Distinguishing Common Ratio Preferences from Common Ratio Effects Using Paired Valuation Tasks

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Online Appendix

A Proofs

Proof of Proposition 1: By Assumption 1, a person with $m^*_{AB} = m^*_{CD} \equiv m^*$ chooses A over B when $M \geqslant \Gamma(m^*, \varepsilon_{AB})$, and chooses C over D when $M \geqslant \Gamma(m^*, \varepsilon_{CD})$. Define $\bar{\varepsilon}(M)$ such that $\Gamma(m^*, \bar{\varepsilon}(M)) = M$. Then $\Gamma(m, 0) = m$ for all m and Γ increasing in ε together imply $\bar{\varepsilon}(M) = 0$ when $M = m^*$ and $\bar{\varepsilon}$ is increasing in M. Finally, using $\bar{\varepsilon}(M)$ and the fact that $\varepsilon_{CD} \stackrel{d}{=} k\varepsilon_{AB}$, the choice probabilities as a function of M are $\Pr(A) = \Pr(\varepsilon_{AB} < \bar{\varepsilon}(M))$ and $\Pr(C) = \Pr(\varepsilon_{CD} < \bar{\varepsilon}(M)) = \Pr(\varepsilon_{AB} < \bar{\varepsilon}(M)/k)$.

(1) $M - m^* > 0$ implies $\bar{\varepsilon}(M) > 0$ and thus, given $\Pr(\varepsilon_{AB} < 0) = Z$, $\Pr(A) > Z$ and $\Pr(C) > Z$. Moreover, $k > 1$ implies $\bar{\varepsilon}(M)/k < \bar{\varepsilon}(M)$ and thus $\Pr(A) > \Pr(C)$; $k < 1$ implies $\bar{\varepsilon}(M)/k > \bar{\varepsilon}(M)$ and thus $\Pr(A) < \Pr(C)$; and $k = 1$ implies $\bar{\varepsilon}(M)/k = \bar{\varepsilon}(M)$ and thus $\Pr(A) = \Pr(C)$.

(2) $M - m^* < 0$ implies $\bar{\varepsilon}(M) < 0$ and thus, given $\Pr(\varepsilon_{AB} < 0) = Z$, $\Pr(A) < Z$ and $\Pr(C) < Z$. Moreover, $k > 1$ implies $\bar{\varepsilon}(M)/k > \bar{\varepsilon}(M)$ and thus $\Pr(A) < \Pr(C)$; $k < 1$ implies $\bar{\varepsilon}(M)/k < \bar{\varepsilon}(M)$ and thus $\Pr(A) > \Pr(C)$; and $k = 1$ implies $\bar{\varepsilon}(M)/k = \bar{\varepsilon}(M)$ and thus $\Pr(A) = \Pr(C)$.

(3) $M - m^* = 0$ implies $\bar{\varepsilon}(M) = \bar{\varepsilon}(M)/k = 0$ for all $k > 0$, and thus $\Pr(A) = \Pr(C) = Z$ for all $k > 0$.

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Proof of Proposition 2: Proof of part (1): Because $m_{AB} = \Gamma(m^*_{AB}, \varepsilon_{AB}) = m^*_{AB} + \varepsilon_{AB}$, we have $E(m_{AB}) = m^*_{AB} + E(\varepsilon_{AB})$. Analogously, $E(m_{CD}) = m^*_{CD} + E(\varepsilon_{CD})$. Then $E(\varepsilon_{AB}) = E(\varepsilon_{CD})$ implies $E(\Delta m) = E(m_{CD} - m_{AB}) = m^*_{CD} - m^*_{AB} = \Delta m^*$.

Proof of part (2): By assumption, the joint distribution of $(\varepsilon_{AB}, \varepsilon_{CD})$ has continuous PDF f that satisfies $f(\varepsilon' + z_{AB}, \varepsilon' + z_{CD}) = f(\varepsilon' - z_{AB}, \varepsilon' - z_{CD})$ for all (z_{AB}, z_{CD}). Define $\nu_{AB} \equiv \varepsilon_{AB} - \varepsilon'$ and $\nu_{CD} \equiv \varepsilon_{CD} - \varepsilon'$. Then the joint distribution of (ν_{AB}, ν_{CD}) has continuous PDF g that satisfies $g(\nu_{AB}, \nu_{CD}) = g(-\nu_{AB}, -\nu_{CD})$ for all (ν_{AB}, ν_{CD}). The marginal distribution for ν_{CD}

is $g_{\nu_{CD}}(\nu_{CD}) \equiv \int_{\nu_{AB}=-\infty}^{\infty} g(\nu_{AB}, \nu_{CD}) d\nu_{AB}$, and symmetry around zero implies $\int_{\nu_{CD}=-\infty}^{0} g_{\nu_{CD}}(\nu_{CD}) d\nu_{CD} = \int_{\nu_{CD}=0}^{\infty} g_{\nu_{CD}}(\nu_{CD}) d\nu_{CD} = 1/2$.

If $m_{AB}^* = m_{CD}^* \equiv m^*$, then $m_{AB} = \Gamma(m^*, \varepsilon_{AB})$ and $m_{CD} = \Gamma(m^*, \varepsilon_{CD})$, and thus, given that Γ is increasing in its second argument, $m_{CD} > m_{AB}$ if and only if $\varepsilon_{CD} > \varepsilon_{AB}$, which is equivalent to $\nu_{CD} > \nu_{AB}$. Hence:

$$\begin{aligned}
\Pr(\Delta m > 0) &= \Pr(\nu_{CD} > \nu_{AB}) = \int_{\nu_{CD}=-\infty}^{\infty} \left(\int_{\nu_{AB}=-\infty}^{\nu_{CD}} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} \right) d\nu_{CD} \\
&= \int_{\nu_{CD}=-\infty}^{0} \left(\int_{\nu_{AB}=-\infty}^{\nu_{CD}} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} \right) d\nu_{CD} \\
&\quad + \int_{\nu_{CD}=0}^{\infty} \left(\int_{\nu_{AB}=-\infty}^{\nu_{CD}} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} \right) d\nu_{CD}.
\end{aligned}$$

Note that $\int_{\nu_{AB}=-\infty}^{\nu_{CD}} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} = g_{\nu_{CD}}(\nu_{CD}) - \int_{\nu_{AB}=\nu_{CD}}^{\infty} g(\nu_{AB}, \nu_{CD}) d\nu_{AB}$ (since $\int_{\nu_{AB}=-\infty}^{\infty} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} = g_{\nu_{CD}}(\nu_{CD})$), and note that

$$\int_{\nu_{AB}=\nu_{CD}}^{\infty} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} = \int_{\nu_{AB}=-\infty}^{-\nu_{CD}} g(-\nu_{AB}, \nu_{CD}) d\nu_{AB} = \int_{\nu_{AB}=-\infty}^{-\nu_{CD}} g(\nu_{AB}, -\nu_{CD}) d\nu_{AB}$$

(the first equality uses a simple change in variables replacing ν_{AB} with $-\nu_{AB}$, and the second follows from symmetry about zero). Hence,

$$\begin{aligned}
& \int_{\nu_{CD}=-\infty}^{0} \left(\int_{\nu_{AB}=-\infty}^{\nu_{CD}} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} \right) d\nu_{CD} \\
= & \int_{\nu_{CD}=-\infty}^{0} \left(g_{\nu_{CD}}(\nu_{CD}) - \int_{\nu_{AB}=\nu_{CD}}^{\infty} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} \right) d\nu_{CD} \\
= & \frac{1}{2} - \int_{\nu_{CD}=-\infty}^{0} \left(\int_{\nu_{AB}=-\infty}^{-\nu_{CD}} g(\nu_{AB}, -\nu_{CD}) d\nu_{AB} \right) d\nu_{CD} \\
= & \frac{1}{2} - \int_{\nu_{CD}=0}^{\infty} \left(\int_{\nu_{AB}=-\infty}^{\nu_{CD}} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} \right) d\nu_{CD}
\end{aligned}$$

(the first equality merely substitutes from above, the second equality uses another substitution plus the fact that symmetry around zero implies $\int_{\nu_{CD}=-\infty}^{0} g_{\nu_{CD}}(\nu_{CD}) d\nu_{CD} = 1/2$, and the third equality uses a simple change in variables replacing ν_{CD} with $-\nu_{CD}$). Combining terms yields

$$\begin{aligned}
\Pr(\Delta m > 0) &= \frac{1}{2} - \int_{\nu_{CD}=0}^{\infty} \left(\int_{\nu_{AB}=-\infty}^{\nu_{CD}} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} \right) d\nu_{CD} \\
&\quad + \int_{\nu_{CD}=0}^{\infty} \left(\int_{\nu_{AB}=-\infty}^{\nu_{CD}} g(\nu_{AB}, \nu_{CD}) d\nu_{AB} \right) d\nu_{CD} = \frac{1}{2}.
\end{aligned}$$

An analogous argument can be used to prove that $\Pr(\Delta m < 0) = \Pr(\nu_{CD} < \nu_{AB}) = 1/2$.

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B Additional Analysis

B.1 Predictions for $E(\Delta m)$ when Γ is Non-Linear

In Section I.C, we discuss the possibility of testing the null of $\Delta m^* = 0$ by testing whether the mean of Δm is zero. This test is valid under Assumption 2a where the function Γ is linear in both m and ε, because then $E(\Delta m) = \Delta m^*$. In contrast, if Γ is nonlinear, then it need not be the case that $E(\Delta m) = \Delta m^*$, and thus a test based on the mean of Δm is potentially biased.

To further explore this point, consider the EU model with additive utility noise. Under EU, $m^*_{AB} = m^*_{CD} \equiv m^*$ and therefore $\Delta m^* = 0$. From Example 1, $m_{AB} = u^{-1}\left(u(m^*) + \epsilon_{AB}\right)$ and $m_{CD} = u^{-1}\left(u(m^*) + \epsilon_{CD}/r\right)$, and thus $\Gamma(m, \varepsilon) = u^{-1}(u(m) + \varepsilon)$, $\varepsilon_{AB} = \epsilon_{AB}$, and $\varepsilon_{CD} = \epsilon_{CD}/r$. Suppose further that $E(\epsilon_{AB}) = 0$ and $\epsilon_{CD} \overset{d}{=} k'\epsilon_{AB}$ for some $k' > 0$, and thus $\varepsilon_{CD} \overset{d}{=} k\epsilon_{AB}$ where $k = k'/r$. Then $E(\Delta m)$ depends on k and the curvature of the utility function u as follows:

(1) If $u(x)$ is linear, then $E(m_{AB}) = E(m_{CD}) = m^*$, and thus $E(\Delta m) = 0$.
(2) If $u(x)$ is strictly concave, then $E(m_{AB}) > m^*$ and $E(m_{CD}) > m^*$, and moreover $k = 1$ implies $E(\Delta m) = 0$, $k > 1$ implies $E(\Delta m) > 0$, and $k < 1$ implies $E(\Delta m) < 0$.
(3) If $u(x)$ is strictly convex, then $E(m_{AB}) < m^*$ and $E(m_{CD}) < m^*$, and moreover $k = 1$ implies $E(\Delta m) = 0$, $k > 1$ implies $E(\Delta m) < 0$, and $k < 1$ implies $E(\Delta m) > 0$.

Proof: Given a m^*, define a function $m(\varepsilon) = u^{-1}(u(m^*) + \varepsilon)$, and note $m(0) = m^*$. Then $m_{AB} = m(\varepsilon_{AB})$ and $m_{CD} = m(\varepsilon_{CD})$.

Proof of part (1): If $u(x)$ is linear—that is, $u(x) = \alpha x + \beta$ for some $\alpha > 0$ and any β—then $m(\varepsilon) = m^* + \varepsilon/\alpha$. The results then follow from the same logic as the proof of Proposition 2(1).

Proof of part (2): If $u(x)$ is strictly concave, then $u^{-1}(x)$ is strictly convex and therefore $m(\varepsilon)$ is also strictly convex. By Jensen's inequality, $E_{\varepsilon_{AB}}\left[m(\varepsilon_{AB})\right] > m(E_{\varepsilon_{AB}}\left[\varepsilon_{AB}\right]) = m^*$ and $E_{\varepsilon_{CD}}\left[m(\varepsilon_{CD})\right] > m(E_{\varepsilon_{CD}}\left[\varepsilon_{CD}\right]) = m^*$. If $k = 1$ then $\varepsilon_{CD} \overset{d}{=} \varepsilon_{AB}$, and thus $E_{\varepsilon_{CD}}\left[m(\varepsilon_{CD})\right] = E_{\varepsilon_{AB}}\left[m(\varepsilon_{AB})\right]$. It follows that $E\left[\Delta m\right] = 0$. If instead $k > 1$, then ε_{CD} is a mean-preserving spread of ε_{AB}, and thus, since $m(\varepsilon)$ is convex, $E_{\varepsilon_{CD}}\left[m(\varepsilon_{CD})\right] > E_{\varepsilon_{AB}}\left[m(\varepsilon_{AB})\right]$. It follows that $E\left[\Delta m\right] > 0$. An analogous logic can be used to show that $k < 1$ implies $E\left[\Delta m\right] < 0$.

Proof of part (3): Analogous to the proof of part (2), and so omitted.

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Finally, for the case frequently discussed in the literature of EU with i.i.d. additive utility noise, we have $k' = 1$ and thus $k = 1/r > 1$. Hence, the typical assumption of concave utility would imply $E(\Delta m) > 0$, and thus a test based on the mean of Δm is biased towards rejecting the null of $\Delta m^* = 0$ in favor of a CRP.

B.2 Predictions for Figure 2

We derive predictions for Figure 2 assuming that every individual i has $m^*_{AB,i} = m^*_{CD,i} = m^*_i$ and thus $\Delta m^*_i = 0$. We assume that everyone satisfies Assumption 2a and thus has $m_{AB,i} = m^*_i + \varepsilon_{AB,i}$ and $m_{CD,i} = m^*_i + \varepsilon_{CD,i}$, where $E(\varepsilon_{AB,i}) = E(\varepsilon_{CD,i}) = 0$. We further assume that everyone has median-zero noise, so $\Pr(\varepsilon_{AB,i} < 0) = \Pr(\varepsilon_{CD,i} < 0) = 1/2$. However, we permit heterogeneity in m^*_i and in the distributions of $\varepsilon_{AB,i}$ and $\varepsilon_{CD,i}$.[1]

B.2.1 Predictions for Paired Choice Tasks (Panel A)

For a specific paired choice task, observed behaviors in a population are the observed proportions choosing A over B and C over D, which we denote by $\widehat{\Pr}(A)$ and $\widehat{\Pr}(C)$, respectively. Hence, we need predictions for $\Pr(A)$ and $\Pr(C)$.

Starting at the individual level, a person with $m^*_i < M$ has noise-free preferences that favor A and C, and thus, given the assumption of median-zero noise, must have $1 \geqslant \Pr(A) \geqslant 1/2$ and $1 \geqslant \Pr(C) \geqslant 1/2$. But given the flexibility to choose different distributions for $\varepsilon_{AB,i}$ and $\varepsilon_{CD,i}$, there are no further restrictions on $\Pr(A)$ and $\Pr(C)$. Analogously, a person with $m^*_i > M$ must have $1 \geqslant \Pr(B) \geqslant 1/2$ and $1 \geqslant \Pr(D) \geqslant 1/2$, but there are no further restrictions.

