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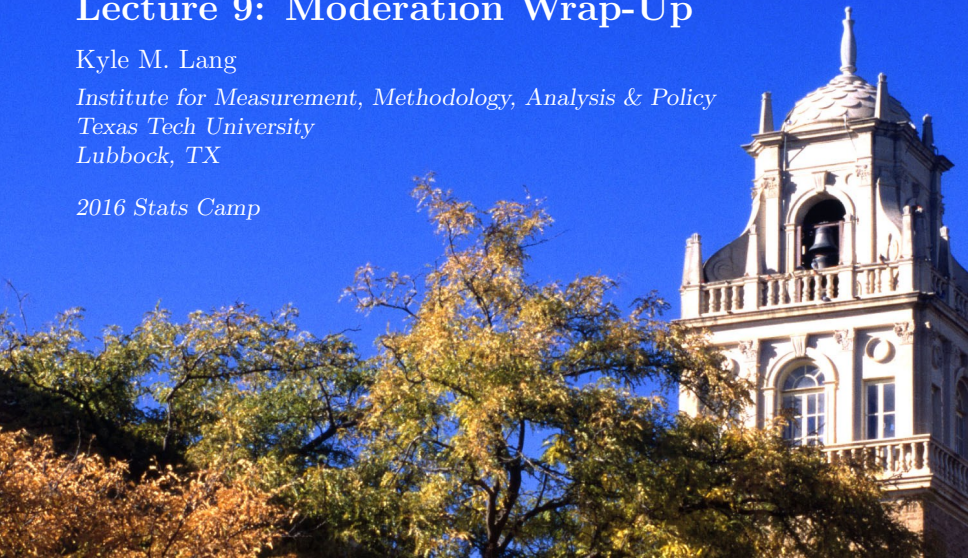


Lecture 9: Moderation Wrap-Up

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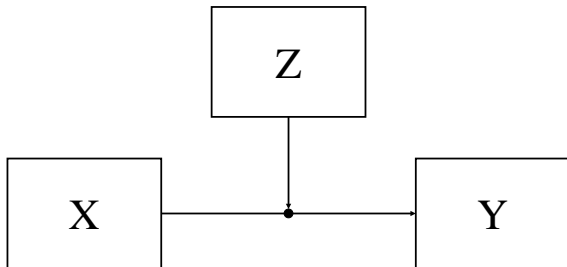
2016 Stats Camp



- Multiple Moderators
- Moderated Moderation
- Categorical Moderation
- Multiple Group Modeling

Starting Point

So far, we've been looking at this type of model:



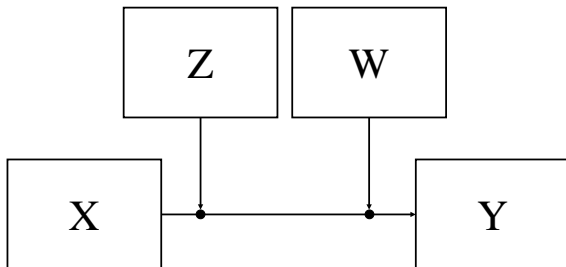
We've had one focal variable and one moderator.

- We've been asking questions about how the focal effect changes as a function of the moderator.
- There's no reason we need to restrict ourselves to a single moderator.

Multiple Moderation

Maybe we suspect that the focal effect changes as a function of two other variables.

- We could fit this type of model:



Now, the focal effect of X on Y changes as a function of both Z and W .

Multiple Moderation

The preceding diagram implies the following formula:

$$Y = \alpha + f(Z, W)X + \beta_2 Z + \beta_3 W + e,$$

Taking $f(Z, W)$ to be the following simple slope:

$$f(Z, W) = \beta_1 + \beta_4 Z + \beta_5 W$$

Produces the following analytic equation:

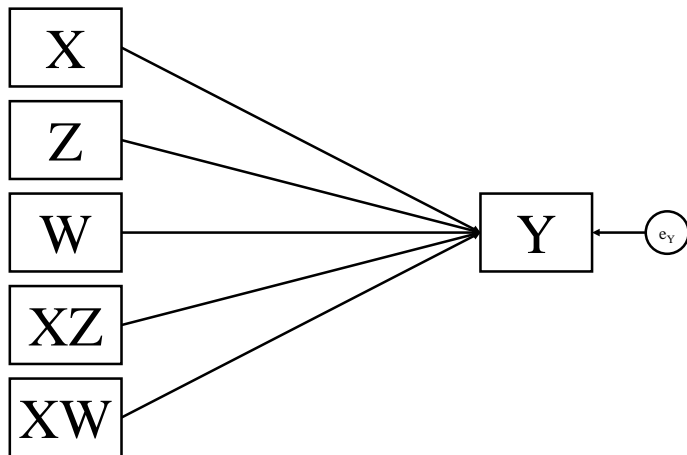
$$Y = \alpha + \beta_1 X + \beta_2 Z + \beta_3 W + \beta_4 XZ + \beta_5 XW + e$$

We can easily fit this model in any regression software

- We can test for significant moderating effects of Z and W by testing for non-zero β_4 and β_5 , respectively.

Multiple Moderation

Our analytic diagram is predictably extended:



Example



```
library(psych)
library(rockchalk)
dat1 <- readRDS("../data/bfiData1.rds")
## Additive model:
out1.1 <- lm(agree ~ conc + open + neuro, data = dat1)
summary(out1.1)
```

Call:

```
lm(formula = agree ~ conc + open + neuro, data = dat1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.78733	-0.41707	0.09673	0.47476	2.12198

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	3.23373	0.12379	26.123	< 2e-16	***
conc	0.06890	0.02647	2.603	0.00929	**
open	0.27661	0.02647	10.449	< 2e-16	***
neuro	-0.10633	0.01205	-8.826	< 2e-16	***

Example



```
Signif. codes:  0      ***      0.001      **      0.01      *      0.05
                  .      0.1          1
```

```
Residual standard error: 0.6966 on 2548 degrees of freedom
```

```
Multiple  $R^2$ : 0.06473, Adjusted  $R^2$ : 0.06363
```

```
F-statistic: 58.79 on 3 and 2548 DF, p-value: < 2.2e-16
```


Example



```
## Additive two-way interaction model:  
out1.2 <- lm(agree ~ open*conc + open*neuro, data = dat1)  
summary(out1.2)
```

Call:

```
lm(formula = agree ~ open * conc + open * neuro, data = dat1  
  )
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.78651	-0.41308	0.09699	0.47778	2.18968

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	2.05739	0.50931	4.040	5.51e-05	***
open	0.58398	0.13111	4.454	8.78e-06	***
conc	0.49645	0.14540	3.414	0.000649	***
neuro	-0.24314	0.08373	-2.904	0.003719	**
open:conc	-0.11115	0.03716	-2.991	0.002803	**
open:neuro	0.03542	0.02124	1.667	0.095589	.

Example



```
Signif. codes:  0      ***      0.001      **      0.01      *      0.05
                  .      0.1          1
```

```
Residual standard error: 0.6957 on 2546 degrees of freedom
```

```
Multiple  $R^2$ : 0.06809, Adjusted  $R^2$ : 0.06626
```

```
F-statistic: 37.21 on 5 and 2546 DF, p-value: < 2.2e-16
```

Example



```
## Center 'conc' on interesting values for SS analysis:  
dat1$concLo  ← with(dat1, conc - quantile(conc, 0.25,  
      na.rm = TRUE))  
dat1$concMid ← with(dat1, conc - quantile(conc, 0.5, na.rm  
      = TRUE))  
dat1$concHi  ← with(dat1, conc - quantile(conc, 0.75,  
      na.rm = TRUE))
```

Example



```
## Test simple slopes via centering:
out1.2.1 <- lm(agree ~ open*concLo + neuro, data = dat1)
summary(out1.2.1)
```

Call:

```
lm(formula = agree ~ open * concLo + neuro, data = dat1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.78565	-0.41336	0.09706	0.47676	2.15172

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	3.34421	0.11416	29.294	< 2e-16	***
open	0.30929	0.02943	10.508	< 2e-16	***
concLo	0.39874	0.13311	2.996	0.00277	**
neuro	-0.10499	0.01205	-8.716	< 2e-16	***
open:concLo	-0.08563	0.03387	-2.528	0.01152	*

Signif. codes:	0	***	0.001	**	0.01	*	0.05
	.	0.1	1				

Example



Residual standard error: 0.6959 on 2547 degrees of freedom
Multiple R^2 : 0.06707, Adjusted R^2 : 0.06561
F-statistic: 45.78 on 4 and 2547 DF, p-value: $< 2.2e-16$

Example



```
out1.2.2 ← lm(agree ~ open*concMid + neuro, data = dat1)
summary(out1.2.2)
```

Call:

```
lm(formula = agree ~ open * concMid + neuro, data = dat1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.78565	-0.41336	0.09706	0.47676	2.15172

