Connecting Common Ratio and Common Consequence Preferences

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Online Appendix

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A Additional Tables and Figures

Table A.1: Participant Demographics

	(1) Full Sample	(2) Any $r = 0.1$	(3) Any $r = 0.2$	(4) Any $r = 0.3$	(5) Any $r = 0.5$	(6) Any $r = 0.8$
Number of Participants	2,102	1,247	1,250	1,246	1,221	1,212
Time Taken (in minutes)	27.3	27.2	27.3	27.3	27.3	27.4
Age	25.2	25.1	25.1	25.4	25.2	25.2
Prolific Score	99.8	99.8	99.8	99.8	99.8	99.8
Number of Approvals	304.9	304.7	298.7	310.5	302.9	305.5
Female	50.0	50.6	50.2	49.9	49.5	50.3
Current Student	41.9	42.0	43.7	41.0	40.1	42.0
College Degree	62.1	62.4	61.8	62.5	62.7	62.5
Working (full- or part-time)	59.3	58.5	59.3	60.8	58.9	60.1
English First Language	57.9	58.9	57.2	59.1	58.9	56.8
Attention Checks						
Incentive Question Correct	95.5	95.4	95.8	95.7	95.8	95.6
Passed Attention Check	96.3	96.2	96.6	96.4	96.2	96.5
Comprehension Questions						
MPL Question Correct	85.2	84.5	85.5	84.5	85.9	84.7
Bin Question Correct	79.4	79.7	79.7	78.9	78.5	79.9
Both Questions Correct	69.4	69.5	69.7	67.7	69.4	69.3
Current Residency						
United States	24.6	25.3	23.2	25.2	26.0	24.6
United Kingdom	38.4	37.9	39.8	39.3	37.3	38.0
Portugal	21.8	21.7	22.5	20.5	21.5	22.9
Spain	5.5	5.3	5.0	5.6	5.2	5.8
Germany	3.1	3.4	2.9	3.0	3.1	2.7

Notes: Column (1): participant demographics for all 2,102 participants. Columns (2) to Column (6): participant demographics if ever assigned to a given value of r across four possible (p, r) pairs. For binary demographic variables, missing or unknown responses are coded as zero. Percentages use all participants in the relevant column as the denominator.

Table A.2: Mean Valuations by p and r

	h_{AB}	$h_{AB'}$	h_{CD}	h'_{CD}	N	h'_{AB}	$h'_{AB'}$	N
Panel A: $r = 0.1$								
$p = 0.3$	36.78	23.83	31.10	34.43	406	36.24	24.92	208
$p = 0.5$	37.99	27.77	31.50	32.59	421	37.62	28.47	203
$p = 0.8$	41.34	36.52	34.91	34.86	422	40.50	35.14	205
$p = 0.9$	40.37	35.20	34.37	33.81	430	40.36	36.38	219
Panel B: $r = 0.2$								
$p = 0.3$	35.63	26.35	32.16	32.07	425	34.89	23.95	212
$p = 0.5$	38.57	29.17	34.00	32.82	468	39.09	30.35	207
$p = 0.8$	39.56	36.36	36.52	36.46	419	38.79	35.59	216
$p = 0.9$	39.42	38.71	35.20	35.34	398	40.22	39.68	194
Panel C: $r = 0.3$								
$p = 0.3$	36.48	29.14	34.49	34.25	399	36.50	28.76	211
$p = 0.5$	39.65	32.95	35.55	35.65	389	38.74	33.89	194
$p = 0.8$	42.18	39.37	35.92	36.44	474	40.88	39.01	249
$p = 0.9$	39.32	40.14	37.09	37.62	435	39.00	40.26	213
Panel D: $r = 0.5$								
$p = 0.3$	37.38	30.17	38.23	38.00	426	37.64	31.48	207
$p = 0.5$	39.28	34.37	39.51	39.58	412	38.62	35.17	221
$p = 0.8$	38.75	37.61	37.82	37.71	388	38.87	36.21	191
$p = 0.9$	38.58	38.67	37.43	36.78	425	39.12	37.36	197
Panel E: $r = 0.8$								
$p = 0.3$	37.34	34.54	36.73	36.89	446	36.73	35.07	237
$p = 0.5$	38.04	37.45	38.67	38.25	412	38.81	36.98	193
$p = 0.8$	40.64	41.25	42.56	42.56	399	40.50	41.84	215
$p = 0.9$	38.32	39.48	37.87	38.01	414	38.21	38.71	212

Notes: Table presents mean valuations for each (p, r) combination. Each participant provides a valuation for four (p, r) combinations subject to the restriction that they see each p exactly once. For two (p, r) pairs, participants report all six valuations: h_{AB}, $h_{AB'}$, h_{CD}, h'_{AB}, $h'_{AB'}$, and h'_{CD}. For the remaining two (p, r) pairs, participants provide four valuations: h_{AB}, $h_{AB'}$, h_{CD}, and h'_{CD}. We randomly label multiple valuations h_{XY} or h'_{XY}, so that it was equally likely that either was presented first.

Table A.3: Correlations Between h_{XY} and h'_{XY} by p and r

	(1) $r = 0.1$	(2) $r = 0.2$	(3) $r = 0.3$	(4) $r = 0.5$	(5) $r = 0.8$
		Panel A: $\rho(h_{AB}, h'_{AB})$			
$p = 0.3$	0.600	0.600	0.581	0.552	0.610
$p = 0.5$	0.715	0.621	0.725	0.682	0.712
$p = 0.8$	0.619	0.596	0.645	0.526	0.731
$p = 0.9$	0.527	0.602	0.534	0.576	0.542
		Panel B: $\rho(h_{AB'}, h'_{AB'})$			
$p = 0.3$	0.497	0.596	0.590	0.416	0.652
$p = 0.5$	0.548	0.406	0.622	0.683	0.652
$p = 0.8$	0.596	0.711	0.558	0.634	0.654
$p = 0.9$	0.455	0.516	0.705	0.503	0.640
		Panel C: $\rho(h_{CD}, h'_{CD})$			
$p = 0.3$	0.452	0.453	0.570	0.538	0.541
$p = 0.5$	0.474	0.512	0.410	0.590	0.583
$p = 0.8$	0.435	0.484	0.461	0.389	0.529
$p = 0.9$	0.462	0.431	0.485	0.453	0.432

Notes: Table reports correlation coefficients calculated using all valuations for which there are multiple measures for a given individual and (p, r). Multiple measures of h_{CD} are available for all observations, and therefore an average sample of 420 observations is used to compute each $\rho(h_{CD}, h'_{CD})$. Multiple measures of h_{AB} and $h_{AB'}$ are available for only half of observations, and therefore an average sample of 210 observations is used to compute each $\rho(h_{AB}, h'_{AB})$ and $\rho(h_{AB'}, h'_{AB'})$. The exact sample sizes for each cell are listed in Appendix Table A.2.

Table A.4: Mean Δ_{CR}, Δ_{CC}, and Δ_{MX} by p and r

Panel A: Mean Δ_{CR}

	$p = 0.3$	$p = 0.5$	$p = 0.8$	$p = 0.9$
$r = 0.1$	$5.68^{*,\dagger}$	$6.49^{*,\dagger}$	$6.42^{*,\dagger}$	$6.00^{*,\dagger}$
$r = 0.2$	$3.48^{*,\dagger}$	$4.57^{*,\dagger}$	$3.04^{*,\dagger}$	$4.22^{*,\dagger}$
$r = 0.3$	$1.99^{*,\dagger}$	$4.10^{*,\dagger}$	$6.26^{*,\dagger}$	$2.23^{*,\dagger}$
$r = 0.5$	-0.85	-0.23	0.93	1.16
$r = 0.8$	0.61	-0.63	$-1.92^{*,\dagger}$	0.45

Panel B: Mean Δ_{CC}

	$p = 0.3$	$p = 0.5$	$p = 0.8$	$p = 0.9$
$r = 0.1$	$-10.60^{*,\dagger}$	$-4.81^{*,\dagger}$	1.66	1.39
$r = 0.2$	$-5.72^{*,\dagger}$	$-3.65^{*,\dagger}$	-0.10	$3.36^{*,\dagger}$
$r = 0.3$	$-5.11^{*,\dagger}$	$-2.70^{*,\dagger}$	2.93^{*}	2.52^{*}
$r = 0.5$	$-7.83^{*,\dagger}$	$-5.22^{*,\dagger}$	-0.11	1.89^{*}
$r = 0.8$	$-2.35^{*,\dagger}$	$-0.80^{\dagger}$	$-1.31^{\dagger}$	1.46^{*}

Panel C: Mean $\Delta_{CR} - \Delta_{CC}$

	$p = 0.3$	$p = 0.5$	$p = 0.8$	$p = 0.9$
$r = 0.1$	$16.28^{*,\dagger}$	$11.30^{*,\dagger}$	$4.76^{*,\dagger}$	$4.61^{*,\dagger}$
$r = 0.2$	$9.19^{*,\dagger}$	$8.22^{*,\dagger}$	$3.14^{*,\dagger}$	$0.86^{\dagger}$
$r = 0.3$	$7.10^{*,\dagger}$	$6.80^{*,\dagger}$	$3.32^{*,\dagger}$	$-0.29^{\ddagger}$
$r = 0.5$	$6.98^{*,\dagger}$	$4.99^{*,\dagger}$	1.04	-0.73
$r = 0.8$	$2.96^{*,\dagger}$	0.17	-0.62	-1.01

Panel D: Mean Δ_{MX}

	$p = 0.3$	$p = 0.5$	$p = 0.8$	$p = 0.9$
$r = 0.1$	$11.32^{*,\dagger}$	$9.15^{*,\dagger}$	$5.36^{*,\dagger}$	$3.98^{*,\dagger}$
$r = 0.2$	$10.94^{*,\dagger}$	$8.74^{*,\dagger}$	$3.19^{*,\dagger}$	0.54
$r = 0.3$	$7.74^{*,\dagger}$	$4.85^{*,\dagger}$	$1.87^{*,\dagger}$	-1.26
$r = 0.5$	$6.16^{*,\dagger}$	$3.45^{*,\dagger}$	$2.66^{*,\dagger}$	$1.76^{\dagger}$
$r = 0.8$	$1.67^{*,\dagger}$	$1.82^{*,\dagger}$	-1.34	-0.50

Notes: Table presents mean values along with corresponding hypothesis tests for $\Delta_{CR} = h_{AB} - h_{CD}$, $\Delta_{CC} = h_{AB'} - h'_{CD}$, $\Delta_{CR} - \Delta_{CC}$, and $\Delta_{MX} = h'_{AB} - h'_{AB'}$. Panels A, B, and C aggregate data across all 8,408 observations, with each entry corresponding to roughly 420 observations. Panel D aggregates across the 4,204 observations for which we elicit h'_{AB} and $h'_{AB'}$, with each entry corresponding to roughly 210 observations. Expected utility null hypothesis corresponds to zero mean or zero sign difference. * denotes that the value is significantly different from zero at the 5 percent level using a means test. † denotes a significant deviation in the direction of the reported sign at the 5 percent level using a sign test. ‡ denotes a significant deviation opposite to the sign of the reported mean at the 5 percent level using a sign test.

Table A.5: Predicting the Prevalence of CR, CC, and MX by p and r

Outcome:	(1) Δ_{CR}	(2) Δ_{CC}	(3) $\Delta_{CR} - \Delta_{CC}$	(4) Δ_{MX}
Probability (p)	1.00	13.96	−12.96	−10.95
	(0.67)	(0.71)	(0.92)	(0.95)
Common Ratio (r)	−9.16	1.82	−10.97	−9.24
	(0.66)	(0.74)	(0.84)	(0.86)
Outcome Mean	2.74	−1.72	4.46	4.07
Observations	8,408	8,408	8,408	4,204

Notes: Table presents ordinary least squares regressions of $\Delta_{CR} = h_{AB} - h_{CD}$, $\Delta_{CC} = h_{AB'} - h'_{CD}$, $\Delta_{CR} - \Delta_{CC}$, and $\Delta_{MX} = h'_{AB} - h'_{AB'}$ on experimental parameters (p, r). Columns (1)-(3) use all 8,408 observations from 2,102 participants, while column (4) uses 4,204 observations from 2,102 participants. Specification also includes a constant that is not reported. Standard errors clustered at individual level in parentheses.

Table A.6: Means and Sign Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Number of Cases				
Probability (p)	Common Ratio (r)	Δ (Mean)	Mean Test (p-value)	$\Delta > 0$	$\Delta = 0$	$\Delta < 0$	Sign Test (p-value)	Δ (Median)
		Panel A: Test of $\Delta^*_{CR} = 0$						
0.3	0.1	5.68	0.000	224	65	117	0.000	4
0.3	0.2	3.48	0.000	208	60	157	0.009	0
0.3	0.3	1.99	0.016	186	72	141	0.015	0
0.3	0.5	−0.85	0.243	160	93	173	0.511	0
0.3	0.8	0.61	0.363	176	79	191	0.465	0
0.5	0.1	6.49	0.000	245	71	105	0.000	5
0.5	0.2	4.57	0.000	249	93	126	0.000	1
0.5	0.3	4.10	0.000	215	52	122	0.000	2
0.5	0.5	−0.23	0.722	153	97	162	0.652	0
0.5	0.8	−0.63	0.295	146	112	154	0.686	0
0.8	0.1	6.42	0.000	278	50	94	0.000	6
0.8	0.2	3.04	0.000	239	60	120	0.000	3
0.8	0.3	6.26	0.000	299	62	113	0.000	4
0.8	0.5	0.93	0.214	176	65	147	0.119	0
0.8	0.8	−1.92	0.004	121	76	202	0.000	−1
0.9	0.1	6.00	0.000	291	55	84	0.000	3
0.9	0.2	4.22	0.000	236	61	101	0.000	2
0.9	0.3	2.23	0.002	230	74	131	0.000	1
0.9	0.5	1.16	0.112	191	77	157	0.077	0
0.9	0.8	0.45	0.443	177	62	175	0.958	0
		Panel B: Test of $\Delta^*_{CC} = 0$						
0.3	0.1	−10.60	0.000	93	36	277	0.000	−8
0.3	0.2	−5.72	0.000	129	50	246	0.000	−3
0.3	0.3	−5.11	0.000	121	59	219	0.000	−2
0.3	0.5	−7.83	0.000	96	59	271	0.000	−6
0.3	0.8	−2.35	0.002	156	73	217	0.002	0
0.5	0.1	−4.81	0.000	127	54	240	0.000	−4
0.5	0.2	−3.65	0.000	128	69	271	0.000	−4
0.5	0.3	−2.70	0.002	119	64	206	0.000	−1
0.5	0.5	−5.22	0.000	106	67	239	0.000	−4
0.5	0.8	−0.80	0.240	136	85	191	0.003	0
0.8	0.1	1.66	0.062	171	86	165	0.785	0
0.8	0.2	−0.10	0.894	164	60	195	0.113	0
0.8	0.3	2.93	0.000	216	77	181	0.088	0
0.8	0.5	−0.11	0.887	155	76	157	0.955	0
0.8	0.8	−1.31	0.071	149	46	204	0.004	−1
0.9	0.1	1.39	0.059	170	111	149	0.263	0
0.9	0.2	3.36	0.000	182	81	135	0.010	0
0.9	0.3	2.52	0.002	193	70	172	0.295	0
0.9	0.5	1.89	0.009	170	73	182	0.558	0
0.9	0.8	1.46	0.026	170	72	172	0.957	0
		Panel C: Test of $\Delta^*_{MX} = 0$						
0.3	0.1	11.32	0.000	143	27	38	0.000	9
0.3	0.2	10.94	0.000	161	18	33	0.000	10
0.3	0.3	7.74	0.000	127	43	41	0.000	5
0.3	0.5	6.16	0.000	127	35	45	0.000	5
0.3	0.8	1.67	0.031	114	41	82	0.027	0
0.5	0.1	9.15	0.000	144	30	29	0.000	10
0.5	0.2	8.74	0.000	139	38	30	0.000	6
0.5	0.3	4.85	0.000	113	36	45	0.000	4
0.5	0.5	3.45	0.000	111	48	62	0.000	1
0.5	0.8	1.82	0.048	89	48	56	0.008	0
0.8	0.1	5.36	0.000	132	35	38	0.000	5
0.8	0.2	3.19	0.001	125	35	56	0.000	4
0.8	0.3	1.87	0.049	144	36	69	0.000	2
0.8	0.5	2.66	0.009	107	32	52	0.000	2
0.8	0.8	−1.34	0.117	70	53	92	0.099	0
0.9	0.1	3.98	0.001	134	37	48	0.000	3
0.9	0.2	0.54	0.634	87	37	70	0.201	0
0.9	0.3	−1.26	0.218	86	40	87	1.000	0
0.9	0.5	1.76	0.103	95	45	57	0.003	0
0.9	0.8	−0.50	0.519	79	42	91	0.399	0

Notes: Means test and sign test for Δ_{CR}, Δ_{CC}, and Δ_{MX} for each (p, r) combination. We conduct a two-sided t-test for the difference in means. We also conduct a two-sided sign test, where we exclude all ties (instances of $\Delta_Z = 0$). See Appendix C.1 for test descriptions.

Table A.7: Decomposition Estimates Using Sample Variances and Covariances

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	36.60	24.20	32.76	127.57	116.63	121.34	89.60	113.51	149.90	67.60	72.33	59.02	0.59	0.51	0.45
0.30	0.20	35.38	25.55	32.11	128.19	125.59	112.58	89.40	93.15	135.46	83.78	83.58	51.81	0.59	0.57	0.45
0.30	0.30	36.49	29.01	34.37	136.26	154.58	142.43	94.33	92.86	107.37	112.63	102.50	98.28	0.59	0.62	0.57
0.30	0.50	37.47	30.60	38.11	112.96	89.81	116.68	94.05	134.99	99.86	105.38	96.68	70.63	0.55	0.40	0.54
0.30	0.80	37.13	34.72	36.81	118.54	141.79	110.51	75.12	79.78	93.66	123.11	99.39	98.90	0.61	0.64	0.54
0.50	0.10	37.87	28.00	32.04	131.74	118.41	103.05	45.82	87.38	114.88	66.46	39.88	57.31	0.74	0.58	0.47
0.50	0.20	38.73	29.53	33.41	114.48	84.97	104.47	77.30	116.24	100.13	74.02	51.62	45.28	0.60	0.42	0.51
0.50	0.30	39.35	33.26	35.60	137.46	132.95	77.39	39.14	76.33	111.11	90.80	50.30	49.33	0.78	0.64	0.41
0.50	0.50	39.05	34.65	39.55	141.52	149.10	111.93	59.96	68.07	77.58	128.19	105.99	98.14	0.70	0.69	0.59
0.50	0.80	38.29	37.30	38.46	124.54	142.36	98.81	47.91	70.29	70.71	121.28	95.32	100.29	0.72	0.67	0.58
0.80	0.10	41.06	36.07	34.89	95.20	131.89	79.57	86.22	91.60	103.12	87.95	30.56	50.51	0.52	0.59	0.44
0.80	0.20	39.30	36.10	36.49	92.16	132.02	82.28	55.71	58.57	87.54	73.91	45.93	71.78	0.62	0.69	0.48
0.80	0.30	41.73	39.25	36.18	124.91	129.88	70.67	78.15	111.98	83.25	96.18	45.22	55.22	0.62	0.54	0.46
0.80	0.50	38.79	37.14	37.77	77.64	107.64	56.87	66.41	58.58	89.09	60.79	38.08	44.72	0.54	0.65	0.39
0.80	0.80	40.59	41.46	42.56	125.53	141.80	87.45	52.95	67.88	77.78	120.60	77.93	75.43	0.70	0.68	0.53
0.90	0.10	40.37	35.60	34.09	108.44	83.80	68.31	86.15	104.57	79.63	72.62	31.18	56.60	0.56	0.44	0.46
0.90	0.20	39.68	39.02	35.27	119.39	109.76	58.06	68.12	106.57	76.72	102.61	33.54	48.55	0.64	0.51	0.43
0.90	0.30	39.21	40.18	37.35	80.60	148.54	79.39	76.88	64.15	84.33	88.51	45.70	64.85	0.51	0.70	0.48
0.90	0.50	38.75	38.25	37.10	91.12	88.15	57.69	84.15	101.63	69.62	73.62	43.71	46.43	0.52	0.46	0.45
0.90	0.80	38.28	39.22	37.94	78.65	102.70	44.32	67.37	61.36	58.67	86.33	49.02	50.54	0.54	0.63	0.43
0.63	0.38	38.71	34.46	36.14	113.35	121.62	89.19	71.74	87.97	93.52	91.82	61.92	64.68	0.61	0.58	0.48

Notes: Table reports decomposition estimates calculated from relevant sample variances and covariances (see Section 4.4 and Appendix D.1 for details). The final line presents averages over all 20 rows.

Table A.8: Preference-Noise Decomposition Using Estimates from Appendix Table A.7

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	3.83	−8.56	12.39	104.23	119.93	108.99	343.74	383.35	312.11	0.30	0.31	0.35
0.30	0.20	3.27	−6.56	9.83	73.62	134.56	86.22	298.48	363.17	268.77	0.25	0.37	0.32
0.30	0.30	2.12	−5.36	7.48	73.69	100.46	65.58	275.39	300.68	252.76	0.27	0.33	0.26
0.30	0.50	−0.65	−7.52	6.87	36.28	65.23	–	230.20	300.08	221.04	0.16	0.22	–
0.30	0.80	0.32	−2.09	2.41	30.27	54.50	14.12	199.05	227.95	169.01	0.15	0.24	0.08
0.50	0.10	5.82	−4.04	9.87	155.04	106.84	117.24	315.74	309.10	250.45	0.49	0.35	0.47
0.50	0.20	5.33	−3.88	9.20	115.72	98.88	51.41	293.15	315.25	244.95	0.39	0.31	0.21
0.50	0.30	3.75	−2.34	6.09	114.25	111.68	88.81	264.49	299.11	204.27	0.43	0.37	0.43
0.50	0.50	−0.50	−4.90	4.40	41.46	64.75	34.24	179.00	210.41	162.27	0.23	0.31	0.21
0.50	0.80	−0.18	−1.16	0.98	32.72	40.58	24.35	151.34	181.59	142.55	0.22	0.22	0.17
0.80	0.10	6.18	1.18	5.00	113.65	110.43	51.20	302.99	305.16	229.02	0.38	0.36	0.22
0.80	0.20	2.81	−0.39	3.20	82.58	70.74	76.35	225.84	216.85	190.64	0.37	0.33	0.40
0.80	0.30	5.55	3.07	2.48	105.13	90.11	62.43	266.53	285.35	252.56	0.39	0.32	0.25
0.80	0.50	1.02	−0.62	1.65	58.34	75.08	63.69	213.84	222.75	188.68	0.27	0.34	0.34
0.80	0.80	−1.97	−1.10	−0.87	57.12	78.38	26.13	187.86	224.04	146.96	0.30	0.35	0.18
0.90	0.10	6.27	1.51	4.77	114.38	38.91	46.99	280.17	223.11	237.71	0.41	0.17	0.20
0.90	0.20	4.41	3.75	0.66	110.37	70.73	23.93	255.21	254.02	198.62	0.43	0.28	0.12
0.90	0.30	1.86	2.83	−0.97	68.58	98.24	52.12	229.78	246.71	193.15	0.30	0.40	0.27
0.90	0.50	1.65	1.15	0.50	61.40	52.99	32.02	215.16	224.23	217.79	0.29	0.24	0.15
0.90	0.80	0.34	1.27	−0.93	24.93	45.94	8.68	150.98	165.97	137.42	0.17	0.28	0.06
0.63	0.38	2.56	−1.69	4.25	78.69	81.45	54.45	243.95	262.94	211.04	0.31	0.30	0.25

Notes: Table calculates model-implied variances of Δ_Z's and Δ^*_Z's using the decomposition estimates from Table A.7 (see Section 4.4 and Appendix D.2 for details). Absence of entry for $\widehat{var}(\Delta^*_{MX})$ when $p = 0.30$ and $r = 0.50$ due to fact that, when calculating $var(\Delta^*_Z)$ from sample variances and covariances, nothing guarantees that they are positive (see Appendix D.2). The final line presents averages over all 20 rows.

