Exposure to Common Forms of Early Life Adversity is Associated with Sensory Over-Responsivity in Adulthood

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Background: Exposure to early life adversity (e.g. trauma, maltreatment, or neglect) is implicated in a third of adult mental illness (1). As a result, much of the neurobehavioral research on early life adversity has focused on the development of high-level cognitive and socioemotional processes that, if disrupted, are thought to increase the risk of psychopathology (2–4). However, an emerging body of evidence suggests that early life adversity may also confer increased childhood risk for sensory over-responsivity (SOR), a pattern of impairing and extreme sensitivity to environmental stimuli (5–8). These sensory processing differences are over-represented in individuals with varied forms of psychopathology, and have been prospectively linked to later anxiety and behavioral problems in otherwise typically developing children, suggesting these sensory challenges may contribute to the later mental health difficulties (8–17).

Goal: In a separate dataset, we showed that youth who had experienced either previous institutional (e.g. orphanage) or foster caregiving had highly elevated SOR in adolescence, and SOR mediated the relationship between institutional/foster caregiving and elevated internalizing and externalizing symptoms in these youth (18). This study examines whether reported associations between early life adversity and SOR (which has primarily been studied in previously institutionalized youth) extend to less extreme, more common forms of early adversity like childhood neglect, trauma, or poverty. We also hope to evaluate if early adversity-linked sensory symptoms persist into adulthood, since previous research (including our recent study) has focused on childhood and adolescence.

Dataset Description: Data was collected from 275 adults 18-35 living in the United States, using surveys on Amazon's Mechanical Turk. 257 responses passed quality control checks. Sample items from each questionnaire can be found in **Figure 1**. Additionally, summaries for each measure and a scatterplot matrix for all variables are in **Table 1** and **Figure 2**.

Outcome (Sensory Over-Responsivity): The outcome for this analysis is the Glasgow Sensory Questionnaire Hypersensitivity Subscale Score (hereafter the GSQ), a self-report measure of SOR that has been validated in the general adult population (19). This measure assesses SOR on 21 items that use a 0 (never) to 4 (always) Likert scale across seven sensory modalities (visual, auditory, gustatory, olfactory, tactile, vestibular, and proprioceptive). Scores on the subscale range from 0 (lowest SOR) to 84 (highest SOR).

Predictors: Our primary predictor is a continuous measure of early life adversity, with age, assigned sex at birth, and concurrent perceived stress included as covariates.

Early Life Adversity: Early life adversity exposure was measured using the Childhood Trauma Questionnaire Short Form (20), a validated 28-item measure of childhood abuse (physical, sexual, or emotional) and neglect (physical or emotional). Sample items are provided in **Figure 1**. Responses range from 1 (never true) to 5 (very often true), and scores range from 28 (low early adversity) to 140 (high adversity). To aid interpretation, scores were mean centered at 21.13.

Female: Given inconsistent sex differences in SOR reported in children with histories of ELA (8), we included assigned sex at birth as a covariate, with males coded as zero and females coded as one.

Age: Given age-related reductions in adversity-related SOR that have been observed in children (8), we included age (18-35 years) as a covariate, mean-centered at 31.27 years.

Concurrent Perceived Stress: We included the Perceived Stress Scale (PSS) as a covariate to control for the possible influence of perceived stress on self-reports of early adversity. The PSS is a well-validated 10-item (0-4 Likert) measure. Scores range from 0-40, with higher scores indicating greater perceived stress. Scores were mean centered at 19.5.

Model: The proposed model for this analysis is a multiple linear regression, such that y (GSQ score) is

$$y_i = \beta_0 + \beta_1 * CTQ_i + \beta_2 * FEMALE_i + \beta_3 * AGE_i + \beta_4 * PSS_i + \epsilon_i$$

where i indexes the participant (row), ranging from 1 to 257, and the error terms $\varepsilon_i \mid \sigma^2 \sim N(0, \sigma^2)$ are a priori independent and identically distributed given σ^2. This model was run using JAGS (code in Appendix 1), with 11,000 iterations, 5 chains, a thinning interval of one, and a total burn-in of 1000, resulting in a total of 50,000 samples.

Model Priors:

Intercept	$\beta_0 \sim N(12, 19.98)$
CTQ	$\beta_1 \sim N(2.19, 9)$
Female	$\beta_2 \sim N(0, 25)$
Age	$\beta_3 \sim N(0, 25)$
PSS	$\beta_4 \sim N(2.5, 9)$
Sigma	$\sigma \sim Gamma(5.23, 0.572)$

No work directly compares the GSQ hypersensitivity subscale to our predictors, so priors were set by converting reported effects from analyses that used analogue measures. We selected the prior distribution for the intercept (CTQ = 21.13, PSS = 19.5, male, 31.27 years old) in our population sample of adults by taking the mean and standard deviation of reported means for GSQ hypersensitivity across several population samples (19,21–24). Using this information, we chose a prior

mean of 12 and prior SD of 4.47, with the expectation that the 95% of values would fall between 3.06 and 20.94. The prior distribution for β_1, the early adversity/CTQ coefficient, was selected by converting a reported relationship between the CTQ and the Adolescent/Adult Sensory Profile Sensitivity Score (an SOR measure that is correlated at .91 with GSQ hypersensitivity) in bipolar adults to a GSQ compatible scale (25). Based on this, the prior mean for β_1 was set to 2.190 and prior SD to 3, to reflect a small but positive expected effect with 95% of values falling between -4.19 and 8.19. While previously institutionalized child samples have sometimes shown sex differences in SOR (8), we did not expect significant sex differences in adult GSQ scores given reported data (19,21–24). We therefore set the prior distribution for β_2 to have a mean of 0, with SD of 5, to reflect an expectation that β_2 fall between -10 and 10. Although studies of previously institutionalized youth suggest early life adversity-associated SOR may decrease with age, again, given no evidence of age effects in adult populations and our previous adolescent sample (19,21–24), we did not expect any age effects in this adult sample. Since no SOR age effects have been reported in adults and our previous data cannot be analyzed in conjunction with this data (different measures, populations, and reporters), we set the β_3 prior mean to 0, and converted age effect estimates from the Adolescent/Adult Sensory Profile in our adolescent sample to the GSQ to set a prior SD of 5, with an expectation of 95% of values falling between -10 and 10.Though no studies have examined PSS-GSQ relationships, we converted a reported relationship between PSS and another sensory sensitivity measure, the Highly Sensitive Person Scale, and set the β_4 prior distribution with mean 2.5 and SD of 3 to reflect an expected small but positive effect in the range of -4.5 to 8.5,. Lastly, we used the mean GSQ SD across populations (9.15), and the standard deviation of the SDs (4.47) to set the prior for σ as a gamma distribution with a= 5.23 and b = 0.572 (19,21–24).