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	3.50370	0.10564	33.166	< 2e-16 ***
open	0.27503	0.02645	10.398	< 2e-16 ***
concMid	0.39874	0.13311	2.996	0.00277 **
neuro	-0.10499	0.01205	-8.716	< 2e-16 ***
open:concMid	-0.08563	0.03387	-2.528	0.01152 *

Signif. codes:	0	***	0.001	**	0.01	*	0.05
	.	0.1	1				

Residual standard error: 0.6959 on 2547 degrees of freedom

Example



```
Multiple  $R^2$ : 0.06707, Adjusted  $R^2$ : 0.06561  
F-statistic: 45.78 on 4 and 2547 DF, p-value: < 2.2e-16
```

Example



```
out1.2.3 ← lm(agree ~ open*concHi + neuro, data = dat1)
summary(out1.2.3)
```

Call:

```
lm(formula = agree ~ open * concHi + neuro, data = dat1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.78565	-0.41336	0.09706	0.47676	2.15172

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	3.66320	0.12230	29.952	< 2e-16	***
open	0.24078	0.03000	8.026	1.52e-15	***
concHi	0.39874	0.13311	2.996	0.00277	**
neuro	-0.10499	0.01205	-8.716	< 2e-16	***
open:concHi	-0.08563	0.03387	-2.528	0.01152	*

Signif. codes:	0	***	0.001	**	0.01	*	0.05
.	0.1		1				

Residual standard error: 0.6959 on 2547 degrees of freedom

Example



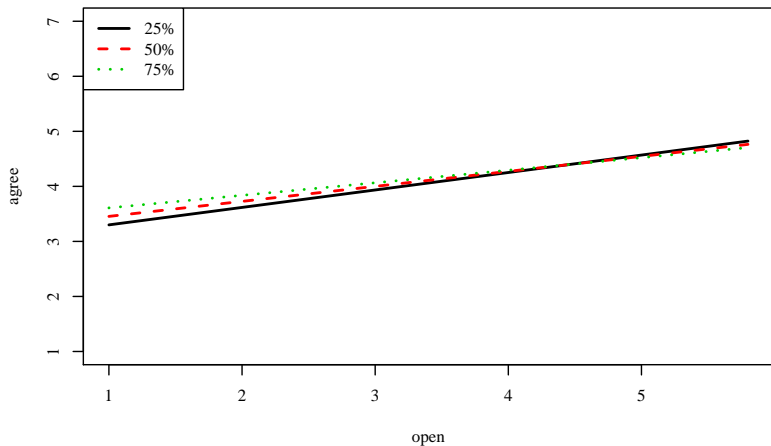
```
Multiple  $R^2$ : 0.06707, Adjusted  $R^2$ : 0.06561  
F-statistic: 45.78 on 4 and 2547 DF, p-value: < 2.2e-16
```

Example



```
## Plot the simple slopes:
par(family = "serif", cex = 0.75)
plotOut1.2 ← plotSlopes(model = out1.2,
                        plotx = "open",
                        modx = "conc",
                        plotPoints = FALSE,
                        modxVals =
                            quantile(dat1$conc,
                                    c(0.25, 0.5, 0.75),
                                    na.rm = TRUE)
                        )
```

Example



Example



```
par(family = "serif", cex = 0.75)
testOut1.2 ← testSlopes(plotOut1.2)
```

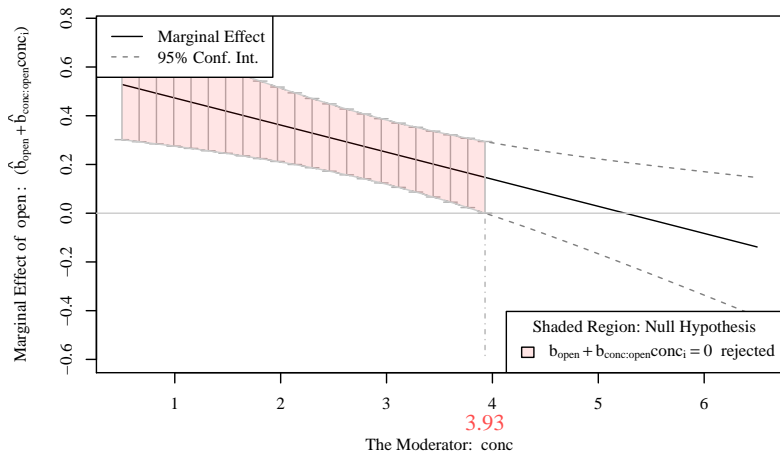
Values of conc OUTSIDE this interval:

lo	hi
3.930435	9.927895

cause the slope of $(b_1 + b_2 \cdot \text{conc})$ open to be statistically significant

```
plot(testOut1.2)
```

Example



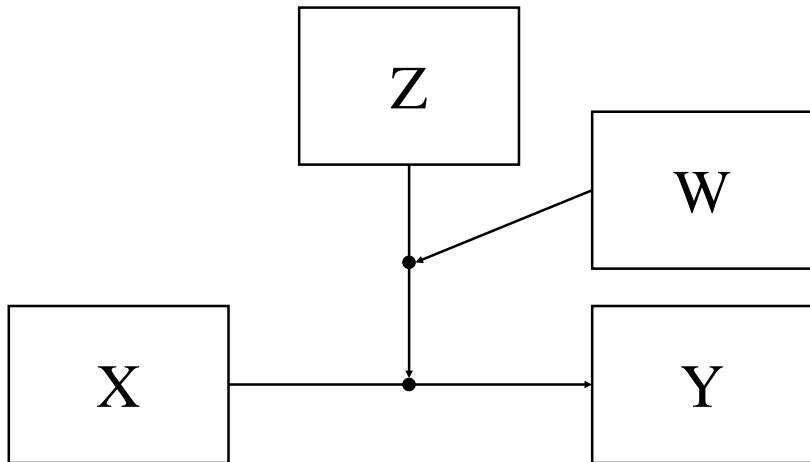
The additive two-way interaction model is more flexible than the simple single-moderator model, but it still imposes constraints.

- The moderating effect of Z (or W) on the $X \rightarrow Y$ relation is assumed to be constant across levels of W (or Z).
- I.e., the moderation is not moderated

We can relax this constraint by modeling moderation of the moderated effect using a three-way interaction.

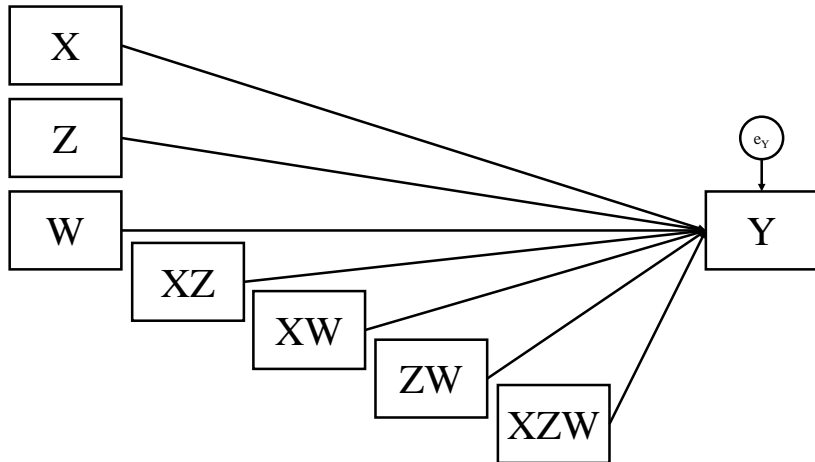
Moderated Moderation

Moderated moderation implies the following conceptual diagram:



Moderated Moderation

The preceding conceptual diagram implies this analytic diagram:



Moderated Moderation

The preceding diagram represents the following equation:

$$Y = \alpha + \beta_1 X + \beta_2 Z + \beta_3 W + \beta_4 XZ + \beta_5 XW + \beta_6 ZW + \beta_7 XZW + e$$

Which can be restructured into:

$$\begin{aligned} Y &= \alpha + (\beta_1 + \beta_4 Z + \beta_5 W + \beta_7 ZW)X + \beta_2 Z + \beta_3 W + \beta_6 ZW + e \\ &= \alpha + g(Z, W)X + \beta_2 Z + \beta_3 W + \beta_6 ZW + e \end{aligned}$$

With moderated moderation, the simple slope is given by:

$$g(Z, W) = \beta_1 + \beta_4 Z + \beta_5 W + \beta_7 ZW$$

Which has the same structure as a single moderator model.

- Three-way simple slopes represent the moderated effect of Z on the $X \rightarrow Y$ relation at conditional values of W .

Example



```
## Three-way interaction model:  
out1.3 <- lm(agree ~ open*conc*neuro, data = dat1)  
summary(out1.3)
```

```
Call:  
lm(formula = agree ~ open * conc * neuro, data = dat1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.79789	-0.41779	0.09925	0.47556	2.10928

