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SUPPLEMENTARY INFORMATION
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Neurocomputational mechanisms underlying motivated seeing

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Supplementary Note 1: Impaired performance on the task was not due to differences in perceptual sensitivity. Participants who were more strongly biased by the motivation manipulation made more incorrect categorizations in the experimental task. We argue that this is because these participants were more strongly motivated to see the motivation-consistent category. An alternative account is that biased participants had lower perceptual sensitivity (i.e. worse at distinguishing faces and scenes). That is to say, biased participants relied more on the bet information not because they were more affected by their motivation to see a particular category, but because they had less access to objective perceptual information.

We can test this alternative hypothesis by examining the effect of % scene on the drift rate at the between-subject level, which, when controlling for the effects of motivation, provides a proxy measure of perceptual sensitivity. Consider an image that has 55% scene – relative to a participant with high perceptual sensitivity, a participant with low perceptual sensitivity would accumulate evidence more slowly towards the scene threshold, which would be reflected as a drift rate that is *less positive*. Conversely, for an image with 45% scene, the participant with low perceptual sensitivity would accumulate evidence more slowly towards the face threshold, which would be reflected as a drift rate that is *less negative*. As such, participants with lower perceptual sensitivity would also exhibit a weaker relationship between % scene and drift rate (*Supplementary Figure 1A*). We thus fit a model with a different drift rate for each level of % scene and each motivation consistent category (i.e. 2 levels of motivation x 9 levels of percentage scene = 18 parameters), and examined if participants with stronger motivational bias also have a weaker relationship between % scene and drift rate.

Individual differences in motivational bias did not moderate the relationship between % scene and drift rate (linear mixed effects model (lme): two-tailed, one sample $t(535) = -0.908$, $p = 0.419$, b = -0.02, 95% CI = -0.08 to 0.03), suggesting that individual differences in bias were not related to subjective perceptual uncertainty. Unsurprisingly, individual differences in motivational bias moderated the effect of motivation on the drift rate (lme: two-tailed, one sample $t(535) = 2.55$, $p = 0.01$, b = 0.15, 95% CI = 0.01 to 0.28). To better interpret this result, we plot the drift rate at each level of % scene separately for high bias and low bias participants (*Supplementary Figure 1B*). The main effect of % scene and drift rate were visually indistinguishable between the two groups. In contrast, the effect of motivation on the drift rate was clearly stronger in the High Bias group. These results suggest that biased participants made more mistakes not because they were less sensitive to the objective sensory information, but because they were more motivated to see the motivation consistent category.

Supplementary Note 2: Effects of motivational bias were not confounded with general differences in attention. Participants who were more biased in their categorizations could have also performed worse because they were less attentive to the task. Given that attention has a strong influence on perceptual sensitivity[1], the preceding analyses showing that motivational bias did not correlate with perceptual sensitivity indicates that this is unlikely.

As a second control analysis, we examined whether motivational bias correlated with performance on the localizer task (categorizing a face as male or female, and a scene as indoor or outdoor). If biased participants were "bad" participants who did not attend to the task, they might also perform poorly on the localizer task. Motivational bias did not correlate with performance on the localizer task (Pearson $r = -0.121$, p = 0.523), though performance on the localizer task was close to ceiling (M = 97.7%, SE = 0.3%), and it is possible that this analysis does not have the sensitivity to detect a relationship between motivational bias and localizer task performance.

We thus ran a third control analysis that relied on the multivariate classifier's accuracy in classifying whether participants were seeing a face or a scene during the localizer task. Attention enhances category-specific patterns in the visual cortex[2], and would improve the classifier's ability to classify the presented image. Thus, classifier accuracy can be taken as a proxy measure of participants' attention during the localizer task. For each participant, we randomly divided the localizer data into five equally sized sets of trials. The classifier was then trained on four sets and tested on the fifth, held-out set. This procedure was repeated five times, holding out a different set each time, to calculate the five-fold cross-validation accuracy (M = 81.8%, SE = 1.2%).

Cross-validation accuracy on the localizer task was not correlated with motivational bias in the main experiment (Pearson $r = 0.149$, $p = 0.432$), providing additional evidence that motivational bias was not related to differences in general attention. Importantly, this result also indicates that the effect of motivation on classifier probability in the main experiment could not be explained by differences in the classifier's ability to pick up on category-selective activity. Taken together, these results suggest that participants who were more biased made more incorrect categorizations and showed greater biases in category-selective neural activity in the main experiment, not because they were less attentive, but because they were more affected by the motivation manipulation.

Supplementary Note 3: Model recovery study indicates that DIC reliably recovers the true model from simulated data. To assess whether DIC is an accurate metric for model comparison, we ran a model recovery study to examine how often DIC identifies the true model from simulated data. We simulated choice and reaction time data with parameter values sampled from the posterior distribution estimated when fitting each of the four models (*z & v* model, *z* model, *v* model and *null* model) to participants' data. For each model, we generated 100 datasets, each with the same number of participants and trials as the original dataset. The simulated datasets reflect the pattern of choice and reaction times if participants' behavior were perfectly described by the models. We then fit all four models to each dataset, and assessed how often DIC correctly identified the model that generated that dataset.

