Linking Subjective and Incentivized Risk Attitudes: The Importance of Losses

Online Appendix

Johannes G. Jaspersen* Marc A. Ragin† Justin R. Sydnor‡

*Leibniz Universität Hannover, Institut für Versicherungsbetriebslehre, jgj@ivbl.uni-hannover.de.

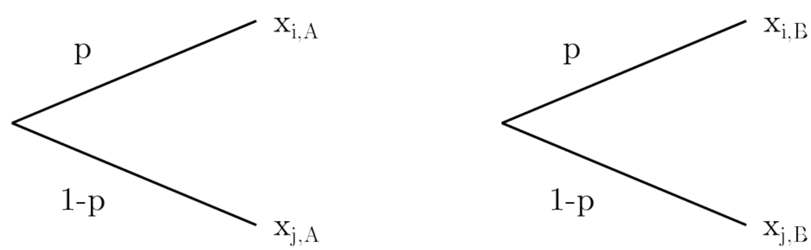
†University of Georgia, Terry College of Business, Department of Insurance, Legal Studies, and Real Estate, mragin@uga.edu.

‡Corresponding author. University of Wisconsin-Madison, Wisconsin School of Business, Department of Risk and Insurance, justin.sydnor@wisc.edu, (608) 263-2138.

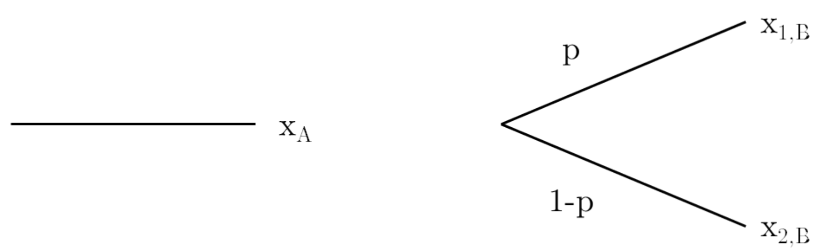
Online Appendix A Theory on Preference Elicitation

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 A1.

Figure A1: Graphical illustrations of of the different choice tables



(a) Schematic representation of choices in the UC1, UC2, LD1, LD2 and LA tables.



(b) Schematic representation of choices in the CP table

In accordance with the definitions of prospects in Section 2.2, $i = 1$ and $j = 2$ in Tables GD1, GD2, and LA and $i = 2$ and $j = 1$ in Tables LD1 and LD2.

A.1 Utility Curvature and Likelihood Insensitivity 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 x_1, the indifference large gain on Lottery B fulfills

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

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

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

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

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

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 up to one. Under this probability measure, we know from (A.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:

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

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

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

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

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

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

From the construction of the table, we know $u^+(x_{2,A}) - u^+(x_{1,A})) < u^+(x_{2,B}) - u^+(x_{1,B}))$. (A.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.

To see that the increased inverse S-shape of the probability weighting function maps into larger likelihood insensitivity, we adopt the likelihood insensitivity index of Abdellaoui et al. (2011). In their measure of the concept, they approximate the probability weighting function by a linear function with intercept c and slope s. They then measure likelihood insensitivity by $1 - s$. Our elicitation procedure measures two points of $w^+(p)$, namely $w^+(.2)$ and $w^+(.9)$. A linear function going through these two points would imply the two equalities $c + 0.2s = w^+(0.2)$ and $c + 0.9s = w^+(0.9)$. Substituting and rearranging renders $s = 0.7^{-1}(w^+(0.9) - w^+(0.2))$. An increased inverse S-shape implies a larger value of $w^+(.2)$ and a smaller value of $w^+(.9)$. Thus, such an increase decreases $w^+(0.9) - w^+(0.2)$ and thus increases the likelihood insensitivity index $1 - s$.

A.2 Utility Curvature and Likelihood Insensitivity in the Loss Domain

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

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

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

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

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

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

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 likelihood insensitivity 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:

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

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

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

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

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

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

From the construction of the table, we know $u^-(x_{2,A}) - u^-(x_{1,A})) < u^-(x_{2,B}) - u^-(x_{1,B})) < 0$. (A.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. The argument linking increased inverse S-shape to increased likelihood insensitivity is analogous to that in the gain domain.

A.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 leaving to indifference fulfills

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

or equivalently

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

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

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

There is no consensus on the correct index for loss aversion. Abdellaoui et al. (2007) review several different measures. When adopting their index of $LA = \frac{-\lambda u^-(-x)}{u^+(x)}$, we can observe that it is ceteris paribus increasing in λ. The same argument applies to most other indices they discuss.

A.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 EUT. All evaluations of uncertain payments are made by a utility function $u(x)$ and evaluations of certain payments are made by a value function $v(x)$.[1] 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 $u(x)$ not to change, that 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 $\hat{v}(x)$.

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

$$\hat{v}(x_A) = w^+(p)u^+(\hat{x}_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \tag{A.17}$$

Subtracting (A.16) from (A.17), we gain

$$\hat{v}(x_A) - v(x_A) = w^+(p)[u^+(\hat{x}_{2,B}) - u^+(x_{2,B})]. \tag{A.18}$$

Which 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.

We mention in Section 2.3 of the main text that both EUT and CPT imply weakly fewer choices for Lottery A in Table CP than in Table GD1. In the notation of this appendix, this would imply $x_{2,B}^{CP} \leq x_{2,B}^{GD1}$ with the superindex indicating the choice table. We show here the stronger statement that both imply $x_{2,B}^{CP} < x_{2,B}^{GD1}$.[2] Indifference in both tables implies the following two equalities (note that x_A in CP equals $x_{1,A}$ in GD1):

$$w^+(p)u^+(x_{2,B}^{CP}) + (1 - w^+(p))u^+(x_{1,B}) = u^+(x_{1,A}), \tag{A.19}$$

$$w^+(p)u^+(x_{2,B}^{GD1}) + (1 - w^+(p))u^+(x_{1,B}) = w^+(p)u^+(x_{2,A}) + (1 - w^+(p))u^+(x_{1,A}). \tag{A.20}$$

Subtracting (A.19) from (A.20) renders

$$w^+(p)[u^+(x_{2,B}^{GD1}) - u^+(x_{2,B}^{CP})] = w^+(p)[u^+(x_{2,A}) - u^+(x_{1,A})]. \tag{A.21}$$

By construction of the table, $u^+(x_{2,A}) - u^+(x_{1,A}) > 0$ and thus $u^+(x_{2,B}^{GD1}) > u^+(x_{2,B}^{CP})$ which implies $x_{2,B}^{CP} < x_{2,B}^{GD1}$. The prediction for EUT follows from setting $w^+(p) = p$ and $u^+ = u$.

