Connecting Common Ratio and Common Consequence Preferences

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September 23, 2024

Supplementary Material

C Predictions of Existing Non-EU Models (for Table 1)

In this appendix, we derive the predictions presented in Table 1. To review the structure, given parameters (M, p, r), h^*_{AB}, $h^*_{AB'}$, and h^*_{CD} are the *indifference values* that satisfy the following indifference conditions:

$$(M, 1) \sim (h^*_{AB}, p)$$

$$(M, 1) \sim (h^*_{AB'}, pr; M, 1-r)$$

$$(M, r) \sim (h^*_{CD}, pr)$$

The objects of interest are then:

$$\Delta^*_{CR} \equiv h^*_{AB} - h^*_{CD}$$

$$\Delta^*_{CC} \equiv h^*_{AB'} - h^*_{CD}$$

$$\Delta^*_{MX} \equiv h^*_{AB} - h^*_{AB'}$$

C.1 Original Prospect Theory (OPT)

Under original prospect theory (OPT) as in Kahneman and Tversky (1979), the indifference values are determined from:

$$\begin{aligned}
v(M) &= \pi(p)v(h^*_{AB}) & \iff \quad & h^*_{AB} = v^{-1}\left(\frac{1}{\pi(p)}v(M)\right) \\
v(M) &= \pi(pr)v(h^*_{AB'}) + \pi(1-r)v(M) & \iff \quad & h^*_{AB'} = v^{-1}\left(\frac{1-\pi(1-r)}{\pi(pr)}v(M)\right) \\
\pi(r)v(M) &= \pi(pr)v(h^*_{CD}) & \iff \quad & h^*_{CD} = v^{-1}\left(\frac{\pi(r)}{\pi(pr)}v(M)\right)
\end{aligned}$$

Hence:

$$\begin{aligned}
\Delta^*_{CR} > 0 \quad &\iff \quad h^*_{AB} > h^*_{CD} \quad \iff \quad \frac{1}{\pi(p)} > \frac{\pi(r)}{\pi(pr)} \\
\Delta^*_{CC} > 0 \quad &\iff \quad h^*_{AB'} > h^*_{CD} \quad \iff \quad 1 - \pi(1-r) > \pi(r) \\
\Delta^*_{MX} > 0 \quad &\iff \quad h^*_{AB} > h^*_{AB'} \quad \iff \quad \frac{1}{\pi(p)} > \frac{1-\pi(1-r)}{\pi(pr)}
\end{aligned}$$

In this formulation, $v(x)$ is a value function defined over experimental gains and losses, but note that as long as v is monotonically increasing, its form is irrelevant to OPT's predictions for the sign of Δ^*_{CR}, Δ^*_{CC}, and Δ^*_{MX}. In contrast, $\pi(q)$ is a probability weighting function that transforms probabilities into decision weights, and its form fully determines those predictions. Here, we derive predictions using the functional form from Tversky and Kahneman (1992):

$$\pi(q) = \frac{q^\delta}{\left[q^\delta + (1-q)^\delta\right]^{1/\delta}}$$

This one-parameter functional form nests the EU case of $\pi(q) = q$ when $\delta = 1$. For $\delta \in (0.279, 1)$, it has the inverse-S shape emphasized by Tversky and Kahneman (1992) and the subsequent literature: It is initially concave and then convex, with overweighting ($\pi(q) > q$) for small q and then underweighting ($\pi(q) < q$) for larger q.[3] Tversky and Kahneman (1992) suggest a δ of roughly 0.6. For $\delta > 1$, this functional form initially yields an S-shape—initially convex and then concave with underweighting for small q and then overweighting for larger q—but eventually becomes convex with underweighting for all $q \in (0, 1)$.

<u>OPT Result:</u>

(1) $\delta \in (0.279, 1)$ implies $\Delta^*_{CR} > 0$ and $\Delta^*_{CC} > 0$; Δ^*_{MX} can be positive or negative depending on (p, r) combination.

(2) $\delta > 1$ implies $\Delta^*_{CR} < 0$, $\Delta^*_{CC} > 0$, and $\Delta^*_{MX} < 0$.

Proof: Consider first the Δ^*_{CR} results. Rearranging the condition above yields

$$\Delta^*_{CR} : 0 \quad \Longleftrightarrow \quad \frac{\pi(pr)}{\pi(r)} : \pi(p)$$

which we can write as

$$\frac{(pr)^\delta}{\left[(pr)^\delta + (1-pr)^\delta\right]^{1/\delta}} \frac{\left[(r)^\delta + (1-r)^\delta\right]^{1/\delta}}{(r)^\delta} : \frac{(p)^\delta}{\left[(p)^\delta + (1-p)^\delta\right]^{1/\delta}}.$$

Canceling terms and then taking both sides to the power δ yields

$$\frac{(r)^\delta + (1-r)^\delta}{(pr)^\delta + (1-pr)^\delta} : \frac{1}{(p)^\delta + (1-p)^\delta}$$

$$\left[(p)^\delta + (1-p)^\delta\right]\left[(r)^\delta + (1-r)^\delta\right] : (pr)^\delta + (1-pr)^\delta$$

[3] For $\delta \in (0, 0.279)$, $\pi(q)$ is nonmonotonic (Ingersoll, 2008).

$$(pr)^\delta + (p(1-r))^\delta + (r(1-p))^\delta + ((1-p)(1-r))^\delta : (pr)^\delta + (1-pr)^\delta$$

$$(p(1-r))^\delta + (r(1-p))^\delta + ((1-p)(1-r))^\delta : (1-pr)^\delta$$

Note that we can rewrite this as

$$a^\delta + b^\delta + c^\delta : d^\delta$$

where $a = p(1-r)$, $b = r(1-p)$, $c = (1-p)(1-r)$, and $d = 1-pr$, and note that $a+b+c = d$. Then because the function $f(x) = x^\delta$ is concave when $\delta < 1$, it follows that $a+b+c = d$ implies $f(a)+f(b)+f(c) > f(d)$, and thus $\delta < 1$ implies $\Delta^*_{CR} > 0$. Analogously, $f(x)$ is convex when $\delta > 1$, so $a+b+c = d$ implies $f(a)+f(b)+f(c) < f(d)$, and thus $\delta > 1$ implies $\Delta^*_{CR} < 0$.

Next consider the Δ^*_{CC} results. Rearranging the condition above yields

$$\Delta^*_{CC} : 0 \quad \Longleftrightarrow \quad 1 : \pi(r) + \pi(1-r)$$

which we can write as

$$1 : \frac{(r)^\delta}{[(r)^\delta + (1-r)^\delta]^{1/\delta}} + \frac{(1-r)^\delta}{[(r)^\delta + (1-r)^\delta]^{1/\delta}}$$

$$1 : \left[(r)^\delta + (1-r)^\delta\right]^{1-1/\delta}$$

When $\delta < 1$: $r < 1$ and $\delta < 1$ implies $r^\delta > r$ and $(1-r)^\delta > 1-r$ and thus $(r)^\delta + (1-r)^\delta > 1$. In addition, $\delta < 1$ implies $1 - 1/\delta < 0$, and thus $\left[(r)^\delta + (1-r)^\delta\right]^{1-1/\delta} < 1$ and therefore $\Delta^*_{CC} > 0$.

When $\delta > 1$: $r < 1$ and $\delta > 1$ implies $r^\delta < r$ and $(1-r)^\delta < 1-r$ and thus $(r)^\delta + (1-r)^\delta < 1$. In addition, $\delta > 1$ implies $1-1/\delta > 0$, and thus $\left[(r)^\delta + (1-r)^\delta\right]^{1-1/\delta} < 1$ and therefore again $\Delta^*_{CC} > 0$.

Finally, when $\delta > 1$, the combination of $\Delta^*_{CR} < 0$ and $\Delta^*_{CC} > 0$ implies $\Delta^*_{MX} = \Delta^*_{CR} - \Delta^*_{CC} < 0$. In contrast, for $\delta < 1$, it is possible for Δ^*_{MX} to be positive or negative.

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C.2 Cumulative Prospect Theory (CPT)

Cumulative prospect theory (CPT) as in Tversky and Kahneman (1992) differs from OPT only for gambles with more than one non-zero outcome. In our context, this means they differ only in the evaluation of lottery B'. Hence, the h^*_{AB} and h^*_{CD} indifference values are as in OPT, but the $h^*_{AB'}$ indifference value is now determined from:

$$v(M) = \pi(pr)v(h^*_{AB'}) + (\pi(pr+1-r) - \pi(pr))v(M)$$

$$\iff \quad h^*_{AB'} = v^{-1}\left(\frac{1-(\pi(pr+1-r)-\pi(pr))}{\pi(pr)}v(M)\right)$$

Hence, we now have:

$$\begin{aligned}
\Delta^*_{CR} > 0 &\iff h^*_{AB} > h^*_{CD} &\iff& \frac{1}{\pi(p)} > \frac{\pi(r)}{\pi(pr)} \\
\Delta^*_{CC} > 0 &\iff h^*_{AB'} > h^*_{CD} &\iff& 1-(\pi(pr+1-r)-\pi(pr)) > \pi(r) \\
\Delta^*_{MX} > 0 &\iff h^*_{AB} > h^*_{AB'} &\iff& \frac{1}{\pi(p)} > \frac{1-(\pi(pr+1-r)-\pi(pr))}{\pi(pr)}
\end{aligned}$$

As in OPT, the value function v is irrelevant for the model's predictions for the sign of Δ^*_{CR}, Δ^*_{CC}, and Δ^*_{MX}, which are fully determined by the form of the probability weighting function π. Here, we again derive predictions using the functional form from Tversky and Kahneman (1992).

CPT Result:

(1) $\delta \in (0.279, 1)$ implies $\Delta^*_{CR} > 0$ and $\Delta^*_{CC} > 0$; Δ^*_{MX} can be positive or negative.

(2) $\delta > 1$ implies $\Delta^*_{CR} < 0$; Δ^*_{CC} and Δ^*_{MX} can be positive or negative.

Proof: The Δ^*_{CR} equations are the same as in OPT, and thus the proof from the OPT Result still holds. So we just need to prove that $\delta \in (0.279, 1)$ implies $\Delta^*_{CC} > 0$.

We begin with two preliminary results. First, note that for all $\delta > 0.279$,

$$\pi(1/2) = \frac{(1/2)^\delta}{[2(1/2)^\delta]^{1/\delta}} = \left(\frac{1}{2}\right)^{\delta - \frac{\delta-1}{\delta}} < \frac{1}{2} \qquad \text{because } \delta - \frac{\delta-1}{\delta} > 1.$$

Second, we prove that

$$\pi(1-a) - \pi(1-b) > \pi(b) - \pi(a) \qquad \text{for any } 0 \leqslant a < b \leqslant 1/2 \tag{C.1}$$

In words, equation (C.1) says that $\pi(q)$ is steeper for q above $1/2$ than for q below $1/2$. To prove this, we rewrite the inequality in equation (C.1) as $\pi(a) + \pi(1-a) > \pi(b) + \pi(1-b)$, which yields

$$\frac{(a)^\delta + (1-a)^\delta}{[(a)^\delta + (1-a)^\delta]^{(1/\delta)}} > \frac{(b)^\delta + (1-b)^\delta}{[(b)^\delta + (1-b)^\delta]^{(1/\delta)}}$$

$$\left[(a)^{\delta}+(1-a)^{\delta}\right]^{1-(1/\delta)}>\left[(b)^{\delta}+(1-b)^{\delta}\right]^{1-(1/\delta)}$$

Then because

$$\frac{d\left[(x)^{\delta}+(1-x)^{\delta}\right]^{1-(1/\delta)}}{dx}=(1-(1/\delta))\left[(x)^{\delta}+(1-x)^{\delta}\right]^{-(1/\delta)}\delta(x^{\delta-1}-(1-x)^{\delta-1})$$

is negative as long as $\delta<1$ and $x<1/2$, equation (C.1) follows.

We now prove that $\delta\in(0.279,1)$ implies $\Delta^*_{CC}>0$. The Δ^*_{CC} condition can be written as

$$\Delta^*_{CC}>0\quad\Longleftrightarrow\quad\frac{1+\pi(pr)}{2}>\frac{\pi(pr+1-r)+\pi(r)}{2}$$

Let's define z such that $\min\{r,pr+1-r\}\equiv pr+z$, and note that this implies that $\max\{r,pr+1-r\}=1-z$ (so that $(r)+(pr+1-r)=(pr+z)+(1-z)=1+pr$). We can then rewrite the Δ^*_{CC} condition as

$$\Delta^*_{CC}>0\quad\Longleftrightarrow\quad\frac{1+\pi(pr)}{2}>\frac{\pi(pr+z)+\pi(1-z)}{2}$$

The LHS is the y-value for the midpoint of the line segment that connects the points $(pr,\pi(pr))$ and $(1,1)$, while the RHS is the y-value for the midpoint of the line segment that connects the points $(pr+z,\pi(pr+z))$ and $(1-z,\pi(1-z))$, where the x-value for both midpoints is $(1+pr)/2$. Given the inverse-S shape of $\pi(q)$ for $\delta\in(0.279,1)$ and the fact that $\pi(1/2)<1/2$, the LHS line segment can intersect $\pi(q)$ for at most one $\bar{q}\in(pr,1)$. Moreover, if such a $\bar{q}$ exists, then $pr<\bar{q}<1/2$, $\pi(pr)>pr$ and $\pi(\bar{q})>\bar{q}$.

If such a $\bar{q}$ does not exist, then the LHS line segment must be everywhere above the RHS line segment, and thus the Δ^*_{CC} condition holds.

If such a $\bar{q}$ exists but $pr+z>\bar{q}$, then again the LHS line segment must be everywhere above the RHS line segment, and thus the Δ^*_{CC} condition holds.

Finally, suppose such a $\bar{q}$ exists but $pr+z<\bar{q}<1/2$. If π is concave at $\bar{q}$ and thus concave for all $q<\bar{q}$, then $\pi(pr+z)-\pi(pr)<\pi(z)<1-\pi(1-z)$ (where the first inequality follows from the concavity of π for $q<\bar{q}$ and the second inequality follows from equation (C.1) with $a=0$ and $b=z<1/2$), and thus the Δ^*_{CC} condition holds. Suppose instead π is convex at $\bar{q}$ and thus convex for all $q>\bar{q}$. Because $pr+z<\bar{q}<1/2$ and thus $1-pr-z>1/2$, we have $\pi(pr+z)-\pi(pr)<\pi(1-pr)-\pi(1-pr-z)<1-\pi(1-z)$ (where the first inequality follows from equation (C.1) and the second inequality follows from the fact that π is convex for all $q>\bar{q}$). Hence, again the Δ^*_{CC}

condition holds.

This covers all cases, and hence $\delta \in (0.279, 1)$ implies $\Delta^*_{CC} > 0$.

Finally, we note that a symmetric argument does not work for $\delta > 1$ because equation (C.1) does not flip to maintain the symmetry. More precisely, if $pr + z > \bar{q}$, an analogous argument implies that $\Delta^*_{CC} < 0$. But when $pr+z < \bar{q}$, equation (C.1) still implies $\pi(pr+z)-\pi(pr) < \pi(1-pr)-\pi(1-pr-z)$, and this creates the possibility that $\Delta^*_{CC} > 0$—in fact, it is easy to generate such examples.

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C.3 Kőszegi-Rabin Loss Aversion Under CPE

We next consider predictions from the Kőszegi-Rabin (2007) model of loss aversion when we apply choice-acclimating personal equilibrium (CPE). Under CPE, the utility from a lottery $X \equiv (x, q_H; 0, q_L)$ where $x > 0$ and $q_H + q_L = 1$ is

$$U(X) = q_H u(x) - \Lambda q_H q_L u(x)$$

and the utility from a lottery $Y \equiv (x, q_H; y, q_M; 0, q_L)$ where $x > y > 0$ and $q_H + q_M + q_L = 1$ is

$$U(Y) = q_H u(x) + q_M u(y) - \Lambda q_H (q_M + q_L) u(x) - \Lambda q_M (q_L - q_H) u(y).$$

where the parameter Λ is a measure of loss aversion.[4] $\Lambda > 0$ implies loss aversion (losses loom larger than gains), and $\Lambda < 0$ implies gain attraction (gains loom larger than losses).In this formulation, u is the person's intrinsic utility over outcomes (e.g., that might be used under EU), where we have normalized $u(0) = 0$.

Applied to our context, the indifference values are determined from:

$$\begin{aligned}
u(M) &= pu(h^*_{AB}) - \Lambda p(1-p)u(h^*_{AB}) \\
u(M) &= pru(h^*_{AB'}) + (1-r)u(M) - \Lambda pr(1-pr)u(h^*_{AB'}) - \Lambda(1-r)r(1-2p)u(M) \\
ru(M) - \Lambda r(1-r)u(M) &= pru(h^*_{CD}) - \Lambda pr(1-pr)u(h^*_{CD})
\end{aligned}$$

[4] The Kőszegi and Rabin (2007) model has two parameters, a parameter η which captures the relative importance of gain-loss utility versus intrinsic utility, and a parameter λ that captures loss aversion. However, under CPE these parameters always appear as the product $\eta(\lambda - 1)$ and thus cannot be distinguished, so we define $\Lambda \equiv \eta(\lambda - 1)$.

from which we can derive:

$$h^*_{AB} = u^{-1}\left(\frac{1}{p(1-\Lambda(1-p))}u(M)\right)$$
$$h^*_{AB'} = u^{-1}\left(\frac{1+\Lambda(1-r)(1-2p)}{p(1-\Lambda(1-pr))}u(M)\right)$$
$$h^*_{CD} = u^{-1}\left(\frac{1-\Lambda(1-r)}{p(1-\Lambda(1-pr))}u(M)\right).$$

To ensure this model is well-behaved, we put two restrictions on the range of Λ. First, if Λ becomes too positive, utility can be *decreasing* in h. For instance, the utility from lottery D can be written as $[pr - \Lambda pr(1-pr)]u(h)$, and this is increasing in h only if $\Lambda < 1/(1-pr)$. To rule out these perverse cases, we restrict $\Lambda \leqslant 1$. Second, if Λ becomes too negative, the indifference values can be smaller than M. For instance, $h^*_{AB} > M$ requires $1/(p(1-\Lambda(1-p))) > 1$ or $\Lambda > -1/p$. To rule out these perverse cases, we restrict $\Lambda \geqslant -1$.

