

PSY.308d.DA5

Prompt

Parents with anxiety disorders tend to have children with anxiety disorders as well (see everything ever written by Bogels, Borelli, Wood, or Rapee). This has led some to hypothesize that anxiety is genetically transmitted. However, you think there might be something else going on. Parental overcontrol, the excess regulation of a child's emotion, cognition, and behavior is strongly related to child anxiety. You wonder if anxious parents are more overcontrolling, leading to child anxiety. You decided to conduct a study to figure this out.

Variables: Parent_Anxiety: 1-20 (higher scores indicating higher anxiety symptoms) Child_Anxiety: 1-20 (higher scores indicating higher anxiety symptoms) Parent_OC: 1-20 (higher scores indicating greater use of over-control)

Research Question: Does parental overcontrol mediate the relationship between parent anxiety and child anxiety?

(1) *General assignment:* Conduct the appropriate analysis using bootstrapping techniques. Report the proper assumptions and statistics in the results section. In the discussion section, provide a summary of what you found, discuss the implications, and give at least one limitation and future research direction. Don't forget to include a table for descriptives, correlations, and regression models.

(2) *Conceptual component:* Conduct the same analysis, but use the Sobel test instead of bootstrapping to test the indirect effect. *Report the statistics in your results section.* Provide a summary of what of the findings were for this analysis and compare it to your bootstrapped analysis findings. If the two analyses found different outcomes, determine which results are more appropriate and justify your decision (Hint: What is a known issue with the Sobel test?).

#Prep

```
library(pacman)
p_load(psych, jmv, medmod, lavaan, multilevel)
```

#Read in your data

```
datboot <- read.csv("https://www.dropbox.com/s/dsplwa2mppfhmu7/Psy.308d.DA5.csv?dl=1")
```

Descriptives

```
desc <- descriptives(datboot,
  vars = c('Parent_Anxiety', 'Child_Anxiety', 'Parent_OC'),
  hist = TRUE,
  sd = TRUE,
  min = TRUE,
  max = TRUE,
  skew = TRUE,
  kurt = TRUE)
```