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.58747	0.96633	-0.608	0.54328	
open	1.27903	0.25747	4.968	7.23e-07	***
conc	1.20831	0.26559	4.550	5.63e-06	***
neuro	0.73766	0.32240	2.288	0.02222	*
open:conc	-0.29722	0.06935	-4.286	1.89e-05	***
open:neuro	-0.21616	0.08091	-2.672	0.00760	**
conc:neuro	-0.25632	0.08244	-3.109	0.00190	**
open:conc:neuro	0.06541	0.02028	3.225	0.00128	**

Example



```
Signif. codes:  0      ***      0.001      **      0.01      *      0.05
                  .      0.1          1
```

```
Residual standard error: 0.6945 on 2544 degrees of freedom
```

```
Multiple  $R^2$ : 0.07189, Adjusted  $R^2$ : 0.06933
```

```
F-statistic: 28.15 on 7 and 2544 DF, p-value: < 2.2e-16
```

Example



```
## Test simple slopes via centering:  
dat1$neuroLo ←  
  with(dat1,  
    neuro - quantile(neuro, 0.05, na.rm = TRUE)  
  )  
dat1$neuroMid ←  
  with(dat1,  
    neuro - quantile(neuro, 0.5, na.rm = TRUE)  
  )  
dat1$neuroHi ←  
  with(dat1,  
    neuro - quantile(neuro, 0.95, na.rm = TRUE)  
  )
```

Example



```
out1.4.1 ← lm(agree ~ open*conc*neuroLo, data = dat1)
summary(out1.4.1)
```

Call:

```
lm(formula = agree ~ open * conc * neuroLo, data = dat1)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.79789	-0.41779	0.09925	0.47556	2.10928

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	0.29772	0.68387	0.435	0.66335	
open	1.01964	0.18561	5.494	4.33e-08	***
conc	0.90073	0.19180	4.696	2.79e-06	***
neuroLo	0.73766	0.32240	2.288	0.02222	*
open:conc	-0.21872	0.05099	-4.289	1.86e-05	***
open:neuroLo	-0.21616	0.08091	-2.672	0.00760	**
conc:neuroLo	-0.25632	0.08244	-3.109	0.00190	**
open:conc:neuroLo	0.06541	0.02028	3.225	0.00128	**

Example



```
Signif. codes:  0      ***      0.001      **      0.01      *      0.05
                  .      0.1          1
```

```
Residual standard error: 0.6945 on 2544 degrees of freedom
```

```
Multiple  $R^2$ : 0.07189, Adjusted  $R^2$ : 0.06933
```

```
F-statistic: 28.15 on 7 and 2544 DF, p-value: < 2.2e-16
```

Example



```
out1.4.2 ← lm(agree ~ open*conc*neuroMid, data = dat1)
summary(out1.4.2)
```

Call:

```
lm(formula = agree ~ open * conc * neuroMid, data = dat1)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.79789	-0.41779	0.09925	0.47556	2.10928

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1.62552	0.57429	2.831	0.00468	**
open	0.63055	0.14845	4.248	2.24e-05	***
conc	0.43936	0.15119	2.906	0.00369	**
neuroMid	0.73766	0.32240	2.288	0.02222	*
open:conc	-0.10098	0.03883	-2.601	0.00936	**
open:neuroMid	-0.21616	0.08091	-2.672	0.00760	**
conc:neuroMid	-0.25632	0.08244	-3.109	0.00190	**
open:conc:neuroMid	0.06541	0.02028	3.225	0.00128	**

Example



```
Signif. codes:  0      ***      0.001      **      0.01      *      0.05
                  .      0.1          1
```

```
Residual standard error: 0.6945 on 2544 degrees of freedom
```

```
Multiple  $R^2$ : 0.07189, Adjusted  $R^2$ : 0.06933
```

```
F-statistic: 28.15 on 7 and 2544 DF, p-value: < 2.2e-16
```


Example



```
out1.4.3 ← lm(agree ~ open*conc*neuroHi, data = dat1)
summary(out1.4.3)
```

Call:

```
lm(formula = agree ~ open * conc * neuroHi, data = dat1)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.79789	-0.41779	0.09925	0.47556	2.10928

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	3.24838	1.03730	3.132	0.00176	**
open	0.15500	0.25391	0.610	0.54161	
conc	-0.12454	0.25621	-0.486	0.62694	
neuroHi	0.73766	0.32240	2.288	0.02222	*
open:conc	0.04293	0.06158	0.697	0.48578	
open:neuroHi	-0.21616	0.08091	-2.672	0.00760	**
conc:neuroHi	-0.25632	0.08244	-3.109	0.00190	**
open:conc:neuroHi	0.06541	0.02028	3.225	0.00128	**

Example



```
Signif. codes:  0      ***      0.001      **      0.01      *      0.05
                  .      0.1          1
```

```
Residual standard error: 0.6945 on 2544 degrees of freedom
```

```
Multiple  $R^2$ : 0.07189, Adjusted  $R^2$ : 0.06933
```

```
F-statistic: 28.15 on 7 and 2544 DF, p-value: < 2.2e-16
```

Example



```
## Construct product terms to facilitate J-N technique:  
dat1$openXneuro ← with(dat1, neuro*open)  
dat1$concXneuro ← with(dat1, neuro*conc)  
dat1$openXconc ← with(dat1, open*conc)  
dat1$openXconcXneuro ← with(dat1, open*conc*neuro)
```

Example



```
out1.5 <- lm(agree ~ open + conc + neuro +  
             openXconc + openXneuro + concXneuro +  
             openXconc*neuro,  
             data = dat1)  
summary(out1.5)
```

Call:

```
lm(formula = agree ~ open + conc + neuro + openXconc +  
    openXneuro +  
    concXneuro + openXconc * neuro, data = dat1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.79789	-0.41779	0.09925	0.47556	2.10928

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.58747	0.96633	-0.608	0.54328	
open	1.27903	0.25747	4.968	7.23e-07	***
conc	1.20831	0.26559	4.550	5.63e-06	***
neuro	0.73766	0.32240	2.288	0.02222	*
openXconc	-0.29722	0.06935	-4.286	1.89e-05	***

Example



```
openXneuro      -0.21616      0.08091     -2.672     0.00760 **
concXneuro      -0.25632      0.08244     -3.109     0.00190 **
neuro:openXconc  0.06541      0.02028      3.225     0.00128 **
---
Signif. codes:  0      ***      0.001      **      0.01      *      0.05
                  .      0.1          1

Residual standard error: 0.6945 on 2544 degrees of freedom
Multiple  $R^2$ : 0.07189, Adjusted  $R^2$ : 0.06933
F-statistic: 28.15 on 7 and 2544 DF, p-value: < 2.2e-16
```

```
sum(coef(out1.3) - coef(out1.5))# Same as above
```

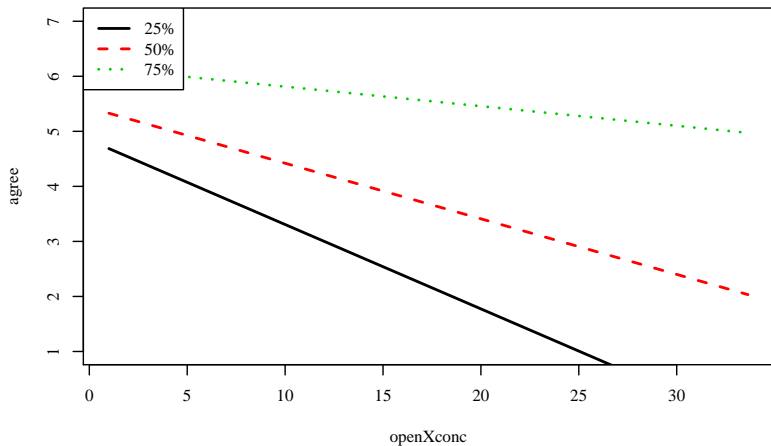
```
[1] 0
```

Example



```
par(family = "serif", cex = 0.75)
plotOut1.5 ← plotSlopes(model = out1.5,
                        plotx = "openXconc",
                        modx = "neuro",
                        plotPoints = FALSE,
                        modxVals =
                        quantile(dat1$neuro,
                                c(0.25, 0.5, 0.75),
                                na.rm = TRUE)
                        )
```

Example



Example



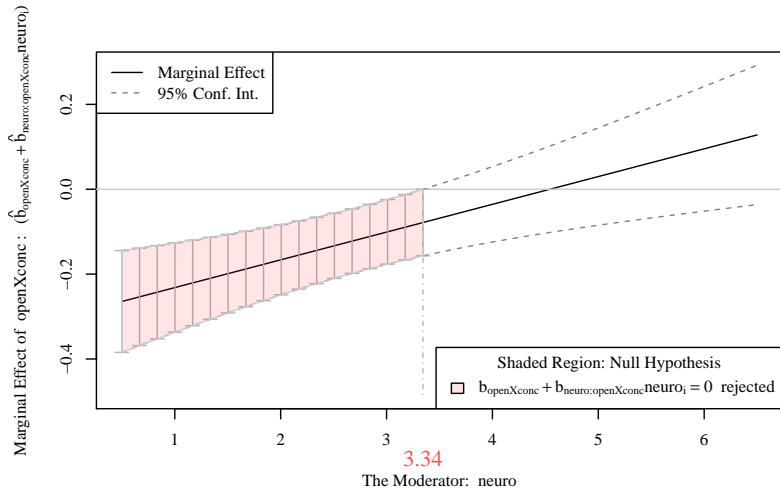
```
par(family = "serif", cex = 0.75)
testOut1.5 ← testSlopes(plotOut1.5)
```

Values of neuro OUTSIDE this interval:

```
      lo      hi
3.343832 7.745048
cause the slope of (b1 + b2*neuro)openXconc to be
statistically significant
```

```
plot(testOut1.5)
```


Example



Categorical Variable Moderation



When the moderator is a categorical variable, moderation implies between-group differences in the focal effect.

