ONLINE APPENDIX

for

Measuring and Controlling for the Compromise Effect When Estimating Risk Preference Parameters

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1 Complete Set of Fixed Prospects and Alternatives for Each Pull Treatment and Part of the Experiment

Below, we list the complete set of fixed prospects and alternative outcomes faced by the participants in the experiment, for each Pull treatment. Online Appendix Table 1.1 lists the fixed prospects and alternative outcomes for Part A (Part B is identical to Part A but with all amounts multiplied by -1). Online Appendix Table 1.2 lists the fixed prospects and the unfixed parts of the alternative prospects for Parts C and D.

Online Appendix Table 1.1: Fixed Prospects and Alternative Outcomes for Part A, by Pull Treatment

	#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
Fixed Prospects	x_l	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	50	50	50	50	50	50	50	100	100	100	100	100
	x_h	50	50	50	100	100	100	100	100	200	200	200	200	200	400	400	100	100	100	150	150	150	150	150	200	200	200	200	200
	$P(x_l)$	0.90	0.50	0.10	0.95	0.75	0.50	0.25	0.05	0.99	0.90	0.50	0.10	0.01	0.99	0.01	0.90	0.50	0.10	0.95	0.75	0.50	0.25	0.05	0.95	0.75	0.50	0.25	0.05
	$P(x_h)$	0.10	0.50	0.90	0.05	0.25	0.50	0.75	0.95	0.01	0.10	0.50	0.90	0.99	0.01	0.99	0.10	0.50	0.90	0.05	0.25	0.50	0.75	0.95	0.05	0.25	0.50	0.75	0.95
	EU[t]	9.7	15.9	23.9	15.2	22.4	28.8	36.3	47.3	21.0	31.9	52.2	78.6	97.0	38.0	175.9	41.3	46.4	52.9	46.6	52.8	58.3	64.8	74.4	73.0	78.8	84.0	90.1	99.1
Alternative Sure Outcomes	Pull 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		0.5	1.2	1.6	0.7	1.7	2.3	2.9	3.8	0.7	2.1	4.7	6.3	77.4	1.3	154.7	53.7	71.0	93.4	53.0	66.6	87.6	114.7	142.2	103.7	119.4	142.1	168.7	193.3
		1.4	3.1	4.2	2.0	4.4	6.2	7.6	9.1	1.8	5.6	12.4	16.7	84.3	3.5	168.5	53.9	71.5	93.6	53.4	67.7	88.9	115.7	142.4	103.9	120.1	143.0	169.3	193.5
		2.8	6.3	8.5	4.0	9.0	12.7	15.5	17.9	3.6	11.3	25.3	34.0	95.7	7.2	191.5	54.2	72.2	93.8	54.0	69.6	91.2	117.4	142.8	104.2	121.4	144.5	170.4	193.7
		5.2	11.7	15.7	7.4	16.5	23.4	28.6	32.6	6.6	20.9	46.8	62.7	114.8	13.2	229.6	54.7	73.5	94.3	54.9	72.7	95.0	120.1	143.5	104.8	123.4	147.0	172.2	194.2
		9.2	20.6	27.6	13.0	29.1	41.2	50.4	57.0	11.6	36.8	82.3	110.5	146.4	23.3	292.9	55.6	75.6	95.0	56.5	77.9	101.3	124.7	144.7	105.7	126.7	151.2	175.3	195.0
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2
	Pull 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		1.3	2.9	3.9	1.9	4.2	5.9	7.2	8.6	1.7	5.3	11.7	15.8	83.7	3.3	167.3	53.9	71.4	93.6	53.4	67.6	88.8	115.6	142.4	103.8	120.1	142.9	169.3	193.5
		3.0	6.7	9.0	4.2	9.5	13.4	16.4	18.9	3.8	12.0	26.7	35.9	97.0	7.6	194.0	54.2	72.3	93.9	54.0	69.8	91.5	117.5	142.9	104.2	121.5	144.6	170.5	193.8
		5.1	11.5	15.4	7.3	16.2	22.9	28.1	32.0	6.5	20.5	45.9	61.6	114.0	13.0	228.1	54.7	73.4	94.2	54.9	72.6	94.9	120.0	143.5	104.7	123.3	146.9	172.2	194.2
		7.9	17.6	23.6	11.1	24.9	35.2	43.1	48.8	9.9	31.5	70.3	94.4	135.8	19.9	271.5	55.3	74.9	94.7	56.0	76.2	99.2	123.1	144.3	105.4	125.6	149.8	174.2	194.7
		11.4	25.4	34.1	16.1	35.9	50.8	62.2	70.2	14.4	45.4	101.6	136.3	163.5	28.7	327.1	56.0	76.7	95.4	57.4	80.8	104.7	127.2	145.3	106.2	128.5	153.4	176.9	195.4
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2
	Pull 0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		2.6	5.9	7.9	3.7	8.3	11.8	14.4	16.7	3.3	10.5	23.6	31.6	94.2	6.7	188.3	54.2	72.1	93.8	53.9	69.3	90.9	117.1	142.8	104.2	121.2	144.3	170.3	193.7
		5.3	11.8	15.8	7.5	16.7	23.6	28.9	32.9	6.7	21.1	47.1	63.2	115.1	13.3	230.3	54.7	73.5	94.3	54.9	72.8	95.1	120.2	143.6	104.8	123.4	147.0	172.3	194.2
		7.9	17.7	23.7	11.2	25.0	35.4	43.3	49.0	10.0	31.6	70.7	94.9	136.1	20.0	272.2	55.3	74.9	94.8	56.0	76.2	99.3	123.2	144.3	105.4	125.6	149.8	174.3	194.7
		10.5	23.6	31.6	14.9	33.3	47.1	57.7	65.2	13.3	42.2	94.3	126.5	157.1	26.7	314.1	55.9	76.3	95.2	57.1	79.7	103.4	126.2	145.1	106.0	127.8	152.6	176.3	195.2
		13.2	29.5	39.5	18.6	41.7	58.9	72.2	81.3	16.7	52.7	117.9	158.1	178.0	33.3	356.1	56.4	77.7	95.7	58.1	83.1	107.6	129.3	145.9	106.6	130.1	155.3	178.3	195.7
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2
	Pull -1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		4.5	10.0	13.4	6.3	14.1	19.9	24.4	27.9	5.6	17.8	39.9	53.5	108.7	11.3	217.3	54.6	73.1	94.1	54.6	71.7	93.8	119.2	143.3	104.6	122.7	146.2	171.6	194.1
		7.9	17.8	23.8	11.2	25.1	35.5	43.5	49.3	10.1	31.8	71.1	95.4	136.4	20.1	272.9	55.3	74.9	94.8	56.0	76.3	99.3	123.2	144.3	105.4	125.7	149.9	174.3	194.7
		10.7	23.9	32.0	15.1	33.8	47.8	58.5	66.0	13.5	42.7	95.5	128.2	158.2	27.0	316.4	55.9	76.4	95.3	57.1	79.9	103.7	126.4	145.1	106.0	128.0	152.7	176.4	195.2
		12.8	28.7	38.5	18.1	40.5	57.3	70.2	79.1	16.2	51.3	114.7	153.9	175.2	32.4	350.4	56.4	77.5	95.6	58.0	82.7	107.1	128.8	145.8	106.5	129.8	155.0	178.0	195.6
		14.5	32.4	43.5	20.5	45.8	64.8	79.4	89.4	18.3	58.0	129.7	174.0	188.6	36.7	377.1	56.7	78.4	95.9	58.6	84.9	109.7	130.8	146.2	106.9	131.2	156.7	179.3	196.0
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2
	Pull -2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		6.6	14.8	19.8	9.3	20.9	29.5	36.2	41.1	8.4	26.4	59.1	79.3	125.8	16.7	251.5	55.0	74.2	94.5	55.5	74.5	97.2	121.7	143.9	105.1	124.5	148.4	173.3	194.5
		10.6	23.7	31.8	15.0	33.5	47.3	58.0	65.4	13.4	42.3	94.7	127.0	157.4	26.8	314.8	55.9	76.3	95.2	57.1	79.8	103.5	126.3	145.1	106.0	127.9	152.6	176.3	195.2
		13.0	29.0	38.9	18.4	41.0	58.0	71.1	80.1	16.4	51.9	116.1	155.8	176.5	32.8	352.9	56.4	77.6	95.7	58.0	82.9	107.3	129.0	145.8	106.6	129.9	155.1	178.1	195.7
		14.4	32.2	43.3	20.4	45.6	64.5	79.0	88.9	18.2	57.7	129.0	173.1	187.9	36.5	375.9	56.7	78.3	95.9	58.6	84.8	109.6	130.7	146.2	106.9	131.1	156.7	179.2	195.9
		15.3	34.2	45.9	21.6	48.3	68.4	83.7	94.3	19.3	61.2	136.7	183.5	194.8	38.7	389.7	56.9	78.8	96.1	59.0	85.9	111.0	131.7	146.5	107.1	131.8	157.6	179.9	196.1
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2

NOTES: Part A consists of 28 problems. Each problem appears on a separate screen and involves choices between a fixed prospect (x_l, $P(x_l)$; x_h, $P(x_h)$) and seven alternative sure outcomes. The different Pull treatments vary the second through sixth alternative sure outcomes presented with each fixed prospect on each screen. The 28 prospects and alternatives in Part B are identical to those in Part A but with all dollar amounts multiplied by -1.

[t] EU refers to the expected utility of the fixed prospects, calculated with the parameter estimates reported by Fehr-Duda and Epper (2012, Table 3) for their representative sample. (In the estimation of the CPT model (with or without compromise effects), one σ_q is estimated for each group of screens and the screens are grouped together based on the expected value of their fixed prospects.)

Online Appendix Table 1.2: Fixed Prospects and Unfixed Parts of the Alternative Prospects for Parts C and D, by Pull Treatment

	Problem #		1	2	3	4	5	6	7	8
Fixed Prospects	x_1		0	0	0	0	-20	-50	50	100
	x_2		0	0	0	0	50	150	120	300
Alternative Prospects	y_1		-25	-50	-100	-150	-50	-125	20	25
	y_2	Pull 2	0	0	0	0	50	150	120	300
			2	5	10	15	53	157	123	307
			7	13	26	40	58	170	128	320
			13	27	54	81	66	190	136	340
			25	50	99	149	80	224	150	374
			44	87	175	262	102	281	172	431
			75	150	300	450	140	375	210	525
		Pull 1	0	0	0	0	50	150	120	300
			6	12	25	37	57	169	127	319
			14	28	57	85	67	193	137	343
			24	49	97	146	79	223	149	373
			37	75	149	224	95	262	165	412
			54	108	215	323	115	312	185	462
			75	150	300	450	140	375	210	525
		Pull 0	0	0	0	0	50	150	120	300
			13	25	50	75	65	188	135	338
			25	50	100	150	80	225	150	375
			38	75	150	225	95	263	165	413
			50	100	200	300	110	300	180	450
			63	125	250	375	125	338	195	488
			75	150	300	450	140	375	210	525
		Pull -1	0	0	0	0	50	150	120	300
			21	42	85	127	75	213	145	363
			38	75	151	226	95	263	165	413
			51	101	203	304	111	302	181	452
			61	122	243	365	123	332	193	482
			69	138	275	413	133	356	203	506
			75	150	300	450	140	375	210	525
		Pull -2	0	0	0	0	50	150	120	300
			31	63	125	188	88	244	158	394
			50	100	201	301	110	301	180	451
			62	123	246	369	124	335	194	485
			68	137	274	410	132	355	202	505
			73	145	290	435	137	368	207	518
			75	150	300	450	140	375	210	525

NOTES: Part C consists of Problems 1-4; Part D consists of Problems 5-8. Each problem appears on a separate screen and involves choices between a fixed prospect (x_1, 0.50; x_2, 0.50) and seven alternative prospects (y_1, 0.50; y_2, 0.50). For each problem, y_1 is fixed and y_2 is unfixed. The different Pull treatments vary the unfixed part (y_2) of the second through sixth alternative prospects on each screen.

2 Algorithm to Determine the Second Through Sixth Alternatives for Each Pull Treatment and Part of the Experiment

As described in the paper, the Pull 1 and Pull 2 treatments are designed to resemble T&K's experiment, in which the second through sixth alternatives are "logarithmically spaced between the extreme outcomes of the prospect" (T&K, p. 305). Conversely, in the Pull -1 and Pull -2 treatments, the alternatives are more densely concentrated at the monetary amounts farther from zero. Pull 2 and Pull -2 are more skewed than Pull 1 and Pull -1.

We use the following algorithm to determine the second through sixth alternative outcomes for screen q in Pull 1 and Pull 2 for Part A (in the gain domain):

· Label the alternative outcomes for screen q, in decreasing monetary amounts, x_{q1}, x_{q2},...,x_{q7} and define $\Delta_q \equiv x_{q1} - x_{q7}$.

· Recall that (as described in the paper) x_{q1} and x_{q7} (the first and seventh alternatives of screen q) are identical across treatments and correspond to the screen's fixed prospect's certainty equivalents for CRRA expected-utility-maximizers with CRRA parameters $\gamma = -1$ and $\gamma = 0.99$.

· For Pull 1, let $k = 0.3$ and solve $(1+a)^6 k\Delta_q = (1+k)\Delta_q$ for a. Then, let $z_i = (1+a)^{(7-i)} k\Delta_q$, $i = 1, ..., 7$. These seven z_i points form a log scale from $k\Delta_q$ to $(1+k)\Delta_q$.

· We then "shift" the log scale formed by these z_i points so that the scale starts at x_{q7} and ends at x_{q1}: $x_{qi} = z_i + (x_{q7} - k\Delta_q)$, $i = 2, ..., 6$, and round to the nearest dime.

· The algorithm for Pull 2 is identical, except that we let $k = 0.05$.

In Pull -1 and Pull -2, the spacing between x_{qi} and $x_{q(i+1)}$ is equal to the spacing between $x_{q(7-i)}$ and $x_{q(7-i+1)}$ $(i = 1, ..., 6)$ in Pull 1 and Pull 2, respectively.

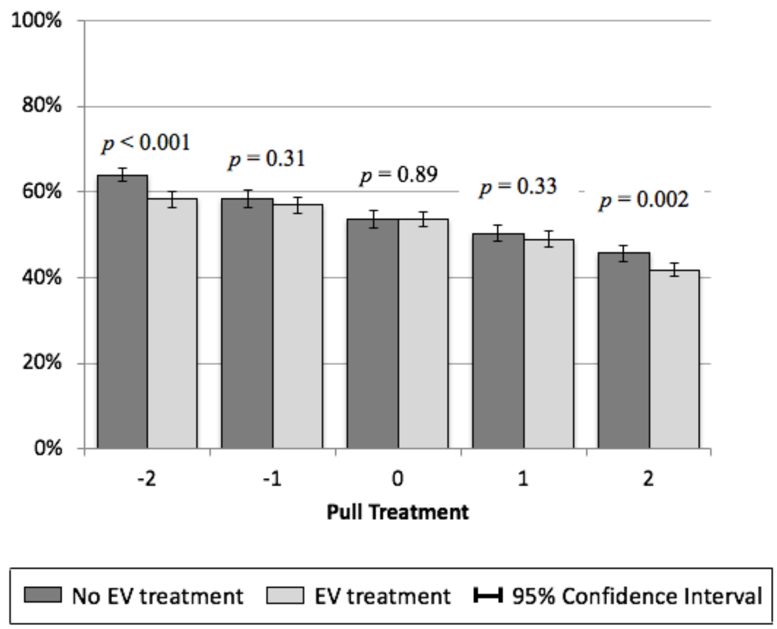
The amounts for Part B are identical to the amounts for Part A, multiplied by -1.

For Parts C and D, we use the same algorithm to determine the parts of the second through sixth alternatives that are not fixed. (Recall that the alternatives in Parts C and D are risky prospects with two possible realizations, and that one of these two realizations is fixed across the seven alternatives and the other varies across alternatives–i.e. it is not fixed.)

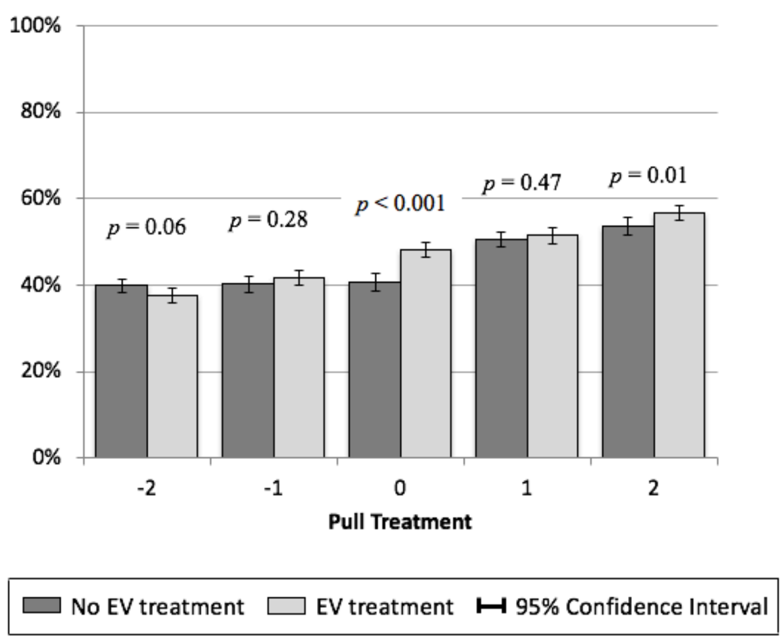
3 Summary Statistics of the Raw Data from the Experiment

Online Appendix Figures 3.1-3.4 show the percentage of choices where the safe option was chosen, by Pull and EV treatments, separately for Parts A, B, C, and D of the experiment. (For Part D, Online Appendix Figure 3.4 shows the percentage of choices where the option involving the smallest possible loss was selected.) The figures also show p values for t-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment. To compute the percentages, each row of the MPL was counted as a choice, and data from the 28 participants whose data were excluded from the estimation data for the main analyses in the main text (see Section 3.3 of the main text) were excluded here too. The figure captions provide additional details.

