Moderation Analysis

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Moderation Analysis

To summarize the exploratory analyses, we found that race and sex were confounding factors to the association between childhood trauma and cognition. Now that we have created multiple visualizations and evaluated confounding, we will move into the crux of our analysis - moderation analysis. We will be specifically focusing on how substance abuse moderates the association between trauma and cognition. To outline our analysis, it will be broken down into three sections: Composite cognition, Episodic Memory, Executive Functioning. To evaluate moderation, we will both look at aggregated substance abuse and break down by each substance. We will construct linear mixed models to evaluate the significance of interaction terms and then compare the interaction models to the null model without substance abuse and model without interaction effect. Linear mixed models were utilized since the data set is not independent. Participants would sampled through cluster sampling, thus we see participants from the same family. This violates the assumption of independence as there is likely relationships between different observations.

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.4     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

##
## Attaching package: 'nlme'

## The following object is masked from 'package:dplyr':
##
##     collapse

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
```

```
##
## Attaching package: 'lme4'

## The following object is masked from 'package:nlme':
##
##     lmList

##
## Attaching package: 'lmerTest'

## The following object is masked from 'package:lme4':
##
##     lmer

## The following object is masked from 'package:stats':
##
##     step

## Loading required package: arm

## Loading required package: MASS

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

##
## arm (Version 1.12-2, built: 2021-10-15)

## Working directory is C:/Users/araja/Documents/R/Data Science 2/Childhood-Trauma-Study

##
## Attaching package: 'MuMIn'

## The following object is masked from 'package:arm':
##
##     coefplot

## Rows: 592 Columns: 2453

## -- Column specification --------------------------------------------------------
## Delimiter: "\t"
## chr    (1): BACIDATE
## dbl (2452): M2ID, BACRAGE, BACBYR, BACRSEX, BACA1, BACA2, BACAS6A, BACAS6B, ...

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.

## Joining, by = "M2ID"
## Joining, by = "M2ID"
## Joining, by = "M2ID"
```

Drug Use

Before we dive into our analysis, let us take a quick look at substance abuse in the dataset.

```
midus %>%
  group_by(drug_use) %>%
  summarize(n_obs=n())
```

```
## # A tibble: 2 x 2
##   drug_use n_obs
##   <chr>    <int>
## 1 No        1002
## 2 Yes        106
```

From this table we see the proportion of those who used ANY substance is low ~ 9.6%(n=106). This low proportion should be noted as we interpret our models and the moderation effect of substance abuse.

tranquilizer	n_obs
No	1070
Yes	35
NA	3

stimulants	n_obs
No	1079
Yes	26
NA	3

inhallants	n_obs
No	1089
Yes	15
NA	4

depressants	n_obs
No	1053
Yes	52
NA	3

marijuana	n_obs
No	1100
Yes	2
NA	6

cocaine	n_obs
No	1091
Yes	14
NA	3

hallucinogens	n_obs
No	1091
Yes	14
NA	3

heroin	n_obs
Yes	2
No	1102
NA	4

From the tables above we can see the number of those who indicated use of any of the substances over the past 12 months. Of the substances, we see the number of those who indicated use of marijuana or heroin is equal to 2. This value is quite low, and thus would be too sparse to be meaningfully included in our model. Though the other substances do not have a significantly high number of observations that answered yes, the n is still above 10 so they will be included during regression analysis.

Composite Cognition

We will begin our moderation analysis by looking at composite cognition as our outcome variable. Before we dive in we will look create a null model to evaluate the unadjusted association between trauma composite cognition.

```
null_model_composite <-lmer(composite_cognition ~ threat + deprivation + (1|family_id), data=midus)

summary(null_model_composite)
```

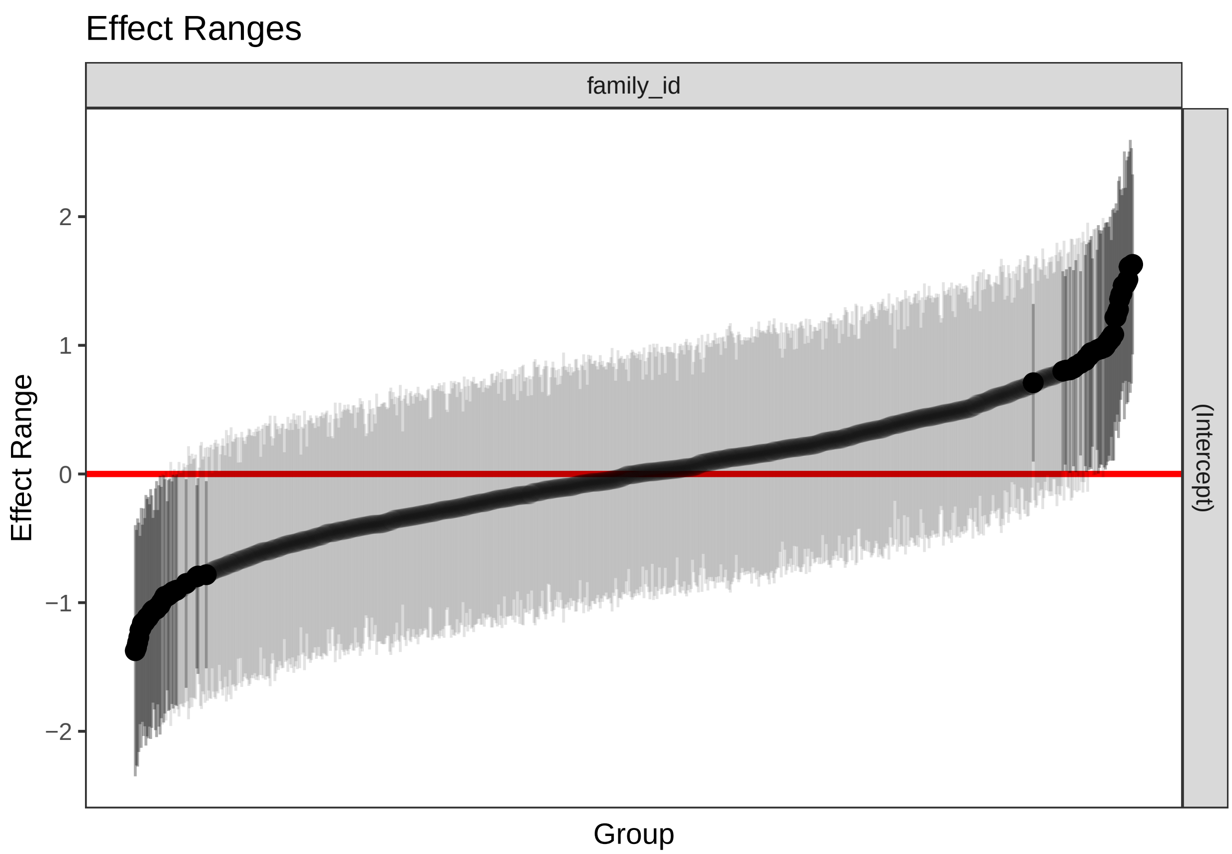
```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: composite_cognition ~ threat + deprivation + (1 | family_id)
##    Data: midus
##
## REML criterion at convergence: 2680.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.97770 -0.48149 -0.01154  0.46162  2.31229
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.5005   0.7074
##  Residual              0.4295   0.6554
## Number of obs: 979, groups:  family_id, 844
```

```
##
## Fixed effects:
##                Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)    0.195993   0.096412 959.516042   2.033   0.0423 *
## threat         0.004418   0.004936 975.862030   0.895   0.3710
## deprivation   -0.012721   0.006795 966.357730  -1.872   0.0615 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) threat
## threat      -0.292
## deprivation -0.476 -0.664
```

```
confint(null_model_composite, level = 0.95, method = "Wald")
```

```
##                    2.5 %       97.5 %
## .sig01                NA           NA
## .sigma                NA           NA
## (Intercept)  0.007030025 0.3849563091
## threat      -0.005256256 0.0140916493
## deprivation -0.026037748 0.0005963049
```

```
plotREsim(REsim(null_model_composite))
```



From the fixed effects of this null model, we conclude that threat and deprivation are not significant predictors at the significance level of 0.05. Moreover if we look at the confidence interval for each of the parameters they include 0. However, it should be noted that the association between threat and deprivation is confounded by a multitude of factors as stated in our exploratory analysis. These factors are sex and race. Moreover since age and education are significantly associated with composite cognition, we will include them in our full model with covariates. One final point on the model is that the differences between families explains 53.8% of variance not explained by our fixed effects. Thus including family as a random effect is essential.

```
summary(lmer(composite_cognition ~ threat + deprivation + drug_use + (1|family_id), data=midus))
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: composite_cognition ~ threat + deprivation + drug_use + (1 |
##     family_id)
##    Data: midus
##
## REML criterion at convergence: 2682
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.97100 -0.48819 -0.01467  0.46493  2.36079
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.4972   0.7051
##  Residual              0.4323   0.6575
## Number of obs: 979, groups:  family_id, 844
##
## Fixed effects:
##               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)   0.196555   0.096405 958.040790   2.039   0.0417 *
## threat        0.004715   0.004946 974.821108   0.953   0.3407
## deprivation  -0.012594   0.006798 965.599634  -1.852   0.0643 .
## drug_useYes  -0.092266   0.103056 945.927117  -0.895   0.3709
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) threat dprvtn
## threat      -0.290
## deprivation -0.476 -0.661
## drug_useYes -0.005 -0.063 -0.025
```

I additionally wanted to run a model that just included childhood trauma and aggregated substance abuse, but the predictors remain insignficant in the model at significance level 0.05. I should be noted that though that parameter estimates for drug use and deprivation are high.

```
model_covariates <- lmer(composite_cognition ~ threat + deprivation + age + sex + race + education + dru

summary(model_covariates)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
```

```
## Formula: composite_cognition ~ threat + deprivation + age + sex + race +
##     education + drug_use + (1 | family_id)
##    Data: midus
##
## REML criterion at convergence: 2381.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.35581 -0.54052 -0.00609  0.49793  2.56312
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2626   0.5125
##  Residual              0.3926   0.6266
## Number of obs: 976, groups:  family_id, 842
##
## Fixed effects:
##                        Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)            1.124082   0.380625 955.890145   2.953 0.003221 **
## threat                -0.004709   0.004332 951.220164  -1.087 0.277306
## deprivation           -0.000173   0.005921 955.920393  -0.029 0.976695
## age                   -0.031868   0.002379 830.086178 -13.396  < 2e-16 ***
## sexFemale              0.126974   0.054321 942.311780   2.337 0.019624 *
## raceBlack             -0.772934   0.167426 870.605714  -4.617 4.49e-06 ***
## raceNative American    0.265759   0.234007 949.272518   1.136 0.256373
## raceAsian             -0.817355   0.472562 923.592546  -1.730 0.084031 .
## raceOther             -0.574656   0.168266 940.866135  -3.415 0.000665 ***
## education3             0.205162   0.362614 954.018698   0.566 0.571672
## education4             0.077401   0.441372 883.411676   0.175 0.860833
## education5             0.518027   0.334178 951.858600   1.550 0.121438
## education6             0.543518   0.335891 951.434742   1.618 0.105965
## education7             0.713721   0.352218 951.613713   2.026 0.043006 *
## education8             0.614985   0.340475 950.026025   1.806 0.071195 .
## education9             1.081838   0.334286 950.922589   3.236 0.001253 **
## education10            0.961937   0.350088 949.218340   2.748 0.006115 **
## education11            1.221414   0.335631 945.884711   3.639 0.000288 ***
## education12            1.220584   0.351427 951.207738   3.473 0.000537 ***
## drug_useYes           -0.075147   0.090454 950.528261  -0.831 0.406307
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 20 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
r.squaredGLMM(model_covariates)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the help page.
```

```
##            R2m       R2c
## [1,] 0.3066476 0.5845634
```

We see from the model above that despite adding the covariates, deprivation and threat are still not considered significant predictors in composite cognition at the significance level of 0.05. However from the model we glean that sex, age, and higher level education are significant predictors in composite cognition score.Moreover, the random effects for family are still significant. It is important to note that substance abuse is also not significant in this model.

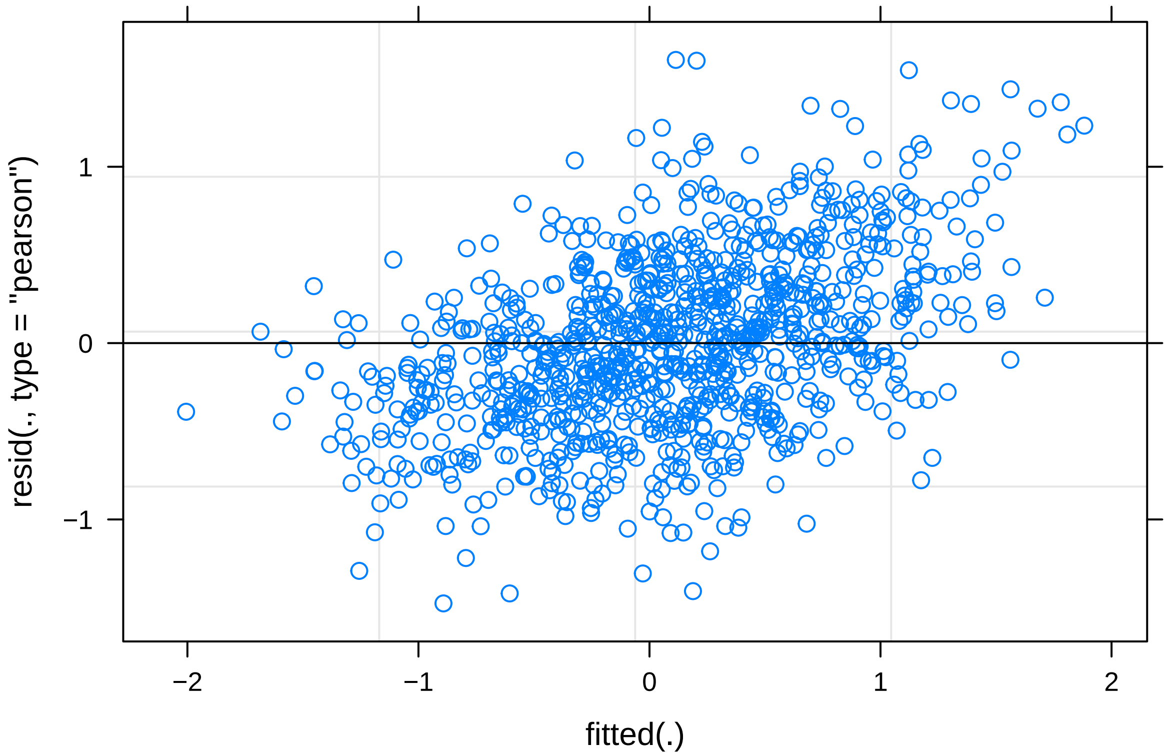
To evaluate model fit, there is no perfect measure. But if we look at the marginal Rˆ2 we get a value equal to 0.3066, and conditional Rˆ2 is 0.5845. This is OK, and does not indicate a great model fit.

Lets now look at the residuals plot.