- This simplifies probing considerably
- The simple slopes are given (almost) directly in the output

Recall the simple slope formula:

$$SS = \beta_1 + \beta_3 Z$$

Because Z is a dummy code, this formula reduces to:

$$SS = \beta_1, \text{ or}$$

$$SS = \beta_1 + \beta_3$$

Example



```
## Marginal focal effect:  
out2.1 <- lm(conc ~ neuro, data = dat1)  
summary(out2.1)
```

```
Call:  
lm(formula = conc ~ neuro, data = dat1)  
  
Residuals:  
      Min       1Q   Median       3Q      Max   
-2.55547 -0.33353  0.00824  0.36098  1.85381  
  
Coefficients:  
              Estimate Std. Error t value Pr(>|t|)      
(Intercept)  3.437327   0.029659  115.90  <2e-16 ***  
neuro         0.118144   0.008844   13.36  <2e-16 ***  
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
  
Residual standard error: 0.533 on 2550 degrees of freedom  
Multiple R2: 0.0654, Adjusted R2: 0.06504  
F-statistic: 178.4 on 1 and 2550 DF, p-value: < 2.2e-16
```

Example



```
## Moderated by highest education attained:  
out2.2 <- lm(conc ~ neuro*educ, data = dat1)  
summary(out2.2)
```

Call:

```
lm(formula = conc ~ neuro * educ, data = dat1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.52324	-0.34119	0.01457	0.36247	1.86213

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	3.72924	0.10864	34.326	< 2e-16	***
neuro	0.01259	0.03156	0.399	0.689990	
educ2	-0.32892	0.11497	-2.861	0.004258	**
educ3	-0.30738	0.12102	-2.540	0.011146	*
neuro:educ2	0.11033	0.03346	3.297	0.000990	***
neuro:educ3	0.12755	0.03552	3.591	0.000336	***

Signif. codes:	0	***	0.001	**	0.01	*	0.05
	.	0.1	1				

Example



Residual standard error: 0.5308 on 2546 degrees of freedom
Multiple R^2 : 0.0746, Adjusted R^2 : 0.07278
F-statistic: 41.05 on 5 and 2546 DF, p-value: < 2.2e-16

```
## Test for omnibus moderation:  
anova(out2.1, out2.2)
```

Analysis of Variance Table

Model 1: conc ~ neuro

Model 2: conc ~ neuro * educ

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	2550	724.47				
2	2546	717.35	4	7.1285	6.3251	4.617e-05 ***

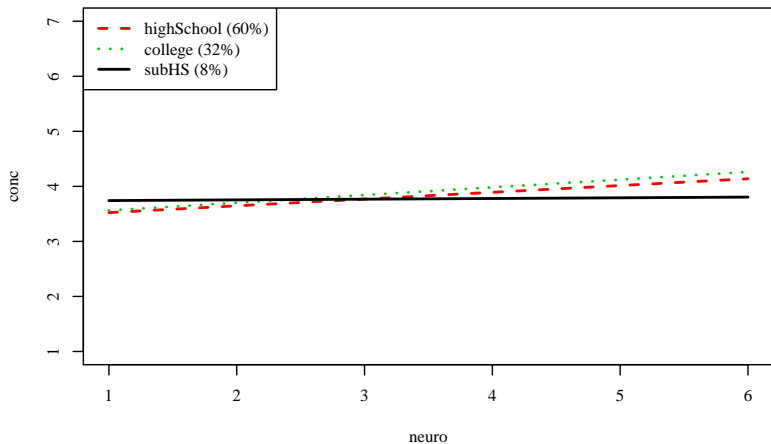
Signif. codes:	0	***	0.001	**	0.01	*	0.05
	.	0.1	1				

Example



```
par(family = "serif", cex = 0.75)
plotSlopes(out2.2,
            plotx = "neuro",
            modx = "educ",
            plotPoints = FALSE)
```

Example



Example



```
## Compute simple slopes by hand:
ssSubHS ← coef(out2.2)[2]
ssHighSchool ← sum(coef(out2.2)[c(2, 5)])
ssCollege ← sum(coef(out2.2)[c(2, 6)])
## Compute simple slopes using centering:
dat1$educ2 ← relevel(dat1$educ, ref = "highSchool")
dat1$educ3 ← relevel(dat1$educ, ref = "college")
out2.3 ← lm(conc ~ neuro*educ2, data = dat1)
out2.4 ← lm(conc ~ neuro*educ3, data = dat1)
```


Example



```
## By hand:  
ssSubHS
```

```
neuro  
0.0125915
```

```
## By centering:  
as.matrix(coef(out2.2))
```

```
          [,1]  
(Intercept) 3.7292366  
neuro        0.0125915  
educ2       -0.3289176  
educ3       -0.3073786  
neuro:educ2  0.1103337  
neuro:educ3  0.1275497
```

Example



```
## By hand:  
ssHighSchool
```

```
[1] 0.1229252
```

```
## By centering:  
as.matrix(coef(out2.3))
```

```
                [,1]  
(Intercept)    3.40031894  
neuro           0.12292519  
educ2subHS      0.32891761  
educ2college    0.02153898  
neuro:educ2subHS -0.11033369  
neuro:educ2college 0.01721601
```

Example



```
## By hand:  
ssCollege
```

```
[1] 0.1401412
```

```
## By centering:  
as.matrix(coef(out2.4))
```

```
              [,1]  
(Intercept)  3.42185792  
neuro         0.14014120  
educ3subHS    0.30737863  
educ3highSchool -0.02153898  
neuro:educ3subHS -0.12754971  
neuro:educ3highSchool -0.01721601
```

Example



```
summary(out2.2)
```

Call:

```
lm(formula = conc ~ neuro * educ, data = dat1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.52324	-0.34119	0.01457	0.36247	1.86213

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	3.72924	0.10864	34.326	< 2e-16	***
neuro	0.01259	0.03156	0.399	0.689990	
educ2	-0.32892	0.11497	-2.861	0.004258	**
educ3	-0.30738	0.12102	-2.540	0.011146	*
neuro:educ2	0.11033	0.03346	3.297	0.000990	***
neuro:educ3	0.12755	0.03552	3.591	0.000336	***

Signif. codes:	0	***	0.001	**	0.01	*	0.05
	.	0.1	1				

Residual standard error: 0.5308 on 2546 degrees of freedom

Multiple R^2 : 0.0746, Adjusted R^2 : 0.07278

F-statistic: 41.05 on 5 and 2546 DF, p-value: < 2.2e-16

Example



```
summary(out2.3)
```

Call:

```
lm(formula = conc ~ neuro * educ2, data = dat1)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.52324	-0.34119	0.01457	0.36247	1.86213

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	3.40032	0.03761	90.401	< 2e-16 ***
neuro	0.12293	0.01111	11.063	< 2e-16 ***
educ2subHS	0.32892	0.11497	2.861	0.00426 **
educ2college	0.02154	0.06525	0.330	0.74134
neuro:educ2subHS	-0.11033	0.03346	-3.297	0.00099 ***
neuro:educ2college	0.01722	0.01972	0.873	0.38277

Signif. codes:	0	***	0.001	**	0.01	*	0.05
	.	0.1	1				

Residual standard error: 0.5308 on 2546 degrees of freedom

Multiple R^2 : 0.0746, Adjusted R^2 : 0.07278

F-statistic: 41.05 on 5 and 2546 DF, p-value: < 2.2e-16

Example



```
summary(out2.4)
```

```
Call:
```

```
lm(formula = conc ~ neuro * educ3, data = dat1)
```

```
Residuals:
```

Min	1Q	Median	3Q	Max
-2.52324	-0.34119	0.01457	0.36247	1.86213

```
Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	3.42186	0.05331	64.183	< 2e-16 ***
neuro	0.14014	0.01629	8.601	< 2e-16 ***
educ3subHS	0.30738	0.12102	2.540	0.011146 *
educ3highSchool	-0.02154	0.06525	-0.330	0.741340
neuro:educ3subHS	-0.12755	0.03552	-3.591	0.000336 ***
neuro:educ3highSchool	-0.01722	0.01972	-0.873	0.382770

```
---
```

Signif. codes:	0	***	0.001	**	0.01	*	0.05
.	0.1		1				

```
Residual standard error: 0.5308 on 2546 degrees of freedom
```

```
Multiple  $R^2$ : 0.0746, Adjusted  $R^2$ : 0.07278
```

```
F-statistic: 41.05 on 5 and 2546 DF, p-value: < 2.2e-16
```

Moderation via Multiple Group SEM



When our moderator is a categorical variable, we can use multiple group CFA/SEM to test for moderation.