At the population level, then, we can parse the population into those who prefer A and C (AC types) and those who prefer B and D (BD types), and characterize the population by five parameters:

$$\begin{aligned}
q &= \text{the proportion of the population who are } AC \text{ types.}\\
\lambda_A &= \text{the proportion of } AC \text{ types who actually choose } A \text{ over } B.\\
\lambda_C &= \text{the proportion of } AC \text{ types who actually choose } C \text{ over } D.\\
\lambda_B &= \text{the proportion of } BD \text{ types who actually choose } B \text{ over } A.\\
\lambda_D &= \text{the proportion of } BD \text{ types who actually choose } D \text{ over } C.
\end{aligned}$$

As a function of these five parameters, the population's $(\Pr(A), \Pr(C))$ will be

$$\begin{aligned}
\Pr(A) &= q\lambda_A + (1-q)(1-\lambda_B)\\
\Pr(C) &= q\lambda_C + (1-q)(1-\lambda_D).
\end{aligned}$$

The only constraints on these parameters are that $q \in [0,1]$ and that each $\lambda_A, \lambda_C, \lambda_B, \lambda_D \in [1/2, 1]$. One can then show (see proof below) that the set of possible predictions for the population include any $(\Pr(A), \Pr(C))$ combinations that satisfy

$$\Pr(A) \leqslant \frac{1}{2} \text{ and } 0 \leqslant \Pr(C) \leqslant \Pr(A) + \frac{1}{2} \text{ or}$$

[1] The assumptions of mean-zero and median-zero noise serve to limit the set of possible outcomes; if we were to relax these assumptions, even more outcomes would be possible even under the null of everyone having $\Delta m^*_i = 0$.

$$\Pr(A) \geqslant \frac{1}{2} \text{ and } \Pr(A) - \frac{1}{2} \leqslant \Pr(C) \leqslant 1.$$

These combinations are depicted by the gray shaded region in panel A of Figure 2. To provide some intuition, consider one possible extreme point where $\Pr(A) = 75\%$ and $\Pr(C) = 25\%$. This outcome occurs when the population is equally split between AC types and BD types (i.e., $q = 1/2$), where the AC types make no errors in the AB choice but respond randomly in the CD choice (i.e., $\lambda_A = 1$ while $\lambda_C = 1/2$), while the BD types make no errors in the CD choice but respond randomly in the AB choice (i.e., $\lambda_B = 1/2$ while $\lambda_D = 1$).

This example illustrates how the full gray shaded region takes advantage of being able to have AC types be more impacted by noise on one type of choice (above, on the CD choice) while BD types are more impacted by noise on the other type of choice (above, on the AB choice). However, significant deviations from the 45-degree line are still possible even if we impose that both types must be more impacted by noise in the same choice. For instance, suppose we impose—consistent with the logic of EU with i.i.d. additive utility noise—that both types must be more impacted by noise in the CD choice. This restriction creates additional constraints that $\lambda_A \geqslant \lambda_C$ and $\lambda_B \geqslant \lambda_D$. Even with this additional constraint, one can still show that the set of possible predictions for the population include any $(\Pr(A), \Pr(C))$ combinations that satisfy[2]

$$\frac{\Pr(A)}{2} \leqslant \Pr(C) \leqslant \frac{1}{2} + \frac{\Pr(A)}{2}$$

Hence, significant deviations from the 45-degree line are still possible. For instance, one possibility is $\Pr(A) = 2/3$ and $\Pr(C) = 1/3$. This outcome occurs when the population has 2/3 AC types and 1/3 BD types (i.e., $q = 2/3$), where the AC types make no errors in the AB choice but respond randomly in the CD choice (i.e., $\lambda_A = 1$ while $\lambda_C = 1/2$), while the BD types make no errors in either choice (i.e., $\lambda_B = \lambda_C = 1$).

Proof of conditions for gray area in Figure 2 panel A: For any fixed $\Pr(A) = \omega$, we find the parameters $(q, \lambda_A, \lambda_C, \lambda_B, \lambda_D)$ that minimize $\Pr(C)$ and those that maximize $\Pr(C)$. The constraints are $q \in [0, 1]$ and $\lambda_A, \lambda_C, \lambda_B, \lambda_D \in [1/2, 1]$.

To minimize $\Pr(C)$: First note that, for $\omega \leqslant 1/2$, setting $q = 0$, $\lambda_B = 1 - \omega$, and $\lambda_D = 1$ implies $\Pr(A) = \omega$ and $\Pr(C) = 0$, so the minimum $\Pr(C) = 0$. For $\omega \geqslant 1/2$, we clearly want λ_C to be as small as possible and λ_D to be as large as possible, and thus we set $\lambda_C = 1/2$ and $\lambda_D = 1$. Then $\Pr(C) = q/2$, so we choose λ_A and λ_B to minimize q. Because $\Pr(A) = \omega$ implies $q = (\omega - (1 - \lambda_B))/(\lambda_A - (1 - \lambda_B))$, we minimize q by setting $\lambda_A = 1$ and $\lambda_B = 1/2$. Hence, the parameters that minimize $\Pr(C)$ are $q = 2\omega - 1$, $\lambda_A = \lambda_D = 1$, and $\lambda_B = \lambda_C = 1/2$, which imply the minimum $\Pr(C) = (2\omega - 1)/2 = \omega - 1/2$.

To maximize $\Pr(C)$: First note that, for $\omega \geqslant 1/2$, setting $q = 1$, $\lambda_A = \omega$, and $\lambda_C = 1$ implies

[2] We omit the proof of this condition since we do not use it in the main text, but the approach is similar to the proof of the prior condition.

$\Pr(A) = \omega$ and $\Pr(C) = 1$, so the maximum $\Pr(C) = 1$. For $\omega \leqslant 1/2$, we clearly want λ_C to be as large as possible and λ_D to be as small as possible, and thus we set $\lambda_C = 1$ and $\lambda_D = 1/2$. Then $\Pr(C) = q + (1-q)/2$, so we choose λ_A and λ_B to maximize q. Because $\Pr(A) = \omega$ implies $q = (\omega - (1-\lambda_B))/(\lambda_A - (1-\lambda_B))$, we maximize q by setting $\lambda_A = 1/2$ and $\lambda_B = 1$. Hence, the parameters that maximize $\Pr(C)$ are $q = 2\omega$, $\lambda_A = \lambda_D = 1/2$, and $\lambda_B = \lambda_C = 1$, which imply the maximum $\Pr(C) = 2\omega + (1-2\omega)/2 = \omega + 1/2$.

It follows that (i) for any fixed $\Pr(A) \leqslant 1/2$, we must have $0 \leqslant \Pr(C) \leqslant \Pr(A) + 1/2$, and (ii) for any fixed $\Pr(A) \geqslant 1/2$, we must have $\Pr(A) - 1/2 \leqslant \Pr(C) \leqslant 1$.

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B.2.2 Predictions for Paired Valuation Tasks (Panel B)

For a specific paired valuation task, observed behaviors in a population are the population averages for the two reported valuations, which we denote by $\widehat{E}(m_{AB})$ and $\widehat{E}(m_{CD})$, respectively. Hence, we need predictions for $E(m_{AB})$ and $E(m_{CD})$.

Under Assumption 2a, individual i states valuations $m_{AB,i} = m_i^* + \varepsilon_{AB,i}$ and $m_{CD,i} = m_i^* + \varepsilon_{CD,i}$, where $E(\varepsilon_{AB,i}) = E(\varepsilon_{CD,i}) = 0$. It follows immediately that, if we let $\bar{m}^*$ denote the population average for m_i^*, then the predicted population averages for the two reported valuations are $E(m_{AB}) = \bar{m}^*$ and $E(m_{CD}) = \bar{m}^*$. Hence, the set of possible predictions for the population include any $(E(m_{AB}), E(m_{CD}))$ such that $E(m_{AB}) = E(m_{CD})$, which is equivalent to the 45-degree line in panel B of Figure 2.

B.3 Data for Figure 2

B.3.1 Data for Panel A of Figure 2

For the data in panel A, we rely on the meta-study by (Blavatskyy et al., 2023). In their Table 1, they provide information on 143 CRE paired-choice experiments taken from 39 studies. Specifically, for each experiment, they provide the total number of participants (N) along with the number of participants that chose each of the four possible choice patterns (N_{AC}, N_{BD}, N_{AD}, and N_{BC}). We use this data to construct the empirical choice ratios as

$$\widehat{\Pr}(A) = \frac{N_{AC} + N_{AD}}{N} \qquad \text{and} \qquad \widehat{\Pr}(C) = \frac{N_{AC} + N_{BC}}{N}.$$

We then depict each of these 143 experiments as one circle in panel A, where the location of the circle is given by its $(\widehat{\Pr}(A), \widehat{\Pr}(C))$ and the size of the circle is proportional to its N.

B.3.2 Data for Panel B of Figure 2

For panel B, we are not aware of any analogous meta-study, and Blavatskyy et al. (2023) do not mention any CRE experiments that use valuations. We therefore conducted our own search. We identified only six studies that use valuations in the context of the CRE:

(1) Freeman et al. (2019) use a modified form of valuations in the context of the CRE. Specifically, they elicit probability equivalents in which they hold fixed outcomes H and M and vary the probability p. Thus, the valuations they elicit do not fit into the framework that we depict in panel B.

(2) Schneider and Shor (2017) elicit (hypothetical) minimum prices at which participants would be willing to sell binary lotteries A, B, C, and D using the Kahneman-Tversky parameters $(M = \$3000, H = \$4000, p = 0.8, r = .25)$. While this pricing task is a type of valuation, it does not generate data that fit into the framework that we depict in panel B.

(3) Dean and Ortoleva (2019) conduct two paired h-valuations, using $(M = \$4, p = 0.8, r = 0.25)$ and $(M = \$8, p = 0.8, r = 0.25)$. The paper does not report statistics that would permit us to calculate the average valuations. However, we contacted the authors and they provided the average valuations: For the first pair, $\widehat{E}(h_{AB}) = \$5.80$ and $\widehat{E}(h_{CD}) = \$5.27$; for the second pair, $\widehat{E}(h_{AB}) = \$10.66$ and $\widehat{E}(h_{CD}) = \$9.97$. Because these are h-valuations while panel B depicts m-valuations, for presentation purposes we transform these values by setting $\widehat{E}(m_{AB}) = M$ and $\widehat{E}(m_{CD}) = M(\widehat{E}(h_{AB})/\widehat{E}(h_{CD}))$. Hence, these two experiments appear in panel B at the locations $(\widehat{E}(m_{AB}) = \$4, \widehat{E}(m_{CD}) = \$4.40)$ and $(\widehat{E}(m_{AB}) = \$8, \widehat{E}(m_{CD}) = \$8.55)$.

(4) Castillo and Eil (2014) conduct three m-valuations, an AB valuation for $(H = \$10, p = 0.4)$ and CD valuations for $(H = \$10, p = 0.4, r = 0.5)$ and $(H = \$10, p = 0.4, r = 0.25)$. We treat these as two paired m-valuation experiments, one for $(H = \$10, p = 0.4, r = 0.5)$ and one for $(H = \$10, p = 0.4, r = 0.25)$ (these are not independent experiments because they use the same AB valuation, but this is not important for our illustrative purposes). The paper does not report any statistics, but the authors provided the average valuations: In panel B, the first experiment appears at $(\widehat{E}(m_{AB}) = \$3.95, \widehat{E}(m_{CD}) = \$3.98)$, and the second experiment appears at $(\widehat{E}(m_{AB}) = \$3.95, \widehat{E}(m_{CD}) = \$4.41)$.

They also conduct three h-valuations, an AB valuation for $(M = \$4, p = 0.4)$ and CD valuations for $(M = \$4, p = 0.4, r = 0.5)$ and $(M = \$4, p = 0.4, r = 0.25)$. We treat these as two paired h-valuation experiments. The average valuations provided by the authors for the three valuations are \$9.77, \$9.95, and \$10.22. Using the same transformation as we do for the paired h-valuations in Dean and Ortoleva (2019), these two experiments appear in panel B at the locations $(\widehat{E}(m_{AB}) = \$4, \widehat{E}(m_{CD}) = \$3.93)$ and $(\widehat{E}(m_{AB}) = \$4, \widehat{E}(m_{CD}) = \$3.82)$.

(5) Chapman et al. (2022) conduct two paired h-valuations, using ($M = \$2.50, p = 0.8, r = 0.25$) and ($M = \$4, p = 0.75, r = 0.2$). The paper does not report any statistics that would permit us to calculate the four average valuations. We contacted the authors but thus far they have not provided us with any additional information.

(6) Agranov and Ortoleva (forthcoming) conduct two paired h-valuations, using ($M = \$14, p = 0.8, r = 0.25$) and ($M = \$16, p = 0.8, r = 0.25$). Because the authors use these valuations primarily as control variables while studying something else, the paper does not report any statistics for these valuations. We contacted the authors but thus far they have not provided us with any additional information.

B.4 Development for h-Tasks

In Section I.C, we fix (H, p, r) and focus on behavior as a function of M, which links directly to our m-tasks. Here, we revisit some of the analysis from Section I.C when we instead fix (M, p, r) and focus on behavior as a function of H, which links directly to our h-tasks. Note that, while we use some of the same notation below as we use in Section I.C, we are now referring to different (though analogous) objects.

Assuming underlying preferences are monotonic and continuous, for each (M, p, r) a person will have an underlying pair of indifference points (h^*_{AB}, h^*_{CD}) such that their underlying (noise-free) preferences satisfy:

- Prefer $A \equiv (M, 1)$ over $B \equiv (H, p)$ if and only if $H \leqslant h^*_{AB}$, and
- Prefer $C \equiv (M, r)$ over $D \equiv (H, rp)$ if and only if $H \leqslant h^*_{CD}$.

Here, EU implies $h^*_{AB} = h^*_{CD}$, whereas a CRP would mean $h^*_{AB} > h^*_{CD}$ (an individual would prefer combination AD for any $H \in (h^*_{CD}, h^*_{AB})$), and an RCRP would mean $h^*_{AB} < h^*_{CD}$. To parallel the development in the main text, where $\Delta m^* > 0$ reflects a CRP, we define $\Delta h^* = h^*_{AB} - h^*_{CD}$ so that $\Delta h^* > 0$ reflects a CRP while $\Delta h^* < 0$ reflects an RCRP.

Given these underlying preferences, Assumption 1h is the analogue for Assumption 1:

Assumption 1h: Impact of Noise on Choices and Valuations

A person's *realized indifference points* (h_{AB}, h_{CD}) are $h_{AB} \equiv \Gamma(h^*_{AB}, \varepsilon_{AB})$ and $h_{CD} \equiv \Gamma(h^*_{CD}, \varepsilon_{CD})$, where $(\varepsilon_{AB}, \varepsilon_{CD})$ are noise draws from a continuous joint distribution with convex support, and where Γ is increasing in both arguments and has $\Gamma(h, 0) = h$ for all h. Then:

- In an AB choice task, the person chooses $A \equiv (M, 1)$ over $B \equiv (H, p)$ if and only if $H \leqslant h_{AB} \equiv \Gamma(h^*_{AB}, \varepsilon_{AB})$,

- In a CD choice task, the person chooses $C \equiv (M, r)$ over $D \equiv (H, rp)$ if and only if $H \leqslant h_{CD} \equiv \Gamma(h^*_{CD}, \varepsilon_{CD})$,
- In an AB valuation task, the person states valuation $h_{AB} \equiv \Gamma(h^*_{AB}, \varepsilon_{AB})$, and
- In a CD valuation task, the person states valuation $h_{CD} \equiv \Gamma(h^*_{CD}, \varepsilon_{CD})$.

Assumptions 2ah and 2bh are the analogues for Assumptions 2a and 2b:

Assumption 2ah: $\Gamma(h, \varepsilon) = h + \varepsilon$, $\varepsilon_{CD} \overset{d}{=} k\varepsilon_{AB}$ for some $k > 0$, and $E(\varepsilon_{AB}) = E(\varepsilon_{CD}) = 0$.

Assumption 2bh: $\Gamma(h, \varepsilon)$ is potentially nonlinear in h and ε, but $\varepsilon_{CD} \overset{d}{=} k\varepsilon_{AB}$ for some $k > 0$, and ε_{AB} is symmetric about 0.

