Supplement

We report two additional estimation procedures to complement the nonlinear regression (NLR) estimation reported in the main text. The additional estimation procedures were (1) a restricted maximum likelihood nonlinear mixed (REML-NLME) regression model and (2) a Bayesian nonlinear mixed (Bayes-NLME) regression model. Overall, the results of these two estimation procedures were similar to each other and similar to those reported in the main text using NLR.

Two-outcome gambles

Table S1: Coefficients for the restricted maximum likelihood nonlinear mixed regression with heterogenous error term

The REML-NLME model offers some benefits over the individual subject nonlinear regression model reported in the paper. Namely, REML-NLME offers shrinkage of the coefficients based on the variability of each subject's data and reduces the effective number of parameters that are being estimated (see Pinheiro & Bates, 2000). However, the model comes at the cost of having to make additional assumptions that are beyond OPT and CPT regarding the distribution of the three unknown parameters. We conducted a heterogeneous error version of the REML-NLME to be consistent with the subject-level NLRs reported in the main text, which defined a separate error term for each subject. A reduced REML-NLME regression model with a single error variance for all 47 subjects yielded a residual standard deviation that was more than twice as high as the heterogeneous error model, suggesting heterogeneity in error variance and support for the model with a heterogeneous error variance. The REML-NLME regression was implement in *R* using the *nlme* package.

Table S1 reports the coefficients for the 47 subjects as well as the fixed effect estimates for the REML-NLME regression.

The variances for the random effects were V(α)=0.052, V(δ)=0.106 and V(γ)=0.094. The correlations between the random effects were Cor(α, δ)=-0.127, Cor(α, γ)=0.204 and Cor(δ, γ)=0.214

	α	δ	γ
1	0.653	0.489	0.388
2	0.307	1.072	0.655
3	0.769	1.161	0.406
4	0.588	0.213	0.154
5	0.460	0.991	0.282
6	0.702	1.264	0.897
7	0.597	0.384	0.203
8	0.388	0.399	0.362
9	0.525	0.885	0.859
10	0.484	0.862	0.506
11	0.730	1.150	0.628
12	0.700	0.860	0.494
13	0.359	1.284	1.499
14	0.605	0.645	0.355
15	0.977	0.918	1.020
16	0.885	0.885	1.167
17	0.934	0.866	0.997
18	0.656	0.500	0.187
19	0.559	1.275	0.292
20	0.883	0.667	0.640
21	0.719	0.914	0.561
22	0.390	1.143	0.871
23	0.583	0.722	0.513
24	1.035	0.944	1.006
25	0.766	1.118	0.573
26	1.050	1.102	0.947
27	0.993	0.653	0.811
28	0.630	1.038	0.663
29	0.625	1.128	0.294
30	0.614	0.797	0.530
31	0.789	0.777	0.717
32	0.898	0.776	0.764
33	0.843	0.709	0.112
34	1.206	1.431	0.319
35	0.799	1.075	0.708
36	0.685	1.052	0.525
37	0.772	0.819	0.555
38	0.705	0.900	0.206
39	0.766	0.889	0.714
40	0.910	1.226	0.879
41	1.021	0.682	1.068
42	1.029	0.549	0.829
43	0.810	1.361	0.710
44	1.013	1.123	0.280
45	0.538	0.520	0.226
46	0.986	1.015	0.339
47	0.742	0.801	0.753
fixed effect	0.738	0.894	0.606

Table S1: Restricted Maximum Likelihood Nonlinear Mixed Regression Estimates (Heterogeneous Error)

Table S2: Coefficients for the Bayesian nonlinear mixed regression with heterogenous error term

To compare with the REML-NLME model, we implemented the analogous model in a Bayesian context. The Bayesian model offers additional advantages over a frequentist approach to nonlinear mixed model regression, such as additional flexibility in the choice of the prior distributions over the parameters and the ability to probe the posterior distribution. To be consistent with the REML-NLME estimation we assumed normally distributed priors on the three prospect theory parameters. We followed a basic modeling strategy mostly using default arguments to the *brm* command in *R*'s *brms* package, which offers a convenient interface to the *STAN* Bayesian modeling framework. We used the lower bound feature (set to 0) for each of the three parameters to avoid negative parameter values. A more complete Bayesian analysis would involve sensitivity analyses over the choice of prior, different choices for the various command arguments, and examination of other approaches to maintaining the scale of the parameters to be non-negative (such as reparameterization of the parameters). Various criteria such as convergence metrics and posterior predictive checks suggested acceptable fits.