- Categorical moderators define groups
- Significant moderation with categorical moderators implies between-group differences in the focal effect
- These hypotheses are easily tested with multiple group SEM

WHITEBOARD TIME!

Example



```
library(lavaan)
library(semTools)
dat2 <- readRDS("../data/bfiData2.rds")
## Multiple group moderation:
mod1 <- "
conc =~ C1 + C2 + C3 + C4 + C5
neuro =~ N1 + N2 + N3 + N4 + N5
"
```


Example



```
fit1 ← measurementInvariance(mod1,  
  data = dat2,  
  group = "educ",  
  std.lv = TRUE)
```

Measurement invariance models:

```
Model 1 : fit.configural  
Model 2 : fit.loadings  
Model 3 : fit.intercepts  
Model 4 : fit.means
```

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
fit.configural	102	85428	85971	1039.1			
fit.loadings	118	85427	85877	1070.0	30.927	16	0.0137462
*							
fit.intercepts	134	85456	85813	1131.4	61.399	16	3.037e-07

fit.means	138	85468	85801	1150.8	19.324	4	0.0006788

Signif. codes:	0	***	0.001	**	0.01	*	0.05
.	0.1		1				

Fit measures:

	cfi	rmsea	cfi.delta	rmsea.delta
fit.configural	0.874	0.104	NA	NA
fit.loadings	0.871	0.097	0.002	0.007
fit.intercepts	0.865	0.094	0.006	0.004
fit.means	0.863	0.093	0.002	0.001

Example



```
mod2 ← "  
conc =~ C1 + C2 + C3 + C4 + C5  
neuro =~ N1 + N2 + N3 + N4 + N5  
  
conc ~ neuro  
  
conc ~ c(1.0, NA, NA)*conc  
neuro ~ c(1.0, NA, NA)*neuro  
  
conc ~ c(0.0, NA, NA)*1.0  
neuro ~ c(0.0, NA, NA)*1.0  
"
```

Example



```
fit2 ← lavaan(mod2,  
              data = dat2,  
              std.lv = FALSE,  
              auto.fix.first = FALSE,  
              auto.var = TRUE,  
              int.ov.free = TRUE,  
              group = "educ",  
              group.equal = c("loadings", "intercepts")  
)
```

Example



```
summary(fit2)
```

```
lavaan (0.5-20) converged normally after 79 iterations
```

Number of observations per group	
highSchool	1536
subHS	192
college	824

Estimator	ML
Minimum Function Test Statistic	1131.438
Degrees of freedom	134
P-value (Chi-square)	0.000

```
Chi-square for each group:
```

highSchool	573.289
subHS	108.925
college	449.224

```
Parameter Estimates:
```

Example



Information	Expected
Standard Errors	Standard

Group 1 [highSchool]:

Latent Variables:

		Estimate	Std.Err	Z-value	P(> z)
conc	=~				
C1	(.p1.)	0.573	0.027	21.471	0.000
C2	(.p2.)	0.678	0.029	23.706	0.000
C3	(.p3.)	0.634	0.028	22.666	0.000
C4	(.p4.)	-0.897	0.031	-29.235	0.000
C5	(.p5.)	-0.947	0.036	-26.307	0.000
neuro	=~				
N1	(.p6.)	1.305	0.033	39.285	0.000
N2	(.p7.)	1.247	0.032	38.701	0.000
N3	(.p8.)	1.205	0.034	35.309	0.000
N4	(.p9.)	0.909	0.034	26.982	0.000
N5	(.10.)	0.837	0.035	23.998	0.000

Regressions:

Estimate	Std.Err	Z-value	P(> z)
----------	---------	---------	---------

Example



```
conc ~
neuro          -0.359      0.035   -10.208      0.000
```

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		0.000			
neuro		0.000			
C1	(.26.)	4.571	0.027	170.017	0.000
C2	(.27.)	4.442	0.029	152.180	0.000
C3	(.28.)	4.379	0.028	154.381	0.000
C4	(.29.)	2.434	0.032	75.721	0.000
C5	(.30.)	3.186	0.037	85.494	0.000
N1	(.31.)	2.940	0.039	75.566	0.000
N2	(.32.)	3.509	0.038	93.494	0.000
N3	(.33.)	3.224	0.038	83.772	0.000
N4	(.34.)	3.197	0.035	91.203	0.000
N5	(.35.)	2.975	0.035	84.171	0.000

Variances:

		Estimate	Std.Err	Z-value	P(> z)
conc		1.000			
neuro		1.000			
C1		1.109	0.045	24.781	0.000

Example



C2	1.187	0.050	23.872	0.000
C3	1.201	0.049	24.414	0.000
C4	0.893	0.048	18.572	0.000
C5	1.600	0.073	22.053	0.000
N1	0.840	0.046	18.316	0.000
N2	0.830	0.044	19.003	0.000
N3	1.219	0.055	22.298	0.000
N4	1.701	0.067	25.564	0.000
N5	1.962	0.075	26.138	0.000

Group 2 [subHS]:

Latent Variables:

		Estimate	Std.Err	Z-value	P(> z)
conc =~					
C1	(.p1.)	0.573	0.027	21.471	0.000
C2	(.p2.)	0.678	0.029	23.706	0.000
C3	(.p3.)	0.634	0.028	22.666	0.000
C4	(.p4.)	-0.897	0.031	-29.235	0.000
C5	(.p5.)	-0.947	0.036	-26.307	0.000
neuro =~					
N1	(.p6.)	1.305	0.033	39.285	0.000

Example



N2	(.p7.)	1.247	0.032	38.701	0.000
N3	(.p8.)	1.205	0.034	35.309	0.000
N4	(.p9.)	0.909	0.034	26.982	0.000
N5	(.10.)	0.837	0.035	23.998	0.000

Regressions:

	Estimate	Std.Err	Z-value	P(> z)
conc ~				
neuro	-0.252	0.105	-2.396	0.017

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		-0.261	0.095	-2.741	0.006
neuro		0.016	0.081	0.202	0.840
C1	(.26.)	4.571	0.027	170.017	0.000
C2	(.27.)	4.442	0.029	152.180	0.000
C3	(.28.)	4.379	0.028	154.381	0.000
C4	(.29.)	2.434	0.032	75.721	0.000
C5	(.30.)	3.186	0.037	85.494	0.000
N1	(.31.)	2.940	0.039	75.566	0.000
N2	(.32.)	3.509	0.038	93.494	0.000
N3	(.33.)	3.224	0.038	83.772	0.000
N4	(.34.)	3.197	0.035	91.203	0.000

Example



```
N5      (.35.)      2.975      0.035      84.171      0.000
```

Variances:

	Estimate	Std.Err	Z-value	P(> z)
conc	1.061	0.170	6.237	0.000
neuro	0.905	0.120	7.540	0.000
C1	1.263	0.142	8.919	0.000
C2	1.270	0.148	8.568	0.000
C3	1.437	0.162	8.855	0.000
C4	1.192	0.160	7.466	0.000
C5	1.748	0.217	8.039	0.000
N1	1.014	0.146	6.965	0.000
N2	1.236	0.161	7.681	0.000
N3	1.310	0.165	7.937	0.000
N4	1.507	0.170	8.888	0.000
N5	2.042	0.221	9.232	0.000

Group 3 [college]:

Latent Variables:

	Estimate	Std.Err	Z-value	P(> z)
conc =~				

Example



C1	(.p1.)	0.573	0.027	21.471	0.000
C2	(.p2.)	0.678	0.029	23.706	0.000
C3	(.p3.)	0.634	0.028	22.666	0.000
C4	(.p4.)	-0.897	0.031	-29.235	0.000
C5	(.p5.)	-0.947	0.036	-26.307	0.000
neuro =~					
N1	(.p6.)	1.305	0.033	39.285	0.000
N2	(.p7.)	1.247	0.032	38.701	0.000
N3	(.p8.)	1.205	0.034	35.309	0.000
N4	(.p9.)	0.909	0.034	26.982	0.000
N5	(.10.)	0.837	0.035	23.998	0.000

Regressions:

	Estimate	Std.Err	Z-value	P(> z)
conc ~				
neuro	-0.278	0.052	-5.354	0.000

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		-0.168	0.053	-3.139	0.002
neuro		-0.092	0.045	-2.056	0.040
C1	(.26.)	4.571	0.027	170.017	0.000
C2	(.27.)	4.442	0.029	152.180	0.000