In EU and PT, Assumptions 2ah and 2bh apply under the same assumptions as Assumptions 2a and 2b:

Example 1h: Expected Utility and Prospect Theory

If a person evaluates a lottery (x, q) with $x > 0$ as $\pi(q)u(x)$, the underlying indifference points satisfy

$$\begin{aligned} u(M) = \pi(p)u(h^*_{AB}) \qquad &\Leftrightarrow \qquad h^*_{AB} = u^{-1}\left(\frac{1}{\pi(p)}u(M)\right) \\ \pi(r)u(M) = \pi(rp)u(h^*_{CD}) \qquad &\Leftrightarrow \qquad h^*_{CD} = u^{-1}\left(\frac{\pi(r)}{\pi(rp)}u(M)\right) \end{aligned}$$

One way to incorporate noise is by assuming that $h_{AB} = h^*_{AB} + \varepsilon_{AB}$ and $h_{CD} = h^*_{CD} + \varepsilon_{CD}$. This formulation satisfies Assumption 2ah as long as $\varepsilon_{CD} \overset{d}{=} k\varepsilon_{AB}$ for some $k > 0$ and $E(\varepsilon_{AB}) = E(\varepsilon_{CD}) = 0$.

Alternatively, one might incorporate additive utility noise by assuming that the realized indifference points satisfy

$$\begin{aligned} u(M) = \pi(p)u(h_{AB}) + \epsilon_{AB} \qquad &\Leftrightarrow \qquad h_{AB} = u^{-1}\left(u(h^*_{AB}) - \epsilon_{AB}/\pi(p)\right) \\ \pi(r)u(M) = \pi(rp)u(h_{CD}) + \epsilon_{CD} \qquad &\Leftrightarrow \qquad h_{CD} = u^{-1}\left(u(h^*_{CD}) - \epsilon_{CD}/\pi(rp)\right) \end{aligned}$$

where ϵ_{AB} and ϵ_{CD} reflect additive utility noise.[3] This formulation fits Assumption 1h with $\Gamma(h, \varepsilon) = u^{-1}(u(h) + \varepsilon)$, $\varepsilon_{AB} = -\epsilon_{AB}/\pi(p)$, and $\varepsilon_{CD} = -\epsilon_{CD}/\pi(rp)$. This formulation further satisfies Assumption 2bh as long as ϵ_{AB} is symmetric about 0 and $\epsilon_{CD} \overset{d}{=} k'\epsilon_{AB}$ for some $k' > 0$. Finally, EU with additive utility noise that is i.i.d. across the AB and CD choice tasks implies $\varepsilon_{CD} = \varepsilon_{AB}/r$.

[3]The latter equations use $u(M)/\pi(p) = u(h^*_{AB})$ and $\pi(r)u(M)/\pi(rp) = u(h^*_{CD})$.

Because this formulation is exactly parallel to our formulation for m-tasks, analogues for Propositions 1 and 2 and for Corollary 1 follow straightforwardly, and so are omitted.

Finally, consider analogues to the predictions for stage 2 behavior from Section IV.A. As in the text, consider the case of Assumption 2ah where a person with underlying indifference values (h^*_{AB}, h^*_{CD}) would choose A over B when $H \leqslant h^*_{AB} + \varepsilon_{AB}$ and would choose C over D when $H \leqslant h^*_{CD} + \varepsilon_{CD}$, where $\varepsilon_{CD} \overset{d}{=} k\varepsilon_{AB}$. For this case, the probability of making CRE choices (A and D) minus the probability of making RCRE choices (B and C) is

$$CRE - RCRE \equiv \Pr(A) - \Pr(C) = \Pr\left(-\varepsilon_{AB} < (h^*_{AB} - H)\right) - \Pr\left(-\varepsilon_{AB} < \frac{1}{k}(h^*_{CD} - H)\right).$$

Defining $\Psi \equiv (h^*_{CD} - H)/k$, and substituting $\bar{h}^* \equiv (h^*_{AB} + h^*_{CD})/2$ and $\Delta h^* = h^*_{AB} - h^*_{CD}$, we can rewrite this as:

$$CRE - RCRE = \Pr\left(-\varepsilon_{AB} < \Psi + 0.5\left(1 + \frac{1}{k}\right)\Delta h^* + \left(1 - \frac{1}{k}\right)(\bar{h}^* - H)\right) - \Pr\left(-\varepsilon_{AB} < \Psi\right).$$

This equation is analogous to equation 3 from Section IV.A. It yields similar intuitions, and could also be used to construct a figure analogous to Figure 7.

For some of our empirical analysis in Section IV, we increase power by (i) combining data across different values for p and r and (ii) combining data for both h-tasks and m-tasks. Because these differences in parameters and the type of task may impact the extent of differential noise (i.e., k), we make a correction to the scaled value difference and the scaled distance to indifference. To do so in a disciplined way, we use the correction that would be valid under EU with additive i.i.d. utility noise.[4] If we let ϵ reflect the additive utility noise, then for the m-tasks $\varepsilon_{AB} \overset{d}{=} \epsilon$ and $\varepsilon_{CD} \overset{d}{=} \epsilon/r$ (see Example 1), which motivates using $0.5(1+r)\Delta m$ for the scaled value difference and $(1-r)(M-\bar{m})$ for the scaled distance to indifference (as discussed in Section IV.A).

For the h-tasks, and using the same ϵ reflect the additive utility noise, we have instead that $\varepsilon_{AB} \overset{d}{=} -\epsilon/p$ and $\varepsilon_{CD} \overset{d}{=} -\epsilon/(rp)$ (see Example 1h). We can then define $\Psi' \equiv rp(h^*_{CD} - H)$ write:

$$\begin{aligned} CRE - RCRE &= \Pr(-\varepsilon_{AB} < h^*_{AB} - H) - \Pr(-\varepsilon_{CD} < h^*_{CD} - H) \\ &= \Pr\left(\epsilon < \Psi' + 0.5(1+r)p\Delta h^* + (1-r)p(\bar{h}^* - H)\right) - \Pr\left(\varepsilon_{AB} < \Psi'\right). \end{aligned}$$

This formulation thus suggests using $0.5(1 + r)p\Delta h^*$ for the scaled value difference, and using $(1 - r)p(\bar{h}^* - H)$ for the scaled difference to indifference.

[4] We reiterate the point from footnote 38 that this correction is not perfect because our data are inconsistent with EU with additive i.i.d. utility noise; nonetheless, we use that case to impose some discipline on what we use for this correction. See also our discussion in Appendix B.7

B.5 Revisiting Choices versus Valuations

In this section, we provide a stylized example, within the context of our specific experimental tasks, the bias in paired choice tasks and how paired valuation tasks are immune to that bias. Consider for simplicity an expected value maximizer who chooses lottery A over lottery B when $EV(A) - EV(B) > \epsilon_{AB}$, and chooses lottery C over lottery D when $EV(C) - EV(D) > \epsilon_{CD}$. Suppose further that ϵ_{AB} and ϵ_{CD} are i.i.d., and specifically each takes on the values 1 and -1 with equal probability.

Table B.1 illustrates how this person would behave for six rows in an experimental task with $H = \$29$ (we use $H = \$29$ instead of $H = \$30$ as in our study to eliminate indifference), $p = 0.5$, and $r = 0.5$. Columns (2) and (3) present six paired choice tasks (one in each row) for M varying from \$12 to \$17. Column (4) presents the expected-value differences for each row. Columns (5)-(8) present combined behavior for the paired choice task in each row as a function of the four possible realizations of $(\epsilon_{AB}, \epsilon_{CD})$. Based on these, column (9) presents the prediction for $CRE - RCRE = \Pr(A) - \Pr(C)$ for the paired choice task in each row if it were presented in an isolated paired choice task. This last column reveals that, despite there being no CRP or RCRP, if we happen to choose experimental parameters such that the participant moderately prefers A and C—as in row 5—then we will observe a CRE, and if we happen to choose experimental parameters such that the participant moderately prefers B and D—as in row 2—then we will observe an RCRE.

The bottom panel of the Table B.1 illustrates how valuations can solve the problem. Applying our approach of taking the average value of M at the switching rows to be our measure of the realized indifference point, the table presents for each of the four possible realizations of $(\epsilon_{AB}, \epsilon_{CD})$ the measured indifference points m_{AB} and m_{CD} along with $\Delta m \equiv m_{CD} - m_{AB}$. The table illustrates that, while the noise leads to positive and negative realizations of Δm, these realizations average out to zero.

This stylized example highlights how a full understanding of behavior requires observing outcomes across all six rows of the table. However, the paired-choice-task approach in the prior literature typically studies behavior from only one row, thus yielding only a partial view of behavior. Moreover, as discussed in Section I.D, the prior literature has focused on a selected set of parameter configurations that are more like row 5 in Table B.1. In contrast, our paired-valuation-task approach reveals a more complete view of behavior.

Table B.1: Stylized Example With Additive Noise

Row	Lottery A (Lottery C)	Lottery B (Lottery D)	$EU(A) - EU(B)$ $EU(C) - EU(D)$	ϵ_{AB} ϵ_{CD} -1 -1	 -1 1	 1 -1	 1 1	$\Pr(A)-$ $\Pr(C)$
...	...	...	...	...	...	...	...	...
1	100% chance \$12 (50% chance \$12)	50% chance \$29 (25% chance \$29)	-2.50 -1.25	BD	BD	BD	BD	0
2	100% chance \$13 (50% chance \$13)	50% chance \$29 (25% chance \$29)	-1.50 -0.75	BC	BD	BC	BD	$-\frac{1}{2}$
3	100% chance \$14 (50% chance \$14)	50% chance \$29 (25% chance \$29)	-0.50 -0.25	AC	AD	BC	BD	0
4	100% chance \$15 (50% chance \$15)	50% chance \$29 (25% chance \$29)	0.50 0.25	AC	AD	BC	BD	0
5	100% chance \$16 (50% chance \$16)	50% chance \$29 (25% chance \$29)	1.50 0.75	AC	AD	AC	AD	$\frac{1}{2}$
6	100% chance \$17 (50% chance \$17)	50% chance \$29 (25% chance \$29)	2.50 1.25	AC	AC	AC	AC	0
...	...	...	...	...	...	...	...	...
			Measured m_{AB}	13.5	13.5	15.5	15.5	
			Measured m_{CD}	12.5	16.5	12.5	16.5	
			Measured Δm	-1	3	-3	1	

Note: The pair of choices in row 5 will exhibit a CRE, with $\Pr(A) > \Pr(C)$. The pair of choices in row 2 will exhibit an RCRE, with $\Pr(A) < \Pr(C)$.

B.6 Impact of Distance to Indifference Without Noise

Our analysis in Section IV focuses on the impact of distance to indifference in the presence of choice noise, where we present theoretical predictions in Figure 7, and we plot empirical relationships in Figures 8 and 9 that confirm those theoretical predictions. In this section, we support the claims made in footnote 37 that predictions for Figures 8 and 9 would be very different in the absence of choice noise, that is, when all variation in the data is due to heterogeneity in preferences.

Suppose that there is heterogeneity in (m^*_{AB}, m^*_{CD}), where we focus on heterogeneity in $\bar{m}^* \equiv (m^*_{AB} + m^*_{CD})/2$ and $\Delta m^* = m^*_{CD} - m^*_{AB}$. The development below assumes that $\bar{m}^*$ and Δm^* are independently distributed, motivated by the fact that we observe limited empirical correlations between the $\bar{m}$'s and Δm's elicited in stage 1 of our experiment—across the 15 combinations of (p, r), these correlations range from -0.04 to 0.10, with a mean of 0.04. Hence, we let $Q_{\bar{m}^*}(\bar{m}^*)$ denote the population distribution of $\bar{m}^*$, and $Q_{\Delta m^*}(\Delta m^*)$ denote the population distribution of Δm^*, and assume $Q_{\bar{m}^*}$ and $Q_{\Delta m^*}$ are independent of each other.

Consider first the behavior of an individual characterized by (m^*_{AB}, m^*_{CD}) with $\Delta m^* > 0$ (i.e., with a CRP) as a function of an offered M at stage 2. In the absence of noise, this individual will exhibit a CRE if $m^*_{AB} < M < m^*_{CD}$; otherwise, they will exhibit neither a CRE nor an RCRE. This condition can be rewritten as $-\Delta m^* < 2(M - \bar{m}^*) < \Delta m^*$, or, equivalently, $\Delta m^* > 2|M - \bar{m}^*|$. Notice the symmetry around a zero distance to indifference: Whether the person exhibits a CRE does not depend on whether $M - \bar{m}^*$ is positive or negative; all that matters is whether the magnitude of Δm^* is larger than the magnitude of $2(M - \bar{m}^*)$.

Next consider the behavior of an individual characterized by (m^*_{AB}, m^*_{CD}) with $\Delta m^* < 0$ (i.e., with an RCRP). By an analogous logic, in the absence of noise, the person will exhibit an RCRE when $\Delta m^* < 2(M - \bar{m}^*) < -\Delta m^*$, or, equivalently, $\Delta m^* < -2|M - \bar{m}^*|$. Again, note the symmetry around a zero distance to indifference. Moreover, note the symmetry around a zero value difference: For a fixed distance to indifference, a person with $\Delta m^* = \delta > 0$ exhibits a CRE if and only if a person with $\Delta m^* = -\delta$ exhibits an RCRE.

Now consider the behavior of a population as a function of the distance to indifference $M - \bar{m}^*$, that is, a prediction to compare to Figure 8. Because this essentially controls for $\bar{m}^*$, and because the distribution of Δm^* is independent of $\bar{m}^*$, the distribution $Q_{\bar{m}^*}$ of $\bar{m}^*$ is irrelevant for this prediction. Given an $M - \bar{m}^* = d$, anyone with $\Delta m^* > 2|d|$ will exhibit a CRE while anyone with $\Delta m^* < -2|d|$ will exhibit an RCRE, and thus $CRE - RCRE = (1 - Q_{\Delta m^*}(2|d|)) - Q_{\Delta m^*}(-2|d|)$. Simplifying, the prediction is

$$CRE - RCRE = 1 - Q_{\Delta m^*}(2d) - Q_{\Delta m^*}(-2d) \equiv C(d).$$

Hence, predicted behavior for this population depends on the nature of the distribution $Q_{\Delta m^*}$. Various possibilities can arise; but we highlight two points. First, if the distribution $Q_{\Delta m^*}$ is symmetric around zero—so that $1 - Q_{\Delta m^*}(2d) = Q_{\Delta m^*}(-2d)$ for all d—then $C(d) = 0$ for all d. Hence, if all variation in the data is due to heterogeneity in preferences, then $CRE - RCRE$ can depend on the distance to indifference only if the distribution of Δm^* is asymmetric, which is not what we see in Figure 6(B). Second, even when $Q_{\Delta m^*}$ is asymmetric, $C(d)$ must still be symmetric around $d = 0$. In other words, if all variation in the data is due to heterogeneity in preferences, then whatever $CRE - RCRE$ we see for some positive value of $M - \bar{m}^*$, we ought to see the same $CRE - RCRE$ for that same negative value of $M - \bar{m}^*$. This is not what we see in Figure 8.

