Appendices

A Choice tables for preference elicitation

Table A.1: Preference motive elicitation tables for certainty preference and loss aversion

	Certainty Preference Table (CP)				**Loss Aversion Table (LA)**			
	Lottery A	Lottery B			Lottery A		Lottery B	
p	1.00	0.20	0.80	\$	+0.50	−0.20	+5.00	−2.00
\$	2.00	2.50	1.00	p	*0.00*	*1.00*	*0.00*	*1.00*
	2.00	4.50	1.00		0.05	0.95	0.05	0.95
	2.00	4.75	1.00		0.10	0.90	0.10	0.90
	2.00	5.00	1.00		0.15	0.85	0.15	0.85
	2.00	5.50	1.00		0.20	0.80	0.20	0.80
	2.00	6.00	1.00		0.25	0.75	0.25	0.75
	2.00	6.50	1.00		0.30	0.70	0.30	0.70
	2.00	7.00	1.00		0.35	0.65	0.35	0.65
	2.00	8.00	1.00		0.40	0.60	0.40	0.60
	2.00	9.00	1.00		0.45	0.55	0.45	0.55
	2.00	10.00	1.00		0.50	0.50	0.50	0.50
	2.00	12.00	1.00		0.55	0.45	0.55	0.45
	2.00	15.00	1.00		0.60	0.40	0.60	0.40
	2.00	20.00	1.00		0.65	0.35	0.65	0.35
	2.00	30.00	1.00		0.70	0.30	0.70	0.30
	2.00	60.00	1.00		0.75	0.25	0.75	0.25
					0.80	0.20	0.80	0.20
					0.85	0.15	0.85	0.15
					0.90	0.10	0.90	0.10
					0.95	0.05	0.95	0.05
					1.00	*0.00*	*1.00*	*0.00*

Note: A row in each of the two tables above represents a choice set presented to the subject. In the certainty preference table (left), row values are the possible dollar outcomes and column headings are the probabilities of obtaining the given outcome. In the loss aversion table (right), column headings are the dollar outcomes and row values are the probabilities of obtaining each outcome. Losses and gains are relative to the $5.00 earned in the real effort task to begin the experiment. Italicized rows indicate a stochastically-dominated choice.

Table A.2: Preference motive elicitation tables for utility curvature and probability weighting in the gain and loss domains

	Gain Domain Table 1 (GD1)					**Gain Domain Table 2 (GD2)**			
	Lottery A		Lottery B			Lottery A		Lottery B	
p	0.2	0.8	0.2	0.8	p	0.9	0.1	0.9	0.1
$	*2.50*	*2.00*	*2.50*	*1.00*	$	*2.00*	*1.50*	*2.00*	*0.50*
	2.50	2.00	4.50	1.00		2.00	1.50	2.05	0.50
	2.50	2.00	4.75	1.00		2.00	1.50	2.10	0.50
	2.50	2.00	5.00	1.00		2.00	1.50	2.15	0.50
	2.50	2.00	5.50	1.00		2.00	1.50	2.20	0.50
	2.50	2.00	6.00	1.00		2.00	1.50	2.25	0.50
	2.50	2.00	6.50	1.00		2.00	1.50	2.30	0.50
	2.50	2.00	7.00	1.00		2.00	1.50	2.35	0.50
	2.50	2.00	8.00	1.00		2.00	1.50	2.45	0.50
	2.50	2.00	9.00	1.00		2.00	1.50	2.55	0.50
	2.50	2.00	10.00	1.00		2.00	1.50	2.65	0.50
	2.50	2.00	12.00	1.00		2.00	1.50	2.80	0.50
	2.50	2.00	15.00	1.00		2.00	1.50	3.00	0.50
	2.50	2.00	20.00	1.00		2.00	1.50	3.25	0.50
	2.50	2.00	30.00	1.00		2.00	1.50	3.50	0.50
	2.50	2.00	60.00	1.00		2.00	1.50	3.75	0.50

	Loss Domain Table 1 (LD1)					**Loss Domain Table 2 (LD2)**			
	Lottery A		Lottery B			Lottery A		Lottery B	
p	0.1	0.9	0.1	0.9	p	0.8	0.2	0.8	0.2
$	*-0.75*	*-0.25*	*-0.75*	*-0.50*	$	*-1.75*	*-0.10*	*-1.75*	*-0.50*
	-1.20	-0.25	-0.75	-0.50		-1.95	-0.10	-1.75	-0.50
	-1.25	-0.25	-0.75	-0.50		-2.00	-0.10	-1.75	-0.50
	-1.30	-0.25	-0.75	-0.50		-2.05	-0.10	-1.75	-0.50
	-1.40	-0.25	-0.75	-0.50		-2.10	-0.10	-1.75	-0.50
	-1.50	-0.25	-0.75	-0.50		-2.15	-0.10	-1.75	-0.50
	-1.60	-0.25	-0.75	-0.50		-2.20	-0.10	-1.75	-0.50
	-1.70	-0.25	-0.75	-0.50		-2.30	-0.10	-1.75	-0.50
	-1.85	-0.25	-0.75	-0.50		-2.40	-0.10	-1.75	-0.50
	-2.00	-0.25	-0.75	-0.50		-2.50	-0.10	-1.75	-0.50
	-2.15	-0.25	-0.75	-0.50		-2.60	-0.10	-1.75	-0.50
	-2.35	-0.25	-0.75	-0.50		-2.75	-0.10	-1.75	-0.50
	-2.65	-0.25	-0.75	-0.50		-2.90	-0.10	-1.75	-0.50
	-3.00	-0.25	-0.75	-0.50		-3.05	-0.10	-1.75	-0.50
	-3.40	-0.25	-0.75	-0.50		-3.25	-0.10	-1.75	-0.50
	-4.00	-0.25	-0.75	-0.50		-3.50	-0.10	-1.75	-0.50

Note: A row in each of the four tables above represents a choice set presented to the subject. Row values are the possible dollar outcomes from the displayed lotteries. Column headings are the probability of obtaining the given outcome. Gains and losses are relative to the $5.00 earned in the real effort task to begin the experiment. Italicized rows indicate a stochastically-dominated choice.

In Table A.3, we report the Spearman rank correlations of the lottery choices. We designed the tables so that they measure different aspects of the preference functional, so the correlations are relatively low. One might be concerned that low correlations are the result of random choice. The high correlation between the choices in the GD1 and CP lottery tables, however, indicates deliberate behavior by subjects, as the lotteries in these two tables are similar.

Table A.3: Spearman rank correlations of lottery choices

	GD1	GD2	LD1	LD2	LA
GD1	1.000	.	.	.	.
GD2	0.046	1.000	.	.	.
LD1	-0.266	0.110	1.000	.	.
LD2	-0.010	-0.161	0.148	1.000	.
LA	0.197	0.202	0.011	0.037	1.000
CP	0.605	0.015	-0.231	0.028	0.182

Note: For our sample size of 1,730 subjects, a correlation is statistically significant at the 10% level if it is larger than 0.040, at the 5% level if it is larger than 0.047, and at the 1% level if it is larger than 0.062 (in absolute values).

B Theory on preference elicitation

This paper uses the same experimental data and preference measures as the study in Jaspersen, Ragin, and Sydnor (2020). Since the analysis there does not consider the insurance demand tasks, both studies analyze distinct research questions. However, because they both use the same preference measures, the contents of this appendix are to a large part identical to a corresponding appendix in Jaspersen, Ragin, and Sydnor (2020).

B.1 Nonparametric Preference Measures

There are six tables in the elicitation procedure: GD1, GD2, LD1, LD2, LA and CP. The first five are repeated choices between two binary lotteries, the last one is the choice between a binary lottery and a certain outcome. The choices are depicted in Figure B.1.

In accordance with Section 2.1, $i = 1$ and $j = 2$ in tables GD1, GD2, and LA and $i = 2$ and $j = 1$ in tables LD1 and LD2.

B.1.1 Utility Curvature and Probability Weighting in the Gain Domain

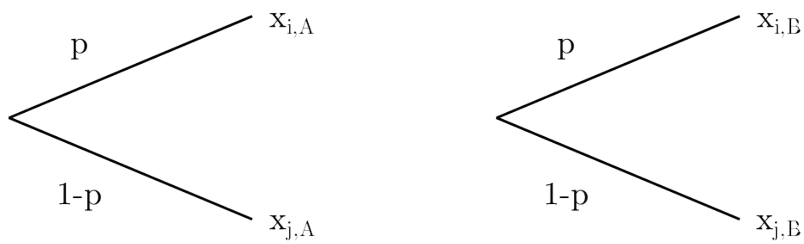
Assuming a full CPT preference functional, we evaluate the lotteries in the GD1/ GD2 tables as $EV = w^+(p)u^+(large\ gain) + (1 - w^+(p))u^+(small\ gain)$. In these tables, only the large gain of Lottery B changes. Adopting the notation that the large gain is x_2 and the small gain is x_1, the indifference large gain on Lottery B fulfills

$$w^+(p)u^+(x_{2,A}) + (1 - w^+(p))u^+(x_{1,A}) = w^+(p)u^+(x_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \tag{B.1}$$

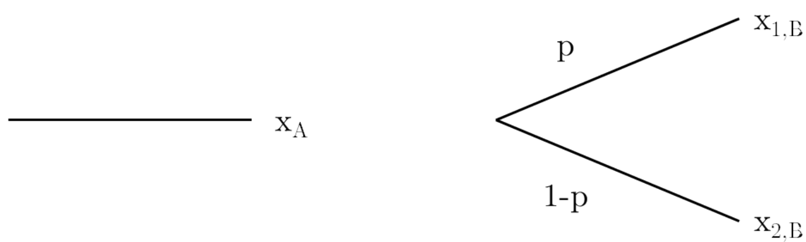
We first consider the *ceteris paribus* elicitation of utility curvature. When changing the indifference value for $x_{2,B}$ to $\hat{x}_{2,B}$ and keeping everything but the utility function fixed, we signify the change in the utility function by the transformation $g(\cdot)$ of which we know that it must be increasing. The new indifference relationship implies

$$w^+(p)g(u^+(x_{2,A})) + (1 - w^+(p))g(u^+(x_{1,A})) = w^+(p)g(u^+(\hat{x}_{2,B})) + (1 - w^+(p))g(u^+(x_{1,B})). \tag{B.2}$$

Figure B.1: Graphical illustrations of the different choice tables



(a) Schematic representation of choices in the GD1, GD2, LD1, LD2 and LA tables.



(b) Schematic representation of choices in the CP table

From $g'(\cdot) > 0$, we know that $g(u^+(\hat{x}_{2,B})) - g(u^+(x_{2,B})) > 0$. We can thus see from (B.2) that

$$w^+(p)g(u^+(x_{2,A})) + (1 - w^+(p))g(u^+(x_{1,A})) > w^+(p)g(u^+(x_{2,B})) + (1 - w^+(p))g(u^+(x_{1,B})). \quad \text{(B.3)}$$

We proceed by using w^+ to define ω as a probability measure of the random variables $\tilde{x}$ and, respectively, $u^+(\tilde{x})$. This can be done because $w^+(p) \in [0, 1]$ and all payoffs are in the gain domain, so the decision weights add to one. Under this probability measure, we know from (B.1) that the expectation of $u^+(\tilde{x})$ is equal between lotteries A and B. From p being equal for both lotteries, we further know the skewness of $u^+(\tilde{x})$ under the probability measure ω to be equal between both lotteries (Ebert, 2015). From Chiu (2010) we thus know that Lottery B is a mean-preserving spread in $u^+(\tilde{x})$ under the probability measure ω. As such $\mathbb{E}_\omega[g(u^+(\tilde{x}_A))] > \mathbb{E}_\omega[g(u^+(\tilde{x}_B))]$ is true if and only if $g'' < 0$. Thus, a higher value of $x_{2,B}$ in GD1 and GD2 implies more concave utility curvature.

For the *ceteris paribus* elicitation of the probability weighting function, we again consider the indifference relationship at two points $x_{2,B}$ and $\hat{x}_{2,B}$ with $x_{2,B} < \hat{x}_{2,B}$. The respective probability weighting functions for the two indifference relationships are w^+ and $\hat{w}^+$. We have the two equalities:

$$w^+(p)u^+(x_{2,A}) + (1 - w^+(p))u^+(x_{1,A}) = w^+(p)u^+(x_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \quad \text{(B.4)}$$

$$\hat{w}^+(p)u^+(x_{2,A}) + (1 - \hat{w}^+(p))u^+(x_{1,A}) = \hat{w}^+(p)u^+(\hat{x}_{2,B}) + (1 - \hat{w}^+(p))u^+(x_{1,B}). \quad \text{(B.5)}$$

We subtract (B.4) from (B.5) and add $\hat{w}^+(p)[u(x_{2,B}) - u(x_{2,B})]$ on the right hand side to obtain

$$\begin{aligned}[\hat{w}^+(p) - w^+(p)][u^+(x_{2,A}) - u^+(x_{1,A}))] = \quad & [\hat{w}^+(p) - w^+(p)][u^+(x_{2,B}) - u^+(x_{1,B}))] \\ & + \hat{w}^+(p)[u^+(\hat{x}_{2,B}) - u^+(x_{2,B}))]. \quad \text{(B.6)}\end{aligned}$$

Since $\hat{w}^+(p)[u^+(\hat{x}_{2,B}) - u^+(x_{2,B})) > 0$, (B.6) becomes

$$[\hat{w}^+(p) - w^+(p)][u^+(x_{2,A}) - u^+(x_{1,A}))] > [\hat{w}^+(p) - w^+(p)][u^+(x_{2,B}) - u^+(x_{1,B}))]. \quad \text{(B.7)}$$

From the construction of the table, we know $u^+(x_{2,A}) - u^+(x_{1,A})) < u^+(x_{2,B}) - u^+(x_{1,B}))$. (B.7) thus implies $\hat{w}^+(p) < w^+(p)$. A switching row lower in the GD1/GD2 tables thus leads to a smaller decision weight on the large outcome of each lottery.

