Online Supplement To

The construct-behavior gap in behavioral decision research:
A challenge beyond replicability

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1 Unanimous Preference, Deterministic Responses:

Suppose momentarily that all respondents have preference patterns OVG_8 for gains (1|1|1|1 on the left of Table 4 of the article) and OVL_4 for losses (1|1 on the right of Table 4 of the article), i.e., the combined preference OV_{32} (1|1|1|1|1|1 in Table 5 of the article). They can vary somewhat in their weighting and utility functions (see Section 6 below for a discussion). But suppose that they agree on this preference pattern. If they do not make errors in their choices, then a randomly sampled respondent will deterministically choose Option H in every decision problem. Hence, the coding 1|1|1|1|1|1 in OV_{32} of Table 5 effectively shows the six binary choice 'probabilities' in the deterministic special case in which everyone has preference OV_{32} and nobody makes a response error:

$$P_{HL}(1) = P_{HL}(2) = P_{HL}(3) = P_{HL}(4) = P_{HL}(5) = P_{HL}(6) = 1.$$

Likewise, every other preference pattern Table 5 gives choice probabilities for a unanimous preference and error-free choices.

2 Unanimous Preference, Probabilistic Responses:

Some papers treat the participants of a study as though they shared a unanimous preference (Ungemach et al., 2009). Some papers go further and use the same parameter values for all decision makers including, in this literature, Fox and Hadar (2006), who focussed on CPT-MED. The simplest way to create models in which the preference is unanimous and responses are error-prone is to take one row of Table 5 and to replace the zeros and ones by probabilities between zero and one. Unless we entertain the possibility that a person could be more likely to choose what he does not prefer than what he prefers, we should place an upper bound on error rates. Say, we limit error probabilities to be no higher than some upper bound $\tau = 0.50$. According to this model, if the unanimous preference is OV_{32} then, with $\wedge$ denoting the logical AND, the choice probabilities satisfy

$$\begin{array}{rrcl} & P_{HL}(1) & \geq & 1/2 \\ \wedge & P_{HL}(2) & \geq & 1/2 \\ \wedge & P_{HL}(3) & \geq & 1/2 \\ \wedge & P_{HL}(4) & \geq & 1/2 \\ \wedge & P_{HL}(5) & \geq & 1/2 \\ \wedge & P_{HL}(6) & \geq & 1/2. \end{array}$$

Of course, this includes the possibility, seen earlier, that all error rates are zero and that these choice probabilities all equal 1. Next, consider a scenario with two possible preference states. If the unanimous preference is one of either OV_1 or OV_2, then

$$\text{either} \left\{ \begin{array}{rrl} & P_{HL}(1) & \leq 1/2 \\ \wedge & P_{HL}(2) & \leq 1/2 \\ \wedge & P_{HL}(3) & \leq 1/2 \\ \wedge & P_{HL}(4) & \leq 1/2 \\ \wedge & P_{HL}(5) & \leq 1/2 \\ \wedge & P_{HL}(6) & \leq 1/2, \end{array} \right. \qquad \text{or} \left\{ \begin{array}{rrl} & P_{HL}(1) & \leq 1/2 \\ \wedge & P_{HL}(2) & \leq 1/2 \\ \wedge & P_{HL}(3) & \leq 1/2 \\ \wedge & P_{HL}(4) & \leq 1/2 \\ \wedge & P_{HL}(5) & \leq 1/2 \\ \wedge & P_{HL}(6) & \geq 1/2. \end{array} \right.$$

We are now ready to formulate the general case.

Two Models of Response Errors:

According to our first two models, respondents can vary arbitrarily in their parameter values $\gamma, \delta, \alpha, \beta, \lambda$ as long as they share a single preference pattern $\succ$. Each participant can make a probabilistic error in each choice. Let τ denote the upper bound on the error probability. We consider high ($\tau = \frac{1}{2}$) or moderate ($\tau = \frac{1}{4}$) bounds on error rates. Formally, a randomly selected respondent chooses x over y with probability P_{xy}, where

$$\begin{gathered} P_{xy} \geq 1 - \tau \\ \text{if and only if} \\ x \text{ is preferred to } y \text{ in the unanimous preference state } \succ . \end{gathered} \tag{O1}$$

We will refer to this model as *Deterministic CPT with Overweighting and with Response Error*, because it treats the CPT compatible preference as fixed and deterministic and it attributes all heterogeneity in behavior to probabilistic error/noise in responses. Regenwetter et al. (2014) call this type of model a *supermajority specification of* $\succ$. While they model individual participants, we consider models for data pooled across participants.

We treat the unanimous preference pattern $\succ$ as a free parameter that we infer from the data, similar to UNG's approach. The case of $\tau = \frac{1}{2}$ (but not smaller τ) contains "Fechnerian" (e.g., Luce, Thurstone/Probit, logistic/Logit) models (Hey and Orme, 1994; McFadden, 2001; Luce, 1959; Thurstone, 1927) as nested submodels, but this error model is more general. While Fechnerian models assume fixed values of $\gamma, \delta, \alpha, \beta, \lambda$, this model only assumes a fixed core preference pattern. While Fechnerian models spell out a very specific relationship between 'strength of preference' and error probabilities, here, the actual error probabilities may depend in any way on the decision problem. Technically, it can also depend on the decision maker, but, for tractability, our likelihood function in the data analysis uses one Binomial parameter per decision problem.

Table OLS1: All 6 preference patterns consistent with CPT and power utility in 3D when considering only Decision Problems 1, 2, 3, as well as the corresponding constraints on binary choice probabilities when $\tau = \frac{1}{2}$.

Preference pattern	Dec. Prob. 1	2	3	Constraints on choice probabilities
I	0	0	0	$P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2$
II	0	0	1	$P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2$
III	0	1	0	$P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \leq 1/2$
IV	0	1	1	$P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \geq 1/2$
V	1	1	0	$P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \leq 1/2$
VI	1	1	1	$P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \geq 1/2$

Though Deterministic CPT with Overweighting and with Response Error can be stated quite simply (O1), it has unusual mathematical and statistical properties. For example, the parameters $\gamma, \delta, \alpha, \beta, \lambda$ are not uniquely identifiable, yet, the model is testable. The model can, in fact, be extremely parsimonious (e.g., on the Cash II stimuli in the article). To see what it means to keep track of every preference pattern consistent with CPT, consider first only the first three decision problems, so that we can limit our sample space to $[0, 1]^3$ and include a 3D visualization. Table OLS1 shows the six preference patterns that are consistent with CPT (by "projecting" Table 5 onto Decision Problems 1, 2, 3) and it shows the constraints on the binary choice probabilities that go with each preference pattern when $\tau = \frac{1}{2}$. (Notice that

$P_{LH}(1) = 1 - P_{HL}(1), P_{LH}(2) = 1 - P_{HL}(2), P_{LH}(3) = 1 - P_{HL}(3))$. Figure OLS1 uses $P_{HL}(1), P_{HL}(2), P_{HL}(3)$ as coordinates to visualize these constraints on choice probabilities on the left, as well as the corresponding constraints for $\tau = \frac{1}{4}$ on the right. In both displays, the shaded regions are the permissible combinations of choice probabilities according to the model.

All in all, however, testing Deterministic CPT with Overweighting and with Response Error amounts to testing a highly complex compound hypothesis. Instead of six possible preference patterns like we did in Table OLS1 and Figure OLS1, we must consider 32 of them in a six-dimensional space, thereby getting 32 "hypercubes" in 6D instead of 6 cubes in 3D. As before let $\wedge$ denote the logical AND. Let $\vee$ denote the logical OR. The Null Hypothesis of CPT with $\tau = \frac{1}{2}$ is as follows: (Components with good or perfect fit in some of the data are marked with $*$ in the right.)

$$
H_0 : \begin{cases}
\quad [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \le 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \le 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \le 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \le 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \le 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \le 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \le 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \le 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2]* \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \ge 1/2 \wedge P_{HL}(6) \ge 1/2]* \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \ge 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2]* \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \ge 1/2 \wedge P_{HL}(6) \ge 1/2] \\
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\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \le 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \ge 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2]* \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \ge 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2]* \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \le 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \ge 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2]* \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \le 1/2 \wedge P_{HL}(5) \ge 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \le 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \le 1/2 \wedge P_{HL}(6) \ge 1/2] \\
\vee \ [P_{HL}(1) \ge 1/2 \wedge P_{HL}(2) \ge 1/2 \wedge P_{HL}(3) \ge 1/2 \wedge P_{HL}(4) \ge 1/2 \wedge P_{HL}(5) \ge 1/2 \wedge P_{HL}(6) \ge 1/2].
\end{cases}
$$

The Alternative Hypothesis, for the frequentist approach, states that the choice probabilities do not satisfy these constraints, and therefore,

$$
H_A : \left\{ \begin{array}{ll}
 & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \leq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \leq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \leq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \leq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \leq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \leq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \geq 1/2 \wedge P_{HL}(4) \leq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \leq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \leq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \leq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \leq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \geq 1/2] \\
\vee & [P_{HL}(1) \geq 1/2 \wedge P_{HL}(2) \geq 1/2 \wedge P_{HL}(3) \leq 1/2 \wedge P_{HL}(4) \geq 1/2 \wedge P_{HL}(5) \geq 1/2 \wedge P_{HL}(6) \leq 1/2].
\end{array} \right.
$$

In other words, H_0 is the Null Hypothesis of adherence to CPT with overweighting under the assumption of unanimous preference (but not necessarily unanimous parameters $\gamma, \delta, \alpha, \beta, \tau$) and that error probabilities are bounded by 50%.

For any size τ, this model may fit perfectly (its p-value can equal 1). For example, considering just two constraints, if one predicts that $P_{xy} \geq \frac{1}{2}$ and $P_{wv} \leq \frac{1}{2}$ and one observes that x is chosen over y in 75% and w over v in 30% of observations, then this constitutes a perfect fit. (Of course a prefect fit does not imply that the model generated the data.) In Figure OLS1, this would mean that the observed proportions form a point inside one of the shaded cubes. On the other hand, in a finite/small sample of responses, even if this Null Hypothesis holds, there can nonetheless be more than 50% observations with response errors, due to sampling variability. (Even if a coin is slightly loaded towards heads, a small number of tosses can yield more than half tails. With increasing sample size, the proportions of the various response errors in iid samples converge to the corresponding underlying response error probabilities.) In Figure OLS1, the observed proportions may form a point that is not in the interior of any of the shaded cubes, even if the data sample is

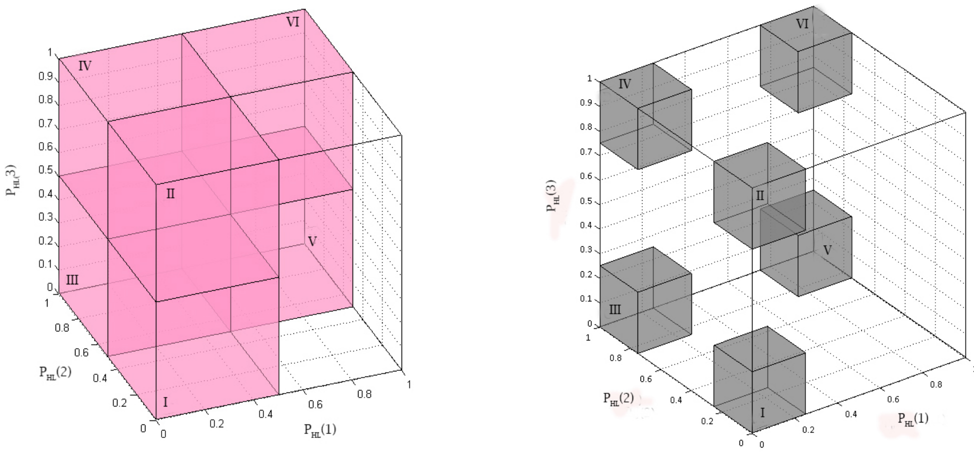

Figure OLS1: 3D visualization of the first two models, constrained to Decision Problems 1, 2, 3 (left: $\tau = \frac{1}{2}$, right: $\tau = \frac{1}{4}$).

generated by probabilities that belong to one of the shaded cubes.

It is evident from Figure OLS1 that the three-dimensional model with six permissible preference patterns is hardly parsimonious. The model's restrictiveness grows exponentially in the number of decision problems, and drops linearly in the number of permissible preference patterns. Even with few decision problems and many permissible preference patterns, however, it can generate restrictive predictions when τ is small. As we saw, CPT allows 32 preference patterns on these six problems. When $\tau = \frac{1}{2}$, the parameter space occupies $\frac{32}{2^6} = 50\%$ of the empirical sample space. However, when $\tau = \frac{1}{4}$, the parameter space occupies $\frac{32}{4^6} = 0.78\% < 1\%$ of the empirical sample space. In comparison, for the Cash II stimuli, these proportions are $\frac{12}{2^{10}} \sim 1\%$, and $\frac{12}{4^{10}} \sim 10^{-5}$, respectively.

3 Probabilistic CPT with Overweighting & without Response Error

This class of models like Probabilistic CPT with Overweighting and without Response Error tends to have a far more complicated mathematical structure than models assuming a unanimous preference compounded with probabilistic errors. Like them, it has unidentifiable parameters, yet is testable. Like them, it may yield a perfect fit. Models of this type can be extraordinarily parsimonious (see Regenwetter and Davis-Stober, 2012, for an example).

