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.

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: $\rho(h_{AB}, h'_{AB})$		
$p = 0.3$	0.256	0.369	0.422	0.372	0.617
$p = 0.5$	0.402	0.464	0.540	0.586	0.696
$p = 0.8$	0.428	0.545	0.395	0.447	0.641
$p = 0.9$	0.314	0.497	0.402	0.519	0.548
			Panel B: $\rho(h_{AB'}, h'_{AB'})$		
$p = 0.3$	0.254	0.492	0.439	0.433	0.545
$p = 0.5$	0.320	0.406	0.445	0.619	0.614
$p = 0.8$	0.564	0.444	0.461	0.475	0.584
$p = 0.9$	0.292	0.514	0.385	0.355	0.483
			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: Means and Sign Tests

Probability (p)	(1) Common Ratio (r)	(2) Δ (Mean)	(3) Mean Test (p-value)	(4) Number of Cases: $\Delta > 0$	(5) Number of Cases: $\Delta = 0$	(6) Number of Cases: $\Delta < 0$	(7) Sign Test (p-value)	(8) 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 Supplementary Material D.1 for test descriptions.

Table A.5: 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 4.2 and Supplementary Material E.1 for details). The final line presents averages over all 20 rows.

Table A.6: Preference-Noise Decomposition Using Estimates from Appendix Table A.5

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.5 (see Section 4.2 and Supplementary Material E.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 Supplementary Material E.2). The final line presents averages over all 20 rows.

Table A.7: Sensitivity of Results to Experimental Parameters in our Stage 2 Experiments

Panel A. Experimental-Parameter Sensitivity

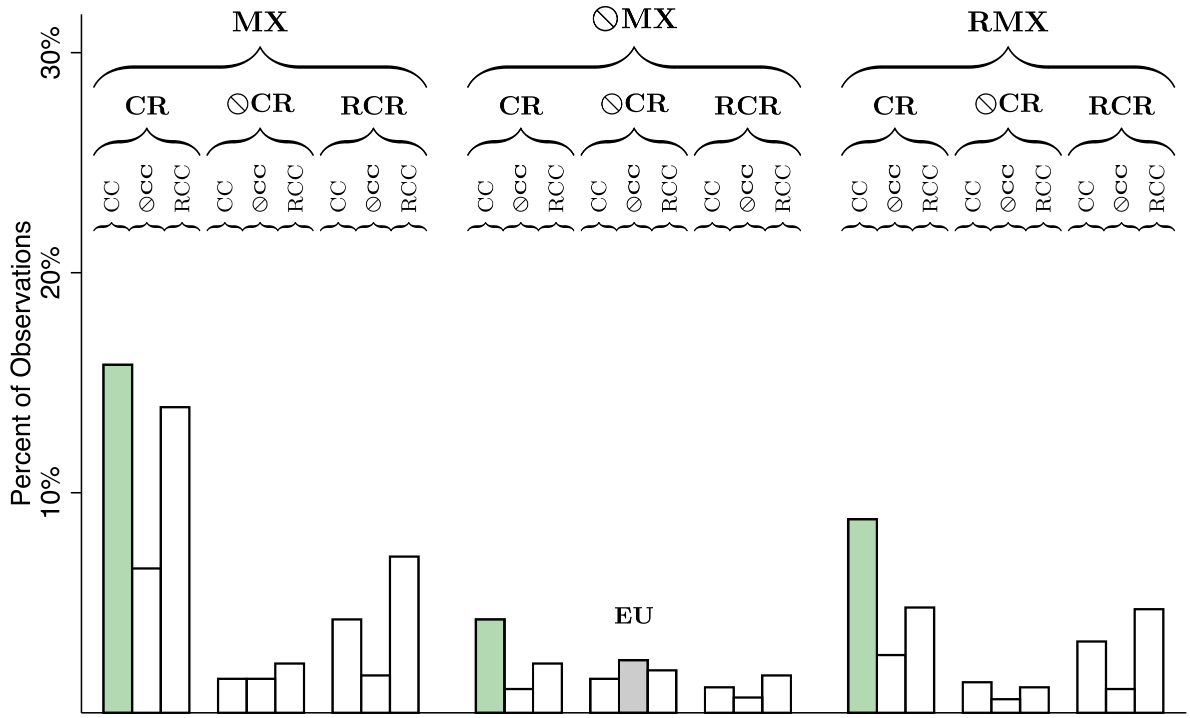
	(1) CR Study	(2) CC Study	(3) MX Study
Probability (p)	23.25	49.57	−28.62
	(6.16)	(6.14)	(5.89)
Common Ratio (r)	−35.19	−2.70	−29.88
	(2.47)	(2.52)	(2.30)
Outcome Mean	10.45	−5.77	16.00
Experiments	120	120	120
Observations	8,408	8,408	8,408