We have structured the tables such that $p^{GD1} < p^{GD2}$ and assume the inflection point of the probability weighting function to be between these two probabilities. Under this construction, if the decision weight on p^{GD1} becomes smaller, we have less inverse S-shape or more S-shape in the weighting function. If the decision weight on p^{GD2} becomes smaller, we have more inverse S-shape or less S-shape in the weighting function.

B.1.2 Utility Curvature and Probability Weighting in the Loss Domain

Assuming a full CPT preference functional, we evaluate the lotteries in the LD1/LD2 tables as $EV = w^-(p)u^-(large\ loss) + (1 - w^-(p))u^-(small\ loss)$. In these tables only the large loss in Lottery A changes. The indifference gain fulfills

$$w^-(p)u^-(x_{2,A}) + (1 - w^-(p))u^-(x_{1,A}) = w^-(p)u^-(x_{2,B}) + (1 - w^-(p))u^-(x_{1,B}). \quad \text{(B.8)}$$

We change the indifference value to $\hat{x}_{2,A} < x_{2,A}$ and the utility function gets transformed by function $g(\cdot)$. The new indifference value now fulfills

$$w^-(p)g(u^-(\hat{x}_{2,A})) + (1 - w^-(p))g(u^-(x_{1,A})) = w^-(p)g(u^-(x_{2,B}) + (1 - w^-(p))g(u^-(x_{1,B})). \quad \text{(B.9)}$$

We again use the positive first derivatives of $u(\cdot)$ and $g(\cdot)$ and transform (B.9) such that

$$w^-(p)g(u^-(x_{2,A})) + (1 - w^-(p))g(u^-(x_{1,A})) > w^-(p)g(u^-(x_{2,B}) + (1 - w^-(p))g(u^-(x_{1,B})). \quad \text{(B.10)}$$

We proceed as in the gain domain. Under the probability measure ω defined by w^-, the utility lottery of Lottery A is a mean-preserving spread of that of Lottery B. As such, $\mathbb{E}_\omega[g(u^-(\tilde{x}_A))] > \mathbb{E}_\omega[g(u^-(\tilde{x}_B))]$ if and only if $g'' < 0$. Thus, a more negative value of $x_{2,A}$ (and thus a later switching row) is, ceteris paribus, associated with more convex utility curvature/ less risk aversion.

For probability weighting, we again consider two different indifference relationships. One at $x_{A,2}$ and one at $\hat{x}_{A,2}$ with $\hat{x}_{A,2} < x_{A,2}$ and different probability weighting functions w^- and $\hat{w}^-$. We have the two equalities:

$$w^-(p)u^-(x_{2,A}) + (1 - w^-(p))u^-(x_{1,A}) = w^-(p)u^-(x_{2,B}) + (1 - w^-(p))u^-(x_{1,B}). \quad \text{(B.11)}$$

$$\hat{w}^-(p)u^-(\hat{x}_{2,A}) + (1 - \hat{w}^-(p))u^-(x_{1,A}) = \hat{w}^-(p)u^-(x_{2,B}) + (1 - \hat{w}^-(p))u^-(x_{1,B}). \quad \text{(B.12)}$$

We subtract (B.11) from (B.12) and add $\hat{w}(p)[u(x_{2,A}) - u(x_{2,A})]$ on the left hand side to obtain

$$\begin{aligned}[\hat{w}^-(p) - w^-(p)][u^-(x_{2,A}) - u^-(x_{1,A}))] = {} & [\hat{w}^-(p) - w^-(p)][u^-(x_{2,B}) - u^-(x_{1,B}))]. \\ +\hat{w}^-(p)[u^-(\hat{x}_{2,A}) - u^-(x_{2,A}))] & \end{aligned} \quad \text{(B.13)}$$

Since $\hat{w}^-(p)[u^-(\hat{x}_{2,A}) - u^-(x_{2,A})) < 0$, (B.13) becomes

$$[\hat{w}^-(p) - w^-(p)][u^-(x_{2,A}) - u^-(x_{1,A}))] > [\hat{w}^-(p) - w^-(p)][u^-(x_{2,B}) - u^-(x_{1,B}))]. \quad \text{(B.14)}$$

From the construction of the table, we know $u^-(x_{2,A}) - u^-(x_{1,A})) < u^-(x_{2,B}) - u^-(x_{1,B})) < 0$. (B.7) thus implies $\hat{w}^-(p) < w^-(p)$. A switching row lower in the LD1/LD2 tables thus leads to a smaller decision weight on the more negative outcome of each lottery.

Since in CPT, the probability weighting function uses the upper Choquet integral in the gain domain and the lower Choquet integral in the loss domain, the implications of this theoretical result can be interpreted as for the gain domain described above. We have structured the tables such that $p^{LD1} < p^{LD2}$ and assume the inflection point of the probability weighting function to be between these two probabilities. Under this construction, if the decision weight on p^{LD1} becomes smaller, we have less inverse S-shape or more S-shape in the weighting function. If the decision weight on p^{LD2} becomes smaller, we have more inverse S-shape or less S-shape in the weighting function.

B.1.3 Loss Aversion

Assuming a full CPT preference functional, we evaluate the lotteries in the LA table as $EV = w^+(p)u^+(gain) + \lambda w^-(1-p)u^-(loss)$. As such, the probability of the gain leading to indifference fulfills

$$w^+(p)u^+(x_{2,A}) + \lambda w^-(1-p)u^-(x_{1,A}) = w^+(p)u^+(x_{2,B}) + \lambda w^-(1-p)u^-(x_{1,B}) \tag{B.15}$$

or equivalently

$$\lambda = \frac{w^+(p)(u^+(x_{2,B}) - u^+(x_{2,A}))}{w^-(1-p)(u^-(x_{1,A}) - u^-(x_{1,B}))}. \tag{B.16}$$

Given functions w^+, w^-, u^+, u^-, we can see that a higher indifference probability always leads to a higher λ. Observe

$$\frac{\partial \lambda}{\partial p} = \frac{\frac{\partial w^+(p)}{\partial p}(u^+(x_{2,B}) - u^+(x_{2,A}))}{w^-(1-p)(u^-(x_{1,A}) - u^-(x_{1,B}))} - \frac{\partial w^-(1-p)}{\partial p}\frac{w^+(p)(u^+(x_{2,B}) - u^+(x_{2,A}))}{[w^-(1-p)(u^-(x_{1,A}) - u^-(x_{1,B}))]^2} > 0. \tag{B.17}$$

B.1.4 Certainty Preference

To accommodate a preference for certainty, we utilize the model of Schmidt (1998). We integrate this model into CPT similarly as he has integrated it into EU. All evaluations of uncertain payments are made by a utility function $u(x)$ and evaluations of certain payments are made by a value function $v(x)$.[36] For a preference regarding certainty to appear, the utility and value functions must differ, whereas the difference is usually assumed to be monotonic for all values of x (Vieider, 2018). As such, when we can observe $v(x) > u(x)$ ($v(x) < u(x)$) for some value of x, we assume the preference for (against) certainty to persist everywhere in the preferences of the individual except at zero. Zero is excluded such that the prospect-theoretic convention that the utility/value function crosses at the origin is upheld.

The only table in which a certain payment appears is the CP table. It is structured such that $x_{2,B} > x_A > x_{1,B} > 0$. It is obvious that when we assume that $u(x)$ does not change, a higher value of $x_{2,B}$ implies a stronger certainty effect. Consider the two equalities implied by indifference values $x_{2,B}$ and $\hat{x}_{2,B}$ with $\hat{x}_{2,B} > x_{2,B}$ and the corresponding value functions $v(x)$ and $\hat{v}(x)$.

$$v(x_A) = w^+(p)u^+(x_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \tag{B.18}$$

$$\hat{v}(x_A) = w^+(p)u^+(\hat{x}_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \tag{B.19}$$

[36] See Schmidt (1998) for a discussion of the terminology "utility function" and "value function."

Subtracting (B.18) from (B.19), we gain

$$\hat{v}(x_A) - v(x_A) = w^+(p)[u^+(\hat{x}_{2,B}) - u^+(x_{2,B})]. \tag{B.20}$$

By assumption, $\hat{x}_{2,B} > x_{2,B}$ renders $\hat{v}(x_A) > v(x_A)$ and thus with a fixed utility function of $u(x)$ an increase in the certainty preference.

B.2 Analysis Using Parametric Preference Measures

For the parametric measures of the preference parameters, we assume that a switch from Lottery A to Lottery B at row h implies that the subject would be indifferent between the average lotteries A and B between rows $h-1$ and h. In every table, only one value varies with each row. As such, the average lotteries are the simple mid-point between the two different values. We signify this indifference value with a bar. When the switch occurred at a corner solution (which did not violate FOSD), then we assume the indifference value to be the same distance below the value indicated in the row as it would be above it if the switch occurred one row before the corner solution.

For the utility function and the probability weighting function, we assume the parametric forms summarized in Section 2.1. Using these assumptions, we identify the values of γ^+, γ^-, β^+, β^-, λ and κ which solve the six equations

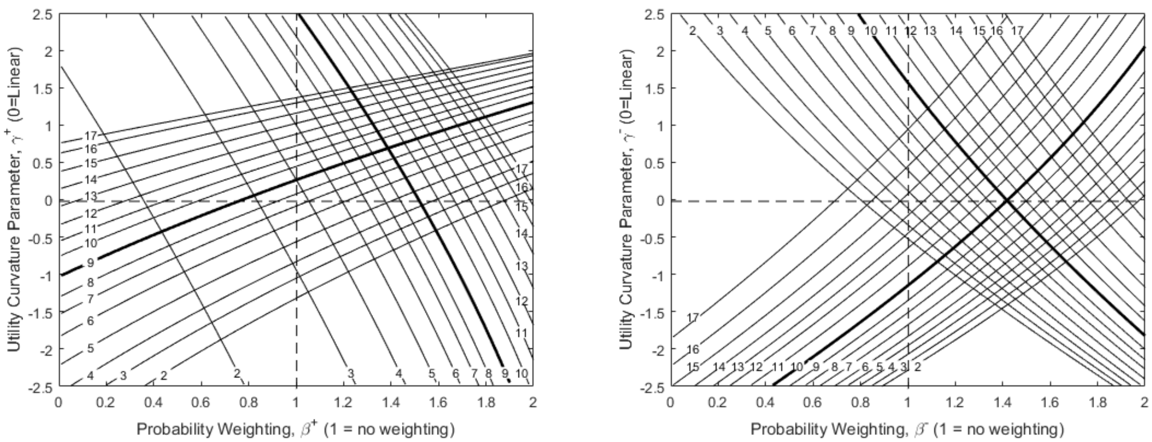
$$\begin{array}{lcl}
w^+(p^{GD1})u^+(x^{GD1}_{1,A}) + (1-w^+(p^{GD1}))u^+(x^{GD1}_{2,A}) & = & w^+(p^{GD1})u^+(\bar{x}^{GD1}_{1,B}) + (1-w^+(p^{GD1}))u^+(x^{GD1}_{2,B}) \\
w^+(p^{GD2})u^+(x^{GD2}_{1,A}) + (1-w^+(p^{GD2}))u^+(x^{GD2}_{2,A}) & = & w^+(p^{GD2})u^+(\bar{x}^{GD2}_{1,B}) + (1-w^+(p^{GD2}))u^+(x^{GD2}_{2,B}) \\
w^-(p^{LD1})u^-(\bar{x}^{LD1}_{1,A}) + (1-w^-(p^{LD1}))u^-(x^{LD1}_{2,A}) & = & w^-(p^{LD1})u^-(x^{LD1}_{1,B}) + (1-w^-(p^{LD1}))u^-(x^{LD1}_{2,B}) \\
w^-(p^{LD2})u^-(\bar{x}^{LD2}_{1,A}) + (1-w^-(p^{LD2}))u^-(x^{LD2}_{2,A}) & = & w^-(p^{LD2})u^-(x^{LD2}_{1,B}) + (1-w^-(p^{LD2}))u^-(x^{LD2}_{2,B}) \\
w^+(\bar{p}^{LA})u^+(x^{LA}_{1,A}) + \lambda w^-(1-\bar{p}^{LA})u^-(x^{LA}_{2,A}) & = & w^+(\bar{p}^{LA})u^+(x^{LA}_{1,B}) + \lambda w^-(1-\bar{p}^{LA})u^-(x^{LA}_{2,B}) \\
v(x^{CP}_A) & = & w^+(p^{CP})u^+(\bar{x}^{CP}_{1,B}) + (1-w^+(p^{CP}))u^+(x^{CP}_{2,B}).
\end{array} \tag{B.21}$$

Subjects who chose a lottery which was first-order dominated by another one were excluded from the analysis. The first two equations jointly determine γ^+ and β^+. Every pair of choices in both tables lead to a unique vector of these two variables. Similarly, the third and fourth equation jointly determine γ^- and β^-. The implied values from the possible combinations of answers both in the gain domain and in the loss domain are displayed in Figure B.2. Here, the upward-sloping lines indicate choices in Table GD1 (LD2) and downward-sloping lines indicate choices in GD2 (LD1). We designed the tables such that switching in the middle is consistent with common elicited values of the respective parameters, and we indicate these choices with thick lines. The lines for the tables differ in the sign of their slope because in tables GD1 and LD2 the safer lottery has a worse outcome in the low-probability event than the riskier lottery while in tables GD2 and LD1, the safer lottery has a better outcome in the low-probability event than the risky lottery. As such, more safe choices in GD1 and LD2 can either be caused by more concave utility or by less inverse-S probability weighting, while more safe choices in GD2 and LD1 can either be caused by more concave utility or by more inverse-S probability weighting. The difference in slopes along with the chosen parameters for the tables ensure that each choice combination has exactly one intersection in Figure B.2 and thus implies a unique utility curvature/probability weighting pair.