Results: Our primary model has good convergence – the autocorrelation plots for the fixed effects quickly approach 0 (**Figure 3**), and all time-series plots are stable (**Figure 4**). No problems were encountered in running this model or in conducting the sensitivity analyses (see below). Our findings (reported in **Table 2**; plotted in **Figure 5**) suggest that increased reported early life adversity (CTQ) is positively associated with elevated SOR symptoms (GSQ), such that a one unit increase in CTQ is associated with a 0.403 unit increase in GSQ (β_1 = 0.403, SD = 0.046, 95% CI: 0.329-0.479). Likewise, perceived stress positively predicted SOR (β_4 = 0.975, SD = 0.243, 95% CI: 0.577 – 1.377), such that a one unit higher perceived stress was associated with 0.975 higher SOR score. Sex/Female (β_2 = 1.241, SD = 1.339, 95% CI: -0.954

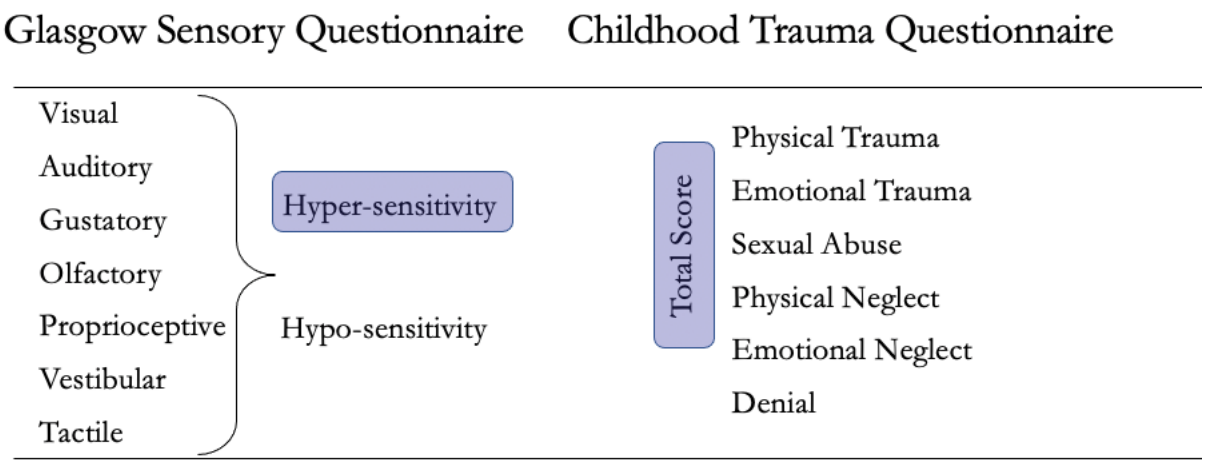
– 3.462) and age (β_3 = 0.109, SD = 0.213, 95% CI: -0.24 - 0.457) did not significantly predict GSQ scores. Unsurprisingly, posterior distributions for CTQ and PSS were moderately correlated (see **Figure 6** for scatterplot matrix).

Sensitivity Analyses: We conducted various analyses to test model sensitivity to various priors and model specifications, which we report in **Tables 3-10**. For these, we used a) the original prior means and two or three levels of (decreased) precision for all four predictors (CTQ : **Table 3**; Female: **Table 5**; Age: **Table 7**; PSS: **Table 9**), b) a t model (df = 3) in place of a normal distribution model c) null priors (mean = 0) with the original precision for all four predictors, which used the original intercept prior (CTQ: **Table 4**; Female: **Table 6**; Age: **Table 8**; PSS: **Table 10**), and d) alternate priors for the CTQ and PSS based on our adolescent data -- again, different measures, reporters, and populations -- (CTQ : **Table 4**, PSS : **Table 10**– specifications in appendix). CTQ positively predicted GSQ across every prior tested, with a mean β_1 estimate of approximately .4 for all models (**Table 3-4**). Likewise, PSS effects were positive, significant, and fairly stable (approximately .96) for all models (**Table 9-10**), with a slightly larger point estimate for the t model (perhaps because this model de-weights data points that are far from the mean). The t model also resulted in relatively large decreases in the estimates for the intercept and for sigma. Age and sex effects were null across all models tested (**Table 4-7**). Given the distribution of our data, we'd like to explore applying a log link model in the future, but for now, our sensitivity analyses give us confidence in the observed small but positive effects of CTQ and PSS on GSQ scores.

Conclusion: We find that increased retrospectively reported early life adversity (CTQ) is associated with elevated sensory over-responsivity symptoms (GSQ), controlling for age, sex, and current perceived stress (PSS). These findings were stable across a wide range of sensitivity analyses. This suggests that common forms of early life adversity may confer risk for sensory processing challenges that persist into adulthood. Future work should evaluate prospective links between early adversity, SOR, and adult mental health, and investigate possible neurobehavioral mechanisms for this pattern of findings.

Additional Measure Information

Figure 1: Description and Sample Items for Primary Variables GSQ (Sensory Over-Responsivity) and CTQ (Early Adversity)



- Do you find certain noises/pitches of sound annoying?
- Do bright lights ever hurt your eyes/cause a headache?
- Do you hate the feel or texture of certain foods in your mouth?

- My parents were too drunk or high to take care of the family.
- People in my family hit me so hard that it left me with bruises or marks.
- There was someone in my family who helped me feel important or special (R)

