Mediation, Moderation, and Conditional Process Analysis

Instructor: Amanda K. Montoya

STATISTICAL HORIZONS

18-20 April 2024
Statistical Horizons, Virtual

Understanding causal effects

Hagtvedt, H., & Patrick, V. M. (2008). Art infusion: The influence of visual art on the perception and evaluation of consumer products. *Journal of Marketing Research, 45*, 379-389.

HENRIK HAGTVEDT and VANESSA M. PATRICK*

In this research, the authors investigate the phenomenon of "art infusion," in which the presence of visual art has a favorable influence on the evaluation of consumer products through a content-independent spillover of luxury perceptions. In three studies, the authors demonstrate the art infusion phenomenon in both real-world and controlled environments using a variety of stimuli in the contexts of packaging, advertising, and product design.

Keywords: visual art, luxury, aesthetics, spillover effects, packaging, advertising, product design

Art Infusion: The Influence of Visual Art on the Perception and Evaluation of Consumer Products

How does the presence of visual art alter the way people view a consumer product? Throughout history, art has had the ability to arouse the imagination and capture the attention. Therefore, it is not surprising that art images are often used to promote unrelated products—for example, by being displayed in advertisements (Hetsroni and Tukachinsky 2005). It is proposed that such "high-culture images reach more people more often through advertising than through any other medium" (Hoffman 2002, p. 6). Other times, art becomes an integrated part of a product, such as when furniture is artistically designed or a painting is printed on a shirt. Some companies, such as De Beers, use art in image promotion, conveying the idea that diamonds, like paintings, are unique works of art (Epstein 1982). Sometimes, art is even created for the sole purpose of marketing a product, such as in the enduring Absolut Vodka advertising campaign (Lewis 1996).

It is clear that influential marketing practitioners believe that art somehow has the power to influence consumer perceptions. Vast amounts of money are spent on representing visual art in conjunction with products, in the hope that the products will become more marketable as a result. However, the issue of whether these beliefs are well founded remains unresolved. Furthermore, there is little evidence to suggest that marketing professionals have been provided with the scientific basis necessary to use visual art in a strategic manner rather than purely on the basis of experience and intuition. Supplying this basis is a complex endeavor. However, the current research represents an initial step to analyze systematically the influence of visual art on consumer evaluations of the products with which it is associated. This influence represents a fundamental gap in current understanding, not only in terms of the $23.5 billion global art market (Kusin & Company 2002) but also in terms of the potential impact of art on other markets and marketing activities.

In this research, we examine the phenomenon of "art infusion," which we broadly define as the general influence of the presence of art on consumer perceptions and evaluations of products with which it is associated. More specifically, we theorize that perceptions of luxury associated with visual art spill over from the artwork onto products with which it is associated, leading to more favorable evaluations of these products. Furthermore, we propose that this influence does not depend on the content of the specific artwork—that is, what is depicted in the artwork—but rather on general connotations of luxury associated with visual art.

In Study 1, we demonstrate the art infusion phenomenon in a real-world setting. In this study, consumers are briefly exposed to art or nonart images, which are matched for

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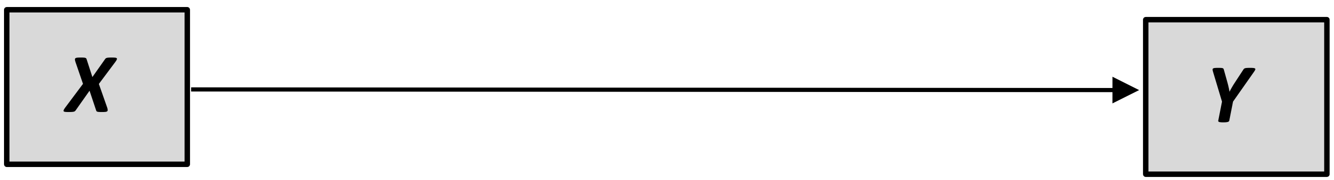


PHOTO or PAINTING

PRODUCT EVALUATION

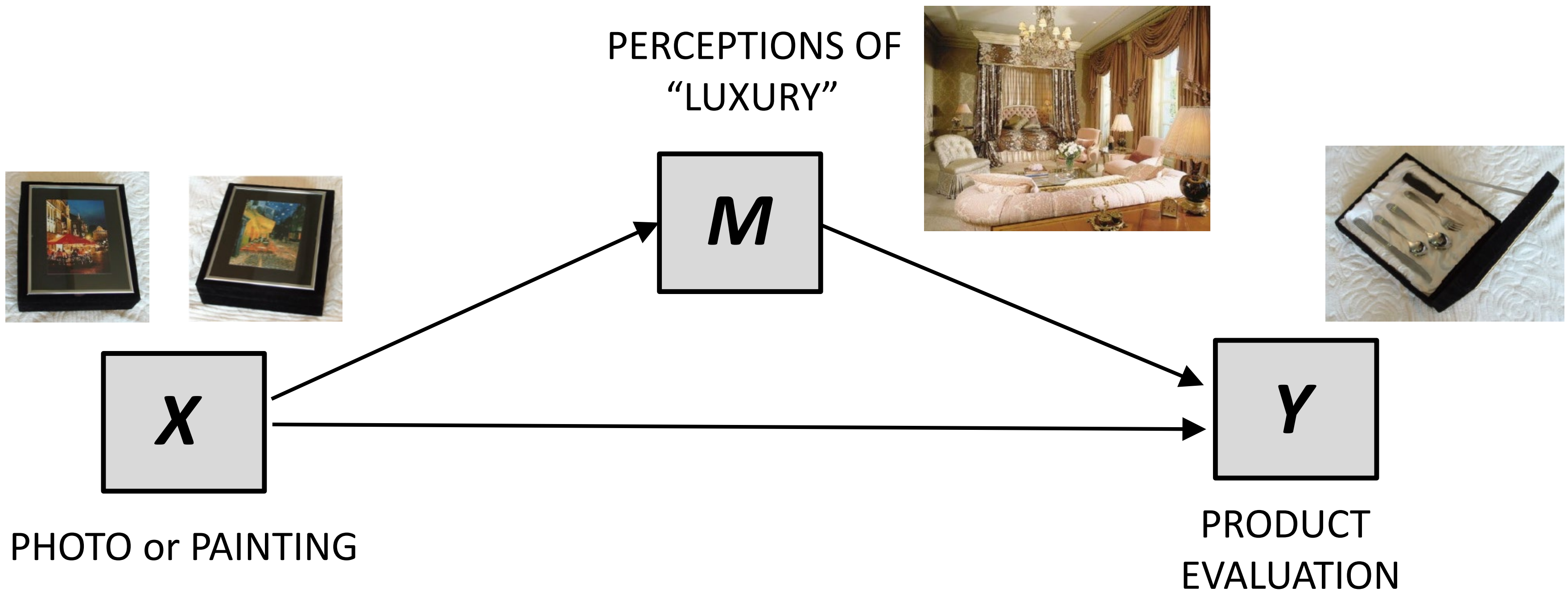
The product with the impressionist painting on the box was evaluated more favorably than the product with a photograph of a similar scene.

Remaining Questions:

- How does this effect occur? What is the *mechanism* that produces it?
- Is the effect consistent across type of product, type of consumer, and so forth.

These are the important questions!

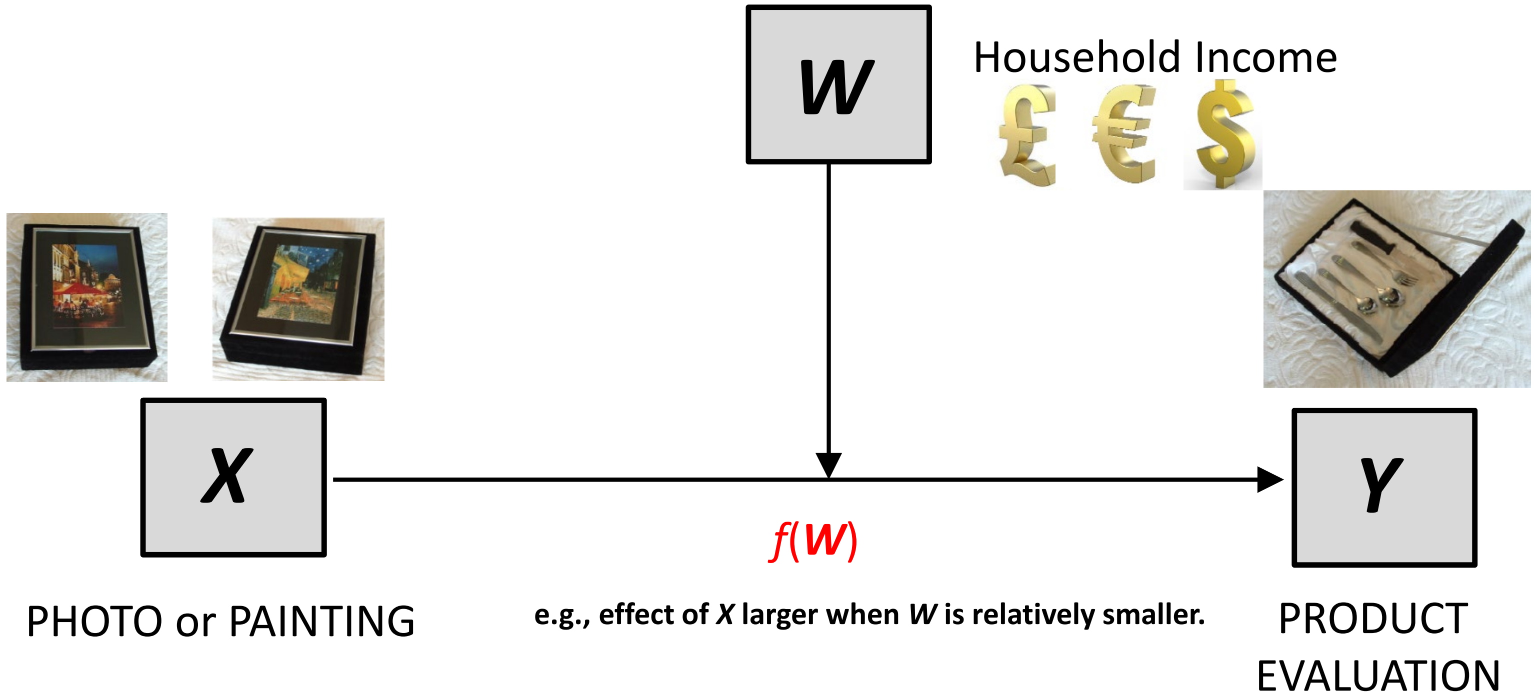
A simple mediation model



Art-infused product was perceived as more “luxurious,” and this greater perceived luxury translated into a more favorable product evaluation. Thus, the infusion of the product with art influenced product evaluation at least partly through the “mechanism” of perceived luxuriousness.

Mediation analysis is about estimating and making inferences about such *indirect effects*.

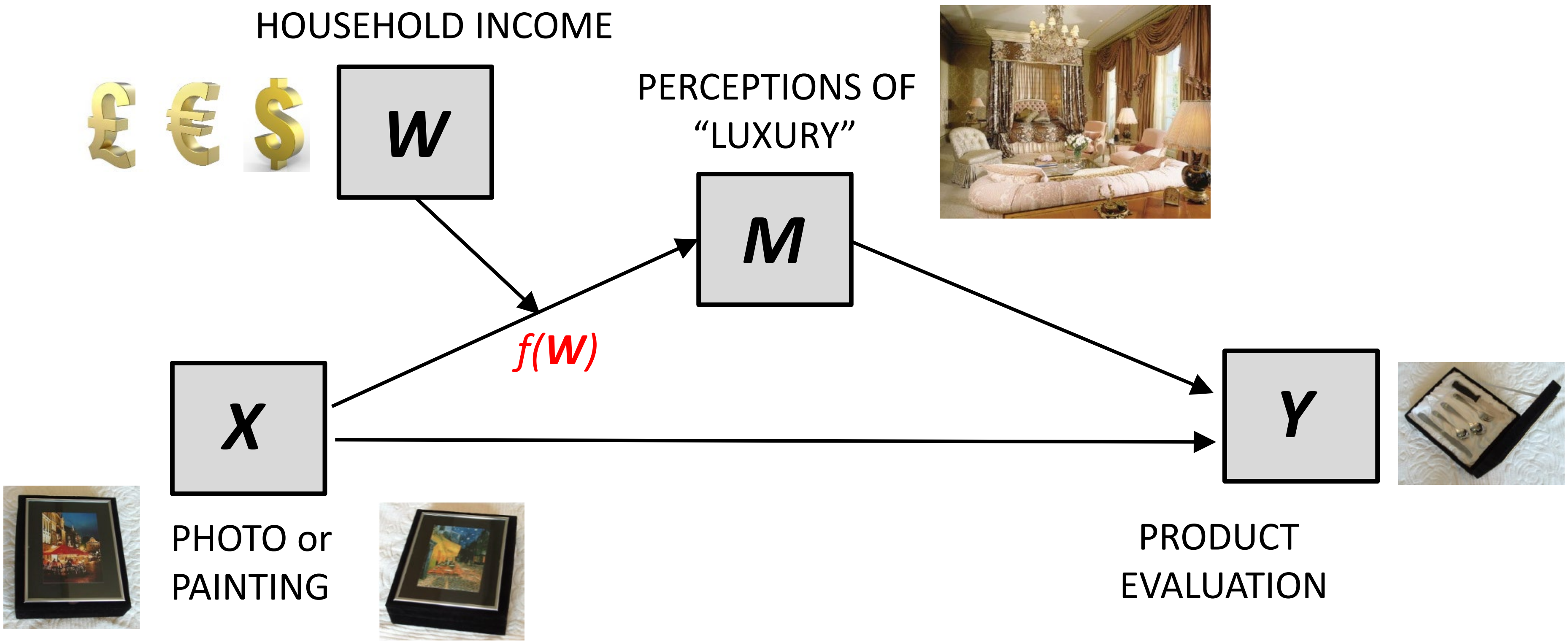
Moderation



Is this effect of art infusion larger among those with less income? Is the size of the effect dependent on (or a function of) income? In this case, income is a *moderator* of the effect of art infusion on product evaluation.

Moderation analysis is about the estimation of *contingent effects*, i.e., examining the boundary conditions of effects or the factors that make effects large versus small, positive versus negative.

Combining moderation and mediation



Does art infusion result in greater perceptions of luxury more so among those with less income? If so, then the indirect effect of art infusion on product evaluation through perceptions of luxury depends on income. Thus, the strength of this “mechanism” may depend on income. Mediation can be moderated.

In this class

- After a review of OLS regression, we start with questions of "**HOW**"— **statistical mediation analysis**

  "Direct," "indirect," and "total effects" in path models and how to test hypotheses in such models using OLS regression and various computational tools developed for this purpose.

- We then move to questions of "**WHEN**"--**moderation analysis**

  Estimation and interpretation of models in which a predictor can have different effects on an outcome depending on the value of another variable in the model.

- We then explore models that combine moderation and mediation— **"conditional process analysis"**

- With fundamentals covered, we address more complex models and issues in mediation and moderation analysis, such as multiple mediators and multi-categorical independent variables and repeated-measures mediation.

What you'll need

- **This course is hands-on. Hopefully you brought a laptop with R 3.6.1, SPSS 19+ or SAS 9.1+ with PROC IML. If not, that is ok. You'll still benefit.**

`SPSS Code` `SAS Code` `R Code`

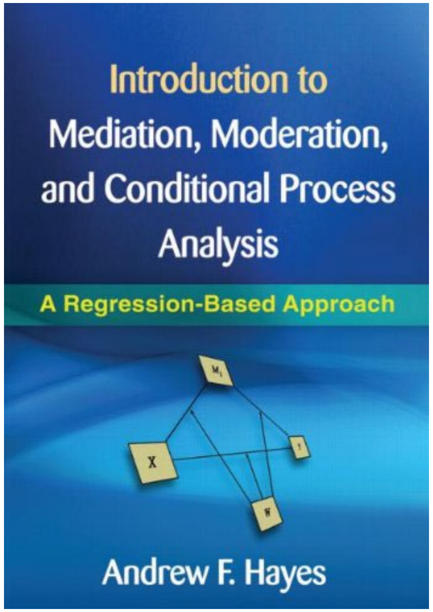
- **Various files emailed to you by StatHorizon**
  - SPSS, SAS, and R data folders. SPSS data files are ready to go. SAS files are programs thus must be executed to make them "work" files. R files are CSV and need to be read into R.
  - SPSS, SAS, and R PROCESS folders. This contains the PROCESS macro we'll heavily rely on, and some documents related to it.
  - Miscellaneous folder. Various files, including some PDFs and other miscellaneous things of relevance to this course.
- **A lot of stamina.**

What we will and won't do

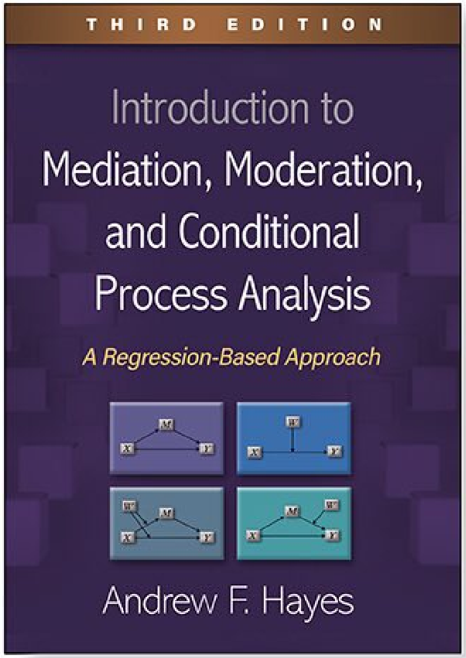
- We will stick with fairly simple models to cover basic principles, with continuous outcomes, and cross-sectional or experimental data.
- Statistical mediation analysis. No discussion of counterfactuals, "potential outcomes," directed graphs, or other approaches to thinking about cause.
- Everything OLS-regression-based.
- No dichotomous outcomes, nothing multilevel.

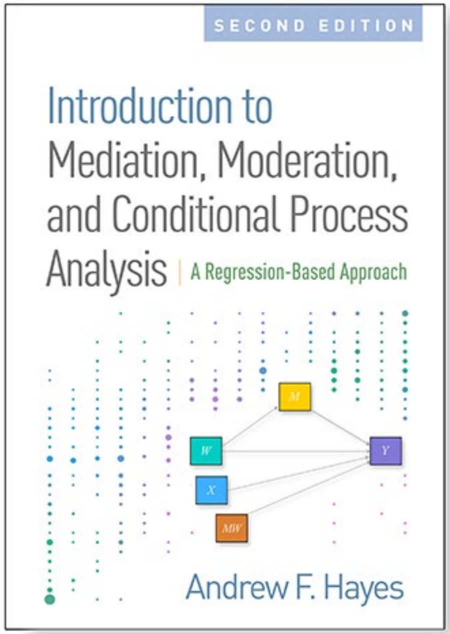
Although the principles are not software specific, their implementation is facilitated with the use of a "macro" which makes otherwise tedious things very simple and effortless. You will learn about PROCESS.

This course is a companion to...



2013





2017

3rd Ed. January 2022

(Contains all documentation for PROCESS for R)

www.guilford.com

Example for the class "inspired by"…

Bayram-Ozdemir, S. & Stattin, H. (2014). Why and when is ethnic harassment a risk for immigrant adolescents' school adjustment? Understanding the processes and conditions. ***Journal of Youth and Adolescence, 43***, 1252-1265.

J Youth Adolescence (2014) 43:1252–1265
DOI 10.1007/s10964-013-0038-y

EMPIRICAL RESEARCH

Why and When is Ethnic Harassment a Risk for Immigrant Adolescents' School Adjustment? Understanding the Processes and Conditions

Sevgi Bayram Özdemir · Håkan Stattin

Received: 5 July 2013 / Accepted: 7 October 2013 / Published online: 17 October 2013

Abstract Ethnically harassed immigrant youth are at risk for experiencing a wide range of school adjustment problems. However, it is still unclear why and under what conditions experiencing ethnic harassment leads to school adjustment difficulties. To address this limitation in the literature, we examined two important questions. First, we investigated whether self-esteem and/or depressive symptoms would mediate the associations between ethnic harassment and poor school adjustment among immigrant youth. Second, we examined whether immigrant youths' perception of school context would play a buffering role in the pathways between ethnic harassment and school adjustment difficulties. The sample (n = 330; M_{age} = 14.07, SD = .90; 49 % girls at T1) was drawn from a longitudinal study in Sweden. The results revealed that experiencing ethnic harassment led to a decrease in immigrant youths' self-esteem over time, and that youths' expectations of academic failure increased. Further, youths' relationships with their teachers and their perceptions of school democracy moderated the mediation processes. Specifically, when youth had poor relationships with their teachers *or* perceived their school context as less democratic, being exposed to ethnic harassment led to a decrease in their self-esteem. In turn, they reported low school satisfaction and perceived themselves as being unsuccessful in school. Such indirect effects were not observed when youth had high positive relationships with their teachers *or* perceived their school as offering a democratic environment. These findings highlight the importance of understanding underlying processes and conditions in the examination of the effects of ethnic devaluation experiences in order to reach a more comprehensive understanding of immigrant youths' school adjustment.

Keywords Immigrant youth · School adjustment · Ethnic harassment · Ethnic victimization · Depression · Self-esteem

Introduction

Adjustment and success in academic life is a key factor for immigrant youths' integration into the host culture and their future prospects (Health et al. 2008). Thus, this issue has become one of the policy priorities for immigrant-receiving countries, and extensive efforts have been made to identify the factors that may play a role in the school adjustment and performance of immigrant youth. Experience of ethnic harassment (i.e., negative treatments or derogatory comments in relation to ethnic background) is one of the major contextual stressors for immigrant youth (Garcia Coll et al. 1996) and poses a threat to their school adjustment.