Based on the inferred values of γ^+, β^+, γ^- and β^- and the known parametric forms of u^+, w^+, u^- and w^-, λ and κ can be inferred from the equations

$$\lambda = \frac{w^+(\bar{p}^{LA})(u^+(x^{LA}_{2,B}) - u^+(x^{LA}_{2,A}))}{w^-(1-\bar{p}^{LA})(u^-(x^{LA}_{1,A}) - u^-(x^{LA}_{1,B}))} \tag{B.22}$$

Figure B.2: Range of elicitable parameters for utility curvature and probability weighting



(a) Possible gain domain preferences implied by the number of safe choices in Tables GD1 (upward-sloping lines) and GD2 (downward-sloping lines).

(b) Possible loss domain preferences implied by the number of safe choices in Tables LD1 (downward-sloping lines) and LD2 (upward-sloping lines).

Note: The figure displays the parameters for utility curvature and probability weighting implied by the choices in Tables GD1 and GD2 (panel(a)) and LD1 and LD2 (panel (b)). The number on each line denotes the number of safe lottery choices in the respective table. The intersection of two lines sets the parameter pair.

and

$$\kappa^{1-\gamma} = \frac{w^+(p^{CP/GD1})u^+(\bar{x}_{2,B}^{CP}) + (1 - w^+(p^{CP/GD1}))u^+(x_{1,B}^{CP/GD1})}{w^+(p^{CP/GD1})u^+(\bar{x}_{2,B}^{GD1}) + (1 - w^+(p^{CP/GD1}))u^+(x_{1,B}^{CP/GD1})}. \tag{B.23}$$

In Equation (B.23), the index $CP/GD1$ indicates that the values are equal in both tables.

Directly eliciting values of λ and κ results in bad measures of loss aversion and certainty preference (Abdellaoui et al., 2007; Schmidt, 1998). For loss aversion, the shapes of u^+ and u^- also influence how utility is traded off between the gain domain and the loss domain. We thus use an index for loss aversion that takes this into account. We use the negative average ratio of utility in the loss domain and the gain domain over the spectrum of relevant values for the LA table. Formally, our loss aversion index is described by

$$\hat{\lambda} = -\int_0^5 \frac{\lambda u^-(-x)}{u^+(x)dx} dx. \tag{B.24}$$

For certainty preferences, we use the marginal certainty preference index suggested by Schmidt (1998):

$$\hat{\kappa} = \frac{v(x) - u(x)}{u'(x)}. \tag{B.25}$$

C Accuracy of linear approximation

The agent faces lottery $(w - \alpha pqL - (1-\alpha)L, \quad p; \quad w - \alpha pqL, \quad 1-p)$. Under the subjective probability distortion Ω, this implies mean $\mu_\Omega = w - \alpha pqL - \Omega(1-\alpha)L$ and variance $\sigma_\Omega^2 = ((1-\alpha)L)^2\Omega(1-\Omega)$. The second-order Taylor approximation states that $\mathbb{E}_\Omega[U] = \mu_\Omega - \frac{1}{2}r\sigma_\Omega^2$ and thus $\mathbb{E}_\Omega[U] = w - \alpha pqL - \Omega(1-\alpha)L - \frac{r}{2}\Omega(1-\Omega)((1-\alpha)L)^2$. Rearranging renders the approximated solution

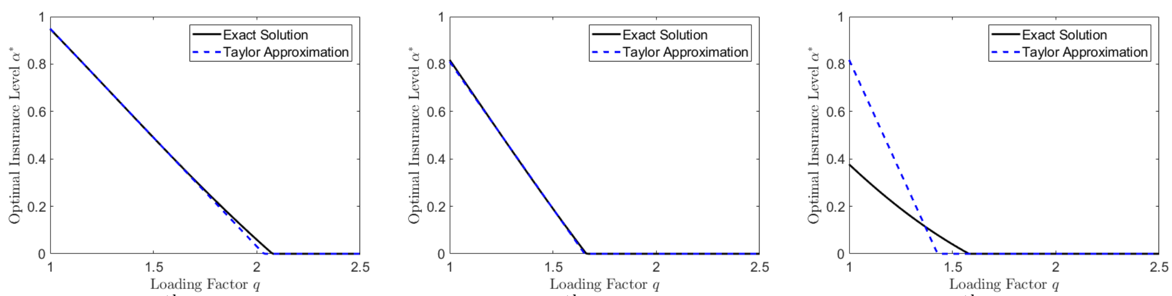
$$\alpha^* = 1 + \frac{1}{r(1-\Omega)L} - \frac{p}{r\Omega(1-\Omega)L}q. \tag{C.1}$$

This function is linear in q. However, this does not imply that optimal insurance demand under quadratic utility is linear in the loading, because Taylor approximations are only exact when the risk is normally distributed – which is not the case in our setting. Using Equation (9) and quadratic utility of the form $U(x) = ax - bx^2$ with $a, b > 0$, we can express the exact solution to optimal insurance demand as

$$\alpha^* = \frac{(a - 2bw)(\Omega - qp) + 2b(1 - qp)\Omega L}{2bL[(qp)^2 + (1 - 2qp)\Omega]}. \tag{C.2}$$

This term is not linear in q. However, the Taylor approximation is still close to the exact solution in many cases. To evaluate the quality of the approximation, we use the 25^{th}, 50^{th}, and 75^{th} percentile of responses for $q = 1.25$ and $q = 1.50$. Based on these values and setting $a = 1$ without loss of generality, we solve Equation (C.1) numerically for r and Ω.[37] Similarly, we use the two given choices and solve equation (C.2) for the implied values of b and Ω. Based on these solutions, we plot the implied demand by the b, Ω pair for the exact solution and by the r, Ω pair for the approximation over $q \in [1, 2.5]$ in Figure C.1.

Figure C.1: Graphical evaluation of the Taylor approximation in insurance choices with $p = 10\%$ for different percentiles of $\alpha_{1.25}$ and $\alpha_{1.50}$ in the insurance demand data



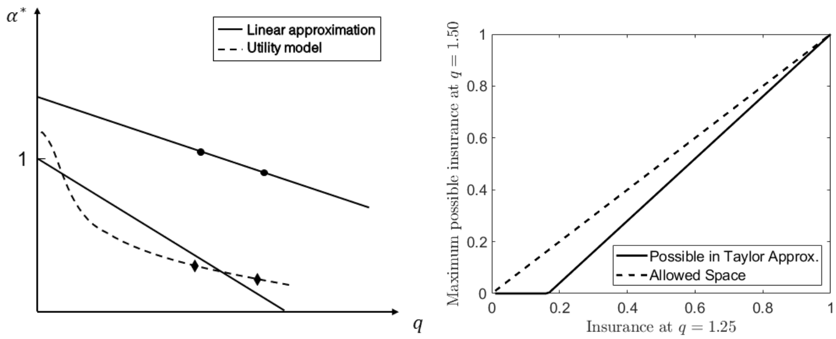
(a) 75^{th} percentile (b) 50^{th} percentile (c) 25^{th} percentile

As we can see in the figure, the approximation fares well when evaluating the 75^{th} or 50^{th} percentile. However, it breaks down for the 25^{th} percentile. The linear approximation in Equation (C.1) implies a minimum intercept of 1 for $q = 0$. The idea is that no matter what level of risk aversion the individual has, they will still accept free insurance coverage if it is offered. In addition, the slope of α^* in the approximation is linear in q. Thus, the approximation cannot model very flat reactions to the loading with very low initial levels of insurance at $q = 1.25$. We illustrate this concept in panel (a) of Figure C.2. While the linear approximation (indicated by the solid line) can model the two dots on the demand curve, it cannot model the two diamonds because of its restrictions. The utility model in Equation C.2 (indicated by the dashed line), however, can model the two diamonds (as is shown in Jaspersen et al., 2020), because it has the ability to slope upwards before the intercept.

Equation (C.1) shows that given any level of insurance demand at $q = 1.25$, the maximum possible slope is $-\frac{1-\alpha_{1.25}}{1.25}$. Thus, any level of $\alpha_{1.25}$ sets an upper bound on the level of $\alpha_{1.50}$ that can be accommodated by the model. Specifically, the maximal level is $\alpha_{1.50}^{max} = 1 - \frac{1-\alpha_{1.25}}{1.25} 1.5$. Thus, for lower values of $\alpha_{1.25}$, only fairly low values of $\alpha_{1.50}^{max}$ are possible. To illustrate the extent of this issue, the dashed line in panel (b) of Figure C.2 shows the allowed space of insurance demand at $q = 1.25$ and $q = 1.50$ in the probability distortion model of Equation (9). The space can be

[37] The model in Equation (9) is invariant in its predictions towards positive affine transformations of $U(\cdot)$, and thus we maintain generality.

Figure C.2: Problematic aspects of the Taylor approximation in insurance decisions with binary risks



(a) Illustration of insurance choices impossible to approximate with a second-order Taylor approximation

(b) Possible $\alpha_{1.25}/\ \alpha_{1.50}$ combinations for second-order Taylor approximation

Note: Lines for the diamonds in panel (a) are exemplary sketches and do not necessarily display the exact demand functions implied by Equations (C.1) and (C.2).

approximated by $\alpha_{1.25} \geq \alpha_{1.50}$. In contrast, the solid line in the same panel shows the solutions possible in the linear approximation. The area between the two lines is the set of $\alpha_{1.25}, \alpha_{1.50}$ combinations for which the linear approximation breaks down. Since we observe a sizable number of insurance choices in this wedge, the linear model and the predictions from Equation (9) differ substantially in the analysis reported in Section 5.

D Summary statistics

Table D.1: Summary statistics for nonparametric preference measures

	University Only $n = 378$		mTurk Only $n = 1,352$		Full Sample $n = 1,730$	
	Mean	Median	Mean	Median	Mean	Median
UC^+	14.83	15.00	14.77	15.00	14.78	15.00
PW^+	1.04	1.00	2.91	2.00	2.50	2.00
CP	-0.51	0.00	-0.51	0.00	-0.51	0.00
UC^-	20.06	20.00	20.59	21.00	20.47	21.00
PW^-	-3.00	-3.00	-0.67	0.00	-1.18	0.00
LA	11.30	11.00	11.83	12.00	11.71	12.00

Note: The labels UC, PW, CP, and LA denote our measures of utility curvature, probability weighting, certainty preference, and loss aversion, respectively. Superscripts $^+$ ($^-$) indicate that the measure was elicited in the gain (loss) domain.

Table D.2: Correlation table for nonparametric preference measures

	UC^{+}_{std}	PW^{+}_{std}	CP_{std}	UC^{-}_{std}	PW^{-}_{std}	LA_{std}
UC^{+}_{std}	1.000	.	.	.	.	.
PW^{+}_{std}	0.044	1.000	.	.	.	.
CP_{std}	-0.304	0.268	1.000	.	.	.
UC^{-}_{std}	-0.120	0.120	0.034	1.000	.	.
PW^{-}_{std}	0.008	0.294	0.005	0.214	1.000	.
LA_{std}	0.289	-0.010	-0.015	0.016	-0.038	1.000

Note: For our sample size of 1,730 subjects, a correlation is statistically significant at the 10% level if it is larger than 0.040, at the 5% level if it is larger than 0.047, and at the 1% level if it is larger than 0.062 (in absolute values).

