Emotion-Cognition Interactions in Attention-Deficit/Hyperactivity Disorder: Increased Early Attention Capture and Weakened Attentional Control in Emotional Contexts

SUPPLEMENTAL INFORMATION

SUPPLEMENTAL METHODS

Screening and Diagnosis

After an initial screening phone call, a parent/guardian and teacher completed standardized rating scales, including the Conners' Rating Scales, 3rd edition and the ADHD Rating Scale (ADHD-RS). The parent/guardian also completed a semi-structured clinical interview (Kiddie Schedule for Affective Disorders and Schizophrenia, K-SADS) administered by a Master's-level clinician who had achieved research reliability. The parent/guardian reported on lifetime and current symptom levels, as well as age of onset and impairment.

Total symptom counts were calculated by combining parent (K-SADS) and teacher (ADHD-RS) report using an "OR" algorithm. For the majority of cases (n= 104), children were assigned to the ADHD group if they had 6+ symptoms of inattention and/or 6+ symptoms hyperactivity-impulsivity, and met criteria for impairment and age of onset based on the K-SADS. Those in the typically-developing control group were required to have 3 or fewer symptoms within each ADHD symptom domain and 4 or fewer total ADHD symptoms.

For a minority of cases (n= 26), teacher ratings were not available at the time of data analysis to create the "OR" algorithm symptom counts. In these cases, the diagnosis assigned was based on review by a diagnostic team who reviewed cases for the larger longitudinal study (Karalunas et al., 2017; Nigg et al., 2018). This diagnostic team included a child psychiatrist and licensed child psychologist. Blind to one another's ratings and to the cognitive test scores, they formed a diagnostic opinion based on all available information (parent ratings and clinical interview, self-report ratings, IQ and academic achievement testing, medication and developmental history). Their agreement rate was satisfactory (ADHD, kappa=.88). Disagreements were conferenced and consensus reached. Cases where consensus was not readily

achieved were excluded. Agreement between the two diagnostic approaches in cases where both were available was >90%.

Exclusion Criteria. Adolescents were excluded from the current study if they were prescribed long-acting, non-stimulant psychotropic medications; had self-reported history of neurological impairment such as seizures or head injury with loss of consciousness; had a history of substance abuse; had prior diagnosis of intellectual disability, autism spectrum disorder, or psychosis; were currently experiencing a major depressive episode; or had estimated IQ < 70.

Raw EEG data were resampled to 250 Hz and referenced offline to the average of all channels. EEG signals were filtered using an IIR filter with a bandwidth of .01–50 Hz. Eye artifacts were removed through independent component analysis (Jung et al., 2000). Epochs from -200 to 1000 ms were time-locked to the onset of the face stimuli. A 200 ms prestimulus period was used for baseline correction. Trials were discarded from the analyses if they contained baseline drift or movement artifacts greater than 90 μV. Based on *a priori* criteria, a participant's data for a given condition were excluded from analyses if >50% of the total trials were rejected due to artifacts of any type (<2% of cases for any condition).

LBA Methods

The go/no-go implementation of the LBA is similar to the standard LBA for 2-choice tasks; however, because RTs for no-go choices are not observed, the calculation of likelihood for model-fitting is slightly different. The likelihood of go RTs given a set of model parameters is calculated in DMC using a standard method for 2-choice LBA tasks: assigning likelihood values to RTs given the "defective" probability density function for these responses predicted by the model (Turner, Sederberg, Brown, & Steyvers, 2013). The likelihood of no-go responses is

calculated by integrating the "defective" probability density function for no-go responses, and assigning all no-go responses in a given condition the same likelihood value.

In the current study, the mean of the drift rate distribution (*v*) was free to vary by type of stimulus (go, no-go), emotion condition (positive, negative, neutral), and type of response accumulator (correct, incorrect). After estimation, rates for the error accumulator were subtracted from those of the correct accumulator to obtain an index of overall efficiency in reaching the correct response, providing a drift rate parameter that is comparable to that of drift rate in the diffusion model. The boundary height parameter (*b*) was allowed to vary by type of response (go, no-go) and emotion condition (positive, negative, neutral). The non-decision time (*t0*) parameter was allowed to vary by emotion condition, and the drift variability (*sv*) parameter was allowed to vary by type of response accumulator (correct vs. incorrect). However, *sv* for the error accumulator was fixed to 1 as a scaling parameter (Donkin, Brown, & Heathcote, 2009). The start point variability (*A*) parameter was also fixed in the hierarchical model to the group average of this parameter from initial fixed-effects (single subject) fits (.85 for participants with ADHD and .67 for controls) because simulation studies conducted prior to model fitting suggested that this procedure allowed better parameter recovery for the hierarchical model.