desc

##

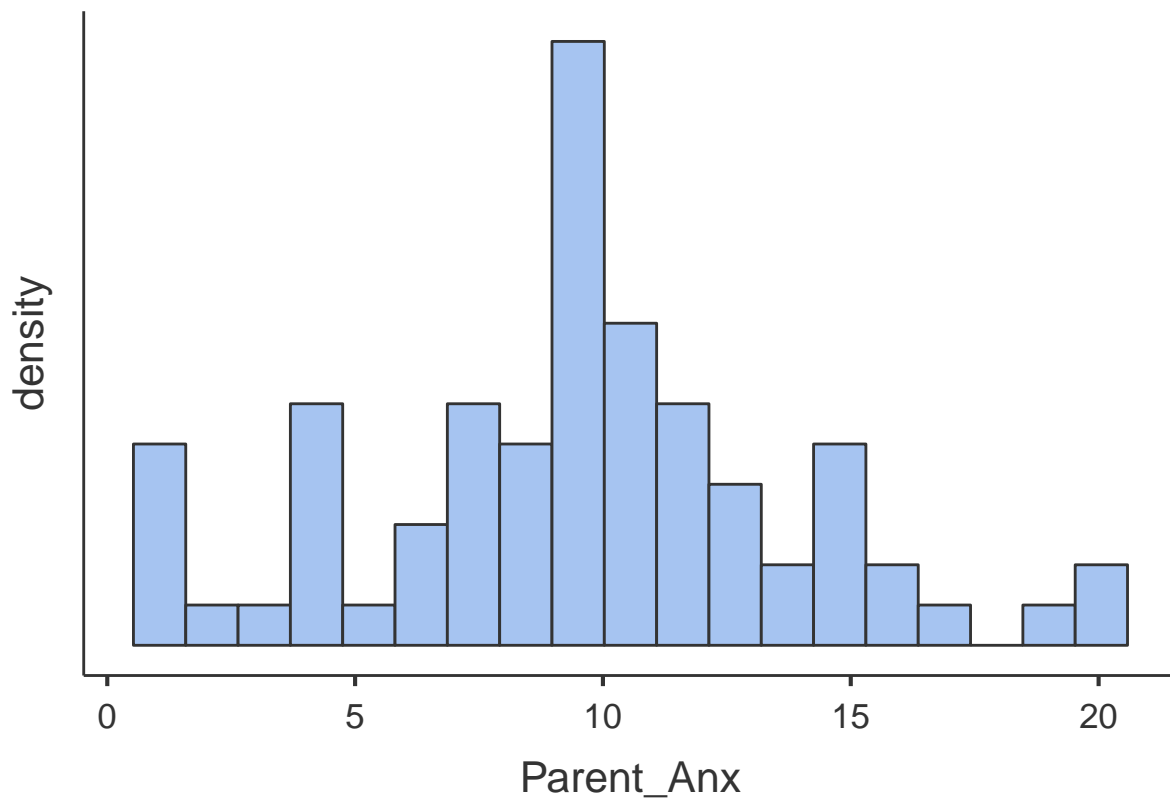
DESCRIPTIVES

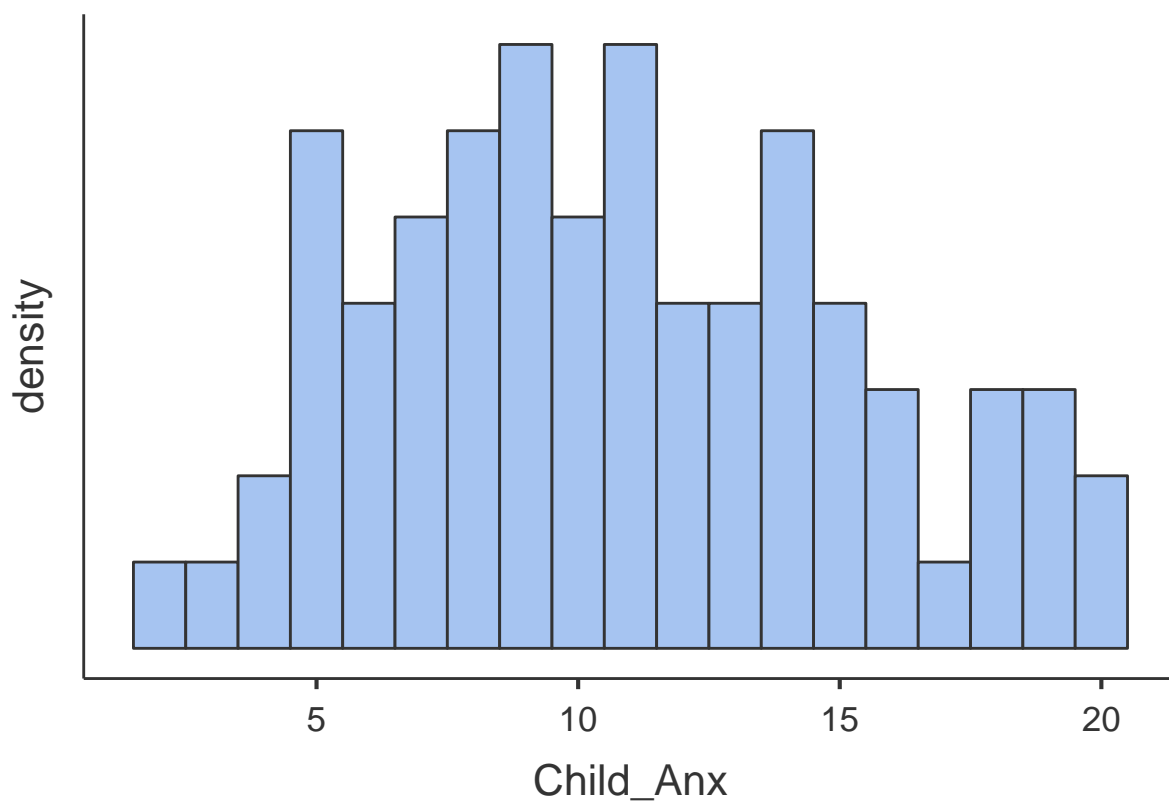
##

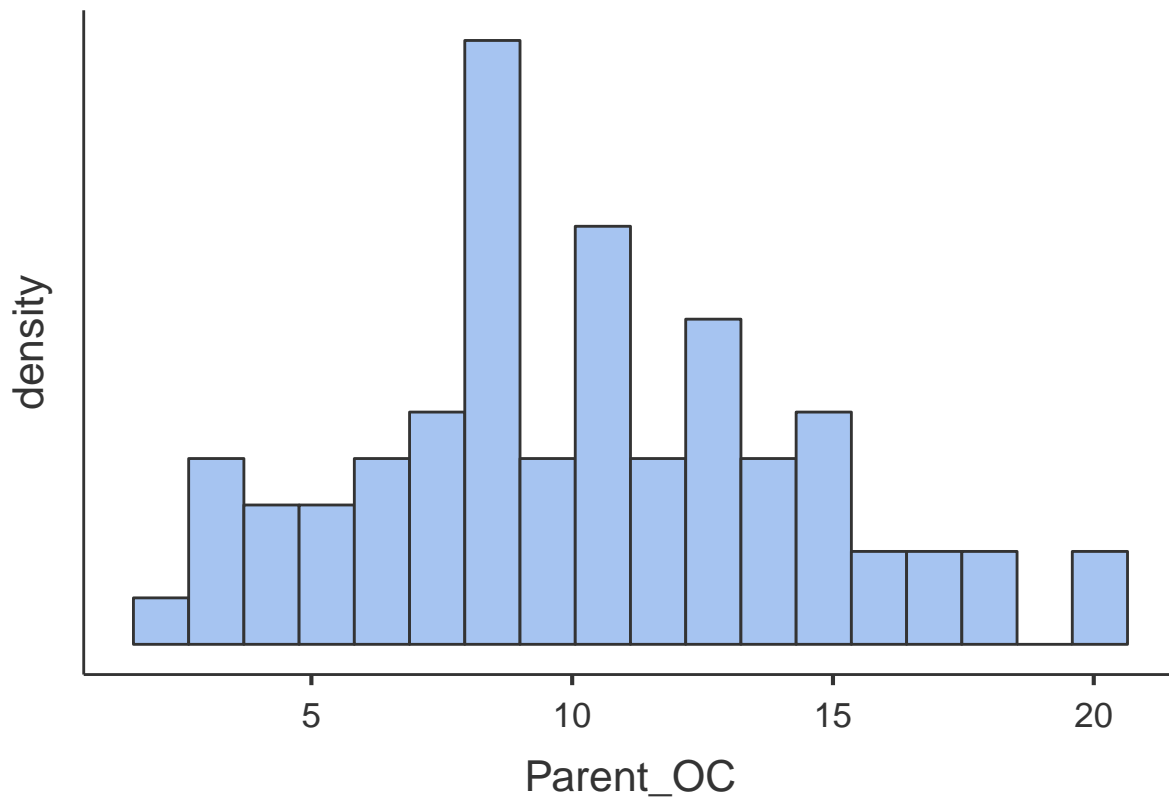
Descriptives

```
## -----
##               Parent_Anxiety   Child_Anxiety   Parent_OC
## -----
##      N               74             74             74
```

##	Missing	0	0	0
##	Mean	9.54	10.8	10.3
##	Median	10.0	10.5	10.5
##	Standard deviation	4.53	4.49	4.31
##	Minimum	1	2	2
##	Maximum	20	20	20
##	Skewness	0.0261	0.254	0.130
##	Std. error skewness	0.279	0.279	0.279
##	Kurtosis	-0.195	-0.721	-0.542
##	Std. error kurtosis	0.552	0.552	0.552
##	-----			







```
cat("\n")
```

```
corr <- corrMatrix(datboot,
  vars = c('Parent_Anxiety', 'Child_Anxiety', 'Parent_OC'),
  flag = TRUE)
corr
```

```
##
## CORRELATION MATRIX
##
## Correlation Matrix
## -----
##               Parent_Anxiety   Child_Anxiety   Parent_OC
## -----
## Parent_Anxiety  Pearson's r      -           0.618      0.602
##                p-value           -           < .001     < .001
##
## Child_Anxiety   Pearson's r              -           0.675
##                p-value                  -           < .001
##
## Parent_OC       Pearson's r                      -
##                p-value                      -
## -----
## Note. * p < .05, ** p < .01, *** p < .001
```

Assumptions:

1. Missing Data - **NONE**

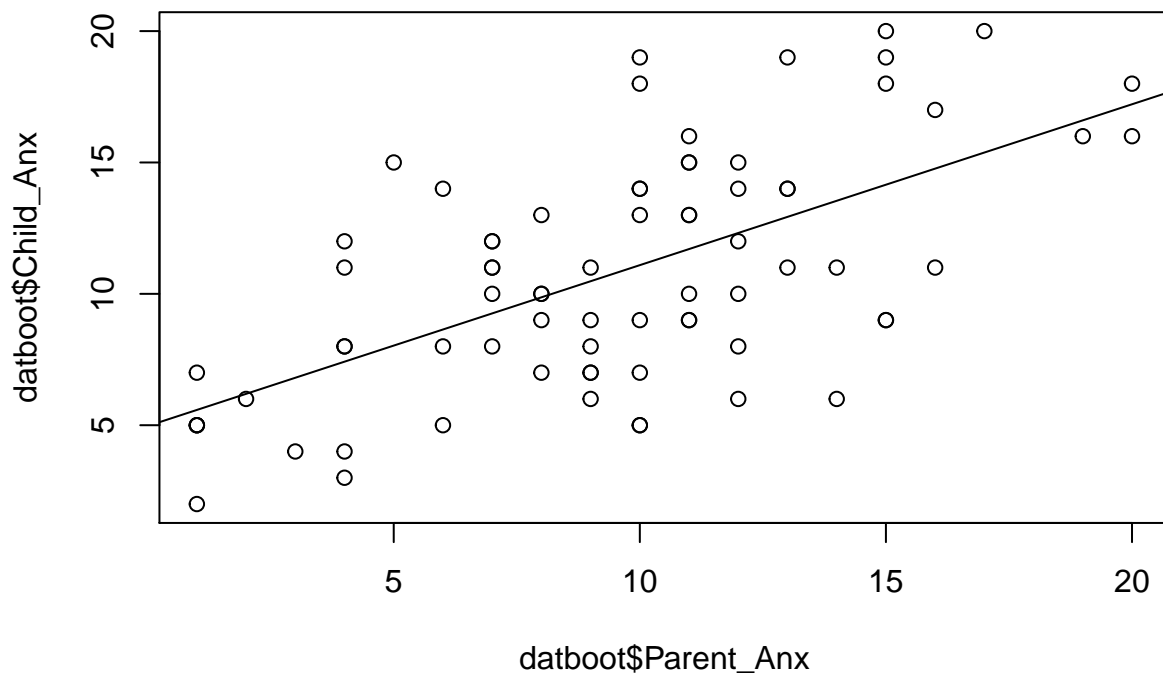
2. Univariate a. Normality **PASSED**, b. Linearity and c. Outliers
3. Multivariate a. Normality **PASSED** and b. Outliers **REMOVED**
4. Heteroscedsticity **PASSED**
5. Multi-collinearity **EXPECTED**

