

FSEM Real Data Analysis

Load Libraries

```
# requires blimp installation: www.appliedmissingdata.com/blimp
# install.packages('remotes')
# install.packages('ggplot2')
# install.packages('GGally')
# remotes::install_github("bkeller2/fdir")
# remotes::install_github('blimp-stats/rblimp')

library(fdir)
library(rblimp)
library(ggplot2)
library(GGally)
```

Read Data

```
# Set working directory to the folder that contains the R script
set()
load('fsem.rda')
```

Inspect Distributions

Histograms of the raw data show that two of the three inflammation indicators (IL6 and CRP) and the drinks per drinking day outcome (DPDD) have positively skewed distributions. These variables will be normalized in the analysis models using the Yeo–Johnson transformation.

```
# Distributions and correlations for raw variables
```

```
ggpairs(  
  fsem[, c('Age', 'Sex', 'ELS', 'IL6', 'TNF', 'CRP', 'DPDD', 'HDD')],  
  upper = list(continuous = wrap("cor", size = 3)),  
  lower = list(continuous = wrap("points", alpha = 0.5, size = 0.7)),  
  diag = list(continuous = wrap("barDiag", colour= "black", fill = "grey80"))  
) + ggtitle("Distributions and Correlations of Raw Variables")
```



Confirmatory Factor Analysis for the Inflammation Mediator

The confirmatory factor analysis (CFA) model for the inflammation mediator is identified by setting the latent variable's mean to zero (the default, no syntax required) and its variance to one. A positive-valued prior is assigned to the first loading to ensure that all loadings are positive.

```
# Inflammation CFA with Yeo-Johnson indicators
cfa <- rblimp(
  data = fsem,
  latent = 'Inflammation', # Define latent variable
  model = '
    Inflammation ~~ Inflammation@1; # Fix factor variance to 1
    Inflammation -> yjt(CRPz)@lo1prior yjt(IL6z) TNFz;', # Measurement model
  parameters = 'lo1prior ~ truncate(0, Inf);', # Positive prior distribution
  seed = 90291,
  burn = 10000,
  iter = 20000
)

# Print output
output(cfa)

##
## -----
##
##                               Blimp
##                               3.2.20
##
##      Blimp was developed with funding from Institute of
##      Education Sciences awards R305D150056 and R305D190002.
##
##      Craig K. Enders, P.I. Email: cenders@psych.ucla.edu
##      Brian T. Keller, Co-P.I. Email: btkeller@missouri.edu
##      Han Du, Co-P.I. Email: hdu@psych.ucla.edu
```

```

##           Roy Levy, Co-P.I. Email: roy.levy@asu.edu
##
##           Programming and Blimp Studio by Brian T. Keller
##
##           There is no expressed license given.
## -----
##
##
## ALGORITHMIC OPTIONS SPECIFIED:
##
## Imputation method:           Fully Bayesian model-based
## MCMC algorithm:              Full conditional Metropolis sampler with
##                               Auto-Derived Conditional Distributions
## Between-cluster imputation model: Not applicable, single-level imputation
## Prior for random effect variances: Not applicable, single-level imputation
## Prior for residual variances:  Zero sum of squares, df = -2 (PRIOR2)
## Prior for predictor variances: Unit sum of squares, df = 2 (XPRIOR1)
## Chain Starting Values:       Random starting values
##
##
##

```

The maximum potential scale reduction factor diagnostic (Gelman & Rubin, 1992) should be less than approximately 1.05 at the final iteration of the burn-in period, which was set to 10,000 iterations.

```

## BURN-IN POTENTIAL SCALE REDUCTION (PSR) OUTPUT:
##
## NOTE: Split chain PSR is being used. This splits each chain's
##       iterations to create twice as many chains.
##
## Comparing iterations across 2 chains   Highest PSR   Parameter #
##                               251 to 500           1.075           7

```

```

##          501 to 1000          1.080          15
##          751 to 1500          1.045           9
##         1001 to 2000          1.090           9
##         1251 to 2500          1.088           4
##         1501 to 3000          1.089           9
##         1751 to 3500          1.032           9
##         2001 to 4000          1.143          10
##         2251 to 4500          1.039           9
##         2501 to 5000          1.032          10
##         2751 to 5500          1.066          10
##         3001 to 6000          1.048          10
##         3251 to 6500          1.037          10
##         3501 to 7000          1.008          10
##         3751 to 7500          1.011           9
##         4001 to 8000          1.015          17
##         4251 to 8500          1.020          16
##         4501 to 9000          1.026          17
##         4751 to 9500          1.057          16
##         5001 to 10000         1.013          17
##
##
## METROPOLIS-HASTINGS ACCEPTANCE RATES:
##
## Chain 1:
##
## Variable              Type      Probability   Target Value
## yjt(CRPz)             parameter    0.504       0.500
## yjt(IL6z)             parameter    0.405       0.500
##
## NOTE: Suppressing printing of 1 chains.
##       Use keyword 'tuneinfo' in options to override.
##
##

```

```

## DATA INFORMATION:
##
## Sample Size:          99
## Missing Data Info:
##           miss %      1
##           -----
##           CRPz = 0.0    -
##           IL6z = 0.0    -
##           TNFz = 0.0    -
##           -----
##           % 100.0
##
##
## MODEL INFORMATION:
##
## NUMBER OF PARAMETERS
## Outcome Models:      11
## Predictor Models:    0
##
## FACTORS
## Level-1:              Inflammation
##
## MODELS
## [1] Inflammation ~ Intercept@0
## [2] yjt(CRPz) ~ Intercept Inflammation@lo1prior
## [3] yjt(IL6z) ~ Intercept Inflammation
## [4] TNFz ~ Intercept Inflammation
##
## PRIORS SPECIFIED
## [1] lo1prior ~ truncate(0, inf)
##
##
## WARNING MESSAGES:
##
## No warning messages.

```

```
##
## MODEL FIT:
##
## INFORMATION CRITERIA
##
## Conditional Likelihood
## DIC2 906.402
## WAIC 943.679
##
##
```

The CORRELATIONS AMONG RESIDUALS table shows the estimated correlations for every pair of residuals in the model. The correlations are quite small and none are significant. The factor model appears to provide adequate fit.

```
## CORRELATIONS AMONG RESIDUALS:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
##
## Correlations
```

	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
Inflammation, yjt(CRPz)	0.003	0.145	-0.285	0.283	0.000	0.995	19651.416
Inflammation, yjt(IL6z)	-0.001	0.145	-0.281	0.280	0.000	0.996	20083.986
Inflammation, TNFz	-0.000	0.146	-0.280	0.285	0.000	0.998	19612.147
yjt(CRPz), yjt(IL6z)	0.026	0.145	-0.260	0.306	0.031	0.860	5741.725
yjt(CRPz), TNFz	0.028	0.142	-0.253	0.299	0.036	0.849	2154.687
yjt(IL6z), TNFz	0.010	0.136	-0.263	0.267	0.004	0.949	2254.710

```
##
##
```

Each variable in the model has its own summary table. The values in the Estimate column are posterior medians, the StdDev column contains “Bayesian standard errors”, and the 2.5% and 97.5% columns give the 95% credible interval limits. The ChiSq and PValue columns contain frequentist significance tests (Asparouhov & Muthén, 2021). The rightmost column of the tables—the effective number of MCMC samples—is essentially the number of independent estimates on which the parameter summaries are based after removing autocorrelations from the MCMC process. Gelman et al. (2014, p. 287) recommend that these values should exceed 100. If any of the values fall below this threshold, increase the number of iterations after the burn-in period (specified as 20,000 for this analysis).

```
## OUTCOME MODEL ESTIMATES:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
##
## Latent Variable: Inflammation
##
## Parameters
```

	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff

## Variances:							
## Residual Var.	@ 1.000	---	---	---	---	---	---
##							
## Proportion Variance Explained							
## by Coefficients	0.000	0.000	0.000	0.000	---	---	nan
## by Residual Variation	1.000	0.000	1.000	1.000	---	---	nan
##							
##	-----						
##							
##							
##							

Outcome Variable: yjt(CRPz)

##

## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##	-----						
## Variances:							
## Residual Var.	0.316	0.118	0.068	0.543	---	---	327.862
##							
## Coefficients:							
## Intercept	-0.281	0.089	-0.456	-0.109	10.109	0.001	3184.857
## Inflammation	0.553	0.119	0.324	0.791	21.577	0.000	425.090
##							
## Transformation:							
## Yeo-Johnson (lambda)	-0.081	0.169	-0.442	0.215	---	---	1793.861
##							
## Standardized Coefficients:							
## Inflammation	0.692	0.132	0.421	0.941	27.248	0.000	346.783
##							
## Proportion Variance Explained							
## by Coefficients	0.479	0.181	0.177	0.886	---	---	285.368
## by Residual Variation	0.521	0.181	0.114	0.823	---	---	285.368

##

##

##

##

##

##

Outcome Variable: yjt(IL6z)

##

## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##	-----						
## Variances:							
## Residual Var.	0.336	0.102	0.101	0.522	---	---	416.683
##							
## Coefficients:							
## Intercept	-0.246	0.082	-0.410	-0.084	8.919	0.003	3835.312
## Inflammation	0.472	0.111	0.272	0.710	18.559	0.000	519.623

```

##
## Transformation:
##   Yeo-Johnson (lambda)      -0.036      0.153      -0.368      0.228      ---      ---      2165.283
##
## Standardized Coefficients:
##   Inflammation              0.622      0.129      0.376      0.903      23.268      0.000      387.788
##
## Proportion Variance Explained
##   by Coefficients           0.387      0.165      0.141      0.815      ---      ---      360.686
##   by Residual Variation      0.613      0.165      0.185      0.859      ---      ---      360.686
##
## -----
##
##
## Outcome Variable:  TNFz
##
## Parameters                  Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## Variances:
##   Residual Var.             0.855      0.149      0.605      1.191      ---      ---      5162.535
##
## Coefficients:
##   Intercept                 -0.001      0.103      -0.201      0.203      0.000      0.995      9459.928
##   Inflammation              0.421      0.131      0.170      0.690      10.344      0.001      2980.859
##
## Standardized Coefficients:
##   Inflammation              0.406      0.115      0.170      0.618      12.314      0.000      2457.462
##
## Proportion Variance Explained
##   by Coefficients           0.165      0.093      0.029      0.382      ---      ---      2490.811
##   by Residual Variation      0.835      0.093      0.618      0.971      ---      ---      2490.811
##
## -----
##

```

```
##
##
## Additional Parameters:
##
## Parameters          Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##
##    lo1prior          0.553        0.119      0.324      0.791      21.577      0.000      425.090
## -----
##
```

Mediation Model

The syntax in this section specifies a mediation model where early life stress (ELS) influences the inflammation latent variable which, in turn, predicts two indicators of alcohol use: drinks per drinking day (DPDD) and the count of number of heavy drinking days (HDD). Age and sex are covariates in the equations, and both are centered at their grand means. The regression equations are as follows.

$$INFLAMMATION_i = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(AGE_i) + \varepsilon_i$$

$$yjt(DPDD_i) = b_{0,DPDD} + b_{1,DPDD}(INFLAMMATION_i) + b_{2,DPDD}(ELS_i) + b_{3,DPDD}(SEX_i) + b_{4,DPDD}(AGE_i) + \epsilon_i$$

$$\ln(HDD_i) = b_{0,HDD} + b_{1,HDD}(INFLAMMATION_i) + b_{2,HDD}(ELS_i) + b_{3,HDD}(SEX_i) + b_{4,HDD}(AGE_i)$$