Table D.3: Summary statistics for demographic and experiment variables

	University		mTurk		Total	
	Mean	SD	Mean	SD	Mean	SD
Age	21.48	2.34	36.14	10.81	32.94	11.37
Dummy for female	0.72	0.45	0.40	0.49	0.47	0.50
Dummy for US	1.00	0.00	0.85	0.36	0.88	0.32
Dummy for white	0.69	0.46	0.69	0.46	0.69	0.46
Dummy for black	0.04	0.20	0.06	0.24	0.06	0.23
Dummy for asian	0.29	0.45	0.21	0.41	0.23	0.42
Dummy for latino	0.02	0.15	0.06	0.25	0.06	0.23
GRQ	5.28	2.13	5.23	2.76	5.24	2.63
Final payment to subject	6.41	4.65	6.23	5.05	6.27	4.97
Dummy for made $\geq$ 1 FOSD choice	0.14	0.34	0.30	0.46	0.26	0.44
Num times violated FOSD	1.44	0.73	1.75	0.98	1.72	0.96
Dummy for pref task instr wrong	0.12	0.32	0.14	0.35	0.13	0.34
Dummy for ins task instr wrong	0.17	0.37	0.18	0.38	0.18	0.38
Understanding score	1.94	0.80	1.76	0.82	1.80	0.82
Education:						
Less than high school	0.00		0.01		0.00	
High school graduate	0.24		0.10		0.13	
Some college, no degree	0.57		0.20		0.28	
Associate's college degree	0.02		0.11		0.09	
Bachelor's college degree	0.13		0.44		0.37	
Master's degree	0.03		0.12		0.10	
Doctoral degree	0.00		0.01		0.01	
Professional degree (JD, MD)	0.00		0.02		0.01	
Income ($ USD):						
Less than 5,000	0.00		0.06		0.04	
5,000–9,999	0.00		0.06		0.04	
10,000–24,999	0.00		0.16		0.13	
25,000–49,999	0.00		0.28		0.22	
50,000–74,999	0.00		0.20		0.16	
75,000–99,999	0.00		0.13		0.10	
100,000–149,999	0.00		0.08		0.06	
150,000 or greater	0.00		0.04		0.03	

Note: Summary statistics are presented for the 378 in-person subjects at a university laboratory, the 1,352 online subjects recruited through Amazon mTurk, and all 1,730 subjects together. GRQ is the self-reported risk aversion measure of Dohmen et al. (2011). Final payment to the subject does not include the $6 "show-up fee" paid to university participants. Num times violated FOSD is conditional on having violated FOSD at least once. Understanding score is the subject's rating of how easy or difficult the study was to understand, with 1 indicating very easy, 5 indicating very difficult, and 3 indicating a neutral response.

Table D.4: Spearman rank correlations of coverage levels

Loss prob	5%		10%				20%		40%	70%	
Loading	1.50	2.50	1.00	1.25	1.50	2.50	1.25	1.50	1.50	0.80	1.00
	P5L150	P5L250	P10L100	P10L125	P10L150	P10L250	P20L125	P20L150	P40L150	P70L080	P70L100
P5L150	1.000	.	.	.	.	.	.	.	.	.	.
P5L250	0.729	1.000	.	.	.	.	.	.	.	.	.
P10L100	0.676	0.631	1.000	.	.	.	.	.	.	.	.
P10L125	0.699	0.670	0.706	1.000	.	.	.	.	.	.	.
P10L150	0.709	0.705	0.689	0.739	1.000	.	.	.	.	.	.
P10L250	0.660	0.706	0.641	0.687	0.719	1.000	.	.	.	.	.
P20L125	0.583	0.566	0.628	0.677	0.631	0.623	1.000	.	.	.	.
P20L150	0.576	0.564	0.632	0.686	0.654	0.646	0.732	1.000	.	.	.
P40L150	0.347	0.329	0.386	0.432	0.414	0.433	0.557	0.591	1.000	.	.
P70L080	0.102	0.068	0.211	0.189	0.139	0.149	0.279	0.296	0.443	1.000	.
P70L100	0.076	0.048	0.147	0.131	0.120	0.154	0.233	0.289	0.495	0.644	1.000
P70L125	0.035	0.053	0.066	0.107	0.106	0.113	0.204	0.255	0.485	0.519	0.642

Note: Insurance scenarios are labeled in the first column and the third row as P[probability]L[loading * 100]. For our sample size of 1,730 subjects, a correlation is statistically significant at the 10% level if it is larger than 0.040, at the 5% level if it is larger than 0.047, and at the 1% level if it is larger than 0.062 (in absolute values).

E Tobit regressions

Table E.1: Tobit regressions of coverage level on standardized preference motives separately

Panel (a): Nonparam. measures	(1)	(2)	(3)	(4)	(5)	(6)
Motive	UC^+_{std}	PW^+_{std}	CP_{std}	UC^-_{std}	PW^-_{std}	LA_{std}
Coefficient	2.31*	0.69	−0.93	2.45*	3.86***	3.17**
	(0.98)	(0.99)	(0.90)	(1.00)	(0.92)	(1.04)
FOSD violators	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.01	0.01	0.01	0.01	0.01	0.01
N subjects	1,730	1,730	1,730	1,730	1,730	1,730
N choices	20,760	20,760	20,760	20,760	20,760	20,760
N left-censored	4,321	4,321	4,321	4,321	4,321	4,321
N uncensored	12,871	12,871	12,871	12,871	12,871	12,871
N right-censored	3,568	3,568	3,568	3,568	3,568	3,568
Panel (b): Param. measures	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Motive	γ^+_{std}	β^+_{std}	$\hat{\kappa}_{std}$	γ^-_{std}	β^-_{std}	$\hat{\lambda}_{std}$
Coeff	2.90**	2.85**	−1.92	3.04**	3.44***	2.79*
	(1.11)	(1.14)	(1.22)	(1.14)	(1.07)	(1.31)
FOSD violators	No	No	No	No	No	No
Pseudo R^2	0.01	0.01	0.01	0.01	0.01	0.01
N subjects	1,276	1,276	1,276	1,276	1,276	1,276
N choices	15,312	15,312	15,312	15,312	15,312	15,312
N left-censored	3,220	3,220	3,220	3,220	3,220	3,220
N uncensored	9,456	9,456	9,456	9,456	9,456	9,456
N right-censored	2,636	2,636	2,636	2,636	2,636	2,636

Note: Tobit regressions are specified with a left-censored limit of 0 and a right-censored limit of 100. Dependent variable is the coverage level selected by subject i. All models contain fixed effects for each of the 12 insurance scenarios. Regressions of parametric preference motives are limited to the 1,276 non FOSD-violating subjects. In each panel, p-values have been adjusted using the Šidák (1967) method, adjusting for the six hypotheses tested in each panel. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table E.2: Tobit regressions of coverage level on joint preferences

Nonparam./Param.	Nonparametric		Parametric	
	(1)	(2)	(3)	(4)
$UC^{+}_{std}/\gamma^{+}_{std}$	1.62	1.63	4.01***	4.03***
	(1.07)	(1.07)	(1.20)	(1.20)
$PW^{+}_{std}/\beta^{+}_{std}$	−0.57	0.96	1.92	3.86*
	(1.10)	(1.37)	(1.25)	(1.59)
$CP_{std}/\hat{k}_{std}$	−0.33	−0.34	−1.67	−1.67
	(1.02)	(1.02)	(1.23)	(1.23)
$UC^{-}_{std}/\gamma^{-}_{std}$	1.91	1.92	2.40	2.41
	(1.02)	(1.02)	(1.20)	(1.20)
$PW^{-}_{std}/\beta^{-}_{std}$	3.73***	5.76***	2.62*	4.52**
	(0.99)	(1.27)	(1.15)	(1.51)
$LA_{std}/\hat{\lambda}_{std}$	2.82**	2.81*	4.21**	4.20**
	(1.06)	(1.05)	(1.41)	(1.42)
Prob ≥ 40		49.95***		53.24***
		(1.88)		(2.17)
Prob $\geq 40 \times PW^{+}_{std}/\beta^{+}_{std}$		−4.48***		−5.63***
		(1.32)		(1.55)
Prob $\geq 40 \times PW^{-}_{std}/\beta^{-}_{std}$		−5.92***		−5.51***
		(1.33)		(1.59)
FOSD violators	Yes	Yes	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject
Pseudo R^2	0.01	0.01	0.02	0.02
N subjects	1,730	1,730	1,276	1,276
N choices	20,760	20,760	15,312	15,312
N left-censored	4,321	4,321	3,220	3,220
N uncensored	12,871	12,871	9,456	9,456
N right-censored	3,568	3,568	2,636	2,636

Note: Tobit regressions are specified with a left-censored limit of 0 and a right-censored limit of 100. Dependent variable is the coverage level selected by subject i. All models contain fixed effects for each of the 12 insurance scenarios. Column 1 contains only the nonparametric preference scales. Column 2 adds an interaction between the PW preferences and a dummy for "high probability" (Prob $\geq 40 = 1$ if the probability of loss is 40% or 70%). Columns 3 and 4 replicate columns 1 and 2 using the parametric preferences. In each column, p-values have been adjusted using the Šidák (1967) method. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

F Analysis with alternative samples

Table F.1: Regression of coverage level on nonparametric preferences, excluding subjects who made FOSD-violating choices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UC^{+}_{std}	1.99**						1.32	1.32
	(0.78)						(0.86)	(0.86)
PW^{+}_{std}		1.10					0.65	1.83
		(0.77)					(0.82)	(1.05)
CP_{std}			−0.76				−0.72	−0.72
			(0.81)				(0.90)	(0.90)
UC^{-}_{std}				2.25**			1.99*	1.99
				(0.79)			(0.82)	(0.82)
PW^{-}_{std}					2.00**		1.13	2.25
					(0.70)		(0.78)	(1.00)
LA_{std}						4.57***	4.20***	4.20***
						(0.91)	(0.92)	(0.92)
Prob ≥ 40								37.00***
								(1.28)
Prob $\geq 40 \times PW^{+}_{std}$								−3.54***
								(1.06)
Prob $\geq 40 \times PW^{-}_{std}$								−3.38**
								(1.06)
FOSD violators	No	No	No	No	No	No	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject	Subject	Subject	Subject	Subject
R^2	0.13	0.12	0.12	0.13	0.13	0.13	0.14	0.14
N choices	15,312	15,312	15,312	15,312	15,312	15,312	15,312	15,312
N subjects	1,276	1,276	1,276	1,276	1,276	1,276	1,276	1,276

Note: Sample is restricted to subjects who did not violate FOSD. Dependent variable is the coverage level selected by subject i. All models contain fixed effects for each of the 12 insurance scenarios. Columns 1-6 replicate columns 1-6 in Panel A of Table 6, with p-values adjusted for six hypotheses using the Šidák (1967) method. Columns 7 and 8 replicate columns 1 and 2 in Table 7, with Šidák-adjusted p-values for the hypotheses in each column. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table F.2: Correlation between actual and predicted coverage levels, by number of law of demand violations

Model	0 violations (24.4%)	1 violation (26.4%)	2 violations (22.5%)	3+ violations (26.6%)
EV	0.249	0.288	0.261	0.252
EU^{+}	0.185	0.217	0.230	0.131
EU^{-}	0.220	0.245	0.204	0.148
DT^{+}	0.049	0.029	−0.001	−0.028
DT^{-}	0.055	0.028	0.021	−0.127
KR	0.063	0.024	0.108	0.029
$RDEU^{+}$	0.026	−0.070	−0.087	−0.146
$RDEU^{-}$	0.094	0.029	0.022	−0.126
CPT^{-}	0.105	0.033	0.017	−0.108
CPT^{NLIB}	0.069	−0.019	0.019	−0.110
EV_{CP}	0.098	0.114	0.089	0.096
DT^{+}_{CP}	−0.003	−0.028	−0.042	−0.034
DT^{-}_{CP}	−0.007	−0.007	−0.010	−0.079
EU^{+}_{CP}	0.006	0.066	0.101	0.041
EU^{-}_{CP}	0.003	0.067	0.090	0.021
$RDEU^{+}_{CP}$	−0.012	−0.074	−0.093	−0.114
$RDEU^{-}_{CP}$	0.020	−0.008	−0.011	−0.085

G Alternatively scaled insurance choices

The analysis in the main text treats insurance demand as a continuous and cardinal scaled measure. This appendix demonstrates that our results are robust to alternative assumptions about the scale of the variable. The first two columns of Table G.1 compare the correlations between observed demand and model predictions when treating insurance demand as cardinal (column 1, equal to analysis in main text) and treating it as ordinal (column 2).

The other analyses reported in this appendix treat insurance demand as a discrete measure. In the first analysis, we round answers of subjects in the experiment to the nearest increment of 25%. We adjust our predictions such that they indicate which of five possible discrete alternatives (0%, 25%, 50%, 75%, 100%) maximizes the objective function of the subject. Analyses are then carried out using estimators that take the ordinal nature of the reported scales into account. The correlations reported in the rightmost two columns of Table G.1 are calculated as Kendall's Tau. The regressions in Tables G.2 use an ordered logit estimator. In the analyses using predicted insurance demand as the independent variable, we use dummy variables to indicate the predicted value. The second analysis of insurance demand as a discrete measure restricts observations and predictions even more and only considers no insurance (0%) or full insurance (100%) as possible options. The results in Tables G.3 use logit estimators and a dummy variable for 100% coverage to reflect this binary nature of insurance demand.