With these restrictions in place:

$$\begin{array}{ccccccc}
\Delta^*_{CR} > 0 & \Longleftrightarrow & h^*_{AB} > h^*_{CD} & \Longleftrightarrow & \dfrac{1}{p(1-\Lambda(1-p))} & > & \dfrac{1-\Lambda(1-r)}{p(1-\Lambda(1-pr))} \\
\Delta^*_{CC} > 0 & \Longleftrightarrow & h^*_{AB'} > h^*_{CD} & \Longleftrightarrow & 1+\Lambda(1-r)(1-2p) & > & 1-\Lambda(1-r) \\
\Delta^*_{MX} > 0 & \Longleftrightarrow & h^*_{AB} > h^*_{AB'} & \Longleftrightarrow & \dfrac{1}{p(1-\Lambda(1-p))} & > & \dfrac{1+\Lambda(1-r)(1-2p)}{p(1-\Lambda(1-pr))}
\end{array}$$

Note that, much as for the value function under OPT and CPT, the utility function u is irrelevant for the model's predictions for the sign of Δ^*_{CR}, Δ^*_{CC}, and Δ^*_{MX}, where in this model these are fully determined by the value of the parameter Λ.

Koszegi-Rabin CPE Result:

(1) $\Lambda \in (0,1]$ implies $\Delta^*_{CR} > 0$, $\Delta^*_{CC} > 0$, and $\Delta^*_{MX} < 0$.

(2) $\Lambda \in [-1,0)$ implies $\Delta^*_{CR} < 0$, $\Delta^*_{CC} < 0$, and $\Delta^*_{MX} > 0$.

Proof: Consider first the Δ^*_{CR} condition, which we can write as:

$$\Delta^*_{CR} : 0 \quad \Longleftrightarrow \quad \frac{1}{1-\Lambda(1-p)} : \frac{1-\Lambda(1-r)}{1-\Lambda(1-pr)}$$

The LHS is independent of r. The RHS is equal to the LHS when $r = 1$, and moreover

$$\frac{dRHS}{dr} = \frac{(1-\Lambda(1-pr))\Lambda - (1-\Lambda(1-r))\Lambda p}{(1-\Lambda(1-pr))^2} = \frac{(1-p)(\Lambda-\Lambda^2)}{(1-\Lambda(1-pr))^2}$$

If $\Lambda \in (0,1]$, then $\Lambda - \Lambda^2 > 0$ and thus $dRHS/dr > 0$, from which it follows that $\Delta^*_{CR} > 0$ for all $r < 1$.

If $\Lambda \in [-1,0)$, then $\Lambda - \Lambda^2 < 0$ and thus $dRHS/dr < 0$, from which it follows that $\Delta^*_{CR} < 0$ for all $r < 1$.

Next consider the Δ^*_{CC} condition, which we can write as:

$$\begin{aligned}
\Delta^*_{CC} : 0 \quad &\Longleftrightarrow \quad 1 + \Lambda(1-r)(1-2p) \quad : \quad 1 - \Lambda(1-r) \\
&\Longleftrightarrow \qquad 2\Lambda(1-r)(1-p) \quad : \quad 0
\end{aligned}$$

Since the LHS is positive for $\Lambda \in (0,1]$ and negative for $\Lambda \in [-1,0)$, $\Delta^*_{CC} > 0$ for any $\Lambda \in (0,1]$ and $\Delta^*_{CC} < 0$ for any $\Lambda \in [-1,0)$.

Finally consider the Δ^*_{MX} condition, which we can write as:

$$\Delta^*_{MX} : 0 \quad \Longleftrightarrow \frac{1}{1-\Lambda(1-p)} : \frac{1 + \Lambda(1-r)(1-2p)}{1-\Lambda(1-pr)}$$

The LHS is independent of r. The RHS is equal to the LHS when $r = 1$, and moreover

$$\begin{aligned}
\frac{dRHS}{dr} &= \frac{(1-\Lambda(1-pr))(-\Lambda(1-2p)) - (1+\Lambda(1-r)(1-2p))\Lambda p}{(1-\Lambda(1-pr))^2} \\
&= \frac{\Lambda(p-1) + \Lambda^2(1-2p)(1-p)}{(1-\Lambda(1-pr))^2} = \frac{(1-p)\Lambda\left[-1+\Lambda(1-2p)\right]}{(1-\Lambda(1-pr))^2}
\end{aligned}$$

For $\Lambda \in (0,1]$, $p > 1/2$ clearly implies $dRHS/dr < 0$, and when $p < 1/2$ then $\Lambda \leqslant 1$ implies $-1 + \Lambda(1-2p) < 0$ and thus again $dRHS/dr < 0$. It follows that $\Delta^*_{MX} < 0$ for any $\Lambda \in (0,1]$.

For $\Lambda \in [-1,0)$, $p < 1/2$ clearly implies $dRHS/dr > 0$, and when $p > 1/2$ then $\Lambda \geqslant -1$ implies $-1 + \Lambda(1-2p) < 0$ and thus again $dRHS/dr > 0$. It follows that $\Delta^*_{MX} > 0$ for any $\Lambda \in [-1,0)$.

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C.4 Bell Disappointment Aversion (Bell DA)

Next, we consider predictions from Bell's (1985) model of disappointment aversion. Under this model, the utility from a lottery $X \equiv (x_1, p_1; ...; x_N, p_N)$ is

$$U(X) = \left(\sum_{n=1}^{N} p_n u(x_n)\right) - \beta \left(\sum_{n=1}^{N} p_n I\left(u(x_n) < \bar{U}\right)\left(\bar{U} - u(x_n)\right)\right),$$

where $u(\cdot)$ is an intrinsic utility function, and $\bar{U} \equiv \sum_{i=1}^{N} p_i u(x_i)$ is the expected intrinsic utility. When the parameter $\beta > 0$, it reflects a (constant) marginal disutility of disappointment experienced when one's realized intrinsic utility is below the expected intrinsic utility. If $\beta < 0$, then $-\beta$ effectively reflects a (constant) marginal utility of elation experienced when one's realized intrinsic utility is above the expected intrinsic utility.[5]

Applied to our context, the indifference values for h^*_{AB} and h^*_{CD} are determined from:

$$\begin{aligned} u(M) &= pu(h^*_{AB}) - \beta(1-p)(pu(h^*_{AB}) - 0) \\ ru(M) - \beta(1-r)(ru(M) - 0) &= pru(h^*_{CD}) - \beta(1-pr)(pru(h^*_{CD}) - 0) \end{aligned}$$

and thus

$$h^*_{AB} = u^{-1}\left(\frac{1}{p(1-\beta(1-p))}u(M)\right) \qquad \text{and} \qquad h^*_{CD} = u^{-1}\left(\frac{1-\beta(1-r)}{p(1-\beta(1-pr))}u(M)\right)$$

Note that for two-outcome lotteries such as our lotteries B, C, and D, the utilities under Bell DA are equivalent to those under Koszegi-Rabin CPE, where β replaces Λ. Hence, we need an analogous restriction that the range of β is $[-1, 1]$.

For the $h^*_{AB'}$ indifference value, we must carefully assess whether, at the indifference value, $u(M)$ is larger or smaller than the expected intrinsic utility $pru(h^*_{AB'}) + (1-r)u(M)$ because that matters for the utility from lottery B'. We can write $pru(h^*_{AB'}) + (1-r)u(M) > u(M)$ as $u(h^*_{AB'}) > u(M)/p$. If we assume that $u(h^*_{AB'}) > u(M)/p$, then the $h^*_{AB'}$ is determined from:

$$\begin{aligned} u(M) = \; & pru(h^{*(1)}_{AB'}) + (1-r)u(M) - \beta(1-r)(pru(h^{*(1)}_{AB'}) + (1-r)u(M) - u(M)) \\ & -\beta r(1-p)(pru(h^{*(1)}_{AB'}) + (1-r)u(M) - 0) \end{aligned}$$

[5] Bell (1985) further assumes that $u(x) = x$ and has separate parameters for disappointment (d) and elation (e). His model is equivalent to the version in the text with $\beta = d - e$. Loomes and Sugden (1986) also use this formulation, but they consider nonlinear disappointment and elation.

$$\iff \quad h^{*(1)}_{AB'} = u^{-1}\left(\frac{1-\beta p(1-r)}{p(1-\beta(1-pr))}u(M)\right)$$

Note that as long as $1-\beta(1-pr) > 0$, $u(h^*_{AB'}) > u(M)/p$ when $1-\beta p(1-r) > 1-\beta(1-pr)$, or $\beta(1-p) > 0$, which holds as long as $\beta > 0$. Since $1-\beta(1-pr) > 0$ for all $\beta \in [0,1]$, it follows that $h^*_{AB'} = h^{*(1)}_{AB'}$ for all $\beta \in [0,1]$.

If we instead assume that $u(h^*_{AB'}) < u(M)/p$, then the $h^*_{AB'}$ is determined from:

$$u(M) = pru(h^{*(2)}_{AB'}) + (1-r)u(M) - \beta r(1-p)(pru(h^{*(2)}_{AB'}) + (1-r)u(M) - 0)$$

$$\iff \quad h^{*(2)}_{AB'} = u^{-1}\left(\frac{1+\beta(1-p)(1-r)}{p(1-\beta r(1-p))}u(M)\right)$$

Note that as long as $1-\beta r(1-p) > 0$, $u(h^*_{AB'}) < u(M)/p$ when $1+\beta(1-p)(1-r) < 1-\beta r(1-p)$, or $\beta(1-p) < 0$, which holds as long as $\beta < 0$. Since $1-\beta r(1-p) > 0$ for all $\beta \in [-1,0]$, it follows that $h^*_{AB'} = h^{*(2)}_{AB'}$ for all $\beta \in [-1,0]$.

Given these indifference values:

$$\begin{array}{llllll}
\Delta^*_{CR} > 0 & \iff & h^*_{AB} > h^*_{CD} & \iff & \dfrac{1}{1-\beta(1-p)} > \dfrac{1-\beta(1-r)}{1-\beta(1-pr)} & \\
\Delta^*_{CC} > 0 & \iff & h^*_{AB'} > h^*_{CD} & \iff & 1-\beta p(1-r) > 1-\beta(1-r) & \text{if } \beta \in [0,1] \\
 & & & & \dfrac{1+\beta(1-p)(1-r)}{1-\beta r(1-p)} > \dfrac{1-\beta(1-r)}{1-\beta(1-pr)} & \text{if } \beta \in [-1,0] \\
\Delta^*_{MX} > 0 & \iff & h^*_{AB} > h^*_{AB'} & \iff & \dfrac{1}{1-\beta(1-p)} > \dfrac{1-\beta p(1-r)}{1-\beta(1-pr)} & \text{if } \beta \in [0,1] \\
 & & & & \dfrac{1}{1-\beta(1-p)} > \dfrac{1+\beta(1-p)(1-r)}{1-\beta r(1-p)} & \text{if } \beta \in [-1,0]
\end{array}$$

Hence, under Bell DA, the model's predictions for the sign of Δ^*_{CR}, Δ^*_{CC}, and Δ^*_{MX} are determined by the value of the parameter β.

Bell DA Result:

(1) $\beta \in (0,1)$ implies $\Delta^*_{CR} > 0$, $\Delta^*_{CC} > 0$, and $\Delta^*_{MX} < 0$.

(2) $\beta \in (-1,0)$ implies $\Delta^*_{CR} < 0$, $\Delta^*_{CC} < 0$, and $\Delta^*_{MX} > 0$.

Proof: For Δ^*_{CR}, the condition is equivalent to that under Koszegi-Rabin CPE, and thus the proof is the same.

Next consider the Δ^*_{CC} condition.

For $\beta \in [0,1]$, $\Delta^*_{CC} > 0$ if $1 - \beta p(1-r) > 1 - \beta(1-r)$ or $\beta(1-r)(1-p) > 0$, which holds for any $\beta \in [0,1]$.

For $\beta \in [-1,0]$, $\Delta^*_{CC} < 0$ if

$$\begin{aligned}
\frac{1+\beta(1-p)(1-r)}{1-\beta r(1-p)} &< \frac{1-\beta(1-r)}{1-\beta(1-pr)} \\
(1+\beta(1-p)(1-r))(1-\beta(1-pr)) &< (1-\beta(1-r))(1-\beta r(1-p)) \\
\beta((1-p)(1-r)-(1-pr)) - \beta^2(1-p)(1-r)(1-pr) &< -\beta(1-pr) + \beta^2(1-p)(1-r)r \\
\beta(1-p)(1-r)(1-\beta(1-pr+r)) &< 0
\end{aligned}$$

which holds for any $\beta \in [-1,0]$.

Finally consider the Δ^*_{MX} condition.

For $\beta \in [0,1]$:

$$\Delta^*_{MX} : 0 \quad \Longleftrightarrow \frac{1}{1-\beta(1-p)} > \frac{1-\beta p(1-r)}{1-\beta(1-pr)}$$

The LHS is independent of r. The RHS is equal to the LHS when $r = 1$, and moreover

$$\frac{dRHS}{dr} = \frac{(1-\beta(1-pr))(\beta p) - (1-\beta p(1-r))(\beta p)}{(1-\beta(1-pr))^2} = \frac{-\beta^2 p(1-p)}{(1-\beta(1-pr))^2}$$

Hence, $\beta \in [0,1]$ implies $dRHS/dr < 0$, and thus $\Delta^*_{MX} < 0$ for any $r < 1$.

For $\beta \in [-1,0]$:

$$\Delta^*_{MX} : 0 \quad \Longleftrightarrow \frac{1}{1-\beta(1-p)} > \frac{1+\beta(1-p)(1-r)}{1-\beta r(1-p)}$$

The LHS is independent of r. The RHS is equal to the LHS when $r = 1$, and moreover

$$\frac{dRHS}{dr} = \frac{(1-\beta r(1-p))(-\beta(1-p)) - (1-\beta(1-p)(1-r))(-\beta(1-p))}{(1-\beta r(1-p))^2} = \frac{\beta^2(1-p)^2}{(1-\beta(1-pr))^2}$$

Hence, $\beta \in [-1,0]$ implies $dRHS/dr > 0$, and thus $\Delta^*_{MX} > 0$ for any $r < 1$.

■

C.5 Gul Disappointment Aversion (Gul DA)

We next consider predictions from the Gul (1991) model of disappointment aversion. Under this model, the utility from a lottery $X \equiv (x_1, p_1; ...; x_N, p_N)$ is the $U(X)$ that satisfies

$$U(X) = \left(\sum_{n=1}^{N} p_n u(x_n)\right) - \beta \left(\sum_{n=1}^{N} p_n I\left(u(x_n) < U(X)\right)\left(U(X) - u(x_n)\right)\right),$$

where $u(x)$ is an intrinsic utility function, and a person experiences disappointment when their realized intrinsic utility is below the overall utility of the lottery $U(X)$. As in Bell DA, $\beta > 0$ is disappointment aversion while $\beta < 0$ is elation-loving. Applying this to binary gambles of the form $X \equiv (x, q_H; 0, q_L)$, this becomes

$$U(X) = q_H u(x) - \beta q_L (U(X) - 0)) \quad \Longleftrightarrow \quad U(X) = \frac{q_H}{1 + \beta q_L} u(x).$$

Gul imposes $\beta > -1$, which guarantees that $U(X)$ is increasing in the payoff x for any q_L. This model does not require an upper bound for β. The indifference values h^*_{AB} and h^*_{CD} are given by:

$$\begin{aligned}
u(M) &= \frac{p}{1+\beta(1-p)} u(h^*_{AB}) \quad \Longleftrightarrow \quad h^*_{AB} = u^{-1}\left(\frac{1+\beta(1-p)}{p} u(M)\right) \\
\tfrac{r}{1+\beta(1-r)} u(M) &= \tfrac{pr}{1+\beta(1-pr)} u(h^*_{CD}) \quad \Longleftrightarrow \quad h^*_{CD} = u^{-1}\left(\frac{1+\beta(1-pr)}{p(1+\beta(1-r))} u(M)\right)
\end{aligned}$$

For the $h^*_{AB'}$ indifference value, in principle, we must carefully assess whether, at the indifference value, $u(M)$ is larger or smaller than $U(B')$ (analogous to what we did for Bell DA). However, because $h^*_{AB'}$ is determined by the condition $u(M) = U(B')$, we know that $u(M) = U(B')$ at $H = h^*_{AB'}$. It follows that, at $H = h^*_{AB'}$, we have:

$$U(B') = pru(H) + (1-r)u(M) - \beta r(1-p)(U(B') - 0)$$

or

$$U(B') = \frac{pr}{1+\beta r(1-p)} u(H) + \frac{1-r}{1+\beta r(1-p)} u(M).$$

Then $h^*_{AB'}$ is derived from

$$u(M) = \frac{pr}{1+\beta r(1-p)} u(h^*_{AB'}) + \frac{1-r}{1+\beta r(1-p)} u(M) \quad \Longleftrightarrow \quad h^*_{AB'} = u^{-1}\left(\frac{1+\beta(1-p)}{p} u(M)\right)$$

Notice that $h^*_{AB'} = h^*_{AB}$ and thus $\Delta^*_{MX} = 0$ (a well known property of Gul DA) and thus $\Delta^*_{CR} = \Delta^*_{CC}$. Hence, there is only one remaining condition to consider:

$$\Delta^*_{CR} = \Delta^*_{CC} > 0 \iff h^*_{AB} = h^*_{AB'} > h^*_{CD} \iff 1 + \beta(1-p) > \tfrac{1+\beta(1-pr)}{1+\beta(1-r)}$$

Hence, under Gul DA, the model's predictions for the sign of Δ^*_{CR}, Δ^*_{CC}, and Δ^*_{MX} are determined by the value of the parameter β.

Gul DA Result:

(1) $\beta > 0$ implies $\Delta^*_{CR} = \Delta^*_{CC} > 0$ and $\Delta^*_{MX} = 0$.

(2) $\beta \in (-1, 0)$ implies $\Delta^*_{CR} = \Delta^*_{CC} < 0$, and $\Delta^*_{MX} = 0$.