Example



C3	(.28.)	4.379	0.028	154.381	0.000
C4	(.29.)	2.434	0.032	75.721	0.000
C5	(.30.)	3.186	0.037	85.494	0.000
N1	(.31.)	2.940	0.039	75.566	0.000
N2	(.32.)	3.509	0.038	93.494	0.000
N3	(.33.)	3.224	0.038	83.772	0.000
N4	(.34.)	3.197	0.035	91.203	0.000
N5	(.35.)	2.975	0.035	84.171	0.000

Variances :

	Estimate	Std.Err	Z-value	P(> z)
conc	1.139	0.098	11.634	0.000
neuro	0.865	0.063	13.807	0.000
C1	1.178	0.064	18.364	0.000
C2	1.142	0.065	17.467	0.000
C3	1.093	0.062	17.713	0.000
C4	0.952	0.067	14.255	0.000
C5	1.633	0.100	16.405	0.000
N1	0.807	0.058	13.850	0.000
N2	0.820	0.057	14.498	0.000
N3	1.122	0.068	16.394	0.000
N4	1.630	0.087	18.807	0.000
N5	1.882	0.098	19.207	0.000

Example



```
mod3 ← "  
conc =~ C1 + C2 + C3 + C4 + C5  
neuro =~ N1 + N2 + N3 + N4 + N5  
  
conc ~ c(b1, b1, b1)*neuro  
  
conc ~ c(1.0, NA, NA)*conc  
neuro ~ c(1.0, NA, NA)*neuro  
  
conc ~ c(0.0, NA, NA)*1.0  
neuro ~ c(0.0, NA, NA)*1.0  
"
```

Example



```
fit3 ← lavaan(mod3,  
              data = dat2,  
              std.lv = FALSE,  
              auto.fix.first = FALSE,  
              auto.var = TRUE,  
              int.ov.free = TRUE,  
              group = "educ",  
              group.equal = c("loadings", "intercepts")  
)
```

Example



```
summary(fit3)
```

```
lavaan (0.5-20) converged normally after 82 iterations
```

Number of observations per group	
highSchool	1536
subHS	192
college	824

Estimator	ML
Minimum Function Test Statistic	1133.785
Degrees of freedom	136
P-value (Chi-square)	0.000

```
Chi-square for each group:
```

highSchool	574.222
subHS	109.473
college	450.090

```
Parameter Estimates:
```

Example



Information	Expected
Standard Errors	Standard

Group 1 [highSchool]:

Latent Variables:

		Estimate	Std.Err	Z-value	P(> z)
conc	=~				
C1	(.p1.)	0.575	0.027	21.516	0.000
C2	(.p2.)	0.679	0.029	23.743	0.000
C3	(.p3.)	0.635	0.028	22.707	0.000
C4	(.p4.)	-0.898	0.031	-29.262	0.000
C5	(.p5.)	-0.949	0.036	-26.367	0.000
neuro	=~				
N1	(.p6.)	1.307	0.033	39.323	0.000
N2	(.p7.)	1.249	0.032	38.734	0.000
N3	(.p8.)	1.207	0.034	35.334	0.000
N4	(.p9.)	0.910	0.034	26.987	0.000
N5	(.10.)	0.839	0.035	24.010	0.000

Regressions:

Estimate	Std.Err	Z-value	P(> z)
----------	---------	---------	---------

Example



```

conc ~
neuro      (b1)      -0.330      0.029      -11.365      0.000

```

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		0.000			
neuro		0.000			
C1	(.26.)	4.571	0.027	170.418	0.000
C2	(.27.)	4.442	0.029	152.673	0.000
C3	(.28.)	4.379	0.028	154.796	0.000
C4	(.29.)	2.434	0.032	76.041	0.000
C5	(.30.)	3.187	0.037	85.740	0.000
N1	(.31.)	2.940	0.039	75.506	0.000
N2	(.32.)	3.509	0.038	93.434	0.000
N3	(.33.)	3.224	0.039	83.699	0.000
N4	(.34.)	3.197	0.035	91.151	0.000
N5	(.35.)	2.975	0.035	84.126	0.000

Variances:

		Estimate	Std.Err	Z-value	P(> z)
conc		1.000			
neuro		1.000			
C1		1.107	0.045	24.765	0.000

Example



C2	1.184	0.050	23.859	0.000
C3	1.199	0.049	24.404	0.000
C4	0.898	0.048	18.626	0.000
C5	1.603	0.073	22.047	0.000
N1	0.838	0.046	18.279	0.000
N2	0.828	0.044	18.968	0.000
N3	1.219	0.055	22.286	0.000
N4	1.703	0.067	25.564	0.000
N5	1.963	0.075	26.136	0.000

Group 2 [subHS]:

Latent Variables:

		Estimate	Std.Err	Z-value	P(> z)
conc =~					
C1	(.p1.)	0.575	0.027	21.516	0.000
C2	(.p2.)	0.679	0.029	23.743	0.000
C3	(.p3.)	0.635	0.028	22.707	0.000
C4	(.p4.)	-0.898	0.031	-29.262	0.000
C5	(.p5.)	-0.949	0.036	-26.367	0.000
neuro =~					
N1	(.p6.)	1.307	0.033	39.323	0.000

Example



N2	(.p7.)	1.249	0.032	38.734	0.000
N3	(.p8.)	1.207	0.034	35.334	0.000
N4	(.p9.)	0.910	0.034	26.987	0.000
N5	(.10.)	0.839	0.035	24.010	0.000

Regressions:

		Estimate	Std.Err	Z-value	P(> z)
conc ~					
neuro	(b1)	-0.330	0.029	-11.365	0.000

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		-0.259	0.095	-2.721	0.007
neuro		0.016	0.081	0.201	0.841
C1	(.26.)	4.571	0.027	170.418	0.000
C2	(.27.)	4.442	0.029	152.673	0.000
C3	(.28.)	4.379	0.028	154.796	0.000
C4	(.29.)	2.434	0.032	76.041	0.000
C5	(.30.)	3.187	0.037	85.740	0.000
N1	(.31.)	2.940	0.039	75.506	0.000
N2	(.32.)	3.509	0.038	93.434	0.000
N3	(.33.)	3.224	0.039	83.699	0.000
N4	(.34.)	3.197	0.035	91.151	0.000

Example



```
N5      (.35.)      2.975      0.035      84.126      0.000
```

Variances:

	Estimate	Std.Err	Z-value	P(> z)
conc	1.054	0.169	6.216	0.000
neuro	0.896	0.119	7.551	0.000
C1	1.264	0.142	8.917	0.000
C2	1.272	0.148	8.569	0.000
C3	1.434	0.162	8.851	0.000
C4	1.196	0.160	7.477	0.000
C5	1.742	0.217	8.026	0.000
N1	1.013	0.145	6.978	0.000
N2	1.242	0.161	7.705	0.000
N3	1.312	0.165	7.951	0.000
N4	1.507	0.169	8.893	0.000
N5	2.045	0.221	9.236	0.000

Group 3 [college]:

Latent Variables:

	Estimate	Std.Err	Z-value	P(> z)
conc =~				

Example



C1	(.p1.)	0.575	0.027	21.516	0.000
C2	(.p2.)	0.679	0.029	23.743	0.000
C3	(.p3.)	0.635	0.028	22.707	0.000
C4	(.p4.)	-0.898	0.031	-29.262	0.000
C5	(.p5.)	-0.949	0.036	-26.367	0.000
neuro =~					
N1	(.p6.)	1.307	0.033	39.323	0.000
N2	(.p7.)	1.249	0.032	38.734	0.000
N3	(.p8.)	1.207	0.034	35.334	0.000
N4	(.p9.)	0.910	0.034	26.987	0.000
N5	(.10.)	0.839	0.035	24.010	0.000

Regressions:

		Estimate	Std.Err	Z-value	P(> z)
conc ~					
neuro	(b1)	-0.330	0.029	-11.365	0.000

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		-0.173	0.053	-3.239	0.001
neuro		-0.092	0.045	-2.056	0.040
C1	(.26.)	4.571	0.027	170.418	0.000
C2	(.27.)	4.442	0.029	152.673	0.000

Example



C3	(.28.)	4.379	0.028	154.796	0.000
C4	(.29.)	2.434	0.032	76.041	0.000
C5	(.30.)	3.187	0.037	85.740	0.000
N1	(.31.)	2.940	0.039	75.506	0.000
N2	(.32.)	3.509	0.038	93.434	0.000
N3	(.33.)	3.224	0.039	83.699	0.000
N4	(.34.)	3.197	0.035	91.151	0.000
N5	(.35.)	2.975	0.035	84.126	0.000

Variances :

