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

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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 $\varepsilon_{CD} \overset{d}{=} k\varepsilon_{AB}$, 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 $k > 0$.

■

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 $\Pr(\Delta m < 0) = \Pr(\nu_{CD} < \nu_{AB}) = 1/2$. ∎

B   Additional Theoretical Results

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

In Section 2.1, 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, 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, $m_{AB} = u^{-1}(u(m^*) + \epsilon_{AB})$ and $m_{CD} = u^{-1}(u(m^*) + \epsilon_{CD}/r)$, 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 $\epsilon_{CD} \stackrel{d}{=} k'\epsilon_{AB}$ for some $k' > 0$, and thus $\varepsilon_{CD} \stackrel{d}{=} k\epsilon_{AB}$ 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, $E_{\varepsilon_{AB}}[m(\varepsilon_{AB})] > m(E_{\varepsilon_{AB}}[\varepsilon_{AB}]) = m^*$ and $E_{\varepsilon_{CD}}[m(\varepsilon_{CD})] > m(E_{\varepsilon_{CD}}[\varepsilon_{CD}]) = m^*$. If $k = 1$ then $\varepsilon_{CD} \stackrel{d}{=} \varepsilon_{AB}$, and thus $E_{\varepsilon_{CD}}[m(\varepsilon_{CD})] = E_{\varepsilon_{AB}}[m(\varepsilon_{AB})]$. It follows that $E[\Delta m] = 0$. If instead $k > 1$, then ε_{CD} is a mean-preserving spread of ε_{AB}, and thus, since $m(\varepsilon)$ is convex, $E_{\varepsilon_{CD}}[m(\varepsilon_{CD})] > E_{\varepsilon_{AB}}[m(\varepsilon_{AB})]$. It follows that $E[\Delta m] > 0$. An analogous logic can be used to show that $k < 1$ implies $E[\Delta m] < 0$.

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

■

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 1

We derive predictions for Figure 1 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 as well, 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 $\varepsilon_{CD,i}$.[42]

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:

q = the proportion of the population who are AC types.
λ_A = the proportion of AC types who actually choose A over B.
λ_C = the proportion of AC types who actually choose C over D.
λ_B = the proportion of BD types who actually choose B over A.
λ_D = the proportion of BD types who actually choose D over C.

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

$$\Pr(A) = q\lambda_A + (1-q)(1-\lambda_B)$$
$$\Pr(C) = q\lambda_C + (1-q)(1-\lambda_D).$$

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

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

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[42]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 1. To illustrate the logic, 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 on the AB choice and are random on the CD choice (i.e., $\lambda_A = 1$ while $\lambda_C = 1/2$), the BD types make no errors on the CD choice and are random on 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 the AC types be more impacted by noise on one type of choice (above, on the CD choice) while the 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 the same type of noise. 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 for 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[43]

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

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 on the AB choice and are random on the CD choice (i.e., $\lambda_A = 1$ while $\lambda_C = 1/2$), while the BD types make no errors on either choice (i.e., $\lambda_B = \lambda_C = 1$).

Proof of conditions for gray area in Figure 1 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

[43]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 $\Pr(A) - 1/2 \leqslant \Pr(C) \leqslant 1$.

■

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 1.

B.3   Data for Figure 1

B.3.1   Data for Panel A of Figure 1

For the data in panel A, we rely on the recent meta-study by (Blavatskyy et al., 2022). 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

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

Each of these 143 experiments is then depicted 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 1

For panel B, we are not aware of any analogous meta-study, and Blavatskyy et al. (2022) 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 (2021) 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 2.1, 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 2.1 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 2.1, 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 $D \equiv (H, pr)$ if and only if $H \leqslant h^*_{CD}$.