The hierarchical modeling method was used to estimate posterior distributions of LBA model parameters for individual participants, as well as group-level parameters which describe the group distributions of the Control and ADHD groups, separately. Group distributions were assumed to be normal distributions truncated at 0, and described by location (μ; approximates the group mean) and scale (σ; approximates the group standard deviation) hyper-parameters. Group hyper-parameters were fit to distributions of the individual-level parameters and simultaneously acted as priors for the individual parameters, preventing outlier estimates. We specified priors for

all group-level hyper-parameters, including exponential distributions with a scale of 1 for all σ parameters and the following truncated normal (TN) distribution priors for all μ parameters:

$$b \sim TN(\mu = 1, \sigma = .5, 0, \infty)$$
$$vc \sim TN(\mu = 2, \sigma = 1, 0, \infty)$$
$$ve \sim TN(\mu = 2, \sigma = 1, 0, \infty)$$
$$svc \sim TN(\mu = 1, \sigma = 1, 0, \infty)$$
$$t0 \sim TN(\mu = .5, \sigma = .5, .1, \infty)$$

Markov chain Monte-Carlo simulations using the differential evolution method to address parameter correlation (DE-MCMC: Turner et al., 2013) were used to sample from posterior distributions of all group- and individual-level parameters. Start points for the simulations were drawn from initial fixed effects fits conducted at the individual-subject level, and sampling was run for a burn-in period until convergence was indicated both by a Gelman-Rubin statistic < 1.1 for all parameters (Gelman & Rubin, 1992) and by visual inspection. After the burn-in period, 4000 iterations of 66 chains, thinned by 20 to save file space, were retained for analysis (13,200 samples in total for each group).

Assessment of Model Fit. Posterior predictive plots (Gelman, Meng, & Stern, 1996) which displayed the joint cumulative distribution functions of empirical and predicted RT data at 5 quantiles (.1, .3, .5, .7, and .9), were generated by averaging data across participants in each group (**Figure S2**). The plots suggested that the model provided an excellent description of the timing and probability of correct go ("hit") and incorrect no-go ("false alarm") responses, with some slight misfit in slower RT quantiles. As a result, we concluded that model fit was adequate.

Calculation of Odds Ratios. Following previous work using hierarchical LBA analyses (Weigard, Huang-Pollock, & Brown, 2016; Winkel et al., 2016), we report evidence for effects

using odds ratios (ORs). ORs were calculated for all effects by subtracting the distribution of one condition from that of another, and determining the ratio of samples above vs. below 0, or vice versa in cases where the majority of samples were below 0. ORs were calculated for two-factor interaction effects by first calculating difference distributions for effects of the first factor at each level of the second factor, and then calculating an OR for differences between these difference distributions. We interpret ORs following Jeffreys' (1961) recommendations for Bayes factors: ORs > 3:1 were considered "substantial" evidence of an effect, ORs > 10:1 were considered "strong" evidence, ORs > 30:1 were considered "very strong", and ORs > 100:1 were considered "decisive".

Plausible Values Correlation Analysis

We estimated correlation coefficients (Pearson's *r*) for relationships between emotion-related changes in LBA parameters of interest and corresponding changes in ERPs, as well as for relationships between changes in LBA parameters of interest and possible confounding factors that differed between groups (IQ and parental income, as reported in the main text). A "plausible values" analysis (Ly et al., 2017) was therefore conducted in DMC to estimate posterior distributions of the population's *r* for these relationships. First, the posterior distribution for the sample's *r* was calculated by assessing the correlation between the covariate and each individual-level posterior sample for the LBA parameter of interest. Next, following methods outlined by (Ly, Marsman, & Wagenmakers, 2018), posterior distributions for the population's *r* were calculated using a uniform prior which spanned *r* values from -1 to 1. Once population posterior distributions were estimated, 95% credible intervals, which represent the range in which there is a .95 probability that the true population *r* value falls, were estimated and used for inference (**Table S1 and S2**).