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

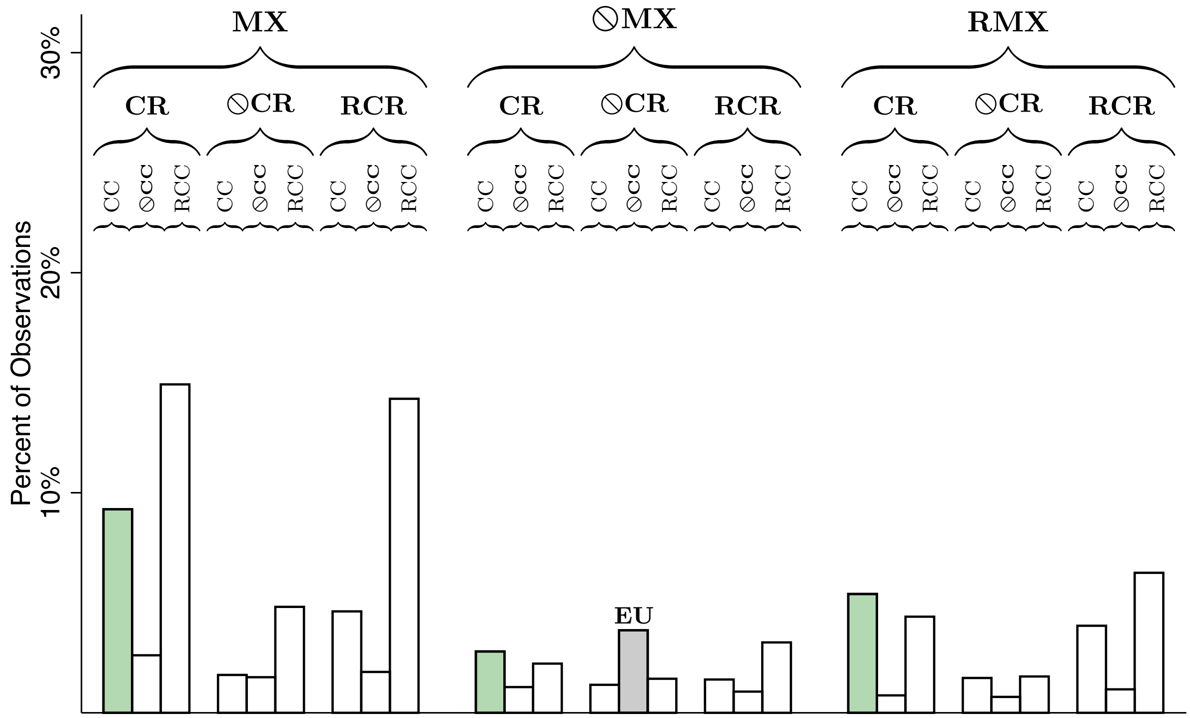
Notes: Panel A presents linear regressions that assess the sensitivity of experimental results from CR, CC, or MX studies from our stage 2 experiments. The specifications include the probability of the high outcome (p), the common ratio (r) linearly, and a constant. Column (1) presents the results for 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 CC 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.

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



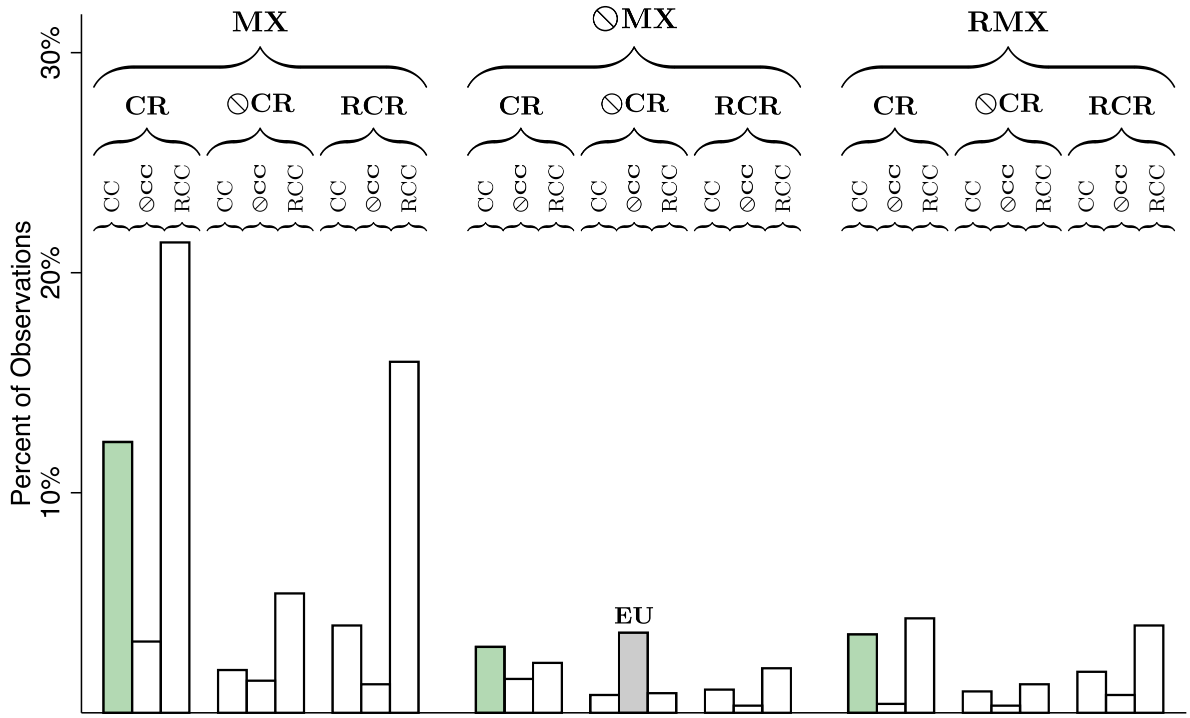
Notes: Figure presents histogram of $(sign(\Delta_{CR}), sign(\Delta_{CC}), sign(\Delta_{MX}))$ combinations, where $\Delta_{CR} = h_{AB} - h_{CD}$, $\Delta_{CC} = h_{AB'} - h'_{DE}$, and $\Delta_{MX} = h'_{AB} - h'_{AB'}$. Each variable can have three potential signs, leading to 27 possible patterns. 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 $p \notin \{0.8, 0.9\}$