Proof: The Δ^*_{CR} condition is:

$$\Delta^*_{CR} : 0 \iff 1 + \beta(1-p) : \frac{1+\beta(1-pr)}{1+\beta(1-r)}$$

The LHS is independent of r. The RHS is equal to the LHS when $r = 1$, and moreover

$$\frac{dRHS}{dr} = \frac{(1+\beta(1-r))(-\beta p) - (1+\beta(1-pr))(-\beta)}{(1+\beta(1-r))^2} = \frac{(\beta+\beta^2)(1-p)}{(1+\beta(1-r))^2}$$

Hence, $\beta > 0$ implies $dRHS/dr > 0$ and thus $\Delta^*_{CR} = \Delta^*_{CC} > 0$, while $\beta \in (-1, 0)$ implies $dRHS/dr < 0$ and thus $\Delta^*_{CR} = \Delta^*_{CC} < 0$.

■

C.6 Cautious Expected Utility (CEU)

We next consider the implications of the *cautious expected utility (CEU)* model introduced by Cerreia-Vioglio et al. (2015). Unlike the models above, their focus is a representation theorem and not a parameterized model, but firm predictions for our context follow from their axioms.

To illustrate, suppose we fix $H = h^*_{AB}$ so that $B \sim A$. Because lottery A is a sure amount, their key axiom of *negative certainty independence (NCI)* implies that $rB + (1-r)0 \gtrsim rA + (1-r)0$ for any $r \in (0, 1)$. Because $rB + (1-r)0 = D$ and $rA + (1-r)0 = C$, CEU permits a CRP (i.e., $\Delta^*_{CR} > 0$) but not an RCRP. NCI also implies (see page 697 of Cerreia-Vioglio et al. (2015)) that

$rB + (1-r)A \sim B$ for any $r \in (0,1)$. Because $rB + (1-r)A = B'$, CEU implies $A \sim B \sim B'$ and thus $\Delta^*_{MX} = 0$. Finally, $\Delta^*_{MX} = 0$ implies $\Delta^*_{CC} = \Delta^*_{CR}$.

To summarize, when the predictions of CEU differ from EU, those predictions are $\Delta^*_{CC} = \Delta^*_{CR} > 0$ and $\Delta^*_{MX} = 0$, i.e., the CRP-CCP-$\oslash$MXP pattern.

C.7 Puri Simplicity Preferences

Finally, we consider the implications of the model of *simplicity preferences* introduced by Puri (2024). Under this model, the utility from a lottery $X \equiv (x_1, p_1; ...; x_N, p_N)$ is

$$U(X) = \sum_{n=1}^{N} p_n u(x_n) - \omega(N).$$

The first term is a standard EU term, and $\omega(N)$ is a complexity cost term that is increasing in N—i.e., lotteries with more possible outcomes have a larger complexity cost. Here, we derive predictions for our context under the assumption that $\omega(1) < \omega(2) < \omega(3)$.

To derive predictions, it is convenient to fix the parameters (M, p, r) and then define $EU(X|h)$ to be the expected utility of lottery $X \in \{B, B', D\}$ as a function of h. Also, recall that, for any h, $EU(C) - EU(D|h) = EU(A) - EU(B'|h) = r(EU(A) - EU(B|h))$.

Under this model, h^*_{CD} must satisfy $EU(C) - \omega(2) = EU(D|h^*_{CD}) - \omega(2)$ and therefore $EU(C) = EU(D|h^*_{CD})$. This in turn implies $EU(A) = EU(B|h^*_{CD})$ and thus $EU(A) - \omega(1) > EU(B|h^*_{CD}) - \omega(2)$. It follows that $h^*_{AB} > h^*_{CD}$ and thus $\Delta^*_{CR} > 0$. Similarly, it also implies $EU(A) = EU(B'|h^*_{CD})$ and thus $EU(A) - \omega(1) > EU(B'|h^*_{CD}) - \omega(3)$. It follows that $h^*_{AB'} > h^*_{CD}$ and thus $\Delta^*_{CC} > 0$.

Under this model, h^*_{AB} must satisfy $EU(A) - \omega(1) = EU(B|h^*_{AB}) - \omega(2)$ and therefore $EU(A) < EU(B|h^*_{AB})$. Since B' is a mixture of A and B, we must have $EU(A) < EU(B'|h^*_{AB}) < EU(B|h^*_{AB})$ and thus $EU(B'|h^*_{AB}) - \omega(3) < EU(B|h^*_{AB}) - \omega(2)$. It follows that $EU(A) - \omega(1) > EU(B'|h^*_{AB}) - \omega(3)$ and thus $h^*_{AB'} > h^*_{AB}$ and $\Delta^*_{MX} < 0$.

To summarize, if $\omega(1) < \omega(2) < \omega(3)$, then Puri simplicity preferences predict $\Delta^*_{CR} > 0$, $\Delta^*_{CC} > 0$, and $\Delta^*_{MX} < 0$, i.e., the CRP-CCP-RMXP pattern.

D The Impact of Noise on Valuations and Choices

In Section 2.5, we discuss the impact of noise on valuation tasks and binary choice tasks, and the inferential challenges that arise as a result. This appendix formalizes the intuition in that section by replicating and expanding on the theoretical results in McGranaghan et al. (2024).

We assume that the same underlying preferences drive behavior for both valuation tasks and binary choice tasks. Using the notation from Section 2.2, a person will have three underlying indifference values h^*_{AB}, $h^*_{AB'}$, and h^*_{CD} for a fixed (p, r, M) that satisfy:

- Prefer A over B if and only if $H < h^*_{AB}$,
- Prefer A over B' if and only if $H < h^*_{AB'}$, and
- Prefer C over D if and only if $H < h^*_{CD}$.

We can then characterize that person's CR, CC, and MX preferences by $\Delta^*_{CR} \equiv h^*_{AB} - h^*_{CD}$, $\Delta^*_{CC} \equiv h^*_{AB'} - h^*_{CD}$, and $\Delta^*_{MX} \equiv h^*_{AB} - h^*_{AB'}$. EU implies $\Delta^*_{CC} = \Delta^*_{CR} = \Delta^*_{MX} = 0$.

D.1 The Impact of Noise on Valuations

In Section 2.5, we provide an intuitive argument for how paired valuation tasks might yield unbiased inference even in the presence of noise. Here, we provide a formal argument.

To combine a participant's underlying preferences with noise to generate their stated valuations, we begin with an assumption that is more general than the one used in Section 2.5:

Assumption 1v: Impact of Noise on Valuations

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

In Assumption 1v, the function Γ permits a variety of models for how a person's underlying indifference points combine with choice noise to generate their stated valuations. We highlight two special cases of Assumption 1v:

Assumption 2a: $\Gamma(h,\varepsilon) = h + \varepsilon$, and $E(\varepsilon_{AB}) = E(\varepsilon_{AB'}) = E(\varepsilon_{CD}) = 0$.

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

Assumption 2a is the assumption we use in Section 2.5 and represents the simple case in which stated valuations are given by the true underlying preference plus a mean-zero error term. Assumption 2b is less straightforward at first glance, but it is consistent with assumptions researchers frequently use when analyzing choice data, where they model noise as a symmetric additive perturbation of utility in the spirit of McFadden (1974, 1981). To illustrate, consider the following example:

Example: Expected Utility and Prospect Theory

Suppose that a person evaluates a lottery (x, q) with $x > 0$ as $\pi(q)u(x)$, and evaluates a lottery $(x, q; y, s)$ with $x > y > 0$ as $\pi(q)u(x) + w(q, s)u(y)$. This formulation reduces to EU when $\pi(q) = q$, $w(q, s) = s$, and $u(x)$ is a Bernoulli utility function. This formulation reduces to CPT when $\pi(q)$ is a probability weighting function, $w(q, s) = \pi(q + s) - \pi(q)$, and $u(x)$ is a value function defined over gains and losses. Finally, this formulation reduces to OPT when $\pi(q)$ is a probability weighting function, $w(q, s) = \pi(s)$, and $u(x)$ is a value function defined over gains and losses.

With this formulation, the underlying indifference points satisfy

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

Now suppose we incorporate additive utility noise in the spirit of McFadden (1974, 1981) by assuming that the stated valuations satisfy

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

where ϵ_{AB}, $\epsilon_{AB'}$, and ϵ_{CD} reflect additive utility noise.[6] When applying this approach, it is common to further assume that ϵ_{CD} has some distribution that is symmetric about 0 (e.g., a mean-zero normal or logistic distribution), and that $\epsilon_{AB} \overset{d}{=} k'_{AB}\epsilon_{CD}$ and $\epsilon_{AB'} \overset{d}{=} k'_{AB'}\epsilon_{CD}$ for some $k'_{AB} > 0$ and $k'_{AB'} > 0$ (e.g., when the error terms all have the same distributional form but are permitted to have different variances). If so, then this formulation fits Assumption 2b with $\Gamma(h, \varepsilon) = u^{-1}(u(h) - \varepsilon)$, where $\varepsilon_{AB} = k'_{AB}\epsilon_{CD}/\pi(p)$, $\varepsilon_{AB'} = k'_{AB'}\epsilon_{CD}/\pi(pr)$, and $\varepsilon_{CD} = \epsilon_{CD}/\pi(pr)$. Finally, EU with additive utility noise that is i.i.d. across the AB, AB', and CD choices (so $k'_{AB} = k'_{AB'} = 1$) implies $\varepsilon_{AB} = r\varepsilon_{CD}$ and $\varepsilon_{AB'} = \varepsilon_{CD}$.

Proposition 1v describes when unbiased tests of the null of $\Delta^*_Z = 0$, $Z \in \{CR, CC, MX\}$, are possible using paired valuation tasks and Assumption 2a or 2b.

Proposition 1v *(Paired Valuation Tasks Can Yield Unbiased Tests):* Consider a person who provides stated valuations $(h_{AB}, h_{AB'}, h_{CD})$.

(1) Under Assumption 2a, $E(\Delta_Z) = \Delta^*_Z$ for all $Z \in \{CR, CC, MX\}$.

(2) Under Assumption 2b, $\Pr(\Delta_Z > 0) = \Pr(\Delta_Z < 0) = 1/2$ for all $Z \in \{CR, CC, MX\}$.

The proof and intuition for Proposition 1 are virtually the same as those for Proposition 2 in McGranaghan et al. (2024), and thus we omit them here. Part (1) establishes that we can test the null of $\Delta^*_Z = 0$ under Assumption 2a using a means test. Part (2) establishes that we can test the null of $\Delta^*_Z = 0$ under Assumption 2b using a sign test that tests whether the observed proportions of $\Delta_Z > 0$ and $\Delta_Z < 0$ are the same.[7] These are the two tests reported in Table 4.

D.2 The Impact of Noise on Choices

In Section 2.5, we describe how noise can make it problematic to infer preferences when comparing behavior across binary choice tasks. We provide a formal argument here. To model how a participant's underlying preferences combine with noise to generate their choices in the three binary choice tasks, we use the following alternative to Assumption 1v:

[6] The latter equations use $(1/\pi(p))u(M) = u(h^*_{AB})$, $((1 - w(pr, 1 - r))/\pi(pr))u(M) = u(h^*_{AB'})$, and $(\pi(r)/\pi(pr))u(M) = u(h^*_{CD})$.

[7] Our formal test uses the following logic. If $\Pr(\Delta_Z > 0) = \Pr(\Delta_Z < 0) = 1/2$ for every observation, the likelihood of observing at most n instances of $\Delta_Z > 0$ out of N observations is equal to $G(n, N)$, where G denotes the cumulative distribution function for a binomial distribution with a 50 percent success rate. Hence, if we observe n_+ instances of $\Delta_Z > 0$ and n_- instances of $\Delta_Z < 0$, the p-value for a two-sided sign test under the null of $\Delta^*_Z = 0$ is $2 * G(\min\{n_+, n_-\}, n_+ + n_-)$.

Assumption 1c: Impact of Noise on Choices

A person's *realized indifference points* are the $(h_{AB}, h_{AB'}, h_{CD})$ described in Assumption 1v. Then:

- In an AB choice task, the person chooses $A \equiv (M, 1)$ over $B \equiv (H, p)$ if and only if $H \leqslant h_{AB} \equiv \Gamma(h^*_{AB}, \varepsilon_{AB})$,
- In an AB' choice task, the person chooses $A \equiv (M, 1)$ over $B' \equiv (H, p; M, 1-r)$ if and only if $H \leqslant h_{AB'} \equiv \Gamma(h^*_{AB'}, \varepsilon_{AB'})$,
- In a CD choice task, the person chooses $C \equiv (M, r)$ over $D \equiv (H, pr)$ if and only if $H \leqslant h_{CD} \equiv \Gamma(h^*_{CD}, \varepsilon_{CD})$.

In a choice task, the observed data comes in the form of the proportion of participants who choose each option. Under Assumption 1c, the relevant proportions are:

$$\Pr(A|AB) = \Pr(H < h_{AB}),\ \Pr(A|AB') = \Pr(H < h_{AB'}), \text{ and } \Pr(C|CD) = \Pr(H < h_{CD}).$$

Proposition 2 establishes conditions under which paired choice tasks yield biased tests of the null of $\Delta^*_Z = 0$, $Z \in \{CR, CC, MX\}$.

Proposition 2 *(Paired Choice Tasks Can Yield Biased Tests)*: Consider a person who has $h^*_{AB} = h^*_{AB'} = h^*_{CD} \equiv h^*$ and thus $\Delta^*_{CR} = \Delta^*_{CC} = \Delta^*_{MX} = 0$. Suppose that $\varepsilon_{AB} \overset{d}{=} k_{AB}\varepsilon_{CD}$ and $\varepsilon_{AB'} \overset{d}{=} k_{AB'}\varepsilon_{CD}$ for some $k_{AB} > 0$ and $k_{AB'} > 0$, and define $\chi \equiv \Pr(\varepsilon_{AB} < 0) = \Pr(\varepsilon_{AB'} < 0) = \Pr(\varepsilon_{CD} < 0)$.

(1) If $h^* - H > 0$ and thus the person has $A \succ B$, $A \succ B'$, and $C \succ D$, then:

(a) $k_{AB} < 1$ implies $\Pr(A|AB) > \Pr(C|CD) > \chi$ (CRE); $k_{AB} > 1$ implies $\Pr(C|CD) > \Pr(A|AB) > \chi$ (RCRE); and $k_{AB} = 1$ implies $\Pr(A|AB) = \Pr(C|CD) = \chi$ (⃠CRE);

(b) $k_{AB'} < 1$ implies $\Pr(A|AB') > \Pr(C|CD) > \chi$ (CCE); $k_{AB'} > 1$ implies $\Pr(C|CD) > \Pr(A|AB') > \chi$ (RCCE); and $k_{AB'} = 1$ implies $\Pr(A|AB') = \Pr(C|CD) = \chi$ (⃠CCE); and

(c) $k_{AB} < k_{AB'}$ implies $\Pr(A|AB) > \Pr(A|AB') > \chi$ (MXE); $k_{AB} > k_{AB'}$ implies $\Pr(A|AB') > \Pr(A|AB) > \chi$ (RMXE); and $k_{AB} = k_{AB'}$ implies $\Pr(A|AB) = \Pr(A|AB') = \chi$ (⃠MXE).

(2) If $h^* - H < 0$ and thus the person has $B \succ A$, $B' \succ A$, and $D \succ C$, then:

(a) $k_{AB} < 1$ implies $\Pr(A|AB) < \Pr(C|CD) < \chi$ (RCRE); $k_{AB} > 1$ implies $\Pr(C|CD) < \Pr(A|AB) < \chi$ (CRE); and $k_{AB} = 1$ implies $\Pr(A|AB) = \Pr(C|CD) = \chi$ (⃠CRE);

(b) $k_{AB'} < 1$ implies $\Pr(A|AB') < \Pr(C|CD) < \chi$ (RCCE); $k_{AB'} > 1$ implies $\Pr(C|CD) < \Pr(A|AB') < \chi$ (CCE); and $k_{AB'} = 1$ implies $\Pr(A|AB') = \Pr(C|CD) = \chi$ (⃠CCE); and

(c) $k_{AB} < k_{AB'}$ implies $\Pr(A|AB) < \Pr(A|AB') < \chi$ (RMXE); $k_{AB} > k_{AB'}$ implies $\Pr(A|AB') < \Pr(A|AB) < \chi$ (MXE); and $k_{AB} = k_{AB'}$ implies $\Pr(A|AB) = \Pr(A|AB') = \chi$ (⃠MXE).

(3) If $h^* - H = 0$ and thus the person has $A \sim B \sim B'$ and $C \sim D$, then $\Pr(A|AB) = \Pr(A|AB') = \Pr(C|CD) = \chi$ for all k_{AB} and $k_{AB'}$.

Again, the proof and intuition for Proposition 2 are virtually the same as the proof and intuition for Proposition 1 in McGranaghan et al. (2024), and thus we omit them here. Also, note that Proposition 2 holds under Assumption 2b, and it would also hold under Assumption 2a if in addition to $E(\varepsilon_{AB}) = E(\varepsilon_{AB'}) = E(\varepsilon_{CD}) = 0$ we also have $\varepsilon_{AB} \overset{d}{=} k_{AB}\varepsilon_{CD}$ and $\varepsilon_{AB'} \overset{d}{=} k_{AB'}\varepsilon_{CD}$ for some $k_{AB} > 0$ and $k_{AB'} > 0$. Hence, paralleling Corollary 1 in McGranaghan et al., paired choice tasks can yield biased tests while paired valuation tasks yield unbiased tests under the same assumptions about noise.

Beyond replicating the CRE result from Proposition 1 in McGranaghan et al. (2024) and extending it the CCE and MXE experiments, Proposition 2 also illustrates that the potential for misleading conclusions is even greater when attempting to identify preference patterns by comparing behavior across three binary choices. In particular, even when the true underlying preferences involve ⃠CRP, ⃠CCP, and ⃠MXP, many different patterns can emerge across the three choice tasks depending on the values for k_{AB} and $k_{AB'}$ and the experimenter-chosen parameter H. For instance, if $k_{AB'} < k_{AB} < 1$, then $H < h^*$ would lead to pattern CRE-CCE-RMXE, while $H > h^*$ would lead to pattern RCRE-RCCE-MXE. Alternatively, if $k_{AB} < 1 < k_{AB'}$, then $H < h^*$ would lead to pattern CRE-RCCE-MXE, while $H > h^*$ would lead to pattern RCRE-CCE-RMXE. Many other patterns are possible, and the only cases where the prediction would be the pattern ⃠CRE-⃠CCE-⃠MXE that corresponds to underlying preferences are the knife-edge cases where either distance to indifference is zero, $h^* - H = 0$, or differential noise is absent, $k_{AB} = k_{AB'} = 1$.