Research on ethnic minority adolescents in the U.S. and Europe has shown that a substantial number of youth are treated badly and victimized by their peers, teachers, and neighbors, at school and in other contexts (e.g., Huynh and Fuligni 2010; Liebkind et al. 2004; Verkuyten and Thijs 2002). Such negative experiences have been linked to a wide range of school outcomes. Youth who are harassed on the basis of their ethnic origin tend to develop negative beliefs about their academic competence and rewards of schooling (Eccles et al. 2006; Wong et al. 2003), display

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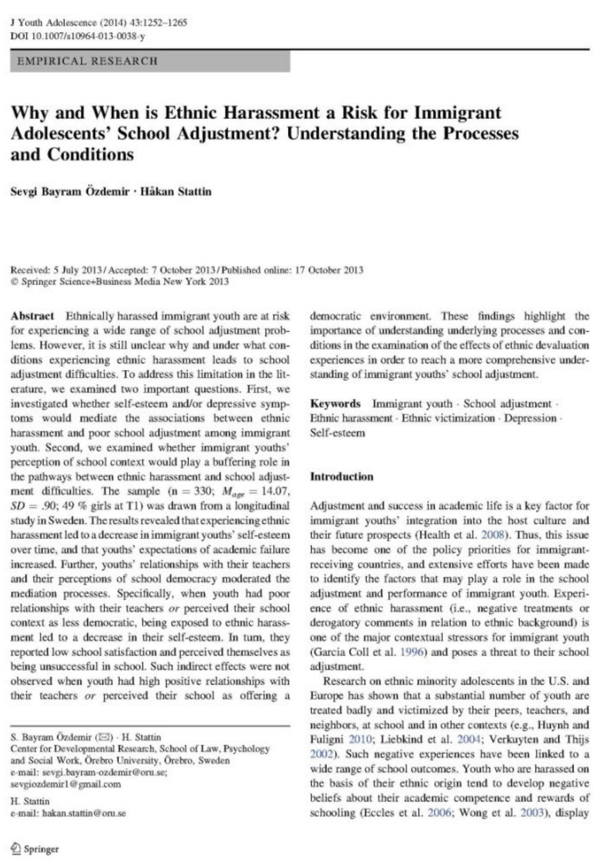

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Springer

330 7th to 9th grade students in Sweden measured in the spring term (T1) and again one year later (T2).

All were first or second generation immigrants who reported at least some ethnic harassment.

HARASS: 6-item measure of ethnicity-related harassment frequency (scaled 1 to 5). T1 only.

POSREL: 6-item measure of positivity of relationships with teachers (scaled 1 to 4). T1 only.

SE: 10-item Rosenberg self-esteem scale (scaled 1 to 4). T1 and T2.

DEP: 20-item Center for Epidemiological Studies Depression Scale for Children (scaled 1 to 4). T1 and T2.

FAIL: 4-item measure of perceived academic failure at school (scaled 1 to 4). T1 and T2.

SATIS: 5-item measure of satisfaction in school (scaled 1 to 5). T1 and T2.

All are continuous variables scaled such that higher = more.

The Data: HARASS

SPSS

*harass.sav [DataSet3] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Gra

	harass	se2	dep2	satis2
1	2.16	3.80	1.25	4.80
2	2.33	2.90	1.95	4.20
3	1.16	3.80	1.95	5.00
4	2.50	2.50	2.15	3.00
5	1.33	3.00	1.90	2.60
6	1.16	2.50	1.25	3.40
7	1.50	2.10	2.05	2.40
8	1.50	3.30	1.75	2.80
9	1.83	2.70	2.15	3.20
10	1.33	2.80	2.45	4.00

The SPSS file is ready for analysis.

SAS

harass

```
data harass;
  input harass se2 dep2 satis2 fa
datalines;
2.16 3.80 1.25 4.80 1.00 1.66 3.6
2.33 2.90 1.95 4.20 1.75 2.83 2.8
1.16 3.80 1.95 5.00 1.50 3.16 3.8
2.50 2.50 2.15 3.00 2.00 2.00 3.1
1.33 3.00 1.90 2.60 1.00 2.83 2.6
1.16 2.50 1.25 3.40 1.25 2.83 2.8
1.50 2.10 2.05 2.40 1.50 3.00 1.8
1.50 3.30 1.75 2.80 1.25 3.00 3.4
1.83 2.70 2.15 3.20 1.50 3.50 2.9
1.33 2.80 2.45 4.00 2.00 3.16 2.8
1.33 2.60 1.70 3.60 1.75 3.16 3.0
```

The SAS version is a SAS program that must be executed to produce a temporary work data file.

R

	harass	se2	dep2	satis2	fail2	posrel	se1	dep1	sa
1	2.16	3.8	1.25	4.8	1.00	1.66	3.6	1.10	
2	2.33	2.9	1.95	4.2	1.75	2.83	2.8	2.25	
3	1.16	3.8	1.95	5.0	1.50	3.16	3.8	1.95	
4	2.50	2.5	2.15	3.0	2.00	2.00	3.1	1.25	
5	1.33	3.0	1.90	2.6	1.00	2.83	2.6	1.55	
6	1.16	2.5	1.25	3.4	1.25	2.83	2.8	1.45	
7	1.50	2.1	2.05	2.4	1.50	3.00	1.8	2.10	
8	1.50	3.3	1.75	2.8	1.25	3.00	3.4	1.55	
9	1.83	2.7	2.15	3.2	1.50	3.50	2.9	2.20	
10	1.33	2.8	2.45	4.0	2.00	3.16	2.8	1.25	
11	1.33	2.6	1.70	3.6	1.75	3.16	3.0	2.05	
12	1.00	2.1	2.30	2.8	1.25	1.33	3.0	2.10	
13	1.66	3.1	2.00	3.8	2.00	2.66	3.2	1.55	
14	1.16	3.5	1.55	3.8	1.25	2.50	3.2	1.75	
15	1.33	2.7	1.35	3.4	1.50	3.00	3.8	1.15	
16	1.66	3.1	1.20	4.4	1.75	4.00	3.4	1.80	

```
filelocation <-
"C:\\Data\\harass.csv"
harass <- read.csv(filelocation,
header = TRUE)
```

These are not the actual data from this study. They were generated to produce similar results to the published study.

Setting Up in R

A few packages I'm going to use throughout the workshop:

```
install.packages(c("mosaic", "ggformula", "jtools"))
library(mosaic)
library(ggformula)
library(jtools)
```

Loading in data:

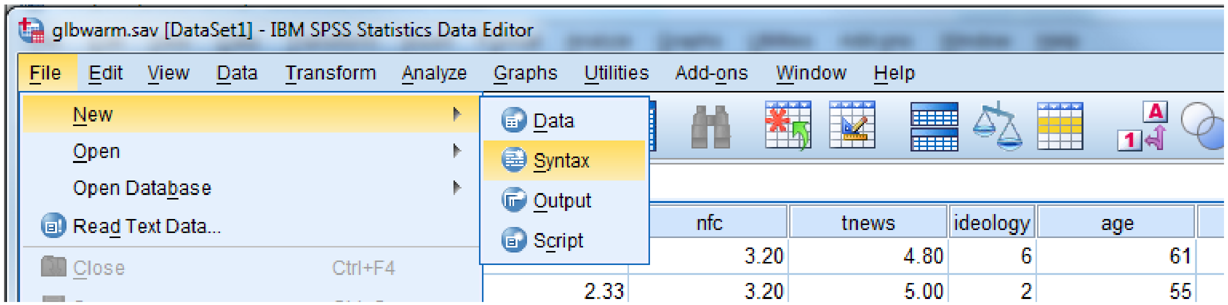
```
filelocation <- "C:\\Your\\Path\\Here\\harass.csv"
harass <- read.csv(filelocation, header = TRUE)
```

You are welcome to deviate from the way I do things, if you have a preferred package for certain types of operations, feel free to do so.

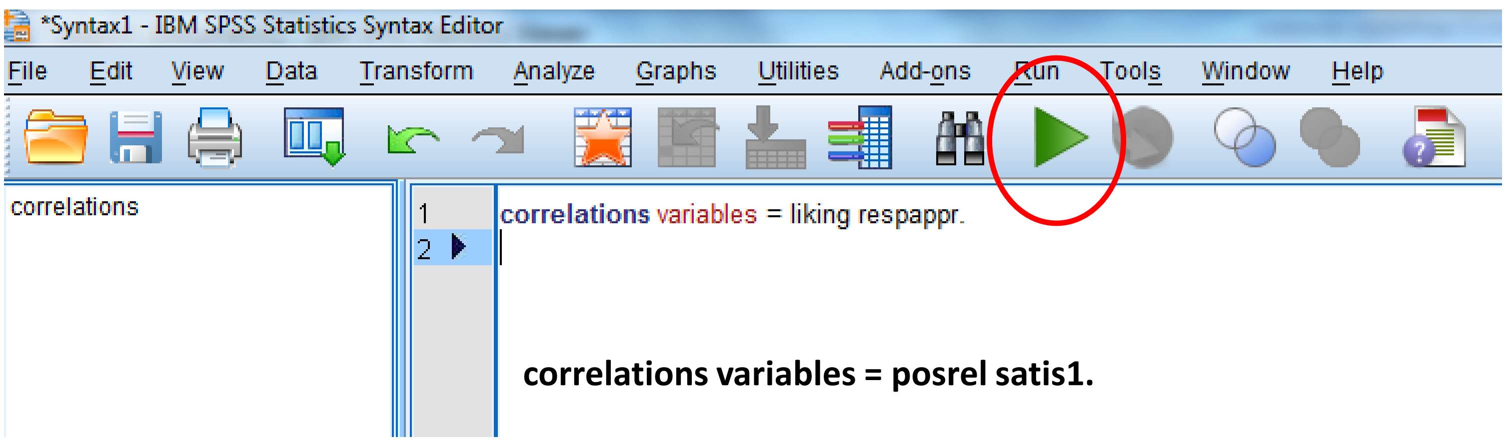
Using SPSS syntax

We will use syntax to instruct SPSS what to do in this class. There are many benefits of learning how to write SPSS syntax.

(1) Open a new syntax window (File > New > Syntax)



(2) Type your command(s) into the blank window that opens



correlations variables = posrel satis1.

(3) Click and drag to highlight code you want to execute and press the “play” button or select various options under “Run” in the syntax window menu.

A quick review of regression analysis

- Linear regression is the foundation of this class.
- Used throughout science as a means of “modeling” the relationship between variables.
- Many of the kinds of analyses and statistics you already know about can be expressed in the form of a linear regression model
  - independent groups *t* test
  - analysis of variance

Pearson’s coefficient of correlation (*r*) is the building block of linear regression analysis. Consider the correlation between positivity of relationships with teachers and satisfaction at school (measured contemporaneously).

Correlations

		posrel	satis1
posrel	Pearson Correlation	1	.458
	Sig. (2-tailed)		.000
	N	330	330
satis1	Pearson Correlation	.458	1
	Sig. (2-tailed)	.000	
	N	330	330

```
        Pearson's product-moment correlation

data:  posrel and satis1
t = 9.3298, df = 328, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.3681961 0.5392569
sample estimates:
      cor
0.4579553
```

SPSS code in black box

```
correlations variables = posrel satis1.
```

R code in grey box

```
cor.test(satis1~posrel, data = harass)
```

SAS code in white box

```
proc corr data=harass;var posrel satis1;run;
```

A scatterplot

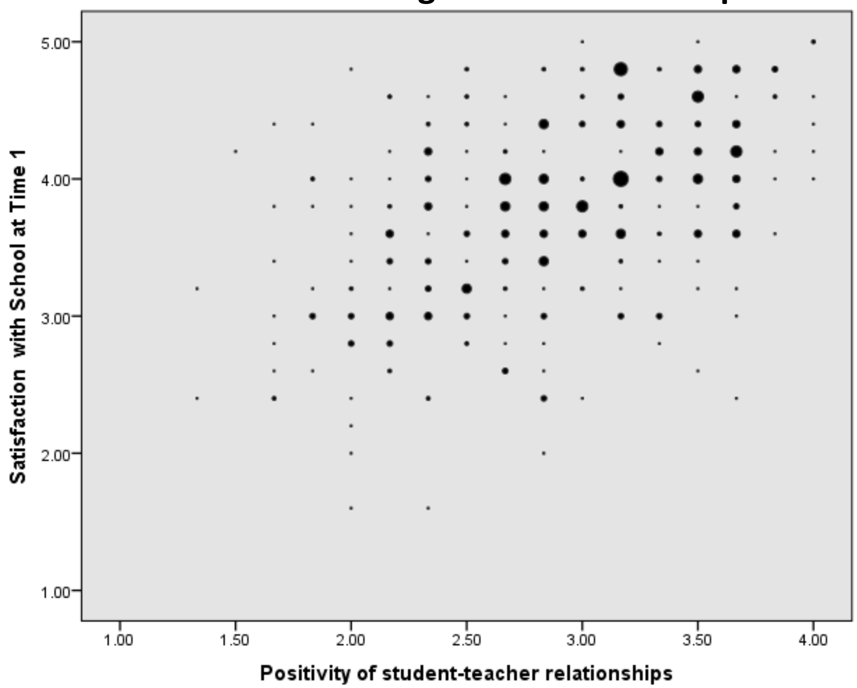
Consider a scatterplot visually depicting this relationship:

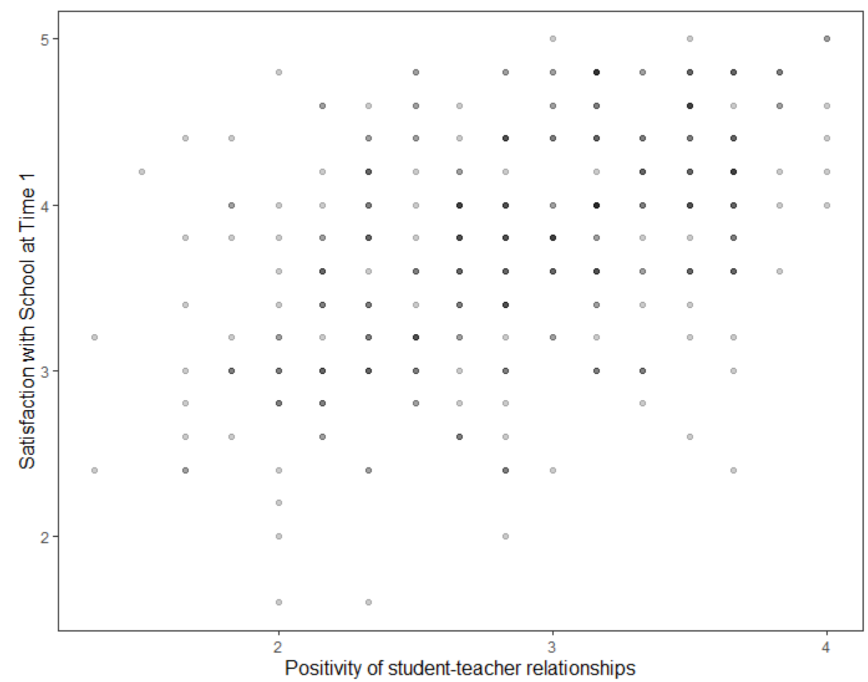
```
graph/scatterplot=posrel with satis1.
```

```
proc sgscatter data=harass;plot satis1*posrel;run;
```

```
gf_point(satis1~posrel, data = harass, alpha = .2, xlab = "Positivity of student-teacher relationships", ylab = "Satisfaction with School at Time 1")+theme_apa()
```

After "binning" to see the overlap:





If you had to draw a single straight line through this plot that "best fits" the relationship, where would you draw it? At its heart, this is the problem regression analysis solves.

OLS (Ordinary Least Squares) linear regression

Goal: Derive the equation ("model") for the line representing the association between independent variable *X* and dependent variable *Y* that "best fits" the data.

The "simple regression model" (i.e., only one variable on the right hand side) takes the form

$$Y_i = b_0 + b_1 X_i + e_i$$

Using the <u>ordinary least squares</u> criterion, there is only one line described by the function

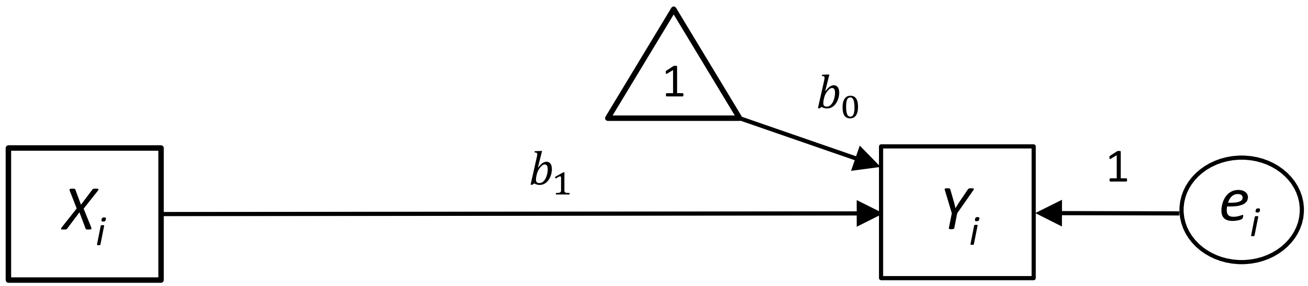
$$\hat{Y}_i = b_0 + b_1 X_i \qquad\qquad e_i = Y_i - \hat{Y}_i$$

that "best fits" the data, where $\hat{Y}_i$ is the estimated or fitted value of Y_i, and "best fit" is defined as the line that minimizes the sum of the squared residuals ($SS_{residual}$), summed over all *n* cases in the data. This is called the LEAST SQUARES criterion.

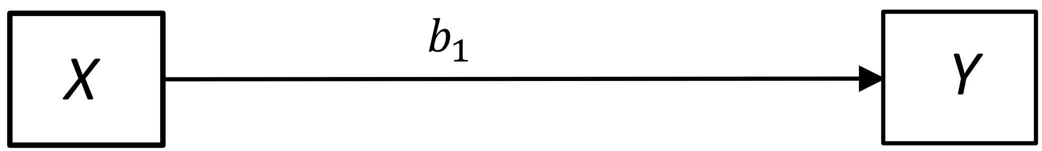
$$SS_{residual} = \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 = \sum_{i=1}^{n} e_i^2$$

A visual representation

$$Y_i = b_0 + b_1 X_i + e_i$$



or, in shorthand,



In a diagram such as this, ⟶ represents "predictor of" or "component of" but not necessarily "cause of," although the association could be causal. So *X* is a predictor of *Y* (and *perhaps* a cause of *Y*) in this diagram.

Easier to do in SPSS and then explain

This is an easy problem for a computer with an OLS regression routine. We estimate Y from X, or regress Y on X. X = POSREL (positivity of teacher-student relationships), Y = SATIS1 (satisfaction with school).

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.458[a]	.210	.207	.61840

a. Predictors: (Constant), posrel

$SS_{residual}$ = 125.433

No other $\{b_0, b_1\}$pair would produce a smaller value of $SS_{residual}$.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33.263	1	33.263	86.980	.000[b]
	Residual	$\boxed{125.433}$	328	.382		
	Total	158.696	329			

a. Dependent Variable: satis1

b. Predictors: (Constant), posrel

$$\hat{Y}_i = b_0 + b_1 X_i$$

$$\hat{Y}_i = 2.245 + 0.531 X_i$$

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.245	.166		13.527	.000	1.918	2.571
X	posrel	.531	.057	.458	9.326	.000	.419	.643

a. Dependent Variable: satis1

This is the best fitting OLS regression model, assuming a linear association between X and Y.

```
regression/statistics defaults ci/dep=satis1/method=enter posrel.
```

```
proc reg data=harass;model satis1 = posrel/stb clb;run;
```

Same thing in R

This is an easy problem for a computer with an OLS regression routine. We estimate *Y* from *X*, or regress *Y* on *X*. *X* = POSREL (positivity of teacher-student relationships), *Y* = SATIS1 (satisfaction with school).

```
> model <- lm(satis1~posrel, data = harass)
> anova(model)
Analysis of Variance Table

Response: satis1
           Df  Sum Sq Mean Sq F value    Pr(>F)
posrel      1  33.282  33.282  87.044 < 2.2e-16 ***
Residuals 328 125.414   0.382
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(model)

Call:
lm(formula = satis1 ~ posrel, data = harass)

Residuals:
     Min       1Q   Median       3Q      Max
-1.88289 -0.38879  0.01121  0.47659  1.49226

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.24622    0.16572   13.55   <2e-16 ***
posrel       0.53076    0.05689    9.33   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6184 on 328 degrees of freedom
Multiple R-squared:  0.2097,    Adjusted R-squared:  0.2073
F-statistic: 87.04 on 1 and 328 DF,  p-value: < 2.2e-16
```

X

$SS_{residual}$ = 125.433

No other $\{b_0, b_1\}$pair would produce a smaller value of $SS_{residual}$.