```
confint(model_covariates, level = 0.95, method = "Wald")
```

```
##                          2.5 %       97.5 %
## .sig01                      NA           NA
## .sigma                      NA           NA
## (Intercept)         0.37807162  1.870093182
## threat             -0.01319950  0.003781611
## deprivation        -0.01177751  0.011431490
## age                -0.03653115 -0.027205723
## sexFemale           0.02050596  0.233441206
## raceBlack          -1.10108235 -0.444786104
## raceNative American -0.19288595  0.724404353
## raceAsian          -1.74355860  0.108849409
## raceOther          -0.90445041 -0.244861204
## education3         -0.50554794  0.915871415
## education4         -0.78767085  0.942473606
## education5         -0.13695089  1.173004143
## education6         -0.11481737  1.201852692
## education7          0.02338785  1.404054922
## education8         -0.05233425  1.282304631
## education9          0.42664849  1.737027130
## education10         0.27577701  1.648096321
## education11         0.56358850  1.879238743
## education12         0.53179972  1.909367305
## drug_useYes        -0.25243246  0.102138602
```

```
plot(model_covariates)
```



From looking at the residuals plot, we do not see any deviations from the linear form as there is relatively constant variance across the fitted range. Thus assumptions are met for this model. Good!

Model with Interactions

```
model_covariates_interactions <- lmer(composite_cognition ~ threat + deprivation + age + sex + race + ed

summary(model_covariates_interactions)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: composite_cognition ~ threat + deprivation + age + sex + race +
##     education + drug_use + threat * drug_use + deprivation *
##     drug_use + (1 | family_id)
##    Data: midus
##
## REML criterion at convergence: 2394.7
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.35378 -0.53559 -0.01023  0.49831  2.56879
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2640   0.5138
##  Residual              0.3926   0.6266
## Number of obs: 976, groups:  family_id, 842
```

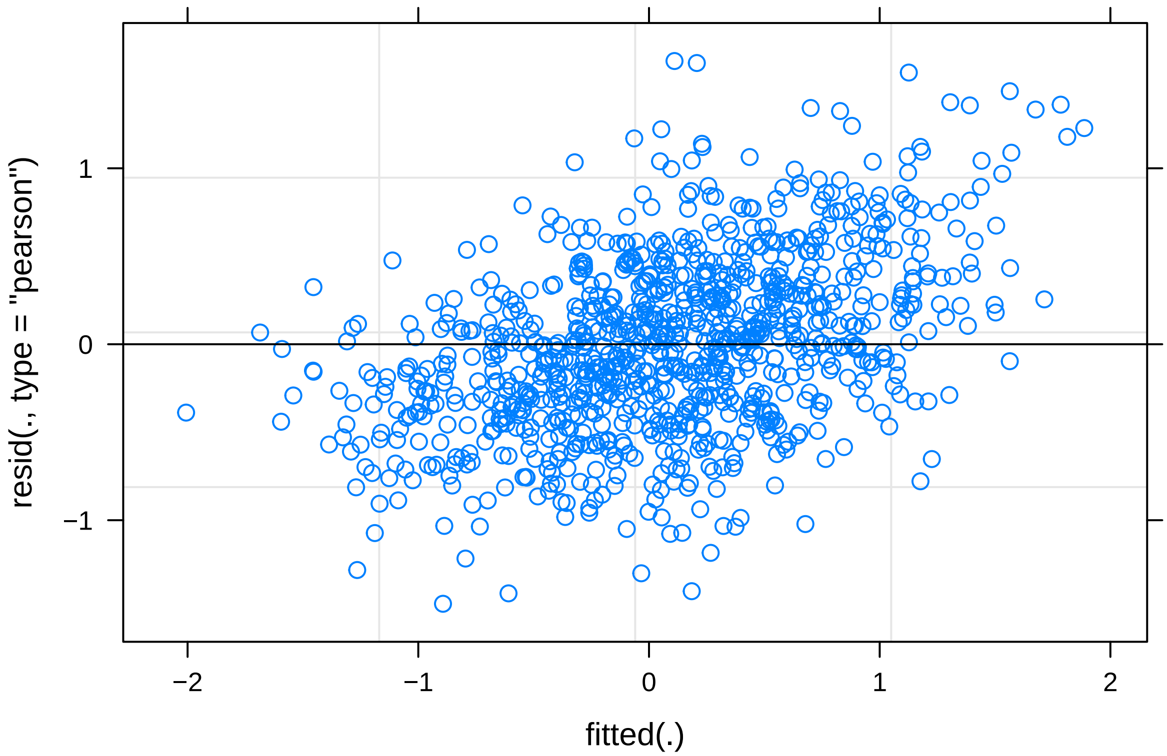
```
##
## Fixed effects:
##                           Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)              1.142e+00  3.835e-01  9.539e+02   2.978 0.002979 **
## threat                  -4.858e-03  4.646e-03  9.526e+02  -1.046 0.296054
## deprivation             -6.645e-04  6.312e-03  9.527e+02  -0.105 0.916175
## age                     -3.190e-02  2.388e-03  8.261e+02 -13.356  < 2e-16 ***
## sexFemale                1.274e-01  5.439e-02  9.406e+02   2.342 0.019404 *
## raceBlack               -7.753e-01  1.680e-01  8.685e+02  -4.615 4.53e-06 ***
## raceNative American      2.590e-01  2.357e-01  9.422e+02   1.099 0.271983
## raceAsian               -8.142e-01  4.733e-01  9.217e+02  -1.720 0.085748 .
## raceOther               -5.769e-01  1.685e-01  9.388e+02  -3.423 0.000646 ***
## education3               1.950e-01  3.640e-01  9.521e+02   0.536 0.592367
## education4               8.264e-02  4.419e-01  8.818e+02   0.187 0.851714
## education5               5.139e-01  3.347e-01  9.497e+02   1.535 0.125002
## education6               5.392e-01  3.364e-01  9.493e+02   1.603 0.109344
## education7               7.100e-01  3.527e-01  9.495e+02   2.013 0.044376 *
## education8               6.068e-01  3.414e-01  9.479e+02   1.778 0.075796 .
## education9               1.077e+00  3.348e-01  9.488e+02   3.217 0.001340 **
## education10              9.576e-01  3.506e-01  9.471e+02   2.732 0.006422 **
## education11              1.218e+00  3.362e-01  9.436e+02   3.622 0.000308 ***
## education12              1.217e+00  3.519e-01  9.491e+02   3.459 0.000565 ***
## drug_useYes             -1.816e-01  2.709e-01  9.351e+02  -0.670 0.502906
## threat:drug_useYes       8.546e-04  1.199e-02  9.474e+02   0.071 0.943201
## deprivation:drug_useYes  4.664e-03  1.780e-02  9.534e+02   0.262 0.793390
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 22 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
r.squaredGLMM(model_covariates_interactions)
```

```
##            R2m       R2c
## [1,] 0.3063237 0.5852234
```

The model summary above shows that the interaction effects between aggregated drug use and childhood trauma are not significant at the significance level of 0.05. Random effects from family still remain significant for this model. When evaluating model fit, we get similar marginal R^2 and conditional R^2 values to the previous model without interactions. Thus we do not see much greater model fit. Lets look at the residual plot for this model.

```
plot(model_covariates_interactions)
```



Residual plots indicate fairly constant variance across fitted values, thus model assumption is met! Now lets evaluate if there are any difference between the models.

```
anova(model_covariates,model_covariates_interactions)
```

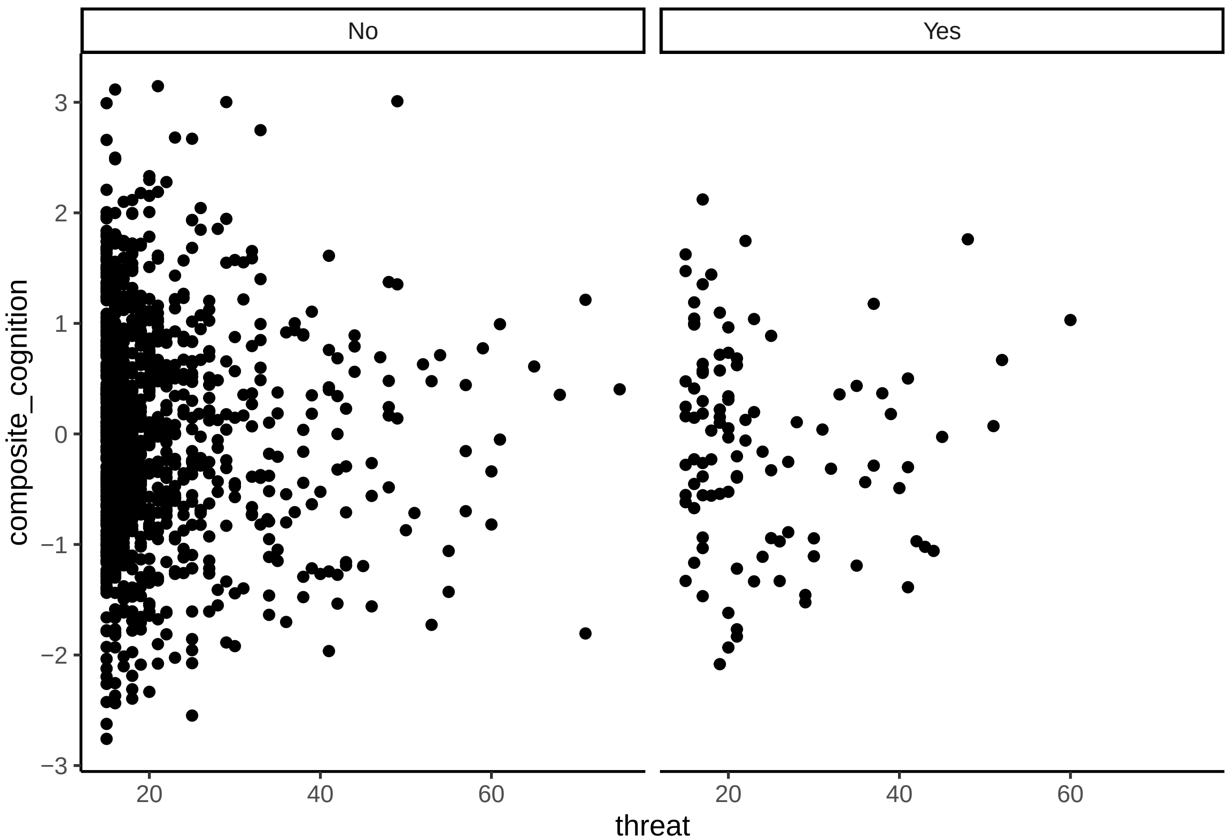
```
## refitting model(s) with ML (instead of REML)

## Data: midus
## Models:
## model_covariates: composite_cognition ~ threat + deprivation + age + sex + race + education + drug_us
## model_covariates_interactions: composite_cognition ~ threat + deprivation + age + sex + race + educat
##                               npar    AIC    BIC  logLik deviance  Chisq Df
## model_covariates                22 2357.2 2464.6 -1156.6   2313.2
## model_covariates_interactions   24 2361.0 2478.2 -1156.5   2313.0 0.1783  2
##                               Pr(>Chisq)
## model_covariates
## model_covariates_interactions     0.9147
```

From the output we see that AIC does not decrease, BIC decreases and a p-value >0.05. These three values indicate that interaction aeffects are not significant in the model. Thus we would opt for the model without interaction effects as the better model.

Though from our regression analysis we would conclude interaction effects are not significant, let's conduct some additional analysis to further confirm these results.

```
ggplot(aes(threat,composite_cognition), data = midus) +
  geom_point() +
  facet_wrap(~ drug_use) +
  theme_classic()
```

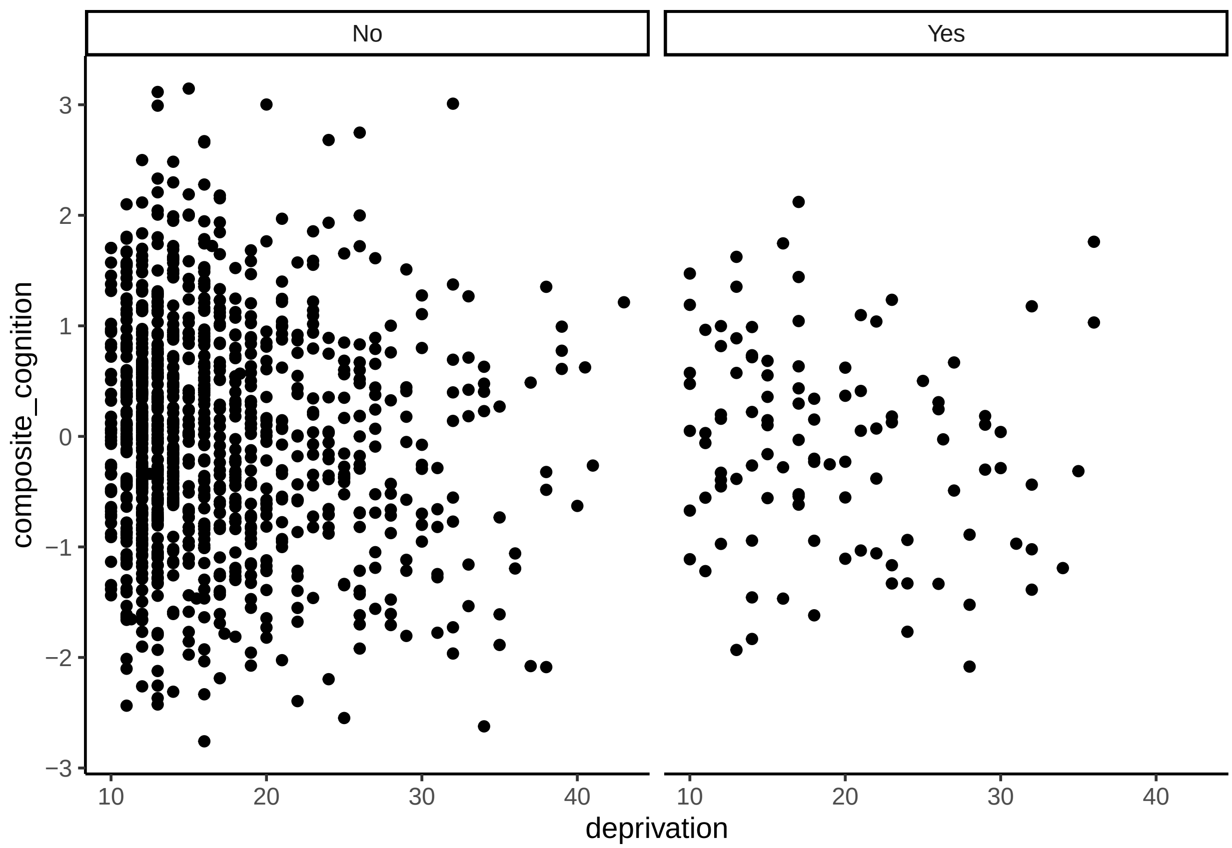
```
## Warning: Removed 7 rows containing missing values (geom_point).
```



The graph above plots threat trauma scores vs composition cognition z-scores by Drug use.

```
ggplot(aes(deprivation,composite_cognition), data = midus) +
  geom_point() +
  facet_wrap(~ drug_use) +
  theme_classic()
```

```
## Warning: Removed 4 rows containing missing values (geom_point).
```



The plot above shows deprivation vs composite cognition by drug use.

From looking at the two plots, we do not see significant difference in correlations between traum and composite cognition z score when separated by drug use.

We will now evaluate estimated means.

```
m_threat<- mean(midus$threat, na.rm = TRUE)
sd_threat<- sd(midus$threat, na.rm = TRUE)

emm <- emmeans(model_covariates_interactions, pairwise ~ threat*drug_use, cov.keep = 3, at = list(
  threat = c(m_threat-sd_threat, m_threat, m_threat+sd_threat)), level = 0.95)
summary(emm)
```

```
## $emmeans
##  threat drug_use emmean    SE  df lower.CL upper.CL
##    12.4 No       -0.370 0.127 949   -0.618   -0.121
##    21.5 No       -0.414 0.122 941   -0.654   -0.174
##    30.6 No       -0.458 0.132 935   -0.717   -0.198
##    12.4 Yes      -0.462 0.184 949   -0.822   -0.101
##    21.5 Yes      -0.498 0.146 949   -0.784   -0.211
##    30.6 Yes      -0.534 0.172 943   -0.871   -0.197
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
```

```
## $contrasts
##  contrast                                      estimate     SE  df t.ratio
##  12.4356734406012 No - 21.5030881017257 No     0.04405 0.0422 952   1.044
##  12.4356734406012 No - 30.5705027628503 No     0.08810 0.0844 952   1.044
##  12.4356734406012 No - 12.4356734406012 Yes    0.09188 0.1474 954   0.623
##  12.4356734406012 No - 21.5030881017257 Yes    0.12818 0.1018 947   1.259
##  12.4356734406012 No - 30.5705027628503 Yes    0.16448 0.1401 950   1.174
##  21.5030881017257 No - 30.5705027628503 No     0.04405 0.0422 952   1.044
##  21.5030881017257 No - 12.4356734406012 Yes    0.04783 0.1426 954   0.335
##  21.5030881017257 No - 21.5030881017257 Yes    0.08413 0.0933 947   0.902
##  21.5030881017257 No - 30.5705027628503 Yes    0.12043 0.1331 951   0.905
##  30.5705027628503 No - 12.4356734406012 Yes    0.00378 0.1500 953   0.025
##  30.5705027628503 No - 21.5030881017257 Yes    0.04008 0.1030 952   0.389
##  30.5705027628503 No - 30.5705027628503 Yes    0.07638 0.1391 951   0.549
##  12.4356734406012 Yes - 21.5030881017257 Yes   0.03630 0.1016 940   0.357
##  12.4356734406012 Yes - 30.5705027628503 Yes   0.07260 0.2032 940   0.357
##  21.5030881017257 Yes - 30.5705027628503 Yes   0.03630 0.1016 940   0.357
##  p.value
##   0.9031
##   0.9031
##   0.9893
##   0.8071
##   0.8493
##   0.9031
##   0.9994
##   0.9460
##   0.9453
##   1.0000
##   0.9988
##   0.9941
##   0.9992
##   0.9992
##   0.9992
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
simpleSlope <- emtrends(model_covariates_interactions, pairwise ~ drug_use, var = "threat", level = 0.95
summary(simpleSlope)
```

```
## $emtrends
##  drug_use threat.trend      SE  df lower.CL upper.CL
##  No           -0.00486 0.00466 952   -0.014  0.00428
##  Yes          -0.00400 0.01120 940   -0.026  0.01799
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast  estimate    SE  df t.ratio p.value
##  No - Yes -0.000855 0.012 947  -0.071  0.9432
##
```

```
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
```

The purpose of this estimated marginal means analysis is to test if there is a significant difference in mean composite cognition scores at different levels of threat scores for those who did or did not use substances. From this analysis, we confirm there are not significant differences.