Table G.1: Correlation between actual and predicted coverage levels

	Continuous		25% bins	0% or 100%
Model	Pearson	Kendall's Tau	Kendall's Tau	Kendall's Tau
EV	0.261	0.201	0.212	0.247
EU^{+}	0.189	0.123	0.144	0.123
EU^{-}	0.205	0.142	0.157	0.150
DT^{+}	0.015	0.011	0.009	0.004
DT^{-}	−0.002	0.001	−0.007	−0.016
KR	0.053	0.043	0.047	0.050
$RDEU^{+}$	−0.064	−0.050	−0.059	−0.088
$RDEU^{-}$	0.010	0.008	0.004	−0.015
CPT^{-}	0.017	0.013	0.008	−0.008
CPT^{NLIB}	−0.008	−0.014	−0.019	−0.037
EV_{CP}	0.098	0.051	0.029	0.021
DT^{+}_{CP}	−0.025	−0.004	−0.009	−0.008
DT^{-}_{CP}	−0.023	−0.006	−0.013	−0.020
EU^{+}_{CP}	0.050	−0.003	−0.001	0.003
EU^{-}_{CP}	0.042	−0.005	−0.003	0.009
$RDEU^{+}_{CP}$	−0.069	−0.036	−0.043	−0.036
$RDEU^{-}_{CP}$	−0.019	−0.015	−0.019	−0.025

Note: For our sample size of 1,276 subjects for whom we can make parametric predictions, the correlation is statistically significant at the 10% level if it is larger than 0.047, at the 5% level if it is larger than 0.055, and at the 1% level if it is larger than 0.073 (in absolute values).

Table G.2: Ordered logit regressions of coverage level (rounded to nearest 25%) on joint preferences

Nonparam./Param.	Nonparametric		Parametric	
	(1)	(2)	(3)	(4)
$UC^+_{std}/\gamma^+_{std}$	0.05	0.04	0.12***	0.12**
	(0.03)	(0.03)	(0.04)	(0.04)
PW^+_{std}/β^+_{std}	−0.00	0.05	0.08	0.15**
	(0.03)	(0.05)	(0.04)	(0.05)
$CP_{std}/\hat{\kappa}_{std}$	−0.02	−0.02	−0.06	−0.06
	(0.03)	(0.03)	(0.04)	(0.04)
$UC^-_{std}/\gamma^-_{std}$	0.05	0.05	0.07	0.08
	(0.03)	(0.03)	(0.04)	(0.04)
PW^-_{std}/β^-_{std}	0.10***	0.18***	0.06	0.13*
	(0.03)	(0.04)	(0.04)	(0.05)
$LA_{std}/\hat{\lambda}_{std}$	0.10**	0.10**	0.13**	0.13*
	(0.03)	(0.03)	(0.05)	(0.05)
Prob ≥ 40		1.78***		1.90***
		(0.07)		(0.09)
Prob $\geq 40 \times PW^+_{std}/\beta^+_{std}$		−0.14**		−0.18***
		(0.04)		(0.05)
Prob $\geq 40 \times PW^-_{std}/\beta^-_{std}$		−0.19***		−0.17***
		(0.04)		(0.05)
FOSD violators	Yes	Yes	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject
Pseudo R^2	0.039	0.041	0.045	0.047
N choices	20,760	20,760	15,312	15,312
N subjects	1,730	1,730	1,276	1,276

Note: Dependent variable is the coverage level selected by subject i, rounded to the nearest 25%. All models contain fixed effects for each of the 12 insurance scenarios. Column 1 contains only the nonparametric preference scales. Column 2 adds an interaction between the PW preferences and a dummy for "high probability" (Prob $\geq 40 = 1$ if the probability of loss is 40% or 70%). Columns 3 and 4 replicate columns 1 and 2 using the parametric preferences. In each column, p-values have been adjusted using the Šidák (1967) method. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table G.3: Ordered logit regressions of coverage level (rounded to 0% or 100%) on joint preferences

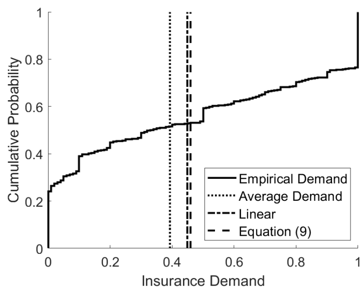
Nonparam./Param.	Nonparametric		Parametric	
	(1)	(2)	(3)	(4)
$UC^{+}_{std}/\gamma^{+}_{std}$	0.04	0.04	0.11**	0.12*
	(0.04)	(0.04)	(0.04)	(0.04)
$PW^{+}_{std}/\beta^{+}_{std}$	0.01	0.06	0.11**	0.15**
	(0.04)	(0.04)	(0.04)	(0.05)
$CP_{std}/\hat{\kappa}_{std}$	−0.02	−0.02	−0.05	−0.05
	(0.04)	(0.04)	(0.04)	(0.04)
$UC^{-}_{std}/\gamma^{-}_{std}$	0.05	0.05	0.09*	0.09
	(0.04)	(0.04)	(0.04)	(0.04)
$PW^{-}_{std}/\beta^{-}_{std}$	0.12***	0.17***	0.06	0.11
	(0.04)	(0.04)	(0.04)	(0.05)
$LA_{std}/\hat{\lambda}_{std}$	0.11**	0.11**	0.13**	0.14**
	(0.04)	(0.04)	(0.05)	(0.05)
Prob ≥ 40		2.26***		2.47***
		(0.08)		(0.10)
Prob $\geq 40 \times PW^{+}_{std}/\beta^{+}_{std}$		−0.18***		−0.14
		(0.05)		(0.06)
Prob $\geq 40 \times PW^{-}_{std}/\beta^{-}_{std}$		−0.16**		−0.20**
		(0.05)		(0.06)
FOSD violators	Yes	Yes	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject
Pseudo R^2	0.097	0.100	0.113	0.115
N choices	20,760	20,760	15,312	15,312
N subjects	1,730	1,730	1,276	1,276

Note: Dependent variable is coverage level selected by subject i, rounded to the closer of 0% or 100%. All models contain fixed effects for each of the 12 insurance scenarios. Column 1 contains only the nonparametric preference scales. Column 2 adds an interaction between the PW preferences and a dummy for "high probability" (Prob $\geq 40 = 1$ if the probability of loss is 40% or 70%). Columns 3 and 4 replicate columns 1 and 2 using the parametric preferences. In each column, p-values have been adjusted using the Šidák (1967) method. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

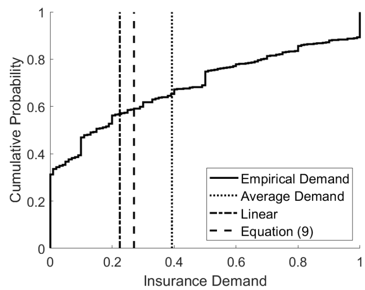
H Additional results on preferences from insurance choices

H.1 CDFs of model predictions

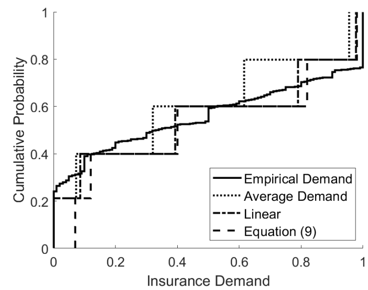
Figure H.1: Cumulative distribution functions of model predictions and empirically observed choices at $p = 10\%$ for $q = 1.00$ and $q = 2.50$ and for the different levels of aggregation



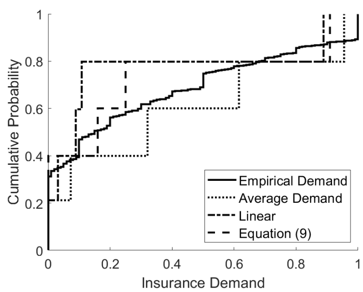
(a) Representative Agent at $q = 1.00$



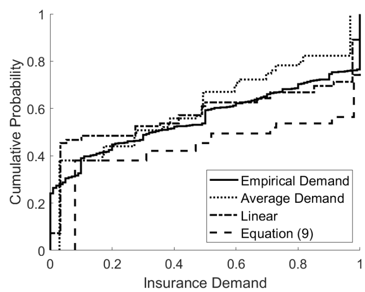
(b) Representative Agent at $q = 2.50$



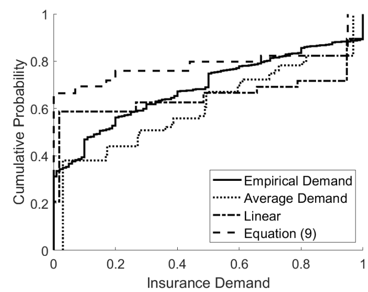
(c) Quintiles at $q = 1.00$



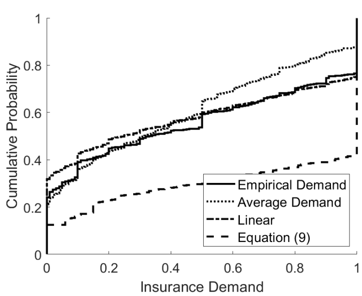
(d) Quintiles at $q = 2.50$



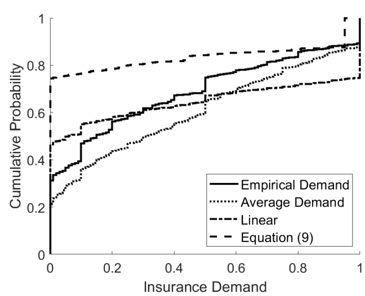
(e) Grid at $q = 1.00$



(f) Grid at $q = 2.50$



(g) Individual at $q = 1.00$

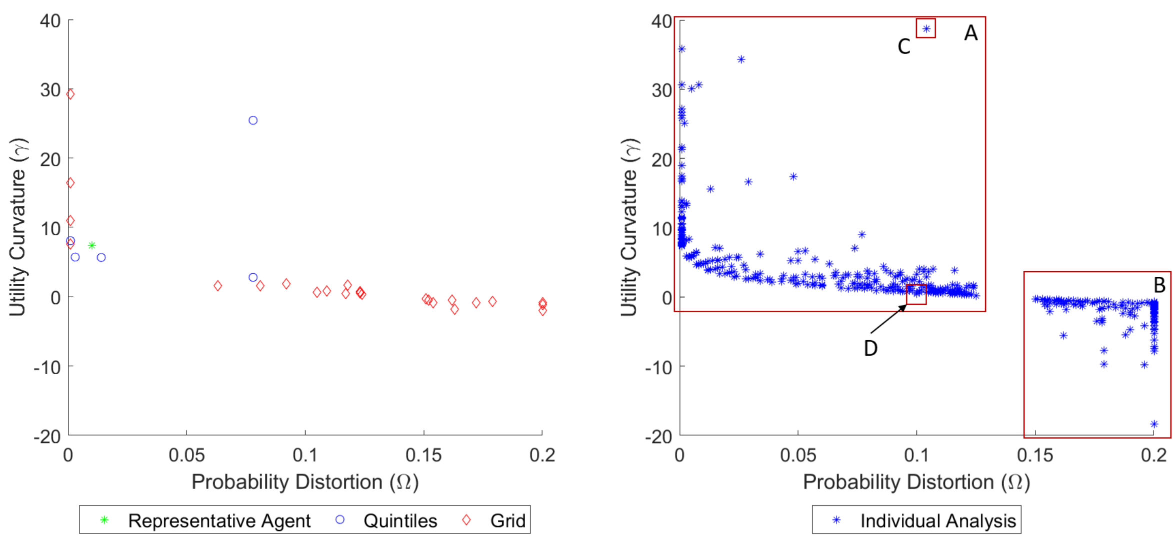


(h) Individual at $q = 2.50$

H.2 Elicited preferences and analysis with restricted sample

The preference elicitation from insurance choices makes three assumptions such that all insurance choices can be matched to preference parameters. First, for subjects who choose full insurance at both of the intermediate loads, we code the choice in the $q = 1.25$ scenario as 99% coverage and the choice when $q = 1.50$ as 98% coverage. Second, for subjects who choose higher levels of insurance at the 1.50 load than the 1.25 load, we use the value of Ω which leads to the smallest distance between the two utility curvature parameters implied by the insurance choices. Third, for the corner solution of no insurance coverage at both intermediate loads, we set $\Omega = p$ and utility curvature to the parameter which implies $\alpha^* = 0$ at $q = 1.25$. These three assumptions are not necessary for the aggregation levels of the representative agent or the quintiles. Panel (a) of Figure H.2 shows that all elicited preference parameters for these aggregation levels imply risk aversion and underweighted probabilities. When considering the grid aggregation, there are 10 grid squares where insurance demand is higher for $q = 1.50$ than for $q = 1.25$. The elicitation procedure described in Section 5 leads to risk seeking and probability overweighting preferences for these subjects.

Figure H.2: Scatter plot of elicited preferences according to Equation (9) at the four levels of aggregation



(a) Representative Agent, Quintiles, and Grid

(b) Individual

Note: Each data point is a preference pair elicited from the insurance choices at the respective level of aggregation. Red boxes in panel (b) mark subsets of subjects showing specific preference patterns.