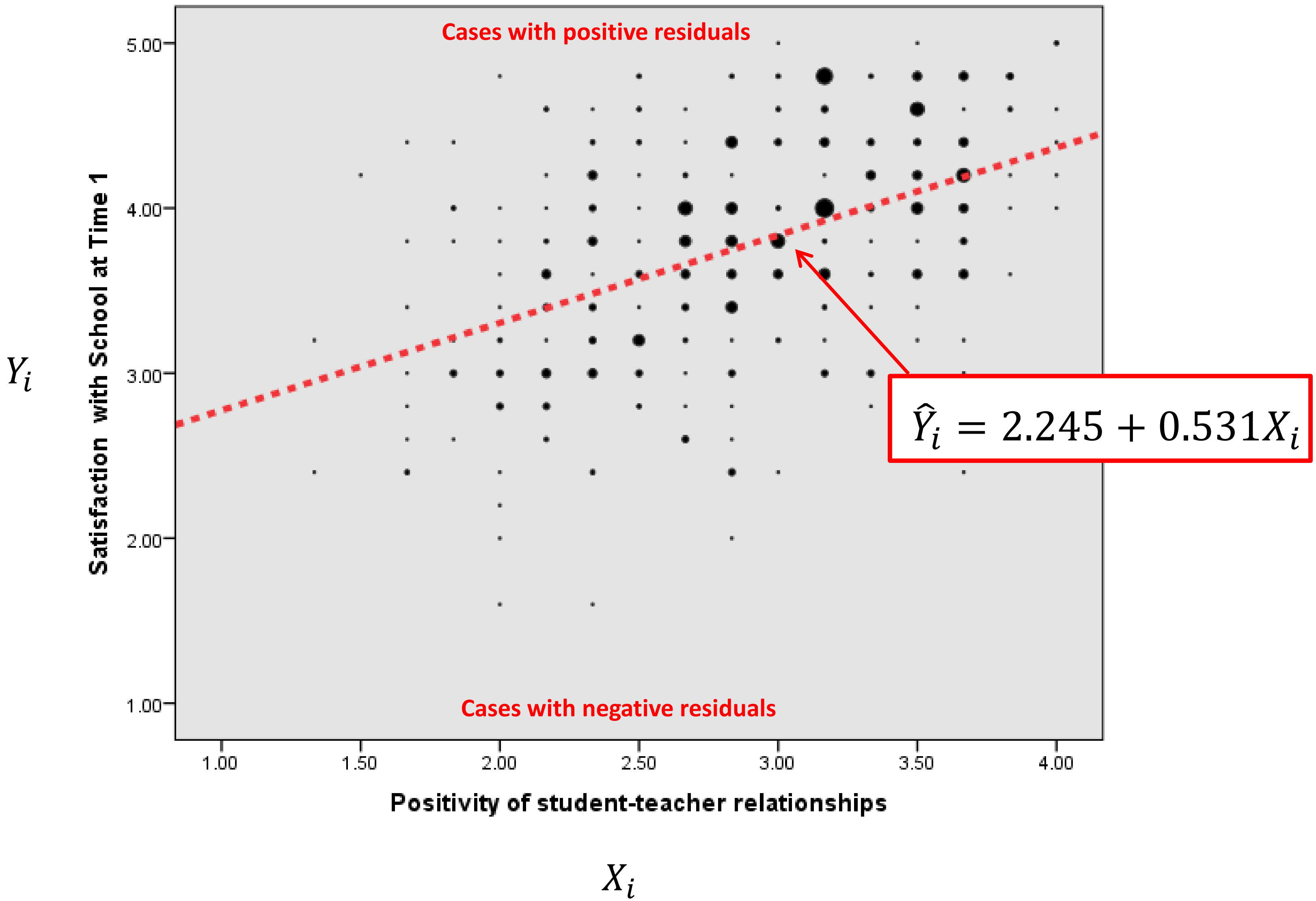
$$\hat{Y}_i = b_0 + b_1 X_i$$

$$\hat{Y}_i = 2.245 + 0.531 X_i$$

This is the best fitting OLS regression model, assuming a linear association between *X* and *Y*.

```
model <- lm(posrel~satis1, data = harass)
anova(model)
summary(model)
```

The model in visual form



Interpretation of b_0 and b_1

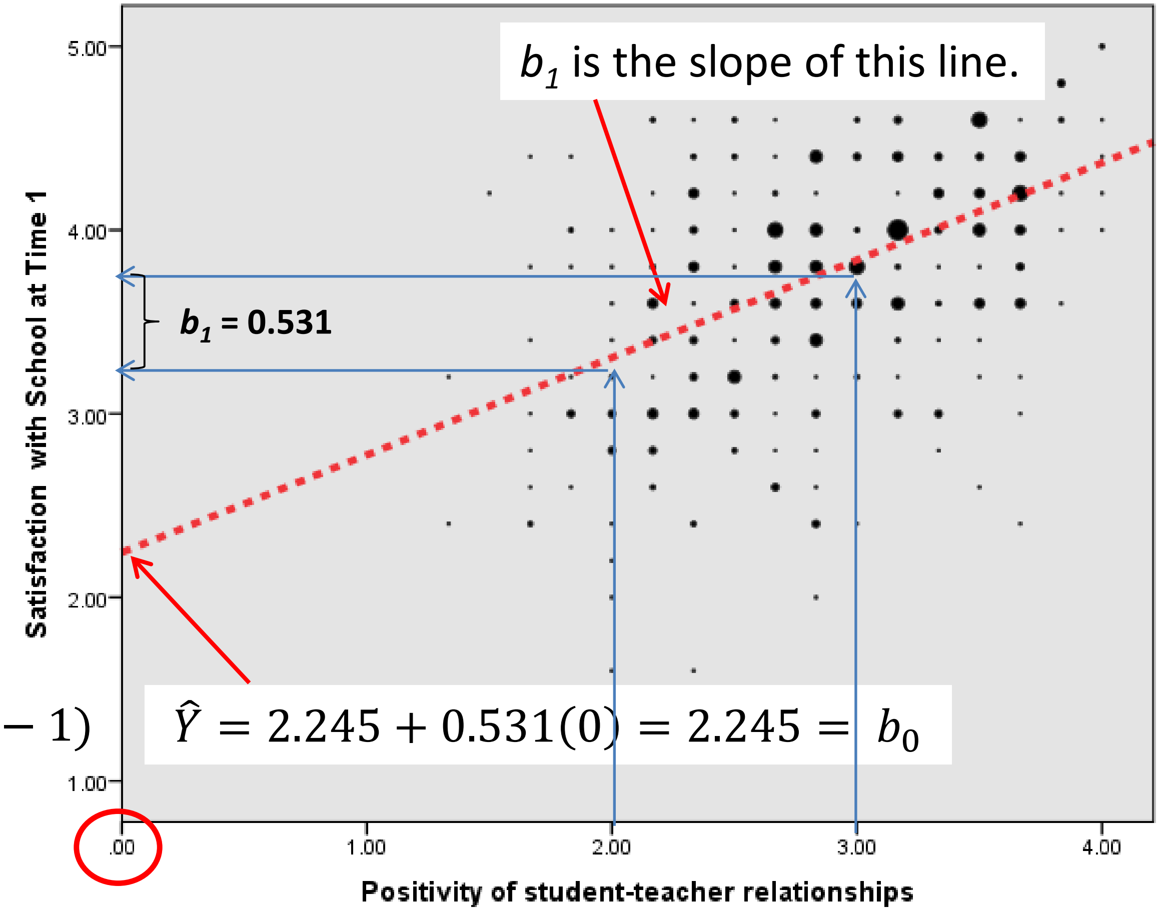
$$\hat{Y}_i = b_0 + b_1 X_i$$

$$\hat{Y}_i = 2.245 + 0.531 X_i$$

b_1 = estimated difference in Y between two cases that differ by one unit on X. The sign of b_1 speaks to the sign of the association between X and Y.

$$b_1 = \hat{Y}|(X = \theta) - \hat{Y}|(X = \theta - 1)$$

b_0 = estimated value of Y when X = 0. This is not meaningful here.



Two kids that differ by one unit in the positivity of their student-teacher relationships are estimated to differ by b_1 = 0.531 units in satisfaction with school. The kid that is **higher** in positivity of those relationships is estimated to be *more* satisfied (because b_1 is positive).

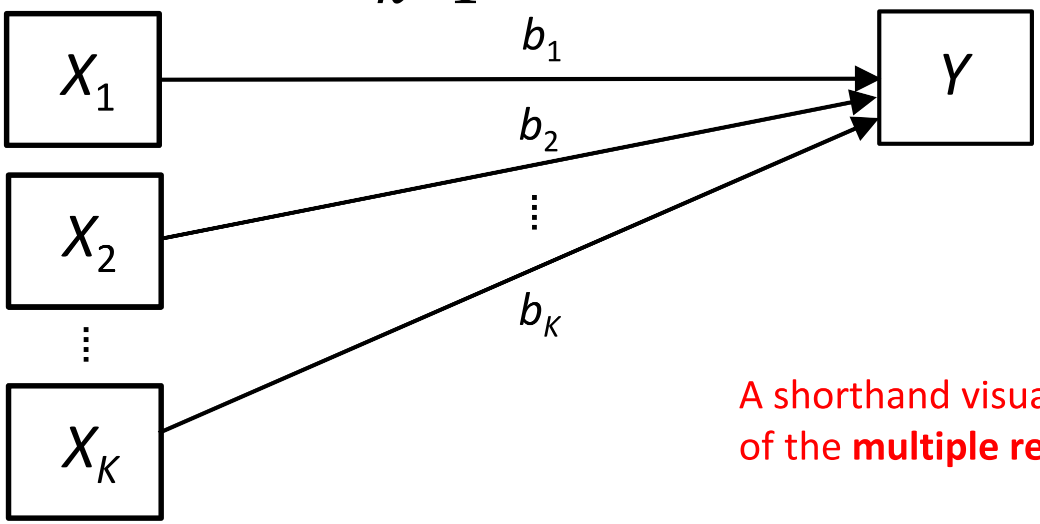
Multiple predictors

Multiple predictors variables are handled with ease, without modification to the estimation process. But this results in some interpretational changes.

$$Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + b_3 X_{3i} + \ \ldots + b_K X_{Ki} + e_i$$

or, more concisely,

$$Y_i = b_0 + \sum_{k=1}^{K} b_k X_{ki} + e_i$$



A shorthand visual representation of the **multiple regression** model.

A multiple regression model (SPSS)

```
regression/statistics defaults ci/dep=satis1/method=enter posrel harass se1.
```

```
proc reg data=harass;model satis1 = posrel harass se1/stb clb;run;
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.545[a]	.297	.290	.58503

a. Predictors: (Constant), se1, posrel, harass

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	47.120	3	15.707	45.891	.000[b]
	Residual	$\boxed{111.576}$	326	.342		
	Total	158.696	329			

a. Dependent Variable: satis1

b. Predictors: (Constant), se1, posrel, harass

$SS_{residual}$ = 111.576

No other set of *b* values would produce a smaller value of $SS_{residual}$.

X_1 = positivity of teacher-student relationships

X_2 = harassment frequency

X_3 = self-esteem.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.479	.309		4.788	.000	.871	2.087
	posrel	.472	.055	.408	8.519	.000	.363	.581
	harass	-.145	.090	-.078	-1.613	.108	-.322	.032
	se1	.373	.064	.276	5.828	.000	.247	.499

a. Dependent Variable: satis1

$$\widehat{Y}_i = 1.479 + 0.472X_{1i} - 0.145X_{2i} + 0.373X_{3i}$$

A multiple regression model (R)

```
mult.model <- lm(satis1~posrel+harass+se1, data = harass)
anova(mult.model)
summary(mult.model)
```

```
> mult.model <- lm(satis1~posrel+harass+se1, data = harass)
> anova(mult.model)
Analysis of Variance Table

Response: satis1
           Df  Sum Sq Mean Sq F value    Pr(>F)    
posrel      1  33.282  33.282 97.2428 < 2.2e-16 ***
harass      1   2.214   2.214  6.4678   0.01145 *  
se1         1  11.624  11.624 33.9617  1.35e-08 ***
Residuals 326 111.576   0.342                      
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(mult.model)

Call:
lm(formula = satis1 ~ posrel + harass + se1, data = harass)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.86980 -0.34967 -0.01479  0.40951  1.75736 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.47888    0.30890   4.788 2.57e-06 ***
posrel       0.47230    0.05544   8.519 6.03e-16 ***
harass      -0.14514    0.08997  -1.613    0.108    
se1          0.37292    0.06399   5.828 1.35e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.585 on 326 degrees of freedom
Multiple R-squared:  0.2969,	Adjusted R-squared:  0.2904 
F-statistic: 45.89 on 3 and 326 DF,  p-value: < 2.2e-16
```

$SS_{residual}$ = 111.576

No other set of *b* values would produce a smaller value of $SS_{residual}$.

X_1 = positivity of teacher-student relationships

X_2 = harassment frequency

X_3 = self-esteem.

$$\widehat{Y}_i = 1.479 + 0.472X_{1i} - 0.145X_{2i} + 0.373X_{3i}$$

The meaning of the values of *b*

$$\underbrace{\hat{Y}_i}_{\text{Satisfaction}} = 1.479 + \underbrace{0.472X_{1i}}_{\text{Positive relationships}} - \underbrace{0.145X_{2i}}_{\text{harassment}} + \underbrace{0.373X_{3i}}_{\text{Self-esteem}}$$

Two kids *the same on all predictors except the positivity of their teacher relationships* (X_1) but who differ by one unit in such positivity will differ by b_1 = 0.472 units in estimated satisfaction with school ($\hat{Y}$), where more positivity corresponds to higher satisfaction.

> b_1, the partial regression coefficient for X_1, quantifies how differences in positivity of the student-teacher relationship relates to differences in satisfaction with school when *all other predictor variables in the model are held constant*, or "statistically controlling for" those other variables.

Two people the same on all predictors except ethnic harassment (X_2) who *differ by one unit in harassment* will differ by b_2 = 0.145 units in estimated satisfaction with school ($\hat{Y}$), where higher harassment corresponds to lower satisfaction.

> b_2, the partial regression coefficient for X_2, quantifies how *differences in frequency in the experience of ethnic harassment relate to differences in school satisfaction* when all other predictor variables in the model are held constant, or "statistically controlling for" those other variables. The negative sign for b_2 means those who experience *more* harassment are estimated to be *less* satisfied with school.

Statistical inference

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i} + b_3X_{3i} + \ ... + b_KX_{Ki} + e_i$$

The constant, values of *b* are sample-specific. They are sample-specific estimates of a corresponding population or process model (the "true" model):

$$Y_i = \widetilde{b_0} + \widetilde{b_1}X_{1i} + \widetilde{b_2}X_{2i} + \widetilde{b_3}X_{3i} + \ ... + \widetilde{b_K}X_{Ki} + \widetilde{e}_i$$

Departures between the "true model" and the obtained model resulting from our data are used to test hypotheses about the "true values" of *b*.

Departures between the true and the obtained model are assumed to be driven by **"random" processes**, such as random sampling, random assignment variation, measurement error, etc., unless the data suggest otherwise. We attempt to estimate the true model using our data, hoping that our estimates of the true values of that model are accurate.

Null hypothesis testing for $\widetilde{b}$

$$Y_i = \widetilde{b_0} + \widetilde{b_1}X_{1i} + \widetilde{b_2}X_{2i} + \widetilde{b_3}X_{3i} + \ \ldots + \widetilde{b_K}X_{Ki} + \widetilde{e_i}$$

In any study, we observe only b_j, the sample estimate of $\widetilde{b_j}$. We often are interested in making an inference about the size of $\widetilde{b_j}$, or testing a hypothesis about its value.

e.g., Null hypothesis test about $\widetilde{b_j}$:

Assume $\widetilde{b_1}$ equals some specific value. Typically, we assume $\widetilde{b_1}$ = 0 under the **null hypothesis** (i.e., X_1 is unrelated to Y when all other variables in the model are held constant).

$$H_0: \widetilde{b_1} = 0$$
$$H_a: \widetilde{b_1} \neq 0$$

If H_0 is true, then b_1 / s_{b_1} follows the $t(df_{residual})$ distribution, where s_{b_1} is the estimated standard error of b_1. Using the t distribution, we generate a p-value and reject H_0 in favor of H_a if $p \leq \alpha$-level chosen for the test (usually .05). In that case, the result is "statistically significant."

Statistical inference for partial regression coefficients

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	47.120	3	15.707	45.891	.000[b]
	Residual	111.576	326	.342		
	Total	158.696	329			

a. Dependent Variable: satis1

b. Predictors: (Constant), se1, posrel, harass

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.479	.309		4.788	.000	.871	2.087
	posrel	.472	.055	.408	8.519	.000	.363	.581
	harass	-.145	.090	-.078	-1.613	.108	-.322	.032
	se1	.373	.064	.276	5.828	.000	.247	.499

a. Dependent Variable: satis1

H_0: $\widetilde{b_1} = 0$

H_a: $\widetilde{b_1} \neq 0$

$b_1 = 0.472$, se(b_1) = 0.055,
$t(326) = 8.519$, $p < 0.001$

Reject H_0 in favor of H_a

H_0: $\widetilde{b_2} = 0$

H_a: $\widetilde{b_2} \neq 0$

$b_2 = -0.145$, se(b_2) = 0.090,
$t(326) = -1.613$, $p = 0.108$

Do not reject H_0

Two kids equal in ethnic harassment frequency and self esteem but who differ in the positivity of their student-teacher relationships differ from each other in satisfaction more than can be explained by chance. The observed and statistically significant positive partial relationship tells us that kids with more positive student-teacher relationships are more satisfied with school.

Two kids equal in the positivity of their student-teacher relationships and their self-esteem but who differ in ethnic harassment frequency do not differ in their satisfaction *any more than would be expected by "chance."*

Interval estimation (SPSS and SAS)

```
regression/statistics defaults ci/dep=satis1/method=enter posrel harass se1.
```

```
proc reg data=harass;model satis1 = posrel harass se1/stb clb;run;
```

Inferences can also be framed as an interval such that this interval will capture the true value a certain percentage of the time. As a rough rule-of-thumb, we can be 95% confident that the true value resides within <u>about</u> 2 standard errors of the obtained estimate.

$$b_j - 2s_{b_j} \leq \widetilde{b_j} \leq b_j + 2s_{b_j}$$

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.479	.309		4.788	.000	.871	2.087
	posrel	.472	.055	.408	8.519	.000	.363	.581
	harass	-.145	.090	-.078	-1.613	.108	-.322	.032
	se1	.373	.064	.276	5.828	.000	.247	.499

a. Dependent Variable: satis1

We can be 95% confident $\widetilde{b_1}$ is somewhere between 0.363 and 0.581
We can be 95% confident $\widetilde{b_2}$ is somewhere between -0.322 and 0.032.

Interval estimation (R)

```
confint(mult.model)
```

Inferences can also be framed as an interval such that this interval will capture the true value a certain percentage of the time. As a rough rule-of-thumb, we can be 95% confident that the true value resides within <u>about</u> 2 standard errors of the obtained estimate.

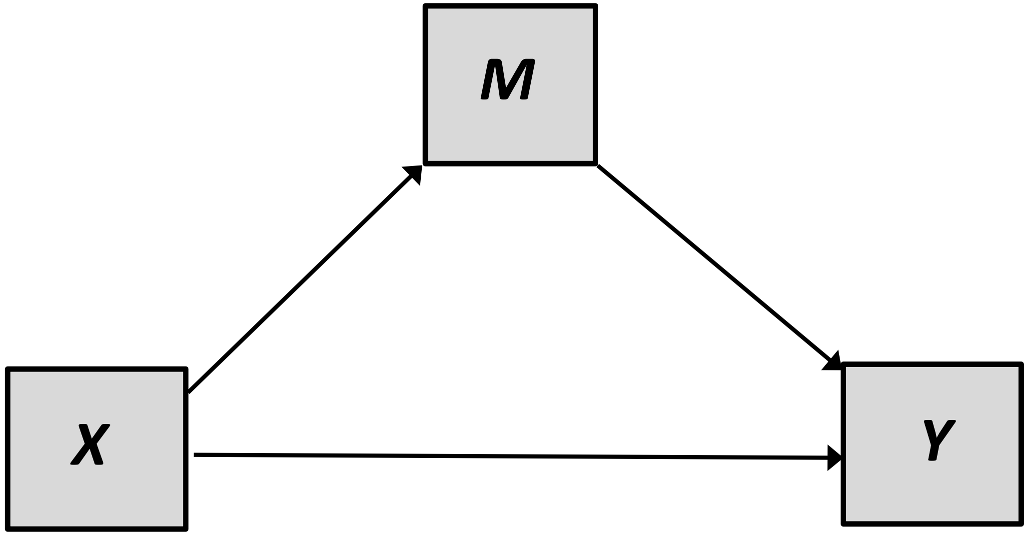
$$b_j - 2s_{b_j} \leq \widetilde{b_j} \leq b_j + 2s_{b_j}$$