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

[2] Note that due to the interval nature of the choice tables, this can still imply the same switching row in CP and $GD1$.

References

Abdellaoui, M., Baillon, A., Placido, L., and Wakker, P. P. (2011). The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review*, 101(2):695–723.

Abdellaoui, M., Bleichrodt, H., and Paraschiv, C. (2007). Loss aversion under prospect theory: A parameter-free measurement. *Management Science*, 53(10):1659–1674.

Chiu, W. H. (2010). Skewness preference, risk taking and expected utility maximisation. *The Geneva Risk and Insurance Review*, 35(2):108–129.

Ebert, S. (2015). On skewed risks in economic models and experiments. *Journal of Economic Behavior & Organization*, 112(4):85–97.

Schmidt, U. (1998). A measurement of the certainty effect. *Journal of Mathematical Psychology*, 42(1):32–47.

Vieider, F. M. (2018). Certainty preference, random choice, and loss aversion: A comment on "Violence and Risk Preference: Experimental Evidence from Afghanistan". *American Economic Review*, 108(8):2366–2382.

Wakker, P. P. (2008). Explaining the characteristics of the power (CRRA) utility family. *Health Economics*, 17(12):1329–1344.

Online Appendix B 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 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 following parametric forms:

$$U(x) = \begin{cases} \frac{(x+1)^{1-\gamma^+}}{1-\gamma^+} - \frac{1}{1-\gamma^+} & \text{for } x \geq 0 \\ -\lambda\left(\frac{(1-x)^{1-\gamma^-}}{1-\gamma^-} - \frac{1}{1-\gamma^-}\right) & \text{for } x < 0. \end{cases} \tag{B.1}$$

and

$$w^{+/-}(p) = exp\left(-(-ln(p))^{\beta^{+/-}}\right). \tag{B.2}$$

The utility function closely resembles the typical isoelastic function but does not quite exhibit constant absolute risk aversion. Our slight adaptation allows utility to cross the origin, which is required by cumulative prospect theory. Adapting the isoelastic form permits us to elicit relative risk aversion greater than 1 from our preference tables, which would not be possible with the power function of Wakker (2008). We capture the certainty effect through $v(x) = k^{1-\gamma}u(x)$. This ensures $v(x) > u(x)\,\forall\, x > 0$ and $v(0) = u(0) = 0$.

Using these assumptions, we identify the values of γ^+, γ^-, β^+, β^-, λ and k which solve the six equations

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

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

$$\lambda = \frac{w^+(\bar{p}^{LA})(u^+(x_{2,B}^{LA}) - u^+(x_{2,A}^{LA}))}{w^-(1-\bar{p}^{LA})(u^-(x_{1,A}^{LA}) - u^-(x_{1,B}^{LA}))} \tag{B.3}$$

and

$$k^{1-\gamma} = \frac{w^+(p^{CP/GD1})u^+(\bar{x}_{2,B}^{CP}) + (1-w^+(p^{CP/GD1}))u^+(x_{1,B}^{CP/GD1})}{w^+(p^{CP/GD1})u^+(\bar{x}_{2,B}^{GD1}) + (1-w^+(p^{CP/GD1}))u^+(x_{1,B}^{CP/GD1})}. \tag{B.4}$$

In equation (B.4), the index $CP/GD1$ indicates that the values are equal in both tables.

Directly eliciting values of λ and k results in bad measures of loss aversion and certainty preference (Schmidt, 1998; Abdellaoui et al., 2007). 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

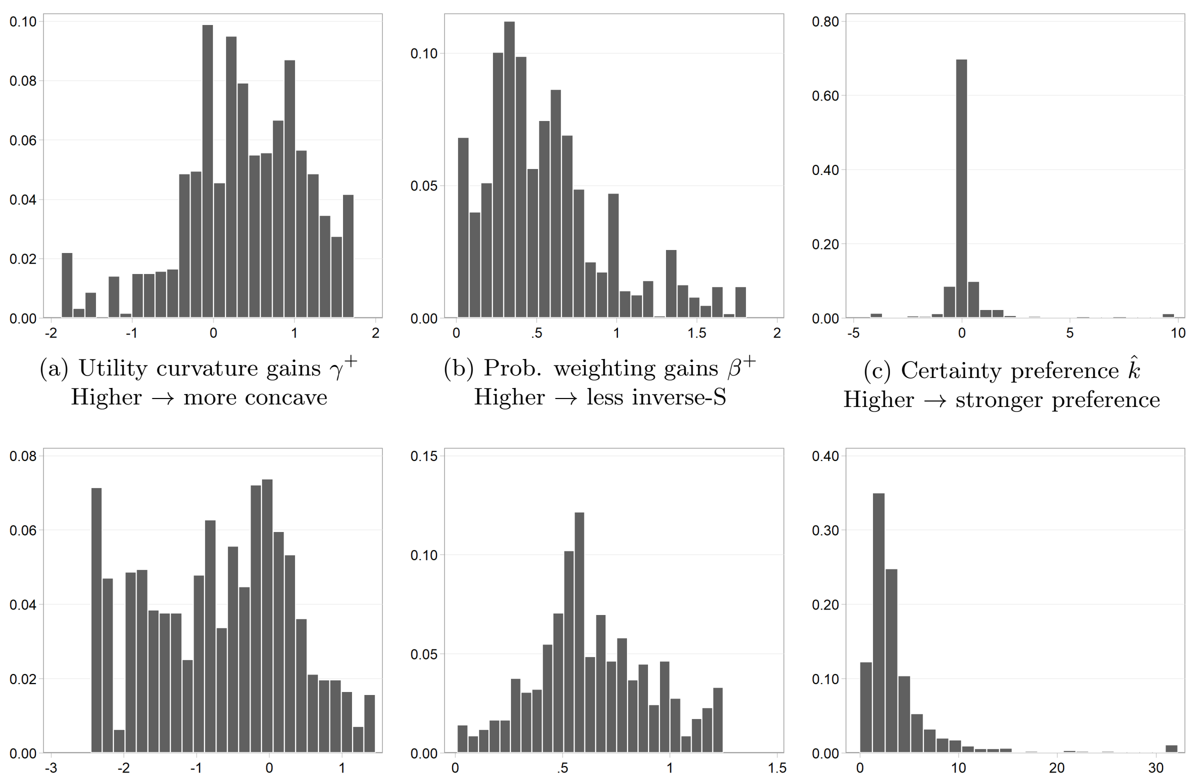
$$\hat{\lambda} = -\int_0^5 \frac{\lambda u^-(-x)}{u^+(x)dx} dx. \tag{B.5}$$