At first sight, it might seem hopeless to derive any empirical constraints, leave alone parsimonious constraints, from a theory this general. Indeed, since Decision Problems 3 & 4 do not at all constrain preferences under CPT with overweighting, they also do not constrain choice probabilities when preferences are allowed to be heterogeneous. However, it is apparent from Table OLS1 that, whenever a decision maker prefers H (i.e., there is a "1" entry) in Decision Problem 1, she also prefers H in Decision Problem 2, regardless of the CPT parameter values (with $\gamma < 1, \delta < 1$) that generate the preference pattern. Hence, no matter what probability distribution governs the probabilistic preferences, if the only possible preference states are I-VI in Table OLS1, then it must be that $P_{HL}(2) \geq P_{HL}(1)$.

Now, consider all 32 preferences consistent with CPT with overweighting, for all six decision problems, listed in the left of Table 5 in the article. Close inspection reveals that, regardless of the preference states, whenever H is preferred to L in Decision Problem 1, then H is also preferred to L in Decision Problem 2, but the converse does not hold. We have concluded this already from

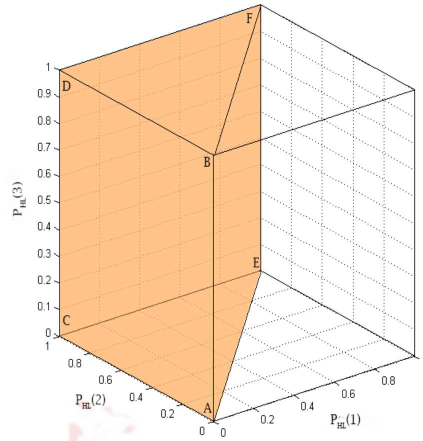

Figure OLS2: 3D visualization of Probabilistic CPT with Overweighting and without Response Error, constrained to Decision Problems 1, 2, 3.

Table OLS1. But Table 5 also shows that, whenever H is preferred to L in Decision Problem 5, then it is also preferred in Decision Problem 2, but the converse does not hold. Furthermore, whenever H is preferred to L in Decision Problem 5, then it is also preferred in Decision Problem 6, and the converse does not hold. From this, we can derive the following predictions: If binary choice probabilities, for these six decision problems, can be represented by Probabilistic CPT with Overweighting and without Response Error (Eqs. 3 and 4 of the article) then it has to hold that

$$P_{HL}(6) \geq P_{HL}(5), \qquad P_{HL}(2) \geq P_{HL}(1), \qquad \text{and} \qquad P_{HL}(2) \geq P_{HL}(5), \tag{O2}$$

regardless of the probability distribution over preference states.

The natural next question is whether there may be additional constraints we could derive. In general, for models of this kind, finding a complete list of predictions can be extremely difficult. It is rather straightforward that none of our constraints imply each other. In general, however, for models of this kind, creating a complete, yet nonredundant list of constraints can be a challenge that requires specialized mathematical methods and computational automation. For example, Regenwetter and Davis-Stober (2012) considered a model that is fully characterized by more than 75,000 nonredundant inequality constraints. We used the public domain software PORTA[1] to prove that the above conditions completely characterize all binary choice probabilities for this model.

Figure OLS2 displays this model in the three-dimensional case for Decision Problems 1, 2, 3. The permissible choice probabilities form a triangular prism that cuts the cube of all binary choice probabilities in half, thanks to the constraint $P_{HL}(2) \geq P_{HL}(1)$. The rectangle forming the boundary between the model and its complement is characterized by the equation $P_{HL}(2) = P_{HL}(1)$.

Overall, when considering all six decision problems, the permissible binary choice probabilities form an analogous geometric object as the triangular prism in Figure OLS2, except that this is a six-dimensional convex polytope. Just like the triangular prism in Figure OLS2 is characterized as the space 'behind' the rectangular face that is defined by $P_{HL}(2) = P_{HL}(1)$, the six-dimensional convex polytope is characterized by three 5-dimensional faces that satisfy the Equations $P_{HL}(6) = P_{HL}(5)$, $P_{HL}(2) = P_{HL}(1)$, and $P_{HL}(2) = P_{HL}(5)$.

Similarly, inspection of the right hand side of Table 5 in the article reveals that binary choice probabilities consistent with Probabilistic CPT with Underweighting and without Response Error

[1] `http://typo.zib.de/opt-long_projects/Software/Porta`

must satisfy

$$P_{HL}(1) \geq P_{HL}(2) \geq P_{HL}(5) \geq P_{HL}(6), \qquad \text{and } P_{HL}(4) \geq P_{HL}(3).$$

The Porta software confirms that these conditions are necessary and sufficient for choice probabilities to be consistent with Probabilistic CPT with Underweighting and without Response Error.

4 Order-Constrained Inference:

Because we are dealing with data pooled across individuals, in a two-alternative forced choice task, we assume that each observed pairwise choice is the outcome of a Bernoulli random variable. This Bernoulli random variable describes, for a given pair of choice alternatives, the probability that a randomly sampled respondent makes one choice or the other. The frequentist statistical analyses assume that multiple such observations within and across decision makers form independent and identically distributed realizations, i.e., Binomials. Mathematically, the empirical sample space for six pairwise choices forms a six-dimensional unit hypercube $[0,1]^6$, with each coordinate encoding the probability of "success" of a Binomial whose number of repetitions (here, this is the number of participants who provided a response for this pair of choice alternatives) is the number of observations for that decision problem. The independence assumption is relaxed to exchangeability (Bernardo, 1996) in the Bayesian analyses.

Testing multiple simultaneous inequality constraints (e.g., mathematical Display O1 or Display O2) in a single joint test long posed an elusive statistical problem. The likelihood functions of the models in Display O1 and in manuscript Eqs. 3 & 4 do not have the familiar asymptotic χ^2 distributions of 'well-behaved' models. But suitable "order-constrained" likelihood based methods are now available. We use the QTest public-domain software (Regenwetter et al., 2014) that renders these models accessible to main-stream researchers by providing a graphical user interface, automating certain quantitative model specifications, as well as automating certain order-constrained statistical analyses.

A new, and not yet publicly released, version of QTest likewise computes Bayes factors for Hypotheses of the form of H_0, against the Encompassing Model $[0,1]^6$. For Deterministic CPT with Response Error, and assuming uninformative priors, QTest computes the Bayes factor analytically, whereas the BFs for Probabilistic CPT require Monte Carlo sampling methods. The latest version of QTest is available from the first author.

5 Monotonic Utility

Table OLS2 shows how the list of the preference patterns expands when relaxing the assumption of a power utility function for money (used throughout the article) to a monotonic function. In a grid search of the parameter space, we assigned each gain a utility value between 0.01 and 1, each loss a value between −0.01 and −1, with better outcomes being assigned higher values than worse outcomes, and with all utility values multiples of 0.001. This generalization leads to 36 distinct preference states for overweighting (rather then 32 for power utility) and 36 preference patterns for underweighting (rather than 15 for power utility). Of these, 16 patterns are shared by over- and underweighting.

Table OLS2: Preference patterns for the decision problems in HER, UNG, and HAU, consistent with CPT and monotonic utility. Left side is for overweighting ($MOV_1 - MOV_{36}$), right side is for underweighting ($MUN_1 - MUN_{36}$). Patterns we did not also find with power utility are in bold.

Overweighting							Underweighting						
Preference pattern	Decision Problem 1	2	3	4	5	6	Preference pattern	Decision Problem 1	2	3	4	5	6
MOV_1	0	0	0	0	0	0	MUN_1	0	0	0	0	0	0
							MUN_2	**0**	**0**	**0**	**0**	**1**	**0**
MOV_2	0	0	0	0	0	1							
MOV_3	**0**	**0**	**0**	**0**	**1**	**1**	MUN_3	**0**	**0**	**0**	**0**	**1**	**1**
MOV_4	0	0	0	1	0	0	MUN_4	0	0	0	1	0	0
							MUN_5	**0**	**0**	**0**	**1**	**1**	**0**
MOV_5	0	0	0	1	0	1							
MOV_6	**0**	**0**	**0**	**1**	**1**	**1**	MUN_6	**0**	**0**	**0**	**1**	**1**	**1**
MOV_7	0	0	1	0	0	0	MUN_7	**0**	**0**	**1**	**0**	**0**	**0**
MOV_8	0	0	1	0	0	1							
							MUN_8	**0**	**0**	**1**	**0**	**1**	**0**
MOV_9	**0**	**0**	**1**	**0**	**1**	**1**	MUN_9	**0**	**0**	**1**	**0**	**1**	**1**
MOV_{10}	0	0	1	1	0	0	MUN_{10}	0	0	1	1	0	0
MOV_{11}	0	0	1	1	0	1							
							MUN_{11}	**0**	**0**	**1**	**1**	**1**	**0**
MOV_{12}	**0**	**0**	**1**	**1**	**1**	**1**	MUN_{12}	**0**	**0**	**1**	**1**	**1**	**1**
MOV_{13}	0	1	0	0	0	0							
MOV_{14}	0	1	0	0	0	1							
MOV_{15}	0	1	0	0	1	1							
MOV_{16}	0	1	0	1	0	0							
MOV_{17}	0	1	0	1	0	1							
MOV_{18}	0	1	0	1	1	1							
MOV_{19}	0	1	1	0	0	0							
MOV_{20}	0	1	1	0	0	1							
MOV_{21}	0	1	1	0	1	1							
MOV_{22}	0	1	1	1	0	0							
MOV_{23}	0	1	1	1	0	1							
MOV_{24}	0	1	1	1	1	1							
							MUN_{13}	1	0	0	0	0	0
							MUN_{14}	**1**	**0**	**0**	**0**	**1**	**0**
							MUN_{15}	**1**	**0**	**0**	**0**	**1**	**1**
							MUN_{16}	**1**	**0**	**0**	**1**	**1**	**0**
							MUN_{17}	1	0	0	1	0	0
							MUN_{18}	**1**	**0**	**0**	**1**	**1**	**1**
							MUN_{19}	**1**	**0**	**1**	**0**	**0**	**0**
							MUN_{20}	**1**	**0**	**1**	**0**	**1**	**0**

Table 1: continued

Overweighting							Underweighting						
Preference pattern	Decision Problem 1	2	3	4	5	6	Preference pattern	Decision Problem 1	2	3	4	5	6
							MUN_{21}	**1**	**0**	**1**	**0**	**1**	**1**
							MUN_{22}	1	0	1	1	0	0
							MUN_{23}	**1**	**0**	**1**	**1**	**1**	**0**
							MUN_{24}	**1**	**0**	**1**	**1**	**1**	**1**
							MUN_{25}	1	1	0	1	1	0
MOV_{25}	1	1	0	0	0	0	MUN_{26}	1	1	0	0	0	0
							MUN_{27}	1	1	0	0	1	0
MOV_{26}	1	1	0	0	0	1							
MOV_{27}	1	1	0	0	1	1	MUN_{28}	1	1	0	0	1	1
MOV_{28}	1	1	0	1	0	0	MUN_{29}	1	1	0	1	0	0
MOV_{29}	1	1	0	1	0	1							
MOV_{30}	1	1	0	1	1	1	MUN_{30}	1	1	0	1	1	1
MOV_{31}	1	1	1	0	0	0	MUN_{31}	**1**	**1**	**1**	**0**	**0**	**0**
MOV_{32}	1	1	1	0	0	1							
							MUN_{32}	**1**	**1**	**1**	**0**	**1**	**0**
MOV_{33}	1	1	1	0	1	1	MUN_{33}	**1**	**1**	**1**	**0**	**1**	**1**
MOV_{34}	1	1	1	1	0	0	MUN_{34}	1	1	1	1	0	0
MOV_{35}	1	1	1	1	0	1							
							MUN_{35}	1	1	1	1	1	0
MOV_{36}	1	1	1	1	1	1	MUN_{36}	1	1	1	1	1	1

Tables OLS3 and OLS4 report the quantitative goodness-of-fit for CPT with overweighting and CPT with underweighting, respectively. The tables illustrate how frequentist fit improves when relaxing from a power to a monotonic utility function, whereas the Bayes factors penalize the more flexible latter model. The results for the monotonic case reinforce the substantive conclusions drawn in the article.

Table OLS3: Quantitative goodness-of-fit of CPT with overweighting, assuming either **Power** or **Monotonic** utility. We report the frequentist p-value (p) and Bayes factor (BF), for three probabilistic specifications, on the HER, UNG, and HAU data. Grey shaded results highlight $p < 0.01$, respectively BF < 0.3; boldfaced results highlight $p > 0.10$, respectively BF > 3.2.