	Estimate	Std.Err	Z-value	P(> z)
conc	1.132	0.097	11.640	0.000
neuro	0.860	0.062	13.828	0.000
C1	1.179	0.064	18.362	0.000
C2	1.148	0.066	17.486	0.000
C3	1.096	0.062	17.718	0.000
C4	0.951	0.067	14.262	0.000
C5	1.621	0.099	16.366	0.000
N1	0.810	0.058	13.894	0.000
N2	0.824	0.057	14.542	0.000
N3	1.122	0.068	16.399	0.000
N4	1.627	0.086	18.806	0.000
N5	1.880	0.098	19.206	0.000

Example



```
diffVec ← fitMeasures(fit3)[c("chisq", "df")] -  
          fitMeasures(fit2)[c("chisq", "df")]  
pchisq(diffVec[1], diffVec[2], lower = FALSE)
```

```
      chisq  
0.3093433
```

Example



```
mod4 ← "  
conc =~ C1 + C2 + C3 + C4 + C5  
neuro =~ N1 + N2 + N3 + N4 + N5  
  
conc ~ c(b1, b1, b2)*neuro  
  
conc ~ c(1.0, NA, NA)*conc  
neuro ~ c(1.0, NA, NA)*neuro  
  
conc ~ c(0.0, NA, NA)*1.0  
neuro ~ c(0.0, NA, NA)*1.0  
"
```

Example



```
fit4 ← lavaan(mod4,  
              data = dat2,  
              std.lv = FALSE,  
              auto.fix.first = FALSE,  
              auto.var = TRUE,  
              int.ov.free = TRUE,  
              group = "educ",  
              group.equal = c("loadings", "intercepts")  
            )
```


Example



```
summary(fit4)
```

```
lavaan (0.5-20) converged normally after 75 iterations
```

Number of observations per group

highSchool	1536
subHS	192
college	824

Estimator	ML
-----------	----

Minimum Function Test Statistic	1132.387
---------------------------------	----------

Degrees of freedom	135
--------------------	-----

P-value (Chi-square)	0.000
----------------------	-------

Chi-square for each group:

highSchool	573.494
subHS	109.779
college	449.114

Parameter Estimates:

Example



Information
Standard Errors

Expected
Standard

Group 1 [highSchool]:

Latent Variables:

		Estimate	Std.Err	Z-value	P(> z)
conc =~					
C1	(.p1.)	0.574	0.027	21.493	0.000
C2	(.p2.)	0.679	0.029	23.735	0.000
C3	(.p3.)	0.635	0.028	22.691	0.000
C4	(.p4.)	-0.897	0.031	-29.229	0.000
C5	(.p5.)	-0.947	0.036	-26.305	0.000
neuro =~					
N1	(.p6.)	1.306	0.033	39.305	0.000
N2	(.p7.)	1.248	0.032	38.715	0.000
N3	(.p8.)	1.205	0.034	35.313	0.000
N4	(.p9.)	0.909	0.034	26.975	0.000
N5	(.10.)	0.837	0.035	23.992	0.000

Regressions:

Estimate Std.Err Z-value P(>|z|)

Example



```

conc ~
neuro      (b1)      -0.349      0.034      -10.380      0.000

```

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		0.000			
neuro		0.000			
C1	(.26.)	4.571	0.027	170.141	0.000
C2	(.27.)	4.442	0.029	152.312	0.000
C3	(.28.)	4.379	0.028	154.494	0.000
C4	(.29.)	2.434	0.032	75.849	0.000
C5	(.30.)	3.186	0.037	85.603	0.000
N1	(.31.)	2.940	0.039	75.537	0.000
N2	(.32.)	3.509	0.038	93.472	0.000
N3	(.33.)	3.224	0.038	83.753	0.000
N4	(.34.)	3.197	0.035	91.190	0.000
N5	(.35.)	2.975	0.035	84.164	0.000

Variances:

		Estimate	Std.Err	Z-value	P(> z)
conc		1.000			
neuro		1.000			
C1		1.108	0.045	24.771	0.000

Example



C2	1.186	0.050	23.857	0.000
C3	1.200	0.049	24.403	0.000
C4	0.895	0.048	18.603	0.000
C5	1.601	0.073	22.063	0.000
N1	0.839	0.046	18.296	0.000
N2	0.829	0.044	18.988	0.000
N3	1.219	0.055	22.298	0.000
N4	1.702	0.067	25.566	0.000
N5	1.963	0.075	26.139	0.000

Group 2 [subHS]:

Latent Variables:

		Estimate	Std.Err	Z-value	P(> z)
conc =~					
C1	(.p1.)	0.574	0.027	21.493	0.000
C2	(.p2.)	0.679	0.029	23.735	0.000
C3	(.p3.)	0.635	0.028	22.691	0.000
C4	(.p4.)	-0.897	0.031	-29.229	0.000
C5	(.p5.)	-0.947	0.036	-26.305	0.000
neuro =~					
N1	(.p6.)	1.306	0.033	39.305	0.000

Example



N2	(.p7.)	1.248	0.032	38.715	0.000
N3	(.p8.)	1.205	0.034	35.313	0.000
N4	(.p9.)	0.909	0.034	26.975	0.000
N5	(.10.)	0.837	0.035	23.992	0.000

Regressions:

		Estimate	Std.Err	Z-value	P(> z)
conc ~					
neuro	(b1)	-0.349	0.034	-10.380	0.000

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		-0.259	0.095	-2.716	0.007
neuro		0.016	0.081	0.201	0.841
C1	(.26.)	4.571	0.027	170.141	0.000
C2	(.27.)	4.442	0.029	152.312	0.000
C3	(.28.)	4.379	0.028	154.494	0.000
C4	(.29.)	2.434	0.032	75.849	0.000
C5	(.30.)	3.186	0.037	85.603	0.000
N1	(.31.)	2.940	0.039	75.537	0.000
N2	(.32.)	3.509	0.038	93.472	0.000
N3	(.33.)	3.224	0.038	83.753	0.000
N4	(.34.)	3.197	0.035	91.190	0.000

Example



```
N5      (.35.)      2.975      0.035      84.164      0.000
```

Variances:

	Estimate	Std.Err	Z-value	P(> z)
conc	1.056	0.170	6.208	0.000
neuro	0.896	0.119	7.550	0.000
C1	1.264	0.142	8.916	0.000
C2	1.272	0.148	8.564	0.000
C3	1.433	0.162	8.848	0.000
C4	1.197	0.160	7.476	0.000
C5	1.742	0.217	8.030	0.000
N1	1.012	0.145	6.980	0.000
N2	1.243	0.161	7.710	0.000
N3	1.314	0.165	7.957	0.000
N4	1.507	0.169	8.895	0.000
N5	2.046	0.221	9.238	0.000

Group 3 [college]:

Latent Variables:

	Estimate	Std.Err	Z-value	P(> z)
conc =~				

Example



C1	(.p1.)	0.574	0.027	21.493	0.000
C2	(.p2.)	0.679	0.029	23.735	0.000
C3	(.p3.)	0.635	0.028	22.691	0.000
C4	(.p4.)	-0.897	0.031	-29.229	0.000
C5	(.p5.)	-0.947	0.036	-26.305	0.000
neuro =~					
N1	(.p6.)	1.306	0.033	39.305	0.000
N2	(.p7.)	1.248	0.032	38.715	0.000
N3	(.p8.)	1.205	0.034	35.313	0.000
N4	(.p9.)	0.909	0.034	26.975	0.000
N5	(.10.)	0.837	0.035	23.992	0.000

Regressions:

		Estimate	Std.Err	Z-value	P(> z)
conc ~					
neuro	(b2)	-0.277	0.052	-5.348	0.000

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		-0.168	0.053	-3.137	0.002
neuro		-0.092	0.045	-2.056	0.040
C1	(.26.)	4.571	0.027	170.141	0.000
C2	(.27.)	4.442	0.029	152.312	0.000

Example



C3	(.28.)	4.379	0.028	154.494	0.000
C4	(.29.)	2.434	0.032	75.849	0.000
C5	(.30.)	3.186	0.037	85.603	0.000
N1	(.31.)	2.940	0.039	75.537	0.000
N2	(.32.)	3.509	0.038	93.472	0.000
N3	(.33.)	3.224	0.038	83.753	0.000
N4	(.34.)	3.197	0.035	91.190	0.000
N5	(.35.)	2.975	0.035	84.164	0.000

Variances :

	Estimate	Std.Err	Z-value	P(> z)
conc	1.138	0.098	11.640	0.000
neuro	0.864	0.063	13.809	0.000
C1	1.178	0.064	18.359	0.000
C2	1.141	0.065	17.460	0.000
C3	1.093	0.062	17.706	0.000
C4	0.953	0.067	14.269	0.000
C5	1.634	0.100	16.409	0.000
N1	0.807	0.058	13.845	0.000
N2	0.820	0.057	14.497	0.000
N3	1.122	0.068	16.397	0.000
N4	1.630	0.087	18.808	0.000
N5	1.882	0.098	19.208	0.000