Table A.9: Sensitivity of Results to Experimental Parameters in our Stage 2 Experiments

Panel A. Experimental-Parameter Sensitivity

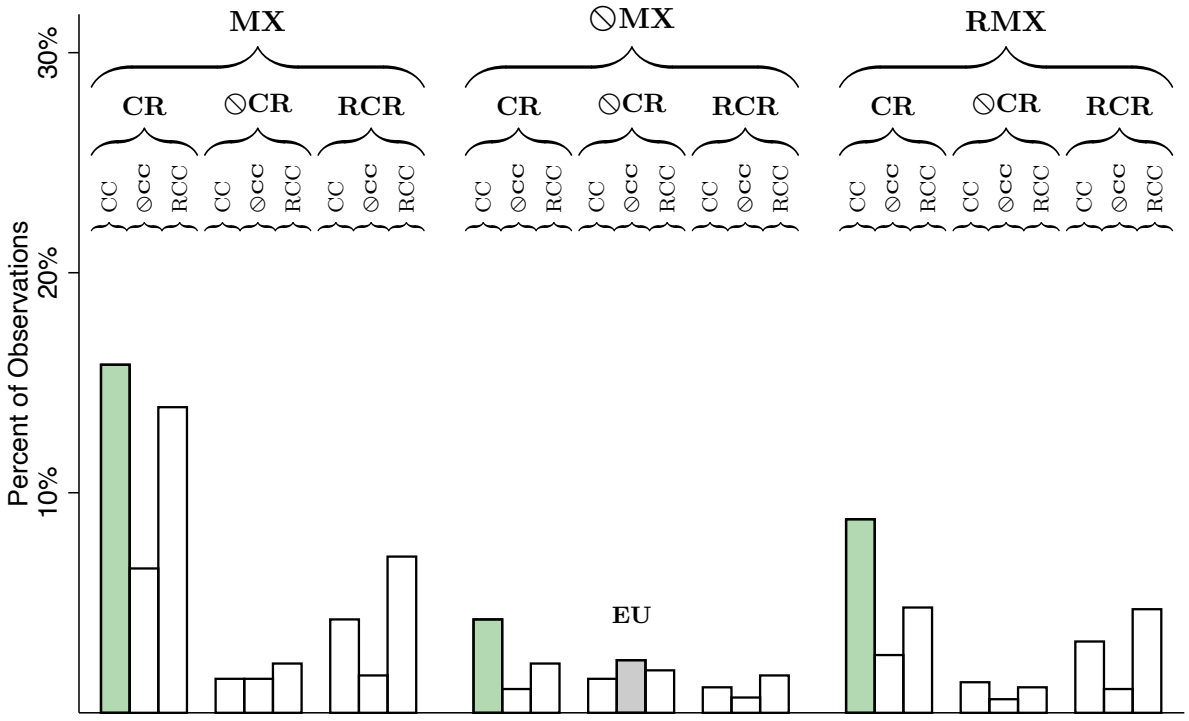
	(1) CR Study	(2) CC Study	(3) MX Study
Probability (p)	23.25	49.57	−28.62
	(6.16)	(6.14)	(5.89)
Common Ratio (r)	−35.19	−2.70	−29.88
	(2.47)	(2.52)	(2.30)
Outcome Mean	10.45	−5.77	16.00
Experiments	120	120	120
Observations	8,408	8,408	8,408

Panel B. Canonical vs. Non-Canonical Parameters

	(4) Canonical	(5) Non-Canonical	(6) Difference
	(i): KT Parameters		
CRE − RCRE	17.02	9.67	−7.35
	(8.36)	(13.76)	[−1.86]
Experiments	12	108	120
	(ii): Allais Parameters		
CCE − RCCE	7.91	−6.51	−14.41
	(5.93)	(12.96)	[−2.73]
Experiments	6	114	120

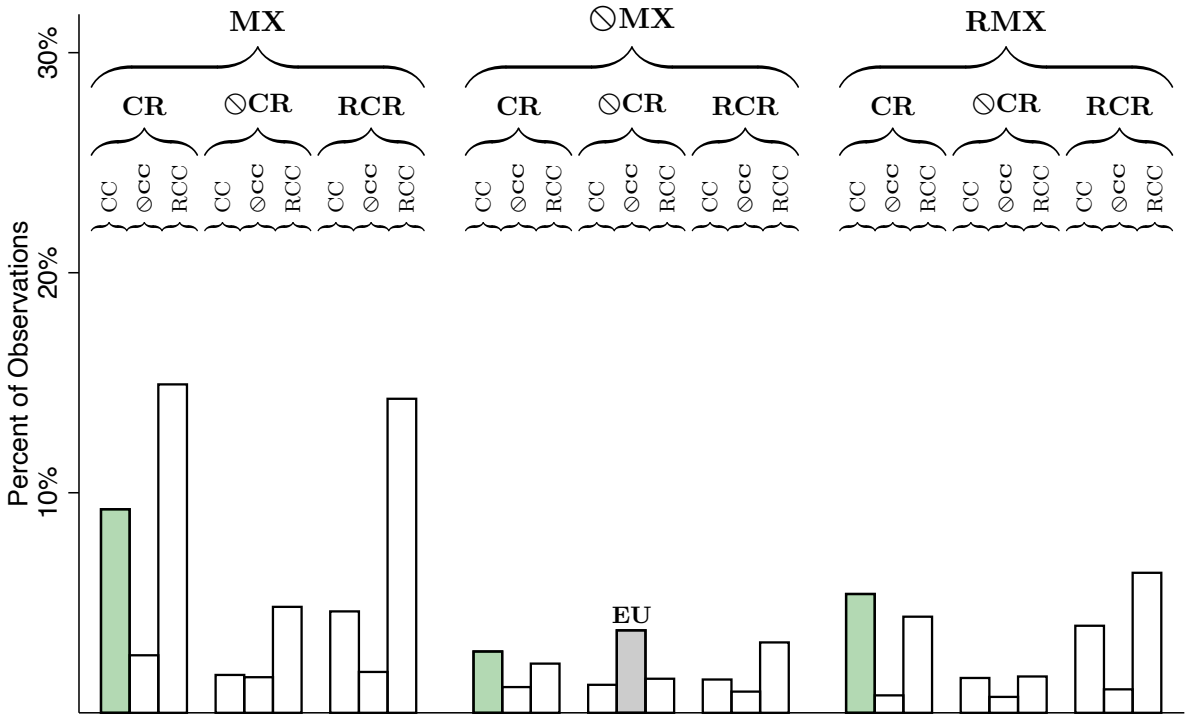
Notes: Panel A presents linear regressions that assess the sensitivity of experimental results from CR, CC, or MX studies from our stage 2 experiments. Panel A uses participant-pair regressions controlling for the probability of the high outcome (p), the common scaling factor (r), the high outcome (H), relative stakes ($30/(pH)$), and a constant, with standard errors clustered by participant. Column (1) presents the results for the 120 CR experiments that we conducted in stage 2 of our experiment, where the outcome is the net share of participants displaying a CRE relative to an RCRE, $CRE - RCRE$. Column (2) presents the results for the 120 CC experiments that we conducted in stage 2 of our experiment, where the outcome is the net share of participants displaying a CCE relative to an RCCE, $CCE - RCCE$. Column (3) presents the results for the 120 MX experiments that we conducted in stage 2 of our experiment, where the outcome is the net share of participants displaying a MXE relative to an RMXE, $MXE - RMXE$. Standard errors are in parentheses. Panel B presents the average of these outcomes based on whether our stage 2 experiments were conducted at the canonical parameters in Kahneman and Tversky (1979) ($p = 0.8$, $r \in \{0.2, 0.3\}$) or Allais (1953) ($p = 0.9$, $r = 0.1$). Standard deviations are in parentheses, and t-statistics are in brackets. Panel B weights cells by pair counts.

Figure A.1: Histogram of Response Patterns for $r \in \{0.1, 0.2, 0.3\}$ and $p \in \{0.8, 0.9\}$



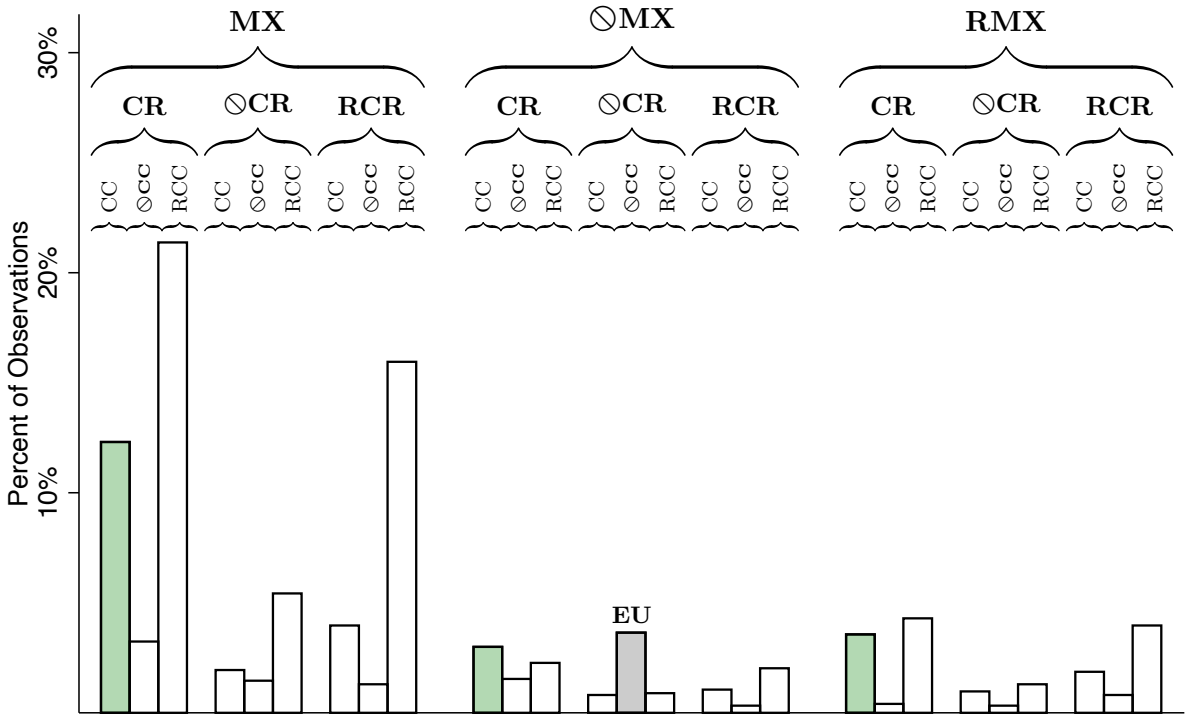
Notes: Figure presents histogram of $(sign(\Delta_{CR}), sign(\Delta_{CC}), sign(\Delta_{MX}))$ combinations, where $\Delta_{CR} = h_{AB} - h_{CD}$, $\Delta_{CC} = h_{AB'} - h'_{CD}$, and $\Delta_{MX} = h'_{AB} - h'_{AB'}$. Each variable can have three potential signs, leading to 27 possible patterns. These signs correspond to the named patterns (e.g., CR to $\Delta_{CR} > 0$, RCR to $\Delta_{CR} < 0$, and ⊘CR to $\Delta_{CR} = 0$). The histogram covers the 1,296 observations from the parameters $r \in \{0.1, 0.2, 0.3\}$ and $p \in \{0.8, 0.9\}$ for which we elicit h'_{AB} and $h'_{AB'}$. Patterns marked in light green are ones with $\Delta_{CR} > 0$ and $\Delta_{CC} > 0$.

Figure A.2: Histogram of Response Patterns for $r \notin \{0.1, 0.2, 0.3\}$ or $p \notin \{0.8, 0.9\}$



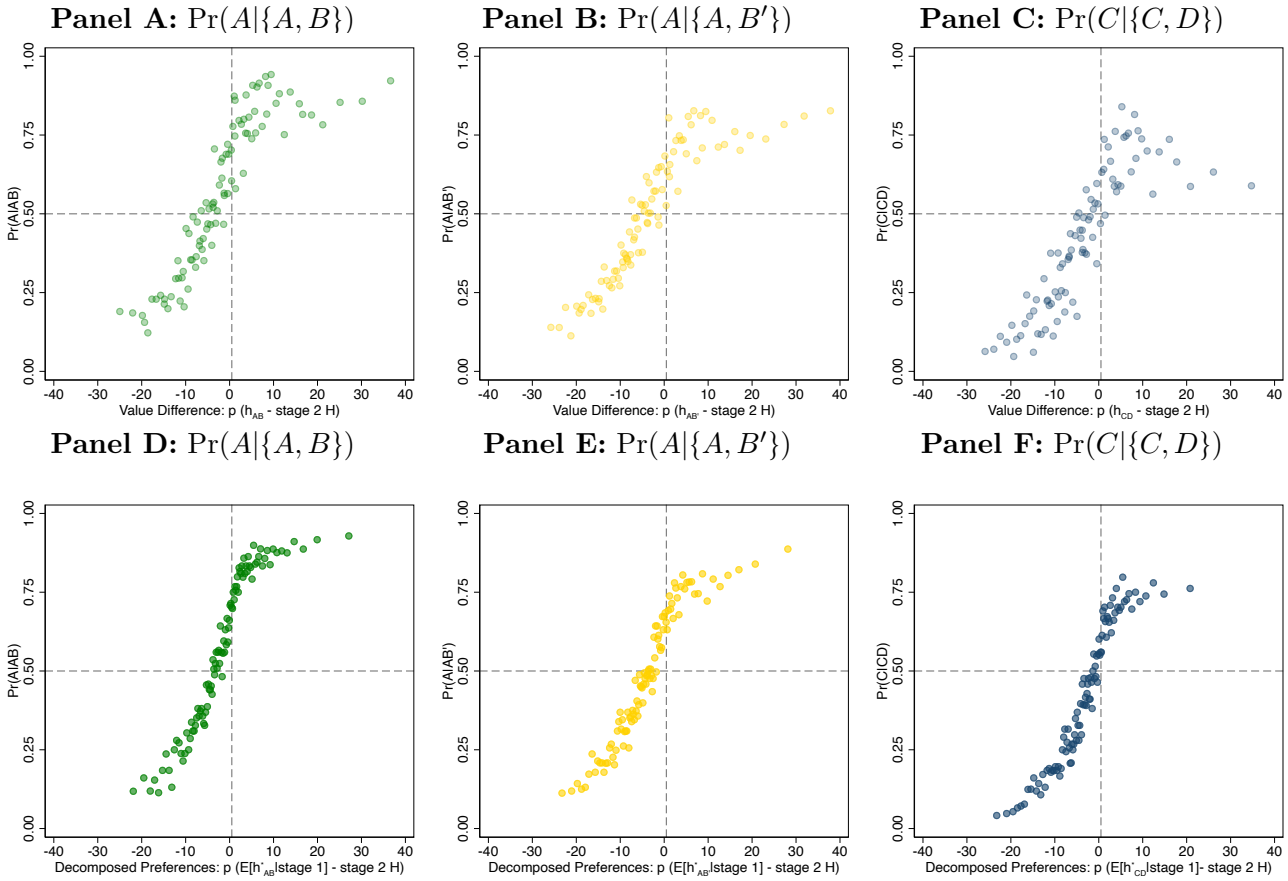
Notes: Figure presents histogram of $(sign(\Delta_{CR}), sign(\Delta_{CC}), sign(\Delta_{MX}))$ combinations, where $\Delta_{CR} = h_{AB} - h_{CD}$, $\Delta_{CC} = h_{AB'} - h'_{CD}$, and $\Delta_{MX} = h'_{AB} - h'_{AB'}$. Each variable can have three potential signs, leading to 27 possible patterns. These signs correspond to the named patterns (e.g., CR to $\Delta_{CR} > 0$, RCR to $\Delta_{CR} < 0$, and ⊘CR to $\Delta_{CR} = 0$). The histogram covers the 2,908 observations from the parameters $r \notin \{0.1, 0.2, 0.3\}$ or $p \notin \{0.8, 0.9\}$ for which we elicit h'_{AB} and $h'_{AB'}$. Patterns marked in light green are ones with $\Delta_{CR} > 0$ and $\Delta_{CC} > 0$.

Figure A.3: Histogram of Response Patterns for $r \in \{0.1, 0.2, 0.3\}$ and $p \in \{0.3, 0.5\}$



Notes: Figure presents histogram of $(sign(\Delta_{CR}), sign(\Delta_{CC}), sign(\Delta_{MX}))$ combinations, where $\Delta_{CR} = h_{AB} - h_{CD}$, $\Delta_{CC} = h_{AB'} - h'_{CD}$, and $\Delta_{MX} = h'_{AB} - h'_{AB'}$. Each variable can have three potential signs, leading to 27 possible patterns. These signs correspond to the named patterns (e.g., CR to $\Delta_{CR} > 0$, RCR to $\Delta_{CR} < 0$, and ⊘CR to $\Delta_{CR} = 0$). The histogram covers the 1,235 observations from the parameters $r \in \{0.1, 0.2, 0.3\}$ and $p \in \{0.3, 0.5\}$ for which we elicit h'_{AB} and $h'_{AB'}$. Patterns marked in light green are ones with $\Delta_{CR} > 0$ and $\Delta_{CC} > 0$.

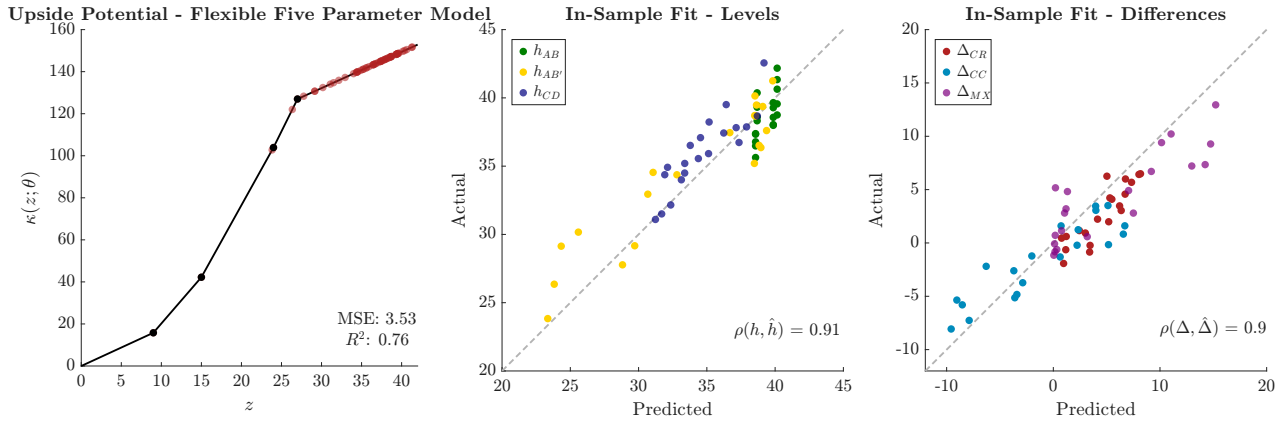
Figure A.4: Predicting Stage 2 Choice Probabilities using Stage 1 Valuations



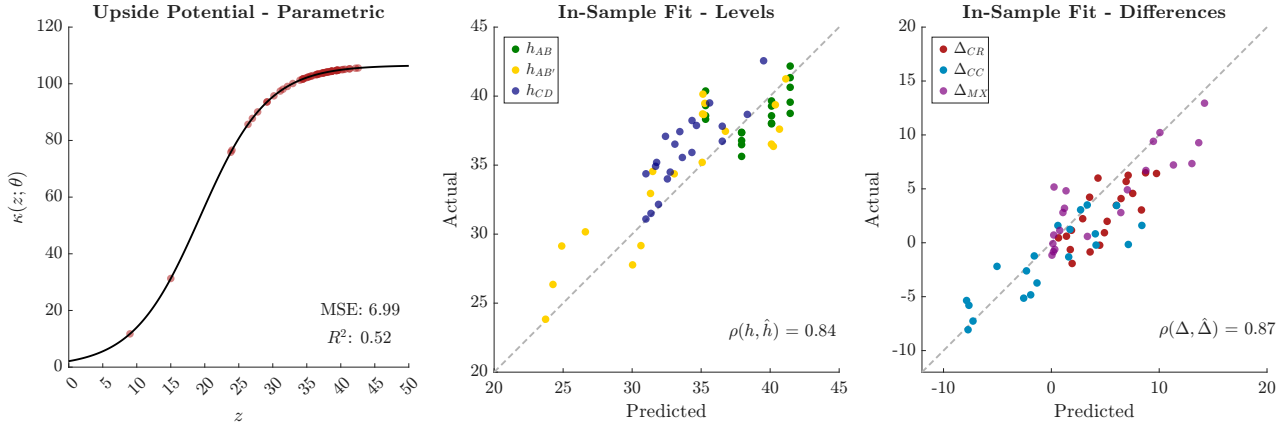
Notes: Figure relates individual stage 1 measures of $h_{XY} - H$ to stage 2 choice shares $\Pr(X|\{X, Y\})$. Panels A-C use raw stage 1 responses. Panels D-F use the estimated population distribution of preferences from the decomposition in Section 4.4 combined with a participant's raw stage 1 valuations to generate a posterior preference measure $E[h^*_{XY}|\text{stage 1}]$ for that participant. For each x-axis, one hundred equally sized bins are constructed with approximately 168 observations per bin. Within each bin, the stage 2 choice share is calculated to construct the y-axis. Due to a large number 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 Appendix C.3 for details).

Figure A.5: Structural Estimates and Model Fit

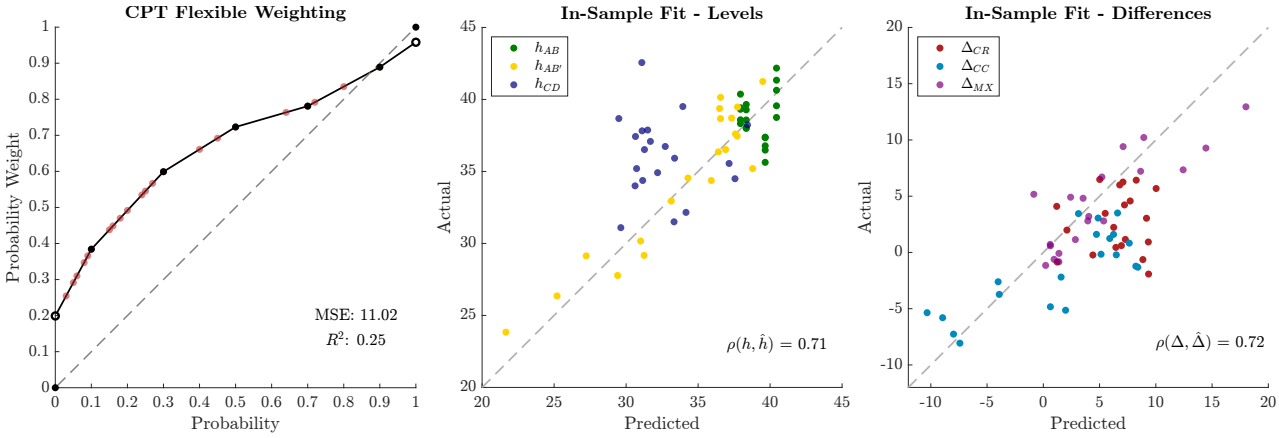
Panel A: Upside Potential Estimates – Flexible Five Parameter Model



Panel B: Upside Potential Estimates – Parametric Functional Form



Panel C: CPT Probability Weighting Estimates – Flexible Functional Form



Notes: This figure presents the estimated parameter functions and model fit for our model of upside potential with a flexible (Panel A) and a parametric (Panel B) functional form, along with the best-fitting CPT model with a flexible form (Panel C). The left panels depict the estimated functions, κ or π. The middle panels depict the in-sample fit for our three valuations, h_{AB}, $h_{AB'}$, and h_{CD}. The right panels depict the in-sample fit for our three preference measures, Δ_{CR}, Δ_{CC}, and Δ_{MX}.