In the individual-level analysis, all three assumptions come into play. Panel (b) of Figure H.2 shows all elicited preference pairs for the 1,730 subjects and categorizes them into four groups. Group A are subjects whose insurance choices do not require any of the three assumptions. Subjects in group B show an increasing demand in the loading of the insurance policy, violating the law of demand. Subjects in group C are those that chose full insurance at both loadings and were set to 99% and 98% coverage for the two loading factors, respectively. Subjects in group D were those which chose 0% insurance coverage for both loading factors and were set to have no probability weighting and only mild risk aversion of $\gamma = 0.41$ such that they exactly maximize expected utility at $\alpha = 0$ for $q = 1.25$.

It is obvious that all three assumptions in the preference elicitation procedure have significant consequences for the implied preferences. To assess the sensitivity of our results in Section 5, we thus repeat the analysis using only subjects from group A in the scatter plot above. That is, we only use subjects who display a strictly lower insurance demand at $q = 1.50$ than at $q = 1.25$. As we can see from Table H.1, results are broadly consistent with the analysis including all subjects.

Table H.1: Goodness of fit analysis at 10% loss probability for structural models calibrated with insurance choices of a restricted sample

	Individual Distance			Population Distance		
Prediction Model	Average	Linear	Eq. (9)	Average	Linear	Eq. (9)
Aggregation Level						
Representative Agent	0.127	0.235	0.282	0.600	0.771	0.796
Quintiles	0.090	0.187	0.179	0.293	0.596	0.500
Grid	0.090	0.158	0.153	0.267	0.475	0.404
Individual	0.087	0.154	0.209	0.219	0.395	0.321

Note: The table reports the results of our calibration analysis in which we use the coverage level decisions in the scenarios with loss probability 10% and loading factors 1.25 and 1.50 to calibrate the decision model in Equation (9) and use it to predict insurance demand in the scenarios with loss probability 10% and loading factors 1.00 and 2.50. The sample of subjects is restricted to those which display $\alpha_{1.50} < \alpha 1.25$. We offer two non-utility models for comparison. The first non-utility model uses the average demand for loading factors 1.25 and 1.50 to predict demand in the other two scenarios. The second non-utility model calibrates an individual linear demand function $\alpha = bq + c$ for predictions. Individual distances are Euclidean distances, population distances are Kolmogorov-Smirnoff distances.

I Experiment supporting materials

Here, we provide screenshots of the full experiment given to the mTurk subjects. In-person subjects completed an identical experiment, without some mTurk-specific questions (e.g., entering the mTurk worker ID). Each box represents a different screen.

The experiment begins with a browser compatibility test and confirmation of the mTurk worker ID. This also prevents bots from continuing the experiment.

Before we begin, we need to make sure your browser is compatible with our study.

Set the slider to 75.

| **1417500** |

0 10 20 30 40 50 60 70 80 90 100

Slider 75

What is the red number that appears between the lines above the slider? If you don't see a number, enter 100.

Please verify that the ID in the field below is your correct Amazon Mechanical Turk ID.

- If it is your ID, please click "Next."
- If it is not your ID, or if no ID is displayed, please enter your ID and click "Next."

Then, subjects are presented with an overview of the experiment.

Overview

Thank you for participating in this study. You will begin this experiment by completing a typing task to earn $5.00. Your final payment at the end of this experiment may be more or less than $5.00, depending partly on your later choices and partly on chance.

After you complete the typing task, we will ask you a series of economic questions. In these questions, you may gain additional money or lose some of your $5.00. Whether you have a gain or a loss is based on the draw of colored balls from a bucket. In different questions you will be asked to make decisions related to these buckets that can affect how much you earn. Each question is designated with a number (Q1, Q2, Q3, etc…). At the end of the experiment, the computer will randomly select a question number. We will apply your choice in that question and the computer will play it out for real money.

Even though only one of your choices will count, you will not know in advance which question will be used to determine your ultimate earnings. Therefore, you should think about each of them carefully before submitting your choice.

There are no correct answers - we are simply interested in your preferences for risky versus safe outcomes.

Following the overall instructions, subjects complete the real-effort task. This involves manually typing a passage correctly into the provided text box. Every character must be correct to pass.[38] The font used in this passage is resistant to optical character recognition. There were five possible passages, and each subject was randomly assigned to complete two of them.

Typing Task

Please type all text from the blue box into the text entry box below, matching capitalization and punctuation. All spaces are single. You do not need to match the line breaks.

For instance, on the planet Earth, man had always assumed that he was more intelligent than dolphins because he had achieved so much (the wheel, New York, wars and so on) whilst all the dolphins had ever done was muck about in the water having a good time. But conversely, the dolphins had always believed that they were far more intelligent than man for precisely the same reasons. (Douglas Adams, 1978)

Subjects are then notified of their payment for the task.

Thank you for completing the typing task. Your compensation for completing this task is $5.00.

Please click the button below to continue to the next stage of the experiment.

[38]If the subject took longer than three minutes for a particular passage, we allowed them to continue to the next passage. This was not disclosed to subjects. In every case, the subject had entered the full text but had made a typo.

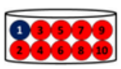
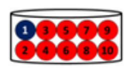
The lottery task begins with a set of instructions and three questions to ensure subjects understood them.

Part 1 Instructions

In this part, you must decide whether you would prefer to draw a ball from Bucket A or Bucket B. Each bucket contains a mixture of colored balls, and the color of the ball you draw will determine how much you gain or lose. We will tell you the mixture of the balls and the dollar value of each colored ball, and you should consider this information in choosing a bucket.

Here is an example of the buckets you will see in this part. Use the buttons in the middle to indicate whether you would prefer to draw from Bucket A or Bucket B.

You currently have $5.00.

	Bucket A				Bucket B
	● Gain $0.50 ● Lose $0.20 Ball mixture: 10% ●, 90% ●				● Gain $5.00 ● Lose $2.00 Ball mixture: 10% ●, 90% ●
Example		● Gain $0.50 ● Lose $0.20	○ ○	● Gain $5.00 ● Lose $2.00	

Here are a few questions to make sure you understand the instructions.

What would happen if you drew a red ball from Bucket B?

○ Gain $0.50
○ Lose $0.20
○ Gain $5.00
◉ Lose $2.00

What is the chance of drawing a blue ball from Bucket A?

◉ 10%
○ 20%
○ 50%
○ 90%

If you lost $2.00, what would your total payment be at the end of this experiment?

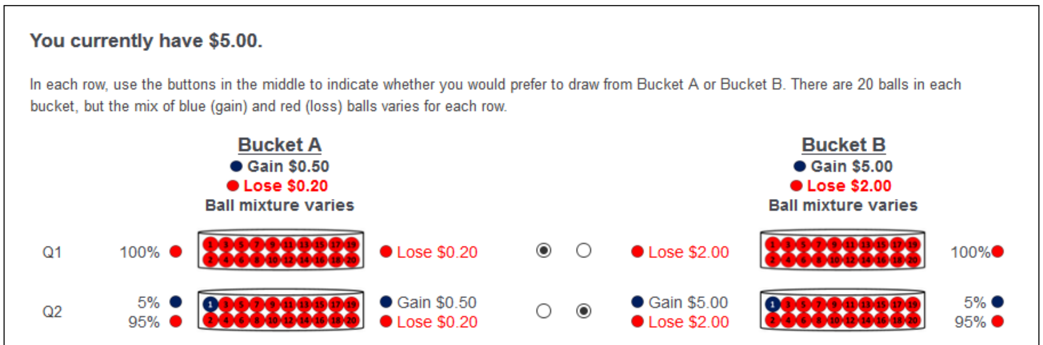
○ $0.00
○ $2.00
◉ $3.00
○ $5.00

Subjects who answer the questions correctly may continue to the lottery task. Subjects who answer incorrectly may not continue until they have answered the questions correctly.

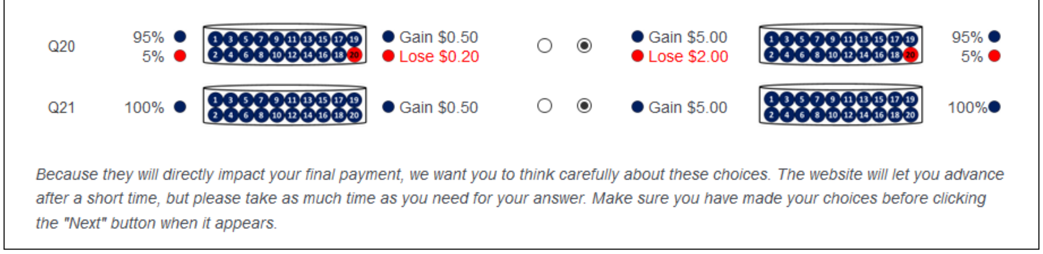
> Yes, that's right. Now we will ask you to make similar choices between two buckets.

Lotteries are presented in random order, and question numbers update automatically. In this example, the LA questions are presented first.

LA



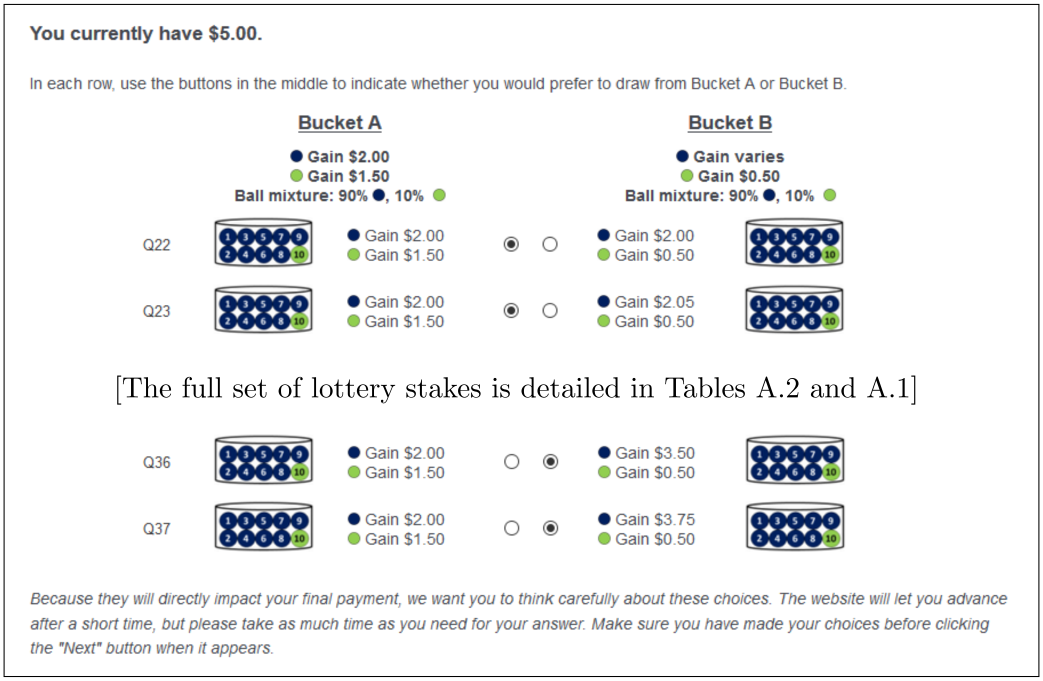
[The full set of lottery stakes is detailed in Tables A.2 and A.1]



To encourage subjects to make careful choices, the "Next" button is hidden for 20 seconds on each lottery page.

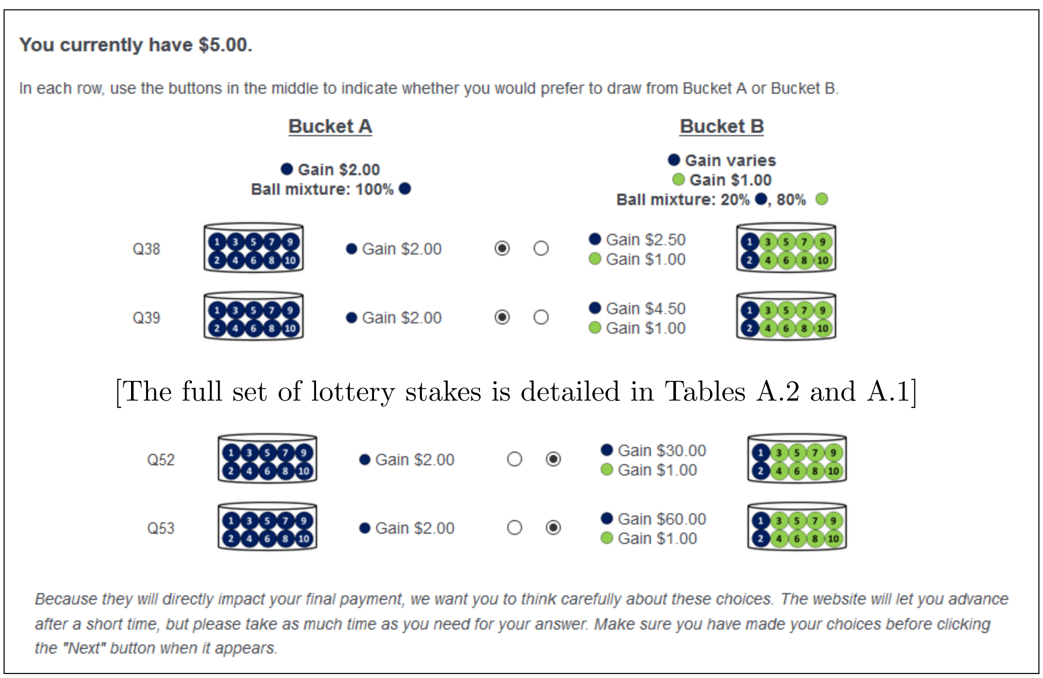
In this example, the GD2 lottery is randomly-selected to appear second.