```
m_deprivation<- mean(midus$deprivation, na.rm = TRUE)
sd_deprivation<- sd(midus$deprivation, na.rm = TRUE)

emm_deprivation <- emmeans(model_covariates_interactions, pairwise ~ deprivation*drug_use, cov.keep = 3
  deprivation = c(m_deprivation-sd_deprivation, m_deprivation, m_deprivation+sd_deprivation)), level = 
summary(emm_deprivation)
```

```
## $emmeans
##  deprivation drug_use emmean    SE  df lower.CL upper.CL
##         10.8 No       -0.408 0.132 942   -0.667   -0.149
##         17.1 No       -0.412 0.122 941   -0.652   -0.172
##         23.4 No       -0.416 0.125 946   -0.661   -0.172
##         10.8 Yes      -0.521 0.185 949   -0.884   -0.158
##         17.1 Yes      -0.496 0.146 949   -0.783   -0.209
##         23.4 Yes      -0.471 0.175 951   -0.815   -0.127
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                     estimate     SE  df t.ratio
##  10.8228179885588 No - 17.1007246376812 No     0.00417 0.0397 953   0.105
##  10.8228179885588 No - 23.3786312868035 No     0.00834 0.0794 953   0.105
##  10.8228179885588 No - 10.8228179885588 Yes    0.11299 0.1508 954   0.749
##  10.8228179885588 No - 17.1007246376812 Yes    0.08788 0.1013 952   0.868
##  10.8228179885588 No - 23.3786312868035 Yes    0.06277 0.1410 953   0.445
##  17.1007246376812 No - 23.3786312868035 No     0.00417 0.0397 953   0.105
##  17.1007246376812 No - 10.8228179885588 Yes    0.10882 0.1460 953   0.745
##  17.1007246376812 No - 17.1007246376812 Yes    0.08371 0.0934 947   0.897
##  17.1007246376812 No - 23.3786312868035 Yes    0.05860 0.1350 954   0.434
##  23.3786312868035 No - 10.8228179885588 Yes    0.10465 0.1518 953   0.689
##  23.3786312868035 No - 17.1007246376812 Yes    0.07954 0.1016 943   0.783
##  23.3786312868035 No - 23.3786312868035 Yes    0.05443 0.1404 954   0.388
##  10.8228179885588 Yes - 17.1007246376812 Yes -0.02511 0.1051 952  -0.239
##  10.8228179885588 Yes - 23.3786312868035 Yes -0.05022 0.2103 952  -0.239
##  17.1007246376812 Yes - 23.3786312868035 Yes -0.02511 0.1051 952  -0.239
##  p.value
##   1.0000
##   1.0000
##   0.9756
##   0.9541
##   0.9978
##   1.0000
##   0.9762
##   0.9473
```

```
##   0.9980
##   0.9831
##   0.9705
##   0.9989
##   0.9999
##   0.9999
##   0.9999
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
summary(emtrends(model_covariates_interactions, pairwise ~ drug_use, var = "deprivation", level = 0.95))
```

```
## $emtrends
##  drug_use deprivation.trend      SE  df lower.CL upper.CL
##  No               -0.000665 0.00633 953  -0.0131   0.0117
##  Yes               0.004000 0.01675 952  -0.0289   0.0369
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE  df t.ratio p.value
##  No - Yes -0.00466 0.0178 953  -0.262  0.7936
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
```

The purpose of this estimated marginal means analysis is to test if there is a significant difference in mean composite cognition scores at different levels of deprivation scores for those who did or did not use substances. From this analysis, we confirm there are not significant differences.

Now that we have looked at aggregated substance use, lets break down by substances.

```
model_substances <- lmer(composite_cognition ~ age + sex + education + race +tranquilizer + stimulants +
```

```
## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
```

```
summary(model_substances)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: composite_cognition ~ age + sex + education + race + tranquilizer +
##     stimulants + painkillers + depressants + inhallants + cocaine +
##     hallucinogens + threat + deprivation + (1 | family_id)
##    Data: midus
##
## REML criterion at convergence: 2373.7
##
## Scaled residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -2.34562 -0.53378 -0.01742  0.50439  2.55710
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2611   0.5110
##  Residual              0.3973   0.6303
## Number of obs: 971, groups:  family_id, 839
##
## Fixed effects:
##                       Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)          1.026e+00  4.589e-01  9.031e+02   2.237 0.025555 *
## age                 -3.230e-02  2.415e-03  8.185e+02 -13.376  < 2e-16 ***
## sexFemale            1.233e-01  5.470e-02  9.317e+02   2.253 0.024468 *
## education3           3.178e-01  4.396e-01  9.190e+02   0.723 0.469933
## education4           1.654e-01  5.061e-01  9.425e+02   0.327 0.743880
## education5           6.366e-01  4.153e-01  9.127e+02   1.533 0.125697
## education6           6.766e-01  4.169e-01  9.142e+02   1.623 0.104967
## education7           8.482e-01  4.300e-01  9.186e+02   1.972 0.048867 *
## education8           7.340e-01  4.208e-01  9.181e+02   1.744 0.081425 .
## education9           1.207e+00  4.156e-01  9.136e+02   2.905 0.003761 **
## education10          1.079e+00  4.286e-01  9.215e+02   2.517 0.012001 *
## education11          1.335e+00  4.179e-01  9.151e+02   3.195 0.001444 **
## education12          1.344e+00  4.298e-01  9.179e+02   3.127 0.001822 **
## raceBlack           -7.536e-01  1.705e-01  8.592e+02  -4.421 1.11e-05 ***
## raceNative American  2.432e-01  2.353e-01  9.394e+02   1.034 0.301597
## raceAsian           -8.130e-01  4.737e-01  9.144e+02  -1.716 0.086469 .
## raceOther           -5.756e-01  1.719e-01  9.316e+02  -3.348 0.000847 ***
## tranquilizerYes      2.103e-01  1.563e-01  9.393e+02   1.346 0.178729
## stimulantsYes        1.107e-02  1.914e-01  9.357e+02   0.058 0.953893
## painkillersYes      -7.307e-02  3.053e-01  9.190e+02  -0.239 0.810861
## depressantsYes      -1.009e-01  1.320e-01  9.409e+02  -0.764 0.444957
## inhallantsYes       -2.873e-01  2.370e-01  9.385e+02  -1.212 0.225865
## cocaineYes          -1.899e-01  3.633e-01  9.153e+02  -0.523 0.601359
## threat              -5.097e-03  4.362e-03  9.407e+02  -1.169 0.242865
## deprivation          2.297e-04  5.972e-03  9.460e+02   0.038 0.969328
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 25 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it

## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
```

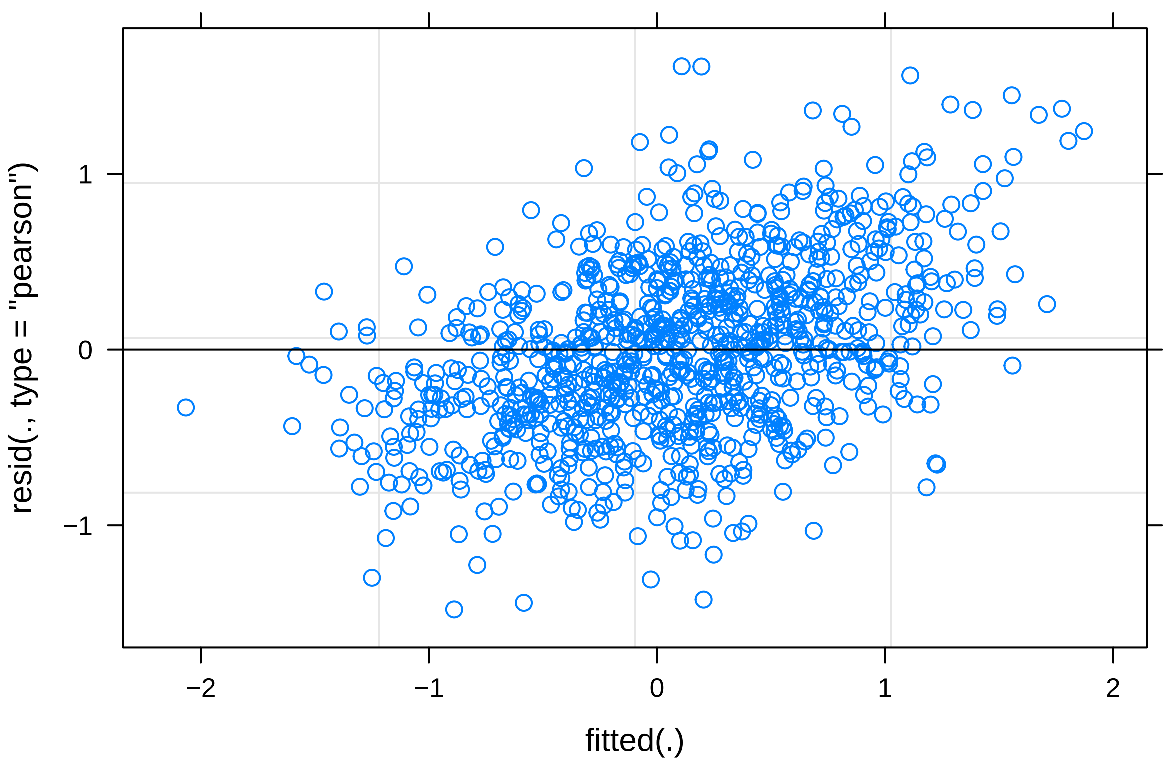
```
r.squaredGLMM(model_substances)
```

```
##            R2m       R2c
## [1,] 0.3057485 0.5810773
```

From this model we see that the predictors for the specific substances are not significant at the significance level of 0.05. However though the p-value indicates non-significance, I will look at each individual substance parameter. The slope parameters for painkillers, depressants, inhallants and cocaine mean that those individuals who indicated use of these substances over the past 12 months had on average a lower composite cognition score compared to those who indicated no use. Moreover, the random effects of grouping by family is significant.

To evaluate model fit, we looked at R^2 values. The marginal r^2 is 0.3057 and the conditional r^2 is 0.5811. These values indicate OK model fit, but not great.

```
plot(model_substances)
```



Residual plots indicate fairly constant variance across fitted values, thus model assumption is met!

```
model_substances_interactions <- lmer(composite_cognition ~ age + sex + education + race +tranquilizer +
```

```
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
summary(model_substances_interactions)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: composite_cognition ~ age + sex + education + race + tranquilizer +
##     stimulants + painkillers + depressants + inhallants + cocaine +
##     hallucinogens + threat + deprivation + stimulants * threat +
##     stimulants * deprivation + painkillers * threat + painkillers *
##     deprivation + inhallants * threat + inhallants * deprivation +
```

```
##     cocaine * threat + cocaine * deprivation + hallucinogens *
##     threat + hallucinogens * deprivation + tranquilizer * threat +
##     tranquilizer * deprivation + (1 | family_id)
##    Data: midus
##
## REML criterion at convergence: 2415.2
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.33775 -0.53120 -0.01614  0.49477  2.55031
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2637   0.5135
##  Residual              0.3983   0.6311
## Number of obs: 971, groups:  family_id, 839
##
## Fixed effects:
##                              Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)                 9.963e-01  4.627e-01  8.928e+02   2.154 0.031546
## age                        -3.225e-02  2.434e-03  8.080e+02 -13.249  < 2e-16
## sexFemale                   1.235e-01  5.511e-02  9.228e+02   2.242 0.025198
## education3                  2.941e-01  4.425e-01  9.096e+02   0.665 0.506428
## education4                  1.619e-01  5.080e-01  9.326e+02   0.319 0.750058
## education5                  6.523e-01  4.171e-01  9.025e+02   1.564 0.118219
## education6                  6.889e-01  4.187e-01  9.041e+02   1.645 0.100283
## education7                  8.449e-01  4.318e-01  9.086e+02   1.957 0.050696
## education8                  7.542e-01  4.228e-01  9.082e+02   1.784 0.074779
## education9                  1.222e+00  4.174e-01  9.035e+02   2.927 0.003504
## education10                 1.097e+00  4.306e-01  9.115e+02   2.547 0.011020
## education11                 1.353e+00  4.197e-01  9.050e+02   3.225 0.001307
## education12                 1.356e+00  4.315e-01  9.077e+02   3.143 0.001729
## raceBlack                  -7.097e-01  1.776e-01  8.450e+02  -3.995 7.03e-05
## raceNative American         2.345e-01  2.406e-01  9.305e+02   0.975 0.329886
## raceAsian                  -8.160e-01  4.753e-01  9.044e+02  -1.717 0.086346
## raceOther                  -5.775e-01  1.724e-01  9.215e+02  -3.349 0.000843
## tranquilizerYes             4.146e-01  5.211e-01  9.331e+02   0.796 0.426421
## stimulantsYes               2.137e-01  6.474e-01  9.331e+02   0.330 0.741475
## painkillersYes             -1.344e+00  1.322e+00  9.067e+02  -1.016 0.309789
## depressantsYes             -1.212e-01  1.366e-01  9.284e+02  -0.888 0.375022
## inhallantsYes               3.359e-02  8.730e-01  8.783e+02   0.038 0.969314
## cocaineYes                  3.244e+00  3.622e+00  9.036e+02   0.895 0.370805
## threat                     -4.331e-03  4.570e-03  9.319e+02  -0.948 0.343509
## deprivation                 8.615e-05  6.261e-03  9.358e+02   0.014 0.989024
## stimulantsYes:threat       -1.616e-02  3.249e-02  9.208e+02  -0.497 0.619114
## stimulantsYes:deprivation   1.135e-02  3.844e-02  9.212e+02   0.295 0.767852
## painkillersYes:threat      -1.592e-02  4.332e-02  9.095e+02  -0.368 0.713282
## painkillersYes:deprivation  8.677e-02  8.670e-02  9.059e+02   1.001 0.317157
## inhallantsYes:threat       -3.214e-02  2.207e-02  9.183e+02  -1.456 0.145664
## inhallantsYes:deprivation   2.344e-02  4.204e-02  9.357e+02   0.558 0.577207
## cocaineYes:threat          -8.687e-03  4.862e-02  9.058e+02  -0.179 0.858234
## cocaineYes:deprivation     -1.863e-01  1.878e-01  9.046e+02  -0.992 0.321466
## tranquilizerYes:threat      2.074e-02  2.690e-02  9.268e+02   0.771 0.440800
## tranquilizerYes:deprivation -3.849e-02  3.565e-02  9.298e+02  -1.080 0.280574
```

```
##
## (Intercept)                 *
## age                         ***
## sexFemale                   *
## education3
## education4
## education5
## education6
## education7                  .
## education8                  .
## education9                  **
## education10                 *
## education11                 **
## education12                 **
## raceBlack                   ***
## raceNative American
## raceAsian                   .
## raceOther                   ***
## tranquilizerYes
## stimulantsYes
## painkillersYes
## depressantsYes
## inhallantsYes
## cocaineYes
## threat
## deprivation
## stimulantsYes:threat
## stimulantsYes:deprivation
## painkillersYes:threat
## painkillersYes:deprivation
## inhallantsYes:threat
## inhallantsYes:deprivation
## cocaineYes:threat
## cocaineYes:deprivation
## tranquilizerYes:threat
## tranquilizerYes:deprivation
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 35 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it

## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
r.squaredGLMM(model_substances_interactions)
```

```
##            R2m       R2c
## [1,] 0.3070766 0.5830981
```

With this model, we are looking to see if any of the interaction effects are significant. From reviewing the model summary we see that non of the interaction terms are significant at the 0.05 significance level. This indicates that interaction effects between childhood trauma(deprivation and threat) and substances are not significant. Lets compare the the two models/

```
anova(model_substances,model_substances_interactions,test="Chi")
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: midus
## Models:
## model_substances: composite_cognition ~ age + sex + education + race + tranquilizer + stimulants + pa
## model_substances_interactions: composite_cognition ~ age + sex + education + race + tranquilizer + st
##                               npar    AIC    BIC  logLik deviance  Chisq Df
## model_substances                27 2355.6 2487.3 -1150.8   2301.6
## model_substances_interactions   37 2370.3 2550.8 -1148.2   2296.3 5.2876 10
##                               Pr(>Chisq)
## model_substances
## model_substances_interactions     0.8712
```

From the test, we see that AIC does not decrease, BIC increases and the p-value is well above 0.05. This indicates that the model with interactions is not significantly better, thus we would choose the model without interactions.

Conclusions:

First, from regression analysis and calculated estimated marginal means, we conclude the interaction effects between drug use and childhood trauma(deprivation and threat) are not significant. To test for the significance of the interaction effects, we constructed a model that had interaction terms between drug use and deprivation and drug use and threat. Neither of these terms were significant at the 0.05 level. Furthermore, we we went on to compare the model with the interactions to the model with all the covariates and no interactions and found no sigifnicant difference. Thus we chose the model without interaction terms as the better model. Then we constructed models that broke substance abuse down into specific substances. When evaluating the slope parameters for the specific substances in the model, we did not find any of the slope parameters to be significant. It should be noted despite non-significance, some of the parameter values were significantly high. For example, those who indicated as having used inhallants or cocaine, had a significantly lower composite cognition z score as opposed to those who did not. So despite insigificant p values, the parameters are interpretable. Now we tested interaction effects. The interaction model yielded no significant parameters regards to interaction terms between childhood depprivation and threat and specific substance use. Furthermore when comparing the two models, we found no signficant difference; therefore we would choose the model without interaction terms as the better model. Thus to contextualize our results within the framework of the study, we conclude that substance abuse is NOT a moderator in the association between childhood trauma and cognition.

Episodic Memory

Now lets conduct a moderation analysis with episodic memory as our primary outcome variable. We will start with an unadjusted analysis.

