Online Appendix

A Proofs

Proof of Proposition 1: By assumption, 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 implies $\bar{\varepsilon}(M) = 0$ when $M = m^*$, and Γ increasing in ε implies that $\bar{\varepsilon}$ 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 $\Pr(\varepsilon_{AB} < 0) = 1/2$, $\Pr(A) > 1/2$ and $\Pr(C) > 1/2$. 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 $\Pr(\varepsilon_{AB} > 0) = 1/2$, $\Pr(A) < 1/2$ and $\Pr(C) < 1/2$. 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 $\Pr(A) = \Pr(C) = 1/2$ for all $k > 0$.

■

Proof of Proposition 2: Fix a specific paired choice task. We can parse the population into those who prefer A and C (AC types) and those who prefer B and D (BD types), where the assumption that $m^*_{AB,i} = m^*_{CD,i}$ for all i implies there are no other types. If there are no restrictions on the heterogeneity in preferences or choice noise, then, without loss of generality, we can characterize a 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

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

Proof of part (1): For any fixed $\Pr(A) = \omega$, we choose the parameters $(q, \lambda_A, \lambda_C, \lambda_B, \lambda_D)$ to minimize $\Pr(C)$ and to maximize $\Pr(C)$. Given the assumptions of part (1), the constraints on the parameters are $q \in [0, 1]$, $1 \geqslant \lambda_A \geqslant \lambda_C \geqslant 1/2$, and $1 \geqslant \lambda_B \geqslant \lambda_D \geqslant 1/2$.

To minimize $\Pr(C)$: We clearly want λ_C to be as small as possible and λ_D to be as large as possible, and we thus set $\lambda_C = 1/2$ and $\lambda_D = \lambda_B \equiv \lambda'$. Then $\Pr(A) = \omega$ implies $(1-q)(1-\lambda') = \omega - q\lambda_A$ and therefore $\Pr(C) = q/2 + \omega - q\lambda_A$, from which it follows that to minimize $\Pr(C)$ we (i) set $\lambda_A = 1$ and (ii) want to choose λ' to maximize q. Then $\Pr(A) = \omega$ and $\lambda_A = 1$ implies $q = (\omega - (1-\lambda'))/(1-(1-\lambda'))$, which is maximized at $\lambda' = 1$. Hence, the parameters that minimize $\Pr(C)$ are $q = \omega$, $\lambda_A = \lambda_B = \lambda_D = 1$, and $\lambda_C = 1/2$, which imply the minimum $\Pr(C) = \omega/2$.

To maximize $\Pr(C)$: We clearly want λ_C to be as large as possible and λ_D to be as small as possible, and we thus set $\lambda_D = 1/2$ and $\lambda_C = \lambda_A \equiv \lambda'$. Then $\Pr(A) = \omega$ implies $q\lambda' = \omega - (1-q)(1-\lambda_B)$ and therefore $\Pr(C) = \omega - (1-q)(1-\lambda_B) + (1-q)/2$, from which it follows that to maximize $\Pr(C)$ we (i) set $\lambda_B = 1$ and (ii) want to choose λ' to minimize q. Then $\Pr(A) = \omega$ and $\lambda_B = 1$ implies $q = \omega/\lambda'$, which is minimized at $\lambda' = 1$. Hence, the parameters that maximize $\Pr(C)$ are $q = \omega$, $\lambda_A = \lambda_B = \lambda_C = 1$, and $\lambda_D = 1/2$, which imply the maximum $\Pr(C) = \omega + (1-\omega)/2 = 1/2 + \omega/2$.

It follows that, for any fixed $\Pr(A)$, we must have $\Pr(A)/2 \leqslant \Pr(C) \leqslant 1/2 + \Pr(A)/2$.