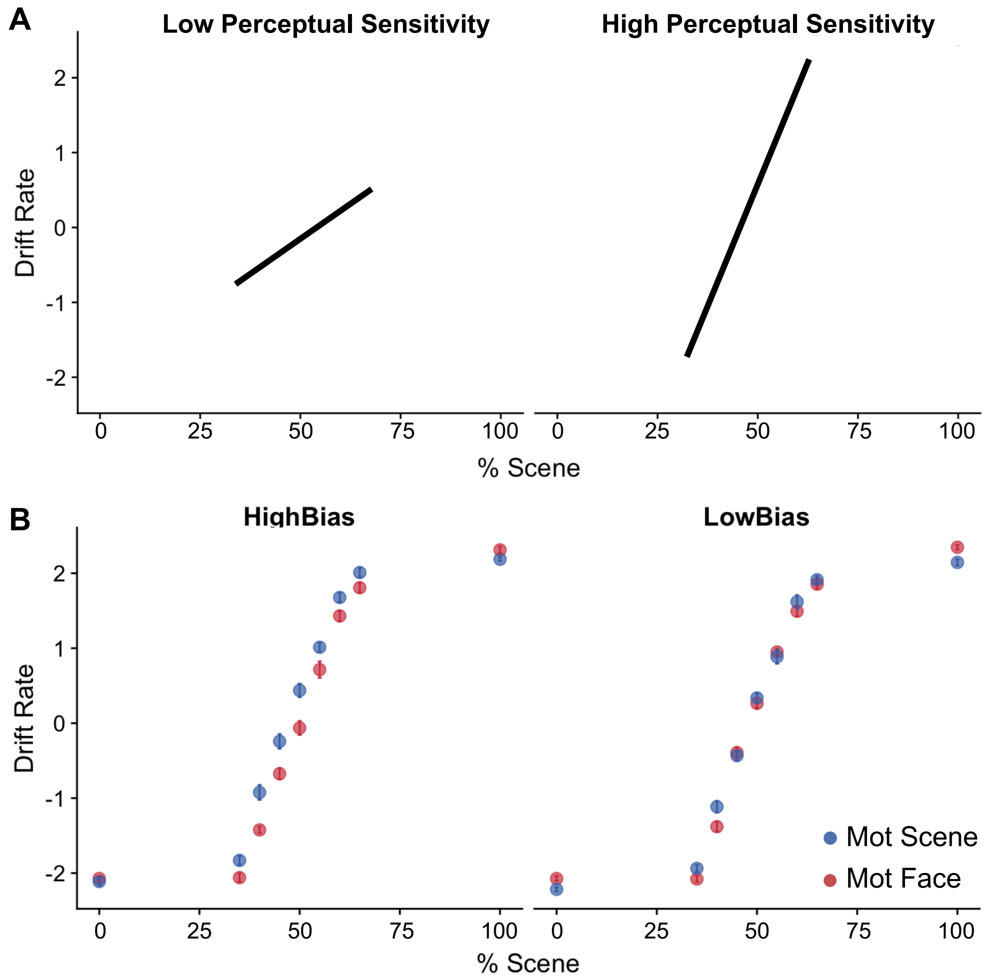
DIC correctly identified the true model in 76.5% of the simulations (*Supplementary Figure 5A*). In almost all cases where DIC selected the wrong model (86 out of 94), there was only weak evidence in favor of the incorrectly selected model ($|\Delta DIC| < 5$; *Supplementary Figure 5B*). In contrast, the model fits to experimental data yielded much larger differences in DIC in favor of the *z & v* model (*z & v* vs. *z*: $\Delta DIC = -84$; *z & v* vs. *v*: $\Delta DIC = -11$, *null*: $\Delta DIC = -200$). These results support the use of DIC as a model comparison metric, and indicate that the DIC results reported in our manuscript provide strong evidence that the *z & v* model is the model that best fits participants' behavior.

Supplementary Note 4: Model fits of *z & v* model provide a closer match to empirical data than the other models. Conditional response functions provide a visual illustration of *how* the *z & v* model fits the data better than the other models (*Supplementary Figure 6*). Each conditional response function plots response proportions as a function of reaction time quantiles[3], separately for each motivated category. The differences between the models can be seen at each level of % scene (*Supplementary Figure 6A*). For the ease of exposition, we averaged the function across all levels of % scene (*Supplementary Figure 6B*).

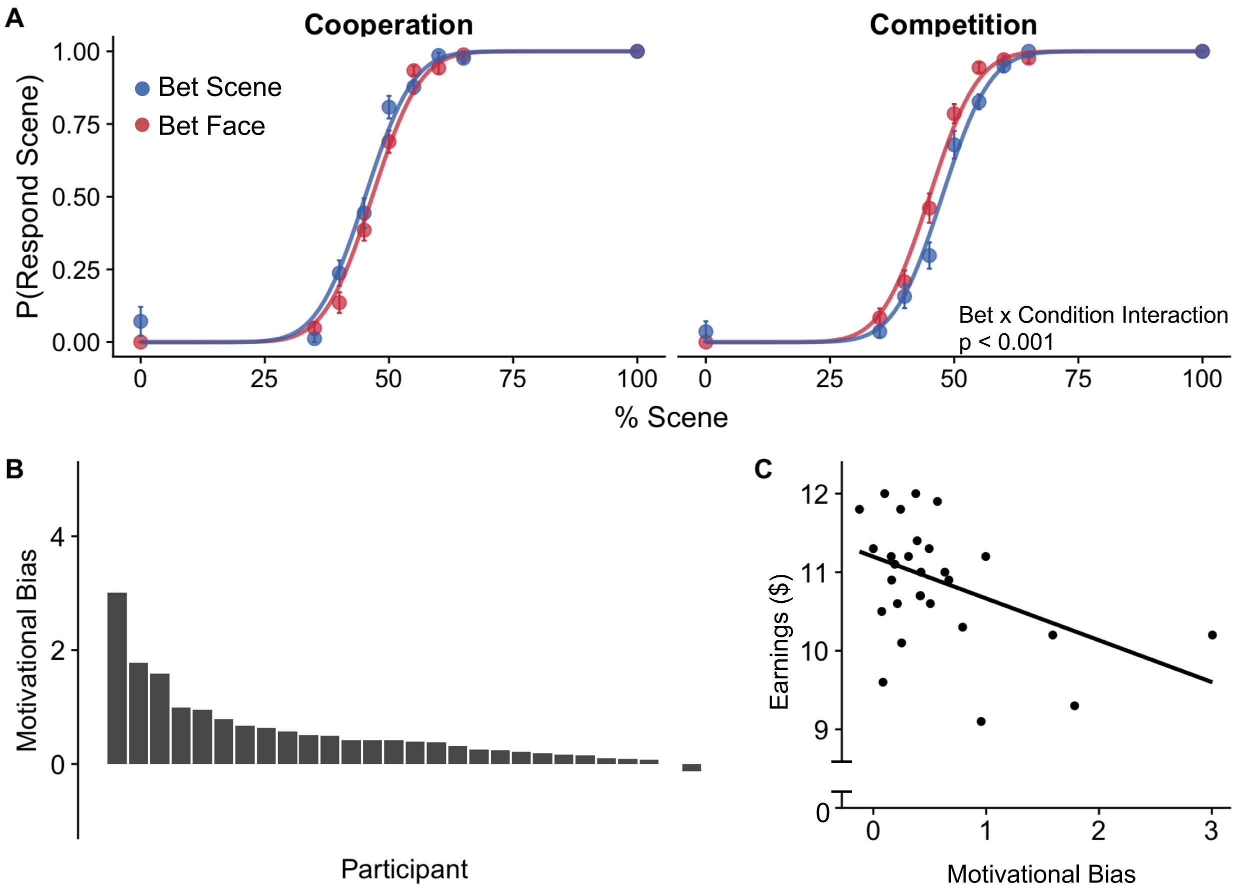
For all models with a bias mechanism (*z&v, z, v*), the proportion of scene responses was higher when participants were motivated to see more scene than when participants were motivated to see more face. For the *z* model, the difference is most pronounced for trials with short RTs (e.g., Q1) and is no longer present for trials with longer RTs (e.g., Q4-Q5). For the *v* model, the difference is constant across all RT quantiles. An intuitive explanation for these patterns is that a bias in starting point (*z* bias) would have the strongest effect early on in a trial, while a bias in drift rate (*v* bias) acts on evidence accumulation throughout a trial (see also *Supplementary Figure 3*). A model with both biases would have an RT pattern that falls between that of the *z* model and that of *v* model. Hence for the *z & v* model, the effect of motivation is strongest in the first quantile, diminishes for longer RTs, but remains visible even at the slowest quantile.

