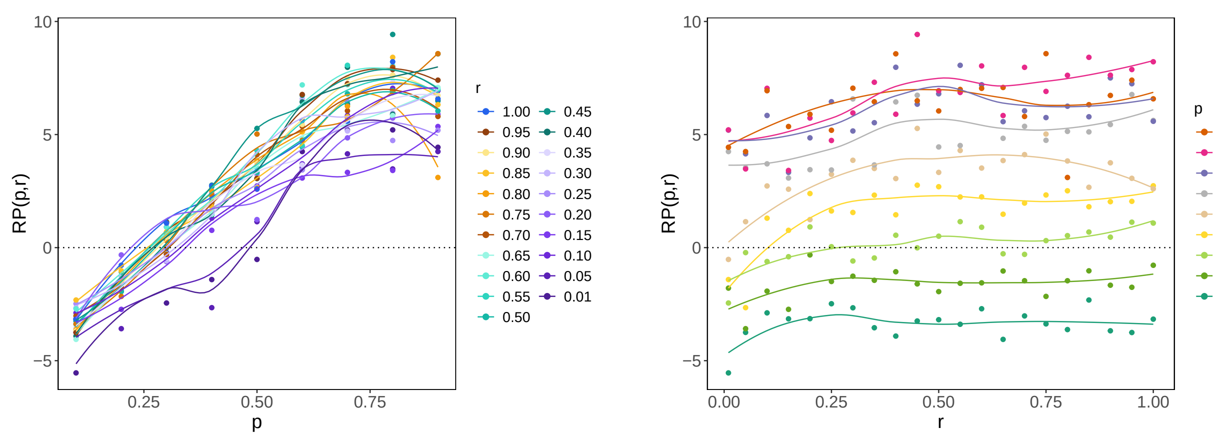
Much as for our high-quality data, Appendix Figures C.3 and C.4 and Appendix Table C.2 replicate the aggregate results in Figures 1 and 2 and Table 2 using only the data on the 696 participants who got at least one quiz question correct. Again, the main message is essentially unchanged—and in particular, Results 1 and 2 also emerge from the subsample based on quiz questions.

Figure C.3: Mean Normalized Risk Premium $RP(p, r)$ by (p, r) (Quiz Subsample)



Notes: Figure construction follows Figure 1. Figure presents mean normalized risk premium $RP(p, r)$ for each of the 189 (p, r) combinations. For each (p, r), $RP(p, r)$ is the mean of $RP_i(p, r)$ across all observations for that (p, r), including repeats. For each (p, r), color of circle captures sign of $RP(p, r)$, with red indicating risk aversion and green indicating risk tolerance, while size of circle captures the magnitude of $RP(p, r)$. Filled points correspond to (p, r) for which $H_0 : RP(p, r) = 0$ is rejected at the 5% level. Based on 20,880 observations from the 696 participants who got at least one quiz question correct, or roughly 110 observations for each circle.

Figure C.4: $RP(p, r)$ Variation Across p and r (Quiz Subsample)



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

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

Notes: Figure construction follows Figure 2. Panel (a) presents mean normalized risk premium $RP(p, r)$ against p, showing a separate line for each value of r. Panel (b) plots $RP(p, r)$ against r, showing a separate line for each value of p. Lines in both panels correspond to LOESS fits. Based on 20,880 observations from the 696 participants who got at least one quiz question correct, or roughly 110 observations for each (p, r).

Table C.2: Parametric and Non-Parametric p and r Comparative Statics (Quiz Subsample)

	p **Comparative Statics When** $\bar{r} = \bar{s}$			r **Comparative Statics When** $\bar{p} = \bar{s}$		
$\bar{s}$	β_p (SE)	τ_p^a (SE)	N	β_r (SE)	τ_r^a (SE)	N
0.01	13.759 (1.340)	0.405 (0.046)	940			
0.05	11.055 (1.133)	0.272 (0.047)	939			
0.10	13.588 (1.069)	0.380 (0.041)	1019	0.304 (0.491)	-0.075 (0.020)	2172
0.15	10.243 (0.967)	0.345 (0.032)	1033			
0.20	10.467 (0.938)	0.261 (0.042)	959	0.672 (0.466)	-0.029 (0.021)	2287
0.25	10.735 (0.882)	0.309 (0.038)	1119			
0.30	12.781 (0.942)	0.428 (0.039)	955	1.685 (0.450)	0.022 (0.020)	2469
0.35	13.261 (0.921)	0.435 (0.041)	944			
0.40	15.088 (0.871)	0.509 (0.040)	985	2.595 (0.496)	0.070 (0.022)	2198
0.45	14.714 (0.872)	0.489 (0.035)	986			
0.50	12.841 (0.820)	0.402 (0.040)	1057	2.144 (0.481)	0.080 (0.021)	2416
0.55	13.482 (0.824)	0.479 (0.035)	1013			
0.60	14.232 (0.854)	0.486 (0.035)	907	2.271 (0.531)	0.064 (0.021)	2359
0.65	13.348 (0.825)	0.433 (0.035)	1067			
0.70	13.405 (0.820)	0.488 (0.034)	1052	1.870 (0.557)	0.052 (0.024)	2257
0.75	14.702 (0.834)	0.481 (0.037)	1000			
0.80	11.631 (0.827)	0.450 (0.036)	977	3.612 (0.586)	0.150 (0.024)	2291
0.85	12.575 (0.779)	0.445 (0.033)	1107			
0.90	14.357 (0.883)	0.467 (0.034)	1017	1.312 (0.571)	0.095 (0.022)	2431
0.95	15.036 (0.915)	0.499 (0.034)	942			
1.00	12.493 (0.943)	0.358 (0.047)	862			
Total			20880			20880

Notes: Entries reflect separate comparative-static measures using observations from 696 participants in quiz subsample. In each row, column (2) reports estimated coefficient β_p from regression specification in equation 3 using all observations in quiz subsample with $\bar{r} = \bar{s}$ (number of observations N reported in column (3)); standard error reported in parentheses is clustered by participant using CR2. In each row, column (4) reports weighted mean τ_p^a of individual $\tau_{p,i}^a$ calculated from equation 5 using all individuals in quiz subsample who saw at least two distinct values of p for $\bar{r} = \bar{s}$ (number of individuals m reported in column (5)); weight for individual i is $w_i = N_{p,i} / \sum_j N_{p,j}$; standard error in parentheses is corresponding weighted empirical standard error $\hat{\sigma}_w \cdot \sqrt{\sum_i w_i^2}$, where $\hat{\sigma}_w^2 = (1/(1-\sum_j w_j^2) \sum_i w_i(\hat{\tau}_{p,i}^a - \tau_p^a)^2$. Columns (6) and (7) are analogous to columns (2) and (3), reporting estimated coefficient β_r from regression specification in equation 4 using all observations in quiz subsample with $\bar{p} = \bar{s}$. Columns (8) and (9) are analogous to columns (4) and (5), reporting calculated τ_r^a using all individuals in quiz subsample who saw at least two distinct values of r for $\bar{p} = \bar{s}$.

D Additional Details for Model Implications (for Section 4)

D.1 Model-Implied Risk-Premium Maps for PT, PPW, and SSV

In Section 4, we describe the implications of six models: (i) expected utility with global risk aversion (EU); (ii) probability weighting (PW); (iii) prospect theory (PT); (iv) proportional probability weighting (PPW); (v) S-shaped value function (SSV); and (vi) upside potential (UP). In the text, we provide the model-implied risk premium maps for EU, PW, and UP (in Figures 3, 4, and 5). In this section, we provide the model-implied risk-premium maps for PT, PPW, and SSV.

Because the text provides a less complete coverage of these three models, we provide a little more detail for each.

Prospect Theory (PT): Under PT, a person evaluates gambles using both a probability weighting function $\pi(q)$ and a value function $v(x)$. Specifically, the indifference valuation $m^*(p,r)$ is given by

$$\pi(r)v(m^*(p,r)) = \pi(pr)v(H) \qquad \Longleftrightarrow \qquad m^*(p,r) = v^{-1}\left(\frac{\pi(pr)}{\pi(r)}v(H)\right).$$

Here, we consider the case where $v(x) = x^\alpha$, in which case the indifference valuation $m^*(p,r)$ is given by

$$\pi(r)(m^*(p,r))^\alpha = \pi(pr)(H)^\alpha \qquad \Longleftrightarrow \qquad m^*(p,r) = \left(\frac{\pi(pr)}{\pi(r)}\right)^{1/\alpha} H,$$

and the normalized risk premium is given by

$$RP^*(p,r) = pH - m^*(p,r) = pH - \left(\frac{\pi(pr)}{\pi(r)}\right)^{1/\alpha} H = \left(p - \left(\frac{\pi(pr)}{\pi(r)}\right)^{1/\alpha}\right) H.$$

Appendix Figure D.1 depicts how $RP^*(p,r)$ depends on (p,r) using both the functional forms and parameter values suggested by Tversky and Kahneman (1992).

Proportional Probability Weighting (PPW): PPW is a post-hoc variant of prospect theory that can be applied when comparing two binary lotteries wherein a person applies probability weighting to the ratio of the winning probabilities. Under PPW, the indifference valuation $m^*(p,r)$ is given by

$$m^*(p,r) = \pi\left(\frac{pr}{r}\right) H = \pi(p)H,$$

and the normalized risk premium is given by

$$RP^*(p,r) = pH - m^*(p,r) = (p - \pi(p))H.$$

Note that, under PPW, $m^*(p,r)$ and $RP^*(p,r)$ are both independent of r. Appendix Figure D.2 depicts how $RP^*(p,r)$ depends on (p,r) using the functional form and parameter value suggested by Tversky and Kahneman (1992).