Proof of part (2): We proceed as in the proof of part (1), except now the constraints are relaxed to $q \in [0, 1]$ 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 $\omega \geqslant 1/2$, as for part (a), we still want λ_C to be as small as possible and λ_D to be as large as possible, which with the weaker constraints means 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 $\Pr(A) = \omega$ and $\Pr(C) = 1$, so the maximum $\Pr(C) = 1$. For $\omega \leqslant 1/2$, as for part (a), we still want λ_C to be as large as possible and λ_D to be as small as possible, which with the weaker constraints means 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 $\Pr(A) - 1/2 \leqslant \Pr(C) \leqslant 1$.

■

Proof of Proposition 3: By assumption, $w_A v(m^*_{AB}) = w_B v(H)$ and $w_A v(m_{AB}) = w_B v(H) + \epsilon_{AB} = w_A v(m^*_{AB}) + \epsilon_{AB}$. This equation defines m_{AB} as a function of ϵ_{AB}, and solving yields $m_{AB}(\epsilon_{AB}) = v^{-1}(v(m^*_{AB}) + \epsilon_{AB}/w_A)$. Analogously, we can derive the function $m_{CD}(\epsilon_{CD}) = v^{-1}(v(m^*_{CD}) + \epsilon_{CD}/w_C)$. Note that $m_{AB}(0) = m^*_{AB}$ and $m_{CD}(0) = m^*_{CD}$.

Proof of part (1): Suppose $v(x)$ is linear, that is, $v(x) = \alpha x + \beta$ for some $\alpha > 0$ and any β. Then $v^{-1}(x) = (x - \beta)/\alpha$ and thus $m_{AB}(\epsilon_{AB}) = v^{-1}(v(m^*_{AB}) + \epsilon_{AB}/w_A) = v^{-1}(\alpha m^*_{AB} + \beta + \epsilon_{AB}/w_A) = m^*_{AB} + \epsilon_{AB}/(w_A\alpha)$. It immediately follows that, because $E_{\epsilon_{AB}}(\epsilon_{AB}) = 0$, $E_{\epsilon_{AB}}[m_{AB}(\epsilon_{AB})] = m^*_{AB}$. An analogous logic implies $E_{\epsilon_{CD}}[m_{CD}(\epsilon_{CD})] = m^*_{CD}$. Finally, if $\Delta m^* \equiv m^*_{CD} - m^*_{AB} = 0$, then $E[\Delta m] = E_{\epsilon_{CD}}[m_{CD}(\epsilon_{CD})] - E_{\epsilon_{AB}}[m_{AB}(\epsilon_{AB})] = m^*_{CD} - m^*_{AB} = 0$.

Proof of part (2): If $v(x)$ is strictly concave, then $v^{-1}(x)$ is strictly convex and therefore $m_{AB}(\epsilon_{AB})$ and $m_{CD}(\epsilon_{CD})$ are both strictly convex. By Jensen's inequality we have $E_{\epsilon_{AB}}[m_{AB}(\epsilon_{AB})] > m_{AB}(E_{\epsilon_{AB}}[\epsilon_{AB}]) = m^*_{AB}$ and $E_{\epsilon_{CD}}[m_{CD}(\epsilon_{CD})] > m_{CD}(E_{\epsilon_{CD}}[\epsilon_{CD}]) = m^*_{CD}$, thus establishing part (a).

For part (b), note that $\Delta m^* = 0$ implies $m^*_{CD} = m^*_{AB}$ and thus $m_{CD}(\epsilon_{CD}) = m_{AB}(\epsilon')$ where $\epsilon' = (w_A/w_C)\epsilon_{CD}$ and thus $\epsilon' \stackrel{d}{=} (w_A/w_C)\kappa\epsilon_{AB}$. If $\kappa = w_C/w_A$, then $\epsilon' \stackrel{d}{=} \epsilon_{AB}$, and thus $E_{\epsilon_{CD}}[m_{CD}(\epsilon_{CD})] = E_{\epsilon'}[m_{AB}(\epsilon')] = E_{\epsilon_{AB}}[m_{AB}(\epsilon_{AB})]$. It follows that $E[\Delta m] = E_{\epsilon_{CD}}[m_{CD}(\epsilon_{CD})] - E_{\epsilon_{AB}}[m_{AB}(\epsilon_{AB})] = 0$. If instead $\kappa > w_C/w_A$, then ϵ' is a mean-preserving spread of ϵ_{AB}, and thus $E_{\epsilon_{CD}}[m_{CD}(\epsilon_{CD})] = E_{\epsilon'}[m_{AB}(\epsilon')] > E_{\epsilon_{AB}}[m_{AB}(\epsilon_{AB})]$. It follows that