Proposition 2 establishes that choice tasks can yield a wide set of patterns when the true underlying preferences are ⃠CRP-⃠CCP-⃠MXP. The same can hold even when people have different underlying preferences. To illustrate, consider behavior under Assumption 2a with the additional assumption of $\varepsilon_{AB} \overset{d}{=} k_{AB}\varepsilon_{CD}$ and $\varepsilon_{AB'} \overset{d}{=} k_{AB'}\varepsilon_{CD}$ for some $k_{AB} > 0$ and $k_{AB'} > 0$. Under these assumptions, we can write the choice proportions as follows:

$$
\begin{aligned}
\Pr(A|AB) &= \Pr(H < h^*_{AB} + \varepsilon_{AB}) &&= \Pr\left(-\varepsilon_{CD} < \tfrac{1}{k_{AB}}(h^*_{AB} - H)\right)\\
\Pr(A|AB') &= \Pr(H < h^*_{AB'} + \varepsilon_{AB'}) &&= \Pr\left(-\varepsilon_{CD} < \tfrac{1}{k_{AB'}}(h^*_{AB'} - H)\right)\\
\Pr(C|CD) &= \Pr(H < h^*_{CD} + \varepsilon_{CD}) &&= \Pr\left(-\varepsilon_{CD} < h^*_{CD} - H\right)
\end{aligned}
$$

We next define $\bar{h}^*_{CR} \equiv (h^*_{AB} + h^*_{CD})/2$, $\bar{h}^*_{CC} \equiv (h^*_{AB'} + h^*_{CD})/2$, and $\bar{h}^*_{MX} \equiv (h^*_{AB} + h^*_{AB'})/2$, which are the average indifference values for the three paired valuations. Using these, and recalling for choices that $CRE - RCRE = \Pr(A|AB) - \Pr(C|CD)$, $CCE - RCCE = \Pr(A|AB') - \Pr(C|CD)$, and $MXE - RMXE = \Pr(A|AB) - \Pr(A|AB')$, we can derive predicted behavior in choice tasks:

$$
\begin{aligned}
CRE - RCRE &= \Pr\left(-\varepsilon_{CD} < h^*_{CD} - H + \Psi_{CR}\right) - \Pr\left(-\varepsilon_{CD} < h^*_{CD} - H\right)\\
CCE - RCCE &= \Pr\left(-\varepsilon_{CD} < h^*_{CD} - H + \Psi_{CC}\right) - \Pr\left(-\varepsilon_{CD} < h^*_{CD} - H\right)\\
MXE - RMXE &= \Pr\left(-\varepsilon_{AB'} < h^*_{AB'} - H + \Psi_{MX}\right) - \Pr\left(-\varepsilon_{AB'} < h^*_{AB'} - H\right)
\end{aligned}
\tag{D.1}
$$

where

$$
\begin{aligned}
\Psi_{CR} &= 0.5\left(\tfrac{1}{k_{AB}} + 1\right)\Delta^*_{CR} + \left(\tfrac{1}{k_{AB}} - 1\right)(\bar{h}^*_{CR} - H)\\
\Psi_{CC} &= 0.5\left(\tfrac{1}{k_{AB'}} + 1\right)\Delta^*_{CC} + \left(\tfrac{1}{k_{AB'}} - 1\right)(\bar{h}^*_{CC} - H)\\
\Psi_{MX} &= 0.5\left(\tfrac{k_{AB'}}{k_{AB}} + 1\right)\Delta^*_{MX} + \left(\tfrac{k_{AB'}}{k_{AB}} - 1\right)(\bar{h}^*_{MX} - H)
\end{aligned}
\tag{D.2}
$$

Hence, whether one's choices exhibit a CRE, CCE, or MXE depends on whether Ψ_{CR}, Ψ_{CC}, or Ψ_{MX} are positive or negative. In the the knife-edge cases where $\bar{h}^*_Z - H = 0$ for $Z \in \{CR, CC, MX\}$ or $k_{AB} = k_{AB'} = 1$, $\Psi_{CR} \propto \Delta^*_{CR}$, $\Psi_{CC} \propto \Delta^*_{CC}$, and $\Psi_{MX} \propto \Delta^*_{MX}$. Generalizing our earlier conclusion, in these knife-edge cases, choices will reveal the qualitative direction of underlying preferences.

In contrast, when $\bar{h}^*_Z - H \neq 0$ for $Z \in \{CR, CC, MX\}$ and k_{AB} and $k_{AB'}$ are not equal to one, then we have differential noise, and whether one exhibits a CRE, CCE, or MXE also depend on the relevant *distance to indifference*, i.e., $\bar{h}^*_{CR} - H$, $\bar{h}^*_{CC} - H$, or $\bar{h}^*_{MX} - H$. Indeed, if we fix the experimental parameters (M, p, r) and the associated underlying preferences $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$, we can use equation (D.2) to derive predicted behavior as a function of the experimenter-chosen parameter H:

$$
CRE - RCRE > 0 \Leftrightarrow \Psi_{CR} > 0 \Leftrightarrow \begin{cases} H > \bar{h}^*_{CR} - \dfrac{k_{AB} + 1}{2(k_{AB} - 1)}\Delta^*_{CR} & \text{if } k_{AB} > 1\\ H < \bar{h}^*_{CR} + \dfrac{k_{AB} + 1}{2(1 - k_{AB})}\Delta^*_{CR} & \text{if } k_{AB} < 1\\ \Delta^*_{CR} > 0 & \text{if } k_{AB} = 1 \end{cases}
$$

$$CCE - RCCE > 0 \Leftrightarrow \Psi_{CC} > 0 \Leftrightarrow \begin{cases} H > \bar{h}^*_{CC} - \dfrac{k_{AB'}+1}{2(k_{AB'}-1)}\Delta^*_{CC} & \text{if } k_{AB'} > 1 \\ H < \bar{h}^*_{CC} + \dfrac{k_{AB'}+1}{2(1-k_{AB'})}\Delta^*_{CC} & \text{if } k_{AB'} < 1 \\ \Delta^*_{CC} > 0 & \text{if } k_{AB'} = 1 \end{cases}$$

$$MXE - RMXE > 0 \Leftrightarrow \Psi_{MX} > 0 \Leftrightarrow \begin{cases} H < \bar{h}^*_{MX} + \dfrac{k_{AB'}+k_{AB}}{2(k_{AB'}-k_{AB})}\Delta^*_{MX} & \text{if } k_{AB} < k_{AB'} \\ H > \bar{h}^*_{MX} - \dfrac{k_{AB'}+k_{AB}}{2(k_{AB}-k_{AB'})}\Delta^*_{MX} & \text{if } k_{AB} > k_{AB'} \\ \Delta^*_{MX} > 0 & \text{if } k_{AB} = k_{AB'} \end{cases}$$

Note that if the experimenter chooses $H = \bar{h}^*_{CR}$, then participants' $CRE - RCRE$ will reveal the sign of their underlying Δ^*_{CR}. An analogous point holds when the experimenter chooses $H = \bar{h}^*_{CC}$ or $H = \bar{h}^*_{MX}$. However, without observing valuations, it is hard for the experimenter to select these H's. Moreover, if the experimenter is trying to use choices to identify patterns across the three preferences, a single H may not be sufficient to accurately infer all three preferences.

Finally, we highlight how, as the experimenter varies the experimental parameter H, a variety of biased patterns can emerge. For example, suppose $h^*_{AB} = 36$, $h^*_{AB'} = 34$, and $h^*_{CD} = 30$, in which case underlying preferences have the pattern CRP, CCP, MXP. If in addition $k_{AB} = 0.5$ while $k_{AB'} = 1.5$, participants would exhibit a CRE for $H < 42$, a CCE for $H > 22$, and an MXE for $H < 37$. Hence, for $H \in (22, 37)$, participants would exhibit the CRE-CCE-MXE pattern consistent with their underlying preferences. However, for H outside of this range we might observe the patterns CRE-RCCE-MXE, CRE-CCE-RMXE, or RCRE-CCE-RMXE.

The message is clear: If one wants to learn about patterns of CR-CC-MX preferences so as to be able to assess models of risk preferences, then using choice tasks will be problematic. In contrast, under the same assumptions as the analysis here, valuation tasks can be used to get unbiased measures of the underlying preferences Δ^*_{CR}, Δ^*_{CC}, and Δ^*_{MX}.

D.3 Connecting Stage 1 Valuations and Stage 2 Choices

Our discussion in Supplementary Material D.1 and D.2 assumes that the same underlying preferences drive behavior for both valuation tasks and choice tasks, and thus there should be a strong connection between the two. In Section 4.3 of the main paper, we provide some evidence on that connection. Here, we provide the underlying theory on which that evidence is based. Again, this follows a similar treatment in McGranaghan et al. (2024).

Specifically, we consider Assumption 2a with the additional assumptions that $\varepsilon_{AB} \overset{d}{=} k_{AB}\varepsilon_{CD}$ and

$\varepsilon_{AB'} \stackrel{d}{=} k_{AB'}\varepsilon_{CD}$ for some $k_{AB} > 0$ and $k_{AB'} > 0$. In this case, equations D.1 and D.2 characterize the predictions for stage 2 choices as a function of underlying indifference values h^*_{AB}, $h^*_{AB'}$, and h^*_{CD}. At the same time, Proposition 1 part 1 establishes that a participant's stage 1 valuations h_{AB}, $h_{AB'}$, and h_{CD} are unbiased measures of those underlying indifference values.

Hence, we conduct the following empirical analyses. First, we either (i) use each participant's stage 1 stated valuations h_{AB}, $h_{AB'}$, and h_{CD} to directly generate (noisy) empirical measures Δ_{CR}, Δ_{CC}, Δ_{MX}, $\bar{h}_{CR}$, $\bar{h}_{CC}$, and $\bar{h}_{MX}$, or (ii) use each participant's stage 1 stated valuations h_{AB}, $h_{AB'}$, and h_{CD} combined with our decomposition from Section 4.2 to generate posterior measures of an individual's underlying preferences $E[\Delta^*_{CR}|stage1]$, $E[\Delta^*_{CC}|stage1]$, $E[\Delta^*_{MX}|stage1]$, $E[\bar{h}^*_{CR}|\text{stage 1}]$, $E[\bar{h}^*_{CC}|\text{stage 1}]$, and $E[\bar{h}^*_{MX}|\text{stage 1}]$ (see Supplementary Material E.4 for details). We then test the following predictions from equations D.1 and D.2:

(1) A person's observed $CRE - RCRE$, $CCE - RCCE$, and $MXE - RMXE$ at stage 2 should depend positively on their associated stage 1 value difference Δ_{CR}, Δ_{CC}, Δ_{MX}.

(2) With one caveat, a person's observed $CRE - RCRE$, $CCE - RCCE$, and $MXE - RMXE$ at stage 2 should depend positively on their associated distance to indifference $\bar{h}_{CR} - H$, $\bar{h}_{CC} - H$, $\bar{h}_{MX} - H$ when the noise is more impactful for the second choice (the CD choice for CRE and CCE, the AB' choice for MXE), and should depend negatively on their associated distance to indifference when the noise is more impactful for the first choice. The caveat is that, while this prediction holds when the magnitude of the relevant distance to indifference is not too large, when that magnitude gets large enough (positive or negative), the relationship reverses because $\Pr(-\varepsilon_Z < h^*_Z - H)$ approaches zero (as in Figure 7 of McGranaghan et al. (2024)).

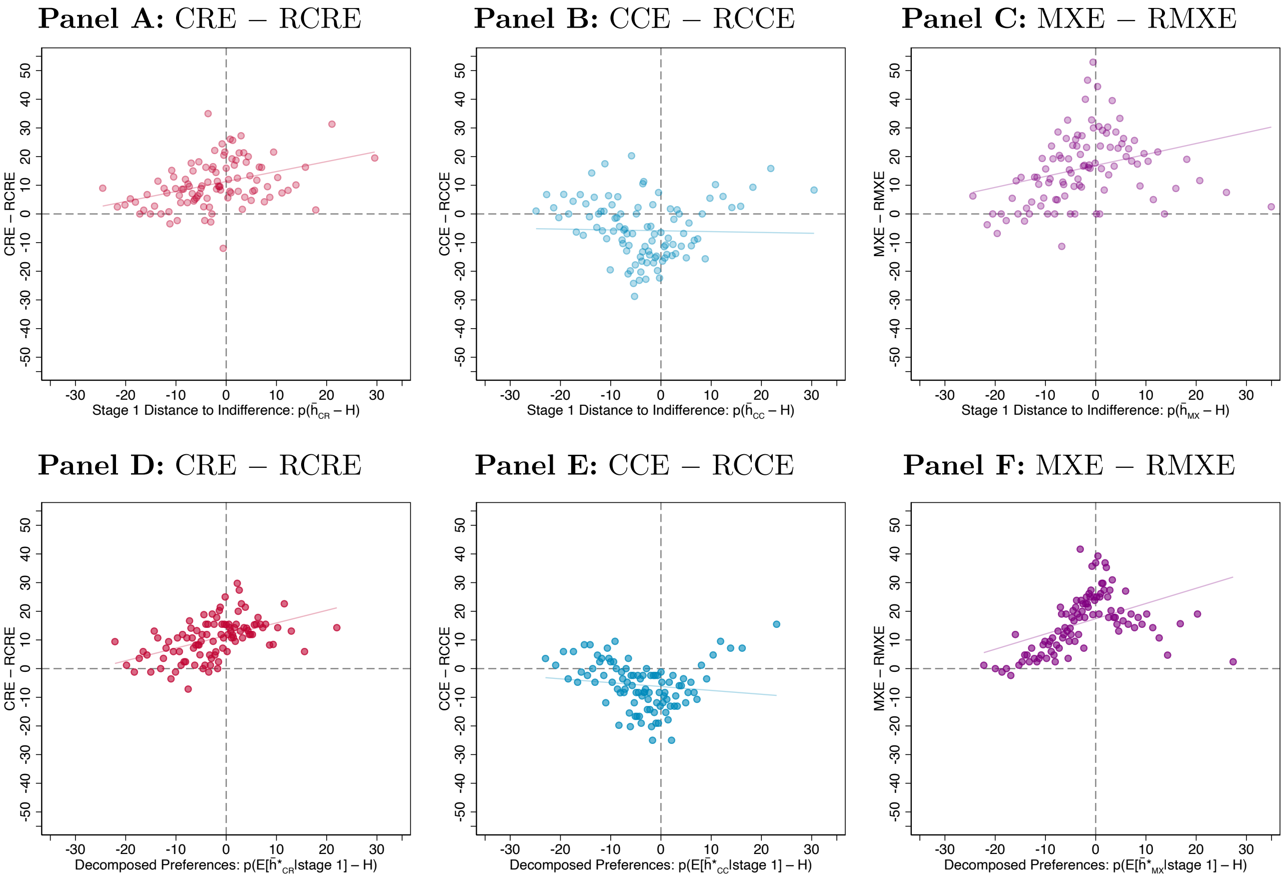
When we test these predictions, we increase power by combining data across different combinations of (p, r). Because for each preference the impact of the value difference or the distance to indifference is larger for larger p, in our empirical analyses we multiply these terms by p to make them more comparable across different values for p.

We visually assess prediction (1) in Figure 6 and we visually assess prediction (2) in Supplementary Figure D.1. Panels A-C of Supplementary Table D.1 provide corresponding formal tests via regressions of $CRE - RCRE$, $CCE - RCCE$, and $MXE - RMXE$ from stage 2 on the corresponding values of Δ_Z and $\bar{h}_Z - H$ from stage 1 (in both cases normalized by p). In each panel, four different specifications are provided: (1) ordinary least squares using the full sample of 8408 stage 2 observations; (2) ordinary least squares using samples of 4204 stage 2 observations for which multiple elicitations of relevant h valuations were conducted at stage 1; (3) two-stage least squares using samples of 4204 stage 2 observations for which multiple elicitations of relevant h valuations were conducted at stage 1 and instrumenting for Δ_Z and $\bar{h}_Z - H$ with the alternate elicitation's values, which accounts for potential measurement error in Δ_Z and $\bar{h}_Z - H$; (4) ordinary least squares using the full sample of 8408 stage 2 observations, but replacing Δ_Z and $\bar{h}_Z - H$ with the posterior expectations of preference given stage 1 behavior (i.e., $E[\Delta^*_Z|\text{stage 1}]$ $E[\bar{h}^*_Z - H|\text{stage 1}]$.

Figure 6 and Supplementary Table D.1 show substantial support for prediction (1) with significant linkages between values of Δ_Z and corresponding differences in choice probabilities for CR, CC, and MX problems across all specifications. Supplementary Figure D.1 and Supplementary Table D.1 also document the relevance of prediction (2) for all three problems. For CR problems, the data show a significant positive relationship between $\bar{h}_{CR} - H$ and $CRE - RCRE$ across all specifications, indicating that noise is more impactful for the CD choice than the AB choice. For CC problems the data using raw valuations in columns (1) through (3) show limited relationship between $\bar{h}_{CC} - H$ and $CCE - RCCE$. However, when using the posterior expectation of preferences in column (4), the data show a significant negative relationship between $E[\bar{h}^*_{CC}|\text{stage 1}] - H$ and $CCE - RCCE$, indicating that noise is more impactful for the AB' choice than the CD choice. For MX problems the data show a significant positive relationship between $\bar{h}_{MX} - H$ and $MXE - RMXE$ across all specifications, indicating that noise is more impactful for the AB' choice than the AB choice. All three problems show the hallmarks of differential noise and the combined data suggest that noise has the most impact on AB' choices, followed by CD choices, followed by AB choices.

Interestingly, these conclusions differ from the predictions of EU with additive i.i.d utility noise. In particular, Example 1 from Supplementary Material D.1 derives that, under EU with additive i.i.d. utility noise, $\varepsilon_{AB} = r\varepsilon_{CD}$ and $\varepsilon_{AB'} = \varepsilon_{CD}$. In words, under EU with additive i.i.d utility noise, the impact of noise on the AB' and CD choices should be the same, and both should be larger than the impact of noise on the AB choice.