B Predictions of Existing Non-EU Models

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:

$$\begin{aligned}(M,1) &\sim (h^*_{AB}, p)\\ (M,1) &\sim (h^*_{AB'}, pr; M, 1-r)\\ (M,r) &\sim (h^*_{CD}, pr)\end{aligned}$$

The objects of interest are then:

$$\begin{aligned}\Delta^*_{CR} &\equiv h^*_{AB} - h^*_{CD}\\ \Delta^*_{CC} &\equiv h^*_{AB'} - h^*_{CD}\\ \Delta^*_{MX} &\equiv h^*_{AB} - h^*_{AB'}\end{aligned}$$

B.1 Original Prospect Theory (OPT)

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

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

Hence:

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

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):

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

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.[1] 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 $q \in (0, 1)$.

OPT Result:

(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

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

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

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

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

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

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

Note that we can rewrite this as

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

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

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

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

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

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.

■

B.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:

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

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

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 $\delta > 0.279$,

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

Second, we prove that

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

In words, equation (B.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 (B.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 (B.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 (B.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 (B.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 (B.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 (B.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.

■

B.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.[2] $\Lambda > 0$ 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:

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

from which we can derive:

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

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 $\Lambda \geqslant -1$.

[2] 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 $\Lambda \equiv \eta(\lambda - 1)$.

With these restrictions in place:

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

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.

Kőszegi-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:

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

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:

$$\Delta^*_{CC} : 0 \iff 1+\Lambda(1-r)(1-2p) \;:\; 1-\Lambda(1-r)$$

$$\iff \qquad 2\Lambda(1-r)(1-p) \;:\; 0$$

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:

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

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

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

$$= \frac{\Lambda(p-1) + \Lambda^2(1-2p)(1-p)}{(1-\Lambda(1-pr))^2} = \frac{(1-p)\Lambda\left[-1+\Lambda(1-2p)\right]}{(1-\Lambda(1-pr))^2}$$

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 $\Lambda \in [-1,0)$.

■

B.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.[3]

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

$$u(M) = pu(h^*_{AB}) - \beta(1-p)(pu(h^*_{AB}) - 0)$$

$$ru(M) - \beta(1-r)(ru(M) - 0) = pru(h^*_{CD}) - \beta(1-pr)(pru(h^*_{CD}) - 0)$$

and thus

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

[3]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.

Note that for two-outcome lotteries such as our lotteries B, C, and D, the utilities under Bell DA are equivalent to those under Kőszegi-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:

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

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

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:

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

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 Kőszegi-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 $\beta \in [0,1]$:

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

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

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

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 $r < 1$.

■

B.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:

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

$$\tfrac{r}{1+\beta(1-r)} u(M) = \tfrac{pr}{1+\beta(1-pr)} u(h^*_{CD}) \iff h^*_{CD} = u^{-1}\left(\frac{1 + \beta(1-pr)}{p(1 + \beta(1-r))} u(M) \right)$$

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 $\Delta^*_{CR} = \Delta^*_{CC} < 0$.

■

B.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-⃠MXP pattern.

B.7 Puri Simplicity Preferences

Finally, we consider the implications of the model of *simplicity preferences* introduced by Puri (2025). 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.

C 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 $\Delta^*_{CC} = \Delta^*_{CR} = \Delta^*_{MX} = 0$.

C.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 C1v: 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 C1v, 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 C1v:

Assumption C2a: $\Gamma(h, \varepsilon) = h + \varepsilon$, and $E(\varepsilon_{AB}) = E(\varepsilon_{AB'}) = E(\varepsilon_{CD}) = 0$.

Assumption C2b: $\Gamma(h, \varepsilon)$ 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 C2a 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 C2b 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.[4] 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

[4]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 $(\pi(r)/\pi(pr))u(M) = u(h^*_{CD})$.

C2b 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 C1v describes when unbiased tests of the null of $\Delta^*_Z = 0$, $Z \in \{CR, CC, MX\}$, are possible using paired valuation tasks and Assumption C2a or C2b.

Proposition C1v *(Paired Valuation Tasks Can Yield Unbiased Tests):* Consider a person who provides stated valuations $(h_{AB}, h_{AB'}, h_{CD})$.

(1) Under Assumption C2a, $E(\Delta_Z) = \Delta^*_Z$ for all $Z \in \{CR, CC, MX\}$.

(2) Under Assumption C2b, $\Pr(\Delta_Z > 0) = \Pr(\Delta_Z < 0) = 1/2$ for all $Z \in \{CR, CC, MX\}$.

The proof and intuition for Proposition C1v 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 C2a using a means test. Part (2) establishes that we can test the null of $\Delta^*_Z = 0$ under Assumption C2b using a sign test that tests whether the observed proportions of $\Delta_Z > 0$ and $\Delta_Z < 0$ are the same.[5] These are the two tests reported in Table A.4.

C.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 C1v:

Assumption C1c: Impact of Noise on Choices

A person's *realized indifference points* are the $(h_{AB}, h_{AB'}, h_{CD})$ described in Assumption C1v. Then:

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

[5] 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 $2 * G(\min\{n_+, n_-\}, n_+ + n_-)$.

- 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 C1c, 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 C2c establishes conditions under which paired choice tasks yield biased tests of the null of $\Delta^*_Z = 0$, $Z \in \{CR, CC, MX\}$.

Proposition C2c *(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 $\Pr(A|AB) = \Pr(C|CD) = \chi$ ($\oslash$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 $\Pr(A|AB') = \Pr(C|CD) = \chi$ ($\oslash$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 $\Pr(A|AB) = \Pr(A|AB') = \chi$ ($\oslash$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 $\Pr(A|AB) = \Pr(C|CD) = \chi$ ($\oslash$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 $\Pr(A|AB') = \Pr(C|CD) = \chi$ ($\oslash$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 $\Pr(A|AB) = \Pr(A|AB') = \chi$ ($\oslash$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 C2c 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 C2c holds under Assumption C2b, and it would also hold under Assumption C2a if in addition to $E(\varepsilon_{AB}) = E(\varepsilon_{AB'}) = E(\varepsilon_{CD}) = 0$ we also have $\varepsilon_{AB} \stackrel{d}{=} k_{AB}\varepsilon_{CD}$ and $\varepsilon_{AB'} \stackrel{d}{=} k_{AB'}\varepsilon_{CD}$ 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 C2c 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 C2c 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 C2a with the additional assumption of $\varepsilon_{AB} \stackrel{d}{=} k_{AB}\varepsilon_{CD}$ and $\varepsilon_{AB'} \stackrel{d}{=} k_{AB'}\varepsilon_{CD}$ for some $k_{AB} > 0$ and $k_{AB'} > 0$. Under these assumptions, we can write the choice proportions as follows:

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

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:

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

where

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

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 depends 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 (C.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}.

C.3 Connecting Stage 1 Valuations and Stage 2 Choices

Our discussion in Appendix C.1 and C.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 4.5 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 C2a with the additional assumptions that $\varepsilon_{AB} \overset{d}{=} k_{AB}\varepsilon_{CD}$ and $\varepsilon_{AB'} \overset{d}{=} k_{AB'}\varepsilon_{CD}$ for some $k_{AB} > 0$ and $k_{AB'} > 0$. In this case, equations C.1 and C.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 C1v 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 4.4 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 Appendix D.4 for details). We then test the following predictions from equations C.1 and C.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.

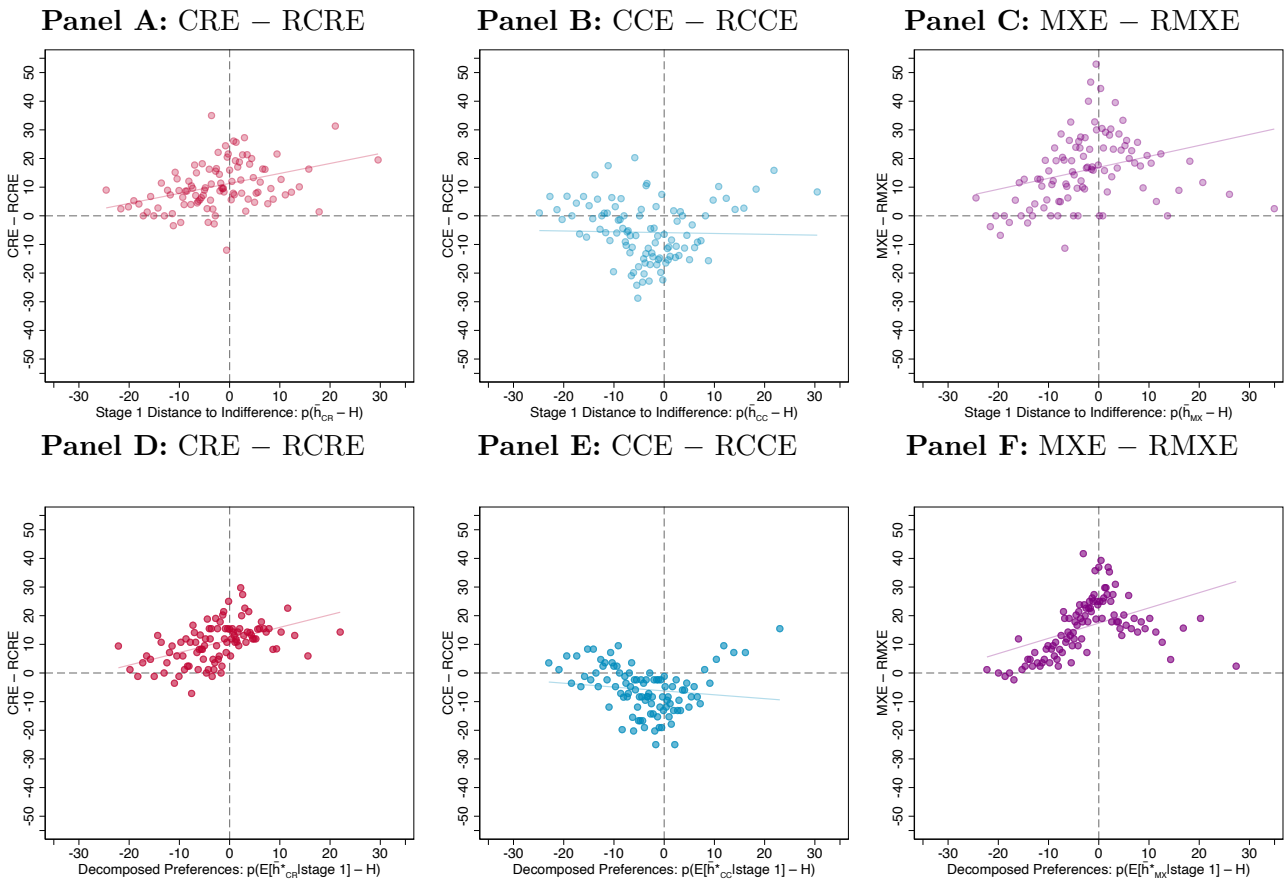
We visually assess prediction (1) in Figure 7 and we visually assess prediction (2) in Appendix Figure C.1. Panels A-C of Appendix Table C.1 provide corresponding formal tests via regressions of $CRE-RCRE$, $CCE-RCCE$, and $MXE-RMXE$ from stage 2 on the corresponding values of Δ_Z and $\bar{h}_Z - H$ 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 7 and Appendix Table C.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. Appendix Figure C.1 and Appendix Table C.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 Appendix C.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 C.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 4.4 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. There are 100 bins in every panel. 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 Appendix C.3 for details).

Table C.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	15.91	15.91	16
Individuals	2102	2102	2102	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 (RCCE), 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. All specifications include p and r fixed effects, with standard errors clustered by participant. 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 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 4.4 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 Appendix C.3 for details).

D Further Details on Decomposing Preference and Noise

In this appendix, we provide further details for the decomposition exercise in Section 4.4. 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 5 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.

D.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

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

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. 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:

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

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

Each entry in $\mathbf{V}(\boldsymbol{h})$ is a theoretical prediction for an empirical moment. For instance, $var(h_{AB}) = \theta^2_{AB} + \sigma^2_{AB}$, and $cov(h_{AB}, h'_{AB}) = \theta^2_{AB}$. 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:

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

To calculate the sample moments, we proceed as follows. Recall that roughly 420 participants provide valuations for each (p, r), but only half of those (roughly 210) provide all six valuations $(h_{AB}, h_{AB'}, h_{CD}, h'_{AB}, h'_{AB'}, h'_{CD})$, while the other half (again roughly 210) provide only four valuations $(h_{AB}, h_{AB'}, h_{CD}, h'_{CD})$. Given this, for each (p, r):

- To calculate $E_s(h_{XY})$ and $var_s(h_{XY})$, we include all observations of h_{XY} including repeats. Hence, for $XY \in \{AB, AB'\}$, these moments are calculated using roughly 630 observations, and for $XY \in \{CD\}$, these moments are calculated using roughly 840 observations.

- To calculate $cov_s(h_{XY}, h'_{XY})$, we include all pairs that we have (which is always 0 or 1 per participant who faced that (p, r)). Hence, for $XY \in \{AB, AB'\}$, this moment is calculated using roughly 210 observations, and for $XY \in \{CD\}$, this moment is calculated using roughly 420 observations.

- To calculate $cov_s(h_{XY}, h_{WZ})$, we include all (h_{XY}, h_{WZ}) pairs (which we have for every participant who faced that (p, r)), and we also include the (h'_{XY}, h'_{WZ}) pairs for the participants who provided all six valuations for that (p, r). Hence, all three of these moments are calculated using roughly 630 observations.

Using this approach to calculate the sample moments, Appendix Table A.7 reports estimates for the model's 12 parameters for each of the 20 (p, r) combinations.

Appendix D.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.

D.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.7 report the estimated proportion of the variability for each elicited indifference value that is due to preferences—i.e., the ratio $\widehat{var}(h^*_{XY})/\widehat{var}(h_{XY}) = \hat{\theta}^2_{XY}/(\hat{\theta}^2_{XY} + \hat{\sigma}^2_{XY})$ 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.8 uses the estimates in Appendix Table A.7 to calculate these six variances for each (p, r) combination.[6] The last three columns of Appendix Table A.8 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}, 30 percent of the variation in Δ_{CC}, and 25 percent of the variation in Δ_{MX}.

D.3 Simulating Preference Patterns

We next investigate what the histogram of response patterns from Figure 5 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:

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

[6] 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.

For each (p, r) combination, we use the estimated parameters in Appendix Table A.7 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.[7] Figure 6 presents the distribution of preference patterns when we aggregate across all 20 (p, r) combinations.

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 5 and 6, 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).

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

In Section 4.5 and Appendix C.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

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

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

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 7) and $\bar{h}^*_Z$ terms (for Appendix Figure C.1). It is straightforward to use the parameter estimates in Appendix Table A.7 to generate $\boldsymbol{\mu}^*_{\text{post}}$ for each participant.[8] 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 7 and Appendix Figure C.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.

D.5 Decomposition Using MLE

Our analysis in Appendix D.1 through D.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 Appendix D.2 does not require

[8] 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.

any distributional assumptions.

Here we describe an alternative approach to estimate the parameters via MLE. We assume as in Appendix D.4 that $\boldsymbol{h}^*$, the ε_{XY} terms, and the ε'_{XY} terms are all jointly normally 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. Appendix Tables D.1 and D.2 provide MLE results analogous to those of Appendix Tables A.7 and A.8, where Appendix Table D.2 is constructed from Appendix Table D.1 in exactly the same way that Appendix Table A.8 is constructed from Appendix Table A.7 (see Appendix D.2).

The message from the MLE estimation is much the same as that for our simpler estimation based on sample moments. Appendix Figure D.1 compares the MLE estimates from Appendix Table D.1 to the estimates from Appendix Table A.7. 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 D.1: Decomposition Estimates Using MLE (Levels)

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	36.32	23.89	32.96	165.72	142.30	171.21	87.27	129.38	187.73	65.22	75.75	50.90	0.66	0.52	0.48
0.30	0.20	35.68	26.01	32.37	147.88	148.81	132.19	111.17	109.70	150.86	86.45	74.29	52.92	0.57	0.58	0.47
0.30	0.30	36.55	29.08	35.59	154.91	173.54	158.78	110.22	108.48	130.01	114.77	99.71	84.06	0.58	0.62	0.55
0.30	0.50	38.12	30.79	38.27	131.12	100.42	123.34	98.47	167.92	120.87	107.12	101.86	83.57	0.57	0.37	0.51
0.30	0.80	38.55	34.93	37.08	123.18	125.81	112.63	79.66	89.28	120.25	108.92	97.83	92.47	0.61	0.58	0.48
0.50	0.10	37.13	27.20	32.21	144.02	128.73	111.15	56.11	102.89	129.35	60.59	30.98	52.74	0.72	0.56	0.46
0.50	0.20	39.09	29.91	33.36	141.93	84.57	120.34	76.70	142.77	112.80	73.01	52.22	43.15	0.65	0.37	0.52
0.50	0.30	38.99	33.78	35.43	138.49	146.69	75.83	62.08	77.64	124.71	84.85	41.46	43.56	0.69	0.65	0.38
0.50	0.50	38.97	34.15	40.02	158.14	157.17	122.18	61.86	73.42	84.33	124.47	109.29	101.97	0.72	0.68	0.59
0.50	0.80	38.65	37.31	38.24	133.73	150.45	98.27	44.89	84.00	77.84	123.83	92.35	99.00	0.75	0.64	0.56
0.80	0.10	41.73	35.66	34.30	122.38	148.05	91.53	73.99	122.34	127.81	82.03	33.24	55.65	0.62	0.55	0.42
0.80	0.20	39.46	36.02	36.23	85.48	154.69	94.78	65.08	62.81	103.52	77.09	45.94	72.38	0.57	0.71	0.48
0.80	0.30	41.96	39.24	35.81	142.87	157.14	78.15	81.71	122.15	95.29	93.58	54.73	53.78	0.64	0.56	0.45
0.80	0.50	39.01	36.96	37.95	80.20	109.95	59.97	72.98	69.23	98.05	65.54	38.58	38.32	0.52	0.61	0.38
0.80	0.80	40.88	41.40	42.78	129.48	153.71	81.27	54.50	73.24	90.39	124.83	77.86	69.38	0.70	0.68	0.47
0.90	0.10	40.02	35.44	34.10	117.75	103.71	83.53	108.62	119.50	98.60	83.33	30.79	56.43	0.52	0.46	0.46
0.90	0.20	39.83	38.93	34.90	122.09	143.76	75.25	86.71	97.02	95.03	106.11	44.12	48.54	0.58	0.60	0.44
0.90	0.30	38.33	38.95	36.92	92.02	187.01	92.09	82.05	68.90	95.55	94.46	52.51	67.51	0.53	0.73	0.49
0.90	0.50	39.39	38.74	37.72	99.10	110.57	63.43	93.54	113.06	78.71	86.81	43.83	53.60	0.51	0.49	0.45
0.90	0.80	38.39	39.50	38.11	85.16	115.05	49.05	69.71	66.60	61.51	87.58	48.53	52.27	0.55	0.63	0.44
0.62	0.38	38.85	34.39	36.22	125.78	137.11	99.75	78.87	100.02	109.16	92.53	62.29	63.61	0.61	0.58	0.47

Note: Decomposition estimates from MLE exercise. Final line presents averages over all 20 rows.

Table D.2: Decomposition Estimates Using MLE (Differences)

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	3.36	-9.07	12.43	185.44	211.71	177.59	460.44	528.82	394.23	0.40	0.40	0.45
0.30	0.20	3.31	-6.36	9.67	131.49	175.15	123.79	393.52	435.72	344.67	0.33	0.40	0.36
0.30	0.30	0.96	-6.51	7.47	114.26	164.18	98.90	354.49	402.68	317.60	0.32	0.41	0.31
0.30	0.50	-0.14	-7.48	7.34	50.74	56.61	17.30	270.08	345.40	283.69	0.19	0.16	0.06
0.30	0.80	1.47	-2.16	3.62	40.16	53.50	31.15	240.06	263.03	200.09	0.17	0.20	0.16
0.50	0.10	4.93	-5.01	9.93	193.21	134.40	151.56	378.67	366.64	310.57	0.51	0.37	0.49
0.50	0.20	5.73	-3.45	9.18	157.85	118.61	80.49	347.34	374.18	299.96	0.45	0.32	0.27
0.50	0.30	3.56	-1.65	5.21	131.40	135.41	115.48	318.19	337.75	255.20	0.41	0.40	0.45
0.50	0.50	-1.05	-5.87	4.82	61.74	75.41	66.37	207.93	233.17	201.65	0.30	0.32	0.33
0.50	0.80	0.41	-0.93	1.34	47.30	50.71	36.51	170.03	212.55	165.40	0.28	0.24	0.22
0.80	0.10	7.44	1.36	6.07	147.44	128.28	106.38	349.24	378.43	302.70	0.42	0.34	0.35
0.80	0.20	3.23	-0.21	3.44	88.38	104.71	86.00	256.97	271.03	213.89	0.34	0.39	0.40
0.80	0.30	6.15	3.43	2.72	111.56	127.73	112.85	288.56	345.16	316.71	0.39	0.37	0.36
0.80	0.50	1.06	-0.99	2.05	63.01	93.28	59.06	234.05	260.56	201.27	0.27	0.36	0.29
0.80	0.80	-1.90	-1.38	-0.52	55.03	96.23	33.52	199.91	259.85	161.26	0.28	0.37	0.21
0.90	0.10	5.92	1.34	4.58	139.70	74.38	54.81	346.92	292.48	282.93	0.40	0.25	0.19
0.90	0.20	4.93	4.03	0.90	109.09	121.93	53.62	290.83	313.98	237.35	0.38	0.39	0.23
0.90	0.30	1.41	2.02	-0.62	79.09	144.08	90.12	256.69	308.54	241.07	0.31	0.47	0.37
0.90	0.50	1.68	1.02	0.66	74.86	66.80	36.06	247.12	258.57	242.67	0.30	0.26	0.15
0.90	0.80	0.28	1.39	-1.10	37.15	59.56	25.06	168.37	187.67	161.37	0.22	0.32	0.16
0.62	0.38	2.64	-1.82	4.46	100.94	109.63	77.83	288.97	318.81	256.71	0.33	0.34	0.29

Note: Decomposition estimates calculated from the MLE exercise. Final line presents averages over all 20 rows.