$E[\Delta m] = E_{\epsilon_{CD}}[m_{CD}(\epsilon_{CD})] - E_{\epsilon_{AB}}[m_{AB}(\epsilon_{AB})] > 0$. An analogous logic can be used to show that $\kappa < w_C/w_A$ implies $E[\Delta m] < 0$.

■

Proof of Proposition 4: Formally, the assumption that the joint distribution of $(\varepsilon_{AB}, \varepsilon_{CD})$ is symmetric around zero means that $(\varepsilon_{AB}, \varepsilon_{CD})$ has a continuous probability distribution f that satisfies $f(\varepsilon_{AB}, \varepsilon_{CD}) = f(-\varepsilon_{AB}, -\varepsilon_{CD})$ for all $(\varepsilon_{AB}, \varepsilon_{CD})$. The marginal distribution for ε_{CD} is $f_{\varepsilon_{CD}}(\varepsilon_{CD}) \equiv \int_{\varepsilon_{AB}=-\infty}^{\infty} f(\varepsilon_{AB}, \varepsilon_{CD}) d\varepsilon_{AB}$, and symmetry around zero implies $\int_{\varepsilon_{CD}=-\infty}^{0} f_{\varepsilon_{CD}}(\varepsilon_{CD}) d\varepsilon_{CD} = \int_{\varepsilon_{CD}=0}^{\infty} f_{\varepsilon_{CD}}(\varepsilon_{CD}) d\varepsilon_{CD} = 1/2$.

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 $\varepsilon_{CD} > \varepsilon_{AB}$. Hence:

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

Note that $\int_{\varepsilon_{AB}=-\infty}^{\varepsilon_{CD}} f(\varepsilon_{AB}, \varepsilon_{CD}) d\varepsilon_{AB} = f_{\varepsilon_{CD}}(\varepsilon_{CD}) - \int_{\varepsilon_{AB}=\varepsilon_{CD}}^{\infty} f(\varepsilon_{AB}, \varepsilon_{CD}) d\varepsilon_{AB}$ (since $\int_{\varepsilon_{AB}=-\infty}^{\infty} f(\varepsilon_{AB}, \varepsilon_{CD}) d\varepsilon_{AB} = f_{\varepsilon_{CD}}(\varepsilon_{CD})$), and note that

$$
\int_{\varepsilon_{AB}=\varepsilon_{CD}}^{\infty} f(\varepsilon_{AB}, \varepsilon_{CD}) d\varepsilon_{AB} = \int_{\varepsilon_{AB}=-\infty}^{-\varepsilon_{CD}} f(-\varepsilon_{AB}, \varepsilon_{CD}) d\varepsilon_{AB} = \int_{\varepsilon_{AB}=-\infty}^{-\varepsilon_{CD}} f(\varepsilon_{AB}, -\varepsilon_{CD}) d\varepsilon_{AB}
$$

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

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

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

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

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

■

B Additional Theoretical Results

B.1 EU with Additive Choice Noise

In this section, we consider the case of EU with additive choice noise to support some of the claims made in the main manuscript.

We begin with the implications of EU for paired choice tasks of the form:

***AB* Choice**:	Lottery A	$\equiv (M, 1)$	vs.	Lottery $B \equiv (H, p)$
***CD* Choice**:	Lottery C	$\equiv (M, r)$	vs.	Lottery $D \equiv (H, rp)$,

Normalizing $u(0) = 0$, the person's noise-free preferences imply

$$\begin{aligned} EU(A) - EU(B) &= u(M) - pu(H) \qquad \text{and} \\ EU(C) - EU(D) &= ru(M) - rpu(H) = r\left[u(M) - pu(H)\right]. \end{aligned}$$

Fixing (H, p, r), the person will prefer A and C for any $M > m^*$, and they will prefer B and D for any $M < m^*$, where m^* is their indifference point that satisfies $u(m^*) = pu(H)$.