Covariates. Groups differed in sex, median income, and IQ (see **Table 1** for sample description). There is general consensus that each of these reflect genuine differences in the population of adolescents with and without ADHD (Dennis et al., 2009; Miller et al., 2018) and are not due simply to sampling error. Nonetheless, each ERP model was initially run with these variables as covariates. None significantly interacted with the effects of interest. Similarly, each demographic variable was correlated with the significant effects from the LBA models using the plausible values correlation analyses described above (Ly et al., 2017) and no relationships were found to be credibly different from 0. Given the conceptual concerns with using population-level differences as covariates (Dennis et al., 2009) and the lack of statistically-significant interactions between these demographic variables and the effects of interest, we report results without covariates as the primary analyses below.

SUPPLEMENTAL RESULTS

Reaction Time and Accuracy Results

For reaction time, a 3 (emotion) x 2 (diagnosis) repeated-measures ANOVA indicated a main effect of emotion ($F[2, 250]= 21.3$, $p < .001$, partial $\eta^2 = .15$). Adolescents responded fastest in the positive condition, consistent with increased approach, and slowest in the negative condition, consistent with increased withdrawal. There was no main effect of diagnosis ($F[1, 125]= 1.5$, $p = .223$, partial $\eta^2 = .01$) and no diagnosis x emotion interaction ($F[2, 250]= 0.50$, $p = .608$, partial $\eta^2 = .00$).

For no-go accuracy, a 3 (emotion) x 2 (diagnosis) repeated-measures ANOVA indicated a main effect of emotion ($F[2, 250]= 6.7$, $p = .001$, $\eta^2 = .05$). Adolescents were most accurate in the positive condition as compared to negative or neutral. There was also a significant main

effect of diagnosis (F[1, 125]= 13.7, $p < .001$, $\eta^2 = .10$); adolescents with ADHD were less accurate than those without ADHD. There was no diagnosis x emotion interaction a (F[2, 250]= 1.3, $p < .273$, $\eta^2 = .01$).

LBA Results for Neutral Condition

Drift rate. In the neutral condition, there was decisive evidence that adolescents with ADHD had slower drift rates than non-ADHD controls for go trials (OR=175.00) and substantial evidence for slower drift rates in ADHD for no-go trials (OR=5.63). Effects are consistent with prior literature using non-emotional tasks.

Boundary. In the neutral condition, there was little evidence for group differences in boundary height for no-go responses (OR=2.94), consistent with prior literature using non-emotional tasks. There was decisive evidence that adolescents with ADHD had lower boundary heights for go responses than their peers (OR=824.00), indicating a bias towards "going" that is also consistent with prior research using non-emotional tasks.

Parameter Recovery Study

Sequential sampling models (SSMs) such as the LBA often display tradeoffs between mean drift rate (v) and response boundary (b) parameters, in which behavioral effects in one of these parameters are incorrectly attributed to the other parameter in recovered parameter estimates. These tradeoffs can sometimes compromise interpretability by preventing accurate recovery of v and b parameter values. As our primary effects of interest were in v and b parameters, we conducted a parameter recovery study based on previously-used methods (Lerche, Voss & Nagler, 2017; Ratcliff & Childers, 2015; White, Servant & Logan, 2018) in order to assess whether values of these parameters could be accurately recovered from data that had similar qualities to the empirical data included in the current study.

First, we used the medians of the group-level μ and σ parameter posteriors obtained from our fits of the LBA to empirical data to generate simulated behavioral data from simulated ADHD and control groups, where individual-level parameters in these groups were drawn from the positive-truncated normal distributions specified by the μ and σ posterior medians. The groups were identical in size to the empirical ADHD and control groups, and had the same number of trials per condition and per subject. Next, we used methods identical to those described above to fit hierarchical Bayesian LBA models to data from each simulated group. Finally, following previous SSM parameter recovery studies (Lerche et al., 2017; Ratcliff & Childers, 2015; White et al., 2018), we assessed correlations between the individual-level values of our main parameters of interest (Δv and Δb for the positive and negative conditions relative to the neutral condition) that were used to simulate the data and the individual-level parameter values that were recovered from the data (posterior medians). As the goal of our study was to detect individual and group differences in parameter values, this method for assessing recovery is ideal because it indexes how reliably the model captures individual differences in relevant parameters (Lerche et al., 2017). We adopted the criteria outlined by White et al. (2018) for determining the quality of recovery: recovery was considered "poor/unacceptable" if $r < .50$, "fair" if $.50 < r < .75$, "good" of $.75 < r < .90$ and "excellent" if $r > .90$