Data Set (Exper. Condition)	Unanimous $\succ$. Response error rates $\leq \tau = 50\%$.		Unanimous $\succ$. Response error rates $\leq \tau = 25\%$.		Heterogenous Preference. No response error.	
HER	p	BF	p	BF	p	BF
Power						
Description	**1**	1.9	.0102	$< .001$	**1**	**3.7**
Experience	**.37**	.6	$< .001$	$< .001$	$< .001$	$< .001$
Monotonic						
Description	**1**	1.7	.0102	$< .001$	**1**	**3.4**
Experience	**.37**	.5	$< .001$	$< .001$	$< .001$	$< .001$
UNG	p	BF	p	BF	p	BF
Power						
Description	**1**	1.6	$< .001$	$< .001$	**1**	2.9
Experience	**1**	1.5	.051	.008	**.25**	1.3
Matched-Sampling	**1**	1.9	$< .001$	$< .001$	**1**	**3.2**
Matched-Sampling 2	**.17**	.2	$< .001$	$< .001$	.007	.002
Monotonic						
Description	**1**	1.5	$< .001$	$< .001$	**1**	2.4
Experience	**1**	1.3	.051	.007	**.25**	1
Matched-Sampling	**1**	1.7	$< .001$	$< .001$	**1**	2.7
Matched-Sampling 2	**.17**	.2	$< .001$	$< .001$	.007	.003
HAU	p	BF	p	BF	p	BF
Power						
Description	**.28**	.6	$< .001$	$< .001$	.011	.05
Experience 1	**1**	1.5	$< .001$	$< .001$	**.27**	1.1
Experience 2	**1**	1.3	$< .001$	$< .001$	**.31**	1.3
Experience 3	**1**	1.8	$< .001$	$< .001$	**.44**	1.7
Monotonic						
Description	**.28**	.5	$< .001$	$< .001$	.011	.04
Experience 1	**1**	1.3	$< .001$	$< .001$	**.23**	.9
Experience 2	**1**	1.1	$< .001$	$< .001$	**.34**	1.1
Experience 3	**1**	1.6	$< .001$	$< .001$	**.42**	1.4

Table OLS4: Quantitative goodness-of-fit of CPT with underweighting, assuming either **Power** or **Monotonic** utility. We report the frequentist p-value (p) and Bayes factor (BF), for three probabilistic specifications, on the HER, UNG, and HAU data. Grey shaded results highlight $p < 0.01$, respectively BF < 0.3; boldfaced results highlight $p > 0.10$, respectively BF > 3.2.

Data Set (Exper. Condition)	Unanimous $\succ$. Response error rates $\leq \tau = 50\%$.		Unanimous $\succ$. Response error rates $\leq \tau = 25\%$.		Heterogenous Preference. No response error.	
Power						
HER	p	BF	p	BF	p	BF
Description	**.103**	.02	$< .001$	$< .001$	$< .01$	$< .001$
Experience	**1**	**4.3**	.011	$< .03$	**1**	**34**
Monotonic						
Description	**.17**	.13	$< .001$	$< .001$	.03	.01
Experience	**1**	1.8	.011	$< .01$	**1**	**3**
Power						
UNG	p	BF	p	BF	p	BF
Description	**.15**	.04	$< .001$	$< .001$	$< .01$	$< .01$
Experience	**1**	**3.9**	.051	$< .03$	.03	1.3
Matched-Sampling	**.44**	2.1	$< .01$	$< .001$	**.2**	.96
Matched-Sampling 2	**1**	2.7	$< .001$	$< .001$	**.3**	**7.1**
Monotonic						
Description	**.26**	.12	$< .001$	$< .001$	.014	$< .01$
Experience	**1**	1.65	.051	$< .01$	.03	.1
Matched-Sampling	**.44**	.9	$< .01$	$< .001$	**.2**	.13
Matched-Sampling 2	**1**	1.8	$< .001$	$< .001$	**1**	**3.7**
Power						
HAU	p	BF	p	BF	p	BF
Description	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$
Experience 1	**1**	**4.1**	$< .001$	$< .001$	.09	**3.7**
Experience 2	**1**	2.4	$< .001$	$< .001$	**.33**	1.9
Experience 3	**1**	**3.9**	$< .001$	$< .001$	**.12**	3.16
Monotonic						
HAU	p	BF	p	BF	p	BF
Description	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$
Experience 1	**1**	1.7	$< .001$	$< .001$	.09	.32
Experience 2	**1**	1.1	$< .001$	$< .001$	**.17**	.49
Experience 3	**1**	1.6	$< .001$	$< .001$	**.12**	.28

6 Estimated Preference Patterns and Weighting Parameters for Deterministic CPT with Overweighting and Response Error

Table OLS5 illustrates what we can or cannot infer about the weighting parameters from the stimuli in HER, UNG, and HAU, when requiring unanimous preference. We consider this question through the lens of Deterministic CPT with Overweighting and Response Error, when $\tau = \frac{1}{2}$. This illustration also shows how unanimous preference does not at all require unanimous parameter values in CPT.

Table OLS5: Ranges of values of γ, δ that generate the best fitting unanimous preference pattern in Deterministic CPT with Overweighting and Response Error, when $\tau = \frac{1}{2}$.

Preference Pattern		Best fitting weighting parameters γ	δ	Data set
L H H L L H	OV_6	$[.251, .891]$	$[.021 - .911]$	Hertwig et al. `Description` Ungemach et al. `Description`*
L H L L H H	OV_{11}	$[.001, .991]$	$[.251 - .891]$	Hau et al. `Description`*
H H L L L L	OV_{21}	$[.001, .991]$	$[.921, .991]$	Hertwig et al. `Experience` Hau et al. `Experience 1*& 2*`
H H L H L L	OV_{24}	$[.911, .991]$	$[.921, .991]$	Hau et al. `Experience 3`* Ungemach et al. `Free Sampling`*
L H L L L L	OV_9	$[.001, .991]$	$\{.311\} \cup [.331 - .991]$	Ungemach et al. `Matched Sampling 1`*
H H H L L L	OV_{27}	$[.251, .891]$	$[.921, .991]$	Ungemach et al. `Matched Sampling 2`

Note: For each pattern on the left, the right most entry lists the data sets for which this is the best fitting pattern. The ranges are not confidence intervals. Cases marked $*$ yield a perfect fit.

Each preference pattern that can be generated from CPT with overweighting can originate from uncountably infinitely many parameter values for $\alpha, \beta, \delta, \gamma, \lambda$ (in the appropriate ranges). For each best-fitting preference pattern, we show the ranges of values that $\delta < 1, \gamma < 1$ can take. These ranges are not confidence intervals, rather they are ranges of possible parameter values that can generate the same single best-fitting preference pattern (with suitable adjustments of the other parameters in their permitted ranges). With the exception of HAU `Description`, the second best fitting patterns also account for the data, hence further enlarging the range of γ, δ. We are not aware of well-established methods to generate confidence regions, but γ can plausibly cover the entire $[0, 1]$ range and δ a large part.

In some cases, different people, who share the same best-fitting preference pattern, say, OV_{11}, can use widely different parameter values in CPT. For preference pattern OV_{24} this is not the case as the ranges of δ, γ, that are consistent with OV_{24}, are rather tight.

7 Description-Experience Gap

Tables OLS6, OLS7, and OLS8 give the 32, 660, and 250 distinct joint preference states for `Description` and `Experience` for Hypotheses I, II and III, respectively.

Table OLS6: List of 32 joint preferences for `Description` and `Experience` of Hertwig et al. (2004), according to CPT, consistent with Hypothesis I, based on a grid search of joint parameter values. Each joint preference can be constructed with a constant $\alpha, \beta, \lambda, \delta < 1, \gamma < 1$ for `Description` and `Experience`.

	`Description`						`Experience`					
	1	2	3	4	5	6	1	2	3	4	5	6
OV'_1	0	0	0	0	0	0	0	0	0	0	0	0
OV'_2	0	0	0	0	0	1	0	0	0	0	0	1
OV'_3	0	0	0	1	0	0	0	0	0	1	0	0
OV'_4	0	0	0	1	0	1	0	0	0	1	0	1
OV'_5	0	0	1	0	0	0	0	0	1	0	0	0
OV'_6	0	0	1	0	0	1	0	0	1	0	0	1
OV'_7	0	0	1	1	0	0	0	0	1	1	0	0
OV'_8	0	0	1	1	0	1	0	0	1	1	0	1
OV'_9	0	1	0	0	0	0	0	1	0	0	0	0
OV'_{10}	0	1	0	0	0	1	0	1	0	0	0	1
OV'_{11}	0	1	0	0	1	1	0	1	0	0	1	1
OV'_{12}	0	1	0	1	0	0	0	1	0	1	0	0
OV'_{13}	0	1	0	1	0	1	0	1	0	1	0	1
OV'_{14}	0	1	0	1	1	1	0	1	0	1	1	1
OV'_{15}	0	1	1	0	0	0	0	1	1	0	0	0
OV'_{16}	0	1	1	0	0	1	0	1	1	0	0	1
OV'_{17}	0	1	1	0	1	1	0	1	1	0	1	1
OV'_{18}	0	1	1	1	0	0	0	1	1	1	0	0
OV'_{19}	0	1	1	1	0	1	0	1	1	1	0	1
OV'_{20}	0	1	1	1	1	1	0	1	1	1	1	1
OV'_{21}	1	1	0	0	0	0	1	1	0	0	0	0
OV'_{22}	1	1	0	0	0	1	1	1	0	0	0	1
OV'_{23}	1	1	0	0	1	1	1	1	0	0	1	1
OV'_{24}	1	1	0	1	0	0	1	1	0	1	0	0
OV'_{25}	1	1	0	1	0	1	1	1	0	1	0	1
OV'_{26}	1	1	0	1	1	1	1	1	0	1	1	1
OV'_{27}	1	1	1	0	0	0	1	1	1	0	0	0
OV'_{28}	1	1	1	0	0	1	1	1	1	0	0	1
OV'_{29}	1	1	1	0	1	1	1	1	1	0	1	1
OV'_{30}	1	1	1	1	0	0	1	1	1	1	0	0
OV'_{31}	1	1	1	1	0	1	1	1	1	1	0	1
OV'_{32}	1	1	1	1	1	1	1	1	1	1	1	1

Table OLS7: List of 660 joint preferences for `Description` and `Experience` of Hertwig et al. (2004), according to CPT, consistent with Hypothesis II, based on a grid search of joint parameter values. Each joint preference can be constructed with a constant α, β, λ across conditions, $\delta_d, \gamma_d < 1$ for `Description` and $\delta_e, \gamma_e < 1$ for `Experience`.

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{1}	0	0	1	0	0	0	0	0	1	1	0	1
OO_{2}	0	0	1	1	0	0	0	0	1	0	0	1
OO_{3}	0	0	1	0	0	0	0	0	1	0	0	1
OO_{4}	0	0	1	0	0	0	0	0	0	1	0	1
OO_{5}	0	0	0	1	0	0	0	0	1	0	0	1
OO_{6}	0	0	1	0	0	0	0	0	0	0	0	1
OO_{7}	0	0	0	0	0	0	0	0	1	0	0	1
OO_{8}	0	0	0	1	0	0	0	0	0	0	0	1
OO_{9}	0	0	0	0	0	0	0	0	0	1	0	1
OO_{10}	0	0	0	0	0	0	0	0	1	1	0	1
OO_{11}	0	0	0	0	0	0	0	0	0	0	0	1
OO_{12}	0	0	1	1	0	0	0	0	0	1	0	1
OO_{13}	0	0	0	1	0	0	0	0	1	1	0	1
OO_{14}	0	0	0	1	0	0	0	0	0	1	0	1
OO_{15}	0	0	1	1	0	0	0	0	1	1	0	1
OO_{16}	0	0	1	0	0	1	0	0	1	1	0	0
OO_{17}	0	0	1	1	0	1	0	0	1	0	0	0
OO_{18}	0	0	1	0	0	1	0	0	1	0	0	0
OO_{19}	0	0	1	0	0	1	0	0	0	1	0	0
OO_{20}	0	0	0	1	0	1	0	0	1	0	0	0
OO_{21}	0	0	1	0	0	1	0	0	0	0	0	0
OO_{22}	0	0	0	0	0	1	0	0	1	0	0	0
OO_{23}	0	0	0	1	0	1	0	0	0	0	0	0
OO_{24}	0	0	0	0	0	1	0	0	0	1	0	0
OO_{25}	0	0	0	0	0	1	0	0	1	1	0	0
OO_{26}	0	0	0	0	0	1	0	0	0	0	0	0
OO_{27}	0	0	1	1	0	1	0	0	0	1	0	0
OO_{28}	0	0	0	1	0	1	0	0	1	1	0	0
OO_{29}	0	0	0	1	0	1	0	0	0	1	0	0
OO_{30}	0	0	1	1	0	1	0	0	1	1	0	0
OO_{31}	0	0	1	0	0	0	0	0	1	1	0	0
OO_{32}	0	0	1	1	0	0	0	0	1	0	0	0
OO_{33}	0	0	1	0	0	0	0	0	1	0	0	0
OO_{34}	0	0	1	0	0	0	0	0	0	1	0	0
OO_{35}	0	0	0	1	0	0	0	0	1	0	0	0
OO_{36}	0	0	1	0	0	0	0	0	0	0	0	0
OO_{37}	0	0	0	0	0	0	0	0	1	0	0	0
OO_{38}	0	0	0	1	0	0	0	0	0	0	0	0
OO_{39}	0	0	0	0	0	0	0	0	0	1	0	0
OO_{40}	0	0	0	0	0	0	0	0	1	1	0	0
OO_{41}	0	0	0	0	0	0	0	0	0	0	0	0
OO_{42}	0	0	1	1	0	0	0	0	0	1	0	0
OO_{43}	0	0	0	1	0	0	0	0	1	1	0	0
OO_{44}	0	0	0	1	0	0	0	0	0	1	0	0
OO_{45}	0	0	1	1	0	0	0	0	1	1	0	0
OO_{46}	0	0	1	0	0	0	0	1	1	1	0	0
OO_{47}	0	0	1	1	0	0	0	1	1	0	0	0
OO_{48}	0	0	1	0	0	0	0	1	1	0	0	0
OO_{49}	0	0	1	0	0	0	0	1	0	1	0	0
OO_{50}	0	0	0	1	0	0	0	1	1	0	0	0
OO_{51}	0	0	1	0	0	0	0	1	0	0	0	0
OO_{52}	0	0	0	0	0	0	0	1	1	0	0	0
OO_{53}	0	0	0	1	0	0	0	1	0	0	0	0
OO_{54}	0	0	0	0	0	0	0	1	0	1	0	0
OO_{55}	0	0	0	0	0	0	0	1	1	1	0	0
OO_{56}	0	0	0	0	0	0	0	1	0	0	0	0
OO_{57}	0	0	1	1	0	0	0	1	0	1	0	0
OO_{58}	0	0	0	1	0	0	0	1	1	1	0	0
OO_{59}	0	0	0	1	0	0	0	1	0	1	0	0
OO_{60}	0	0	1	1	0	0	0	1	1	1	0	0
OO_{61}	0	1	1	0	0	0	0	0	1	1	0	0
OO_{62}	0	1	1	1	0	0	0	0	1	0	0	0
OO_{63}	0	1	1	0	0	0	0	0	1	0	0	0
OO_{64}	0	1	1	0	0	0	0	0	0	1	0	0
OO_{65}	0	1	0	1	0	0	0	0	1	0	0	0
OO_{66}	0	1	1	0	0	0	0	0	0	0	0	0
OO_{67}	0	1	0	0	0	0	0	0	1	0	0	0
OO_{68}	0	1	0	1	0	0	0	0	0	0	0	0
OO_{69}	0	1	0	0	0	0	0	0	0	1	0	0
OO_{70}	0	1	0	0	0	0	0	0	1	1	0	0
OO_{71}	0	1	0	0	0	0	0	0	0	0	0	0
OO_{72}	0	1	1	1	0	0	0	0	0	1	0	0
OO_{73}	0	1	0	1	0	0	0	0	1	1	0	0
OO_{74}	0	1	0	1	0	0	0	0	0	1	0	0
OO_{75}	0	1	1	1	0	0	0	0	1	1	0	0
OO_{76}	0	0	1	0	0	0	0	1	1	1	0	1
OO_{77}	0	0	1	1	0	0	0	1	1	0	0	1
OO_{78}	0	0	1	0	0	0	0	1	1	0	0	1
OO_{79}	0	0	1	0	0	0	0	1	0	1	0	1
OO_{80}	0	0	0	1	0	0	0	1	1	0	0	1