```
> confint(mult.model)
                 2.5 %     97.5 %
(Intercept)  0.8711918 2.08657573
posrel       0.3632338 0.58136565
harass      -0.3221223 0.03184945
sel          0.2470333 0.49881065
```

95.0% Confidence Interval for B	
Lower Bound	Upper Bound
.871	2.087
.363	.581
-.322	.032
.247	.499

We can be 95% sure $\widetilde{b_1}$ is somewhere between 0.363 and 0.581
We can be 95% sure $\widetilde{b_2}$ is somewhere between -0.322 and 0.032.

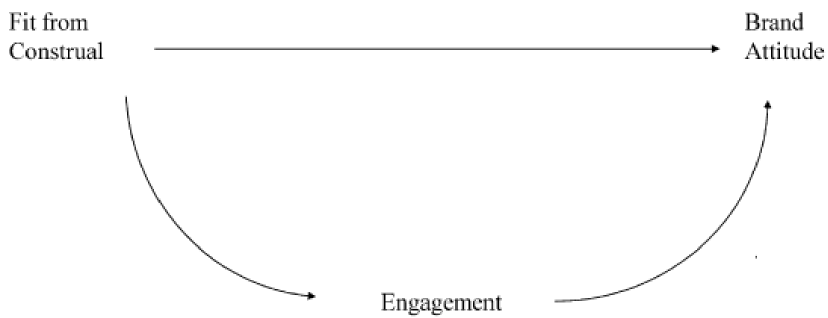
Statistical mediation analysis



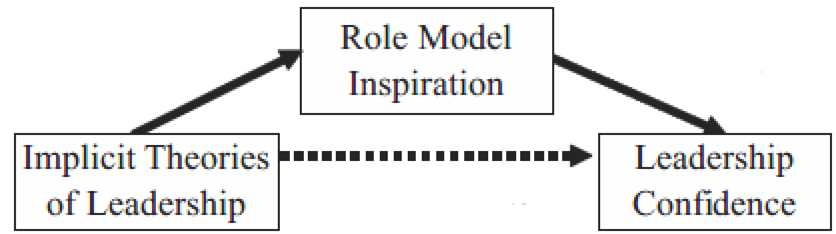
The "simple mediation" model

A mediation model links an assumed cause (*X*) to an assumed effect (*Y*) at least in part via an intermediary variable (*M*). An intermediary variable can be a psychological state, a cognitive process, an affective response, or any other conceivable "mechanism" through which *X* exerts an effect on *Y*. *X* affects *M* which in turn affects *Y*.

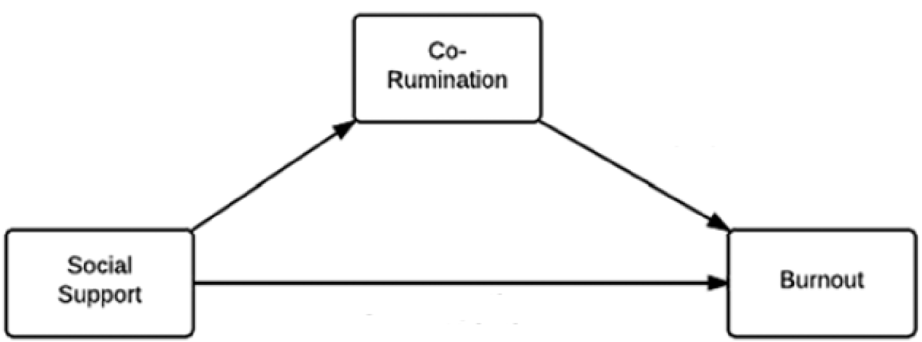
Some examples in the literature



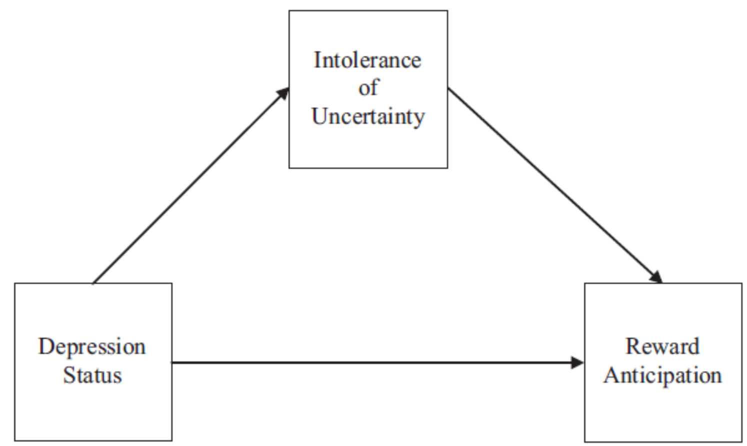
Lee, A. Y., Keller, P. A., & Sternthal, B. (2010). Value from regulatory construal fit: Persuasive impact of fit between consumer goals and message concreteness. ***Journal of Consumer Research***, *36*, 735-747.



Hoyt, C. L., Burnette, J. L., & Innella, A. N. (2012). I can do that: The impact of implicit theories on leadership model effectiveness. ***Personality and Social Psychology Bulletin***, *38*, 257-268.



Boren, J. P. (2014). The relationship between co-rumination, social support, stress, and burnout among working adults. ***Management Communication Quarterly***, *28*, 3-25.

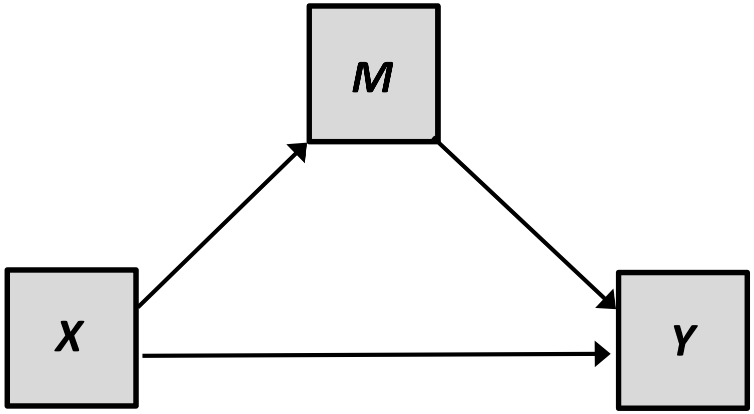


Nelson, B. D., Shankman, S. A., & Proudfit, G. H. (2014). Intolerance of uncertainty mediates reduced reward anticipation in major depressive disorder. ***Journal of Affective Disorders***, *158*, 108-113.

The most basic intervening variable model

- For *M* to be an intermediary, it must be located *causally between* *X* and *Y*.

- *M* is sometimes called a "mediator", but it goes by other names as well.



- Mediator models are causal models and carry with them the usual criteria for making causal claims.

  Difficult to establish cause statistically or otherwise. Theory is sometimes the sole foundation upon which our causal claims rest. That's ok so long as we recognize this.

Understanding Cause & Effect

As scientists we're often looking to support a claim that "X causes Y." Many of us are familiar with the phrase "correlation is not causation." But what then is needed to support a claim of cause?

Often we rely on experimentation to help us support the claim of cause. But what happens when we cannot (ethically or practically) manipulate our causal variable?

Consider the claim "Smoking tobacco causes lung cancer." Is it unethical to randomize people to smoke or not smoke. How then do we know this claim is true?

Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations

Research on tobacco use easily found evidence for 1 & 2, and slowly over time accumulation of evidence supported 3.

Understanding Cause & Effect

Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations

The following methods are frequently used to support the claim of cause. Which conditions for cause are supported by each method?

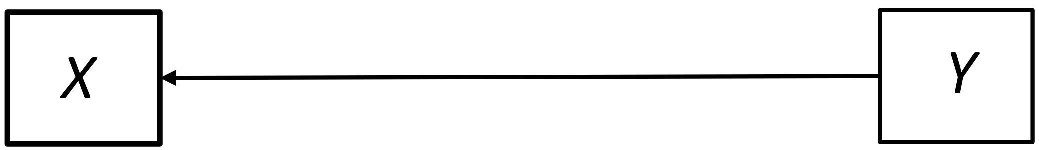
Experimental Manipulation:

Longitudinal Studies:

Cross-sectional Data Collection analyzed using Linear Regression:

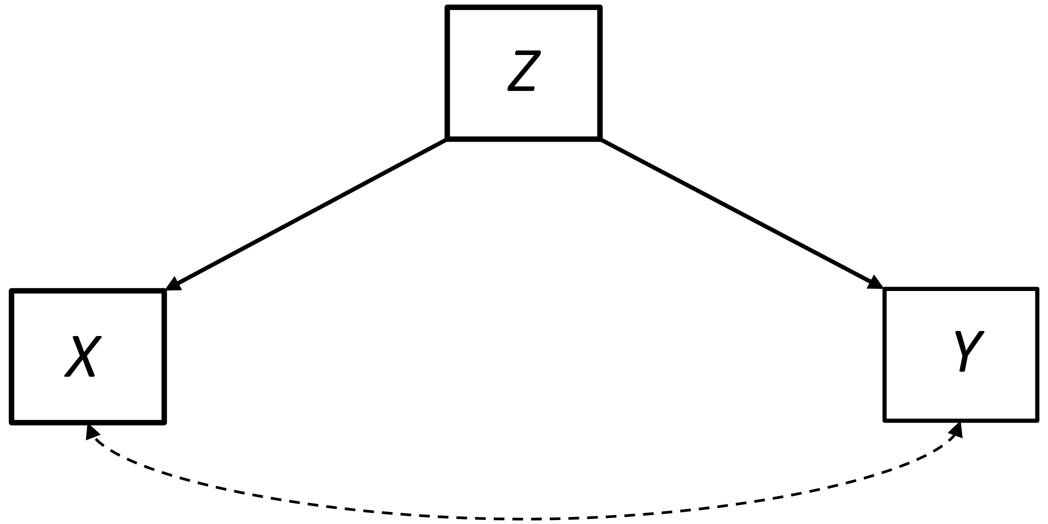
If it's not cause, what is it?

Effect/Reverse Causation: It's possible that *X* is an effect of *Y*, rather than *Y* being an effect of *X*



If it's not cause, what is it?

Spurious association: when relationship between X and Y is induced by a shared cause.

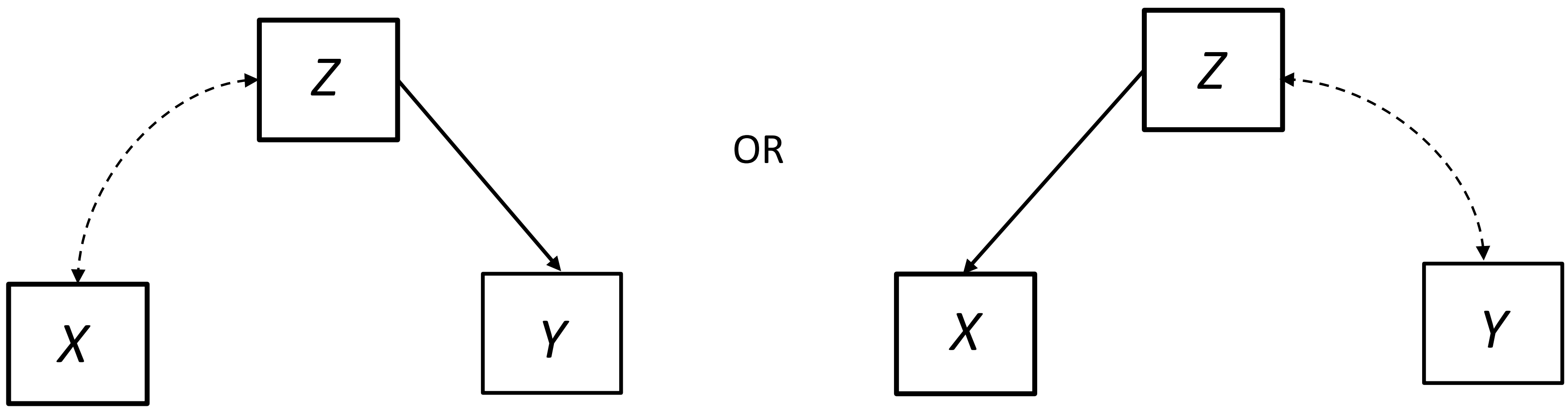


Example: [Skirt length theory](#) is one that suggests that skirt lengths predict the stock market (short skirt → market going up). Likely this is not a causal relationship but rather both skirt length and market trends are influenced by other larger cultural/economic trends.

Controlling for *Z* helps us eliminate spurious explanations.

If it’s not cause, what is it?

Epiphenominality: X and Y are related because X is correlated with a cause of Y



Example: Having an increased risk of breast cancer (Y) concurrent with taking an antibiotic is an **epiphenomenon**. It is not the antibiotic that is causing the increased risk, but the increased inflammation associated with the bacterial infection (Z) that prompted the taking of an antibiotic (X).

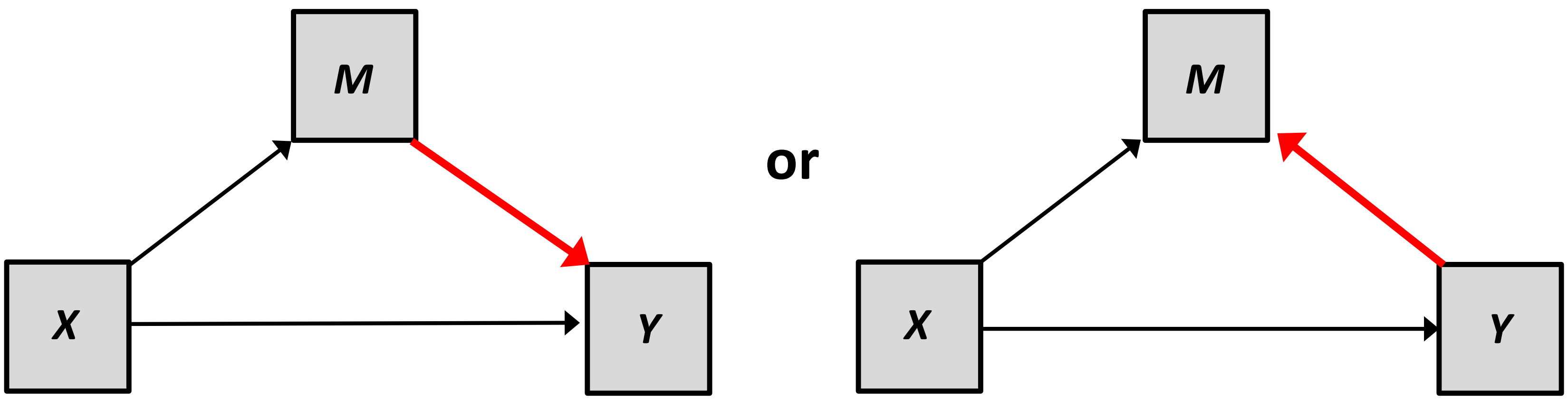
Controlling for *Z* helps us eliminate epiphenomenal explanations.

Why does this matter?

In all the analyses we conduct in this class, we assume that the relationships we're estimating are causal. However, the models we estimate do not provide support for the cause, rather is it an assumption.

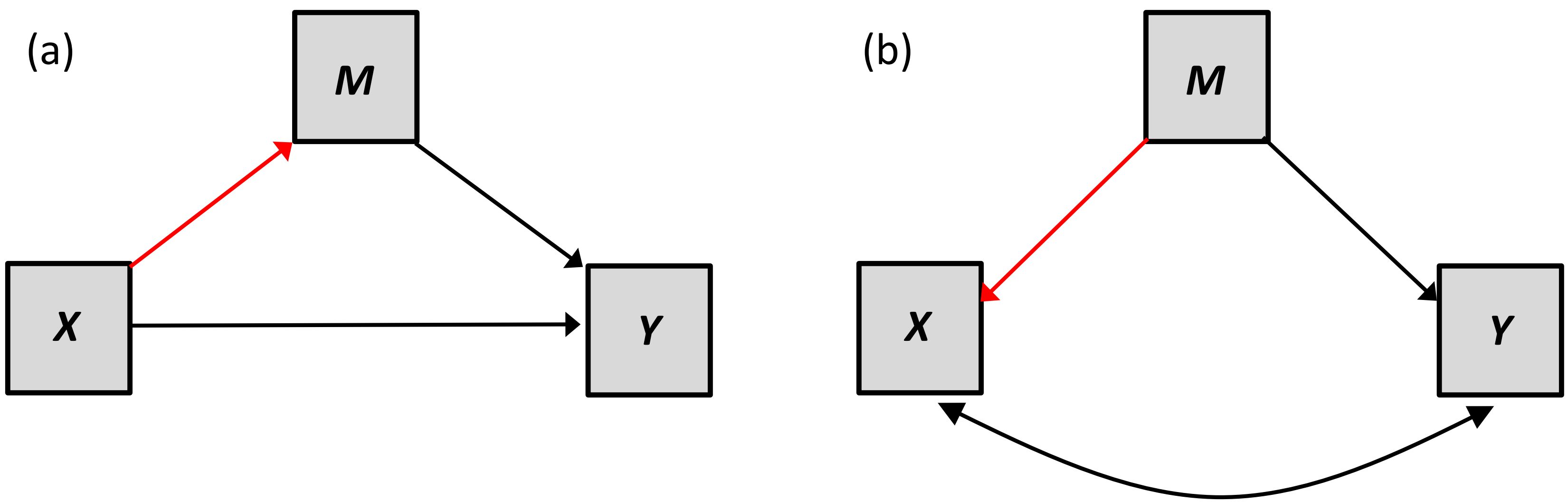
It is up to you as a responsible user of these models to provide support for cause. This comes from good design of studies, accumulative evidence, not from statistical analysis!

Even when we manipulate X, we are not completely safe!



Mediation and spuriousness

Mediation analysis cannot distinguish between (a)mediation and (b)spuriousness. If (b) can be deemed plausible, that weakens the case for (a) regardless of what the data analysis tells you.

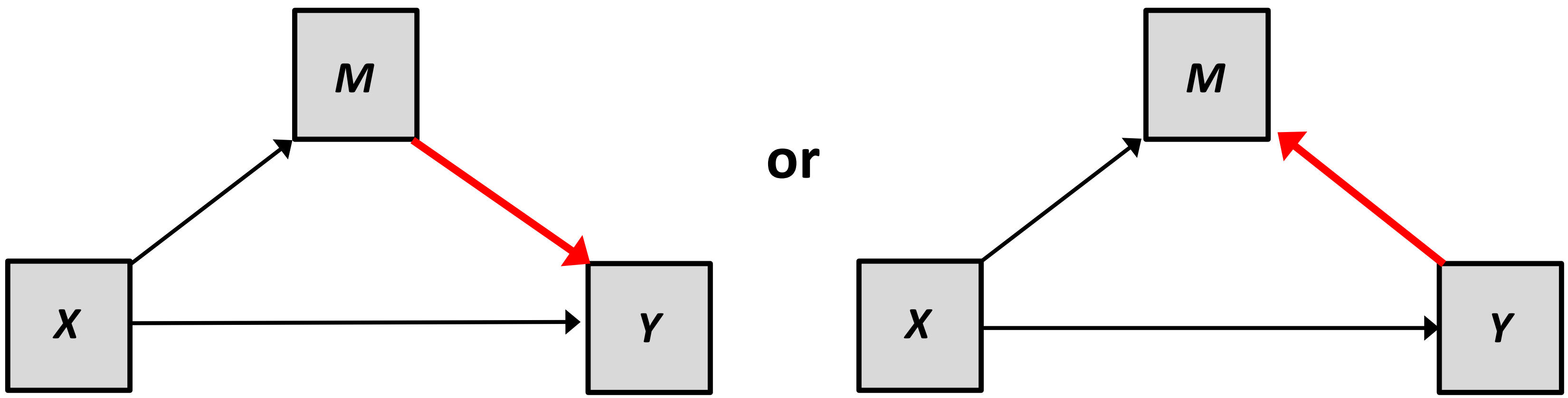


Inferences are always design-bound.

Mediation is a causal process, but causal claims are only justified if the design allows such claims, regardless of what the statistics say.

Causal order

Manipulation of and random assignment to *X* affords causal inference for the effect of *X* on *M* and *Y*, but not the effect of *M* on *Y*. We cannot establish causal order for the *M*-*Y* path using the methods that are the focus here. Theory is important. Multiple studies can help, one of which involves manipulation of *M*.



When *X* is not experimentally manipulated, all paths are subject to potential alternative causal orders.

MacKinnon, D. P. & Pirlott, A. G. (2015). Statistical Approaches for Enhancing Causal Interpretation of the M to Y Relation in Mediation Analysis. *Personality and Social Psychology Review, 19*(1), 30 – 43.

Understanding causal effects

Consider two male, Caucasian politicians. One of these two has been convicted of political corruption. Which one is it?

Understanding causal effects

Never Convicted

Convicted

Understanding causal effects

Lin, C., Adolphs, R., & Alvarez, R. M. (2018). Inferring whether officials are corruptible from looking at their faces. *Psychological Science, 29*(11), 1807-1823.

Table 1. Results for Correctly Categorized Officials Based on Aggregate-Level Trait Inferences and Individual-Level Trait Inferences From Study 1

	Aggregate-level accuracy				Average individual-level accuracy[a]				
Trait	Percentage of correctly categorized officials ($N = 72$)	Lower bound of 95% CI	$\chi^2(1)$	p	Mean accuracy ($N = 82$)	SD	Lower bound of 95% CI	$t(81)$	Cohen's d
Corruptibility	69.44%	59.22%	10.13	< .001	55.73%	6.95%	54.46%	7.47	0.82
Dishonesty	70.83%	60.67%	11.68	< .001	54.82%	6.41%	53.64%	6.81	0.75
Selfishness	66.67%	56.36%	7.35	.003	55.10%	6.76%	53.86%	6.83	0.75
Trustworthiness	68.06%	57.79%	8.68	.002	55.03%	6.41%	53.85%	7.10	0.78
Generosity	63.89%	53.53%	5.01	.013	54.97%	5.99%	53.87%	7.51	0.83

Note: CI = confidence interval.
[a]All ps for this variable are less than .001.

Research Article

Inferring Whether Officials Are Corruptible From Looking at Their Faces

Psychological Science
2018, Vol. 29(11) 1807–1823

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Abstract
While inferences of traits from unfamiliar faces prominently reveal stereotypes, some facial inferences also correlate with real-world outcomes. We investigated whether facial inferences are associated with an important real-world outcome closely linked to the face bearer's behavior: political corruption. In four preregistered studies ($N = 325$), participants made trait judgments of unfamiliar government officials on the basis of their photos. Relative to peers with clean records, federal and state officials convicted of political corruption (Study 1) and local officials who violated campaign finance laws (Study 2) were perceived as more corruptible, dishonest, selfish, and aggressive but similarly competent, ambitious, and masculine (Study 3). Mediation analyses and experiments in which the photos were digitally manipulated showed that participants' judgments of how corruptible an official looked were causally influenced by the face width of the stimuli (Study 4). The findings shed new light on the complex causal mechanisms linking facial appearances with social behavior.

Keywords
face perception, corruption, social attribution, stereotyping, political psychology, open data, open materials, preregistered

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Faces are rich in information: They provide clues about gender, race, age, and trait attributes, which are inferred spontaneously and ubiquitously (Engell, Haxby, & Todorov, 2007; Todorov, 2017). Moreover, such inferences often guide our social behavior—for instance, we decide whom to trust on the basis of how trustworthy a face looks (Rezlescu, Duchaine, Olivola, & Chater, 2012; Van't Wout & Sanfey, 2008). Many trait judgments made by participants across generations and cultures show consensus (Cogsdill, Todorov, Spelke, & Banaji, 2014; Lin, Adolphs, & Alvarez, 2017; Rule et al., 2010). But are trait judgments from faces accurate?

Previous research has shown that trait judgments from faces can be associated with important real-world social outcomes, such as dating and mating (Olivola et al., 2014; Valentine, Li, Penke, & Perrett, 2014), earnings and fundraising (Genevsky & Knutson, 2015; Hamermesh, 2011; Ravina, 2012), science communication (Gheorghiu, Callan, & Skylark, 2017), sentencing decisions (Berry & Zebrowitz-McArthur, 1988; Blair, Judd, & Chapleau, 2004; Wilson & Rule, 2015; Zebrowitz & McDonald, 1991), and leader selection (Todorov, Mandisodza, Goren, & Hall, 2005; for reviews, see Antonakis & Eubanks, 2017; Todorov, Olivola, Dotsch, & Mende-Siedlecki, 2015). Yet this prior research on the association between trait judgments from faces and real-world outcomes leaves open two important questions. First, most associations have focused on prosocial outcomes (e.g., correlations between competence judgments and election success; Todorov et al., 2005). Second, most associations are plausibly driven not by the behavior of the targets whose face is being judged but by the interests of the perceivers who are making the judgments (e.g., correlations between interesting-looking scientists and the perceiver's interest in their work). Here, we investigated an antisocial judgment that

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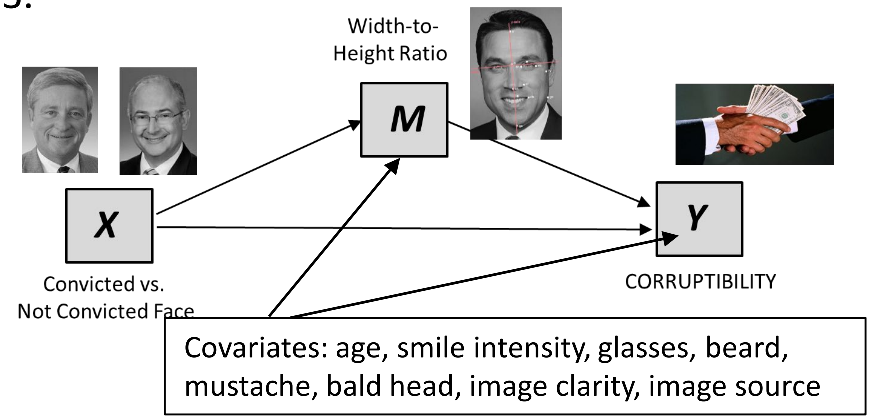
Corruption Paper Discussion

Lin, C., Adolphs, R., & Alvarez, R. M. (2018). Inferring whether officials are corruptible from looking at their faces*. Psychological Science, 29*(11), 1807-1823.

Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations



1. Data from Studies 1 – 3 were combined to run the above mediation analysis. Have the necessary conditions for cause been met? Which necessary conditions does the mediation analysis support? Which require further support?
   (Hint: Think about what would make you feel more confident in this causal order)

2. Study 4b experimentally manipulated the width-to-height ratios of faces to measure the impact on corruptibility. Which condition for cause does this help support? Are we now completely convinced about the causal claims of this mediation analysis?

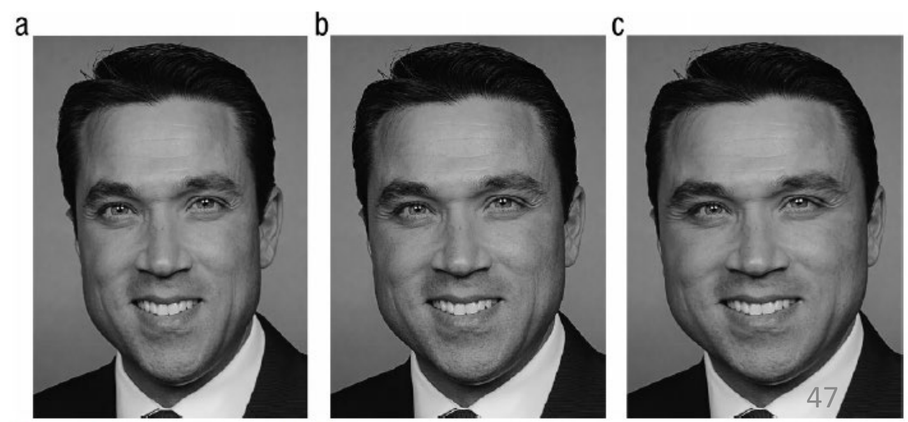
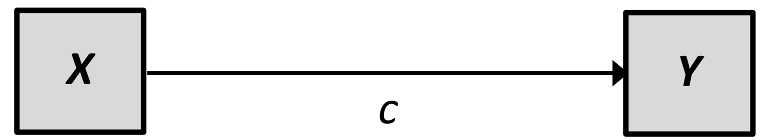
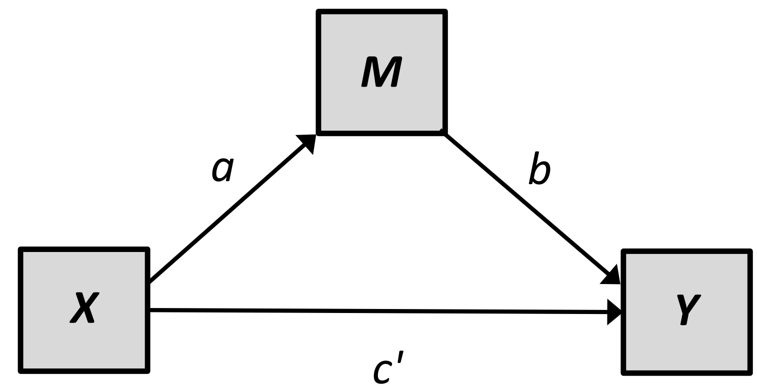


Fig. 6. Example of the same face in (a) slim, (b) original, and (c) fat versions.

Path analysis: Total, direct, and indirect effects

A "simple mediation" model





Let a, b, c, and c' be quantifications of causal effects, such as regression coefficients in an OLS model (or maximum likelihood path estimates in a structural equation model)

$$\hat{Y}_i = c_0 + cX_i$$

$$\widehat{M}_i = a_0 + aX_i$$

$$\hat{Y}_i = c'_0 + c'X_i + bM_i$$

c = "total effect" of X on Y

$a \times b$ = "indirect effect" of X on Y

c' = "direct effect" of X on Y

total effect = direct effect + indirect effect

$c \quad = \quad c' \quad + \quad (a \times b)$

indirect effect = total effect – direct effect

$(a \times b) \quad = \quad c \quad - \quad c'$

Example for the class “inspired by”…

Bayram-Ozdemir, S. & Stattin, H. (2014). Why and when is ethnic harassment a risk for immigrant adolescents’ school adjustment? Understanding the processes and conditions. ***Journal of Youth and Adolescence, 43***, 1252-1265.

J Youth Adolescence (2014) 43:1252–1265
DOI 10.1007/s10964-013-0038-y

EMPIRICAL RESEARCH

Why and When is Ethnic Harassment a Risk for Immigrant Adolescents’ School Adjustment? Understanding the Processes and Conditions

Sevgi Bayram Özdemir · Håkan Stattin

Received: 5 July 2013 / Accepted: 7 October 2013 / Published online: 17 October 2013

Abstract Ethnically harassed immigrant youth are at risk for experiencing a wide range of school adjustment problems. However, it is still unclear why and under what conditions experiencing ethnic harassment leads to school adjustment difficulties. To address this limitation in the literature, we examined two important questions. First, we investigated whether self-esteem and/or depressive symptoms would mediate the associations between ethnic harassment and poor school adjustment among immigrant youth. Second, we examined whether immigrant youths’ perception of school context would play a buffering role in the pathways between ethnic harassment and school adjustment difficulties. The sample (n = 330; M_{age} = 14.07, SD = .90; 49 % girls at T1) was drawn from a longitudinal study in Sweden. The results revealed that experiencing ethnic harassment led to a decrease in immigrant youths’ self-esteem over time, and that youths’ expectations of academic failure increased. Further, youths’ relationships with their teachers and their perceptions of school democracy moderated the mediation processes. Specifically, when youth had poor relationships with their teachers *or* perceived their school context as less democratic, being exposed to ethnic harassment led to a decrease in their self-esteem. In turn, they reported low school satisfaction and perceived themselves as being unsuccessful in school. Such indirect effects were not observed when youth had high positive relationships with their teachers *or* perceived their school as offering a democratic environment. These findings highlight the importance of understanding underlying processes and conditions in the examination of the effects of ethnic devaluation experiences in order to reach a more comprehensive understanding of immigrant youths’ school adjustment.

Keywords Immigrant youth · School adjustment · Ethnic harassment · Ethnic victimization · Depression · Self-esteem

Introduction

Adjustment and success in academic life is a key factor for immigrant youths’ integration into the host culture and their future prospects (Health et al. 2008). Thus, this issue has become one of the policy priorities for immigrant-receiving countries, and extensive efforts have been made to identify the factors that may play a role in the school adjustment and performance of immigrant youth. Experience of ethnic harassment (i.e., negative treatments or derogatory comments in relation to ethnic background) is one of the major contextual stressors for immigrant youth (Garcia Coll et al. 1996) and poses a threat to their school adjustment.

Research on ethnic minority adolescents in the U.S. and Europe has shown that a substantial number of youth are treated badly and victimized by their peers, teachers, and neighbors, at school and in other contexts (e.g., Huynh and Fuligni 2010; Liebkind et al. 2004; Verkuyten and Thijs 2002). Such negative experiences have been linked to a wide range of school outcomes. Youth who are harassed on the basis of their ethnic origin tend to develop negative beliefs about their academic competence and rewards of schooling (Eccles et al. 2006; Wong et al. 2003), display

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330 7th to 9th grade students in Sweden measured in the spring term (T1) and again one year later (T2).

All were first or second generation immigrants who reported at least some ethnic harassment.

HARASS: 6-item measure of ethnicity-related harassment frequency (scaled 1 to 5). T1 only.

POSREL: 6-item measure of positivity of relationships with teachers (scaled 1 to 4). T1 only.

SE: 10-item Rosenberg self-esteem scale (scaled 1 to 4). T1 and T2.

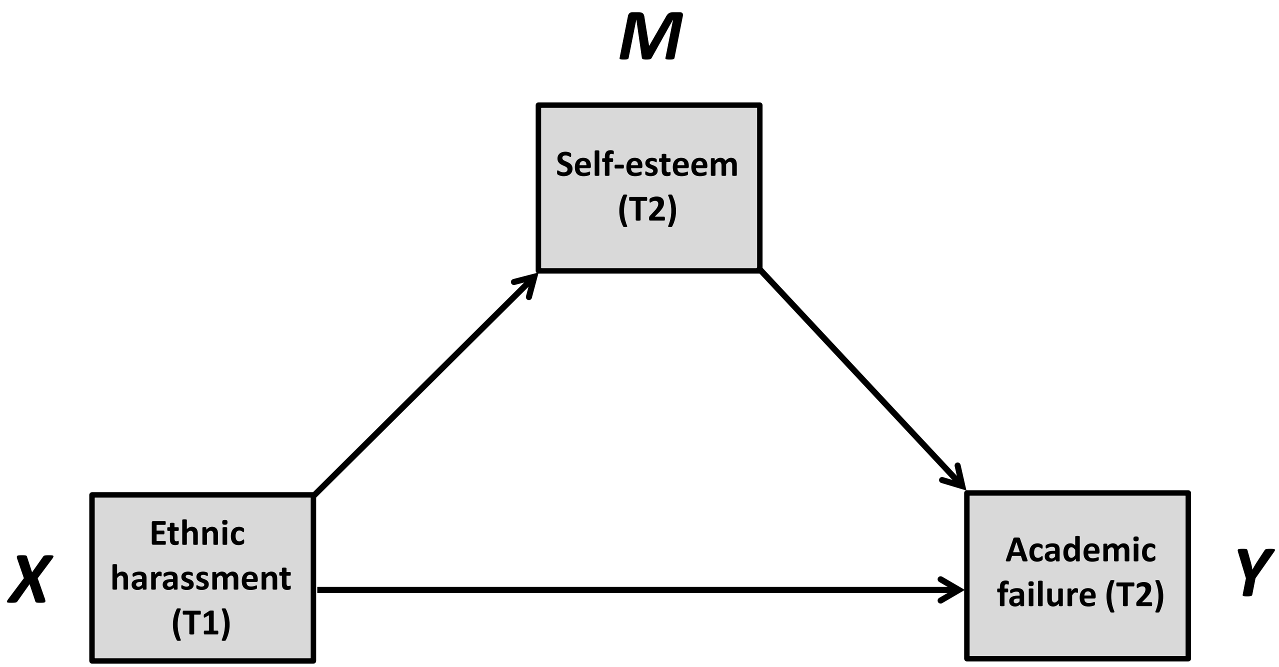
DEP: 20-item Center for Epidemiological Studies Depression Scale for Children (scaled 1 to 4). T1 and T2.

FAIL: 4-item measure of perceived academic failure at school (scaled 1 to 4). T1 and T2.

SATIS: 5-item measure of satisfaction in school (scaled 1 to 5). T1 and T2.

All are continuous variables scaled such that higher = more.

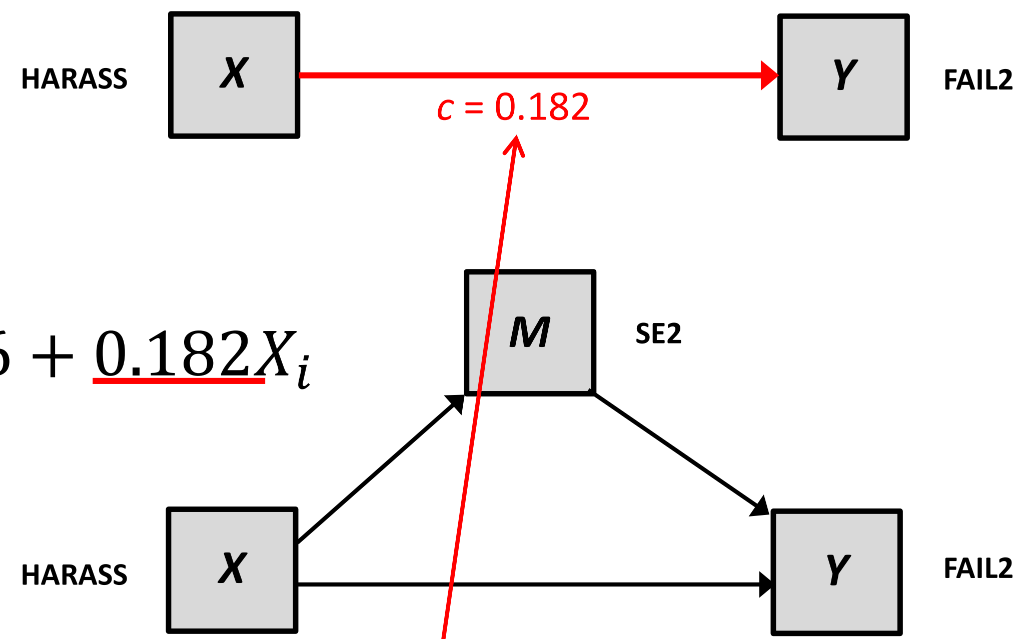
Our question



Does ethnic harassment influence school performance by affecting self-esteem which in turn affects performance.

Asking this question does not require evidence that there is a bivariate relationship between *X* (ethnic harassment) and *Y* (performance)

Using a set of OLS regression analyses



$$\widehat{Y}_i = 1.346 + \underline{0.182}X_i$$

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.346	.113		11.866	.000
	harass	$\boxed{.182}$	.073	.136	2.478	.014

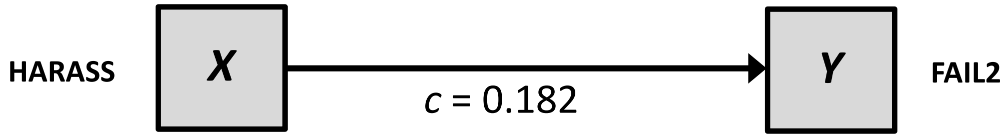
a. Dependent Variable: fail2

SPSS:
```
regression/dep=fail2/method=enter harass.
```

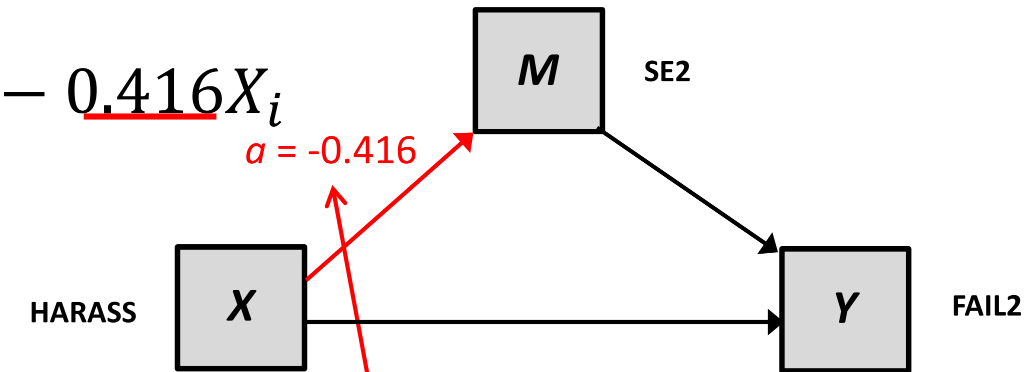
SAS:
```
proc reg data=harass;model fail2=harass;run;
```

R:
```
lm(fail2~harass, data = harass)
```

Using a set of OLS regression analyses



$$\widehat{M}_i = 3.597 - 0.416X_i$$



Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.597	.123		29.123	.000
	harass	$\boxed{-.416}$	.080	-.276	-5.209	.000

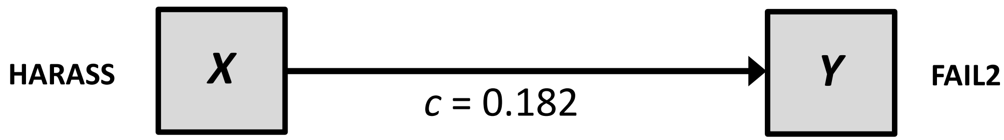
a. Dependent Variable: se2