Figure S3 displays scatterplots and correlation coefficients for the relationships between parameters used to simulate data and the parameters recovered from those data, separately for each simulated group. Although there was some variability in individuals' recovered parameter estimates, especially for parameters from no-go trials (which would be expected given the lower number of these trials) correlations between simulated and recovered parameter values indicated "good" to "excellent" recovery for all parameters of interest. Inspection of the scatterplots also

indicated that there was no strong indication of a bias in parameter estimates, which would have been apparent if dots in the plot fell either mostly above or mostly below the diagonal line representing a perfect relationship. Therefore, we concluded that, although absolute parameter values are not recovered perfectly, the model is able to reliably estimate individual differences in parameter values, which suggests that our analyses of selective parameters' ADHD-related differences and relationships with covariates can be interpreted.

SUPPLEMENTAL TABLES

Table S1. Results from plausible values correlation analyses testing whether changes in LBA parameters in the positive relative to the neutral condition (Positive Δ) correlate with corresponding changes in ERPs in the positive relative to neutral condition. (We focus on the positive condition because this is where group-level effects for parameters were observed.) Median posterior values for the population correlation coefficient (Median *r*) represent the most likely value for this coefficient. Credible intervals represent the lower (2.5%) and upper (97.5%) bounds of the range in which there is a 95% chance that the true *r* value falls. No *r* values in this analysis were credibly different from 0.

Relationship	**Control Group**			**ADHD Group**		
	Median *r*	Credible Interval		Median *r*	Credible Interval	
		2.5%	97.5%		2.5%	97.5%
Positive Δ*v.*go ~ Positive ΔP1 Amp.	-0.06	-0.32	0.20	-0.11	-0.39	0.19
Positive Δ*v.*go ~ Positive ΔN2 Amp.	0.11	-0.17	0.36	0.11	-0.19	0.38
Positive Δ*v.*go ~ Positive ΔN170 Amp.	-0.19	-0.44	0.08	-0.02	-0.30	0.27
Positive Δ*v.*go ~ Positive ΔP1 Latency	-0.15	-0.41	0.13	0.04	-0.25	0.31
Positive Δ*v.*no-go ~ Positive ΔP1 Amp.	0.00	-0.30	0.30	-0.07	-0.36	0.22
Positive Δ*v.*no-go ~ Positive ΔN2 Amp.	-0.01	-0.30	0.29	-0.20	-0.47	0.10
Positive Δ*v.*no-go ~ Positive ΔN170 Amp.	-0.21	-0.48	0.09	0.13	-0.16	0.42
Positive Δ*v.*no-go ~ Positive ΔP1 Latency	0.00	-0.31	0.30	0.07	-0.22	0.36
Positive Δ*b.*go ~ Positive ΔP1 Amp.	-0.03	-0.30	0.24	0.06	-0.23	0.34
Positive Δ*b.*go ~ Positive ΔN2 Amp.	0.25	-0.02	0.49	0.03	-0.25	0.30
Positive Δ*b.*go ~ Positive ΔN170 Amp.	-0.14	0.39	0.13	-0.10	-0.37	0.18
Positive Δ*b.*go ~ Positive ΔP1 Latency	-0.16	-0.41	0.12	0.02	-0.24	0.29
Positive Δ*b.*no-go ~ Positive ΔP1 Amp.	-0.02	-0.32	0.28	0.01	-0.30	0.32
Positive Δ*b.*no-go ~ Positive ΔN2 Amp.	0.02	-0.28	0.32	0.00	-0.31	0.30
Positive Δ*b.*no-go ~ Positive ΔN170 Amp.	-0.17	-0.45	0.13	0.26	-0.06	0.53
Positive Δ*b.*no-go ~ Positive ΔP1 Latency	-0.12	-0.40	0.18	-0.02	-0.33	0.29

Table S2. Results from plausible values correlation analyses (Ly et al., 2017) testing changes in LBA parameters in the positive relative to the neutral condition (Positive Δ) correlate with parent rated ADHD symptoms and emotional traits. Median posterior values for the population correlation coefficient (Median *r*) represent the most likely value for this coefficient. Credible intervals represent the lower (2.5%) and upper (97.5%) bounds of the range in which there is a 95% chance that the true *r* value falls. No *r* values in this analysis were credibly different from 0.