S-Shaped Value Function (SSV): SSV is another post-hoc variant of prospect theory wherein a person applies a linear probability weighting function but uses a value function $v(x)$ that is S-shaped in the gain domain. Under SSV, the indifference valuation $m^*(p,r)$ is given by

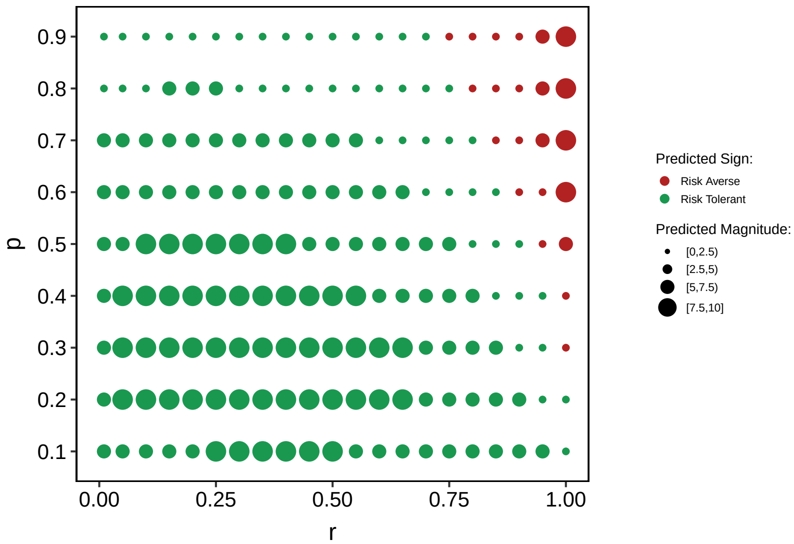
$$rv(m^*(p,r)) = prv(H) \qquad \Longleftrightarrow \qquad m^*(p,r) = v^{-1}(pH),$$

and the normalized risk premium is given by

$$RP^*(p,r) = pH - m^*(p,r) = pH - v^{-1}(pH).$$

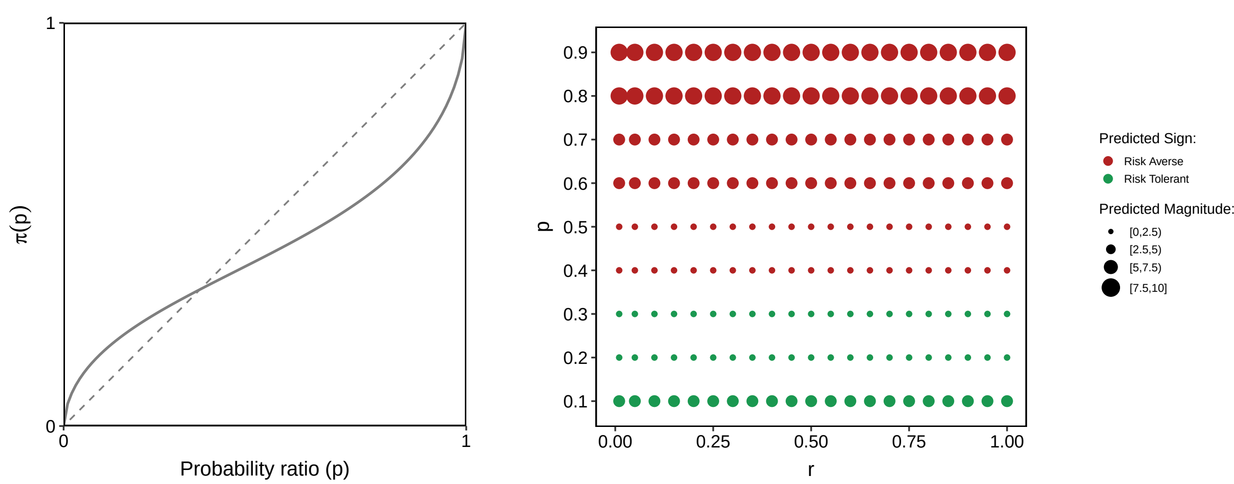
Note that, under SSV, $m^*(p,r)$ and $RP^*(p,r)$ are both independent of r. Appendix Figure D.3 depicts how $RP^*(p,r)$ depends on (p,r). Since there is no focal S-shaped value function in the literature, Appendix Figure D.3 uses the function that we estimate in Section 5 when using the full sample.

Figure D.1: Predictions of Prospect Theory (PT)



Notes: Figure depicts risk-premium map under PT assuming functional forms and parameter values suggested by Tversky and Kahneman (1992)—specifically, assuming value function $v(x) = x^{\alpha}$ with $\alpha = 0.88$ and probability weighting function $\pi(q) = q^{\gamma}/[q^{\gamma} + (1-q)^{\gamma}]^{1/\gamma}$ with $\gamma = 0.61$. Under PT with these functional forms, $RP^{*}(p,r) = \left(p - \left(\frac{\pi(pr)}{\pi(r)}\right)^{1/\alpha}\right)H$, and figure assumes $H = 30$. For each (p,r), circle characterizes predicted $RP^{*}(p,r)$, where color of circle captures sign (green is positive, red is negative), and size of circle capture magnitude.

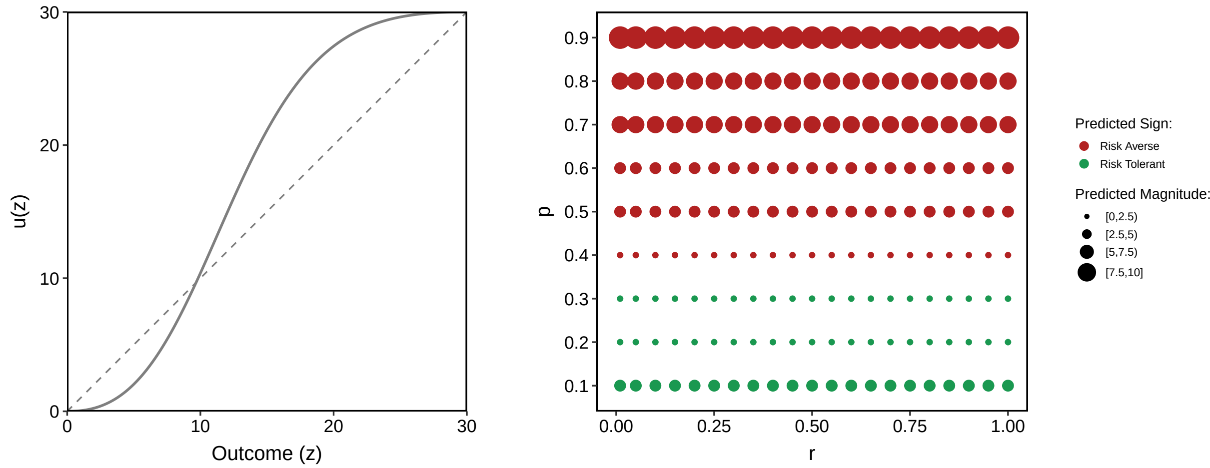
Figure D.2: Predictions of Proportional Probability Weighting (PPW)



(a) Probability Weighting Function $\pi(q)$ (b) Predicted Risk Premia Over (p,r)

Notes: Figure depicts risk-premium map under PPW assuming functional form and parameter value suggested by Tversky and Kahneman (1992)—specifically, assuming probability weighting function $\pi(q) = q^{\gamma}/[q^{\gamma} + (1-q)^{\gamma}]^{1/\gamma}$ with $\gamma = 0.61$. Under PPW, $RP^{*}(p,r) = (p - \pi(p))H$, and figure assumes $H = 30$. Panel (a) plots $\pi(q)$. In panel (b), for each (p,r), circle characterizes predicted $RP^{*}(p,r)$, where color of circle captures sign (green is positive, red is negative), and size of circle capture magnitude.

Figure D.3: Predictions of S-shaped Value Function (SSV)



(a) S-Shaped Value Function $v(x)$

(b) Predicted Risk Premia Over (p, r)

Notes: Figure depicts risk-premium map under SSV assuming functional form and parameter values from full-sample estimation reported in Table 3 in Section 5—specifically, assuming $v(x) = \gamma(x/H)^\delta / [\gamma(x/H)^\delta + (1 - x/H)^\delta]$ with $\gamma = 2.375$ and $\delta = 2.166$. Under SSV, $RP^*(p, r) = pH - v^{-1}(pH)$, and figure assumes $H = 30$. Panel (a) plots $v(x)$. In panel (b), for each (p, r), circle characterizes predicted $RP^*(p, r)$, where color of circle captures sign (green is positive, red is negative), and size of circle capture magnitude.

D.2 Details of the Upside Potential (UP) Model

This section provides a more detailed description of the UP model and derives the results described in Section 4.3.

McGranaghan et al. (2025) propose the following psychology: A person first identifies a set of outcomes that they consider to be "winning" outcomes, and then trades off (i) the total probability of winning versus (ii) an expected valuation of those winnings. Formally, McGranaghan et al. assume that if W denotes the set of winning outcomes, then the person evaluates a lottery $Y \equiv (x_1, q_1; ...; x_N, q_N)$ as

$$U(Y) = \underbrace{\left(\sum_{i=1}^{N} q_i u(x_i)\right)}_{EU} + \underbrace{\left(\sum_{j=1}^{N} q_j I(x_j \in W)\right)}_{\substack{\text{probability of} \\ \text{winning something}}} \underbrace{\left(\sum_{k=1}^{N} q_k I(x_k \in W)\kappa(x_k)\right)}_{\substack{\text{expected valuation} \\ \text{of winnings}}}. \tag{D.10}$$

The first term is standard expected utility. The second term captures preferences for UP as the total probability of winning multiplied by an expected valuation of those winnings. The function κ is assumed to be weakly increasing with $\kappa(x) \geq 0$ for all x. As discussed in more detail by McGranaghan et al., the UP model falls within the broader class of "quadratic utility" models (Machina, 1982; Chew et al., 1991).