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

$$\hat{k} = \frac{v(x) - u(x)}{u'(x)}. \tag{B.6}$$

The distributions of the elicited parameters are given in Figure B1. The captions provide a directional interpretation of each parametric measure, similar to Figure 2. The results for the regression analyses using the parametric measures are given in the tables below, which are analogous to those using the non-parametric measures in Tables 3, 4, and B1, respectively. Note from Figure B1 that interpreting the parametric measures β^+, β^-, and γ^- is the reverse of interpreting their non-parametric counterparts (PW^+, PW^-, and UC^-, respectively), so the coefficient estimates are expected to have the opposite sign. We observe some extreme values for the ratios $\hat{\lambda}$ and $\hat{k}$, so we winsorize them at the 1st and 99th percentiles.

Figure B1: Distributions of parametric preference scales



(a) Utility curvature gains γ^+
Higher $\rightarrow$ more concave

(b) Prob. weighting gains β^+
Higher $\rightarrow$ less inverse-S

(c) Certainty preference $\hat{k}$
Higher $\rightarrow$ stronger preference

(d) Utility curvature losses γ^-
Higher $\rightarrow$ less concave

(e) Prob. weighting losses β^-
Higher $\rightarrow$ less inverse-S

(f) Loss aversion index $\hat{\lambda}$
Higher $\rightarrow$ more loss averse

Table B1: Results of the single-preference (parametric) ordered probit regressions, with GRQ_{std} as the dependent variable

Dependent var:	GRQ_{std}					
Explanatory var:	γ^{+}_{std}	β^{+}_{std}	k_{std}	γ^{-}_{std}	β^{-}_{std}	λ_{std}
Panel A: Scales only						
Est coeff	−0.010	0.035	−0.005	0.166***	0.010	−0.109***
	(0.029)	(0.028)	(0.029)	(0.030)	(0.029)	(0.033)
	[0.734]	[0.207]	[0.866]	[0.000]	[0.731]	[0.001]
Controls	No	No	No	No	No	No
Pseudo R^2	0.000	0.000	0.000	0.006	0.000	0.003
χ^2	0.12	1.59	0.03	30.99	0.12	10.71
N	1,276	1,276	1,276	1,276	1,276	1,276
Panel B: Include controls						
Est coeff	−0.015	0.030	0.013	0.143***	0.013	−0.086*
	(0.030)	(0.029)	(0.029)	(0.031)	(0.029)	(0.034)
	[0.624]	[0.292]	[0.665]	[0.000]	[0.653]	[0.011]
Controls	No	No	No	No	No	No
Pseudo R^2	0.025	0.025	0.025	0.029	0.025	0.026
χ^2	139.63	140.71	139.26	164.29	139.66	140.49
N	1,276	1,276	1,276	1,276	1,276	1,276
Panel C: mTurk only						
Est coeff	−0.015	0.019	0.040	0.145***	−0.023	−0.083*
	(0.035)	(0.035)	(0.031)	(0.035)	(0.034)	(0.035)
	[0.662]	[0.594]	[0.197]	[0.000]	[0.496]	[0.019]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.031	0.031	0.032	0.036	0.031	0.033
χ^2	139.54	139.18	140.50	162.03	138.96	139.71
N	950	950	950	950	950	950
Panel D: In-person only						
Est coeff	−0.061	0.056	−0.125*	0.108	0.120	−0.085
	(0.054)	(0.055)	(0.048)	(0.065)	(0.063)	(0.075)
	[0.260]	[0.312]	[0.009]	[0.097]	[0.058]	[0.261]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.007	0.007	0.008	0.008	0.009	0.006
χ^2	9.47	8.94	15.62	10.45	11.16	9.71
N	326	326	326	326	326	326

Note: The dependent variable in each column is GRQ_{std}, with the explanatory variable of interest the standardized parametric preference scale listed in the table header. Stars *, **, and *** denote statistical significance with Šidák-Holm-corrected p-values at the 0.10, 0.05, and 0.01 levels, respectively. Heteroskedasticity-robust standard errors are in parentheses, and the unadjusted p-values are in square brackets. $\hat{\lambda}$ and $\hat{k}$ are winsorized at the 1st and 99th percentiles before standardizing. Controls include age, gender, ethnicity, education, the probability of a "bad" outcome in the randomly-selected lottery to play out, a dummy for whether the subject experienced the bad outcome, an interaction of these two, a dummy for incorrectly answering one of the "understanding" questions following the lottery instructions, and dummies for the menu display of the GRQ and the preference elicitation lotteries. In Panels C and D, we repeat our Panel B regressions using only mTurk responses and in-person responses, respectively. We omit education from the regressions reported in Panel D, as there is insufficient variation in education for our sample comprised primarily of college students.

Table B2: Results of the multiple-preference (parametric) ordered probit regression analysis with GRQ_{std} as the dependent variable

	(1)	(2)
Utility curvature gains (γ^{+}_{std})	−0.065	−0.059
	(0.032)	(0.033)
	[0.043]	[0.072]
Probability weighting gains (β^{+}_{std})	0.056	0.046
	(0.032)	(0.033)
	[0.075]	[0.162]
Certainty preference ($\hat{k}_{std}$)	−0.014	0.002
	(0.029)	(0.029)
	[0.641]	[0.934]
Utility curvature losses (γ^{-}_{std})	0.172***	0.148***
	(0.031)	(0.033)
	[0.000]	[0.000]
Probability weighting losses (β^{-}_{std})	−0.041	−0.031
	(0.032)	(0.032)
	[0.203]	[0.344]
Loss aversion index ($\hat{\lambda}_{std}$)	−0.107**	−0.086*
	(0.035)	(0.035)
	[0.002]	[0.014]
Controls	No	Yes
FOSD Violators	No	No
Pseudo R^2	0.009	0.031
χ^2	48.16	177.66
N	1,276	1,276

Note: The dependent variable is *GRQ*. *GRQ* and the parametric preference scales are standardized values. Stars *, **, and *** denote statistical significance with Šidák-Holm-corrected p-values at the 0.10, 0.05, and 0.01 levels, respectively. Heteroskedasticity-robust standard errors are in parentheses, and the unadjusted p-values are in square brackets. $\hat{\lambda}$ and $\hat{k}$ are winsorized at the 1^{st} and 99^{th} percentiles before standardizing. Controls include age, gender, ethnicity, education, a dummy for mTurk subjects, the probability of a "bad" outcome in the randomly-selected lottery to play out, a dummy for whether the subject experienced the bad outcome, an interaction of these two, a dummy for incorrectly answering one of the "understanding" questions following the lottery instructions, and dummies for the menu display of the GRQ and the preference elicitation lotteries.