Relationship	**Control Group**			**ADHD Group**		
	Median *r*	Credible Interval		Median *r*	Credible Interval	
		2.5%	97.5%		2.5%	97.5%
Positive Δ*v.*go ~ Inattention	0.11	-0.17	0.36	0.10	-0.18	0.36
Positive Δ*v.*go ~ Hyperactivity	-0.03	-0.29	0.24	-0.08	-0.34	0.19
Positive Δ*v.*no-go ~ Inattention	-0.17	-0.44	0.14	-0.13	-0.40	0.16
Positive Δ*v.*no-go ~ Hyperactivity	-0.12	-0.40	0.18	-0.14	-0.40	0.15
Positive Δ*b.*go ~ Inattention	0.12	-0.15	0.36	0.02	-0.24	0.29
Positive Δ*b.*go ~ Hyperactivity	-0.05	-0.32	0.21	-0.02	-0.28	0.25
Positive Δ*b.*no-go ~ Inattention	-0.07	-0.35	0.23	0.06	-0.25	0.35
Positive Δ*b.*no-go ~ Hyperactivity	-0.05	-0.34	0.26	-0.01	-0.31	0.29
Positive Δ*v.*go ~ Parent Surgency	-0.07	-0.32	0.20	0.03	-0.25	0.30
Positive Δ*v.*go ~ Parent HIP	-0.05	-0.31	0.22	-0.08	-0.35	-.20
Positive Δ*v.*go ~ Child Surgency	0.02	-0.24	0.28	-0.22	-0.49	0.08
Positive Δ*v.*go ~ Child HIP	0.08	-0.19	0.34	-0.23	-0.49	0.07
Positive Δ*v.*no-go ~ Parent Surgency	0.11	-0.19	0.39	-0.15	-0.42	0.14
Positive Δ*v.*no-go ~ Parent HIP	0.01	-0.29	0.30	-0.12	-0.40	0.17
Positive Δ*v.*no-go ~ Child Surgency	0.02	-0.28	0.31	-0.14	-0.43	0.16
Positive Δ*v.*no-go ~ Child HIP	-0.04	-0.33	0.26	-0.11	-0.39	0.20
Positive Δ*b.*go ~ Parent Surgency	-0.05	-0.31	0.21	-0.19	-0.44	0.09
Positive Δ*b.*go ~ Parent HIP	-0.06	-0.31	0.21	-0.26	-0.50	0.02
Positive Δ*b.*go ~ Child Surgency	0.10	-0.17	0.35	-0.26	-0.51	0.02
Positive Δ*b.*go ~ Child HIP	0.15	-0.11	0.40	-0.15	-0.41	0.14
Positive Δ*b.*no-go ~ Parent Surgency	0.13	-0.16	0.40	-0.11	-0.40	0.20
Positive Δ*b.*no-go ~ Parent HIP	0.04	-0.25	0.32	-0.04	-0.33	0.26
Positive Δ*b.*no-go ~ Child Surgency	0.07	-0.23	0.35	-0.03	-0.34	0.29
Positive Δ*b.*no-go ~ Child HIP	0.05	-0.24	0.34	0.00	-0.31	0.32

Table S3. Correlations between ERP amplitudes and parent rated ADHD symptoms and emotional traits. * = p < .05, **= p<.01. Hyp-Imp= Hyperactivity-Impulsivity. TMCQ= Temperament in Middle Childhood Questionnaire. HIP= High-intensity pleasure seeking.

	Parent Conners' Inattention	Parent Conners' Hyp-Imp	Parent TMCQ Surgency	Parent TMCQ HIP	Parent TMCQ Fear
P1 Happy Amp.	.18	-.03	-0.12	0.02	
N170 Happy Amp.	.02	.27*	0.12	0.08	
LPP Happy Amp.	.07	.40**	0.10	-0.02	
N2 Happy Amp.	.12	.07	-0.20	-0.06	
P1 Fear Amp.	-.08	-.01			0.39**
N170 Fear Amp.	.42**	.16			-0.06
LPP Fear Amp.	.15	.01			0.18
N2 Fear Amp.	-.01	-.07			0.21

SUPPLEMENTAL FIGURES

Figure S1. Topographic plots for each ERP component by task condition and group showing similar topography for the components across groups and conditions overall, allowing for selection of the same electrodes in each group and condition for comparison of effects.