Here, EU implies $h^*_{AB} = h^*_{CD}$, whereas a CRP would mean $h^*_{AB} > h^*_{CD}$ (so the person 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 $H \leqslant h_{AB} \equiv \Gamma(h^*_{AB}, \varepsilon_{AB})$,

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- In a CD choice task, the person chooses $C \equiv (M, r)$ over $D \equiv (H, pr)$ 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

$$u(M) = \pi(p)u(h_{AB}^*) \qquad \Leftrightarrow \qquad h_{AB}^* = u^{-1}\left(\frac{1}{\pi(p)}u(M)\right)$$

$$\pi(r)u(M) = \pi(pr)u(h_{CD}^*) \qquad \Leftrightarrow \qquad h_{CD}^* = u^{-1}\left(\frac{\pi(r)}{\pi(pr)}u(M)\right)$$

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

$$u(M) = \pi(p)u(h_{AB}) + \epsilon_{AB} \qquad \Leftrightarrow \qquad h_{AB} = u^{-1}\left(u(h_{AB}^*) - \epsilon_{AB}/\pi(p)\right)$$

$$\pi(r)u(M) = \pi(pr)u(h_{CD}) + \epsilon_{CD} \qquad \Leftrightarrow \qquad h_{CD} = u^{-1}\left(u(h_{CD}^*) - \epsilon_{CD}/\pi(pr)\right)$$

where ϵ_{AB} and ϵ_{CD} reflect additive utility noise.[44] This formulation fits Assumption 1h with $\Gamma(h, \varepsilon) = u^{-1}(u(h) + \varepsilon)$, $\varepsilon_{AB} = -\epsilon_{AB}/\pi(p)$, and $\varepsilon_{CD} = -\epsilon_{CD}/\pi(pr)$. 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 $\varepsilon_{CD} = \varepsilon_{AB}/r$.

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[44]The latter equations use $u(M)/\pi(p) = u(h_{AB}^*)$ and $\pi(r)u(M)/\pi(pr) = u(h_{CD}^*)$.

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 5.1. 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 1 from Section 5.1. It yields similar intuitions, and could also be used to construct a figure analogous to Figure 6.

For some of our empirical analysis in Section 5, 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 likely 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.[45] 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 5.1).

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 $\varepsilon_{CD} \overset{d}{=} -\epsilon/(pr)$ (see Example 1h). We can then define $\Psi' \equiv pr(h^*_{CD} - H)$ write:

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

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.

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[45] We reiterate the point from footnote 35 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.

B.5 Impact of Distance to Indifference Without Noise

Our analysis in Section 5 focuses on the impact of distance to indifference in the presence of choice noise, where we present theoretical predictions in Figure 6, and we plot empirical relationships in Figures 7 and 8 that confirm those theoretical predictions. In this section, we support the claims made in footnote 33 that predictions for Figures 7 and 8 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). An analogous logic yields that, 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 7. 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 $M - \bar{m}^* = d$, a CRE is exhibited by anyone with $\Delta m^* > 2|d|$ while an RCRE is exhibited by anyone with $\Delta m^* < -2|d|$, 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, $CRE - RCRE$ can depend on the distance to indifference only if the distribution of Δm^* is asymmetric, which is not what we see in Figure 5(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 7.

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 8. 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 8.

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 7 and 8. 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 7), and the additional assumption that the distribution of $\bar{m}^*$ is symmetric around $\bar{m}^* = E(\bar{m}^*)$ (used for predictions for Figure 8). It is possible that, with the appropriate assumptions about correlated heterogeneity and asymmetric distributions, one might be able to generate predictions closer to Figures 7 and 8.

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

Decision 36 of 40: Please choose your preferred option.

Option A	Option B
80% chance of $0	100% chance of $4
20% chance of $30	

Option A	Option B

>>

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

Decision 33 of 40: Please choose your preferred option.

Option A	Option B
40% chance of $0	88% chance of $0
60% chance of $4	12% chance of $30

Option A	Option B

>>

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

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C.2.2 *h*-Choice Tasks

Decision 28 of 40: Please choose your preferred option.

Option A	Option B
100% chance of $6	80% chance of $0
	20% chance of $20

Option A   Option B

>>

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

Decision 28 of 40: Please choose your preferred option.