```
regression/dep=se2/method=enter harass.
```

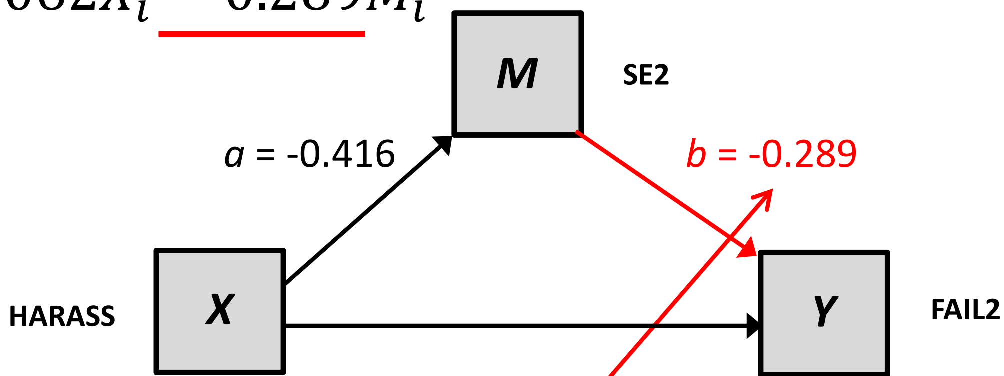
```
proc reg data=harass;model se2=harass;run;
```

```
lm(se2~harass, data = harass)
```

Using a set of OLS regression analyses



$$\widehat{Y}_i = 2.385 + 0.062X_i \underline{- 0.289}M_i$$



Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.385	.204		11.676	.000
	harass	.062	.072	.046	.850	.396
	se2	$\boxed{-.289}$	.048	-.324	-5.988	.000

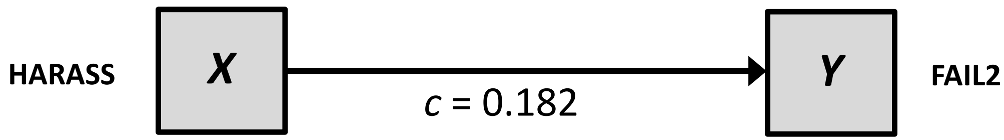
a. Dependent Variable: fail2

```
regression/dep=fail2/method=enter harass se2.
```

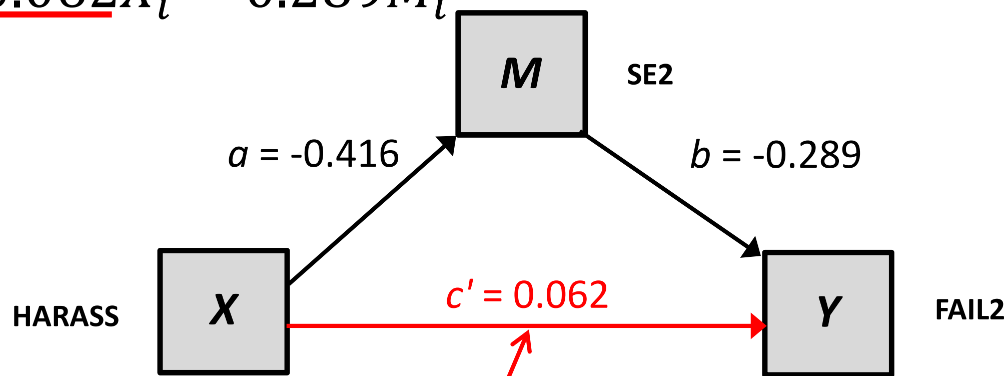
```
proc reg data=harass;model fail2=harass se2;run;
```