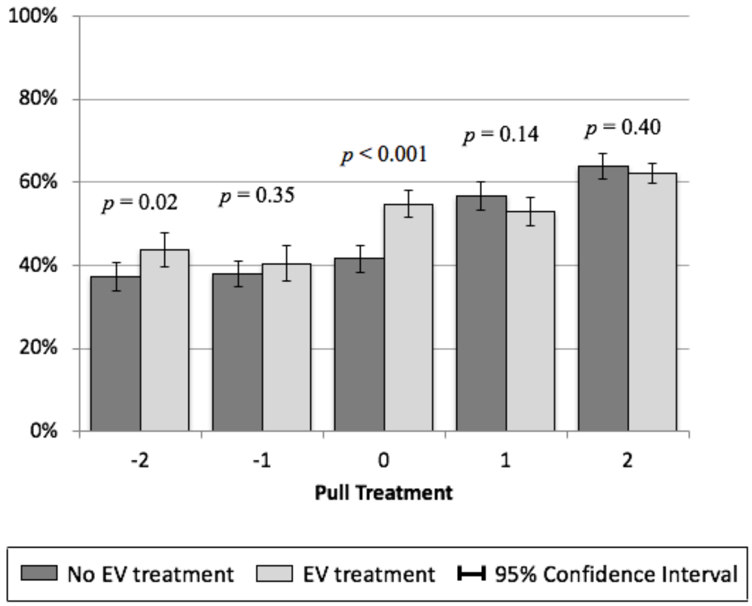
Although these figures may give readers a sense of the underlying data we collected in our experiment, caution is warranted when interpreting them because the different Pull treatments involve different sets of choices, and the raw data are thus not directly comparable across treatments. For example, consider Online Appendix Figure 3.1, which shows the percentages of safe choices in Part A. The percentages are lower in the Pull 2 treatment and higher in the Pull -2 treatment. Recall that the alternative prospects in the Pull 2 treatment involve amounts that are closer to zero, and the alternative prospects in the Pull -2 treatment involve amounts that are further away from zero. In the absence of a compromise effect, a participant with a given certainty equivalent for a gamble on a given screen will thus select the safe option less frequently in the Pull 2 treatment than in the Pull -2 treatment. The existence of a compromise effect would partially mitigate this tendency but would not fully counter it. Because of this, Online Appendix Figure 3.1 shows that the percentage of safe choices decreases in Pull, even though theoretical considerations suggest (see Section 4 of the main text), and our empirical results confirm, that estimates of risk aversion (i.e., $\hat{\gamma}$, $\hat{\gamma}^+$, $\hat{\gamma}^-$) increase in Pull.



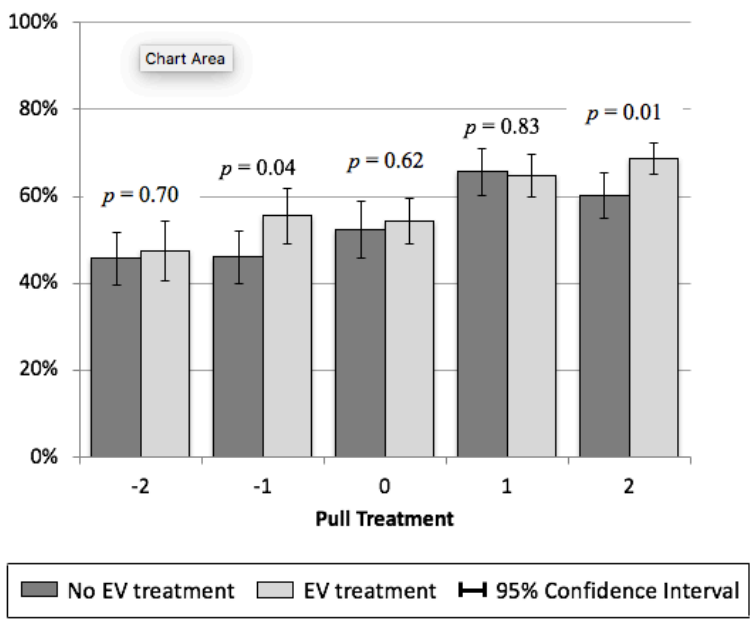
Online Appendix Figure 3.1. Percentage of choices where the safe option was chosen in Part A, by Pull and EV treatments. (In Part A, the safe options are the alternative prospects; each row of the MPL is counted as a choice.) The *p* values at the top of the bars are for *t*-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment.



Online Appendix Figure 3.2. Percentage of choices where the safe option was chosen in Part B, by Pull and EV treatments. (In Part B, the safe options are the alternative prospects; each row of the MPL is counted as a choice.) The *p* values at the top of the bars are for *t*-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment.



Online Appendix Figure 3.3. Percentage of choices where the safe option was chosen in Part C, by Pull and EV treatments. (In Part C, we define the safe option in a row as selecting "Don't take the gamble"; each row of the MPL is counted as a choice.) The p values at the top of the bars are for t-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment.



Online Appendix Figure 3.4. Percentage of choices where the option involving the smaller possible loss was chosen in Part D, by Pull and EV treatments. (All choices in Part D involve two gambles, gamble 1 and gamble 2, each of which involves a 50% chance of a loss; the possible loss in gamble 1 is always smaller than that in gamble 2; thus, the figure shows the percentage of choices where gamble 1 was selected; each row of the MPL is counted as a choice.) The p values at the top of the bars are for t-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment.

4 Complete Results for the Estimations Summarized in Tables 1-4 of the Paper

4.1 Complete Results for Table 1 in the Paper: ML Estimates of All Parameters in the Model with the Compromise Effect

4.1.1 Parts A-D Together

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                                                  Number of obs   =      30566
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -55378.806                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .2417204   .0160087    15.10   0.000      .210344    .2730969
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .6193999   .0151086    41.00   0.000     .5897876    .6490122
-------------+----------------------------------------------------------------
beta         |
       _cons |   1.118809   .0245974    45.48   0.000     1.070599    1.167019
-------------+----------------------------------------------------------------
lambda       |
       _cons |   1.311381    .034214    38.33   0.000     1.244323    1.378439
-------------+----------------------------------------------------------------
sA1          |
       _cons |   6.946555   .3952036    17.58   0.000      6.17197    7.721139
-------------+----------------------------------------------------------------
sA2          |
       _cons |    11.9386   .7371196    16.20   0.000     10.49387    13.38333
-------------+----------------------------------------------------------------
sA3          |
       _cons |   14.78461   1.152642    12.83   0.000     12.52548    17.04375
-------------+----------------------------------------------------------------
sA4          |
       _cons |   24.60433   1.958008    12.57   0.000      20.7667    28.44196
-------------+----------------------------------------------------------------
sA5          |
       _cons |   50.82841   5.950401     8.54   0.000     39.16584    62.49098
-------------+----------------------------------------------------------------
sB1          |
       _cons |   12.75788   .8051541    15.85   0.000      11.1798    14.33595
-------------+----------------------------------------------------------------
sB2          |
       _cons |   18.61553   1.335685    13.94   0.000     15.99763    21.23342
-------------+----------------------------------------------------------------
sB3          |
       _cons |   19.94524   1.513185    13.18   0.000     16.97945    22.91103
-------------+----------------------------------------------------------------
sB4          |
       _cons |   26.32082   2.728525     9.65   0.000     20.97301    31.66864
-------------+----------------------------------------------------------------
sB5          |
       _cons |    38.0273   4.955181     7.67   0.000     28.31533    47.73928
-------------+----------------------------------------------------------------
sC1          |
       _cons |    7.88043   .5498168    14.33   0.000     6.802809    8.958052
-------------+----------------------------------------------------------------
sC2          |
       _cons |    19.3701   1.596884    12.13   0.000     16.24026    22.49993
-------------+----------------------------------------------------------------
sD           |
       _cons |   12.24018   1.141905    10.72   0.000     10.00209    14.47827
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.0907861   .0119494    -7.60   0.000    -.1142064   -.0673657
-------------+----------------------------------------------------------------
pi2          |
       _cons |  -.0075387     .00137    -5.50   0.000    -.0102238   -.0048537
------------------------------------------------------------------------------
```

4.1.2 Part A (Gain Domain Only)

```
                                                  Number of obs   =      13804
                                                        Wald chi2(0)    =          .
Log pseudolikelihood = -23915.434                       Prob > chi2     =          .

                                (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .4475485   .0195434    22.90   0.000     .4092441    .4858529
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .5640233   .0146757    38.43   0.000     .5352594    .5927871
-------------+----------------------------------------------------------------
beta         |
       _cons |   .8581722   .0325624    26.35   0.000     .7943512    .9219933
-------------+----------------------------------------------------------------
sA1          |
       _cons |   3.884443   .1827219    21.26   0.000     3.526315    4.242572
-------------+----------------------------------------------------------------
sA2          |
       _cons |   5.745609    .326979    17.57   0.000     5.104742    6.386476
-------------+----------------------------------------------------------------
sA3          |
       _cons |   6.100672   .4205729    14.51   0.000     5.276364    6.924979
-------------+----------------------------------------------------------------
sA4          |
       _cons |   9.034794   .6918451    13.06   0.000     7.678803    10.39079
-------------+----------------------------------------------------------------
sA5          |
       _cons |   15.36957   1.827406     8.41   0.000     11.78792    18.95122
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.1344342   .0176732    -7.61   0.000    -.1690732   -.0997953
-------------+----------------------------------------------------------------
pi2          |
       _cons |   .0016748   .0019178     0.87   0.383    -.0020841    .0054337
------------------------------------------------------------------------------
```

4.1.3 Part B (Loss Domain Only)

```
                                                  Number of obs   =      13804
                                                  Wald chi2(0)    =          .
Log pseudolikelihood =  -25399.65                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gamma _cons	-.1056974	.0431253	-2.45	0.014	-.1902214	-.0211734
alpha _cons	.6897954	.0220424	31.29	0.000	.6465931	.7329978
beta _cons	1.47058	.0611999	24.03	0.000	1.35063	1.590529
sB1 _cons	26.54978	3.935111	6.75	0.000	18.83711	34.26246
sB2 _cons	48.94547	8.469511	5.78	0.000	32.34554	65.54541
sB3 _cons	66.25618	13.01421	5.09	0.000	40.74879	91.76357
sB4 _cons	107.4424	23.30718	4.61	0.000	61.7612	153.1237
sB5 _cons	217.0596	56.99872	3.81	0.000	105.3442	328.7751
pi1 _cons	-.144331	.018166	-7.95	0.000	-.1799357	-.1087262
pi2 _cons	-.0043143	.0022595	-1.91	0.056	-.0087428	.0001143

4.2 Complete Results for Table 2 in the Paper: ML Estimates of All Parameters in the Parameterized Model with the Compromise Effect

4.2.1 Parts A-D Together

```
                                                  Number of obs   =      30566
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -55224.557                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gamma _cons	.206111	.0256492	8.04	0.000	.1558395	.2563824
alpha _cons	.5557754	.0185143	30.02	0.000	.5194881	.5920627
beta _cons	1.189692	.037368	31.84	0.000	1.116453	1.262932
lambda _cons	1.270673	.0533319	23.83	0.000	1.166145	1.375202
phi1_gamma _cons	.0083344	.0172273	0.48	0.629	-.0254305	.0420994
phi2_gamma _cons	.0576824	.0350184	1.65	0.100	-.0109523	.1263172
phi1_alpha _cons	-.0174391	.0092667	-1.88	0.060	-.0356014	.0007233
phi2_alpha _cons	.1302331	.0284477	4.58	0.000	.0744766	.1859896
phi1_beta _cons	-.0004308	.0219806	-0.02	0.984	-.0435121	.0426504
phi2_beta _cons	-.1321397	.0476646	-2.77	0.006	-.2255607	-.0387187
phi1_l _cons	-.0531334	.0293479	-1.81	0.070	-.1106541	.0043874
phi2_l _cons	.0749102	.0741481	1.01	0.312	-.0704173	.2202377
sA1 _cons	8.471337	.7346861	11.53	0.000	7.031379	9.911295
sA2 _cons	13.99402	1.328479	10.53	0.000	11.39024	16.59779
sA3 _cons	15.8456	1.954131	8.11	0.000	12.01557	19.67562
sA4 _cons	29.64206	3.712833	7.98	0.000	22.36504	36.91908
sA5 _cons	66.62124	11.41515	5.84	0.000	44.24796	88.99452
sB1 _cons	14.62046	1.472035	9.93	0.000	11.73532	17.50559
sB2 _cons	21.02752	2.417808	8.70	0.000	16.2887	25.76634
sB3 _cons	24.01024	3.085625	7.78	0.000	17.96252	30.05795
sB4 _cons	29.3427	4.5028	6.52	0.000	20.51737	38.16802

sB5						
_cons	46.349	8.681106	5.34	0.000	29.33435	63.36366
sC1						
_cons	8.091364	.9009637	8.98	0.000	6.325508	9.85722
sC2						
_cons	20.51948	2.878159	7.13	0.000	14.8784	26.16057
sD						
_cons	16.03147	2.278884	7.03	0.000	11.56494	20.49801
phi1_sA1						
_cons	.0787081	.3413576	0.23	0.818	-.5903405	.7477566
phi2_sA1						
_cons	-2.757494	.8594604	-3.21	0.001	-4.442005	-1.072982
phi1_sA2						
_cons	.0824369	.7700597	0.11	0.915	-1.426852	1.591726
phi2_sA2						
_cons	-3.545769	1.657203	-2.14	0.032	-6.793827	-.2977101
phi1_sA3						
_cons	.2790316	1.095298	0.25	0.799	-1.867712	2.425776
phi2_sA3						
_cons	-1.995147	2.573782	-0.78	0.438	-7.039667	3.049372
phi1_sA4						
_cons	-3.35317	2.193181	-1.53	0.126	-7.651726	.9453867
phi2_sA4						
_cons	-6.249444	4.151368	-1.51	0.132	-14.38598	1.887088
phi1_sA5						
_cons	-6.356309	6.008805	-1.06	0.290	-18.13335	5.420733
phi2_sA5						
_cons	-21.68732	12.76104	-1.70	0.089	-46.69849	3.323855
phi1_sB1						
_cons	-.3858308	.747751	-0.52	0.606	-1.851396	1.079734
phi2_sB1						
_cons	-3.229005	1.798479	-1.80	0.073	-6.75396	.2959493
phi1_sB2						
_cons	-.8176172	1.426382	-0.57	0.567	-3.613275	1.978041
phi2_sB2						
_cons	-4.1457	2.926864	-1.42	0.157	-9.882248	1.590848
phi1_sB3						
_cons	-1.020451	1.586598	-0.64	0.520	-4.130126	2.089223
phi2_sB3						
_cons	-6.994841	3.584155	-1.95	0.051	-14.01966	.0299745
phi1_sB4						
_cons	-2.661792	2.884826	-0.92	0.356	-8.315947	2.992364
phi2_sB4						
_cons	-4.413494	5.222461	-0.85	0.398	-14.64933	5.822341
phi1_sB5						
_cons	-8.1278	4.800149	-1.69	0.090	-17.53592	1.28032
phi2_sB5						
_cons	-7.753461	9.176378	-0.84	0.398	-25.73883	10.23191
phi1_sC1						
_cons	-.5049022	.4824912	-1.05	0.295	-1.450567	.4407631
phi2_sC1						
_cons	-.21316	1.213742	-0.18	0.861	-2.592051	2.165731
phi1_sC2						
_cons	-1.76451	1.556722	-1.13	0.257	-4.81563	1.286609

phi2_sC2						
_cons	-1.913247	3.618202	-0.53	0.597	-9.004794	5.178299
phi1_sD						
_cons	-1.814308	1.001584	-1.81	0.070	-3.777376	.14876
phi2_sD						
_cons	-5.404312	2.380116	-2.27	0.023	-10.06925	-.7393695
pi1						
_cons	-.0896071	.0122324	-7.33	0.000	-.1135822	-.065632
pi2						
_cons	-.0076155	.0013797	-5.52	0.000	-.0103198	-.0049113

4.2.2 Part A (Gain Domain Only)

```
                                                  Number of obs   =      13804
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -23838.856                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
gamma _cons	.4234537	.0278263	15.22	0.000	.3689151	.4779922
alpha _cons	.5051478	.0183603	27.51	0.000	.4691622	.5411334
beta _cons	.9105968	.0478594	19.03	0.000	.8167942	1.004399
phi1_gamma _cons	.0110312	.0178499	0.62	0.537	-.0239539	.0460163
phi2_gamma _cons	.0334443	.0391302	0.85	0.393	-.0432496	.1101381
phi1_alpha _cons	-.0150514	.0090778	-1.66	0.097	-.0328434	.0027407
phi2_alpha _cons	.1242067	.0276327	4.49	0.000	.0700477	.1783657
phi1_beta _cons	-.004172	.0267502	-0.16	0.876	-.0566015	.0482574
phi2_beta _cons	-.095354	.0633599	-1.50	0.132	-.2195372	.0288292
sA1 _cons	4.496528	.2830979	15.88	0.000	3.941666	5.05139
sA2 _cons	6.404707	.4869965	13.15	0.000	5.450211	7.359202
sA3 _cons	6.242768	.5770657	10.82	0.000	5.11174	7.373796
sA4 _cons	10.20512	1.10953	9.20	0.000	8.03048	12.37976
sA5 _cons	18.74995	3.110022	6.03	0.000	12.65442	24.84548
phi1_sA1 _cons	.0212634	.1603163	0.13	0.894	-.2929508	.3354776
phi2_sA1 _cons	-1.149381	.3552096	-3.24	0.001	-1.845579	-.4531833
phi1_sA2 _cons	.0265432	.318068	0.08	0.933	-.5968587	.6499451
phi2_sA2 _cons	-1.144326	.6541053	-1.75	0.080	-2.426349	.1376964
phi1_sA3 _cons	.2628053	.3820786	0.69	0.492	-.486055	1.011665
phi2_sA3 _cons	-.3724247	.8463344	-0.44	0.660	-2.03121	1.28636
phi1_sA4 _cons	-.9776202	.7639582	-1.28	0.201	-2.474951	.5197105
phi2_sA4 _cons	-1.321611	1.373165	-0.96	0.336	-4.012966	1.369743
phi1_sA5 _cons	-1.934792	1.857262	-1.04	0.298	-5.574958	1.705374

```
-------------+----------------------------------------------------------------
phi2_sA5     |
       _cons |  -4.312429   3.602988    -1.20   0.231    -11.37416    2.749297
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.1387867   .0178033    -7.80   0.000    -.1736807   -.1038928
-------------+----------------------------------------------------------------
pi2          |
       _cons |   .0023069   .0018789     1.23   0.220    -.0013756    .0059895
------------------------------------------------------------------------------
```

4.2.3 Part B (Loss Domain Only)

Number of obs	=	13804
Wald chi2(0)	=	.
Prob > chi2	=	.