Finally, consider the behavior of a population as a function of the average distance to indifference $M - E(\bar{m}^*)$, that is, a prediction to compare to Figure 9. Define $z = \bar{m}^* - E(\bar{m}^*)$, $H(z) \equiv Q_{\bar{m}^*}(E(\bar{m}^*) + z)$, and assume that distribution H has a PDF h. Suppose $M - E(\bar{m}^*) = d$, in which case all people with $\bar{m}^*$ have $M - \bar{m}^* = (d + E(\bar{m}^*)) - (z + E(\bar{m}^*)) = d - z$, and thus that group will have $CRE - RCRE = C(d - z)$. Integrating over z, the overall population will have

$$CRE - RCRE = \int_{z=-\infty}^{\infty} C(d - z)h(z)dz \equiv \bar{C}(d).$$

If we then assume $Q_{\bar{m}^*}$ is symmetric around $\bar{m}^* = E(\bar{m}^*)$, which implies H is symmetric around

$z = 0$, we have

$$\begin{aligned}\bar{C}(-d) &= \int_{z=-\infty}^{\infty} C(-d-z)h(z)dz = \int_{z'=-\infty}^{\infty} C(-d+z')h(-z')dz \\ &= \int_{z'=-\infty}^{\infty} C(d-z')h(z')dz = \bar{C}(d),\end{aligned}$$

where the second equality uses a change of variables with $z' = -z$ and the third equality uses $C(x) = C(-x)$ and $h(-z') = h(z')$ given the symmetry of H around $z = 0$. It follows that, if all variation in the data is due to heterogeneity in preferences, and if the distribution of $\bar{m}^*$ is symmetric about $\bar{m}^* = E(\bar{m}^*)$, then whatever $CRE - RCRE$ we see for some positive value of $M - E(\bar{m}^*)$, we ought to see the same $CRE - RCRE$ for that same negative value of $M - E(\bar{m}^*)$. This is not what we see in Figure 9.

Hence, under the conditions described above, a model in which all variation in the data is due to heterogeneity in preferences would generate very different predictions from what we see in Figures 8 and 9. Of course, we make some simplifying assumptions above, most notably the assumption that the distributions of $\bar{m}^*$ and Δm^* are independent (used for predictions for Figure 8), and the additional assumption that the distribution of $\bar{m}^*$ is symmetric around $\bar{m}^* = E(\bar{m}^*)$ (used for predictions for Figure 9). It is possible that, with the appropriate assumptions about correlated heterogeneity and asymmetric distributions, one might be able to generate predictions closer to Figures 8 and 9.

B.7 Assessment of Corrected Regressors in Tables 5, 6, and D.10

In Table 5, to increase statistical power, we combine data for the three different values of r. However, we need to correct for the fact that r may impact the magnitude of the coefficients on Δm and $M - \bar{m}$ (via its impact on k in equation 3). Motivated by the EU case where $k = 1/r$, we use the corrected regressors $0.5(1+r)\Delta m$ and $(1-r)(M - \bar{m})$.

As we note in footnote 38, this correction is not perfect. To assess the impact of this correction, Appendix Table B.2 reports the equivalent of Column (3) of Table 5 broken out by r. Panel A merely uses the regressors Δm and $M - \bar{m}$. The qualitative results are much the same as in Table 5—both regressors have a significant positive impact for each r, except for $M - \bar{m}$ when $r = 0.6$. Moreover, consistent with the need to correct for r and the directional effects in equation 3, the coefficient on Δm increases with r while the coefficient on $M - \bar{m}$ decreases with r.

Panel B instead uses our corrected regressors, still running separate regressions for each r. Here, the estimated coefficients are more stable in magnitude across r, and they are similar to those in column (3) of Table 5 but with larger standard errors. On net, then, it appears that the corrected regressors perform as intended: They increase precision without changing the qualitative results.

We separately perform analogous analyses for Appendix Table D.10 and Table 6 (although we do not report the results here). For the former, which is the analogue of Table 5 for h choice tasks, this analysis reaches much the same conclusions. For the latter, which is the analogue of Table 5 for the experiment-level analysis, running separate regressions for each r leads to estimates with large standard errors due to the low sample sizes ($N = 40$ for each r); hence, while a similar message seems to emerge, we are cautious in concluding too much.

Table B.2: Predicting Individual-Level $CRE - RCRE$ Separately by r

	(1)	(2)	(3)
	Outcome: $CRE - RCRE \in \{-1, 0, 1\}$		
	$r = 0.2$	$r = 0.4$	$r = 0.6$
	Panel A: Unscaled Estimates		
Value Difference: Δm	0.64	0.78	0.90
	(0.18)	(0.15)	(0.19)
Distance to Indifference: $M - \bar{m}$	0.76	0.61	0.06
	(0.23)	(0.22)	(0.23)
	Panel B: Scaled Estimates		
Scaled Value Difference: $\frac{1+r}{2}\Delta m$	1.06	1.11	1.12
	(0.31)	(0.21)	(0.24)
Scaled Distance to Indifference: $(1 - r)(M - \bar{m})$	0.90	0.89	0.41
	(0.26)	(0.32)	(0.49)
Outcome Mean	3.02	3.76	1.14
Individuals	298	303	299
Observations	1,490	1,515	1,495

Note: OLS regressions using individual-level m-task data with the dependent variable $CRE - RCRE \in \{-1, 0, 1\}$ separately for each common ratio $r \in \{0.2, 0.4, 0.6\}$. Panel A presents estimates using the unscaled regressors, and panel B presents estimates using the scaled regressors. All specifications include p fixed effects, as well as controls for gender, education, age, language, student status, employment, and the number of previous Prolific approvals. All numbers are reported in percentage points; individual-cluster-robust standard errors in parentheses.

B.8 Our Experiments and Prior Experiments

In Section IV.D, we compare behavior in our stage 2 experiments to that observed in the prior literature by developing a measure of whether an experiment is more representative of prior studies or more representative of our study based on the experimenter-chosen values for p, r, and $M/(pH)$. This section provides details for this analysis.

We first create a combined data set of 263 observations consisting of our own and prior experiments. We then regress an indicator for an observation coming from a prior study on p, r, and $M/(pH)$. Based on inspection, we expect a nonlinear impact of $M/(pH)$ because the vast majority of prior experiments have $M/(pH) \in [0.75, 1]$ while our experiments have more representation for $M/(pH) < 0.75$ and $M/(pH) > 1$. Hence, letting y_i be a dummy variable for whether experiment i comes from a prior study, we run a logistic regression based on the following specification:

$$
\begin{aligned}
y_i^* &= \beta_0 + \beta_1 p_i + \beta_2 r_i + \beta_3 \mathbb{1}\left[M/(pH)_i \in [0.75, 1]\right] + \beta_4 \mathbb{1}\left[M/(pH)_i > 1\right] + \varepsilon_i \\
y_i &= \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
$$

Panel A of Table B.3 presents the estimates. An experiment is more likely to come from a prior study if it has a larger p, a smaller r, or an $M/(pH) \in [0.75, 1]$. Using the estimated coefficients from this regression, we can assign to each experiment a predicted likelihood that it comes from a prior study. Specifically, the predicted likelihood for experiment i is

$$
\Pr(-\varepsilon_i < \hat{\beta}_0 + \hat{\beta}_1 p_i + \hat{\beta}_2 r_i + \hat{\beta}_3 \mathbb{1}\left[M/(pH)_i \in [0.75, 1]\right] + \hat{\beta}_4 \mathbb{1}\left[M/(pH)_i > 1\right])
$$

using a standard logistic distribution for ε_i. This predicted likelihood indicates how representative an experiment is of prior studies. Importantly, this predicted likelihood depends on only an experiment's experimenter-chosen values for p, r, and $M/(pH)$, and is independent of the experiment's observed realization for $CRE - RCRE$.

We next compare experiments based on whether they are more representative of prior studies (predicted likelihood larger than 0.50) or more representative of our study (predicted likelihood smaller than 0.50). Panel B of Table B.3 reports the sample-weighted average $CRE - RCRE$ for experiments grouped by different predicted likelihoods and by experiment type. As discussed in Section IV.D, among the 143 prior experiments, 112 are more representative of prior studies and have an average $CRE - RCRE$ of 25.8 percent, while the other 31 have an average of 4.5 percent. Among our 120 experiments, 40 are more representative of prior studies and have an average $CRE - RCRE$ of 8.4 percent, while the other 80 have an average of -0.1 percent. In other words, when we (or prior studies) use experimental parameters that are more representative of prior studies, we find more CRE; in contrast, when we (or prior studies) use experimental parameters that are less representative of prior studies, we find much less CRE.

Table B.3: Comparing Prior Experiments to Our Experiments Using Predicted Likelihoods

Panel A: Logistic Regression (**DV:** Prior Study Indicator)

Variable:	p	r	$\mathbb{1}[M/(pH) \in [0.75, 1]]$	$\mathbb{1}[M/(pH) > 1]$	Constant
Coefficient	3.516	−1.463	1.744	0.583	−2.527
Standard Error	(0.738)	(0.832)	(0.327)	(0.676)	(0.694)

Panel B: $CRE - RCRE$ by Predicted Likelihood

More Representative of Prior Studies (Predicted Likelihood > 0.50)			More Representative of Our Study (Predicted Likelihood < 0.50)		
	N	$CRE - RCRE$		N	$CRE - RCRE$
Prior Literature	112	24.7%	Prior Literature	31	4.5%
Our Experiments	40	8.4%	Our Experiments	80	−0.1%

Note: Panel A reports results from logistic regression using the specification in the text. Panel B presents the number of experiments and the average $CRE - RCRE$ for the subset of experiments that are more representative of prior studies or our study based on the predicted likelihoods. All average $CRE - RCRE$ are calculated by weighting by the number of observations in the experiments.

C Screenshots from the Online Experiment

C.1 Screenshots from Stage 1: Valuation Tasks

C.1.1 m-Valuation Tasks

Decision 6 of 40: Please complete the decision problem below.

Reminder: Please indicate which option you prefer on each row by clicking on the row where you would like to switch from choosing the option on the left to choosing the option on the right.

(Note that you cannot click on the submit button until you have selected an answer. In order to progress, your choices must "switch" from Option A to Option B, like shown below. You will have to click once on Option A and once on Option B, in the subsequent row, to proceed. You can also click Option A in all rows, or Option B in all rows.)

OPTION A:		OPTION B:
80% CHANCE OF $0, 20% CHANCE OF $30	OR	100% CHANCE OF **$0**
80% CHANCE OF $0, 20% CHANCE OF $30	OR	100% CHANCE OF **$1**
80% CHANCE OF $0, 20% CHANCE OF $30	OR	100% CHANCE OF **$2**
80% CHANCE OF $0, 20% CHANCE OF $30	OR	100% CHANCE OF **$3**
80% CHANCE OF $0, 20% CHANCE OF $30	OR	100% CHANCE OF **$27**
80% CHANCE OF $0, 20% CHANCE OF $30	OR	100% CHANCE OF **$28**
80% CHANCE OF $0, 20% CHANCE OF $30	OR	100% CHANCE OF **$29**
80% CHANCE OF $0, 20% CHANCE OF $30	OR	100% CHANCE OF **$30**

Figure C.1: Example Price List for Stage 1 AB m-Valuation Task with $p = 0.2$

OPTION A:		OPTION B:
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$0**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$1**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$2**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$3**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$4**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$5**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$6**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$7**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$8**
	....	
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$28**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$29**
80% CHANCE OF \$0, 20% CHANCE OF \$30	OR	100% CHANCE OF **\$30**

>>

Figure C.2: Example Price List for Stage 1 AB m-Valuation Task with $p = 0.2$ (with example completion)

OPTION A:		OPTION B:
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$0**
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$1**
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$2**
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$3**
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$4**
	....	
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$27**
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$28**
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$29**
88% CHANCE OF $0, 12% CHANCE OF $30	OR	40% CHANCE OF $0 60% CHANCE OF **$30**

Figure C.3: Example Price List for Stage 1 CD m-Valuation Task with $p = 0.2$ and $r = 0.6$

C.1.2 h-Valuation Tasks

OPTION A:		OPTION B:
100% CHANCE OF $6	OR	80% CHANCE OF $0, 20% CHANCE OF **$6**
100% CHANCE OF $6	OR	80% CHANCE OF $0, 20% CHANCE OF **$7**
100% CHANCE OF $6	OR	80% CHANCE OF $0, 20% CHANCE OF **$8**
100% CHANCE OF $6	OR	80% CHANCE OF $0, 20% CHANCE OF **$9**
	....	
100% CHANCE OF $6	OR	80% CHANCE OF $0, 20% CHANCE OF **$33**
100% CHANCE OF $6	OR	80% CHANCE OF $0, 20% CHANCE OF **$34**
100% CHANCE OF $6	OR	80% CHANCE OF $0, 20% CHANCE OF **$35**
100% CHANCE OF $6	OR	80% CHANCE OF $0, 20% CHANCE OF **$36**

Figure C.4: Example Price List for Stage 1 *AB* h-Valuation Task with $p = 0.2$

OPTION A:		OPTION B:
40% CHANCE OF \$0 60% CHANCE OF \$6	OR	88% CHANCE OF \$0, 12% CHANCE OF **\$6**
40% CHANCE OF \$0 60% CHANCE OF \$6	OR	88% CHANCE OF \$0, 12% CHANCE OF **\$7**
40% CHANCE OF \$0 60% CHANCE OF \$6	OR	88% CHANCE OF \$0, 12% CHANCE OF **\$8**
40% CHANCE OF \$0 60% CHANCE OF \$6	OR	88% CHANCE OF \$0, 12% CHANCE OF **\$9**
	....	
40% CHANCE OF \$0 60% CHANCE OF \$6	OR	88% CHANCE OF \$0, 12% CHANCE OF **\$33**
40% CHANCE OF \$0 60% CHANCE OF \$6	OR	88% CHANCE OF \$0, 12% CHANCE OF **\$34**
40% CHANCE OF \$0 60% CHANCE OF \$6	OR	88% CHANCE OF \$0, 12% CHANCE OF **\$35**
40% CHANCE OF \$0 60% CHANCE OF \$6	OR	88% CHANCE OF \$0, 12% CHANCE OF **\$36**

Figure C.5: Example Price List for Stage 1 CD h-Valuation Task with $p = 0.2$ and $r = 0.6$

C.2 Screenshots from Stage 2: Binary-Choice Tasks

C.2.1 m-Choice Tasks

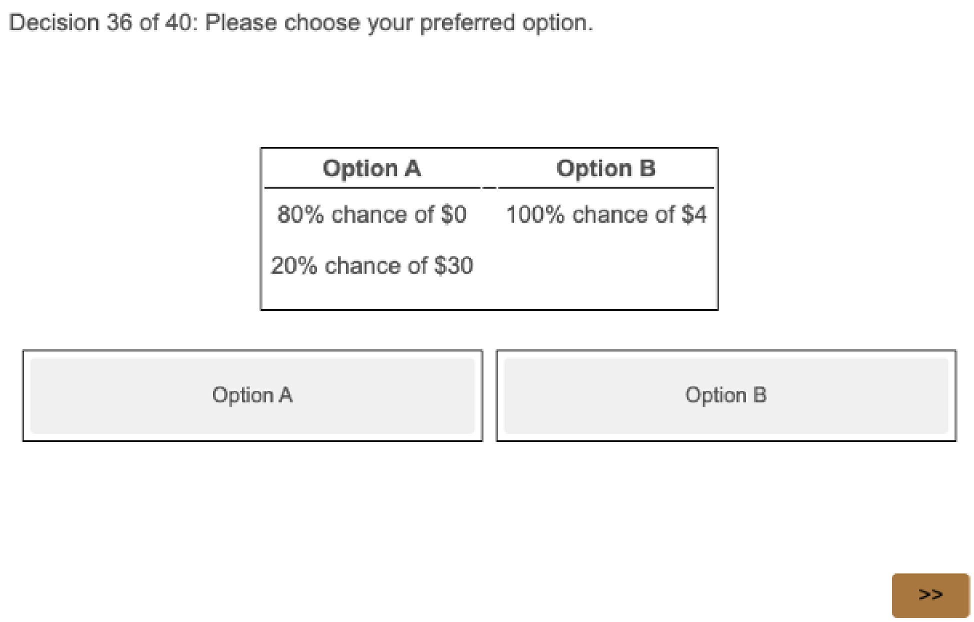

Figure C.6: Example Stage 2 Binary $AB(M)$ Choice Task with $p = 0.2$ and $M = \$4$