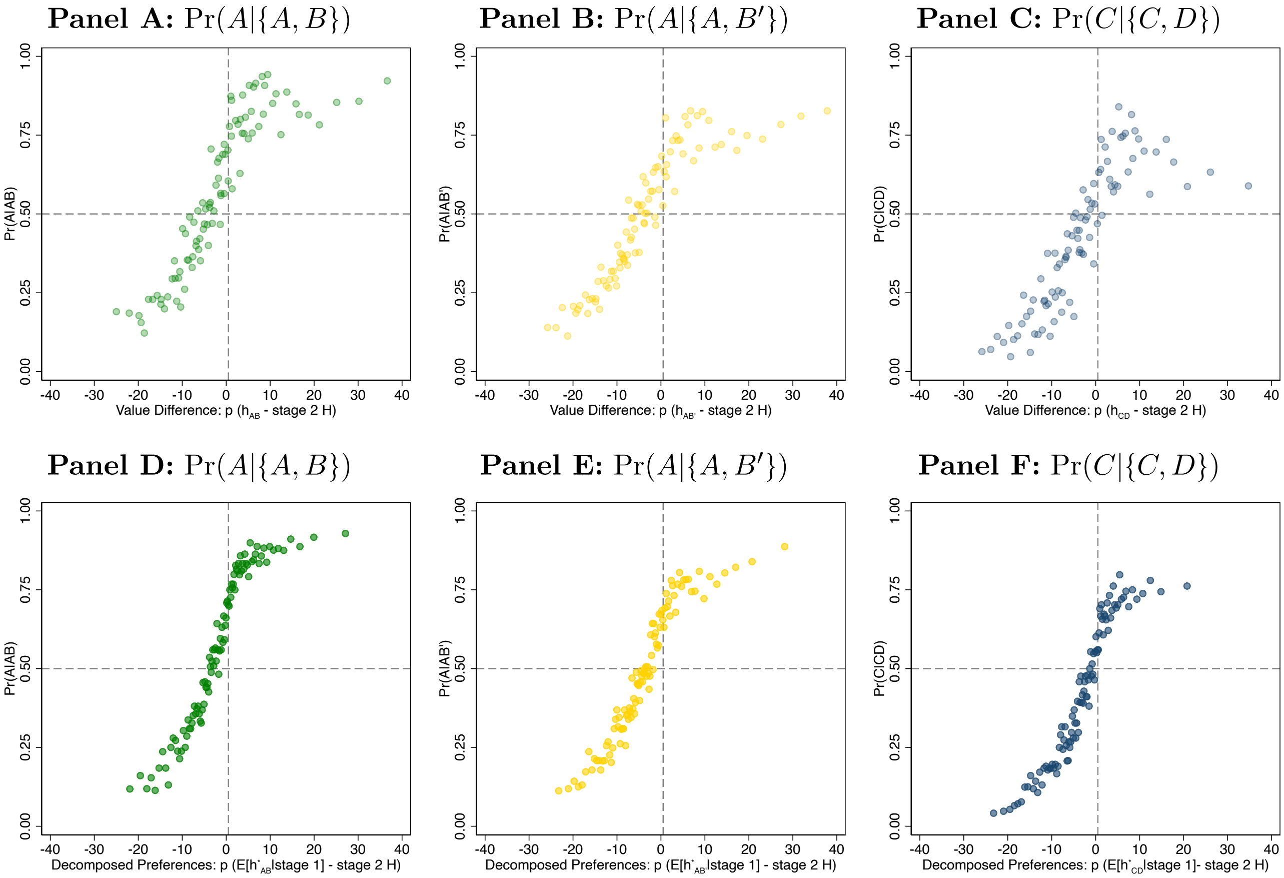
Notes: Figure presents histogram of $(sign(\Delta_{CR}), sign(\Delta_{CC}), sign(\Delta_{MX}))$ combinations, where $\Delta_{CR} = h_{AB} - h_{CD}$, $\Delta_{CC} = h_{AB'} - h'_{DE}$, and $\Delta_{MX} = h'_{AB} - h'_{AB'}$. Each variable can have three potential signs, leading to 27 possible patterns. 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 $\Delta_{CR} = h_{AB} - h_{CD}$, $\Delta_{CC} = h_{AB'} - h'_{DE}$, 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 2,508 observations from the parameters $r \in \{0.1, 0.2, 0.3\}$ or $p \in \{0.3, 0.5\}$ for which we elicit h'_{AB} and $h'_{AB'}$. Patterns marked in light green are ones with $\Delta_{CR} > 0$ and $\Delta_{CC} > 0$.

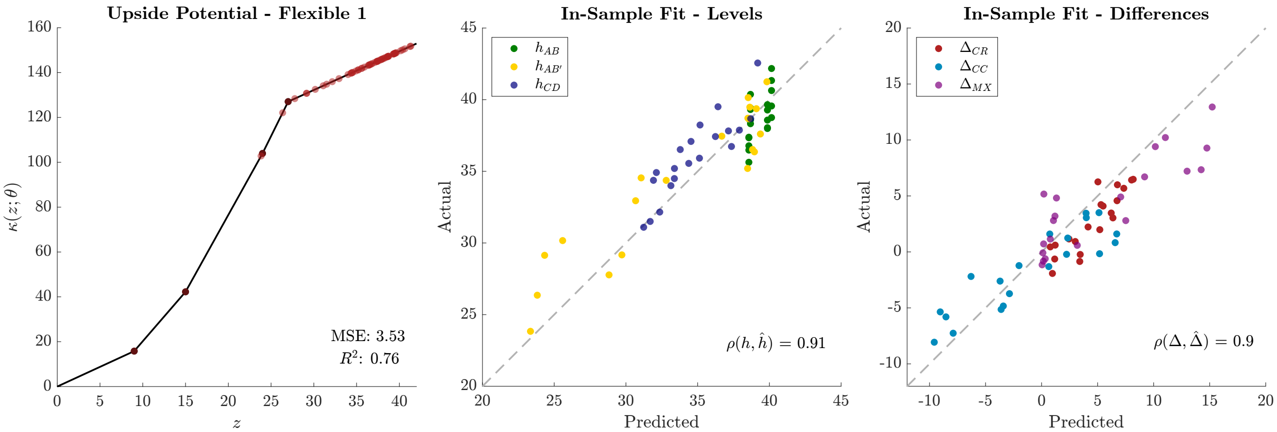
Figure A.4: Predicting Stage 2 Choice Probabilities using Stage 1 Valuations