2b. Univariate Linearity

```
# Scatterplots [Assumption 2b]
```

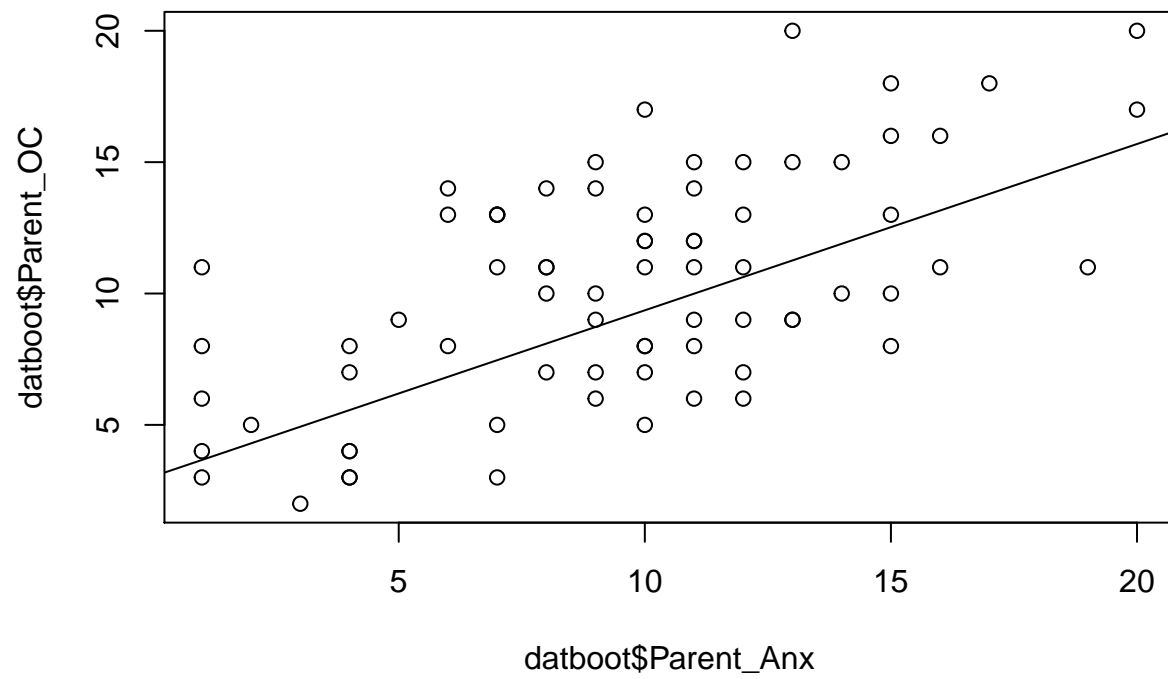
```
# Y ~ X [path c]
```

```
plot(datboot$Parent_Anx, datboot$Child_Anx, abline(lm(datboot$Child_Anx ~ datboot$Parent_Anx)))
```

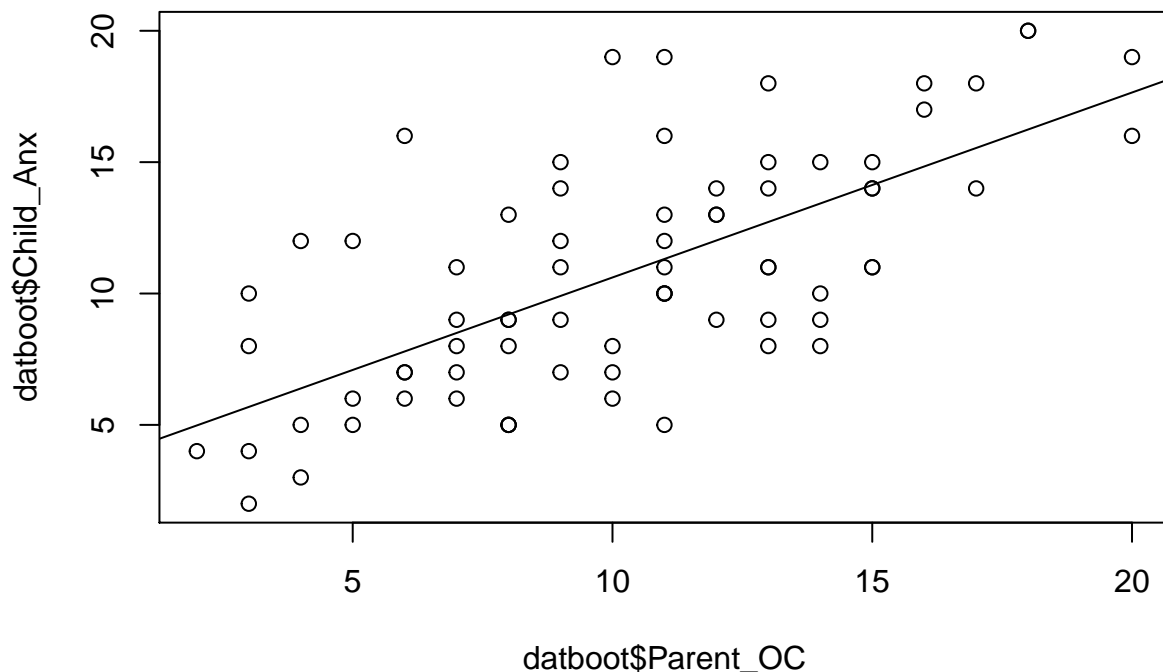


```
# M ~ X [path a]
```

```
plot(datboot$Parent_Anx, datboot$Parent_OC, abline(lm(datboot$Parent_Anx ~ datboot$Parent_OC)))
```



```
# Y ~ M [path b]  
plot(datboot$Parent_OC, datboot$Child_Anx, abline(lm(datboot$Child_Anx ~ datboot$Parent_OC)))
```



2c. Univariate Outliers

```
#Identify outliers
#scale() converts to z scores - "3" refers to standard deviations
datboot[abs(scale(datboot$Parent_Anxiety)) > 3, ]

## [1] Participant Parent_Anxiety Parent_OC Child_Anxiety
## <0 rows> (or 0-length row.names)

datboot[abs(scale(datboot$Child_Anxiety)) > 3, ]

## [1] Participant Parent_Anxiety Parent_OC Child_Anxiety
## <0 rows> (or 0-length row.names)

datboot[abs(scale(datboot$Parent_OC)) > 3, ]

## [1] Participant Parent_Anxiety Parent_OC Child_Anxiety
## <0 rows> (or 0-length row.names)

#There are a total of 0 independent observations that contain outliers
```

3a. Multivariate Normality

```
#look at residuals and the Q-Q plot for independent variables (should be no relationship)
#Observe Leverage (Mahalanobis' Distance) + Discrepancy (= Influence; Cook's Distance)

# Y ~ X + M
model.multi_norm <- linReg(data = datboot,
  dep = 'Child_Anxiety',
  covs = c('Parent_Anxiety', 'Parent_OC'),
```

```

blocks = list(c('Parent_Anxiety', 'Parent_OC')),
modelTest = TRUE,
r2Adj = TRUE,
stdEst = TRUE,
ciStdEst = TRUE,
qqPlot = TRUE, ##QQ plot
resPlots = TRUE) ##residuals plot