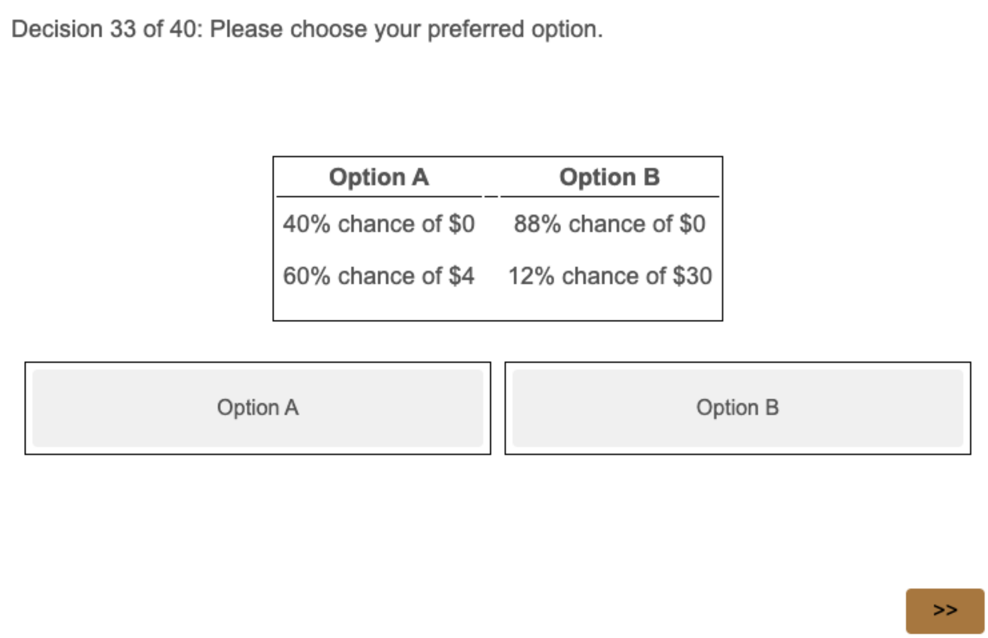

Figure C.7: Example Stage 2 Binary $CD(M)$ Choice Task with $p = 0.2$, $r = 0.6$, and $M = \$4$

C.2.2 h-Choice Tasks

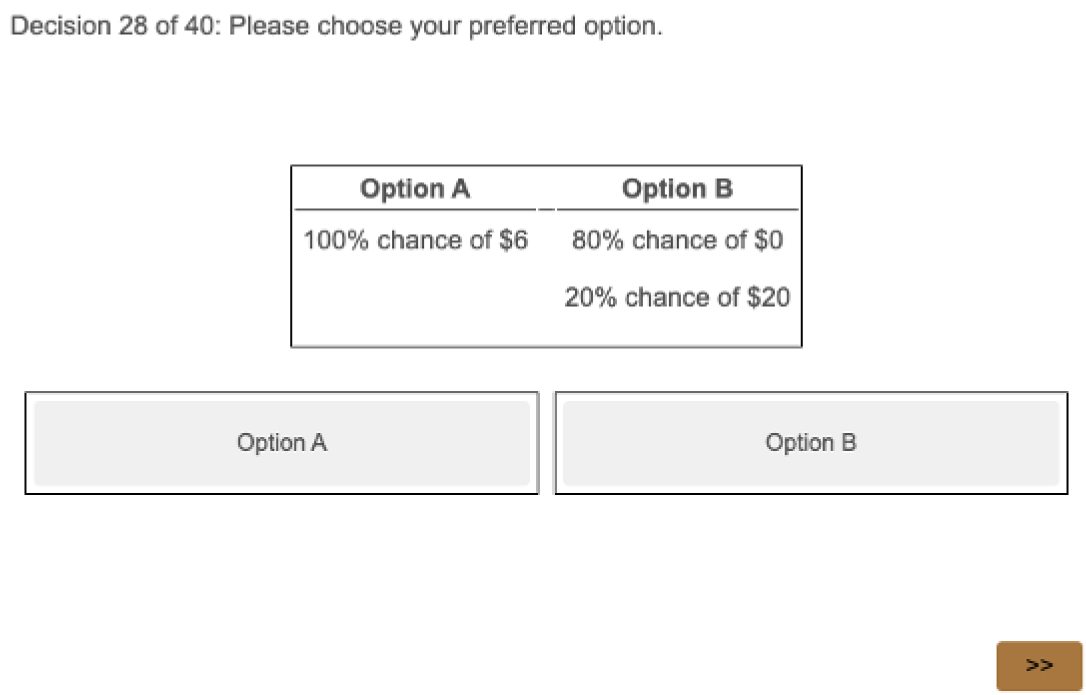

Figure C.8: Example Stage 2 Binary $AB(H)$ Choice Task with $p = 0.2$ and $H = \$20$

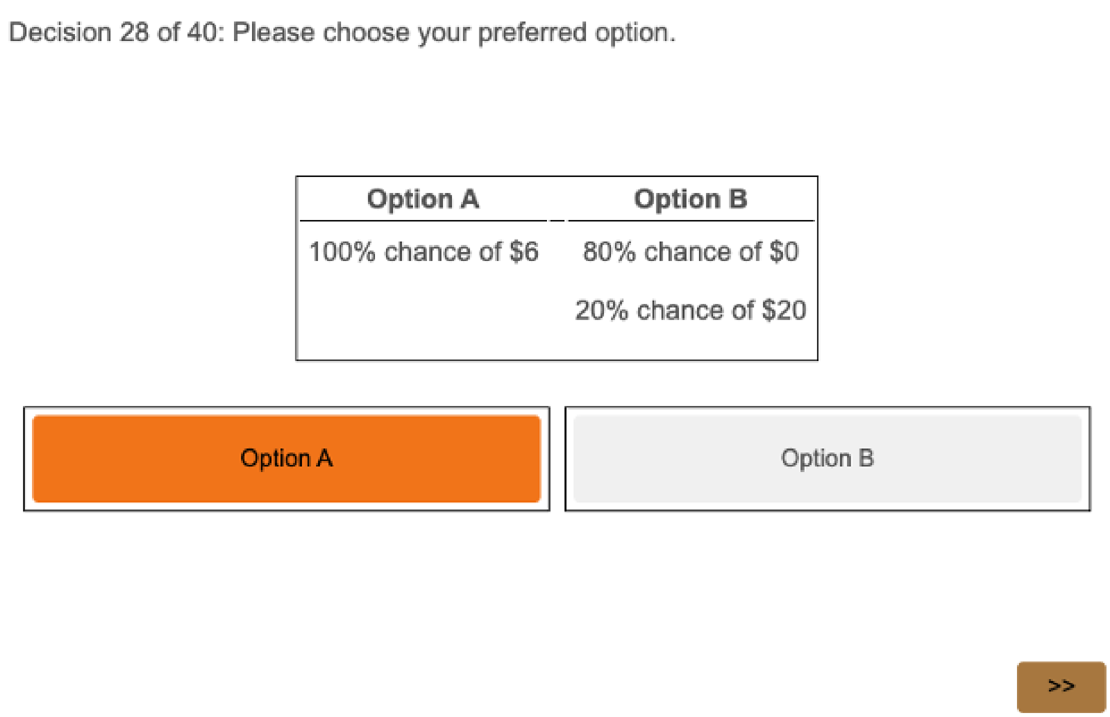

Figure C.9: Example Stage 2 Binary $AB(H)$ Choice Task with $p = 0.2$, and $H = \$20$ (with example completion)

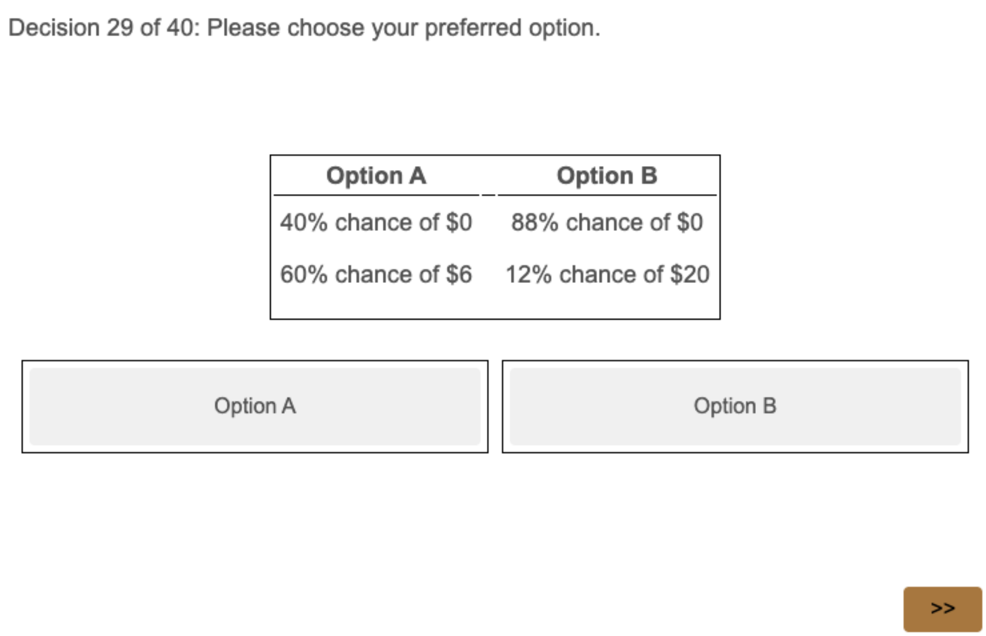

Figure C.10: Example Stage 2 Binary $CD(H)$ Choice Task with $p = 0.2$, $r = 0.6$, and $H = \$20$

C.3 Screenshots from Comprehension Checks and Visual Puzzle Task

Quiz Question #1:
Imagine a person who values the lottery shown in Option A below at exactly $24.50. That is, he would rather have the lottery than any sure amount less than $24.50, but would rather have the sure amount for any amount greater than $24.50.

How would this person fill out the list below?

OPTION A:		OPTION B:
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$0**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$1**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$2**
	....	
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$28**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$29**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$30**

Figure C.11: Incentivized Comprehension Check 1: Multiple Price List

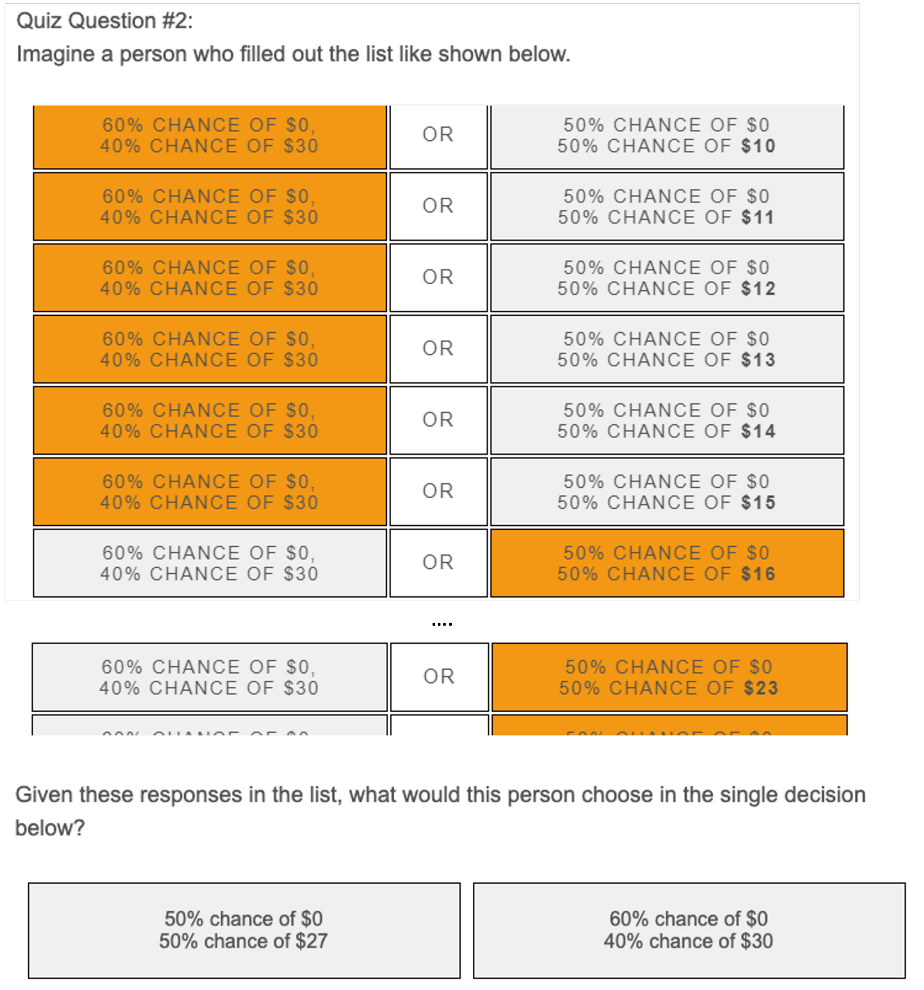

Figure C.12: Incentivized Comprehension Check 2: Binary-Choice Task

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

>>

Figure C.13: Example: Camouflaged Animal Task

D Supplementary Figures and Tables

Table D.1: Participant Demographics

	Full Sample	$r = 0.2$	$r = 0.4$	$r = 0.6$
Number of Participants	900	298	303	299
Time Taken (in minutes)	27.3	27.3	27.8	26.9
Age	22.4	22.5	22.2	22.5
Prolific Score	99.9	99.9	99.9	99.9
Number of Approvals	32.2	30.3	34.5	31.9
Female	50.0	50.7	49.8	49.5
Current Student	64.8	61.1	71.6	61.5
College Degree	49.3	48.0	49.2	50.8
Working (full- or part-time)	44.2	45.0	40.9	46.8
English First Language	52.0	48.7	49.5	57.9
Attention Checks				
Incentive Question Correct	92.3	93.3	92.1	91.6
Passed Attention Check	83.7	82.2	85.1	83.6
Comprehension Questions				
MPL Question Correct	83.9	81.5	84.8	85.3
Bin Question Correct	86.2	85.9	86.1	86.6
Both Questions Correct	74.0	70.8	75.2	75.9
Current Residency				
United States	51.4	47.7	49.2	57.5
United Kingdom	6.3	7.0	5.9	6.0
Portugal	22.1	22.1	24.4	19.7
Spain	5.4	6.4	4.0	6.0
Germany	4.7	5.4	4.6	4.0

Note: Participant demographics for all 900 participants. Each participant assigned to a single value of r.