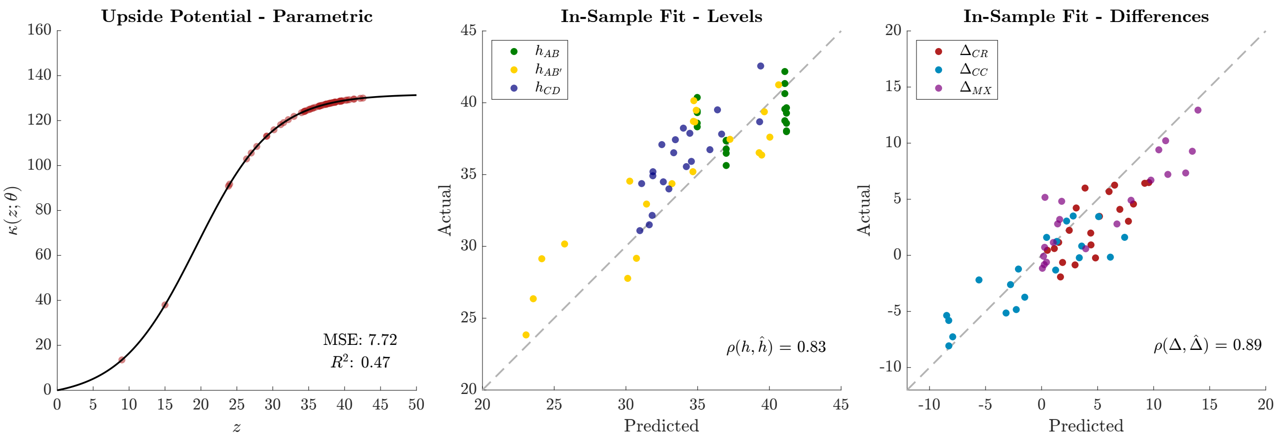
Notes: Figure relates individual stage 1 measures of $h_{XY} - H$ to stage 2 choice shares $\Pr(X|\{X,Y\})$. Panels A-C use raw stage 1 responses. Panels D-F use the estimated population distribution of preferences from the decomposition in Section 4.2 combined with a participant's raw stage 1 valuations 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 Supplementary Material D.3 for details).

Figure A.5: Structural Estimates and Model Fit

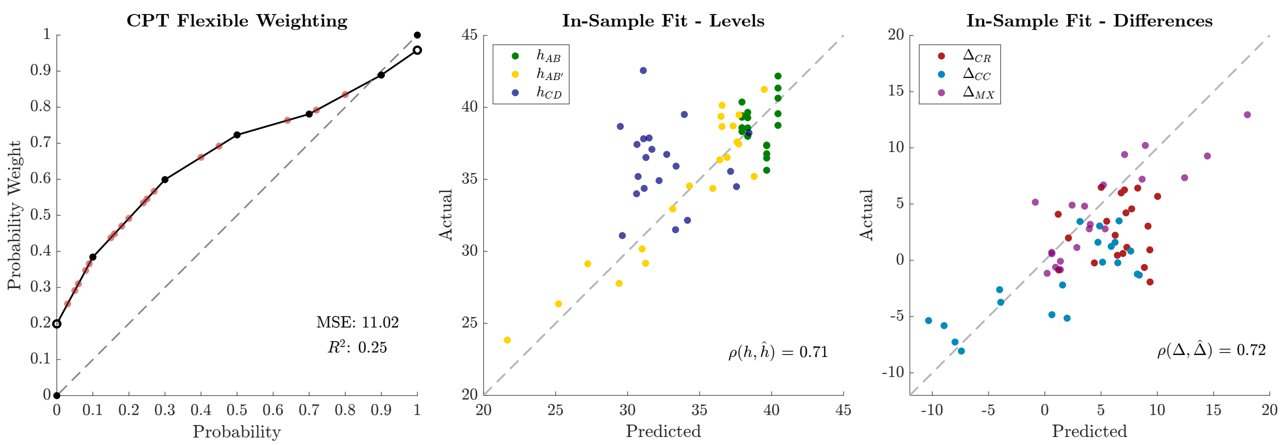
Panel A: Upside Potential Estimates − Flexible Five Parameter Model



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 Upside-Potential Model: Predictions