* Scales used for this analysis are highlighted in blue

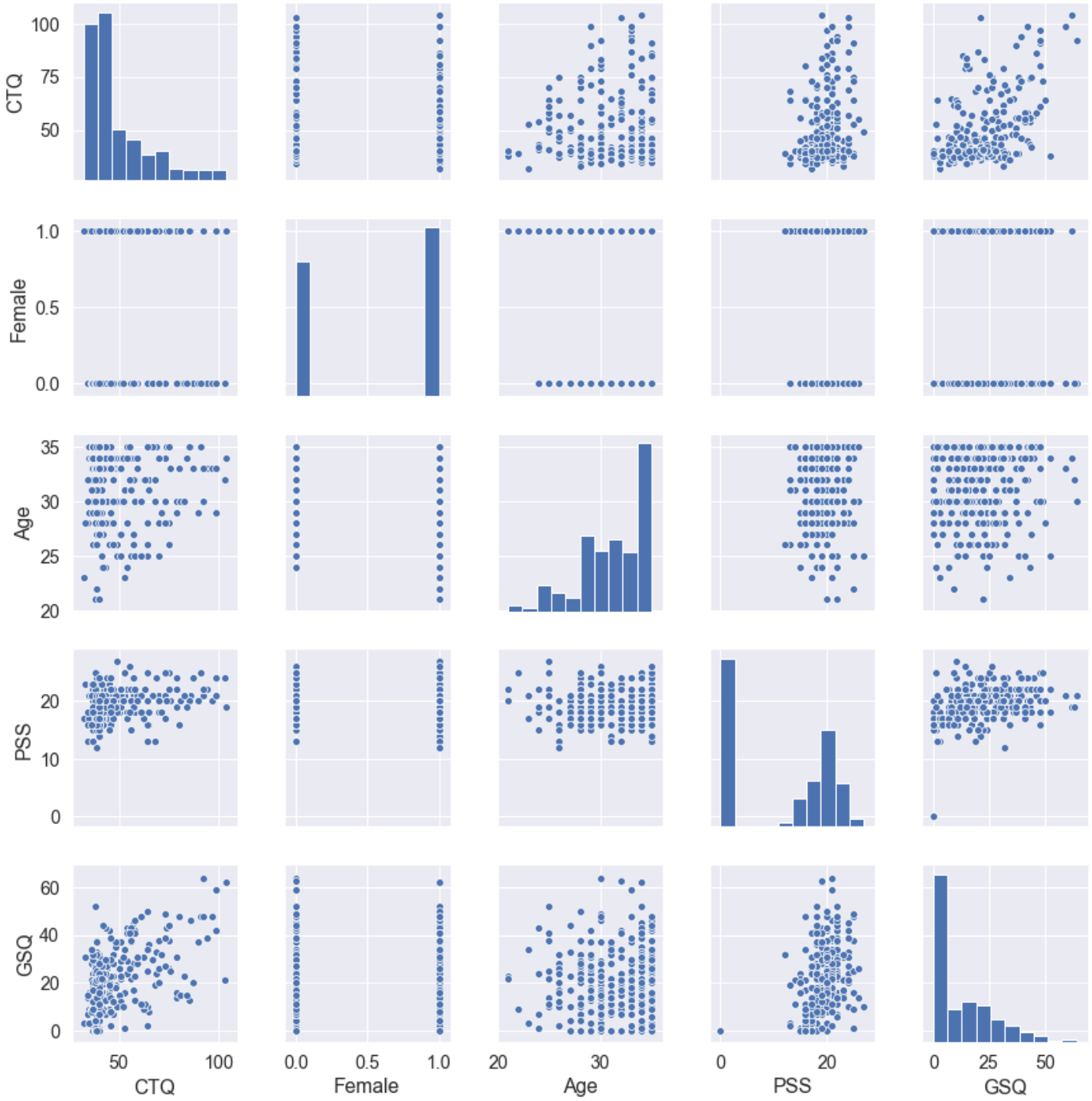
Data Summary

Table 1: Summary statistics for predictors (CTQ, Assigned Sex at Birth, Age, and PSS) and the outcome variable (GSQ). 44% of participants in this sample are female, and 56% are male.

	mean	**std**	**min**	**max**
CTQ *Range: 28-140*	48.879	15.377	32	104
Age *Range: 18-35*	31.206	3.279	21	35
PSS *Range:0-40*	19.529	2.671	12	27
GSQ *Range: 0-84*	20.985	13.361	0	64

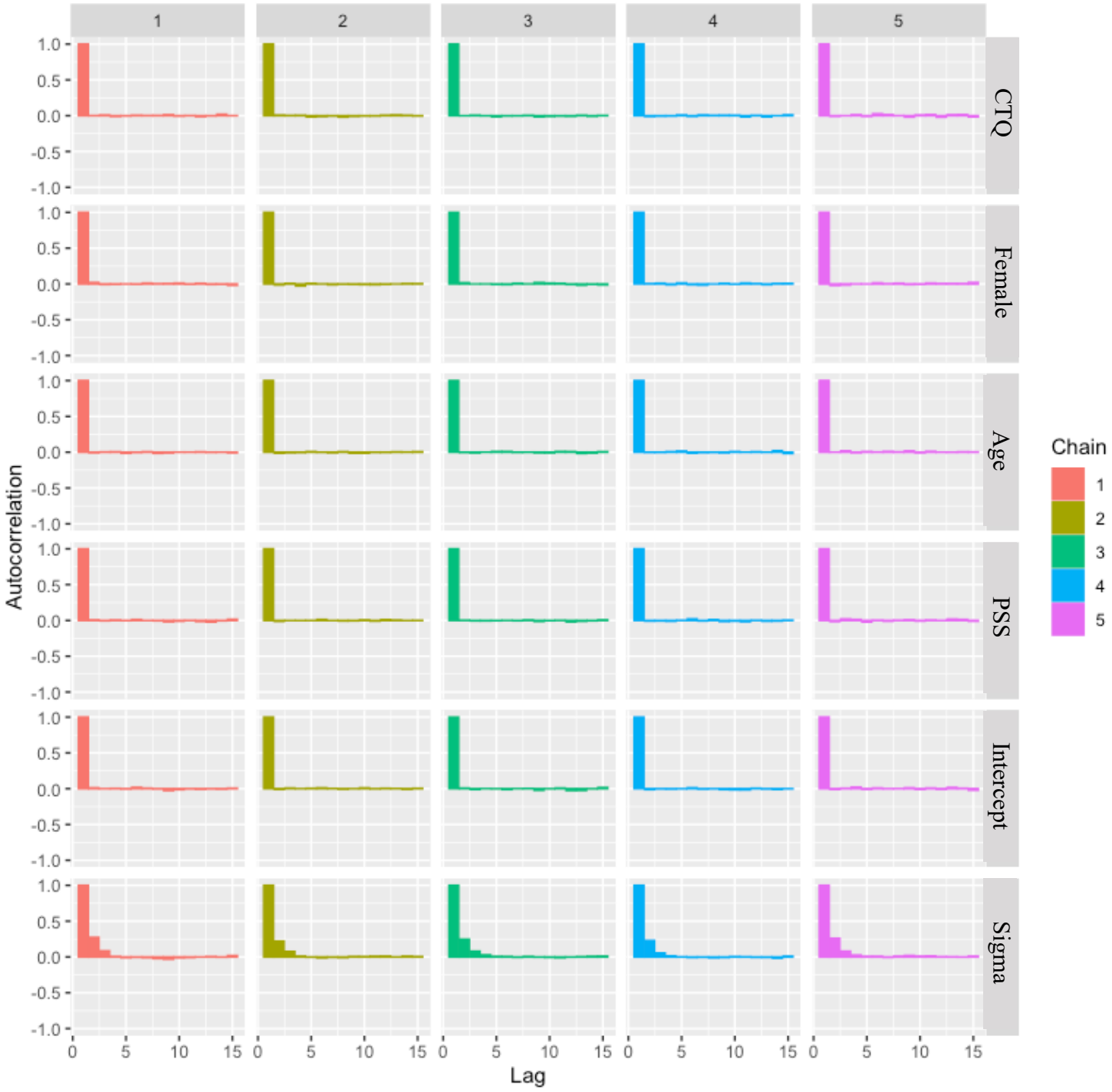
Scatterplot Matrix of Raw Data

Figure 2: Scatterplot matrices for predictors and outcome.