Applied to the binary lotteries that are the focus of this paper, the UP model says that a person evaluates a lottery $Y \equiv (x, q)$ as

$$U(Y) = qu(x) + (q)(q\kappa(x)).$$

McGranaghan et al. further suggest the simplification of assuming the EU term is linear, so that the person cares about the expected value of a lottery and also its upside potential, yielding the equation

$$U(Y) = qx + (q)(q\kappa(x)) \tag{D.11}$$

that appears in the Section 4.3.

Using equation D.11, the valuation $m^*(p, r)$ is the M that satisfies the equation

$$rM + r^2\kappa(M) = prH + (pr)^2\kappa(H).$$

We can write this as $F(m^*(p, r), p, r) = 0$ where

$$F(M, p, r) \equiv [M - pH] + r[\kappa(M) - p^2\kappa(H)]. \tag{D.12}$$

Because F is strictly increasing in M, there is a unique $m^*(p, r) \in (0, H)$ that satisfies $F(m^*(p, r), p, r) = 0$. Under the minimal assumption that κ is differentiable for all $x > 0$, we can now prove the result that is stated in Section 4.3:

<u>Result</u>: If $m^*(p, r)$ is derived from $F(m^*(p, r), p, r) = 0$, then:

$$\kappa(pH) > p^2\kappa(H) \iff RP^*(p, r) > 0 \iff \frac{\partial RP^*(p, r)}{\partial r} > 0 \qquad \text{and}$$

$$\kappa(pH) < p^2\kappa(H) \iff RP^*(p, r) < 0 \iff \frac{\partial RP^*(p, r)}{\partial r} < 0.$$

<u>Proof</u>: Consider first the results regarding $RP^*(p, r)$. If $\kappa(pH) > p^2\kappa(H)$, it follows from equation D.12 that $F(pH, p, r) > 0$. Because F is strictly increasing in M, we must have $m^*(p, r) < pH$ to obtain $F(m^*(p, r), p, r) = 0$, and thus $RP^*(p, r) \equiv pH - m^*(p, r) > 0$. For the converse, if $RP^*(p, r) \equiv pH - m^*(p, r) > 0$, it follows from $F(m^*(p, r), p, r) = 0$ that $\kappa(m^*(p, r)) > p^2\kappa(H)$. Given $pH > m^*(p, r)$ and κ strictly increasing, we must have $\kappa(pH) > p^2\kappa(H)$.

An analogous argument yields $\kappa(pH) < p^2\kappa(H)$ if and only if $RP^*(p, r) < 0$. Also note that these arguments imply $\kappa(pH) > p^2\kappa(H)$ if and only if $\kappa(m^*(p, r)) > p^2\kappa(H)$, and also $\kappa(pH) < p^2\kappa(H)$ if and only if $\kappa(m^*(p, r)) < p^2\kappa(H)$; we use these below.

Now consider the results regarding $\frac{\partial RP^*}{\partial r}$. Because $F(m^*(p, r), p, r) = 0$, the implicit function theorem implies

$$\frac{\partial m^*}{\partial r} = \frac{-F_r(m^*(p, r), p, r)}{F_m(m^*(p, r), p, r)} = \frac{-[\kappa(m^*(p, r)) - p^2\kappa(H)]}{1 + r\kappa'(m^*(p, r))}.$$

Because κ is increasing, the denominator is positive. Hence, it follows that

$$\kappa(pH) > p^2\kappa(H) \iff \kappa(m^*(p, r)) - p^2\kappa(H) > 0 \iff \frac{\partial RP^*(p, r)}{\partial r} > 0 \qquad \text{and}$$

$$\kappa(pH) < p^2\kappa(H) \iff \kappa(m^*(p, r)) - p^2\kappa(H) < 0 \iff \frac{\partial RP^*(p, r)}{\partial r} < 0.$$

That completes the proof.

E Additional Estimation Details (for Section 5)

This section provides additional details on the aggregate-level estimation reported in Table 3 in Section 5, and also provides the model-fit figures referenced in Section 5.

As described in Section 5, for each model, we conduct two exercises:

> **Exercise 1**: We estimate the model using only the aggregate means when $r = 1$ (i.e., off 9 aggregate means). For these estimates, we compare models based on both their in-sample performance as well as their out-of-sample performance when we use the estimates to predict behavior throughout the remainder of the parameter space (i.e., for the 180 other aggregate means when $r < 1$).
>
> **Exercise 2**: We estimate the model using all 189 aggregate means, in which case we compare models using in-sample performance.

For both exercises, our two performance measures are the root mean-squared error (RMSE) and correlation between predicted and observed mean $RP(p, r)$.

Data and Estimation Sample

For each (p, r), we define the mean valuation $m(p, r)$ to be the mean of $m_i(p, r)$ across all observations for that (p, r), including repeats. All estimators target the $m(p, r)$'s directly.

We let $\mathcal{S}$ denote the estimation sample. For Exercise 1, $\mathcal{S} = \{(p, r) : r = 1\}$; note that this includes nine observations. For Exercise 2, $\mathcal{S}$ includes all 189 observations.

Estimator

For each model $\mathcal{M}$ with parameter vector θ, we let $m^{\mathcal{M}}(p, r; \theta)$ denote the model-implied valuation. We then estimate θ by nonlinear least squares. In other words, given an estimation sample $\mathcal{S}$ and model $\mathcal{M}$ with parameter vector θ, the estimator is

$$\hat{\theta} \;=\; \arg\min_{\theta} \sum_{(p,r)\in\mathcal{S}} \big(m(p, r) - m^{\mathcal{M}}(p, r; \theta)\big)^2.$$

Each optimization uses the Levenberg–Marquardt algorithm (`minpack.lm::nlsLM`) with convergence tolerances of 10^{-10} on both the parameter and function norms.

Functional Forms

The PW, PT, and PPW models require an inverse-S-shaped probability weighting function. The SSV and UP models require an S-shaped value or upside potential function. It turns out that the two-parameter family from Lattimore et al. (1992) has the flexibility to capture both, and thus to put the models on equal footing, we use that functional form throughout. Specifically, we use the functional form from equation 7:

$$f(z;\gamma,\delta) \;\equiv\; \frac{\gamma z^{\delta}}{\gamma z^{\delta}+(1-z)^{\delta}}.$$

To ensure that f is increasing for each model, δ and γ must be positive; in our estimation, we restrict them both to be at least 0.01.

For PW, PT, and PPW, we assume the probability weighting function is

$$\pi(q;\gamma,\delta) \;=\; f(q;\gamma,\delta) \;=\; \frac{\gamma\, q^{\delta}}{\gamma\, q^{\delta}+(1-q)^{\delta}}.$$

For SSV and UP, we assume the value or upside-potential function is

$$v(x;\gamma,\delta,B) \;=\; \kappa(x;\gamma,\delta,B) \;=\; B\cdot f(x/H;\gamma,\delta) \;=\; B\cdot\frac{\gamma\,(x/H)^{\delta}}{\gamma\,(x/H)^{\delta}+(1-x/H)^{\delta}}.$$

Note that this specification implies $v(0;\gamma,\delta,B)=\kappa(0;\gamma,\delta,B)=0$ and $v(H;\gamma,\delta,B)=\kappa(H;\gamma,\delta,B)=B$ for all (γ,δ). We discuss the role of B in the specific models below.

Formulas for Model-Predicted $m^{\mathcal{M}}(p,r;\theta)$

Each model's predicted valuation $m^{\mathcal{M}}(p,r;\theta)$ is obtained from the indifference condition stated below; where no closed form exists, we solve for m numerically on $[0,H]$.

Probability Weighting (PW): From Section 4.2, the closed-form solution for the model-predicted valuation is:

$$m^{\mathrm{PW}}(p,r;\theta)=\frac{\pi(pr;\gamma,\delta)}{\pi(r;\gamma,\delta)}H,$$

and thus the parameter vector is $\theta=(\gamma,\delta)$.

Prospect Theory (PT): From Section D.1, the closed-form solution for the model-predicted valuation is:

$$m^{\mathrm{PT}}(p,r;\theta)=\left(\frac{\pi(pr;\gamma,\delta)}{\pi(r;\gamma,\delta)}\right)^{1/\alpha}H,$$

and thus the parameter vector is $\theta=(\gamma,\delta,\alpha)$.

Proportional Probability Weighting (PPW): From Section D.1, the closed-form solution for the model-predicted valuation is:

$$m^{\mathrm{PPW}}(p,r;\theta)=\pi(p;\gamma,\delta)H,$$

and thus the parameter vector is $\theta=(\gamma,\delta)$.

S-Shaped Value Function (SSV): From Section D.1, $m^{\mathrm{SSV}}(p,r;\theta)$ satisfies the equation:

$$v(m^{\mathrm{SSV}}(p,r;\theta);\gamma,\delta)=p\,v(H;\gamma,\delta).$$

In this equation, the B in v cancels, and thus we suppress it (and it is of course not identified). Hence, the parameter vector is $\theta = (\gamma, \delta)$. There is no closed-form solution for $m^{\text{SSV}}(p, r; \theta)$, and thus we solve for it using numerical methods.

Upside Potential (UP): From Section 4.3, $m^{\text{UP}}(p, r; \theta)$ satisfies the equation:

$$r\, m^{\text{UP}}(p, r; \theta) + r^2\, \kappa(m^{\text{UP}}(p, r; \theta); \gamma, \delta, B) = pr\, H + (pr)^2\, \kappa(H; \gamma, \delta, B).$$

There is no closed-form solution for $m^{\text{UP}}(p, r; \theta)$, and thus we solve for it using numerical methods. In principle, the parameter vector is $\theta = (\gamma, \delta, B)$. However, for any set $\mathcal{B} \equiv [B_L, B_H]$ to which we constrain B, we estimate $\hat{B} = B_H$. Hence, we instead choose a value for B and take the parameter vector to be $\theta = (\gamma, \delta)$. Appendix Table E.1 reports estimates for both Exercise 1 and Exercise 2 for $B \in \{100, 200, 300, 400, 500\}$. By the time that $B = 300$, the estimates and RMSE's change very little; hence, we chose to report the estimates for $B = 300$ in Table 3 in Section 5.