Table D.2: Summary Statistics: m-Valuations

	p	Mean	SD	Percentile 10th	25th	50th	75th	90th
				Panel A: $r = 0.2$ (298 participants)				
m_{AB}	0.1	8.86	6.56	0.50	4.50	9.50	10.50	15.50
m_{CD}	0.1	7.31	6.67	0.50	2.50	5.50	9.50	15.50
m_{AB}	0.2	10.75	6.59	2.50	5.50	9.50	14.50	19.50
m_{CD}	0.2	9.46	7.05	0.50	4.50	9.50	11.50	19.50
m_{AB}	0.5	15.95	6.34	9.50	13.50	15.00	19.50	24.50
m_{CD}	0.5	15.99	7.01	7.50	10.50	15.50	20.50	24.50
m_{AB}	0.8	19.54	7.06	9.50	15.50	19.50	24.50	29.50
m_{CD}	0.8	20.55	7.46	9.50	15.50	22.50	25.50	29.50
m_{AB}	0.9	22.78	7.32	10.50	19.50	24.50	29.50	29.50
m_{CD}	0.9	21.31	8.00	9.50	14.50	24.50	28.50	29.50
				Panel B: $r = 0.4$ (303 participants)				
m_{AB}	0.1	7.29	5.83	0.50	3.50	5.50	9.50	14.50
m_{CD}	0.1	6.66	6.15	0.50	2.50	4.50	9.50	14.50
m_{AB}	0.2	9.33	6.12	0.50	4.50	9.50	13.50	15.50
m_{CD}	0.2	8.20	5.88	0.50	4.50	7.50	10.50	15.50
m_{AB}	0.5	14.48	6.37	6.50	10.50	14.50	19.50	20.50
m_{CD}	0.5	13.27	6.71	4.50	9.50	14.50	15.50	20.50
m_{AB}	0.8	19.22	7.43	9.50	14.50	19.50	24.50	29.50
m_{CD}	0.8	18.63	7.41	9.50	14.50	19.50	24.50	27.50
m_{AB}	0.9	21.55	7.59	9.50	19.50	24.50	26.50	29.50
m_{CD}	0.9	21.39	8.10	9.50	18.50	24.50	27.50	29.50
				Panel C: $r = 0.6$ (299 participants)				
m_{AB}	0.1	6.76	5.46	0.50	2.50	5.50	9.50	14.50
m_{CD}	0.1	6.27	5.61	0.50	2.50	4.50	9.50	12.50
m_{AB}	0.2	8.57	5.59	0.50	4.50	9.50	10.50	15.50
m_{CD}	0.2	8.70	5.99	0.50	4.50	9.50	10.50	15.50
m_{AB}	0.5	14.36	6.37	5.50	10.50	14.50	18.50	20.50
m_{CD}	0.5	12.32	6.25	4.50	9.50	13.50	15.50	19.50
m_{AB}	0.8	19.36	7.12	9.50	14.50	19.50	24.50	29.50
m_{CD}	0.8	18.11	7.05	9.50	13.50	19.50	23.50	25.50
m_{AB}	0.9	23.05	6.94	11.50	19.50	24.50	28.50	29.50
m_{CD}	0.9	21.01	7.04	10.50	15.50	22.50	26.50	29.50

Note: Summary statistics for all 30 m-valuations. Each participant was assigned a single r, and completed all 10 m-valuations for that value of r. Each valuation is equal to the average value of M at the participant's switching rows in a multiple-price list (MPL). Each MPL permits the valuations to range from -0.50 to 30.50.

Table D.3: Adjusting the Sign Test for Ties (m-Valuation Tasks)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Cases			Sign Tests		
p	$\Delta m > 0$ (CRE)	$\Delta m = 0$	$\Delta m < 0$ ($RCRE$)	Default (p-value)	Equal Split (p-value)	Prop. Split (p-value)
		Panel A: $r = 0.2$ (298 participants)				
0.1	79	75	144	0.000	0.000	0.000
0.2	80	73	145	0.000	0.000	0.000
0.5	123	60	115	0.650	0.685	0.524
0.8	140	54	104	0.025	0.042	0.013
0.9	127	42	129	0.950	0.954	0.862
		Panel B: $r = 0.4$ (303 participants)				
0.1	103	71	129	0.101	0.135	0.051
0.2	97	65	141	0.005	0.011	0.001
0.5	104	62	137	0.039	0.066	0.016
0.8	127	41	135	0.665	0.646	0.566
0.9	124	52	127	0.900	0.909	0.818
		Panel C: $r = 0.6$ (299 participants)				
0.1	94	90	115	0.166	0.247	0.083
0.2	111	84	104	0.682	0.729	0.563
0.5	89	65	145	0.000	0.001	0.000
0.8	113	57	129	0.335	0.355	0.247
0.9	79	60	160	0.000	0.000	0.000

Note: Columns (2)-(4) report raw frequencies of $\Delta m > 0$, $\Delta m = 0$, and $\Delta m < 0$ (identical to those reported in columns (4)-(6) in Table 3). Column (5) reports the p-values for the default sign tests (identical to those reported in column (7) in Table 3) that exclude all ties (instances of $\Delta m = 0$). The adjusted sign tests in column (6) split ties equally between $\Delta m > 0$ and $\Delta m < 0$. The adjusted sign tests in column (7) split ties in proportion to the observed share of $\Delta m > 0$ and $\Delta m < 0$.

Table D.4: Predictions for Δm under PT Versus Observed Δm in Data

	(1)	(2)	(3)	(4)
		Current Estimates:		
	Lower Bound	Point Estimate	Upper Bound	Data
		Panel A: $r = 0.2$		
$p = 0.1$	4.07	4.76	5.45	-1.55
$p = 0.2$	5.66	6.40	7.15	-1.29
$p = 0.5$	7.82	8.54	9.26	0.04
$p = 0.8$	7.20	7.84	8.48	1.00
$p = 0.9$	5.78	6.36	6.94	-1.47
		Panel B: $r = 0.4$		
$p = 0.1$	4.02	4.69	5.36	-0.63
$p = 0.2$	5.62	6.34	7.06	-1.14
$p = 0.5$	7.94	8.63	9.31	-1.22
$p = 0.8$	7.56	8.19	8.82	-0.60
$p = 0.9$	6.17	6.75	7.33	-0.16
		Panel C: $r = 0.6$		
$p = 0.1$	2.66	3.15	3.64	-0.49
$p = 0.2$	3.89	4.45	5.01	0.14
$p = 0.5$	5.89	6.49	7.09	-2.05
$p = 0.8$	5.89	6.47	7.05	-1.26
$p = 0.9$	4.84	5.37	5.90	-2.03

Note: Columns (1)-(4) present predictions for $\Delta m^* \equiv m^*_{CD} - m^*_{AB}$ under a PT model with $\pi(q) = q^\gamma/[q^\gamma + (1-q)^\gamma]^{1/\gamma}$ and $v(x) = x^\alpha$. Columns (1)-(3) use parameter estimates based on our stage 1 m_{AB}-valuations reported in Appendix Table E.1, with separate estimates for each r. Column (2) reports predictions using the point estimates, while columns (1) and (3) report lower and upper bounds of the 95 percent confidence interval computed using the delta method. Column (4) reports mean Δm values in our data from the m-valuation tasks.

Table D.5: Summary Statistics: h-Valuations

	p	Mean	SD	Percentile 10th	25th	50th	75th	90th
				Panel A: $r = 0.2$ (298 participants)				
h_{AB}	0.1	19.99	9.50	7.50	10.50	19.50	29.50	32.50
h_{CD}	0.1	21.66	9.72	9.50	12.50	23.50	30.50	33.50
h_{AB}	0.2	22.54	8.26	11.50	15.50	21.50	29.50	34.50
h_{CD}	0.2	24.49	8.78	12.50	18.50	25.50	30.50	36.50
h_{AB}	0.5	30.59	8.26	19.50	24.50	29.50	35.50	44.50
h_{CD}	0.5	28.95	7.68	19.50	24.50	29.50	32.50	39.50
h_{AB}	0.8	36.54	8.74	26.50	29.50	34.50	40.50	51.50
h_{CD}	0.8	32.22	6.83	24.50	28.50	30.00	35.50	41.50
h_{AB}	0.9	35.92	8.54	27.50	29.50	34.50	39.50	49.50
h_{CD}	0.9	33.82	7.43	27.50	28.50	30.50	36.50	44.50
				Panel B: $r = 0.4$ (303 participants)				
h_{AB}	0.1	21.48	9.37	9.50	14.50	20.50	29.50	33.50
h_{CD}	0.1	24.01	8.86	9.50	18.50	26.50	31.50	33.50
h_{AB}	0.2	24.46	7.95	13.50	19.50	24.50	30.50	36.50
h_{CD}	0.2	26.04	8.48	13.50	19.50	29.50	32.50	36.50
h_{AB}	0.5	30.34	7.34	20.50	25.50	29.50	33.50	40.50
h_{CD}	0.5	31.39	7.06	22.50	28.50	30.50	35.50	40.50
h_{AB}	0.8	36.07	8.57	26.50	29.50	34.50	39.50	49.50
h_{CD}	0.8	34.22	7.21	27.50	29.50	31.50	39.50	45.50
h_{AB}	0.9	35.66	8.66	27.50	29.50	33.50	39.50	50.50
h_{CD}	0.9	34.53	7.37	27.50	29.50	32.50	37.50	43.50
				Panel C: $r = 0.6$ (299 participants)				
h_{AB}	0.1	22.54	9.09	9.50	14.50	24.50	30.50	33.50
h_{CD}	0.1	23.27	9.51	9.50	14.50	26.50	30.50	33.50
h_{AB}	0.2	25.07	8.00	14.50	19.50	25.50	30.50	36.50
h_{CD}	0.2	24.24	8.47	12.50	17.50	24.50	30.50	36.50
h_{AB}	0.5	30.16	7.20	20.50	24.50	29.50	33.50	40.50
h_{CD}	0.5	30.88	7.43	20.50	25.50	29.50	35.50	40.50
h_{AB}	0.8	35.13	8.18	24.50	29.50	33.50	39.50	48.50
h_{CD}	0.8	34.29	7.67	26.50	29.50	31.50	39.50	45.50
h_{AB}	0.9	35.29	8.38	27.50	29.50	32.50	39.50	49.50
h_{CD}	0.9	34.52	6.82	27.50	29.50	32.50	38.50	44.50

Note: Summary statistics for all 30 h-valuations. Each participant was assigned a single r, and completed all 10 h-valuations for that value of r. Each valuation is equal to the average value of H at the participant's switching rows in a multiple-price list (MPL). Each MPL permits the valuations to range from $p30 - 0.50$ to $p30 + 30.50$.

Table D.6: Adjusting the Sign Test for Ties (h-Valuation Tasks)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Cases			Sign Tests		
p	$\Delta h > 0$ (CRE)	$\Delta h = 0$	$\Delta h < 0$ ($RCRE$)	Default (p-value)	Equal Split (p-value)	Prop. Split (p-value)
		Panel A: $r = 0.2$ (298 participants)				
0.1	100	60	138	0.016	0.032	0.006
0.2	94	53	151	0.000	0.001	0.000
0.5	136	81	81	0.000	0.001	0.000
0.8	174	45	79	0.000	0.000	0.000
0.9	143	64	91	0.001	0.003	0.000
		Panel B: $r = 0.4$ (303 participants)				
0.1	82	59	162	0.000	0.000	0.000
0.2	92	65	146	0.001	0.002	0.000
0.5	101	70	132	0.049	0.085	0.021
0.8	148	47	108	0.015	0.021	0.006
0.9	138	47	118	0.235	0.251	0.168
		Panel C: $r = 0.6$ (299 participants)				
0.1	100	71	128	0.074	0.105	0.037
0.2	131	65	103	0.077	0.105	0.037
0.5	93	85	121	0.065	0.105	0.021
0.8	136	47	116	0.231	0.247	0.165
0.9	126	54	119	0.702	0.729	0.644

Note: Columns (2)-(4) report raw frequencies of $\Delta h > 0$, $\Delta h = 0$, and $\Delta h < 0$ (identical to those reported in columns (4)-(6) in Table 4). Column (5) reports the p-values for the default sign tests (identical to those reported in column (7) in Table 4) that exclude all ties (instances of $\Delta h = 0$). The adjusted sign tests in column (6) split ties equally between $\Delta h > 0$ and $\Delta h < 0$. The adjusted sign tests in column (7) split ties in proportion to the observed share of $\Delta h > 0$ and $\Delta h < 0$.

Table D.7: Correlations of Risk Premia across Corresponding m- and h-Valuations

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variant	r	**Panel A:** Pearson's Correlation					**Panel B:** Spearman's Rank Correlation				
		$p = 0.1$	$p = 0.2$	$p = 0.5$	$p = 0.8$	$p = 0.9$	$p = 0.1$	$p = 0.2$	$p = 0.5$	$p = 0.8$	$p = 0.9$
AB	0.2	0.19*	0.30*	0.42*	0.31*	0.34*	0.30*	0.28*	0.36*	0.34*	0.35*
CD	0.2	0.21*	0.26*	0.25*	0.21*	0.30*	0.23*	0.26*	0.18*	0.22*	0.30*
AB	0.4	0.19*	0.25*	0.34*	0.34*	0.25*	0.34*	0.41*	0.30*	0.30*	0.27*
CD	0.4	0.03	0.11	0.04	0.28*	0.16*	0.23*	0.30*	0.14*	0.22*	0.20*
AB	0.6	0.15*	0.25*	0.44*	0.27*	0.33*	0.33*	0.33*	0.37*	0.27*	0.33*
CD	0.6	0.19*	0.16*	0.12*	0.30*	0.22*	0.40*	0.32*	0.17*	0.27*	0.22*

Note: Correlations between m_z/H and M/h_z (where $H = 30$ and $M = p30$) for each of the 30 combinations of (p, r) and $x \in \{AB, CD\}$. Panel A reports Pearson's correlations; panel B reports Spearman's rank correlations. * denotes that a correlation is statistically significant at the 5 percent level.

Table D.8: Correlations across p for Paired m-Valuation Tasks

	Panel A: Correlations of $pH - \bar{m}$ across p					**Panel B:** Correlations of Δm across p				
	$p =$					$p =$				
	0.1	0.2	0.5	0.8	0.9	0.1	0.2	0.5	0.8	0.9
	(i) $r = 0.2$					**(i)** $r = 0.2$				
$p = 0.1$	1.00					1.00				
$p = 0.2$	0.61*	1.00				0.16*	1.00			
$p = 0.5$	0.42*	0.43*	1.00			0.01	0.15*	1.00		
$p = 0.8$	0.12	0.20*	0.33*	1.00		0.06	0.11	0.11	1.00	
$p = 0.9$	0.09	0.11	0.26*	0.53*	1.00	0.03	0.13	0.16*	0.25*	1.00
	(ii) $r = 0.4$					**(ii)** $r = 0.4$				
$p = 0.1$	1.00					1.00				
$p = 0.2$	0.56*	1.00				0.05	1.00			
$p = 0.5$	0.33*	0.37*	1.00			0.10	0.16*	1.00		
$p = 0.8$	0.08	0.15*	0.37*	1.00		0.08	0.16*	0.31*	1.00	
$p = 0.9$	0.05	0.15	0.32*	0.54*	1.00	0.08	0.07	0.21*	0.28*	1.00
	(iii) $r = 0.6$					**(iii)** $r = 0.6$				
$p = 0.1$	1.00					1.00				
$p = 0.2$	0.61*	1.00				0.09	1.00			
$p = 0.5$	0.40*	0.49*	1.00			0.04	−0.04	1.00		
$p = 0.8$	0.09	0.26*	0.40*	1.00		0.10	0.00	0.04	1.00	
$p = 0.9$	0.06	0.13	0.28*	0.49*	1.00	0.10	−0.09	0.09	0.19*	1.00

Note: Spearman's rank correlations of $pH - \bar{m}$ across p (panel A) and of Δm across p (panel B) for the 15 paired m-valuation tasks. * denotes that a correlation is statistically significant at the 5 percent level.

Table D.9: Correlations of Value Differences across Corresponding m- and h-Valuations

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
r	**Panel A:** Pearson's Correlation					**Panel B:** Spearman's Rank Correlation				
	$p = 0.1$	$p = 0.2$	$p = 0.5$	$p = 0.8$	$p = 0.9$	$p = 0.1$	$p = 0.2$	$p = 0.5$	$p = 0.8$	$p = 0.9$
0.2	0.10	0.16*	0.19*	0.29*	0.28*	0.13*	0.10	0.12*	0.32*	0.30*
0.4	−0.01	0.08	0.17*	0.26*	0.16*	0.12*	0.15*	0.15*	0.24*	0.14*
0.6	−0.02	0.01	0.28*	0.20*	0.20*	0.02	−0.00	0.24*	0.14*	0.14*

Note: Correlations between $(m_{CD}/H - m_{AB}/H)$ and $(M/h_{CD} - M/h_{AB})$ (where $H = 30$ and $M = p30$) for each of the 15 combinations of (p, r). Panel A reports Pearson's correlations; panel B reports Spearman's rank correlations. * denotes that a correlation is statistically significant at the 5 percent level.