Option A	Option B
100% chance of $6	80% chance of $0
	20% chance of $20

Option A   Option B

>>

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

Option A	Option B
40% chance of $0	88% chance of $0
60% chance of $6	12% chance of $20

Option A	Option B

>>

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

Quiz Question #2:

Imagine a person who filled out the list like shown below.

60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF $10
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF $11
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF $12
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF $13
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF $14
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF $15
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF $16

....

60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF $23

Given these responses in the list, what would this person choose in the single decision below?

50% chance of $0 50% chance of $27	60% chance of $0 40% chance of $30

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

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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

	Overall	$r = 0.2$	$r = 0.4$	$r = 0.6$
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
Profilic Score	99.9	99.9	99.9	99.9
Number of Approvals	32.2	30.3	34.5	31.9
Female	51.4	52.3	50.8	51.2
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)
		Panel A: Pearson's Correlation					**Panel B:** Spearman's Rank Correlation				
Variant	r	$p = 0.1$	$p = 0.2$	$p = 0.5$	$p = 0.8$	$p = 0.9$	$p = 0.1$	$p = 0.2$	$p = 0.5$	$p = 0.8$	$p = 0.9$
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_x/H and M/h_x (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) $r = 0.2$										
$p = 0.1$	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) $r = 0.4$										
$p = 0.1$	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) $r = 0.6$										
$p = 0.1$	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				
$p\frac{1+r}{2}\Delta h$	2.02		1.96	7.62
	(0.22)		(0.22)	(1.35)
Distance to Indifference				
$p(1-r)(\bar{h} - H)$		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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
r	p	M	Mean $\bar{m}$	Mean Δm	AC	AD (CRE)	BC (RCRE)	BD	$CRE - RCRE$	p-value	N
0.2	0.1	1	8.41	−0.46	9.0	7.7	6.4	76.9	1.3	0.765	78
0.2	0.1	3	7.93	−2.27	30.7	16.0	9.3	44.0	6.7	0.254	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	0.483	77
0.2	0.2	1	10.26	−1.49	2.6	6.5	2.6	88.3	3.9	0.260	77
0.2	0.2	4	9.80	−1.68	31.6	7.9	27.6	32.9	−19.7	0.003	76