Figures for Each Model

Figures E.1-E.5 illustrate the estimations for each model. For each model, there are two estimations, one for Exercise 1 and one for Exercise 2. For each estimation, there is a panel for each estimated nonlinear function and also a panel to illustrate the model fit. The latter requires explanation, and the explanation differs for Exercise 1 and Exercise 2.

For Exercise 1: Here, we estimate $\hat{\theta}$ using only the nine (p, r) combinations with $r = 1$. Using $\hat{\theta}$, we generate predicted valuations $\hat{m}^{\mathcal{M}}(p, r) = m^{\mathcal{M}}(p, r; \hat{\theta})$ for all 189 (p, r) combinations, and map them to predicted risk premia using $\widehat{RP}^{\mathcal{M}}(p, r) = pH - \hat{m}^{\mathcal{M}}(p, r)$. We then plot the observed risk premium $RP(p, r)$ against the predicted risk premium $\widehat{RP}^{\mathcal{M}}(p, r)$, with the 45-degree line for reference. Finally, we use black points to mark the $r = 1$ cells used for the estimation, and red points to mark the remaining $r < 1$ cells.

For Exercise 2: Here, we estimate $\hat{\theta}$ using all 189 (p, r) combinations. Using $\hat{\theta}$, we generate predicted valuations $\hat{m}^{\mathcal{M}}(p, r) = m^{\mathcal{M}}(p, r; \hat{\theta})$ for all 189 (p, r) combinations, and map them to predicted risk premia using $\widehat{RP}^{\mathcal{M}}(p, r) = pH - \hat{m}^{\mathcal{M}}(p, r)$. We then plot the observed risk premium $RP(p, r)$ against the predicted risk premium $\widehat{RP}^{\mathcal{M}}(p, r)$, with the 45-degree line for reference. All points are black since there is no distinction between in-sample and out-of-sample cells.

Observational Equivalence of PPW and SSV (Given Our Functional Forms)

In Section 5, we claim that, given our functional-form assumptions, PPW and SSV are observationally equivalent. Specifically, one can show for any (p, r) and $\theta \equiv (\gamma, \delta)$, there exists $\theta' \equiv (\gamma', \delta')$ such that $m^{\text{SSV}}(p, r; \theta') = m^{\text{PPW}}(p, r; \theta)$. We now prove this claim.

Recall equation 7:

$$f(z; \gamma, \delta) \;\equiv\; \frac{\gamma z^{\delta}}{\gamma z^{\delta} + (1 - z)^{\delta}}.$$

We first derive that

$$f^{-1}(y;\gamma,\delta) = f(y;\gamma^{-1/\delta},1/\delta)$$

Proof: Let $y = f(z;\gamma,\delta)$ and then solve for z:

$$\begin{aligned}
& y = \frac{\gamma z^{\delta}}{\gamma z^{\delta} + (1-z)^{\delta}} \\
\iff \quad & \gamma z^{\delta} y + (1-z)^{\delta} y = \gamma z^{\delta} \\
\iff \quad & (1-z)^{\delta} y = \gamma z^{\delta}(1-y) \\
\iff \quad & (1-z) y^{1/\delta} = \gamma^{1/\delta} z (1-y)^{1/\delta} \\
\iff \quad & z = \frac{\gamma^{-1/\delta} y^{1/\delta}}{\gamma^{-1/\delta} y^{1/\delta} + (1-y)^{1/\delta}} \\
\iff \quad & z = f(y;\gamma^{-1/\delta},1/\delta)
\end{aligned}$$

Next, recall that in general under PPW:

$$m^{\text{PPW}}(p,r;\theta) = \pi(p;\gamma,\delta)H.$$

Given our functional-form assumption of $\pi(p;\gamma,\delta) = f(p;\gamma,\delta)$, this becomes

$$\frac{m^{\text{PPW}}(p,r;\theta)}{H} = f(p;\gamma,\delta)$$

Finally, recall that in general under SSV:

$$v(m^{\text{SSV}}(p,r;\theta);\gamma,\delta) = p\, v(H;\gamma,\delta).$$

Given our functional-form assumption of $v(x;\gamma,\delta) = f(x/H;\gamma,\delta)H$, and noting $v(H;\gamma,\delta) = H$ for all (γ,δ), this becomes

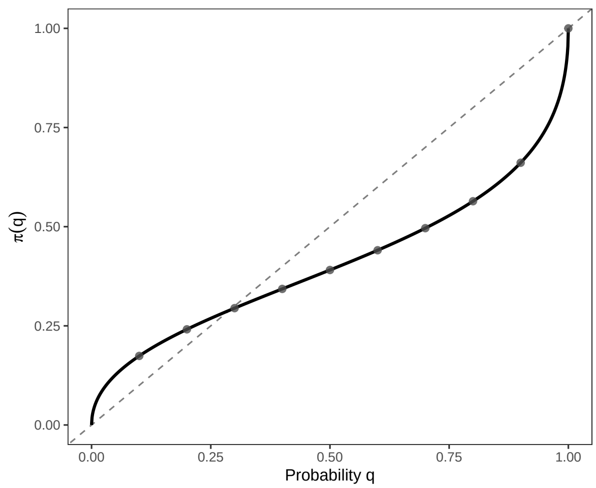
$$f\left(\frac{m^{\text{SSV}}(p,r;\theta)}{H};\gamma,\delta\right)H = pH$$

or

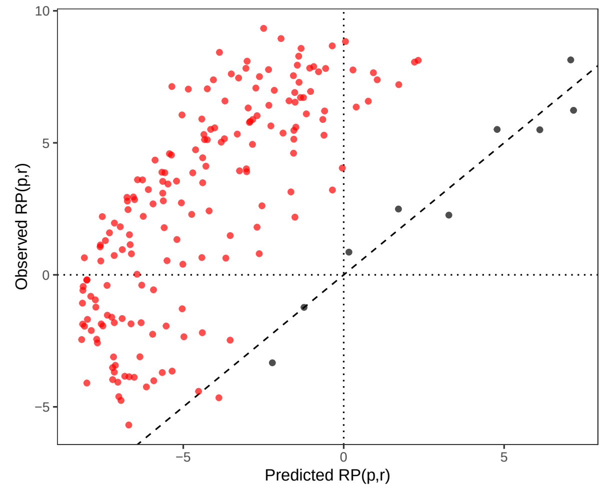
$$\frac{m^{\text{SSV}}(p,r;\theta)}{H} = f^{-1}(p;\gamma,\delta) = f(p;\gamma^{-1/\delta},1/\delta).$$

Hence, for any (p,r) and $\theta \equiv (\gamma,\delta)$, if $\theta' = (\gamma^{-1/\delta},1/\delta)$, then $m^{\text{SSV}}(p,r;\theta') = m^{\text{PPW}}(p,r;\theta)$. The claim follows.

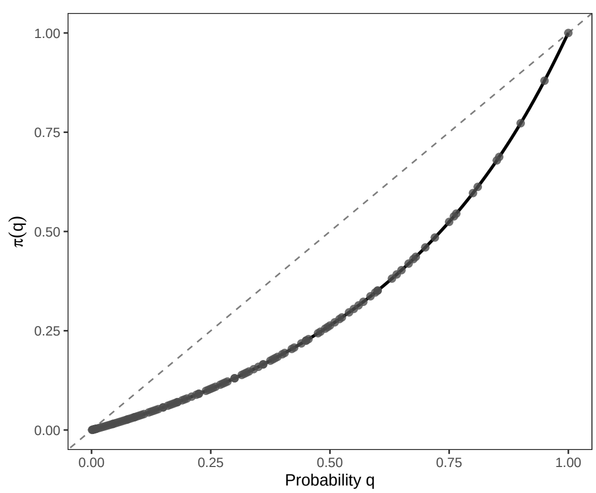
Figure E.1: Probability Weighting (PW): Estimated $\pi(q)$ and Model Fit



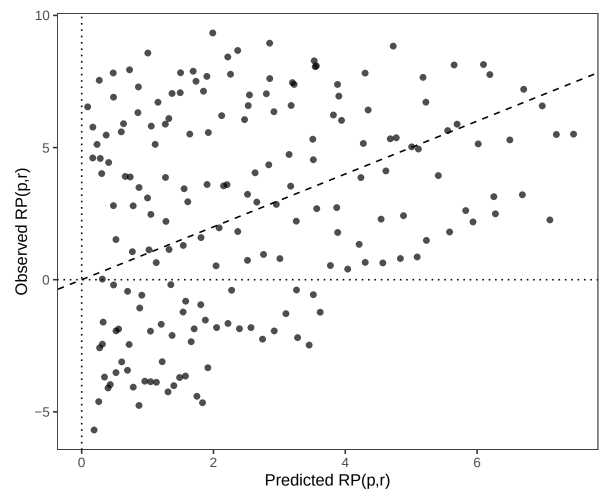
(a) PW Estimated $\pi(q)$: Exercise 1



(b) PW Model Fit: Exercise 1



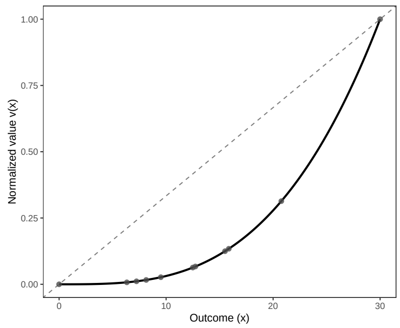
(c) PW Estimated $\pi(q)$: Exercise 2



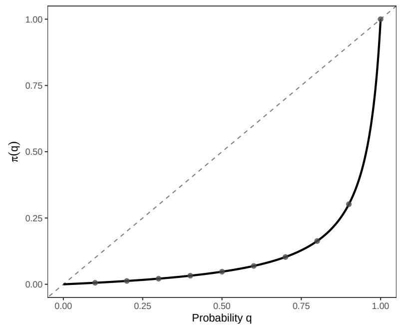
(d) PW Model Fit: Exercise 2

Notes: Figure depicts estimated $\pi(q)$ and model fit for PW model. Functional form is $\pi(q) = \gamma q^\delta / [\gamma q^\delta + (1-q)^\delta]$, where we estimate (γ, δ) using nonlinear least squares. For panels (a) and (b), parameters estimated using the nine observations of $m(p,r)$ with $r = 1$. Panel (a) depicts $\pi(q)$ given estimated parameters $\gamma = 0.641$ and $\delta = 0.506$. Panel (b) depicts model fit by plotting, for each of the 189 (p,r) combinations, the observed $RP(p,r)$ against the model implied $\widehat{RP}^{PW}(p,r)$ given the $\pi(q)$ from panel (a); panel (b) also shows the 45-degree line for reference. In panel (b), black points correspond to the nine in-sample observations with $r = 1$, while red points correspond to the 180 out-of-sample observations with $r < 1$. For panels (c) and (d), parameters estimated using all 189 observations of $m(p,r)$. Panel (c) depicts $\pi(q)$ given estimated parameters $\gamma = 0.357$ and $\delta = 1.025$. Panel (d) again depicts model fit by plotting, for each of the 189 (p,r) combinations, the observed $RP(p,r)$ against the model implied $\widehat{RP}^{PW}(p,r)$ given the $\pi(q)$ from panel (c). Since all 189 observations are in sample, all points are black.