```

```
model.multi_norm
```

```
##
```

```
## LINEAR REGRESSION
```

```
##
```

```
## Model Fit Measures
```

```
## -----
```

Model	R	R ²	Adjusted R ²	F	df1	df2	p
1	0.725	0.526	0.512	39.4	2	71	< .001

```
## -----
```

```
##
```

```
##
```

```
## MODEL SPECIFIC RESULTS
```

```
##
```

```
## MODEL 1
```

```
##
```

```
## Model Coefficients
```

```
## -----
```

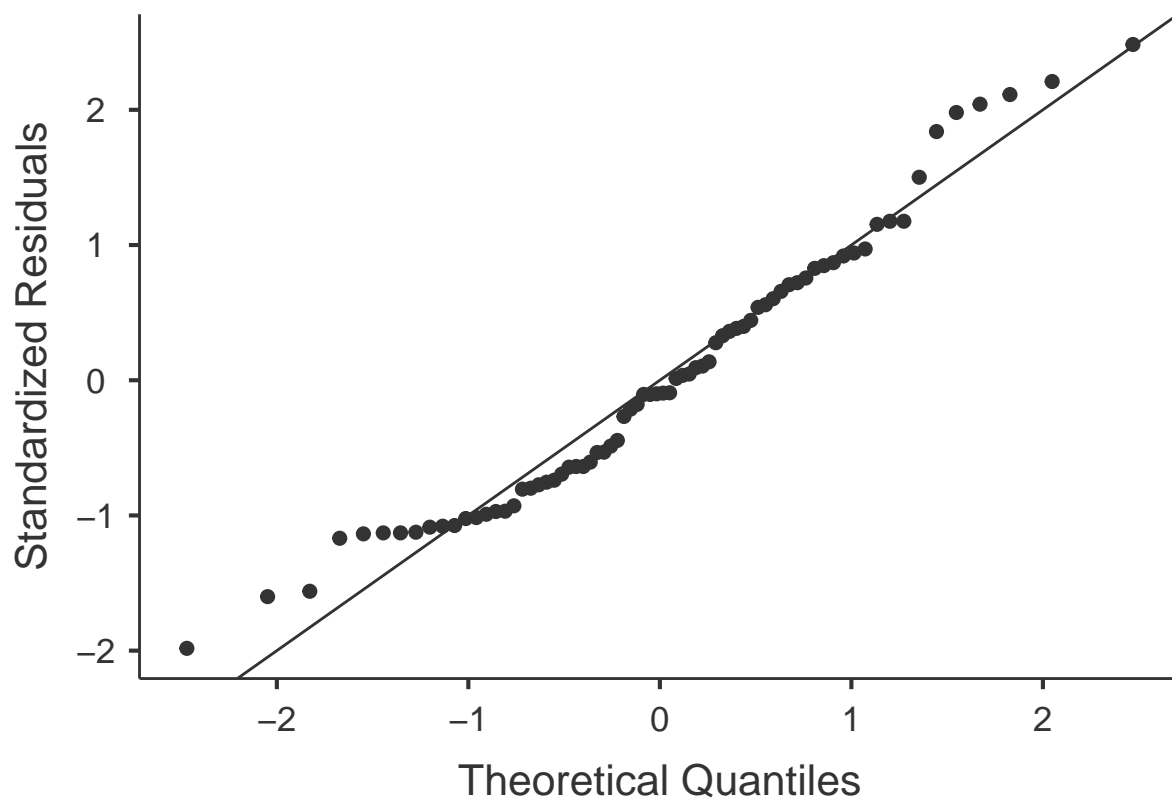
Predictor	Estimate	SE	t	p	Stand. Estimate	Lower	Upper
Intercept	2.575	0.998	2.58	0.012			
Parent_Anxiety	0.328	0.101	3.24	0.002	0.331	0.127	0.535
Parent_OC	0.496	0.107	4.65	< .001	0.476	0.272	0.680