0.2	0.2	7	10.25	−0.83	40.3	9.7	27.8	22.2	−18.1	0.011	72
0.2	0.2	10	10.12	−1.10	84.9	4.1	8.2	2.7	−4.1	0.321	73
0.2	0.5	5	16.42	0.69	3.4	10.3	9.2	77.0	1.1	0.810	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	0.259	81
0.2	0.5	14	14.98	−0.93	39.4	22.5	21.1	16.9	1.4	0.859	71
0.2	0.8	8	20.49	−0.16	1.5	9.0	13.4	76.1	−4.5	0.443	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	0.223	81
0.2	0.8	20	19.96	0.89	25.3	39.2	15.2	20.3	24.1	0.003	79
0.2	0.9	10	21.70	−0.91	6.3	8.9	6.3	78.5	2.5	0.567	79
0.2	0.9	14	23.20	−1.61	2.4	13.1	7.1	77.4	6.0	0.227	84
0.2	0.9	18	21.08	−2.41	7.1	24.3	14.3	54.3	10.0	0.180	70
0.2	0.9	22	22.02	−0.94	16.9	36.9	9.2	36.9	27.7	0.001	65
0.4	0.1	1	7.71	−0.80	11.4	13.9	7.6	67.1	6.3	0.228	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	0.596	89
0.4	0.1	8	7.02	−0.90	93.1	0.0	5.2	1.7	−5.2	0.083	58
0.4	0.2	1	8.86	−0.61	9.0	10.1	3.4	77.5	6.7	0.083	89
0.4	0.2	4	8.95	−2.20	32.9	14.5	18.4	34.2	−3.9	0.552	76
0.4	0.2	7	9.74	−0.78	70.1	7.5	11.9	10.4	−4.5	0.409	67
0.4	0.2	10	7.52	−1.00	88.7	8.5	2.8	0.0	5.6	0.159	71
0.4	0.5	5	13.89	0.48	17.9	4.8	16.7	60.7	−11.9	0.018	84
0.4	0.5	8	13.52	−1.26	13.8	12.5	27.5	46.2	−15.0	0.033	80
0.4	0.5	11	14.90	−2.32	32.2	13.6	27.1	27.1	−13.6	0.103	59
0.4	0.5	14	13.46	−2.14	46.2	11.2	21.2	21.2	−10.0	0.117	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	0.320	79
0.4	0.8	16	18.47	−0.97	10.3	26.9	12.8	50.0	14.1	0.048	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	0.007	89
0.4	0.9	14	22.30	0.12	4.6	12.3	4.6	78.5	7.7	0.133	65
0.4	0.9	18	20.51	−0.29	4.0	17.3	6.7	72.0	10.7	0.059	75
0.4	0.9	22	21.37	−1.09	36.5	32.4	13.5	17.6	18.9	0.015	74
0.6	0.1	1	6.82	−0.25	15.5	15.5	9.9	59.2	5.6	0.349	71
0.6	0.1	3	6.68	−0.94	51.5	8.8	11.8	27.9	−2.9	0.597	68
0.6	0.1	5	6.23	−1.17	72.7	7.8	5.2	14.3	2.6	0.531	77
0.6	0.1	8	6.37	0.30	78.3	9.6	8.4	3.6	1.2	0.798	83
0.6	0.2	1	8.39	1.15	6.1	7.6	1.5	84.8	6.1	0.103	66
0.6	0.2	4	9.12	−1.15	37.7	11.5	16.4	34.4	−4.9	0.471	61
0.6	0.2	7	8.68	0.17	72.8	10.9	6.5	9.8	4.3	0.320	92
0.6	0.2	10	8.41	0.24	88.8	5.0	2.5	3.8	2.5	0.418	80
0.6	0.5	5	14.54	−2.62	14.3	5.2	22.1	58.4	−16.9	0.004	77
0.6	0.5	8	12.79	−2.14	15.3	16.7	30.6	37.5	−13.9	0.086	72
0.6	0.5	11	13.27	−2.13	38.9	13.3	24.4	23.3	−11.1	0.086	90
0.6	0.5	14	12.57	−1.07	45.0	10.0	21.7	23.3	−11.7	0.109	60
0.6	0.8	8	18.29	−1.49	4.3	7.6	5.4	82.6	2.2	0.567	92
0.6	0.8	12	18.37	−1.35	10.1	16.5	8.9	64.6	7.6	0.181	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	0.398	60
0.6	0.9	10	20.74	−3.40	8.3	6.9	2.8	81.9	4.2	0.260	72
0.6	0.9	14	22.65	−0.14	7.6	11.4	8.9	72.2	2.5	0.620	79
0.6	0.9	18	21.99	−2.23	7.7	26.9	9.0	56.4	17.9	0.007	78
0.6	0.9	22	22.70	−2.54	17.1	34.3	15.7	32.9	18.6	0.027	70