Log pseudolikelihood = -25343.262

(Std. Err. adjusted for 493 clusters in subjectId)

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gamma						
_cons	-.1182055	.0515039	-2.30	0.022	-.2191512	-.0172598
alpha						
_cons	.6167516	.0270155	22.83	0.000	.5638022	.6697009
beta						
_cons	1.524137	.0864916	17.62	0.000	1.354616	1.693657
phi1_gamma						
_cons	-.0323206	.026049	-1.24	0.215	-.0833758	.0187345
phi2_gamma						
_cons	.0021699	.0666094	0.03	0.974	-.1283821	.1327218
phi1_alpha						
_cons	-.015365	.0138902	-1.11	0.269	-.0425892	.0118593
phi2_alpha						
_cons	.1562935	.041995	3.72	0.000	.0739848	.2386022
phi1_beta						
_cons	.0416922	.0419585	0.99	0.320	-.040545	.1239294
phi2_beta						
_cons	-.0899068	.1142436	-0.79	0.431	-.3138202	.1340066
sB1						
_cons	30.30175	5.372766	5.64	0.000	19.77132	40.83218
sB2						
_cons	54.05663	11.22242	4.82	0.000	32.06108	76.05217
sB3						
_cons	77.57128	18.36838	4.22	0.000	41.56992	113.5726
sB4						
_cons	114.6108	29.8461	3.84	0.000	56.11348	173.108
sB5						
_cons	245.3845	78.64632	3.12	0.002	91.2406	399.5285
phi1_sB1						
_cons	3.35427	2.574001	1.30	0.193	-1.69068	8.399219
phi2_sB1						
_cons	-4.428698	6.519832	-0.68	0.497	-17.20733	8.349938
phi1_sB2						
_cons	8.864135	6.508522	1.36	0.173	-3.892334	21.6206
phi2_sB2						
_cons	-2.77284	13.97422	-0.20	0.843	-30.16182	24.61614
phi1_sB3						
_cons	10.54686	9.041151	1.17	0.243	-7.173474	28.26719
phi2_sB3						
_cons	-12.92712	20.86169	-0.62	0.535	-53.81528	27.96105
phi1_sB4						
_cons	16.18807	17.86578	0.91	0.365	-18.82821	51.20435
phi2_sB4						
_cons	1.286831	41.29134	0.03	0.975	-79.64271	82.21637
phi1_sB5						
_cons	13.1091	39.94809	0.33	0.743	-65.18772	91.40592
phi2_sB5						
_cons	-5.218528	102.6074	-0.05	0.959	-206.3253	195.8882

```
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.1416346   .0175073    -8.09   0.000    -.1759483    -.107321
-------------+----------------------------------------------------------------
pi2          |
       _cons |  -.0048271   .0022178    -2.18   0.030    -.0091739   -.0004803
------------------------------------------------------------------------------
```

4.3 Complete Results for Table 3 in the Paper: ML Estimates of All Parameters in the Model Without the Compromise Effect

4.3.1 Parts A-D Together

```
   Number of obs   =      30566
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -59956.628                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .2032792   .0118117    17.21   0.000     .1801287    .2264296
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .5742118   .0099229    57.87   0.000     .5547632    .5936604
-------------+----------------------------------------------------------------
beta         |
       _cons |   1.123419    .016066    69.93   0.000      1.09193    1.154908
-------------+----------------------------------------------------------------
lambda       |
       _cons |   1.336537    .027142    49.24   0.000     1.283339    1.389734
-------------+----------------------------------------------------------------
sA1          |
       _cons |   5.708549    .239734    23.81   0.000     5.238679    6.178419
-------------+----------------------------------------------------------------
sA2          |
       _cons |    9.63376   .4560246    21.13   0.000     8.739968    10.52755
-------------+----------------------------------------------------------------
sA3          |
       _cons |   10.28831   .6149238    16.73   0.000     9.083077    11.49353
-------------+----------------------------------------------------------------
sA4          |
       _cons |   16.67114   1.062706    15.69   0.000     14.58827      18.754
-------------+----------------------------------------------------------------
sA5          |
       _cons |   40.83873   3.415513    11.96   0.000     34.14445    47.53302
-------------+----------------------------------------------------------------
sB1          |
       _cons |   9.962969   .5151478    19.34   0.000     8.953298    10.97264
-------------+----------------------------------------------------------------
sB2          |
       _cons |    14.3498   .8522449    16.84   0.000     12.67943    16.02017
-------------+----------------------------------------------------------------
sB3          |
       _cons |   13.56155   .8975655    15.11   0.000     11.80235    15.32075
-------------+----------------------------------------------------------------
sB4          |
       _cons |   18.37978   1.542214    11.92   0.000     15.35709    21.40246
-------------+----------------------------------------------------------------
sB5          |
       _cons |   35.11393   3.572159     9.83   0.000     28.11263    42.11524
-------------+----------------------------------------------------------------
sC1          |
       _cons |   6.672262   .3618274    18.44   0.000     5.963093    7.381431
-------------+----------------------------------------------------------------
sC2          |
       _cons |   17.22871   1.122964    15.34   0.000     15.02774    19.42968
-------------+----------------------------------------------------------------
sD           |
       _cons |   9.602215   .6499856    14.77   0.000     8.328267    10.87616
------------------------------------------------------------------------------
```

4.3.2 Part A (Gain Domain Only)

```
                                                  Number of obs   =      13804
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -25604.111                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gamma _cons	.3626102	.0138369	26.21	0.000	.3354904	.38973
alpha _cons	.5384385	.0109185	49.31	0.000	.5170386	.5598384
beta _cons	.9583001	.0197127	48.61	0.000	.9196639	.9969363
sA1 _cons	3.818816	.1399444	27.29	0.000	3.54453	4.093102
sA2 _cons	5.622384	.2526493	22.25	0.000	5.1272	6.117567
sA3 _cons	5.233887	.3046054	17.18	0.000	4.636871	5.830902
sA4 _cons	7.676197	.4847189	15.84	0.000	6.726165	8.626228
sA5 _cons	16.47294	1.412336	11.66	0.000	13.70481	19.24107

4.3.3 Part B (Loss Domain Only)

```
                                                Number of obs   =      13804
                                                   Wald chi2(0)    =          .
Log pseudolikelihood = -28140.868                  Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   -.009619    .021813    -0.44   0.659    -.0523716    .0331337
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .6153074   .0130953    46.99   0.000      .589641    .6409737
-------------+----------------------------------------------------------------
beta         |
       _cons |   1.296382   .0301646    42.98   0.000      1.23726    1.355503
-------------+----------------------------------------------------------------
sB1          |
       _cons |   12.89018    .973089    13.25   0.000     10.98297     14.7974
-------------+----------------------------------------------------------------
sB2          |
       _cons |   22.02498   1.999303    11.02   0.000     18.10642    25.94354
-------------+----------------------------------------------------------------
sB3          |
       _cons |    24.2498   2.615078     9.27   0.000     19.12434    29.37526
-------------+----------------------------------------------------------------
sB4          |
       _cons |   38.28514   4.688734     8.17   0.000     29.09539    47.47489
-------------+----------------------------------------------------------------
sB5          |
       _cons |   90.63866   13.18273     6.88   0.000     64.80098    116.4763
------------------------------------------------------------------------------
```

4.4 Complete Results for Table 4 in the Paper: ML Estimates of All Parameters in the Parameterized Model Without the Compromise Effect

4.4.1 Parts A-D Together

```
Number of obs   =      30566
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -59426.702                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .1962763   .0159212    12.33   0.000     .1650714    .2274813
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .5353259   .0123991    43.17   0.000     .5110242    .5596277
-------------+----------------------------------------------------------------
beta         |
       _cons |   1.143144   .0219723    52.03   0.000     1.100079    1.186209
-------------+----------------------------------------------------------------
lambda       |
       _cons |   1.317612   .0396838    33.20   0.000     1.239834    1.395391
-------------+----------------------------------------------------------------
phi1_gamma   |
       _cons |   .0415339   .0089828     4.62   0.000      .023928    .0591398
-------------+----------------------------------------------------------------
phi2_gamma   |
       _cons |   .0008474   .0233336     0.04   0.971    -.0448856    .0465805
-------------+----------------------------------------------------------------
phi1_alpha   |
       _cons |  -.0352166   .0062937    -5.60   0.000    -.0475521   -.0228811
-------------+----------------------------------------------------------------
phi2_alpha   |
       _cons |   .0886372   .0185971     4.77   0.000     .0521876    .1250869
-------------+----------------------------------------------------------------
phi1_beta    |
       _cons |     .02773   .0100495     2.76   0.006     .0080333    .0474268
-------------+----------------------------------------------------------------
phi2_beta    |
       _cons |  -.0405865   .0276623    -1.47   0.142    -.0948035    .0136306
-------------+----------------------------------------------------------------
phi1_l       |
       _cons |  -.1465308   .0217653    -6.73   0.000    -.1891899   -.1038716
-------------+----------------------------------------------------------------
phi2_l       |
       _cons |   .0856586    .058742     1.46   0.145    -.0294736    .2007907
-------------+----------------------------------------------------------------
sA1          |
       _cons |   6.202134   .3622788    17.12   0.000     5.492081    6.912187
-------------+----------------------------------------------------------------
sA2          |
       _cons |   10.20917   .6587717    15.50   0.000     8.918006    11.50034
-------------+----------------------------------------------------------------
sA3          |
       _cons |   10.37908   .8519371    12.18   0.000     8.709315    12.04885
-------------+----------------------------------------------------------------
sA4          |
       _cons |   18.00332   1.480613    12.16   0.000     15.10137    20.90527
-------------+----------------------------------------------------------------
sA5          |
       _cons |   44.42177   4.854223     9.15   0.000     34.90767    53.93588
-------------+----------------------------------------------------------------
sB1          |
       _cons |   10.66456   .7235959    14.74   0.000     9.246338    12.08278
-------------+----------------------------------------------------------------
sB2          |
       _cons |   15.45323   1.193821    12.94   0.000     13.11338    17.79307
-------------+----------------------------------------------------------------
sB3          |
       _cons |    14.8943   1.267181    11.75   0.000     12.41067    17.37793
```

sB4						
_cons	19.47978	2.045269	9.52	0.000	15.47113	23.48844
sB5						
_cons	39.81084	4.923973	8.09	0.000	30.16004	49.46165
sC1						
_cons	6.942697	.5228935	13.28	0.000	5.917845	7.967549
sC2						
_cons	18.2909	1.636653	11.18	0.000	15.08312	21.49868
sD						
_cons	11.0663	.9256105	11.96	0.000	9.252138	12.88046
phi1_sA1						
_cons	-.3837757	.165735	-2.32	0.021	-.7086103	-.0589412
phi2_sA1						
_cons	-1.023599	.4515057	-2.27	0.023	-1.908534	-.1386645
phi1_sA2						
_cons	-1.05196	.3478069	-3.02	0.002	-1.733649	-.3702714
phi2_sA2						
_cons	-.8517713	.882325	-0.97	0.334	-2.581096	.8775539
phi1_sA3						
_cons	-1.162615	.4383028	-2.65	0.008	-2.021672	-.303557
phi2_sA3						
_cons	-.1026005	1.145723	-0.09	0.929	-2.348177	2.142976
phi1_sA4						
_cons	-3.27874	.8584398	-3.82	0.000	-4.961251	-1.596229
phi2_sA4						
_cons	-.6770411	1.895494	-0.36	0.721	-4.392141	3.038059
phi1_sA5						
_cons	-8.270104	2.730715	-3.03	0.002	-13.62221	-2.918001
phi2_sA5						
_cons	-2.279285	5.984907	-0.38	0.703	-14.00949	9.450918
phi1_sB1						
_cons	-1.921642	.3686271	-5.21	0.000	-2.644137	-1.199146
phi2_sB1						
_cons	-.4233126	.8821363	-0.48	0.631	-2.152268	1.305643
phi1_sB2						
_cons	-3.230316	.6095607	-5.30	0.000	-4.425033	-2.035599
phi2_sB2						
_cons	-.4855926	1.32408	-0.37	0.714	-3.080741	2.109556
phi1_sB3						
_cons	-3.529583	.6733545	-5.24	0.000	-4.849334	-2.209832
phi2_sB3						
_cons	-.7983987	1.497648	-0.53	0.594	-3.733734	2.136937
phi1_sB4						
_cons	-5.021189	1.159367	-4.33	0.000	-7.293506	-2.748872
phi2_sB4						
_cons	.6409199	2.176438	0.29	0.768	-3.624821	4.906661
phi1_sB5						
_cons	-12.37504	2.595848	-4.77	0.000	-17.46281	-7.287273
phi2_sB5						
_cons	1.847428	4.616137	0.40	0.689	-7.200034	10.89489
phi1_sC1						
_cons	-1.409292	.2647771	-5.32	0.000	-1.928246	-.8903385
phi2_sC1						
_cons	.1640563	.6275231	0.26	0.794	-1.065866	1.393979

```
-------------+----------------------------------------------------------------
phi1_sC2     |
       _cons |  -4.479169   .8319998    -5.38   0.000    -6.109859   -2.848479
-------------+----------------------------------------------------------------
phi2_sC2     |
       _cons |   .2207494   1.770406     0.12   0.901    -3.249184    3.690682
-------------+----------------------------------------------------------------
phi1_sD      |
       _cons |  -2.736951   .5005148    -5.47   0.000    -3.717942    -1.75596
-------------+----------------------------------------------------------------
phi2_sD      |
       _cons |  -.8269326   1.058469    -0.78   0.435    -2.901493    1.247628
------------------------------------------------------------------------------
```

4.4.2 Part A (Gain Domain Only)

```
                                                  Number of obs   =      13804
                                                   Wald chi2(0)    =          .
Log pseudolikelihood = -25405.825                  Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gamma _cons	.353284	.0182659	19.34	0.000	.3174835	.3890845
alpha _cons	.497086	.0139917	35.53	0.000	.4696627	.5245093
beta _cons	.9801244	.027654	35.44	0.000	.9259235	1.034325
phi1_gamma _cons	.0405741	.0120417	3.37	0.001	.0169728	.0641755
phi2_gamma _cons	.0025484	.028743	0.09	0.929	-.0537868	.0588837
phi1_alpha _cons	-.0305431	.0070018	-4.36	0.000	-.0442663	-.0168198
phi2_alpha _cons	.0930661	.0210508	4.42	0.000	.0518073	.1343249
phi1_beta _cons	.0053596	.0154684	0.35	0.729	-.0249578	.0356771
phi2_beta _cons	-.0445406	.038949	-1.14	0.253	-.1208792	.0317981
sA1 _cons	4.148472	.2173676	19.09	0.000	3.722439	4.574505
sA2 _cons	5.968931	.3746306	15.93	0.000	5.234669	6.703194
sA3 _cons	5.309521	.433876	12.24	0.000	4.459139	6.159902
sA4 _cons	8.322197	.7192379	11.57	0.000	6.912516	9.731877
sA5 _cons	18.08268	2.036236	8.88	0.000	14.09173	22.07363
phi1_sA1 _cons	-.2270423	.1240069	-1.83	0.067	-.4700913	.0160067
phi2_sA1 _cons	-.6813952	.3070209	-2.22	0.026	-1.283145	-.0796452
phi1_sA2 _cons	-.5242444	.238329	-2.20	0.028	-.9913607	-.0571282
phi2_sA2 _cons	-.5413533	.5415599	-1.00	0.317	-1.602791	.5200845
phi1_sA3 _cons	-.5326923	.2629498	-2.03	0.043	-1.048064	-.0173202
phi2_sA3 _cons	-.1230266	.6450056	-0.19	0.849	-1.387214	1.141161
phi1_sA4 _cons	-1.405904	.4909182	-2.86	0.004	-2.368086	-.4437217
phi2_sA4 _cons	-.3779393	.9823201	-0.38	0.700	-2.303251	1.547373
phi1_sA5 _cons	-3.254219	1.354181	-2.40	0.016	-5.908365	-.6000737
phi2_sA5 _cons	-1.032615	2.713097	-0.38	0.703	-6.350188	4.284959

4.4.3 Part B (Loss Domain Only)

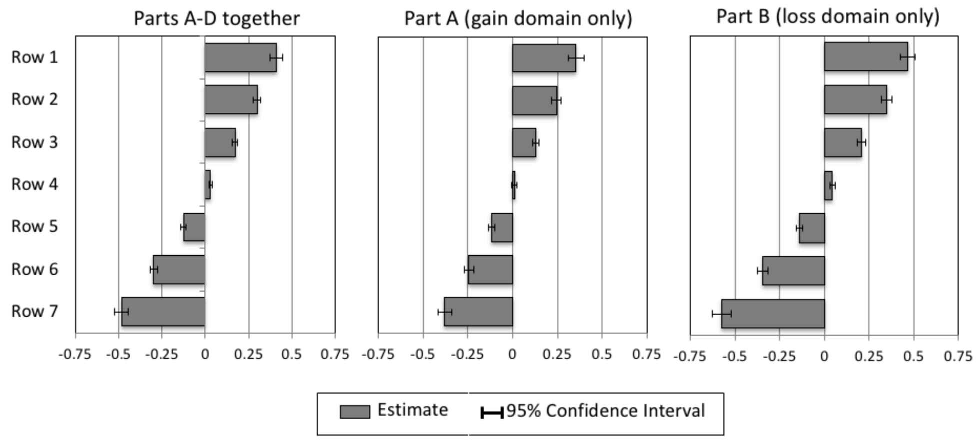
```
                                                  Number of obs   =      13804
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -27851.955                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |  -.0031566   .0260451    -0.12   0.904    -.0542041    .0478909
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .5772309    .016438    35.12   0.000      .545013    .6094489
-------------+----------------------------------------------------------------
beta         |
       _cons |    1.30456   .0371034    35.16   0.000     1.231839    1.377282
-------------+----------------------------------------------------------------
phi1_gamma   |
       _cons |    .063236   .0116521     5.43   0.000     .0403983    .0860737
-------------+----------------------------------------------------------------
phi2_gamma   |
       _cons |  -.0219581   .0303238    -0.72   0.469    -.0813916    .0374754
-------------+----------------------------------------------------------------
phi1_alpha   |
       _cons |  -.0425013   .0082642    -5.14   0.000    -.0586988   -.0263039
-------------+----------------------------------------------------------------
phi2_alpha   |
       _cons |   .0889148   .0248289     3.58   0.000      .040251    .1375785
-------------+----------------------------------------------------------------
phi1_beta    |
       _cons |   .0392595   .0147204     2.67   0.008      .010408     .068111
-------------+----------------------------------------------------------------
phi2_beta    |
       _cons |  -.0233409   .0398406    -0.59   0.558    -.1014271    .0547452
-------------+----------------------------------------------------------------
sB1          |
       _cons |   13.53282   1.195238    11.32   0.000     11.19019    15.87544
-------------+----------------------------------------------------------------
sB2          |
       _cons |   22.99171   2.437006     9.43   0.000     18.21527    27.76816
-------------+----------------------------------------------------------------
sB3          |
       _cons |   25.49915   3.128879     8.15   0.000     19.36666    31.63164
-------------+----------------------------------------------------------------
sB4          |
       _cons |   39.57846   5.502788     7.19   0.000     28.79319    50.36372
-------------+----------------------------------------------------------------
sB5          |
       _cons |   100.1441   16.38849     6.11   0.000     68.02324    132.2649
-------------+----------------------------------------------------------------
phi1_sB1     |
       _cons |  -2.036972   .4820761    -4.23   0.000    -2.981824    -1.09212
-------------+----------------------------------------------------------------
phi2_sB1     |
       _cons |  -.5454671   1.147932    -0.48   0.635    -2.795372    1.704438
-------------+----------------------------------------------------------------
phi1_sB2     |
       _cons |  -4.321136   .9942535    -4.35   0.000    -6.269837   -2.372435
-------------+----------------------------------------------------------------
phi2_sB2     |
       _cons |  -.3476178   2.106143    -0.17   0.869    -4.475582    3.780347
-------------+----------------------------------------------------------------
phi1_sB3     |
       _cons |  -5.536534   1.292043    -4.29   0.000    -8.068892   -3.004175
-------------+----------------------------------------------------------------
phi2_sB3     |
       _cons |  -.7679326   2.732935    -0.28   0.779    -6.124387    4.588522
-------------+----------------------------------------------------------------
phi1_sB4     |
       _cons |  -10.11871   2.497848    -4.05   0.000     -15.0144   -5.223022
-------------+----------------------------------------------------------------
phi2_sB4     |
       _cons |   2.072809   4.528289     0.46   0.647    -6.802474    10.94809
-------------+----------------------------------------------------------------
phi1_sB5     |
       _cons |  -32.18525   7.360669    -4.37   0.000     -46.6119    -17.7586
-------------+----------------------------------------------------------------
phi2_sB5     |
       _cons |   7.573371    11.6346     0.65   0.515    -15.23002    30.37677
------------------------------------------------------------------------------
```