Table S2 reports the coefficients for the 47 subjects as well as the fixed effect estimates for the Bayes-NLME regression.

The variances for the random effects were V(α)=0.056, V(δ)=0.128 and V(γ)=0.106. The correlations between the random effects were Cor(α, δ)=-0.086, Cor(α, γ)=0.196 and Cor(δ, γ)=0.201.

	α	δ	γ
1	0.632	0.541	0.383
2	0.313	1.114	0.659
3	0.755	1.235	0.405
4	0.567	0.240	0.147
5	0.456	1.045	0.282
6	0.687	1.327	0.893
7	0.578	0.420	0.199
8	0.379	0.448	0.359
9	0.515	0.939	0.860
10	0.478	0.918	0.506
11	0.724	1.212	0.633
12	0.681	0.929	0.491
13	0.361	1.340	1.510
14	0.600	0.709	0.357
15	0.954	0.976	1.014
16	0.871	0.945	1.166
17	0.913	0.928	0.992
18	0.648	0.557	0.187
19	0.552	1.341	0.292
20	0.854	0.732	0.634
21	0.705	0.979	0.560
22	0.403	1.179	0.881
23	0.575	0.783	0.513
24	1.012	0.987	0.998
25	0.761	1.181	0.580
26	1.035	1.173	0.951
27	0.966	0.715	0.805
28	0.628	1.101	0.692
29	0.617	1.192	0.295
30	0.597	0.866	0.527
31	0.780	0.843	0.719
32	0.882	0.841	0.764
33	0.835	0.764	0.113
34	1.197	1.523	0.323
35	0.784	1.134	0.708
36	0.675	1.117	0.526
37	0.756	0.876	0.553
38	0.700	0.958	0.207
39	0.749	0.950	0.711
40	0.898	1.295	0.882
41	0.996	0.740	1.063
42	0.994	0.616	0.821
43	0.794	1.433	0.708
44	1.002	1.198	0.281
45	0.528	0.568	0.224
46	0.955	1.093	0.336
47	0.736	0.865	0.757
fixed effect	0.725	0.954	0.604

Table S2: Bayesian Nonlinear Mixed Regression Estimates (Heterogeneous Error)

Figure S1: Coefficient Plot

Figure S1 shows the parameter estimates reported in the main text using nonlinear regression and the estimates for both the REML-NLME and Bayes NLME models. The points were jittered in the vertical direction to uncover points that are superimposed. The vertical axis represents subject number so does not change the value of the parameter, which is represented in the horizontal direction.