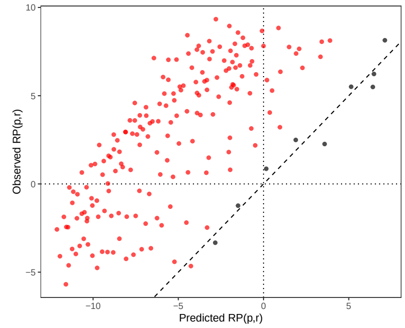
Figure E.2: Prospect Theory (PT): Estimated $\pi(q)$ and $v(x)$ and Model Fit



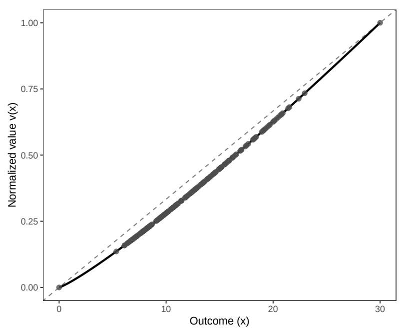
(a) PT Estimated $v(x)$: Exercise 1



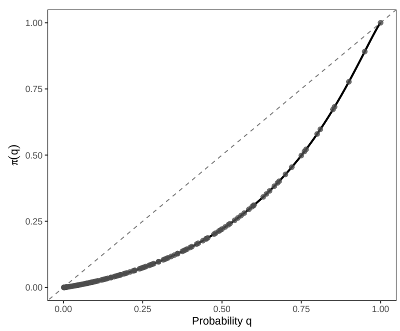
(b) PT Estimated $\pi(q)$: Exercise 1



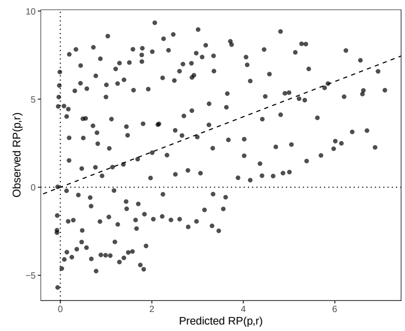
(c) PT Model Fit: Exercise 1



(d) PT Estimated $v(x)$: Exercise 2



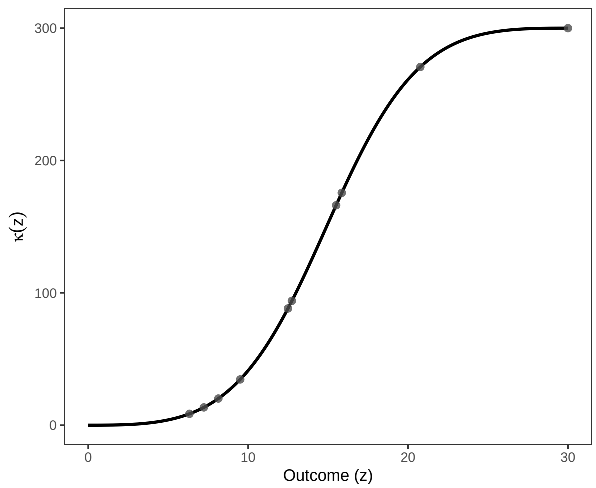
(e) PT Estimated $\pi(q)$: Exercise 2



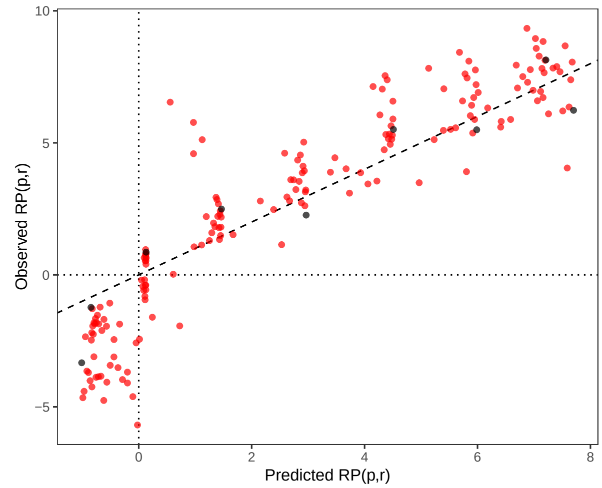
(f) PT Model Fit: Exercise 2

Notes: Figure depicts estimated $v(x)$ and $\pi(q)$ and model fit for PT model. Functional forms are $v(x) = x^{\alpha}$ and $\pi(q) = \gamma q^{\delta}/[\gamma q^{\delta} + (1-q)^{\delta}]$, where we estimate (γ, δ, α) using nonlinear least squares. For panels (a), (b), and (c), parameters estimated using the nine observations of $m(p,r)$ with $r = 1$. Panel (a) depicts $v(x)$ given estimated parameter $\alpha = 3.153$, and panel (b) depicts $\pi(q)$ given estimated parameters $\gamma = 0.050$ and $\delta = 0.983$. Panel (c) depicts model fit by plotting, for each of the 189 (p,r) combinations, the observed $RP(p,r)$ against the model implied $\widehat{RP}^{PT}(p,r)$ given the functions from panels (a) and (b); panel (c) also shows the 45-degree line for reference. In panel (c), black points correspond to the nine in-sample observations with $r = 1$, while red points correspond to the 180 out-of-sample observations with $r < 1$. For panels (d), (e), and (f), parameters estimated using all 189 observations of $m(p,r)$. Panel (d) depicts $v(x)$ given estimated parameter $\alpha = 1.156$, and panel (e) depicts $\pi(q)$ given estimated parameters $\gamma = 0.283$ and $\delta = 1.143$. Panel (f) again depicts model fit by plotting, for each of the 189 (p,r) combinations, the observed $RP(p,r)$ against the model implied $\widehat{RP}^{PT}(p,r)$ given the functions in panels (d) and (e). Since all 189 observations are in sample, all points are black.

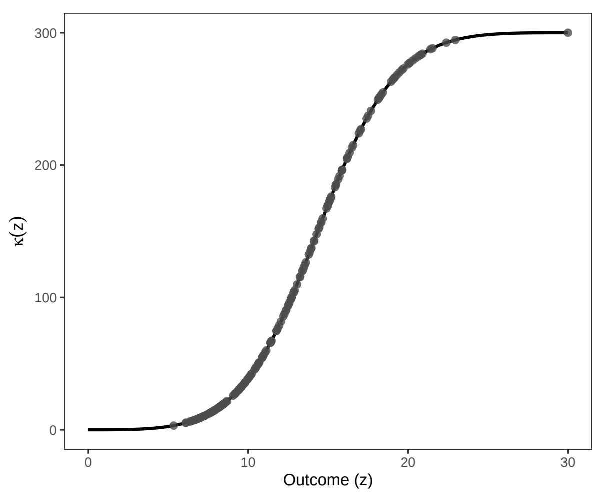
Figure E.3: Upside Potential (UP): Estimated $\kappa(x)$ and Model Fit



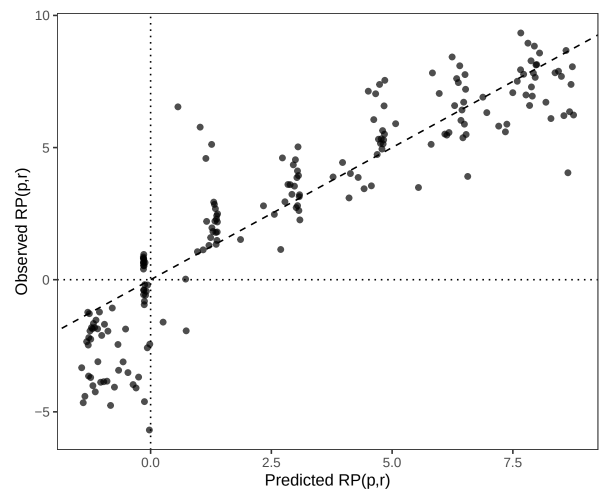
(a) UP Estimated $\kappa(x)$: Exercise 1