Table OLS7: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{81}	0	0	1	0	0	0	0	1	0	0	0	1
OO_{82}	0	0	0	0	0	0	0	1	1	0	0	1
OO_{83}	0	0	0	1	0	0	0	1	0	0	0	1
OO_{84}	0	0	0	0	0	0	0	1	0	1	0	1
OO_{85}	0	0	0	0	0	0	0	1	1	1	0	1
OO_{86}	0	0	0	0	0	0	0	1	0	0	0	1
OO_{87}	0	0	1	1	0	0	0	1	0	1	0	1
OO_{88}	0	0	0	1	0	0	0	1	1	1	0	1
OO_{89}	0	0	0	1	0	0	0	1	0	1	0	1
OO_{90}	0	0	1	1	0	0	0	1	1	1	0	1
OO_{91}	0	1	1	0	0	1	0	0	1	1	0	0
OO_{92}	0	1	1	1	0	1	0	0	1	0	0	0
OO_{93}	0	1	1	0	0	1	0	0	1	0	0	0
OO_{94}	0	1	1	0	0	1	0	0	0	1	0	0
OO_{95}	0	1	0	1	0	1	0	0	1	0	0	0
OO_{96}	0	1	1	0	0	1	0	0	0	0	0	0
OO_{97}	0	1	0	0	0	1	0	0	1	0	0	0
OO_{98}	0	1	0	1	0	1	0	0	0	0	0	0
OO_{99}	0	1	0	0	0	1	0	0	0	1	0	0
OO_{100}	0	1	0	0	0	1	0	0	1	1	0	0
OO_{101}	0	1	0	0	0	1	0	0	0	0	0	0
OO_{102}	0	1	1	1	0	1	0	0	0	1	0	0
OO_{103}	0	1	0	1	0	1	0	0	1	1	0	0
OO_{104}	0	1	0	1	0	1	0	0	0	1	0	0
OO_{105}	0	1	1	1	0	1	0	0	1	1	0	0
OO_{106}	0	0	1	0	0	0	0	1	1	1	1	1
OO_{107}	0	0	1	1	0	0	0	1	1	0	1	1
OO_{108}	0	0	1	0	0	0	0	1	1	0	1	1
OO_{109}	0	0	1	0	0	0	0	1	0	1	1	1
OO_{110}	0	0	0	1	0	0	0	1	1	0	1	1
OO_{111}	0	0	1	0	0	0	0	1	0	0	1	1
OO_{112}	0	0	0	0	0	0	0	1	1	0	1	1
OO_{113}	0	0	0	1	0	0	0	1	0	0	1	1
OO_{114}	0	0	0	0	0	0	0	1	0	1	1	1
OO_{115}	0	0	0	0	0	0	0	1	1	1	1	1
OO_{116}	0	0	0	0	0	0	0	1	0	0	1	1
OO_{117}	0	0	1	1	0	0	0	1	0	1	1	1
OO_{118}	0	0	0	1	0	0	0	1	1	1	1	1
OO_{119}	0	0	0	1	0	0	0	1	0	1	1	1
OO_{120}	0	0	1	1	0	0	0	1	1	1	1	1

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{121}	0	1	1	0	1	1	0	0	1	1	0	0
OO_{122}	0	1	1	1	1	1	0	0	1	0	0	0
OO_{123}	0	1	1	0	1	1	0	0	1	0	0	0
OO_{124}	0	1	1	0	1	1	0	0	0	1	0	0
OO_{125}	0	1	0	1	1	1	0	0	1	0	0	0
OO_{126}	0	1	1	0	1	1	0	0	0	0	0	0
OO_{127}	0	1	0	0	1	1	0	0	1	0	0	0
OO_{128}	0	1	0	1	1	1	0	0	0	0	0	0
OO_{129}	0	1	0	0	1	1	0	0	0	1	0	0
OO_{130}	0	1	0	0	1	1	0	0	1	1	0	0
OO_{131}	0	1	0	0	1	1	0	0	0	0	0	0
OO_{132}	0	1	1	1	1	1	0	0	0	1	0	0
OO_{133}	0	1	0	1	1	1	0	0	1	1	0	0
OO_{134}	0	1	0	1	1	1	0	0	0	1	0	0
OO_{135}	0	1	1	1	1	1	0	0	1	1	0	0
OO_{136}	0	0	1	0	0	1	0	0	1	1	0	1
OO_{137}	0	0	1	1	0	1	0	0	1	0	0	1
OO_{138}	0	0	1	0	0	1	0	0	1	0	0	1
OO_{139}	0	0	1	0	0	1	0	0	0	1	0	1
OO_{140}	0	0	0	1	0	1	0	0	1	0	0	1
OO_{141}	0	0	1	0	0	1	0	0	0	0	0	1
OO_{142}	0	0	0	0	0	1	0	0	1	0	0	1
OO_{143}	0	0	0	1	0	1	0	0	0	0	0	1
OO_{144}	0	0	0	0	0	1	0	0	0	1	0	1
OO_{145}	0	0	0	0	0	1	0	0	1	1	0	1
OO_{146}	0	0	0	0	0	1	0	0	0	0	0	1
OO_{147}	0	0	1	1	0	1	0	0	0	1	0	1
OO_{148}	0	0	0	1	0	1	0	0	1	1	0	1
OO_{149}	0	0	0	1	0	1	0	0	0	1	0	1
OO_{150}	0	0	1	1	0	1	0	0	1	1	0	1
OO_{151}	0	0	1	0	0	1	0	1	1	1	0	1
OO_{152}	0	0	1	1	0	1	0	1	1	0	0	1
OO_{153}	0	0	1	0	0	1	0	1	1	0	0	1
OO_{154}	0	0	1	0	0	1	0	1	0	1	0	1
OO_{155}	0	0	0	1	0	1	0	1	1	0	0	1
OO_{156}	0	0	1	0	0	1	0	1	0	0	0	1
OO_{157}	0	0	0	0	0	1	0	1	1	0	0	1
OO_{158}	0	0	0	1	0	1	0	1	0	0	0	1
OO_{159}	0	0	0	0	0	1	0	1	0	1	0	1
OO_{160}	0	0	0	0	0	1	0	1	1	1	0	1

Table OLS7: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{161}	0	0	0	0	0	1	0	1	0	0	0	1
OO_{162}	0	0	1	1	0	1	0	1	0	1	0	1
OO_{163}	0	0	0	1	0	1	0	1	1	1	0	1
OO_{164}	0	0	0	1	0	1	0	1	0	1	0	1
OO_{165}	0	0	1	1	0	1	0	1	1	1	0	1
OO_{166}	0	1	1	0	0	1	0	0	1	1	0	1
OO_{167}	0	1	1	1	0	1	0	0	1	0	0	1
OO_{168}	0	1	1	0	0	1	0	0	1	0	0	1
OO_{169}	0	1	1	0	0	1	0	0	0	1	0	1
OO_{170}	0	1	0	1	0	1	0	0	1	0	0	1
OO_{171}	0	1	1	0	0	1	0	0	0	0	0	1
OO_{172}	0	1	0	0	0	1	0	0	1	0	0	1
OO_{173}	0	1	0	1	0	1	0	0	0	0	0	1
OO_{174}	0	1	0	0	0	1	0	0	0	1	0	1
OO_{175}	0	1	0	0	0	1	0	0	1	1	0	1
OO_{176}	0	1	0	0	0	1	0	0	0	0	0	1
OO_{177}	0	1	1	1	0	1	0	0	0	1	0	1
OO_{178}	0	1	0	1	0	1	0	0	1	1	0	1
OO_{179}	0	1	0	1	0	1	0	0	0	1	0	1
OO_{180}	0	1	1	1	0	1	0	0	1	1	0	1
OO_{181}	0	1	1	0	0	0	0	1	1	1	0	1
OO_{182}	0	1	1	1	0	0	0	1	1	0	0	1
OO_{183}	0	1	1	0	0	0	0	1	1	0	0	1
OO_{184}	0	1	1	0	0	0	0	1	0	1	0	1
OO_{185}	0	1	0	1	0	0	0	1	1	0	0	1
OO_{186}	0	1	1	0	0	0	0	1	0	0	0	1
OO_{187}	0	1	0	0	0	0	0	1	1	0	0	1
OO_{188}	0	1	0	1	0	0	0	1	0	0	0	1
OO_{189}	0	1	0	0	0	0	0	1	0	1	0	1
OO_{190}	0	1	0	0	0	0	0	1	1	1	0	1
OO_{191}	0	1	0	0	0	0	0	1	0	0	0	1
OO_{192}	0	1	1	1	0	0	0	1	0	1	0	1
OO_{193}	0	1	0	1	0	0	0	1	1	1	0	1
OO_{194}	0	1	0	1	0	0	0	1	0	1	0	1
OO_{195}	0	1	1	1	0	0	0	1	1	1	0	1
OO_{196}	0	1	1	0	0	1	0	1	1	1	0	0
OO_{197}	0	1	1	1	0	1	0	1	1	0	0	0
OO_{198}	0	1	1	0	0	1	0	1	1	0	0	0
OO_{199}	0	1	1	0	0	1	0	1	0	1	0	0
OO_{200}	0	1	0	1	0	1	0	1	1	0	0	0

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{201}	0	1	1	0	0	1	0	1	0	0	0	0
OO_{202}	0	1	0	0	0	1	0	1	1	0	0	0
OO_{203}	0	1	0	1	0	1	0	1	0	0	0	0
OO_{204}	0	1	0	0	0	1	0	1	0	1	0	0
OO_{205}	0	1	0	0	0	1	0	1	1	1	0	0
OO_{206}	0	1	0	0	0	1	0	1	0	0	0	0
OO_{207}	0	1	1	1	0	1	0	1	0	1	0	0
OO_{208}	0	1	0	1	0	1	0	1	1	1	0	0
OO_{209}	0	1	0	1	0	1	0	1	0	1	0	0
OO_{210}	0	1	1	1	0	1	0	1	1	1	0	0
OO_{211}	0	1	1	0	0	0	0	1	1	1	0	0
OO_{212}	0	1	1	1	0	0	0	1	1	0	0	0
OO_{213}	0	1	1	0	0	0	0	1	1	0	0	0
OO_{214}	0	1	1	0	0	0	0	1	0	1	0	0
OO_{215}	0	1	0	1	0	0	0	1	1	0	0	0
OO_{216}	0	1	1	0	0	0	0	1	0	0	0	0
OO_{217}	0	1	0	0	0	0	0	1	1	0	0	0
OO_{218}	0	1	0	1	0	0	0	1	0	0	0	0
OO_{219}	0	1	0	0	0	0	0	1	0	1	0	0
OO_{220}	0	1	0	0	0	0	0	1	1	1	0	0
OO_{221}	0	1	0	0	0	0	0	1	0	0	0	0
OO_{222}	0	1	1	1	0	0	0	1	0	1	0	0
OO_{223}	0	1	0	1	0	0	0	1	1	1	0	0
OO_{224}	0	1	0	1	0	0	0	1	0	1	0	0
OO_{225}	0	1	1	1	0	0	0	1	1	1	0	0
OO_{226}	0	1	1	0	0	0	0	1	1	1	1	1
OO_{227}	0	1	1	1	0	0	0	1	1	0	1	1
OO_{228}	0	1	1	0	0	0	0	1	1	0	1	1
OO_{229}	0	1	1	0	0	0	0	1	0	1	1	1
OO_{230}	0	1	0	1	0	0	0	1	1	0	1	1
OO_{231}	0	1	1	0	0	0	0	1	0	0	1	1
OO_{232}	0	1	0	0	0	0	0	1	1	0	1	1
OO_{233}	0	1	0	1	0	0	0	1	0	0	1	1
OO_{234}	0	1	0	0	0	0	0	1	0	1	1	1
OO_{235}	0	1	0	0	0	0	0	1	1	1	1	1
OO_{236}	0	1	0	0	0	0	0	1	0	0	1	1
OO_{237}	0	1	1	1	0	0	0	1	0	1	1	1
OO_{238}	0	1	0	1	0	0	0	1	1	1	1	1
OO_{239}	0	1	0	1	0	0	0	1	0	1	1	1
OO_{240}	0	1	1	1	0	0	0	1	1	1	1	1