```
null_model_episodic <-lmer(episodic_memory ~ threat + deprivation + (1|family_id), data=midus)

summary(null_model_episodic)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: episodic_memory ~ threat + deprivation + (1 | family_id)
##    Data: midus
##
## REML criterion at convergence: 2585.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.2860 -0.5780 -0.0774  0.5541  3.4103
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2263   0.4757
##  Residual              0.5877   0.7666
## Number of obs: 979, groups:  family_id, 844
##
## Fixed effects:
##              Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)  0.073687   0.090306 920.411289   0.816    0.415
## threat       0.006174   0.004670 957.736676   1.322    0.187
## deprivation -0.006671   0.006483 972.725712  -1.029    0.304
##
## Correlation of Fixed Effects:
##             (Intr) threat
## threat      -0.278
## deprivation -0.482 -0.671
```

```r
confint(null_model_episodic, level = 0.95, method = "Wald")
```

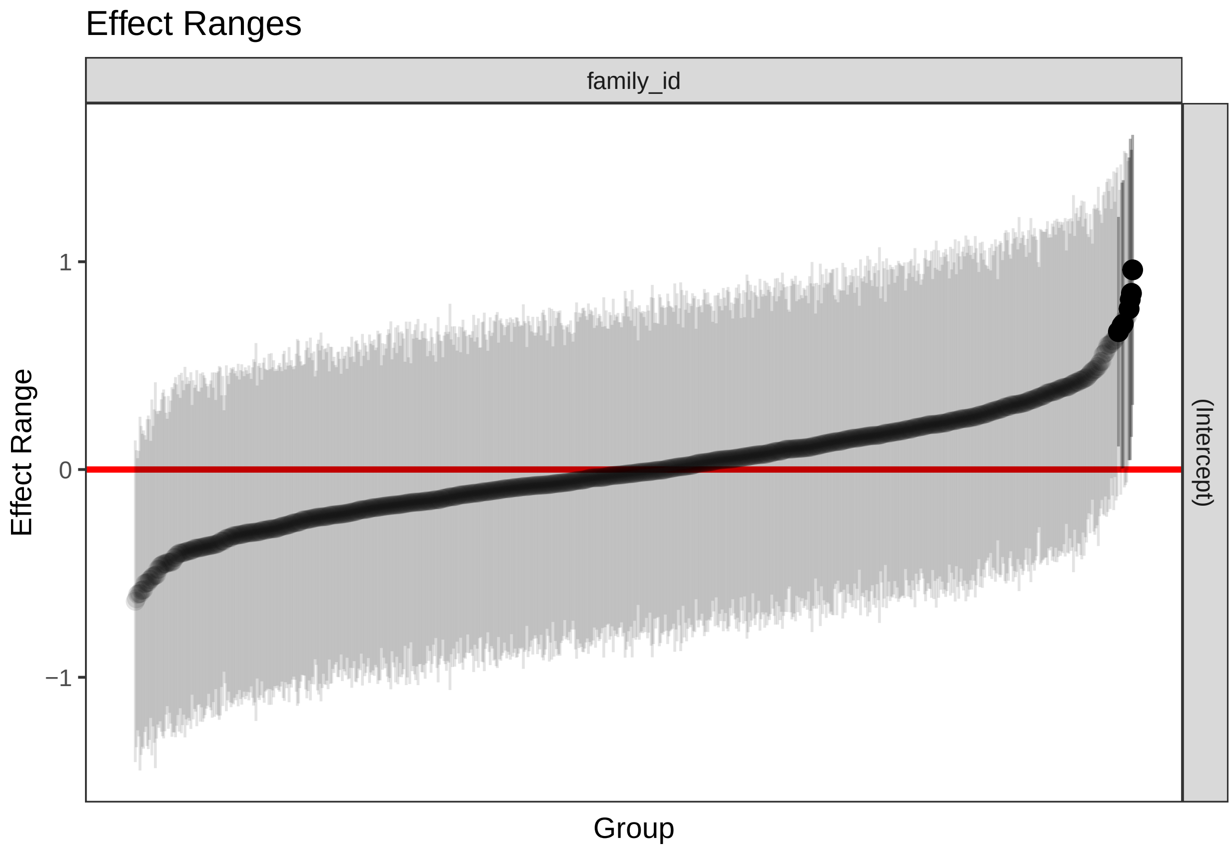
```
##                   2.5 %      97.5 %
## .sig01               NA          NA
## .sigma               NA          NA
## (Intercept) -0.10330838 0.250683290
## threat      -0.00297975 0.015327154
## deprivation -0.01937801 0.006036628
```

```r
r.squaredGLMM(null_model_episodic)
```

```
##             R2m       R2c
## [1,] 0.00185063 0.2793282
```

From the model above, we can evaluate the unadjusted association. At the significance level of 0.05, we conclude threat and deprivation scores are not significant predictors of episodic memory. The slope parameters are also very small as shown by the model summary. If we evaluate model fit, we can look at the marginal and conditional r^2. The marignal r^2 is 0.0019 and the conditional r^2 is 0.279. These values are very low. Thus we say the model fit is poor.

```r
plotREsim(REsim(null_model_episodic))
```



Now let us look at association between childhood trauma and episodic memory when adjusting for confounders and covariates.

```
episodic_model_covariates <- lmer(episodic_memory ~ threat + deprivation + age + sex + race + education

summary(episodic_model_covariates)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## episodic_memory ~ threat + deprivation + age + sex + race + education +
##     drug_use + (1 | family_id)
##    Data: midus
##
##      AIC      BIC   logLik deviance df.resid
##   2346.8   2454.2  -1151.4   2302.8      954
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3258 -0.6427 -0.0807  0.5666  3.5161
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.1171   0.3423
##  Residual              0.5057   0.7111
## Number of obs: 976, groups:  family_id, 842
```

```
##
## Fixed effects:
##                        Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)            1.028682   0.373508 969.521374   2.754   0.0060 **
## threat                -0.006474   0.004233 954.113510  -1.529   0.1266
## deprivation            0.005343   0.005814 969.242831   0.919   0.3583
## age                   -0.022533   0.002280 826.959508  -9.884   <2e-16 ***
## sexFemale              0.579391   0.052890 934.541751  10.955   <2e-16 ***
## raceBlack             -0.406112   0.161524 897.066889  -2.514   0.0121 *
## raceNative American   -0.241302   0.228052 926.779997  -1.058   0.2903
## raceAsian             -0.127315   0.460824 967.565425  -0.276   0.7824
## raceOther             -0.153991   0.164522 970.794454  -0.936   0.3495
## education3            -0.407369   0.357238 975.688897  -1.140   0.2544
## education4            -0.489437   0.440837 954.512104  -1.110   0.2672
## education5            -0.108411   0.329728 975.929625  -0.329   0.7424
## education6            -0.044739   0.331466 975.911485  -0.135   0.8927
## education7            -0.013308   0.347597 975.843357  -0.038   0.9695
## education8             0.010996   0.336217 975.613750   0.033   0.9739
## education9             0.207562   0.329951 975.859204   0.629   0.5295
## education10            0.043437   0.345794 975.523057   0.126   0.9001
## education11            0.290623   0.331902 974.543441   0.876   0.3814
## education12            0.287482   0.346767 975.974058   0.829   0.4073
## drug_useYes            0.087193   0.089324 975.441531   0.976   0.3292
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 20 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

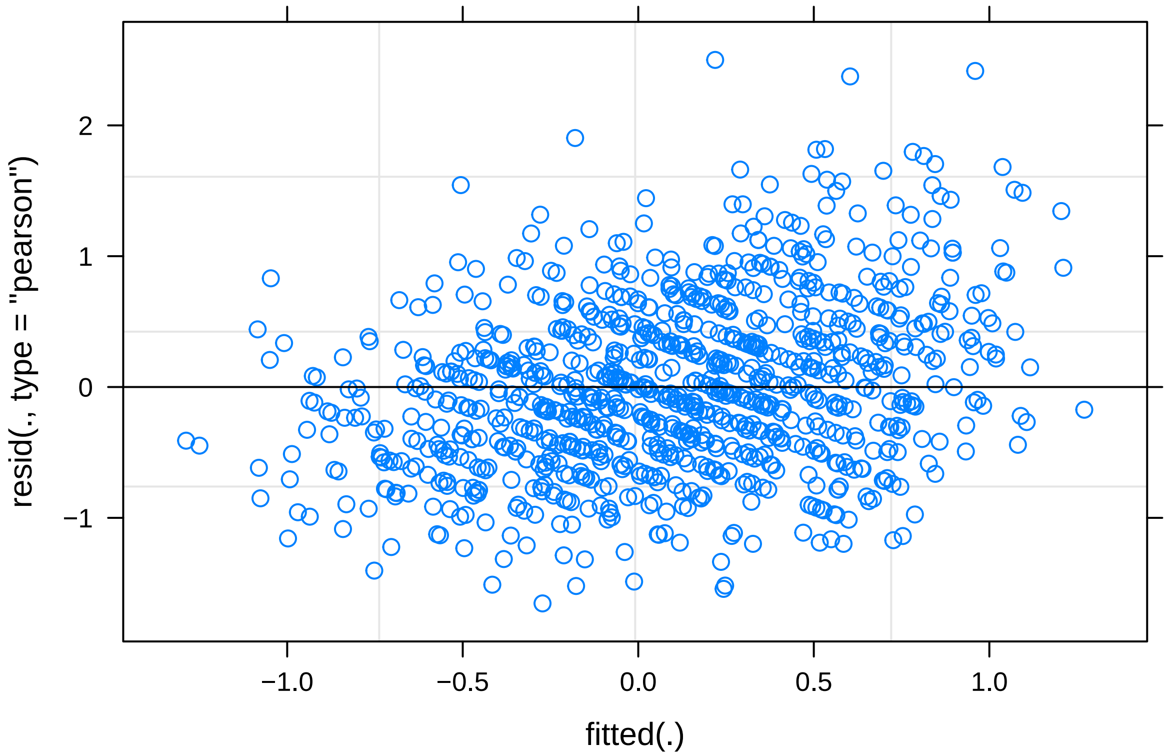
```
r.squaredGLMM(episodic_model_covariates)
```

```
##            R2m       R2c
## [1,] 0.2356284 0.3793891
```

After adjusting for covariates, threat and deprivation are still not significant predictors at the significance level of 0.05. The slope parameters are also fairly low. In the model, sex, age, and race comparing those who identify as black to those who identify as white, is significant. We should note that the random effects off grouping by family is not as significant as random effects only explain 18.8% of the variation not explained by fixed effects.

To evaluate model fit, we see that the marginal r^2 is 0.235 and the conditional r^2 is 0.3794. These values are very low and indicate poor model fit.

```
plot(episodic_model_covariates)
```



The residuals plot shows us that there is constant variance across fitted values, thus assumption is met. Good!

Let us now evaluate the interaction effect between aggregated drug use and trauma.

```
episodic_model_covariates_interactions <- lmer(episodic_memory ~ threat + deprivation + age + sex + race

summary(episodic_model_covariates_interactions)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## episodic_memory ~ threat + deprivation + age + sex + race + education +
##     drug_use + threat * drug_use + deprivation * drug_use + (1 |
##     family_id)
##    Data: midus
##
##      AIC      BIC   logLik deviance df.resid
##   2350.2   2467.4  -1151.1   2302.2      952
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3122 -0.6409 -0.0792  0.5617  3.5111
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
```

```
##  family_id (Intercept) 0.1186   0.3443
##  Residual              0.5040   0.7099
## Number of obs: 976, groups:  family_id, 842
##
## Fixed effects:
##                          Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)              1.041234   0.375785 968.905082   2.771   0.0057 **
## threat                  -0.007609   0.004542 957.879953  -1.675   0.0942 .
## deprivation              0.005945   0.006197 969.994268   0.959   0.3376
## age                     -0.022476   0.002286 822.765353  -9.834   <2e-16 ***
## sexFemale                0.579314   0.052898 934.594993  10.952   <2e-16 ***
## raceBlack               -0.402813   0.161874 895.715517  -2.488   0.0130 *
## raceNative American     -0.257435   0.229056 920.146501  -1.124   0.2614
## raceAsian               -0.132998   0.461023 967.379622  -0.288   0.7730
## raceOther               -0.154594   0.164584 970.634872  -0.939   0.3478
## education3              -0.425084   0.358128 975.634322  -1.187   0.2355
## education4              -0.482166   0.440830 954.344758  -1.094   0.2743
## education5              -0.109767   0.329824 975.923887  -0.333   0.7394
## education6              -0.045134   0.331572 975.914265  -0.136   0.8918
## education7              -0.012788   0.347644 975.840626  -0.037   0.9707
## education8               0.004624   0.336698 975.634617   0.014   0.9890
## education9               0.204025   0.330055 975.861549   0.618   0.5366
## education10              0.041706   0.345845 975.527917   0.121   0.9040
## education11              0.291525   0.332015 974.520496   0.878   0.3801
## education12              0.285085   0.346765 975.973258   0.822   0.4112
## drug_useYes             -0.036354   0.268157 971.786157  -0.136   0.8922
## threat:drug_useYes       0.007820   0.011735 973.064878   0.666   0.5053
## deprivation:drug_useYes -0.003249   0.017468 974.865082  -0.186   0.8525
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 22 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
r.squaredGLMM(episodic_model_covariates_interactions)
```

```
##            R2m       R2c
## [1,] 0.2360172 0.3815108
```

From the model we see that the interaction terms are not significant at the 0.05 significance level. This is our first indicator that the interaction effects between aggregated substance abuse and childhood trauma is not significant. We will now compare the two models.

```
anova(episodic_model_covariates,episodic_model_covariates_interactions, test="Chi")
```

```
## Data: midus
## Models:
## episodic_model_covariates: episodic_memory ~ threat + deprivation + age + sex + race + education + di
## episodic_model_covariates_interactions: episodic_memory ~ threat + deprivation + age + sex + race + e
##                                        npar    AIC    BIC  logLik deviance
```