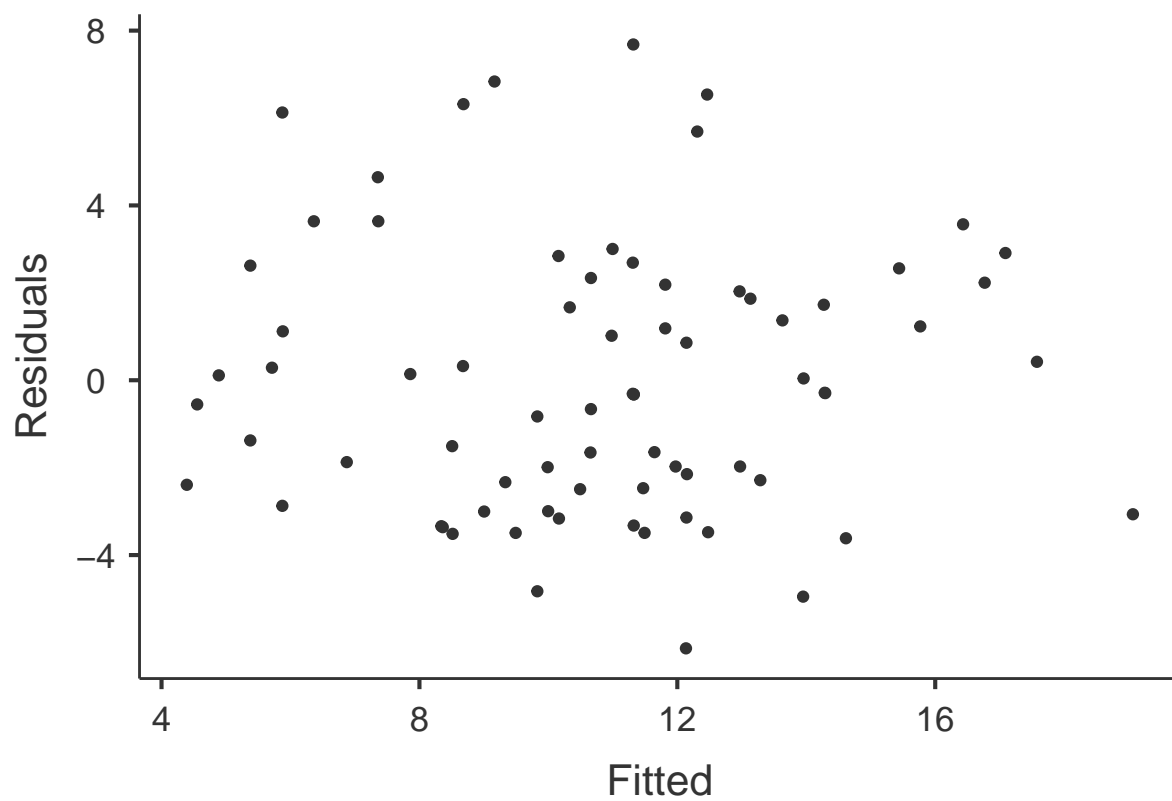
```
## -----
```

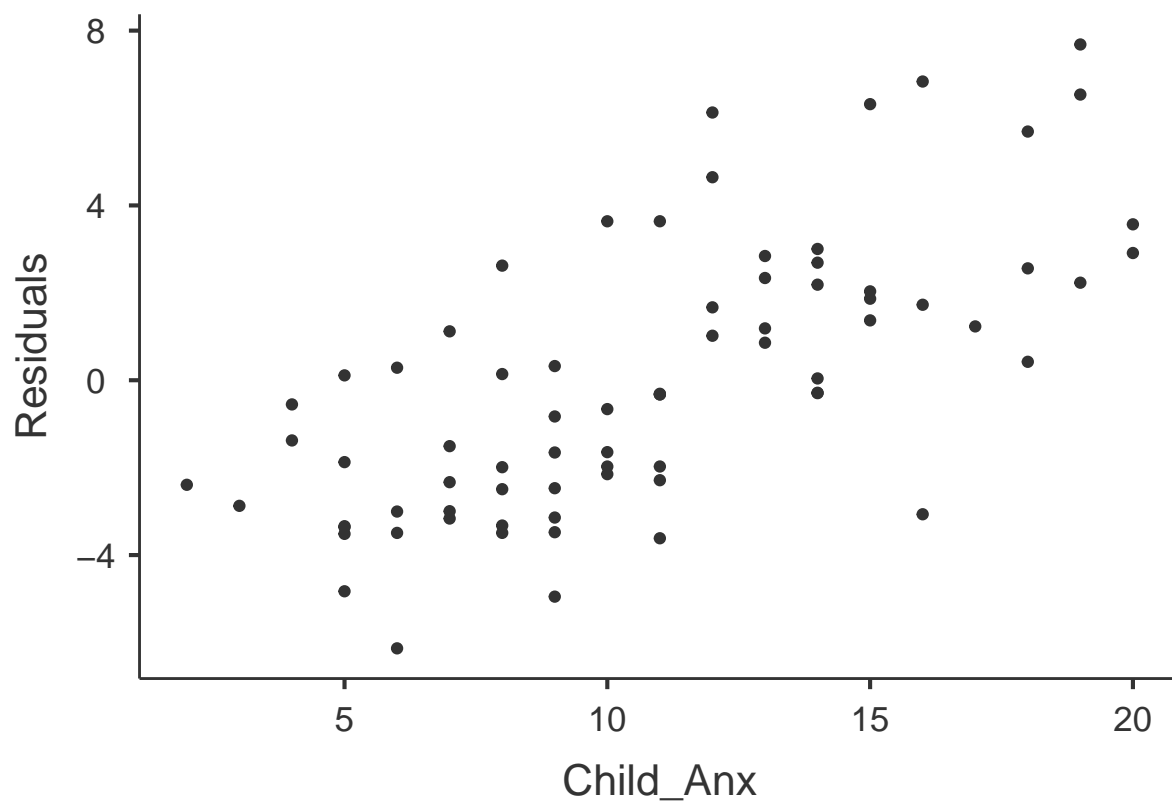
```
##
```

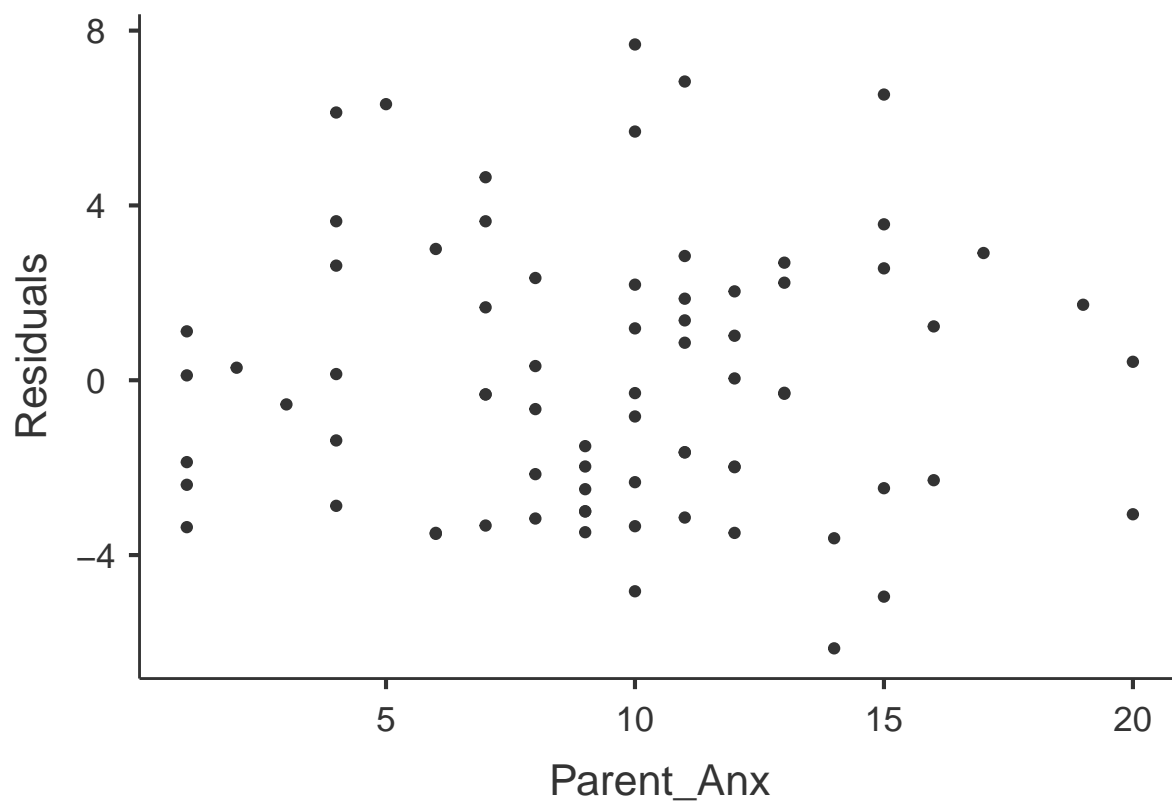
```
##
```

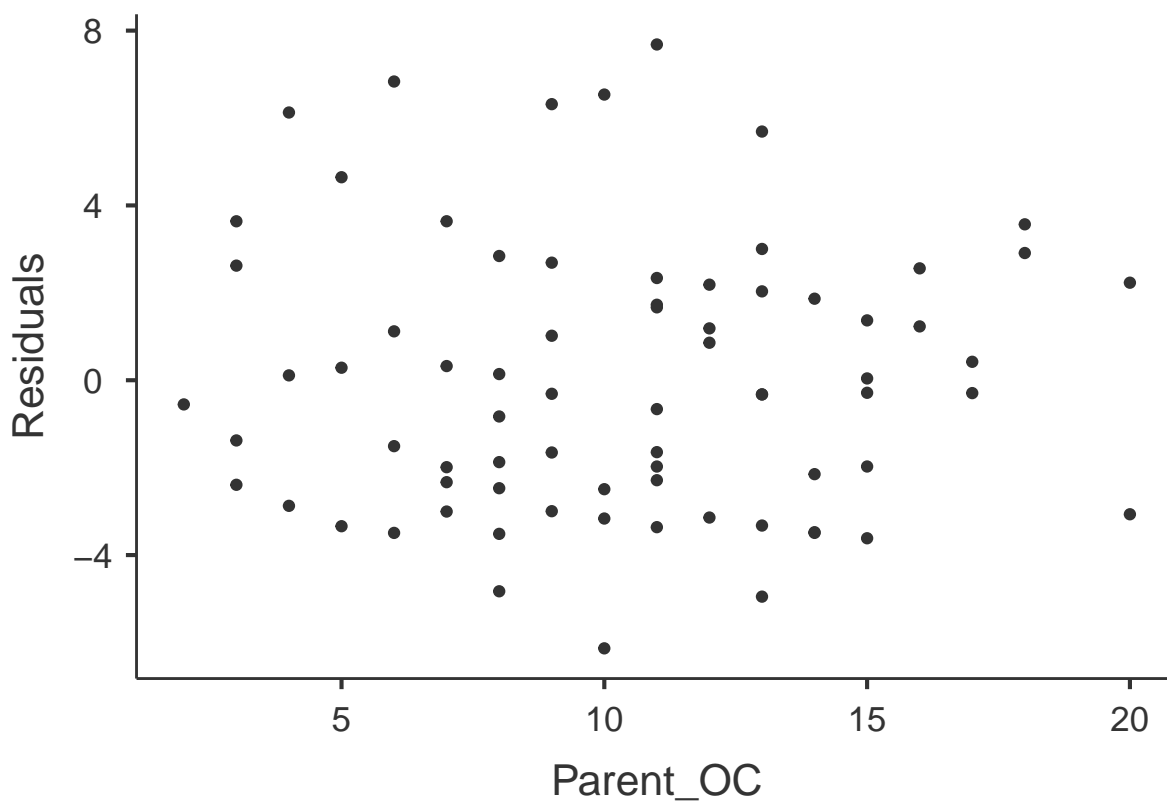
```
## ASSUMPTION CHECKS
```









```
#Alternate not using jum library
#model <- lm(model, data)
#plot(model)
```