Online Appendix C Experiment Implementation

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

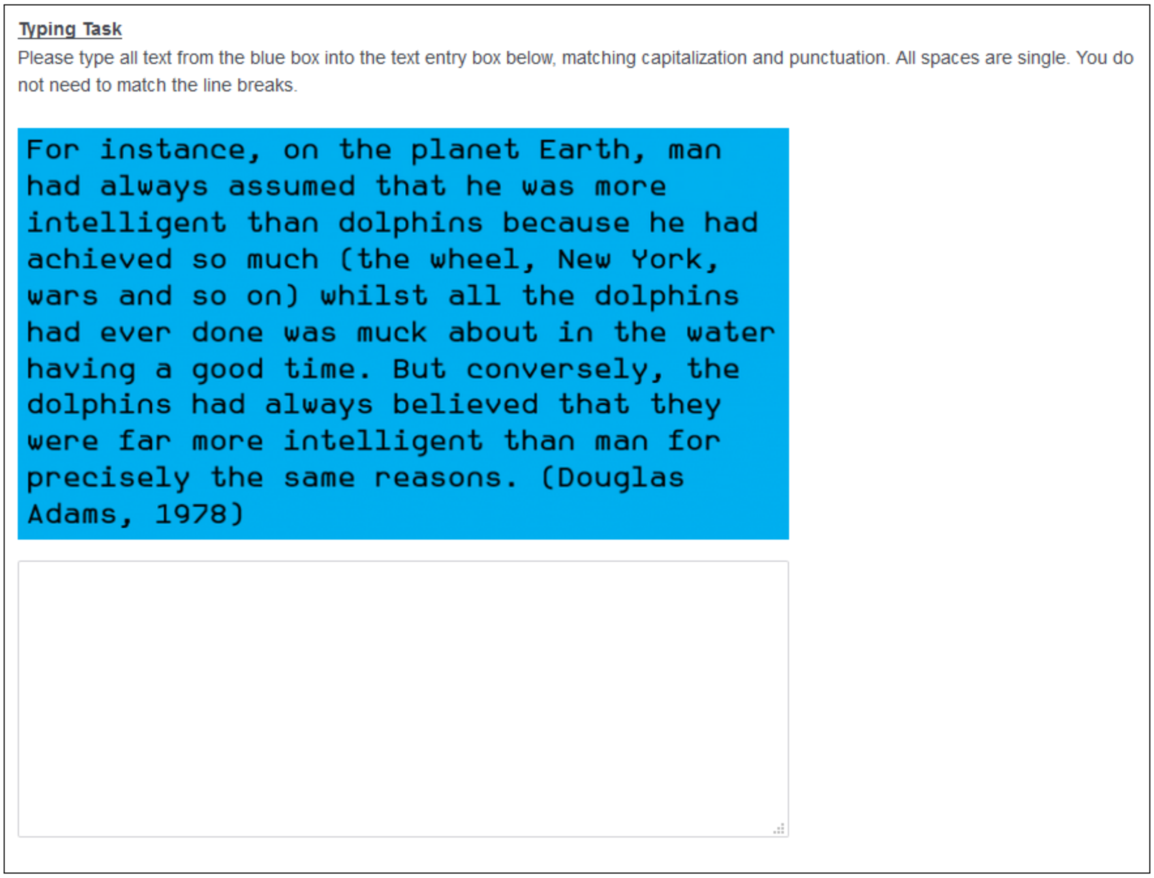
Thank you for participating in this study. You will begin this experiment by completing a typing task to earn \$5.00. Your final payment at the end of this experiment may be more or less than \$5.00, depending partly on your later choices and partly on chance.

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.

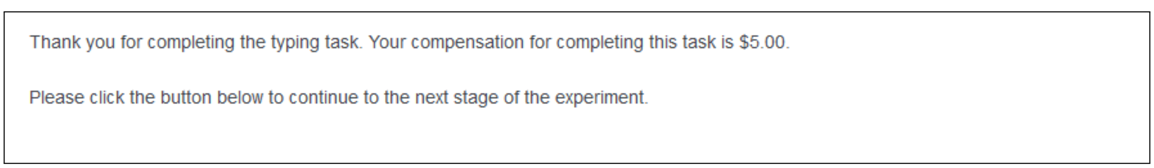
Following the overall instructions, subjects complete the real-effort task. This involves manually typing a passage correctly into the provided text box. Every character must be correct to pass.[3] The font used in this passage is resistant to optical character recognition. There were five possible passages, 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.

[3] 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.

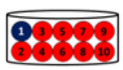
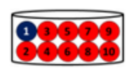
The lottery task begins with a set of instructions and three questions to ensure subjects understood them.

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 ● Gain $0.50 ● Lose $0.20 Ball mixture: 10% ●, 90% ●				Bucket B ● 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