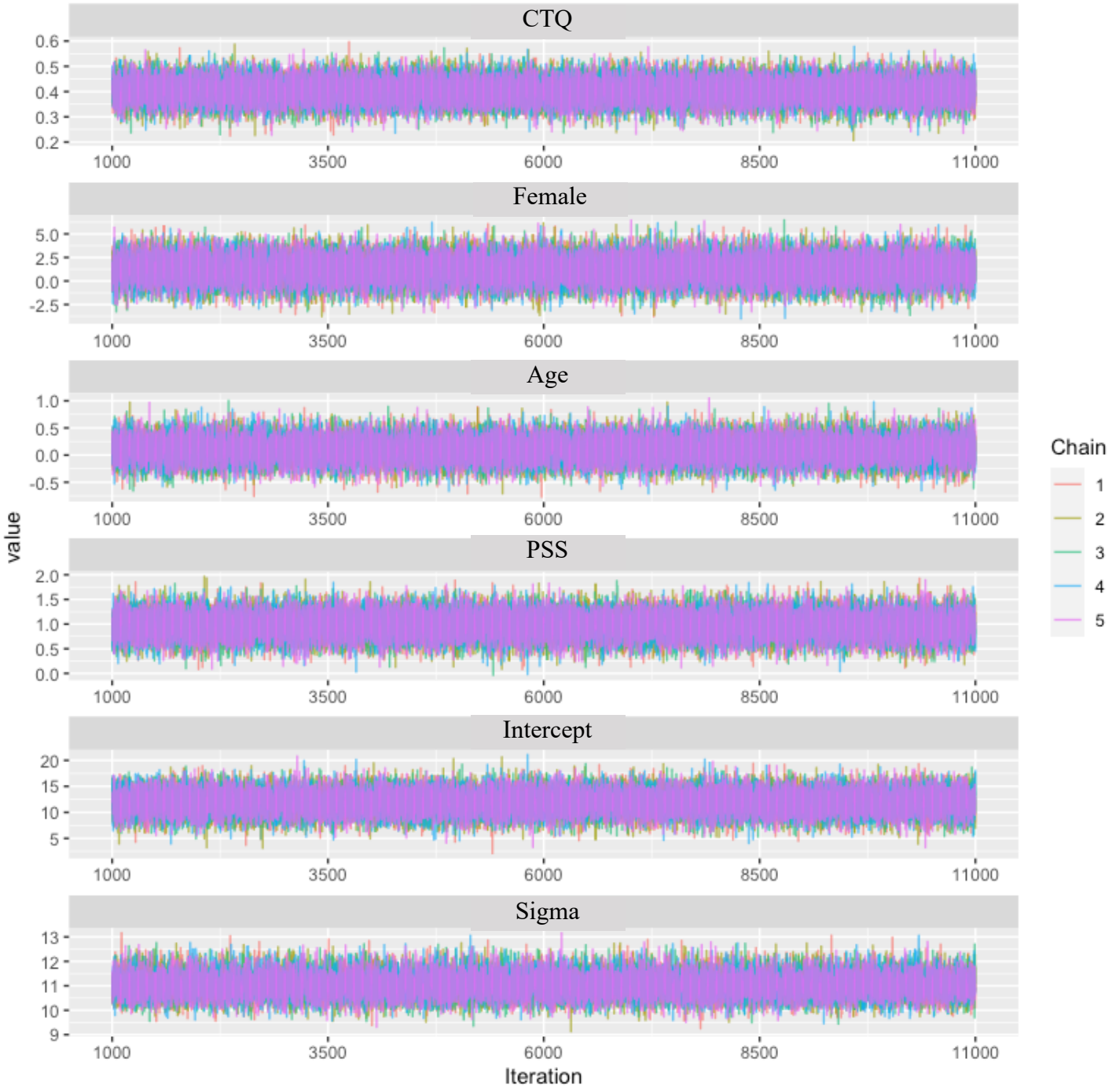
Model Convergence: Parameter Autocorrelation

Figure 3: This model has good convergence – the autocorrelation plots for all parameters of interest rapidly approach 0



Model Convergence: Time Series Plots

Figure 4: Time series plots for all coefficients of interest appear to be stable across iterations