3b. Multivariate Outliers

```
#Check and remove multivariate outliers based on Cook's distance (CD)
#for Mahalanobis' Distance (leverage only), see /Regression/Regression_Diagnostics.Rmd for how-to
#CD = Influence = Leverage + Discrepancy (Discrepancy = how much an observation deviates from the overa
```

```
#create model
model.cook <- lm(datboot$Child_Anxiety ~ datboot$Parent_Anxiety + datboot$Parent_OC)
model.cook
```

```
##
## Call:
## lm(formula = datboot$Child_Anxiety ~ datboot$Parent_Anxiety + datboot$Parent_OC)
##
## Coefficients:
##      (Intercept)      datboot$Parent_Anxiety      datboot$Parent_OC
##           2.5754              0.3284              0.4962
```

```
summary(model.cook)
```

```
##
## Call:
## lm(formula = datboot$Child_Anxiety ~ datboot$Parent_Anxiety + datboot$Parent_OC)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.134 -2.451 -0.302  2.148  7.683
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      2.5754     0.9978   2.581  0.01192 *
## datboot$Parent_Anx  0.3284     0.1015   3.236  0.00184 **
## datboot$Parent_OC   0.4962     0.1067   4.650  1.5e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.137 on 71 degrees of freedom
## Multiple R-squared:  0.5258, Adjusted R-squared:  0.5124
## F-statistic: 39.36 on 2 and 71 DF,  p-value: 3.145e-12

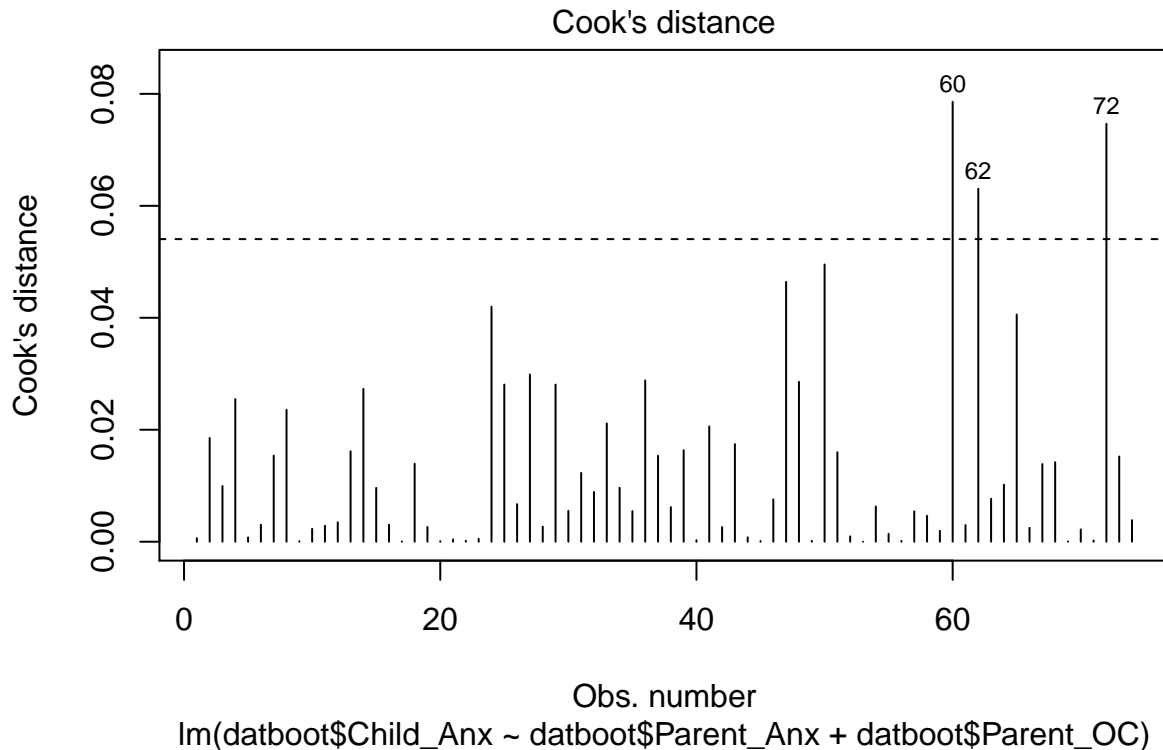
#find cook's distance for that model
datboot$cook <- cooks.distance(model.cook)

#create the cutoff [> 4/N]
cook.cutoff <- 4/nrow(datboot)
print(paste("Our Cook cutoff =", round(cook.cutoff, 3), "- anything above this value will be removed"))

## [1] "Our Cook cutoff = 0.054 - anything above this value will be removed"

#plot it out
plot(model.cook, which = 4, cook.levels = cook.cutoff)

#Add a cutoff line
abline(h = cook.cutoff, lty = 2)
```



```
#Show and remove all outliers above your cutoff line
datboot.no.outliers <- datboot[!(datboot$cook) > cook.cutoff, ]

print(paste("There were", nrow(datboot), "observations before removing multivariate outliers"))

## [1] "There were 74 observations before removing multivariate outliers"

print(paste("We removed outlier observation #:", datboot[(datboot$cook) > cook.cutoff, 1], "with a Cook's distance of", datboot[(datboot$cook) > cook.cutoff, 2]))

## [1] "We removed outlier observation #: 60 with a Cook's distance = 0.079"
## [2] "We removed outlier observation #: 62 with a Cook's distance = 0.063"
## [3] "We removed outlier observation #: 72 with a Cook's distance = 0.075"

print(paste("We now have", nrow(datboot.no.outliers), "total observations saved in the new dataset after removing 3 outliers"))

## [1] "We now have 71 total observations saved in the new dataset after removing 3 outliers"

#N is now 39 after removing 1 multivariate outlier observation(s)
#was 40 after removing 0 univariate outlier observation(s)
#was 40 after removing 0 observation(s) with missing parameters
#was 40 originally (total 1 observation(s) removed from original dataset - 3%)
```

4. Heteroscedasticity

```
p_load(car)
#Breusch-Pagan test
#H0 = no change in variance across residuals.
model.breusch_pagan <- lm(datboot.no.outliers$Child_Anx ~ datboot.no.outliers$Parent_Anx + datboot.no.outliers$Parent_OC)
ncvTest(model.breusch_pagan)
```

```
## Non-constant Variance Score Test
## Variance formula: ~ fitted.values
## Chisquare = 0.0003392379, Df = 1, p = 0.98531
```

```
#not significant = homoscedastic
#If violated use Box-cox transformation [boxcox(model)] in library MASS
```