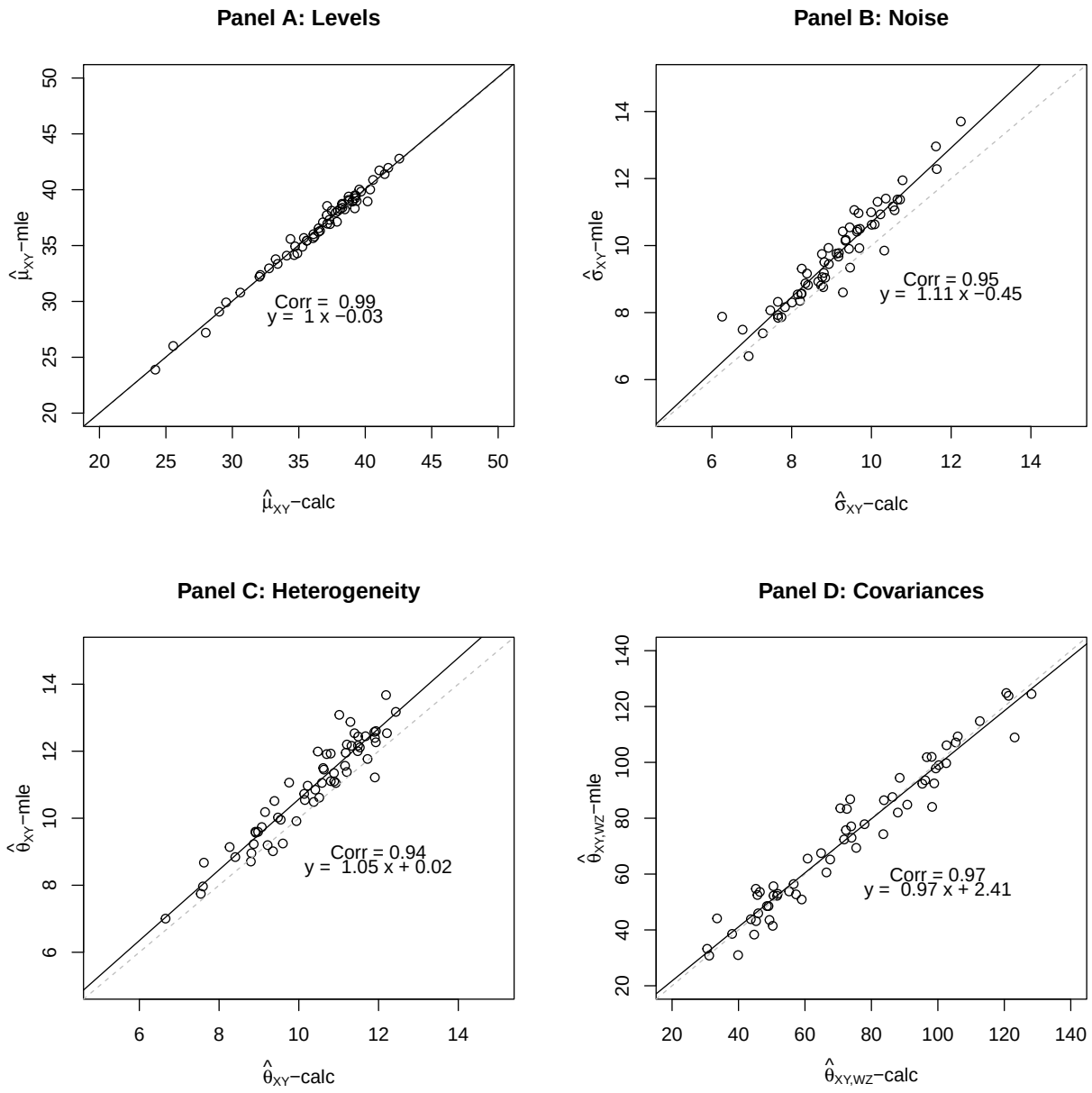


Figure D.1: Comparison of Decomposition Results (Direct Calculation vs. MLE)

Notes: Figure relates calculated quantities from Table A.7 to MLE estimates from Appendix Table D.1. Each panel compares the estimates for the 20 (p, r) parameter cells; the grand-average row is excluded. Correlations and fitted lines use these parameter-cell estimates.

E Upside-Potential Model: Analysis

E.1 Main Predictions of the Upside-Potential Model

In this section, we provide proofs for Propositions 1 and 2 from Section 5.1 of the main text. For completeness, we replicate the model assumptions here.

Suppose that a person has in mind a set W of outcomes that they consider "winning" outcomes, and then that person evaluates a lottery $X \equiv (x_1, q_1; ...; x_N, q_N)$ as

$$U(X) = \left(\sum_{i=1}^{N} q_i u(x_i)\right) \quad + \left(\sum_{j=1}^{N} q_j I(x_j \in W)\right)\left(\sum_{k=1}^{N} q_k I(x_k \in W)\kappa(x_k)\right). \tag{E.1}$$

To ensure that the model is well-behaved, we assume that u and κ are both strictly increasing in x, and that $\kappa(x) \geqslant 0$ for all $x \in W$.

It will be useful for intuitions and proofs to define $Ef(X) \equiv \sum_{i=1}^{N} q_i f(x_i)$, which is an expected utility from lottery X given utility function f. If we then define $v(x) \equiv I(x \in W)$ and $w(x) \equiv I(x \in W)\kappa(x)$, we can rewrite $U(X)$ as

$$U(X) = Eu(X) + (Ev(X))\,(Ew(X))\,.$$

We first note that, as long as the winning set W satisfies $x \in W$ implies $x' \in W$ for all $x' > x$, the UP model respects first-order stochastic dominance: If lottery X' FOSD lottery X, standard results imply $Eu(X') > Eu(X)$, $Ev(X') \geqslant Ev(X) \geqslant 0$, and $Ew(X') \geqslant Ew(X) \geqslant 0$, from which it immediately follows that $U(X') > U(X)$.[1]

Before we can derive predictions for the upside potential model in equation (E.1), we must make an assumption on what outcomes are included in the set W of winning outcomes. For our experiment in which people face only binary and trinary lotteries that yield either zero or a positive amount, a natural assumption is that all positive outcomes are included in the set of winning outcomes while zero is not (again, we discuss this assumption more in Section 5.3). We apply this assumption throughout the analysis below.

For parameters (M, p, r), lotteries $A \equiv (M, 1)$ and $C \equiv (M, r)$ are independent of h, but lotteries $B(h) \equiv (h, p)$, $B'(h) \equiv (h, pr; M, 1-r)$, and $D(h) \equiv (h, pr)$ are functions of h. Note that $C = rA$ and thus $Eu(C) = rEu(A)$, $D(h) = rB(h)$ and thus $Eu(D(h)) = rEu(B(h))$ for any h, and $B'(h) = (1-r)A + rB$ and thus $Eu(B'(h)) = (1-r)Eu(A) + rEu(B(h))$ for any h.

It is straightforward to show that, in the UP model, $U(B(h))$, $U(B'(h))$, and $U(D(h))$ are all continuous and increasing in h for all $h \geqslant M$, which implies that h^*_{AB}, $h^*_{AB'}$, and h^*_{CD} all exist and

[1] The inequalities $Ev(X') \geqslant Ev(X)$ and $Ew(X') \geqslant Ew(X)$ are weak because it could be that both X' and X contain no outcomes in the winning set W, in which case $Ev(X') = Ev(X) = 0$, and $Ew(X') = Ew(X) = 0$.

are unique. The value h^*_{AB} satisfies $U(A) = U(B(h^*_{AB}))$, which we can write as

$$Eu(A) + \kappa(M) = Eu(B(h^*_{AB})) + p^2\kappa(h^*_{AB}). \tag{E.2}$$

The value $h^*_{AB'}$ satisfies $U(A) = U(B'(h^*_{AB'}))$, which we can write as

$$Eu(A) + \kappa(M) = Eu(B'(h^*_{AB'})) + (pr + 1 - r)\left[pr\kappa(h^*_{AB'}) + (1 - r)\kappa(M)\right]. \tag{E.3}$$

The value h^*_{CD} satisfies $U(C) = U(D(h^*_{CD}))$, which we can write as

$$Eu(C) + r^2\kappa(M) = Eu(D(h^*_{CD})) + (pr)^2\kappa(h^*_{CD}). \tag{E.4}$$

Proposition A1 derives predictions from these equations (Part 1 is Proposition 1 in the text):

Proposition A1. Suppose that $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$ is derived from equations (E.2), (E.3), and (E.4). For any $u(x)$ that is strictly increasing in x and $\kappa(x)$ that is strictly increasing in x and has $\kappa(x) \geqslant 0$ for all $x > 0$:

(1) A person must exhibit one of the following seven patterns of behavior:

P1:	$0 > \Delta^*_{CR} > \Delta^*_{CC}$ and $\Delta^*_{MX} > 0$	(RCRP−RCCP−MXP)
P12:	$0 = \Delta^*_{CR} > \Delta^*_{CC}$ and $\Delta^*_{MX} > 0$	($\oslash$CRP−RCCP−MXP)
P2:	$\Delta^*_{CR} > 0 > \Delta^*_{CC}$ and $\Delta^*_{MX} > 0$	(CRP−RCCP−MXP)
P23:	$\Delta^*_{CR} > \Delta^*_{CC} = 0$ and $\Delta^*_{MX} > 0$	(CRP−$\oslash$CCP−MXP)
P3:	$\Delta^*_{CR} > \Delta^*_{CC} > 0$ and $\Delta^*_{MX} > 0$	(CRP−CCP−MXP)
P34:	$\Delta^*_{CR} = \Delta^*_{CC} > 0$ and $\Delta^*_{MX} = 0$	(CRP−CCP− $\oslash$MXP)
P4:	$\Delta^*_{CC} > \Delta^*_{CR} > 0$ and $\Delta^*_{MX} < 0$	(CRP−CCP−RMXP).

(2) More precisely:

(a) Whether a person exhibits a CRP, $\oslash$CRP, or an RCRP depends on whether h^*_{AB} is such that $\kappa(M)$ is greater than, equal to, or less than $p^2\kappa(h^*_{AB})$, or equivalently on whether $Eu(B(h^*_{AB}))$ is greater than, equal to, or less than $Eu(A)$.

(b) Whether a person exhibits an MXP, $\oslash$MXP, or an RMXP depends on whether h^*_{AB} is such that $\kappa(M)$ is less than, equal to, or greater than $p\kappa(h^*_{AB})$.

(c) Whether a person exhibits a CCP, a $\oslash$CCP, or an RCCP depends on whether $h^*_{AB'}$ is such that $\kappa(M)$ is greater than, equal to, or less than $\left(\frac{p}{2-p}\right)\kappa(h^*_{AB'})$.

(d) If h^*_{AB} is such that $\kappa(M) < p^2\kappa(h^*_{AB})$ and thus the person has an RCRP, then the person must also exhibit an MXP and an RCCP. Hence, the person must exhibit pattern P1.

(e) If h^*_{AB} is such that $\kappa(M) = p^2\kappa(h^*_{AB})$ and thus the person has $\oslash$CRP, then the person must also exhibit an MXP and an RCCP. Hence, the person must exhibit pattern P12.

(f) If h^*_{AB} is such that $\kappa(M) > p^2\kappa(h^*_{AB})$ and thus the person has CRP, then the person could exhibit an MXP, $\oslash$MXP, or an RMXP. If the person exhibits either $\oslash$MXP or an RMXP, then they must exhibit CCP; otherwise, they could have CCP, $\oslash$CCP, or an RCCP. Hence, the person must exhibit one of patterns P2, P23, P3, P34, or P4.

Proof: The statement in part (1) follows directly from parts (2d), (2e), and (2f), so we only need to prove each of the statements in part (2).

Proof of part (2a): We can rewrite equation (E.2) as

$$\kappa(M) - p^2\kappa(h^*_{AB}) = Eu(B(h^*_{AB})) - Eu(A).$$

Hence, whether h^*_{AB} is such that $\kappa(M)$ is greater than, equal to, or less than $p^2\kappa(h^*_{AB})$ is equivalent to whether $Eu(B(h^*_{AB}))$ is greater than, equal to, or less than $Eu(A)$.

Because $Eu(C) = rEu(A)$ and $Eu(D(h)) = rEu(B(h))$ for all h, the comparison between $U(C)$ and $U(D(h^*_{AB}))$ can be written as

$$\begin{aligned} Eu(C) + r^2\kappa(M) &: Eu(D(h^*_{AB})) + (pr)^2\kappa(h^*_{AB}) \\ rEu(A) + r^2\kappa(M) &: rEu(B(h^*_{AB})) + (pr)^2\kappa(h^*_{AB}) \\ r(\kappa(M) - p^2\kappa(h^*_{AB})) &: Eu(B(h^*_{AB})) - Eu(A) \end{aligned}$$

If h^*_{AB} is such that $\kappa(M) > p^2\kappa(h^*_{AB})$, which implies $\kappa(M) - p^2\kappa(h^*_{AB}) = Eu(B(h^*_{AB})) - Eu(A) > 0$, then $r(\kappa(M) - p^2\kappa(h^*_{AB})) < Eu(B(h^*_{AB})) - Eu(A)$. It follows that $U(C) < U(D(h^*_{AB}))$ and thus $h^*_{CD} < h^*_{AB}$, that is, CRP. Analogously, if h^*_{AB} is such that $\kappa(M) < p^2\kappa(h^*_{AB})$, then the person exhibits RCRP, and if h^*_{AB} is such that $\kappa(M) = p^2\kappa(h^*_{AB})$, then the person exhibits $\oslash$CRP.

Proof of part (2b): Because, for any h, $Eu(B'(h)) = (1-r)Eu(A) + rEu(B(h))$, we have

$$U(B'(h)) = (1-r)Eu(A) + rEu(B(h)) + (1-r+pr)((1-r)\kappa(M) + pr\kappa(h)).$$

Since $Eu(A)$ and $Eu(B(h))$ are independent of r,

$$\frac{d[U(B'(h))]}{dr} = Eu(B(h)) - Eu(A) + (-(1-p))((1-r)\kappa(M) + pr\kappa(h)) + (1-r+pr)(p\kappa(h) - \kappa(M))$$

and thus

$$\frac{d^2[U(B'(h))]}{dr^2} = -2(1-p)(p\kappa(h) - \kappa(M)).$$

If h^*_{AB} is such that $\kappa(M) < p\kappa(h^*_{AB})$, then $\frac{d^2[U(B'(h))]}{dr^2} < 0$ for all $r \in [0,1]$. Because $U(A) = U(B(h^*_{AB}))$ (by the definition of h^*_{AB}), $\frac{d^2[U(B'(h))]}{dr^2} < 0$ implies $U(B'(h^*_{AB})) > U(A) = U(B(h^*_{AB}))$ for any $r \in (0,1)$, and thus $h^*_{AB'} < h^*_{AB}$, that is the person exhibits a MXP. Analogously, if h^*_{AB} is such that $\kappa(M) > p\kappa(h^*_{AB})$, then the person exhibits RMXP, and if h^*_{AB} is such that $\kappa(M) = p\kappa(h^*_{AB})$, then the person exhibits $\oslash$MXP.

Proof of part (2c): Because, for any h, $Eu(B'(h)) = (1-r)Eu(A) + rEu(B(h))$, we can rewrite equation E.3 as

$$rEu(A) + \kappa(M) = rEu(B(h^*_{AB'})) + (pr + 1 - r)\left[pr\kappa(h^*_{AB'}) + (1-r)\kappa(M)\right].$$

Substituting $Eu(C) = rEu(A)$ and $Eu(D(h^*_{AB'})) = rEu(B(h^*_{AB'}))$ and rearranging the other terms, this becomes

$$Eu(C) + r^2\kappa(M) = Eu(D(h^*_{AB'})) + (pr)^2\kappa(h^*_{AB'}) + (1-r)r\left(p\kappa(h^*_{AB'}) - (2-p)\kappa(M)\right).$$

If $h^*_{AB'}$ is such that $\kappa(M) > \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'})$, it follows that $Eu(C) + r^2\kappa(M) < Eu(D(h^*_{AB'})) + (pr)^2\kappa(h^*_{AB'})$, and thus $h^*_{CD} < h^*_{AB'}$, that is the person exhibits a CCP. Analogously, if $h^*_{AB'}$ is such that $\kappa(M) < \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'})$, then the person exhibits RCCP, and if $h^*_{AB'}$ is such that $\kappa(M) = \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'})$, then the person exhibits $\oslash$CCP.

Proof of parts (2d) and (2e): If h^*_{AB} is such that $\kappa(M) \leqslant p^2\kappa(h^*_{AB})$, so that the person exhibits RCRP or $\oslash$CRP, then we must have $\kappa(M) < p\kappa(h^*_{AB})$. Thus from part (2b) the person must exhibit an MXP. Finally, because $\Delta^*_{CC} = \Delta^*_{CR} - \Delta^*_{MX}$, the combination of $\Delta^*_{CR} \leqslant 0$ and $\Delta^*_{MX} > 0$ implies $\Delta^*_{CC} < 0$, that is, an RCCP.

Proof of part (2f): If h^*_{AB} is such that $\kappa(M) > p^2\kappa(h^*_{AB})$, so that the person exhibits CRP, it is possible that $\kappa(M)$ is less than, greater than, or equal to $p\kappa(h^*_{AB})$, and thus from part (2b) the person could exhibit an MXP, $\oslash$MXP, or an RMXP. If the person exhibits either $\oslash$MXP or an RMXP, because $\Delta^*_{CC} = \Delta^*_{CR} - \Delta^*_{MX}$, the combination of $\Delta^*_{CR} > 0$ and $\Delta^*_{MX} \leqslant 0$ implies $\Delta^*_{CC} > 0$, that is, a CCP. Finally, if the person exhibits CRP and MXP, it is straightforward to generate examples in which the person exhibits CCP, $\oslash$CCP, or RCCP.

■

Proposition A2, which is equivalent to Proposition 2 in the text, considers the special cases $u(x) = x$ and possibly also $\kappa(x) = \phi x$ for some $\phi > 0$.

Proposition A2. Suppose that $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$ is derived from equations (E.2), (E.3), and (E.4). If $u(x) = x$, then:

(1) If $\kappa(x)$ is strictly increasing in x and has $\kappa(x) \geqslant 0$ for all $x > 0$, then:

(a) If $ph^*_{AB} > M$ (i.e., if the person is risk averse in the AB decision), then $\Delta^*_{CR} > 0$ and thus the person must exhibit one of patterns P2, P23, P3, P34, or P4.

(b) If $ph^*_{AB} = M$ (i.e., if the person is risk neutral in the AB decision), then $\Delta^*_{CR} = 0$ and thus the person must exhibit pattern P12.

(c) If $ph^*_{AB} < M$ (i.e., if the person is risk loving in the AB decision), then then $\Delta^*_{CR} > 0$ and thus the person must exhibit pattern P1.

(2) If $\kappa(x) = \phi x$ for some $\phi > 0$, then $ph^*_{AB} > M$ (i.e., the person is risk averse in the AB decision), $\Delta^*_{CR} > 0$, and $\Delta^*_{MX} > 0$, and thus the person must exhibit one of patterns P2, P23, or P3.

Proof: Proof of part (1): When $u(x) = x$, whether $Eu(B(h^*_{AB}))$ is greater than, equal to, or less than $Eu(A)$ is equivalent to whether ph^*_{AB} is greater than, equal to, or less than M. In addition, from the proof of Proposition A1 part (2a), whether $Eu(B(h^*_{AB}))$ is greater than, equal to, or less than $Eu(A)$ is equivalent to whether h^*_{AB} is such that $\kappa(M)$ is greater than, equal to, or less than $p^2\kappa(h^*_{AB})$.

It follows that $ph^*_{AB} > M$ implies $Eu(B(h^*_{AB})) > Eu(A)$ and thus $\kappa(M) > p^2\kappa(h^*_{AB})$, and then part (2f) from Proposition A1 implies that the person must exhibit one of patterns P2, P23, P3, P34, or P4. Analogously, $ph^*_{AB} = M$ implies $\kappa(M) = p^2\kappa(h^*_{AB})$, and thus part (2e) from Proposition A1 implies that the person must exhibit pattern P12; and $ph^*_{AB} < M$ implies $\kappa(M) < p^2\kappa(h^*_{AB})$, and thus part (2d) from Proposition A1 implies that the person must exhibit pattern P1.

Proof of part (2): When $u(x) = x$ and $\kappa(x) = \phi x$, equation (E.2) becomes $M + \phi M = ph^*_{AB} + p^2\phi h^*_{AB}$ or $\phi(M - p^2h^*_{AB}) = ph^*_{AB} - M$. Because $ph^*_{AB} > p^2h^*_{AB}$, this condition can hold only if $ph^*_{AB} > M > p^2h^*_{AB}$, and thus $p\kappa(h^*_{AB}) > \kappa(M) > p^2\kappa(h^*_{AB})$ (since $\kappa(x) = \phi x$). Applying the conditions from parts (2a) and (2b) of Proposition A1, $\kappa(M) > p^2\kappa(h^*_{AB})$ implies CRP, while $\kappa(M) < p\kappa(h^*_{AB})$ implies MXP. It is straightforward to generate examples in which the person exhibits CCP, $\oslash$CCP, or RCCP, and thus patterns P2, P23, and P3 are all possible.

■

E.2 Relationship to Quadratic Utility

The material in this section draws heavily from Chew et al. (1991), where we present everything in terms of discrete lotteries of the form $X \equiv (x_1, q_1; ...; x_N, q_N)$. We begin with the definition of quadratic utility (Machina, 1982; Chew et al., 1991):

Definition: A person has *quadratic utility* if their utility functional U can be expressed as

$$U(X) = \sum_{i=1}^{N} \sum_{j=1}^{N} \phi(x_i, x_j) q_i q_j$$

for some symmetric function ϕ.

Quadratic utility is a broad class that includes a number of sub-cases—indeed, it includes standard expected utility as a special case: $\phi(x, y) = (u(x) + u(y))/2$ yields $U(X) = \sum_{i=1}^{N} u(x_i) q_i$.

The UP model in equation (E.1) is also a special case of quadratic utility. In particular, if $\phi(x, y) = (u(x) + u(y))/2 + (v(x)w(y) + v(y)w(x))/2$, quadratic utility yields the functional

$$U(X) = \left(\sum_{i=1}^{N} q_i u(x_i) \right) + \left(\sum_{j=1}^{N} q_j v(x_j) \right) \left(\sum_{k=1}^{N} q_k w(x_k) \right). \tag{E.5}$$

If we further use $v(z) = I(z \in W)$ and $w(z) = I(z \in W)\kappa(z)$, then we obtain equation (E.1). While this sub-case of quadratic utility has not been studied before (to the best of our knowledge), it in fact combines together two sub-cases that have been studied before but neither of which can explain well our empirical patterns.

Machina (1982) studies the utility functional

$$U(X) = \left(\sum_{i=1}^{N} q_i u(x_i) \right) + \left(\sum_{j=1}^{N} q_j v(x_j) \right)^2. \tag{E.6}$$

This functional is the sum of an expected-utility functional and a second expected-utility functional squared, where $v(x) \geqslant 0$ for all x to keep the model well behaved.[2] This functional corresponds to quadratic utility with $\phi(x, y) = (u(x) + u(y))/2 + v(x)v(y)$. Machina (1982) highlights how this functional can generate a CRP and a CCP. However, it also generates preferences with an aversion to mixtures of any two lotteries, as pointed out by Chew et al. (1991), and thus a global RMXP in our context (except for two knife-edge cases). Hence, it will be not able to accommodate the dominant patterns in our data that involve an MXP.