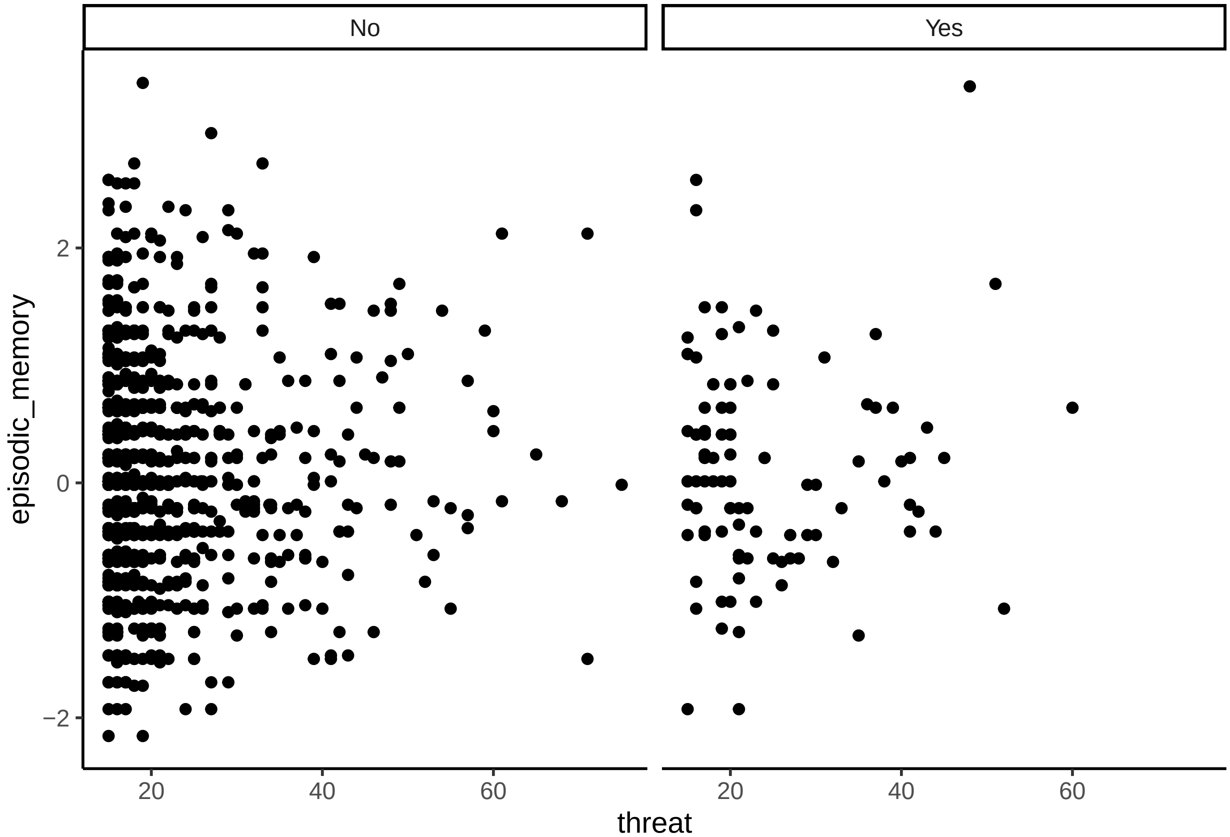
```
## episodic_model_covariates                  22 2346.8 2454.2 -1151.4   2302.8
## episodic_model_covariates_interactions   24 2350.2 2467.4 -1151.1   2302.2
##                                          Chisq Df Pr(>Chisq)
## episodic_model_covariates
## episodic_model_covariates_interactions 0.5523  2     0.7587
```

The AIC did not decrease, the BIC increased, and the p-value is well above 0.05. The values indicate that the model with interactions is not significantly better than the model without interaction terms. Thus by the law of parsimony, we would choose the model without interaction terms. Though regression analysis shows us the interaction is not significant, lets conduct additional analysis.

```
ggplot(aes(threat,episodic_memory), data = midus) +
  geom_point() +
  facet_wrap(~ drug_use) +
  theme_classic()
```

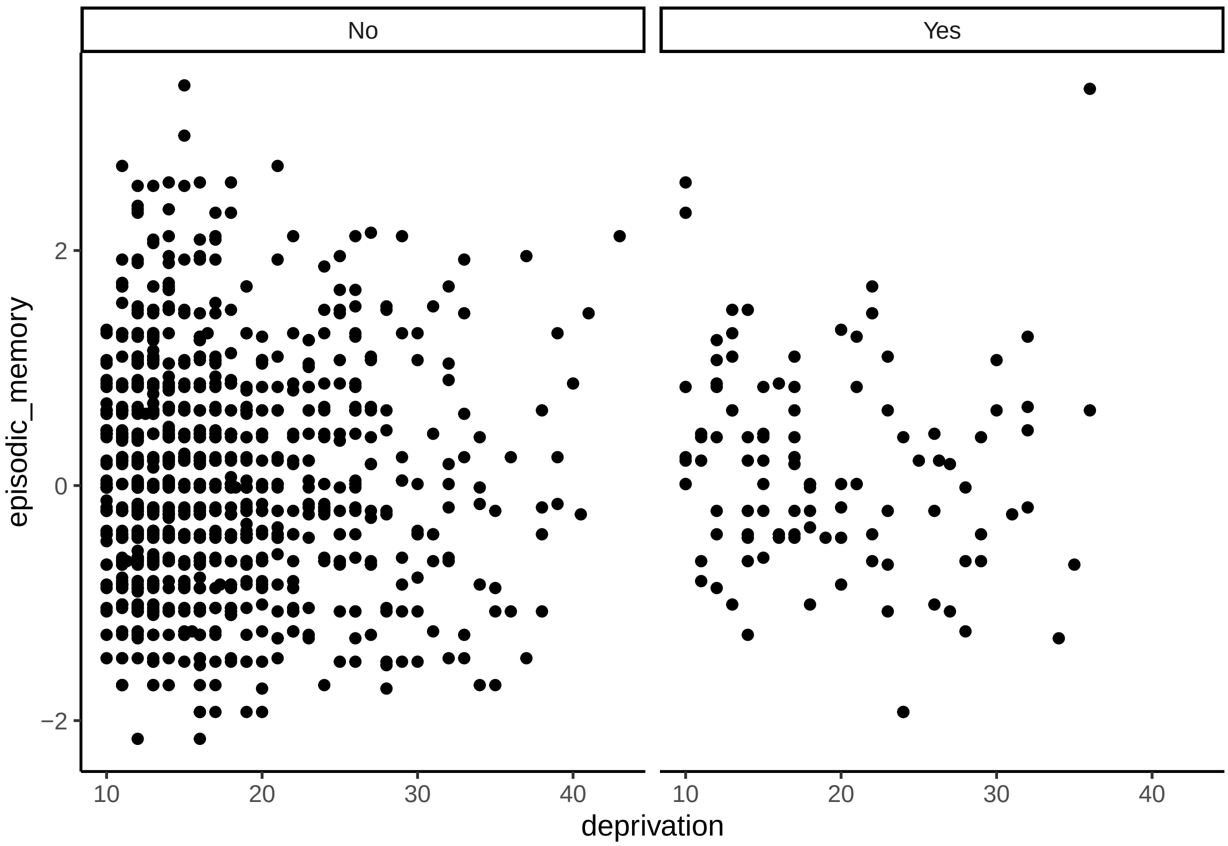
```
## Don't know how to automatically pick scale for object of type haven_labelled/vctrs_vctr/double. Defa
```

```
## Warning: Removed 7 rows containing missing values (geom_point).
```




```
ggplot(aes(deprivation,episodic_memory), data = midus) +
  geom_point() +
  facet_wrap(~ drug_use) +
  theme_classic()
```

```
## Don't know how to automatically pick scale for object of type haven_labelled/vctrs_vctr/double. Defa

## Warning: Removed 4 rows containing missing values (geom_point).
```



The plots about indicate that the correlation between childhood threat vs episodic, childhood deprivation vs episodic memory, does not significantly change by indication of drug use.

We will now investigate estimated marginal means.

```
emm_episodic <- emmeans(episodic_model_covariates_interactions, pairwise ~ threat*drug_use, cov.keep = 
  threat = c(m_threat-sd_threat, m_threat, m_threat+sd_threat)), level = 0.95)
summary(emm_episodic)
```

```
## $emmeans
##  threat drug_use emmean    SE  df lower.CL upper.CL
##    12.4 No       -0.121 0.125 995   -0.368  0.12474
##    21.5 No       -0.190 0.121 989   -0.428  0.04677
##    30.6 No       -0.259 0.130 978   -0.515 -0.00379
##    12.4 Yes      -0.116 0.182 995   -0.473  0.24154
##    21.5 Yes      -0.114 0.145 993   -0.397  0.17008
##    30.6 Yes      -0.112 0.170 991   -0.445  0.22159
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
```

```
## $contrasts
##  contrast                                    estimate     SE  df t.ratio
##  12.4356734406012 No - 21.5030881017257 No    0.06899 0.0417 979   1.653
##  12.4356734406012 No - 30.5705027628503 No    0.13799 0.0835 979   1.653
##  12.4356734406012 No - 12.4356734406012 Yes  -0.00583 0.1466 999  -0.040
##  12.4356734406012 No - 21.5030881017257 Yes  -0.00774 0.1015 998  -0.076
##  12.4356734406012 No - 30.5705027628503 Yes  -0.00966 0.1388 995  -0.070
##  21.5030881017257 No - 30.5705027628503 No    0.06899 0.0417 979   1.653
##  21.5030881017257 No - 12.4356734406012 Yes  -0.07482 0.1417 998  -0.528
##  21.5030881017257 No - 21.5030881017257 Yes  -0.07674 0.0930 998  -0.825
##  21.5030881017257 No - 30.5705027628503 Yes  -0.07865 0.1319 996  -0.597
##  30.5705027628503 No - 12.4356734406012 Yes  -0.14381 0.1488 996  -0.967
##  30.5705027628503 No - 21.5030881017257 Yes  -0.14573 0.1024 998  -1.423
##  30.5705027628503 No - 30.5705027628503 Yes  -0.14764 0.1378 996  -1.071
##  12.4356734406012 Yes - 21.5030881017257 Yes -0.00192 0.1004 993  -0.019
##  12.4356734406012 Yes - 30.5705027628503 Yes -0.00383 0.2008 993  -0.019
##  21.5030881017257 Yes - 30.5705027628503 Yes -0.00192 0.1004 993  -0.019
##  p.value
##   0.5635
##   0.5635
##   1.0000
##   1.0000
##   1.0000
##   0.5635
##   0.9951
##   0.9629
##   0.9913
##   0.9284
##   0.7129
##   0.8928
##   1.0000
##   1.0000
##   1.0000
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
summary(emtrends(episodic_model_covariates_interactions, pairwise ~ drug_use, var = "threat", level = 0
```

```
## $emtrends
##  drug_use threat.trend     SE  df lower.CL upper.CL
##  No          -0.007609 0.0046 979  -0.0166  0.00142
##  Yes          0.000211 0.0111 993  -0.0215  0.02194
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE  df t.ratio p.value
##  No - Yes -0.00782 0.0119 995  -0.658  0.5105
##
## Results are averaged over the levels of: sex, race, education
```

```
## Degrees-of-freedom method: kenward-roger
```

```
emm_episodic_deprivation <- emmeans(episodic_model_covariates_interactions, pairwise ~ deprivation*drug_
  deprivation = c(m_deprivation-sd_deprivation, m_deprivation, m_deprivation+sd_deprivation)), level = 0
summary(emm_deprivation)
```

```
## $emmeans
##  deprivation drug_use emmean    SE  df lower.CL upper.CL
##         10.8 No       -0.408 0.132 942   -0.667   -0.149
##         17.1 No       -0.412 0.122 941   -0.652   -0.172
##         23.4 No       -0.416 0.125 946   -0.661   -0.172
##         10.8 Yes      -0.521 0.185 949   -0.884   -0.158
##         17.1 Yes      -0.496 0.146 949   -0.783   -0.209
##         23.4 Yes      -0.471 0.175 951   -0.815   -0.127
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                    estimate     SE  df t.ratio
##  10.8228179885588 No - 17.1007246376812 No    0.00417 0.0397 953   0.105
##  10.8228179885588 No - 23.3786312868035 No    0.00834 0.0794 953   0.105
##  10.8228179885588 No - 10.8228179885588 Yes   0.11299 0.1508 954   0.749
##  10.8228179885588 No - 17.1007246376812 Yes   0.08788 0.1013 952   0.868
##  10.8228179885588 No - 23.3786312868035 Yes   0.06277 0.1410 953   0.445
##  17.1007246376812 No - 23.3786312868035 No    0.00417 0.0397 953   0.105
##  17.1007246376812 No - 10.8228179885588 Yes   0.10882 0.1460 953   0.745
##  17.1007246376812 No - 17.1007246376812 Yes   0.08371 0.0934 947   0.897
##  17.1007246376812 No - 23.3786312868035 Yes   0.05860 0.1350 954   0.434
##  23.3786312868035 No - 10.8228179885588 Yes   0.10465 0.1518 953   0.689
##  23.3786312868035 No - 17.1007246376812 Yes   0.07954 0.1016 943   0.783
##  23.3786312868035 No - 23.3786312868035 Yes   0.05443 0.1404 954   0.388
##  10.8228179885588 Yes - 17.1007246376812 Yes -0.02511 0.1051 952  -0.239
##  10.8228179885588 Yes - 23.3786312868035 Yes -0.05022 0.2103 952  -0.239
##  17.1007246376812 Yes - 23.3786312868035 Yes -0.02511 0.1051 952  -0.239
##  p.value
##   1.0000
##   1.0000
##   0.9756
##   0.9541
##   0.9978
##   1.0000
##   0.9762
##   0.9473
##   0.9980
##   0.9831
##   0.9705
##   0.9989
##   0.9999
##   0.9999
##   0.9999
##
## Results are averaged over the levels of: sex, race, education
```

```
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
summary(emtrends(episodic_model_covariates_interactions, pairwise ~ drug_use, var = "deprivation", level
```

```
## $emtrends
##  drug_use deprivation.trend      SE  df lower.CL upper.CL
##  No                 0.00595 0.00628 992 -0.00638   0.0183
##  Yes                0.00270 0.01661 997 -0.02989   0.0353
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE  df t.ratio p.value
##  No - Yes  0.00325 0.0177 997   0.184  0.8543
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
```

From the estimated means analysis, we see there are not significant differences in mean episodic memory z scores at different levels of deprivation or threat when controlling for substance use. Thus from the estimated marginal means, regression analysis, and visualizations, we conclude interaction effects between childhood trauma and substance abuse is not significant.

Lets now look at the interaction effects if we break down by specific substances.

```
episodic_model_substances <- lmer(episodic_memory ~ age + sex + education + race +tranquilizer + stimula
```

```
## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
```

```
summary(episodic_model_substances)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: episodic_memory ~ age + sex + education + race + tranquilizer +
##     stimulants + painkillers + depressants + inhallants + cocaine +
##     hallucinogens + threat + deprivation + (1 | family_id)
##    Data: midus
##
##      AIC      BIC   logLik deviance df.resid
##   2346.8   2478.5  -1146.4   2292.8      944
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3191 -0.6410 -0.0750  0.5652  3.4958
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.1197   0.3459
##  Residual              0.5045   0.7103
```

```
## Number of obs: 971, groups:  family_id, 839
##
## Fixed effects:
##                       Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)          1.087e+00  4.456e-01  9.489e+02   2.439   0.0149 *
## age                 -2.280e-02  2.312e-03  8.220e+02  -9.859   <2e-16 ***
## sexFemale            5.767e-01  5.318e-02  9.304e+02  10.844   <2e-16 ***
## education3          -4.227e-01  4.282e-01  9.616e+02  -0.987   0.3238
## education4          -5.289e-01  4.990e-01  9.688e+02  -1.060   0.2895
## education5          -1.443e-01  4.043e-01  9.611e+02  -0.357   0.7212
## education6          -8.813e-02  4.059e-01  9.615e+02  -0.217   0.8282
## education7          -6.594e-02  4.190e-01  9.630e+02  -0.157   0.8750
## education8          -3.552e-02  4.100e-01  9.630e+02  -0.087   0.9310
## education9           1.600e-01  4.046e-01  9.614e+02   0.395   0.6926
## education10          7.403e-03  4.178e-01  9.641e+02   0.018   0.9859
## education11          2.471e-01  4.069e-01  9.618e+02   0.607   0.5438
## education12          2.468e-01  4.186e-01  9.616e+02   0.590   0.5556
## raceBlack           -3.972e-01  1.643e-01  8.909e+02  -2.418   0.0158 *
## raceNative American -2.512e-01  2.290e-01  9.250e+02  -1.097   0.2730
## raceAsian           -1.338e-01  4.613e-01  9.624e+02  -0.290   0.7719
## raceOther           -1.633e-01  1.679e-01  9.659e+02  -0.973   0.3309
## tranquilizerYes      4.068e-02  1.541e-01  9.704e+02   0.264   0.7918
## stimulantsYes        8.571e-04  1.871e-01  9.676e+02   0.005   0.9963
## painkillersYes      -2.022e-01  2.974e-01  9.635e+02  -0.680   0.4967
## depressantsYes       1.170e-01  1.301e-01  9.704e+02   0.899   0.3688
## inhallantsYes        7.234e-02  2.338e-01  9.698e+02   0.309   0.7571
## cocaineYes          -7.958e-02  3.538e-01  9.621e+02  -0.225   0.8221
## threat              -6.688e-03  4.255e-03  9.494e+02  -1.572   0.1164
## deprivation          5.861e-03  5.854e-03  9.647e+02   1.001   0.3170
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 25 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it

## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
```

```
r.squaredGLMM(episodic_model_substances)
```

```
##            R2m       R2c
## [1,] 0.2350387 0.3816996
```