Table OLS7: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{241}	0	1	1	0	1	1	0	1	1	1	0	0
OO_{242}	0	1	1	1	1	1	0	1	1	0	0	0
OO_{243}	0	1	1	0	1	1	0	1	1	0	0	0
OO_{244}	0	1	1	0	1	1	0	1	0	1	0	0
OO_{245}	0	1	0	1	1	1	0	1	1	0	0	0
OO_{246}	0	1	1	0	1	1	0	1	0	0	0	0
OO_{247}	0	1	0	0	1	1	0	1	1	0	0	0
OO_{248}	0	1	0	1	1	1	0	1	0	0	0	0
OO_{249}	0	1	0	0	1	1	0	1	0	1	0	0
OO_{250}	0	1	0	0	1	1	0	1	1	1	0	0
OO_{251}	0	1	0	0	1	1	0	1	0	0	0	0
OO_{252}	0	1	1	1	1	1	0	1	0	1	0	0
OO_{253}	0	1	0	1	1	1	0	1	1	1	0	0
OO_{254}	0	1	0	1	1	1	0	1	0	1	0	0
OO_{255}	0	1	1	1	1	1	0	1	1	1	0	0
OO_{256}	0	1	1	0	0	0	1	1	1	1	0	0
OO_{257}	0	1	1	1	0	0	1	1	1	0	0	0
OO_{258}	0	1	1	0	0	0	1	1	1	0	0	0
OO_{259}	0	1	1	0	0	0	1	1	0	1	0	0
OO_{260}	0	1	0	1	0	0	1	1	1	0	0	0
OO_{261}	0	1	1	0	0	0	1	1	0	0	0	0
OO_{262}	0	1	0	0	0	0	1	1	1	0	0	0
OO_{263}	0	1	0	1	0	0	1	1	0	0	0	0
OO_{264}	0	1	0	0	0	0	1	1	0	1	0	0
OO_{265}	0	1	0	0	0	0	1	1	1	1	0	0
OO_{266}	0	1	0	0	0	0	1	1	0	0	0	0
OO_{267}	0	1	1	1	0	0	1	1	0	1	0	0
OO_{268}	0	1	0	1	0	0	1	1	1	1	0	0
OO_{269}	0	1	0	1	0	0	1	1	0	1	0	0
OO_{270}	0	1	1	1	0	0	1	1	1	1	0	0
OO_{271}	1	1	1	0	0	0	0	1	1	1	0	0
OO_{272}	1	1	1	1	0	0	0	1	1	0	0	0
OO_{273}	1	1	1	0	0	0	0	1	1	0	0	0
OO_{274}	1	1	1	0	0	0	0	1	0	1	0	0
OO_{275}	1	1	0	1	0	0	0	1	1	0	0	0
OO_{276}	1	1	1	0	0	0	0	1	0	0	0	0
OO_{277}	1	1	0	0	0	0	0	1	1	0	0	0
OO_{278}	1	1	0	1	0	0	0	1	0	0	0	0
OO_{279}	1	1	0	0	0	0	0	1	0	1	0	0
OO_{280}	1	1	0	0	0	0	0	1	1	1	0	0

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{281}	1	1	0	0	0	0	0	1	0	0	0	0
OO_{282}	1	1	1	1	0	0	0	1	0	1	0	0
OO_{283}	1	1	0	1	0	0	0	1	1	1	0	0
OO_{284}	1	1	0	1	0	0	0	1	0	1	0	0
OO_{285}	1	1	1	1	0	0	0	1	1	1	0	0
OO_{286}	0	1	1	0	0	1	0	1	1	1	1	1
OO_{287}	0	1	1	1	0	1	0	1	1	0	1	1
OO_{288}	0	1	1	0	0	1	0	1	1	0	1	1
OO_{289}	0	1	1	0	0	1	0	1	0	1	1	1
OO_{290}	0	1	0	1	0	1	0	1	1	0	1	1
OO_{291}	0	1	1	0	0	1	0	1	0	0	1	1
OO_{292}	0	1	0	0	0	1	0	1	1	0	1	1
OO_{293}	0	1	0	1	0	1	0	1	0	0	1	1
OO_{294}	0	1	0	0	0	1	0	1	0	1	1	1
OO_{295}	0	1	0	0	0	1	0	1	1	1	1	1
OO_{296}	0	1	0	0	0	1	0	1	0	0	1	1
OO_{297}	0	1	1	1	0	1	0	1	0	1	1	1
OO_{298}	0	1	0	1	0	1	0	1	1	1	1	1
OO_{299}	0	1	0	1	0	1	0	1	0	1	1	1
OO_{300}	0	1	1	1	0	1	0	1	1	1	1	1
OO_{301}	0	1	1	0	1	1	0	1	1	1	0	1
OO_{302}	0	1	1	1	1	1	0	1	1	0	0	1
OO_{303}	0	1	1	0	1	1	0	1	1	0	0	1
OO_{304}	0	1	1	0	1	1	0	1	0	1	0	1
OO_{305}	0	1	0	1	1	1	0	1	1	0	0	1
OO_{306}	0	1	1	0	1	1	0	1	0	0	0	1
OO_{307}	0	1	0	0	1	1	0	1	1	0	0	1
OO_{308}	0	1	0	1	1	1	0	1	0	0	0	1
OO_{309}	0	1	0	0	1	1	0	1	0	1	0	1
OO_{310}	0	1	0	0	1	1	0	1	1	1	0	1
OO_{311}	0	1	0	0	1	1	0	1	0	0	0	1
OO_{312}	0	1	1	1	1	1	0	1	0	1	0	1
OO_{313}	0	1	0	1	1	1	0	1	1	1	0	1
OO_{314}	0	1	0	1	1	1	0	1	0	1	0	1
OO_{315}	0	1	1	1	1	1	0	1	1	1	0	1
OO_{316}	0	1	1	0	0	1	0	1	1	1	0	1
OO_{317}	0	1	1	1	0	1	0	1	1	0	0	1
OO_{318}	0	1	1	0	0	1	0	1	1	0	0	1
OO_{319}	0	1	1	0	0	1	0	1	0	1	0	1
OO_{320}	0	1	0	1	0	1	0	1	1	0	0	1

Table OLS7: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{321}	0	1	1	0	0	1	0	1	0	0	0	1
OO_{322}	0	1	0	0	0	1	0	1	1	0	0	1
OO_{323}	0	1	0	1	0	1	0	1	0	0	0	1
OO_{324}	0	1	0	0	0	1	0	1	0	1	0	1
OO_{325}	0	1	0	0	0	1	0	1	1	1	0	1
OO_{326}	0	1	0	0	0	1	0	1	0	0	0	1
OO_{327}	0	1	1	1	0	1	0	1	0	1	0	1
OO_{328}	0	1	0	1	0	1	0	1	1	1	0	1
OO_{329}	0	1	0	1	0	1	0	1	0	1	0	1
OO_{330}	0	1	1	1	0	1	0	1	1	1	0	1
OO_{331}	0	1	1	0	0	1	1	1	1	1	0	0
OO_{332}	0	1	1	1	0	1	1	1	1	0	0	0
OO_{333}	0	1	1	0	0	1	1	1	1	0	0	0
OO_{334}	0	1	1	0	0	1	1	1	0	1	0	0
OO_{335}	0	1	0	1	0	1	1	1	1	0	0	0
OO_{336}	0	1	1	0	0	1	1	1	0	0	0	0
OO_{337}	0	1	0	0	0	1	1	1	1	0	0	0
OO_{338}	0	1	0	1	0	1	1	1	0	0	0	0
OO_{339}	0	1	0	0	0	1	1	1	0	1	0	0
OO_{340}	0	1	0	0	0	1	1	1	1	1	0	0
OO_{341}	0	1	0	0	0	1	1	1	0	0	0	0
OO_{342}	0	1	1	1	0	1	1	1	0	1	0	0
OO_{343}	0	1	0	1	0	1	1	1	1	1	0	0
OO_{344}	0	1	0	1	0	1	1	1	0	1	0	0
OO_{345}	0	1	1	1	0	1	1	1	1	1	0	0
OO_{346}	1	1	1	0	0	0	0	1	1	1	0	1
OO_{347}	1	1	1	1	0	0	0	1	1	0	0	1
OO_{348}	1	1	1	0	0	0	0	1	1	0	0	1
OO_{349}	1	1	1	0	0	0	0	1	0	1	0	1
OO_{350}	1	1	0	1	0	0	0	1	1	0	0	1
OO_{351}	1	1	1	0	0	0	0	1	0	0	0	1
OO_{352}	1	1	0	0	0	0	0	1	1	0	0	1
OO_{353}	1	1	0	1	0	0	0	1	0	0	0	1
OO_{354}	1	1	0	0	0	0	0	1	0	1	0	1
OO_{355}	1	1	0	0	0	0	0	1	1	1	0	1
OO_{356}	1	1	0	0	0	0	0	1	0	0	0	1
OO_{357}	1	1	1	1	0	0	0	1	0	1	0	1
OO_{358}	1	1	0	1	0	0	0	1	1	1	0	1
OO_{359}	1	1	0	1	0	0	0	1	0	1	0	1
OO_{360}	1	1	1	1	0	0	0	1	1	1	0	1
OO_{361}	0	1	1	0	0	1	1	1	1	1	0	1
OO_{362}	0	1	1	1	0	1	1	1	1	0	0	1
OO_{363}	0	1	1	0	0	1	1	1	1	0	0	1
OO_{364}	0	1	1	0	0	1	1	1	0	1	0	1
OO_{365}	0	1	0	1	0	1	1	1	1	0	0	1
OO_{366}	0	1	1	0	0	1	1	1	0	0	0	1
OO_{367}	0	1	0	0	0	1	1	1	1	0	0	1
OO_{368}	0	1	0	1	0	1	1	1	0	0	0	1
OO_{369}	0	1	0	0	0	1	1	1	0	1	0	1
OO_{370}	0	1	0	0	0	1	1	1	1	1	0	1
OO_{371}	0	1	0	0	0	1	1	1	0	0	0	1
OO_{372}	0	1	1	1	0	1	1	1	0	1	0	1
OO_{373}	0	1	0	1	0	1	1	1	1	1	0	1
OO_{374}	0	1	0	1	0	1	1	1	0	1	0	1
OO_{375}	0	1	1	1	0	1	1	1	1	1	0	1
OO_{376}	1	1	1	0	0	1	0	1	1	1	0	1
OO_{377}	1	1	1	1	0	1	0	1	1	0	0	1
OO_{378}	1	1	1	0	0	1	0	1	1	0	0	1
OO_{379}	1	1	1	0	0	1	0	1	0	1	0	1
OO_{380}	1	1	0	1	0	1	0	1	1	0	0	1
OO_{381}	1	1	1	0	0	1	0	1	0	0	0	1
OO_{382}	1	1	0	0	0	1	0	1	1	0	0	1
OO_{383}	1	1	0	1	0	1	0	1	0	0	0	1
OO_{384}	1	1	0	0	0	1	0	1	0	1	0	1
OO_{385}	1	1	0	0	0	1	0	1	1	1	0	1
OO_{386}	1	1	0	0	0	1	0	1	0	0	0	1
OO_{387}	1	1	1	1	0	1	0	1	0	1	0	1
OO_{388}	1	1	0	1	0	1	0	1	1	1	0	1
OO_{389}	1	1	0	1	0	1	0	1	0	1	0	1
OO_{390}	1	1	1	1	0	1	0	1	1	1	0	1
OO_{391}	0	1	1	0	0	1	1	1	1	1	1	1
OO_{392}	0	1	1	1	0	1	1	1	1	0	1	1
OO_{393}	0	1	1	0	0	1	1	1	1	0	1	1
OO_{394}	0	1	1	0	0	1	1	1	0	1	1	1
OO_{395}	0	1	0	1	0	1	1	1	1	0	1	1
OO_{396}	0	1	1	0	0	1	1	1	0	0	1	1
OO_{397}	0	1	0	0	0	1	1	1	1	0	1	1
OO_{398}	0	1	0	1	0	1	1	1	0	0	1	1
OO_{399}	0	1	0	0	0	1	1	1	0	1	1	1
OO_{400}	0	1	0	0	0	1	1	1	1	1	1	1