5. Multi-collinearity

```
#Multicollinearity is expected in mediation
```

```
model.multicoll <- linReg(data = datboot.no.outliers,
  dep = 'Child_Anx',
  cov = c('Parent_Anx', 'Parent_OC'),
  blocks = list(c('Parent_Anx', 'Parent_OC')),
  modelTest = TRUE,
  r2Adj = TRUE,
  stdEst = TRUE,
  ciStdEst = TRUE,
  collin = TRUE) #this line does the thing
model.multicoll
```

```
##
## LINEAR REGRESSION
##
## Model Fit Measures
## -----
##      Model      R      R2      Adjusted R2      F      df1      df2      p
## -----
##           1      0.771      0.594           0.582      49.7       2       68      < .001
## -----
##
##
## MODEL SPECIFIC RESULTS
##
## MODEL 1
##
## Model Coefficients
## -----
##      Predictor      Estimate      SE      t      p      Stand. Estimate      Lower      Upper
## -----
##      Intercept           1.899      0.9375      2.03      0.047
##      Parent_Anx           0.263      0.0954      2.76      0.007           0.269      0.0747      0.464
##      Parent_OC           0.594      0.1004      5.92      < .001           0.576      0.3820      0.771
## -----
##
##
## ASSUMPTION CHECKS
##
## Collinearity Statistics
## -----
##              VIF      Tolerance
## -----
##      Parent_Anx      1.59      0.629
##      Parent_OC      1.59      0.629
## -----
```


#Tolerance for all variables indicates low/no multicollinearity

Mediation 1. Regression a. $Y \sim X$ b. $M \sim X$ c. $Y \sim X + M$

2. No bootstrapping

a. Model

b. Sobel Test

3. Bootstrapping

1. Regression a. $Y \sim X$

```
model1 <- linReg(data = datboot.no.outliers,
  dep = 'Child_Anxiety',
  covs = 'Parent_Anxiety',
  blocks = list(c('Parent_Anxiety')),
  modelTest = TRUE,
  stdEst = TRUE,
  ci = TRUE,
  ciWidth = 95)
```

model1

##

LINEAR REGRESSION

##

Model Fit Measures

Model	R	R ²	F	df1	df2	p
1	0.620	0.385	43.2	1	69	< .001

##

##

MODEL SPECIFIC RESULTS

##

MODEL 1

##

Model Coefficients

Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate
Intercept	4.826	0.9730	2.885	6.767	4.96	< .001	
Parent_Anxiety	0.607	0.0924	0.423	0.791	6.57	< .001	0.620

##

b. $M \sim X$

```
model2 <- linReg(data = datboot.no.outliers,
  dep = 'Parent_OC',
  covs = 'Child_Anxiety',
  blocks = list(c('Child_Anxiety')),
  modelTest = TRUE,
  stdEst = TRUE,
  ci = TRUE,
  ciWidth = 95)
```

model2

```
##
## LINEAR REGRESSION
##
## Model Fit Measures
## -----
##      Model      R      R²      F      df1      df2      p
## -----
##           1      0.740      0.548      83.7        1       69      < .001
## -----
##
##
## MODEL SPECIFIC RESULTS
##
## MODEL 1
##
## Model Coefficients
## -----
##      Predictor      Estimate      SE      Lower      Upper      t      p      Stand. Estimate
## -----
##      Intercept          2.814      0.9018      1.015      4.613      3.12      0.003
##      Child_Anxiety          0.719      0.0785      0.562      0.875      9.15      < .001      0.740
## -----
```

c. $Y \sim X + M$

```
model13 <- linReg(data = datboot.no.outliers,
  dep = 'Child_Anxiety',
  covs = c('Parent_Anxiety', 'Parent_OC'),
  blocks = list(c('Parent_Anxiety', 'Parent_OC')),
  modelTest = TRUE,
  stdEst = TRUE,
  ci = FALSE,
  ciWidth = 95)
```

model13

```
##
## LINEAR REGRESSION
##
## Model Fit Measures
## -----
##      Model      R      R²      F      df1      df2      p
## -----
##           1      0.771      0.594      49.7        2       68      < .001
## -----
##
##
## MODEL SPECIFIC RESULTS
##
## MODEL 1
##
## Model Coefficients
## -----
##      Predictor      Estimate      SE      t      p      Stand. Estimate
## -----
##      Intercept          1.899      0.9375      2.03      0.047
```

```
##      Parent_Anx      0.263      0.0954      2.76      0.007      0.269
##      Parent_OC      0.594      0.1004      5.92      < .001      0.576
##      -----
```

2. No bootstrapping

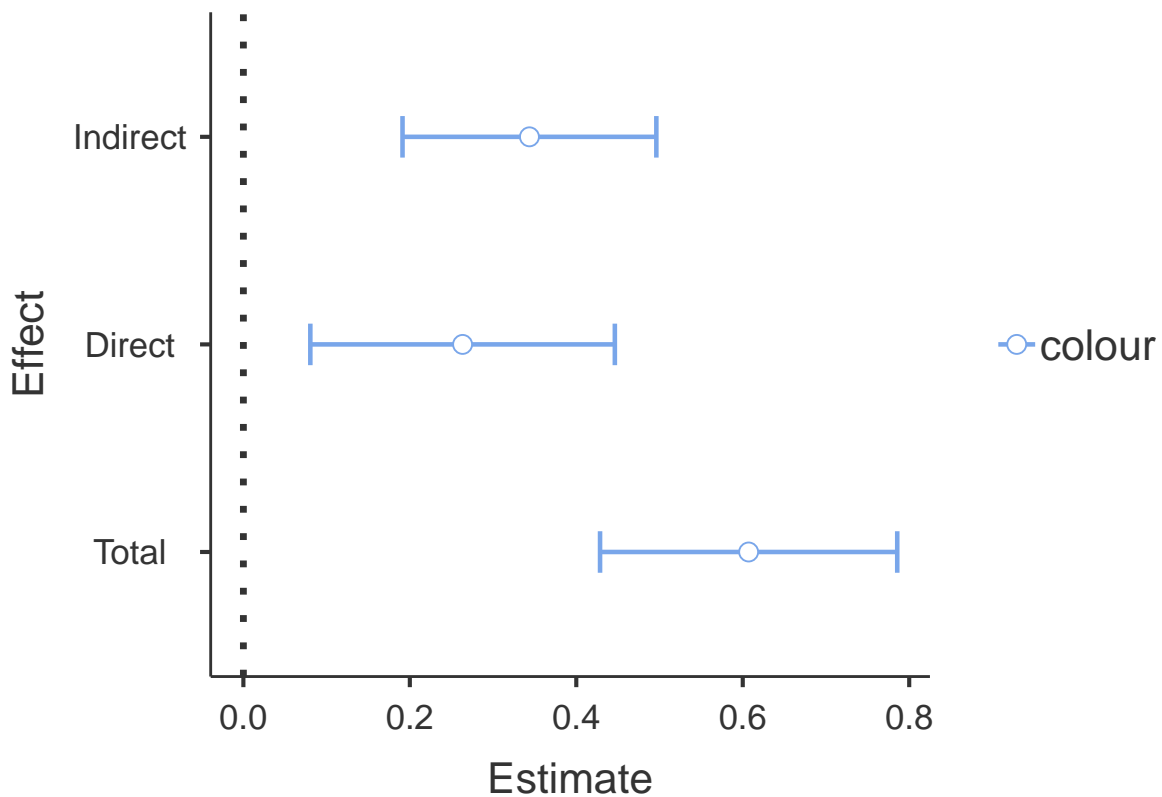
a. Model b. Sobel Test

```
# (a * b) = (c - c') = Indirect Effect [i.e., amount of mediation]
# Z = Sobel test
# a = Path Estimate from X to M
# b = Path Estimate from M to Y
# c = Total Estimate (Direct Estimate + Indirect Estimate)
# c' = Direct Estimate
```

```
med <- medmod::med(datboot.no.outliers,
  dep = 'Child_Anxiety',
  pred = 'Parent_Anxiety',
  med = 'Parent_OC',
  pm = TRUE,
  ci = FALSE,
  paths = TRUE,
  label = TRUE,
  estPlot = TRUE)
med
```

```
##
## MEDIATION
##
## Mediation Estimates
## -----
##      Effect      Label      Estimate      SE      Z      p      % Mediation
## -----
##      Indirect    a x b      0.344      0.0778      4.42      < .001      56.6
##      Direct      c      0.263      0.0933      2.82      0.005      43.4
##      Total      c + a x b      0.607      0.0911      6.66      < .001      100.0
## -----
##
## Path Estimates
## -----
##      Label      Estimate      SE      Z      p
## -----
##      Parent_Anxiety <U+2192> Parent_OC      a      0.579      0.0894      6.47      < .001
##      Parent_OC      <U+2192> Child_Anxiety      b      0.594      0.0983      6.04      < .001
##      Parent_Anxiety <U+2192> Child_Anxiety      c      0.263      0.0933      2.82      0.005
## -----

## Scale for 'colour' is already present. Adding another scale for
## 'colour', which will replace the existing scale.
```