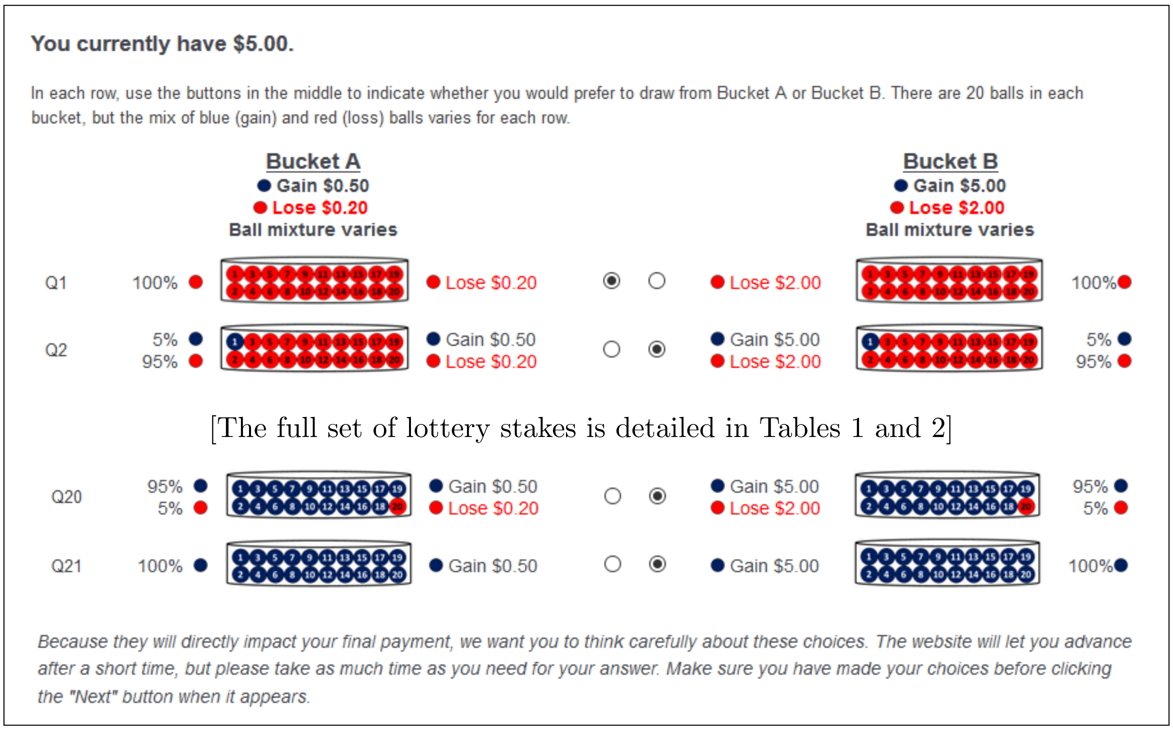
◯ $5.00

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.

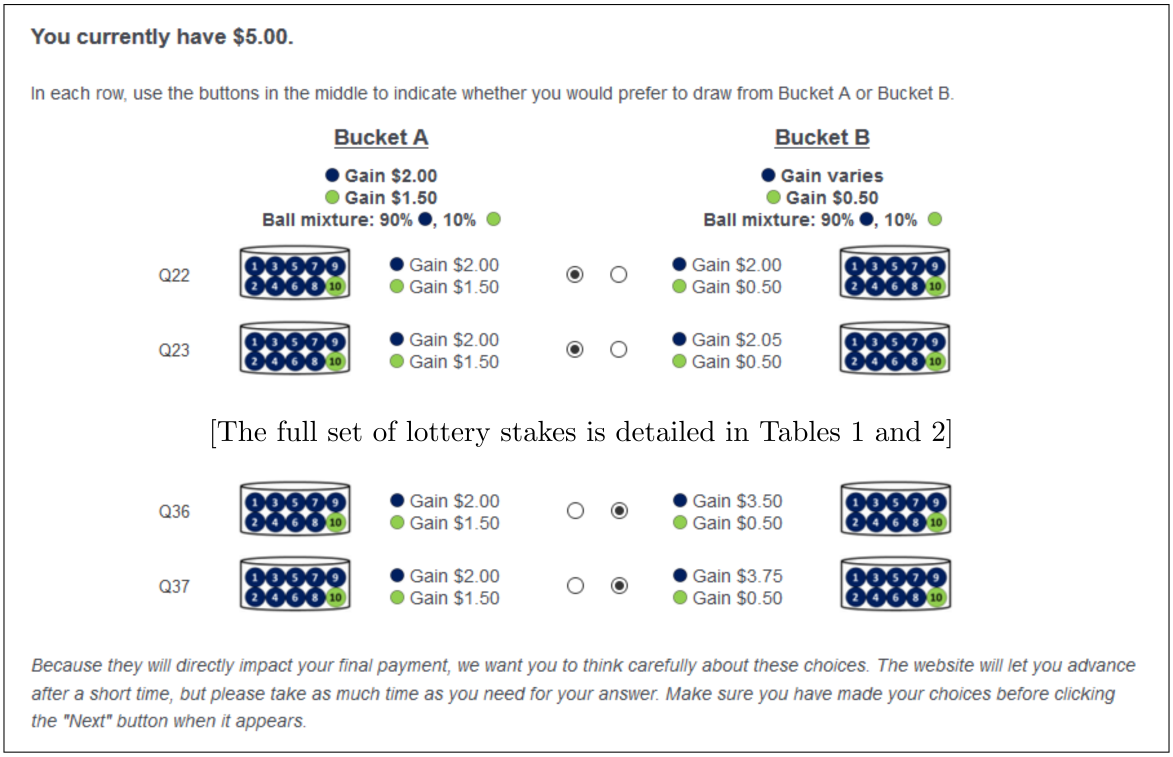
LA



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


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 $2.00 ● Gain $1.50 Ball mixture: 90% ●, 10% ●			● Gain varies ● Gain $0.50 Ball mixture: 90% ●, 10% ●
Q22	● Gain $2.00 ● Gain $1.50	◉	○	● Gain $2.00 ● Gain $0.50
Q23	● Gain $2.00 ● Gain $1.50	◉	○	● Gain $2.05 ● Gain $0.50

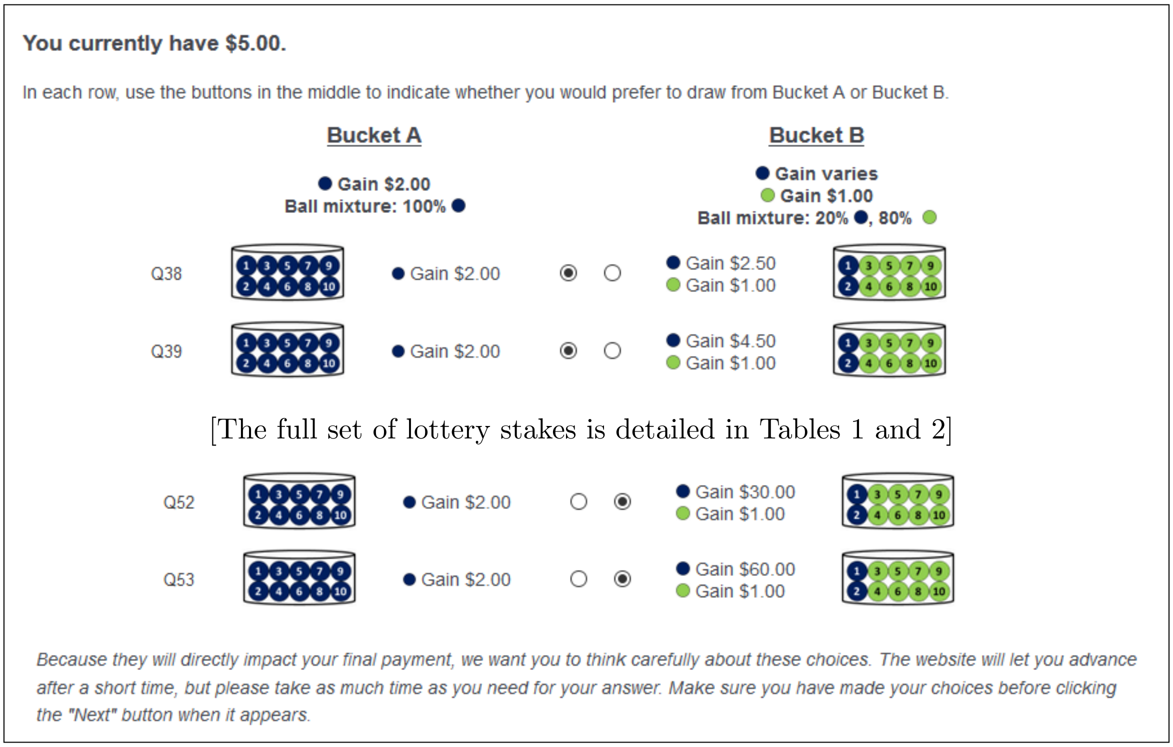
[The full set of lottery stakes is detailed in Tables 1 and 2]