(b) UP Model Fit: Exercise 1



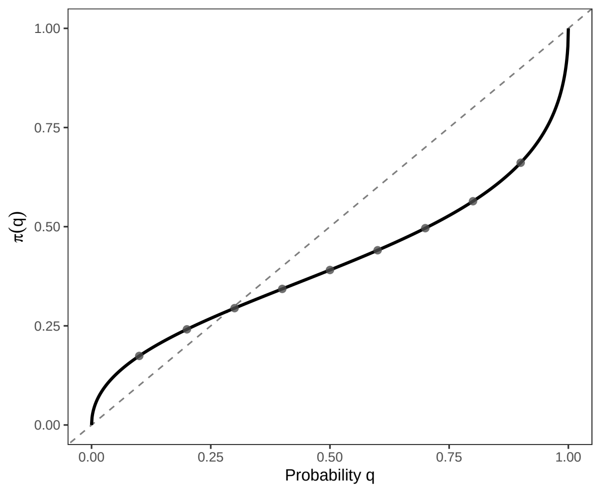
(c) UP Estimated $\kappa(x)$: Exercise 2



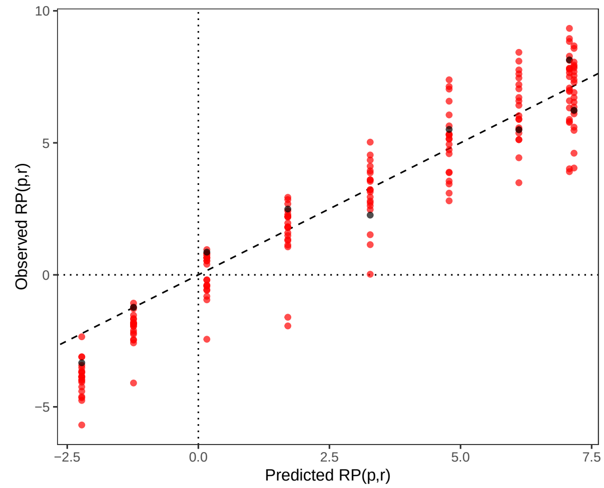
(d) UP Model Fit: Exercise 2

Notes: Figure depicts estimated $\kappa(x)$ and model fit for UP model. Functional form is $\kappa(x) = B\gamma(x/H)^{\delta}/[\gamma(x/H)^{\delta} + (1-x/H)^{\delta}]$, where we set $H = 30$ and $B = 300$ and then estimate (γ, δ) using nonlinear least squares. For panels (a) and (b), parameters estimated using the nine observations of $m(p,r)$ with $r = 1$. Panel (a) depicts $\kappa(x)$ given estimated parameters $\gamma = 1.035$ and $\delta = 2.699$. Panel (b) depicts model fit by plotting, for each of the 189 (p,r) combinations, the observed $RP(p,r)$ against the model implied $\widehat{RP}^{UP}(p,r)$ given the $\kappa(x)$ from panel (a); panel (b) also shows the 45-degree line for reference. In panel (b), black points correspond to the nine in-sample observations with $r = 1$, while red points correspond to the 180 out-of-sample observations with $r < 1$. For panels (c) and (d), parameters estimated using all 189 observations of $m(p,r)$. Panel (c) depicts $\kappa(x)$ given estimated parameters $\gamma = 1.310$ and $\delta = 3.145$. Panel (d) again depicts model fit by plotting, for each of the 189 (p,r) combinations, the observed $RP(p,r)$ against the model implied $\widehat{RP}^{UP}(p,r)$ given the $\kappa(x)$ from panel (c). Since all 189 observations are in sample, all points are black.

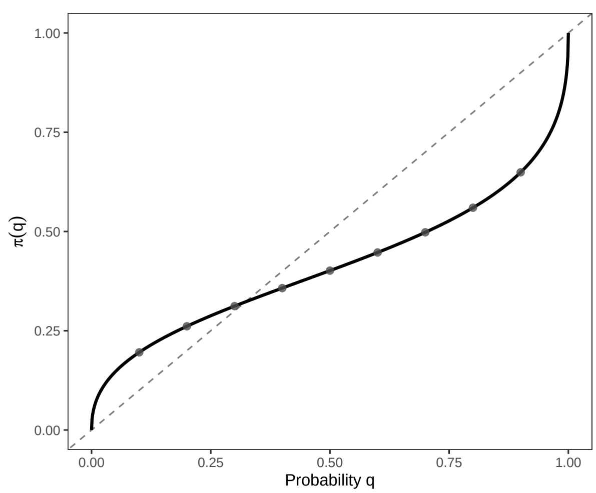
Figure E.4: Proportional Probability Weighting (PPW): Estimated $\pi(q)$ and Model Fit



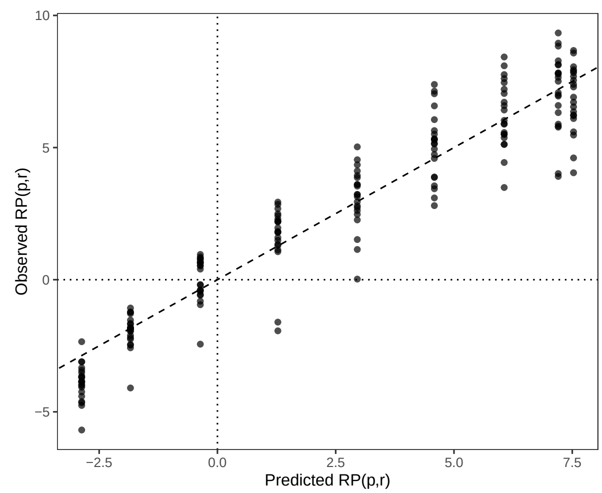
(a) PPW Estimated $\pi(q)$: Exercise 1



(b) PPW Model Fit: Exercise 1



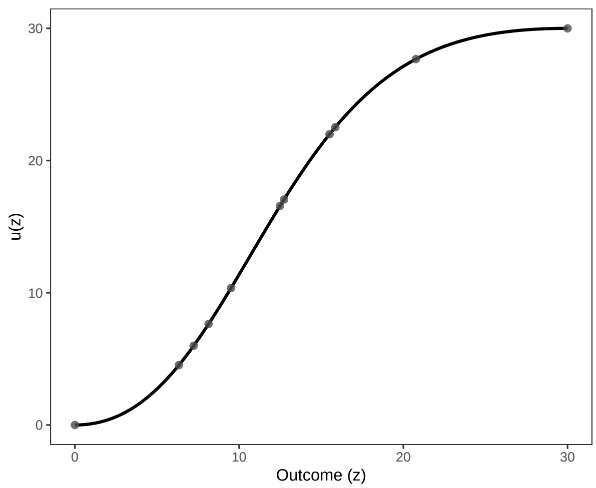
(c) PPW Estimated $\pi(q)$: Exercise 2



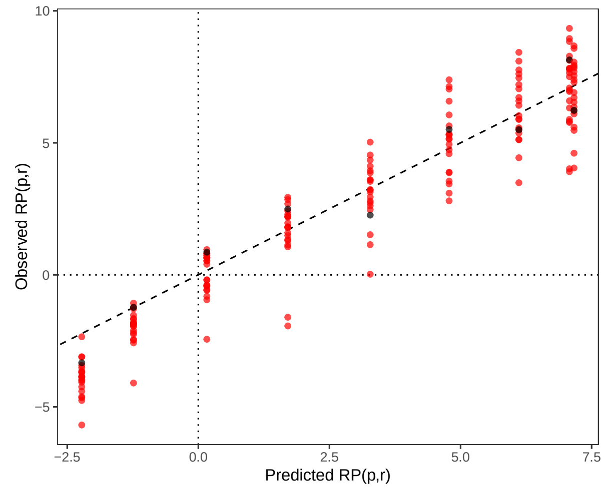
(d) PPW Model Fit: Exercise 2

Notes: Figure depicts estimated $\pi(q)$ and model fit for PPW model. Functional form is $\pi(q) = \gamma q^{\delta}/[\gamma q^{\delta} + (1-q)^{\delta}]$, where we estimate (γ, δ) using nonlinear least squares. For panels (a) and (b), parameters estimated using the nine observations of $m(p,r)$ with $r = 1$. Panel (a) depicts $\pi(q)$ given estimated parameters $\gamma = 0.641$ and $\delta = 0.506$. Panel (b) depicts model fit by plotting, for each of the 189 (p,r) combinations, the observed $RP(p,r)$ against the model implied $\widehat{RP}^{PPW}(p,r)$ given the $\pi(q)$ from panel (a); panel (b) also shows the 45-degree line for reference. In panel (b), black points correspond to the nine in-sample observations with $r = 1$, while red points correspond to the 180 out-of-sample observations with $r < 1$. For panels (c) and (d), parameters estimated using all 189 observations of $m(p,r)$. Panel (c) depicts $\pi(q)$ given estimated parameters $\gamma = 0.671$ and $\delta = 0.462$. Panel (d) again depicts model fit by plotting, for each of the 189 (p,r) combinations, the observed $RP(p,r)$ against the model implied $\widehat{RP}^{PPW}(p,r)$ given the $\pi(q)$ from panel (c). Since all 189 observations are in sample, all points are black. Note that PPW and SSV are observationally equivalent given the functional forms that we use, and this equivalence is reflected in panels (b) and (d) here being identical to panels (b) and (d) in Appendix Figure E.5.