We can see that the empirical data is clearly inconsistent with that of the *z* and *null* models. It is less easy to adjudicate between the *z & v* model and *v* model. Visual inspection suggests that the effect of motivation does indeed diminish with increasing RT, and this pattern is particularly pronounced when we examined the trials at 50% scene, which is also the condition with the most number of trials. This would suggest that the empirical data best matches simulated data generated by the *z & v* model. While it is possible to quantify the extent to which the conditional response function matches that of the *z & v* model, we believe this would be redundant with the formal comparison using DIC.

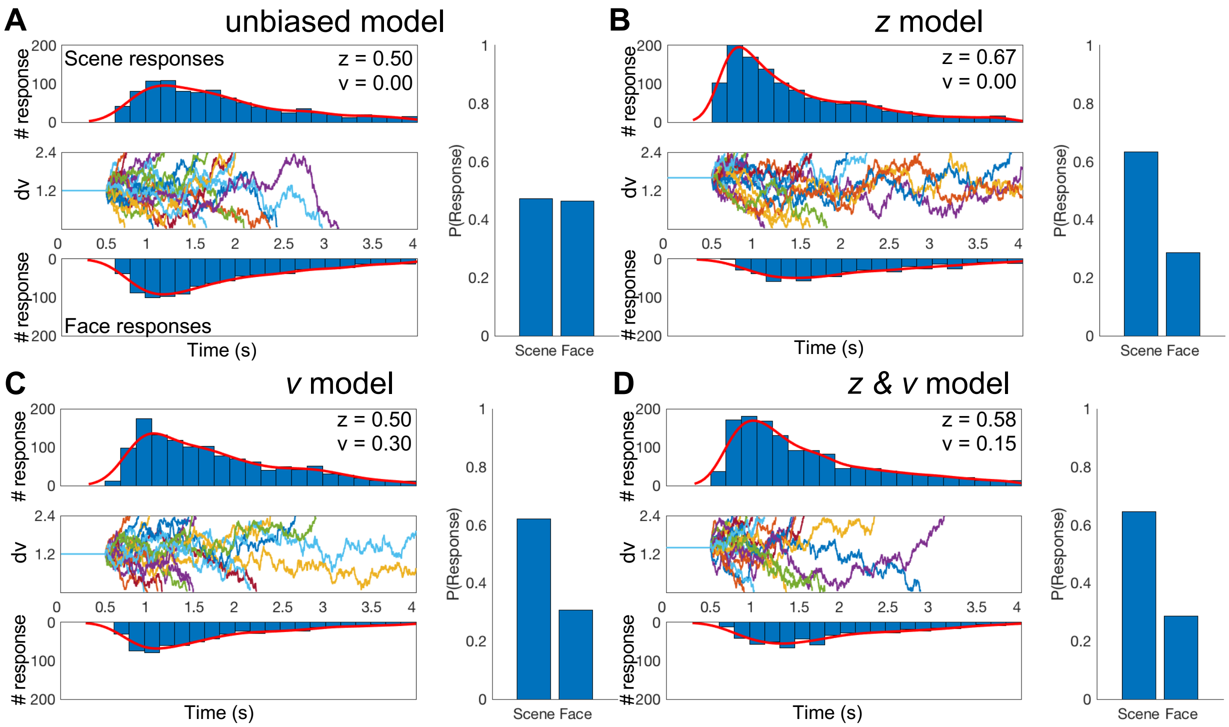
Supplementary Figures



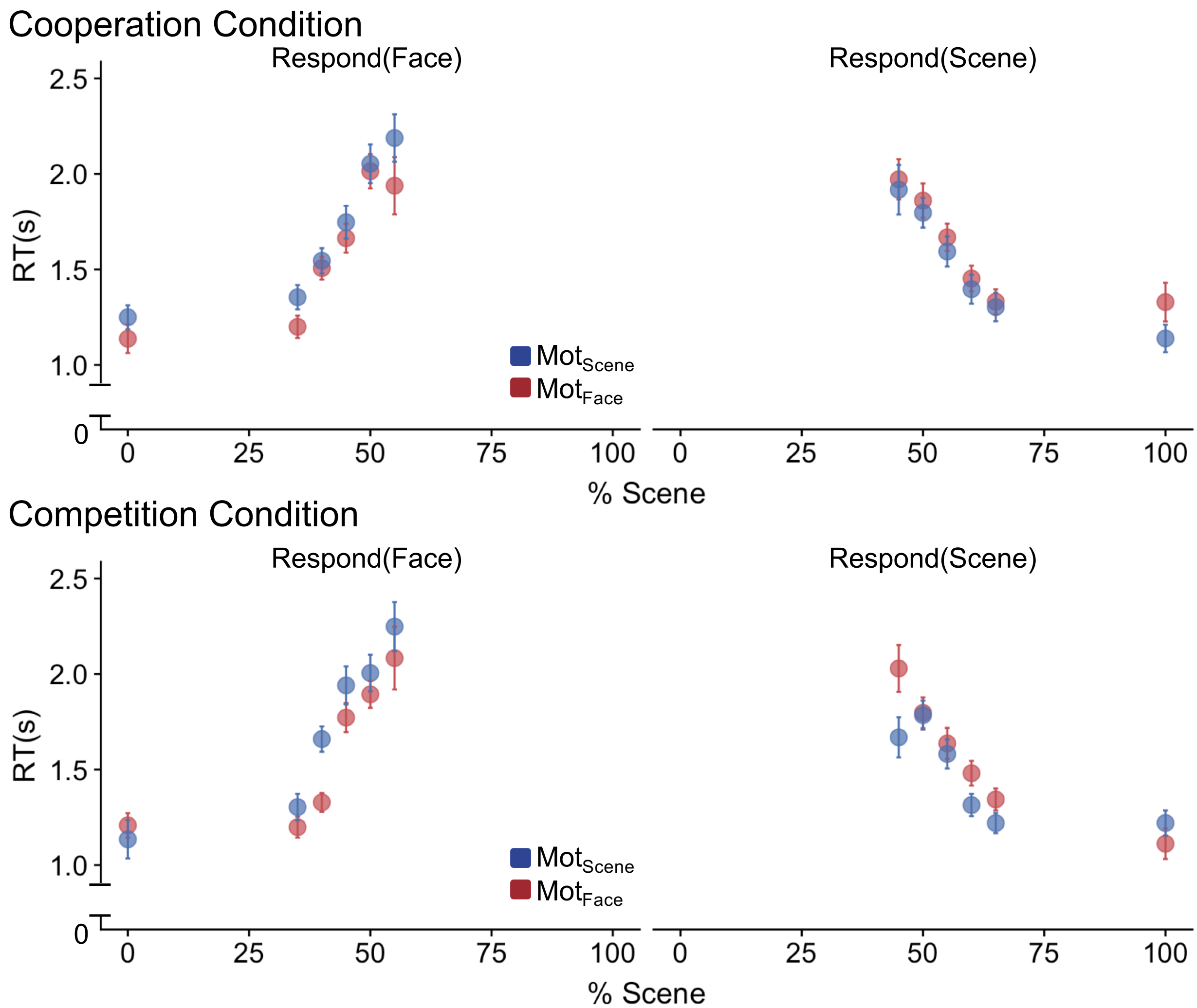
Supplementary Figure 1. Motivational bias was not related to perceptual sensitivity. A. Schematic illustration of relationship between % scene and drift rate for an individual with low perceptual sensitivity (left) and an individual with high sensitivity (right). For an individual with low perceptual sensitivity, the drift rate for face majority images (i.e. % scene < 50%) will be less negative, while the drift rate for scene majority images (i.e. % scene > 50%) will be less positive, resulting in an overall weaker relationship between % scene and drift rate. **B. Relationship between % scene and drift rate, separately for High Bias and Low Bias participants.** The two groups differed only in the effect of motivation on the drift rate (i.e. vertical distance between blue and red dots; lme: two-tailed, one sample $t(535) = 2.55$, $p = 0.010$, b = 0.15, 95% CI = 0.01 to 0.28), and not in the relationship between % scene and drift rate (i.e. average slope; lme: two-tailed, one sample $t(535) = -0.908$, $p = 0.419$, b = -0.02, 95% CI = -0.08 to 0.03). Blue: drift rate when participants were motivated to see more scene. Red: drift rate when participants were motivated to see more face. Error bars indicate across-subject SEM.