Table OLS7: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{401}	0	1	0	0	0	1	1	1	0	0	1	1
OO_{402}	0	1	1	1	0	1	1	1	0	1	1	1
OO_{403}	0	1	0	1	0	1	1	1	1	1	1	1
OO_{404}	0	1	0	1	0	1	1	1	0	1	1	1
OO_{405}	0	1	1	1	0	1	1	1	1	1	1	1
OO_{406}	1	1	1	0	1	1	0	1	1	1	0	1
OO_{407}	1	1	1	1	1	1	0	1	1	0	0	1
OO_{408}	1	1	1	0	1	1	0	1	1	0	0	1
OO_{409}	1	1	1	0	1	1	0	1	0	1	0	1
OO_{410}	1	1	0	1	1	1	0	1	1	0	0	1
OO_{411}	1	1	1	0	1	1	0	1	0	0	0	1
OO_{412}	1	1	0	0	1	1	0	1	1	0	0	1
OO_{413}	1	1	0	1	1	1	0	1	0	0	0	1
OO_{414}	1	1	0	0	1	1	0	1	0	1	0	1
OO_{415}	1	1	0	0	1	1	0	1	1	1	0	1
OO_{416}	1	1	0	0	1	1	0	1	0	0	0	1
OO_{417}	1	1	1	1	1	1	0	1	0	1	0	1
OO_{418}	1	1	0	1	1	1	0	1	1	1	0	1
OO_{419}	1	1	0	1	1	1	0	1	0	1	0	1
OO_{420}	1	1	1	1	1	1	0	1	1	1	0	1
OO_{421}	0	1	1	0	1	1	0	1	1	1	1	1
OO_{422}	0	1	1	1	1	1	0	1	1	0	1	1
OO_{423}	0	1	1	0	1	1	0	1	1	0	1	1
OO_{424}	0	1	1	0	1	1	0	1	0	1	1	1
OO_{425}	0	1	0	1	1	1	0	1	1	0	1	1
OO_{426}	0	1	1	0	1	1	0	1	0	0	1	1
OO_{427}	0	1	0	0	1	1	0	1	1	0	1	1
OO_{428}	0	1	0	1	1	1	0	1	0	0	1	1
OO_{429}	0	1	0	0	1	1	0	1	0	1	1	1
OO_{430}	0	1	0	0	1	1	0	1	1	1	1	1
OO_{431}	0	1	0	0	1	1	0	1	0	0	1	1
OO_{432}	0	1	1	1	1	1	0	1	0	1	1	1
OO_{433}	0	1	0	1	1	1	0	1	1	1	1	1
OO_{434}	0	1	0	1	1	1	0	1	0	1	1	1
OO_{435}	0	1	1	1	1	1	0	1	1	1	1	1
OO_{436}	1	1	1	0	0	0	0	1	1	1	1	1
OO_{437}	1	1	1	1	0	0	0	1	1	0	1	1
OO_{438}	1	1	1	0	0	0	0	1	1	0	1	1
OO_{439}	1	1	1	0	0	0	0	1	0	1	1	1
OO_{440}	1	1	0	1	0	0	0	1	1	0	1	1

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{441}	1	1	1	0	0	0	0	1	0	0	1	1
OO_{442}	1	1	0	0	0	0	0	1	1	0	1	1
OO_{443}	1	1	0	1	0	0	0	1	0	0	1	1
OO_{444}	1	1	0	0	0	0	0	1	0	1	1	1
OO_{445}	1	1	0	0	0	0	0	1	1	1	1	1
OO_{446}	1	1	0	0	0	0	0	1	0	0	1	1
OO_{447}	1	1	1	1	0	0	0	1	0	1	1	1
OO_{448}	1	1	0	1	0	0	0	1	1	1	1	1
OO_{449}	1	1	0	1	0	0	0	1	0	1	1	1
OO_{450}	1	1	1	1	0	0	0	1	1	1	1	1
OO_{451}	0	1	1	0	1	1	1	1	1	1	0	0
OO_{452}	0	1	1	1	1	1	1	1	1	0	0	0
OO_{453}	0	1	1	0	1	1	1	1	1	0	0	0
OO_{454}	0	1	1	0	1	1	1	1	0	1	0	0
OO_{455}	0	1	0	1	1	1	1	1	1	0	0	0
OO_{456}	0	1	1	0	1	1	1	1	0	0	0	0
OO_{457}	0	1	0	0	1	1	1	1	1	0	0	0
OO_{458}	0	1	0	1	1	1	1	1	0	0	0	0
OO_{459}	0	1	0	0	1	1	1	1	0	1	0	0
OO_{460}	0	1	0	0	1	1	1	1	1	1	0	0
OO_{461}	0	1	0	0	1	1	1	1	0	0	0	0
OO_{462}	0	1	1	1	1	1	1	1	0	1	0	0
OO_{463}	0	1	0	1	1	1	1	1	1	1	0	0
OO_{464}	0	1	0	1	1	1	1	1	0	1	0	0
OO_{465}	0	1	1	1	1	1	1	1	1	1	0	0
OO_{466}	0	1	1	0	1	1	1	1	1	1	0	1
OO_{467}	0	1	1	1	1	1	1	1	1	0	0	1
OO_{468}	0	1	1	0	1	1	1	1	1	0	0	1
OO_{469}	0	1	1	0	1	1	1	1	0	1	0	1
OO_{470}	0	1	0	1	1	1	1	1	1	0	0	1
OO_{471}	0	1	1	0	1	1	1	1	0	0	0	1
OO_{472}	0	1	0	0	1	1	1	1	1	0	0	1
OO_{473}	0	1	0	1	1	1	1	1	0	0	0	1
OO_{474}	0	1	0	0	1	1	1	1	0	1	0	1
OO_{475}	0	1	0	0	1	1	1	1	1	1	0	1
OO_{476}	0	1	0	0	1	1	1	1	0	0	0	1
OO_{477}	0	1	1	1	1	1	1	1	0	1	0	1
OO_{478}	0	1	0	1	1	1	1	1	1	1	0	1
OO_{479}	0	1	0	1	1	1	1	1	0	1	0	1
OO_{480}	0	1	1	1	1	1	1	1	1	1	0	1

Table OLS7: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{481}	1	1	1	0	0	1	0	1	1	1	1	1
OO_{482}	1	1	1	1	0	1	0	1	1	0	1	1
OO_{483}	1	1	1	0	0	1	0	1	1	0	1	1
OO_{484}	1	1	1	0	0	1	0	1	0	1	1	1
OO_{485}	1	1	0	1	0	1	0	1	1	0	1	1
OO_{486}	1	1	1	0	0	1	0	1	0	0	1	1
OO_{487}	1	1	0	0	0	1	0	1	1	0	1	1
OO_{488}	1	1	0	1	0	1	0	1	0	0	1	1
OO_{489}	1	1	0	0	0	1	0	1	0	1	1	1
OO_{490}	1	1	0	0	0	1	0	1	1	1	1	1
OO_{491}	1	1	0	0	0	1	0	1	0	0	1	1
OO_{492}	1	1	1	1	0	1	0	1	0	1	1	1
OO_{493}	1	1	0	1	0	1	0	1	1	1	1	1
OO_{494}	1	1	0	1	0	1	0	1	0	1	1	1
OO_{495}	1	1	1	1	0	1	0	1	1	1	1	1
OO_{496}	0	1	1	0	1	1	1	1	1	1	1	1
OO_{497}	0	1	1	1	1	1	1	1	1	0	1	1
OO_{498}	0	1	1	0	1	1	1	1	1	0	1	1
OO_{499}	0	1	1	0	1	1	1	1	0	1	1	1
OO_{500}	0	1	0	1	1	1	1	1	1	0	1	1
OO_{501}	0	1	1	0	1	1	1	1	0	0	1	1
OO_{502}	0	1	0	0	1	1	1	1	1	0	1	1
OO_{503}	0	1	0	1	1	1	1	1	0	0	1	1
OO_{504}	0	1	0	0	1	1	1	1	0	1	1	1
OO_{505}	0	1	0	0	1	1	1	1	1	1	1	1
OO_{506}	0	1	0	0	1	1	1	1	0	0	1	1
OO_{507}	0	1	1	1	1	1	1	1	0	1	1	1
OO_{508}	0	1	0	1	1	1	1	1	1	1	1	1
OO_{509}	0	1	0	1	1	1	1	1	0	1	1	1
OO_{510}	0	1	1	1	1	1	1	1	1	1	1	1
OO_{511}	1	1	1	0	1	1	0	1	1	1	1	1
OO_{512}	1	1	1	1	1	1	0	1	1	0	1	1
OO_{513}	1	1	1	0	1	1	0	1	1	0	1	1
OO_{514}	1	1	1	0	1	1	0	1	0	1	1	1
OO_{515}	1	1	0	1	1	1	0	1	1	0	1	1
OO_{516}	1	1	1	0	1	1	0	1	0	0	1	1
OO_{517}	1	1	0	0	1	1	0	1	1	0	1	1
OO_{518}	1	1	0	1	1	1	0	1	0	0	1	1
OO_{519}	1	1	0	0	1	1	0	1	0	1	1	1
OO_{520}	1	1	0	0	1	1	0	1	1	1	1	1

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{521}	1	1	0	0	1	1	0	1	0	0	1	1
OO_{522}	1	1	1	1	1	1	0	1	0	1	1	1
OO_{523}	1	1	0	1	1	1	0	1	1	1	1	1
OO_{524}	1	1	0	1	1	1	0	1	0	1	1	1
OO_{525}	1	1	1	1	1	1	0	1	1	1	1	1
OO_{526}	1	1	1	0	0	0	1	1	1	1	0	1
OO_{527}	1	1	1	1	0	0	1	1	1	0	0	1
OO_{528}	1	1	1	0	0	0	1	1	1	0	0	1
OO_{529}	1	1	1	0	0	0	1	1	0	1	0	1
OO_{530}	1	1	0	1	0	0	1	1	1	0	0	1
OO_{531}	1	1	1	0	0	0	1	1	0	0	0	1
OO_{532}	1	1	0	0	0	0	1	1	1	0	0	1
OO_{533}	1	1	0	1	0	0	1	1	0	0	0	1
OO_{534}	1	1	0	0	0	0	1	1	0	1	0	1
OO_{535}	1	1	0	0	0	0	1	1	1	1	0	1
OO_{536}	1	1	0	0	0	0	1	1	0	0	0	1
OO_{537}	1	1	1	1	0	0	1	1	0	1	0	1
OO_{538}	1	1	0	1	0	0	1	1	1	1	0	1
OO_{539}	1	1	0	1	0	0	1	1	0	1	0	1
OO_{540}	1	1	1	1	0	0	1	1	1	1	0	1
OO_{541}	1	1	1	0	0	1	1	1	1	1	0	0
OO_{542}	1	1	1	1	0	1	1	1	1	0	0	0
OO_{543}	1	1	1	0	0	1	1	1	1	0	0	0
OO_{544}	1	1	1	0	0	1	1	1	0	1	0	0
OO_{545}	1	1	0	1	0	1	1	1	1	0	0	0
OO_{546}	1	1	1	0	0	1	1	1	0	0	0	0
OO_{547}	1	1	0	0	0	1	1	1	1	0	0	0
OO_{548}	1	1	0	1	0	1	1	1	0	0	0	0
OO_{549}	1	1	0	0	0	1	1	1	0	1	0	0
OO_{550}	1	1	0	0	0	1	1	1	1	1	0	0
OO_{551}	1	1	0	0	0	1	1	1	0	0	0	0
OO_{552}	1	1	1	1	0	1	1	1	0	1	0	0
OO_{553}	1	1	0	1	0	1	1	1	1	1	0	0
OO_{554}	1	1	0	1	0	1	1	1	0	1	0	0
OO_{555}	1	1	1	1	0	1	1	1	1	1	0	0
OO_{556}	1	1	1	0	0	0	1	1	1	1	0	0
OO_{557}	1	1	1	1	0	0	1	1	1	0	0	0
OO_{558}	1	1	1	0	0	0	1	1	1	0	0	0
OO_{559}	1	1	1	0	0	0	1	1	0	1	0	0
OO_{560}	1	1	0	1	0	0	1	1	1	0	0	0