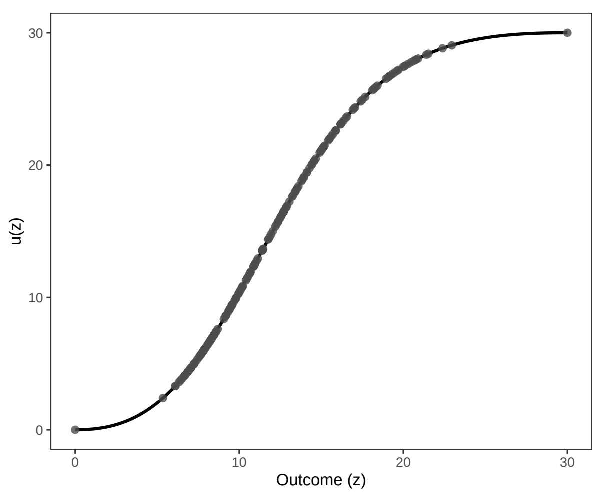
Figure E.5: S-shaped Value Function (SSV): Estimated $v(x)$ and Model Fit



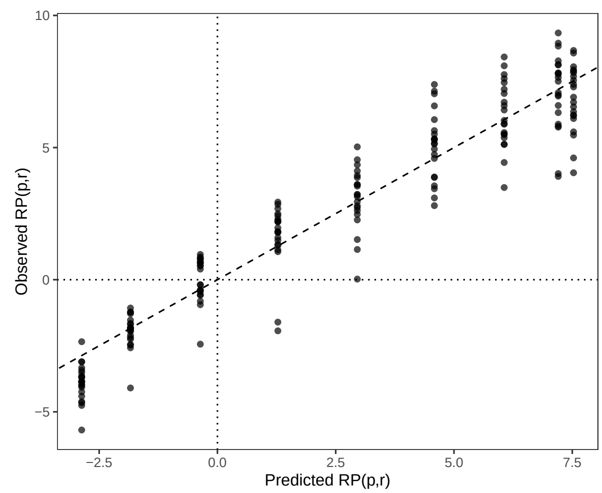
(a) SSV Estimated $v(x)$: Exercise 1



(b) SSV Model Fit: Exercise 1



(c) SSV Estimated $v(x)$: Exercise 2



(d) SSV Model Fit: Exercise 2

Notes: Figure depicts estimated $v(x)$ and model fit for SSV model. Functional form is $v(x) = \gamma(x/H)^\delta/[\gamma(x/H)^\delta + (1 - x/H)^\delta]$, where we set $H = 30$ and then estimate (γ, δ) using nonlinear least squares. For panels (a) and (b), parameters estimated using the nine observations of $m(p, r)$ with $r = 1$. Panel (a) depicts $v(x)$ given estimated parameters $\gamma = 2.404$ and $\delta = 1.975$. Panel (b) depicts model fit by plotting, for each of the 189 (p, r) combinations, the observed $RP(p, r)$ against the model implied $\widehat{RP}^{SSV}(p, r)$ given the $v(x)$ from panel (a); panel (b) also shows the 45-degree line for reference. In panel (b), black points correspond to the nine in-sample observations with $r = 1$, while red points correspond to the 180 out-of-sample observations with $r < 1$. For panels (c) and (d), parameters estimated using all 189 observations of $m(p, r)$. Panel (c) depicts $v(x)$ given estimated parameters $\gamma = 2.375$ and $\delta = 2.166$. Panel (d) again depicts model fit by plotting, for each of the 189 (p, r) combinations, the observed $RP(p, r)$ against the model implied $\widehat{RP}^{SSV}(p, r)$ given the $v(x)$ from panel (c). Since all 189 observations are in sample, all points are black. Note that SSV and PPW are observationally equivalent given the functional forms that we use, and this equivalence is reflected in panels (b) and (d) here being identical to panels (b) and (d) in Appendix Figure E.4.

Table E.1: UP Model Estimates and Predictive Performance for Different Values of B

	Estimated Using Nine Observations with $r = 1$				Estimated Using All 189 Observations		
B	$\widehat{\gamma}$	$\widehat{\delta}$	In-Sample RMSE	Out-of-Sample RMSE	$\widehat{\gamma}$	$\widehat{\delta}$	RMSE
100	1.265	2.823	1.212	2.069	2.154	3.600	1.900
200	1.086	2.722	1.175	1.859	1.487	3.245	1.740
300	1.035	2.699	1.149	1.766	1.310	3.145	1.669
400	1.012	2.687	1.132	1.712	1.227	3.098	1.627
500	0.998	2.680	1.120	1.676	1.177	3.069	1.597

Notes: Entries reflect estimated parameters $(\widehat{\gamma}, \widehat{\delta})$ and measure of model performance for the UP model described in Section 4. Using the function f from equation 7, functional form for κ function is $\kappa(x) = B \cdot f(x/H; \gamma, \delta)$; each row reflects a different assumed value for B. Parameters $(\widehat{\gamma}, \widehat{\delta})$ estimated via non-linear least squares by minimizing the squared distance between model-implied $m^*(p, r)$ and observed mean response $m(p, r)$. In left panel, model estimated using only nine aggregate means when $r = 1$; in right panel, model estimated using all 189 aggregate means. Model performance measure is root mean-squared error (RMSE); left panel reports both in-sample performance across nine observations with $r = 1$ and out-of-sample performance across 180 observations with $r < 1$; right panel reports (in-sample) performance across all 189 observations.

F Additional Individual-Level Tables and Figures (for Section 6)

Figure 6 in Section 6 provides an overview of the heterogeneity in our data by depicting the distributions of $\beta_{p,i}$ and $\beta_{r,i}$, where these are estimated at the individual-$\bar{r}$ or individual-$\bar{p}$ level using equations 8 and 9. To improve readability, both panels of Figure 6 are truncated. Appendix Figure F.1 presents untruncated versions of each panel.

We can similarly calculate $\tau^a_{p,i}$ at the individual-$\bar{r}$ level and $\tau^a_{r,i}$ at the individual-$\bar{p}$ level; Appendix Figure F.2 is analogous to Figure F.1, and yields much the same message. On one hand, the feature of having normalized risk premia that increase with p appears to be a robust phenomena exhibited by most individuals—indeed, 91.5% of subjects have an average $\tau^a_{p,i}$ that is positive, and 59.2% have an average $\tau^a_{p,i}$ that is larger than 0.4. On the other hand, the evidence on sub- versus superproportionality is more mixed—roughly half of subjects (54.9%) have an average $\tau^a_{r,i}$ that is positive (on average subproportional), 44% have an average $\tau^a_{r,i}$ that is negative (on average superproportional), and the remaining 1.1% average exactly zero.

Table 4 in Section 6 provides a subject-level look at whether people exhibit the tendency to show both the PB-TK effect and the connection between risk attitudes and sub- vs. superproportionality. In Table 4, each subject appears only once, and for each we use the largest and smallest values for p that they saw. As a robustness check, we repeat this exercise using all ordered pairs for each subject—that is, for all (p, p') with $p < p'$ where the subject saw both p and p'. Since each subject saw five values for p, each participant contributes $\binom{5}{2} = 10$ pairwise comparisons. Appendix Table F.1 reports this alternative classification. The same key pattern emerges: the table is organized such that the UP model predicts observations to be on the main diagonal, and indeed within each row, the cell on the main diagonal is the modal outcome.

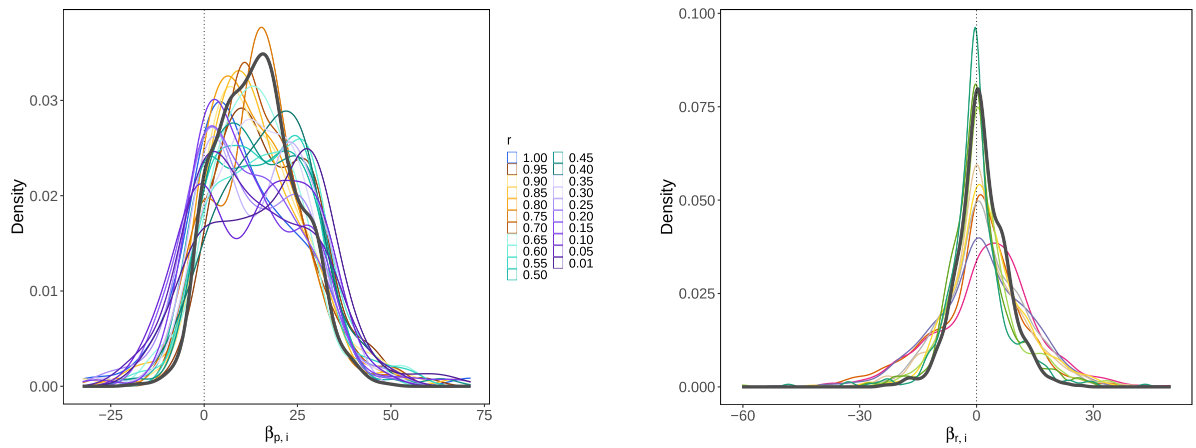
At the end of Section 6, we summarize results from when we conduct individual-level estimates for probability weighting (PW) and upside potential (UP), following exactly the estimation procedures of our aggregate approach. Table F.2 presents these results.

Table F.1: Classification of All Subject-p-p' Combinations (with $p < p'$)

Risk Aversion at $r = 1$ for p and $p' > p$	Sub- versus Superproportionality for p and $p' > p$				Total
	$\beta^p_{r,i} \geq 0$, $\beta^{p'}_{r,i} \geq 0$	$\beta^p_{r,i} \geq 0$, $\beta^{p'}_{r,i} < 0$	$\beta^p_{r,i} < 0$, $\beta^{p'}_{r,i} \geq 0$	$\beta^p_{r,i} < 0$, $\beta^{p'}_{r,i} < 0$	
$\alpha^p_{r,i} \geq 0$, $\alpha^{p'}_{r,i} \geq 0$	2098 (51.9% of Row) (26.2% of Total)	727 (18.0% of Row) (9.1% of Total)	559 (13.8% of Row) (7.0% of Total)	654 (16.2% of Row) (8.2% of Total)	4039 (50.5%)
$\alpha^p_{r,i} \geq 0$, $\alpha^{p'}_{r,i} < 0$	101 (18.9% of Row) (1.3% of Total)	292 (54.8% of Row) (3.6% of Total)	11 (2.1% of Row) (0.1% of Total)	127 (23.8% of Row) (1.6% of Total)	533 (6.7%)
$\alpha^p_{r,i} < 0$, $\alpha^{p'}_{r,i} \geq 0$	541 (23.2% of Row) (6.8% of Total)	170 (7.3% of Row) (2.1% of Total)	1100 (47.3% of Row) (13.8% of Total)	514 (22.1% of Row) (6.4% of Total)	2328 (29.1%)
$\alpha^p_{r,i} < 0$, $\alpha^{p'}_{r,i} < 0$	142 (12.8% of Row) (1.8% of Total)	221 (19.9% of Row) (2.8% of Total)	164 (14.8% of Row) (2.1% of Total)	579 (52.2% of Row) (7.2% of Total)	1110 (13.9%)
Total	2882 (36.0%)	1410 (17.6%)	1834 (22.9%)	1874 (23.4%)	8000 (100%)

Notes: For each subject, we consider all pairs of distinct probabilities $p < p'$ that they saw; since each subject saw five values of p, each contributes $\binom{5}{2} = 10$ pairwise comparisons, yielding $N = 8{,}000$ comparisons across 800 subjects. For each probability in a pair, $(\alpha_{r,i}, \beta_{r,i})$ is estimated from the regression $RP_i(p, r) = \alpha_{r,i} - \beta_{r,i}(1 - r) + \varepsilon_{r,i}$. Rows classify each pair by risk aversion at $r = 1$ for p and p' (positive $\alpha_{r,i}$ is risk averse, negative $\alpha_{r,i}$ is risk tolerant). Columns classify each pair by sub- versus superproportionality for p and p' (positive $\beta_{r,i}$ is subproportional, negative $\beta_{r,i}$ is superproportional). Cells report the count, the within-row percentage (% of Row), and the overall percentage (% of Total). The last row and column report marginal totals. Based on 8,000 pairwise comparisons from 800 subjects.