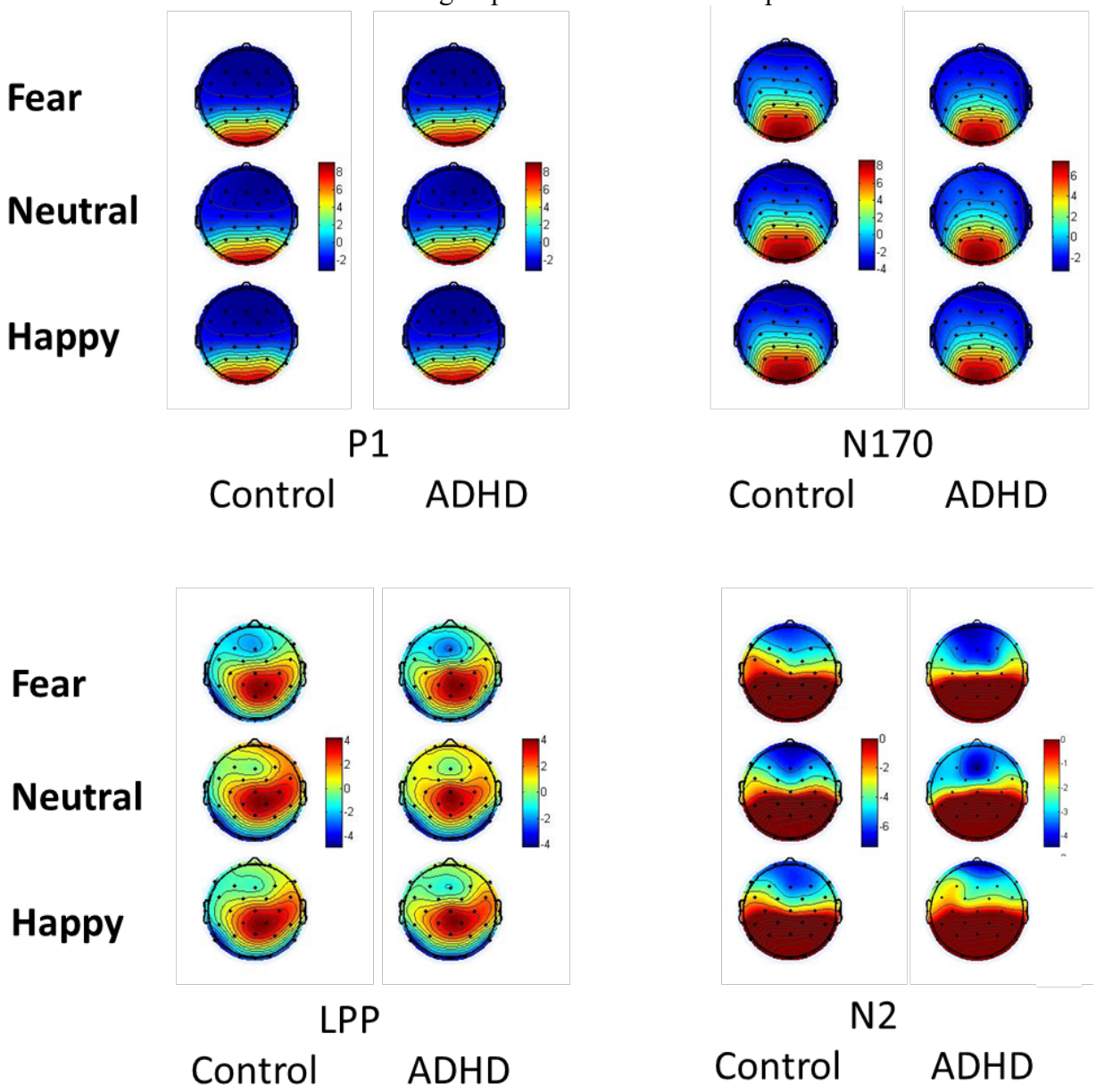


Figure S2. Joint cumulative distribution function plots comparing the cumulative probability and timing of a range of RT quantiles (.1, .3, .5, .7, and .9) from different response types for empirical (circles) and model-predicted (Xs) data in each group and condition. Black = correct go trials ("hits"); Grey = incorrect no-go trials ("false alarms").