From the model above, we see none of the model parameters for the specific substances are not significant at the 0.05 level. In this model, the significant predictors are age, sex and race comparing those who identify as black with those who identify as white. WThe r^2 values are fairly low and the deviance is fairly high - two indications of poor model fit. Lets now look at the interactions of trauma to individual substances.

```
episodic_model_substances_interactions <- lmer(composite_cognition ~ age + sex + education + race +tranq
```

```
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
summary(episodic_model_substances_interactions)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: composite_cognition ~ age + sex + education + race + tranquilizer +
##     stimulants + painkillers + depressants + inhallants + cocaine +
##     hallucinogens + threat + deprivation + stimulants * threat +
##     stimulants * deprivation + painkillers * threat + painkillers *
##     deprivation + inhallants * threat + inhallants * deprivation +
##     cocaine * threat + cocaine * deprivation + hallucinogens *
##     threat + hallucinogens * deprivation + tranquilizer * threat +
##     tranquilizer * deprivation + (1 | family_id)
##    Data: midus
##
##      AIC      BIC   logLik deviance df.resid
##   2370.3   2550.8  -1148.2   2296.3      934
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.38897 -0.54313 -0.01659  0.50538  2.59604
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2519   0.5019
##  Residual              0.3860   0.6213
## Number of obs: 971, groups:  family_id, 839
##
## Fixed effects:
##                            Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)               9.963e-01  4.541e-01  9.270e+02   2.194 0.028486
## age                      -3.226e-02  2.389e-03  8.380e+02 -13.502  < 2e-16
## sexFemale                 1.235e-01  5.410e-02  9.573e+02   2.283 0.022655
## education3                2.942e-01  4.344e-01  9.444e+02   0.677 0.498375
## education4                1.622e-01  4.988e-01  9.671e+02   0.325 0.745043
## education5                6.523e-01  4.095e-01  9.372e+02   1.593 0.111475
## education6                6.891e-01  4.110e-01  9.389e+02   1.677 0.093960
## education7                8.453e-01  4.239e-01  9.434e+02   1.994 0.046414
## education8                7.537e-01  4.150e-01  9.430e+02   1.816 0.069649
## education9                1.222e+00  4.097e-01  9.382e+02   2.983 0.002931
## education10               1.098e+00  4.227e-01  9.463e+02   2.597 0.009564
## education11               1.353e+00  4.120e-01  9.397e+02   3.285 0.001057
## education12               1.356e+00  4.236e-01  9.424e+02   3.201 0.001417
## raceBlack                -7.096e-01  1.743e-01  8.770e+02  -4.070 5.13e-05
## raceNative American       2.338e-01  2.362e-01  9.652e+02   0.990 0.322349
## raceAsian                -8.159e-01  4.666e-01  9.391e+02  -1.749 0.080657
## raceOther                -5.774e-01  1.693e-01  9.565e+02  -3.411 0.000674
## tranquilizerYes           4.141e-01  5.115e-01  9.682e+02   0.810 0.418412
## stimulantsYes             2.140e-01  6.356e-01  9.682e+02   0.337 0.736401
## painkillersYes           -1.343e+00  1.298e+00  9.414e+02  -1.035 0.300889
## depressantsYes           -1.210e-01  1.341e-01  9.629e+02  -0.902 0.367093
## inhallantsYes             3.117e-02  8.573e-01  9.107e+02   0.036 0.971002
## cocaineYes                3.243e+00  3.556e+00  9.383e+02   0.912 0.362052
## threat                   -4.329e-03  4.486e-03  9.668e+02  -0.965 0.334813
```

```
## deprivation                   9.110e-05  6.147e-03  9.708e+02   0.015 0.988179
## stimulantsYes:threat         -1.615e-02  3.189e-02  9.558e+02  -0.506 0.612752
## stimulantsYes:deprivation     1.132e-02  3.774e-02  9.562e+02   0.300 0.764275
## painkillersYes:threat        -1.594e-02  4.252e-02  9.444e+02  -0.375 0.707815
## painkillersYes:deprivation    8.678e-02  8.510e-02  9.407e+02   1.020 0.308096
## inhallantsYes:threat         -3.212e-02  2.166e-02  9.533e+02  -1.483 0.138500
## inhallantsYes:deprivation     2.351e-02  4.127e-02  9.708e+02   0.570 0.569057
## cocaineYes:threat            -8.710e-03  4.773e-02  9.406e+02  -0.182 0.855236
## cocaineYes:deprivation       -1.862e-01  1.843e-01  9.394e+02  -1.010 0.312683
## tranquilizerYes:threat        2.076e-02  2.641e-02  9.619e+02   0.786 0.431911
## tranquilizerYes:deprivation -3.850e-02  3.500e-02  9.649e+02  -1.100 0.271664
##
## (Intercept)                 *
## age                         ***
## sexFemale                   *
## education3
## education4
## education5
## education6                  .
## education7                  *
## education8                  .
## education9                  **
## education10                 **
## education11                 **
## education12                 **
## raceBlack                   ***
## raceNative American
## raceAsian                   .
## raceOther                   ***
## tranquilizerYes
## stimulantsYes
## painkillersYes
## depressantsYes
## inhallantsYes
## cocaineYes
## threat
## deprivation
## stimulantsYes:threat
## stimulantsYes:deprivation
## painkillersYes:threat
## painkillersYes:deprivation
## inhallantsYes:threat
## inhallantsYes:deprivation
## cocaineYes:threat
## cocaineYes:deprivation
## tranquilizerYes:threat
## tranquilizerYes:deprivation
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 35 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

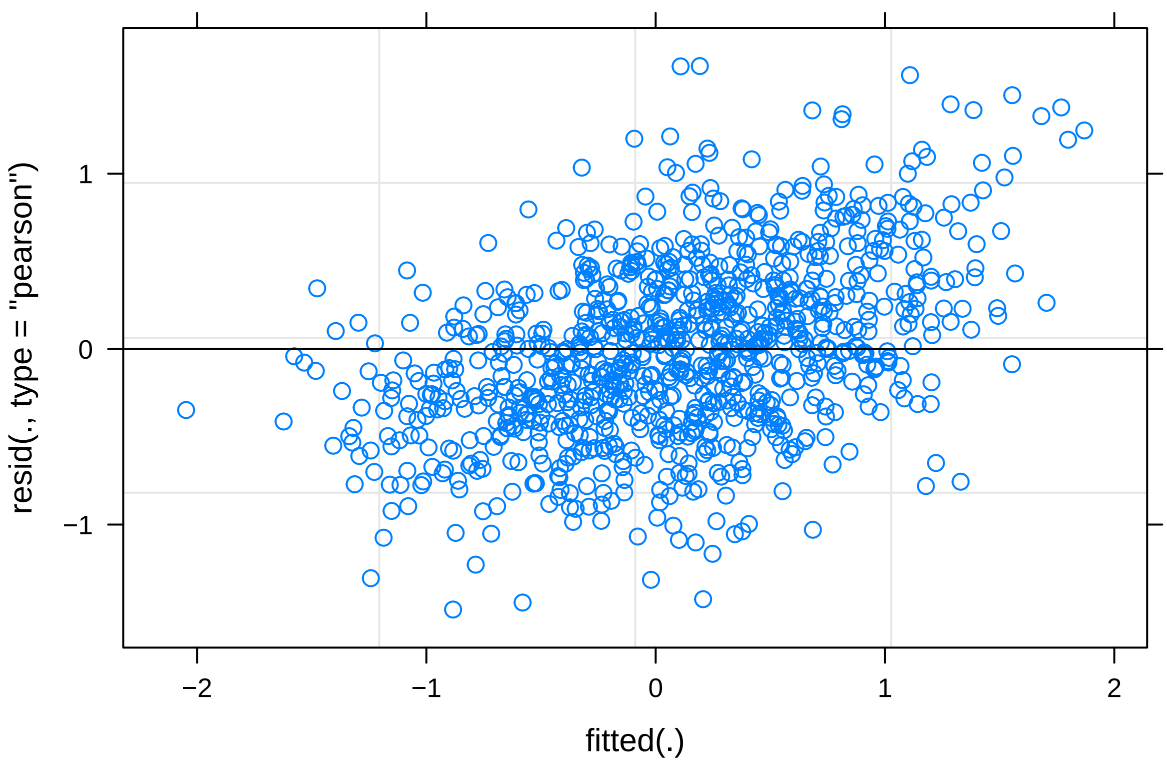
```
## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
r.squaredGLMM(episodic_model_substances_interactions)
```

```
##            R2m       R2c
## [1,] 0.3150531 0.5855151
```

The individual slope parameters for the interaction terms are not significant at the 0.05 significance level. Though the individual slope parameters are not significant we can look at model fit. From the model fit, we see that the marginal R^2 value is 0.315 and the conditionoal r^2 value is 0.5855 - this is OK but it is also significantly better than the model without interactions. Let's look at the residuals plot to confirm our assumptions.

```
plot(episodic_model_substances_interactions)
```



The residuals plot confirm fairly constant variance across the range of fitted values, thus the assumption is met. Good!

We will now compare the models.

```
anova(episodic_model_substances,episodic_model_substances_interactions,test="Chi")
```

```
## Data: midus
## Models:
```

```
## episodic_model_substances: episodic_memory ~ age + sex + education + race + tranquilizer + stimulants
## episodic_model_substances_interactions: composite_cognition ~ age + sex + education + race + tranquil
##                                        npar    AIC    BIC  logLik deviance
## episodic_model_substances                27 2346.8 2478.5 -1146.4   2292.8
## episodic_model_substances_interactions   37 2370.3 2550.8 -1148.2   2296.3
##                                        Chisq Df Pr(>Chisq)
## episodic_model_substances
## episodic_model_substances_interactions     0 10          1
```

From the summary we see that the AIC, BIC and deviance significantly decreases. Moreover the p-value is significantly lower than 0.05, thus we conclude the model with interactions is significantly better.Thus we would choose the model with interactions as the final model.

Conclusions

From conducting regression analysis, we actually were able to gather some interesting results. When looking at aggregated substance abuse, we did not find significant results. The slope parameter estimate for drug use was not particularly high nor was it significant at the 0.05 significance level. Then after running a model with interaction effects, we found none of the interaction terms to be significant. Finally, after comparing the two models, the model with interaction terms was not significantly better, thus we conclude the interaction effect between overall substance abuse and childhood trauma is not significant. However, when breaking down substance abuse by substance, we saw different results. After running a model that included specific substances as parameters, we saw some significant results. Though none of the slope parameters had a significant p-value, many of the parameter estimates indicated a major difference in episodic memory based on substance use. Moreover, we found that the model with interaction effects also was significantly different than the model with no interactions. Thus there is indication that the interaction effects are in fact significant. In the context of the study, we conclude there is a possible moderation effect from individual substance abuse on the association between childhood trauma and episodic memory.

Executive Function

We will now conduct moderation analysis with executive function z scores as the outcome variable.

Let's start by looking at the unadjusted relationship between childhood trauma and executive functioning.

```r
null_model_exec <- lmer(executive_func ~ threat + deprivation + (1|family_id), data=midus)

summary(null_model_exec)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: executive_func ~ threat + deprivation + (1 | family_id)
##    Data: midus
##
## REML criterion at convergence: 2454.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.2594 -0.4471  0.0001  0.4322  2.4856
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
```

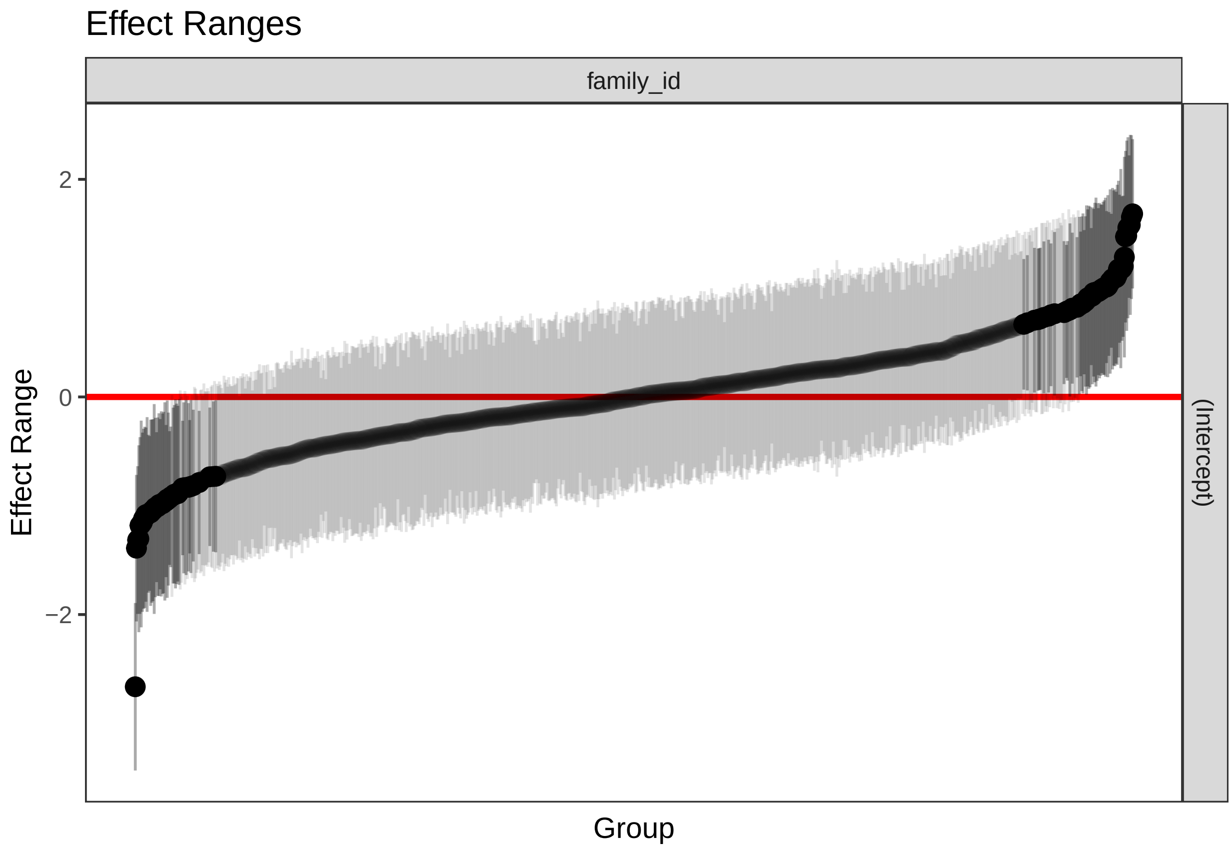
```
##  family_id (Intercept) 0.4458   0.6677
##  Residual              0.3025   0.5500
## Number of obs: 979, groups:  family_id, 844
##
## Fixed effects:
##              Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)   0.345884   0.086155 966.811260   4.015 6.41e-05 ***
## threat        0.005031   0.004397 975.136843   1.144   0.2528
## deprivation  -0.013564   0.006034 952.832225  -2.248   0.0248 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) threat
## threat      -0.296
## deprivation -0.474 -0.661
```

```
r.squaredGLMM(null_model_exec)
```

```
##              R2m       R2c
## [1,] 0.005103812 0.5978089
```

From the null model, we see that deprivation is a significant predictor in executive functioning score. We would interpret the slope parameter as for every point increase in deprivation score, executive functioning decreases on average by 0.014. We also conclude that the random effects due to family are significant as it explains ~60% of the variation not explained by the fixed effects. If we look at model fit, we see that the marginal r^2 is 0.005, while the condition r^2 is 0.598 - not great.

```
plotREsim(REsim(null_model_exec))
```



The effects plot indicates the presence of an outlier in the dataset.

Let's look at the association of childhood trauma and executive functioning when adjusted for covariates and confounders.