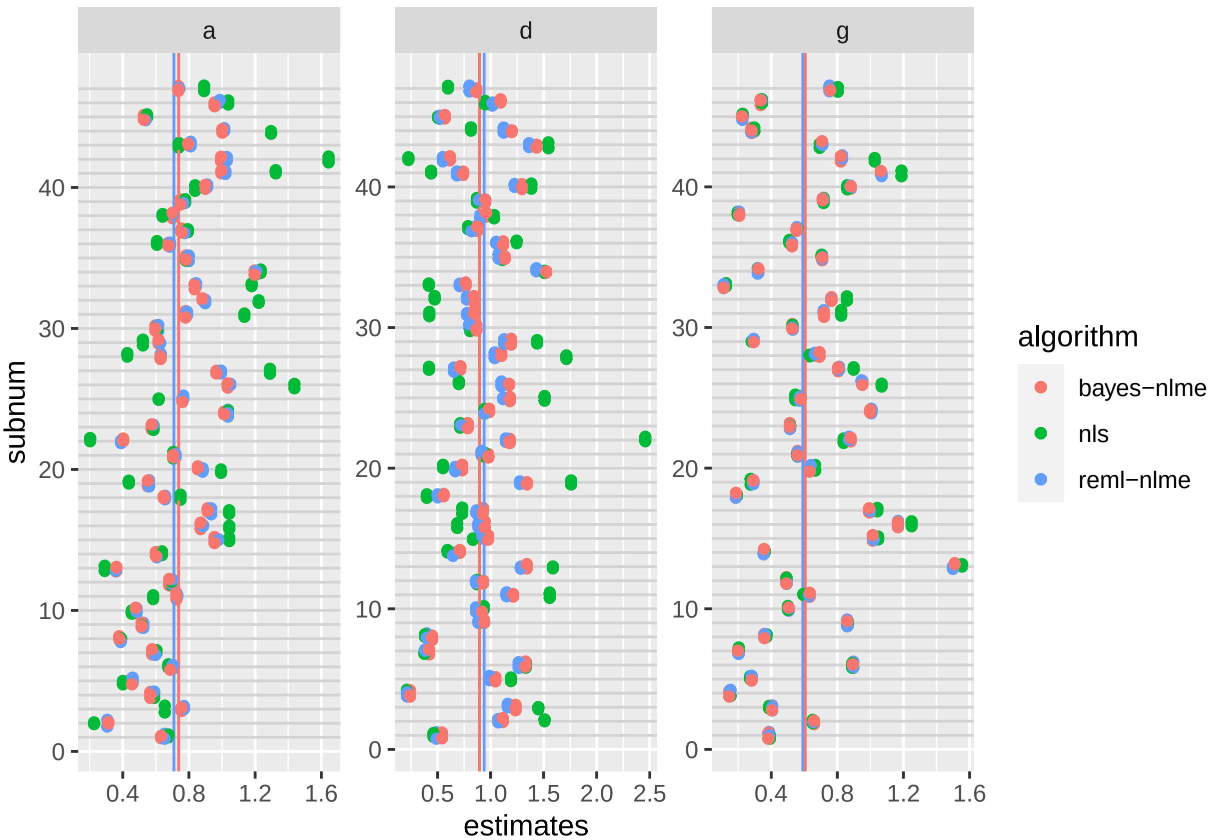

Figure S1: Coefficient Comparison: Subject number on the vertical axis, coefficient value on the horizontal axis.

Three-outcome gambles

REML-NLME

Figure S2 shows the REML-NLME plot corresponding to Figure 2 in the main text (NLR) using the fixed effects estimates. The general pattern is consistent with the NLR results reported in the text.

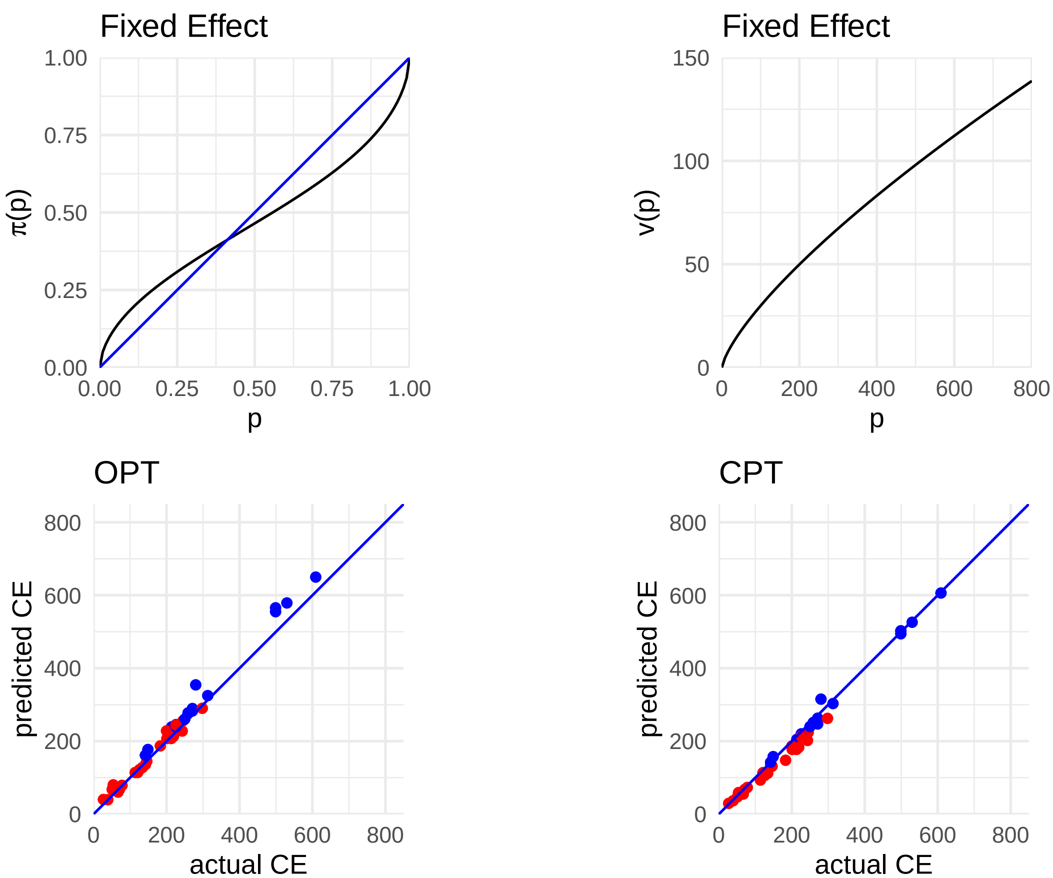

Figure S2: Actual vs Predicted CE for REML-NLME.