Figure D.1: Predicting Stage 2 Results using Stage 1 Distance to Indifference



Notes: Figure relates individual stage 1 measures of $\bar{h}_{CR} - H$, $\bar{h}_{CC} - H$, and $\bar{h}_{MX} - H$ to stage 2 measures of $CRE - RCRE$, $CCE - RCCE$, and $MXE - RMXE$, respectively. Panels A-C use raw stage 1 responses. Panels D-F use the estimated population distribution of preferences from the decomposition in Section 4.2 combined with a participant's raw stage 1 valuations to generate posterior preference measures $E[\bar{h}^*_{CR}|\text{stage } 1]$, $E[\bar{h}^*_{CC}|\text{stage } 1]$, and $E[\bar{h}^*_{MX}|\text{stage } 1]$ for that participant. For each x-axis, one hundred equally sized bins are constructed with approximately 84 observations per bin for the CR and CC panels and approximately 42 observations for the MX panels. Within each bin, the value of stage 2 choice differences is calculated to construct the y-axes. Due to a large of observations at some values, there are 94, 93, and 91 unique bins in panels A, B, and C, respectively. To make valuations comparable across (p, r), all stage 1 measures are scaled by p to control for the fact that a fixed value of the measure is predicted to yield a larger stage 2 effect the larger is p (see Supplementary Material D.3 for details).

Table D.1: Regressions Predicting Stage 2 Binary Choices Using Stage 1 Valuations

	(1) Full Sample	(2) Multiple Observations Available	(3) 2SLS	(4) Decomposed Preferences
	Panel A. $CRE - RCRE \in \{-1, 0, 1\}$			
$p\Delta_{CR}$	1.07	1.08	2.60	2.77
	(0.07)	(0.09)	(0.26)	(0.16)
$p(\bar{h}_{CR} - H)$	0.40	0.30	0.20	0.32
	(0.07)	(0.09)	(0.12)	(0.08)
Outcome Mean	10.45	10.04	10.04	10.45
	Panel B. $CCE - RCCE \in \{-1, 0, 1\}$			
$p\Delta_{CC}$	0.96	0.87	2.92	3.26
	(0.07)	(0.09)	(0.36)	(0.18)
$p(\bar{h}_{CC} - H)$	−0.03	−0.01	−0.16	−0.46
	(0.07)	(0.09)	(0.14)	(0.08)
Outcome Mean	−5.77	−4.69	−4.69	−5.77
	Panel C. $MXE - RMXE \in \{-1, 0, 1\}$			
$p\Delta_{MX}$	0.80	0.93	3.17	3.00
	(0.07)	(0.10)	(0.44)	(0.23)
$p(\bar{h}_{MX} - H)$	0.39	0.43	0.62	0.65
	(0.06)	(0.07)	(0.11)	(0.07)
Outcome Mean	16.00	15.91	15.91	16.00
Individuals	2102	1051	1051	2102
Observations	8,408	4,204	4,204	8,408

Notes: Table presents linear regressions of individuals' stage 2 decisions on stage 1 measures of their Δ_Z and $\bar{h}_Z - H$ for $Z \in \{CR, CC, MX\}$. Panel A presents results for CR experiments, where the outcome is 1 if the participant chose A and D (CRE), -1 if they chose B and C (RCRE), and zero otherwise. Panel B presents results for CC experiments, where the outcome is 1 if the participant chose A and D (CCE), -1 if they chose B' and C (RCRE), and zero otherwise. Panel C presents results for MX experiments, where the outcome is 1 if the participant chose A and B' (MXE), -1 if they chose B and A (RMXE), and zero otherwise. Columns (1)-(3) use raw stage 1 responses. Column (1) presents the full sample results for all four (p, r) combinations that participants saw. For panel C, we use the valuations h'_{AB} or $h'_{AB'}$ for the half of (p, r) that they exist for, and h_{AB} or $h_{AB'}$ otherwise. Column (2) restricts the sample to only the half of (p, r) conditions for which which we have multiple measures of all three valuations. Column (3) leverages these multiple observations to implement instrumental variable regressions using two-stage least squares, where we instrument for $p\Delta$ and $p(\bar{h} - H)$ with their duplicate measures. For Column (4), we use the estimated population distribution of preferences from the decomposition in Section 4.2 combined with a participant's raw stage 1 valuations to generate posterior preference measures $E[\Delta^*_Z|\text{stage 1}]$ and $E[\bar{h}^*_Z|\text{stage 1}]$. To make valuations comparable across (p, r), all stage 1 measures are scaled by p to control for the fact that a fixed value of the measure is predicted to yield a larger stage 2 effect the larger is p (see Supplementary Material D.3 for details).

E Further Details on Decomposing Preference and Noise

In this appendix, we provide further details for the decomposition exercise in Section 4.2. In this exercise, we derive an estimate for the population distribution of underlying preferences along with the magnitude of decision noise. We then use these estimates for three purposes. First, we assess how much of the variability in our data is due to heterogeneity in preferences versus noise. Second, we derive what the histogram of response patterns from Figure 4 would look like if we were to remove the decision noise. Third, we construct refined measures of individual preferences that attempt to remove some of the noise.

E.1 Underlying Model and Estimating Its Parameters

For a fixed (p, r, M), let $\boldsymbol{h}^* \equiv (h^*_{AB}, h^*_{AB'}, h^*_{CD})$ be a vector of underlying indifference values. The population distribution of $\boldsymbol{h}^*$ has expectation $E(\boldsymbol{h}^*) \equiv (\mu^*_{AB}, \mu^*_{AB'}, \mu^*_{CD}) \equiv \boldsymbol{\mu}^*$ and variance-covariance matrix

$$\mathbf{V}\begin{pmatrix} h^*_{AB} \\ h^*_{AB'} \\ h^*_{CD} \end{pmatrix} \equiv \begin{pmatrix} \theta^2_{AB} & \theta_{AB,AB'} & \theta_{AB,CD} \\ \theta_{AB,AB'} & \theta^2_{AB'} & \theta_{AB',CD} \\ \theta_{AB,CD} & \theta_{AB',CD} & \theta^2_{CD} \end{pmatrix} \equiv \boldsymbol{\Sigma}^*. \tag{E.1}$$

For $XY \in \{AB, AB', CD\}$, we assume a person's two elicited XY valuations are

$$h_{XY} = h^*_{XY} + \varepsilon_{XY} \qquad \text{and} \qquad h'_{XY} = h^*_{XY} + \varepsilon'_{XY},$$

where $E(\varepsilon_{XY}) = E(\varepsilon'_{XY}) = 0$, $var(\varepsilon_{XY}) = var(\varepsilon'_{XY}) = \sigma^2_{XY}$, and ε_{XY} and ε'_{XY} are independent of each other, of the underlying preferences, and of all other noise draws. Note that this model has twelve parameters: three μ^*_{XY} terms, three θ^2_{XY} terms, three $\theta_{XY,WZ}$ terms, and three σ^2_{XY} terms.

Now let $\boldsymbol{h} \equiv (h_{AB}, h_{AB'}, h_{CD}, h'_{AB}, h'_{AB'}, h'_{CD})$ denote a vector of observed valuations.[8] Under these assumptions, we can derive the predicted mean and variance-covariance matrix for the observed $\boldsymbol{h}$ as a function of the 12 parameters of the underlying model:

$$E(\boldsymbol{h}) = (\mu^*_{AB}, \mu^*_{AB'}, \mu^*_{CD}, \mu^*_{AB}, \mu^*_{AB'}, \mu^*_{CD}) \equiv \boldsymbol{\mu}$$

[8] Recall that each participant faces four (p, r) combinations. For two of those, the participant provides all six valuations, while for the other two, they provide only $(h_{AB}, h_{AB'}, h_{CD}, h'_{CD})$. Although we write everything in this appendix based on the former case, we use all of our data in the analysis, making the appropriate adjustments when only the CD response has multiple elicitations.

$$\mathbf{V}(\boldsymbol{h}) = \begin{pmatrix} \theta_{AB}^2+\sigma_{AB}^2 & \theta_{AB,AB'} & \theta_{AB,CD} & \theta_{AB}^2 & \theta_{AB,AB'} & \theta_{AB,CD} \\ \theta_{AB,AB'} & \theta_{AB'}^2+\sigma_{AB'}^2 & \theta_{AB',CD} & \theta_{AB,AB'} & \theta_{AB'}^2 & \theta_{AB',CD} \\ \theta_{AB,CD} & \theta_{AB',CD} & \theta_{CD}^2+\sigma_{CD}^2 & \theta_{AB,CD} & \theta_{AB',CD} & \theta_{CD}^2 \\ \theta_{AB}^2 & \theta_{AB,AB'} & \theta_{AB,CD} & \theta_{AB}^2+\sigma_{AB}^2 & \theta_{AB,AB'} & \theta_{AB,CD} \\ \theta_{AB,AB'} & \theta_{AB'}^2 & \theta_{AB',CD} & \theta_{AB,AB'} & \theta_{AB'}^2+\sigma_{AB'}^2 & \theta_{AB',CD} \\ \theta_{AB,CD} & \theta_{AB',CD} & \theta_{CD}^2 & \theta_{AB,CD} & \theta_{AB',CD} & \theta_{CD}^2+\sigma_{CD}^2 \end{pmatrix} \equiv \boldsymbol{\Sigma}$$

Each entry in $\mathbf{V}(\boldsymbol{h})$ is a theoretical prediction for an empirical moment. For instance, $var(h_{AB}) = \theta_{AB}^2 + \sigma_{AB}^2$, and $cov(h_{AB}, h'_{AB}) = \theta_{AB}^2$. Hence, we can obtain estimates for the 12 model parameters by calculating the relevant sample moments or combination of sample moments. Specifically, using "hats" to denote estimates and the subscript s to denote sample moments, we can derive estimates for the model's 12 parameters using:

$$\begin{aligned} \widehat{\mu}_{XY}^* &= E_s(h_{XY}) \\ \widehat{\theta}_{XY}^2 &= cov_s(h_{XY}, h'_{XY}) \\ \widehat{\theta}_{XY,WZ} &= cov_s(h_{XY}, h_{WZ}) \\ \widehat{\sigma}_{XY}^2 &= var_s(h_{XY}) - cov_s(h_{XY}, h'_{XY}) \end{aligned}$$

Using this approach, Appendix Table A.5 reports estimates for the model's 12 parameters for each of the 20 (p, r) combinations.[9]

Supplementary Material E.5 describes a more sophisticated estimation approach using MLE. Because that approach requires additional distributional assumptions, is more time-consuming, and is sensitive to starting values and other estimation details, we prefer the approach described here. We note, however, that the MLE approach yields very similar estimates.

E.2 Assessing the Role of Heterogeneity versus Noise

Given these estimates, we can assess how much of the variability in our data is due to heterogeneity in preferences versus noise. Consider first variability in the elicited indifference values h_{AB}, $h_{AB'}$, and h_{CD}. The last three columns of Appendix Table A.5 report the estimated proportion of the variability for each elicited indifference value that is due to preferences—i.e., the ratio $\widehat{var}(h_{XY}^*)/\widehat{var}(h_{XY}) =$

[9]In Appendix Table A.5, we use observations from both h_{XY} and h'_{XY} to calculate $E_s(h_{XY})$ and $var_s(h_{XY})$. Similarly, we treat an individual participant's (h_{XY}, h_{WZ}) and their (h'_{XY}, h'_{WZ}) as two separate observations when calculating $cov_s(h_{XY}, h_{WZ})$.

$\hat{\theta}^2_{XY}/(\hat{\theta}^2_{XY} + \hat{\sigma}^2_{XY})$ for each $XY \in \{AB, AB', CD\}$. Averaging across the 20 (p, r) combinations, preference heterogeneity accounts for 61 percent of the variation in h_{AB}, 58 percent of the variation in $h_{AB'}$, and 48 percent of the variation in h_{CD}.

Next consider variability in the preference measures Δ_{CR}, Δ_{CC}, and Δ_{MX}. For $\Delta_{CR} \equiv h_{AB} - h_{CD}$, it is straightforward to derive that

$$\begin{aligned} & var(\Delta_{CR}) = var(\Delta^*_{CR}) + \sigma^2_{AB} + \sigma^2_{CD} \\ \text{and} \quad & var(\Delta^*_{CR}) = \theta^2_{AB} + \theta^2_{CD} - 2\theta_{AB,CD}. \end{aligned}$$

One can perform analogous derivations for Δ_{CC} and Δ_{MX}. Appendix Table A.6 uses the estimates in Appendix Table A.5 to calculate these six variances for each (p, r) combination.[10] The last three columns of Appendix Table A.6 report the proportion of the variability for each preference measure that is due to preferences—i.e., the ratio $\widehat{var}(\Delta^*_Z)/\widehat{var}(\Delta_Z)$ for each $Z \in \{CR, CC, MX\}$. Averaging across the 20 (p, r) combinations, preference heterogeneity accounts for 31 percent of the variation in Δ_{CR}, 31 percent of the variation in Δ_{CC}, and 25 percent of the variation in Δ_{MX}.

E.3 Simulating Preference Patterns

We next investigate what the histogram of response patterns from Figure 4 would look like if we were to remove the decision noise. To do so, we make the additional assumption that the underlying preferences have a joint normal distribution:

$$\boldsymbol{h}^* \sim N(\boldsymbol{\mu}^*, \boldsymbol{\Sigma}^*).$$

For each (p, r) combination, we use the estimated parameters in Appendix Table A.5 to generate 100,000 draws from a joint normal distribution for $\boldsymbol{h}^*$. We then convert each h^*_{XY} draw into the midpoint of its two closest integers (e.g., any draw strictly between \$2 and \$3 is converted to \$2.50). This approach is consistent with the valuations response scales in our experiment, since the switching rows for anyone with an underlying h^*_{XY} strictly between \$2 and \$3 would be the \$2 and \$3 rows, in which case we would assign them a valuation of \$2.50. We then use these converted h^*_{XY} terms to generate the Δ^*_Z terms.[11] Figure 5 presents the distribution of preference patterns when we aggregate across all 20 (p, r) combinations.

[10] When calculating things in this way, nothing guarantees that the calculated $var(\Delta^*_Z) > 0$, and indeed there is one instance where this problem arises (for Δ_{MX} when $(p, r) = (0.3, 0.5)$). We ignore this case and focus on the other 59 cases.

[11] When carrying out this exercise, we do not impose the upper and lower bounds of our experimental price lists.

Note that this approach permits null preference patterns, including EU consistency. However, it does not permit preference patterns which would imply intransitivities between h^*_{AB}, $h^*_{AB'}$, and h^*_{CD}. Of the 27 possible preference patterns in Figures 4 and 5, only 13 can therefore emerge from our simulation of preferences. The remaining 14 patterns can still emerge in the data due to decision noise (and the fact that we have independent measures of the three preferences).

E.4 Using the Decomposition to Refine Measures of Individual Preferences

In Section 4.3 and Supplementary Material D.3, we link an individual's stage 1 valuations to their stage 2 choices. Specifically, we create measures of individual preferences using stage 1 valuations, and then use those measures to predict stage 2 choice patterns. The simplest way to create measures of individual preferences is to take their stage 1 valuations at face value; for example, a measure of their underlying Δ^*_{CR} is simply $\Delta_{CR} = h_{AB} - h_{CD}$. An alternative approach is to combine a participant's stage 1 valuations with our decomposition estimates to generate refined measures of their individual preferences. Intuitively, the decomposition provides us with a prior for each participant's $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$, and a participant's valuations provide a signal that we can use to generate the corresponding posterior.

If $\boldsymbol{h}^*$, the ε_{XY} terms, and the ε'_{XY} terms are all jointly normally distributed, then $(\boldsymbol{h}^*, \boldsymbol{h})$ is also jointly normally distributed, specifically:

$$\begin{pmatrix} \boldsymbol{h}^* \\ \boldsymbol{h} \end{pmatrix} \sim N\left(\begin{pmatrix} \boldsymbol{\mu}^* \\ \boldsymbol{\mu} \end{pmatrix}, \begin{pmatrix} \boldsymbol{\Sigma}^* & \boldsymbol{\Sigma_{12}} \\ \boldsymbol{\Sigma_{21}} & \boldsymbol{\Sigma} \end{pmatrix} \right),$$

where

$$\boldsymbol{\Sigma_{12}} = \begin{pmatrix} \theta^2_{AB} & \theta_{AB,AB'} & \theta_{AB,CD} & \theta^2_{AB} & \theta_{AB,AB'} & \theta_{AB,CD} \\ \theta_{AB,AB'} & \theta^2_{AB'} & \theta_{AB',CD} & \theta_{AB,AB'} & \theta^2_{AB'} & \theta_{AB',CD} \\ \theta_{AB,CD} & \theta_{AB',CD} & \theta^2_{CD} & \theta_{AB,CD} & \theta_{AB',CD} & \theta^2_{CD} \end{pmatrix}.$$

Hence, if participant i provides a set of valuations $\boldsymbol{h}_i$, the conditional distribution of $\boldsymbol{h}^*$ given $\boldsymbol{h} = \boldsymbol{h}_i$ is $\boldsymbol{h}^*|_{\boldsymbol{h}=\boldsymbol{h}_i} \sim N(\boldsymbol{\mu}^*_{\text{post}}, \boldsymbol{\Sigma}^*_{\text{post}})$ where

$$\boldsymbol{\mu}^*_{\text{post}} = \boldsymbol{\mu}^* + \boldsymbol{\Sigma_{12}}\boldsymbol{\Sigma}^{-1}(\boldsymbol{h}_i - \boldsymbol{\mu})$$
$$\boldsymbol{\Sigma}^*_{\text{post}} = \boldsymbol{\Sigma}^* - \boldsymbol{\Sigma_{12}}\boldsymbol{\Sigma}^{-1}\boldsymbol{\Sigma_{21}}.$$

Again, our goal is to obtain more precise measures of a participant's Δ^*_Z terms (for Figure 6) and $\bar{h}^*_Z$ terms (for Supplementary Figure D.1). It is straightforward to use the parameter estimates in Appendix Table A.5 to generate $\boldsymbol{\mu}^*_{\text{post}}$ for each participant.[12] We denote the components of $\boldsymbol{\mu}^*_{\text{post}}$ by $E[h^*_{AB}|\text{stage 1}]$, $E[h^*_{AB'}|\text{stage 1}]$, and $E[h^*_{CD}|\text{stage 1}]$. These represent our more refined measure of the participant's h^* terms. We then use these define the following more refined measures for the Δ^*_Z terms and $\bar{h}^*_{XY}$ terms.

$$
\begin{aligned}
E[\Delta^*_{CR}|\text{stage 1}] &\equiv E[h^*_{AB}|\text{stage 1}] - E[h^*_{CD}|\text{stage 1}] \\
E[\Delta^*_{CC}|\text{stage 1}] &\equiv E[h^*_{AB'}|\text{stage 1}] - E[h^*_{CD}|\text{stage 1}] \\
E[\Delta^*_{MX}|\text{stage 1}] &\equiv E[h^*_{AB}|\text{stage 1}] - E[h^*_{AB'}|\text{stage 1}] \\
E[\bar{h}^*_{CR}|\text{stage 1}] &\equiv (E[h^*_{AB}|\text{stage 1}] + E[h^*_{CD}|\text{stage 1}])/2 \\
E[\bar{h}^*_{CC}|\text{stage 1}] &\equiv (E[h^*_{AB'}|\text{stage 1}] + E[h^*_{CD}|\text{stage 1}])/2 \\
E[\bar{h}^*_{MX}|\text{stage 1}] &\equiv (E[h^*_{AB}|\text{stage 1}] + E[h^*_{AB'}|\text{stage 1}])/2
\end{aligned}
$$

The refined measures $E[h^*_{AB}|\text{stage 1}]$, $E[h^*_{AB'}|\text{stage 1}]$, and $E[h^*_{CD}|\text{stage 1}]$ are all tightly correlated with their respective raw measures h_{AB}, $h_{AB'}$, and h_{CD}, with correlations of 0.89, 0.88, 0.83, respectively. Similarly, $E[\Delta^*_{CR}|\text{stage 1}]$, $E[\Delta^*_{CC}|\text{stage 1}]$, and $E[\Delta^*_{MX}|\text{stage 1}]$ are tightly correlated with Δ_{CR}, Δ_{CC}, and Δ_{MX}, with correlations of 0.79, 0.79, 0.69, respectively. Finally, $E[\bar{h}^*_{CR}|\text{stage 1}]$, $E[\bar{h}^*_{CC}|\text{stage 1}]$, and $E[\bar{h}^*_{MX}|\text{stage 1}]$ are tightly correlated with $\bar{h}_{CR}$, $\bar{h}_{CC}$, and $\bar{h}_{MX}$, with correlations of 0.91, 0.91, 0.92, respectively. In Figure 6 and Supplementary Figure D.1, we predict stage 2 choices using both the raw measures and the refined measures. The qualitative conclusions are much the same, although the refined measures make the link between stages more precise.