Look at this in comparison to the indirect mediation estimate.

sobel(X, M, Y)

cat("\n")

```
sobel(datboot.no.outliers$Parent_Anx, datboot.no.outliers$Parent_OC, datboot.no.outliers$Child_Anx)
```

```
## $`Mod1: Y~X`
```

```
##      Estimate Std. Error  t value    Pr(>|t|)
```

```
## (Intercept) 4.825577 0.97296433 4.959665 4.863136e-06
```

```
## pred      0.607077 0.09240246 6.569922 7.931925e-09
```

```
##
```

```
## $`Mod2: Y~X+M`
```

```
##      Estimate Std. Error  t value    Pr(>|t|)
```

```
## (Intercept) 1.8994837 0.93752054 2.026072 4.668296e-02
```

```
## pred      0.2633798 0.09537577 2.761496 7.391486e-03
```

```
## med      0.5939162 0.10040604 5.915144 1.195656e-07
```

```
##
```

```
## $`Mod3: M~X`
```

```
##      Estimate Std. Error  t value    Pr(>|t|)
```

```
## (Intercept) 4.9267776 0.95486459 5.159661 2.264567e-06
```

```
## pred      0.5786964 0.09068353 6.381494 1.723080e-08
```

```
##
```

```
## $Indirect.Effect
```

```
## [1] 0.3436972
```

```
##
```

```
## $SE
```

```
## [1] 0.07922674
```

```
##
## $z.value
## [1] 4.338146
##
## $N
## [1] 71
```

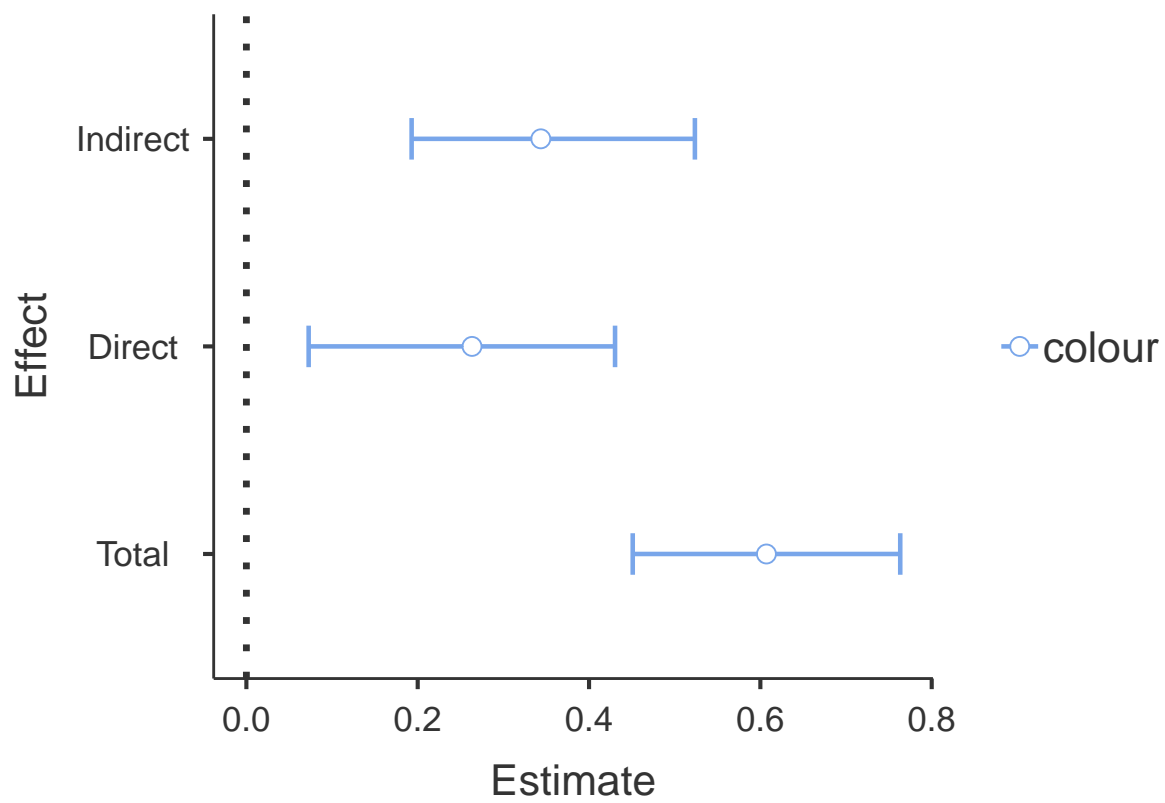
3. Bootstrapping

```
boot <- medmod::med(datboot.no.outliers,
  dep = 'Child_Anxiety',
  pred = 'Parent_Anxiety',
  med = 'Parent_OC',
  estMethod = 'bootstrap',
  bootstrap = 1000,
  pm = TRUE,
  ci = TRUE,
  paths = TRUE,
  label = TRUE,
  estPlot = TRUE)
```

```
boot
```

```
##
## MEDIATION
##
## Mediation Estimates
## -----
##      Effect      Label      Estimate      SE      Lower      Upper      Z      p      % Mediation
## -----
##      Indirect    a × b          0.344    0.0829    0.1929    0.524    4.15    < .001      56.6
##      Direct      c          0.263    0.0911    0.0727    0.430    2.89    0.004      43.4
##      Total      c + a × b        0.607    0.0795    0.4510    0.763    7.64    < .001     100.0
## -----
##
## Path Estimates
## -----
##                                Label      Estimate      SE      Lower      Upper      Z      p
## -----
##      Parent_Anxiety <U+2192> Parent_OC      a          0.579    0.0873    0.4035    0.735    6.63
##      Parent_OC      <U+2192> Child_Anxiety      b          0.594    0.0957    0.4112    0.782    6.20
##      Parent_Anxiety <U+2192> Child_Anxiety      c          0.263    0.0911    0.0727    0.430    2.89
## -----

## Scale for 'colour' is already present. Adding another scale for
## 'colour', which will replace the existing scale.
```



Check the z-values, SE, and p-values for pathways to see differences (X -> Y for this one).