Table OLS7: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{561}	1	1	1	0	0	0	1	1	0	0	0	0
OO_{562}	1	1	0	0	0	0	1	1	1	0	0	0
OO_{563}	1	1	0	1	0	0	1	1	0	0	0	0
OO_{564}	1	1	0	0	0	0	1	1	0	1	0	0
OO_{565}	1	1	0	0	0	0	1	1	1	1	0	0
OO_{566}	1	1	0	0	0	0	1	1	0	0	0	0
OO_{567}	1	1	1	1	0	0	1	1	0	1	0	0
OO_{568}	1	1	0	1	0	0	1	1	1	1	0	0
OO_{569}	1	1	0	1	0	0	1	1	0	1	0	0
OO_{570}	1	1	1	1	0	0	1	1	1	1	0	0
OO_{571}	1	1	1	0	0	0	1	1	1	1	1	1
OO_{572}	1	1	1	1	0	0	1	1	1	0	1	1
OO_{573}	1	1	1	0	0	0	1	1	1	0	1	1
OO_{574}	1	1	1	0	0	0	1	1	0	1	1	1
OO_{575}	1	1	0	1	0	0	1	1	1	0	1	1
OO_{576}	1	1	1	0	0	0	1	1	0	0	1	1
OO_{577}	1	1	0	0	0	0	1	1	1	0	1	1
OO_{578}	1	1	0	1	0	0	1	1	0	0	1	1
OO_{579}	1	1	0	0	0	0	1	1	0	1	1	1
OO_{580}	1	1	0	0	0	0	1	1	1	1	1	1
OO_{581}	1	1	0	0	0	0	1	1	0	0	1	1
OO_{582}	1	1	1	1	0	0	1	1	0	1	1	1
OO_{583}	1	1	0	1	0	0	1	1	1	1	1	1
OO_{584}	1	1	0	1	0	0	1	1	0	1	1	1
OO_{585}	1	1	1	1	0	0	1	1	1	1	1	1
OO_{586}	1	1	1	0	1	1	1	1	1	1	0	0
OO_{587}	1	1	1	1	1	1	1	1	1	0	0	0
OO_{588}	1	1	1	0	1	1	1	1	1	0	0	0
OO_{589}	1	1	1	0	1	1	1	1	0	1	0	0
OO_{590}	1	1	0	1	1	1	1	1	1	0	0	0
OO_{591}	1	1	1	0	1	1	1	1	0	0	0	0
OO_{592}	1	1	0	0	1	1	1	1	1	0	0	0
OO_{593}	1	1	0	1	1	1	1	1	0	0	0	0
OO_{594}	1	1	0	0	1	1	1	1	0	1	0	0
OO_{595}	1	1	0	0	1	1	1	1	1	1	0	0
OO_{596}	1	1	0	0	1	1	1	1	0	0	0	0
OO_{597}	1	1	1	1	1	1	1	1	0	1	0	0
OO_{598}	1	1	0	1	1	1	1	1	1	1	0	0
OO_{599}	1	1	0	1	1	1	1	1	0	1	0	0
OO_{600}	1	1	1	1	1	1	1	1	1	1	0	0

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{601}	1	1	1	0	0	1	1	1	1	1	0	1
OO_{602}	1	1	1	1	0	1	1	1	1	0	0	1
OO_{603}	1	1	1	0	0	1	1	1	1	0	0	1
OO_{604}	1	1	1	0	0	1	1	1	0	1	0	1
OO_{605}	1	1	0	1	0	1	1	1	1	0	0	1
OO_{606}	1	1	1	0	0	1	1	1	0	0	0	1
OO_{607}	1	1	0	0	0	1	1	1	1	0	0	1
OO_{608}	1	1	0	1	0	1	1	1	0	0	0	1
OO_{609}	1	1	0	0	0	1	1	1	0	1	0	1
OO_{610}	1	1	0	0	0	1	1	1	1	1	0	1
OO_{611}	1	1	0	0	0	1	1	1	0	0	0	1
OO_{612}	1	1	1	1	0	1	1	1	0	1	0	1
OO_{613}	1	1	0	1	0	1	1	1	1	1	0	1
OO_{614}	1	1	0	1	0	1	1	1	0	1	0	1
OO_{615}	1	1	1	1	0	1	1	1	1	1	0	1
OO_{616}	1	1	1	0	0	1	1	1	1	1	1	1
OO_{617}	1	1	1	1	0	1	1	1	1	0	1	1
OO_{618}	1	1	1	0	0	1	1	1	1	0	1	1
OO_{619}	1	1	1	0	0	1	1	1	0	1	1	1
OO_{620}	1	1	0	1	0	1	1	1	1	0	1	1
OO_{621}	1	1	1	0	0	1	1	1	0	0	1	1
OO_{622}	1	1	0	0	0	1	1	1	1	0	1	1
OO_{623}	1	1	0	1	0	1	1	1	0	0	1	1
OO_{624}	1	1	0	0	0	1	1	1	0	1	1	1
OO_{625}	1	1	0	0	0	1	1	1	1	1	1	1
OO_{626}	1	1	0	0	0	1	1	1	0	0	1	1
OO_{627}	1	1	1	1	0	1	1	1	0	1	1	1
OO_{628}	1	1	0	1	0	1	1	1	1	1	1	1
OO_{629}	1	1	0	1	0	1	1	1	0	1	1	1
OO_{630}	1	1	1	1	0	1	1	1	1	1	1	1
OO_{631}	1	1	1	0	1	1	1	1	1	1	0	1
OO_{632}	1	1	1	1	1	1	1	1	1	0	0	1
OO_{633}	1	1	1	0	1	1	1	1	1	0	0	1
OO_{634}	1	1	1	0	1	1	1	1	0	1	0	1
OO_{635}	1	1	0	1	1	1	1	1	1	0	0	1
OO_{636}	1	1	1	0	1	1	1	1	0	0	0	1
OO_{637}	1	1	0	0	1	1	1	1	1	0	0	1
OO_{638}	1	1	0	1	1	1	1	1	0	0	0	1
OO_{639}	1	1	0	0	1	1	1	1	0	1	0	1
OO_{640}	1	1	0	0	1	1	1	1	1	1	0	1

Table OLS7: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OO_{641}	1	1	0	0	1	1	1	1	0	0	0	1
OO_{642}	1	1	1	1	1	1	1	1	0	1	0	1
OO_{643}	1	1	0	1	1	1	1	1	1	1	0	1
OO_{644}	1	1	0	1	1	1	1	1	0	1	0	1
OO_{645}	1	1	1	1	1	1	1	1	1	1	0	1
OO_{646}	1	1	1	0	1	1	1	1	1	1	1	1
OO_{647}	1	1	1	1	1	1	1	1	1	0	1	1
OO_{648}	1	1	1	0	1	1	1	1	1	0	1	1
OO_{649}	1	1	1	0	1	1	1	1	0	1	1	1
OO_{650}	1	1	0	1	1	1	1	1	1	0	1	1
OO_{651}	1	1	1	0	1	1	1	1	0	0	1	1
OO_{652}	1	1	0	0	1	1	1	1	1	0	1	1
OO_{653}	1	1	0	1	1	1	1	1	0	0	1	1
OO_{654}	1	1	0	0	1	1	1	1	0	1	1	1
OO_{655}	1	1	0	0	1	1	1	1	1	1	1	1
OO_{656}	1	1	0	0	1	1	1	1	0	0	1	1
OO_{657}	1	1	1	1	1	1	1	1	0	1	1	1
OO_{658}	1	1	0	1	1	1	1	1	1	1	1	1
OO_{659}	1	1	0	1	1	1	1	1	0	1	1	1
OO_{660}	1	1	1	1	1	1	1	1	1	1	1	1

Table OLS8: List of 250 joint preferences for `Description` and `Experience` of Hertwig et al. (2004), according to CPT, consistent with Hypothesis III, based on a grid search of joint parameter values. Each joint preference can be constructed with a constant α, β, λ across conditions, $\delta_d, \gamma_d < 1$ for `Description` and $\delta_e, \gamma_e > 1$ for `Experience`. Populations with sufficiently high concentrations of the shaded states violate one or more inequality constraints of Table 1 in Hertwig et al. (2004), due to the boldfaced entries (see text for details).

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OU_{1}	0	0	1	0	0	0	0	0	1	1	0	0
OU_{2}	0	0	1	0	0	1	0	0	1	1	0	0
OU_{3}	0	1	1	0	0	0	0	0	1	1	0	0
OU_{4}	0	1	1	0	0	1	0	0	1	1	0	0
OU_{5}	0	1	1	0	1	1	0	0	1	1	0	0
OU_{6}	0	0	1	0	0	0	1	0	1	1	0	0
OU_{7}	**1**	1	1	0	0	0	**0**	0	1	1	0	0
OU_{8}	0	1	1	0	0	0	1	0	1	1	0	0
OU_{9}	0	1	1	0	0	0	1	1	1	1	0	0
OU_{10}	0	1	1	0	0	1	1	0	1	1	0	0
OU_{11}	0	1	1	0	0	1	1	1	1	1	0	0
OU_{12}	0	1	1	0	**0**	1	1	1	1	1	**1**	0
OU_{13}	0	1	1	0	**0**	1	1	1	1	1	**1**	1
OU_{14}	0	1	1	0	1	1	1	0	1	1	0	0
OU_{15}	0	1	1	0	1	1	1	1	1	1	0	0
OU_{16}	0	1	1	0	1	1	1	1	1	1	1	0
OU_{17}	0	1	1	0	1	1	1	1	1	1	1	1
OU_{18}	1	1	1	0	0	0	1	0	1	1	0	0
OU_{19}	1	1	1	0	0	1	1	0	1	1	0	0
OU_{20}	1	1	1	0	1	1	1	0	1	1	0	0
OU_{21}	1	1	1	0	0	1	1	1	1	1	0	0
OU_{22}	1	1	1	0	0	0	1	1	1	1	0	0
OU_{23}	1	1	1	0	1	1	1	1	1	1	0	0
OU_{24}	1	1	1	0	1	1	1	1	1	1	1	0
OU_{25}	1	1	1	0	1	1	1	1	1	1	1	1
OU_{26}	0	0	1	0	0	0	0	0	0	1	0	0
OU_{27}	0	0	1	0	0	1	0	0	0	1	0	0
OU_{28}	0	1	1	0	0	0	0	0	0	1	0	0
OU_{29}	0	1	1	0	0	1	0	0	0	1	0	0
OU_{30}	0	1	1	0	1	1	0	0	0	1	0	0
OU_{31}	0	0	1	0	0	0	1	0	0	1	0	0
OU_{32}	**1**	1	1	0	0	0	**0**	0	0	1	0	0
OU_{33}	0	1	1	0	0	0	1	0	0	1	0	0
OU_{34}	0	1	1	0	0	0	1	1	0	1	0	0
OU_{35}	0	1	1	0	0	1	1	0	0	1	0	0
OU_{36}	0	1	1	0	0	1	1	1	0	1	0	0
OU_{37}	0	1	1	0	**0**	1	1	1	0	1	**1**	0
OU_{38}	0	1	1	0	**0**	1	1	1	0	1	**1**	1
OU_{39}	0	1	1	0	1	1	1	0	0	1	0	0
OU_{40}	0	1	1	0	1	1	1	1	0	1	0	0
OU_{41}	0	1	1	0	1	1	1	1	0	1	1	0
OU_{42}	0	1	1	0	1	1	1	1	0	1	1	1
OU_{43}	1	1	1	0	0	0	1	0	0	1	0	0
OU_{44}	1	1	1	0	0	1	1	0	0	1	0	0
OU_{45}	1	1	1	0	1	1	1	0	0	1	0	0
OU_{46}	1	1	1	0	0	1	1	1	0	1	0	0
OU_{47}	1	1	1	0	0	0	1	1	0	1	0	0
OU_{48}	1	1	1	0	1	1	1	1	0	1	0	0
OU_{49}	1	1	1	0	1	1	1	1	0	1	1	0
OU_{50}	1	1	1	0	1	1	1	1	0	1	1	1
OU_{51}	0	0	1	0	0	0	0	0	0	0	0	0
OU_{52}	0	0	1	0	0	1	0	0	0	0	0	0
OU_{53}	0	1	1	0	0	0	0	0	0	0	0	0
OU_{54}	0	1	1	0	0	1	0	0	0	0	0	0
OU_{55}	0	1	1	0	1	1	0	0	0	0	0	0
OU_{56}	0	0	1	0	0	0	1	0	0	0	0	0
OU_{57}	**1**	1	1	0	0	0	**0**	0	0	0	0	0
OU_{58}	0	1	1	0	0	0	1	0	0	0	0	0
OU_{59}	0	1	1	0	0	0	1	1	0	0	0	0
OU_{60}	0	1	1	0	0	1	1	0	0	0	0	0
OU_{61}	0	1	1	0	0	1	1	1	0	0	0	0
OU_{62}	0	1	1	0	**0**	1	1	1	0	0	**1**	0
OU_{63}	0	1	1	0	**0**	1	1	1	0	0	**1**	1
OU_{64}	0	1	1	0	1	1	1	0	0	0	0	0
OU_{65}	0	1	1	0	1	1	1	1	0	0	0	0
OU_{66}	0	1	1	0	1	1	1	1	0	0	1	0
OU_{67}	0	1	1	0	1	1	1	1	0	0	1	1
OU_{68}	1	1	1	0	0	0	1	0	0	0	0	0
OU_{69}	1	1	1	0	0	1	1	0	0	0	0	0
OU_{70}	1	1	1	0	1	1	1	0	0	0	0	0
OU_{71}	1	1	1	0	0	1	1	1	0	0	0	0
OU_{72}	1	1	1	0	0	0	1	1	0	0	0	0
OU_{73}	1	1	1	0	1	1	1	1	0	0	0	0
OU_{74}	1	1	1	0	1	1	1	1	0	0	1	0
OU_{75}	1	1	1	0	1	1	1	1	0	0	1	1
OU_{76}	0	0	0	0	0	0	0	0	0	1	0	0
OU_{77}	0	0	0	0	0	1	0	0	0	1	0	0
OU_{78}	0	1	0	0	0	0	0	0	0	1	0	0
OU_{79}	0	1	0	0	0	1	0	0	0	1	0	0
OU_{80}	0	1	0	0	1	1	0	0	0	1	0	0