Original Model Results – Parameter Estimates

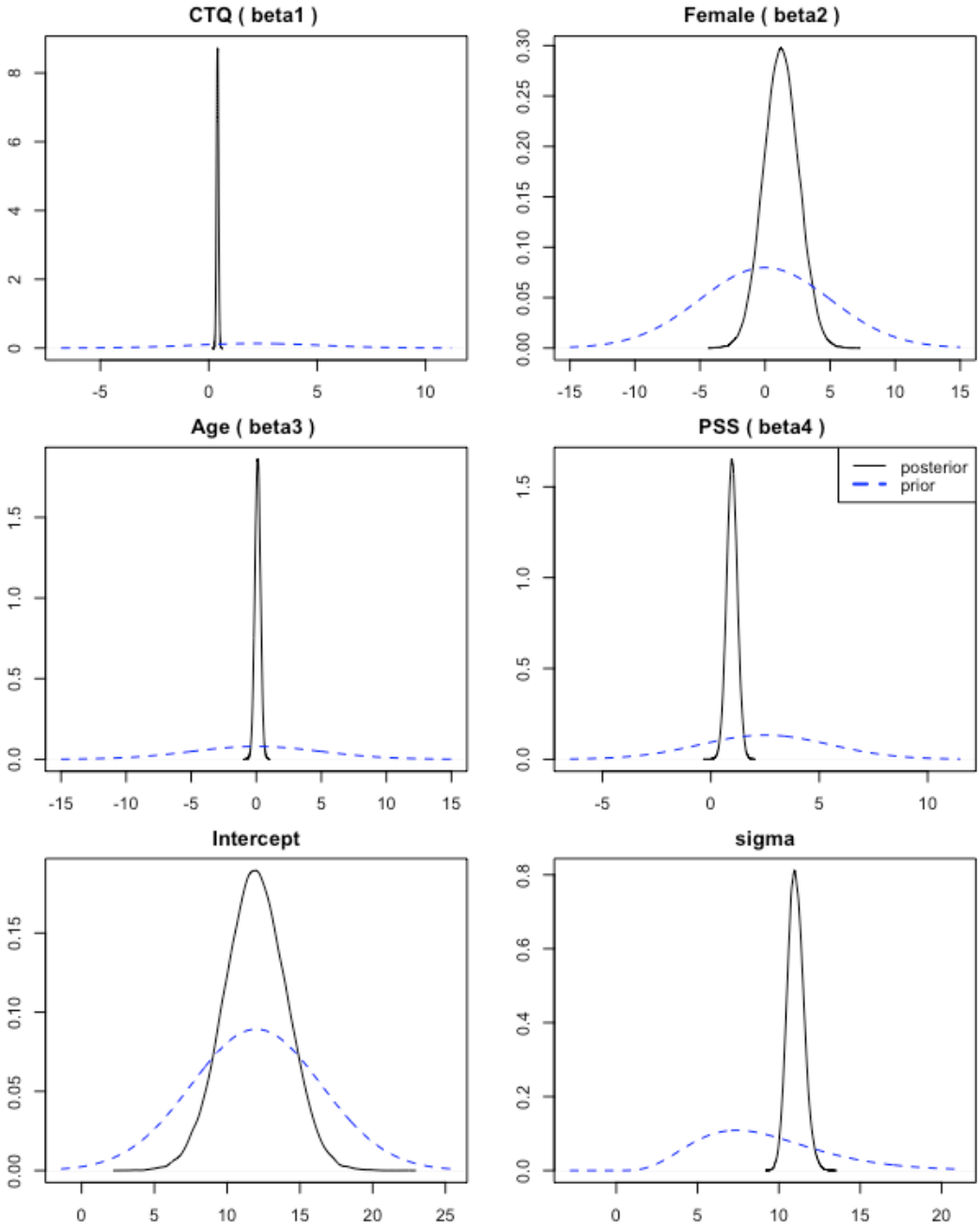
Table 2: Higher levels of early life adversity (CTQ) and of perceived stress (PSS) are associated with small increases in self-reported sensory over-responsivity (GSQ hypersensitivity). Age and assigned sex at birth are not associated with sensory over-responsivity in this model.

	mean	sd	2.50%	97.50%	P>0
CTQ (beta1)	0.403	0.046	0.329	0.479	1
Female (beta2)	1.241	1.339	-0.954	3.462	0.822
Age (beta3)	0.109	0.213	-0.24	0.457	0.696
PSS (beta4)	0.975	0.243	0.577	1.377	1
Intercept (beta0)	11.938	2.121	8.447	15.407	
sigma	11.036	0.492	10.265	11.874	

**Significant effects of interest are highlighted in green*

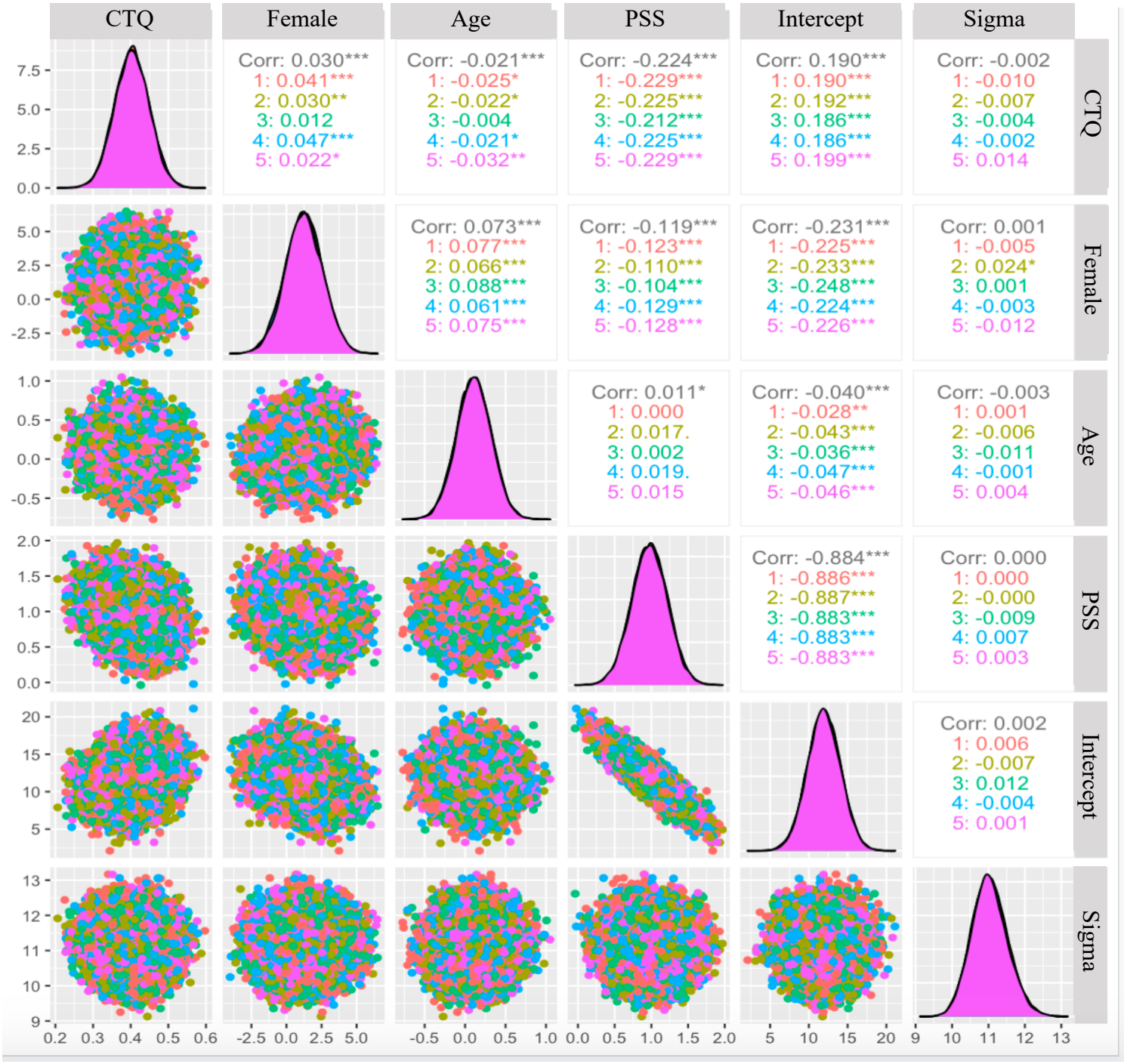
Original Model Results – Density Plots

Figure 5: Higher levels of early life adversity (CTQ total) and perceived stress (PSS total) are associated with increased SOR (GSQ total hypersensitivity). Age and sex (female) are not associated with SOR in this model.