B.1 Predictions for the Upside-Potential Model

In this section, we provide a Proof of Proposition 1 and derive the additional model predictions discussed in Section 5.2 of the main text. For completeness, we replicate the model assumptions here. Given a lottery $(H, q_H; M, q_M; 0, 1 - q_H - q_M)$, a person evaluates the lottery using decision utility function:

$$U = [q_H H + q_M M] + (q_H + q_M) [q_H \kappa(H) + q_M \kappa(M)] \tag{B.1}$$

where $\kappa(x)$ is strictly increasing in x. For binary lotteries with $q_M = 0$, this formulation reduces to

$$U = q_H H + q_H^2 \kappa(H),$$

and for certain payments with $q_M = 1$, it reduces to

$$U = M + \kappa(M).$$

It is worth highlighting that this model respects first order stochastic dominance on its domain, $(H, q_H; M, q_M; 0, 1 - q_H - q_M)$. Consider two lotteries $f = (H, q_H; M, q_M; 0, 1 - q_H - q_M)$ and $g = (H', q'_H; M', q'_M; 0, 1 - q'_H - q'_M)$ and suppose f first order stochastically dominates (fosd) g. One implication of f fosd g is that $q_M + q_H \geqslant q'_M + q'_H$; otherwise f would have higher probability of zero. Standard results from EU with a monotonic utility function imply $[q_H H + q_M M] \geqslant [q'_H H' + q'_M M']$ which in turn implies $[q_H \kappa(H) + q_M \kappa(M)] \geqslant [q'_H \kappa(H') + q'_M \kappa(M')]$ for increasing $\kappa(\cdot)$. Combining these two properties with $q_M + q_H \geqslant q'_M + q'_H$ implies

$$[q_H H + q_M M] + (q_H + q_M) [q_H \kappa(H) + q_M \kappa(M)] \geqslant [q'_H H' + q'_M M'] + (q'_H + q'_M) [q'_H \kappa(H') + q'_M \kappa(M')]$$

and hence $U(f) \geqslant U(g)$.

Applying this model to the context of our experiment, the triplet $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$ solves

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

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

$$rM + r^2 \kappa(M) = pr h^*_{CD} + (pr)^2 \kappa(h^*_{CD}). \tag{B.4}$$

We then characterize behavior in this model in Proposition 1:

Proposition A1. Suppose that $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$ is derived from equations (B.2), (B.3), and (B.4). For any $(p, r) \in (0, 1)^2$ and $\kappa(x)$ that is strictly increasing in X:

(1) A person's Δ^*_{CR}, Δ^*_{CC}, and Δ^*_{MX} satisfy:

(a) $\Delta^*_{CR} > 0$ if and only if $\kappa(M) > p^2\kappa(h^*_{AB}) > p^2\kappa(h^*_{CD})$;
$\Delta^*_{CR} < 0$ if and only if $\kappa(M) < p^2\kappa(h^*_{AB}) < p^2\kappa(h^*_{CD})$; and
$\Delta^*_{CR} = 0$ if and only if $\kappa(M) = p^2\kappa(h^*_{AB}) = p^2\kappa(h^*_{CD})$.

(b) $\Delta^*_{CC} > 0$ if and only if $\kappa(M) > \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'}) > \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$;
$\Delta^*_{CC} < 0$ if and only if $\kappa(M) < \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'}) < \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$; and
$\Delta^*_{CC} = 0$ if and only if $\kappa(M) = \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'}) = \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$.

(c) $\Delta^*_{MX} > 0$ if and only if $\kappa(M) < p\kappa(h^*_{AB'}) < p\kappa(h^*_{AB})$;
$\Delta^*_{MX} < 0$ if and only if $\kappa(M) > p\kappa(h^*_{AB'}) > p\kappa(h^*_{AB})$; and
$\Delta^*_{MX} = 0$ if and only if $\kappa(M) = p\kappa(h^*_{AB'}) = p\kappa(h^*_{AB})$.

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

(3) The 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 $\Delta^*_{MX} > 0$	(⃠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−⃠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− ⃠MXP)
P4:	$\Delta^*_{CC} > \Delta^*_{CR} > 0$ and $\Delta^*_{MX} < 0$	(CRP−CCP−RMXP).

Proof:

(1a) Recall that $\Delta^*_{CR} = h^*_{AB} - h^*_{CD}$, where h^*_{AB} and h^*_{CD} are derived from equations (B.2) and (B.4). We can rewrite equation (B.4) as

$$M + \kappa(M) = ph^*_{CD} + p^2\kappa(h^*_{CD}) + (1-r)\left(\kappa(M) - p^2\kappa(h^*_{CD})\right),$$

and combining this equation with equation (B.2) yields

$$ph^*_{AB} + p^2\kappa(h^*_{AB}) = ph^*_{CD} + p^2\kappa(h^*_{CD}) + (1-r)\left(\kappa(M) - p^2\kappa(h^*_{CD})\right).$$

Proof of CD condition: Because $ph + p^2\kappa(h)$ is strictly increasing in h, this equation implies $h^*_{AB} > h^*_{CD}$ if and only if $\kappa(M) > p^2\kappa(h^*_{CD})$, $h^*_{AB} < h^*_{CD}$ if and only if $\kappa(M) < p^2\kappa(h^*_{CD})$, and $h^*_{AB} = h^*_{CD}$ if and only if $\kappa(M) = p^2\kappa(h^*_{CD})$.

Proof of AB condition: Define $f(h) = ph + p^2\kappa(h) + (1-r)(\kappa(M) - p^2\kappa(h))$, so h^*_{CD} is defined by $f(h^*_{CD}) = M + \kappa(M)$. Because f is strictly increasing in h, $h^*_{AB} > h^*_{CD}$ if and only if $f(h^*_{AB}) > M + \kappa(M)$, which based on equation (B.2) holds if and only if $\kappa(M) > p^2\kappa(h^*_{AB})$. Analogously, $h^*_{AB} < h^*_{CD}$ if and only if $f(h^*_{AB}) < M + \kappa(M)$ or $\kappa(M) < p^2\kappa(h^*_{AB})$, and $h^*_{AB} = h^*_{CD}$ if and only if $f(h^*_{AB}) = M + \kappa(M)$ or $\kappa(M) = p^2\kappa(h^*_{AB})$.