Histograms of the raw data showed that two of the three inflammation indicators (IL6 and CRP) and the drinks per drinking day outcome (DPDD) have positively skewed distributions. It is typical log transform these variables prior to analysis. Instead, they are normalized using the Yeo–Johnson transformation. As before, the CFA model for the inflammation mediator is

identified by setting the latent variable's mean to zero (the default, no syntax required) and its residual variance to one. A positive-valued prior is assigned to the first loading to ensure that all loadings are positive. Finally, the indirect effect for the drinks per drinking day outcome is computed using the usual product of coefficients estimator, as follows.

$$(ab_{DPDD}) = a_1 \times b_{1,DPDD}$$

For the count outcome (HDD), indirect effects are conditional on the value of early life stress (ELS). The conditional indirect effects are computed following procedures described in Hayes and Preacher (2010) and Geldhof et al. (2018, Table 2), as follows. Note that $b_{3,HDD}$ and $b_{4,HDD}$ vanish because the covariates are centered at their grand means.

$$(ab_{HDD}|ELS = 0) = a_1 \times b_{1,HDD} \times e\left(b_0 + b_{1,HDD}(\widehat{INFLAMMATION}|ELS = 0) + b_{2,HDD}(0) + b_{3,HDD}(0) + b_{4,HDD}(0)\right)$$

$$(ab_{HDD}|ELS = 1) = a_1 \times b_{1,HDD} \times e\left(b_0 + b_{1,HDD}(\widehat{INFLAMMATION}|ELS = 1) + b_{2,HDD}(1) + b_{3,HDD}(0) + b_{4,HDD}(0)\right)$$

The indirect effect equations require specific values for the mediator, which are computed as follows (recall that a_0 is fixed at zero for identification).

$$(\widehat{INFLAMMATION}|ELS = 0) = a_0 + a_1(ELS_i) = 0$$

$$(\widehat{INFLAMMATION}|ELS = 1) = a_0 + a_1(ELS_i) = a_1$$

```
# Fit mediation model
med <- rblimp(
  data = fsem,
  ordinal = 'ELS Sex', # Identify binary variables
  count = 'HDD', # Identify count variable
  latent = 'Inflammation', # Define latent variable
  center = 'Sex Age', # Center covariates
  model = '
    mediator: # Arbitrary label to group summary tables in output
    Inflammation ~ 1@0 ELS@a1 Sex Age; # @ labels coefficients
    Inflammation ~~ Inflammation@1; # Fix factor residual variance to 1
    outcomes: # Arbitrary label to group summary tables in output
    yjt(DPDDz) ~ Inflammation@b1_DPDD ELS Sex Age; # @ labels coefficients
    HDD ~ 1@b0_HDD Inflammation@b1_HDD ELS@b2_HDD Sex Age; # @ labels coefficients
    measurement: # Arbitrary label to group summary tables in output
    Inflammation -> yjt(CRPz)@l0lprior yjt(IL6z) TNFz;', # Measurement model
  parameters = '
    indirect_DPDD = a1 * b1_DPDD; # Indirect effect for DPDD
    # Expected values of mediator
    M_ELS0 = 0;
    M_ELS1 = a1;
    # Conditional indirect effects for HDD
    indirect_HDD_ELS0 = a1 * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS0 + b2_HDD*0));
    indirect_HDD_ELS1 = a1 * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS1 + b2_HDD*1));
    l0lprior ~ truncate(0, Inf);', # Positive prior distribution
  seed = 90291,
  burn = 10000,
  iter = 20000
)
```

Print output

output(med)

```
##
## -----
##
##              Blimp
##             3.2.20
##
##      Blimp was developed with funding from Institute of
##      Education Sciences awards R305D150056 and R305D190002.
##
##      Craig K. Enders, P.I. Email: cenders@psych.ucla.edu
##      Brian T. Keller, Co-P.I. Email: btkeller@missouri.edu
##      Han Du, Co-P.I. Email: hdu@psych.ucla.edu
##      Roy Levy, Co-P.I. Email: roy.levy@asu.edu
##
##      Programming and Blimp Studio by Brian T. Keller
##
##      There is no expressed license given.
##
## -----
##
##
## ALGORITHMIC OPTIONS SPECIFIED:
##
##   Imputation method:      Fully Bayesian model-based
##   MCMC algorithm:         Full conditional Metropolis sampler with
##                           Auto-Derived Conditional Distributions
##   Between-cluster imputation model: Not applicable, single-level imputation
##   Prior for random effect variances: Not applicable, single-level imputation
##   Prior for residual variances:    Zero sum of squares, df = -2 (PRIOR2)
##   Prior for predictor variances:   Unit sum of squares, df = 2 (XPRIOR1)
##   Chain Starting Values:          Random starting values
##
```

```
##
## NOTE: The default prior for regression coefficients
##       in categorical models is 'normal( 0.0, 5.0)'
```

The maximum potential scale reduction factor diagnostic (Gelman & Rubin, 1992) should be less than approximately 1.05 at the final iteration of the burn-in period, which was set to 10,000 iterations.

```
## BURN-IN POTENTIAL SCALE REDUCTION (PSR) OUTPUT:
##
## NOTE: Split chain PSR is being used. This splits each chain's
##       iterations to create twice as many chains.
##
## Comparing iterations across 2 chains      Highest PSR      Parameter #
##           251 to 500                      1.206              42
##           501 to 1000                     1.145              41
##           751 to 1500                     1.122              41
##          1001 to 2000                     1.080              46
##          1251 to 2500                     1.109              47
##          1501 to 3000                     1.025              23
##          1751 to 3500                     1.048              47
##          2001 to 4000                     1.018              47
##          2251 to 4500                     1.021              42
##          2501 to 5000                     1.029               5
##          2751 to 5500                     1.020               4
##          3001 to 6000                     1.013              17
##          3251 to 6500                     1.012              43
##          3501 to 7000                     1.020              47
##          3751 to 7500                     1.008              41
##          4001 to 8000                     1.008              41
##          4251 to 8500                     1.019              43
##          4501 to 9000                     1.011              65
##          4751 to 9500                     1.008              47
##          5001 to 10000                    1.009              23
```

```

##
##
## METROPOLIS-HASTINGS ACCEPTANCE RATES:
##
## Chain 1:
##
## Variable                Type      Probability   Target Value
## Inflammation            latent imp    0.518         0.500
## yjt(DPDDz)              parameter    0.492         0.500
## yjt(CRPz)               parameter    0.529         0.500
## yjt(IL6z)               parameter    0.464         0.500
## Sex                    parameter    0.516         0.500
## Age                    parameter    0.460         0.500
##
## NOTE: Suppressing printing of 1 chains.
##       Use keyword 'tuneinfo' in options to override.
##
##
## DATA INFORMATION:
##
## Sample Size:             99
## Missing Data Info:
##           miss %         1
##           -----
##           CRPz = 0.0      -
##           IL6z = 0.0      -
##           TNFz = 0.0      -
##           DPDDz = 0.0     -
##           HDD = 0.0       -
##           Sex = 0.0       -
##           Age = 0.0       -
##           ELS = 0.0       -
##           -----
##           % 100.0
##
##

```

```
##
## MODEL INFORMATION:
##
##   NUMBER OF PARAMETERS
##     Outcome Models:      26
##     Generated Parameters:  5
##     Predictor Models:    10
##
##   PREDICTORS
##     Complete continous:   Age
##     Complete ordinal:    Sex ELS
##
##   FACTORS
##     Level-1:              Inflammation
##
##   CENTERED PREDICTORS
##     Grand Mean Centered:  Sex Age
##
##   MODELS
##
##   mediator:
##     [1] Inflammation ~ ELS@a1 Sex Age
##
##   outcomes:
##     [2] yjt(DPDDz) ~ Intercept Inflammation@b1_dpdd ELS Sex Age
##     [3] HDD ~ Intercept@b0_hdd Inflammation@b1_hdd ELS@b2_hdd Sex Age
##
##   measurement:
##     [4] yjt(CRPz) ~ Intercept Inflammation@lo1prior
##     [5] yjt(IL6z) ~ Intercept Inflammation
##     [6] TNFz ~ Intercept Inflammation
##
##   PRIORS SPECIFIED
##     [1] lo1prior ~ truncate(0, inf)
##
```

```

## GENERATED PARAMETERS
## [1] indirect_DPDD = a1*b1_dpdd
## [2] M_ELS0 = 0
## [3] M_ELS1 = a1
## [4] indirect_HDD_ELS0 = a1*(b1_hdd*exp(b0_hdd+b1_hdd*m_els0+b2_hdd*0))
## [5] indirect_HDD_ELS1 = a1*(b1_hdd*exp(b0_hdd+b1_hdd*m_els1+b2_hdd*1))
##
##
## WARNING MESSAGES:
##
## No warning messages.
##
##
## MODEL FIT:
##
##
## INFORMATION CRITERIA
##
## Conditional Likelihood
## DIC2 1138.649
## WAIC 1180.679
##
##
## CORRELATIONS AMONG RESIDUALS:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
##
## Correlations Estimate StdDev 2.5% 97.5% ChiSq PValue N_Eff
## -----
## Inflammation, yjt(DPDDz) 0.000 0.144 -0.282 0.283 0.000 0.996 20244.396
## Inflammation, yjt(CRPz) 0.076 0.142 -0.207 0.349 0.273 0.601 9186.954
## Inflammation, yjt(IL6z) -0.032 0.144 -0.312 0.249 0.048 0.827 8134.708

```

```
## Inflammation, TNFz          0.021      0.139      -0.250      0.289      0.024      0.877 14642.336 006
## yjt(DPDDz), yjt(CRPz)       0.054      0.130      -0.209      0.299      0.159      0.691 2616.949
## yjt(DPDDz), yjt(IL6z)      -0.024      0.137      -0.292      0.242      0.031      0.861 4324.287
## yjt(DPDDz), TNFz          -0.003      0.119      -0.238      0.229      0.001      0.975 4713.107
## yjt(CRPz), yjt(IL6z)       0.035      0.144      -0.246      0.315      0.059      0.809 1920.949
## yjt(CRPz), TNFz           0.127      0.122      -0.126      0.350      1.014      0.314 2764.683
## yjt(IL6z), TNFz          -0.027      0.135      -0.289      0.232      0.045      0.833 4266.559
##
## -----
##
```

Each variable in the model has its own summary table. The values in the Estimate column are posterior medians, the StdDev column contains “Bayesian standard errors”, and the 2.5% and 97.5% columns give the 95% credible interval limits. The ChiSq and PValue columns contain frequentist significance tests (Asparouhov & Muthén, 2021). The rightmost column of the tables—the effective number of MCMC samples—is essentially the number of independent estimates on which the parameter summaries are based after removing autocorrelations from the MCMC process. Gelman et al. (2014, p. 287) recommend that these values should exceed 100. If any of the values fall below this threshold, increase the number of iterations after the burn-in period (specified as 20,000 for this analysis).

```
## OUTCOME MODEL ESTIMATES:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
## mediator block:
##
```

Latent Variable: Inflammation

##

Grand Mean Centered: Age Sex

##

##

## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
---------------	----------	--------	------	-------	-------	--------	-------

##

Variances:

## Residual Var.	@ 1.000	---	---	---	---	---	---
------------------	---------	-----	-----	-----	-----	-----	-----

##

Coefficients:

## ELS	0.608	0.286	0.074	1.200	4.660	0.031	539.010
--------	-------	-------	-------	-------	-------	-------	---------

## Sex	0.147	0.269	-0.373	0.679	0.306	0.580	3408.679
--------	-------	-------	--------	-------	-------	-------	----------