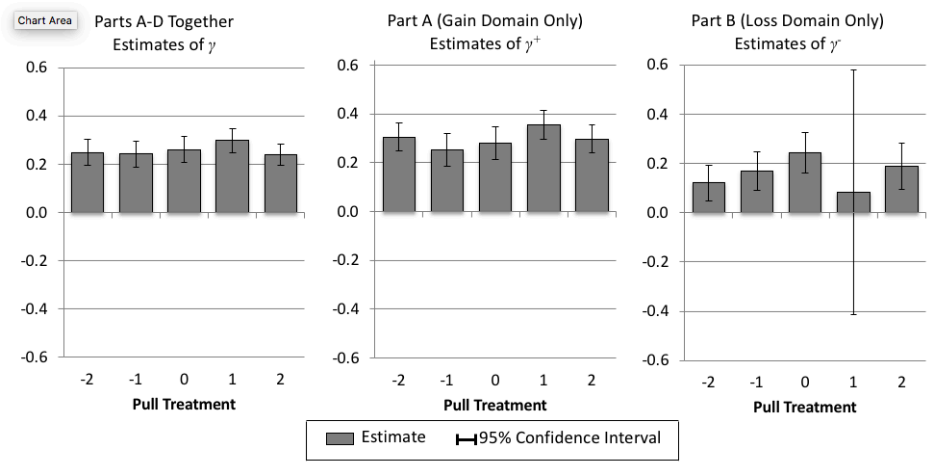
5 Results of Robustness Check with CPT Model with T&K's Probability Weighting Function

As a robustness check, we estimated the CPT model with T&K's probability weighting function $(\omega(p) = p^{\alpha}/(p^{\alpha} + (1-p)^{\alpha})^{1/\alpha})$ instead of the Prelec (1998) probability weighting function. As in the baseline model, utility $u(\cdot)$ is assumed to take the CRRA form (a.k.a. "power utility"), $u(\cdot) = \frac{x^{1-\gamma}}{1-\gamma}$.

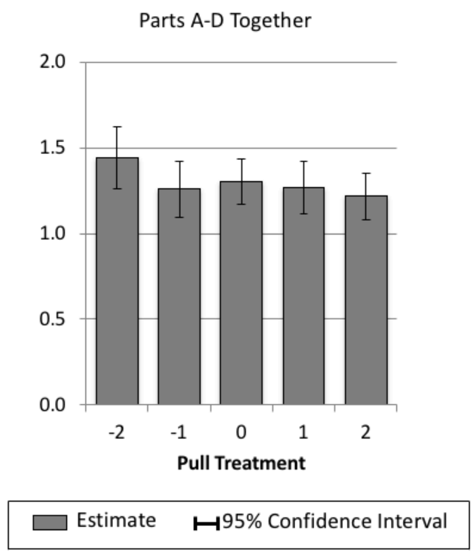
Online Appendix Figures 7.1-7.5 and Online Appendix Tables 7.1-7.4 below are analogous to Figures 6-10 and Tables 1-4 in the main text, respectively, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



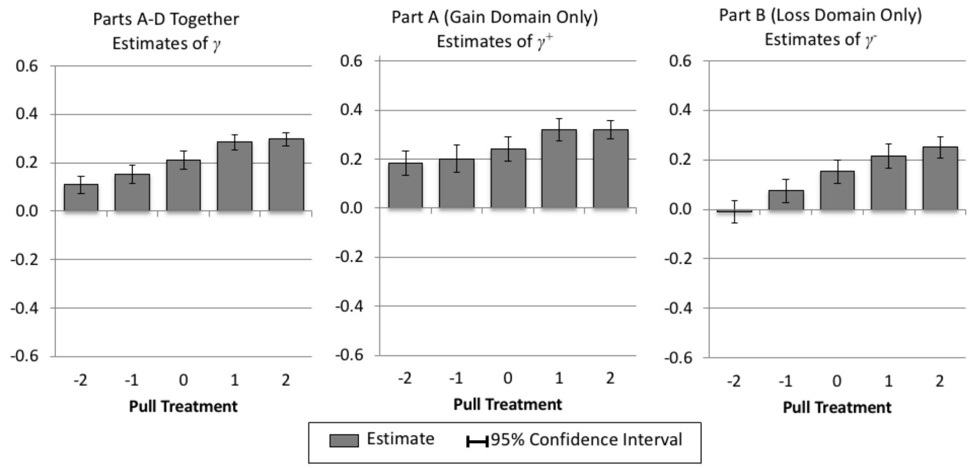
Online Appendix Figure 5.1. Implied estimates of the parameters for the compromise effect c_i as a function of the row i in which a choice appears. This figure is analogous to Figure 6 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



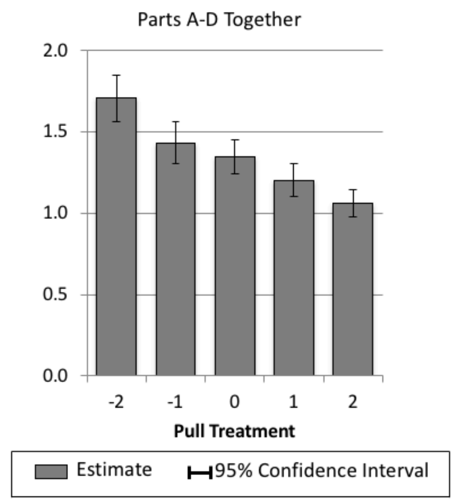
Online Appendix Figure 5.2. Estimates of γ, γ^+ and γ^- by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 7 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



Online Appendix Figure 5.3. Estimates of λ by Pull treatment from the model with the compromise effect, for Parts A-D together. This figure is analogous to Figure 8 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



Online Appendix Figure 5.4. Estimates of γ, γ^+ and γ^- by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 9 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



Online Appendix Figure 5.5. Estimates of λ by Pull treatment from the model without the compromise effect, for Parts A-D together. This figure is analogous to Figure 10 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.

Online Appendix Table 5.1. ML Estimates of Selected Parameters in the Model with the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma, \gamma^+, \gamma^-$	0.267***	0.298***	0.202***
	(0. 011)	(0. 014)	(0. 018)
λ	1.292***		
	(0.034)		
$\alpha, \alpha^+, \alpha^-$	0.645***	0.617***	0.689***
	(0.011)	(0.011)	(0.019)
π_1	-0.089***	-0.102***	-0.084***
	(0.012)	(0.017)	(.017)
π_2	-0.008***	-0. 003	-0.011***
	(0.001)	(0.002)	(0.002)
Log-likelihood	-55,357	-24,018	-25,537
Wald test for π_1, π_2	$p < 1 \times 10^{-144}$	$p < 1 \times 10^{-80}$	$p < 1 \times 10^{-122}$
Parameters	18	9	9
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 1 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 5.2. ML Estimates of Selected Parameters in the Parameterized Model with the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma, \gamma^+, \gamma^-$	γ_0	0.247***	0.283***	0.185***
		(0.018)	(0.021)	(0.025)
	ϕ_1^γ	0.003	0.004	0.006
		(0.009)	(0.010)	(0.014)
	ϕ_2^γ	0.027	.0196	0.018
		(0.024)	(0.028)	(0.034)
λ	λ_0	1.24***		
		(0.049)		
	ϕ_1^λ	-0.048*		
		(0.025)		
	ϕ_2^λ	0.094		
		(0.069)		
$\alpha, \alpha^+, \alpha^-$		0.597***	0.577***	0.630***
		(0.014)	(.014)	(0.021)
π_1		-0.088***	-0.105***	-0.078***
		(0.012)	(0.017)	(0.017)
π_2		-0.008***	-0.002	-0.012***
		(0.001)	(0.002)	(0.002)
Log-likelihood		-55,203	-23,942	-25,476
Wald test for π_1, π_2		$p < 1 \times 10^{-134}$	$p < 1 \times 10^{-84}$	$p < 1 \times 10^{-112}$
Parameters		50	23	23
Individuals		493	493	493
Observations		30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 2 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 5.3. ML Estimates of Selected Parameters in the Model Without the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma, \gamma^+, \gamma^-$	0.219***	0.260***	0.144***
	(0.008)	(0.011)	(0.012)
λ	1.32***		
	(0.027)		
$\alpha, \alpha^+, \alpha^-$	0.615***	0.599***	0.631***
	(0.007)	(0.008)	(0.010)
Log-likelihood	-59,862	-25,681	-28,223
Parameters	16	7	7
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 3 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 5.4. ML Estimates of Selected Parameters in the Parameterized Model Without the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma, \gamma^{+}, \gamma^{-}$	γ_0	0.206***	0.247***	0.137***
		(0.012)	(0.015)	(0.017)
	ϕ_1^{γ}	0.044***	0.041***	0.061***
		(0.006)	(0.007)	(0.009)
	ϕ_2^{γ}	0.009	0.010	-0.003
		(0.018)	(0.021)	(0.025)
λ	λ_0	1.31***		
		(0.040)		
	ϕ_1^{λ}	-0.144***		
		(0.021)		
	ϕ_2^{λ}	0.080		
		(0.057)		
$\alpha, \alpha^{+}, \alpha^{-}$		0.587***	0.571***	0.605***
		(0.009)	(0.010)	(0.012)
Log-likelihood		-59,334	-25,485	-27,937
Parameters		48	21	21
Individuals		493	493	493
Observations		30,566	13,804	13,804

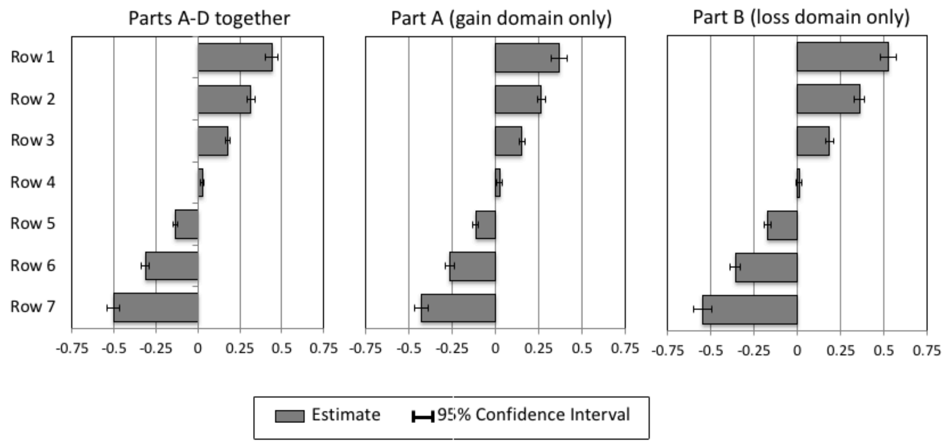
NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 4 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

6 Results of Robustness Check with CPT Model with CARA Utility

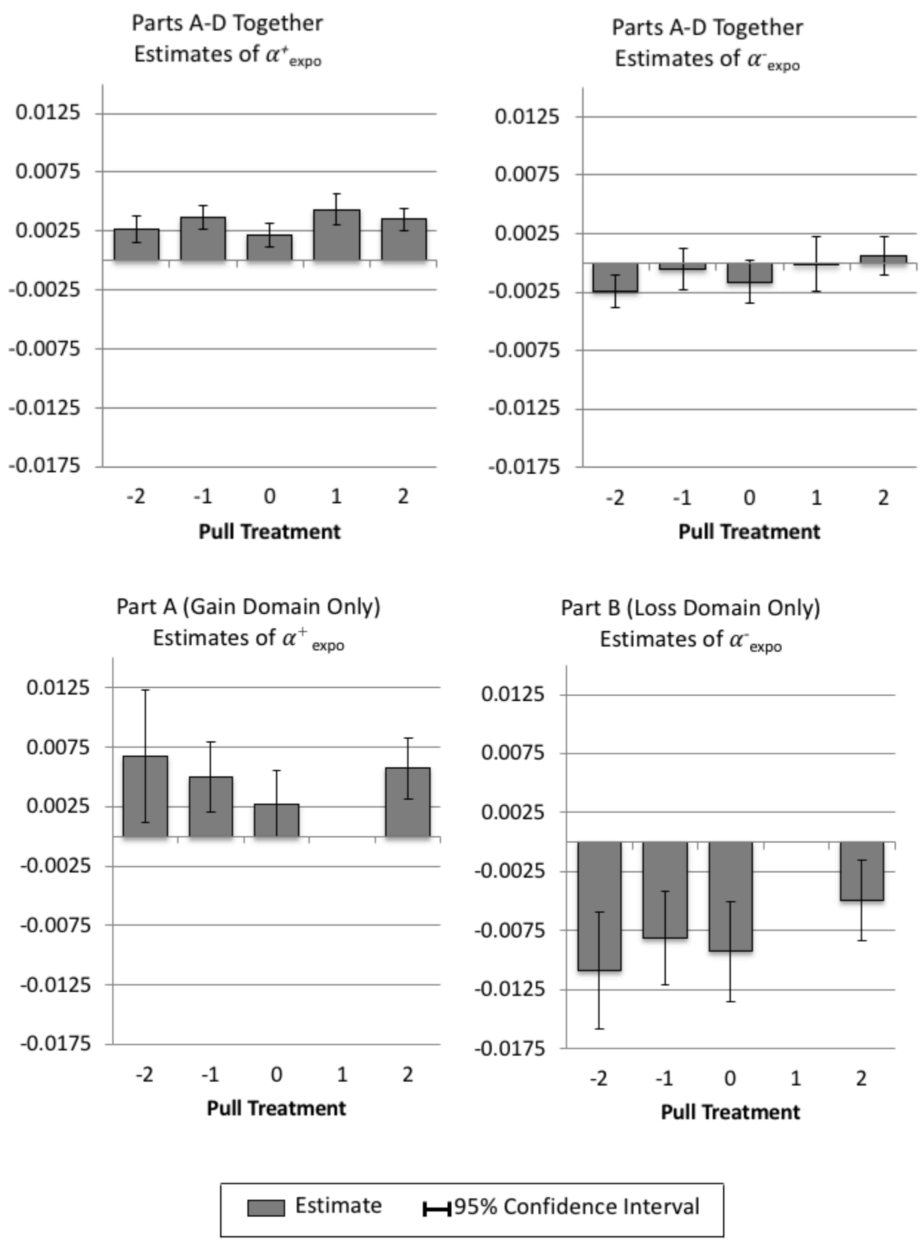
As a robustness check, we estimated the CPT model with CARA (a.k.a. "exponential") utility (Köbberling and Wakker 2005), $u(x) = \frac{1-e^{-\alpha_{expo}^{+}x}}{\alpha_{expo}^{+}}$ if $x \geq 0$, $u(-x) = \frac{1-e^{-\alpha_{expo}^{-}|x|}}{\alpha_{expo}^{-}}$ if $x < 0$, instead of with CRRA utility. As in the baseline model, we used the Prelec (1998) probability weighting function.

For this robustness check with CARA utility, unlike for the baseline CPT model with CRRA utility, we did not impose the assumption that the parameters for the coefficient of (absolute) risk aversion in the gain and in the loss domains are equal to one another (i.e., we did not assume that $\alpha_{expo}^{+} = \alpha_{expo}^{-}$). As Wakker (2010, section 9.6) and Köbberling and Wakker (2005) point out, with CRRA utility, for any λ there exists a range of x values for which the ratio of disutility from a sure loss of x to utility from a sure gain of x, $\frac{-\lambda u^{-}(-x)}{u^{+}(x)}$, is *smaller* than 1, which is the opposite of loss aversion. This issue does not arise with CARA utility, which makes the interpretation of λ in the CPT model with CARA utility with $\alpha_{expo}^{+} \neq \alpha_{expo}^{-}$ less problematic. (A second issue that arises with both CRRA and CARA utility when assuming different risk aversion parameters in the gain and loss domains is that the ratio of disutility from a sure loss of x to utility from a sure gain of x, $\frac{-\lambda u^{-}(-x)}{u^{+}(x)}$, is *not* uniformly equal to λ; this issue also arises with the CPT model with CARA utility, thus making the estimates of λ we report below in this section more difficult to interpret.)