E.5 Decomposition Using MLE

Our analysis in Supplementary Material E.1 through E.4 estimates the model parameters using the relevant sample moments or combination of sample moments. The advantage of this approach is that it requires fewer distributional assumptions and implementation assumptions. For example, our assessment of the relative contributions of preference heterogeneity versus noise in Supplementary Material E.2 does not require any distributional assumptions.

Here we describe an alternative approach to estimate the parameters via MLE. We assume as in Supplementary Material E.4 that $\boldsymbol{h}^*$, the ε_{XY} terms, and the ε'_{XY} terms are all jointly normally

[12]Recall that each participant provides all six valuations for two of their (p, r) combinations, but only four valuations for their remaining two (p, r) combinations. For the latter instances, everything above is adjusted appropriately.

distributed, and therefore, $\boldsymbol{h} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. Recognizing the interval nature of our valuation tasks, an observation provides both a lower bound (ζ) and an upper bound (υ) on the participant's $\boldsymbol{h}$ valuations:

$$\zeta(\boldsymbol{h}) = \begin{pmatrix} \zeta(h_{AB}) \\ \zeta(h_{AB'}) \\ \zeta(h_{CD}) \\ \zeta(h'_{AB}) \\ \zeta(h'_{AB'}) \\ \zeta(h'_{CD}) \end{pmatrix} \qquad \textbf{and} \qquad \upsilon(\boldsymbol{h}) = \begin{pmatrix} \upsilon(h_{AB}) \\ \upsilon(h_{AB'}) \\ \upsilon(h_{CD}) \\ \upsilon(h'_{AB}) \\ \upsilon(h'_{AB'}) \\ \upsilon(h'_{CD}) \end{pmatrix}.$$

For instance, if for an h_{XY} valuation task the person switches between the row with $H = \$32$ and $H = \$33$, then $\zeta(h_{XY}) = 32$ and $\upsilon(h_{XY}) = 33$. For observations censored at the lower bound (i.e., the person always chooses the right-hand option, even when $H = p \cdot \$30$), we set $\zeta(h_{XY}) = -\infty$ and $\upsilon(h_{XY}) = p \cdot \$30$, whereas for observations censored at the upper bound (i.e., the person always chooses the left-hand option even when $H = p \cdot \$30 + \$50$), we set $\zeta(h_{XY}) = p \cdot \$30 + \$50$ and $\upsilon(h_{XY}) = \infty$. Finally, recall that we only collect h'_{AB} and $h'_{AB'}$ for half of observations; all missing valuations are treated as uninformative and assigned $\zeta(h_{XY}) = -\infty$ and $\upsilon(h_{XY}) = \infty$. Missing valuations therefore play no role in the estimation of the parameters as they have a likelihood of 1 (and log-likelihood zero) for all $(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.

Given a participant's observed $\zeta(\boldsymbol{h})$ and $\upsilon(\boldsymbol{h})$, the model-implied likelihood of that observation as a function of the parameters in $(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ is $F(\upsilon(\boldsymbol{h}); \boldsymbol{\mu}, \boldsymbol{\Sigma}) - F(\zeta(\boldsymbol{h}); \boldsymbol{\mu}, \boldsymbol{\Sigma})$, where $F(\cdot; \boldsymbol{\mu}, \boldsymbol{\Sigma})$ is the CDF for $\boldsymbol{h}$ given parameters $(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. From here, it is straightforward to set up the sample log-likelihood summing over all participants.

We run this estimation separately for each of the 20 (p, r) combinations. Supplementary Tables E.1 and E.2 provide MLE results analogous to those of Appendix Tables A.5 and A.6, where Supplementary Table E.2 is constructed from Supplementary Table E.1 in exactly the same way that Appendix Table A.6 is constructed from Appendix Table A.5 (see Supplementary Material E.2).

The message from the MLE estimation is much the same as that for our simpler estimation based on sample moments. Supplementary Figure E.1 compares the MLE estimates from Supplementary Table E.1 to the estimates from Appendix Table A.5. For the most part, the estimated parameters are close to each other, although the MLE approach yields slightly more variability for both noise and preference heterogeneity, which reflects that the MLE approach recognizes the interval nature of the data and the noise implications of censoring. The central conclusion that preference heterogeneity accounts for roughly half of the variation in the h_{XY} measures and one third of the variation in the Δ_Z measures remains the same.

Table E.1: Decomposition Estimates Using Maximum Likelihood Estimation

p	r	$\hat{\mu}^*_{AB}$	$\hat{\mu}^*_{AB'}$	$\hat{\mu}^*_{CD}$	$\hat{\theta}^2_{AB}$	$\hat{\theta}^2_{AB'}$	$\hat{\theta}^2_{CD}$	$\hat{\sigma}^2_{AB}$	$\hat{\sigma}^2_{AB'}$	$\hat{\sigma}^2_{CD}$	$\hat{\theta}_{AB,AB'}$	$\hat{\theta}_{AB,CD}$	$\hat{\theta}_{AB',CD}$	$\frac{\widehat{var}(h^*_{AB})}{\widehat{var}(h_{AB})}$	$\frac{\widehat{var}(h^*_{AB'})}{\widehat{var}(h_{AB'})}$	$\frac{\widehat{var}(h^*_{CD})}{\widehat{var}(h_{CD})}$
0.30	0.10	37.03	24.14	33.04	147.69	136.04	150.43	105.38	129.65	193.25	68.06	76.63	52.16	0.58	0.51	0.44
0.30	0.20	36.04	25.60	32.17	149.83	139.46	133.37	96.94	109.93	158.96	85.88	73.40	53.11	0.61	0.56	0.46
0.30	0.30	36.78	30.11	34.54	162.12	183.93	159.50	106.22	105.03	121.22	116.05	101.52	84.58	0.60	0.64	0.57
0.30	0.50	37.53	30.54	38.22	129.09	105.10	118.30	107.12	146.21	126.43	107.21	101.80	83.18	0.55	0.42	0.48
0.30	0.80	37.47	34.89	36.72	108.62	137.66	118.29	84.72	96.93	105.38	109.60	96.30	95.19	0.56	0.59	0.53
0.50	0.10	38.66	27.61	31.89	138.96	115.90	122.74	58.98	117.67	143.11	57.20	30.33	53.34	0.70	0.50	0.46
0.50	0.20	39.22	29.24	32.83	134.83	89.17	121.31	74.50	132.07	115.20	74.48	53.41	43.38	0.64	0.40	0.51
0.50	0.30	41.60	34.46	35.78	129.94	145.38	82.31	54.98	75.44	133.46	87.18	43.63	41.37	0.70	0.66	0.38
0.50	0.50	38.89	34.68	39.54	143.05	160.35	130.15	72.08	77.24	87.62	124.84	108.39	102.39	0.66	0.67	0.60
0.50	0.80	38.14	37.51	38.71	132.17	154.79	105.14	50.40	76.19	75.23	124.25	92.70	98.89	0.72	0.67	0.58
0.80	0.10	41.54	36.22	34.93	125.32	174.08	96.12	68.54	94.33	126.55	81.72	32.88	59.63	0.65	0.65	0.43
0.80	0.20	39.48	35.83	36.07	87.47	151.90	89.59	66.46	66.86	100.84	76.27	45.64	72.44	0.57	0.69	0.47
0.80	0.30	42.25	40.04	36.25	142.23	140.81	81.39	77.77	138.00	94.99	93.11	53.58	53.87	0.65	0.51	0.46
0.80	0.50	38.87	36.80	37.60	79.11	113.43	58.83	72.05	67.13	97.31	65.57	38.43	38.45	0.52	0.63	0.38
0.80	0.80	40.83	41.67	42.15	125.37	158.22	88.61	53.95	79.62	76.39	124.38	77.51	69.81	0.70	0.67	0.54
0.90	0.10	40.28	35.31	33.73	116.52	105.31	85.49	99.63	133.70	102.50	83.22	31.34	56.45	0.54	0.44	0.45
0.90	0.20	39.54	38.92	34.42	132.46	107.98	74.15	79.80	126.87	87.83	105.26	42.24	49.13	0.62	0.46	0.46
0.90	0.30	38.83	40.05	37.44	94.68	188.40	94.32	91.21	65.10	100.50	94.85	54.39	67.32	0.51	0.74	0.48
0.90	0.50	38.78	37.91	36.43	97.33	99.12	66.35	90.67	118.56	75.38	85.74	44.30	52.80	0.52	0.46	0.47
0.90	0.80	38.16	39.17	37.74	88.16	107.75	51.25	71.33	70.07	62.76	87.17	48.63	52.31	0.55	0.61	0.45
0.62	0.38	39.00	34.53	36.01	123.25	135.74	101.38	79.14	101.33	109.25	92.60	62.35	63.99	0.61	0.57	0.48

Note: Table reports decomposition estimates using MLE (see Supplementary Material E.5 for details). Final line presents averages over all 20 rows.

Table E.2: Preference-Noise Decomposition Using MLE Estimates from Supplementary Table E.1

p	r	$\hat{\Delta}^{**}_{CR}$	$\hat{\Delta}^{**}_{CC}$	$\hat{\Delta}^{**}_{MX}$	$\widehat{var}(\Delta^*_{CR})$	$\widehat{var}(\Delta^*_{CC})$	$\widehat{var}(\Delta^*_{MX})$	$\widehat{var}(\Delta_{CR})$	$\widehat{var}(\Delta_{CC})$	$\widehat{var}(\Delta_{MX})$	$\frac{\widehat{var}(\Delta^*_{CR})}{\widehat{var}(\Delta_{CR})}$	$\frac{\widehat{var}(\Delta^*_{CC})}{\widehat{var}(\Delta_{CC})}$	$\frac{\widehat{var}(\Delta^*_{MX})}{\widehat{var}(\Delta_{MX})}$
0.30	0.10	3.99	-8.90	12.89	144.86	182.15	147.62	443.49	505.06	382.65	0.33	0.36	0.39
0.30	0.20	3.87	-6.57	10.44	136.41	166.61	117.53	392.31	435.49	324.39	0.35	0.38	0.36
0.30	0.30	2.24	-4.42	6.67	118.59	174.26	113.95	346.03	400.51	325.20	0.34	0.44	0.35
0.30	0.50	-0.70	-7.68	6.99	43.80	57.05	19.78	277.35	329.70	273.10	0.16	0.17	0.07
0.30	0.80	0.75	-1.83	2.58	34.32	65.56	27.09	224.42	267.88	208.75	0.15	0.24	0.13
0.50	0.10	6.76	-4.28	11.05	201.05	131.97	140.45	403.14	392.75	317.10	0.50	0.34	0.44
0.50	0.20	6.39	-3.60	9.98	149.33	123.72	75.03	339.02	370.99	281.60	0.44	0.33	0.27
0.50	0.30	5.82	-1.32	7.14	124.99	144.96	100.96	313.43	353.85	231.38	0.40	0.41	0.44
0.50	0.50	-0.65	-4.86	4.22	56.41	85.73	53.72	216.12	250.59	203.04	0.26	0.34	0.26
0.50	0.80	-0.56	-1.19	0.63	51.91	62.13	38.46	177.55	213.55	165.05	0.29	0.29	0.23
0.80	0.10	6.61	1.29	5.32	155.68	150.93	135.96	350.78	371.82	298.84	0.44	0.41	0.45
0.80	0.20	3.42	-0.23	3.65	85.78	96.61	86.83	253.08	264.31	220.15	0.34	0.37	0.39
0.80	0.30	6.00	3.78	2.22	116.47	114.45	96.81	289.23	347.44	312.59	0.40	0.33	0.31
0.80	0.50	1.27	-0.80	2.07	61.07	95.35	61.39	230.43	259.78	200.57	0.27	0.37	0.31
0.80	0.80	-1.32	-0.48	-0.84	58.95	107.20	34.83	189.29	263.21	168.39	0.31	0.41	0.21
0.90	0.10	6.55	1.58	4.97	139.33	77.91	55.39	341.46	314.10	288.72	0.41	0.25	0.19
0.90	0.20	5.12	4.50	0.63	122.12	83.88	29.91	289.76	298.58	236.58	0.42	0.28	0.13
0.90	0.30	1.39	2.61	-1.22	80.22	148.07	93.39	271.94	313.68	249.70	0.30	0.47	0.37
0.90	0.50	2.35	1.49	0.86	75.08	59.86	24.97	241.13	253.80	234.19	0.31	0.24	0.11
0.90	0.80	0.43	1.43	-1.00	42.15	54.37	21.57	176.24	187.20	162.97	0.24	0.29	0.13
0.62	0.38	2.99	-1.47	4.46	99.93	109.14	73.78	288.31	319.71	254.25	0.33	0.34	0.28

Notes: able calculates model-implied variances of Δ_Z's and Δ^*_Z's using the MLE decomposition estimates from Table E.1. Final line presents averages over all 20 rows. rows.

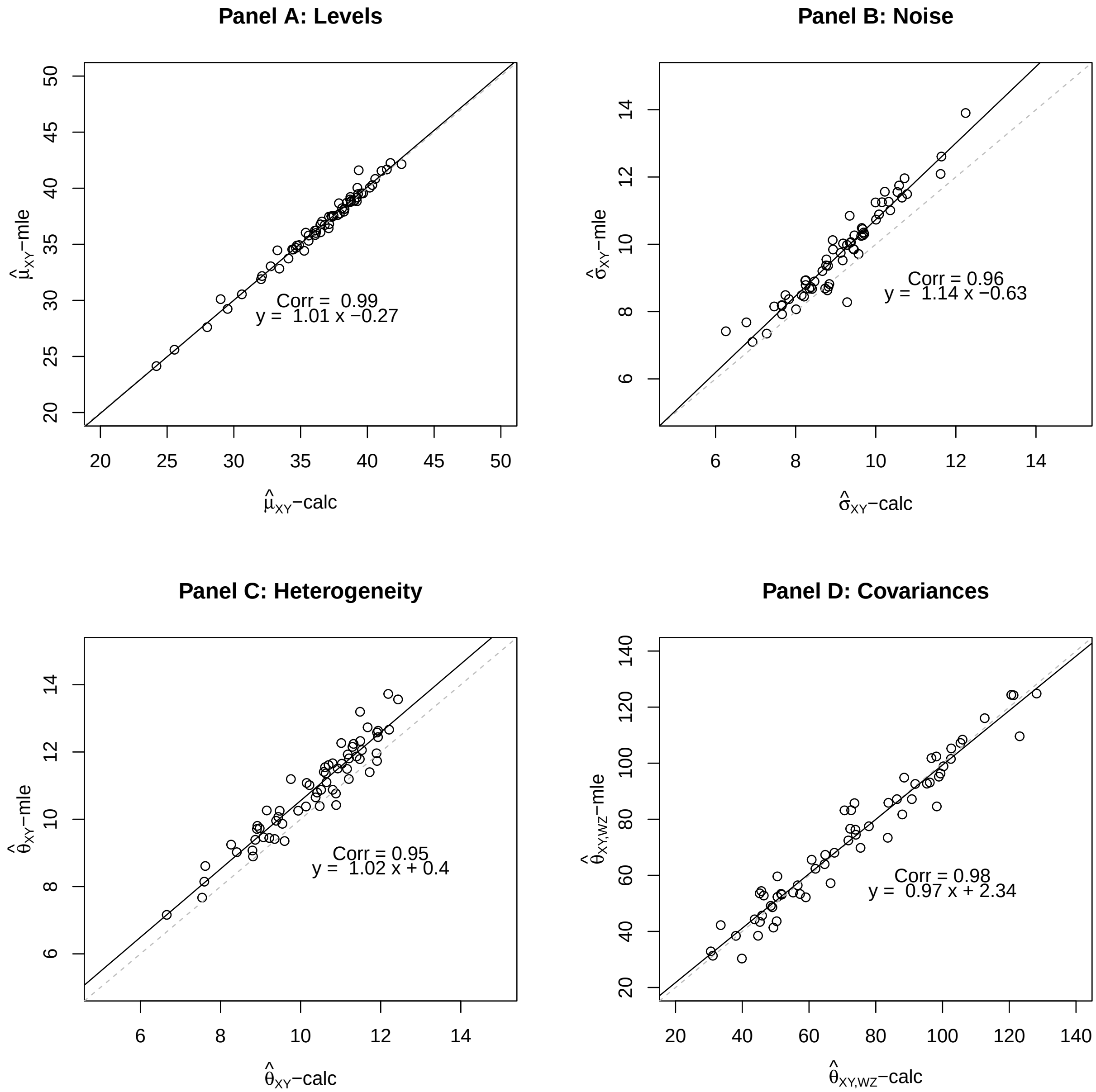


Figure E.1: Comparison of Decomposition Results (Direct Calculation vs. MLE)

Notes: Figure relates calculated quantities from Table A.5 to MLE estimates from Supplementary Table E.1. Correlation reported for all observations in each panel.