[2] In particular, if $v(x) < 0$ for some range of x, then $(v(x))^2$ would be decreasing in x over that range, and thus the model could generate violations of monotonicity.

To be more precise, Proposition A3 in Section E.2.1 fully characterizes the implications of the Machina functional in equation (E.6) for the patterns that could emerge in our context. If $v(x)$ is a positive affine transformation of $u(x)$, then this functional is equivalent to expected utility with utility function $u(x)$, and thus the person exhibits $\oslash$CRP-$\oslash$CCP-$\oslash$MXP. In addition, even if $v(x)$ reflects different expected-utility preferences from $u(x)$, there could be a knife-edge case in which the $\bar{h}$ that makes $u(M) = pu(\bar{h}) + (1-p)u(0)$ just happens to also make $v(M) = pv(\bar{h}) + (1-p)v(0)$, in which case again the person exhibits $\oslash$CRP-$\oslash$CCP-$\oslash$MXP. Otherwise, the person must exhibit one of four patterns: CRP-CCP-RMXP, RCRP-CCP-RMXP, RCRP-$\oslash$CCP-RMXP, or RCRP-RCCP-RMXP. The first of these is a pattern that could emerge from the UP model that we labeled P4. The remaining three are patterns that cannot emerge from the UP model, and that also show up with limited frequency in our data.

Chew et al. (1991) discuss several sub-cases of quadratic utility, for each highlighting the connection between a utility functional and a specific ϕ function. In addition to the expected-utility and the Machina cases described above, they also discuss the case where $\phi(x, y) = (v(x)w(y) + v(y)w(x))/2$, which leads to the utility functional

$$U(X) = \left(\sum_{i=1}^{N} q_i v(x_i)\right)\left(\sum_{j=1}^{N} q_j w(x_j)\right). \tag{E.7}$$

This functional is the product of two expected-utility functionals, where $v(x) \geqslant 0$ and $w(x) \geqslant 0$ for all x to keep the model well behaved. Chew et al. point out how this case generates preferences with an attraction to mixtures of any two lotteries, and thus a global MXP in our context (except for two knife-edge cases). However, it also generates a global $\oslash$CRP and RCCP and thus also will not work for our purposes.

To be more precise, Proposition A4 in Section E.2.1 fully characterizes the implications of the Chew et al. functional in equation (E.7) for the patterns that could emerge in our context. Much as for the Machina functional, if $w(x)$ is a positive affine transformation of $v(x)$, then this functional is equivalent to expected utility with utility function $v(x)$, and even if $w(x)$ reflects different expected-utility preferences from $v(x)$, there could be a knife-edge case in which the $\bar{h}$ that makes $v(M) = pv(\bar{h}) + (1-p)v(0)$ just happens to also make $w(M) = pw(\bar{h}) + (1-p)w(0)$, in which case again the person exhibits $\oslash$CRP-$\oslash$CCP-$\oslash$MXP. Otherwise, the person must exhibit the pattern $\oslash$CRP-RCCP-MXP. This is a pattern that could emerge from the UP model that we labeled P12. However, because much of our data cover other patterns, this case is too restrictive for our purposes.

Finally, note that the utility functional in equation (E.5) reflects a combination of the utility functionals in equations (E.6) and (E.7). However, without any further assumptions on u, v, or w, equation (E.5) would be overly permissive—e.g., by continuity as w approaches v, it would permit the three additional patterns that can emerge from the Machina specification but not from the UP

model. Hence, the additional assumptions that $v(x) = I(x \in W)$ and $w(x) = I(x \in W)\kappa(x)$ have bite in that they shrink the set of permitted patterns down to the seven patterns in Proposition 1, which again are the more prominent patterns in our data.

E.2.1 Propositions and Proofs for Other Quadratic Utility Specifications

In this section, we present the propositions referenced in Section E.2 along with their proofs. We again use the notation from Section E.1. We define $Eu(X) \equiv \sum_{i=1}^{N} q_i u(x_i)$, and define $Ev(X)$ and $Ew(X)$ analogously. And for parameters (M, p, r), we define lotteries $A \equiv (M, 1)$, $B(h) \equiv (h, p)$, $B'(h) \equiv (h, pr; M, 1-r)$, $C \equiv (M, r)$, and $D(h) \equiv (h, pr)$.

Proposition A3: Suppose a person evaluates lotteries according to the Machina functional in equation (E.6). Then:

(1) If there exists $\bar{h}$ such that both $u(M) = pu(\bar{h}) + (1-p)u(0)$ and $v(M) = pv(\bar{h}) + (1-p)v(0)$, then $h^*_{AB} = h^*_{AB'} = h^*_{CD} = \bar{h}$ and thus the person will have $\oslash$CRP-$\oslash$CCP-$\oslash$MXP.

(2) Otherwise, the person must have RMXP combined with either CRP-CCP, RCRP-CCP, RCRP-$\oslash$CCP, or RCRP-RCCP. More precisely:

   (a) The person must exhibit an RMXP.

   (b) Whether a person exhibits a CRP or an RCRP depends on whether h^*_{AB} is such that $pu(h^*_{AB}) + (1-p)u(0)$ is greater than or less than $u(M)$. (If $pu(h^*_{AB}) + (1-p)u(0) = u(M)$, the condition in part 1 must hold and the person will have $\oslash$CRP-$\oslash$CCP-$\oslash$MXP.)

   (c) Suppose h^*_{AB} is such that $pu(h^*_{AB}) + (1-p)u(0) > u(M)$ and thus the person has CRP. The combination of CRP and RMXP implies CCP, and thus the person will exhibit CRP-CCP-RMXP.

   (d) Suppose h^*_{AB} is such that $pu(h^*_{AB}) + (1-p)u(0) < u(M)$ and thus the person has RCRP. The combination of RCRP and RMXP permits any CCP preference, and thus the person could exhibit RCRP-CCP, RCRP-$\oslash$CCP, or RCRP-RCCP.

Proof: For any h, $U(B'(h)) = Eu(B'(h)) + (Ev(B'(h)))^2$. Because $B'(h) = (1-r)A + rB(h)$, we can rewrite this as

$$U(B'(h)) = [(1-r)Eu(A) + rEu(B(h))] + [(1-r)Ev(A) + rEv(B(h))]^2.$$

Since $Eu(A)$, $Eu(B(h))$, $Ev(A)$, and $Ev(B(h))$ are all independent of r, it is straightforward to derive that for all h

$$\frac{dU(B'(h))}{dr} = Eu(B(h)) - Eu(A) + 2[(1-r)Ev(A) + rEv(B(h))][Ev(B(h)) - Ev(A)]$$

and

$$\frac{d^2U(B'(h))}{dr^2} = 2[Ev(B(h)) - Ev(A)]^2.$$

Proof of part (1): Suppose there exists $\bar{h}$ such that both $u(M) = pu(\bar{h}) + (1-p)u(0)$ and $v(M) = pv(\bar{h}) + (1-p)v(0)$, which is necessarily true if v is a positive affine transformation of u, and could happen to be true even if u and v reflect different expected-utility preferences. Because these are equivalent to $Eu(A) = Eu(B(\bar{h}))$ and $Ev(A) = Ev(B(\bar{h}))$, it immediately follows that $h^*_{AB} = \bar{h}$. In addition, these conditions also imply that $rEu(A) = rEu(B(\bar{h}))$ and $r^2Ev(A) = r^2Ev(B(\bar{h}))$, from which it immediately follows that $h^*_{CD} = \bar{h}$. Finally, these conditions further imply that $\frac{dU(B'(\bar{h}))}{dr} = 0$, which implies $h^*_{AB'} = \bar{h}$. The result follows.

Proof of part (2): The statement in part (2) follows directly from parts (2c) and (2d), so we merely prove each of the parts.

Proof of part (2a): If there does not exist $\bar{h}$ such that both $u(M) = pu(\bar{h}) + (1-p)u(0)$ and $v(M) = pv(\bar{h}) + (1-p)v(0)$, then h^*_{AB} must be such that either $Eu(A) > Eu(B(h^*_{AB}))$ and $(Ev(A))^2 < (Ev(B(h^*_{AB})))^2$ or $Eu(A) < Eu(B(h^*_{AB}))$ and $(Ev(A))^2 > (Ev(B(h^*_{AB})))^2$. For either case, $Ev(B(h^*_{AB})) - Ev(A)$ is not equal to zero and thus $\frac{d^2U(B'(h^*_{AB}))}{dr^2} > 0$. Because $U(A) = U(B(h^*_{AB}))$ (by the definition of h^*_{AB}), $\frac{d^2U(B'(h^*_{AB}))}{dr^2} > 0$ implies $U(B'(h^*_{AB})) < U(A) = U(B(h^*_{AB})$ for any $r \in (0,1)$, and thus $h^*_{AB'} > h^*_{AB}$, that is, the person exhibits a RMXP.

Proof of part (2b): First note that the critical condition can be rewritten as whether h^*_{AB} is such that $Eu(B(h^*_{AB}))$ is greater than or less than $Eu(A)$. Next note that the comparison between $U(C)$ and $U(D(h^*_{AB}))$ can be written as

$$\begin{aligned} Eu(C) + (Ev(C))^2 &: Eu(D(h^*_{AB})) + (Ev(D(h^*_{AB})))^2 \\ rEu(A) + (rEv(A))^2 &: rEu(B(h^*_{AB})) + (rEv(B(h^*_{AB})))^2 \\ Eu(A) - Eu(B(h^*_{AB})) &: r[(Ev(B(h^*_{AB})))^2 - (Ev(A))^2] \end{aligned}$$

Because h^*_{AB} must be such that

$$Eu(A) + (Ev(A))^2 = Eu(B(h^*_{AB})) + (Ev(B(h^*_{AB})))^2,$$

we must have

$$Eu(A) - Eu(B(h^*_{AB})) = (Ev(B(h^*_{AB})))^2 - (Ev(A))^2.$$

Hence, if h^*_{AB} is such that $Eu(B(h^*_{AB})) > Eu(A)$, then

$$Eu(A) - Eu(B(h^*_{AB})) < r[(Ev(B(h^*_{AB})))^2 - (Ev(A))^2] < 0$$

and thus $U(C) < U(D(h^*_{AB}))$. Thus, $h^*_{CD} < h^*_{AB}$, that is, the person exhibits a CRP. Analogously, if h^*_{AB} is such that $Eu(B(h^*_{AB})) < Eu(A)$, the person exhibits an RCRP.

Proof of part (2c) and (2d): These follow directly from parts (2a) and (2b) combined with the fact that $\Delta^*_{CC} = \Delta^*_{CR} - \Delta^*_{MX}$.

■

Proposition A4: Suppose a person evaluates lotteries according to the Chew et al. functional in equation (E.7). Then:

(1) If there exists $\bar{h}$ such that both $v(M) = pv(\bar{h}) + (1-p)v(0)$ and $w(M) = pw(\bar{h}) + (1-p)w(0)$, then $h^*_{AB} = h^*_{AB'} = h^*_{CD} = \bar{h}$ and thus the person will have ⊘CRP-⊘CCP-⊘MXP.

(2) Otherwise, the person must exhibit the pattern ⊘CRP-RCCP-MXP.

Proof: For any h, $U(B'(h)) = Ev(B'(h))Ew(B'(h))$. Because $B'(h) = (1-r)A + rB$, we can rewrite this as

$$U(B'(h)) = [(1-r)Ev(A) + rEv(B(h))][(1-r)Ew(A) + rEw(B(h))].$$

Since $Ev(A)$, $Ev(B(h))$, $Ew(A)$, and $Ew(B(h))$ are all independent of r,

$$\frac{dU(B'(h))}{dr} = [Ev(B(h)) - Ev(A)][(1-r)Ew(A) + rEw(B(h))] + [(1-r)Ev(A) + rEv(B(h))][Ew(B(h)) - Ew(A)]$$

and

$$\frac{d^2U(B'(h))}{dr^2} = 2[Ev(B(h)) - Ev(A)][Ew(B(h)) - Ew(A)].$$

Proof of part (1): Suppose there exists $\bar{h}$ such that both $v(M) = pv(\bar{h}) + (1-p)v(0)$ and $w(M) = pw(\bar{h}) + (1-p)w(0)$. Because these are equivalent to $Ev(A) = Ev(B(\bar{h}))$ and $Ew(A) = Ew(B(\bar{h}))$, it immediately follows that $h^*_{AB} = \bar{h}$. In addition, these conditions also imply that $rEv(A) = rEv(B(\bar{h}))$ and $rEw(A) = rEw(B(\bar{h}))$, from which it follows that $h^*_{CD} = \bar{h}$. Finally, these conditions further imply that $\frac{dU(B'(\bar{h}))}{dr} = 0$, which implies $h^*_{AB'} = \bar{h}$. The result follows.

Proof of part (2): h^*_{AB} must satisfy $Ev(A)Ew(A) = Ev(B(h^*_{AB}))Ew(B(h^*_{AB}))$. Because $Ev(C) = rEv(A)$, $Ew(C) = rEw(A)$, $Ev(D(h^*_{AB})) = rEv(B(h^*_{AB}))$, and $Ew(D(h^*_{AB})) = rEw(B(h^*_{AB}))$, it follows that $h^*_{CD} = h^*_{AB}$ and thus the person exhibits ⊘CRP.

Given $v(x) \geqslant 0$ and $w(x) \geqslant 0$ for all x, the h^*_{AB} condition can be rewritten as

$$\frac{Ev(A)}{Ev(B(h^*_{AB}))} = \frac{Ew(B(h^*_{AB}))}{Ew(A)}.$$

If there does not exist $\bar{h}$ such that $Ev(A) = Ev(B(\bar{h}))$ and $Ew(A) = Ew(B(\bar{h}))$, then either $\frac{Ev(A)}{Ev(B(h^*_{AB}))} = \frac{Ew(B(h^*_{AB}))}{Ew(A)} > 1$ or $1 > \frac{Ev(A)}{Ev(B(h^*_{AB}))} = \frac{Ew(B(h^*_{AB}))}{Ew(A)} > 0$. In the former case, $[Ev(B(h^*_{AB})) - Ev(A)] < 0$ while $[Ew(B(h^*_{AB})) - Ew(A)] > 0$, and thus $\frac{d^2U(B'(h))}{dr^2} < 0$. In the latter case, $[Ev(B(h^*_{AB})) - Ev(A)] > 0$ while $[Ew(B(h^*_{AB})) - Ew(A)] < 0$, and thus again $\frac{d^2U(B'(h))}{dr^2} < 0$. Because $U(A) = U(B(h^*_{AB}))$ (by the definition of h^*_{AB}), $\frac{d^2U(B'(h^*_{AB}))}{dr^2} < 0$ implies $U(B'(h^*_{AB})) > U(A) = U(B(h^*_{AB}))$ for any $r \in (0,1)$, and thus $h^*_{AB'} < h^*_{AB}$, that is, the person exhibit an MXP.

Finally, because $\Delta^*_{CC} = \Delta^*_{CR} - \Delta^*_{MX}$, the combination of $\bigcirc\!\!\!\!\backslash$CRP and MXP implies RCCP.

■

E.3 Implications for Indifference Curves in a Marschak-Machina Triangle

In Section 5.3, we describe some implications of the UP model for indifference curves in a Marschak-Machina triangle. In this subsection, we derive those implications. A Marschak-Machina triangle reflects preferences over lotteries of the form $(H, q_H; M, q_M; 0, q_L)$ for fixed amounts $M > 0$ and $H > M$. To simplify notation, we sometimes denote this lottery by (q_L, q_M, q_H).

Below, we prove the following proposition:[3]

Proposition A5: Suppose a person behaves according to the utility functional in equation (E.1). For any Marschak-Machina triangle, indifference curves must show one of the following five patterns:

I1: Exactly one indifference curve is linear, with convex (mixture-loving) indifference curves to the left and concave (mixture-averse) indifference curves to the right of the linear indifference curve, and global fanning out of average slopes.

I2: All indifference curves are concave (mixture-averse), with global fanning out of average slopes.

I3: All indifference curves are convex (mixture-loving), with global fanning out of average slopes.

[3]Chew et al. (1991) describe how quadratic utility can generate three regions of indifference curves, which they label regions I, II, and III. Proposition A5 characterizes the specific ways in which these regions can appear in the UP model, which again is a special case of quadratic utility. Proposition A5 further characterizes how, under the UP model, the average slopes of indifference curves change as we move through a Marschak-Machina triangle (where average slopes are defined below between Lemmas C2 and C3).

I4: All indifference curves are convex (mixture-loving), with fanning out of average slopes to the left and constant average slopes to the right of the indifference curve that contains lottery $A \equiv (0, 1, 0)$.

I5: All indifference curves are convex (mixture-loving), with fanning out of average slopes to the left and fanning in of average slopes to the right of the indifference curve that contains lottery $A \equiv (0, 1, 0)$ (which thus has the flattest average slope).

Figure 9 in Section 5.3 depicts these five patterns of indifference curves. To help connect these five patterns of indifference curves to the seven possible patterns of behavior in Proposition 1, each panel in Figure 9 depicts the five points from our experiment (A, B, B', C, and D), where we have chosen B such that $A \sim B$. For indifference-curve patterns I2, I4, and I5, the behavioral patterns are clear from Figure 9: I2 must yield CRP-CCP-RMXP (P4), I4 must yield ⃠CRP-RCCP-MXP (P12), and I5 must yield RCRP-RCCP-MXP (P1). For indifference-curve pattern I3, it is clear that the person must have CRP and MXP, but any CC preference is possible (so behavioral patterns P2, P23, and P3 are possible). For indifference-pattern I1, the person must have CRP; but any MX preference is possible depending on whether the linear indifference curve is to the right of (as shown), is to the left of, or is the indifference containing A; and when the person has CRP and MXP (as shown), any CC preference is possible (so all behavioral patterns are possible except P1 and P12).

We prove Proposition A5 through a series of lemmas. Lemma A1 establishes that, for the more general functional in equation (E.5) for which the UP model is a special case, each indifference curve in a Marschak-Machina triangle must be linear, concave, or convex (although this lemma does not say that that all indifference curves within a given triangle must have the same shape).[4]

Lemma A1: Suppose a person behaves according to the utility functional in equation (E.5). Then each indifference curve must be linear, concave, or convex.

Proof: Suppose that X and Y are two lotteries that satisfy $U(X) = U(Y)$, and consider lottery $Z \equiv (1 - \alpha)X + \alpha Y$. Note that $\alpha \in (0, 1)$ would make Z yield a point on the line segment $\overline{XY}$, whereas $\alpha < 0$ or $\alpha > 1$ would make Z a point on the line that contains X and Y but outside the line segment $\overline{XY}$.

Given $U(Z) = Eu(Z) + (Ev(Z))(Ew(Z))$, applying usual rules for expected-utility functionals,

[4]We label an indifference curve as convex versus concave based on its shape in a Marschak-Machina triangle with q_L and q_H on the axes; given this labeling, convex (concave) indifference curves are associated with preferences being locally quasi-concave (quasi-convex). Lemma A1 is analogous to Lemma A2.1 in Chew et al. (1991).

we can rewrite this as

$$U(Z) = [(1-\alpha)Eu(X) + \alpha Eu(Y)] + [(1-\alpha)Ev(X) + \alpha Ev(Y)][(1-\alpha)Ew(X) + \alpha Ew(Y)].$$

Differentiating this twice with respect to α yields

$$\frac{d^2[U(Z)]}{d\alpha^2} = 2[Ev(Y) - Ev(X)][Ew(Y) - Ew(X)].$$

Note that $\frac{d^2[U(Z)]}{d\alpha^2}$ is independent of α, and thus there are three cases: (i) It could be that $\frac{d^2[U(Z)]}{d\alpha^2} = 0$, in which case $U(Z) = U(X) = U(Y)$ for all α. (ii) It could be that $\frac{d^2[U(Z)]}{d\alpha^2} < 0$, in which case $U(Z) > U(X) = U(Y)$ for all $\alpha \in (0,1)$ and $U(Z) < U(X) = U(Y)$ for all $\alpha < 0$ and $\alpha > 1$. (iii) It could be that $\frac{d^2[U(Z)]}{d\alpha^2} > 0$, in which case $U(Z) < U(X) = U(Y)$ for all $\alpha \in (0,1)$ and $U(Z) > U(X) = U(Y)$ for all $\alpha < 0$ and $\alpha > 1$.

If case (i) holds, it immediately follows that the indifference curve containing X and Y is linear. Moreover, from case (i), it also follows that if an indifference curve is anywhere linear, then it must be everywhere linear. Given this latter point, the combination of cases (ii) and (iii) imply that all nonlinear indifference curves must be concave or convex. To see this, note that if an indifference curve had both convex and concave regions, then there must be an X and Y that does not satisfy any of cases (i), (ii), and (iii) (given that indifference curves are continuous), which would be a contradiction.

While the above completes the proof of Lemma A1, note that it further follows that if an X and Y satisfy case (i), then the indifference curve that contains X and Y is linear; if an X and Y satisfy case (ii), then the indifference curve that contains X and Y is convex; and (iii) if an X and Y satisfy case (iii), then the indifference curve that contains X and Y is concave.

■

Lemma A2 establishes that for the UP model in equation (E.1), there is a simple condition to check the shape of an indifference curve:

Lemma A2: Suppose a person behaves according to the utility functional in equation (E.1). If lottery $X \equiv (q_L, q_M, q_H)$ and lottery $Y \equiv (p_L, p_M, p_H)$ have $U(X) = U(Y)$, $p_H > q_H$ and $q_M + q_H > p_M + p_H$,[5] then:

(1) If $\frac{\kappa(M)}{\kappa(H)} = \frac{p_H - q_H}{q_M - p_M}$, the indifference curve through X and Y is linear.

[5]Note that $U(X) = U(Y)$ and $p_H > q_H$ together imply $q_M + q_H > p_M + p_H$, because otherwise X would FOSD Y, and the UP model respects FOSD.

(2) If $\dfrac{\kappa(M)}{\kappa(H)} < \dfrac{p_H - q_H}{q_M - p_M}$, the indifference curve through X and Y is convex.

(3) If $\dfrac{\kappa(M)}{\kappa(H)} > \dfrac{p_H - q_H}{q_M - p_M}$, the indifference curve through X and Y is concave.

Proof: If $v(x) = I(x > 0)$ and $w(x) = I(x > 0)\kappa(x)$, then $Ev(X) = q_M + q_H$, $Ev(Y) = p_M + p_H$, $Ew(X) = q_M\kappa(M) + q_H\kappa(H)$, and $Ew(Y) = p_M\kappa(M) + p_H\kappa(H)$. Applying the equation from the proof of Lemma A1,

$$\begin{aligned}\frac{d^2[U(Z)]}{d\alpha^2} &= 2[Ev(Y) - Ev(X)][Ew(Y) - Ew(X)] \\ &= 2[(p_M + p_H) - (q_M + q_H)][(p_M - q_M)\kappa(M) + (p_H - q_H)\kappa(H)].\end{aligned}$$

Because $[(p_M + p_H) - (q_M + q_H)] < 0$, $p_H > q_H$, and $q_M > p_M$, it follows that the sign of $\frac{d^2[U(Z)]}{d\alpha^2} > 0$ depends on how $\frac{\kappa(M)}{\kappa(H)}$ compares to $\frac{p_H - q_H}{q_M - p_M}$. Specifically:

- If $\frac{\kappa(M)}{\kappa(H)} = \frac{p_H - q_H}{q_M - p_M}$, then $\frac{d^2[U(Z)]}{d\alpha^2} = 0$ and we are in case (i) from the proof of Lemma A1, and thus the indifference curve through X and Y is linear.
- If $\frac{\kappa(M)}{\kappa(H)} < \frac{p_H - q_H}{q_M - p_M}$, then $\frac{d^2[U(Z)]}{d\alpha^2} < 0$ and we are in case (ii) from the proof of Lemma A1, and thus the indifference curve through X and Y is convex.
- If $\frac{\kappa(M)}{\kappa(H)} > \frac{p_H - q_H}{q_M - p_M}$, then $\frac{d^2[U(Z)]}{d\alpha^2} > 0$ and we are in case (iii) from the proof of Lemma A1, and thus the indifference curve through X and Y is concave.