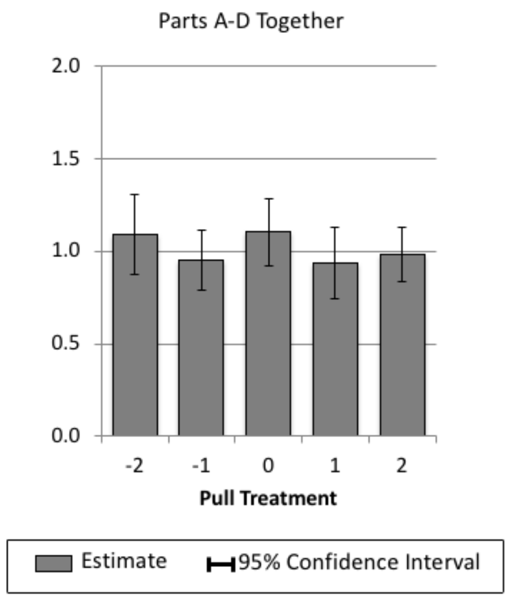
Online Appendix Figures 8.1-8.5 and Online Appendix Tables 8.1-8.4 below are analogous to Figures 6-10 and Tables 1-4 in the main text, respectively, except that the results were obtained by estimating the CPT model with CARA utility.



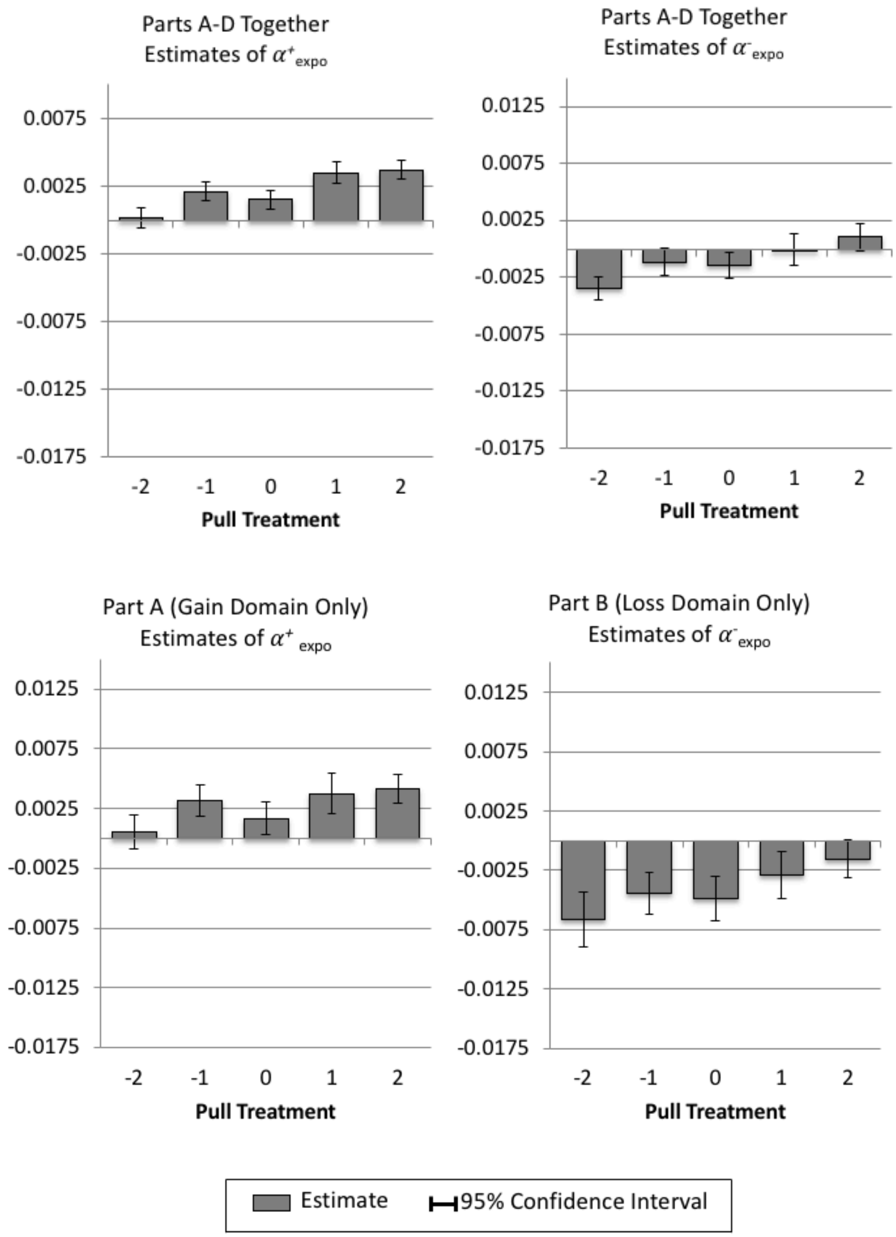
Online Appendix Figure 6.1. Implied estimates of the parameters for the compromise effect c_i as a function of the row i in which a choice appears. This figure is analogous to Figure 6 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.



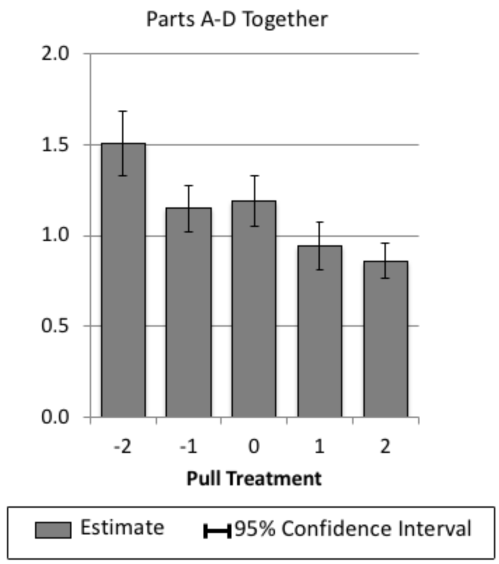
Online Appendix Figure 6.2. Estimates of α^{+}_{expo} and α^{-}_{expo} by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 7 in the main text, except that the results were obtained by estimating the CPT model with CARA utility. We omit the estimates for Pull Treatment 1 in the bottom two panels (Part A only and Part B only) because the MLE algorithm did not converge for these.



Online Appendix Figure 6.3. Estimates of λ by Pull treatment from the model with the compromise effect, for Parts A-D together. This figure is analogous to Figure 8 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.



Online Appendix Figure 6.4. Estimates of α^{+}_{expo} and α^{-}_{expo} by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 9 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.



Online Appendix Figure 6.5. Estimates of λ by Pull treatment from the model without the compromise effect, for Parts A-D together. This figure is analogous to Figure 10 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.

Online Appendix Table 6.1. ML Estimates of Selected Parameters in the Model with the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
α^{+}_{expo}	0.0034***	0.0054***	
	(0.0002)	(0.0007)	
α^{-}_{expo}	-0.0008*		-0.0065***
	(0.0004)		(0.0008)
λ	0.992***		
	(0.040)		
$\alpha, \alpha^{+}, \alpha^{-}$	0.638***	0.592***	0.694***
	(0.016)	(0.016)	(0.019)
$\beta, \beta^{+}, \beta^{-}$	1.331***	1.184***	1.72***
	(0.027)	(0.036)	(0.074)
π_1	-0.105***	-0.084***	-0.160***
	(.012)	(0.018)	(0.018)
π_2	-0.007***	-0.006***	-0.002
	(0.001)	(0.002)	(0.002)
Log-likelihood	-55,410	-24,321	-25,294
Wald test for π_1, π_2	$p < 1 \times 10^{-151}$	$p < 1 \times 10^{-95}$	$p < 1 \times 10^{-126}$
Parameters	20	10	10
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 1 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.

* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 6.2. ML Estimates of Selected Parameters in the Parameterized Model with the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
α^+_{expo}	$\alpha^+_{expo,0}$	0.0034***	0.0067***	
		(0.0004)	(0.0012)	
	$\phi_1^{\alpha^+_{expo}}$	0.0001	-0.0010	
		(0.0002)	(0.0006)	
	$\phi_2^{\alpha^+_{expo}}$	-0.0001	-0.0014	
		(0.0006)	(0.0014)	
α^-_{expo}	$\alpha^-_{expo,0}$	-0.0003		-0.0059***
		(0.0006)		(0.0010)
	$\phi_1^{\alpha^-_{expo}}$	0.0006**		0.0006
		(0.0003)		(0.0004)
	$\phi_2^{\alpha^-_{expo}}$	-0.0009		-0.0009
		(0.0008)		(0.0010)
λ	λ_0	0.973***		
		(0.056)		
	ϕ_1^{λ}	-0.015		
		(0.027)		
	ϕ_2^{λ}	0.037		
		(0.081)		
$\alpha_0, \alpha_0^+, \alpha_0^-$		0.572***	0.533***	0.626***
		(0.020)	(0.021)	(0.025)
$\beta_0, \beta_0^+, \beta_0^-$		1.35***	1.150***	1.74***
		(0.040)	(0.057)	(0.103)
π_1		-0.102***	-0.094***	-0.155***
		(0.012)	(0.018)	(0.018)
π_2		-0.007***	-0.005***	-0.003
		(0.001)	(0.002)	(0.002)
Log-likelihood		-55,246	-24,234	
Wald test for π_1, π_2		$p < 1 \times 10^{-146}$	$p < 1 \times 10^{-105}$	$p < 1 \times 10^{-121}$
Parameters		56	26	26
Individuals		493	493	493
Observations		30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 2 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.

* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 6.3. ML Estimates of Selected Parameters in the Model Without the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
α_{expo}^{+}	0.0021***	0.0023***	
	(0.0002)	(0.0003)	
α_{expo}^{-}	-0.0013***		-0.0045***
	(0.0003)		(0.0004)
λ	1.098***		
	(0.032)		
$\alpha, \alpha^{+}, \alpha^{-}$	0.587***	.554***	0.632***
	(0.010)	(0.011)	(0.012)
$\beta, \beta^{+}, \beta^{-}$	1.309***	1.260***	1.503***
	(0.017)	(0.023)	(0.036)
Log-likelihood	-60,099	-26,197	-27,953
Parameters	18	8	8
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 3 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 6.4. ML Estimates of Selected Parameters in the Parameterized Model Without the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
α^{+}_{expo}	$\alpha^{+}_{expo,0}$	0.0023***	0.0031***	
		(0.0003)	(0.0004)	
	$\phi_1^{\alpha^{+}_{expo}}$	0.0008***	0.0010***	
		(0.0001)	(0.0003)	
	$\phi_2^{\alpha^{+}_{expo}}$	-0.0001	-0.0012*	
		(0.0004)	(0.0006)	
α^{-}_{expo}	$\alpha^{-}_{expo,0}$	-0.0006*		-0.0036***
		(0.0004)		(0.0005)
	$\phi_1^{\alpha^{-}_{expo}}$	0.0009***		0.0011***
		(0.0002)		(0.0002)
	$\phi_2^{\alpha^{-}_{expo}}$	-0.0008*		-0.0009
		(0.0005)		(0.0006)
λ	λ_0	1.115***		
		(0.042)		
	ϕ_1^{λ}	-0.141***		
		(0.021)		
	ϕ_2^{λ}	0.021		
		(0.059)		
$\alpha_0, \alpha_0^{+}, \alpha_0^{-}$		0.547***	0.514***	0.590***
		(0.013)	(0.015)	(0.016)
$\beta_0, \beta_0^{+}, \beta_0^{-}$		1.312***	1.245***	1.49***
		(0.024)	(0.033)	(0.047)
Log-likelihood		-59,571	-26,003	-27,712
Parameters		54	24	24
Individuals		493	493	493
Observations		30,566	13,804	13,804

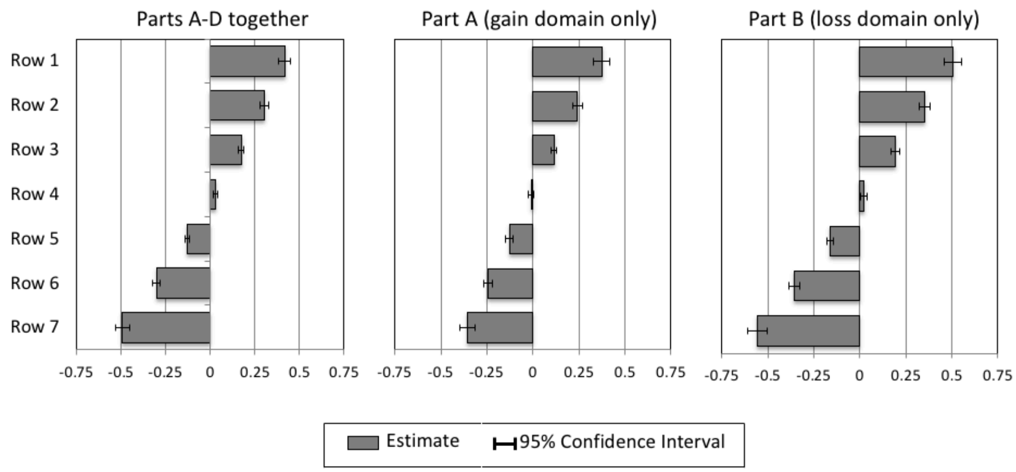
NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 4 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

7 Results of Robustness Check with CPT Model with Expo-Power Utility

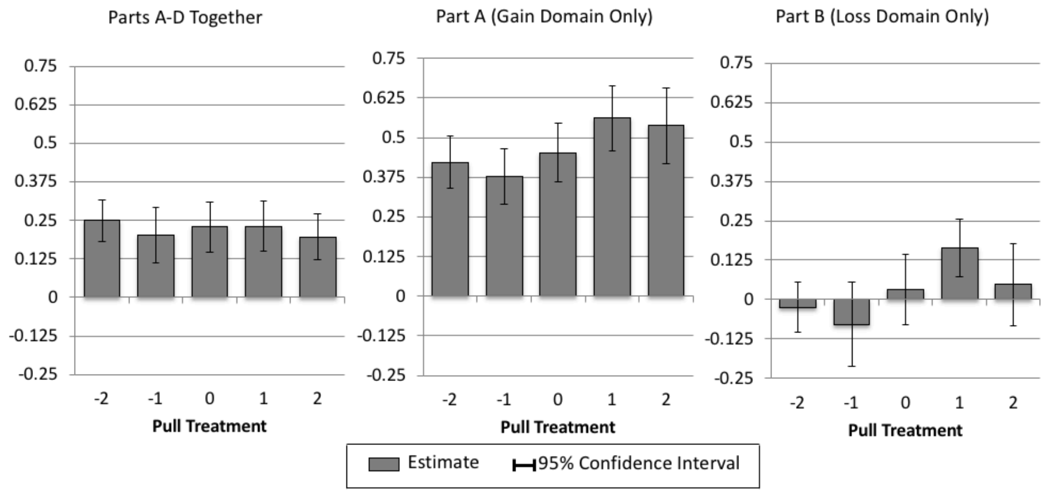
As a robustness check, we estimated the CPT model with expo-power utility (Saha 1993), $u(x) = \frac{1-e^{-\alpha_{e-p}x^{1-\gamma_{e-p}}}}{\alpha_{e-p}}$, instead of with CRRA utility. As in the baseline model, we used the Prelec (1998) probability weighting function.

Online Appendix Figures 9.1-9.9 and Online Appendix Tables 9.1-9.4 below are analogous to Figures 6-10 and Tables 1-4 in the main text, respectively, except that the results were obtained by estimating the CPT model with expo-power utility.

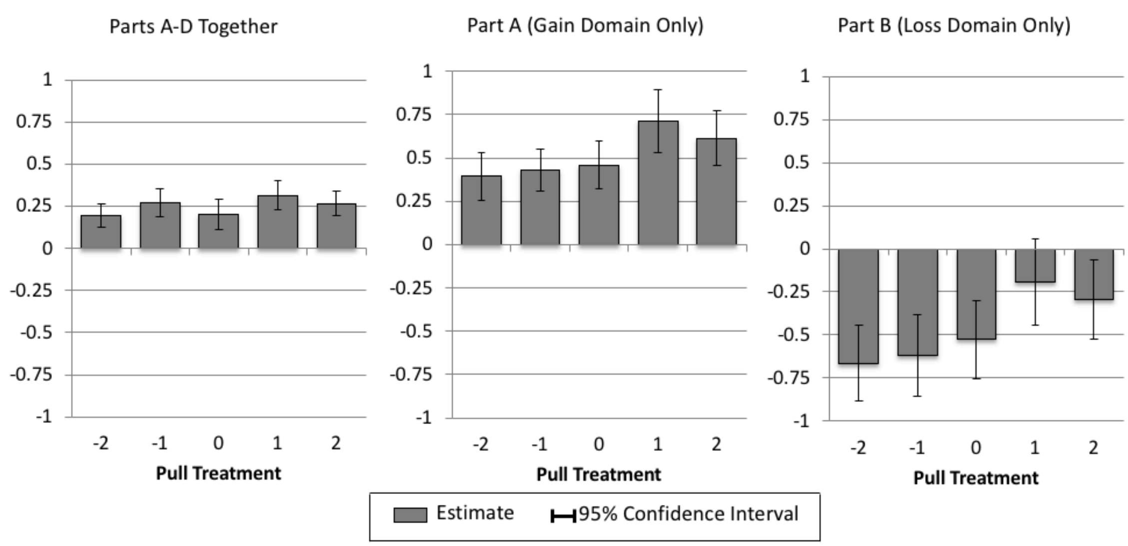
It is difficult to interpret the effects of the Pull treatment on the parameters of expo-power utility because both γ_{e-p} and α_{e-p} capture risk aversion. To see this, note that the Arrow-Pratt coefficient of relative risk aversion is $\frac{-u''(x)x}{u'(x)} = \gamma_{e-p} + \alpha_{e-p}(1-\gamma_{e-p})x^{1-\gamma_{e-p}}$, which depends on both γ_{e-p} and α_{e-p}. As a result, γ_{e-p} and α_{e-p} may move together across Pull treatments in complicated ways, and there is no clear theoretical relationship between γ_{e-p}, α_{e-p} and Pull treatment. For that reason, in Online Appendix Figures 9.2-9.4 and 9.6-9.8, we report estimates of the coefficient of relative risk aversion with $x = 10, 50,$ and 200 by Pull treatment (instead of estimates of γ_{e-p} and α_{e-p} by Pull treatment). Also, in Online Appendix Tables 7.2 and 7.4, we only report the results of parameterized model for Parts A-D together, since it is only meaningful to interpret the effect of the Pull treatment on the parameter λ (and we can only estimate λ using data from Parts A-D together).