	Bucket A			Bucket B
Q36	● Gain $2.00 ● Gain $1.50	○	◉	● Gain $3.50 ● Gain $0.50
Q37	● Gain $2.00 ● Gain $1.50	○	◉	● Gain $3.75 ● Gain $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.

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

CP


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 $2.00 Ball mixture: 100% ●			● Gain varies ● Gain $1.00 Ball mixture: 20% ●, 80% ●
Q38	● Gain $2.00	◉	○	● Gain $2.50 ● Gain $1.00
Q39	● Gain $2.00	◉	○	● Gain $4.50 ● Gain $1.00

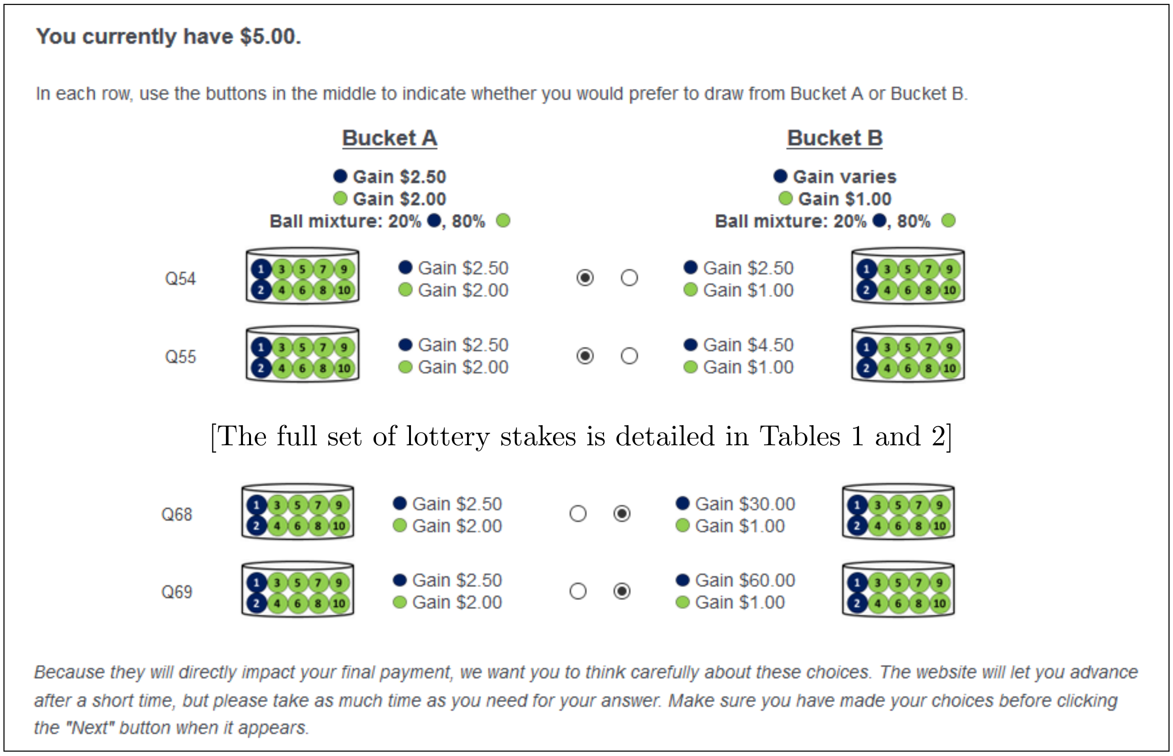
[The full set of lottery stakes is detailed in Tables 1 and 2]

	Bucket A			Bucket B
Q52	● Gain $2.00	○	◉	● Gain $30.00 ● Gain $1.00
Q53	● 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 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