```
exec_model_covariates <- lmer(executive_func ~ threat + deprivation + age + sex + race + education + dru

summary(exec_model_covariates)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## executive_func ~ threat + deprivation + age + sex + race + education +
##     drug_use + (1 | family_id)
##    Data: midus
##
##      AIC      BIC   logLik deviance df.resid
##   2163.9   2271.3  -1060.0   2119.9      954
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.3006 -0.4658 -0.0239  0.4569  2.6190
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2542   0.5042
```

```
##  Residual              0.2784   0.5276
## Number of obs: 976, groups:  family_id, 842
##
## Fixed effects:
##                       Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)          1.193e+00  3.411e-01  9.752e+02   3.498 0.000491 ***
## threat              -4.963e-04  3.889e-03  9.747e+02  -0.128 0.898471
## deprivation         -4.807e-03  5.303e-03  9.729e+02  -0.906 0.364910
## age                 -2.723e-02  2.155e-03  8.445e+02 -12.633  < 2e-16 ***
## sexFemale           -7.388e-02  4.883e-02  9.694e+02  -1.513 0.130567
## raceBlack           -6.862e-01  1.514e-01  8.787e+02  -4.532 6.65e-06 ***
## raceNative American  3.291e-01  2.101e-01  9.748e+02   1.567 0.117553
## raceAsian           -7.173e-01  4.260e-01  9.286e+02  -1.684 0.092550 .
## raceOther           -5.883e-01  1.514e-01  9.562e+02  -3.886 0.000109 ***
## education3           2.228e-01  3.245e-01  9.688e+02   0.687 0.492430
## education4           3.056e-02  3.922e-01  8.638e+02   0.078 0.937916
## education5           5.036e-01  2.989e-01  9.651e+02   1.685 0.092291 .
## education6           4.728e-01  3.004e-01  9.642e+02   1.574 0.115778
## education7           6.644e-01  3.150e-01  9.649e+02   2.109 0.035174 *
## education8           5.577e-01  3.044e-01  9.620e+02   1.832 0.067241 .
## education9           9.677e-01  2.989e-01  9.632e+02   3.238 0.001246 **
## education10          8.508e-01  3.129e-01  9.604e+02   2.719 0.006670 **
## education11          1.062e+00  2.998e-01  9.549e+02   3.541 0.000417 ***
## education12          1.078e+00  3.142e-01  9.633e+02   3.429 0.000631 ***
## drug_useYes         -1.009e-01  8.088e-02  9.635e+02  -1.247 0.212628
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 20 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
r.squaredGLMM(exec_model_covariates)
```

```
##            R2m       R2c
## [1,] 0.2906794 0.6292538
```

After adjusting for the different covariates, threat and deprivation would not be significant predictors at significance level of 0.05. Moreover the parameter estimates for both threat and deprivation are quite low.Though the slope paramter for substance abuse is not significant at 0.05 significance level, it should be noted the parameter estimate is high. The model fit however is not bad.

```
exec_model_covariates_interactions <- lmer(executive_func ~ threat + deprivation + age + sex + race + ed

summary(exec_model_covariates_interactions)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## executive_func ~ threat + deprivation + age + sex + race + education +
##     drug_use + threat * drug_use + deprivation * drug_use + (1 |
```

```
##     family_id)
##    Data: midus
##
##      AIC      BIC   logLik deviance df.resid
##   2167.7   2284.9  -1059.8   2119.7      952
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2973 -0.4645 -0.0246  0.4571  2.6354
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2548   0.5047
##  Residual              0.2778   0.5271
## Number of obs: 976, groups:  family_id, 842
##
## Fixed effects:
##                          Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)             1.205e+00  3.433e-01  9.751e+02   3.512 0.000466 ***
## threat                 -7.830e-07  4.163e-03  9.760e+02   0.000 0.999850
## deprivation            -5.695e-03  5.642e-03  9.673e+02  -1.009 0.312996
## age                    -2.730e-02  2.162e-03  8.424e+02 -12.630  < 2e-16 ***
## sexFemale              -7.337e-02  4.884e-02  9.697e+02  -1.502 0.133323
## raceBlack              -6.909e-01  1.517e-01  8.787e+02  -4.553 6.03e-06 ***
## raceNative American     3.325e-01  2.115e-01  9.712e+02   1.572 0.116285
## raceAsian              -7.106e-01  4.262e-01  9.287e+02  -1.667 0.095813 .
## raceOther              -5.904e-01  1.515e-01  9.561e+02  -3.898 0.000104 ***
## education3              2.217e-01  3.254e-01  9.688e+02   0.682 0.495697
## education4              3.169e-02  3.923e-01  8.643e+02   0.081 0.935636
## education5              4.997e-01  2.990e-01  9.648e+02   1.672 0.094946 .
## education6              4.685e-01  3.005e-01  9.640e+02   1.559 0.119322
## education7              6.606e-01  3.151e-01  9.646e+02   2.097 0.036279 *
## education8              5.525e-01  3.049e-01  9.616e+02   1.812 0.070261 .
## education9              9.646e-01  2.990e-01  9.629e+02   3.226 0.001298 **
## education10             8.470e-01  3.130e-01  9.601e+02   2.706 0.006929 **
## education11             1.057e+00  3.000e-01  9.544e+02   3.524 0.000445 ***
## education12             1.075e+00  3.143e-01  9.631e+02   3.421 0.000649 ***
## drug_useYes            -1.482e-01  2.415e-01  9.413e+02  -0.614 0.539615
## threat:drug_useYes     -3.718e-03  1.076e-02  9.683e+02  -0.345 0.729846
## deprivation:drug_useYes  7.270e-03  1.595e-02  9.758e+02   0.456 0.648639
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 22 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
r.squaredGLMM(exec_model_covariates_interactions)
```

```
##            R2m       R2c
## [1,] 0.2909218 0.6300921
```

The interaction terms are not significant at the 0.05 significance level. This is the first indication that the interaction effects are not significant. We will now compare the models.

```
anova(exec_model_covariates,exec_model_covariates_interactions)
```

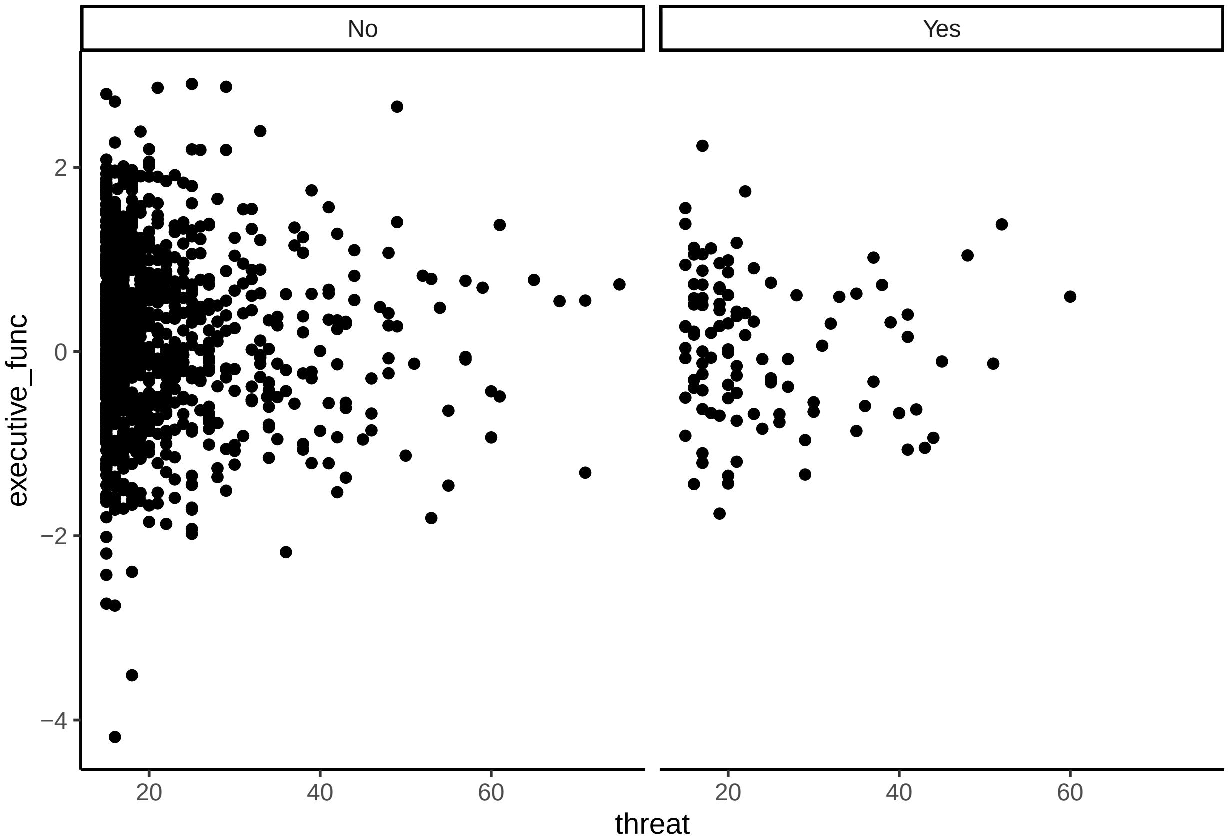
```
## Data: midus
## Models:
## exec_model_covariates: executive_func ~ threat + deprivation + age + sex + race + education + drug_us
## exec_model_covariates_interactions: executive_func ~ threat + deprivation + age + sex + race + educat
##                                    npar    AIC    BIC  logLik deviance  Chisq
## exec_model_covariates                22 2163.9 2271.3 -1060.0   2119.9
## exec_model_covariates_interactions   24 2167.7 2284.9 -1059.8   2119.7 0.2106
##                                    Df Pr(>Chisq)
## exec_model_covariates
## exec_model_covariates_interactions  2        0.9
```

The AIC value does not decrease, BIC increases, and p-value is well above 0.05. The values indicate that the model with interactions is not significantly better than the model without interactions. Based on law of parsimony we would choose the model without interactions as our final model. To further evaluate the interaction effects, we will conduct additional analysis.

```
ggplot(aes(threat,executive_func), data = midus) +
  geom_point() +
  facet_wrap(~ drug_use) +
  theme_classic()
```

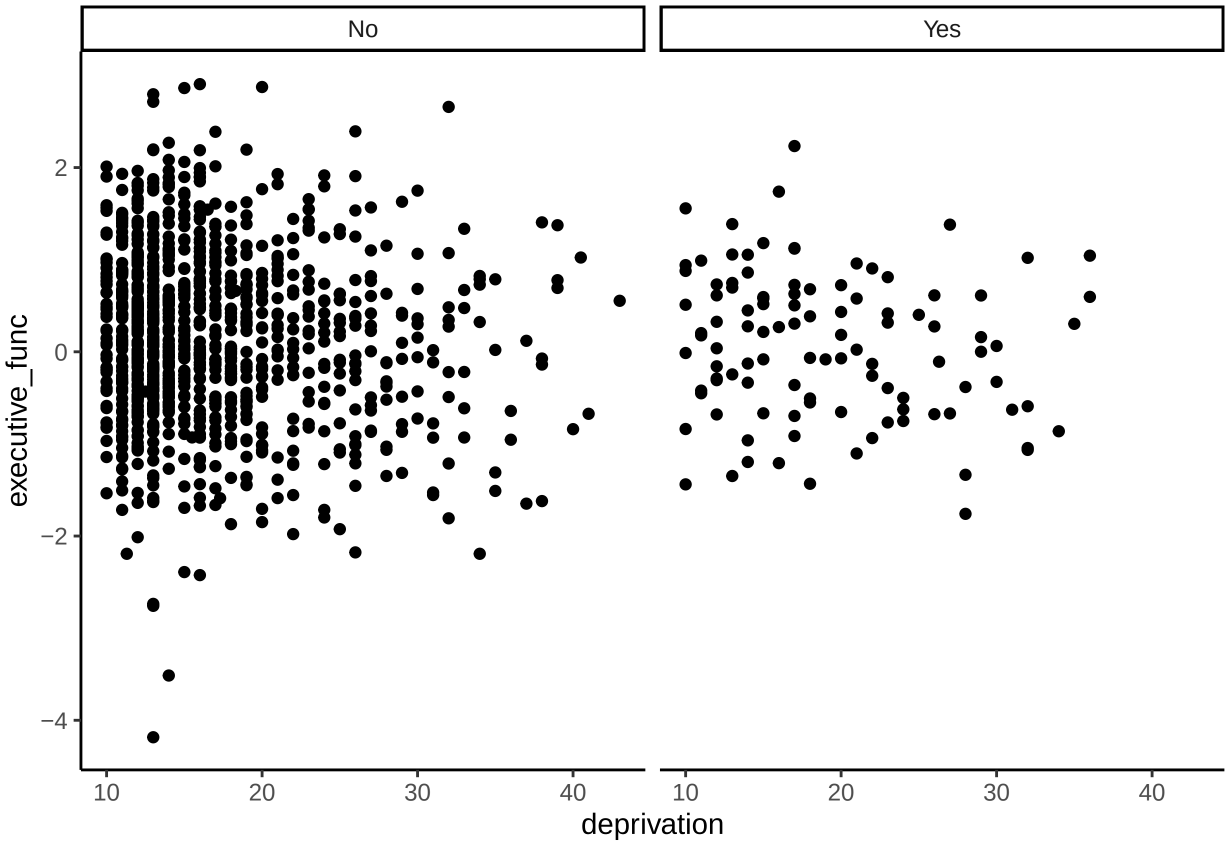
```
## Don't know how to automatically pick scale for object of type haven_labelled/vctrs_vctr/double. Defau
```

```
## Warning: Removed 7 rows containing missing values (geom_point).
```




```
ggplot(aes(deprivation,executive_func), data = midus) +
  geom_point() +
  facet_wrap(~ drug_use) +
  theme_classic()
```

```
## Don't know how to automatically pick scale for object of type haven_labelled/vctrs_vctr/double. Defau

## Warning: Removed 4 rows containing missing values (geom_point).
```



The plots above show that the correlation between deprivation vs executive function and threat vs executive functioning does not change significantly when controlling for substance abuse.

```
emm_exec <- emmeans(exec_model_covariates_interactions, pairwise ~ threat*drug_use, cov.keep = 3, at = l
  threat = c(m_threat-sd_threat, m_threat, m_threat+sd_threat)), level = 0.95)
summary(emm_episodic)
```

```
## $emmeans
##  threat drug_use emmean    SE  df lower.CL upper.CL
##    12.4 No       -0.121 0.125 995   -0.368  0.12474
##    21.5 No       -0.190 0.121 989   -0.428  0.04677
##    30.6 No       -0.259 0.130 978   -0.515 -0.00379
##    12.4 Yes      -0.116 0.182 995   -0.473  0.24154
##    21.5 Yes      -0.114 0.145 993   -0.397  0.17008
##    30.6 Yes      -0.112 0.170 991   -0.445  0.22159
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                     estimate     SE  df t.ratio
##  12.4356734406012 No - 21.5030881017257 No     0.06899 0.0417 979   1.653
##  12.4356734406012 No - 30.5705027628503 No     0.13799 0.0835 979   1.653
##  12.4356734406012 No - 12.4356734406012 Yes   -0.00583 0.1466 999  -0.040
##  12.4356734406012 No - 21.5030881017257 Yes   -0.00774 0.1015 998  -0.076
```

```
##  12.4356734406012 No - 30.5705027628503 Yes  -0.00966 0.1388 995  -0.070
##  21.5030881017257 No - 30.5705027628503 No    0.06899 0.0417 979   1.653
##  21.5030881017257 No - 12.4356734406012 Yes  -0.07482 0.1417 998  -0.528
##  21.5030881017257 No - 21.5030881017257 Yes  -0.07674 0.0930 998  -0.825
##  21.5030881017257 No - 30.5705027628503 Yes  -0.07865 0.1319 996  -0.597
##  30.5705027628503 No - 12.4356734406012 Yes  -0.14381 0.1488 996  -0.967
##  30.5705027628503 No - 21.5030881017257 Yes  -0.14573 0.1024 998  -1.423
##  30.5705027628503 No - 30.5705027628503 Yes  -0.14764 0.1378 996  -1.071
##  12.4356734406012 Yes - 21.5030881017257 Yes -0.00192 0.1004 993  -0.019
##  12.4356734406012 Yes - 30.5705027628503 Yes -0.00383 0.2008 993  -0.019
##  21.5030881017257 Yes - 30.5705027628503 Yes -0.00192 0.1004 993  -0.019
##  p.value
##   0.5635
##   0.5635
##   1.0000
##   1.0000
##   1.0000
##   0.5635
##   0.9951
##   0.9629
##   0.9913
##   0.9284
##   0.7129
##   0.8928
##   1.0000
##   1.0000
##   1.0000
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
summary(emtrends(exec_model_covariates_interactions, pairwise ~ drug_use, var = "threat", level = 0.95)
```

```
## $emtrends
##  drug_use threat.trend      SE  df lower.CL upper.CL
##  No          -7.83e-07 0.00422 998 -0.00828  0.00828
##  Yes         -3.72e-03 0.01018 981 -0.02370  0.01626
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE  df t.ratio p.value
##  No - Yes  0.00372 0.0109 991   0.341  0.7330
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
```

