

## Web Appendix:

### Multiple Goals as Reference Points: One Failure Makes Everything Else Feel Worse

#### Individual-Level Results from Studies 2 and 3

First, we conduct individual-level analyses for Study 2 and 3. We only examine individual fits for the main models from these studies for expositional convenience. That is, we examine the three-parameter baseline model, the five-parameter full additive prospect theory model, the six-parameter full maximum model, and the six-parameter full minimum model.

#### Individual-Level Results in Study 2

The results of the individual-level full models were consistent with the aggregate-level results. Table A1 provides median parameter estimates for individual subject data for Study 2. In the minimum model, median parameters were .71, 2.81, and 21.55 for  $\alpha$ ,  $\lambda$ , and  $\omega$ , respectively. These values are consistent with diminishing sensitivity, loss aversion, and a divergent interaction such that a failure and a success were closer to two failures than two successes. The minimum model was an improvement over additive prospect theory for 43.4% of the participants ( $p < .05$ ), and was an improvement over the baseline model for 70.7% of the participants ( $p < .05$ ). Although participants were mostly best fit by a minimum model but not by a significant amount, it is worth pointing out that we only have 49 observations per person, which may limit power. The maximum model only improved fits for 5% of participants over the additive prospect theory model ( $p < .05$ ).

#### Individual Level Results in Study 3

We again find individual-level results that are consistent with aggregate-level results. At the individual level, the minimum model had parameter values of .62, 2.02, and 10.31, for  $\alpha$ ,  $\lambda$ , and  $\omega$ , respectively (see Table A1), consistent with diminishing sensitivity, loss aversion, and a divergent

interaction. This model fit 47.5% of participants better than did the additive prospect theory model ( $p < .05$ ), and was an improvement for 66.3% of participants over the baseline model ( $p < .05$ ). The maximum model was only an improvement over the additive prospect theory model for 12.5% of participants ( $p < .05$ ).

### Alternative Models

Next, we consider alternative models to describe emotions in settings with multiple goals. Our first set varies the value functions in Equation 1 to allow for an additive discrete “jump” in emotion when crossing the goal, rather than the standard assumption of multiplicative loss aversion. Such models are described by Equation A1 below.

$$V_i(x_i|g_i) = \begin{cases} (x_i - g_i)^\alpha & \text{if } x_i \geq g_i \\ -\delta - (g_i - x_i)^\alpha & \text{if } g_i > x_i \end{cases} \quad (\text{A1})$$

Here  $\delta$  corresponds to an additive jump. We consider three variants of this model: an additive jump that assumes independence between goals (and is described by Equations A1, 2, and 6); a minimum jump model that permits interactions (and is described by Equations A1, 3, 4, and 6); and a maximum jump model that permits interactions (and is described by Equations A1, 3, 5, and 6).

We also consider a second class of models that permit separate weights for the two dimensions. Such models retain the prospect theory valuation function assumptions of Equation 1, but modify Equations 2 and 3 as follows:

$$U(x|g) = \pi \cdot V_1(x_1|g_1) + (1 - \pi) \cdot V_2(x_2|g_2) \quad (\text{A2})$$

$$U(x|g) = \pi \cdot V_1(x_1|g_1) + (1 - \pi) \cdot V_2(x_2|g_2) + \omega \cdot T \quad (\text{A3})$$

We consider three variants of these models: The additive weighted model (and is described by Equations 1, A2, and 6); the minimum weighted model that allows interactions (and is described by

Equations 1, A3, 4, and 6); and the maximum weighted model that allows interactions (and is described by Equations 1, A3, 5, and 6).

We examine another model that captures interactions: the configural weight model (e.g. Birnbaum, 1974). With this model, we assumed valuation using the prospect theory function in Equation 2, but described the interaction as:

$$U(x|g) = V_1(x_1|g_1) + V_2(x_2|g_2) + \gamma|V_1(x_1|g_1) - V_2(x_2|g_2)| \quad (\text{A4})$$

Here, the term,  $\gamma$ , reflects the attribute interactions. When this term is positive, it predicts convergent interactions (mimicking our maximum model). When it is negative, it predicts divergent interactions (mimicking our minimum model). When  $\gamma = 0$  we obtain the standard additive model. As with all our other models, we allow a linear function in Equation 6 to map feelings onto the response scale.