Finally, note that when $\Delta^*_{CR} > 0$ and thus $h^*_{AB} > h^*_{CD}$, κ strictly increasing implies $p^2\kappa(h^*_{AB}) > p^2\kappa(h^*_{CD})$. Analogously, $\Delta^*_{CR} < 0$ implies $p^2\kappa(h^*_{AB}) < p^2\kappa(h^*_{CD})$, and $\Delta^*_{CR} = 0$ implies $p^2\kappa(h^*_{AB}) = p^2\kappa(h^*_{CD})$. The result follows.

(1b) Recall that $\Delta^*_{CC} = h^*_{AB'} - h^*_{CD}$, where $h^*_{AB'}$ and h^*_{CD} are derived from equations (B.3) and (B.4). We can rewrite equation (B.3) as

$$rM + r^2\kappa(M) = prh^*_{AB'} + (pr)^2\kappa(h^*_{AB'}) + (1-r)r\left(p\kappa(h^*_{AB'}) - (2-p)\kappa(M)\right),$$

and combining this equation with equation (B.4) yields

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

Proof of AB' condition: Because $prh + (pr)^2\kappa(h)$ is strictly increasing in h, this equation implies $h^*_{AB'} > h^*_{CD}$ if and only if $\kappa(M) > \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'})$, $h^*_{AB'} < h^*_{CD}$ if and only if $\kappa(M) < \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'})$, and $h^*_{AB'} = h^*_{CD}$ if and only if $\kappa(M) = \left(\frac{p}{2-p}\right)\kappa(h^*_{AB'})$.

Proof of CD condition: Define $f(h) = prh + (pr)^2\kappa(h) + (1-r)r\left(p\kappa(h) - (2-p)\kappa(M)\right)$, so $h^*_{AB'}$ is defined by $f(h^*_{AB'}) = rM + r^2\kappa(M)$. Because f is strictly increasing in h, $h^*_{AB'} > h^*_{CD}$ if and only if $f(h^*_{CD}) < rM + r^2\kappa(M)$, which holds if and only if $\kappa(M) > \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$. Analogously, $h^*_{AB'} < h^*_{CD}$ if and only if $f(h^*_{CD}) > rM + r^2\kappa(M)$ or $\kappa(M) < \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$, and $h^*_{AB'} = h^*_{CD}$ if and only if $f(h^*_{CD}) = rM + r^2\kappa(M)$ or $\kappa(M) = \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$.

Finally, note that when $\Delta^*_{CC} > 0$ and thus $h^*_{AB'} > h^*_{CD}$, κ strictly increasing implies $\left(\frac{p}{2-p}\right)\kappa(h^*_{AB'}) > \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$. Analogously, $\Delta^*_{CC} < 0$ implies $\left(\frac{p}{2-p}\right)\kappa(h^*_{AB'}) < \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$, and $\Delta^*_{CC} = 0$ implies $\left(\frac{p}{2-p}\right)\kappa(h^*_{AB'}) = \left(\frac{p}{2-p}\right)\kappa(h^*_{CD})$.

(1c) Recall that $\Delta^*_{MX} = h^*_{AB} - h^*_{AB'}$, where h^*_{AB} and $h^*_{AB'}$ are derived from equations (B.2) and (B.3). We can rewrite equation (B.3) as

$$M + \kappa(M) = ph^*_{AB'} + p^2\kappa(h^*_{AB'}) + (1-r)(1-p)\left(p\kappa(h^*_{AB'}) - \kappa(M)\right),$$

and combining this equation with equation (B.2) yields

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

Proof of AB' condition: Because $ph + p^2\kappa(h)$ is strictly increasing in h, this equation implies $h^*_{AB} > h^*_{AB'}$ if and only if $\kappa(M) < p\kappa(h^*_{AB'})$, $h^*_{AB} < h^*_{AB'}$ if and only if $\kappa(M) > p\kappa(h^*_{AB'})$, and $h^*_{AB} = h^*_{AB'}$ if and only if $\kappa(M) = p\kappa(h^*_{AB'})$.

Proof of AB condition: Define $f(h) = ph + p^2\kappa(h) + (1-r)(1-p)(p\kappa(h) - \kappa(M))$, so $h^*_{AB'}$ is defined by $f(h^*_{AB'}) = M + \kappa(M)$. Because f is strictly increasing in h, $h^*_{AB} > h^*_{AB'}$ if and only if $f(h^*_{AB}) > M + \kappa(M)$, which holds if and only if $\kappa(M) < p\kappa(h^*_{AB})$. Analogously, $h^*_{AB} < h^*_{AB'}$ if and only if $f(h^*_{AB}) < M + \kappa(M)$ or $\kappa(M) > p\kappa(h^*_{AB})$, and $h^*_{AB} = h^*_{AB'}$ if and only if $f(h^*_{AB}) = M + \kappa(M)$ or $\kappa(M) = p\kappa(h^*_{AB})$.

Finally, note that when $\Delta^*_{MX} > 0$ and thus $h^*_{AB} > h^*_{AB'}$, κ strictly increasing implies $p\kappa(h^*_{AB'}) < p\kappa(h^*_{AB})$. Analogously, $\Delta^*_{MX} < 0$ implies $p\kappa(h^*_{AB'}) > p\kappa(h^*_{AB})$, and $\Delta^*_{MX} = 0$ implies $p\kappa(h^*_{AB'}) = p\kappa(h^*_{AB})$. The result follows.

(2) From 1a, $\Delta^*_{CR} \leqslant 0$ if and only if $\kappa(M) \leqslant p^2\kappa(h^*_{AB}) \leqslant p^2\kappa(h^*_{CD})$. Because $p^2 < \frac{p}{2-p}$ for any $p \in (0,1)$, it follows that $\kappa(M) < \frac{p}{2-p}\kappa(h^*_{CD})$, and thus from 1b it follows that $\Delta^*_{CC} < 0$. Similarly, because $p^2 < p$ for any $p \in (0,1)$, it follows that $\kappa(M) < p\kappa(h^*_{AB})$, and thus from 1c it follows that $\Delta^*_{MX} > 0$.