Figure F.1: Distributions of Individual-Level Sensitivities to p and r (Full Range)

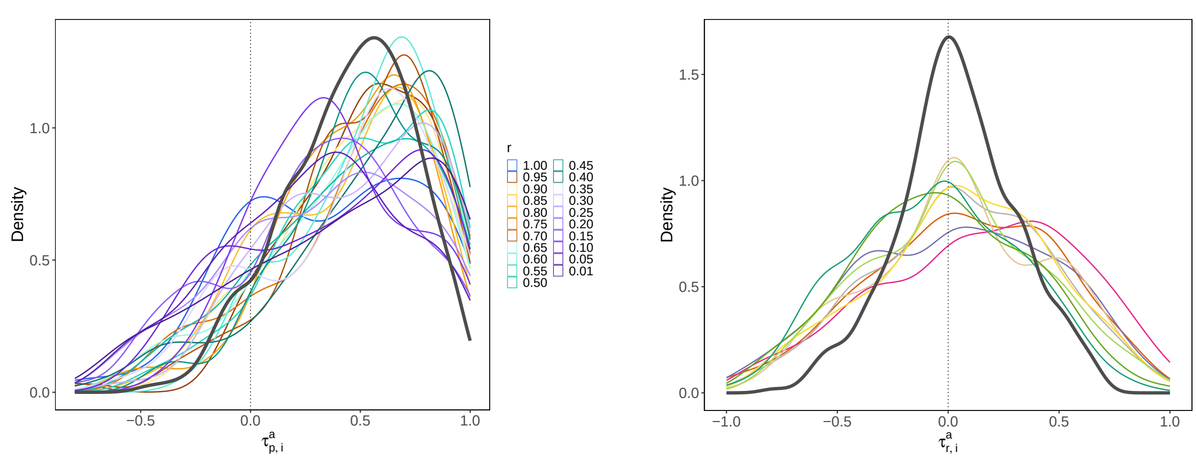


(a) Distribution of $\beta_{p,i}$

(b) Distribution of $\beta_{r,i}$

Notes: Panel (a) depicts kernel density estimates of distribution of $\beta_{p,i}$, where $\beta_{p,i}$ estimated from $RP_i(p, \bar{r}) = \alpha_{p,i} - \beta_{p,i}(1-p) + \varepsilon_{p,i}$. Colored curves correspond to the 21 values of $\bar{r}$; solid black curve overlays density of subject-level averages (each subject's mean $\beta_{p,i}$ across their three values of $\bar{r}$). Panel (b) analogously shows kernel density estimates of distribution of $\beta_{r,i}$, where $\beta_{r,i}$ estimated from $RP_i(\bar{p}, r) = \alpha_{r,i} - \beta_{r,i}(1-r) + \varepsilon_{r,i}$. Colored curves correspond to the 9 values of $\bar{p}$; solid black curve overlays the density of subject-level averages (each subject's mean $\beta_{r,i}$ across their five values of $\bar{p}$). This version uses the full horizontal range; a truncated version that zooms in on the middle of each distribution appears as Figure 6 in the main text.

Figure F.2: Distributions of Individual-Level Kendall's τ^a Measures



(a) Distribution of $\tau^a_{p,i}$.

(b) Distribution of $\tau^a_{r,i}$.

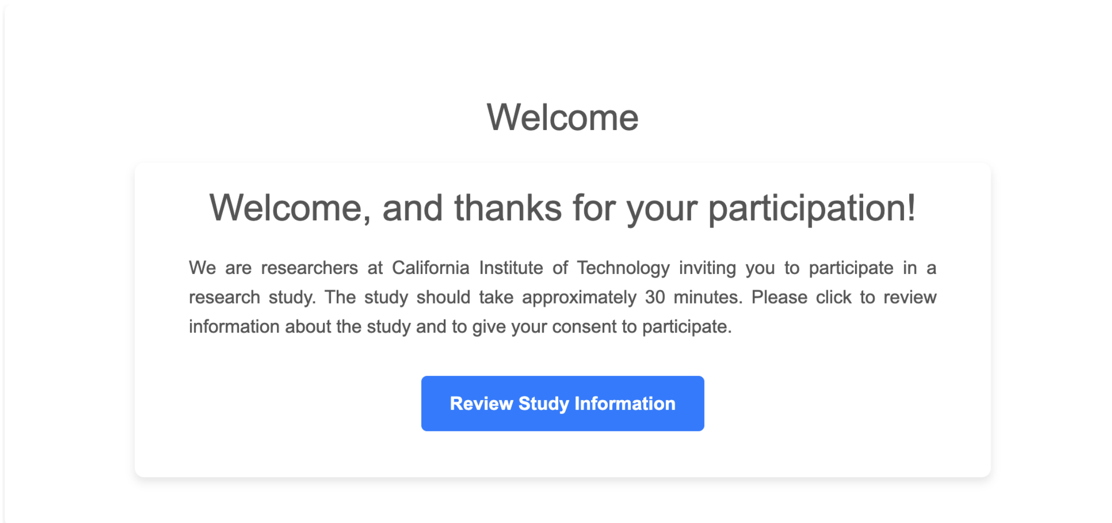
Notes: Panel (a) depicts kernel density estimates of distribution of $\tau^a_{p,i}$, where individual $\tau^a_{p,i}$ calculated from equation 5. Colored curves correspond to the 21 values of $\bar{r}$; solid black curve overlays density of subject-level averages (each subject's mean $\tau^a_{p,i}$ across their three values of $\bar{r}$). Panel (b) analogously shows kernel density estimates of distribution of $\tau^a_{r,i}$, where individual $\tau^a_{r,i}$ calculated from analogue of equation 5. Colored curves correspond to the 9 values of $\bar{p}$; solid black curve overlays the density of subject-level averages (each subject's mean $\tau^a_{r,i}$ across their five values of $\bar{p}$).

Table F.2: Model Comparison from Individual-Level Estimates: PW vs UP

	PW	UP
Panel A: RMSE summary statistics		
N (converged)	800	798
Median	5.56	5.21
IQR $[Q_1, Q_3]$	[4.17, 7.37]	[3.92, 6.88]
Panel B1: Winner classification (all comparisons), N=800		
	N	%
UP wins (RMSE diff ≥ 0.1)	403	50.4
PW wins (RMSE diff ≥ 0.1)	295	36.9
Tied (RMSE diff < 0.1)	100	12.5
UP did not converge	2	0.2
Panel B2: Winner classification (compare if at least one RMSE ≤ 7), N=800		
	N	%
UP wins (RMSE diff ≥ 0.1)	324	40.5
PW wins (RMSE diff ≥ 0.1)	246	30.8
Tied (RMSE diff < 0.1)	85	10.6
No model good enough (both RMSE > 7)	143	17.9
UP did not converge	2	0.2
Panel C: Best-fitting shape distribution under each model		
	PW $\pi(q)$	UP $\kappa(z)$
Convex	23	2
Concave	1	2
Concave-to-convex (inverse S)	348	55
Convex-to-concave (S-shaped)	412	739
Linear	16	0
Fit failed	0	2

Notes: Table summarizes individual-level estimates from non-linear least squares on each subject's 30 observations, analogous to the aggregate estimation in Table 3. PW assumes two-parameter probability-weighting function; UP assumes two-parameter kappa function with scale fixed so that $\kappa(30) = 300$. Both models estimated with the level (γ) and curvature (δ) parameters constrained to be at least 0.01. Panel A reports for each model the number of converging fits, the median RMSE, and the interquartile range $[Q_1, Q_3]$ of the RMSE. Panel B1 classifies every converging pair by which model attains the lower RMSE; a win requires the RMSE gap to exceed 0.1, and smaller gaps are counted as ties. Panel B2 repeats this classification on the subset of individuals for whom at least one model is good enough (RMSE ≤ 7), labelling the rest "No model good enough." While for 17.9% of individuals the winning model in panel B1 has an RMSE larger than 7, Panel B2 reveals that even among individuals where the winning RMSE is less than 7, the proportion of UP-winning to PW-winning is roughly the same. Panel C reports for each model the distribution of best-fitting curve shapes. No fitted curve changes curvature more than once (each has at most one inflection). For PW, 121 fits rest on the γ bound (73 S-shaped, 41 inverse-S, 7 convex) and 2 on the δ bound (2 inverse-S); for UP, 55 rest on the γ bound (54 S-shaped, 1 convex) and 11 on the δ bound (11 inverse-S).

G 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

Security Check

Please complete the security check below to continue.

☐ I'm not a robot — reCAPTCHA Privacy - Terms

Next

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