```
lm(fail2~harass+se2, data = harass)
```

Using a set of OLS regression analyses



$$\widehat{Y}_i = 2.385 + \underline{0.062}X_i - 0.289M_i$$



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	se2	-.289	.048	-.324	-5.988	.000

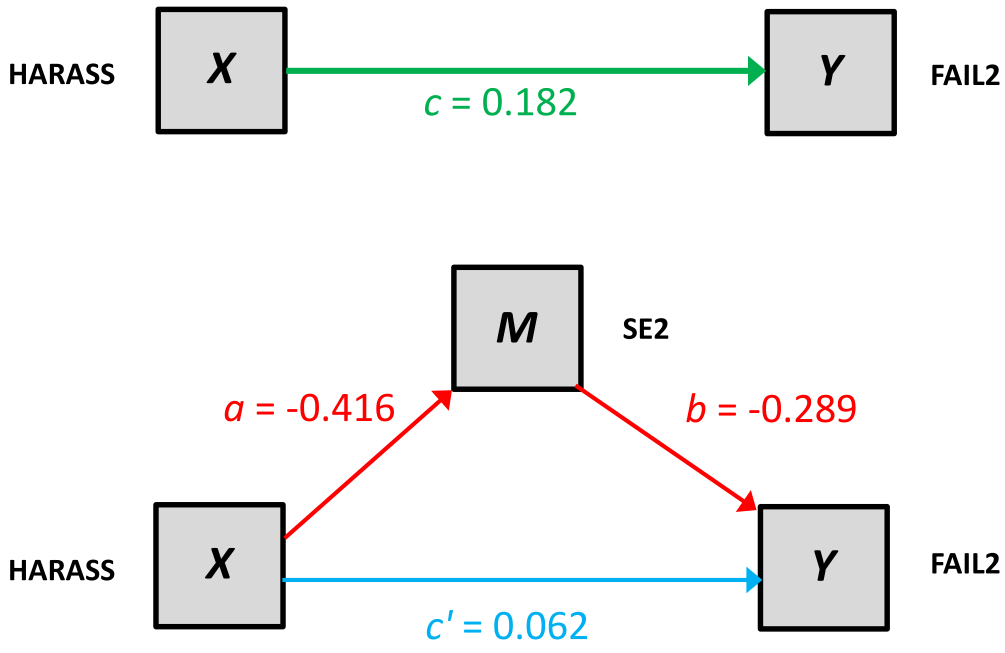
a. Dependent Variable: fail2

```
regression/dep=fail2/method=enter harass se2.
```

```
proc reg data=harass;model fail2=harass se2;run;
```

```
lm(fail2~harass+se2, data = harass)
```

Using a set of OLS regression analyses



Direct effect of X on $Y = c' = 0.062$

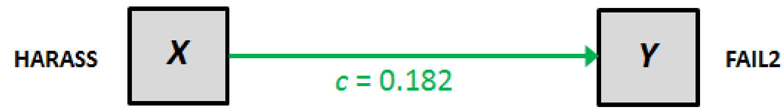
Indirect effect of X on Y via $M = ab = -0.416(-0.289) = 0.120$

Total effect of X on $Y = c' + ab = 0.062 + 0.120 = 0.182 = c$

Interpretation of the total, direct, and indirect effects

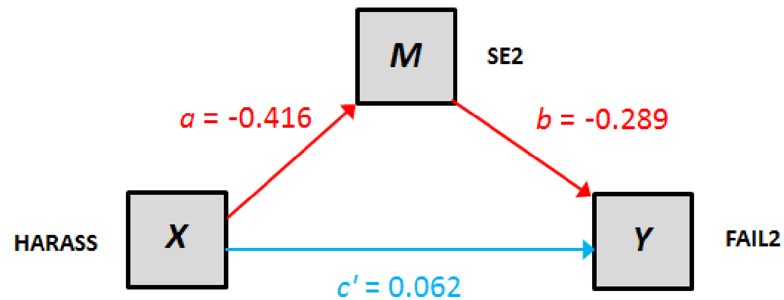
Generic

Total: Two people who differ by one unit on *X* are estimated to differ by *c* units on *Y* on average.



Indirect: They differ by *ab* units on average as a result of the effect of *X* on *M* which in turn affects *Y*.

Direct: The rest of the difference, the difference of *c'* units, is due to the effect of *X* on *Y* independent of *M*.



Direct effect = c' = 0.062
Indirect effect = ab = -0.416(-0.289) = 0.120
Total effect = c = 0.062 + 0.120 = 0.182

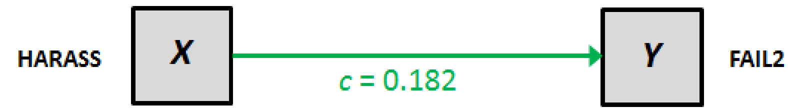
Specific

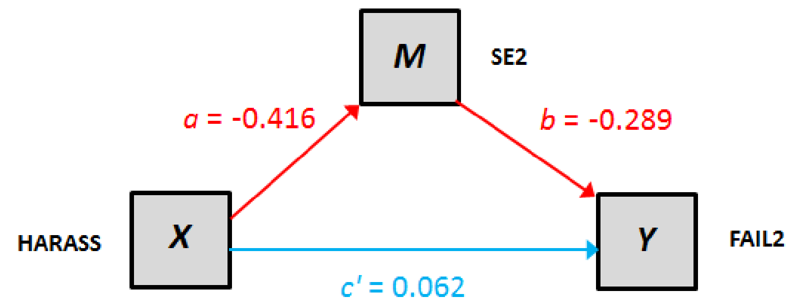
Total: Two kids who differ by one scale point in ethnic harassment are estimated to differ by 0.182 units in perceived academic failure one year later, with the more frequently-harassed kid perceiving greater failure.

Indirect: They differ by 0.120 units in perceived failure as a result of the negative effect of harassment on self esteem a year later, which in turn increases perceived failure.

Direct: Independent of this mechanism, the more harassed kid is estimated to be 0.062 units higher in perceived failure.

Reflecting on Causality in HARASS Analysis





Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations

Must consider each path separately:

HARASS → FAIL2 (Total Effect):
- Covariation ✓
- Temporal Ordering ✓
- Elimination of competing explanations ✗

HARASS → SE2 (*a*-path):
- Covariation ✓
- Temporal Ordering ✓
- Elimination of competing explanations ✗

SE2 → FAIL2 (*b*-path):
- Covariation ✓
- Temporal Ordering ✗
- Elimination of competing explanations ✓

HARASS → FAIL2 (*c*′-path):
- Covariation ✗
- Temporal Ordering ✓
- Elimination of competing explanations ✗

Reflecting on Causality in HARASS Analysis

Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations

- Evidence for causality is mixed, and largely unconvincing
- Covariation is evident from the regression results, but we know correlation is not causation
- While the two time-point design allows *some* paths to be appropriately temporally ordered, self-esteem and perceived academic failure were both measured at Time 2, allowing for a potential reverse in the causal order
- No attempt was made to account for alternative explanations

It works for dichotomous *X* too.

Garcia, D. M., Schmitt, M. T., Branscombe, N. R., & Ellemers, N. (2010). Women's reactions to ingroup members who protest discriminatory treatment: The importance of beliefs about inequality and response appropriateness. ***European Journal of Social Psychology, 49***, 733-745.

European Journal of Social Psychology
Eur. J. Soc. Psychol. **40**, 733–745 (2010)
Published online 6 July 2009 in Wiley InterScience
(www.interscience.wiley.com) **DOI**: 10.1002/ejsp.644

Research article

Women's reactions to ingroup members who protest discriminatory treatment: The importance of beliefs about inequality and response appropriateness

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NYLA R. BRANSCOMBE[3] AND NAOMI ELLEMERS[4]
[1] *University of Guelph, Canada*
[2] *Simon Fraser University, Canada*
[3] *University of Kansas, USA*
[4] *Leiden University, The Netherlands*

Abstract

Our goal was to identify factors that shape women's responses to ingroup members who protest gender discrimination. We predicted and found that women who perceived gender discrimination as pervasive regarded a protest response as being more appropriate than a no protest response and expressed greater liking and less anger towards a female lawyer who protested rather than did not protest an unfair promotion decision. Further, beliefs about the appropriateness of the response to discrimination contributed to evaluations of the protesting lawyer. Perceptions that the complaint was an appropriate response to the promotion decision led to more positive evaluations of an ingroup discrimination protester.

Protest can be an effective means of improving the plight of a devalued group. Historically, there are many examples of protest, even from a single individual, that have advanced a group's social position (e.g. Meritor Savings Bank vs. Vinson, 477 US 57, 1986; Dekker vs. VJV-Centrum ECJ, 1992). Despite the potential gains to be obtained by protesting illegitimate treatment, protestors might not always be appreciated by members of their own group. Whether disadvantaged group members respond positively or negatively to ingroup protestors will likely depend upon the *perceived* implications that the protestor's action has for the ingroup. Unless protest is seen as justified by the social circumstances and an effective means of bringing about positive change, a protestor might be seen as making the ingroup look like complainers. Such threat to the ingroup's reputation could evoke the ire and disdain of the disadvantaged group towards the protestor. Hence, perceptions of the justification for and likely consequences of protest will be critical to others' reactions to an ingroup discrimination claimer. We propose that protest by an ingroup member will be seen as appropriate and thus appreciated to the extent that observers perceive that their ingroup is targeted by pervasive discrimination.

SOCIAL CONSEQUENCES OF CLAIMING DISCRIMINATION

Gender discrimination continues to be widespread throughout Western employment settings (see Charles & Grusky, 2004). The continuation of gender discrimination has substantive negative implications for women's economic and

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Participants (all female) read a narrative about a female attorney who lost a promotion at her firm to a much less qualified male through unequivocally discriminatory actions of the senior partners.

Participants assigned to the 'protest' condition were then told she protested the decision by presenting an argument to the partners about how unfair the decision was.

Participants assigned to the 'no protest' condition were told that although she was disappointed, she accepted the decision and continued working at the firm.

After reading the narrative, the participants evaluated **how appropriate they perceived her response to be**, and also evaluated the characteristics of the attorney, the responses of which were aggregated to produce a measure of **"liking."** Prior to the study, the participants filled out the Modern Sexism Scale.

The data: PROTEST

*protest.sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Add-ons Window Help

9 :

	subnum	cond	sexism	angry	liking	respappr	protest
1	209	2	4.87	2	4.83	4.25	1.00
2	44	0	4.25	1	4.50	5.75	.00
3	124	2	5.00	3	5.50	4.75	1.00
4	232	2	5.50	1	5.66	7.00	1.00
5	30	2	5.62	1	6.16	6.75	1.00
6	140	1	5.75	1	6.00	5.50	1.00
7	27	2	5.12	2	4.66	5.00	1.00
8	64	0	6.62	1	6.50	6.25	.00
9	67	0	5.75	6	1.00	3.00	.00
10	182	0	4.62	1	6.83	5.75	.00
11	85	2	4.75	2	5.00	5.25	1.00
12	109	2	6.12	5	5.66	7.00	1.00
13	122	0	4.87	2	5.83	4.50	.00
14	69	1	5.87	1	6.50	6.25	1.00

SAS users, run this program to make a temporary or “work” data file named PROTEST.

protest

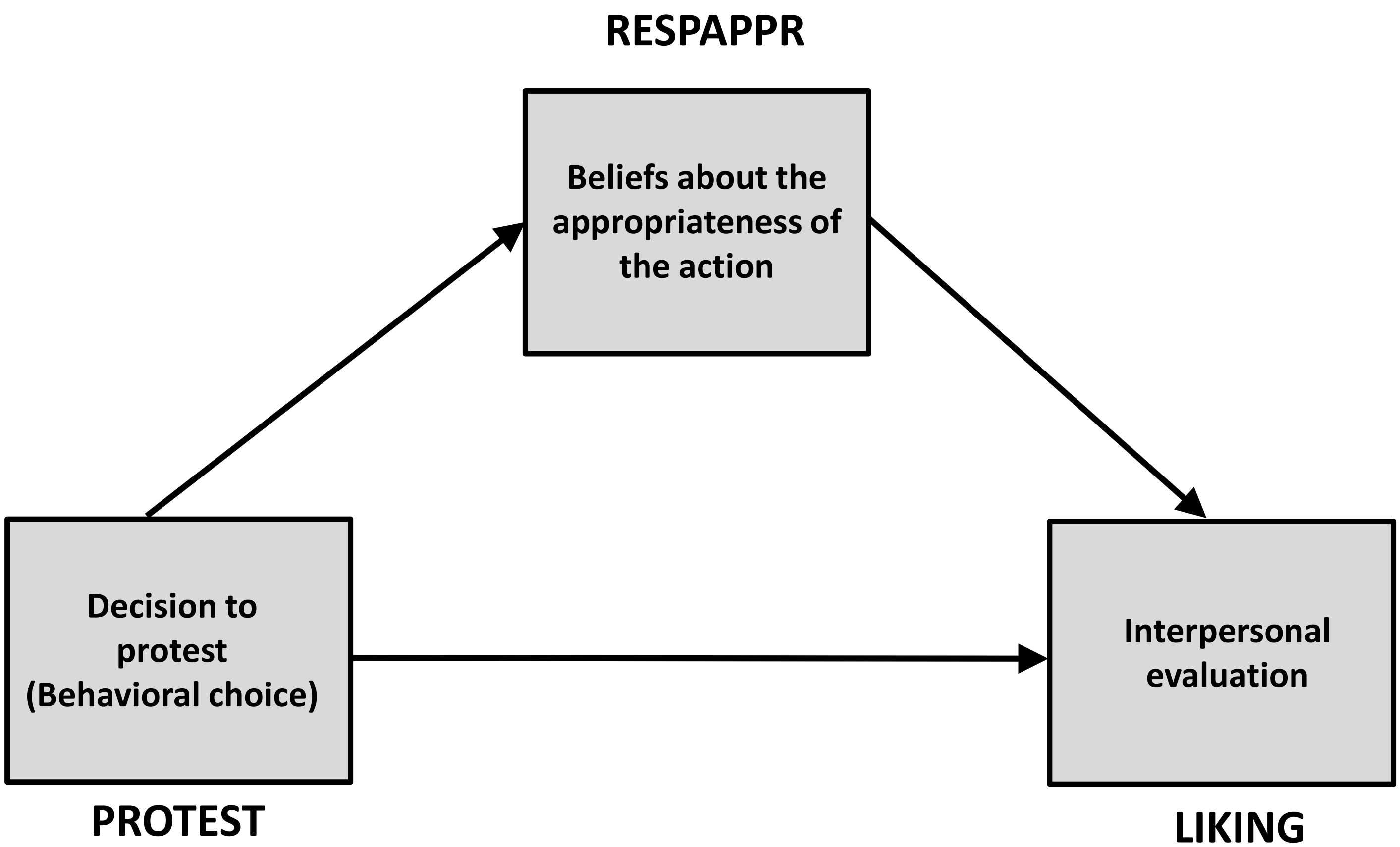
```
data protest;
  input subnum cond sexism angry liking respappr protest;
  cards;
  209 2   4.87    2   4.83    4.25    1.00
  44  0   4.25    1   4.50    5.75    .00
  124 2   5.00    3   5.50    4.75    1.00
  232 2   5.50    1   5.66    7.00    1.00
  30  2   5.62    1   6.16    6.75    1.00
  140 1   5.75    1   6.00    5.50    1.00
  27  2   5.12    2   4.66    5.00    1.00
  64  0   6.62    1   6.50    6.25    .00
  67  0   5.75    6   1.00    3.00    .00
  182 0   4.62    1   6.83    5.75    .00
  85  2   4.75    2   5.00    5.25    1.00
  109 2   6.12    5   5.66    7.00    1.00
  122 0   4.87    2   5.83    4.50    .00
  69  1   5.87    1   6.50    6.25    1.00
```

PROTEST: Experimental condition (1 = protest, 0 = no protest)

LIKING : Evaluation (liking) of the lawyer (higher = more positive evaluation, i.e. like more)

RESPAPPR: A measure of how appropriate the lawyer’s behavior in response to the action of the partners was perceived to be for the situation (higher = more appropriate)

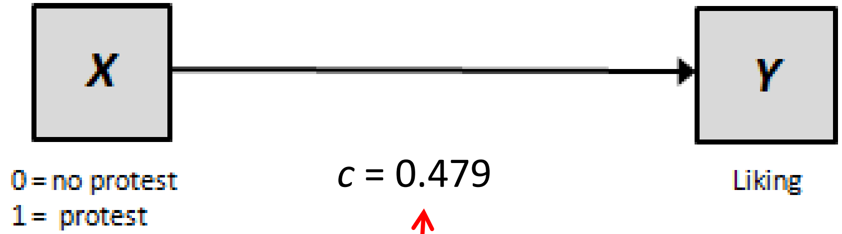
Our question



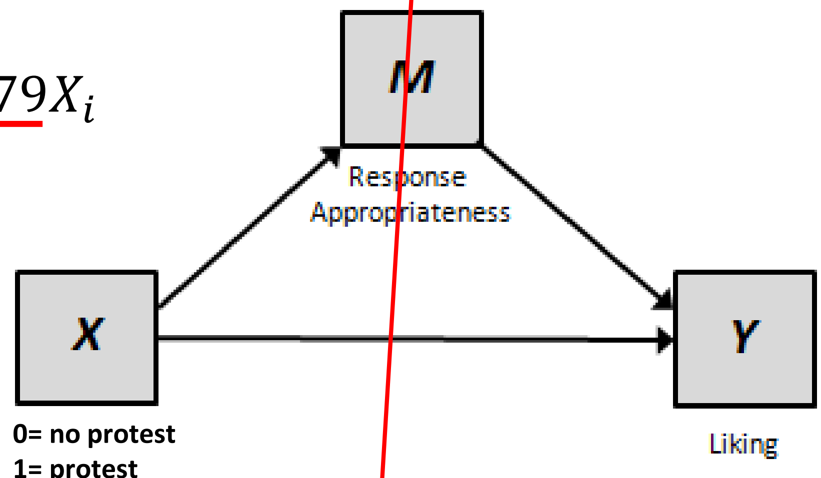
Do perceptions of the appropriateness of the response act as the mechanism through which that choice influences interpersonal evaluation?

Notice that this question is not asked contingent on evidence of simple association between the choice and the evaluation.

Using a set of OLS regression analyses



$$\widehat{Y}_i = 5.313 + \underline{0.479}X_i$$



Because the two groups differ by one unit on *X*, this is the difference between the group means. The attorney was liked more when she protested than when she did not.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.313	.161		33.055	.000
	X: experimental condition (0 = no protest, 1 = protest)	$\boxed{.479}$	.195	.213	2.460	.015

a. Dependent Variable: Y: liking of the target

SPSS:

```
regression/dep=liking/method=enter protest.
```

SAS:

```
proc reg data=protest;model liking=protest;run;
```

R:

```
lm(liking~protest, data = protest)
```

Interpretation when X is dichotomous

$$\hat{Y}_i = 5.310 + 0.479X_i$$

```
means tables = liking by protest.
```

When X = 1 (protest), $\hat{Y}$ = 5.310 + 0.479(1) = 5.789
When X = 0 (no protest), $\hat{Y}$ = 5.310 + 0.479(0) = 5.310

LIKING: liking of the target

PROTEST: experimental condition (0 = no protest, 1 = protest)	Mean	N	Std. Deviation
no protest	5.3102	41	1.30158
protest	5.7889	88	.87669
Total	5.6367	129	1.04970

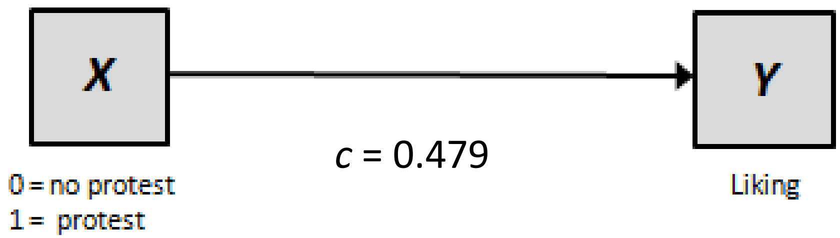
Notice that with X coded 0 and 1, the model yields the group means, *b* is the difference between the group means, and *the regression constant* is the mean for the group coded X = 0 (no protest condition).

More generally, if the two groups are coded by a difference of λ units, such that $X = \theta + \lambda$ for group 1 and $X = \theta$ for group 2,

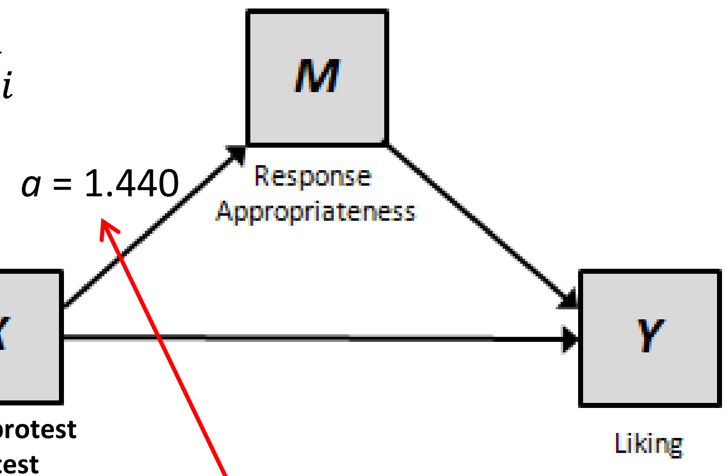
$$b = (\overline{Y}_1 - \overline{Y}_2) / \lambda$$

If you get in the habit of coding a dichotomous variable such that the groups differ by one unit on X, *b* will always be a difference between group means.

Using a set of OLS regression analyses



$$\widehat{M}_i = 3.884 + \underline{1.440}X_i$$



Because the two groups differ by one unit on X, this is the difference between the group means. Protesting was seen as more appropriate for the situation than doing nothing.

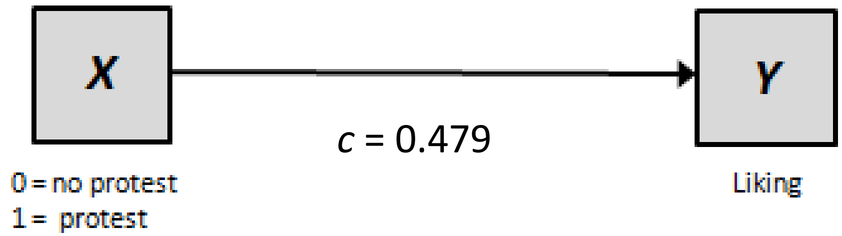
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.884	.183		21.208	.000
	X: experimental condition (0 = no protest, 1 = protest)	$\boxed{1.440}$	.222	.499	6.493	.000