To incorporate additive choice noise, we assume that the person experiences noise draws ϵ_{AB} and ϵ_{CD} such that their observed choices satisfy:

- Choose A over B if and only if $EU(A) - EU(B) = u(M) - pu(H) > \epsilon_{AB}$, and

- Choose C over D if and only if $EU(C) - EU(D) = r\,[u(M) - pu(H)] > \epsilon_{CD}$.

Substituting $u(m^*)$ for $pu(H)$ and rearranging, these become:

- Choose A over B if and only if $M > u^{-1}(u(m^*) + \epsilon_{AB})$, and

- Choose C over D if and only if $M > u^{-1}(u(m^*) + \epsilon_{CD}/r)$.

If we then define $\Gamma(m, \varepsilon) \equiv u^{-1}(u(m) + \varepsilon)$, $\varepsilon_{AB} \equiv \epsilon_{AB}$, and $\varepsilon_{CD} \equiv \epsilon_{CD}/r$, these become:

- Choose A over B if and only if $M > \Gamma(m^*, \varepsilon_{AB})$, and

- Choose C over D if and only if $M > \Gamma(m^*, \varepsilon_{CD})$.

If we now assume $\epsilon_{AB} \overset{d}{=} \epsilon_{CD} \overset{d}{=} \epsilon$ as is often assumed in the prior literature, then we have the case discussed in the text prior to Proposition 1. Moreover, as discussed after Proposition 1, for this case, $\varepsilon_{CD} \overset{d}{=} k\varepsilon_{AB}$ for $k = 1/r > 1$. Thus, under EU with additive i.i.d. choice noise, the noise is more impactful for the CD choices than for the AB choices.

However, if $\epsilon_{CD} \overset{d}{=} k'\epsilon_{AB}$ for some $k' < r$ (i.e., if the variance of ϵ_{AB} is sufficiently larger than the variance of ϵ_{CD}), then $\varepsilon_{CD} \overset{d}{=} k\varepsilon_{AB}$ for $k = k'/r < 1$. Hence, under EU with additive choice noise that is sufficiently larger for the AB choices, the noise can be more impactful for the AB choices than for the CD choices despite the person being closer to indifference for the latter.

B.2 Development for the h-Valuation Tasks

In Sections 2.1-2.3, we fix (H, p, r) and focus on behavior as a function of M, which links directly to our m-valuation tasks. Here, we fix (M, p, r) and focus on behavior as a function of H, which will link directly to our h-valuation tasks.

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

- Prefer $(M, 1)$ over (H, p) if and only if $H \leqslant h^*_{AB}$, and

- Prefer (M, r) over (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.

To model the impact of choice noise, we assume that, when asked to make a choice, the person experiences noise draws ε_{AB} and ε_{CD} such that their observed choices satisfy:

- Choose $(M, 1)$ over (H, p) if and only if $H \leqslant h_{AB} \equiv \Gamma(h^*_{AB}, \varepsilon_{AB})$; and
- Choose (M, r) over (H, pr) if and only if $H \leqslant h_{CD} \equiv \Gamma(h^*_{CD}, \varepsilon_{CD})$, where
- $\Gamma(h, \varepsilon)$ is such that $\Gamma(h, 0) = h$ for all h, and $\Gamma(h, \varepsilon') > \Gamma(h, \varepsilon'')$ for all h and $\varepsilon' > \varepsilon''$.