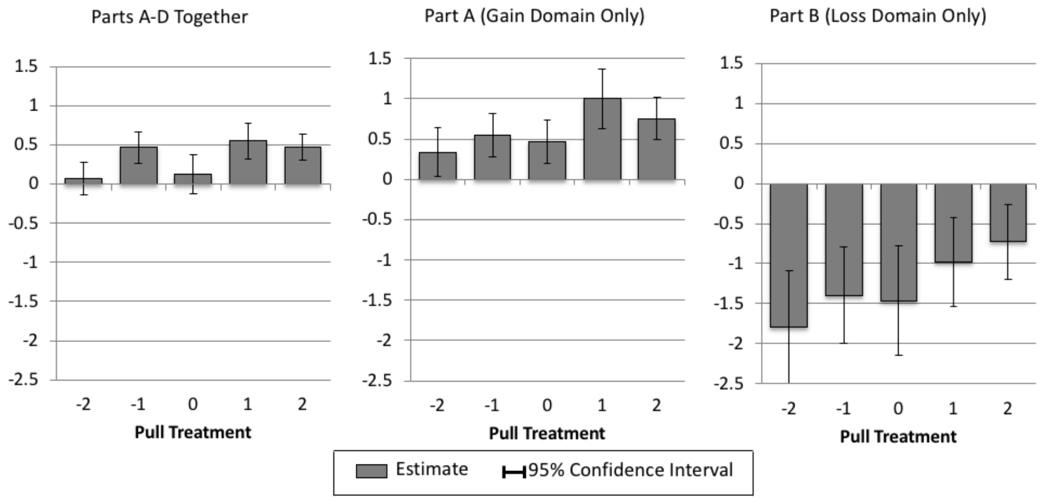
Online Appendix Figure 7.1. Implied estimates of the parameters for the compromise effect c_i as a function of the row i in which a choice appears. This figure is analogous to Figure 6 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility.



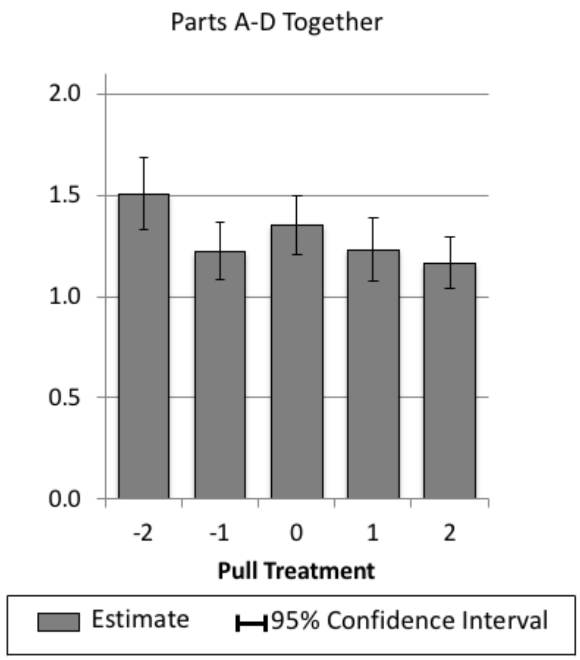
Online Appendix Figure 7.2. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 10) by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 7 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



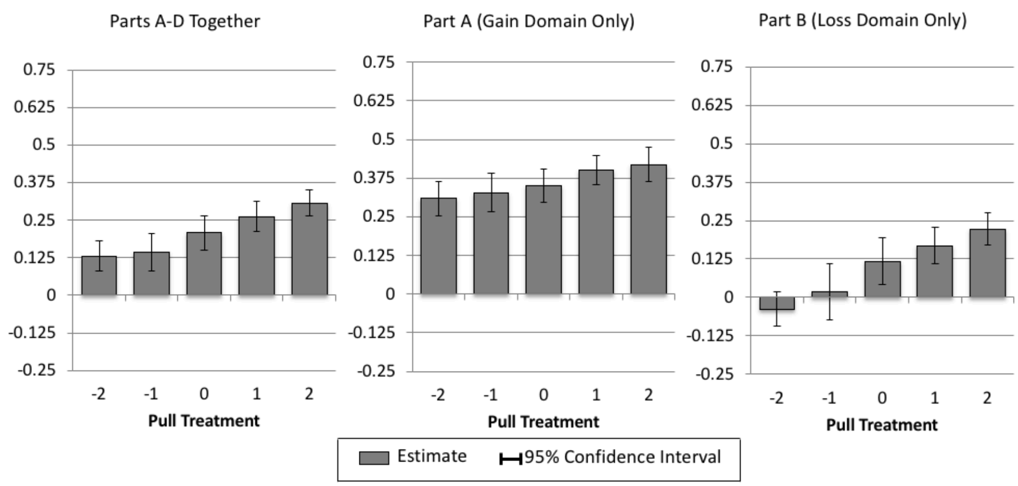
Online Appendix Figure 7.3. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 50) by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 7 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



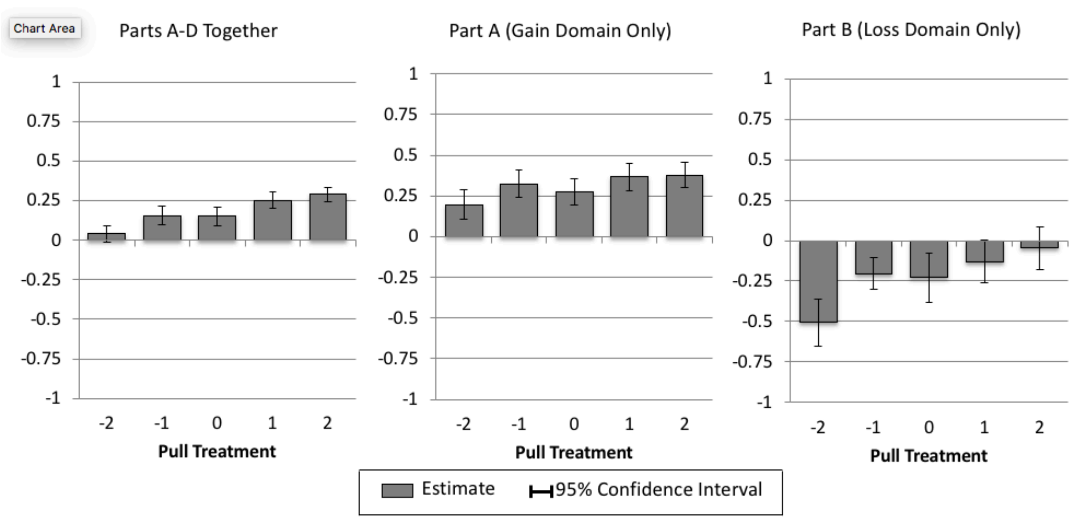
Online Appendix Figure 7.4. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 200) by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 7 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



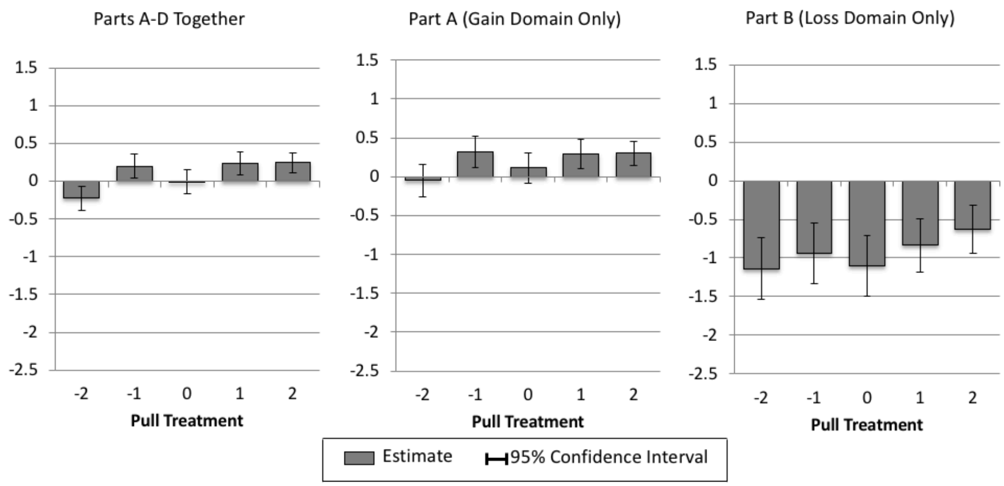
Online Appendix Figure 7.5. Estimates of λ by Pull treatment from the model with the compromise effect, for Parts A-D together. This figure is analogous to Figure 8 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.



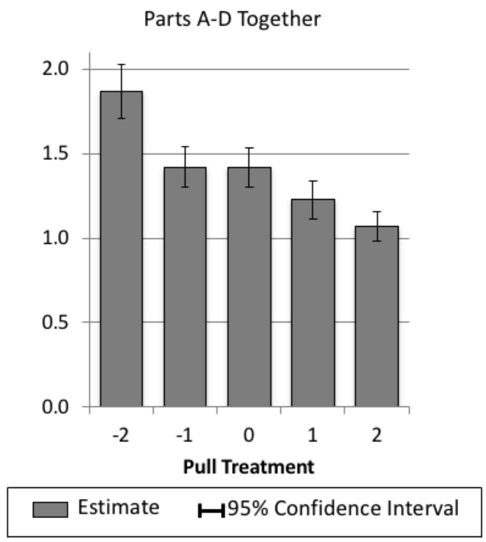
Online Appendix Figure 7.6. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 10) by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 9 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



Online Appendix Figure 7.7. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 50) by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 9 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



Online Appendix Figure 7.8. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 200) by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 9 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



Online Appendix Figure 7.9. Estimates of λ by Pull treatment from the model without the compromise effect, for Parts A-D together. This figure is analogous to Figure 10 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility.

Online Appendix Table 7.1. ML Estimates of Selected Parameters in the Model with the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma_{e-p}, \gamma_{e-p}^{+}, \gamma_{e-p}^{-}$	0.219***	0.427***	0.677***
	(0.020)	(0.020)	(0.044)
$\alpha_{e-p}, \alpha_{e-p}^{+}, \alpha_{e-p}^{-}$	0.0025**	0.0116**	-0.9687***
	(0.0010)	(0.0054)	(0.3114)
λ	1.288***		
	(0.034)		
$\alpha, \alpha^{+}, \alpha^{-}$	0.622***	0.566***	0.679***
	(0.015)	(0.015)	(0.018)
$\beta, \beta^{+}, \beta^{-}$	1.112***	0.837***	1.67***
	(0.025)	(0.037)	(0.075)
π_1	-0.091***	-0.137***	-0.136***
	(0.012)	(0.018)	(0.019)
π_2	-0.008***	0.002	-0.005**
	(0.001)	(0.002)	(0.002)
Log-likelihood	-55,374	-23,912	-25,264
Wald test for π_1, π_2	$p < 1 \times 10^{-146}$	$p < 1 \times 10^{-79}$	$p < 1 \times 10^{-123}$
Parameters	20	11	11
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 1 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility.

* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 7.2. ML Estimates of Selected Parameters in the Parameterized Model with the Compromise Effect

		Parts A-D Together
$\gamma_{e-p,0}$		0.175***
		(0.029)
$\alpha_{e-p,0}$		0.0032***
		(0.0010)
λ	λ_0	1.234***
		(0.049)
	ϕ_1^λ	-0.066**
		(0.026)
	ϕ_2^λ	0.105
		(0.069)
α_0		0.559***
		(0.019)
β_0		1.168***
		(0.037)
π_1		-0.089***
		(0.012)
π_2		-0.008***
		(0.001)
Log-likelihood		-55,210
Wald test for π_1, π_2		$p < 1 \times 10^{-138}$
Parameters		56
Individuals		493
Observations		30,566

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 2 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. Both γ_{e-p} and α_{e-p} capture risk aversion and may move together across Pull treatments in complicated ways, and as a result only estimates related to λ are meaningful in the parameterized model with expo-power utility. We thus only report the results for Parts A-D together.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 7.3. ML Estimates of Selected Parameters in the Model Without the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma_{e-p}, \gamma^+_{e-p}, \gamma^-_{e-p}$	0.244***	0.415***	0.331***
	(0.016)	(0.017)	(0.103)
$\alpha_{e-p}, \alpha^+_{e-p}, \alpha^-_{e-p}$	-0.0046***	-0.0210***	-0.0616
	(0.0015)	(0.0059)	(0.0512)
λ	1.375***		
	(0.030)		
$\alpha, \alpha^+, \alpha^-$	0.574***	0.538***	0.637***
	(0.010)	(0.011)	(0.012)
β, β^+, β^-	1.133***	0.992***	1.476***
	(0.016)	(0.022)	(0.051)
Log-likelihood	-59,933	-25,580	-27,840
Parameters	18	9	9
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 3 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 7.4. ML Estimates of Selected Parameters in the Parameterized Model Without the Compromise Effect

		Parts A-D Together
$\gamma_{e-p,0}$		0.213***
		(0.033)
$\alpha_{e-p,0}$		-0.0014
		(0.0032)
λ	λ_0	1.33***
		(0.045)
	ϕ_1^λ	-0.154***
		(0.021)
	ϕ_2^λ	0.112*
		(0.061)
α_0		0.535***
		(0.012)
β_0		1.149***
		(0.022)
Log-likelihood		-59,414
Parameters		54
Individuals		493
Observations		30,566

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 4 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. Both γ_{e-p} and α_{e-p} capture risk aversion and may move together across Pull treatments in complicated ways, and as a result only estimates related to λ are meaningful in the parameterized model with expo-power utility. We thus only report the results for Parts A-D together.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

8 Numerical Estimates of the Parameters for the Compromise Effect c_i as a Function of the Row i in Which a Choice Appears

Online Appendix Table 8.1 shows the numerical estimates of the parameters for the compromise effect c_i. These results are also shown graphically in Figure 6 of the paper.

Online Appendix Table 8.1. Estimates of the Parameters for the Compromise Effect c_i in the Model with the Compromise Effect, as a Function of the Row i in Which a Choice Appears

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain only)
c_1	0.416***	0.371***	0.515***
	(0.018)	(0.023)	(0.023)
c_2	0.302***	0.242***	0.358***
	(0.012)	(0.013)	(0.015)
c_3	0.174***	0.116***	0.192
	(0.007)	(0.008)	(0.011)
c_4	0.030***	-0.007	0.017*
	(0.005)	(0.008)	(0.009)
c_5	-0.128***	-0.126***	-0.166***
	(0.007)	(0.009)	(0.009)
c_6	-0.302***	-0.242**	-0.358***
	(0.012)	(0.013)	(0.015)
c_7	-0.491***	-0.355***	-0.558***
	(0.020)	(0.020)	(0.027)

NOTE: The estimates of c_i were obtained by transforming the estimates of π_1 and π_2 from Table 1 of the paper, as described in the main text.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

9 Additional Information on the Analysis of the Demographic Correlates of the CPT Model and the Compromise Effect Parameters

As mentioned in Section 8 of the main text, we analyzed the demographic correlates of the four key parameters of the CPT model (γ, λ, α, β) and of the two model parameters that capture the compromise effect (π_1, π_2). Also as mentioned in Section 8 of the main text, in our baseline demographic specification, we estimate our CPT model with the compromise effect using data from Parts A-D together, with these six key model parameters specified as linear functions of a constant, age, sex, a dummy variable indicating whether one has a college degree, SAT Math score, the log of one's parents' combined annual income, as well as dummy variables to control for race. In other words, we substitute γ in the utility function in equation (1) of the main text by:

$$\gamma = \gamma_0 + \phi^{\gamma}_{\text{age}} age + \phi^{\gamma}_{\text{sex}} sex + \phi^{\gamma}_{\text{college}} college + \phi^{\gamma}_{\text{SAT}} SAT\_Math$$
$$+\phi^{\gamma}_{\text{inc.}} \log{(parental\_income)} + \boldsymbol{\phi^{\gamma}_{\text{Other}}} \boldsymbol{Other\_variables},$$

where $\boldsymbol{Other\_variables}$ includes the dummy variables that control for race as well as dummy variables that indicate missing observations for each variable that has missing observations. We also substituted λ, α, β, π_1, and π_2 with analogous parametrized equations.

In addition, we estimated several specifications to verify the robustness of the results from our baseline demographic specification. First, we estimated the baseline demographic specification again, but using data from Part A only, and then using data from Part B only. Second, we estimated a specification akin to the baseline demographic specification using data from Parts A-D together, but with CARA (a.k.a. "exponential") utility (Köbberling and Wakker 2005) (instead of CRRA, a.k.a. "power", utility). As in Online Appendix Section 6, we did not impose the assumption that the parameters for the coefficient of (absolute) risk aversion in the gain and in the loss domains (i.e., α^{+}_{expo} and α^{-}_{expo}, as well as the corresponding parameterized equations) are equal to one another in this specification with CARA utility. Lastly, we employed a two-step procedure in which we first estimated our baseline CPT model with the compromise effect separately for each participant, and then regressed each estimated parameter of interest on the demographic variables (and on the variables included in $\boldsymbol{Other\_variables}$). One limitation of this two-step analysis is that, to ensure that the MLE algorithm converged for sufficiently many participants, we had to reduce the number of parameters in the model by assuming that σ_q is identical across all screens.[1]

We dropped from this analysis data from approximately three dozens of participants who had not provided their age, sex, and/or their highest level of education (unless they

[1] With this assumption, the MLE algorithm still failed to converge for 40 participants; we further dropped from the regression analysis in the second step 35 participants for whom the estimates of the parameter σ_q were particularly large; this left 408 participants for the regression analysis, vs. 458 participants whose data were used in the other demographic specifications (as discussed below).

indicated they were still currently studying). As in all the other analyses reported in the paper, we also dropped from this analysis data from the 28 participants for whom the MLE algorithm does not converge when the CPT model is estimated separately for each participant (in the model without the compromise effect, using data from Parts A-D together, and assuming that σ_q is identical across all screens). This left 458 participants whose data were included in this analysis.

The dummy variables that control for race comprise a dummy variable that is equal to 1 if one's self-reported ethnicity is "Asian", as well as another dummy variable that is equal to 1 if one's self-reported ethnicity is "African-American", "Hispanic", "Native American", or "Other". Most participants for whom these dummies are both equal to 0 reported that their ethnicity is "Caucasian", but a few of these participants did not report their ethnicity.

The dummy variable indicating whether one has a college degree was defined based on responses to the question "what is the highest level of education you have completed?", with the five possible response categories "Additional education beyond college", "Completed college", "Some college", "Completed high school or GED", "Some high school". Participants who responded "Additional education beyond college" or "Completed college" were coded as having completed college. Only participants who were not fulltime students were asked this education question, so many observations are missing for our college dummy variable. Instead of dropping the corresponding participants from this analysis, we coded the college dummy as a constant ("-9") for these participants, and included in the parameterized equations for the parameters of interest another dummy variable indicating whether each participant has missing data for the college variable.