```
regression/dep=respappr/method=enter protest.
```

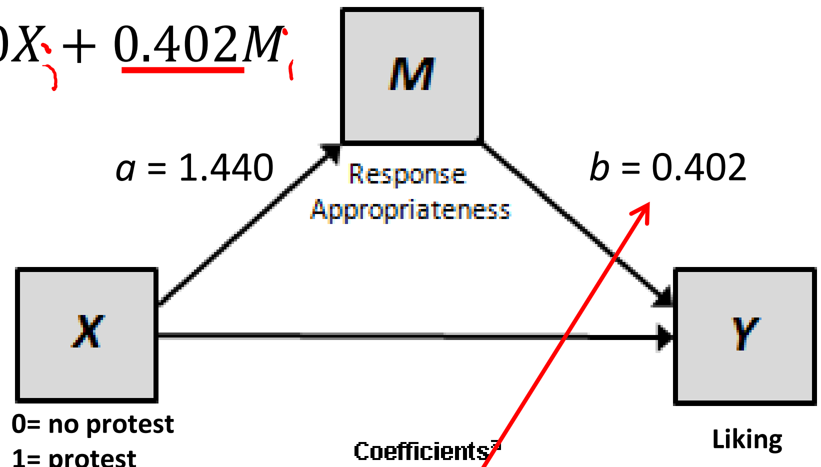
```
proc reg data=protest;model respappr=protest;run;
```

```
lm(respappr~protest, data = protest)
```

Using a set of OLS regression analyses



$$\hat{Y} = 3.751 - 0.100X + 0.402M$$



Holding constant what the attorney did, she was liked more by those who saw her behavior as more appropriate for the situation.

Coefficients[a]

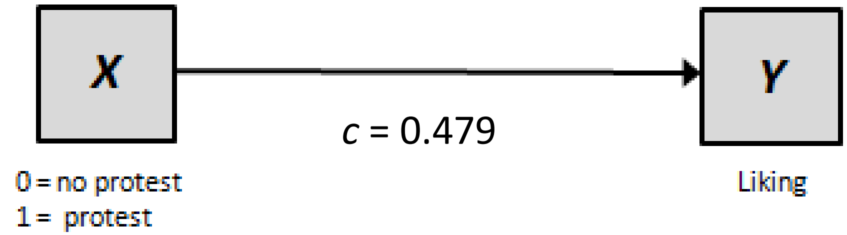
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.751	.306		12.271	.000
	M: appropriateness of response	$\boxed{.402}$	.069	.517	5.789	.000
	X: experimental condition (0 = no protest, 1 = protest)	-.100	.200	-.045	-.501	.617

```
regression/dep=liking/method=enter respappr protest.
```

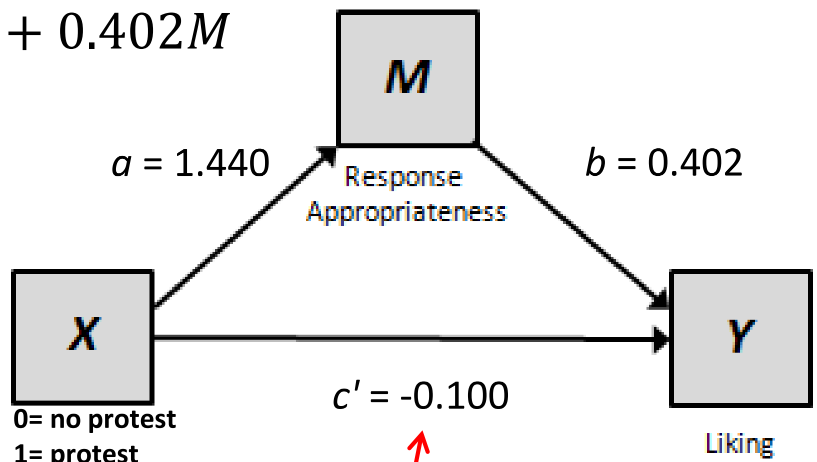
```
proc reg data=protest;model liking=respappr protest;run;
```

```
lm(liking~respappr+protest, data = protest)
```

Using a set of OLS regression analyses



$$\hat{Y} = 3.751 \underline{- 0.100}X + 0.402M$$



Because the two groups differ by one unit on *X*, this is the difference between the group means adjusted for differences between the groups in how appropriate her behavior was perceived as being for the situation (i.e., holding it constant)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.751	.306		12.271	.000
	M: appropriateness of response	.402	.069	.517	5.789	.000
	X: experimental condition (0 = no protest, 1 = protest)	-.100	.200	-.045	-.501	.617

```
regression/dep=liking/method=enter respappr protest.
```

```
proc reg data=protest;model liking=respappr protest;run;
```

```
lm(liking~respappr+protest, data = protest)
```

Interpretation of total, direct, and indirect effects

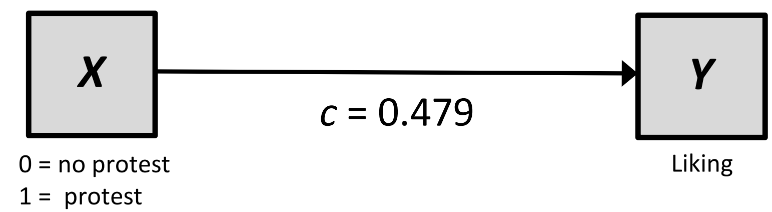
Direct effect = -0.100
Indirect Effect = 1.440(0.402) = 0.579
Total effect = -0.100 + 0.579 = 0.479

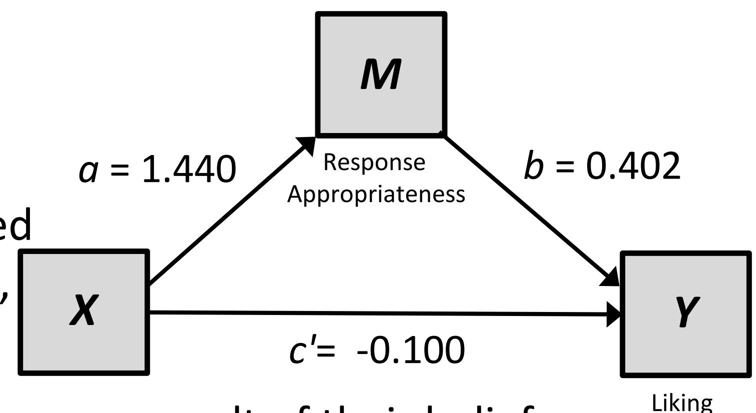
Generic

Total: Two people who differ by one unit on *X* are estimated to differ by *c* units on *Y* on average.

Indirect: They differ by *ab* units on average as a result of the effect of *X* on *M* which in turn affects *Y*.

Direct: The rest of the difference, the difference of *c′* units, is due to the effect of *X* on *Y* independent of *M*.





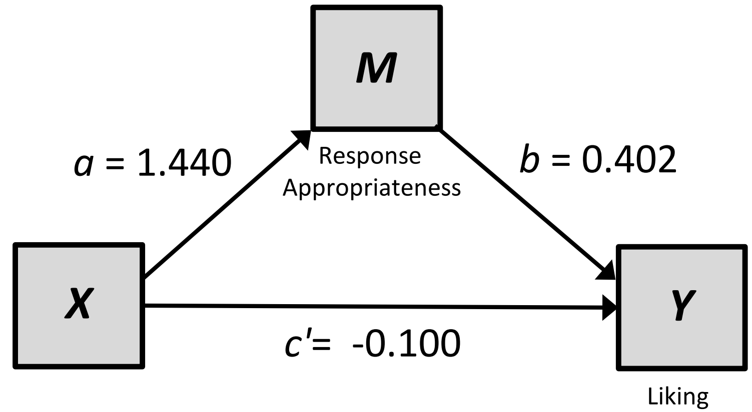
Specific

Total: Participants who were told the lawyer protested (*X* = 1) liked the lawyer 0.479 units **more**, on average, than those who were told she did not protest.

Indirect: They liked her by 0.579 units **more** on average as a result of their beliefs about the appropriateness of her response, which in turn affected their liking.

Direct: Among those equal in their beliefs about the appropriateness of her response, those who were told the lawyer protested liked her 0.100 units **less** (because the sign is negative) than those who were told she did not protest the decision.

Reflecting on Causality in PROTEST Analysis



Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations

Must consider each path separately:

PROTEST → LIKING (Total Effect):

- Covariation ✓
- Temporal Ordering ✓
- Elimination of competing explanations ✓

PROTEST → RESPAPPR (*a*-path):

- Covariation ✓
- Temporal Ordering ✓
- Elimination of competing explanations ✓

RESPAPPR → LIKING (*b*-path):

- Covariation ✓
- Temporal Ordering ✗
- Elimination of competing explanations ✗

PROTEST → LIKING (*c′*-path):

- Covariation ✗
- Temporal Ordering ✓
- Elimination of competing explanations ✗

Reflecting on Causality in HARASS Analysis

Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations

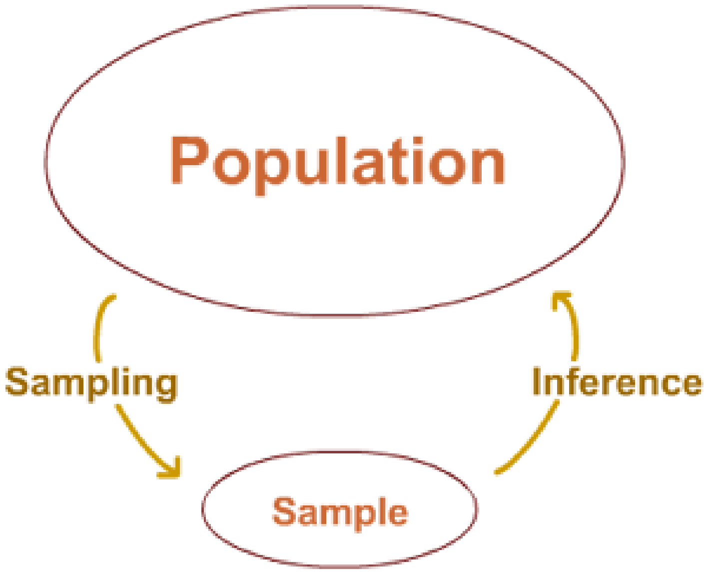
- Evidence for causality is strong for some parts of the model (e.g., c-path and a-path) but because the *b*-path and *c'*-path have limited evidence for causality, we're not certain the indirect effect is an accurate estimate.
- Covariation is evident from the regression results, but we know correlation is not causation
- Randomization of X allows *some* paths to be appropriately temporally ordered, RESPAPPR and LIKING are still measured at the same time, allowing for a potential reverse in the causal order
- No attempt was made to account for alternative explanations for the M→ Y relationship, none is needed for X → M, and X → Y because of randomization

Statistical Inference

Statistical inference: The indirect effect

Statistical inference is how we take information from our sample and generalize to the population.

Up to this point we have made estimates based on the sample, but we were unable to make any claims about what we think the population looks like.

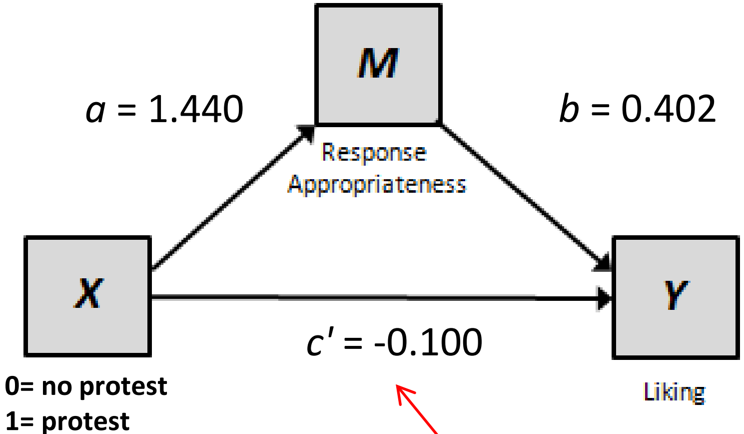


Methods of inference:

- Sobel Test (Normality Test / Delta Method)
- Bootstrap confidence intervals
- Monte Carlo confidence intervals
- Causal Steps Method

Statistical inference: The direct effect

Inference for the direct effect is simple and noncontroversial. The inference can be framed in terms of a hypothesis test or a confidence interval. Any OLS regression program will provide both.



No statistically significant evidence of a direct effect of protest on liking, $c' = -0.100$, $p = 0.617$, 95% CI = (-0.497 to 0.296)

```
regression/statistics defaults ci/ dep=liking/method=enter respappr protest.
```

```
proc reg data=protest;model liking=respappr protest/stb clb; run;
```

```
lm(liking~respappr+protest, data = protest)
```

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3.747	.306		12.255	.000	3.142	4.352
	RESPAPPR: appropriateness of response	.402	.070	.517	5.788	.000	.265	.540
	PROTEST: experimental condition (0 = no protest, 1 = protest)	-.101	.200	-.045	-.502	.616	-.497	.296

Statistical inference: The indirect effect

The indirect effect estimates the influence of X on Y through the mechanism represented by M (i.e., the $X \rightarrow M \rightarrow Y$ sequence). 21st-century mediation analysis bases claims of mediation on evidence that the indirect effect is different from zero.

A popular "20th-century" approach to inference: The Sobel test

Indirect effect

$$Z = \frac{ab}{\sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}}$$

"Second order" estimator of the standard error of *ab*

One version eliminates this term ("first order" estimator) ,

A p-value is derived by assuming normality of the sampling distribution of the indirect effect and using the standard normal distribution for derivation of p. A p-value no greater than α leads to the claim that the indirect effect is statistically different from zero at the α level of significance.

Computation with Protest Data

a = 1.440 s_a = 0.222

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.884	.183		21.208	.000
	X: Protest	$\boxed{1.440}$	$\boxed{.222}$	.499	6.493	.000

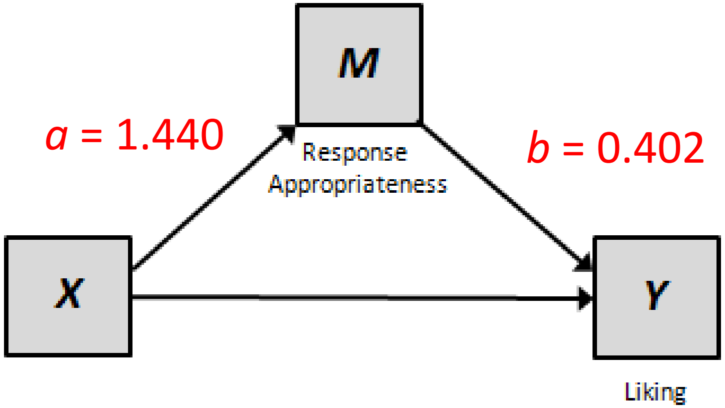
a. Dependent Variable: RESPAPPR: appropriateness of response

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.747	.306		12.255	.000
	RESPAPPR: appropriateness of response	$\boxed{.402}$	$\boxed{.070}$	.517	5.788	.000
	PROTEST: experimental condition (0 = no protest, 1 = protest)	-.101	.200	-.045	-.502	.616

a. Dependent Variable: LIKING: liking of the target

b = 0.402 s_b = 0.070



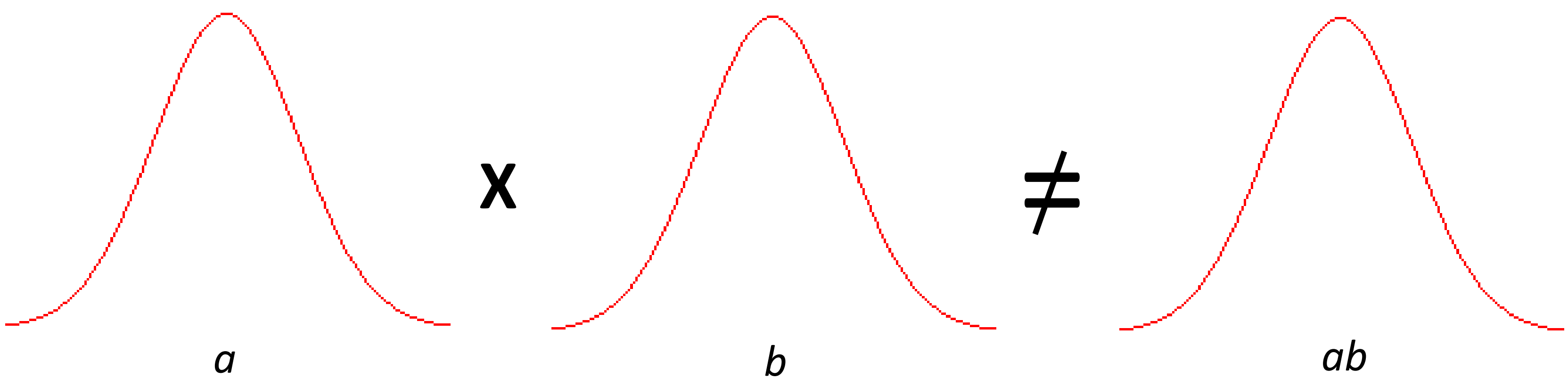
$$Z = \frac{ab}{\sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}}$$

$$Z = \frac{(1.440)(0.402)}{\sqrt{(0.402)^2(0.222)^2+(1.440)^2(0.070)^2+(0.222)^2(0.070)^2}} = \frac{0.5789}{0.1355} = 4.27, p < .0001$$

The indirect effect is statistically significant. But this test has serious problems.

What’s wrong with the Sobel test?

For the Sobel test, the *p*-value is derived by assuming normality of the sampling distribution of the indirect effect and using the standard normal distribution. **Although this assumption is fairly sensible in large samples, it is not in smaller ones. What is a sufficiently large sample is situationally-specific, and typically you won’t know going into the analysis whether or not to trust <u>large sample theory</u>.**



This assumption, which typically will not hold, yields a test that is lower in power than alternatives. **Experts in mediation analysis don’t recommend the use of this test, though it remains popular.** Eventually, researchers will get the message.

The bootstrap confidence interval

Bootstrapping allows us to empirically estimate the sampling distribution of the indirect effect and generate a confidence interval (CI) for estimation and hypothesis testing. **It has become the preferred inferential method for estimating and testing indirect effects.**

(1) Take a random sample of size *n* from the sample *with replacement.*

(2) Estimate the indirect effect in this "resample".

(3) Repeat (1) and (2) a total of *k* times, where *k* is at least 1,000. The larger *k*, the better. I recommend at least 5,000.

(4) Use distribution of the indirect effect over multiple resamples as an approximation of the sampling distribution of the indirect effect.

(5) For 95% CI using "percentile" method, lower and upper bounds are 2.5th and 97.5th percentile in *k* bootstrap estimates of the indirect effect. Variations exist (e.g., 'bias corrected' or 'bias-corrected and accelerated' confidence intervals but they do not perform as well as percentile.)

Bootstrapping

Your data

X	M	Y
4.3	1.4	9.1
1.4	5.4	6.4
4.9	4.3	1.3
5.9	2.3	5.4
6.1	3.3	3.9
3.8	3.1	6.3
2.8	3.2	1.5
9.4	4.1	2.3
4.3	1.3	4.4
4.9	3.7	2.1

a = -0.051 b = -0.844

ab = 0.043

A resampling of your data

X	M	Y
5.9	2.3	5.4
4.9	4.3	1.3
9.4	4.1	2.3
4.9	4.3	1.3
4.3	1.4	9.1
1.4	5.4	6.4
3.8	3.1	6.3
9.4	4.1	2.3
6.1	3.3	3.9
4.3	1.3	4.4

a = 0.020 b = -0.921

ab = -0.018

Bootstrapping

Your data

X	*M*	*Y*
4.3	1.4	9.1
1.4	5.4	6.4
4.9	4.3	1.3
5.9	2.3	5.4
6.1	3.3	3.9
3.8	3.1	6.3
2.8	3.2	1.5
9.4	4.1	2.3
4.3	1.3	4.4
4.9	3.7	2.1

a = -0.051 b = -0.844

ab = 0.043

Another resampling of your data

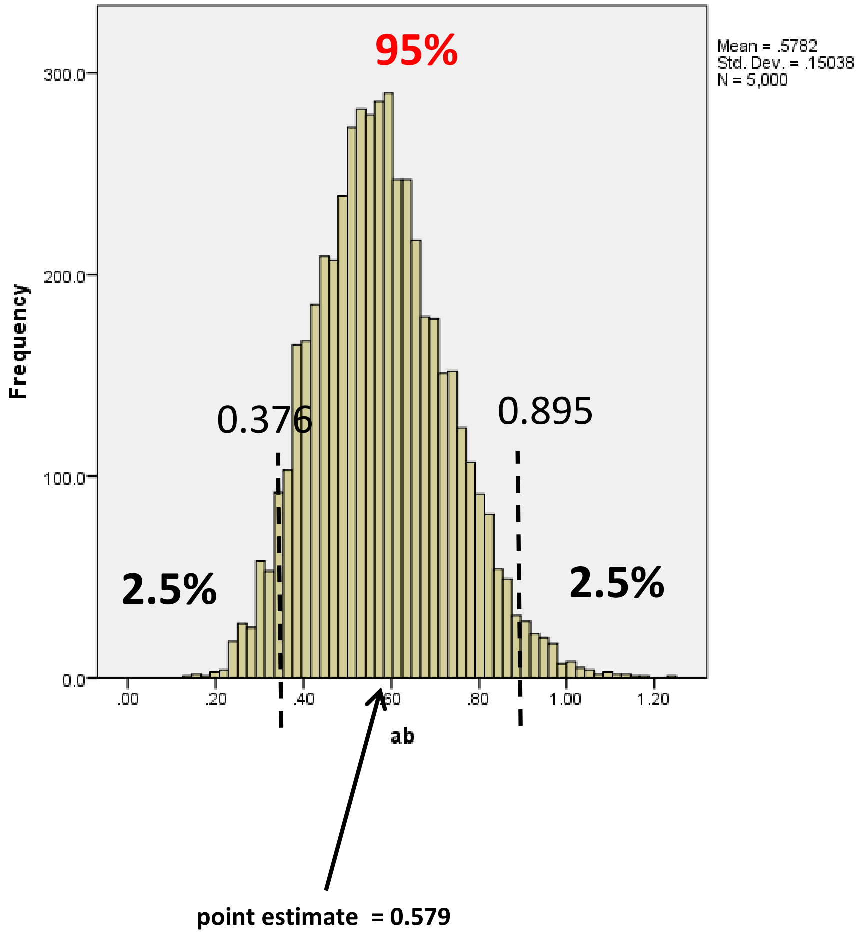
X	*M*	*Y*
6.1	3.3	3.9
4.9	4.3	1.3
2.8	3.2	1.5
4.9	3.7	2.1
3.8	3.1	6.3
9.4	4.1	2.3
2.8	3.2	1.5
4.9	4.3	1.3
4.9	3.7	2.1
1.4	5.4	6.4

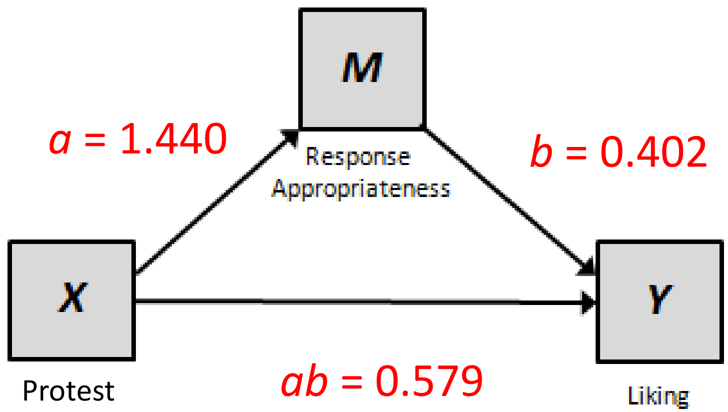
a = -0.034 b = 0.523

ab = -0.017

5,000 bootstrap estimates of the indirect effect

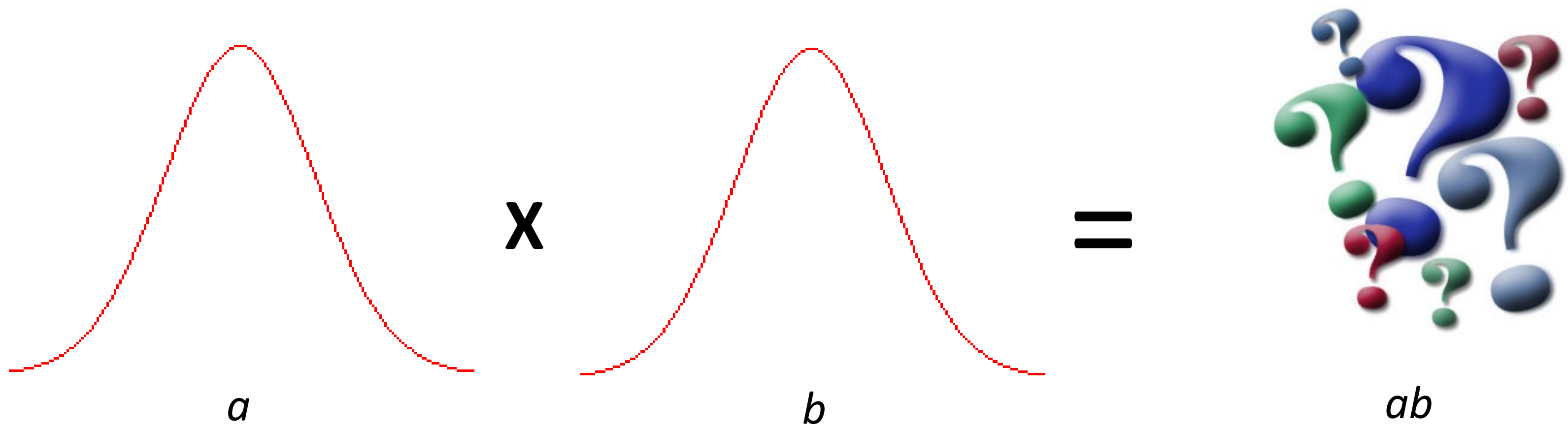
95% of the 5,000 bootstrap estimates of the indirect effect were between 0.376 and 0.895. This is our 95% confidence interval.





Zero is not in the confidence interval, so we **can** claim an indirect effect different from zero with 95% confidence. This is akin to (though not exactly the same as) rejecting the null hypothesis of no indirect effect at the α = 0.05 level of significance.

The Monte Carlo interval



If all of the assumptions of linear regressions are met (or sample sizes are sufficiently large), then we know that *a* and *b* will have normal distributions.

The Monte Carlo confidence intervals takes advantage of this knowledge by simulating normal distributions for *a* and *b* then calculating their product to get an estimated distribution of the indirect effect (*ab*).

The Monte Carlo interval

Monte Carlo empirically estimates the sampling distribution of the indirect effect and generates a confidence interval (CI) for estimation and hypothesis testing. This simulation based method assumes each individual path (*a* and *b*) is normally distributed.

(1) Generate *k* samples from a normal distribution with mean *a* and standard deviation s_a

(2) Generate *k* samples from a normal distribution with mean *b* and standard deviation s_b

(3) Multiply samples together to get a distribution of *k* estimates of *ab.*

(4) Rank order estimates and select estimates which define the lower percentile of ranked *k* estimates and upper percentile of sorted estimates which define CI of interest.

(5) For 95% CI lower and upper bounds are 2.5th and 97.5th percentile in *k* bootstrap estimates of the indirect effect.

The Monte Carlo interval

This method performs well (similarly to bootstrapping) in a variety of simulation studies, but is still less popular.

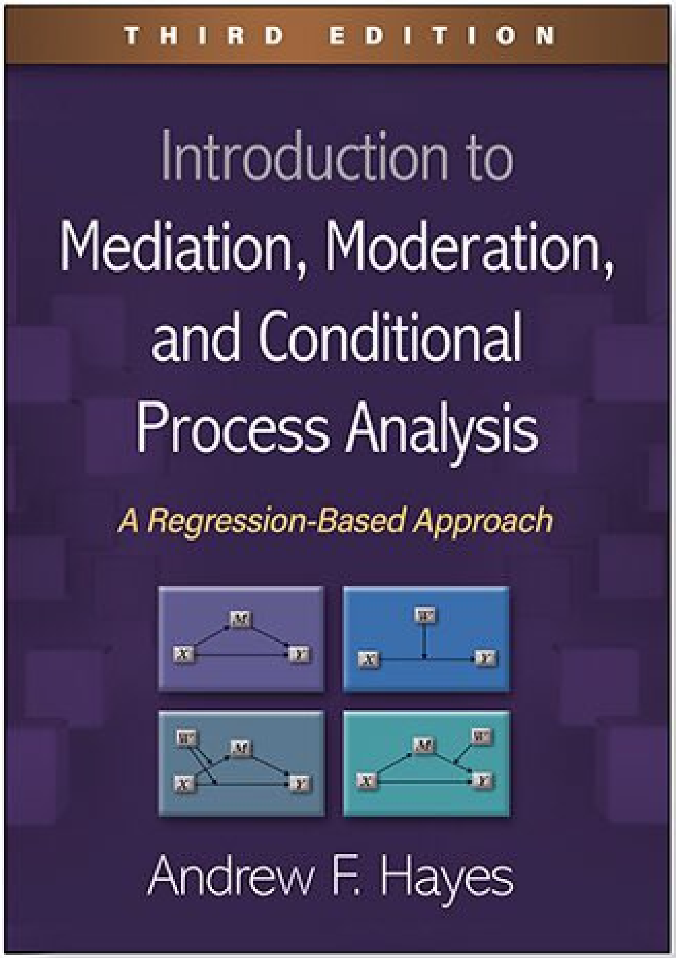
This method makes stronger assumptions than bootstrapping, but does not result in great power.

Add mc = 1 to PROCESS command line to request Monte Carlo CIs