```
emm_exec_deprivation <- emmeans(exec_model_covariates_interactions, pairwise ~ deprivation*drug_use, co
  deprivation = c(m_deprivation-sd_deprivation, m_deprivation, m_deprivation+sd_deprivation)), level = (
summary(emm_deprivation)
```

```
## $emmeans
##  deprivation drug_use emmean    SE  df lower.CL upper.CL
##         10.8 No       -0.408 0.132 942   -0.667   -0.149
##         17.1 No       -0.412 0.122 941   -0.652   -0.172
##         23.4 No       -0.416 0.125 946   -0.661   -0.172
##         10.8 Yes      -0.521 0.185 949   -0.884   -0.158
##         17.1 Yes      -0.496 0.146 949   -0.783   -0.209
##         23.4 Yes      -0.471 0.175 951   -0.815   -0.127
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                    estimate     SE  df t.ratio
##  10.8228179885588 No - 17.1007246376812 No    0.00417 0.0397 953   0.105
##  10.8228179885588 No - 23.3786312868035 No    0.00834 0.0794 953   0.105
##  10.8228179885588 No - 10.8228179885588 Yes   0.11299 0.1508 954   0.749
##  10.8228179885588 No - 17.1007246376812 Yes   0.08788 0.1013 952   0.868
##  10.8228179885588 No - 23.3786312868035 Yes   0.06277 0.1410 953   0.445
##  17.1007246376812 No - 23.3786312868035 No    0.00417 0.0397 953   0.105
##  17.1007246376812 No - 10.8228179885588 Yes   0.10882 0.1460 953   0.745
##  17.1007246376812 No - 17.1007246376812 Yes   0.08371 0.0934 947   0.897
##  17.1007246376812 No - 23.3786312868035 Yes   0.05860 0.1350 954   0.434
##  23.3786312868035 No - 10.8228179885588 Yes   0.10465 0.1518 953   0.689
##  23.3786312868035 No - 17.1007246376812 Yes   0.07954 0.1016 943   0.783
##  23.3786312868035 No - 23.3786312868035 Yes   0.05443 0.1404 954   0.388
##  10.8228179885588 Yes - 17.1007246376812 Yes -0.02511 0.1051 952  -0.239
##  10.8228179885588 Yes - 23.3786312868035 Yes -0.05022 0.2103 952  -0.239
##  17.1007246376812 Yes - 23.3786312868035 Yes -0.02511 0.1051 952  -0.239
##  p.value
##   1.0000
##   1.0000
##   0.9756
##   0.9541
##   0.9978
##   1.0000
##   0.9762
##   0.9473
##   0.9980
##   0.9831
##   0.9705
##   0.9989
##   0.9999
##   0.9999
##   0.9999
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
summary(emtrends(exec_model_covariates_interactions, pairwise ~ drug_use, var = "deprivation", level = 0
```

```
## $emtrends
```

```
##  drug_use deprivation.trend      SE  df lower.CL upper.CL
##  No                -0.00570 0.00572 990  -0.0169  0.00553
##  Yes                0.00157 0.01519 996  -0.0282  0.03138
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE  df t.ratio p.value
##  No - Yes -0.00727 0.0162 998  -0.450  0.6528
##
## Results are averaged over the levels of: sex, race, education
## Degrees-of-freedom method: kenward-roger
```

The estimated means analysis confirms the results above. Thus we conclude the interaction effects between aggregated substance abuse and childhood trauma scores are not significant.

Let's now break down substance abuse by substance.

```
exec_model_substances <- lmer(executive_func ~ age + sex + education + race +tranquilizer + stimulants +
```

```
## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
```

```
summary(exec_model_substances)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: executive_func ~ age + sex + education + race + tranquilizer +
##     stimulants + painkillers + depressants + inhallants + cocaine +
##     hallucinogens + threat + deprivation + (1 | family_id)
##    Data: midus
##
##      AIC      BIC   logLik deviance df.resid
##   2158.7   2290.4  -1052.4   2104.7      944
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2914 -0.4798 -0.0200  0.4643  2.6323
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2531   0.5031
##  Residual              0.2770   0.5263
## Number of obs: 971, groups:  family_id, 839
##
## Fixed effects:
##                       Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)          1.022e+00  4.120e-01  9.136e+02   2.480 0.013329 *
## age                 -2.763e-02  2.178e-03  8.362e+02 -12.683  < 2e-16 ***
## sexFemale           -7.833e-02  4.893e-02  9.643e+02  -1.601 0.109736
## education3           3.736e-01  3.941e-01  9.323e+02   0.948 0.343412
## education4           1.844e-01  4.505e-01  9.662e+02   0.409 0.682364
```

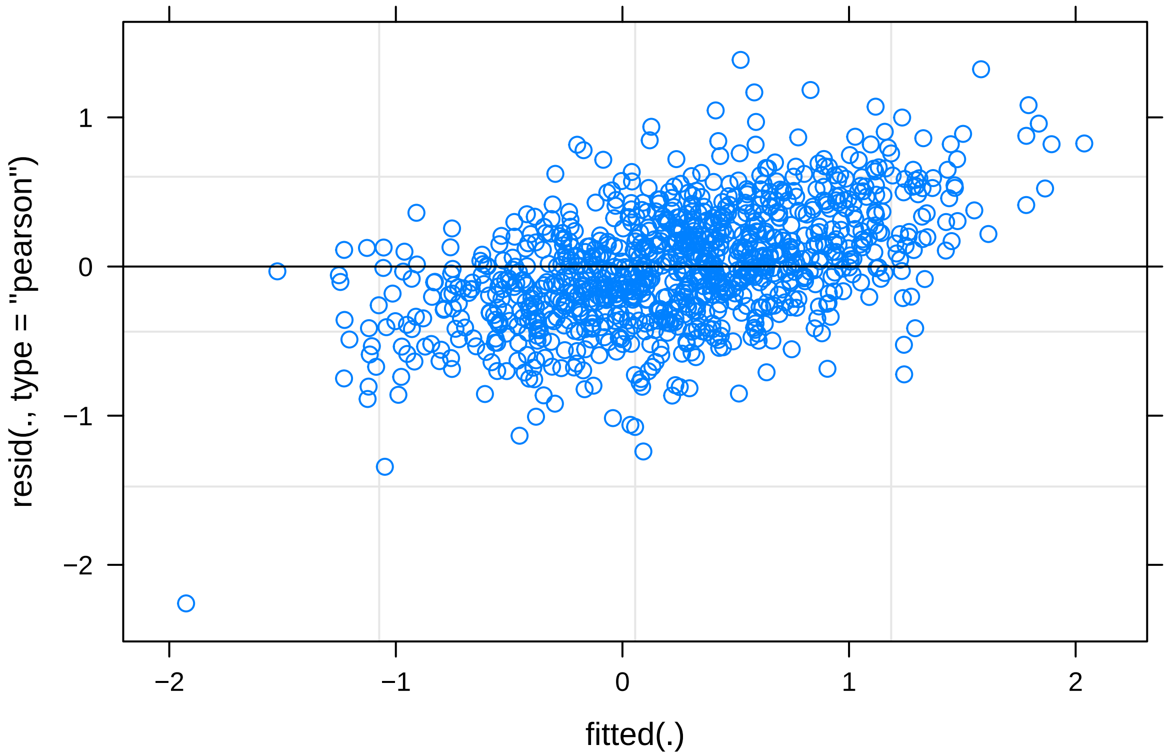
```
## education5          6.885e-01  3.726e-01  9.215e+02   1.848 0.064969 .
## education6          6.802e-01  3.740e-01  9.237e+02   1.818 0.069317 .
## education7          8.708e-01  3.856e-01  9.304e+02   2.258 0.024157 *
## education8          7.473e-01  3.774e-01  9.293e+02   1.980 0.047947 *
## education9          1.167e+00  3.729e-01  9.228e+02   3.129 0.001807 **
## education10         1.034e+00  3.842e-01  9.345e+02   2.692 0.007222 **
## education11         1.244e+00  3.748e-01  9.250e+02   3.320 0.000936 ***
## education12         1.269e+00  3.854e-01  9.303e+02   3.293 0.001028 **
## raceBlack          -6.609e-01  1.535e-01  8.705e+02  -4.307 1.85e-05 ***
## raceNative American  3.048e-01  2.102e-01  9.701e+02   1.450 0.147306
## raceAsian          -7.092e-01  4.250e-01  9.232e+02  -1.669 0.095515 .
## raceOther          -5.886e-01  1.539e-01  9.519e+02  -3.824 0.000140 ***
## tranquilizerYes      2.587e-01  1.390e-01  9.549e+02   1.861 0.062997 .
## stimulantsYes       3.619e-02  1.713e-01  9.574e+02   0.211 0.832672
## painkillersYes     -7.278e-03  2.737e-01  9.307e+02  -0.027 0.978792
## depressantsYes     -1.076e-01  1.174e-01  9.590e+02  -0.916 0.359988
## inhallantsYes      -4.756e-01  2.108e-01  9.541e+02  -2.257 0.024253 *
## cocaineYes         -1.972e-01  3.259e-01  9.253e+02  -0.605 0.545255
## threat             -8.399e-04  3.896e-03  9.695e+02  -0.216 0.829377
## deprivation        -4.484e-03  5.322e-03  9.684e+02  -0.843 0.399685
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 25 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it

## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
```

```
r.squaredGLMM(exec_model_substances)
```

```
##            R2m       R2c
## [1,] 0.2944476 0.6313126
```

Of the parameters related to specific substances, the only parameter that was significant was the one regarding inhallants. Thus we interpret the slope parameter as those who indicated having used inhallants in the past 12 months on average had 0.476 lower z score for episodic memory. This is a stark difference. The overall model fit is also OK - 0.2944 marginal R^2 and 0.6313 conditional r^2.

```
plot(exec_model_substances)
```



Assumptions met, lets move on to the interaction model.

```
exec_substances_interactions <- lmer(executive_func ~ age + sex + education + race +tranquilizer + stimu
```

```
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
summary(exec_substances_interactions)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: executive_func ~ age + sex + education + race + tranquilizer +
##     stimulants + painkillers + depressants + inhallants + cocaine +
##     hallucinogens + threat + deprivation + stimulants * threat +
##     stimulants * deprivation + painkillers * threat + painkillers *
##     deprivation + inhallants * threat + inhallants * deprivation +
##     cocaine * threat + cocaine * deprivation + hallucinogens *
##     threat + hallucinogens * deprivation + tranquilizer * threat +
##     tranquilizer * deprivation + (1 | family_id)
##    Data: midus
##
##      AIC      BIC   logLik deviance df.resid
##   2174.5   2355.0  -1050.3   2100.5      934
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -4.3113 -0.4733 -0.0175  0.4628  2.6526
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  family_id (Intercept) 0.2511   0.5011
##  Residual              0.2766   0.5259
## Number of obs: 971, groups:  family_id, 839
##
## Fixed effects:
##                               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                  1.015e+00  4.133e-01  9.142e+02   2.457 0.014209
## age                         -2.770e-02  2.185e-03  8.350e+02 -12.678  < 2e-16
## sexFemale                   -7.571e-02  4.905e-02  9.650e+02  -1.544 0.122997
## education3                   3.585e-01  3.948e-01  9.339e+02   0.908 0.364060
## education4                   1.792e-01  4.501e-01  9.662e+02   0.398 0.690545
## education5                   6.926e-01  3.724e-01  9.220e+02   1.860 0.063242
## education6                   6.800e-01  3.738e-01  9.244e+02   1.819 0.069169
## education7                   8.622e-01  3.853e-01  9.311e+02   2.238 0.025459
## education8                   7.530e-01  3.772e-01  9.302e+02   1.996 0.046220
## education9                   1.173e+00  3.726e-01  9.235e+02   3.149 0.001693
## education10                  1.042e+00  3.841e-01  9.352e+02   2.713 0.006794
## education11                  1.249e+00  3.746e-01  9.258e+02   3.333 0.000894
## education12                  1.273e+00  3.850e-01  9.307e+02   3.307 0.000980
## raceBlack                   -6.265e-01  1.591e-01  8.670e+02  -3.937 8.91e-05
## raceNative American          2.971e-01  2.138e-01  9.705e+02   1.390 0.164995
## raceAsian                   -7.033e-01  4.243e-01  9.240e+02  -1.658 0.097712
## raceOther                   -5.890e-01  1.536e-01  9.520e+02  -3.834 0.000134
## tranquilizerYes              3.491e-01  4.632e-01  9.680e+02   0.754 0.451278
## stimulantsYes                1.091e-01  5.756e-01  9.674e+02   0.190 0.849732
## painkillersYes              -5.567e-01  1.180e+00  9.277e+02  -0.472 0.637169
## depressantsYes              -1.386e-01  1.209e-01  9.541e+02  -1.146 0.251888
## inhallantsYes               -5.603e-01  7.686e-01  8.709e+02  -0.729 0.466227
## cocaineYes                   2.310e+00  3.234e+00  9.231e+02   0.714 0.475184
## threat                       1.926e-04  4.061e-03  9.704e+02   0.047 0.962183
## deprivation                 -5.428e-03  5.551e-03  9.667e+02  -0.978 0.328428
## stimulantsYes:threat        -9.381e-04  2.895e-02  9.504e+02  -0.032 0.974153
## stimulantsYes:deprivation   -2.481e-04  3.425e-02  9.498e+02  -0.007 0.994222
## painkillersYes:threat       -2.393e-02  3.865e-02  9.320e+02  -0.619 0.536018
## painkillersYes:deprivation   6.353e-02  7.738e-02  9.263e+02   0.821 0.411811
## inhallantsYes:threat        -3.011e-02  1.967e-02  9.447e+02  -1.531 0.126148
## inhallantsYes:deprivation    4.225e-02  3.733e-02  9.709e+02   1.132 0.257935
## cocaineYes:threat            2.090e-03  4.339e-02  9.264e+02   0.048 0.961603
## cocaineYes:deprivation      -1.488e-01  1.676e-01  9.249e+02  -0.888 0.374889
## tranquilizerYes:threat       5.639e-03  2.394e-02  9.597e+02   0.236 0.813859
## tranquilizerYes:deprivation -1.261e-02  3.172e-02  9.637e+02  -0.398 0.691052
##
## (Intercept)                 *
## age                         ***
## sexFemale
## education3
## education4
## education5                  .
## education6                  .
## education7                  *
```

```
## education8                  *
## education9                  **
## education10                 **
## education11                 ***
## education12                 ***
## raceBlack                   ***
## raceNative American
## raceAsian                   .
## raceOther                   ***
## tranquilizerYes
## stimulantsYes
## painkillersYes
## depressantsYes
## inhallantsYes
## cocaineYes
## threat
## deprivation
## stimulantsYes:threat
## stimulantsYes:deprivation
## painkillersYes:threat
## painkillersYes:deprivation
## inhallantsYes:threat
## inhallantsYes:deprivation
## cocaineYes:threat
## cocaineYes:deprivation
## tranquilizerYes:threat
## tranquilizerYes:deprivation
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 35 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it

## fit warnings:
## fixed-effect model matrix is rank deficient so dropping 3 columns / coefficients
```

```
r.squaredGLMM(exec_substances_interactions)
```

```
##            R2m       R2c
## [1,] 0.2976998 0.6319133
```

From running the interactions model, we do not see any significant interaction terms. This is the first indication that interaction effects are not significant, let us now compare models.

```
anova(exec_model_substances,exec_substances_interactions,test="chi")
```

```
## Data: midus
## Models:
## exec_model_substances: executive_func ~ age + sex + education + race + tranquilizer + stimulants + pa
## exec_substances_interactions: executive_func ~ age + sex + education + race + tranquilizer + stimulan
```

```
##                              npar    AIC    BIC  logLik deviance  Chisq Df
## exec_model_substances          27 2158.7 2290.4 -1052.4   2104.7
## exec_substances_interactions   37 2174.5 2355.0 -1050.3   2100.5 4.2018 10
##                              Pr(>Chisq)
## exec_model_substances
## exec_substances_interactions     0.9378
```

From running model comparisons we see the AIC and BIC increase, and the p-vaulue is well above 0.05. Thus we conclude that the model with interactions is not significantly better and therefore choose the model without interactions. We conclude that the analysis does not indicate a moderation effect of substance use on the association between childhood trauma and executive functioning.

Conclusions

The major conclusions we can draw from our analysis regards to the significance of individual substance use parameters as opposed to overall substance use. We found certain individual paramters for substance use to be significant and have a wide range of values. Thus I believe for purposes of interpretation, we would rather choose the model that breaks down substance abuse by substance instead of aggregation. Overall, I would conclude that based on our analyses, substance use does not seem to indicate moderating effects on the association between childhood trauma and executive function cognition.