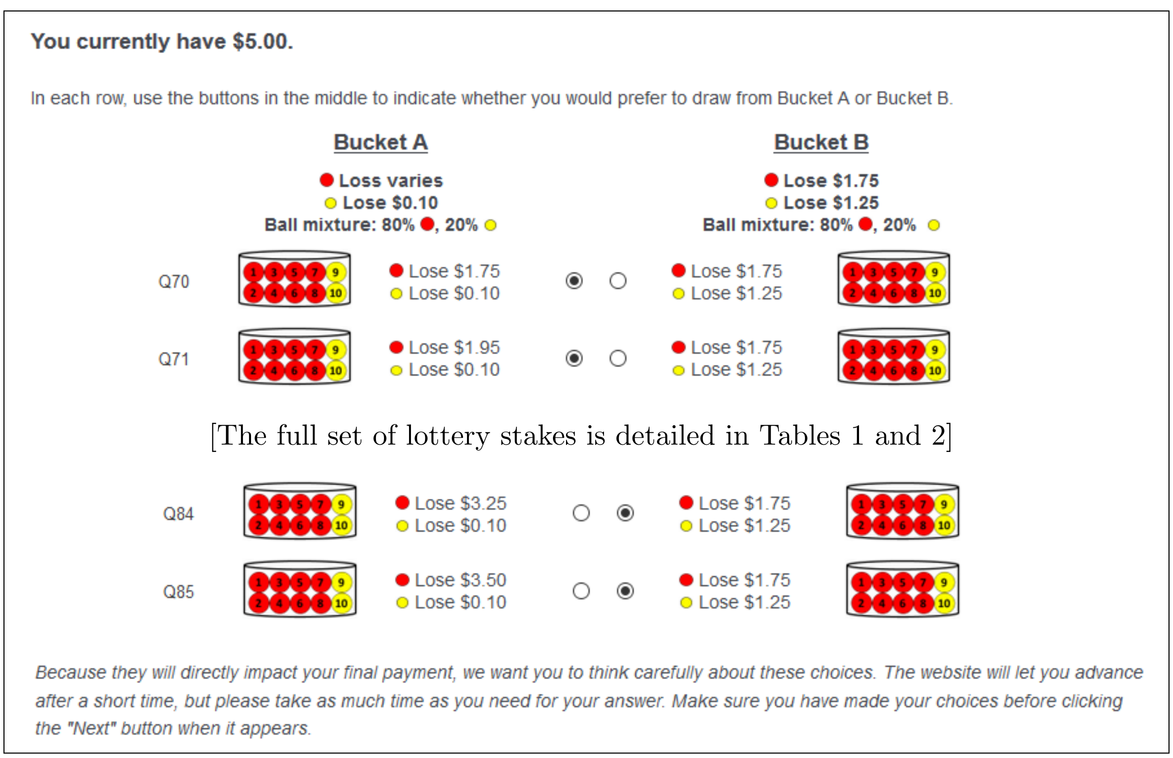
[The full set of lottery stakes is detailed in Tables 1 and 2]

	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

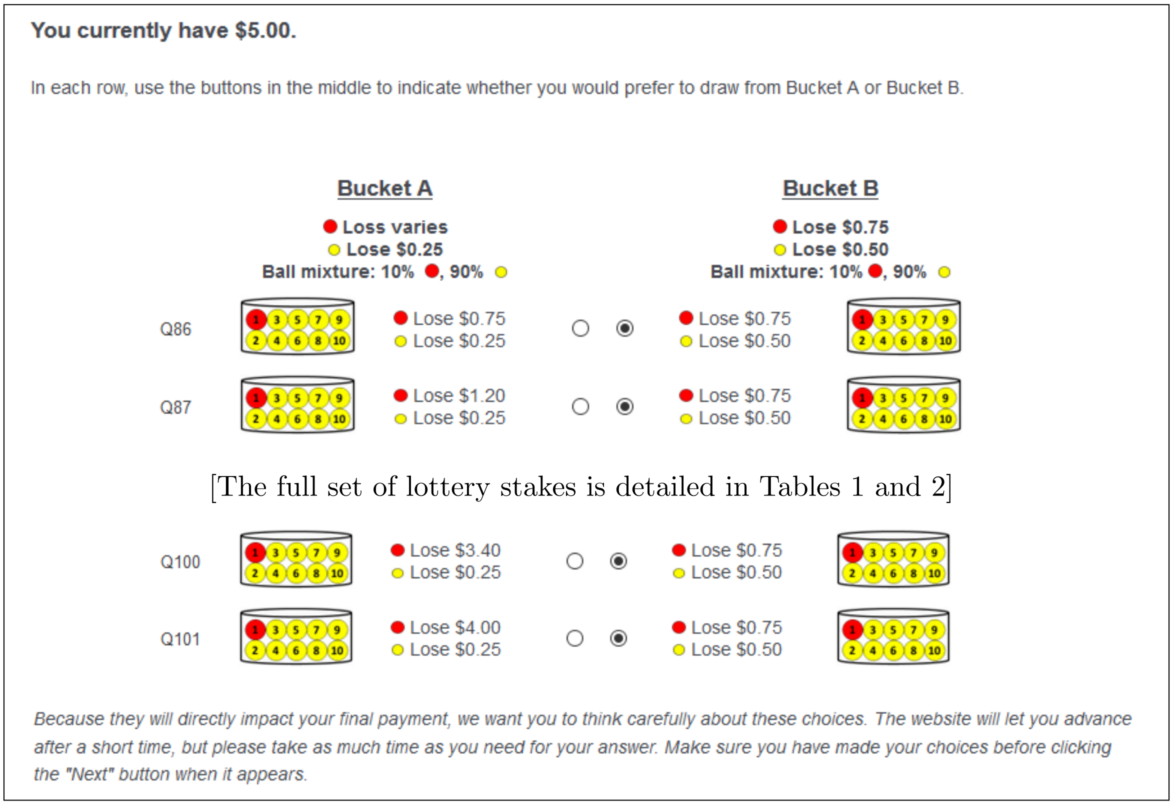
[The full set of lottery stakes is detailed in Tables 1 and 2]

	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.

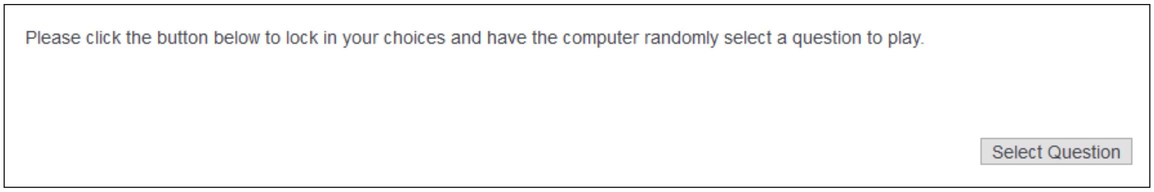
	Bucket A			Bucket B	
		● Loss varies ○ Lose $0.25 Ball mixture: 10% ●, 90% ○		● Lose $0.75 ○ Lose $0.50 Ball mixture: 10% ●, 90% ○	
Q86		● Lose $0.75 ○ Lose $0.25	○ ◉	● Lose $0.75 ○ Lose $0.50	
Q87		● Lose $1.20 ○ Lose $0.25	○ ◉	● Lose $0.75 ○ Lose $0.50	