Table D.10: Predicting Individual-Level $CRE - RCRE$ (h tasks)

	(1)	(2)	(3)	(4)
	Outcome: $CRE - RCRE \in \{-1, 0, 1\}$			
	OLS	OLS	OLS	2SLS
Value Difference				
$\frac{1+r}{2} p \Delta h$	2.02		1.96	7.62
	(0.22)		(0.22)	(1.35)
Distance to Indifference				
$(1 - r)p(\bar{h} - H)$		1.06	0.84	0.21
		(0.24)	(0.24)	(0.44)
Outcome Mean	2.73	2.73	2.73	2.73
Individuals	900	900	900	900
Observations	4,500	4,500	4,500	4,500

Note: OLS regressions using individual-level h-task data with dependent variable $CRE - RCRE \in \{-1, 0, 1\}$. Specifications include p and r fixed effects, as well as controls for gender, education, age, language, student status, employment, and the number of previous Prolific approvals. All numbers reported in percentage points; individual-cluster-robust standard errors in parentheses. For column (4), instruments are $(1 - r)\bar{m}$, $0.5(1 + r)\Delta m$, and $(1 - r)pH$.

Table D.11: Summary of Choice Patterns: Experiments Linked to m-Valuations

(1) r	(2) p	(3) M	(4) Mean $\bar{m}$	(5) Mean Δm	(6) AC	(7) AD (CRE)	(8) BC $(RCRE)$	(9) BD	(10) $CRE - RCRE$	(11) Conlisk p-value	(12) N
0.2	0.1	1	8.41	−0.46	9.0	7.7	6.4	76.9	1.3	0.764	78
0.2	0.1	3	7.93	−2.27	30.7	16.0	9.3	44.0	6.7	0.250	75
0.2	0.1	5	8.38	−1.15	70.6	11.8	10.3	7.4	1.5	0.798	68
0.2	0.1	8	7.64	−2.30	87.0	6.5	3.9	2.6	2.6	0.481	77
0.2	0.2	1	10.26	−1.49	2.6	6.5	2.6	88.3	3.9	0.256	77
0.2	0.2	4	9.80	−1.68	31.6	7.9	27.6	32.9	−19.7	0.002	76
0.2	0.2	7	10.25	−0.83	40.3	9.7	27.8	22.2	−18.1	0.009	72
0.2	0.2	10	10.12	−1.10	84.9	4.1	8.2	2.7	−4.1	0.317	73
0.2	0.5	5	16.42	0.69	3.4	10.3	9.2	77.0	1.1	0.809	87
0.2	0.5	8	15.68	0.19	10.2	18.6	16.9	54.2	1.7	0.829	59
0.2	0.5	11	16.57	0.09	24.7	13.6	21.0	40.7	−7.4	0.256	81
0.2	0.5	14	14.98	−0.93	39.4	22.5	21.1	16.9	1.4	0.858	71
0.2	0.8	8	20.49	−0.16	1.5	9.0	13.4	76.1	−4.5	0.440	67
0.2	0.8	12	19.83	0.58	9.9	22.5	4.2	63.4	18.3	0.002	71
0.2	0.8	16	19.95	2.46	14.8	18.5	11.1	55.6	7.4	0.219	81
0.2	0.8	20	19.96	0.89	25.3	39.2	15.2	20.3	24.1	0.002	79
0.2	0.9	10	21.70	−0.91	6.3	8.9	6.3	78.5	2.5	0.565	79
0.2	0.9	14	23.20	−1.61	2.4	13.1	7.1	77.4	6.0	0.224	84
0.2	0.9	18	21.08	−2.41	7.1	24.3	14.3	54.3	10.0	0.175	70
0.2	0.9	22	22.02	−0.94	16.9	36.9	9.2	36.9	27.7	0.000	65
0.4	0.1	1	7.71	−0.80	11.4	13.9	7.6	67.1	6.3	0.224	79
0.4	0.1	3	6.53	−0.27	63.6	6.5	6.5	23.4	0.0	1.000	77
0.4	0.1	5	6.69	−0.62	75.3	9.0	6.7	9.0	2.2	0.594	89
0.4	0.1	8	7.02	−0.90	93.1	0.0	5.2	1.7	−5.2	0.078	58
0.4	0.2	1	8.86	−0.61	9.0	10.1	3.4	77.5	6.7	0.080	89
0.4	0.2	4	8.95	−2.20	32.9	14.5	18.4	34.2	−3.9	0.550	76
0.4	0.2	7	9.74	−0.78	70.1	7.5	11.9	10.4	−4.5	0.406	67
0.4	0.2	10	7.52	−1.00	88.7	8.5	2.8	0.0	5.6	0.154	71
0.4	0.5	5	13.89	0.48	17.9	4.8	16.7	60.7	−11.9	0.015	84
0.4	0.5	8	13.52	−1.26	13.8	12.5	27.5	46.2	−15.0	0.030	80
0.4	0.5	11	14.90	−2.32	32.2	13.6	27.1	27.1	−13.6	0.098	59
0.4	0.5	14	13.46	−2.14	46.2	11.2	21.2	21.2	−10.0	0.113	80
0.4	0.8	8	19.13	−1.78	2.5	16.5	1.3	79.7	15.2	0.001	79
0.4	0.8	12	19.15	−0.77	6.3	19.0	12.7	62.0	6.3	0.317	79
0.4	0.8	16	18.47	−0.97	10.3	26.9	12.8	50.0	14.1	0.044	78
0.4	0.8	20	18.94	1.45	31.3	40.3	7.5	20.9	32.8	0.000	67
0.4	0.9	10	21.75	0.54	5.6	13.5	2.2	78.7	11.2	0.006	89
0.4	0.9	14	22.30	0.12	4.6	12.3	4.6	78.5	7.7	0.128	65
0.4	0.9	18	20.51	−0.29	4.0	17.3	6.7	72.0	10.7	0.055	75
0.4	0.9	22	21.37	−1.09	36.5	32.4	13.5	17.6	18.9	0.013	74
0.6	0.1	1	6.82	−0.25	15.5	15.5	9.9	59.2	5.6	0.346	71
0.6	0.1	3	6.68	−0.94	51.5	8.8	11.8	27.9	−2.9	0.595	68
0.6	0.1	5	6.23	−1.17	72.7	7.8	5.2	14.3	2.6	0.529	77
0.6	0.1	8	6.37	0.30	78.3	9.6	8.4	3.6	1.2	0.797	83
0.6	0.2	1	8.39	1.15	6.1	7.6	1.5	84.8	6.1	0.098	66
0.6	0.2	4	9.12	−1.15	37.7	11.5	16.4	34.4	−4.9	0.469	61
0.6	0.2	7	8.68	0.17	72.8	10.9	6.5	9.8	4.3	0.317	92
0.6	0.2	10	8.41	0.24	88.8	5.0	2.5	3.8	2.5	0.415	80
0.6	0.5	5	14.54	−2.62	14.3	5.2	22.1	58.4	−16.9	0.003	77
0.6	0.5	8	12.79	−2.14	15.3	16.7	30.6	37.5	−13.9	0.082	72
0.6	0.5	11	13.27	−2.13	38.9	13.3	24.4	23.3	−11.1	0.083	90
0.6	0.5	14	12.57	−1.07	45.0	10.0	21.7	23.3	−11.7	0.104	60
0.6	0.8	8	18.29	−1.49	4.3	7.6	5.4	82.6	2.2	0.565	92
0.6	0.8	12	18.37	−1.35	10.1	16.5	8.9	64.6	7.6	0.177	79
0.6	0.8	16	19.33	−2.19	11.8	19.1	17.6	51.5	1.5	0.843	68
0.6	0.8	20	19.23	0.28	45.0	21.7	15.0	18.3	6.7	0.395	60
0.6	0.9	10	20.74	−3.40	8.3	6.9	2.8	81.9	4.2	0.256	72
0.6	0.9	14	22.65	−0.14	7.6	11.4	8.9	72.2	2.5	0.619	79
0.6	0.9	18	21.99	−2.23	7.7	26.9	9.0	56.4	17.9	0.006	78
0.6	0.9	22	22.70	−2.54	17.1	34.3	15.7	32.9	18.6	0.024	70

Table D.12: Summary of Choice Patterns: Experiments Linked to h-Valuations

(1) r	(2) p	(3) H	(4) Mean $\bar{h}$	(5) Mean Δh	(6) AC	(7) AD (CRE)	(8) BC ($RCRE$)	(9) BD	(10) $CRE - RCRE$	(11) Conlisk p-value	(12) N
0.2	0.1	13	20.99	−1.85	63.5	14.9	13.5	8.1	1.4	0.828	74
0.2	0.1	20	21.10	−1.31	38.6	13.3	16.9	31.3	−3.6	0.550	83
0.2	0.1	25	20.57	−0.85	39.7	19.1	10.3	30.9	8.8	0.177	68
0.2	0.1	30	20.59	−2.67	35.6	9.6	17.8	37.0	−8.2	0.177	73
0.2	0.2	20	22.54	−2.57	52.2	23.2	20.3	4.3	2.9	0.717	69
0.2	0.2	25	23.35	−1.18	49.3	8.2	20.5	21.9	−12.3	0.045	73
0.2	0.2	30	23.58	−1.65	51.4	8.3	18.1	22.2	−9.7	0.104	72
0.2	0.2	35	24.41	−2.35	35.7	13.1	22.6	28.6	−9.5	0.141	84
0.2	0.5	30	30.80	3.46	57.7	22.5	11.3	8.5	11.3	0.098	71
0.2	0.5	35	29.90	1.60	37.2	14.1	14.1	34.6	0.0	1.000	78
0.2	0.5	40	29.65	0.83	12.5	23.6	19.4	44.4	4.2	0.592	72
0.2	0.5	45	28.79	0.77	15.6	10.4	23.4	50.6	−13.0	0.046	77
0.2	0.8	33	34.58	5.23	30.0	41.7	13.3	15.0	28.3	0.001	60
0.2	0.8	38	33.72	5.70	26.9	32.8	11.9	28.4	20.9	0.008	67
0.2	0.8	45	34.86	3.74	11.9	31.7	8.9	47.5	22.8	0.000	101
0.2	0.8	52	34.15	3.01	10.0	17.1	8.6	64.3	8.6	0.154	70
0.2	0.9	35	33.31	0.17	22.2	30.6	18.1	29.2	12.5	0.125	72
0.2	0.9	40	35.30	2.26	9.2	19.7	15.8	55.3	3.9	0.565	76
0.2	0.9	47	34.70	4.03	6.7	25.3	5.3	62.7	20.0	0.001	75
0.2	0.9	54	36.10	1.89	4.0	17.3	8.0	70.7	9.3	0.105	75
0.4	0.1	13	21.38	−2.97	72.7	10.2	5.7	11.4	4.5	0.285	88
0.4	0.1	20	23.86	−0.48	61.7	13.3	8.3	16.7	5.0	0.407	60
0.4	0.1	25	23.56	−3.84	56.7	8.9	11.1	23.3	−2.2	0.639	90
0.4	0.1	30	22.45	−2.00	33.8	12.3	16.9	36.9	−4.6	0.493	65
0.4	0.2	20	25.97	−1.75	73.9	10.1	10.1	5.8	0.0	1.000	69
0.4	0.2	25	25.68	−1.54	57.9	10.5	15.8	15.8	−5.3	0.440	57
0.4	0.2	30	25.81	−2.37	62.7	8.4	12.0	16.9	−3.6	0.468	83
0.4	0.2	35	23.97	−0.80	51.1	12.8	11.7	24.5	1.1	0.836	94
0.4	0.5	30	30.67	−3.69	65.4	12.8	17.9	3.8	−5.1	0.415	78
0.4	0.5	35	30.14	−0.57	41.5	17.1	22.0	19.5	−4.9	0.481	82
0.4	0.5	40	31.00	−0.24	41.2	13.2	25.0	20.6	−11.8	0.113	68
0.4	0.5	45	31.76	0.44	33.3	9.3	29.3	28.0	−20.0	0.003	75
0.4	0.8	33	35.02	1.99	43.2	31.1	2.7	23.0	28.4	0.000	74
0.4	0.8	38	35.37	4.00	16.9	46.5	8.5	28.2	38.0	0.000	71
0.4	0.8	45	35.96	1.08	14.9	24.1	19.5	41.4	4.6	0.518	87
0.4	0.8	52	34.05	0.48	11.3	15.5	9.9	63.4	5.6	0.346	71
0.4	0.9	35	35.76	0.41	26.0	28.8	8.2	37.0	20.5	0.002	73
0.4	0.9	40	33.84	1.95	13.2	26.3	7.9	52.6	18.4	0.004	76
0.4	0.9	47	35.18	0.39	4.2	23.6	9.7	62.5	13.9	0.037	72
0.4	0.9	54	35.59	1.65	8.5	23.2	6.1	62.2	17.1	0.003	82
0.6	0.1	13	21.05	0.34	73.5	4.4	10.3	11.8	−5.9	0.204	68
0.6	0.1	20	22.85	−1.01	60.6	9.9	11.3	18.3	−1.4	0.798	71
0.6	0.1	25	23.33	−0.56	49.4	13.6	13.6	23.5	0.0	1.000	81
0.6	0.1	30	24.09	−1.57	54.4	12.7	10.1	22.8	2.5	0.639	79
0.6	0.2	20	25.94	0.79	74.6	11.3	7.0	7.0	4.2	0.406	71
0.6	0.2	25	23.64	1.07	66.3	8.4	12.0	13.3	−3.6	0.468	83
0.6	0.2	30	25.51	0.80	60.6	15.2	7.6	16.7	7.6	0.194	66
0.6	0.2	35	23.85	0.63	48.1	17.7	13.9	20.3	3.8	0.550	79
0.6	0.5	30	30.22	−1.77	64.2	17.3	11.1	7.4	6.2	0.297	81
0.6	0.5	35	31.13	−2.06	50.7	6.0	29.9	13.4	−23.9	0.000	67
0.6	0.5	40	30.57	0.47	32.9	8.9	27.8	30.4	−19.0	0.004	79
0.6	0.5	45	30.23	0.40	36.1	8.3	20.8	34.7	−12.5	0.045	72
0.6	0.8	33	34.55	2.20	53.3	16.0	18.7	12.0	−2.7	0.697	75
0.6	0.8	38	33.66	1.13	33.9	12.9	27.4	25.8	−14.5	0.067	62
0.6	0.8	45	35.81	0.32	14.8	12.5	19.3	53.4	−6.8	0.256	88
0.6	0.8	52	34.44	−0.15	9.5	17.6	8.1	64.9	9.5	0.104	74
0.6	0.9	35	34.92	0.57	25.3	24.1	21.7	28.9	2.4	0.747	83
0.6	0.9	40	35.09	0.89	13.6	18.5	9.9	58.0	8.6	0.142	81
0.6	0.9	47	34.42	1.49	5.5	16.4	9.6	68.5	6.8	0.250	73
0.6	0.9	54	35.21	0.00	3.2	11.3	6.5	79.0	4.8	0.366	62