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

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
r	p	H	Mean $\bar{h}$	Mean Δh	AC	AD (CRE)	BC (RCRE)	BD	$CRE - RCRE$	p-value	N
0.2	0.1	13	20.99	−1.85	63.5	14.9	13.5	8.1	1.4	0.829	74
0.2	0.1	20	21.10	−1.31	38.6	13.3	16.9	31.3	−3.6	0.552	83
0.2	0.1	25	20.57	−0.85	39.7	19.1	10.3	30.9	8.8	0.182	68
0.2	0.1	30	20.59	−2.67	35.6	9.6	17.8	37.0	−8.2	0.182	73
0.2	0.2	20	22.54	−2.57	52.2	23.2	20.3	4.3	2.9	0.718	69
0.2	0.2	25	23.35	−1.18	49.3	8.2	20.5	21.9	−12.3	0.049	73
0.2	0.2	30	23.58	−1.65	51.4	8.3	18.1	22.2	−9.7	0.109	72
0.2	0.2	35	24.41	−2.35	35.7	13.1	22.6	28.6	−9.5	0.145	84
0.2	0.5	30	30.80	3.46	57.7	22.5	11.3	8.5	11.3	0.103	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	0.594	72
0.2	0.5	45	28.79	0.77	15.6	10.4	23.4	50.6	−13.0	0.049	77
0.2	0.8	33	34.58	5.23	30.0	41.7	13.3	15.0	28.3	0.002	60
0.2	0.8	38	33.72	5.70	26.9	32.8	11.9	28.4	20.9	0.010	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	0.159	70
0.2	0.9	35	33.31	0.17	22.2	30.6	18.1	29.2	12.5	0.129	72
0.2	0.9	40	35.30	2.26	9.2	19.7	15.8	55.3	3.9	0.567	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	0.109	75
0.4	0.1	13	21.38	−2.97	72.7	10.2	5.7	11.4	4.5	0.288	88
0.4	0.1	20	23.86	−0.48	61.7	13.3	8.3	16.7	5.0	0.410	60
0.4	0.1	25	23.56	−3.84	56.7	8.9	11.1	23.3	−2.2	0.640	90
0.4	0.1	30	22.45	−2.00	33.8	12.3	16.9	36.9	−4.6	0.496	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	0.443	57
0.4	0.2	30	25.81	−2.37	62.7	8.4	12.0	16.9	−3.6	0.470	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	0.418	78
0.4	0.5	35	30.14	−0.57	41.5	17.1	22.0	19.5	−4.9	0.483	82
0.4	0.5	40	31.00	−0.24	41.2	13.2	25.0	20.6	−11.8	0.117	68
0.4	0.5	45	31.76	0.44	33.3	9.3	29.3	28.0	−20.0	0.005	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	0.520	87
0.4	0.8	52	34.05	0.48	11.3	15.5	9.9	63.4	5.6	0.349	71
0.4	0.9	35	35.76	0.41	26.0	28.8	8.2	37.0	20.5	0.003	73
0.4	0.9	40	33.84	1.95	13.2	26.3	7.9	52.6	18.4	0.005	76
0.4	0.9	47	35.18	0.39	4.2	23.6	9.7	62.5	13.9	0.040	72
0.4	0.9	54	35.59	1.65	8.5	23.2	6.1	62.2	17.1	0.004	82
0.6	0.1	13	21.05	0.34	73.5	4.4	10.3	11.8	−5.9	0.208	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	0.640	79
0.6	0.2	20	25.94	0.79	74.6	11.3	7.0	7.0	4.2	0.409	71
0.6	0.2	25	23.64	1.07	66.3	8.4	12.0	13.3	−3.6	0.470	83
0.6	0.2	30	25.51	0.80	60.6	15.2	7.6	16.7	7.6	0.199	66
0.6	0.2	35	23.85	0.63	48.1	17.7	13.9	20.3	3.8	0.552	79
0.6	0.5	30	30.22	−1.77	64.2	17.3	11.1	7.4	6.2	0.300	81
0.6	0.5	35	31.13	−2.06	50.7	6.0	29.9	13.4	−23.9	0.001	67
0.6	0.5	40	30.57	0.47	32.9	8.9	27.8	30.4	−19.0	0.005	79
0.6	0.5	45	30.23	0.40	36.1	8.3	20.8	34.7	−12.5	0.049	72
0.6	0.8	33	34.55	2.20	53.3	16.0	18.7	12.0	−2.7	0.698	75
0.6	0.8	38	33.66	1.13	33.9	12.9	27.4	25.8	−14.5	0.072	62
0.6	0.8	45	35.81	0.32	14.8	12.5	19.3	53.4	−6.8	0.259	88
0.6	0.8	52	34.44	−0.15	9.5	17.6	8.1	64.9	9.5	0.109	74
0.6	0.9	35	34.92	0.57	25.3	24.1	21.7	28.9	2.4	0.748	83
0.6	0.9	40	35.09	0.89	13.6	18.5	9.9	58.0	8.6	0.145	81
0.6	0.9	47	34.42	1.49	5.5	16.4	9.6	68.5	6.8	0.254	73
0.6	0.9	54	35.21	0.00	3.2	11.3	6.5	79.0	4.8	0.370	62