Many participants also had missing data for the SAT Math and the log parental income variables. We similarly coded these variables as constants for these participants and included, in the parameterized equations for the parameters of interest, dummy variables indicating whether each participant has missing data for these variables.

Only respondents who reported being full-time students were asked their parents' combined annual income. The log parental income variable was constructed from responses to the question "If you are a full-time student, what is your best guess of your parents' combined annual income?", with possible response categories "Under $20,000", "Between $20,000 and $39,999", "Between $40,000 and $59,999", "Between $60,000 and $79,999", "Between $80,000 and $99,999", and "Over $100,000". We replaced these responses with the midpoint of each interval (e.g., we coded parental income for participants who responded "Between $20,000 and $39,999" as $30,000); for the participants who responded "Under $20,000" and "Over $100,000", we replaced these responses with "$15,000" and "125,000", respectively. Then, we took the logarithm of the resulting variable.

Online Appendix Table 9.1 shows summary statistics for these variables.

Online Appendix Table 9.1. Summary Statistics for the Demographic Covariates

	N	*Mean*	*SD*	*Min*	*Max*
Age	458	27.0	10.9	18	67
Female	458	0.62	0.49	0	1
College	190	0.65	0.48	0	1
SAT Math	328	670	111	200	800
Parental income	237	81,139	40,371	15,000	125,000
Asian	458	0.24	0.43	0	1
Other race	458	0.14	0.35	0	1

NOTE: Additional details on the variables can be found in the text. "Other race" is a dummy variable that is equal to 1 if one reported that one's ethnicity is "African-American", "Hispanic", "Native American", or "Other".

Online Appendix Table 9.2 reports the estimates of the parameters of interest in the baseline demographic specification.

Online Appendix Table 9.2. ML Estimates of Selected Parameters in the Baseline Demographic Specification

	γ	λ	α	β	π_1	π_2
Age	0.0008	-0.0052	0.0027	-0.0004	0.0031**	-0.0002
	(0.0009)	(0.0039)	(0.0024)	(0.0027)	(0.0013)	(0.0002)
Female	0.017	0.090	0.024	-0.016	0.023	-0.003
	(0.013)	(0.058)	(0.029)	(0.031)	(0.026)	(0.003)
College	0.000	-0.029	-0.062	0.030	-0.003	-0.003
	(0.023)	(0.097)	(0.054)	(0.067)	(0.040)	(0.004)
SAT Math	-0.00036***	0.00127***	0.00013	0.00014	-0.00025**	0.00003*
	(0.00009)	(0.00029)	(0.00021)	(0.00026)	(0.00011)	(0.00002)
log(parental income)	-0.002	-0.038	0.031	0.013	-0.024	0.000
	(0.012)	(0.064)	(0.028)	(0.037)	(0.030)	(0.003)
Log-likelihood	-50,659					
Parameters	79					
Individuals	458					
Observations	28,396					

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. All estimates were obtained from one MLE. The estimates in each column indicate the effects of selected demographic covariates on the parameter at the top of the column.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

The estimates from the robustness specifications are available upon request. (We note that the MLE algorithm for the robustness specification that is identical to the baseline demographic specification but only uses data from Part A failed to converge; however, after 2,000 iterations, the estimates were consistent with those from the baseline and other robustness specifications.)

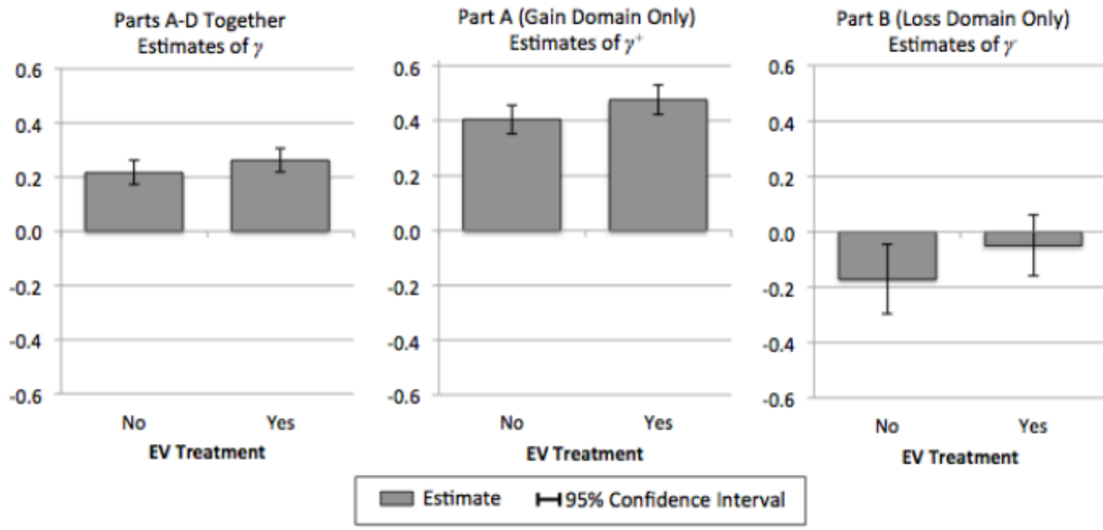
As mentioned in the main text, two results stand out across the baseline and robustness specifications. First, higher SAT Math scores are associated with lower γ—i.e., with lower risk aversion in the gain domain and higher risk aversion (or, equivalently, lower risk seeking) in the loss domain. Second, higher SAT Math scores are associated with *higher* loss aversion (λ). As discussed in the main text, the first result is consistent with the existing literature, while the second is not. The parameter estimates in Online Appendix Table 9.2 imply that a 100-point increase in the SAT Math score is associated with a 0.036-unit increase in the coefficient of relative risk aversion (γ), and a 0.127-unit *increase* in the loss aversion parameter (λ); by comparison our estimates of γ and λ in our baseline CPT model with the compromise effect are 0.242 and 1.311, respectively (from Table 1 of the main text).

While SAT scores are significantly associated with π_1 and marginally significantly associated with π_2, when considering the compromise effect parameters c_i (where i denotes the row of the alternative prospect on the screen, $i = 1,2, \dots ,7$), these two effects cancel out. To see, recall that $c_i = \pi_1(i-4) + \pi_2(i^2-20)$. It follows that

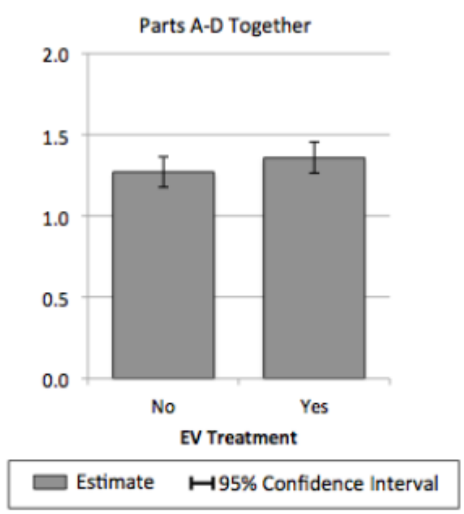
$$\frac{dc_i}{dSAT} = \frac{\partial c_i}{\partial \pi_1}\frac{\partial \pi_1}{\partial \mathrm{SAT}} + \frac{\partial c_i}{\partial \pi_2}\frac{\partial \pi_2}{\partial \mathrm{SAT}} = (i-4)\phi_{SAT}^{\pi_1} + (i^2-20)\phi_{SAT}^{\pi_2}.$$

Thus, in the first and last (i.e., seventh) rows, $\frac{dc_1}{dSAT} = -3\phi_{SAT}^{\pi_1} - 19\phi_{SAT}^{\pi_2}$, and $\frac{dc_2}{dSAT} = 3\phi_{SAT}^{\pi_1} + 29\phi_{SAT}^{\pi_2}$. Across both the baseline and the robustness specifications, $\phi_{SAT}^{\pi_1} \approx 10 \times \phi_{SAT}^{\pi_2}$, and so the effects of SAT Math scores on π_1 and π_2 effectively cancel out when considering the net effect of SAT Math scores on the compromise effect.

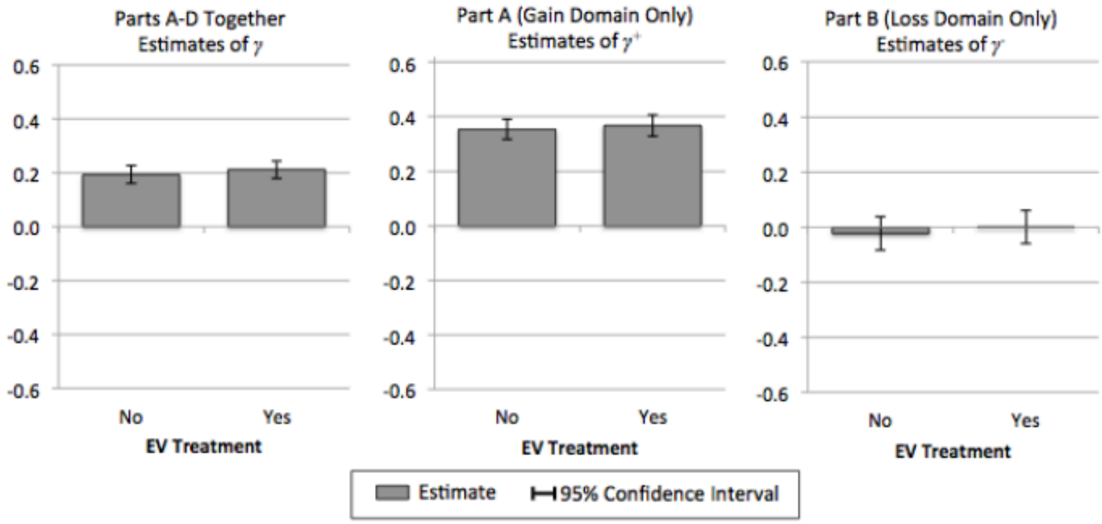
10 Estimates of γ, γ^+, γ^-, and λ by EV Treatment in the Models with and Without the Compromise Effect



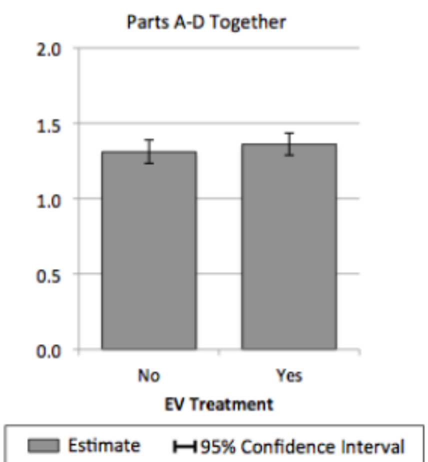
Online Appendix Figure 10.1. Estimates of γ, γ^+, and γ^- by EV treatment, from the model with the compromise effect. The negative estimates of γ^- for Part B reflect risk aversion in the loss domain, unlike what CPT predicts. (γ is not estimated for Parts C and D only because these parts have few questions.)



Online Appendix Figure 10.2. Estimates of λ by EV treatment, from the model with the compromise effect, for Parts A-D together. (λ cannot be estimated for Part A only or Part B only because the questions in these parts are all in the gain or loss domains, and is not estimated for Parts C and D only because these parts have few questions.)



Online Appendix Figure 10.3. Estimates of γ, γ^{+}, and γ^{-} by EV treatment, from the model without the compromise effect. This figure is analogous to Online Appendix Figure 10.1, except that the estimated model does not control for the compromise effect.



Online Appendix Figure 10.4. Estimates of λ by EV treatment, from the model without the compromise effect, for Parts A-D together. This figure is analogous to Online Appendix Figure 10.2, except that the estimated model does not control for the compromise effect.

11 Stata Code to Estimate the Baseline CPT Model with the Compromise Effect

We include below the Stata code used to estimate the baseline CPT model (with CRRA utility and the Prelec (1998) probability weighting function) with the compromise effect, using the data from Parts A-D and from all treatments together. The variable names in the code match the notation used in the main text.

Upon publication of the paper, we will post online the Stata code to estimate the other baseline CPT specifications that use the data from Parts A-D together (including specifications without the compromise effect, specifications that estimate the model for each treatment separately, and specifications with parameterized models). We will also post online the analogous specifications used for the three main sets of robustness checks which we describe in Section 3.4 of the main text. In addition, we will post online the de-identified choice data we collected in the experiment. (To ensure the privacy of the participants is not compromised, we will not post the data from the brief post-experiment questionnaire.)

Stata code:

```
***********************************************************************************************************************
*
* This .do file estimates the parameters of the following specification:
*       - Baseline model:
*               + constant relative risk aversion (CRRA) utility
*               + Prelec probability weights
*       - Includes controls for the compromise effect
*       - The model is estimated using data from all Parts (Parts A, B, C, & D) together
*
***********************************************************************************************************************


* Preliminaries

clear all
set more off, permanently
set memory 600m
set matsize 1000
set trace off

* INPUT FILE REQUIRED:  "Controlling for the Compromise Effect -- Choice data.dta"
* The input file must be located in the following working directory
cd "/User/Directory"


cap log close
log using "1a_CRRA_allParts_CompEffect.txt", text replace

timer clear 1
timer on 1


use "Controlling for the Compromise Effect -- Choice data.dta", clear

keep if notAnOutlier == 1

* Drop the questions designed by K&T to be placebo tests for loss aversion
drop if (gamble_index == 3 | gamble_index == 1) & part == "D"


*****************************************************************
* Define the program

capture program drop myLogLikFcn
program myLogLikFcn

args lnf gamma alpha beta lambda       sA1 sA2 sA3 sA4 sA5   sB1 sB2 sB3 sB4 sB5  sC1 sC2 sD     pi1 pi2

tempvar weight_Xqf_high weight_Xqf_low weight_Xqi_high weight_Xqi_low weight_XqiPlus1_high weight_XqiPlus1_low ///
```

```
util_Xqf_high util_Xqf_low util_Xqi_high util_Xqi_low util_XqiPlus1_high util_XqiPlus1_low ///
c_i c_iPlus1 sigma ///
U_Pqf U_Pqi U_PqiPlus1


* Prelec weighting function w(`X') = exp( -`beta' * (-ln( `X' ))^`alpha' )
foreach X in Xqf_high Xqf_low Xqi_high Xqi_low XqiPlus1_high XqiPlus1_low {
        qui generate double `weight_`X'' = exp( -`beta' * (-ln( prob_`X' ))^`alpha' ) if prob_`X' != 0
        qui replace `weight_`X'' = 0 if prob_`X' == 0
}

* Constant relative risk aversion (CRRA) utility function u(`X') = `X'^(1-`gamma')/(1-`gamma')
foreach X in Xqf_high Xqf_low Xqi_high Xqi_low XqiPlus1_high XqiPlus1_low {
        qui generate double `util_`X'' = abs(`X')^(1-`gamma')/(1-`gamma')
}

* Compromise effect for rows i and i+1
qui generate double `c_i' = ((-4*`pi1' - 20*`pi2') + `pi1' * row_i + `pi2' * row_i^2)
qui generate double `c_iPlus1' = ((-4*`pi1' - 20*`pi2') + `pi1' * row_iPlus1 + `pi2' * row_iPlus1^2)


* Sigma parameter for each group of screens
qui generate double `sigma' = (`sA1'*qA1 + `sA2'*qA2 + `sA3'*qA3 + `sA4'*qA4 + `sA5'*qA5) if part == "A"
qui replace `sigma' = (`sB1'*qB1 + `sB2'*qB2 + `sB3'*qB3 + `sB4'*qB4 + `sB5'*qB5) if part == "B"
qui replace `sigma' = (`sC1' *qC1 + `sC2' *qC2) if part == "C"
qui replace `sigma' = (`sD' * qD ) if part == "D"


* Cumulative Prospect Theory (CPT) Value of the fixed prospect U(.)
qui generate double `U_Pqf' = ( `weight_Xqf_high' * `util_Xqf_high'  +  (1-`weight_Xqf_high') * `util_Xqf_low' ) ///
                              if ( Xqf_low >=0 & Xqf_high >= 0 )
                qui  replace  `U_Pqf'  =  (  -`weight_Xqf_low'  *  `lambda'  *  `util_Xqf_low'   -   (1-`weight_Xqf_low')  *
`lambda' * `util_Xqf_high' ) ///
                                                  if ( Xqf_low <=0 & Xqf_high <= 0 )
                qui  replace  `U_Pqf'  =  (    `weight_Xqf_high'  *  `util_Xqf_high'  -  `weight_Xqf_low'  *  `lambda'  *
`util_Xqf_low' ) ///
                                                          if ( Xqf_high > 0 & Xqf_low < 0 )

* CPT Value of the alternative prospect U(.) for choice i
qui generate double `U_Pqi' = ( `weight_Xqi_high' * `util_Xqi_high'  +  (1-`weight_Xqi_high') * `util_Xqi_low' ) ///
                              if ( Xqi_low >= 0 & Xqi_high >=0 )
                qui replace `U_Pqi' = ( -`weight_Xqi_low' * `lambda' * `util_Xqi_low' - (1-`weight_Xqi_low') * `lambda'
* `util_Xqi_high' ) ///
                                                  if ( Xqi_low <=0 & Xqi_high <= 0 )
                qui  replace  `U_Pqi'  =  (    `weight_Xqi_high'  *  `util_Xqi_high'  -  `weight_Xqi_low'  *  `lambda'  *
`util_Xqi_low' ) ///
                                                          if ( Xqi_high > 0 & Xqi_low < 0 )

* CPT Value of the alternative prospect U(.) for choice i+1
qui  generate  double  `U_PqiPlus1'  =  (  `weight_XqiPlus1_high'  *  `util_XqiPlus1_high'   +   (1-`weight_XqiPlus1_high')  *
`util_XqiPlus1_low' ) ///
                              if ( XqiPlus1_low >= 0 & XqiPlus1_high >= 0 )
                qui  replace  `U_PqiPlus1'  =  (  -`weight_XqiPlus1_low'  *  `lambda'  *  `util_XqiPlus1_low'    -    (1-
`weight_XqiPlus1_low') * `lambda' * `util_XqiPlus1_high' ) ///
                                                  if ( XqiPlus1_low <=0 & XqiPlus1_high <=0 )
                qui replace `U_PqiPlus1' = (   `weight_XqiPlus1_high' * `util_XqiPlus1_high' - `weight_XqiPlus1_low' *
`lambda' * `util_XqiPlus1_low' ) ///
                                                          if ( XqiPlus1_high > 0 & XqiPlus1_low < 0 )


* The Log Likelihood function
quietly replace `lnf' = ln( ///
                                                normal( ( `U_Pqi' - `U_Pqf' ) / `sigma' + `c_i' ) ///
                                                - normal( (`U_PqiPlus1' - `U_Pqf') / `sigma' + `c_iPlus1' ) ///
                                                )

quietly replace `lnf' = ln( ///
                                                1 - normal( (`U_PqiPlus1' - `U_Pqf') / `sigma' + `c_iPlus1' ) ///
                                                ) if Xqi_high == 99999

quietly replace `lnf' = ln( ///
                                                normal( (`U_Pqi' - `U_Pqf') / `sigma' + `c_i' ) ///
                                                ) if XqiPlus1_low == -99999

* The log likelihood function needs to be defined slightly differently when the alternative prospects are increasing
from (a) to (g).
* We subtract the compromise effect here because theoretically, c_iPlus1 > c_i when the alternative prospects are
increasing.

quietly replace `lnf' = ln( ///
                                                normal( ( `U_PqiPlus1' - `U_Pqf' ) / `sigma' - `c_iPlus1' ) ///
                                                - normal( (`U_Pqi' - `U_Pqf') / `sigma' - `c_i' ) ///
                                                ) if increasing == 1

quietly replace `lnf' = ln( ///
                                                1 - normal( (`U_Pqi' - `U_Pqf') / `sigma' - `c_i' ) ///
                                                ) if XqiPlus1_high == 99999 & increasing == 1

quietly replace `lnf' = ln( ///
                                                normal( (`U_PqiPlus1' - `U_Pqf') / `sigma' - `c_iPlus1' ) ///
                                                ) if Xqi_low == -99999 & increasing == 1


end
```

```
*************************************************
* Estimate the model

ml model lf myLogLikFcn /gamma /alpha /beta /lambda  /sA1 /sA2 /sA3 /sA4 /sA5    /sB1 /sB2 /sB3 /sB4 /sB5  /sC1 /sC2
/sD   /pi1 /pi2, technique(nr) vce(cluster subjectNo)


* Initial values from 2a_CRRA_allParts.do
* Set the initial values for pi1 and pi2 equal to 0
* We use these initial values to ensure that the MLE algorithm converges
ml init .2032829 .5742116 1.123415 1.336532       5.708492 9.633632 10.28813 16.67078  40.8376        9.962839 14.34956
13.56126  18.37935  35.11294       6.672186 17.22844     9.602023     0 0, copy


capture noisily ml maximize, difficult showtolerance trace gradient iterate(500)
* capture noisily ml maximize, difficult showtolerance trace gradient iterate(500) coeflegend


******************************************************************
* Wald test for the joint significance of pi1, pi2
* W = Theta^' * ( R(Theta^) * Var^(Theta^) * R'(Theta^) )^-1 * Theta^
* Here, Theta = [pi1, pi2] and R(Theta) = Identity(2)

scalar FirstPiMatrixElement = 18
scalar noPiParameters = 2

mat b = e(b)
mat V = e(V)
mat Theta = b[1,FirstPiMatrixElement...]'
mat RTheta = I(noPiParameters)
mat VarTheta = V[FirstPiMatrixElement...,FirstPiMatrixElement...]
mat WaldStat = Theta' * inv( RTheta * VarTheta * RTheta' ) * Theta
scalar WaldStatScalar = WaldStat[1,1]
scalar pValue = chi2tail(noPiParameters,WaldStatScalar)


scalar list WaldStatScalar

scalar list pValue


******************************************************************
* Computing the implied estimates of the parameters for the compromise effect c_i
* as a function of the row i in which a choise appears.

cap drop _all
set obs 7

gen row = _n
gen rowContextEffect = .
gen rowContextEffectSD = .
gen rowContextEffectCIlow = .
gen rowContextEffectCIhigh = .

forval row = 1/7 {

        * If "_b[/pi1]" and "_b[/pi2]" do not retrieve the MLE estimates, re-run ml maximize using the coeflegend option
(see line 159 above)
        * Then use the proper notation to retrieve the MLE estimates below
        nlcom (-4*_b[/pi1] - 20*_b[/pi2]) + _b[/pi1] * `row' + _b[/pi2] * `row'^2
        *****
        mat bTemp = r(b)
        mat VTemp = r(V)

        replace row = `row' if row == `row'
        replace rowContextEffect = bTemp[1,1] if row == `row'
        replace rowContextEffectSD = sqrt( VTemp[1,1] ) if row == `row'
        replace rowContextEffectCIlow = rowContextEffect - 1.96 * sqrt( VTemp[1,1] ) if row == `row'
        replace rowContextEffectCIhigh = rowContextEffect + 1.96 * sqrt( VTemp[1,1] ) if row == `row'
}

list

******************************************************************


timer off 1
timer list 1



cap log close


* End of do file
```