## Age	0.046	0.014	0.020	0.076	10.889	0.001	958.234
--------	-------	-------	-------	-------	--------	-------	---------

##

Standardized Coefficients:

## ELS	0.256	0.108	0.032	0.457	5.453	0.020	585.515
--------	-------	-------	-------	-------	-------	-------	---------

## Sex	0.062	0.110	-0.156	0.273	0.308	0.579	3502.268
--------	-------	-------	--------	-------	-------	-------	----------

## Age	0.431	0.105	0.201	0.612	16.445	0.000	1136.633
--------	-------	-------	-------	-------	--------	-------	----------

##

Proportion Variance Explained

## by Coefficients	0.270	0.096	0.102	0.474	---	---	599.471
--------------------	-------	-------	-------	-------	-----	-----	---------

## by Residual Variation	0.730	0.096	0.526	0.898	---	---	599.471
--------------------------	-------	-------	-------	-------	-----	-----	---------

##

##

##

##

outcomes block:

##

Outcome Variable: yjt(DPDDz)

##

Grand Mean Centered: Age Sex

##

##

## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
---------------	----------	--------	------	-------	-------	--------	-------

```

## -----
## Variances:
##   Residual Var.      0.748    0.134    0.519    1.046    ---    ---    2663.691
##
## Coefficients:
##   Intercept      -0.202    0.129   -0.457    0.057    2.435    0.119    3965.916
##   Inflammation    0.364    0.126    0.127    0.622    8.530    0.003    1711.314
##   ELS             -0.180    0.213   -0.613    0.227    0.752    0.386    2576.381
##   Sex             -0.189    0.196   -0.577    0.190    0.938    0.333    7883.268
##   Age            -0.017    0.011   -0.040    0.003    2.622    0.105    2302.383
##
## Transformation:
##   Yeo-Johnson (lambda) 0.392    0.137    0.112    0.652    ---    ---    3075.142
##
## Standardized Coefficients:
##   Inflammation    0.438    0.146    0.156    0.734    9.006    0.003    1200.696
##   ELS             -0.093    0.108   -0.307    0.115    0.767    0.381    2470.628
##   Sex             -0.098    0.099   -0.287    0.097    0.962    0.327    7662.988
##   Age            -0.199    0.121   -0.441    0.032    2.710    0.100    2147.601
##
## Proportion Variance Explained
##   by Coefficients    0.171    0.089    0.043    0.385    ---    ---    1316.725
##   by Residual Variation 0.829    0.089    0.615    0.957    ---    ---    1316.725
## -----
##
##
##
## Outcome Variable:  HDD
##
## Grand Mean Centered: Age Sex
##
## Parameters      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----

```

```

## Variances:
## Dispersion Parameter      0.511      0.155      0.276      0.879      ---      ---      701.559
##
## Coefficients:
## Intercept      0.819      0.133      0.556      1.082      37.828      0.000      11151.986
## Inflammation    0.179      0.124     -0.048      0.442      2.216      0.137      2814.868
## ELS           -0.003      0.222     -0.449      0.427      0.001      0.981      5511.640
## Sex            0.153      0.208     -0.257      0.562      0.536      0.464      15153.335
## Age           -0.005      0.011     -0.028      0.016      0.203      0.652      5170.939
##
## Exponentiated Coefficients:
## Intercept      2.268      0.306      1.744      2.950      ---      ---      10917.575
## Inflammation    1.196      0.153      0.953      1.555      ---      ---      2730.490
## ELS            0.997      0.229      0.638      1.533      ---      ---      5956.684
## Sex            1.165      0.251      0.773      1.754      ---      ---      15317.628
## Age            0.995      0.011      0.973      1.017      ---      ---      5199.152
##
## -----
##
##
## measurement block:
##
## Outcome Variable:  yjt(CRPz)
##
## Parameters      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## Variances:
## Residual Var.    0.421      0.082      0.280      0.603      ---      ---      1637.598
##
## Coefficients:
## Intercept      -0.358      0.099     -0.558     -0.170      13.170      0.000      1255.969
## Inflammation    0.379      0.087      0.218      0.560      19.309      0.000      1001.460
##
## Transformation:
## Yeo-Johnson (lambda)  -0.042      0.172     -0.407      0.248      ---      ---      2571.342

```

```

##
## Standardized Coefficients:
##   Inflammation      0.557      0.096      0.349      0.727      33.081      0.000      1299.118
##
## Proportion Variance Explained
##   by Coefficients      0.311      0.104      0.122      0.528      ---      ---      1223.140
##   by Residual Variation      0.689      0.104      0.472      0.878      ---      ---      1223.140
##
## -----
##
##
##
## Outcome Variable:  yjt(IL6z)
##
## Parameters      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## Variances:
##   Residual Var.      0.229      0.080      0.082      0.394      ---      ---      394.381
##
## Coefficients:
##   Intercept      -0.365      0.098      -0.564      -0.178      14.208      0.000      680.432
##   Inflammation      0.493      0.083      0.330      0.653      35.009      0.000      447.238
##
## Transformation:
##   Yeo-Johnson (lambda)      -0.084      0.152      -0.407      0.172      ---      ---      1638.866
##
## Standardized Coefficients:
##   Inflammation      0.762      0.093      0.559      0.921      66.517      0.000      407.851
##
## Proportion Variance Explained
##   by Coefficients      0.581      0.138      0.312      0.849      ---      ---      373.523
##   by Residual Variation      0.419      0.138      0.151      0.688      ---      ---      373.523
##
## -----
##
##

```

```

##
##
## Outcome Variable:  TNFz
##
## Parameters
##      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## Variances:
##   Residual Var.      0.890      0.144      0.659      1.222      ---      ---      6306.814
##
## Coefficients:
##   Intercept      -0.074      0.111      -0.292      0.140      0.455      0.500      2133.798
##   Inflammation      0.324      0.108      0.120      0.547      9.163      0.002      1918.602
##
## Standardized Coefficients:
##   Inflammation      0.368      0.106      0.142      0.557      11.798      0.001      2582.800
##
## Proportion Variance Explained
##   by Coefficients      0.135      0.075      0.020      0.311      ---      ---      2467.640
##   by Residual Variation      0.865      0.075      0.689      0.980      ---      ---      2467.640
##
## -----
##
##
##
## Additional Parameters:
##
## Parameters
##      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##
##   lo1prior      0.379      0.087      0.218      0.560      19.309      0.000      1001.460
##
## -----
##
##
##

```

Indirect effect estimates are in a table labeled GENERATED PARAMETERS. The indirect effect of ELS on DPDD is significant because the 95% credible interval does not contain zero. The conditional indirect effects of ELS on HDD are not significant because zero is inside the 95% interval, albeit just barely.

```
## GENERATED PARAMETERS:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
##
## Parameters      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## indirect_DPDD    0.207      0.138      0.018      0.553      2.727      0.099      743.287
## M_ELS0           0.000      0.000      0.000      0.000      nan        nan        nan
## M_ELS1           0.608      0.286      0.074      1.200      4.660      0.031      539.010
## indirect_HDD_ELS0 0.107      0.131     -0.037      0.470      1.062      0.303     1483.642
## indirect_HDD_ELS1 0.117      0.158     -0.041      0.556      0.951      0.330     1592.151
## -----
##
##
## PREDICTOR MODEL ESTIMATES:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
##
## Complete predictor: Sex
##
## Parameters      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
```

```

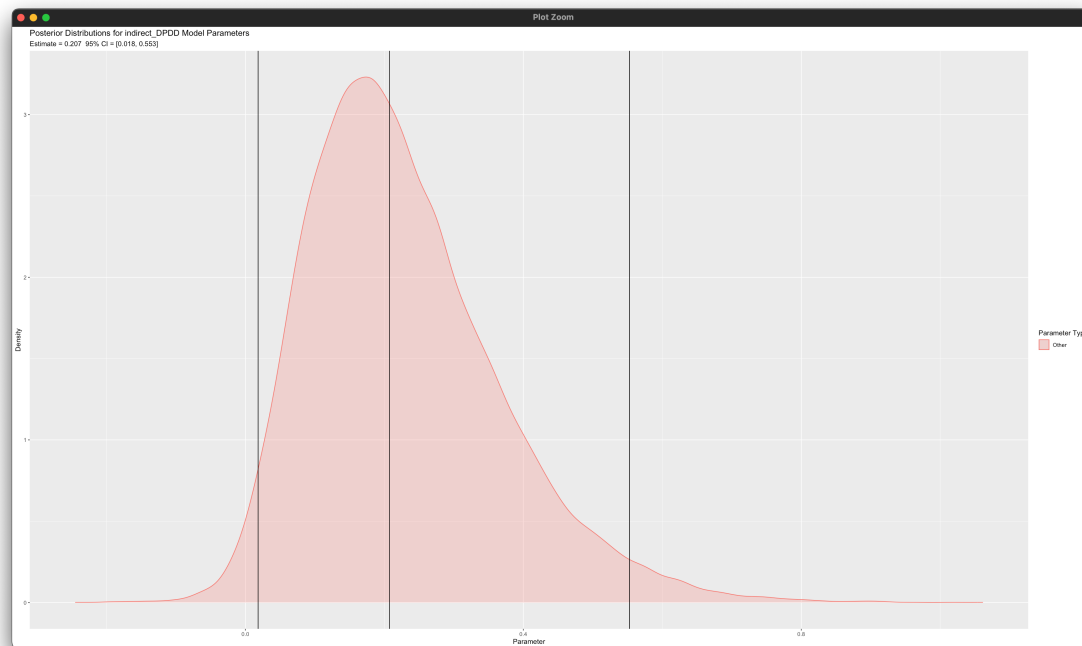
## Grand Mean          -0.263      0.131      -0.535      -0.018      4.147      0.042      2330.797
##
## Level 1:
##   Age                -0.014      0.012      -0.037      0.009      1.344      0.246      8638.893
##   ELS                 0.042      0.157      -0.262      0.353      0.074      0.785      4942.220
##   Residual Var.       1.000      0.000      1.000      1.000      ---      ---      nan
## Thresholds:
##   Tau 1               0.000      0.000      0.000      0.000      ---      ---      nan
##
## -----
##
##
##
## Complete predictor: Age
##
## Parameters           Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##
## Grand Mean           44.299      1.130      42.045      46.539      1538.488      0.000      2427.743
##
## Level 1:
##   Sex                 -1.591      1.360      -4.264      1.094      1.370      0.242      14184.533
##   ELS                 -0.073      1.401      -2.854      2.644      0.003      0.954      13574.489
##   Residual Var.       116.253      17.513      88.715      157.278      ---      ---      17714.625
##
## -----
##
##
##
## Complete predictor: ELS
##
## Parameters           Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##
## Grand Mean           -0.271      0.130      -0.528      -0.018      4.319      0.038      7883.380