Original Model Results – Density Plots

Figure 6: Scatterplot matrices for posterior distributions (colors = chains)



Sensitivity Analyses: CTQ

Table 3: The effect of early life adversity (CTQ total score) on sensory over-responsivity scores remains significant and very consistent across models that use several precisions for the original β_1 prior distribution

	Original Analysis		Original Means, Decreasing Precisions					
	CTQ Prior Mean = 2.19 *Prior SD = 3* *Prior Precision = 0.111*		*CTQ Prior Mean = 2.19* *Prior SD = 6* *Prior Precision = 0.012*		*CTQ Prior Mean = 2.19* *Prior SD = 9* *Prior Precision = 0.004*		*CTQ Prior Mean = 2.19* *Prior SD = 15* *Prior Precision = 0.001*	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
CTQ (beta1)	0.403	0.046	0.403	0.046	0.403	0.046	0.403	0.046
Female (beta2)	1.258	1.329	1.25	1.331	1.245	1.334	1.249	1.332
Age (beta3)	0.108	0.213	0.107	0.212	0.109	0.214	0.106	0.213
PSS (beta4)	0.975	0.244	0.975	0.241	0.975	0.243	0.976	0.243
Intercept (beta0)	11.924	2.119	11.933	2.11	11.932	2.115	11.923	2.112
sigma	11.04	0.489	11.038	0.488	11.033	0.485	11.041	0.487

*****_Significant effects of interest are highlighted in green_

Sensitivity Analyses: CTQ (continued)

Table 4: The effect of early life adversity (CTQ total score) on sensory over-responsivity scores remains significant and very consistent across models using several alternate priors

	Original Analysis *CTQ Prior Mean = 2.19* *Prior SD = 3* *Prior Precision = 0.111*		Original Priors, T Model *CTQ Prior Mean = 2.19* *Prior SD = 3* *Prior Precision = 0.111*		Alternative Prior *CTQ Prior Mean = 3.6* *Prior SD = 3* *Prior Precision = 0.111*		Null Prior *CTQ Prior Mean = 0* *Prior SD = 3* *Prior Precision = 0.111*	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
CTQ (beta1)	0.403	0.046	0.443	0.052	0.404	0.046	0.403	0.046
Female (beta2)	1.258	1.329	1.337	1.323	1.239	1.334	1.259	1.325
Age (beta3)	0.108	0.213	0.213	0.218	0.108	0.214	0.108	0.213
PSS (beta4)	0.975	0.244	1.155	0.257	0.974	0.243	0.959	0.243
Intercept (beta0)	11.924	2.119	9.869	2.217	11.949	2.111	12.053	2.117
sigma	11.04	0.489	8.769	0.518	11.04	0.489	11.038	0.490

**Significant effects of interest are highlighted in green*

Prior Specifications:

Original model: $\beta_1 \sim N(2.19, 9)$, $\tau = 0.111$

T model: $\beta_1 \sim N(2.19, 9)$, $\tau = 0.111$

Alternative prior CTQ: $\beta_1 \sim N(3.6, 9)$, $\tau = 0.111$

Null Prior All Parameters: $\beta_1 \sim N(0, 9)$, $\tau = 0.111$

Sensitivity Analyses: Female

Table 5: There is no significant effect of sex (males = 0, females =1) on sensory over-responsivity scores across models that use several precisions for the original β_2 prior distribution. The point estimate for the female coefficient is fairly stable across models.

	Original Analysis		Original Means, Decreasing Precisions			
	Female Prior Mean = 2.19 *Prior SD = 5* *Prior Precision = 0.04*		*Female Prior Mean = 2.19* *Prior SD = 10* *Prior Precision = 0.01*		*Female Prior Mean = 2.19* *Prior SD = 15* *Prior Precision = 0.004*	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**
CTQ (beta1)	0.403	0.046	0.404	0.046	0.403	0.046
Female (beta2)	1.258	1.329	1.338	1.369	1.328	1.382
Age (beta3)	0.108	0.213	0.109	0.213	0.109	0.214
PSS (beta4)	0.975	0.244	0.974	0.244	0.975	0.242
Intercept (beta0)	11.924	2.119	11.889	2.126	11.891	2.117
sigma	11.04	0.489	11.039	0.491	11.041	0.489

**Significant effects of interest are highlighted in green*

Sensitivity Analyses: Female (continued)

Table 6: There is no significant effect of sex (males = 0, females =1) on sensory over-responsivity scores across models that use several alternate priors for the β_2 prior distribution. The point estimate for the female coefficient is fairly stable across models.

	Original Analysis *Female Prior Mean = 0* *Prior SD = 5* *Prior Precision = 0.04*		Original Priors, T Model *Female Prior Mean = 0* *Prior SD = 5* *Prior Precision = 0.04*		Null Prior *Female Prior Mean = 0* *Prior SD = 5* *Prior Precision = 0.04*	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**
CTQ (beta1)	0.403	0.046	0.443	0.052	0.403	0.046
Female (beta2)	1.258	1.329	1.337	1.323	1.259	1.325
Age (beta3)	0.108	0.213	0.213	0.218	0.108	0.213
PSS (beta4)	0.975	0.244	1.155	0.257	0.959	0.243
Intercept (beta0)	11.924	2.119	9.869	2.217	12.053	2.117
sigma	11.04	0.489	8.769	0.518	11.038	0.490

**Significant effects of interest are highlighted in green*

Prior Specifications:

Original model: $\beta_2 \sim N(0, 25)$, $\tau = 0.04$

T model: $\beta_2 \sim N(0, 25)$, $\tau = 0.04$

Null Prior All Coefficients: $\beta_2 \sim N(0, 25)$, $\tau = 0.04$

Sensitivity Analyses: Age

Table 7: There is no significant effect of age on sensory over-responsivity scores across models that use several precisions for the original β_3 prior distribution. The point estimate for the age coefficient is very stable across models.

	Original Analysis *Age Prior Mean = 0* *Prior SD = 5* *Prior Precision = 0.04*		Original Means, Decreasing Precisions *Age Prior Mean = 0* *Prior SD = 10* *Prior Precision = 0.004*		 *Age Prior Mean = 0* *Prior SD = 15* *Prior Precision = 0.002*	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**
CTQ (beta1)	0.403	0.046	0.404	0.046	0.403	0.046
Female (beta2)	1.258	1.329	1.249	1.335	1.253	1.337
Age (beta3)	0.108	0.213	0.109	0.214	0.109	0.213
PSS (beta4)	0.975	0.244	0.976	0.244	0.976	0.244
Intercept (beta0)	11.924	2.119	11.92	2.117	11.924	2.124
sigma	11.04	0.489	11.044	0.488	11.044	0.489

**Significant effects of interest are highlighted in green*

Sensitivity Analyses: Age

Table 8: There is no significant effect of age on sensory over-responsivity scores across models that use several alternate β_3 prior distributions. The point estimate for the age coefficient is very stable across models.