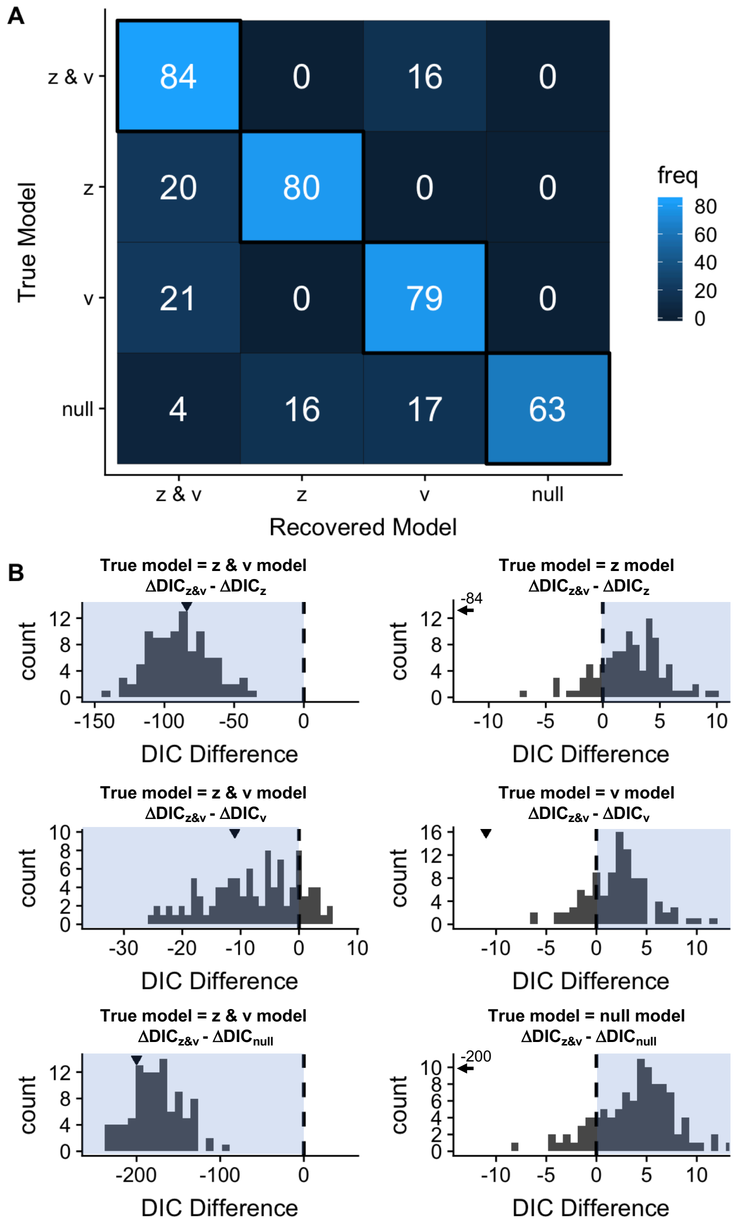
Supplementary Figure 2. Behavioral results were replicated in an independent sample of thirty participants A. Participants were more likely to categorize the ambiguous image as what they wanted to see. *Cooperation Condition:* Participants' psychometric function was shifted left when the teammate bet on more scene (blue) relative to when the teammate bet on more face (red), indicating that less scene evidence is needed to categorize an image as having more scene. *Competition Condition:* Participants' psychometric function was shifted right when the opponent bet on more scene (blue) relative to when the opponent bet on more face (red), indicating that more scene evidence is needed to categorize an image as having more scene. Statistical significance was assessed using a generalized linear mixed-effects model (see Methods). Error bars indicate S.E.M. **B.** Magnitude of bias in each participant, defined as the random slope of the Bet x Condition interaction. **C.** Participants with stronger motivational bias performed worse on the task and received lower earnings (Pearson's r = -0.45, p = 0.015; robust regression: F(1, 26) = 5.98, p = 0.022, b = -0.53, 95% CI = -0.96 to -0.10)