F Upside Potential Model: Estimation

In this section, we describe the details of the structural estimations described in Sections 5.2.3 and 5.3 of the main text, that is, the structural estimation of our upside-potential model and the structural estimation of various prospect-theory models.

F.1 Data and General Approach

Our goal is to assess how different models perform in explaining the broad patterns in our data, and in particular how the empirical valuations h_{AB}, $h_{AB'}$, and h_{CD} react to changes in the experimental parameters (p, r, M). To do so in a tractable and concrete way, we take the data to be the average responses for h_{AB}, $h_{AB'}$, and h_{CD} across the 20 different (p, r) combinations for which we collect responses. Hence, the data consist of 60 observations, and these are presented together in the first three columns of Appendix Table A.2.

Our general approach starts with the specification of a model with parameter vector $\mathbf{\Theta}$. Given a specified model, we derive the model-predicted h^*_{XY}'s, $XY \in \{AB, AB', CD\}$, as a function of the experimental parameters (p, r, M) and the model parameter vector $\mathbf{\Theta}$. We denote these predictions by $h^*_{XY}(p, r, M; \mathbf{\Theta})$. We then use the 60 observations in the data to estimate $\mathbf{\Theta}$ using non-linear least squares—i.e., estimating the equation $h_{XY} = h^*_{XY}(p, r, M; \mathbf{\Theta}) + \varepsilon$. Finally, we assess the performance of each model using (i) its mean-squared error (MSE), (ii) its internal R^2, (iii) the correlation between the model-predicted h^*_{XY}'s and the observed h_{XY}'s, and (iv) the correlation between the model-predicted Δ^*'s and the observed Δ's.

F.2 Estimating the Upside-Potential Model

We estimate the upside potential model in equation (B.1), where the model predictions for h^*_{AB}, $h^*_{AB'}$, and h^*_{CD} are defined by equations (B.2), (B.3), and (B.4) from the Online Appendix. In this model, the sole object to estimate is the function $\kappa(x)$.

It is important to note that our data are not optimal for estimating the shape of κ. Recall that we designed our experiment to study connected CR-CC-MX problems across a broad range of the parameter space. The upside-potential model is our post-hoc attempt to explain the broad patterns that emerged in our data that are inconsistent with existing prominent non-EU models. We did not have this model in mind when we designed our experiment, and the data from our experiment do not have the ideal variation one might want if the goal had been to estimate this model. Nonetheless, this estimation gives some initial indication of what shape of κ may be to rationalize our data.

Because we have no a priori sense of the shape of κ, we begin with a flexible functional form. Within our design, M takes on the values 9, 15, 24, and 27, while Appendix Table A.2 reveals that h takes on values 23.83, 26.35, 27.77 and then various larger values up to 42.56. Hence, we use the following functional form that has $\mathbf{\Theta} \equiv (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6)$:

$$\kappa(x;\mathbf{\Theta}) \equiv \begin{cases} \theta_1 x & \text{if } x \in [0,9] \\ \kappa(9;\mathbf{\Theta}) + \theta_2(x-9) & \text{if } x \in [9,15] \\ \kappa(15;\mathbf{\Theta}) + \theta_3(x-15) & \text{if } x \in [15,24] \\ \kappa(24;\mathbf{\Theta}) + \theta_4(x-24) & \text{if } x \in [24,27] \\ \kappa(27;\mathbf{\Theta}) + \theta_5(x-27) & \text{if } x \in [27,36] \\ \kappa(36;\mathbf{\Theta}) + \theta_6(x-36) & \text{if } x \geqslant 36 \end{cases}$$

In our data, there are 15 instances each of κ getting evaluated at $x = 9$, $x = 15$, $x = 24$, and $x = 27$ (i.e., for each of the four values of M). In contrast, based on the mean h values we observe, there are no $x \in (0,9)$ or $x \in (9,15)$, and only one instance each of $x \in (15,24)$ and $x \in (24,27)$. Hence, θ_1, θ_2, θ_3, and θ_4 primarily capture $\kappa(9)$, $\kappa(15)$, $\kappa(24)$, and $\kappa(27)$—i.e., the values of κ at the four values of M. The remaining 58 values for the h's lie in $x \in (27,43)$. We permit κ to be either linear (i.e., $\theta_5 = \theta_6$) or two-part-linear over this range, where for the latter case we put the kink at $x = 36$ based on wanting similar instances of x above and below the kink.

In Supplementary Table F.1, column (1) reports estimates when we assume κ is two-part linear above $x = 27$, while column (2) reports estimates when we assume κ is linear above $x = 27$. In addition, Supplementary Figures F.1 and F.2 depict for each estimated model (i) the estimated κ function, (ii) the actual h_{XY} valuations against their model-predicted values, and (iii) the actual Δ measures against their model-predicted values.

Both the six and five parameter κ functions fit the data well in-sample, delivering R^2 values above 0.75, correlations between predicted and actual h_{XY} valuations around 0.9, and correlations between predicted and actual Δ measures also around 0.9. Though the six-parameter model provides a slightly better in-sample fit for the levels of response, the five-parameter model performs slightly better in terms of correlation with the key preference measures, Δ_{CR}, Δ_{CC}, and Δ_{MX}. The six-parameter model also exhibits a slight non-monotonicity in the estimated κ function between 27 and 36 with θ_5 estimated to be negative. We believe this, and the slightly worse match to the Δ measures is due to overfitting and lack of variability for all types of h_{XY} in the data. As can be observed in Figure F.1, Panel B, the majority of observations between $x = 27$ and $x = 36$ are h_{CD} responses, while those above $x = 36$ also include h_{AB} and $h_{AB'}$. The six-parameter model can thus effectively dedicate a parameter to fit a single type of data in the $x \in (27, 36)$ region. This yields a slightly better fit of the levels but compromises on fitting differences. Due to this possibility of overfitting, our preferred estimates are those of the five-parameter model.

Within our preferred model, our estimates suggest that κ has an S-shape. In an attempt to capture this shape using a functional form with fewer parameters, we next consider a three-parameter sigmoid function with $\mathbf{\Theta} \equiv (\theta_1, \theta_2, \theta_3)$:

$$\kappa(z, \mathbf{\Theta}) = \theta_1 * \left[\frac{1}{1 + exp(\theta_2(z - \theta_3))}\right] - \theta_1 * \left[\frac{1}{1 + exp(\theta_2(0 - \theta_3))}\right].$$

In this formulation, the first bracketed term is a classic two-parameter sigmoid function (with parameters θ_2 and θ_3) that goes from zero (as $x \to -\infty$) to one (as $x \to \infty$). The third parameter (θ_1) is a multiplier on the bracketed term that makes the first term instead go from zero to θ_1. Finally, the second term subtracts off the value of the first term when it is evaluated at $x = 0$ to ensure that $\kappa(0) = 0$.

Column (3) of Supplementary Table F.1 presents estimates for this functional form, while Supplementary Figure F.3 provides a corresponding illustration of model fit. Again, substantial non-linearity of the κ function emerges in estimation. Imposing this functional form, however, does lead to a substantial reduction in explanatory power for the levels of the h_{XY} valuations. Interestingly, however, this three-parameter functional form delivers correlations between predicted and actual Δ measures close to that of our preferred five-parameter model and exceeding that of the six-parameter model noted above. Panel C of Figure F.3 makes clear that if one's primary objective is to predict Δ_{CR}, Δ_{CC}, and Δ_{MX}, this three-parameter functional matches the 60 differences in the data well.

F.3 Estimating Prospect-Theory Models

As a point of comparison for the fit of our upside potential model, we also estimate several variants of prospect-theory models using the same 60 data points. As in Supplementary Material C.1, under original prospect theory (OPT) as in Kahneman and Tversky (1979), a person's valuations are given by

$$h_{AB} = v^{-1}\left(\frac{1}{\pi(p)}v(M)\right), \; h_{AB'} = v^{-1}\left(\frac{1 - \pi(1-r)}{\pi(pr)}v(M)\right), \text{ and } h_{CD} = v^{-1}\left(\frac{\pi(r)}{\pi(pr)}v(M)\right).$$

As in Supplementary Material C.2, under cumulative prospect theory (CPT) as in Tversky and Kahneman (1992), a person's h_{AB} and h_{CD} valuations are as above, while there $h_{AB'}$ valuation is:

$$h_{AB'} = v^{-1}\left(\frac{1-(\pi(pr+1-r)-\pi(pr))}{\pi(pr)}v(M)\right).$$

For either version, the objects to estimate are the probability weighting function $\pi(q)$ and the value function $v(x)$.

We first estimate these models using functional forms frequently used in the literature. Specifically, we assume the value function is $v(x) = x^{\alpha}$, and we consider both the one-parameter probability weighting function from Tversky and Kahneman (1992),

$$\pi(q) = \frac{q^{\delta}}{\left[q^{\delta}+(1-q)^{\delta}\right]^{1/\delta}},$$

and the two-parameter probability weighting function from Lattimore et al. (1992),

$$\pi(q) = \frac{\gamma q^{\delta}}{\gamma q^{\delta}+(1-q)^{\delta}}.$$

Columns (4) and (5) of Supplementary Table F.1 present estimates for CPT for these two functional forms for $\pi(q)$, and columns (7) and (8) does the same for OPT. Supplementary Figures F.4, F.5, F.7, and F.8 depict for each estimated model (i) the estimated probability weighting function, (ii) the actual h_{XY} valuations against their model-predicted values, and (iii) the actual Δ measures against their model-predicted values.

All four specifications have poor in-sample fit and substantially underperform our three-parameter model of upside potential. The best fitting version of prospect theory is CPT with the two-parameter $\pi(q)$ which has an MSE of 18.03, an R-squared of -0.23, a correlation between predicted and actual h_{XY} valuations of 0.55, and a correlation between predicted and actual Δ measures of 0.7. The negative R^2 value implies that a researcher would be more accurate if they predicted the mean outcome for every response rather than using the model prediction.

Though these PT estimates do not fit our data well, the estimated parameters for the one-parameter probability weighting function are close to those in the existing literature. Using data on certainty equivalents for binary lotteries, Tversky and Kahneman (1992) provide median estimates of $\alpha = 0.88$ and $\theta_1 = 0.61$. Using similar data, Bernheim and Sprenger (2020) estimate $\alpha = 0.94$ and $\theta_1 = 0.72$. In Supplementary Table F.1, our estimates are $\alpha = 0.80$ and $\theta_1 = 0.84$ for CPT, and $\alpha = 0.75$ and $\theta_1 = 0.79$ for OPT.

It is perhaps not surprising that these prominent functional forms for probability weighting perform poorly in explaining our data since they were developed to generate a global CRP and CCP. Hence, it is worth assessing now much better CPT and OPT might perform with a more flexible functional form. Specifically, we consider the following six-part piecewise-linear functional form for probability weighting:

$$\pi(q;\boldsymbol{\Theta}) \equiv \begin{cases} 0 & \text{if } q = 0 \\ \theta_0 + \theta_1 q & \text{if } q \in (0, \bar{q}_1] \\ \pi(\bar{q}_1;\boldsymbol{\Theta}) + \theta_2(q - \bar{q}_1) & \text{if } q \in [\bar{q}_1, \bar{q}_2] \\ \pi(\bar{q}_2;\boldsymbol{\Theta}) + \theta_3(q - \bar{q}_2) & \text{if } q \in [\bar{q}_2, \bar{q}_3] \\ \pi(\bar{q}_3;\boldsymbol{\Theta}) + \theta_4(q - \bar{q}_3) & \text{if } q \in [\bar{q}_3, \bar{q}_4] \\ \pi(\bar{q}_4;\boldsymbol{\Theta}) + \theta_5(q - \bar{q}_4) & \text{if } q \in [\bar{q}_4, \bar{q}_5] \\ \pi(\bar{q}_5;\boldsymbol{\Theta}) + \theta_6(q - \bar{q}_5) & \text{if } q \in [\bar{q}_5, 1) \\ 1 & \text{if } q = 1 \end{cases}$$

Note that to provide OPT and CPT with extra flexibility, this piecewise-linear function permits (but does not require) discontinuities at $q = 0$ and $q = 1$. We selected the five kink points (i.e., the $\bar{q}_i$'s) ex ante based on where $\pi(q)$ would need to be evaluated in each model—putting kinks at q's where π is frequently evaluated while also trying to have similar numbers of instances within each segment. For the OPT model, we chose $(\bar{q}_1, \bar{q}_2, \bar{q}_3, \bar{q}_4, \bar{q}_5) = (0.15, 0.3, 0.5, 0.7, 0.8)$, whereas for CPT we chose $(\bar{q}_1, \bar{q}_2, \bar{q}_3, \bar{q}_4, \bar{q}_5) = (0.15, 0.3, 0.5, 0.8, 0.9)$. Also, note that this specification nests expected utility, $\theta = (0, 1, 1, 1, 1, 1, 1)$.

Columns (6) and (9) of Supplementary Table F.1 present these flexible estimates for CPT and OPT, respectively. Supplementary Figures F.6 and F.9 depict for each estimated model (i) the estimated probability weighting function, (ii) the actual h_{XY} valuations against their model-predicted values, and (iii) the actual Δ measures against their model-predicted values. For OPT, this additional flexibility does relatively little to improve fit, and a researcher would remain more accurate predicting the mean for every observation rather than using the model prediction. In contrast, for CPT, this extra flexibility leads to qualitative fit improvements, roughly halving the MSE to 11.02 and delivering a positive R^2 value. Importantly, however, the MSE of this best-performing CPT model is still around three times larger than that of our preferred upside-potential model, while the R^2 value is approximately three times smaller. This worse fit is particularly notable given that the flexible CPT model has access to three more degrees of freedom than our preferred specification of upside potential.

Table F.1: Estimates of Upside Potential and Probability Weighting

	Upside Potential			CPT Probability Weighting			OPT Probability Weighting		
	Flexible	Flexible	Parametric	Parametric	Parametric	Flexible	Parametric	Parametric	Flexible
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Utility Curvature									
α				0.80	0.43	0.35	0.75	0.73	0.70
				(0.02)	(0.05)	(0.04)	(0.02)	(0.03)	(0.03)
Upside Potential/Weighting Parameters									
θ_1	1.58	1.76	135.34	0.84	1.84	0.20	0.79	0.93	0.04
	(0.26)	(0.32)	(37.59)	(0.03)	(0.22)	(0.04)	(0.02)	(0.02)	(0.01)
θ_2	3.73	4.41	0.19		0.63	1.85		0.75	1.17
	(0.67)	(0.88)	(0.00)		(0.03)	(0.13)		(0.03)	(0.13)
θ_3	6.43	6.86	19.36			1.07			0.94
	(1.04)	(1.36)	(0.39)			(0.05)			(0.06)
θ_4	6.68	7.70				0.62			0.73
	(1.63)	(1.63)				(0.07)			(0.09)
θ_5	−0.25	1.72				0.29			0.51
	(0.41)	(0.54)				(0.10)			(0.13)
θ_6	6.95					0.54			1.32
	(1.68)					(0.11)			(0.21)
θ_7						0.69			0.98
						(0.16)			(0.16)
Observations	60	60	60	60	60	60	60	60	60
Degrees of Freedom	54	55	57	58	57	52	58	57	52
h_{XY}-MSE	2.71	3.53	7.72	33.88	18.03	11.02	26.85	26.17	21.71
h_{XY}-R^2	0.82	0.76	0.47	−1.31	−0.23	0.25	−0.83	−0.78	−0.48
$\rho(h_{XY}, \hat{h}_{XY})$	0.92	0.91	0.83	−0.20	0.55	0.71	0.22	0.30	0.45
Δ-MSE	6.15	7.58	7.51	41.48	24.01	19.92	32.51	31.39	29.31
Δ-R^2	0.66	0.58	0.59	−1.28	−0.32	−0.10	−0.79	−0.73	−0.61
$\rho(\Delta, \hat{\Delta})$	0.88	0.90	0.89	−0.51	0.70	0.72	0.22	0.39	0.49

Note: Non-linear least squares regressions using 60 mean values of $h_{AB}, h_{AB'}, h_{CD}$ as observations. Standard errors in parentheses. R^2 values calculated as $1 - RSS/TSS$, where TSS is sum of squared deviations to the average value among the 60 observations, and RSS is the sum of squared residuals between the estimated model and the data. Negative values indicate that predicting the mean for every observation would yield better fit than the estimated model. MSE values, R^2 values, and correlation between predicted and actual values, ρ, provided for both levels, h_{XY}'s, and differences, Δ's.