```

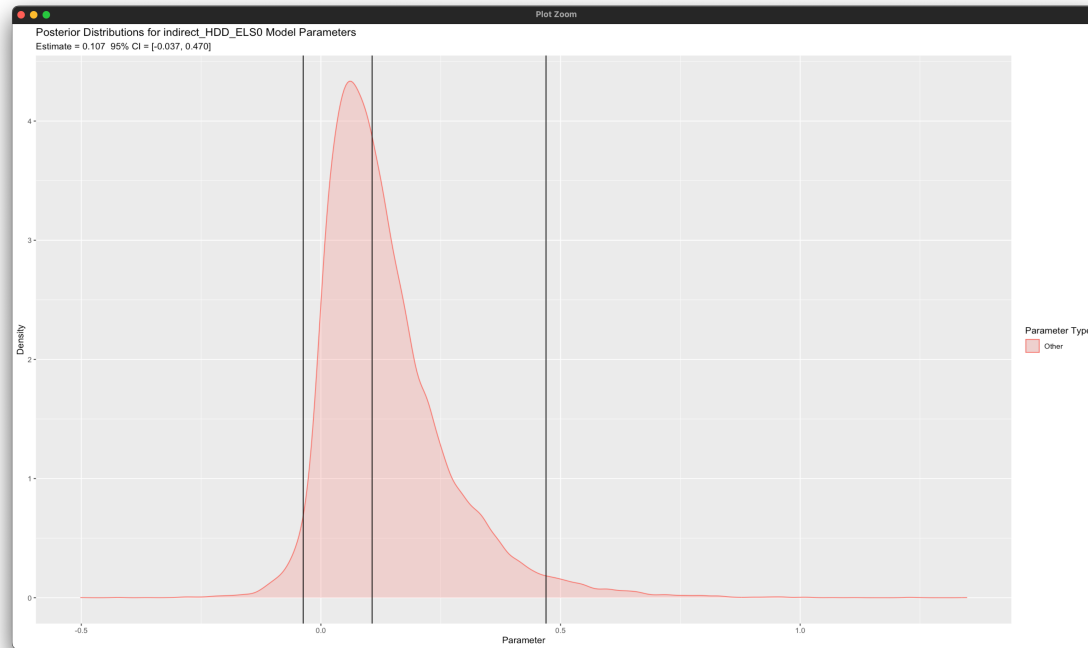
```
##
## Level 1:
## Sex 0.041 0.158 -0.267 0.352 0.073 0.787 4627.783
## Age -0.001 0.012 -0.025 0.023 0.003 0.954 8474.414
## Residual Var. 1.000 0.000 1.000 1.000 --- --- nan
## Thresholds:
## Tau 1 0.000 0.000 0.000 0.000 --- --- nan
##
## -----
```

The `posterior_plot` functions generate kernel density plots of the distribution of indirect effects.

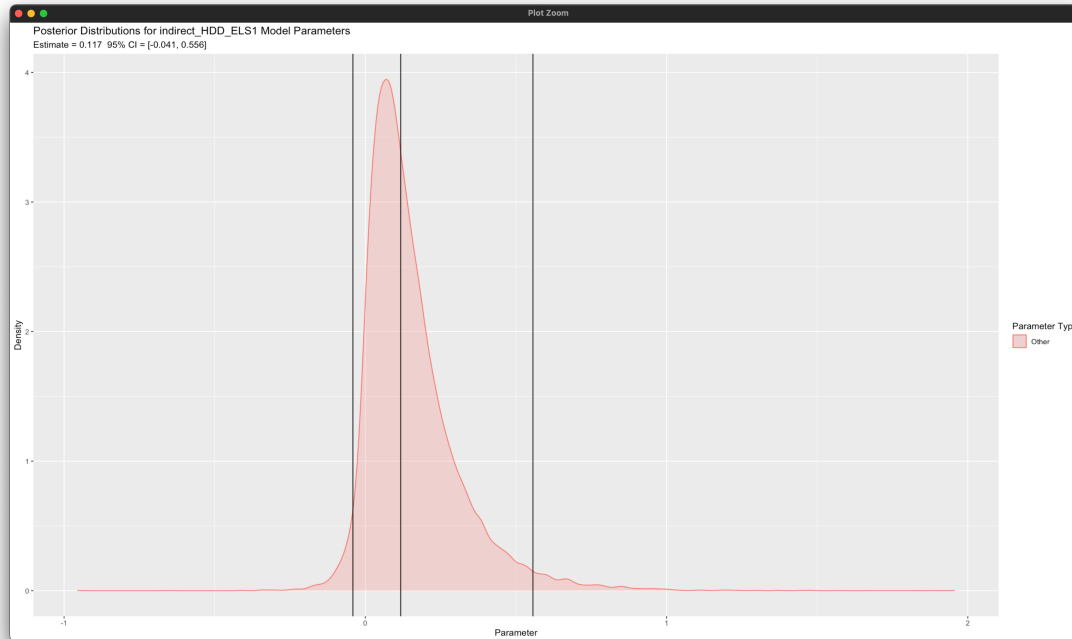
```
# Plot distributions of indirect effects
posterior_plot(med, 'indirect_DPDD')
```



```
posterior_plot(med, 'indirect_HDD_ELS0')
```



```
posterior_plot(med, 'indirect_HDD_ELS1')
```



Moderated Mediation Model

The syntax in this section specifies a moderated mediation model where early life stress (ELS) influences the inflammation latent variable which, in turn, predicts two indicators of alcohol use: drinks per drinking day (DPDD) and the count of number of heavy drinking days (HDD). The path from early life stress (ELS) to inflammation is moderated by sex. Age is a covariate in the equations and is centered at its grand mean. The regression equations are as follows.

$$INFLAMMATION_i = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) + a_4(AGE_i) + \varepsilon_i$$

$$y_{jt}(DPDD_i) = b_{0,DPDD} + b_{1,DPDD}(INFLAMMATION_i) + b_{2,DPDD}(ELS_i) + b_{3,DPDD}(SEX_i) + b_{4,DPDD}(AGE_i) + \epsilon_i$$

$$\ln(HDD_i) = b_{0,HDD} + b_{1,HDD}(INFLAMMATION_i) + b_{2,HDD}(ELS_i) + b_{3,HDD}(SEX_i) + b_{4,HDD}(AGE_i)$$

Histograms of the raw data showed that two of the three inflammation indicators (IL6 and CRP) and the drinks per drinking day outcome (DPDD) have positively skewed distributions. It is typical log transform these variables prior to analysis. Instead, they are normalized using the Yeo–Johnson transformation. As before, the CFA model for the inflammation mediator is identified by setting the latent variable’s mean to zero (the default, no syntax required) and its residual variance to one. A positive-valued prior is assigned to the first loading to ensure that all loadings are positive. Finally, the conditional indirect effect for the drinks per drinking day outcome is computed using the usual product of coefficients estimator within each gender group, as follows.

$$(ab_{DPDD}|SEX = 0) = a_1 \times b_{1,DPDD}$$

$$(ab_{DPDD}|SEX = 1) = (a_1 + a_3) \times b_{1,DPDD}$$

For the count outcome (HDD), indirect effects are conditional on the value of early life stress (ELS). The conditional indirect effects are computed following procedures described in Hayes and Preacher (2010) and Geldhof et al. (2018, Table 2), as follows. Note that $b_{3,HDD}$ and $b_{4,HDD}$ vanish because the covariates are centered at their grand means.

$$(ab_{HDD}|ELS = 0, SEX = 0) =$$

$$a_1 \times b_{1,HDD} \times e\left(b_0 + b_{1,HDD}(\widehat{INFLAMMATION}|ELS = 0, SEX = 0) + b_{2,HDD}(0) + b_{3,HDD}(0) + b_{4,HDD}(0)\right)$$

$$(ab_{HDD}|ELS = 0, SEX = 1) =$$

$$(a_1 + a_3) \times b_{1,HDD} \times e\left(b_0 + b_{1,HDD}(\widehat{INFLAMMATION}|ELS = 0, SEX = 1) + b_{2,HDD}(0) + b_{3,HDD}(1) + b_{4,HDD}(0)\right)$$

$$(ab_{HDD}|ELS = 1, SEX = 0) =$$

$$a_1 \times b_{1,HDD} \times e\left(b_0 + b_{1,HDD}(\widehat{INFLAMMATION}|ELS = 1, SEX = 0) + b_{2,HDD}(1) + b_{3,HDD}(0) + b_{4,HDD}(0)\right)$$

$$(ab_{HDD}|ELS = 1, SEX = 1) =$$

$$(a_1 + a_3) \times b_{1,HDD} \times e\left(b_0 + b_{1,HDD}(\widehat{INFLAMMATION}|ELS = 1, SEX = 1) + b_{2,HDD}(1) + b_{3,HDD}(1) + b_{4,HDD}(0)\right)$$

The indirect effect equations require specific values for the mediator, which are computed as follows (recall that a_0 is fixed at zero for identification).

$$(\widehat{INFLAMMATION}|ELS = 0, SEX = 0) = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) = 0$$

$$(\widehat{INFLAMMATION}|ELS = 0, SEX = 1) = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) = a_2$$

$$(\widehat{INFLAMMATION}|ELS = 1, SEX = 0) = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) = a_1$$

$$(\widehat{INFLAMMATION}|ELS = 1, SEX = 1) = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) = a_1 + a_2 + a_3$$

```

modmed <- rblimp(
  data = fsem,
  ordinal = 'ELS Sex', # Identify binary variables
  count = 'HDD', # Identify count variable
  latent = 'Inflammation', # Define latent variable
  center = 'Age', # Center covariate
  model = '
    mediator: # Arbitrary label to group summary tables in output
    Inflammation ~ 1@0 ELS@a1 Sex@a2 ELS*Sex@a3 Age; # Product of ELS and Sex
    Inflammation ~~ Inflammation@1; # Fix factor residual variance to 1
    outcomes: # Arbitrary label to group summary tables in output
    yjt(DPDDz) ~ Inflammation@b1_DPDD ELS Sex Age; # @ labels coefficients
    HDD ~ 1@b0_HDD Inflammation@b1_HDD ELS@b2_HDD Sex@b3_HDD Age; # @ labels coefficients
    measurement: # Arbitrary label to group summary tables in output
    Inflammation -> yjt(CRPz)@l0lprior yjt(IL6z) TNFz;', # Measurement model
  simple = 'ELS | Sex', # Conditional effects of ELS by Sex
  parameters = '
    # Conditional indirect effects for DPDD
    indirect_DPDD_Sex0 = a1 * b1_DPDD;
    indirect_DPDD_Sex1 = (a1 + a3) * b1_DPDD;
    # Expected values of mediator
    M_ELS0_Sex0 = 0;
    M_ELS0_Sex1 = 0 + a2;
    M_ELS1_Sex0 = 0 + a1;
    M_ELS1_Sex1 = 0 + a1 + a2 + a3;
    # Conditional indirect effects for DPDD
    indirect_HDD_ELS0_Sex0 = a1 * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS0_Sex0));
    indirect_HDD_ELS0_Sex1 = (a1 + a3) * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS0_Sex1 + b3_HDD));
    indirect_HDD_ELS1_Sex0 = a1 * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS1_Sex0 + b2_HDD));
    indirect_HDD_ELS1_Sex1 = (a1 + a3) * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS1_Sex1 + b2_HDD + b3_HDD));
    l0lprior ~ truncate(0, Inf);', # Positive prior distribution
  seed = 90291,
  burn = 10000,
  iter = 20000
)