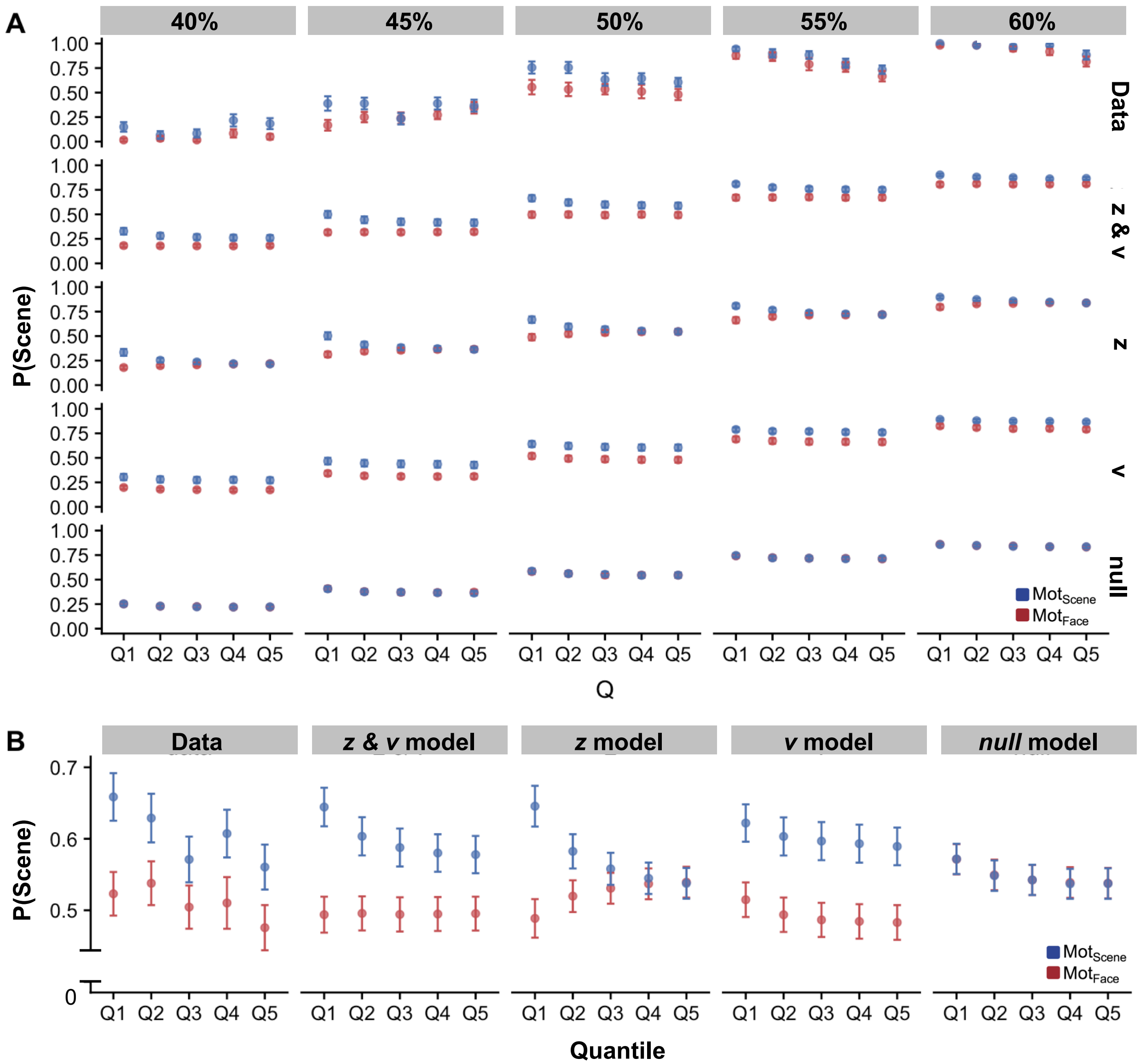
Supplementary Figure 3. Effects of starting point and drift biases on choice and reaction time distributions. Both biases increase the proportion of motivation consistent responses, but have different effects on the shape of reaction time distributions. Each model was simulated 2000 times, but only the first 20 simulated trajectories are shown. Each color indicates a single trajectory. dv: decision variable (i.e. evidence accumulated). **A.** Unbiased model. Left: Simulated trajectories with threshold a = 2.4, non-decision time t = 0.5, relative starting point z = 0.5, drift rate v = 0, and histogram of reaction times for scene (top) and face (bottom) responses. Right: Proportion of scene and face responses. **B.** Model with starting point biased towards the scene threshold, z = 0.67, v = 0.00. This increases the proportion of scene responses, and results in different skews for the two reaction time distributions. Notably, the mode of the reaction time distribution of scene responses is substantially shifted to the left of the reaction time distribution of face responses (i.e. increase in the number of fast motivation consistent responses, and decrease in the number of fast motivation inconsistent responses). **C.** Model with drift rate biased towards the scene threshold, z = 0.50, v = 0.30. This also increases the proportion of scene responses, but with a smaller effect on the shape of reaction time distributions (i.e. increase in the number of both fast and slow motivation consistent responses, and decrease in the number of both fast and slow motivation inconsistent responses). Both reaction time distributions have similar modes. **D.** Model with both starting point and drift rate biased towards the scene threshold, z = 0.58, v = 0.15. This also increases the proportion of scene responses, with an intermediate effect on the shape of reaction time distributions.