GD2



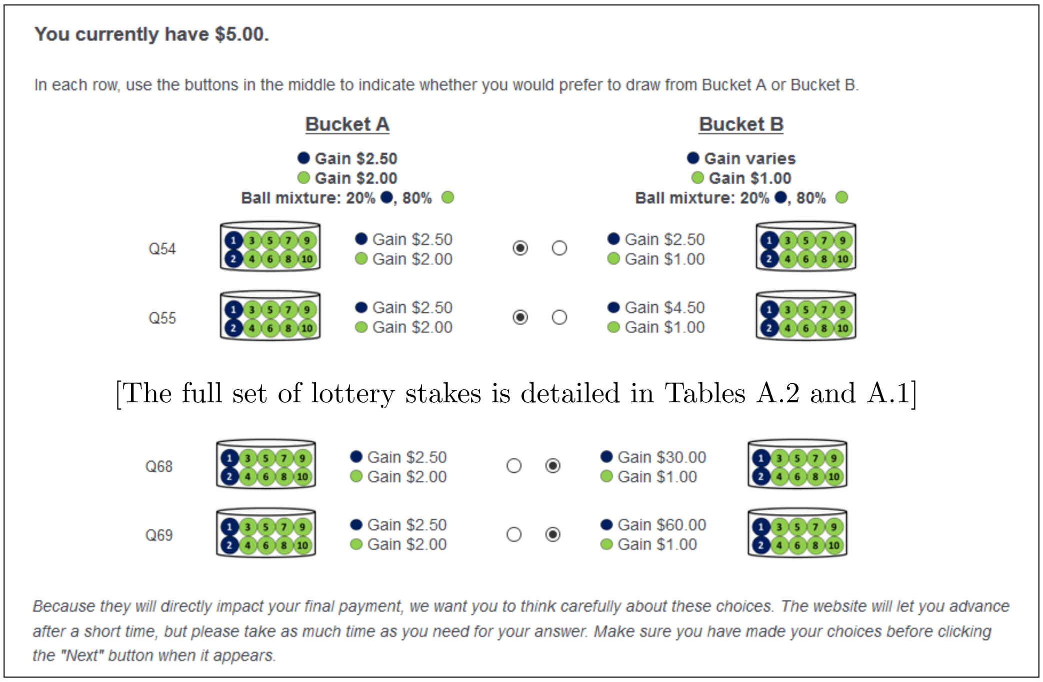
In this example, the CP table is randomly-selected to appear third.

CP



In this example, the GD1 table is randomly-selected to appear fourth.

GD1



You currently have $5.00.

In each row, use the buttons in the middle to indicate whether you would prefer to draw from Bucket A or Bucket B.

	Bucket A			Bucket B
	Gain $2.50 / Gain $2.00 / Ball mixture: 20% ●, 80% ●			Gain varies / Gain $1.00 / Ball mixture: 20% ●, 80% ●
Q54	Gain $2.50 / Gain $2.00	◉	○	Gain $2.50 / Gain $1.00
Q55	Gain $2.50 / Gain $2.00	◉	○	Gain $4.50 / Gain $1.00

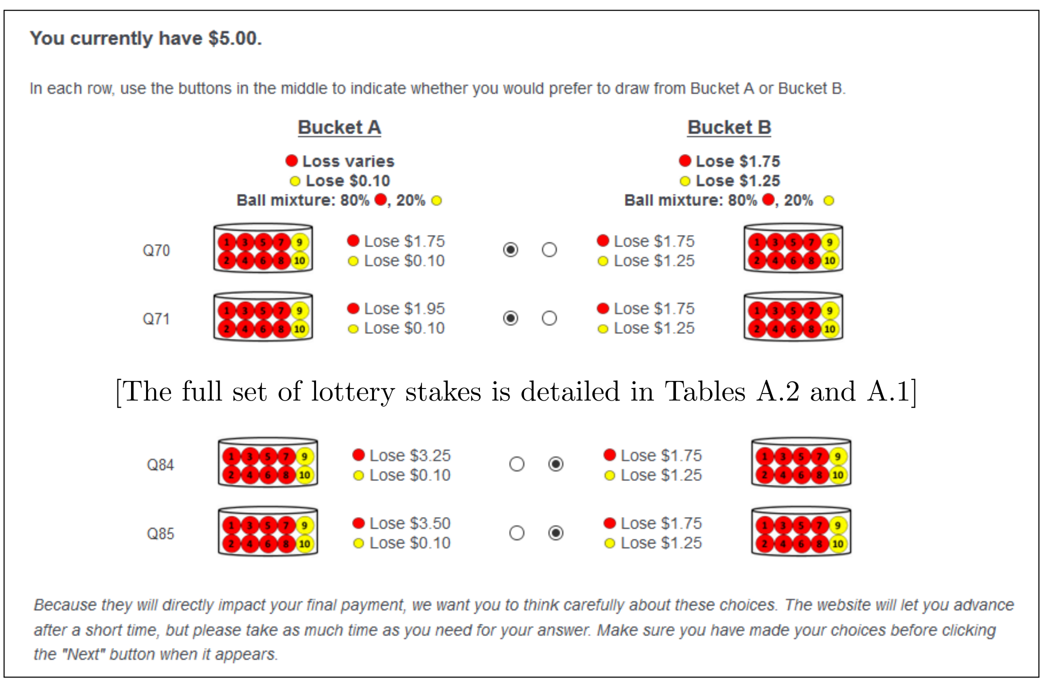
[The full set of lottery stakes is detailed in Tables A.2 and A.1]

	Bucket A			Bucket B
Q68	Gain $2.50 / Gain $2.00	○	◉	Gain $30.00 / Gain $1.00
Q69	Gain $2.50 / Gain $2.00	○	◉	Gain $60.00 / Gain $1.00

Because they will directly impact your final payment, we want you to think carefully about these choices. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choices before clicking the "Next" button when it appears.

In this example, the LD2 table is randomly-selected to appear fifth.

LD2



You currently have $5.00.

In each row, use the buttons in the middle to indicate whether you would prefer to draw from Bucket A or Bucket B.

	Bucket A			Bucket B
	Loss varies / Lose $0.10 / Ball mixture: 80% ●, 20% ●			Lose $1.75 / Lose $1.25 / Ball mixture: 80% ●, 20% ●
Q70	Lose $1.75 / Lose $0.10	◉	○	Lose $1.75 / Lose $1.25
Q71	Lose $1.95 / Lose $0.10	◉	○	Lose $1.75 / Lose $1.25

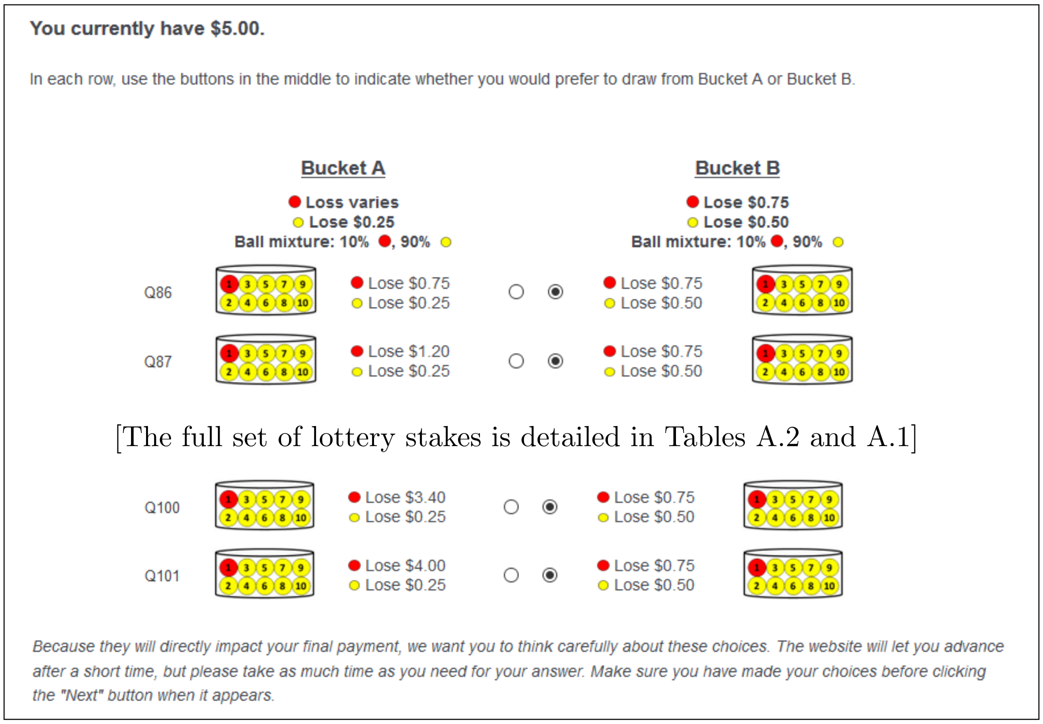
[The full set of lottery stakes is detailed in Tables A.2 and A.1]

	Bucket A			Bucket B
Q84	Lose $3.25 / Lose $0.10	○	◉	Lose $1.75 / Lose $1.25
Q85	Lose $3.50 / Lose $0.10	○	◉	Lose $1.75 / Lose $1.25

Because they will directly impact your final payment, we want you to think carefully about these choices. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choices before clicking the "Next" button when it appears.

Finally, the LD1 table is presented sixth.

LD1


You currently have $5.00.

In each row, use the buttons in the middle to indicate whether you would prefer to draw from Bucket A or Bucket B.

	Bucket A		Bucket B	
	Loss varies Lose $0.25 Ball mixture: 10% red, 90% yellow		Lose $0.75 Lose $0.50 Ball mixture: 10% red, 90% yellow	
Q86	Lose $0.75 Lose $0.25	○ ◉	Lose $0.75 Lose $0.50	
Q87	Lose $1.20 Lose $0.25	○ ◉	Lose $0.75 Lose $0.50	

[The full set of lottery stakes is detailed in Tables A.2 and A.1]

	Bucket A		Bucket B	
Q100	Lose $3.40 Lose $0.25	○ ◉	Lose $0.75 Lose $0.50	
Q101	Lose $4.00 Lose $0.25	○ ◉	Lose $0.75 Lose $0.50	

Because they will directly impact your final payment, we want you to think carefully about these choices. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choices before clicking the "Next" button when it appears.

The insurance task begins with a set of instructions and two questions to ensure subjects understood them.

Part 2 Instructions

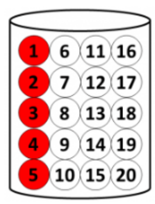
In this part, you will face a number of scenarios in which you may lose $3.00 of your money. Whether you have a loss depends on the draw of one ball from a bucket filled with 20 balls. Drawing a red ball results in a loss of $3.00, while drawing a white ball results in no loss.

You have the option to buy insurance to protect some or all of your money from loss. The <u>price of insurance</u> will be different in every scenario. Scenarios may also have a different <u>chance of loss</u>.

If you want to buy insurance, you must pay for it out of your $5.00 before you draw a ball at the end of the experiment. You may choose to buy varying levels of insurance, from 0% of the potential loss (no insurance) to 100% of the potential loss (full insurance). You may click the slider as many times as you like to see the different options. Your final earnings will depend on the price of the insurance you choose and any uninsured loss you may experience.

Here is an example question so you can see how your choices influence your final payment. Click the slider to practice selecting an insurance amount.

You currently have $5.00.



You have a 25% chance of drawing a red ball and losing $3.00.

For every 10% of the loss you want to cover with insurance, you would have to pay about 9 cents. Please select your desired amount of insurance (if any) using the slider. The exact price of your choice will display below.

- **Insurance coverage: 50%**
- **Before drawing a ball, pay $0.47 for insurance.**

If you draw ●:	If you draw ○:

• $3.00 loss
  ◦ $1.50 covered by insurance
  ◦ $1.50 loss to you
	• No loss

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Set Insurance Level 50

Here are a few questions to make sure you understand the instructions:

<u>Select 50% insurance</u> using the slider above. <u>How much would you need to pay</u> for this insurance before drawing a ball?

- ○ $0.09
- ○ $0.30
- ◉ $0.47
- ○ $0.94
- ○ $1.50

<u>Select 50% insurance</u> using the slider above. If you had this level of insurance and drew a red ball, how much of the $3.00 loss is <u>covered by insurance</u>?