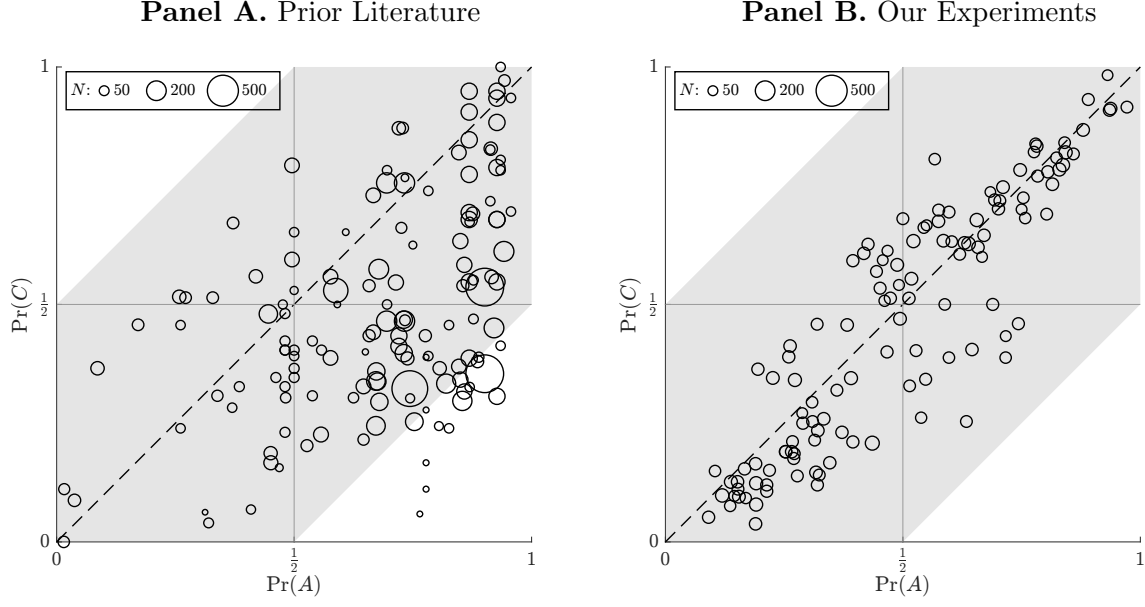**Panel A.** Prior Literature   **Panel B.** Our Experiments

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 are combinations that indicate a CRE, while points above the 45-degree line are combinations that indicate 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. (2022) 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

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

Tversky and Kahneman (1992) propose functional forms $\pi(q) = q^\gamma / [q^\gamma + (1-q)^\gamma]^{1/\gamma}$ and $u(x) = x^\alpha$. Given these functional forms, the underlying indifference valuations are given by:

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

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

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 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.

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 (0.008)	0.580 (0.014)	0.587 (0.014)	0.636 (0.014)
Utility Curvature: $\widehat{\alpha}$	1.209 (0.019)	1.351 (0.040)	1.179 (0.030)	1.112 (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).

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 4 of the main text.

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

$$m_{jit} = \mathbb{1}(j = AB) \left[\frac{p_{it}^{\gamma_{AB}}}{(p_{it}^{\gamma_{AB}} + (1 - p_{it})^{\gamma_{AB}})^{\frac{1}{\gamma_{AB}}}} \right]^{\frac{1}{\alpha_{AB}}}$$

$$+ \mathbb{1}(j = CD) \left[p_{it}^{\gamma_{CD}} \left(\frac{r_i^{\gamma_{CD}} + (1 - r_i)^{\gamma_{CD}}}{(r_i p_{it})^{\gamma_{CD}} + (1 - r_i p_{it})^{\gamma_{CD}}} \right)^{\frac{1}{\gamma_{CD}}} \right]^{\frac{1}{\alpha_{CD}}} + \varepsilon_{it}, \qquad \text{(E.3)}$$

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	9,000	9,000	9,000

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).