Example



```
diffVec ← fitMeasures(fit4)[c("chisq", "df")] -  
          fitMeasures(fit2)[c("chisq", "df")]  
pchisq(diffVec[1], diffVec[2], lower = FALSE)
```

```
      chisq  
0.3299714
```

Several advantages to testing moderation with multiple group SEM

- Remove measurement error from the estimates
- Test for factorial invariance
- *All information needed to plot/probe the simple slopes is contained directly in the output from the unrestricted model*

Example



```
summary(fit2)
```

```
lavaan (0.5-20) converged normally after 79 iterations
```

Number of observations per group	
highSchool	1536
subHS	192
college	824

Estimator	ML
Minimum Function Test Statistic	1131.438
Degrees of freedom	134
P-value (Chi-square)	0.000

```
Chi-square for each group:
```

highSchool	573.289
subHS	108.925
college	449.224

```
Parameter Estimates:
```

Example



Information
Standard Errors

Expected
Standard

Group 1 [highSchool]:

Latent Variables:

		Estimate	Std.Err	Z-value	P(> z)
conc =~					
C1	(.p1.)	0.573	0.027	21.471	0.000
C2	(.p2.)	0.678	0.029	23.706	0.000
C3	(.p3.)	0.634	0.028	22.666	0.000
C4	(.p4.)	-0.897	0.031	-29.235	0.000
C5	(.p5.)	-0.947	0.036	-26.307	0.000
neuro =~					
N1	(.p6.)	1.305	0.033	39.285	0.000
N2	(.p7.)	1.247	0.032	38.701	0.000
N3	(.p8.)	1.205	0.034	35.309	0.000
N4	(.p9.)	0.909	0.034	26.982	0.000
N5	(.10.)	0.837	0.035	23.998	0.000

Regressions:

Estimate Std.Err Z-value P(>|z|)

Example



```

conc ~
neuro          -0.359      0.035   -10.208      0.000

```

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		0.000			
neuro		0.000			
C1	(.26.)	4.571	0.027	170.017	0.000
C2	(.27.)	4.442	0.029	152.180	0.000
C3	(.28.)	4.379	0.028	154.381	0.000
C4	(.29.)	2.434	0.032	75.721	0.000
C5	(.30.)	3.186	0.037	85.494	0.000
N1	(.31.)	2.940	0.039	75.566	0.000
N2	(.32.)	3.509	0.038	93.494	0.000
N3	(.33.)	3.224	0.038	83.772	0.000
N4	(.34.)	3.197	0.035	91.203	0.000
N5	(.35.)	2.975	0.035	84.171	0.000

Variances:

		Estimate	Std.Err	Z-value	P(> z)
conc		1.000			
neuro		1.000			
C1		1.109	0.045	24.781	0.000

Example



C2	1.187	0.050	23.872	0.000
C3	1.201	0.049	24.414	0.000
C4	0.893	0.048	18.572	0.000
C5	1.600	0.073	22.053	0.000
N1	0.840	0.046	18.316	0.000
N2	0.830	0.044	19.003	0.000
N3	1.219	0.055	22.298	0.000
N4	1.701	0.067	25.564	0.000
N5	1.962	0.075	26.138	0.000

Group 2 [subHS]:

Latent Variables:

		Estimate	Std.Err	Z-value	P(> z)
conc	=~				
C1	(.p1.)	0.573	0.027	21.471	0.000
C2	(.p2.)	0.678	0.029	23.706	0.000
C3	(.p3.)	0.634	0.028	22.666	0.000
C4	(.p4.)	-0.897	0.031	-29.235	0.000
C5	(.p5.)	-0.947	0.036	-26.307	0.000
neuro	=~				
N1	(.p6.)	1.305	0.033	39.285	0.000

Example



N2	(.p7.)	1.247	0.032	38.701	0.000
N3	(.p8.)	1.205	0.034	35.309	0.000
N4	(.p9.)	0.909	0.034	26.982	0.000
N5	(.10.)	0.837	0.035	23.998	0.000

Regressions :

	Estimate	Std.Err	Z-value	P(> z)
conc ~				
neuro	-0.252	0.105	-2.396	0.017

Intercepts :

		Estimate	Std.Err	Z-value	P(> z)
conc		-0.261	0.095	-2.741	0.006
neuro		0.016	0.081	0.202	0.840
C1	(.26.)	4.571	0.027	170.017	0.000
C2	(.27.)	4.442	0.029	152.180	0.000
C3	(.28.)	4.379	0.028	154.381	0.000
C4	(.29.)	2.434	0.032	75.721	0.000
C5	(.30.)	3.186	0.037	85.494	0.000
N1	(.31.)	2.940	0.039	75.566	0.000
N2	(.32.)	3.509	0.038	93.494	0.000
N3	(.33.)	3.224	0.038	83.772	0.000
N4	(.34.)	3.197	0.035	91.203	0.000

Example



```
N5      (.35.)      2.975      0.035      84.171      0.000
```

Variances:

	Estimate	Std.Err	Z-value	P(> z)
conc	1.061	0.170	6.237	0.000
neuro	0.905	0.120	7.540	0.000
C1	1.263	0.142	8.919	0.000
C2	1.270	0.148	8.568	0.000
C3	1.437	0.162	8.855	0.000
C4	1.192	0.160	7.466	0.000
C5	1.748	0.217	8.039	0.000
N1	1.014	0.146	6.965	0.000
N2	1.236	0.161	7.681	0.000
N3	1.310	0.165	7.937	0.000
N4	1.507	0.170	8.888	0.000
N5	2.042	0.221	9.232	0.000

Group 3 [college]:

Latent Variables:

	Estimate	Std.Err	Z-value	P(> z)
conc =~				

Example



C1	(.p1.)	0.573	0.027	21.471	0.000
C2	(.p2.)	0.678	0.029	23.706	0.000
C3	(.p3.)	0.634	0.028	22.666	0.000
C4	(.p4.)	-0.897	0.031	-29.235	0.000
C5	(.p5.)	-0.947	0.036	-26.307	0.000
neuro =~					
N1	(.p6.)	1.305	0.033	39.285	0.000
N2	(.p7.)	1.247	0.032	38.701	0.000
N3	(.p8.)	1.205	0.034	35.309	0.000
N4	(.p9.)	0.909	0.034	26.982	0.000
N5	(.10.)	0.837	0.035	23.998	0.000

Regressions:

	Estimate	Std.Err	Z-value	P(> z)
conc ~				
neuro	-0.278	0.052	-5.354	0.000

Intercepts:

		Estimate	Std.Err	Z-value	P(> z)
conc		-0.168	0.053	-3.139	0.002
neuro		-0.092	0.045	-2.056	0.040
C1	(.26.)	4.571	0.027	170.017	0.000
C2	(.27.)	4.442	0.029	152.180	0.000

Example



C3	(.28.)	4.379	0.028	154.381	0.000
C4	(.29.)	2.434	0.032	75.721	0.000
C5	(.30.)	3.186	0.037	85.494	0.000
N1	(.31.)	2.940	0.039	75.566	0.000
N2	(.32.)	3.509	0.038	93.494	0.000
N3	(.33.)	3.224	0.038	83.772	0.000
N4	(.34.)	3.197	0.035	91.203	0.000
N5	(.35.)	2.975	0.035	84.171	0.000

Variances :

	Estimate	Std.Err	Z-value	P(> z)
conc	1.139	0.098	11.634	0.000
neuro	0.865	0.063	13.807	0.000
C1	1.178	0.064	18.364	0.000
C2	1.142	0.065	17.467	0.000
C3	1.093	0.062	17.713	0.000
C4	0.952	0.067	14.255	0.000
C5	1.633	0.100	16.405	0.000
N1	0.807	0.058	13.850	0.000
N2	0.820	0.057	14.498	0.000
N3	1.122	0.068	16.394	0.000
N4	1.630	0.087	18.807	0.000
N5	1.882	0.098	19.207	0.000

Example



```
## Extract info needed to plot simple slopes:
ints ← c(0,
         coef(fit2)[c("conc~1.g2",
                      "conc~1.g3")]
        )
slopes ← coef(fit2)[c("conc~neuro",
                     "conc~neuro.g2",
                     "conc~neuro.g3")]
fScores ← do.call(rbind, predict(fit2))
```

Example



```
par(family = "serif", cex = 0.75)
plot(y = fScores[ , "conc"],
     x = fScores[ , "neuro"],
     type = "n",
     main = "Latent Simple Slopes",
     xlab = "Neuroticism",
     ylab = "Conscientiousness")
abline(a = ints[1], b = slopes[1])
abline(a = ints[2], b = slopes[2], col = "red")
abline(a = ints[3], b = slopes[3], col = "blue")
legend(x = "topright",
       inset = 0.01,
       legend =
         c("High School",
           "College",
           "< High School"),
       col =
         c("black",
           "red",
           "blue"),
       lty = 1)
```

Latent Simple Slopes