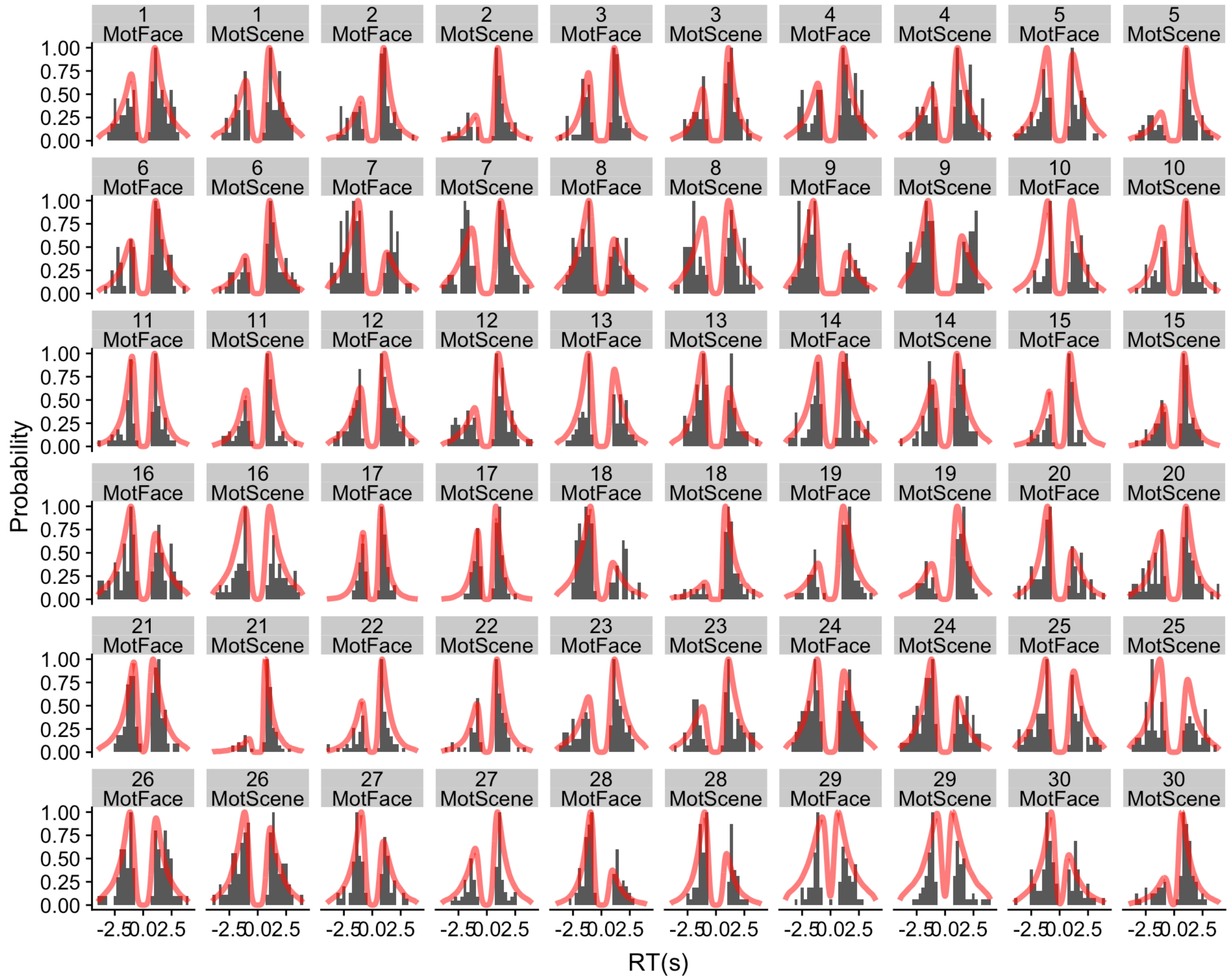
Supplementary Figure 4. Pattern of reaction times were not significantly different between the Cooperation and Competition conditions. There was neither a main effect of Condition (lme: two-tailed, one sample $t(31) = 0.21$, $p = 0.832$, $b = 0.003$, 95% CI = -0.027 to 0.033) nor an interaction effect of Condition and Response (lme: two-tailed, one sample $t(28) = 1.27$, $p = 0.205$, $b = 0.02$, 95% CI = -0.015 to 0.071) on reaction times, suggesting that overall reaction times did not differ significantly between conditions. More importantly, the triple interaction between Condition, Motivation Consistent Category, and Response on reaction times was not significant (lme: two-tailed, one sample $t(24) = 0.328$, $p = 0.328$, $b = 0.010$, 95% CI = -0.090 to 0.127) indicating that the effects of motivation on reaction time were comparable between the two conditions. Trial types with less than 24 trials (i.e. 1% of total trials in each condition) were excluded from the plot because there were too few trials for reliable estimates and they tend to come from a small number of participants. Blue: Motivated to see scene; Red: Motivated to see face. Error bars indicate between-subject SEM.



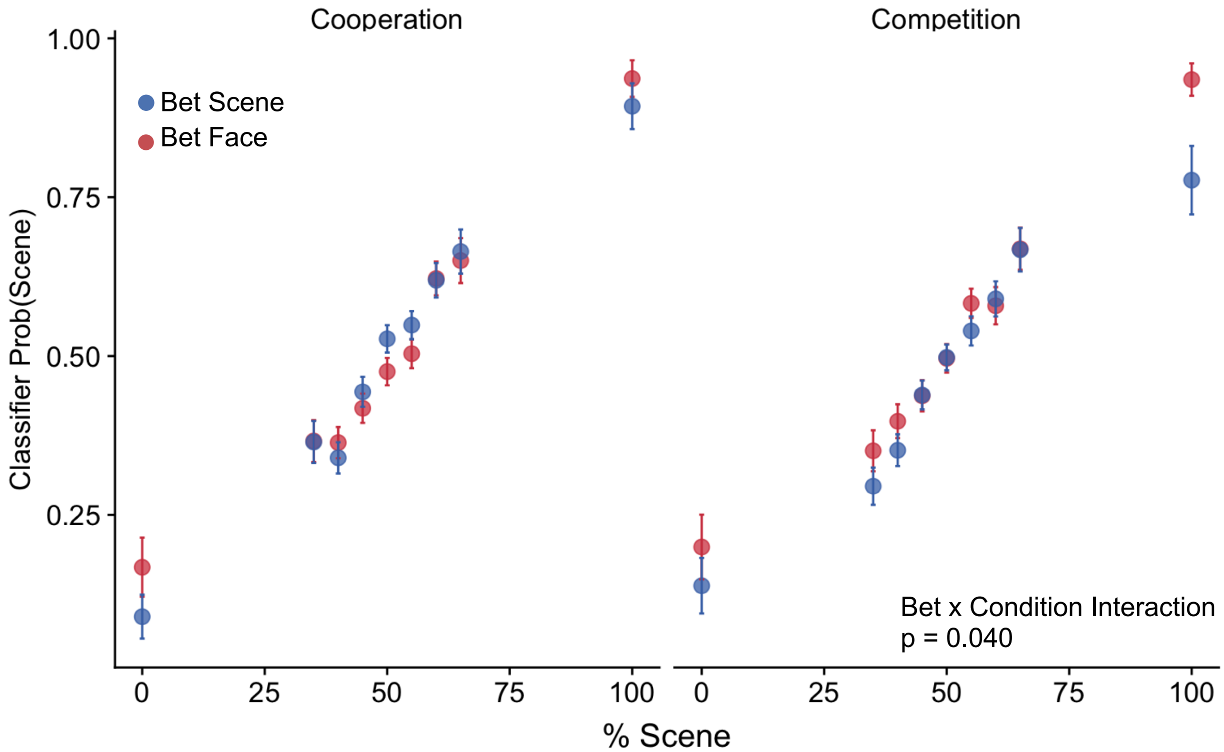
Supplementary Figure 5. DIC correctly identifies the true model used to generate simulated data. A. Confusion matrix when using DIC to identify the model that generated simulated data. Each row indicates the percentage of simulations on which data generated by a particular model is best fit by each of the models. The diagonal indicates accurate model recovery (e.g., correctly identifying *z & v* model when fitting to data generated by the *z & v* model). **B.** Pairwise comparisons of model recovery results between the *z & v* model and the other three models. Histograms show the difference in DIC between the two models when fitting to data generated by different models. Shaded blue region indicates accurate model selection (e.g., $DIC_{z\&v} < DIC_z$ for data generated by the *z & v* model, and $DIC_{z\&v} > DIC_z$ for model generated by the *z* model). For comparison, inverted triangles indicate true DIC difference when fitting the models to participants' data. The true $\Delta DIC_{z\&v}$ - ΔDIC_z and $\Delta DIC_{z\&v}$ - ΔDIC_{null} are much larger than those obtained when fitting the models to data generated by the *z* and *null* models respectively, and are thus indicated with a leftward arrow so as to not distort the scale of the graph. Altogether, these results indicate that DIC is an accurate metric for model comparison, and that our results provide strong evidence that the *z & v* model provided the best fit to participants' behavior.