■

We next introduce notation to talk about the slope of the line segment that connects two lotteries in a Marschak-Machina triangle, which will be useful for evaluating the criterion in Lemma A2, and also for evaluating whether the average slopes of indifference curves are fanning in versus fanning out.

Consider two lotteries $X \equiv (q_L, q_M, q_H)$ and $Y \equiv (p_L, p_M, p_H)$ with $p_H > q_H$ and $q_M + q_H > p_M + p_H$ (and thus $q_M > p_M$ and $p_L > q_L$). Denote the slope of the line segment $\overline{XY}$ by $m(\overline{XY})$, and note that

$$m(\overline{XY}) = \frac{p_H - q_H}{p_L - q_L} = \frac{p_H - q_H}{(q_M - p_M) - (p_H - q_H)}.$$

The critical value in Lemma A2 can then be written as $(p_H - q_H)/(q_M - p_M) = m(\overline{XY})/(m(\overline{XY}) + 1)$, which is increasing in $m(\overline{XY})$. It follows that the steeper (flatter) the line segment $\overline{XY}$, the more likely it is that the indifference curve containing X and Y is convex (concave).

Hence, a natural way to characterize the shape of indifference curves as we move through a Marschak-Machina triangle is to evaluate the slopes of line segments connecting indifferent points on

the edges of the triangle, which reflect the average slopes of indifference curves. Hence, we introduce notation for such lotteries. For a fixed M and H (i.e., for a particular Marschak-Machina triangle):

- Define $A \equiv (0, 1, 0)$, and then define p_0 and B such that $B = (1 - p_0, 0, p_0)$ and $B \sim A$. In other words, A is the vertex, and B is the indifferent point on the hypotenuse.
- For any $s \in [0, 1]$, define $C(s) \equiv (1 - s, s, 0)$, and then define $p_1(s)$ and $D(s)$ such that $D(s) = (1 - p_1(s), 0, p_1(s))$ and $D(s) \sim C(s)$. In other words, $C(s)$ is a point on the x-axis, and $D(s)$ is the indifferent point on the hypotenuse. Note that for $s = 1$, $C(s) = A$ and thus $D(s) = B$, and as $s \to 0$, both $C(s) \to (1, 0, 0)$ and $D(s) \to (1, 0, 0)$.
- For any $s \in [0, 1]$, define $E(s) \equiv (0, s, 1 - s)$, and then define $p_2(s)$ and $F(s)$ such that $F(s) \equiv (1 - p_2(s), 0, p_2(s))$ and $F(s) \sim E(s)$. In other words, $E(s)$ is a point on the y-axis, and $F(s)$ is the indifferent point on the hypotenuse. Note that for $s = 1$, $E(s) = A$ and thus $F(s) = B$, and as $s \to 0$, both $E(s) \to (0, 0, 1)$ and $F(s) \to (0, 0, 1)$.

Using this notation, Lemma A3 characterizes the slopes of line segments connecting indifferent points on the edges of the triangle.

Lemma A3: Suppose a person behaves according to the utility functional in equation (E.1). Then:

(1) For any $s' < s \leqslant 1$:

   (a) If $\kappa(M) > (p_0)^2\kappa(H)$, then for any $s' < s \leqslant 1$, $m(\overline{C(s')D(s')}) < m(\overline{C(s)D(s)})$, that is, indifference curves fan out as we move through the triangle from $\overline{AB}$ toward the lower right.

   (b) If $\kappa(M) = (p_0)^2\kappa(H)$, then for any $s' < s \leqslant 1$, $m(\overline{C(s')D(s')}) = m(\overline{C(s)D(s)})$, that is, indifference curves have the same average slope as we move through the triangle from $\overline{AB}$ toward the lower right.

   (c) If $\kappa(M) < (p_0)^2\kappa(H)$, then for any $s' < s \leqslant 1$, $m(\overline{C(s')D(s')}) > m(\overline{C(s)D(s)})$, that is, indifference curves fan in as we move through the triangle from $\overline{AB}$ toward the lower right.

(2) For any $s' < s \leqslant 1$, $m(\overline{E(s')F(s')}) > m(\overline{E(s)F(s)})$, that is, indifference curves fan out as we move through the triangle from $\overline{AB}$ toward the upper left.

Proof:

Proof of Part (1): Fix an $s \in (0, 1]$, and recall that $p_1(s)$ is the p in lottery $D(s)$. Under the UP model, $C(s) \sim D(s)$ implies $Eu(C(s)) + s^2\kappa(M) = Eu(D(s)) + (p_1(s))^2\kappa(H)$ or

$$Eu(C(s)) - Eu(D(s)) = (p_1(s))^2\kappa(H) - s^2\kappa(M).$$

Define $\alpha = s'/s$ so that $C(s') = \alpha C(s) + (1-\alpha)(1,0,0) = (1-\alpha s, \alpha s, 0)$. Also define $\tilde{D}(s'|s) = \alpha D(s) + (1-\alpha)(1,0,0) = (1-\alpha p_1(s), 0, \alpha p_1(s))$, which is the point on the hypotenuse such that $m(\overline{C(s')\tilde{D}(s'|s)}) = m(\overline{C(s)D(s)})$. Hence, if $C(s') \succ \tilde{D}(s'|s)$, then $D(s')$ must be up the hypotenuse from $\tilde{D}(s'|s)$, and thus $m(\overline{C(s')D(s')}) > m(\overline{C(s)D(s)})$. Analogously, $C(s') \prec \tilde{D}(s'|s)$ implies $m(\overline{C(s')D(s')}) < m(\overline{C(s)D(s)})$, and $C(s') \sim \tilde{D}(s'|s)$ implies $m(\overline{C(s')D(s')}) = m(\overline{C(s)D(s)})$. The comparison between $C(s')$ and $\tilde{D}(s'|s)$ is

$$\begin{aligned} Eu(C(s')) + (\alpha s)^2\kappa(M) &: Eu(\tilde{D}(s'|s)) + (\alpha p_1(s))^2\kappa(H) \\ Eu(C(s')) - Eu(\tilde{D}(s'|s)) &: \alpha^2[(p_1(s))^2\kappa(H) - s^2\kappa(M)] \\ Eu(C(s)) - Eu(D(s)) &: \alpha[(p_1(s))^2\kappa(H) - s^2\kappa(M)] \end{aligned} \tag{E.8}$$

where the last step follows from $Eu(C(s')) - Eu(\tilde{D}(s'|s)) = \alpha[Eu(C(s)) - Eu(D(s))]$.

Proof of part (1a): Suppose $\kappa(M) > (p_0)^2\kappa(H)$. Then $A \sim B$ implies

$$Eu(A) - Eu(B) = (p_0)^2\kappa(H) - \kappa(M) < 0.$$

Applying condition (E.8) for $s = 1$ and thus $p_1(s) = p_0$ and $\alpha = s'$, and recalling $C(1) = A$ and $D(1) = B$, for any $s' \in (0,1)$, the comparison between $C(s')$ and $\tilde{D}(s'|1)$ is

$$Eu(A) - Eu(B) : s'[(p_0)^2\kappa(H) - \kappa(M)].$$

Because $Eu(A) - Eu(B) = (p_0)^2\kappa(H) - \kappa(M) < 0$, $s' \in (0,1)$ implies $C(s') \prec \tilde{D}(s'|1)$ and thus $m(\overline{C(s')D(s')}) < m(\overline{AB})$. Also, because the probability of the high outcome in $\tilde{D}(s'|1)$ is $s'p_0$, the combination of equation (E.4) and $C(s') \prec \tilde{D}(s'|1)$ implies

$$Eu(C(s')) - Eu(\tilde{D}(s'|1)) < (s'p_0)^2\kappa(H) - (s')^2\kappa(M) < 0,$$

where the first inequality follows from $C(s') \prec \tilde{D}(s'|1)$ and the second follows from $(p_0)^2\kappa(H) - \kappa(M) < 0$. Because it further must be that $p_1(s') < s'p_0$ in order to make $D(s') \sim C(s')$, it must also be that $(p_1(s'))^2\kappa(H) - (s')^2\kappa(M) < 0$. It follows that for any $s' \in (0,1)$,

$$Eu(C(s')) - Eu(D(s')) = (p_1(s'))^2\kappa(H) - (s')^2\kappa(M) < 0.$$

Finally, swapping s' for s in the prior statement, given that each of these terms is negative, the result follows directly from applying condition (E.8) to any pair $s \in (0,1]$ and $s' \in (0,s)$.

Proof of part (1b): If $\kappa(M) = (p_0)^2\kappa(H)$, then $Eu(A) - Eu(B) = (p_0)^2\kappa(H) - \kappa(M) = 0$. Because $A = C(1)$ and $B = D(1)$, condition (E.8) implies that, for any $s' \in (0,1)$, we have $C(s') \sim \tilde{D}(s'|1)$,

and thus $m(\overline{C(s')D(s')}) = m(\overline{AB})$. The result follows.

Proof of part (1c): The proof is analogous to the proof for part (1a). Specifically, $\kappa(M) < (p_0)^2\kappa(H)$ implies that $Eu(A) - Eu(B) = (p_0)^2\kappa(H) - \kappa(M) > 0$, which in turn implies that, for all $s' \in (0,1)$, we must have $m(\overline{C(s')D(s')}) > m(\overline{AB})$ and also $Eu(C(s')) - Eu(D(s')) = (p_1(s'))^2\kappa(H) - (s')^2\kappa(M) > 0$. Finally, given that each of these terms is positive, the result follows directly from applying condition (E.8) to any pair $s \in (0,1]$ and $s' \in (0,s)$.

Proof of part (2): Fix an $s \in (0,1]$, and recall that $p_2(s)$ is the p in lottery $F(s)$. Under the UP model, $E(s) \sim F(s)$ implies $Eu(E(s)) + (1)(s\kappa(M) + (1-s)\kappa(H)) = Eu(F(s)) + (p_2(s))^2\kappa(H)$ or

$$Eu(E(s)) - Eu(F(s)) = (p_2(s))^2\kappa(H) - s\kappa(M) - (1-s)\kappa(H).$$

Define $\alpha = s'/s$ so that $E(s') = \alpha E(s) + (1-\alpha)(0,0,1) = (0, \alpha s, \alpha(1-s) + (1-\alpha))$. Also define $\tilde{F}(s'|s) = \alpha F(s) + (1-\alpha)(0,0,1) = (\alpha(1-p_2(s)), 0, \alpha p_2(s) + (1-\alpha))$, which is the point on the hypotenuse such that $m(\overline{E(s')\tilde{F}(s'|s)}) = m(\overline{E(s)F(s)})$. Hence, if $E(s') \succ \tilde{F}(s'|s)$, then $F(s')$ must be up the hypotenuse from $\tilde{F}(s'|s)$, and thus $m(\overline{E(s')F(s')}) > m(\overline{E(s)F(s)})$. We have

$$\begin{aligned} U(E(s')) &= \alpha Eu(E(s)) + (1-\alpha)u(H) + \alpha s\kappa(M) + \alpha(1-s)\kappa(H) + (1-\alpha)\kappa(H) \\ U(\tilde{F}(s'|s)) &= \alpha Eu(F(s)) + (1-\alpha)u(H) + (\alpha p_2(s) + (1-\alpha))^2\kappa(H) \end{aligned}$$

Hence, substituting $\alpha[Eu(E(s)) - Eu(F(s))] = \alpha[(p_2(s))^2\kappa(H) - s\kappa(M) - (1-s)\kappa(H)]$,

$$\begin{aligned} U(E(s')) - U(\tilde{F}(s'|s)) &= (1-\alpha)\kappa(H) - (\alpha p_2(s) + (1-\alpha))^2\kappa(H) + \alpha(p_2(s))^2\kappa(H) \\ &= [1 - \alpha - \alpha^2(p_2(s))^2 - 2\alpha p_2(s)(1-\alpha) - (1-\alpha)^2 + \alpha(p_2(s))^2]\kappa(H) \\ &= (1-\alpha)\alpha(1-p_2(s))^2 > 0. \end{aligned}$$

Hence, for any $s' < s \leqslant 1$, $E(s') \succ \tilde{F}(s'|s)$, and thus $m(\overline{E(s')F(s')}) > m(\overline{E(s)F(s)})$.

■

Finally, we can put it all together to prove Proposition A5:

Proof of Proposition A5: For a fixed (M,H) (i.e., for a specific Marschak-Machina triangle), find p_0 such that $A \equiv (M,1) \sim B \equiv (H,p_0)$.

If $\kappa(M) > (p_0)^2\kappa(H)$, then by Lemma A3 the average slopes of the indifference curves globally fan out, that is, get steeper as we move from the lower right to the upper left. If any indifference curve has average slope m such that $m/(m+1) = \kappa(M)/\kappa(H)$, then applying Lemma A2, that indifference curve is linear, while every indifference curve to its left must be convex and every indifference curve

to its right must be concave (pattern I1). Alternatively, if all indifference curves have slopes such that $m/(m+1) < \kappa(M)/\kappa(H)$, then by Lemma A2 all indifference curves are concave (pattern I2); and if all indifference curves have slopes such that $m/(m+1) > \kappa(M)/\kappa(H)$, then by Lemma A2 all indifference curves are convex (pattern I3).

If instead $\kappa(M) = (p_0)^2\kappa(H)$, then by Lemma A3 average slopes of the indifference curves fan out to the left and are constant to the right of the indifference curve that contains lottery A. Moreover, because $\kappa(M) = (p_0)^2\kappa(H)$ implies $\kappa(M) < p_0\kappa(H)$, it follows from Proposition A1 part (2b) that the indifference curve that contains lottery A is convex. Since all other indifference curves have average slopes that are at least as large as that for this indifference curve, and by Lemma A2 steeper average slopes are more likely to be convex, it follows that every indifference curve must be convex.

Finally, $\kappa(M) < (p_0)^2\kappa(H)$, then by Lemma A3 average slopes of the indifference curves fan out to the left and are fan in to the right of the indifference curve that contains lottery A, and thus this indifference curve has the flattest slope. Moreover, because $\kappa(M) < (p_0)^2\kappa(H)$ implies $\kappa(M) < p_0\kappa(H)$, it follows from Proposition A1 part (2b) that the indifference curve that contains lottery A is convex. Since all other indifference curves with larger average slopes, it again follows from Lemma A2 that every indifference curve must be convex.

■

E.4 Explaining Certainty Equivalents for Binary Gambles

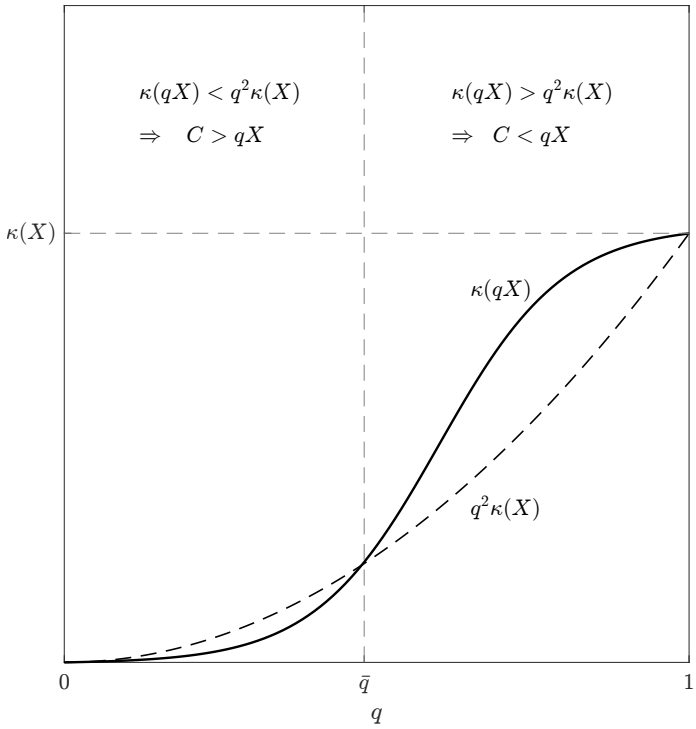
A reliable empirical finding in the experimental literature on risky choice is that, when eliciting certainty equivalents for binary lotteries—i.e., an m such that $(m, 1) \sim (H, p)$—mean certainty equivalents indicate risk aversion ($m < pH$) for larger p but risk tolerance ($m > pH$) for smaller p (see, e.g., Tversky and Kahneman, 1992). In this appendix, we demonstrate that the UP model with an S-shaped κ function similar to the one we estimate can naturally generate this pattern.[6]

Under equation (2) with $u(x) = x$, the certainty equivalent C for a binary lottery (X, q) solves

$$C + \kappa(C) = qX + q^2\kappa(X).$$

[6]Note that our experiment did not consider probabilities below 0.3, which is the typical domain in which risk seeking is observed. Indeed, none of our aggregate results for a given (p, r) combination show risk tolerance. As a result, the specific estimates of our κ functions are not calibrated to capture the changing pattern of risk attitudes across probabilities that is typically observed in the literature. Instead, we consider whether functions with similar shapes could generate the behavioral patterns generally.

Figure E.1: Comparing $\kappa(qX)$ to $q^2\kappa(X)$



Notes: Figure plots $\kappa(qX)$ and $q^2\kappa(X)$ as a function of q (for a fixed X) given an S-shaped upside potential function $\kappa(x)$ for which the initial slope of $\kappa(qX)$ is flatter than that of $q^2\kappa(X)$. Under the UP model, the certainty equivalent C will exhibit risk tolerance ($C > qX$) when $\kappa(qX) < q^2\kappa(X)$, which occurs for probabilities $q < \bar{q}$, and risk aversion ($C < qX$) when $\kappa(qX) > q^2\kappa(X)$, which occurs for probabilities $q > \bar{q}$.

Thus, an individual will be risk tolerant, $C > qX$, if and only if[7]

$$\kappa(qX) < q^2\kappa(X).$$

If κ is S-shaped, with initial convexity followed by concavity, and if the initial slope is flatter than that of $q^2\kappa(X)$, there can naturally emerge a $\bar{q}$ such that $\kappa(qX) < q^2\kappa(X)$ for $q < \bar{q}$, and $\kappa(qX) > q^2\kappa(X)$ for $q > \bar{q}$ (as illustrated in Figure E.1). If so, then the model would indeed generate risk tolerance for small q ($q < \bar{q}$) and risk aversion for large q ($q > \bar{q}$). Therefore, an S-shaped κ function as suggested by Figure 8 can naturally generate the changing patterns of risk tolerance in certainty equivalents across the probability spectrum.

E.5 CRE and Equal-Expected-Value Lotteries

In Section 5.3, we describe how the UP model can generate a (noise-free) CRE for equal-expected-value lotteries only if the EU utility function u within the UP model is convex, which runs counter

[7] If $\kappa(qX) < q^2\kappa(X)$ then $qX + \kappa(qX) < qX + q^2\kappa(X)$, and thus C must be larger than qX. The only-if argument is analogous.

to usual assumptions on u. Here, we provide a proof of that result.

For any (p, r, M), if we create a CR paired-choice-task problem using $H = M/p$, then lotteries A and B have the same expected value (M), and lotteries C and D also have the same expected value (rM). A person would exhibit a (noise-free) CRE in that problem when, for that (p, r, M), their $h^*_{AB} > M/p$ (so they prefer lottery A over lottery B) and their $h^*_{CD} < M/p$ (so they prefer lottery D over lottery C).

The following proposition establishes that, in order for a person to have $h^*_{AB} > \frac{M}{p} > h^*_{CD}$, their function u must be locally convex.

Proposition A6. Suppose that h^*_{AB} and h^*_{CD} are derived from equations (E.2) and (E.4); that $u(x)$ is strictly increasing in x; and that $\kappa(x)$ is strictly increasing in x and has $\kappa(x) \geqslant 0$ for all $x > 0$. If $h^*_{AB} > \frac{M}{p} > h^*_{CD}$, then u must be locally convex, and specifically must satisfy $p(u(M/p) - u(0)) > u(M) - u(0)$.

Proof: From the proof of Proposition A.1, the h^*_{AB} condition in equation (E.2) can be rewritten as

$$\kappa(M) - p^2\kappa(h^*_{AB}) = Eu(B(h^*_{AB})) - Eu(A).$$

Analogously, the h^*_{CD} condition in equation (E.4) can be rewritten as

$$r^2\left(\kappa(M) - p^2\kappa(h^*_{CD})\right) = Eu(D(h^*_{CD})) - Eu(C).$$

If $h^*_{AB} > \frac{M}{p} > h^*_{CD}$, the person exhibits a CRP (i.e., $h^*_{AB} > h^*_{CD}$), and thus by Proposition A1 $\kappa(M) > p^2\kappa(h^*_{AB})$. Because κ is increasing, $h^*_{AB} > h^*_{CD}$ implies $\kappa(M) > p^2\kappa(h^*_{CD})$, and thus $Eu(D(h^*_{CD})) > Eu(C)$. Writing out these expected utilities yields $pru(h^*_{CD}) + (1 - pr)u(0) > rU(M) + (1-r)u(0)$. Because u is increasing and $\frac{M}{p} > h^*_{CD}$, it follows that $pru(M/p) + (1-pr)u(0) > rU(M) + (1 - r)u(0)$, and rearranging yields $p(u(M/p) - u(0)) > u(M) - u(0)$.

■

E.6 Event Splitting

In Section 6, we discuss the implications of our model for event splits—that is, how people feel when choosing between a lottery (H, p) versus a lottery $(H+z, p/2; H-z, p/2)$. Note that the second lottery is obtained from the first by splitting the "event" of a probability p of winning H into two "events", each with probability $p/2$, that maintain the expected value of the lottery. Several recent papers

(e.g., Bernheim and Sprenger (2020)) have found evidence that people dislike such splits, and one might wonder whether such evidence is inconsistent with our finding of mixture-loving preferences.

In our model, a person's preferences for or against event splitting can be determined separately from their preferences for or against mixtures. In particular, Proposition 2 demonstrated that an MXP emerges in our model due to the way that probabilities enter our model. In contrast, the following proposition establishes that preferences for or against event splitting depend on the local curvature of the function κ.

Proposition A7. Suppose a person is presented with a choice between lottery (H, p) and lottery $(H + z, p/2; H - z, p/2)$, and the person chooses based on the decision utility in equation (E.1) with $u(x) = x$. For any $(p, r) \in (0, 1)^2$:

(1) If κ is linear on domain $[H - z, H + z]$, then $(H, p) \sim (H + z, p/2; H - z, p/2)$;

(2) If κ is concave on domain $[H - z, H + z]$, then $(H, p) \succ (H + z, p/2; H - z, p/2)$; and

(3) If κ is convex on domain $[H - z, H + z]$, then $(H, p) \prec (H + z, p/2; H - z, p/2)$.