```

```
# Print output
output(modmed)
```

```
##
## -----
##
##              Blimp
##             3.2.20
##
##      Blimp was developed with funding from Institute of
##      Education Sciences awards R305D150056 and R305D190002.
##
##      Craig K. Enders, P.I. Email: cenders@psych.ucla.edu
##      Brian T. Keller, Co-P.I. Email: btkeller@missouri.edu
##      Han Du, Co-P.I. Email: hdu@psych.ucla.edu
##      Roy Levy, Co-P.I. Email: roy.levy@asu.edu
##
##      Programming and Blimp Studio by Brian T. Keller
##
##      There is no expressed license given.
##
## -----
##
##
## ALGORITHMIC OPTIONS SPECIFIED:
##
##   Imputation method:      Fully Bayesian model-based
##   MCMC algorithm:         Full conditional Metropolis sampler with
##                           Auto-Derived Conditional Distributions
##   Between-cluster imputation model: Not applicable, single-level imputation
##   Prior for random effect variances: Not applicable, single-level imputation
##   Prior for residual variances:   Zero sum of squares, df = -2 (PRIOR2)
##   Prior for predictor variances:  Unit sum of squares, df = 2 (XPRIOR1)
##   Chain Starting Values:         Random starting values
```

```
##
##
## NOTE: The default prior for regression coefficients
##       in categorical models is 'normal( 0.0, 5.0)'
```

The maximum potential scale reduction factor diagnostic (Gelman & Rubin, 1992) should be less than approximately 1.05 at the final iteration of the burn-in period, which was set to 10,000 iterations.

```
## BURN-IN POTENTIAL SCALE REDUCTION (PSR) OUTPUT:
##
## NOTE: Split chain PSR is being used. This splits each chain's
##       iterations to create twice as many chains.
##
## Comparing iterations across 2 chains      Highest PSR      Parameter #
##           251 to 500                      1.235           42
##           501 to 1000                     1.055           37
##           751 to 1500                     1.034           52
##          1001 to 2000                     1.034           10
##          1251 to 2500                     1.050           62
##          1501 to 3000                     1.015           62
##          1751 to 3500                     1.023           62
##          2001 to 4000                     1.039           44
##          2251 to 4500                     1.043           44
##          2501 to 5000                     1.028           44
##          2751 to 5500                     1.016           44
##          3001 to 6000                     1.046           44
##          3251 to 6500                     1.048           44
##          3501 to 7000                     1.026           44
##          3751 to 7500                     1.017           48
##          4001 to 8000                     1.020           48
##          4251 to 8500                     1.009           45
##          4501 to 9000                     1.009           45
##          4751 to 9500                     1.019           49
```

```

##          5001 to 10000          1.010          44
##
##
## METROPOLIS-HASTINGS ACCEPTANCE RATES:
##
## Chain 1:
##
## Variable                Type      Probability   Target Value
## Inflammation            latent imp    0.509        0.500
## yjt(DPDDz)              parameter    0.509        0.500
## yjt(CRPz)               parameter    0.437        0.500
## yjt(IL6z)               parameter    0.481        0.500
## Age                    parameter    0.487        0.500
##
## NOTE: Suppressing printing of 1 chains.
##       Use keyword 'tuneinfo' in options to override.
##
##
## DATA INFORMATION:
##
## Sample Size:            99
## Missing Data Info:
##           miss %        1
##           -----
##           CRPz = 0.0      -
##           IL6z = 0.0      -
##           TNFz = 0.0      -
##           DPDDz = 0.0      -
##           HDD = 0.0       -
##           Sex = 0.0       -
##           Age = 0.0       -
##           ELS = 0.0       -
##           -----
##           % 100.0
##
##

```

```

##
## MODEL INFORMATION:
##
##   NUMBER OF PARAMETERS
##     Outcome Models:      27
##     Generated Parameters: 10
##     Predictor Models:    10
##
##   PREDICTORS
##     Complete continous:   Age
##     Complete ordinal:    Sex ELS
##
##   FACTORS
##     Level-1:              Inflammation
##
##   CENTERED PREDICTORS
##     Grand Mean Centered:  Age
##
##   MODELS
##
##   mediator:
##     [1] Inflammation ~ ELS@a1 Sex@a2 Age ELS*Sex@a3
##
##   outcomes:
##     [2] yjt(DPDDz) ~ Intercept Inflammation@b1_dpdd ELS Sex Age
##     [3] HDD ~ Intercept@b0_hdd Inflammation@b1_hdd ELS@b2_hdd Sex@b3_hdd Age
##
##   measurement:
##     [4] yjt(CRPz) ~ Intercept Inflammation@lo1prior
##     [5] yjt(IL6z) ~ Intercept Inflammation
##     [6] TNFz ~ Intercept Inflammation
##
##   PRIORS SPECIFIED
##     [1] lo1prior ~ truncate(0, inf)
##

```

```

## GENERATED PARAMETERS
## [1] indirect_DPDD_Sex0 = a1*b1_dpdd
## [2] indirect_DPDD_Sex1 = (a1+a3)*b1_dpdd
## [3] M_ELS0_Sex0 = 0
## [4] M_ELS0_Sex1 = 0+a2
## [5] M_ELS1_Sex0 = 0+a1
## [6] M_ELS1_Sex1 = 0+a1+a2+a3
## [7] indirect_HDD_ELS0_Sex0 = a1*(b1_hdd*exp(b0_hdd+b1_hdd*m_els0_sex0))
## [8] indirect_HDD_ELS0_Sex1 = (a1+a3)*(b1_hdd*exp(b0_hdd+b1_hdd*m_els0_sex1+b3_hdd))
## [9] indirect_HDD_ELS1_Sex0 = a1*(b1_hdd*exp(b0_hdd+b1_hdd*m_els1_sex0+b2_hdd))
## [10] indirect_HDD_ELS1_Sex1 = (a1+a3)*(b1_hdd*exp(b0_hdd+b1_hdd*m_els1_sex1+b2_hdd+b3_hdd))
##
##
## WARNING MESSAGES:
##
## WARNING: The focal predictor "ELS" is not centered.
##         Simple intercepts in the conditional effects table are
##         evaluated at a score of zero on the focal predictor.
##
##
##
## MODEL FIT:
##
##
## INFORMATION CRITERIA
##
## Conditional Likelihood
## DIC2 1147.578
## WAIC 1190.328
##
##
## CORRELATIONS AMONG RESIDUALS:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.

```

##								
##								
## Correlations	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff	
##								
##								
## Inflammation, yjt(DPDDz)	0.025	0.145	-0.262	0.304	0.027	0.868	16630.254	506
## Inflammation, yjt(CRPz)	0.058	0.142	-0.222	0.333	0.163	0.687	8707.231	
## Inflammation, yjt(IL6z)	-0.022	0.144	-0.306	0.254	0.025	0.874	7987.313	
## Inflammation, TNFz	0.008	0.139	-0.264	0.280	0.003	0.956	11842.707	
## yjt(DPDDz), yjt(CRPz)	0.050	0.130	-0.212	0.298	0.132	0.716	3817.167	
## yjt(DPDDz), yjt(IL6z)	0.002	0.136	-0.269	0.263	0.000	0.995	3840.709	
## yjt(DPDDz), TNFz	-0.006	0.118	-0.240	0.220	0.005	0.944	7288.231	
## yjt(CRPz), yjt(IL6z)	0.039	0.143	-0.250	0.307	0.063	0.801	1920.327	
## yjt(CRPz), TNFz	0.106	0.125	-0.153	0.335	0.651	0.420	2569.900	
## yjt(IL6z), TNFz	-0.030	0.132	-0.289	0.222	0.052	0.820	5043.330	
##								
##								
##								
##								

Each variable in the model has its own summary table. The values in the Estimate column are posterior medians, the StdDev column contains “Bayesian standard errors”, and the 2.5% and 97.5% columns give the 95% credible interval limits. The ChiSq and PValue columns contain frequentist significance tests (Asparouhov & Muthén, 2021). The rightmost column of the tables—the effective number of MCMC samples—is essentially the number of independent estimates on which the parameter summaries are based after removing autocorrelations from the MCMC process. Gelman et al. (2014, p. 287) recommend that these values should exceed 100. If any of the values fall below this threshold, increase the number of iterations after the burn-in period (specified as 20,000 for this analysis).

```

## OUTCOME MODEL ESTIMATES:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
## mediator block:
##
## Latent Variable: Inflammation
##
## Grand Mean Centered: Age
##
##
## Parameters
##
## Variances:
## Residual Var.
##
## Coefficients:
## ELS
## Sex
## Age
## ELS*Sex
##
## Standardized Coefficients:
## ELS
## Sex
## Age
## ELS*Sex
##
## Proportion Variance Explained
## by Coefficients
## by Residual Variation
##
##

```

	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
Residual Var.	@ 1.000	---	---	---	---	---	---
ELS	0.199	0.360	-0.483	0.927	0.327	0.567	507.159
Sex	-0.312	0.357	-1.042	0.366	0.792	0.374	558.155
Age	0.047	0.015	0.018	0.078	9.510	0.002	743.616
ELS*Sex	1.074	0.581	-0.024	2.268	3.519	0.061	1115.316
ELS	0.081	0.141	-0.196	0.358	0.330	0.566	536.452
Sex	-0.126	0.141	-0.405	0.148	0.809	0.368	523.162
Age	0.423	0.111	0.178	0.612	14.093	0.000	910.813
ELS*Sex	0.328	0.165	-0.008	0.640	3.896	0.048	1053.674
by Coefficients	0.318	0.101	0.134	0.523	---	---	665.617
by Residual Variation	0.682	0.101	0.477	0.866	---	---	665.617

```

##
##
## Conditional Effects
##
##   ELS | Sex @ 0
##   Intercept      0.000    0.000    0.000    0.000      nan      nan      nan
##   Slope          0.199    0.360   -0.483    0.927    0.327    0.567   507.159
##
##   ELS | Sex @ 1
##   Intercept     -0.312    0.357   -1.042    0.366    0.792    0.374   558.155
##   Slope          1.281    0.483    0.406    2.298    7.182    0.007  1243.701
##
## -----
##
## NOTE: Intercepts are computed by setting all predictors
##       not involved in the conditional effect to zero.
##
##
## outcomes block:
##
## Outcome Variable:  yjt(DPDDz)
##
## Grand Mean Centered: Age
##
## Parameters
##
## -----
## Variances:
##   Residual Var.      0.751    0.132    0.532    1.049      ---      ---  3758.070
##
## Coefficients:
##   Intercept     -0.091    0.156   -0.395    0.220    0.332    0.565  2654.127
##   Inflammation    0.346    0.121    0.120    0.594    8.307    0.004  2083.764
##   ELS           -0.179    0.212   -0.607    0.231    0.746    0.388  3292.117
##   Sex           -0.180    0.195   -0.568    0.197    0.874    0.350  6284.059

```

```

##      Age                -0.017      0.011     -0.039      0.004      2.376      0.123      2178.015
##
## Transformation:
##      Yeo-Johnson (lambda)      0.392      0.138      0.108      0.654      ---      ---      3222.029
##
## Standardized Coefficients:
##      Inflammation      0.430      0.142      0.152      0.705      9.117      0.003      1398.821
##      ELS      -0.092      0.107     -0.304      0.116      0.762      0.383      3172.329
##      Sex      -0.093      0.098     -0.285      0.100      0.891      0.345      6052.796
##      Age      -0.189      0.122     -0.432      0.044      2.454      0.117      2020.414
##
## Proportion Variance Explained
##      by Coefficients      0.167      0.084      0.041      0.364      ---      ---      1771.752
##      by Residual Variation      0.833      0.084      0.636      0.959      ---      ---      1771.752
##
## -----
##
##
##
##
## Conditional Effects
##      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##      ELS | Sex @ 0
##      Intercept      -0.091      0.156     -0.395      0.220      0.332      0.565      2654.127
##      Slope      -0.179      0.212     -0.607      0.231      0.746      0.388      3292.117
##
##      ELS | Sex @ 1
##      Intercept      -0.273      0.187     -0.640      0.092      2.109      0.146      1450.592
##      Slope      -0.179      0.212     -0.607      0.231      0.746      0.388      3292.117
##
## -----
##
##
## NOTE: Intercepts are computed by setting all predictors
##       not involved in the conditional effect to zero.
##
##