Table OLS8: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OU_{81}	0	0	0	0	0	0	1	0	0	1	0	0
OU_{82}	**1**	1	0	0	0	0	**0**	0	0	1	0	0
OU_{83}	0	1	0	0	0	0	1	0	0	1	0	0
OU_{84}	0	1	0	0	0	0	1	1	0	1	0	0
OU_{85}	0	1	0	0	0	1	1	0	0	1	0	0
OU_{86}	0	1	0	0	0	1	1	1	0	1	0	0
OU_{87}	0	1	0	0	**0**	1	1	1	0	1	**1**	0
OU_{88}	0	1	0	0	**0**	1	1	1	0	1	**1**	1
OU_{89}	0	1	0	0	1	1	1	0	0	1	0	0
OU_{90}	0	1	0	0	1	1	1	1	0	1	0	0
OU_{91}	0	1	0	0	1	1	1	1	0	1	1	0
OU_{92}	0	1	0	0	1	1	1	1	0	1	1	1
OU_{93}	1	1	0	0	0	0	1	0	0	1	0	0
OU_{94}	1	1	0	0	0	1	1	0	0	1	0	0
OU_{95}	1	1	0	0	1	1	1	0	0	1	0	0
OU_{96}	1	1	0	0	0	1	1	1	0	1	0	0
OU_{97}	1	1	0	0	0	0	1	1	0	1	0	0
OU_{98}	1	1	0	0	1	1	1	1	0	1	0	0
OU_{99}	1	1	0	0	1	1	1	1	0	1	1	0
OU_{100}	1	1	0	0	1	1	1	1	0	1	1	1
OU_{101}	0	0	0	**1**	0	0	0	0	0	**0**	0	0
OU_{102}	0	0	0	**1**	0	1	0	0	0	**0**	0	0
OU_{103}	0	1	0	**1**	0	0	0	0	0	**0**	0	0
OU_{104}	0	1	0	**1**	0	1	0	0	0	**0**	0	0
OU_{105}	0	1	0	**1**	1	1	0	0	0	**0**	0	0
OU_{106}	0	0	0	**1**	0	0	1	0	0	**0**	0	0
OU_{107}	**1**	1	0	**1**	0	**0**	0	0	0	**0**	0	0
OU_{108}	0	1	0	**1**	0	0	1	0	0	**0**	0	0
OU_{109}	0	1	0	**1**	0	0	1	1	0	**0**	0	0
OU_{110}	0	1	0	**1**	0	1	1	0	0	**0**	0	0
OU_{111}	0	1	0	**1**	0	1	1	1	0	**0**	0	0
OU_{112}	0	1	0	**1**	**0**	1	1	1	0	**0**	**1**	0
OU_{113}	0	1	0	**1**	**0**	1	1	1	0	**0**	**1**	1
OU_{114}	0	1	0	**1**	1	1	1	0	0	**0**	0	0
OU_{115}	0	1	0	**1**	1	1	1	1	0	**0**	0	0
OU_{116}	0	1	0	**1**	1	1	1	1	0	**0**	1	0
OU_{117}	0	1	0	**1**	1	1	1	1	0	**0**	1	1
OU_{118}	1	1	0	**1**	0	0	1	0	0	**0**	0	0
OU_{119}	1	1	0	**1**	0	1	1	0	0	**0**	0	0
OU_{120}	1	1	0	**1**	1	1	1	0	0	**0**	0	0

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OU_{121}	1	1	0	**1**	0	1	1	1	0	**0**	0	0
OU_{122}	1	1	0	**1**	0	0	1	1	0	**0**	0	0
OU_{123}	1	1	0	**1**	1	1	1	1	0	**0**	0	0
OU_{124}	1	1	0	**1**	1	1	1	1	0	**0**	1	0
OU_{125}	1	1	0	**1**	1	1	1	1	0	**0**	1	1
OU_{126}	0	0	**0**	0	0	0	0	0	**1**	1	0	0
OU_{127}	0	0	**0**	0	0	1	0	0	**1**	1	0	0
OU_{128}	0	1	**0**	0	0	0	0	0	**1**	1	0	0
OU_{129}	0	1	**0**	0	0	1	0	0	**1**	1	0	0
OU_{130}	0	1	**0**	0	1	1	0	0	**1**	1	0	0
OU_{131}	0	0	**0**	0	0	0	1	0	**1**	1	0	0
OU_{132}	**1**	1	**0**	0	0	0	**0**	0	**1**	1	0	0
OU_{133}	0	1	**0**	0	0	0	1	0	**1**	1	0	0
OU_{134}	0	1	**0**	0	0	0	1	1	**1**	1	0	0
OU_{135}	0	1	**0**	0	0	1	1	0	**1**	1	0	0
OU_{136}	0	1	**0**	0	0	1	1	1	**1**	1	0	0
OU_{137}	0	1	**0**	0	**1**	1	1	1	**1**	1	**0**	0
OU_{138}	0	1	**0**	0	**1**	1	1	1	**1**	1	**0**	1
OU_{139}	0	1	**0**	0	1	1	1	0	**1**	1	0	0
OU_{140}	0	1	**0**	0	1	1	1	1	**1**	1	0	0
OU_{141}	0	1	**0**	0	1	1	1	1	**1**	1	1	0
OU_{142}	0	1	**0**	0	1	1	1	1	**1**	1	1	1
OU_{143}	1	1	**0**	0	0	0	1	0	**1**	1	0	0
OU_{144}	1	1	**0**	0	0	1	1	0	**1**	1	0	0
OU_{145}	1	1	**0**	0	1	1	1	0	**1**	1	0	0
OU_{146}	1	1	**0**	0	0	1	1	1	**1**	1	0	0
OU_{147}	1	1	**0**	0	0	0	1	1	**1**	1	0	0
OU_{148}	1	1	**0**	0	1	1	1	1	**1**	1	0	0
OU_{149}	1	1	**0**	0	1	1	1	1	**1**	1	1	0
OU_{150}	1	1	**0**	0	1	1	1	1	**1**	1	1	1
OU_{151}	0	0	1	1	0	0	0	0	1	1	0	0
OU_{152}	0	0	1	1	0	1	0	0	1	1	0	0
OU_{153}	0	1	1	1	0	0	0	0	1	1	0	0
OU_{154}	0	1	1	1	0	1	0	0	1	1	0	0
OU_{155}	0	1	1	1	1	1	0	0	1	1	0	0
OU_{156}	0	0	1	1	0	0	1	0	1	1	0	0
OU_{157}	**1**	1	1	1	0	**0**	0	0	1	1	0	0
OU_{158}	0	1	1	1	0	0	1	0	1	1	0	0
OU_{159}	0	1	1	1	0	0	1	1	1	1	0	0
OU_{160}	0	1	1	1	0	1	1	0	1	1	0	0

Table OLS8: continued

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OU_{161}	0	1	1	1	0	1	1	1	1	1	0	0
OU_{162}	0	1	1	1	**0**	1	1	1	1	1	**1**	0
OU_{163}	0	1	1	1	**0**	1	1	1	1	1	**1**	1
OU_{164}	0	1	1	1	1	1	1	0	1	1	0	0
OU_{165}	0	1	1	1	1	1	1	1	1	1	0	0
OU_{166}	0	1	1	1	1	1	1	1	1	1	1	0
OU_{167}	0	1	1	1	1	1	1	1	1	1	1	1
OU_{168}	1	1	1	1	0	0	1	0	1	1	0	0
OU_{169}	1	1	1	1	0	1	1	0	1	1	0	0
OU_{170}	1	1	1	1	1	1	1	0	1	1	0	0
OU_{171}	1	1	1	1	0	1	1	1	1	1	0	0
OU_{172}	1	1	1	1	0	0	1	1	1	1	0	0
OU_{173}	1	1	1	1	1	1	1	1	1	1	0	0
OU_{174}	1	1	1	1	1	1	1	1	1	1	1	0
OU_{175}	1	1	1	1	1	1	1	1	1	1	1	1
OU_{176}	0	0	1	1	0	0	0	0	0	1	0	0
OU_{177}	0	0	1	1	0	1	0	0	0	1	0	0
OU_{178}	0	1	1	1	0	0	0	0	0	1	0	0
OU_{179}	0	1	1	1	0	1	0	0	0	1	0	0
OU_{180}	0	1	1	1	1	1	0	0	0	1	0	0
OU_{181}	0	0	1	1	0	0	1	0	0	1	0	0
OU_{182}	**1**	1	1	1	0	0	**0**	0	0	1	0	0
OU_{183}	0	1	1	1	0	0	1	0	0	1	0	0
OU_{184}	0	1	1	1	0	0	1	1	0	1	0	0
OU_{185}	0	1	1	1	0	1	1	0	0	1	0	0
OU_{186}	0	1	1	1	0	1	1	1	0	1	0	0
OU_{187}	0	1	1	1	**0**	1	1	1	0	1	**1**	0
OU_{188}	0	1	1	1	**0**	1	1	1	0	1	**1**	1
OU_{189}	0	1	1	1	1	1	1	0	0	1	0	0
OU_{190}	0	1	1	1	1	1	1	1	0	1	0	0
OU_{191}	0	1	1	1	1	1	1	1	0	1	1	0
OU_{192}	0	1	1	1	1	1	1	1	0	1	1	1
OU_{193}	1	1	1	1	0	0	1	0	0	1	0	0
OU_{194}	1	1	1	1	0	1	1	0	0	1	0	0
OU_{195}	1	1	1	1	1	1	1	0	0	1	0	0
OU_{196}	1	1	1	1	0	1	1	1	0	1	0	0
OU_{197}	1	1	1	1	0	0	1	1	0	1	0	0
OU_{198}	1	1	1	1	1	1	1	1	0	1	0	0
OU_{199}	1	1	1	1	1	1	1	1	0	1	1	0
OU_{200}	1	1	1	1	1	1	1	1	0	1	1	1
OU_{201}	0	0	0	1	0	0	0	0	0	1	0	0
OU_{202}	0	0	0	1	0	1	0	0	0	1	0	0
OU_{203}	0	1	0	1	0	0	0	0	0	1	0	0
OU_{204}	0	1	0	1	0	1	0	0	0	1	0	0
OU_{205}	0	1	0	1	1	1	0	0	0	1	0	0

	Description						Experience					
	1	2	3	4	5	6	1	2	3	4	5	6
OU_{206}	0	0	0	1	0	0	1	0	0	1	0	0
OU_{207}	**1**	1	0	1	0	0	**0**	0	0	1	0	0
OU_{208}	0	1	0	1	0	0	1	0	0	1	0	0
OU_{209}	0	1	0	1	0	0	1	1	0	1	0	0
OU_{210}	0	1	0	1	0	1	1	0	0	1	0	0
OU_{211}	0	1	0	1	0	1	1	1	0	1	0	0
OU_{212}	0	1	0	1	**0**	1	1	1	0	1	**1**	0
OU_{213}	0	1	0	1	**0**	1	1	1	0	1	**1**	1
OU_{214}	0	1	0	1	1	1	1	0	0	1	0	0
OU_{215}	0	1	0	1	1	1	1	1	0	1	0	0
OU_{216}	0	1	0	1	1	1	1	1	0	1	1	0
OU_{217}	0	1	0	1	1	1	1	1	0	1	1	1
OU_{218}	1	1	0	1	0	0	1	0	0	1	0	0
OU_{219}	1	1	0	1	0	1	1	0	0	1	0	0
OU_{220}	1	1	0	1	1	1	1	0	0	1	0	0
OU_{221}	1	1	0	1	0	1	1	1	0	1	0	0
OU_{222}	1	1	0	1	0	0	1	1	0	1	0	0
OU_{223}	1	1	0	1	1	1	1	1	0	1	0	0
OU_{224}	1	1	0	1	1	1	1	1	0	1	1	0
OU_{225}	1	1	0	1	1	1	1	1	0	1	1	1
OU_{226}	0	0	0	0	0	0	0	0	0	0	0	0
OU_{227}	0	0	0	0	0	1	0	0	0	0	0	0
OU_{228}	0	1	0	0	0	0	0	0	0	0	0	0
OU_{229}	0	1	0	0	0	1	0	0	0	0	0	0
OU_{230}	0	1	0	0	1	1	0	0	0	0	0	0
OU_{231}	0	0	0	0	0	0	1	0	0	0	0	0
OU_{232}	**1**	1	0	0	0	0	**0**	0	0	0	0	0
OU_{233}	0	1	0	0	0	0	1	0	0	0	0	0
OU_{234}	0	1	0	0	0	0	1	1	0	0	0	0
OU_{235}	0	1	0	0	0	1	1	0	0	0	0	0
OU_{236}	0	1	0	0	0	1	1	1	0	0	0	0
OU_{237}	0	1	0	0	**0**	1	1	1	0	0	**1**	0
OU_{238}	0	1	0	0	**0**	1	1	1	0	0	**1**	1
OU_{239}	0	1	0	0	1	1	1	0	0	0	0	0
OU_{240}	0	1	0	0	1	1	1	1	0	0	0	0
OU_{241}	0	1	0	0	1	1	1	1	0	0	1	0
OU_{242}	0	1	0	0	1	1	1	1	0	0	1	1
OU_{243}	1	1	0	0	0	0	1	0	0	0	0	0
OU_{244}	1	1	0	0	0	1	1	0	0	0	0	0
OU_{245}	1	1	0	0	1	1	1	0	0	0	0	0
OU_{246}	1	1	0	0	0	1	1	1	0	0	0	0
OU_{247}	1	1	0	0	0	0	1	1	0	0	0	0
OU_{248}	1	1	0	0	1	1	1	1	0	0	0	0
OU_{249}	1	1	0	0	1	1	1	1	0	0	1	0
OU_{250}	1	1	0	0	1	1	1	1	0	0	1	1

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