A final set of models predicts that the overall emotion is based on only one outcome. The first is a simplified-minimum model, as follows

$$U(x|g) = \min(V_1(x_1|g_1), V_2(x_2|g_2)). \quad (\text{A5})$$

The second is a simplified-maximum model, as follows:

$$U(x|g) = \max(V_1(x_1|g_1), V_2(x_2|g_2)). \quad (\text{A6})$$

Value functions are described by prospect theory and the response function is linear (Equation 6).

### **Alternative Model Results – Study 2**

Table A2 presents the parameter estimates and fits of the nine competitor models along with the baseline, additive prospect theory, maximum, and minimum models for Study 2.

Table A2 shows that superior fits occur with a minimum model. For both the jump models and differential weight models, minimum models (Minimum Jump BIC = 383; Minimum Weighted BIC = 353) fit better than the corresponding additive versions (Additive Jump BIC = 450, Likelihood Ratio Test  $D = 71.17, p < .001$ ; Additive Weighted BIC = 434, Likelihood Ratio Test  $D = 85.96, p < .001$ ), and have lower BICs compared to the maximum versions (Maximum Jump BIC = 454; Maximum Weighted BIC =

439). The simplified minimum model has a lower BIC (514) compared to the simplified maximum's BIC (630). Further, the configural weight model has an interaction  $\omega$  value of -.27, which is consistent with the divergent interaction in a minimum model.

Weighted and simplified variants of the models all have parameters consistent with prospect theory (i.e.,  $\lambda > 1$ ,  $\alpha < 1$ ). Interestingly, one of the alternative models with a power function with a jump exhibits only some theory-consistent parameters. Whereas the  $\lambda$  values exceed one (loss aversion) for the additive jump, minimum jump, and maximum jump models, the  $\alpha$  estimates are also greater than one, which indicates increasing sensitivity instead of diminishing sensitivity. However, overall these jump models have poor fit, so we retain the multiplicative structure in other models.

The minimum model presented in the paper has the lowest BIC (348) and AIC (334) compared to other versions of the minimum model such as minimum jump (BIC = 383; AIC = 369), weighted minimum (BIC = 353; AIC = 336), and simplified minimum (BIC = 514; AIC = 503), and even the configural-weight model (BIC = 358; AIC = 344). However, the minimum model presented in the paper does not have the lowest log-likelihood. Adding weights improved log-likelihood directionally, yet the weights attained through these analyses are close to 0.5, which suggests near-equal weighting for each class. Overall, models that allow a divergent interaction outperform those assuming additivity or a convergent interaction.

### **Alternative Model Results – Study 3**

Table A3 provides the parameter estimates and model fits of alternative models. The results are generally similar to those found with alternative models fit to Study 2. The minimum models had better fits compared to their additive and maximum counterparts. The minimum jump model (BIC = 355; AIC = 341) fit better than the corresponding maximum jump (BIC = 395; AIC = 381) and additive jump (BIC = 391; AIC = 379; Likelihood Ratio Test  $D = 79.18$ ,  $p < .001$ ) models. The weighed minimum model (BIC = 336; AIC = 320) had lower BIC than its corresponding additive weighted (BIC = 383; AIC = 369;

Likelihood Ratio Test  $D = 98.82$ ,  $p < .001$ ) and weighted maximum (BIC = 399; AIC = 383) models. The simplified minimum model also had lower BIC (BIC = 492; AIC = 480) compared to the simplified maximum model (BIC = 585; AIC = 574). The interaction term in the configural-weight model was negative, consistent with the divergent interaction.

On the other hand, models with a jump had parameter estimates that were only somewhat consistent with theory, and again had poor fits. The additive jump, minimum jump, and maximum jump models had  $\lambda$  values greater than one, but the additive and maximum jump models had increasing sensitivity ( $\alpha > 1$ ). The value  $\alpha$  for minimum jump model was only weakly indicative of diminishing sensitivity ( $\alpha = .98$ ).