- ○ $0.25
- ○ $0.47
- ○ $0.94
- ◉ $1.50
- ○ $3.00

Next

Subjects who answer the questions correctly may continue to the insurance task. Subjects who answer incorrectly may not continue until they have answered the questions correctly.

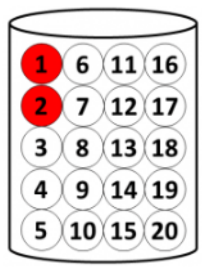
Yes, that's right. Now we will ask you to make similar choices about insurance.

Back Next

Insurance scenarios are presented in random order, and question numbers update automatically. In this example, an insurance scenario with a 10% probability of loss is presented first. We have selected 0% coverage here.

Q102

You currently have $5.00.



You have a 10% chance of drawing a red ball and losing $3.00.

For every 10% of the loss you want to cover with insurance, you would have to pay about 8 cents. Please select your desired amount of insurance (if any) using the slider. The exact price of your choice will display below.

- **Insurance coverage: 0%**
- **Before drawing a ball, pay $0.00 for insurance.**

If you draw ●:	If you draw ○:
• $3.00 loss ◦ $0.00 covered by insurance ◦ $3.00 loss to you	• No loss

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Set Insurance Level 0

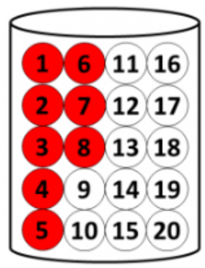
We encourage you to investigate several possible insurance choices by clicking around on the slider. Because it will directly impact your final payment, we want you to think carefully about your insurance choice. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choice before clicking the button to continue when it appears.

To encourage subjects to make careful choices, the "Next" button is hidden for 10 seconds on each insurance page.

The next randomly-selected insurance scenario involves a 40% chance of loss. We have selected 50% coverage here.

Q103

You currently have $5.00.



You have a 40% chance of drawing a red ball and losing $3.00.

For every 10% of the loss you want to cover with insurance, you would have to pay about 18 cents. Please select your desired amount of insurance (if any) using the slider. The exact price of your choice will display below.

- **Insurance coverage: 50%**
- **Before drawing a ball, pay $0.90 for insurance.**

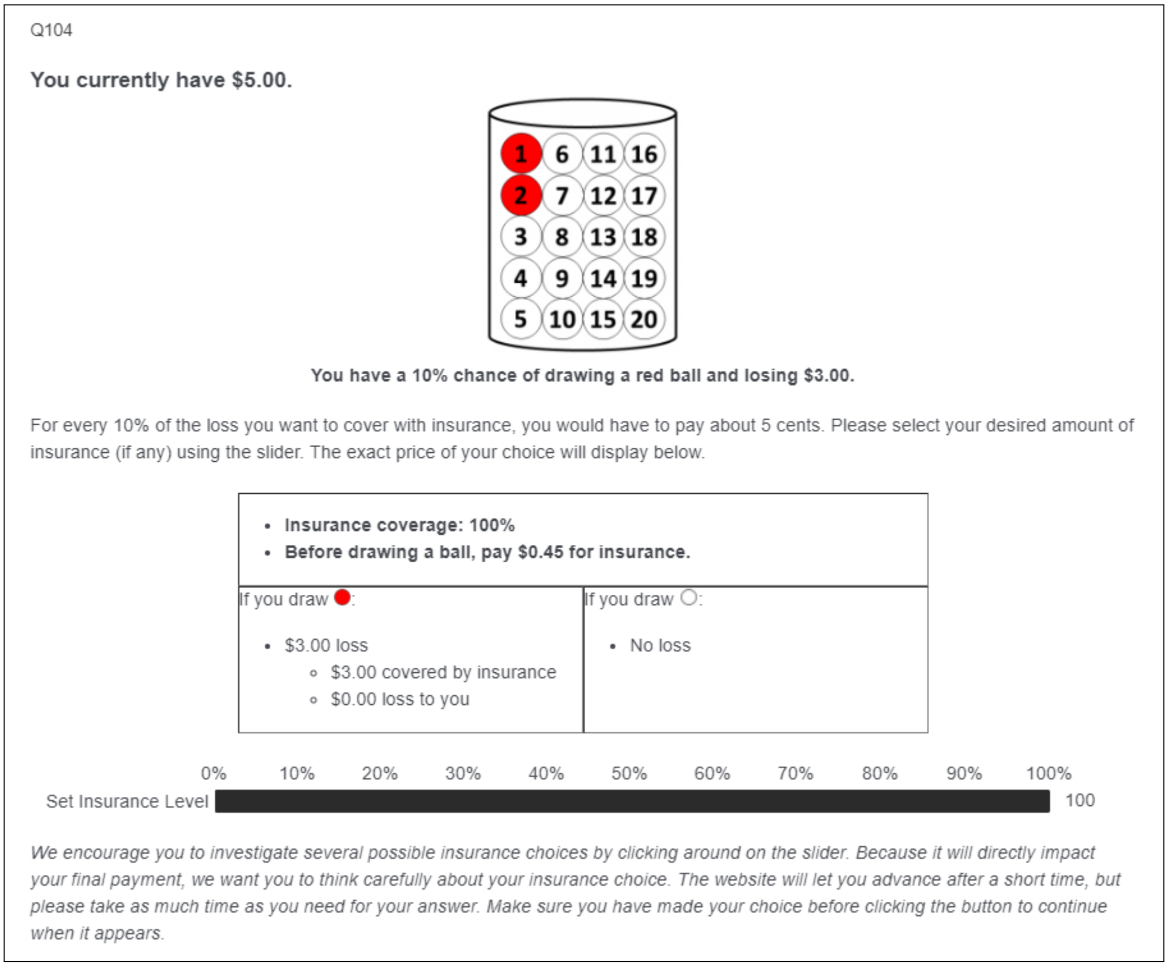
If you draw ●:	If you draw ○:
• $3.00 loss ∘ $1.50 covered by insurance ∘ $1.50 loss to you	• No loss

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Set Insurance Level 50

We encourage you to investigate several possible insurance choices by clicking around on the slider. Because it will directly impact your final payment, we want you to think carefully about your insurance choice. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choice before clicking the button to continue when it appears.

The next randomly-selected insurance scenario again involves a 10% chance of loss. We have selected 100% coverage here.


Q104

You currently have $5.00.

You have a 10% chance of drawing a red ball and losing $3.00.

For every 10% of the loss you want to cover with insurance, you would have to pay about 5 cents. Please select your desired amount of insurance (if any) using the slider. The exact price of your choice will display below.

- **Insurance coverage: 100%**
- **Before drawing a ball, pay $0.45 for insurance.**

If you draw ●:	If you draw ○:
• $3.00 loss ◦ $3.00 covered by insurance ◦ $0.00 loss to you	• No loss

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Set Insurance Level 100

We encourage you to investigate several possible insurance choices by clicking around on the slider. Because it will directly impact your final payment, we want you to think carefully about your insurance choice. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choice before clicking the button to continue when it appears.

The nine remaining insurance scenarios have identical layouts, so we omit them from this appendix. The last question is numbered Q113.

After all choices are made in the experiment, the computer randomly selects one decision to play out.

> Please click the button below to lock in your choices and have the computer randomly select a question to play.
>
> Select Question

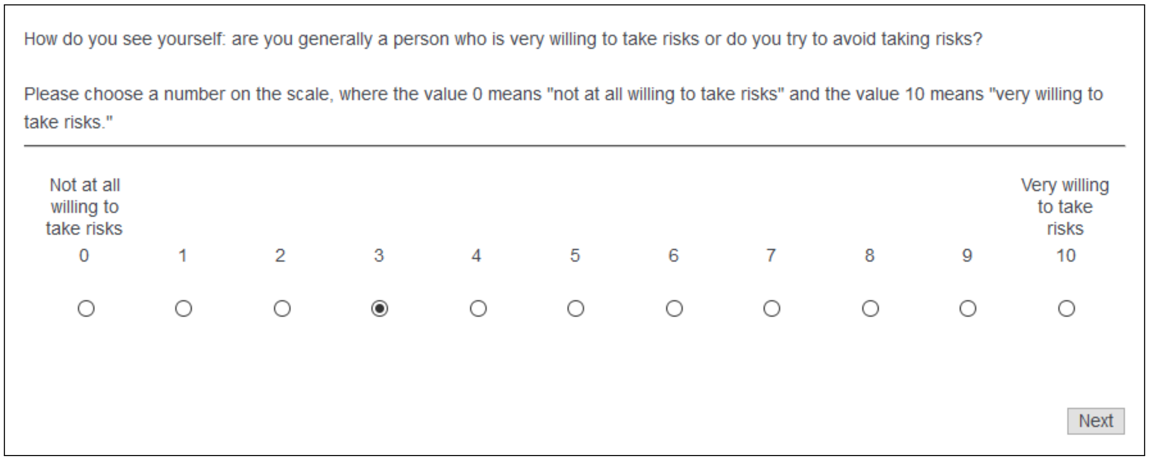
In this example, Question 44 is the randomly-selected decision. We confirm to the subject which selection he/she originally made and the possible outcomes. Then, they click the button to draw a "ball."

> The randomly selected question to play for real money is Question 44.
>
> In this question, you chose Bucket B.
>
> - If you draw a blue ball, then you gain $6.50.
> - If you draw a green ball, then you gain $1.00.
>
> Please click the button below to play this question by drawing a ball.
>
> Draw Ball

The computer then displays the outcome of the draw and outlines the subject's payment. Amazon mTurk requires variable payments to be paid as a "base" plus a "bonus." We were clear in the mTurk posting that our task involved variable payments paid as bonuses. This appears a common way to compensate subjects, and no subjects expressed confusion about the payments. During our pilot studies, we had built a positive reputation in a number of third-party websites for paying bonuses quickly, so nonpayment risk was a minimal concern. All pilot participants were excluded from our main experiment.

> You drew a BLUE ball.
>
> You gain $6.50.
>
> You began this experiment with $5.00 and gained $6.50 on this draw.
>
> Your final payment for participation in this experiment is: **$11.50**. This will be paid with the base payment of $1.00 and a bonus of $10.50.
>
> We have a few more questions before you complete this study and receive your validation code for mTurk.
>
> Next

Immediately after the draw, we ask the GRQ. The direction of the scale (0-10 or 10-0) is randomly assigned.


How do you see yourself: are you generally a person who is very willing to take risks or do you try to avoid taking risks?

Please choose a number on the scale, where the value 0 means "not at all willing to take risks" and the value 10 means "very willing to take risks."

Not at all willing to take risks 0	1	2	3	4	5	6	7	8	9	Very willing to take risks 10
○	○	○	◉	○	○	○	○	○	○	○

Next

Finally, we ask the following demographics questions and follow-up questions about the experiment.

What is your year of birth?

1983

What is your gender?

- (●) Male
- ( ) Female
- ( ) Transgender male
- ( ) Transgender female
- ( ) Gender variant/non-conforming
- ( ) Other
- ( ) Prefer not to answer

In which country do you currently reside?

In which U.S. state do you currently reside?

I do not reside in the United States

What is your race? You may choose all that apply.

- ☐ White or Caucasian
- ☐ Black or African American
- ☐ Hispanic or Latino
- ☐ Asian
- ☐ American Indian or Alaska Native
- ☐ Native Hawaiian or Pacific Islander
- ☐ Other

What was your approximate household income (in U.S. dollars, before taxes) in 2017? If you need to convert your income from another currency, you may calculate it here (opens in a new window).

- ( ) Less than $5,000
- ( ) $5,000 to $9,999
- ( ) $10,000 to $24,999
- ( ) $25,000 to $49,999
- ( ) $50,000 to $74,999
- ( ) $75,000 to $99,999
- ( ) $100,000 to $149,999
- ( ) $150,000 or greater

What is the highest level of school you have completed or the highest degree you have received?

- ○ Less than high school degree
- ○ High school graduate (high school diploma or equivalent including GED)
- ○ Some college but no degree
- ○ Associate degree in college (2-year)
- ○ Bachelor's degree in college (4-year)
- ○ Master's degree
- ○ Professional degree (JD, MD)
- ○ Doctoral degree

We have some final questions about your experience with this study.

Please rate your feelings on how easy or difficult this study was to UNDERSTAND:

Very easy to understand	Easy to understand	Neither easy nor difficult to understand	Difficult to understand	Very difficult to understand
○	○	○	○	○

If you had any technical difficulties completing this study, please explain below:

What do you think we were trying to find out in this study?

After all questions are answered, we provide a final "Submit" screen to remind subjects about the upcoming validation code.

Thank you for completing this study. Please click the button below to submit your responses. The next page will include a validation code. You must enter this validation code in mTurk so we can connect your final outcome in this survey to your mTurk account.

Submit Responses

For mTurk subjects, the study concludes with a validation code to connect their experiment outcomes to their mTurk account. In-person subjects were provided with a validation code to write down and bring to the experimenter for payment.

Thank you for your responses in this survey! Your validation code is:

7472154

Write this number down. Once you close this window, the validation code will disappear and cannot be recovered.

Please return to Amazon Mechanical Turk to enter the above validation code.