In this formulation, the function Γ captures how the person's underlying indifference point combines with noise to generate an effective indifference point that determines their choices. This framework encompasses the simple case in which the effective indifference points h_{AB} and h_{CD} are the truth plus noise, in which case $\Gamma(h^*, \varepsilon) = h^* + \varepsilon$. It also encompasses EU with additive choice noise, in which case $\Gamma(h^*, \varepsilon) = u^{-1}(u(h^*) + \varepsilon)$ where $h^* \equiv h^*_{AB} = h^*_{CD}$, and where $\varepsilon_{AB} = -\epsilon_{AB}/p$ and $\varepsilon_{CD} = -\epsilon_{CD}/(pr)$ (with ϵ_{AB} and ϵ_{CD} defined as in Appendix B.1). With this formulation, analogues for Propositions 1-4 follow straightforwardly, and so are omitted.

Finally, consider analogues to the predictions for stage-2 behavior from Section 5.1. As in the text, we start with the simplest version of the model above where observed choices satisfy:

- AB: Choose $(\$p30, 1)$ over $(\$H, p)$ if and only if $H \leqslant h^*_{AB} + \varepsilon_{AB}$;
- CD: Choose $(\$p30, r)$ over $(\$H, pr)$ if and only if $H \leqslant h^*_{CD} + \varepsilon_{CD}$; and
- $\varepsilon_{AB} \stackrel{d}{=} -\epsilon/p$ and $\varepsilon_{CD} \stackrel{d}{=} -\epsilon/(pr)$.[36]

Under these assumptions:

$$CRE - RCRE \equiv \Pr(A) - \Pr(C) = \Pr(\epsilon/p < h^*_{AB} - H) - \Pr(\epsilon/(pr) < h^*_{CD} - H).$$

[36]The specific dependence on p and r is motivated from the case of EU with additive i.i.d. utility noise. For that case, a person will choose A over B when $u(p30) > pu(H) + \epsilon$, and C over D when $ru(p30) > pru(H) + \epsilon$. Substituting $pu(h^*) = u(p30)$ and rearranging, these inequalities become $u(h^*) - u(H) > \epsilon/p$ and $u(h^*) - u(H) > \epsilon/(pr)$.

Substituting $\bar{h}^* \equiv (h^*_{AB} + h^*_{CD})/2$ and $\Delta h^* = h^*_{AB} - h^*_{CD}$, the predicted likelihood becomes

$$CRE - RCRE = \Pr\left(\epsilon < p(\bar{h}^* - H) + \frac{1}{2}p\Delta h^*\right) - \Pr\left(\epsilon < pr(\bar{h}^* - H) - \frac{1}{2}pr\Delta h^*\right).$$

Finally, to facilitate comparing predictions for different values of r, we focus on the difference between the two probability thresholds. Doing so yields two key variables: (i) a *scaled value difference* term $0.5(1+r)p\Delta h^*$, and (ii) a *scaled distance to indifference* term $(1-r)p(\bar{h}^*-H)$.

Given the parallel structure, one can derive a figure analogous to Figure 5, where we use $0.5(1+r)p\Delta h^*$ in place of $0.5(1+r)\Delta m^*$, and $(1-r)p(\bar{h}^* - H)$ in place of $(1-r)(M - \bar{m}^*)$. The predictions would be analogous: The larger the scaled value difference, the larger is $CRE - RCRE$; and, provided its magnitude is not too large, the larger the scaled distance to indifference, the larger is $CRE - RCRE$. Hence, for the regressions in Sections 5.2 and 5.3 that use the h-valuation data, we use as regressors $0.5(1+r)p\Delta h^*$ and $(1-r)p(\bar{h}^* - H)$.

B.3 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 5, and we plot empirical relationships in Figures 6 and 7 that confirm those theoretical predictions. In this section, we support the claims made in footnote 29 that predictions for Figures 6 and 7 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 6. 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 4b. 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 6.

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 7. 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 7.

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 6 and 7. 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 6), and the additional assumption that the distribution of $\bar{m}^*$ is symmetric around $\bar{m}^* = E(\bar{m}^*)$ (used for predictions for Figure 7). It is possible that, with the appropriate assumptions about correlated heterogeneity and asymmetric distributions, one might be able to generate predictions closer to Figures 6 and 7.