```

```

##
## Outcome Variable:  HDD
##
## Grand Mean Centered: Age
##
## Parameters
##           Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## Variances:
## Dispersion Parameter      0.508      0.151      0.274      0.862      ---      ---      891.627
##
## Coefficients:
## Intercept      0.779      0.156      0.476      1.087      24.979      0.000      9406.942
## Inflammation      0.176      0.116      -0.041      0.414      2.343      0.126      4292.701
## ELS      -0.007      0.224      -0.455      0.429      0.001      0.972      7266.892
## Sex      0.155      0.205      -0.253      0.557      0.579      0.447      12421.567
## Age      -0.005      0.011      -0.026      0.016      0.192      0.661      5656.531
##
## Exponentiated Coefficients:
## Intercept      2.179      0.348      1.609      2.966      ---      ---      9244.148
## Inflammation      1.192      0.141      0.959      1.513      ---      ---      4137.292
## ELS      0.993      0.229      0.634      1.535      ---      ---      7906.208
## Sex      1.168      0.248      0.776      1.745      ---      ---      12326.303
## Age      0.995      0.011      0.974      1.016      ---      ---      5685.069
##
## -----
##
##
##
## Conditional Effects
##           Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## ELS | Sex @ 0
## Intercept      0.095      0.332      -0.575      0.738      0.076      0.783      965.512
## Slope      -0.007      0.224      -0.455      0.429      0.001      0.972      7266.892
##

```

```

## ELS | Sex @ 1
## Intercept      0.251      0.348     -0.447      0.932      0.505      0.477      982.844
## Slope          -0.007      0.224     -0.455      0.429      0.001      0.972     7266.892
##
## -----
##
## NOTE: Intercepts are computed by setting all predictors
##       not involved in the conditional effect to zero.
##
## measurement block:
##
## Outcome Variable:  yjt(CRPz)
##
## Parameters      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## Variances:
## Residual Var.   0.404      0.085      0.249      0.585      ---      ---      1364.370
##
## Coefficients:
## Intercept       -0.315      0.109     -0.534     -0.103      8.375      0.004      592.593
## Inflammation    0.382      0.089      0.221      0.569     18.942      0.000      780.222
##
## Transformation:
## Yeo-Johnson (lambda) -0.037      0.166     -0.397      0.243      ---      ---      2316.667
##
## Standardized Coefficients:
## Inflammation    0.579      0.099      0.367      0.762     33.756      0.000      951.717
##
## Proportion Variance Explained
## by Coefficients 0.336      0.113      0.135      0.581      ---      ---      909.384
## by Residual Variation 0.664      0.113      0.419      0.865      ---      ---      909.384
##
## -----
##

```

```

##
##
## Outcome Variable:  yjt(IL6z)
##
## Parameters          Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## Variances:
##   Residual Var.      0.255      0.077      0.113      0.417      ---      ---      543.589
##
## Coefficients:
##   Intercept          -0.308      0.113      -0.535     -0.091      7.420      0.006      337.952
##   Inflammation        0.457      0.082      0.306      0.629      31.227      0.000      553.578
##
## Transformation:
##   Yeo-Johnson (lambda) -0.085      0.155      -0.417      0.184      ---      ---      1901.052
##
## Standardized Coefficients:
##   Inflammation        0.731      0.091      0.531      0.890      63.013      0.000      523.527
##
## Proportion Variance Explained
##   by Coefficients      0.534      0.130      0.282      0.792      ---      ---      490.310
##   by Residual Variation 0.466      0.130      0.208      0.718      ---      ---      490.310
##
## -----
##
##
## Outcome Variable:  TNFz
##
## Parameters          Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
## Variances:
##   Residual Var.      0.878      0.144      0.648      1.211      ---      ---      6101.507
##
## Coefficients:

```

```

## Intercept -0.035 0.119 -0.278 0.191 0.102 0.750 939.997
## Inflammation 0.328 0.105 0.130 0.541 9.974 0.002 1859.268
##
## Standardized Coefficients:
## Inflammation 0.385 0.105 0.160 0.569 13.020 0.000 2500.698
##
## Proportion Variance Explained
## by Coefficients 0.148 0.078 0.025 0.324 --- --- 2396.867
## by Residual Variation 0.852 0.078 0.676 0.975 --- --- 2396.867
##
## -----
##
##
##
## Additional Parameters:
##
## Parameters Estimate StdDev 2.5% 97.5% ChiSq PValue N_Eff
## -----
##
## lo1prior 0.382 0.089 0.221 0.569 18.942 0.000 780.222
## -----
##
##
##

```

Indirect effect estimates are in a table labeled GENERATED PARAMETERS. The indirect effect of ELS on DPDD is significant because the 95% credible interval does not contain zero. The conditional indirect effects of ELS on HDD are not significant because zero is inside the 95% interval, albeit just barely.

```

## GENERATED PARAMETERS:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##

```

```

##
## Parameters      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##
## indirect_DPDD_Sex0      0.060      0.137      -0.168      0.385      0.301      0.583      558.502
## indirect_DPDD_Sex1      0.419      0.220      0.092      0.939      4.088      0.043      1707.740
## M_ELS0_Sex0      0.000      0.000      0.000      0.000      nan      nan      nan
## M_ELS0_Sex1      -0.312      0.357      -1.042      0.366      0.792      0.374      558.155
## M_ELS1_Sex0      0.199      0.360      -0.483      0.927      0.327      0.567      507.159
## M_ELS1_Sex1      0.957      0.437      0.182      1.884      5.008      0.025      486.969
## indirect_HDD_ELS0_Sex0      0.023      0.100      -0.120      0.282      0.183      0.669      1028.981
## indirect_HDD_ELS0_Sex1      0.239      0.243      -0.072      0.874      1.339      0.247      2504.438
## indirect_HDD_ELS1_Sex0      0.024      0.106      -0.112      0.310      0.199      0.655      992.646
## indirect_HDD_ELS1_Sex1      0.295      0.370      -0.078      1.320      1.049      0.306      2832.783
##
## -----
##
##
## PREDICTOR MODEL ESTIMATES:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
##
## Complete predictor: Sex
##
## Parameters      Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##
## Grand Mean      -0.275      0.132      -0.536      -0.020      4.357      0.037      8349.127
##
## Level 1:
## Age      -0.014      0.012      -0.038      0.009      1.432      0.231      7897.572
## ELS      0.044      0.156      -0.261      0.352      0.079      0.779      5097.508

```

```

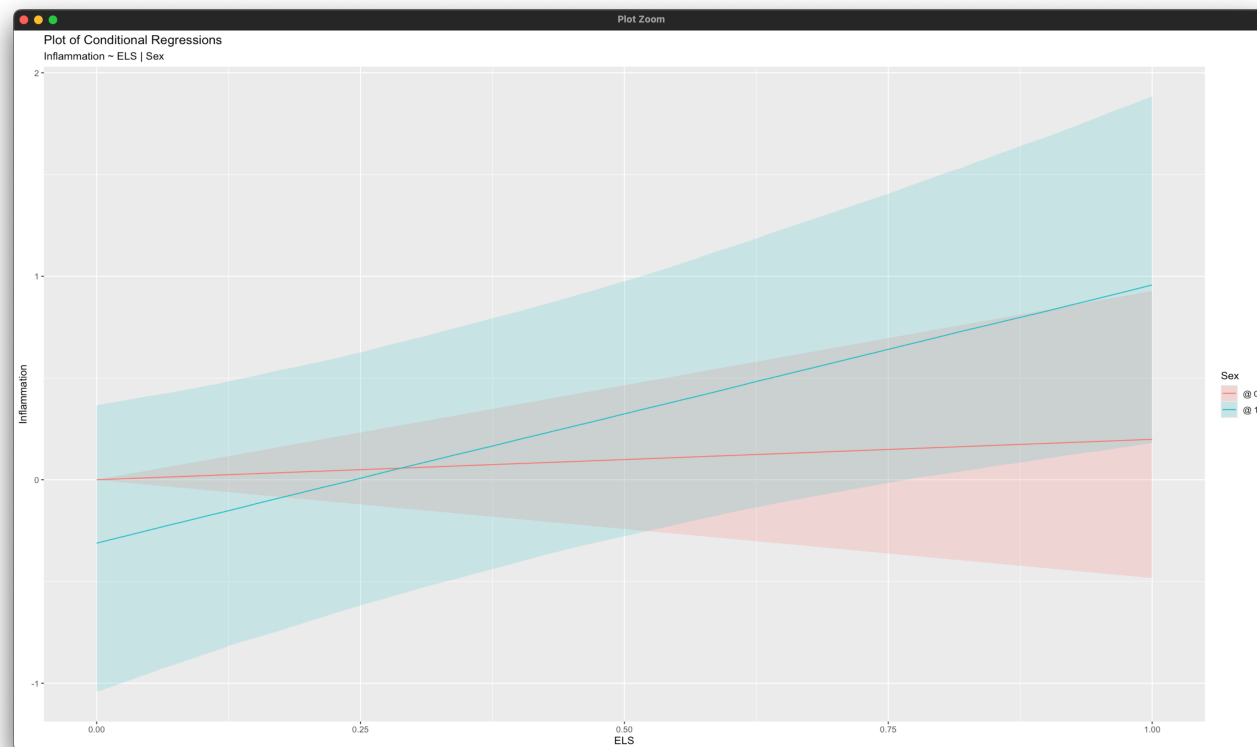
##   Residual Var.          1.000      0.000      1.000      1.000      ---      ---      nan
## Thresholds:
##   Tau 1          0.000      0.000      0.000      0.000      ---      ---      nan
##
## -----
##
##
##
## Complete predictor: Age
##
## Parameters          Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##
## Grand Mean          44.347      1.118      42.177      46.556      1572.209      0.000      2620.552
##
## Level 1:
##   Sex          -1.609      1.364      -4.254      1.106      1.387      0.239      12790.998
##   ELS          -0.060      1.388      -2.772      2.673      0.002      0.963      13332.423
##   Residual Var.      116.380      17.406      88.620      156.634      ---      ---      17147.879
##
## -----
##
##
##
## Complete predictor: ELS
##
## Parameters          Estimate      StdDev      2.5%      97.5%      ChiSq      PValue      N_Eff
## -----
##
## Grand Mean          -0.273      0.130      -0.531      -0.023      4.444      0.035      8459.826
##
## Level 1:
##   Sex          0.043      0.158      -0.267      0.352      0.075      0.784      4970.805
##   Age          -0.001      0.012      -0.024      0.023      0.003      0.955      8576.428
##   Residual Var.      1.000      0.000      1.000      1.000      ---      ---      nan

```

```
## Thresholds:
##   Tau 1          0.000    0.000    0.000    0.000    ---    ---    nan
##
## -----
```