	Original Analysis *Age Prior Mean = 0* *Prior SD = 5* *Prior Precision = 0.04*		Original Priors, T Model *Age Prior Mean = 0* *Prior SD = 5* *Prior Precision = 0.04*		Null Prior *Age Prior Mean = 0* *Prior SD = 5* *Prior Precision = 0.04*	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**
CTQ (beta1)	0.403	0.046	0.443	0.052	0.403	0.046
Female (beta2)	1.258	1.329	1.337	1.323	1.259	1.325
Age (beta3)	0.108	0.213	0.213	0.218	0.108	0.213
PSS (beta4)	0.975	0.244	1.155	0.257	0.959	0.243
Intercept (beta0)	11.924	2.119	9.869	2.217	12.053	2.117
sigma	11.04	0.489	8.769	0.518	11.038	0.490

**Significant effects of interest are highlighted in green*

Prior Specifications:

Original model: $\beta_3 \sim N(0, 25)$, $\tau = 0.04$

T model: $\beta_3 \sim N(0, 25)$, $\tau = 0.04$

Null Prior All Coefficients: $\beta_3 \sim N(0, 25)$, $\tau = 0.04$

Sensitivity Analyses: PSS

Table 9: The effect of concurrent perceived stress (PSS total score) on sensory over-responsivity scores remains significant and quite consistent across models that use several precisions for the original β_4 prior distribution

	Original Analysis		Original Means, Decreasing Precisions					
	PSS Prior Mean = 2.5		PSS Prior Mean = 2.5		PSS Prior Mean = 2.5		PSS Prior Mean = 2.5	
	Prior SD = 3		Prior SD = 6		Prior SD = 9		Prior SD = 15	
	Prior Precision = 0.111		Prior Precision = 0.012		Prior Precision = 0.004		Prior Precision = 0.001	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
CTQ (beta1)	0.403	0.046	0.404	0.046	0.404	0.046	0.403	0.046
Female (beta2)	1.258	1.329	1.257	1.325	1.257	1.332	1.248	1.329
Age (beta3)	0.108	0.213	0.108	0.214	0.106	0.213	0.108	0.213
PSS (beta4)	0.975	0.244	0.968	0.243	0.966	0.243	0.965	0.244
Intercept (beta0)	11.924	2.119	11.986	2.113	12.006	2.118	12.018	2.127
sigma	11.04	0.489	11.033	0.485	11.037	0.489	11.034	0.493

*****_Significant effects are highlighted in green_

Sensitivity Analyses: PSS (continued)

Table 10: The effect of concurrent perceived stress (PSS total score) on sensory over-responsivity scores remains significant and is fairly consistent across models that use several alternate priors. Notably, the point estimate for the effect of PSS is much higher for the analysis that uses a t model (which has long tails and de-weights observations that are far from the mean)

	Original Analysis *PSS Prior Mean = 2.5* *Prior SD = 3* *Prior Precision = 0.111*		Original Priors, T Model *CTQ Prior Mean = 2.5* *Prior SD = 3* *Prior Precision = 0.111*		Alternative Prior *PSS Prior Mean = 0.620* *Prior SD = 3* *Prior Precision = 0.111*		Null Prior *CTQ Prior Mean = 0* *Prior SD = 3* *Prior Precision = 0.111*	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
CTQ (beta1)	0.403	0.046	0.443	0.052	0.404	0.046	0.403	0.046
Female (beta2)	1.258	1.329	1.337	1.323	1.253	1.332	1.259	1.325
Age (beta3)	0.108	0.213	0.213	0.218	0.108	0.213	0.108	0.213
PSS (beta4)	0.975	0.244	1.155	0.257	0.965	0.243	0.959	0.243
Intercept (beta0)	11.924	2.119	9.869	2.217	12.01	2.115	12.053	2.117
sigma	11.04	0.489	8.769	0.518	11.035	0.489	11.038	0.490

**Significant effects are highlighted in green*

Prior Specifications:

Original model: $\beta_4 \sim N(2.5, 9)$, $\tau = 0.111$

T model: $\beta_4 \sim N(2.5, 9)$, $\tau = 0.111$

Alternative prior PSS: $\beta_4 \sim N(0.620, 9)$, $\tau = 0.111$

Null Prior All Coefficients: $\beta_4 \sim N(0, 9)$, $\tau = 0.111$

Appendix 1: JAGS Model Specification and Analysis/Visualization Code

```
library(R2jags)
library(lattice)
library("bayesplot")
library("ggmcmc")

# Set working directory
setwd("/Users/adrianamendezleal/Documents/Data_Analysis/sensory_MTurk/
Final_Wave1_Data_3_1_20/")
getwd()

# summarize posterior samples
mysummary = function(invector) {
  c(mean(invector), sd(invector), quantile(invector, .05),
    quantile(invector,.95),
    length(invector[invector>0])/length(invector))
}

summarize_model<- function (fp.sim){
  Bayes_sum<- apply(fp.sim$BUGSoutput$sims.matrix, 2, mysummary)
  rownames(Bayes_sum) <- c("mean", "sd", "qbp.lower", "qbp.upper","P>0")
  Bayes_sum
}

# helper function for sensitivity analyses
add_row_names_and_store_current_sensitivity_analysis<-
function(temp_model,curr_param_name, curr_sens_param){
  temp_model_w_names<-t(temp_model)
  rownames(temp_model_w_names) <-
paste(rownames(temp_model_w_names),curr_param_name,curr_sens_param, sep = "_")
  all_model <-cbind(all_model,temp_model_w_names)
  return (all_model)
}


# helper functions for plotting
plot_norm_dist = function(mymean, mysd){
  x <- seq(mymean-(3*mysd), mymean+(3*mysd), by = .1)
  y <- dnorm(x, mean=mymean, sd=mysd)
  lines(x, y, type="l", lty=2, col = 'blue')
}

plot_gamma_dist = function(my_a, my_b){
  mysd = sqrt(my_a/(my_b^2))
  mymean = (my_a/my_b)
  x <- seq(mymean-(3*mysd), mymean+(3*mysd), by = .1)
  y <- dgamma(x, shape=my_a, rate=my_b)
  lines(x, y, type="l", lty=2, col = 'blue')
}
```

```
myplotfunction_gamma = function(temp, index_of_data, plot_title, my_a,my_b) {
  mysd = sqrt(my_a/(my_b^2))
  mymean = (my_a/my_b)
  xlim_min = min(c(min(density(temp[,index_of_data])$x),mymean - 3*mysd))
  xlim_max = max(c(max(density(temp[,index_of_data])$x),mymean + 3*mysd))
  plot(density(temp[,index_of_data]), main= plot_title,
xlim=c(xlim_min,xlim_max))
  plot_gamma_dist(my_a, my_b)
}

myplotfunction = function(temp, header_list_plots, index_of_data, coeff_type,
prior_means, prior_sds,mute_coeff) {

  xlim_min = min(c(min(density(temp[,index_of_data])
$x),prior_means[index_of_data] - 3*(1/(sqrt(prior_sds[index_of_data])))))
  xlim_max = max(c(max(density(temp[,index_of_data])
$x),prior_means[index_of_data] + 3*(1/(sqrt(prior_sds[index_of_data])))))
  if (mute_coeff ==1)
    curr_title <-header_list_plots[index_of_data]
  else{
    curr_title <-paste(header_list_plots[index_of_data], " ( ",
coeff_type,toString(index_of_data)," ) ", sep = "")
  }

  plot(density(temp[,index_of_data]), main= curr_title,xlim = c(xlim_min,
xlim_max))
  plot_norm_dist(prior_means[index_of_data],1/
(sqrt(prior_sds[index_of_data])))
  print(1/(sqrt(prior_sds[index_of_data])))
}

# function for main analysis
run_fp_model <- function (x,y, mean_list, pres_list,sigma.a,sigma.b,
mbeta0,precbeta0){

  # model definition
  sink("sens_datamodel.txt")
  cat("
  model
  {
     for(i in 1:N) {
        y[i] ~ dnorm( mu[i] , tau)

        mu[i] <- beta0 + inprod(x[i,] , beta[] )
    }

    beta0 ~ dnorm( mbeta0 , precbeta0)

  for (j in 1:K) {
```

```
    beta[j] ~ dnorm( m[j] , prec[j] )
    }
      sigma ~ dgamma(sigma.a , sigma.b )
      tau <- 1 / (sigma*sigma)
   }
    ",fill = TRUE)
  sink()

  # store inputs for analysis
  all_inputs<-list(N=length(y), K=4, m=mean_list,
  prec=pres_list, sigma.a= sigma.a,
  sigma.b = sigma.b, mbeta0= mbeta0, precbeta0=precbeta0, x=x, y=y)

  inits<-rep(list(list(beta0=0, beta=c(1,1,1,1),sigma=1)),5)

  # store coefficients and sigma
  parameters <- c("beta0", "beta" ,"sigma")

  #run the model
  fp.sim <- jags(all_inputs, inits, parameters, "sens_datamodel.txt",
n.chains=5,
   n.iter=11000, n.burnin=1000, DIC=FALSE, n.thin = 1)

  fp.sim
}

# read in data
sens_data=read.csv("/Users/adrianamendezleal/Documents/Data_Analysis/
sensory_MTurk/Final_Wave1_Data_3_1_20/M234_FP_mean_centered.csv")

# format data
y<-sens_data[,6]
x<-as.matrix(sens_data[,2:5])
header_list_plots = c("CTQ","Female","Age","PSS","Intercept")

# set priors for first analysis

# sigma mean and sd
sigma_mean<- 9.15
sigma_sd<-4

# means and sds for B1 - B4
mean_list<-c(2.19,0,0,2.5)
std_list<-c(3,5,5,3)

# intercept prior mean and sd
mbeta0<-12
stdbeta0<- 4.47
```

```
# calculate precisions, variances, and sigma shape and rate parameters for
priors
var_list <- std_list*std_list
pres_list<-1/var_list
sigma.b <- sigma_mean/(sigma_sd*sigma_sd)
sigma.a <-sigma.b*sigma_mean
precbeta0<-1/(stdbeta0*stdbeta0)

# run original analysis
fp.sim_temp<- run_fp_model (x,y, mean_list, pres_list,sigma.a,sigma.b,
mbeta0,precbeta0)
temp_model<- summarize_model(fp.sim_temp)
temp<- fp.sim_temp$BUGSoutput$sims.matrix

# restructure the data as an mcmc object and generate autocorrelation,
timeseriess, and posterior scatterplot matrices plots
run1.mcmc <- as.mcmc(fp.sim_temp)
run1.ggs <- ggs(run1.mcmc)
ggmcmc(run1.ggs,plot=c("density","traceplot","autocorrelation"))
ggs_autocorrelation(run1.ggs, nLags = 15)
ggs_traceplot(run1.ggs)

# plot original analysis priors and posteriors together
par(mfrow=c(3,2))
par(mar=c(2.1,2.1,2.1,2.1))

for (curr_plot in (1:4)){
  myplotfunction (temp, header_list_plots, curr_plot,
"beta",append(mean_list,c(mbeta0)),append(pres_list,precbeta0),0)
  if (curr_plot == 4){
    legend("topright", legend=c("posterior","prior"), col=c("black",
"blue","red"), lty=1:2 , lwd=c(1,2))
  }
}

myplotfunction (temp, header_list_plots, 5,
"",append(mean_list,c(mbeta0)),append(pres_list,precbeta0),1)
myplotfunction_gamma(temp,6,"sigma",sigma.a,sigma.b)

# run sensitivity analyses for given parameter values (index num corresponds
to beta 1-4)
curr_var_index_num <-4
curr_sens_param_name <-header_list_plots[curr_var_index_num]
curr_var_std_list<-
c(std_list[curr_var_index_num],std_list[curr_var_index_num]*2,std_list[curr_var_index_num]
current_sens_param_list<-1/(curr_var_std_list*curr_var_std_list)
all_model<-c()

for (curr_sens_param in current_sens_param_list){
```

```
  # set precision according to currrent sensitivity analysis
  pres_list[curr_var_index_num]<-curr_sens_param

  # inputs: loop_uneq_var_model(y1, y2,alpha1,alpha2,mu1_pres,mu2_pres)
  fp.sim_temp<- run_fp_model (x,y, mean_list, pres_list,sigma.a,sigma.b,
mbeta0,precbeta0)
  temp_model<- summarize_model(fp.sim_temp)

  # add descriptive row names and store current sensitivity analysis in larger
table
  all_model<-
add_row_names_and_store_current_sensitivity_analysis(temp_model,curr_sens_param_name,round
3))
  }

# save all sensitivity analyses out together in various formats
all_model<-round(all_model,3)
sens_analysis<-all_model[,c(1:2,6:7,11:12,16:17,21:22,26:27)]
sig<-all_model[,c(5,10,15,20,25,30)]
```

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