Proof: Applying equation (E.1) with $u(x) = x$, the decision-utility comparison is

$$pH + p^2\kappa(H) \quad : \quad \frac{p}{2}(H + z) + \frac{p}{2}(H - z) + p\left[\frac{p}{2}\kappa(H + z) + \frac{p}{2}\kappa(H - z)\right]$$

or

$$pH + p^2\left[\kappa(H)\right] \quad : \quad pH + p^2\left[\frac{1}{2}\kappa(H + z) + \frac{1}{2}\kappa(H - z)\right]$$

or

$$\kappa(H) \quad : \quad \frac{1}{2}\kappa(H + z) + \frac{1}{2}\kappa(H - z).$$

The result follows directly.

■

F Upside Potential Model: Estimation

This appendix presents the details of the structural estimation described in Section 5.2 for the UP model. For comparison, Appendix G.1 provides estimates of several prospect-theory specifications.

F.1 Data and General Approach

We evaluate how well alternative models can explain the observed preference patterns and their sensitivity to experimental parameters (p, r, M). As described in Section 5.2, the estimation sample contains 60 aggregate valuations: the mean responses for h_{AB}, $h_{AB'}$, and h_{CD} for each of 20 (p, r) cells (see the first three columns of Appendix Table A.2). We parameterize κ as $\kappa(x; \boldsymbol{\theta})$ and estimate $\boldsymbol{\theta}$ by nonlinear least squares using the 60 observations in the data. For each $XY \in \{AB, AB', CD\}$ and each (p, r, M) experimental parameterization, the model yields $h^*_{XY}(p, r, M; \boldsymbol{\theta})$, and we then use non-linear least squares to estimate

$$h_{XY} = h^*_{XY}(p, r, M; \boldsymbol{\theta}) + \varepsilon.$$

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} and the observed h_{XY}, and (iv) the correlation between the model-predicted Δ^* and the observed Δ.

F.2 Estimating the Upside-Potential Model

We estimate the UP model in equation (2), where the model-implied valuations h^*_{AB}, $h^*_{AB'}$, and h^*_{CD} are defined by equations (3), (4), and (5) in the main text. To isolate the role of UP, we set $u(x) = x$, making the κ function the only object to estimate.[8]

Lacking an a priori sense of the shape of κ, we begin with a flexible functional form. In our experiment, $M \in \{9, 15, 24, 27\}$, and the observed means h range from 23.83 to 42.56 (Appendix Table A.2). Hence, we use a continuous piecewise-linear form with parameter vector $\boldsymbol{\theta} \equiv (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6)$:

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

[8] As noted in Section 5.2, the UP model is post hoc and the experiment was not designed to identify κ. Therefore, identification relies on limited variation in (p, r) over a narrow support of values, and we urge caution in interpreting these estimates.

In our data, κ is evaluated at $x \in \{9, 15, 24, 27\}$ exactly 15 times each (i.e., for each of the four values of M). In contrast, the mean valuations we observe contain no observations in $(0, 9)$ or $(9, 15)$, only one in $(15, 24)$ and one in $(24, 27)$, and the remaining 58 in $(27, 43)$. Thus $\theta_1 - \theta_4$ primarily pin down $\kappa(9)$, $\kappa(15)$, $\kappa(24)$, and $\kappa(27)$. For $x \geqslant 27$, we permit κ to be either linear (i.e., $\theta_5 = \theta_6$) or two-part-linear with a kink at $x = 36$, where this point was chosen to roughly balance observations above and below the kink.

Appendix Table F.1 reports these two specifications: Column (1) allows a two-segment linear κ for $x \geqslant 27$, while column (2) imposes a single linear segment over this range. Appendix Figures F.1 and F.2 show, for each specification, (i) the estimated κ function, (ii) observed versus fitted h_{XY}, and (iii) observed versus fitted Δ.

Both the six- and five-parameter κ specifications fit the data well in-sample, with 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 between 27 and 36 (i.e., $\hat{\theta}_5 < 0$), which we suspect is due to overfitting given limited variation across h_{XY} in this region. As Panel B of Figure F.1 shows, most observations over the range $x \in (27, 36)$ are h_{CD} responses, while for $x > 36$ we also observe h_{AB} and $h_{AB'}$. The six-parameter model can thus dedicate a parameter to fit a single type of data in the $x \in (27, 36)$ region, yielding a slightly better fit of the levels at the expense of differences. Due to this possibility of overfitting, we adopt the five-parameter model as our preferred specification.

Motivated by the S-shape in Panel A of Figure F.2, we set out to find a parsimonious and analytically tractable three-parameter functional form that could capture this essential feature of the κ function. Of those, the best-fitting version we found was the following three-parameter scaled logistic,[9] $\kappa(x; \boldsymbol{\theta})$ with $\boldsymbol{\theta} = (\theta_1, \theta_2, \theta_3)$:

$$\kappa(x; \boldsymbol{\theta}) = \theta_1 \left[\frac{1}{1 + \exp(-\theta_2(x - \theta_3))} \right], \quad \theta_1, \theta_2, \theta_3 > 0. \tag{F.1}$$

The term in brackets represents a classic two-parameter sigmoid function that goes from zero (as $x \to -\infty$) to 1 (as $x \to \infty$). θ_2 controls the steepness and θ_3 determines the inflection point, such that $\kappa(x; \boldsymbol{\theta})$ will be convex for any $x < \theta_3$ and concave for any $x > \theta_3$. Finally, θ_1 is a scale term that sets the upper asymptote.

Column (3) of Table F.1 reports estimates for the logistic specification in (F.1), while Appendix

[9] In addition to the cases described in the main text, we also explored several simple alternatives: (i) a log-over-linear shape $\theta_1\, x \log(1+\theta_2 x)/(1+\theta_3 x)$; (ii) a simple log form $\theta_1\, \log\big(1+(x/\theta_2)^{\theta_3}\big)$; (iii) a ratio of powers $(\theta_1\, x\theta_3 + 1)/(\theta_2^{\theta_3} + x^{\theta_3})$; and (iv) a double log $\theta_1\, \log\big(1 + \log(1 + (x/\theta_2)^{\theta_3})\big)$. While these alternatives can capture an S-shape, they produced a worse model fit.

Table F.1: Upside Potential Estimates

	(1) Flexible 1	(2) Flexible 2	(3) Parametric 1	(4) Parametric 2	(5) Parametric 3
θ_1	1.58	1.76	106.53	105.16	135.30
	(0.26)	(0.32)	(22.62)	(32.52)	(37.58)
θ_2	3.72	4.40	0.20	0.20	0.19
	(0.67)	(0.88)	(0.00)	(0.00)	(0.00)
θ_3	6.43	6.85	19.35	19.30	19.36
	(1.04)	(1.36)	(0.35)	(0.73)	(0.39)
θ_4	6.68	7.70		0.01	
	(1.63)	(1.63)		(0.11)	
θ_5	-0.25	1.72			
	(0.41)	(0.54)			
θ_6	6.95				
	(1.68)				
Observations	60	60	60	60	60
Degrees of Freedom	54	55	57	56	57
MSE – h_{XY} levels	2.71	3.53	6.99	6.99	7.72
R^2 – h_{XY} levels	0.82	0.76	0.52	0.52	0.47
$\rho(h_{XY}, \hat{h}_{XY})$	0.92	0.91	0.84	0.84	0.83
MSE – Δ Differences	6.15	7.58	8.20	8.15	7.51
R^2 – Δ Differences	0.66	0.58	0.55	0.55	0.59
$\rho(\Delta, \hat{\Delta})$ – Δ Differences	0.88	0.90	0.87	0.87	0.89

Notes: Non-linear least squares regressions using 60 mean values of $h_{AB}, h_{AB'}, h_{CD}$ as observations. Standard errors in parentheses. Flexible 1 is a continuous six-parameter piecewise-linear κ with knots at $x \in \{9, 15, 24, 27, 36\}$. Flexible 2 is the five-parameter version with a single linear segment for $x \geqslant 27$ (knots at $9, 15, 24, 27$). Parametric 1 is the three-parameter scaled logistic $\kappa(x; \boldsymbol{\theta}) = \theta_1 \big[1 + \exp\{-\theta_2(x - \theta_3)\}\big]^{-1}$. Parametric 2 augments Parametric 1 with a multiplicative term x^{θ_4}, yielding an unbounded specification with $\kappa(0) = 0$. Parametric 3 is a zero-anchored logistic that subtracts the value at $x = 0$ so that $\kappa(0) = 0$. 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. MSE values, R^2 values, and correlation between predicted and actual values, ρ, provided for both valuation levels (h terms) and differences (Δ terms).

Figure F.3 illustrates in-sample fit. The estimates imply substantial nonlinearity in the κ function with this simple parametric form and a reasonable overall fit (MSE = 6.99, $R^2 = 0.52$). However, imposing this functional form leads to a reduction in explanatory power for the levels of h_{XY} relative to the five-parameter piecewise model. In contrast, the correlation for the difference terms is comparable to the five-parameter model and exceeds those of the six-parameter alternative. Panel C of Figure F.3 shows that the three-parameter model tracks Δ_{CR}, Δ_{CC}, and Δ_{MX} closely across all 60 differences.

A drawback of the three-parameter scaled logistic in (F.1) is that it is bounded above by θ_1, which makes it ill-suited for global predictions and inconsistent with our non-parametric estimates.

To address this, we consider an unbounded four-parameter alternative with $\boldsymbol{\theta} \equiv (\theta_1, \theta_2, \theta_3, \theta_4)$:

$$\kappa(x; \boldsymbol{\theta}) = \theta_1 \left[\frac{x^{\theta_4}}{1 + \exp(-\theta_2(x - \theta_3))} \right], \quad \theta_1, \theta_2, \theta_3, \theta_4 > 0.$$

The multiplicative term x^{θ_4} ensures $\kappa(x) \to \infty$ as $x \to \infty$ and implies $\kappa(0) = 0$. The parameter θ_4 governs the asymptotic growth rate in the limit. We present the estimates of this specification in column (4). Despite permitting κ to be unbounded, we estimate $\theta_4 \approx 0$, which collapses to the prior specification in column (3). In other words, allowing for this additional flexibility does not improve the model fit.[10]

We also consider a zero-anchored κ function that sets $\kappa(0) = 0$. This specification captures the intuition that, in the limit, a person may regard a very small prize as effectively equivalent to no prize:

$$\kappa(x; \boldsymbol{\theta}) = \theta_1 \left[\frac{1}{1 + \exp\{-\theta_2(x - \theta_3)\}} \right] - \theta_1 \left[\frac{1}{1 + \exp\{-\theta_2(0 - \theta_3)\}} \right].$$

In this formulation, the first bracketed term is our specification from column (3). 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 (5) of Appendix Table F.1 presents estimates for this functional form, while Appendix Figure F.3 illustrates model fit. While this model performs reasonably well in matching the data, it underperforms the version in column (3) along all fit dimensions.

[10] We reiterate that while we find that a bounded function provides the best fit for the narrow domain that our data cover, it is unlikely to hold out-of-sample.

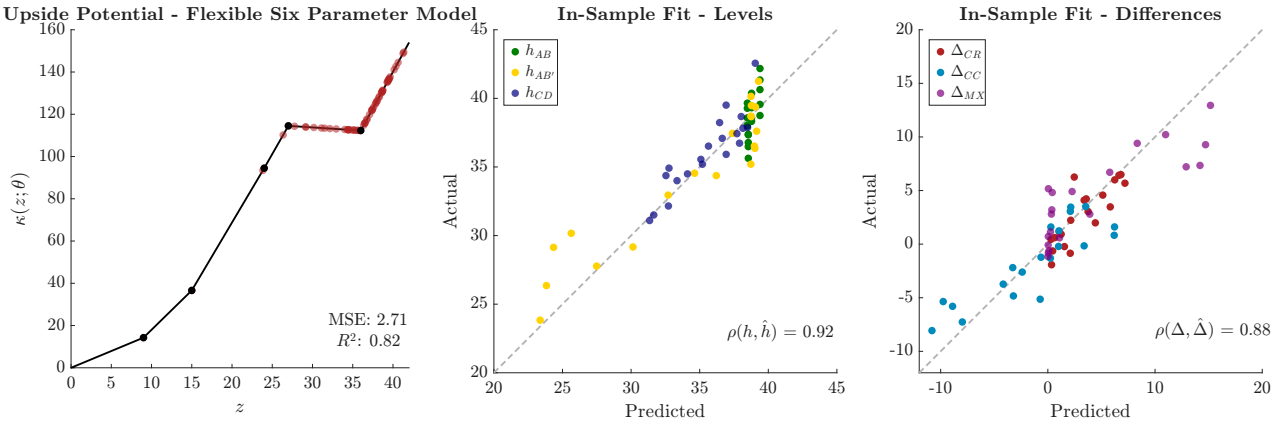


Figure F.1: Upside Potential Estimates - Flexible Six Parameter Model

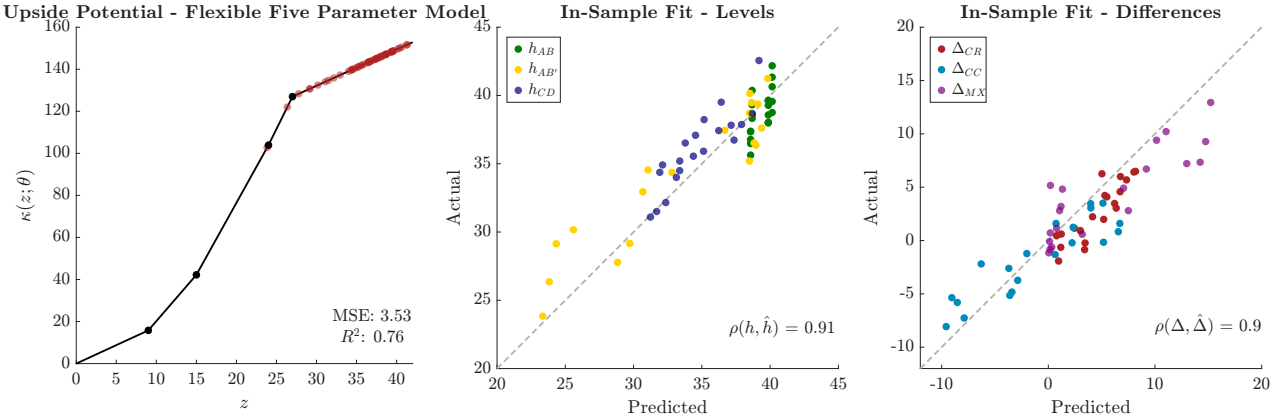


Figure F.2: Upside Potential Estimates - Flexible Five Parameter Model

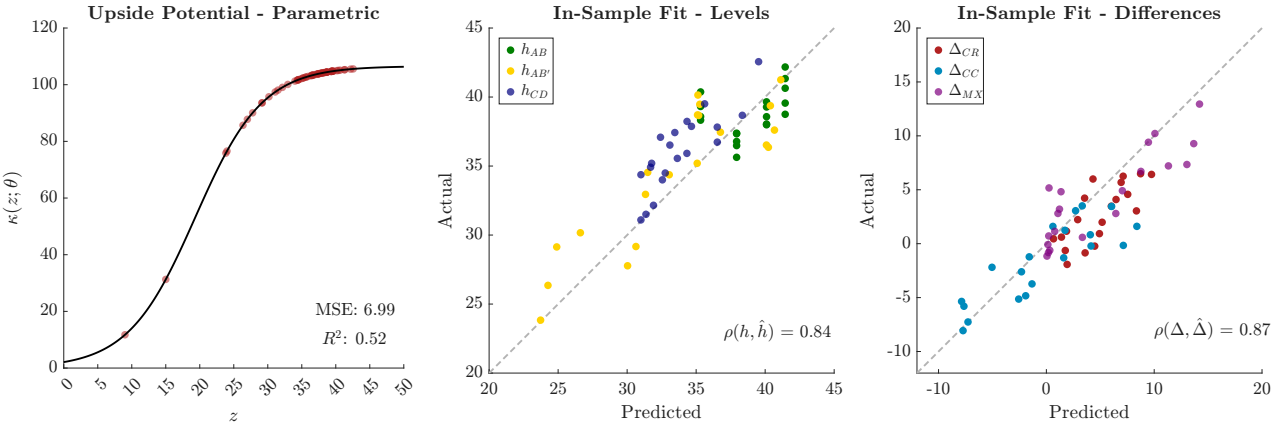


Figure F.3: Upside Potential Estimates - Parametric Functional Form

G Connections and Comparison to Prospect Theory Probability Weighting

In this appendix we provide in-sample comparison of the estimated fits between the UP model and various prospect theory formulations. Appendix G.1 shows that prospect theory fits substantially worse than upside potential even when endowed with more degrees of freedom. Appendix G.2 provides theoretical analysis establishing the distinction between the UP model and probability weighting that generates the differential fit.

G.1 Estimating Prospect-Theory Models

As a benchmark for the UP model, we also estimate several variants of prospect-theory models using the same 60 observations as used in the estimates of Appendix F.2. As in Appendix B.1, under original prospect theory (OPT) from Kahneman and Tversky (1979), a person's valuations are given by

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

As in Appendix B.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 their $h_{AB'}$ 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 begin with some canonical functional forms. 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),

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

and the two-parameter specification from Lattimore et al. (1992),

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

Columns (1) and (2) of Appendix Table G.1 report CPT estimates for these two functional forms for $\pi(q)$, and columns (4) and (5) report the corresponding OPT estimates. Appendix Figures G.1, G.2, G.4, and G.5 depict for each specification: (i) the estimated probability weighting function; (ii)

observed versus model-predicted h_{XY}; and (iii) observed versus model-predicted Δ .

All four prospect-theory specifications have poor in-sample fit and substantially underperform the three-parameter UP model. The best fitting variant 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. A negative R^2 value implies that predicting the sample mean for every response would outperform the model.

Although the PT estimates do not fit our data well overall, the estimated parameters for the one-parameter function are similar to those reported in previous studies. For example, using data on certainty equivalents for binary lotteries, Tversky and Kahneman (1992) report median estimates of $\alpha = 0.88$ and $\theta_1 = 0.61$. Likewise, Bernheim and Sprenger (2020) find $\alpha = 0.94$ and $\theta_1 = 0.72$ using similar data. In Appendix Table G.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 canonical probability-weighting forms perform poorly on our data, as they were designed to generate a global CRP and CCP. We therefore assess how much better CPT and OPT perform with a more flexible specification. Specifically, we consider the following six-part piecewise-linear functional form for probability weighting:

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

To give OPT and CPT additional flexibility, this piecewise-linear function permits (but does not require) discontinuities at $q = 0$ and $q = 1$. We select five interior knots $\{\bar{q}_i\}_{i=1}^5$ ex ante at probabilities where $\pi(\cdot)$ is most frequently evaluated, while roughly balancing observations per segment. For OPT we use $(\bar{q}_1, \ldots, \bar{q}_5) = (0.10, 0.30, 0.50, 0.70, 0.80)$ and for CPT we use $(0.10, 0.30, 0.50, 0.70, 0.90)$. This specification nests EU as a special case $\pi(q) = q$ when $\boldsymbol{\theta} = (0, 1, 1, 1, 1, 1, 1)$.

Columns (3) and (6) of Appendix Table G.1 report the flexible CPT and OPT estimates, respectively. Appendix Figures G.3 and G.6 depict the estimated probability weighting function and corresponding fit measures. For OPT, this added flexibility yields little improvement in fit—predicting the sample for every observation still outperforms the model. For CPT, this added flexibility improves

Table G.1: CPT and OPT Probability Weighting Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	CPT			**OPT**		
	Parametric 1	Parametric 2	Flexible	Parametric 1	Parametric 2	Flexible
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)
Weighting Parameters						
θ_1	0.84	1.84	0.20	0.79	0.93	0.04
	(0.03)	(0.22)	(0.04)	(0.02)	(0.02)	(0.01)
θ_2		0.63	1.85		0.75	1.17
		(0.03)	(0.13)		(0.03)	(0.13)
θ_3			1.07			0.94
			(0.05)			(0.06)
θ_4			0.62			0.73
			(0.07)			(0.09)
θ_5			0.29			0.51
			(0.10)			(0.13)
θ_6			0.54			1.32
			(0.11)			(0.21)
θ_7			0.69			0.98
			(0.16)			(0.16)
Observations	60	60	60	60	60	60
Degrees of Freedom	58	57	52	58	57	52
h_{XY}-MSE	33.88	18.03	11.02	26.85	26.17	21.71
h_{XY}-R^2	−1.31	−0.23	0.25	−0.83	−0.78	−0.48
$\rho(h_{XY}, \hat{h}_{XY})$	−0.20	0.55	0.71	0.22	0.30	0.45
Δ-MSE	41.48	24.01	19.92	32.51	31.39	29.30
Δ-R^2	−1.28	−0.32	−0.10	−0.79	−0.73	−0.61
$\rho(\Delta, \hat{\Delta})$	−0.51	0.70	0.72	0.22	0.39	0.49

Notes: Non-linear least squares regressions for CPT and OPT using 60 mean values of $h_{AB}, h_{AB'}, h_{CD}$. Standard errors in parentheses. Parametric 1 corresponds to the one-parameter ($\theta_1 = \delta$) probability-weighting function in Tversky and Kahneman (1992). Parametric 2 corresponds to the two-parameter ($(\theta_1, \theta_2) = (\gamma, \delta)$) probability-weighting function in Lattimore et al. (1992). Flexible refers to the six-part piecewise-linear functional form, with knots at {0.10,0.30,0.50,0.70,0.90} for CPT and {0.10,0.30,0.50,0.70,0.80} for OPT. 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 valuation levels, h_{XY}, and differences, Δ.

fit, roughly halving the MSE to 11.02 and producing a positive R^2 value. Nonetheless, the MSE for the best-performing CPT model is still around three times larger than our preferred UP model (which has three fewer degrees of freedom), while the R^2 is approximately three times smaller. Indeed, its

MSE is about 60 percent larger and its R^2 is about half as large as even our three-parameter UP model.