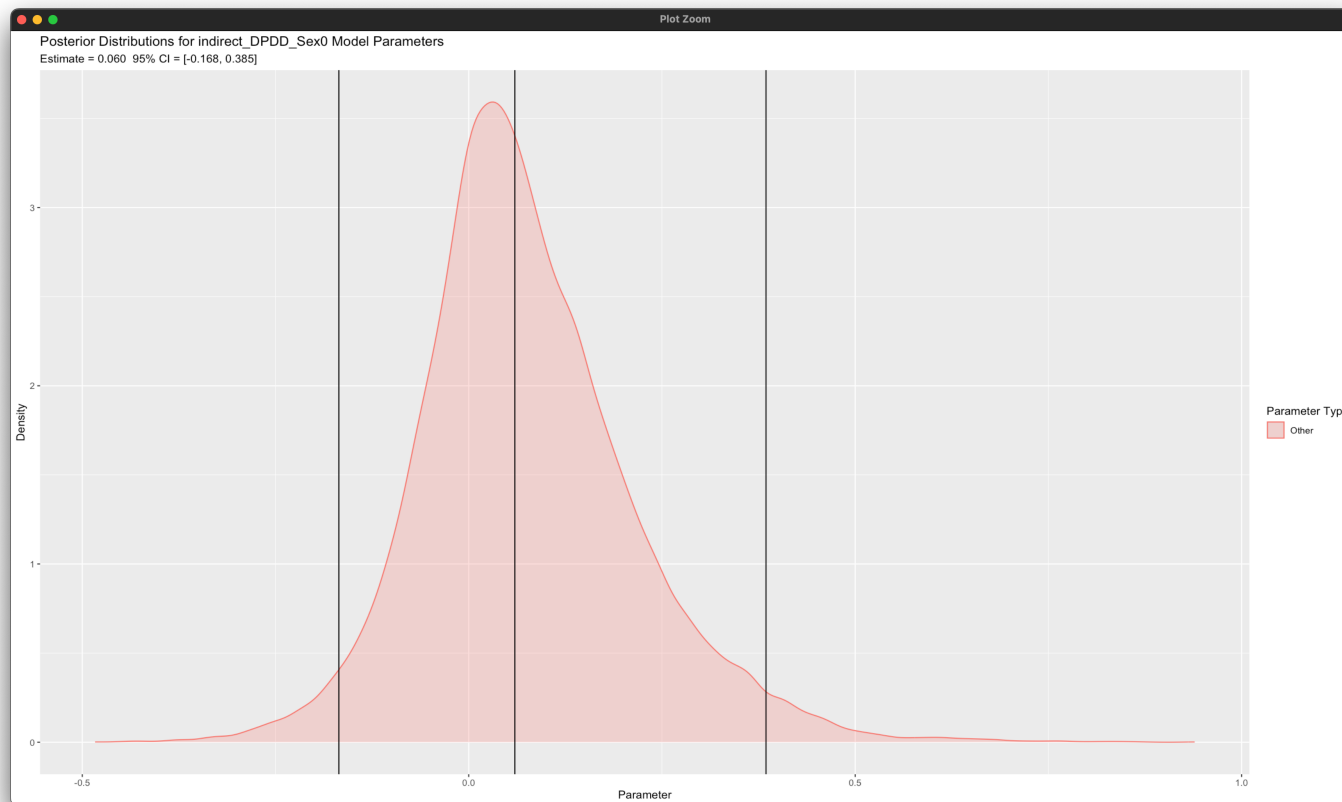
The `simple_plot` function generates a graph of the simple intercepts and slopes for the influence of early life stress (ELS) on the inflammation latent variable.

```
# Plot conditional effect of ELS by Sex
simple_plot(Inflammation ~ ELS | Sex, modmed)
```

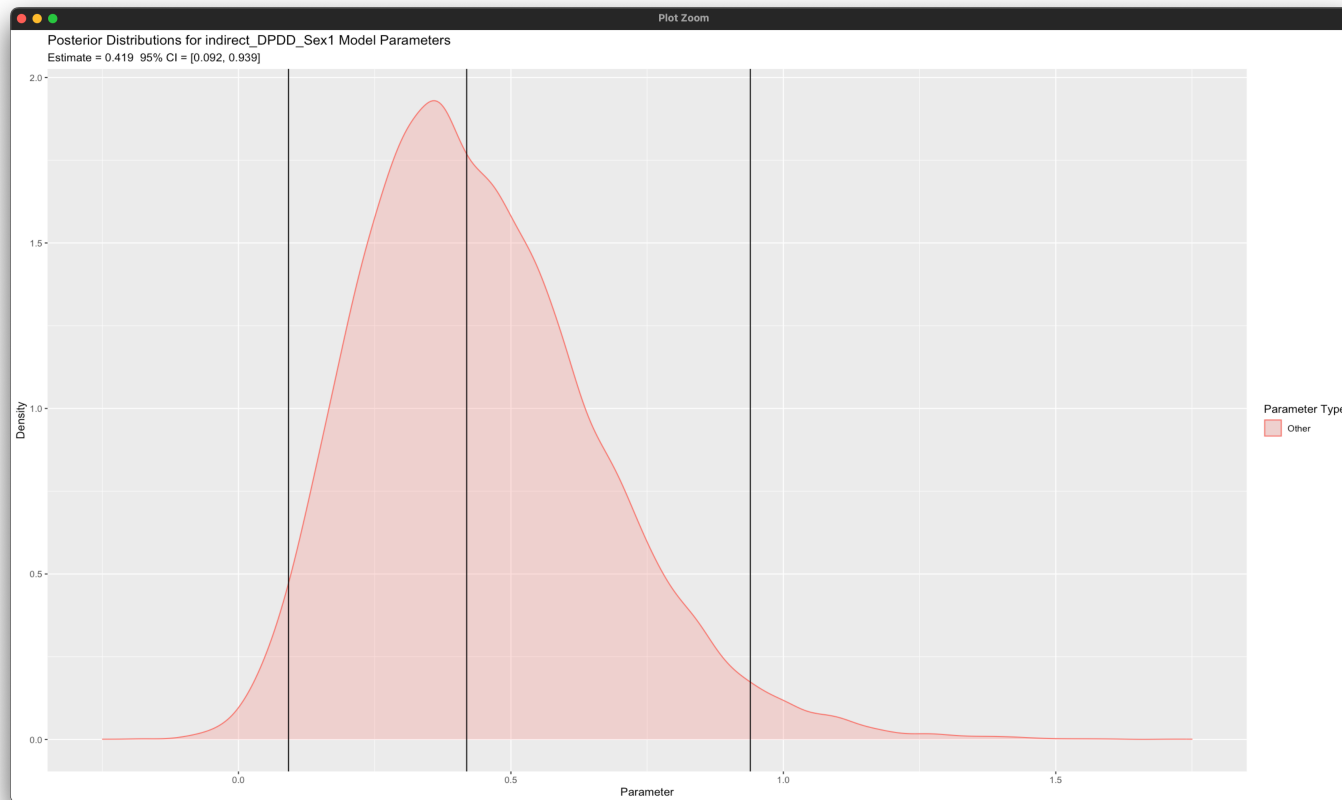


The `posterior_plot` functions generate kernel density plots of the distribution of indirect effects.

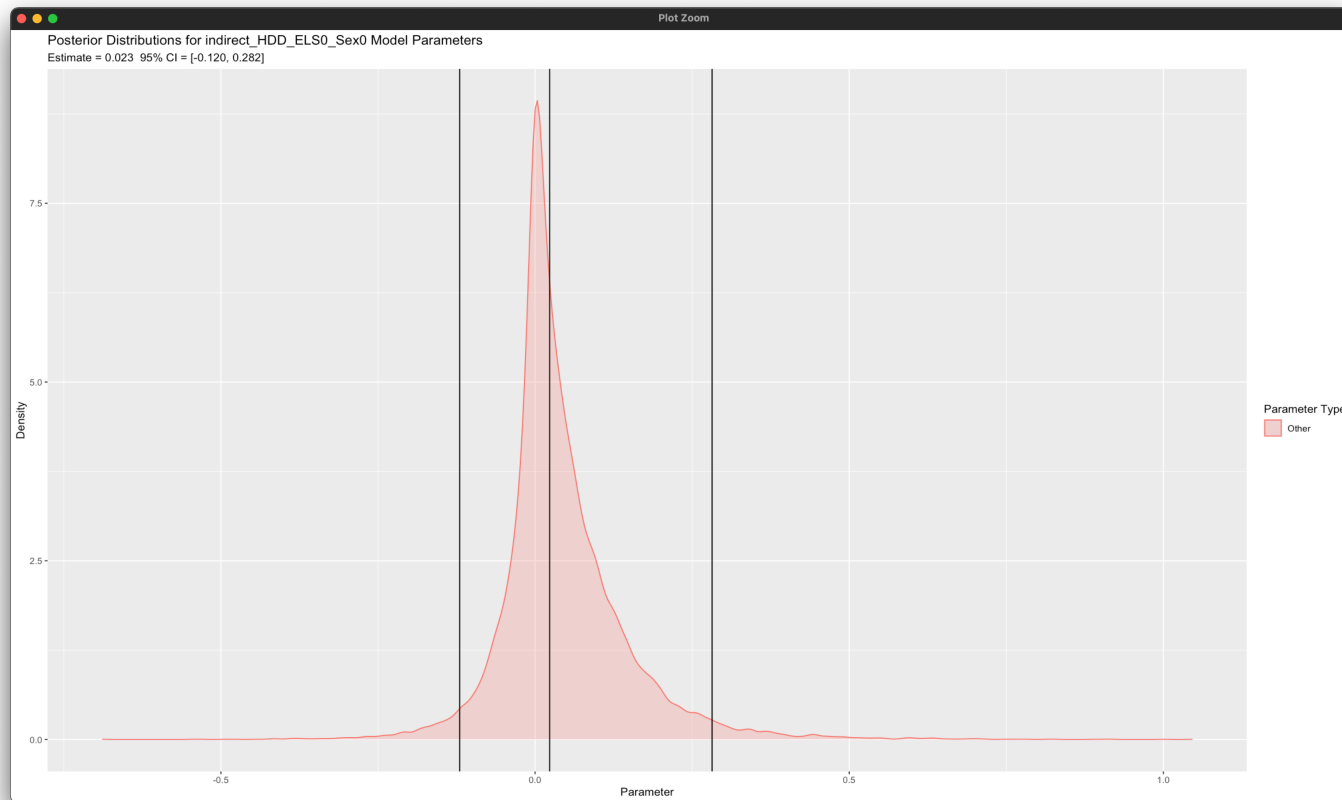
```
# Plot distributions of indirect effects  
posterior_plot(modmed, 'indirect_DPDD_Sex0')
```