From 1b, $\Delta^*_{CC} \leqslant 0$ if and only if $\frac{p}{2-p}\kappa(h^*_{AB'})$. Because $\frac{p}{2-p} < p$ for any $p \in (0,1)$, it follows that $\kappa(M) < p\kappa(h^*_{AB'})$, and thus from 1c it follows that $\Delta^*_{MX} > 0$. The result follows (and note that the "equivalently" sentence follows directly from the initial sentence).

(3) First, recall that $\Delta^*_{MX} = \Delta^*_{CR} - \Delta^*_{CC}$, and thus $\Delta^*_{MX} > 0$ implies $\Delta^*_{CR} > \Delta^*_{CC}$, $\Delta^*_{MX} = 0$ implies $\Delta^*_{CR} = \Delta^*_{CC}$, and $\Delta^*_{MX} < 0$ implies $\Delta^*_{CR} < \Delta^*_{CC}$. The result follows directly from this observation combined with part 2. Specifically, when $\Delta^*_{CR} \leqslant 0$, we must have $\Delta^*_{CC} < 0$ and $\Delta^*_{MX} > 0$, and thus $\Delta^*_{CR} > \Delta^*_{CC}$, yielding patterns P1 and P12. When $\Delta^*_{CR} > 0$ but $\Delta^*_{CC} \leqslant 0$, we must have $\Delta^*_{MX} > 0$ and thus $\Delta^*_{CR} > \Delta^*_{CC}$, yielding patterns P2 and P23. When $\Delta^*_{CR} > 0$ and $\Delta^*_{CC} > 0$ but $\Delta^*_{MX} \geqslant 0$, we must have $\Delta^*_{CR} \geqslant \Delta^*_{CC}$, yielding patterns P3 and P34. Finally, When $\Delta^*_{CR} > 0$, $\Delta^*_{CC} > 0$, and $\Delta^*_{MX} < 0$, we must have $\Delta^*_{CR} < \Delta^*_{CC}$, yielding pattern P4. This completes all possibilities consistent with part 2.

■

In the main text, we discuss the importance of the special case of our model where the function κ is linear (i.e., $\kappa(x) = \phi x$ for some $\phi > 0$). This case highlights that MXP emerges in our model due to the way that probabilities enter, and not because the function κ has some special structure.

Proposition A2. Suppose that $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$ is derived from equations (B.2), (B.3), and (B.4), and further suppose that $\kappa(x) = \phi x$ for some $\phi > 0$. For any $(p, r) \in (0, 1)^2$, we must have:

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

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

(3) Δ^*_{CC} could be positive, negative, or zero.

Proof: When $\kappa(z) = \phi z$, equation (B.2) becomes

$$M + \phi M = p h^*_{AB} + p^2 \phi h^*_{AB} \qquad \Longleftrightarrow \qquad h^*_{AB} = \frac{1+\phi}{1+p\phi}\frac{M}{p},$$

equation (B.3) becomes

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

$$\Longleftrightarrow \qquad h^*_{AB'} = \frac{1 + (2 - p - r + pr)\phi}{1 + (1 - r + pr)\phi}\frac{M}{p},$$

and equation (B.4) becomes

$$rM + r^2\phi M = pr h^*_{CD} + (pr)^2 \phi h^*_{CD} \qquad \Longleftrightarrow \qquad h^*_{CD} = \frac{1 + r\phi}{1 + pr\phi}\frac{M}{p}.$$

We have $\Delta^*_{CR} > 0$ if and only if $h^*_{AB} > h^*_{CD}$, which holds if and only if

$$\frac{1+\phi}{1+p\phi} > \frac{1+r\phi}{1+pr\phi} \quad \Longleftrightarrow \quad (1+\phi)(1+pr\phi) > (1+r\phi)(1+p\phi)$$

$$\Longleftrightarrow \quad 1+\phi+pr\phi+pr\phi^2 > 1+r\phi+p\phi+pr\phi^2 \quad \Longleftrightarrow \quad \phi(1-r)(1-p) > 0.$$

Since this inequality holds for any $(p,r) \in (0,1)^2$, $\Delta^*_{CR} > 0$ for any $(p,r) \in (0,1)^2$.

Next, we have $\Delta^*_{MX} > 0$ if and only if $h^*_{AB} > h^*_{AB'}$, which holds if and only if

$$\frac{1+\phi}{1+p\phi} > \frac{1+(2-p-r+pr)\phi}{1+(1-r+pr)\phi} \quad \Longleftrightarrow \quad (1+\phi)(1+(1-r+pr)\phi) > (1+(2-p-r+pr)\phi)(1+p\phi)$$

$$\Longleftrightarrow \quad 1+(2-r+pr)\phi+(1-r+pr)\phi^2 > 1+(2-r+pr)\phi+(2p-p^2-pr+p^2r)\phi^2$$

$$\Longleftrightarrow \quad 1-r-2p+2pr+p^2-p^2r > 0 \quad \Longleftrightarrow \quad (1-r)(1-p)^2 > 0.$$

Since this inequality holds for any $(p,r) \in (0,1)^2$, it follows that $\Delta^*_{MX} > 0$ for any $(p,r) \in (0,1)^2$.

Finally, it is straightforward to construct examples where Δ^*_{CC} is positive, zero, or negative.

■

According to Proposition A2, our model with a linear κ function predicts behavior must take on one of patterns P2, P23, or P3. While a linear κ function can generate our model pattern P2, we describe in Section 5.1 how a linear κ cannot explain all instances of pattern P2. We provide the details in the following example.