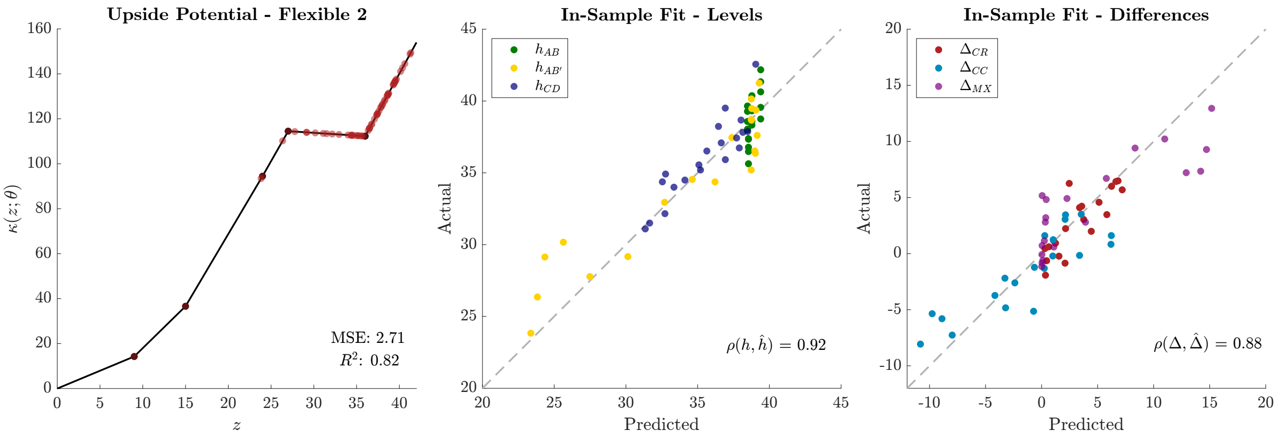


Figure F.1: Upside Potential Estimates - Flexible Six Parameter Model

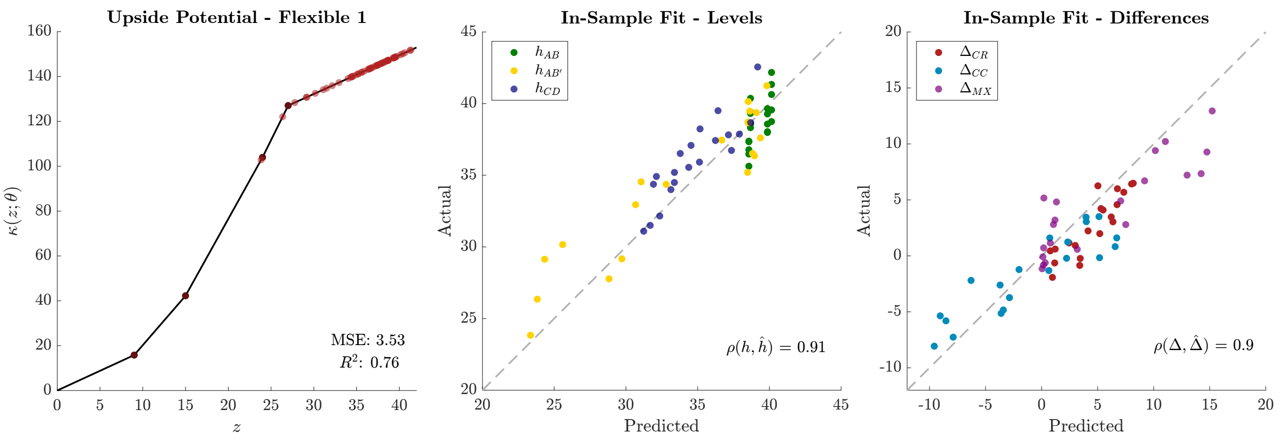


Figure F.2: Upside Potential Estimates - Flexible Five Parameter Model

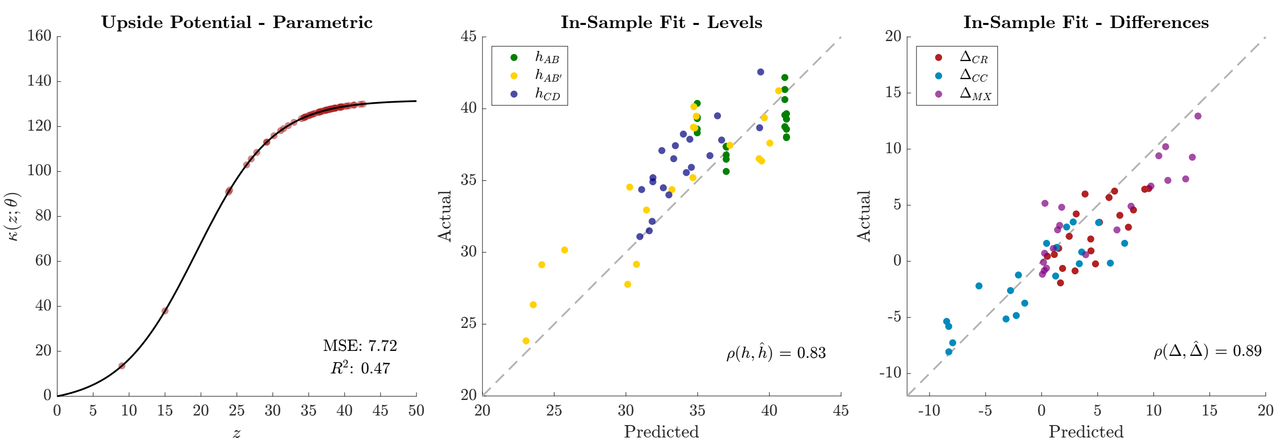


Figure F.3: Upside Potential Estimates - Parametric Functional Form

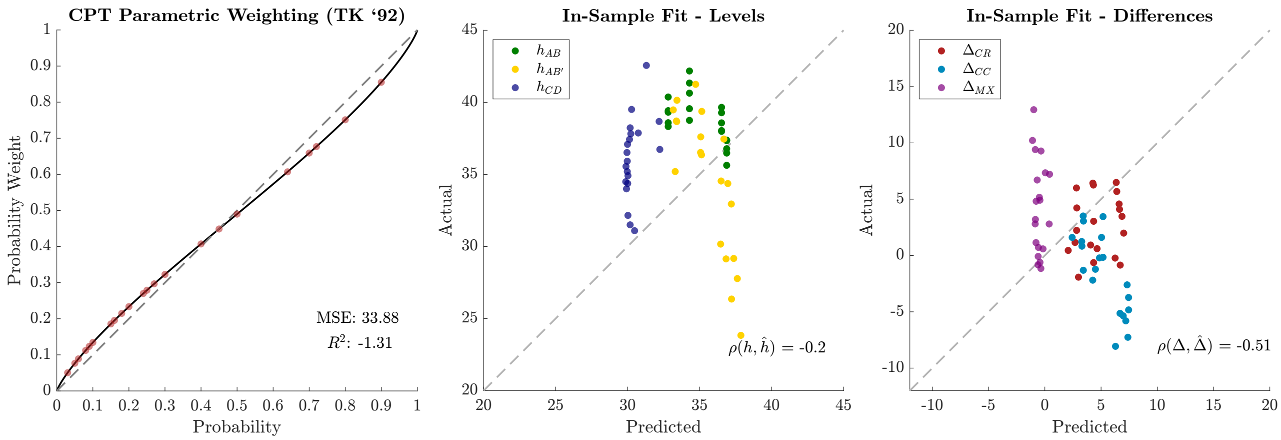


Figure F.4: CPT Probability Weighting Estimates - Parametric One Parameter Weighting Function

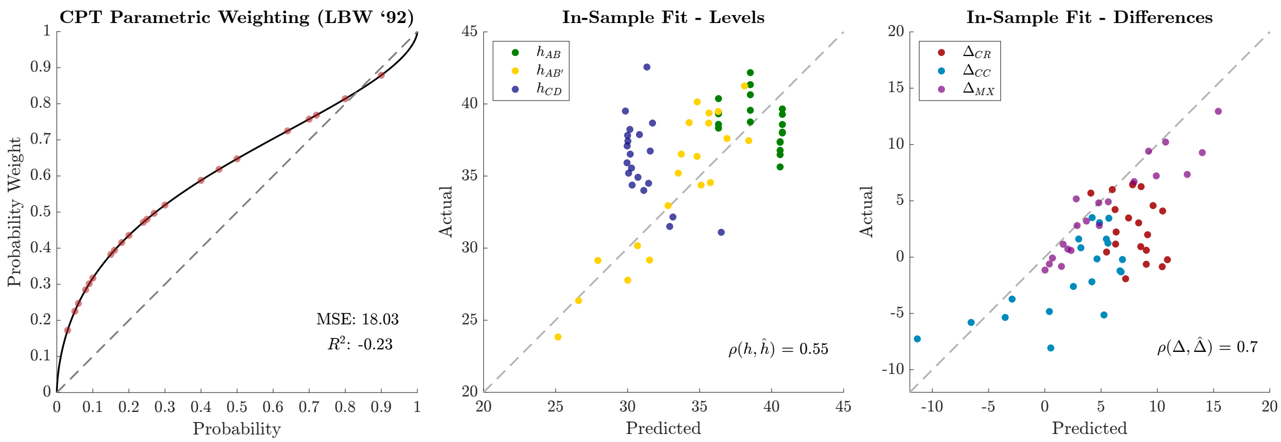


Figure F.5: CPT Probability Weighting Estimates - Parametric Two Parameter Weighting Function

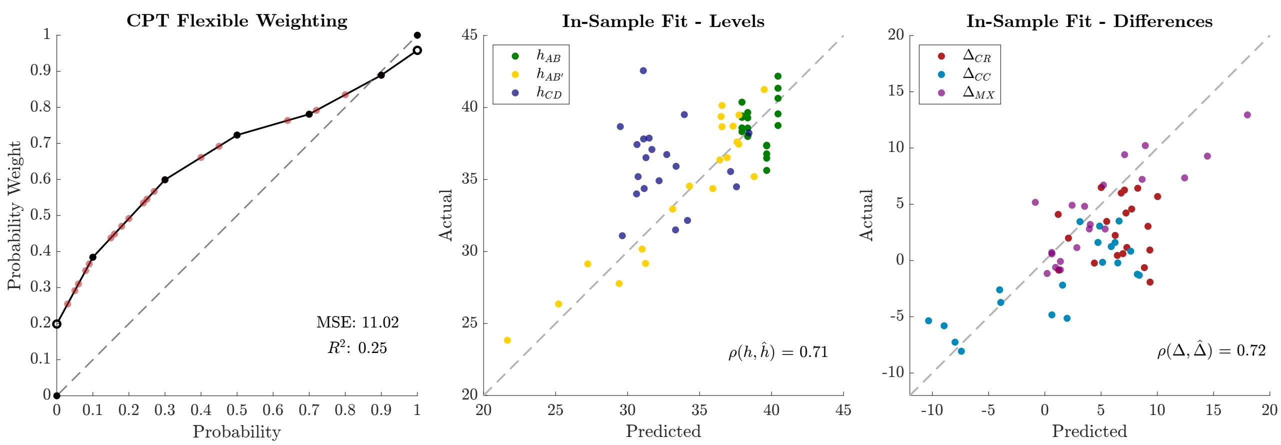


Figure F.6: CPT Probability Weighting Estimates - Flexible Functional Form

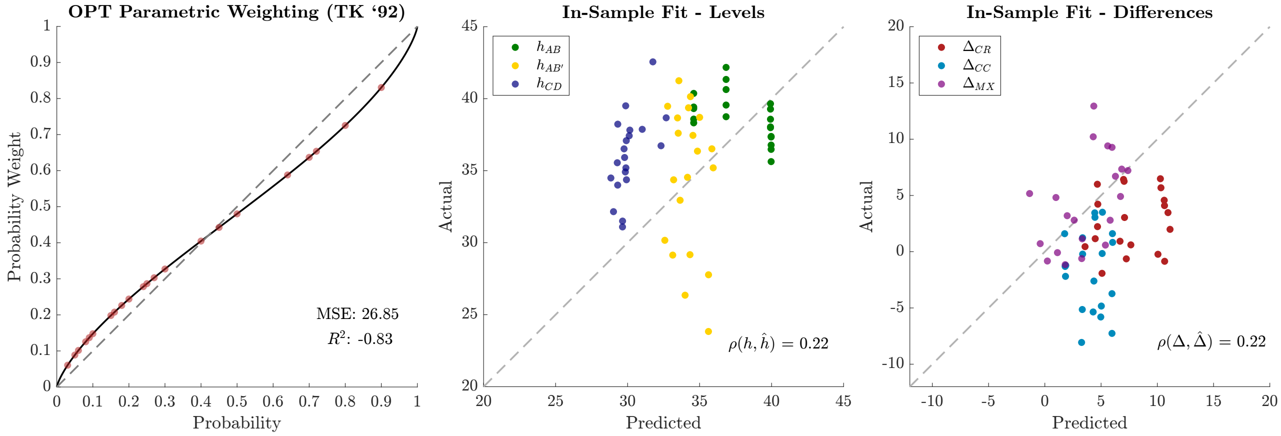


Figure F.7: OPT Probability Weighting Estimates - Parametric One Parameter Weighting Function

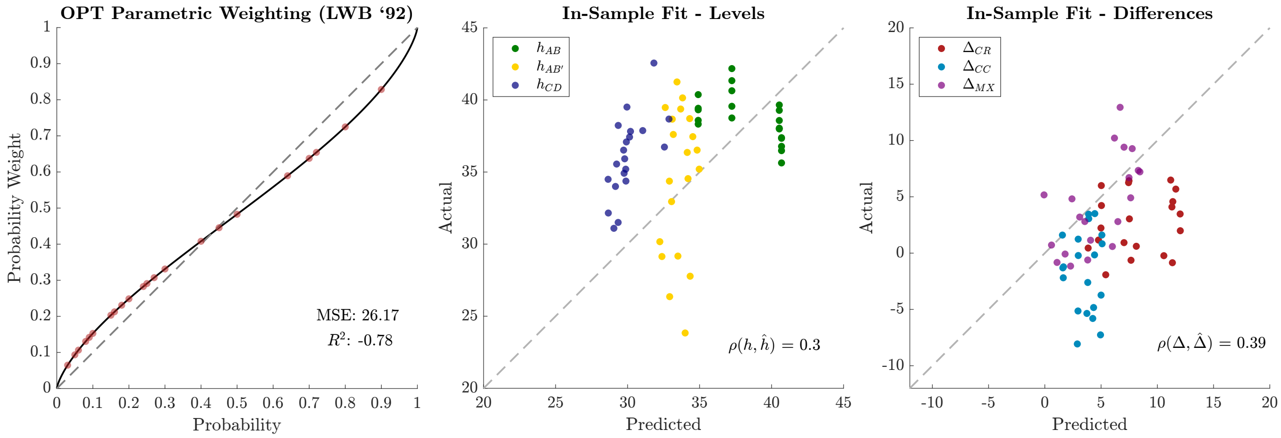


Figure F.8: OPT Probability Weighting Estimates - Parametric Two Parameter Weighting Function

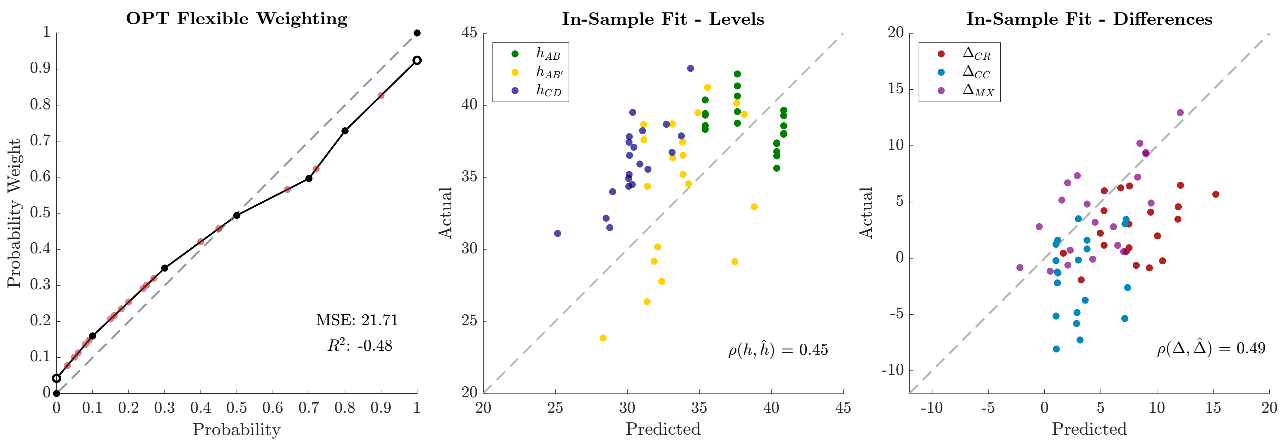


Figure F.9: OPT Probability Weighting Estimates - Flexible Functional Form

G Screenshots from the Online Experiment

OPTION A:		OPTION B:
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$24**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$25**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$26**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$27**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$28**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$29**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$30**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$31**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$32**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$33**
100% CHANCE OF $24	OR	2% CHANCE OF $0 90% CHANCE OF $24 8% CHANCE OF **$34**

Figure G.1: Example Price List for Stage 1 AB' Valuation Task with $p = 0.8$ and $r = 0.1$

OPTION A:		OPTION B:
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$24**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$25**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$26**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$27**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$28**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$29**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$30**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$31**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$32**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$33**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$34**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$35**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$36**
100% CHANCE OF $24	OR	20% CHANCE OF $0 80% CHANCE OF **$37**

Figure G.2: Example Price List for Stage 1 AB Valuation Task with $p = 0.8$ and $r = 0.1$

OPTION A:		OPTION B:
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$24**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$25**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$26**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$27**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$28**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$29**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$30**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$31**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$32**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$33**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$34**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$35**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$36**
90% CHANCE OF $0 10% CHANCE OF $24	OR	92% CHANCE OF $0 8% CHANCE OF **$37**

Figure G.3: Example Price List for Stage 1 CD Valuation Task with $p = 0.8$ and $r = 0.1$

Option A	Option B
	2% chance of $0
100% chance of $24	90% chance of $24
	8% chance of $39

Option A | Option B

Figure G.4: Example AB' Binary Choice from Stage 2 with $p = 0.8$, $r = 0.1$, and $H = 39$

Option A	Option B
100% chance of $24	20% chance of $0
	80% chance of $49

Option A | Option B

Figure G.5: Example AB Binary Choice from Stage 2 with $p = 0.8$, $r = 0.1$, and $H = 49$

Option A	Option B
90% chance of $0	92% chance of $0
10% chance of $24	8% chance of $49

Option A | Option B

Figure G.6: Example CD Binary Choice from Stage 2 with $p = 0.8$, $r = 0.1$, and $H = 49$

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 **$3**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$4**
	...	
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$22**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$23**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$24**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$25**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$26**
25% CHANCE OF $0, 75% CHANCE OF $30	OR	100% CHANCE OF **$27**
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 G.7: Incentivized Comprehension Check #1

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 **$17**
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF **$18**
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF **$19**
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF **$20**
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF **$21**
60% CHANCE OF $0, 40% CHANCE OF $30	OR	50% CHANCE OF $0 50% CHANCE OF **$22**
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

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Figure G.8: Incentivized Comprehension Check #2

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.

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Figure G.9: Example Visual Search Task