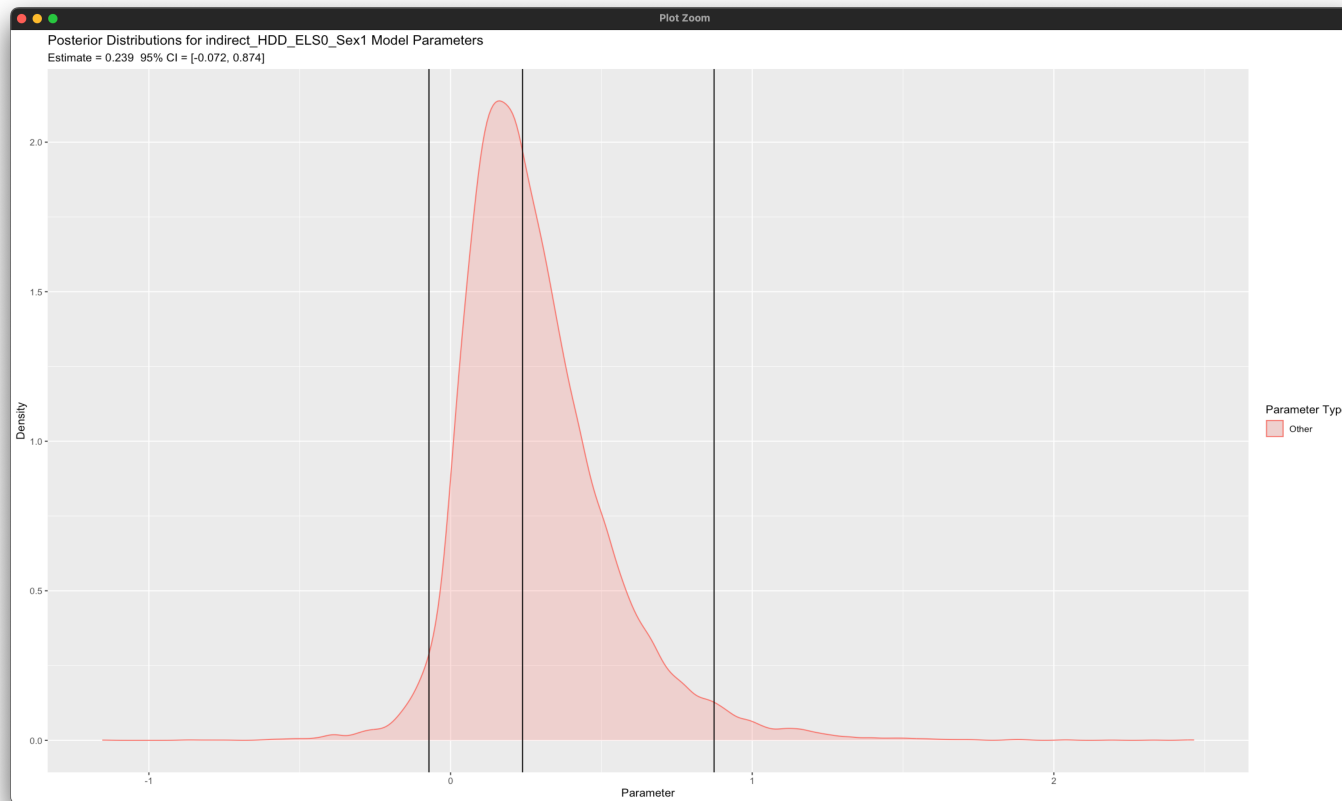
```
posterior_plot(modmed, 'indirect_DPDD_Sex1')
```



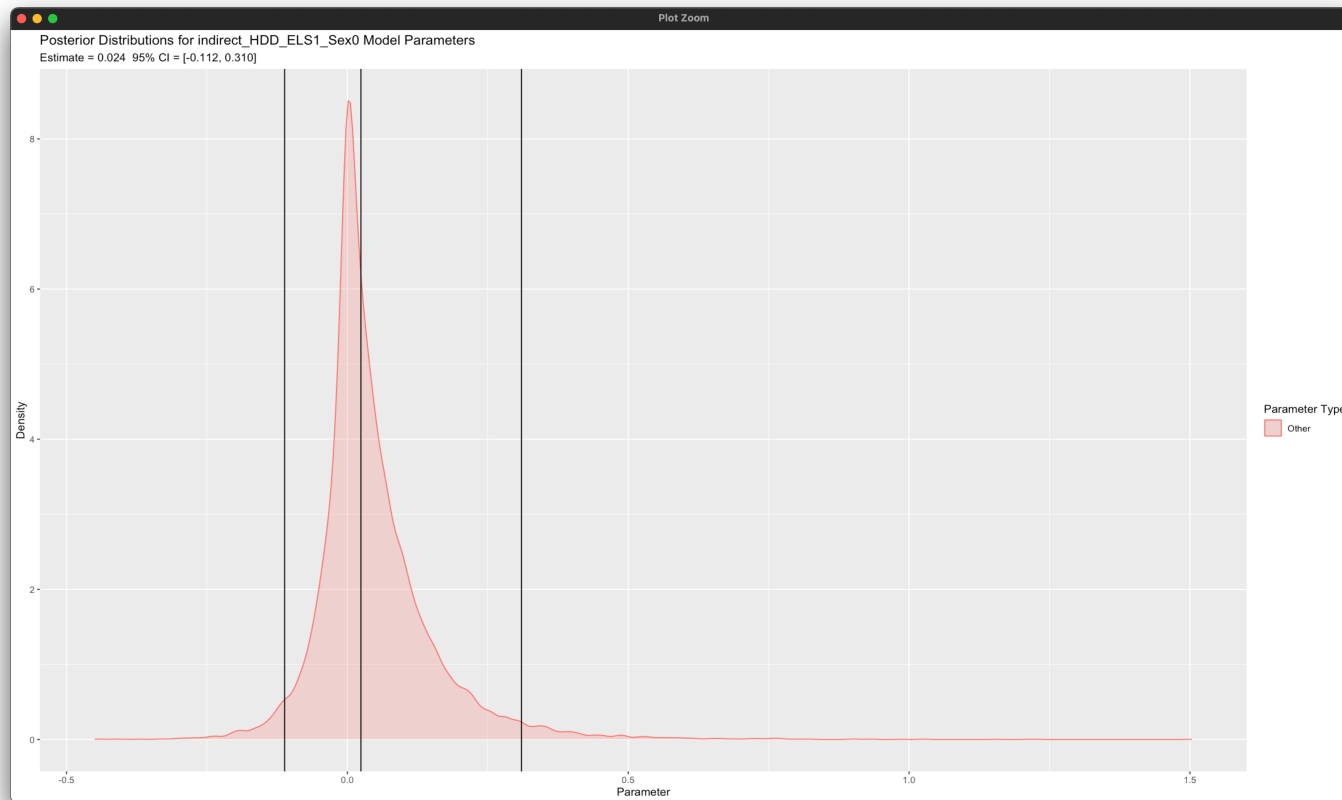
```
posterior_plot(modmed, 'indirect_HDD_ELS0_Sex0')
```



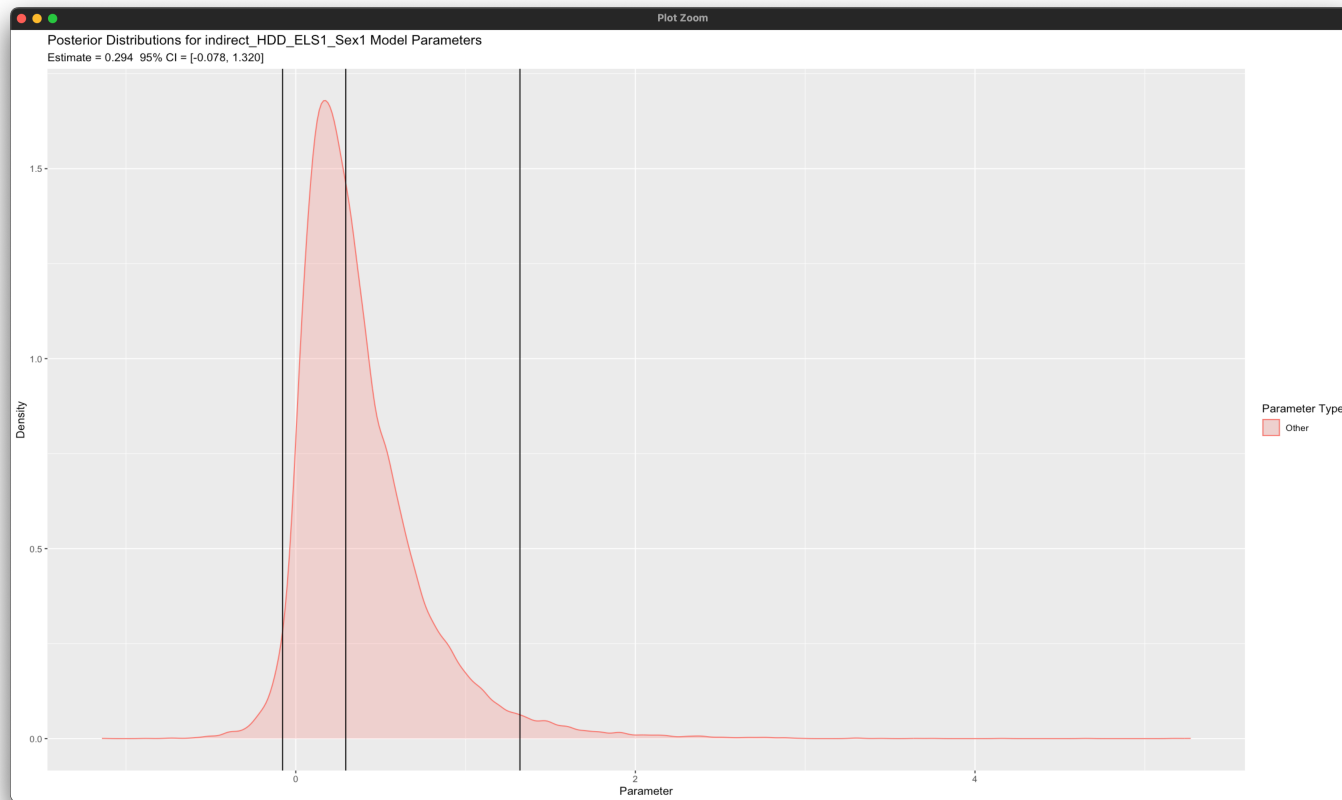
```
posterior_plot(modmed, 'indirect_HDD_ELS0_Sex1')
```



```
posterior_plot(modmed, 'indirect_HDD_ELS1_Sex0')
```



```
posterior_plot(modmed, 'indirect_HDD_ELS1_Sex1')
```



Inspect Distributions

Histograms of the raw data showed that two of the three inflammation indicators (IL6 and CRP) and the drinks per drinking day outcome (DPDD) have positively skewed distributions. These variables were normalized in the analysis models using the Yeo–Johnson transformation. The normalized scores are saved at every MCMC iteration, and Blimp stores the average values of the normalized scores across iterations (along with any missing data imputations) in an object named `@average_imp`. The code below extracts the variable names from this file and graphs the normalized variables for inspection. Relative to the raw data, the transformed variables are more symmetric.

```
# Get variable names from object containing average imputations
names(modmed@average_imp)

## [1] "Sex"          "Age"          "ELS"
## [4] "CRP"          "IL6"          "TNF"
## [7] "CRPz"         "IL6z"         "TNFz"
## [10] "DPDD"         "DPDDz"        "HDD"
## [13] "Inflammation.latent" "yjt.DPDDz."   "yjt.CRPz."
## [16] "yjt.IL6z."    "Sex.latent"   "ELS.latent"
## [19] "Inflammation.residual" "yjt.DPDDz..residual" "HDD.residual"
## [22] "yjt.CRPz..residual" "yjt.IL6z..residual" "TNFz.residual"
## [25] "Inflammation.predicted" "yjt.DPDDz..predicted" "HDD.predicted"
## [28] "yjt.CRPz..predicted" "yjt.IL6z..predicted" "TNFz.predicted"

# Distributions and correlations of analysis variables
ggpairs(
  modmed@average_imp[, c('Age', 'Sex', 'ELS', 'yjt.IL6z.', 'TNFz.', 'yjt.CRPz.', 'yjt.DPDDz.', 'HDD', 'Inflammation.latent')],
  upper = list(continuous = wrap("cor", size = 3)),
  lower = list(continuous = wrap("points", alpha = 0.5, size = 0.7)),
  diag = list(continuous = wrap("barDiag", colour = "black", fill = "grey80"))
) + ggtitle("Distributions and Correlations of Analysis Variables")
```


References

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- Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). *Bayesian data analysis* (3rd ed.). CRC Press.
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- Hayes, A. F., & Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research*, 45(4), 627–660. <https://doi.org/doi.org/10.1080/00273171.2010.498290>