Example: Explaining Mean Valuations when $(p = 0.5, r = 0.2)$ with a κ Function

In our stage 1 data, when $p = 0.5$ and $r = 0.2$, the mean responses are $h_{AB} = 38$, $h_{AB'} = 29$ and $h_{CD} = 33$. Hence, part 1 of Proposition 1 implies that κ must satisfy:

$$\frac{1}{2}\kappa(29) > \frac{1}{3}\kappa(29) > \kappa(15) > \frac{1}{4}\kappa(38).$$

We show here that one can combine the second and third inequalities to derive that:

$$\frac{\kappa(29)-\kappa(15)}{14} > \frac{\kappa(15)-\kappa(0)}{15} \quad \text{and} \quad \frac{\kappa(29)-\kappa(15)}{14} > \frac{\kappa(38)-\kappa(29)}{9}.$$

The second inequality implies $\kappa(29) > 3\kappa(15)$, from which it is straightforward to derive

$$\frac{\kappa(29)-\kappa(15)}{14} > \frac{\kappa(29)-\kappa(15)}{15} > 2\frac{\kappa(15)-\kappa(0)}{15} > \frac{\kappa(15)-\kappa(0)}{15}.$$

The third inequality implies $\kappa(38) < 4\kappa(15)$, which when combined with $\kappa(29) > 3\kappa(15)$ from the middle inequality yields $\kappa(38)-\kappa(29) < \kappa(15)-\kappa(0)$. From this, we can derive

$$\frac{\kappa(38)-\kappa(29)}{9} < \frac{\kappa(15)-\kappa(0)}{9} < 2\frac{\kappa(15)-\kappa(0)}{15} < \frac{\kappa(29)-\kappa(15)}{14}.$$

In Section 5.2.1, we describe the relationship predicted by our model between whether a person exhibits a CRP and their risk aversion in their AB valuation—where a person is risk-averse in the AB valuation when $h^*_{AB} > M/p$, and risk-loving when $h^*_{AB} < M/p$. That exploration is based on the following proposition:

Proposition A3. Suppose that $(h^*_{AB}, h^*_{AB'}, h^*_{CD})$ is derived from equations (B.2), (B.3), and (B.4). For any $(p, r) \in (0, 1)^2$ and $\kappa(x)$ that is strictly increasing in x:

(1) A person's h^*_{AB} satisfies:

- (a) $h^*_{AB} > M/p$ if and only if $\kappa(M) > p^2\kappa(h^*_{AB})$;
- (b) $h^*_{AB} < M/p$ if and only if $\kappa(M) < p^2\kappa(h^*_{AB})$; and
- (c) $h^*_{AB} = M/p$ if and only if $\kappa(M) = p^2\kappa(h^*_{AB})$.

(2) The relationship between a person's h^*_{AB} and Δ^*_{CR} satisfies:

- (a) $h^*_{AB} > M/p$ if and only if $\Delta^*_{CR} > 0$;
- (b) $h^*_{AB} < M/p$ if and only if $\Delta^*_{CR} < 0$; and
- (c) $h^*_{AB} = M/p$ if and only if $\Delta^*_{CR} = 0$.

Proof: (1) From equation (B.2), h^*_{AB} is derived from

$$M + \kappa(M) = ph^*_{AB} + p^2\kappa(h^*_{AB}).$$

Applying this equation, $\kappa(M) > p^2\kappa(h^*_{AB})$ if and only if $M < ph^*_{AB}$ or $h^*_{AB} > M/p$; $\kappa(M) < p^2\kappa(h^*_{AB})$ if and only if $M > ph^*_{AB}$ or $h^*_{AB} < M/p$; and $\kappa(M) = p^2\kappa(h^*_{AB})$ if and only if $M = ph^*_{AB}$ or $h^*_{AB} = M/p$. (2) Follows directly from part 1 combined with Proposition A1 part 1a.

■

Finally, 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 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 A2 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 A4. 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 (B.1). 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 (B.1), the decision-utility comparison is

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

or

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

or

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

The result follows directly.

■

B.2 Distinguishing Upside Potential from Probability Weighting

In Supplementary Material F, 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.[1]

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., $v(z) = z$).[2]

We first assess whether either OPT or CPT with a flexible functional form for π could replicate the predictions from our upside-potential 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'.

When $\kappa(z) = \phi z$, under our upside-potential model, rearranging the conditions from the proof of Proposition A.2, the indifference values are determined from

$$M = \frac{p + p^2\phi}{1+\phi} h^*_{AB} \tag{B.5}$$

$$M = \frac{pr + (pr+1-r)(pr)\phi}{1+\phi} h^*_{AB'} + \frac{(1-r) + (pr+1-r)(1-r)\phi}{1+\phi} M \tag{B.6}$$

$$\frac{r + r^2\phi}{1+\phi} M = \frac{pr + (pr)^2\phi}{1+\phi} h^*_{CD} \tag{B.7}$$

[1] 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.

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

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 upside-potential 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 models. Hence, for decisions that involve only sure amounts or binary lotteries with one winning outcome, our upside-potential 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 (B.6) can be expressed purely as a function of pr, the weight on M in equation (B.6) 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 upside-potential 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 upside-potential 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 upside-potential 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 upside-potential model to the those of OPT or CPT when we assume probability weighting function $\pi(q) = (q + q^2\phi)/(1 + \phi)$.

Proposition A2 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 upside-potential model for the AB and CD tasks and thus both predict a CRP. Proposition A5 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 A5. 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 A2 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 upside-potential 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 upside-potential model and CPT. Under CPT, the weights attached to outcomes depend on their relative ranks, whereas under our upside-potential 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)).