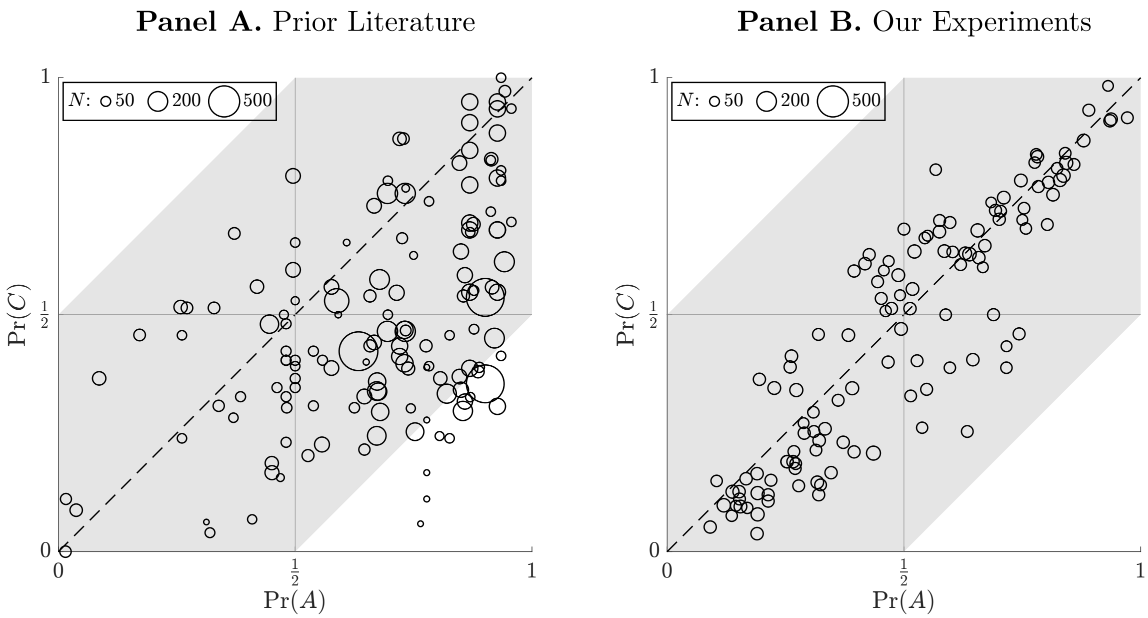

Figure D.1: Prior experiment-level observations for paired choice tasks (panel A) and our experiment-level results (panel B). In each panel, points below the 45-degree line exhibit a CRE, while points above the 45-degree line exhibit an RCRE. The shaded grey regions in both panels denote predicted $(\Pr(A), \Pr(C))$ combinations consistent with $\Delta m^* = 0$ under Assumption 2a. The black circles in panel A depict the 143 experiments surveyed by Blavatskyy et al. (2023) scaled by the number of observations; the black circles in panel B depict the 120 experiments that we run: 60 combinations of (p, r, M) in the m-choice tasks and 60 combinations of (p, r, H) for the h-choice tasks.

E Estimating a PT Model

In this section, we develop a structural PT model and estimate its key parameters. Following our development in Example 1, under PT a person will have underlying indifference valuations m^*_{AB} and m^*_{CD} that satisfy

$$u(m^*_{AB}) = \pi(p)u(H) \quad \text{and}$$
$$\pi(r)u(m^*_{CD}) = \pi(rp)u(H).$$

For our estimation, we use the functional forms from Tversky and Kahneman (1992): $\pi(q) = q^\gamma / [q^\gamma + (1-q)^\gamma]^{1/\gamma}$ and $u(x) = x^\alpha$. The goal is to estimate α and γ.

E.1 Estimating a PT Model Using Stage 1 m Valuations

Given the functional forms, the underlying indifference valuations are given by:

$$(m^*_{AB})^\alpha = \left[\frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}\right](H)^\alpha \qquad \Leftrightarrow \qquad \frac{m^*_{AB}}{H} = \left[\frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}\right]^{\frac{1}{\alpha}}$$

$$(m^*_{CD})^\alpha = \left[\frac{\frac{(rp)^\gamma}{((rp)^\gamma + (1-rp)^\gamma)^{\frac{1}{\gamma}}}}{\frac{r^\gamma}{(r^\gamma + (1-r)^\gamma)^{\frac{1}{\gamma}}}}\right](H)^\alpha \qquad \Leftrightarrow \qquad \frac{m^*_{CD}}{H} = \left[p^\gamma \left(\frac{r^\gamma + (1-r)^\gamma}{(rp)^\gamma + (1-rp)^\gamma}\right)^{\frac{1}{\gamma}}\right]^{\frac{1}{\alpha}}.$$

Incorporating noise in a way that permits using the standard approach of nonlinear least squares estimation, we model the observed valuations of individual i on trial t as

$$\frac{m_{AB,it}}{H} = \left[\frac{p_{it}^\gamma}{(p_{it}^\gamma + (1-p_{it})^\gamma)^{\frac{1}{\gamma}}}\right]^{\frac{1}{\alpha}} + \varepsilon_{it} \tag{E.1}$$

$$\frac{m_{CD,it}}{H} = \left[p_{it}^\gamma \left(\frac{r_i^\gamma + (1-r_i)^\gamma}{(r_i p_{it})^\gamma + (1-r_i p_{it})^\gamma}\right)^{\frac{1}{\gamma}}\right]^{\frac{1}{\alpha}} + \varepsilon_{it} \tag{E.2}$$

where r_i is the common ratio for individual i, p_{it} is the probability that individual i faces on trial t, and ε_{it} is a least-squares error term.

The typical approach in the literature is to use data on m_{AB} valuations and equation (E.1) to estimate the parameters $(\widehat{\alpha}, \widehat{\gamma})$ (Tversky and Kahneman, 1992). Table E.1 presents estimates using our data on m_{AB} valuations. Column (1) contains parameter estimates when using all m_{AB}-valuations and imposing the same $(\widehat{\alpha}, \widehat{\gamma})$ for all r. Our estimate of $\widehat{\gamma} = 0.60$ implies strong overweighting of low probabilities and underweighting of large probabilities. This estimate is in line with the typical values in the literature and is similar in magnitude to the estimate of $\widehat{\gamma} = 0.61$ in

Table E.1: PT Estimates Using Data on m-Valuations

	(1) Overall	(2) $r = 0.2$	(3) $r = 0.4$	(4) $r = 0.6$
Probability Weighting: $\widehat{\gamma}$	0.600	0.580	0.587	0.636
	(0.008)	(0.014)	(0.014)	(0.014)
Utility Curvature: $\widehat{\alpha}$	1.209	1.351	1.179	1.112
	(0.019)	(0.040)	(0.030)	(0.028)

Note: Nonlinear least squares estimation. The model assumes functional forms $\pi(q) = q^{\gamma}/[q^{\gamma} + (1-q)^{\gamma}]^{1/\gamma}$ and $u(x) = x^{\alpha}$. Individual-cluster-robust standard errors in parentheses. Panel A estimates use data on m_{AB}-valuations and the structural equation (E.1).

Tversky and Kahneman (1992). Our estimate of $\widehat{\alpha} = 1.209$ is significantly greater than one, which implies risk seeking in the absence of any probability distortions.

Columns (2)-(4) present separate estimates for each common-ratio factor r. We find qualitatively similar estimates of $(\widehat{\alpha}, \widehat{\gamma})$ across the three values for r, which is reassuring given that r does not enter into equation (E.1). We use the estimates in columns (2)-(4) to construct the PT predictions denoted by the dashed blue and dashed-and-dotted red lines in Figure 5 of the main text.

To formally test for differences in probability weighting between the m_{AB} valuations versus the m_{CD} valuations, we estimate the following joint specification:

$$\begin{aligned} m_{jit} = {} & \mathbb{1}(j = AB) \left[\frac{p_{it}^{\gamma_{AB}}}{\left(p_{it}^{\gamma_{AB}} + (1-p_{it})^{\gamma_{AB}}\right)^{\frac{1}{\gamma_{AB}}}} \right]^{\frac{1}{\alpha_{AB}}} \\ & + \mathbb{1}(j = CD) \left[p_{it}^{\gamma_{CD}} \left(\frac{r_i^{\gamma_{CD}} + (1-r_i)^{\gamma_{CD}}}{(r_i p_{it})^{\gamma_{CD}} + (1 - r_i p_{it})^{\gamma_{CD}}} \right)^{\frac{1}{\gamma_{CD}}} \right]^{\frac{1}{\alpha_{CD}}} + \varepsilon_{it}, \end{aligned} \tag{E.3}$$

where $j \in \{AB, CD\}$ denotes the valuation type. Table E.2 presents the results under different parameter restrictions. Columns (2) and (3) show that we reject the null of a stable γ across the m_{AB} and m_{CD} valuations.

Table E.2: Testing for a Stable Probability Weighting Function

	(1)	(2)	(3)
		Restrictions:	
	$\gamma_{AB} = \gamma_{CD} = \gamma$, $\alpha_{AB} = \alpha_{CD} = \alpha$	$\alpha_{AB} = \alpha_{CD} = \alpha$	None
Probability Weighting			
γ	0.773		
	(0.007)		
γ_{AB}		0.603	0.600
		(0.008)	(0.008)
γ_{CD}		1.162	0.368
		(0.017)	(0.006)
Utility Curvature			
α	0.916	1.198	
	(0.014)	(0.019)	
α_{AB}			1.209
			(0.019)
α_{CD}			0.193
			(0.009)
F-Test: $\gamma_{AB} = \gamma_{CD}$		$p < 0.001$	$p < 0.001$
Individuals	900	900	900
Observations	9000	9000	9000

Note: Nonlinear least squares estimation. The model assumes functional forms $\pi(q) = q^\gamma/[q^\gamma + (1-q)^\gamma]^{1/\gamma}$ and $u(x) = x^\alpha$. Individual-cluster-robust standard errors in parentheses. The estimation uses data on both m_{AB} and m_{CD} valuations and the structural equation (E.3).

E.2 Estimating a PT Model Using Stage 2 Choice Data

To estimate the model use stage 2 choice data, we assume additive utility noise. Analogous to our approach in the prior subsection, we posit a model with differential probability weighting across the AB and CD choices, and then test whether they are the same. Hence, a person will choose A over B when $u(M) - \pi(p)u(H) > \epsilon_{AB}$, which becomes

$$\epsilon_{AB} < M^{\alpha_{AB}} - \left[\frac{p^{\gamma_{AB}}}{(p^{\gamma_{AB}} + (1-p)^{\gamma_{AB}})^{\frac{1}{\gamma_{AB}}}}\right](H)^{\alpha_{AB}} \equiv D_{AB}(M, H, p).$$

Similarly, the person will choose C over D when $\pi(r)u(M) - \pi(rp)u(H) > \epsilon_{CD}$, which becomes

$$\epsilon_{CD} < \left[\frac{r^{\gamma_{CD}}}{(r^{\gamma_{CD}} + (1-r)^{\gamma_{CD}})^{\frac{1}{\gamma_{CD}}}}\right] M^{\alpha_{CD}} - \left[\frac{(rp)^{\gamma_{CD}}}{((rp)^{\gamma_{CD}} + (1-rp)^{\gamma_{CD}})^{\frac{1}{\gamma_{CD}}}}\right](H)^{\alpha_{CD}} \equiv D_{CD}(M, H, p, r).$$

As in the prior subsection, we first estimate the parameters $(\alpha_{AB}, \gamma_{AB})$ using only the AB

choice data. We denote an AB observation by $d_{AB,i} \equiv (a_i; M_i, H_i, p_i)$, where $a_i \in \{A, B\}$ is the person's choice. We further assume that $\epsilon_{AB} \sim N(0, \sigma_{AB}^2)$. Then given parameter vector $\theta \equiv (\alpha_{AB}, \gamma_{AB}, \sigma_{AB})$, the likelihood of observation $d_{AB,i}$ is

$$\ell_{AB}(d_{AB,i};\theta) \equiv \mathbb{1}(a_i = A)\Phi\left(\frac{D_{AB}(M_i, H_i, p_i)}{\sigma_{AB}}\right) + \mathbb{1}(a_i = B)\left(1 - \Phi\left(\frac{D_{AB}(M_i, H_i, p_i)}{\sigma_{AB}}\right)\right),$$

and the overall likelihood function is

$$L(\theta) \equiv \sum_{d_{AB,i}} log(\ell_{AB}(d_{AB,i};\theta)).$$

Column (1) of Table E.3 presents the parameter estimates. Much as for our estimates using valuations data, our estimate of $\widehat{\gamma_{AB}} = 0.71$ implies strong overweighting of low probabilities and underweighting of large probabilities, and is similar in magnitude to that in column (1) of Table E.1.[5]

We next test for differences in probability weighting between the AB choices and the CD choices. We denote a CD observation by $d_{CD,i} \equiv (a_i; M_i, H_i, p_i, r_i)$, where $a_i \in \{C, D\}$ is the person's choice. We further assume that $\epsilon_{CD} \sim N(0, \sigma_{CD}^2)$, and thus the parameter vector is now $\theta \equiv (\alpha_{AB}, \gamma_{AB}, \alpha_{CD}, \gamma_{CD}, \sigma_{AB}, \sigma_{CD})$. The likelihood of a CD observation $d_{CD,i}$ is

$$\ell_{CD}(d_{CD,i};\theta) \equiv \mathbb{1}(a_i = C)\Phi\left(\frac{D_{CD}(M_i, H_i, p_i, r_i)}{\sigma_{CD}}\right) + \mathbb{1}(a_i = D)\left(1 - \Phi\left(\frac{D_{CD}(M_i, H_i, p_i, r_i)}{\sigma_{CD}}\right)\right).$$

The overall likelihood function is then

$$L(\theta) \equiv \sum_{d_{AB,i}} log(\ell_{AB}(d_{AB,i};\theta)) + \sum_{d_{CD,i}} log(\ell_{CD}(d_{CD,i};\theta)).$$

Columns (2)-(4) of Table E.3 presents estimates analogous to those in columns (1)-(3) in Table E.2. Columns (3) and (4) show that we again reject the null of a stable γ across the m_{AB} and m_{CD} valuations.[6]

[5] Our estimate of $\widehat{\alpha_{AB}} = 0.70$, in contrast to that in column (1) of Table E.1, is significantly less than one. While not reported here, we also conduct both estimations while imposing that $\alpha = 1$, and both estimated γ parameters are still less than one, again consistent with inverse-S-shaped probability weighting.

[6] While not reported here, we also conduct the estimations in both Tables E.2 and E.3 while imposing that $\alpha = 1$, and we again reject the null of a stable γ across the m_{AB} and m_{CD} valuations.

Table E.3: PT Estimates Using Stage 2 Choice Data

	(1)	(2)	(3)	(4)
		Restrictions:		
	AB Choices Only	$\gamma_{AB} = \gamma_{CD} = \gamma$, $\alpha_{AB} = \alpha_{CD} = \alpha$	$\alpha_{AB} = \alpha_{CD} = \alpha$	None
Probability Weighting				
γ		0.809		
		(0.011)		
γ_{AB}	0.710		0.737	0.710
	(0.013)		(0.014)	(0.013)
γ_{CD}			0.886	0.461
			(0.020)	(0.014)
Utility Curvature				
α		0.615	0.653	
		(0.008)	(0.010)	
α_{AB}	0.697			0.697
	(0.011)			(0.011)
α_{CD}				0.252
				(0.015)
Utility Noise				
σ_{AB}	2.250	1.974	2.000	2.250
	(0.110)	(0.088)	(0.086)	(0.110)
σ_{CD}		0.906	1.069	0.104
		(0.044)	(0.058)	(0.013)
H_0: $\gamma_{AB} = \gamma_{CD}$			$p < 0.001$	$p < 0.001$
Individuals	900	900	900	900
Observations	4500	9000	9000	9000

Note: Maximum likelihood estimation using stage 2 choice data. The model assumes functional forms $\pi(q) = q^\gamma/[q^\gamma + (1-q)^\gamma]^{1/\gamma}$ and $u(x) = x^\alpha$. The estimation in column (1) uses data on m_{AB} choices, and the estimation in columns (2)-(4) uses data on both m_{AB} and m_{CD} choices. In columns (3) and (4), the null hypothesis of $\gamma_{AB} = \gamma_{CD}$ is tested via a Wald test.

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