12 Original Instructions of the Experiment

Informed Consent

Please consider this information carefully before deciding whether to participate in this research.

Purpose of the research:

The purpose of this study is to examine individual decision-making in an experimental context.

What you will do in this research:

You will sit in front of a computer and be shown a series of questions regarding different monetary scenarios. Your task is simply to indicate which outcome you prefer. If you complete the study, you will have a chance to earn an additional payment (as described below under "Compensation").

Time required:

Participation will take approximately 30 to 45 minutes to complete.

Risks:

There are no anticipated risks associated with participating in this study. The effects of participating should be comparable to those you would experience from viewing a computer monitor for 30 to 45 minutes and using a mouse or keyboard.

Benefits:

At the end of the study, we will provide an explanation of the study and of our hypotheses. We will describe the potential implications of the results of the study both if our hypotheses are supported and if they are disconfirmed. If you wish, you can send an email message to Jonathan Beauchamp (jpbeauch@fas.harvard.edu) or to Brendan Price (priceb@nber.org) and we will send you a copy of any manuscripts based on the research (or summaries of our results).

Compensation:

You will receive a participation fee of $15 for completing the study. If you withdraw from the study without completing it, your participation fee will be decreased as follows:

- You will receive $15 if you finish all four parts (A, B, C, and D).
- You will receive only $11 if you finish only Parts A, B, and C.
- You will receive only $9 if you finish only Parts A and B.
- You will receive only $7 if you finish only Part A.

- You will receive only $5 if you finish none of the four parts of the study.

If you finish all four parts of the study, you will also have have a chance to earn an additional amount of money. At the end of the study, the computer will randomly choose a number from 1 to 6. If it chooses a 6 (a one in six chance), one question from the first part of the study will be selected at random and you may receive an additional payment of no more than $400 on the basis of your answer to that question. Depending on your choices, you may be paid in the form of a monetary gamble giving you a chance of gaining some amount of money and a chance of gaining no additional money.

Although some questions will concern possible monetary losses, you will *not* lose any money as a result of participating in this study.

If you do not finish all four parts, you will not have an opportunity to earn an additional amount of money.

You will be paid by check. In order to receive your payment, you must have listed your current mailing address on your CLER profile so we can mail you your check. Your check will be put in the mail no later than Friday, April 16.

Confidentiality:

Any information that is obtained in connection with this study and that can be identified with you will remain confidential. Your identity will not be stored with your data, and we will not collect your IP address. Your responses will be assigned a code number, and the list connecting your name with this number will be kept in a locked room and will be destroyed once all the data have been collected and analyzed. The data will be kept anonymously for future analysis.

Participation and withdrawal:

Your participation in this study is completely voluntary, and you may withdraw at any time by leaving the study website (no questions will be asked). If you choose to be in this study, you may subsequently withdraw from it at any time. If you withdraw during the course of the study, your participation fee will be determined as described above under "Compensation."

Contact:

If you have questions about this research, please contact Jonathan Beauchamp (jpbeauch@fas.harvard.edu) or Brendan Price (priceb@nber.org). You may also contact the faculty member supervising this work: David Laibson (dlaibson@harvard.edu).

Whom to contact about your rights in this research, for questions, concerns, suggestions, or complaints that are not being addressed by the researcher, or research-related harm:

Jane Calhoun, Harvard University Committee on the Use of Human Subjects in Research, 1414 Mass Ave., 2nd Floor, Cambridge, MA 02138. Phone: 617-495-5459. E-mail: jcalhoun@fas.harvard.edu

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Agreement:

The nature and purpose of this research have been sufficiently explained and I agree to participate in this study. I understand that I am free to withdraw at any time without incurring any penalty.

Part A: Instructions

In this part, you will make choices about 28 monetary scenarios. For example, a scenario might be:

A gamble gives you a 50% chance of gaining $150 and a 50% chance of gaining $50 instead.

After each scenario is presented, you will be asked to indicate if you would prefer to take the gamble or to gain a fixed amount of money for sure. For example, you might be asked:

Would you rather...

◯Take the gamble OR ◯Gain $80.50

If this were an actual question, you would answer it by clicking on one of the two circles. You will be asked a series of such questions for each scenario. You will not be able to change your answers once you have submitted them.

At the end of the experiment, the computer will randomly choose a number from 1 to 6. If it chooses 6 (a one in six chance), <u>one question</u> will be selected at random and you will be paid on the basis of your answer for that question. For example, if 6 were chosen and the above example question were picked, then depending on which circle you clicked, you would be paid either $80.50 or the result of taking the gamble. (The result of taking the gamble would be determined randomly by the computer in accordance with the indicated percent chances.) We know some of the money amounts are large; however, if a large amount is selected to be paid, we *will* pay you that amount of money.

Because the computer might choose 6, and because each of the following decision-making questions has a chance of being selected, you should answer each question as though that question determined your payment. It also helps us in our research if you answer all the questions as truthfully as you can.

There are no right or wrong answers here. Which choice you make is a matter of personal preference. Please pay careful attention to the amounts in each question and answer according to your own preferences.

Part A: Practice

Each scenario will be accompanied by seven questions, lettered (a) through (g). Within each group of seven questions, the site will automatically fill in the answers to certain questions based on the answers you have already provided. For instance, if you indicate that you would prefer to gain $126 over picking a ball from the bag, the site will assume that you would also prefer to gain $135 over picking a ball from the bag, and it will answer that question for you. This feature will appear throughout the study.

Before you begin answering real questions, please practice answering the following example questions until you are ready to go on. Your answers on this page will not be recorded, and they will not affect your final payment.

A bag contains 25 balls marked "gain $150" and 75 balls marked "gain $100."

For each of questions (a) to (g), please mark your preferred option. Would you rather...

(a)	Pick a ball	Gain $150
(b)	Pick a ball	Gain $146
(c)	Pick a ball	Gain $141
(d)	Pick a ball	Gain $135
(e)	Pick a ball	Gain $126
(f)	Pick a ball	Gain $115
(g)	Pick a ball	Gain $100

Continue Clear

Part B: Instructions

In this part, you will again make choices about 28 monetary scenarios. For example, a scenario might be:

A gamble gives you a 75% chance of losing \$40 and a 25% chance of losing \$20 instead.

After each scenario is presented, you will be asked to indicate if you would prefer to take the gamble or to lose a fixed amount of money for sure. For example, you might be asked:

Would you rather...

◯Take the gamble OR ◯Lose \$30.70

If this were an actual question, you would answer it by clicking on one of the two circles. You will be asked a series of such questions for each scenario. You will not be able to change your answers once you have submitted them.

The questions in this part are hypothetical only -- although they concern possible monetary losses, you will not be paid or have to pay any money to us for your answers in this part. Nonetheless, we ask you to answer all the questions as truthfully as you can, as if they were associated with real monetary outcomes.

There are no right and wrong answers here. Which choice you make is a matter of personal preference. Please pay careful attention to the amounts in each question and answer according to your own preferences.

Part C: Instructions

In this part, you will make choices about four monetary scenarios. Each scenario will describe a gamble giving you a 50% chance of losing some amount of money and a 50% chance of instead gaining some amount of money that changes from question to question. For example, a scenario might begin:

A gamble gives you a 50% chance of losing $80 and ...

A question might then complete the scenario with:

... a 50% chance of gaining $120.50 instead.

For each question, you will be asked to indicate whether you would prefer to take the gamble or not to take the gamble:

Would you rather ...

◯Take the gamble OR ◯Not take the gamble

If this were an actual question, you would answer it by clicking on one of the two circles. You will be asked a series of such questions for each scenario. You will not be able to change your answers once you have submitted them.

The questions in this task are hypothetical only -- although they concern possible monetary losses, you will not be paid or have to pay any money to us for your answers in this part. Nonetheless, we ask you to answer all the questions as truthfully as you can, as if they were associated with real monetary outcomes.

There are no right and wrong answers here. Which choice you make is a matter of personal preference. Please pay careful attention to the amounts in each question and answer according to your own preferences.

Part D: Instructions

In this part, you will make choices about four monetary scenarios. Within each scenario, "gamble 1" will stay the same but "gamble 2" will change from question to question. For example, the scenario might begin:

Gamble 1 gives you a 50% chance of losing $60 and a 50% chance of gaining $200 instead.

A description of Gamble 2 might begin:

Gamble 2 gives you a 50% chance of losing $100 and ...

A question might then complete the description of Gamble 2 with:

... a 50% chance of gaining $300.10 instead.

For each question, you will be asked to indicate whether you would prefer to take Gamble 1 or to take Gamble 2, as completed by the question:

Would you rather ...

◯Take gamble 1 OR ◯Take gamble 2

If this were an actual question, you would answer it by clicking on one of the two circles. You will be asked a series of such questions for each scenario. You will not be able to change your answers once you have submitted them.

The questions in this task are hypothetical only -- you will not be paid or have to pay any money to us for your answers. Nonetheless, we ask you to answer all the questions as truthfully as you can, as if they were associated with real monetary outcomes.

There are no right and wrong answers here. Which choice you make is a matter of personal preference. Please pay careful attention to the amounts in each question and answer according to your own preferences.

Debrief

This experiment was conducted to explore people's attitudes towards gains and losses. Prior research suggests that people dislike financial risks and are more sensitive to potential losses than to potential gains. Economic theory provides methods of measuring risk and loss attitudes on the basis of choices about monetary gambles. However, decisions in laboratory experiments are often influenced by seemingly irrelevant factors. A main purpose of our study is to determine whether people's willingness to take monetary gambles is affected by the wording and ordering of the questions we ask.

This concludes your participation in our study. Thank you for participating! We will mail your payment to the mailing address listed on your CLER profile. We will put your check in the mail no later than Friday, April 16. Please contact the study administrator at laibson.study@gmail.com if you have any questions.

13 Screenshots of the Experiment

Screenshots of a randomly selected screen from each part of the experiment are shown below for a participant in the Pull -1 and EV treatments. Each scenario appears on a separate screen in the experiment.

This study consists of a total of 64 scenarios, divided into four parts. You have completed 7 of the 64 scenarios.

Part A: Scenario 8 of 28

For each of questions (a) to (g), please mark your preferred option.

A gamble gives you a 75% chance of gaining $200 and a 25% chance of gaining $100 instead.

On average, you would gain $175 from taking this gamble.

Would you rather...

(a)	○ Take the gamble (gain $175 on average)	OR	◉ Gain $180.30
(b)	○ Take the gamble (gain $175 on average)	OR	◉ Gain $179.30
(c)	◉ Take the gamble (gain $175 on average)	OR	○ Gain $178.00
(d)	◉ Take the gamble (gain $175 on average)	OR	○ Gain $176.40
(e)	◉ Take the gamble (gain $175 on average)	OR	○ Gain $174.30
(f)	◉ Take the gamble (gain $175 on average)	OR	○ Gain $171.60
(g)	◉ Take the gamble (gain $175 on average)	OR	○ Gain $168.30

Continue Clear

This study consists of a total of 64 scenarios, divided into four parts. You have completed 44 of the 64 scenarios.

Part B: Scenario 17 of 28

For each of questions (a) to (g), please mark your preferred option.

A gamble gives you a 50% chance of losing $150 and a 50% chance of losing $50 instead.

On average, you would lose $100 from taking this gamble.

Would you rather...

(a)	○ Take the gamble (lose $100 on average)	OR	◉ Lose $86.70
(b)	○ Take the gamble (lose $100 on average)	OR	◉ Lose $93.80
(c)	○ Take the gamble (lose $100 on average)	OR	◉ Lose $99.30
(d)	○ Take the gamble (lose $100 on average)	OR	◉ Lose $103.70
(e)	○ Take the gamble (lose $100 on average)	OR	◉ Lose $107.10
(f)	○ Take the gamble (lose $100 on average)	OR	◉ Lose $109.70
(g)	◉ Take the gamble (lose $100 on average)	OR	○ Lose $111.80

Continue Clear

This study consists of a total of 64 scenarios, divided into four parts. You have completed 56 of the 64 scenarios.

Part C: Scenario 1 of 4

For each of questions (a) to (g), please mark your preferred option.

A gamble gives you a 50% chance of losing $50 and ...

(a)	... a 50% chance of gaining $0.00 instead.	Take the gamble (lose $25.00 on average)	OR	Don't take the gamble
(b)	... a 50% chance of gaining $42.30 instead.	Take the gamble (lose $3.85 on average)	OR	Don't take the gamble
(c)	... a 50% chance of gaining $75.40 instead.	Take the gamble (gain $12.70 on average)	OR	Don't take the gamble
(d)	... a 50% chance of gaining $101.30 instead.	Take the gamble (gain $25.65 on average)	OR	Don't take the gamble
(e)	... a 50% chance of gaining $121.60 instead.	Take the gamble (gain $35.80 on average)	OR	Don't take the gamble
(f)	... a 50% chance of gaining $137.50 instead.	Take the gamble (gain $43.75 on average)	OR	Don't take the gamble
(g)	... a 50% chance of gaining $150.00 instead.	Take the gamble (gain $50.00 on average)	OR	Don't take the gamble

Continue Clear

This study consists of a total of 64 scenarios, divided into four parts. You have completed 62 of the 64 scenarios.

Part D: Scenario 3 of 4

For each of questions (a) to (g), please mark your preferred option.

Gamble 1 gives you a 50% chance of losing $50 and a 50% chance of gaining $150.

Gamble 2 gives you a 50% chance of losing $125 and ...

(a)	... a 50% chance of gaining $375.00 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $125.00 on average)
(b)	... a 50% chance of gaining $356.30 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $115.65 on average)
(c)	... a 50% chance of gaining $332.50 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $103.75 on average)
(d)	... a 50% chance of gaining $302.00 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $88.50 on average)
(e)	... a 50% chance of gaining $263.10 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $69.05 on average)
(f)	... a 50% chance of gaining $213.40 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $44.20 on average)
(g)	... a 50% chance of gaining $150.00 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $12.50 on average)

Continue Clear

14 References

See the main text's References section (all works cited in this Online Appendix are also cited in the main text).