Estimated parameters in the alternative specifications showed that the model with BIC closest to the minimum model in the paper was the weighted minimum (BIC = 336; AIC = 320). This model also had a value of  $\lambda$  greater than one (consistent with loss aversion) and  $\alpha$  less than one (consistent with diminishing sensitivity). This model again had weights close to 0.5, which suggests the weights for each exercise were near-equal. The simplified minimum model had parameter values consistent with loss aversion ( $\lambda > 1$ ) and diminishing sensitivity ( $\alpha < 1$ ).

**Table A1.***Models of Emotional Ratings for Individual-Level (Medians) Results in Study 2 and 3*

Model	$\lambda$	$\alpha$	$a$	$b$	$\omega$	$\sigma$	$LL$	$AIC$	$BIC$
<b>Study 2</b>									
Baseline Model	1	1	2.34 [1.29, 3.1]	.63 [.58, .67]	0	15.36 [14.26, 16.48]	-203.93	413.86	419.54
Additive Prospect Theory Model <sup>1</sup>	4.41*** [3.6, 5.85]	.50*** [.45, .55]	15.40 [13.23, 18.58]	.66 [.55, .91]	0	12.80 [12.04, 13.8]	-194.45	398.89	408.35
Maximum Model <sup>2</sup>	4.29*** [3.43, 5.52]	.51*** [.46, .55]	14.39 [13.01, 18.23]	.60 [.5, .83]	0.00 [0.00, 0.00]	12.74 [12.04, 13.57]	-194.21	400.42	411.77
Minimum Model <sup>3</sup>	2.81*** [2.2, 3.8]	.71*** [.61, .79]	5.17 [3.55, 6.79]	.33 [.17, .44]	21.55 [14.46, 27.36]	11.92 [10.92, 12.65]	-191.01	394.01	405.36
<b>Study 3</b>									
Baseline Model	1	1	10.01 [7.78, 11.74]	.32 [.28, .35]	0	14.08 [13.04, 14.89]	-199.59	405.17	410.85
Additive Prospect Theory Model <sup>1</sup>	2.47*** [1.97, 3.05]	.41*** [.36, .47]	19.38 [15.92, 22.68]	1.23 [.84, 1.57]	0	12.74 [11.82, 13.39]	-193.24	396.47	405.93
Maximum Model <sup>2</sup>	2.56*** [2.07, 3.13]	.41*** [.35, .47]	18.50 [15.47, 21.05]	.89 [.64, 1.3]	0.00 [0.00, 0.00]	12.45 [11.63, 13.25]	-192.86	397.72	409.07
Minimum Model <sup>3</sup>	2.02*** [1.68, 2.47]	.62*** [.46, .71]	14.22 [11.82, 16.86]	.34 [.18, .52]	10.31 [4.18, 15.58]	11.84 [10.52, 12.59]	-190.12	392.24	403.59

*Note:*  $AIC = 2k - 2LL$ , where  $k$  is the number of parameters in the model and  $LL$  is the best-fit log-likelihood.  $BIC = \log(n)*k - 2LL$ , where  $n$  is the number of observations,  $k$  is number of parameters in the model, and  $LL$  is the best-fit log-likelihood. <sup>1</sup>The Additive Prospect Theory Model includes parameters to test loss aversion ( $\lambda$ ) and diminishing sensitivity ( $\alpha$ ) but has no interaction term to test non-additivity. <sup>2</sup>The Maximum Model includes parameters to test loss aversion ( $\lambda$ ), diminishing sensitivity ( $\alpha$ ), and an interaction term for non-additivity ( $\omega$ ) associated with Eqn 5. <sup>3</sup>The Minimum Model includes parameters to test loss aversion ( $\lambda$ ), diminishing sensitivity ( $\alpha$ ), and an interaction term for non-additivity ( $\omega$ ) associated with Eqn 4. \*\*\*  $p < .001$