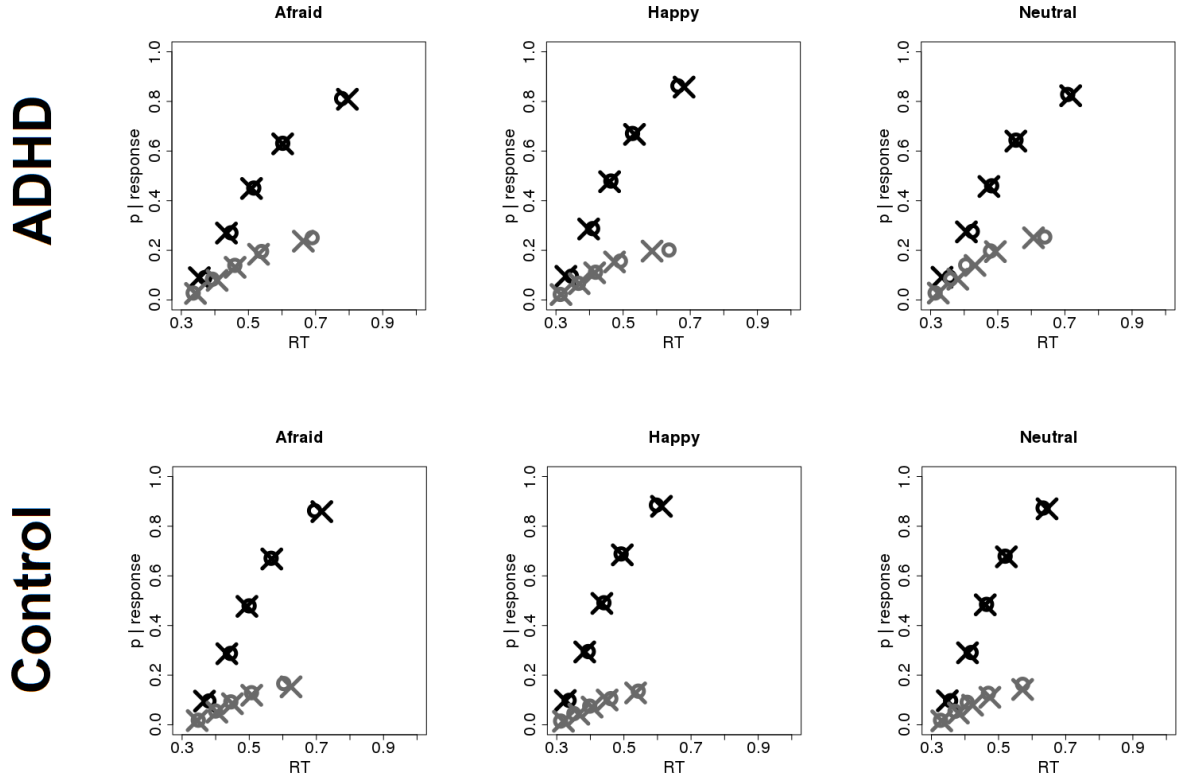
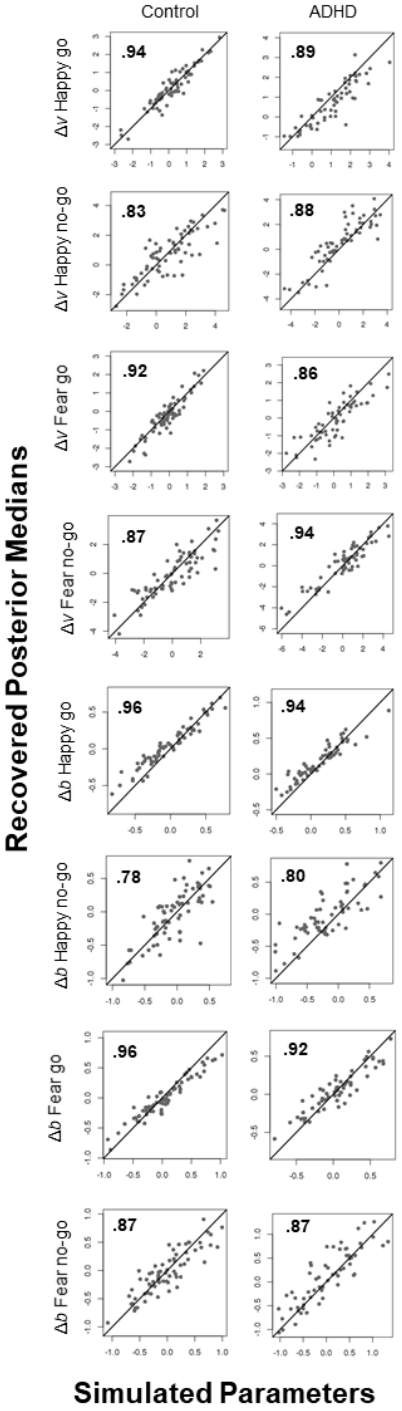


Figure S3. Results from the parameter recovery study in which data was simulated with group-level parameters comparable to those of the empirical Control and ADHD groups. Scatterplots display, for each simulated group, the relationship between the individual-level parameter values used to simulate data and the parameter estimates (medians of the individual-level posteriors) recovered from these data for the primary parameters of interest. The black line represents where points would be clustered if the relationship between simulated and recovered parameters was perfect. Correlation (*r*) values are reported in the upper left corner of each plot.