C Supplementary Figures and Tables

Table C.1: Predictions for Δm under CPT Versus Observed Δm in Data

	(1)	(2)	(3)	(4)	(5)
		Current Estimates:			
	TK Estimates	Lower Bound	Point Estimate	Upper Bound	Data
			Panel A: $r = 0.2$		
$p = 0.1$	3.51	4.07	4.76	5.45	−1.55
$p = 0.2$	5.59	5.66	6.40	7.15	−1.29
$p = 0.5$	9.26	7.82	8.54	9.26	0.04
$p = 0.8$	9.51	7.20	7.84	8.48	1.00
$p = 0.9$	7.93	5.78	6.36	6.94	−1.47
			Panel B: $r = 0.4$		
$p = 0.1$	3.69	4.02	4.69	5.36	−0.63
$p = 0.2$	5.62	5.62	6.34	7.06	−1.14
$p = 0.5$	8.94	7.94	8.63	9.31	−1.22
$p = 0.8$	9.22	7.56	8.19	8.82	−0.60
$p = 0.9$	7.75	6.17	6.75	7.33	−0.16
			Panel C: $r = 0.6$		
$p = 0.1$	3.33	2.66	3.15	3.64	−0.49
$p = 0.2$	4.98	3.89	4.45	5.01	0.14
$p = 0.5$	7.88	5.89	6.49	7.09	−2.05
$p = 0.8$	8.45	5.89	6.47	7.05	−1.26
$p = 0.9$	7.29	4.84	5.37	5.90	−2.03

Note: Columns (1)-(4) present predictions for $\Delta m^* \equiv m^*_{CD} - m^*_{AB}$ under a CPT model with $\pi(q) = q^\gamma/[q^\gamma + (1-q)^\gamma]^{1/\gamma}$ and $v(x) = x^\alpha$. Column (1) uses the parameter values proposed by Tversky and Kahneman (1992): $\gamma = 0.61$ and $\alpha = 0.88$. Columns (2)-(4) instead use parameter estimates based on our stage-1 m_{AB}-valuations reported in Appendix Table D.1, with separate estimates for each r. Column (3) reports predictions using the point estimates, while columns (2) and (4) report lower and upper bounds of the 95-percent confidence interval computed using the delta method. Column (5) reports mean Δm values in our data from the m-valuation tasks.

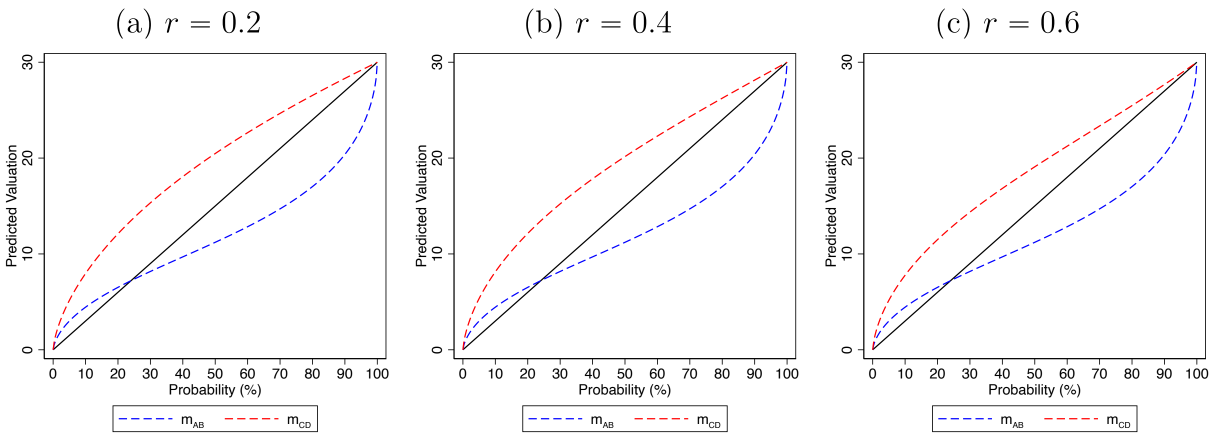

Figure C.1: Predicted m-valuations under CPT. Predictions use functional form and parameter values from Tversky and Kahneman (1992) described in notes for Table C.1.