**Table A2.***Study 2: Models of Emotional Ratings for Aggregate-Level Results*

Model	$\lambda$	$\alpha$	$a$	$b$	$\omega$	weight	$\sigma$	$k$	$LL$	$AIC$	$BIC$
Baseline Model	1	1	2.55	.55	0	.5	7.17	3	-254.16	514.33	521.28
Additive Prospect Theory Model	5.67	.45	19.74	1.03	0	.5	3.68	5	-204.18	418.37	429.96
Maximum Model	5.57	.45	19.64	1.05	$6.83 \times 10^{-6}$	.5	3.68	6	-204.19	420.37	434.28
Minimum Model	3.46	.62	8.90	.66	19.13	.5	2.08	6	-161.20	334.39	348.30
Additive Jump	510.83	1.52	18.68	.04	0	.5	4.20	5	-214.05	438.09	449.68
Maximum Jump	510.07	1.52	18.67	.04	.14	.5	4.20	6	-214.06	440.13	454.03
Minimum Jump	231.36	1.46	7.88	.05	295.14	.5	2.61	6	-178.46	368.92	382.82
Additive Weighted	5.67	.45	19.74	2.07	0	.502	3.68	6	-204.17	420.34	434.25
Maximum Weighted	5.59	.45	19.65	2.09	$1.09 \times 10^{-9}$	.502	3.68	7	-204.17	422.35	438.57
Minimum Weighted	3.46	.62	8.90	1.33	9.56	.501	2.08	7	-161.19	336.38	352.60
Configural Weight	4.36	.37	21.55	1.57	-.27	.5	2.22	6	-166.25	344.49	358.40
Simplified Maximum	2.00	.63	-3.31	1.68	--	--	14.00	5	-304.37	618.73	630.32
Simplified Minimum	4.41	.39	24.91	2.15	--	--	6.46	5	-246.30	502.60	514.19

*Note:*  $AIC = 2k - 2LL$ , where  $k$  is the number of parameters in the model and  $LL$  is the best-fit log-likelihood.  $BIC = \log(n) * k - 2LL$ ,  $n$  is the number of observations,  $k$  is number of parameters in the model, and  $LL$  is the best-fit log-likelihood.

**Table A3.***Study 3: Models of Emotional Ratings for Aggregate-Level Results*

Model	$\lambda$	$\alpha$	$a$	$b$	$\omega$	weight	$\sigma$	$k$	$LL$	$AIC$	$BIC$
Baseline	1	1	12.24	.28	0	.5	5.42	3	-233.15	472.31	479.26
Additive Prospect Theory Model	5.49	.41	25.25	.79	0	.5	2.64	5	-179.21	368.42	380.01
Maximum Model	5.67	.41	25.40	.77	$3.08 \times 10^{-9}$	.5	2.65	6	-179.22	370.44	384.35
Minimum Model	3.72	.52	18.62	.57	13.40	.5	1.89	6	-154.19	320.39	334.29
Additive Jump	2442.7	1.73	25.29	.01	0	.5	2.83	5	-184.49	378.97	390.56
Maximum Jump	2442.7	1.73	25.29	.01	$1.5 \times 10^{-9}$	.5	2.83	6	-184.49	380.97	394.88
Minimum Jump	55.94	.98	16.62	.14	59.91	.5	2.17	6	-164.58	341.16	355.07
Additive Weighted	5.51	.41	25.27	1.58	0	.49	2.62	6	-178.60	369.20	383.11
Maximum Weighted	5.62	.41	25.35	1.54	$1.12 \times 10^{-8}$	.49	2.62	7	-184.59	383.18	399.41
Minimum Weighted	3.75	.52	18.65	1.14	6.73	.49	1.86	7	-153.03	320.06	336.29
Configural Weight	4.26	.35	26.14	1.17	-.22	.5	1.92	6	-155.51	323.01	336.92
Simplified Maximum	2.24	.63	8.19	.98	--	--	10.37	5	-281.87	573.74	585.33
Simplified Minimum	8.46	.43	29.79	.63	--	--	5.77	5	-235.21	480.42	492.01

Note:  $AIC = 2k - 2LL$ , where  $k$  is the number of parameters in the model and  $LL$  is the best-fit log-likelihood.  $BIC = \log(n) \cdot k - 2LL$ ,  $n$  is the number of observations,  $k$  is number of parameters in the model, and  $LL$  is the best-fit log-likelihood.