Supplementary Figure 6. Conditional response functions for empirical and simulated data. A. Each plot shows response proportion as a function of reaction time at each level of % scene, separately for when participants were motivated to see more scene (Blue) and when participants were motivated to see more face (Red). Reaction times for each participant were binned into 5 quantiles (Q1: 20%, Q2: 40%, Q3: 60%, Q4: 80%, Q5: 100%). The response proportion was computed for each quantile and averaged across participants. We also computed the conditional response functions for data generated by all four drift diffusion models. In the empirical data, the effect of motivation diminishes with longer RTs, but remain visible even at the slowest quantile. Only the *z & v* model reproduced this RT pattern (see also Supplementary Note). Motivation has no effect in the *null* model, hence the data in the Mot_{Face} condition is occluded by data in the Mot_{Scene} condition. There were not enough trials at 0%, 35%, 65% and 100% scene to be divided into 5 quantiles. **B.** Conditioned response functions averaged across levels of % scene and then averaged across participants. In both panels, error bars indicate between-subject standard error.



Supplementary Figure 7. Observed and predicted choice and RT distributions for each participant. RTs for face responses were sign-flipped for illustration purposes. For each participant, we plot the RT distributions for face (negative RTs) and scene responses (positive RTs) separately for when the participant was motivated to see more face (MotFace) and for when the participant was motivated to see more scene (MotScene). Blue line indicates model-predicted choice and RT distributions.



Supplementary Figure 8. Motivation biases face and scene selective neural activity during visual categorization. Classifier probability that the presented image was a scene rather than a face based on the BOLD response in the ventral visual stream. Red dots: teammate or opponent betting that the next image will be a face. Scene probability was higher when participants were motivated to see a scene than when participants were motivated to see a face (lme: two-tailed, one-sample $t(4756) = 2.05$, $p = 0.040$, $b = 0.038$, 95% CI = 0.002 to 0.075).

Supplementary Tables

Supplementary Table 1. Fitted values of model parameters. Estimate denotes posterior mean of the corresponding parameter. Square brackets denote 95% credible interval. Convergence was assessed using the Gelman-Rubin $\hat{R}$ statistic. An $\hat{R}$ of greater than 1.1 would indicate convergence problems. $\hat{R}$ was less then 1.02 for all model parameters. *a*: threshold, *t*: non-decision time, $z_{motivation}$: coefficient of the effect of motivation on starting point, $z_{intercept}$: intercept of starting point, $v_{motivation}$: coefficient of the effect of motivation on drift rate, $v_{\%scene}$: coefficient of the effect of percentage scene on drift rate, $v_{intercept}$: intercept of drift rate.

Parameters	Estimate	Gelman-Rubin $\hat{R}$
z & v model		
a	2.373 [2.282, 2.46]	1.0002
t	0.544 [0.466, 0.636]	1.0001
$z_{motivation}$	0.051 [-0.003, 0.105]	1.0007
$z_{intercept}$	0.046 [0.030, 0.068]	1.0057
$v_{motivation}$	0.092 [0.015, 0.168]	1.0000
$v_{\%scene}$	0.702 [0.633, 0.772]	1.0000
$v_{intercept}$	0.094 [-0.014, 0.206]	1.0029
z model		
a	2.369 [2.278, 2.462]	1.0001
t	0.547 [0.470, 0.637]	1.0001
$z_{motivation}$	0.120 [0.052, 0.192]	1.0002
$z_{intercept}$	0.052 [0.034, 0.070]	1.0088
$v_{\%scene}$	0.695 [0.625, 0.769]	1.0000
$v_{intercept}$	0.087 [-0.021, 0.195]	1.0009
v model		
a	2.372 [2.280, 2.466]	1.0000
t	0.542 [0.463, 0.635]	1.0000
$z_{intercept}$	0.056 [0.033, 0.075]	1.0148
$v_{motivation}$	0.121 [0.048, 0.195]	1.0001
$v_{\%scene}$	0.702 [0.636, 0.771]	1.0004
$v_{intercept}$	0.087 [-0.023, 0.196]	1.0017
null model		
a	2.345 [2.256, 2.436]	1.0000
t	0.542 [0.464, 0.633]	1.0002
$z_{intercept}$	0.050 [0.033, 0.076]	1.0013
$v_{\%scene}$	0.686 [0.612, 0.758]	1.0000
$v_{intercept}$	0.087 [-0.021, 0.195]	1.0023

Supplementary Table 2. Difference in NAcc activity between Motivation Consistent and Inconsistent trials. NAcc activity was corrected for hemodynamic lag by shifting the BOLD data by 4 seconds, and time-locked to image onset (t = 0). * two-tailed, one-sample *t*-test, uncorrected $p < 0.05$. Correction for multiple comparison was not performed as we know from the whole-brain contrast that NAcc activity on Motivation Consistent trials was higher than on Motivation Inconsistent trials. The goal of this analysis is to determine *when* this difference first emerged.