SUPPLEMENTAL REFERENCES

Dennis, M., Francis, D. J., Cirino, P. T., Schachar, R., Barnes, M. A., & Fletcher, J. M. (2009). Why IQ is not a covariate in cognitive studies of neurodevelopmental disorders. *Journal of the International Neuropsychological Society, 15*(3), 331-343.

Donkin, C., Brown, S. D., & Heathcote, A. (2009). The overconstraint of response time models: Rethinking the scaling problem. *Psychonomic Bulletin & Review, 16*(6), 1129-1135.

Gelman, A., Meng, X.-L., & Stern, H. (1996). Posterior predictive assessment of model fitness via realized discrepancies. *Statistica sinica*, 733-760.

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical science*, 457-472.

Jeffreys, H. (1961). Theory of probability (3rd edt.) oxford university press. *MR0187257*.

Jung, T.-P., Makeig, S., Humphries, C., Lee, T.-W., Mckeown, M. J., Iragui, V., & Sejnowski, T. J. (2000). Removing electroencephalographic artifacts by blind source separation. *Psychophysiology, 37*(2), 163-178.

Karalunas, S. L., Gustafsson, H. C., Dieckmann, N., Tipsord, J., Mitchell, S. H., & Nigg, J. T. (2017). Heterogeneity in development of aspects of working memory predicts longitudinal ADHD symptom change. *Journal of Abnormal Psychology*.

Lerche, V., Voss, A., & Nagler, M. (2017). How many trials are required for parameter estimation in diffusion modeling? A comparison of different optimization criteria. *Behavior Research Methods*, *49*(2), 513-537.

Ly, A., Boehm, U., Heathcote, A., Turner, B. M., Forstmann, B., Marsman, M., & Matzke, D. (2017). A flexible and efficient hierarchical Bayesian approach to the exploration of

individual differences in cognitive-model-based neuroscience. *Computational models of brain and behavior*, 467-480.

Ly, A., Marsman, M., & Wagenmakers, E. J. (2018). Analytic posteriors for Pearson's correlation coefficient. *Statistica Neerlandica, 72*(1), 4-13.

Miller, L. L., Gustafsson, H. C., Tipsord, J., Song, M., Nousen, E., Dieckmann, N., & Nigg, J. T. (2018). Is the Association of ADHD with Socio-Economic Disadvantage Explained by Child Comorbid Externalizing Problems or Parent ADHD? *Journal of Abnormal Child Psychology, 46*(5), 951-963.

Nigg, J. T., Gustafsson, H. C., Karalunas, S. L., Ryabinin, P., McWeeney, S. K., Faraone, S. V., . . . Wilmot, B. (2018). Working memory and vigilance as multivariate endophenotypes related to common genetic risk for attention-deficit/hyperactivity disorder. *Journal of the American Academy of Child & Adolescent Psychiatry, 57*(3), 175-182.

Ratcliff, R., & Childers, R. (2015). Individual differences and fitting methods for the two-choice diffusion model of decision making. *Decision*, *2*(4), 237.

Turner, B. M., Sederberg, P. B., Brown, S. D., & Steyvers, M. (2013). A method for efficiently sampling from distributions with correlated dimensions. *Psychological methods, 18*(3), 368.

Weigard, A., Huang-Pollock, C. L., & Brown, S. (2016). Evaluating the consequences of impaired monitoring of learned behavior in attention-deficit/hyperactivity disorder using a Bayesian hierarchical model of choice response time.

White, C. N., Servant, M., & Logan, G. D. (2018). Testing the validity of conflict drift-diffusion models for use in estimating cognitive processes: A parameter-recovery study. *Psychonomic bulletin & review*, *25*(1), 286-301.

Winkel, J., Hawkins, G. E., Ivry, R. B., Brown, S. D., Cools, R., & Forstmann, B. U. (2016). Focal striatum lesions impair cautiousness in humans. *cortex, 85*, 37-45.