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

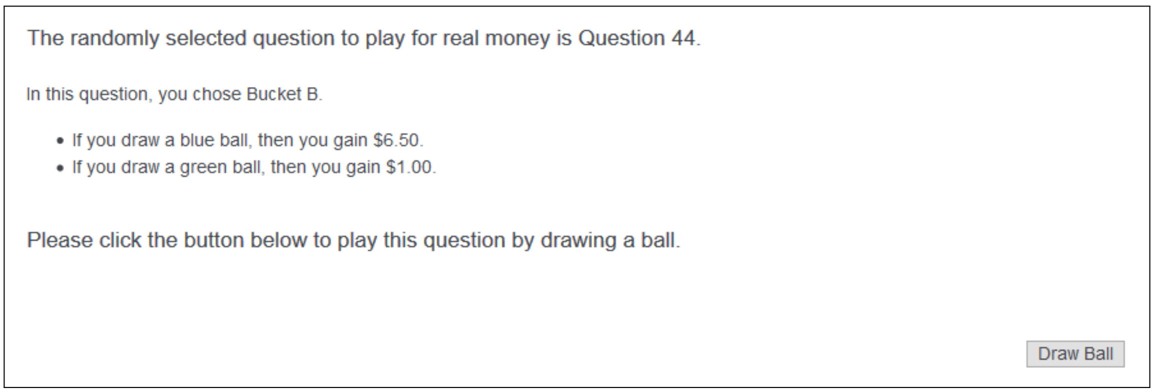
Q100		● Lose $3.40 ○ Lose $0.25	○ ◉	● Lose $0.75 ○ Lose $0.50	
Q101		● Lose $4.00 ○ Lose $0.25	○ ◉	● Lose $0.75 ○ Lose $0.50	

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.

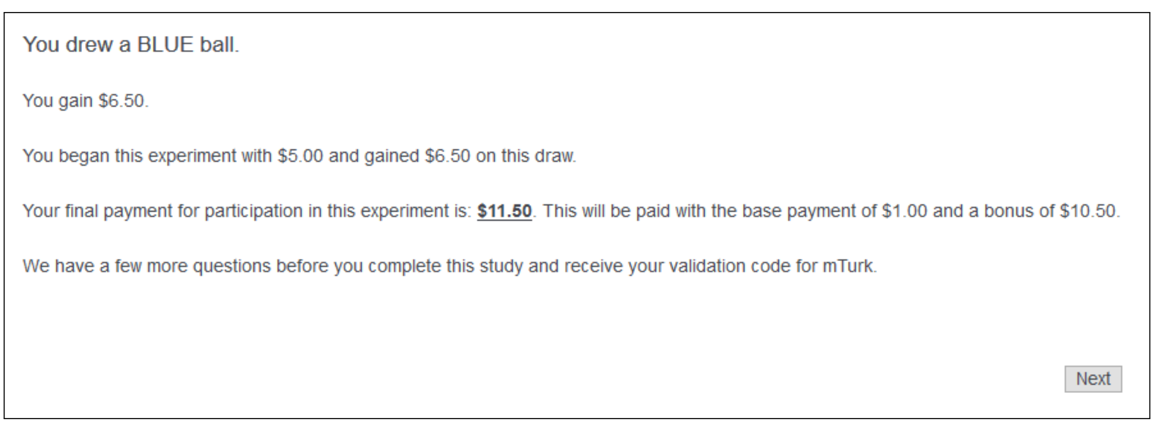
After all choices are made in the experiment, the computer randomly selects one decision to play out.



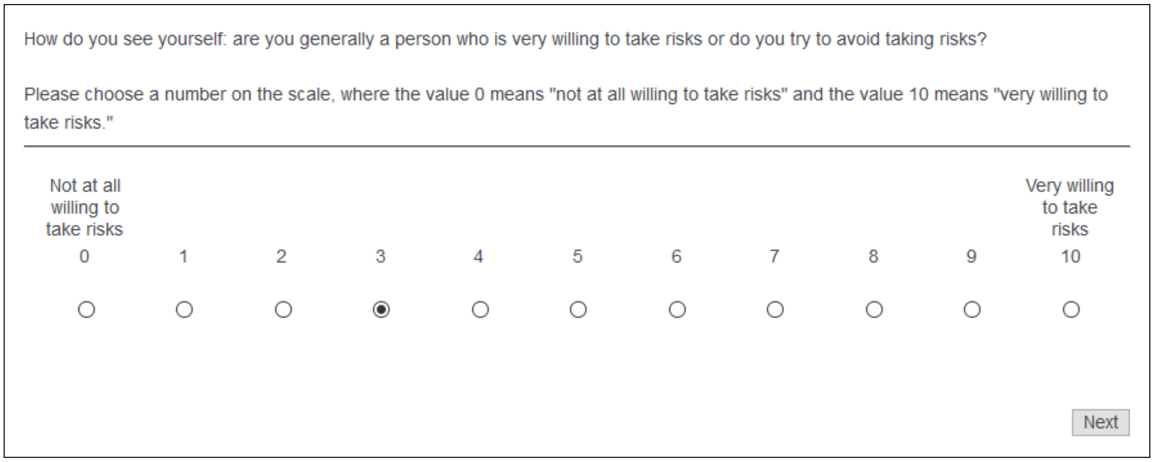
In this example, Question 44 is the randomly-selected decision. We confirm to the subject which selection he/she originally made and the possible outcomes. Then, they click the button to draw a "ball."



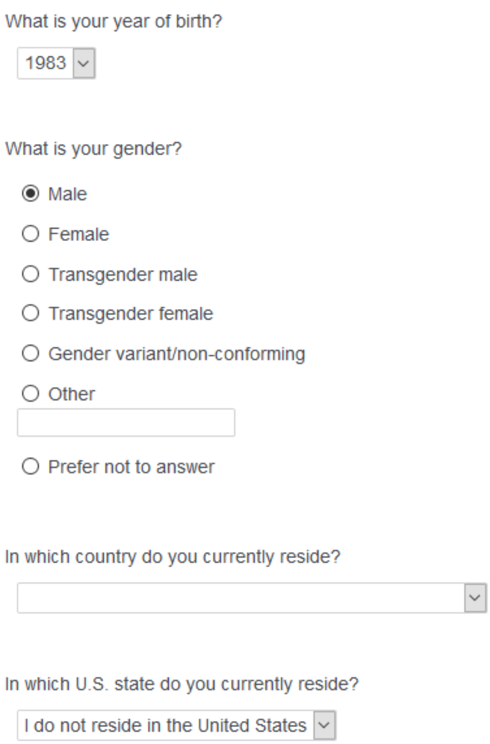
The computer then displays the outcome of the draw and outlines the subject's payment. Amazon mTurk requires variable payments to be paid as a "base" plus a "bonus." We were clear in the mTurk posting that our task involved variable payments paid as bonuses. This appears a common way to compensate subjects, 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.



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



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



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

The study concludes with a validation code to connect their experiment outcomes to their mTurk account.

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.