Time (s)	MotCon	MotIncon	Paired t-test
-8	M = 0.024, SE = 0.018	M = 0.008, SE = 0.027	$t(29) = 0.653$, $p = 0.259$
-6	M = 0.078, SE = 0.024	M = 0.085, SE = 0.025	$t(29) = -0.238$, $p = 0.593$
-4	M = 0.059, SE = 0.023	M = 0.035, SE = 0.027	$t(29) = 0.831$, $p = 0.206$
-2	M = -0.004, SE = 0.027	M = -0.082, SE = 0.028	$t(29) = 2.234$, $p = 0.017$*
0	M = 0.015, SE = 0.028	M = -0.050, SE = 0.028	$t(29) = 2.116$, $p = 0.022$*
2	M = -0.027, SE = 0.027	M = -0.083, SE = 0.027	$t(29) = 1.893$, $p = 0.034$*
4	M = 0.028, SE = 0.025	M = -0.013, SE = 0.026	$t(29) = 1.351$, $p = 0.094$
6	M = 0.047, SE = 0.026	M = 0.073, SE = 0.028	$t(29) = -0.798$, $p = 0.784$
8	M = 0.030, SE = 0.026	M = 0.026, SE = 0.023	$t(29) = 0.124$, $p = 0.451$

Supplementary Table 3. Model specification and estimated coefficients of linear mixed effects models (Choice Data). Models are referred to by their labels (e.g., *M1*, *M2*) in the *Methods* section. Formulas are written in the notation of the lme4 package in R. Random effects are indicated in parentheses. Variable coding - response: face = 0, scene = 1; bet: face = 0, scene = 1; condition: competition = 0, cooperation = 1. [1]A *probit* link function was used. [2]Data from Cooperation condition only. [3]Data from Competition condition only.

	Formula	Term	Estimate	SE	p
M1[1,2]	response ~ % scene + bet + (bet | subj)	intercept	-8.348	0.335	< 0.001
		% scene	0.168	0.006	< 0.001
		bet	0.330	0.131	0.012
M2[1,3]	response ~ % scene + bet + (bet | subj)	intercept	-6.005	0.193	< 0.001
		% scene	0.129	0.004	< 0.001
		bet	-0.466	0.110	< 0.001
M3[1]	response ~ % scene + condition * bet + (condition * bet | subj)	intercept	-6.774	0.220	< 0.001
		% scene	0.145	0.004	< 0.001
		condition	-0.423	0.147	0.004
		bet	-0.506	0.140	< 0.001
		bet * condition	0.810	0.242	0.001

Supplementary Table 4. Model specification and estimated coefficients of linear mixed effects models (Reaction Time Data). Variable coding - motcon_response: motivationally inconsistent responses = 0, motivationally consistent responses = 1; stimulus_uncertainty = |% scene - % face|; [1]Face responses only. [3]Scene responses only. [4]Simulated data generated from *z & v* model.

	Formula	Term	Estimate	SE	p
M4	log(RT) ~ motcon_response + stimulus_uncertainty + (motcon_response + stimulus_uncertainty | subj)	intercept	0.505	0.028	< 0.001
		motcon_response	-0.054	0.019	0.009
		stimulus_uncertainty	-0.005	0.0003	< 0.001
M5[1]	log(RT) ~ motcon_response + stimulus_uncertainty + (motcon_response + stimulus_uncertainty | subj)	intercept	0.486	0.031	< 0.001
		motcon_response	-0.067	0.021	0.004
		stimulus_uncertainty	-0.006	0.000	< 0.001
M6[2]	log(RT) ~ motcon_response + stimulus_uncertainty + (motcon_response + stimulus_uncertainty | subj)	intercept	0.483	0.031	< 0.001
		motcon_response	-0.044	0.021	0.044
		stimulus_uncertainty	-0.005	0.000	< 0.001
M7[3]	log(RT) ~ motcon_response + stimulus_uncertainty + (motcon_response + stimulus_uncertainty | subj)	intercept	0.537	0.027	< 0.001
		motcon_response	-0.043	0.012	0.001
		stimulus_uncertainty	-0.004	0.000	< 0.001
M8[1,4]	log(RT) ~ motcon_response + stimulus_uncertainty + (motcon_response + stimulus_uncertainty | subj)	intercept	0.543	0.029	< 0.001
		motcon_response	-0.049	0.013	< 0.001
		stimulus_uncertainty	-0.004	0.000	< 0.001
M9[2,4]	log(RT) ~ motcon_response + stimulus_uncertainty + (motcon_response + stimulus_uncertainty | subj)	intercept	0.531	0.030	< 0.001
		motcon_response	-0.037	0.013	0.008
		stimulus_uncertainty	-0.004	0.000	< 0.001

Supplementary Table 5. Model specification and estimated coefficients of linear mixed effects models (Classifier Data). Variable coding - classifier_prob: classifier probability that participants were viewing a scene; mot_bias: continuous measure of motivational bias in behavior; bias_group: low bias participants = 0; high bias participants = 1; [1]Data from high bias participants only. [2]Data from low bias participants only.

	Formula	Term	Estimate	SE	p
M10	classifier_prob ~ % scene + condition * bet + (condition * bet | subj)	intercept	0.070	0.019	< 0.001
		% scene	0.009	0.000	< 0.001
		condition	-0.021	0.013	0.108
		bet	-0.021	0.013	0.108
		bet * condition	0.039	0.019	0.040
M11	classifier_prob ~ % scene + condition * bet * mot_bias + (condition * bet | subj)	intercept	0.06	0.02	0.003
		% scene	0.01	0.00	< 0.001
		condition	0.00	0.02	0.951
		bet	0.00	0.02	0.915
		mot_bias	0.01	0.01	0.158
		bet * condition	-0.01	0.02	0.756
		mot_bias * condition	-0.03	0.01	0.034
		bet * mot_bias	-0.02	0.01	0.041
		condition * bet * mot_bias	0.06	0.02	0.001
M12[1]	classifier_prob ~ % scene + condition * bet + (condition * bet | subj)	intercept	0.069	0.027	0.012
		% scene	0.009	0.000	< 0.001
		condition	-0.034	0.019	0.070
		bet	-0.032	0.019	0.084
		bet * condition	0.079	0.027	0.003
M13[2]	classifier_prob ~ % scene + condition * bet + (condition * bet | subj)	intercept	0.072	0.027	0.009
		% scene	0.009	0.000	< 0.001
		condition	-0.009	0.019	0.649
		bet	-0.010	0.019	0.587
		bet * condition	-0.002	0.026	0.953
M14	classifier_prob ~ % scene + condition * bet * bias_group + (condition * bet | subj)	intercept	0.064	0.021	0.003
		% scene	0.009	0.0003	< 0.001
		condition	-0.009	0.019	0.649
		bet	-0.010	0.019	0.588
		bias_group	0.012	0.019	0.523
		bet * condition	-0.002	0.027	0.953
		condition * bias_group	-0.025	0.028	0.337
		bet * bias_group	-0.022	0.027	0.402
		condition * bet * bias_group	0.080	0.037	0.033

Supplementary References

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