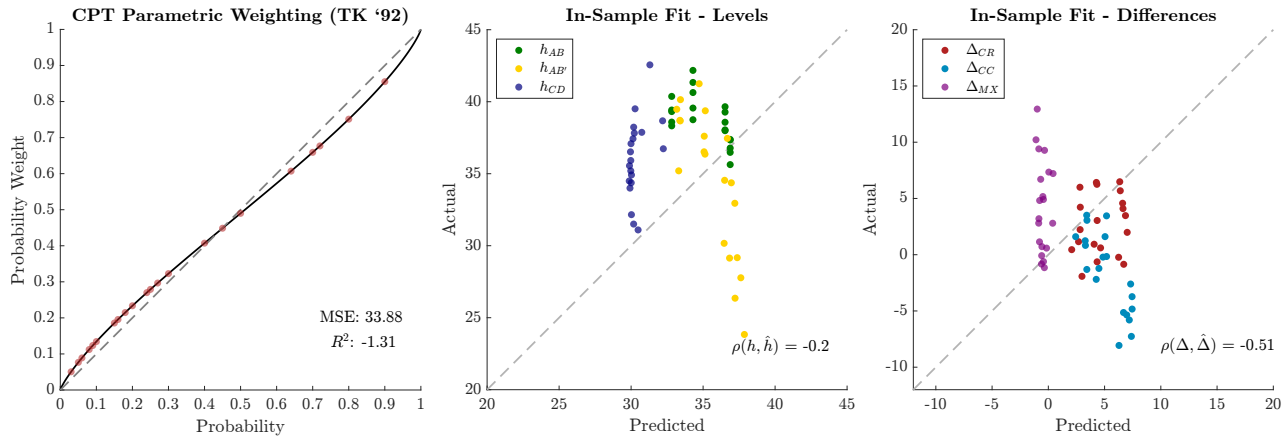


Figure G.1: CPT Probability Weighting Estimates - Parametric One Parameter Weighting Function

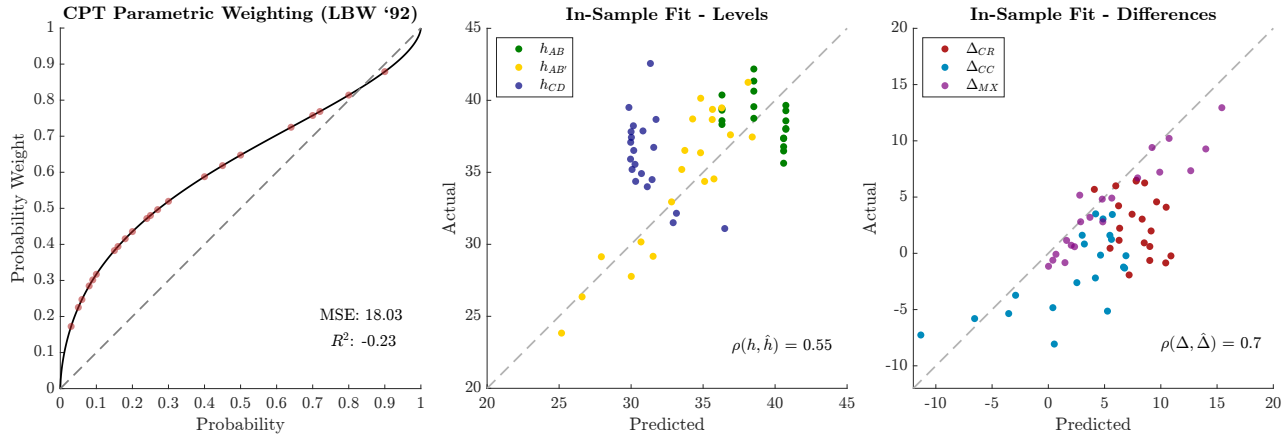


Figure G.2: CPT Probability Weighting Estimates - Parametric Two Parameter Weighting Function

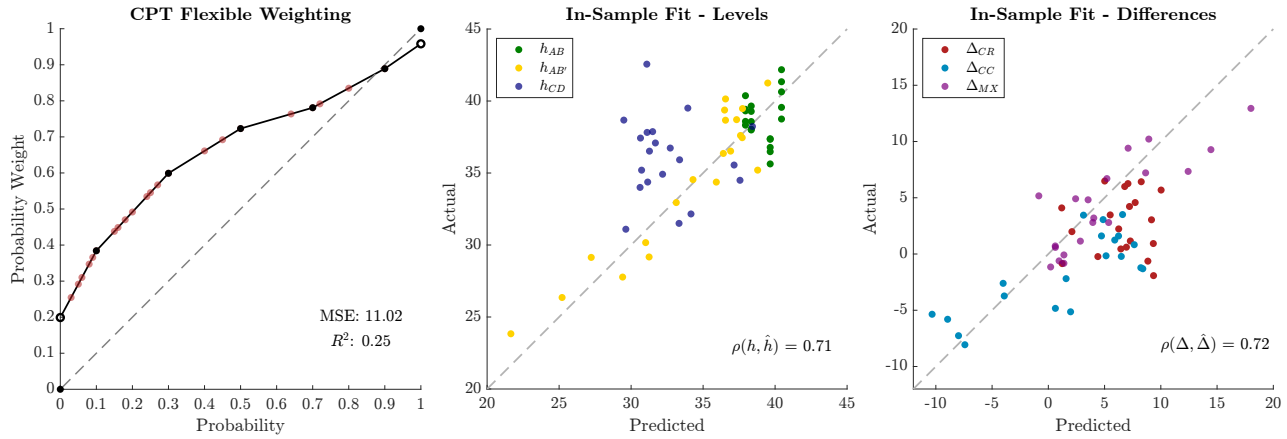


Figure G.3: CPT Probability Weighting Estimates - Flexible Functional Form

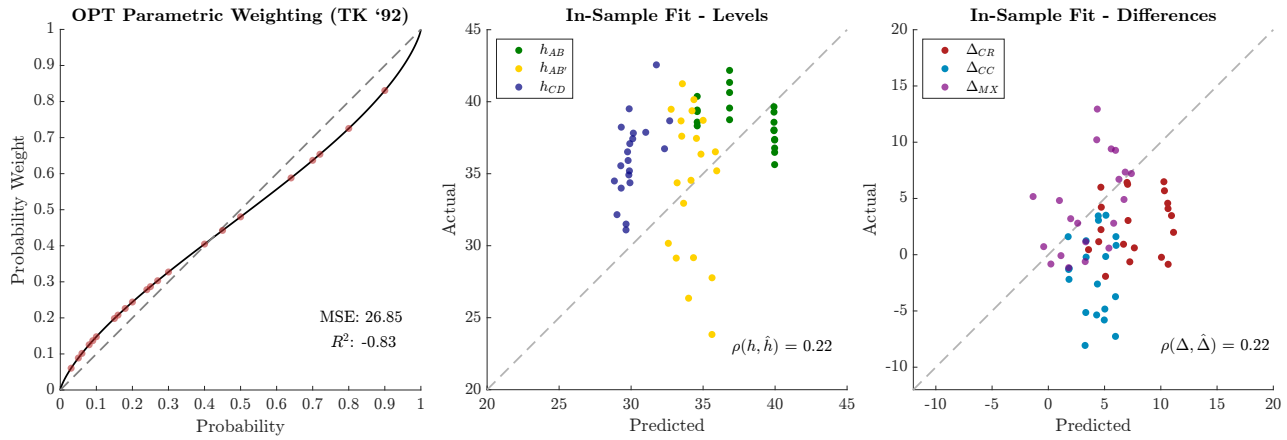


Figure G.4: OPT Probability Weighting Estimates - Parametric One Parameter Weighting Function

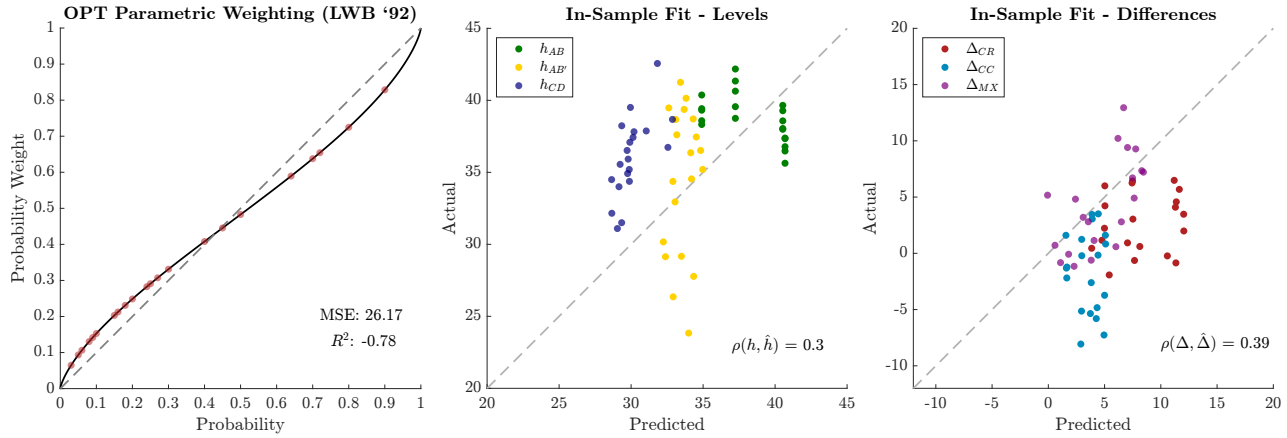


Figure G.5: OPT Probability Weighting Estimates - Parametric Two Parameter Weighting Function

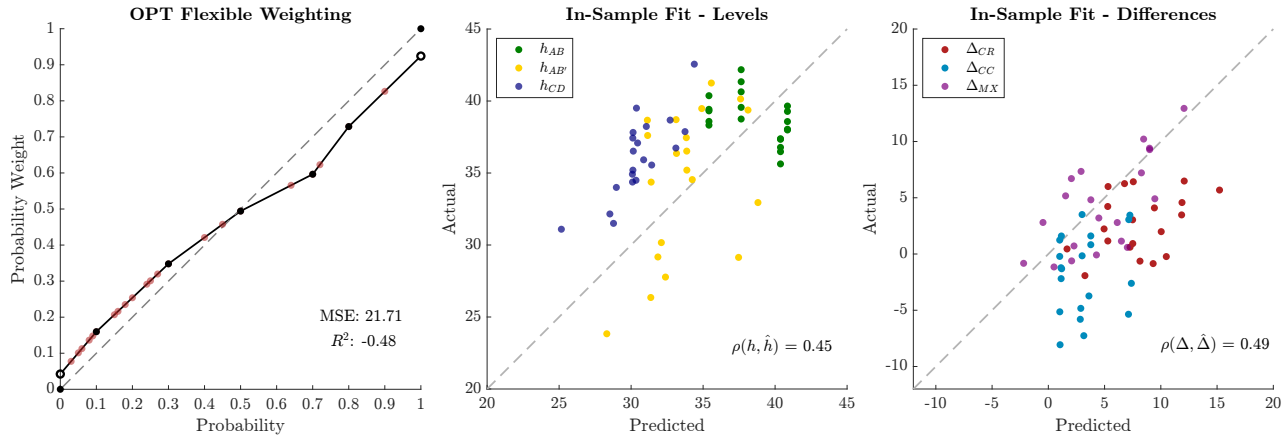


Figure G.6: OPT Probability Weighting Estimates - Flexible Functional Form

G.2 Distinguishing Upside Potential from Probability Weighting

Through Appendices F and G.1, we show that our model of upside potential provides a substantially better quantitative fit of our aggregate data than either CPT or OPT even when permitting flexible functional forms for probability weighting. In this section, we consider what properties of our model are fundamentally distinct from formulations of probability weighting which permit this improved fit.[11]

We focus on the different ways that probabilities enter into the models. Hence, throughout this section, we assume a linear κ function for our model (i.e., $\kappa(z) = \phi z$) and a linear value function for CPT or OPT (i.e., $v(z) = z$).[12]

We first assess whether either OPT or CPT with a flexible functional form for π could replicate the predictions from our UP model. Under OPT with a linear value function, the indifference values $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$ are determined from:

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

Under CPT with a linear value function, the indifference values are determined from:

$$\begin{aligned} M &= \pi(p)h^*_{AB} \\ M &= \pi(pr)h^*_{AB'} + [\pi(pr+1-r) - \pi(pr)]M \\ \pi(r)M &= \pi(pr)h^*_{CD} \end{aligned}$$

As discussed above, OPT and CPT coincide for binary lotteries, but not for the trinary lottery B'.

Under the UP model, when $u(x) = x$ and $\kappa(z) = \phi z$, the indifference values are determined from

$$M = \frac{p + p^2\phi}{1+\phi} h^*_{AB} \tag{G.2}$$

$$M = \frac{pr + (pr+1-r)(pr)\phi}{1+\phi} h^*_{AB'} + \frac{(1-r) + (pr+1-r)(1-r)\phi}{1+\phi} M \tag{G.3}$$

$$\frac{r + r^2\phi}{1+\phi} M = \frac{pr + (pr)^2\phi}{1+\phi} h^*_{CD} \tag{G.4}$$

If we were making predictions for decisions that involve only sure amounts or binary lotteries with one winning outcome, then either OPT or CPT with probability weighting function $\pi(q) = (q + q^2\phi)/(1+\phi)$ will generate the same predictions as our UP model. This general point is reflected in the equations above by the fact that the h^*_{AB} and h^*_{CD} conditions would be the same in all three

[11] We emphasize that a comparison of prospect theory to our model on our data is apt in the sense that the probability weighting function in prospect theory was developed specifically to speak to anomalies in CR and CC problems.

[12] For CPT or OPT, adding a slope parameter to the value function would not change predictions.

models. Hence, for decisions that involve only sure amounts or binary lotteries with one winning outcome, our UP model is a special case of either OPT or CPT, and thus if we had data on only such decisions, our model could not outperform OPT or CPT.

It is for decisions that involve trinary lotteries with two winning outcomes that neither OPT nor CPT can replicate the predictions of our model. To see this under OPT, note that it would need to be the case that the weight on $h^*_{AB'}$ in equation (G.3) can be expressed purely as a function of pr, the weight on M in equation (G.3) can be expressed purely as a function of $(1-r)$, and those two functions would need to be the same. Neither of the first two conditions holds, and thus clearly the third does not as well.

To see this under CPT, note that we can rewrite the CPT condition for $h^*_{AB'}$ as

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

and the UP condition for $h^*_{AB'}$ as

$$M = \frac{pr + (pr+1-r)(pr)\phi}{1+\phi}\left[h^*_{AB'} - M\right] + \frac{(pr+1-r) + (pr+1-r)^2\phi}{1+\phi}M.$$

Here, we can match the weight on M if we use $\pi(q) = (q+q^2\phi)/(1+\phi)$, but there is no way to express the weight on $(h^*_{AB'} - M)$ purely as a function of pr. For decisions that involve trinary lotteries, our UP model is therefore distinct from OPT and CPT even when we assume a linear κ function.

This analysis highlights a key difference between our model and OPT or CPT. For trinary lotteries, both CPT and OPT require that the weight applied to each outcome depend only on that outcome's probability (or cumulative probability in the case of CPT). For lottery B' this means the weight on the highest outcome $h^*_{AB'}$ must be a function solely of that outcome's probability, in this case pr. In contrast, under the UP model, the weight applied to outcome $h^*_{AB'}$ is a function both of pr and the total probability of winning, in this case $pr+1-r$. This fundamental distinction derives from the central psychology of the upside potential model: that winning probabilities can matter more the greater is the total chance of winning.

We can obtain further insights on the differences between the models by comparing the qualitative predictions for our experimental tasks of the UP model to the those of OPT or CPT when we assume probability weighting function $\pi(q) = (q+q^2\phi)/(1+\phi)$.

Proposition 2 establishes that for linear κ, the upside potential model predicts both CRP and MXP, with no prediction for the CC preference. As described above, with probability weighting function $\pi(q) = (q+q^2\phi)/(1+\phi)$, OPT and CPT both replicate the predictions of the UP model for the AB and CD tasks and thus both predict a CRP. Proposition A8 below establishes that OPT and CPT with this weighting function both further predict a CCP and an RMXP. In other words,

the two models would disagree on the MX preference, and might disagree on the CC preference.

Proposition A8. Suppose that $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$ is derived from OPT or CPT with a linear value function and probability weighting function $\pi(q) = \frac{q+q^2\phi}{1+\phi}$. For any $(p,r) \in (0,1)^2$, we must have:

(1) $\Delta^*_{CR} > 0$;

(2) $\Delta^*_{CC} > 0$; and

(3) $\Delta^*_{MX} < 0$.

Proof: First note that part (1) follows from part (1) of Proposition 2 combined with the logic in the text that, when using $\pi(q) = \frac{q+q^2\phi}{1+\phi}$, both OPT and CPT replicate the predictions from the UP model for the AB task and the CD task.

Next, note that under both OPT and CPT, the condition for h^*_{AB} is $M = \frac{p+p^2\phi}{1+\phi} h^*_{AB}$, and thus for any $r \in (0,1)$,

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

Consider the condition for $h^*_{AB'}$ under OPT. Define $f(h) \equiv \frac{pr+(pr)^2\phi}{1+\phi} h + \frac{(1-r)+(1-r)^2\phi}{1+\phi} M$, so under OPT, $h^*_{AB'}$ is defined by $M = f(h^*_{AB'})$. Because for any $r \in (0,1)$, $r\left(\frac{p+p^2\phi}{1+\phi}\right) > \frac{pr+(pr)^2\phi}{1+\phi}$ and $(1-r) > \frac{(1-r)+(1-r)^2\phi}{1+\phi}$, we must have $M > f(h^*_{AB})$. Since f is increasing in h, it follows that $h^*_{AB'} > h^*_{AB}$ and thus $\Delta^*_{MX} < 0$. Finally, the combination of $\Delta^*_{CR} > 0$ and $\Delta^*_{MX} < 0$ implies $\Delta^*_{CC} > 0$.

Now consider the condition for $h^*_{AB'}$ under CPT. Define

$$g(h) \equiv \left(\frac{pr+(pr)^2\phi}{1+\phi}\right)(h - M) + \left(\frac{(1-r+pr)+(1-r+pr)^2\phi}{1+\phi}\right) M,$$

so under CPT, $h^*_{AB'}$ is defined by $M = g(h^*_{AB'})$. Because for any $r \in (0,1)$, $\left(\frac{pr+p^2r\phi}{1+\phi}\right) > \frac{pr+(pr)^2\phi}{1+\phi}$ and $\left(\frac{(1-r+pr)+(1-r+p^2r)\phi}{1+\phi}\right) > \left(\frac{(1-r+pr)+(1-r+pr)^2\phi}{1+\phi}\right)$, we must have $M > g(h^*_{AB})$. Since g is increasing in h, it follows that $h^*_{AB'} > h^*_{AB}$ and thus $\Delta^*_{MX} < 0$. Finally, the combination of $\Delta^*_{CR} > 0$ and $\Delta^*_{MX} < 0$ implies $\Delta^*_{CC} > 0$.

■

Although it is not relevant for our analysis in this paper, we highlight one further distinction between our UP model and CPT. Under CPT, the weights attached to outcomes depend on their relative ranks, whereas under our UP model, they do not. To illustrate, consider a trinary lottery

$(x_1, q_1; x_2, q_2)$. Under CPT, if $x_1 > x_2 > 0$, this lottery is evaluated using $\pi(q_1)x_1 + [\pi(q_1 + q_2) - \pi(q_1)]x_2$, whereas if $x_2 > x_1 > 0$, it is evaluated using $\pi(q_2)x_2 + [\pi(q_1 + q_2) - \pi(q_2)]x_1$. Under our model with a linear κ function, for any $x_1 > 0$ and $x_2 > 0$, it is evaluated using $[1 + (q_1 + q_2)\phi]q_1x_1 + [1 + (q_1 + q_2)\phi]q_2x_2$. The weights that are applied to outcomes x_1 and x_2 under upside potential are symmetric—depending only on each outcome's probability and the total probability of winning—regardless of whether $x_1 > x_2$ or $x_2 > x_1$. This symmetry may be a valuable feature of the upside potential model given recent evidence of rank-independence in choice (Bernheim and Sprenger, 2020; Bernheim et al., 2022).

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

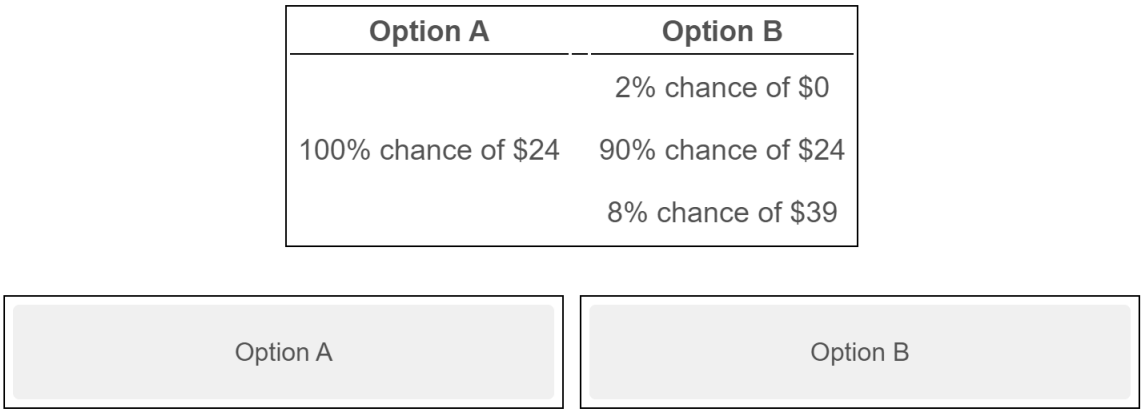


Figure H.4: Example AB' Binary Choice from Stage 2 with $p = 0.8$, $r = 0.1$, and $H = 39$

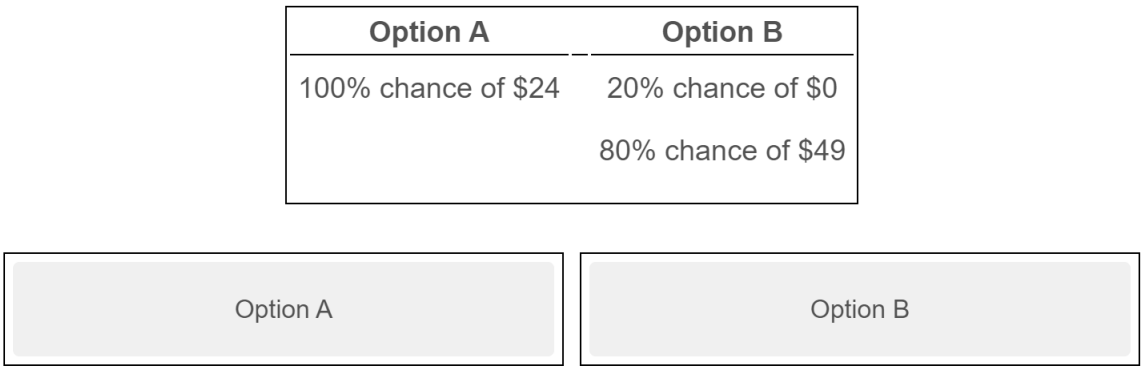


Figure H.5: Example AB Binary Choice from Stage 2 with $p = 0.8$, $r = 0.1$, and $H = 49$

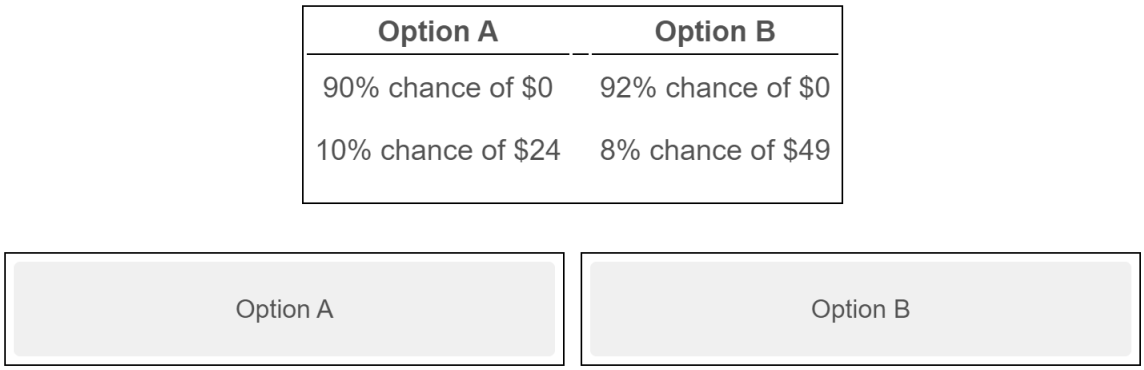


Figure H.6: Example CD Binary Choice from Stage 2 with $p = 0.8$, $r = 0.1$, and $H = 49$

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 H.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 H.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 H.9: Example Visual Search Task

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