Consistent with the finding reported in the main text, the estimated slopes for REML-NLME using the fixed effects indicate that CPT slightly under-predicts ($\beta_C = .964$, $p < .001$) and OPT slightly over-predicts ($\beta_O = 1.074$, $p < .001$); interaction effect testing difference of the two slopes is statistically significant ($p < .001$).

Bayes-NLME

Figure S3 shows the Bayes-NLME plot corresponding to Figure 2 in the main text (NLR) using the fixed effects estimates. The general pattern is consistent with the NLR results reported in the text.

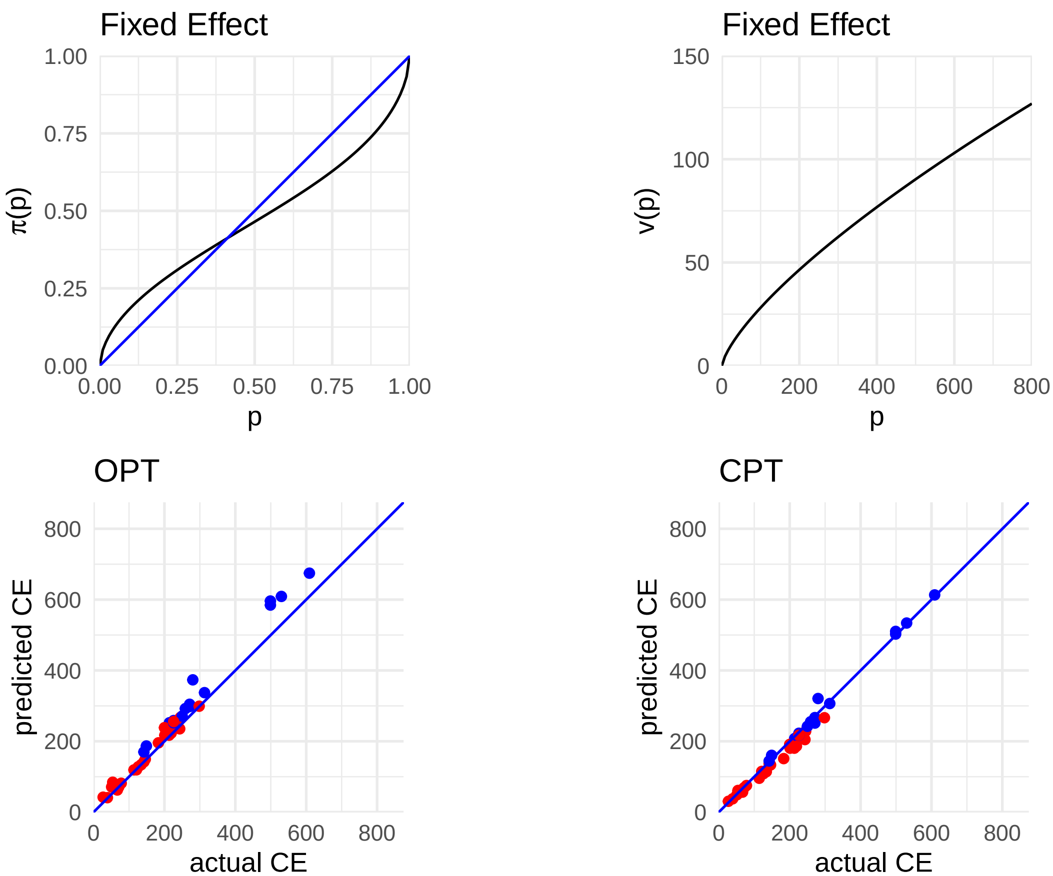

Figure S3: Actual vs Predicted CE for Bayes-NLME.

Consistent with the finding reported in the main text, the estimated slopes for Bayes-NLME using the fixed effects indicate that CPT slightly under-predicts ($\beta_C = .978$, $p < .001$) and OPT slightly over-predicts ($\beta_O = 1.125$, $p < .001$); interaction effect testing difference of the two slopes is statistically significant ($p < .001$).

References

Pinheiro, J. & Bates, D. (2000). Mixed-effects Models in S and S-Plus. Springer: New York.