Table C.2: 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 C.3: 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 C.4: 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 C.5: 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 C.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 C.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_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 C.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 C.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 C.10: 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) p-value	(12) 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 C.11: 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) p-value	(12) 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

Table C.12: 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 $(1-r)pH$.

D Estimating a CPT Model

In this section, we develop a structural CPT model and estimate its key parameters. Following our development in Section 2.3, under CPT a person will have underlying indifference valuations m^*_{AB} and m^*_{CD} that satisfy

$$\begin{aligned} v(m^*_{AB}) &= \pi(p)v(H) \quad \text{and} \\ v(m^*_{CD}) &= \frac{\pi(rp)}{\pi(r)}v(H). \end{aligned}$$

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

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

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

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

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

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

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 (D.1) to estimate the parameters $(\widehat{\alpha}, \widehat{\gamma})$ (Tversky and Kahneman, 1992).

Panel A of Table D.1 presents estimates using our data on m_{AB} valuations. Column (1)

Table D.1: CPT Estimates Using Data on m-Valuations

	(1) Overall	(2) $r = 0.2$	(3) $r = 0.4$	(4) $r = 0.6$
	Panel A: Using Data on m_{AB}-Valuations			
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)
	Panel B: Using Data on m_{CD}-Valuations			
Probability Weighting: $\widehat{\gamma}$	0.368	†	0.289	0.299
	(0.006)		(0.002)	(0.004)
Utility Curvature: $\widehat{\alpha}$	0.193	†	0.064	0.162
	(0.009)		(0.003)	(0.007)
Individuals	900	298	303	299
Observations	4,500	1,490	1,515	1,495

Note: Nonlinear least squares estimation. The model assumes functional forms $\pi(q) = q^\gamma/[q^\gamma + (1-q)^\gamma]^{1/\gamma}$ and $v(x) = x^\alpha$. Individual-cluster-robust standard errors in parentheses. Panel A estimates use data on m_{AB}-valuations and the structural equation (D.1). Panel B estimates use data on m_{CD}-valuations and the structural equation (D.2). † denotes that we were unable to obtain reliable estimates.

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.

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 (D.1). We use the estimates in columns (2)-(4) to construct the CPT predictions denoted by the blue and red dashed lines in Figure 3 of the main text.

While the literature has focused on estimating $(\widehat{\alpha}, \widehat{\gamma})$ using data on m_{AB} valuations and equation (D.1), we can also estimate these parameters using our data on m_{CD} valuations and equation (D.2). Panel B of Table D.1 presents the estimates using data on m_{CD} valuations. The results differ substantially from those using our data on m_{AB} valuations. The estimate of $\widehat{\gamma} = 0.368$ implies extreme probability weighting, and the estimate of $\widehat{\alpha} = 0.193$ implies absurd levels of risk aversion, even at relatively small stakes (Rabin, 2000). Columns (2)-(4) report results when we attempt separate estimates for each common-ratio factor r. The estimates are even more extreme for $r = 0.4$ and $r = 0.6$, and we were unable to obtain reliable estimates for the $r = 0.2$ data.[37]

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:

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

where $j \in \{AB, CD\}$ denotes the valuation type. Table D.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.

[37] For $r = 0.2$, the estimates for $\widehat{\gamma}$ and $\widehat{\alpha}$ do not make sense given the model, as both are large and negative. Moreover, the program cannot compute standard errors for the estimate of alpha.

Table D.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 $v(x) = x^\alpha$. Individual-cluster-robust standard errors in parentheses. The estimation uses data on both m_{AB} and m_{CD} valuations and the structural equation (D.3).