```
Indirect effect(s) of X on Y:
             Effect      MC SE     MC LLCI     MC ULCI
respappr      .5793      .1332       .3369       .8469
```

The Monte Carlo confidence interval also suggests that we are confident the indirect effect is not zero. So all three inferential methods come to the same conclusion, which is comforting.

PROCESS



Published in January 2022 and available through The Guilford Press, Amazon.com, and elsewhere.

- First released in beta form in March of 2012 and later documented in Hayes (2013, IMMCPA, published by The Guilford Press).
- Available for SPSS (in macro and “custom dialog” form), SAS, and R.
- An integration of functions available in my other published macros for mediation and moderation analysis (SOBEL, INDIRECT, MODMED, MODPROBE, MED3C) and a whole lot more, all in one command.
- A handy tool for both “confirmatory” and “exploratory” approaches to data analysis.
- Freely available at www.processmacro.org. The current release is v4.3

processmacro.org

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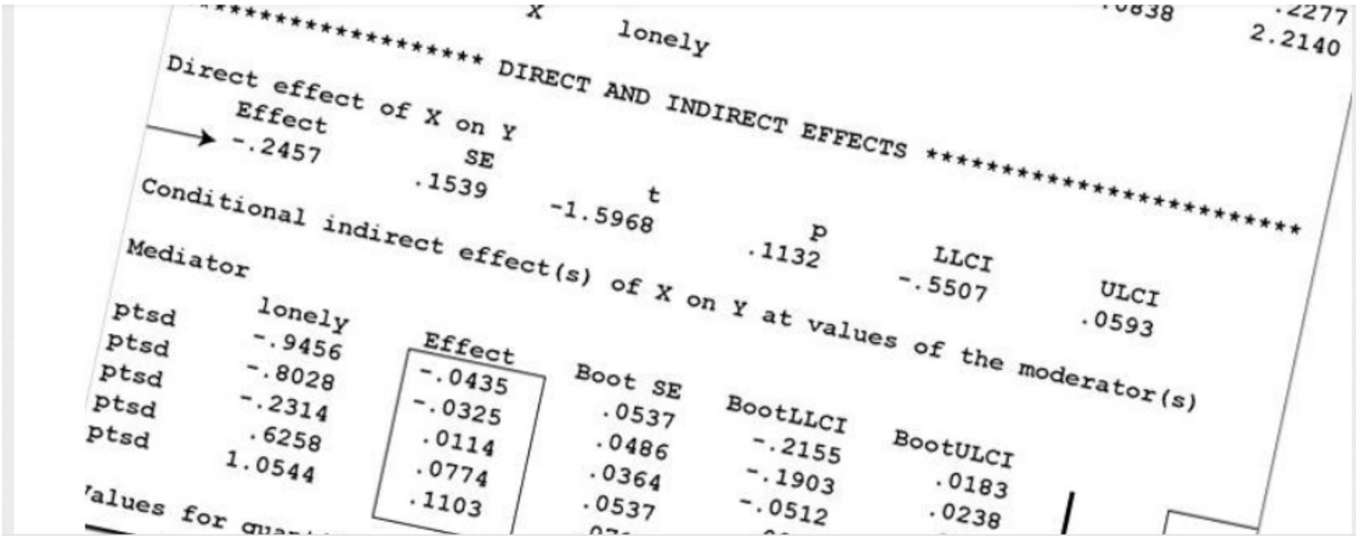
The PROCESS macro for SPSS, SAS, and R



PROCESS is an observed variable OLS and logistic regression path analysis modeling tool. It is widely used through the social, business, and health sciences for estimating direct and indirect effects in single and multiple mediator models (parallel and serial) , two and three way interactions in moderation models along with simple slopes and regions of significance for probing interactions, and conditional indirect effects in moderated mediation models with a single or multiple mediators or moderators. The use of **PROCESS** is described and documented in *Introduction to Mediation, Moderation, and Conditional Process Analysis*, published by The Guilford Press. **PROCESS** was written by Andrew F. Hayes.

Facebook users can stay up to date on the latest developments in **PROCESS** by liking here. Tweeters about **PROCESS** can use the hashtag #processmacro. Email should be directed to afhayes@processmacro.org, but only after reading the FAQ page and the documentation for PROCESS.

Read the documentation (eventually)

The PROCESS documentation is an eventual must-read. It describes how to use PROCESS, as well as its various options, capabilities, and limitations. It is available as Appendix A in Hayes (2022). *Introduction to Mediation, Moderation, and Conditional Process Analysis (3rd Ed)*. At a minimum, you must have the model templates handy, as PROCESS expects you to tell it which model number you are estimating and which variables play what role. You have a mini version of the templates PDF.

Appendix A
Using PROCESS

This appendix describes how to install and execute PROCESS, how to set up a PROCESS command, and it documents its many features, some of which are not described elsewhere in this book. As PROCESS is modified and features are added, supplementary documentation will be released at *www.afhayes.com*. Check this web page regularly for updates. Also available at this page is a complete set of model templates identifying each model that PROCESS can estimate.

This documentation focuses on the SPSS version of PROCESS. All features and functions described below are available in the SAS version as well and work as described here, with minor modifications to the syntax. At the end of this documentation (see page 438), a special section devoted to SAS describes some of the differences in syntax structure for the SAS version compared to what is described below.

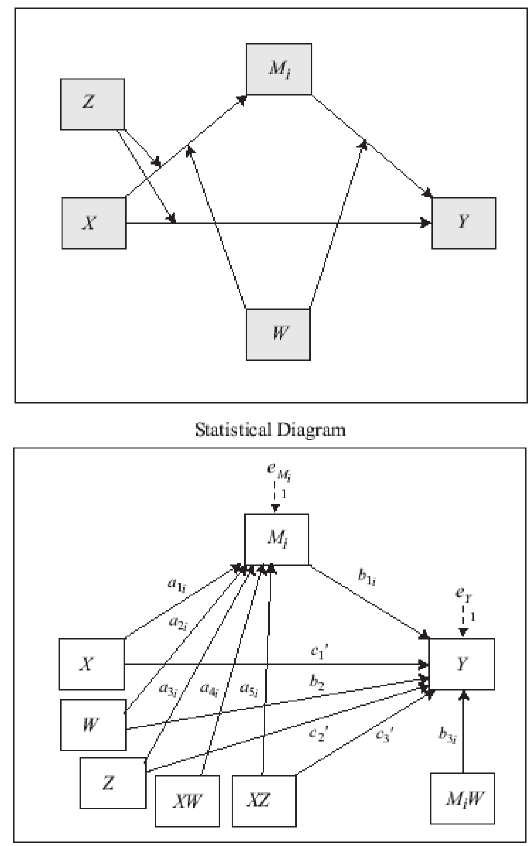
Overview

PROCESS is a computational tool for path analysis–based moderation and mediation analysis as well as their integration in the form of a conditional process model. In addition to estimating unstandardized model coefficients, standard errors, t and p-values, and confidence intervals using either OLS regression (for continuous outcomes) or maximum likelihood logistic regression (for dichotomous outcomes), PROCESS generates direct and indirect effects in mediation models, conditional effects (i.e., "simple slopes") in moderation models, and conditional indirect effects in conditional process models with a single or multiple mediators. PROCESS offers various methods for probing two- and three-way interactions and can construct percentile bootstrap, bias-corrected bootstrap, and Monte Carlo confidence intervals for indirect effects. In mediation models, multiple mediator variables can be specified to operate in parallel or in serial. Heteroscedasticity-consistent standard errors are available for inference about model coeffi-

419

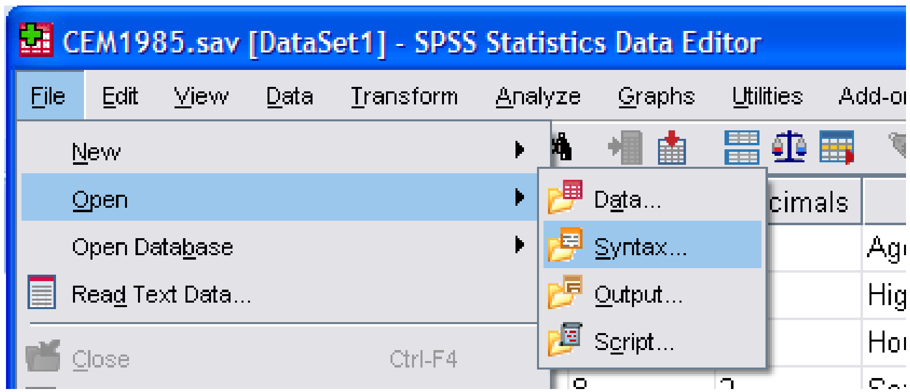
Model 62

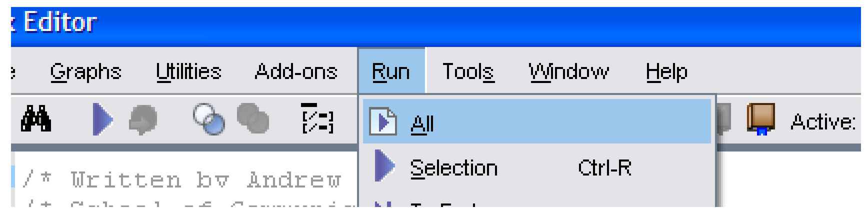
Conceptual Diagram



PROCESS as a syntax-driven macro

Open process.sps as a syntax file and run the entire program **exactly as is.** This produces a new SPSS command called PROCESS. See the documentation for details on the syntax structure. PROCESS goes away when you close SPSS.





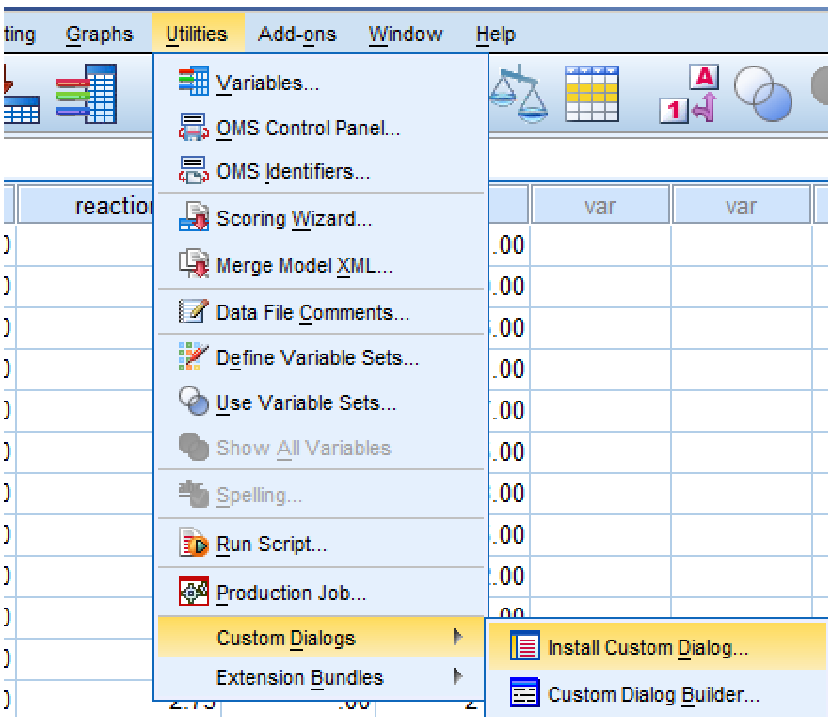
Once PROCESS is defined, you can run a properly-formatted PROCESS command in a new syntax window. Such a command might look something like below. Not all of the arguments below are required.

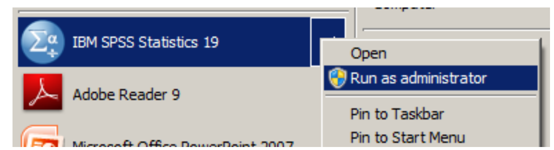
```
process y=liking/x=protest/m=respappr/total=1/normal=1
         /model=4/boot=10000.
```

PROCESS "Custom Dialog"

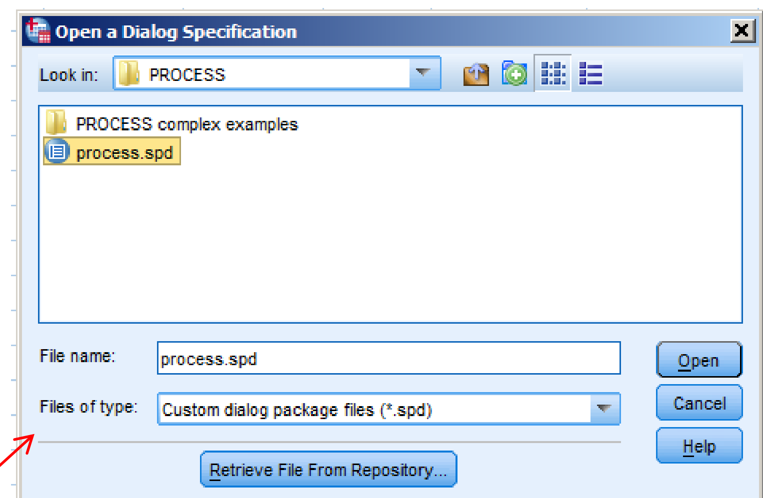
The PROCESS macro must be run at least once in your SPSS session to activate the PROCESS command. Custom Dialog files are permanently installed in SPSS, integrating the procedure into SPSS menus. Use the procedure below. In Windows, installation requires administrative access to your machine. You **probably** have to open SPSS as an administrator as well. You may not have access to do so.

In SPSS 23 and earlier:





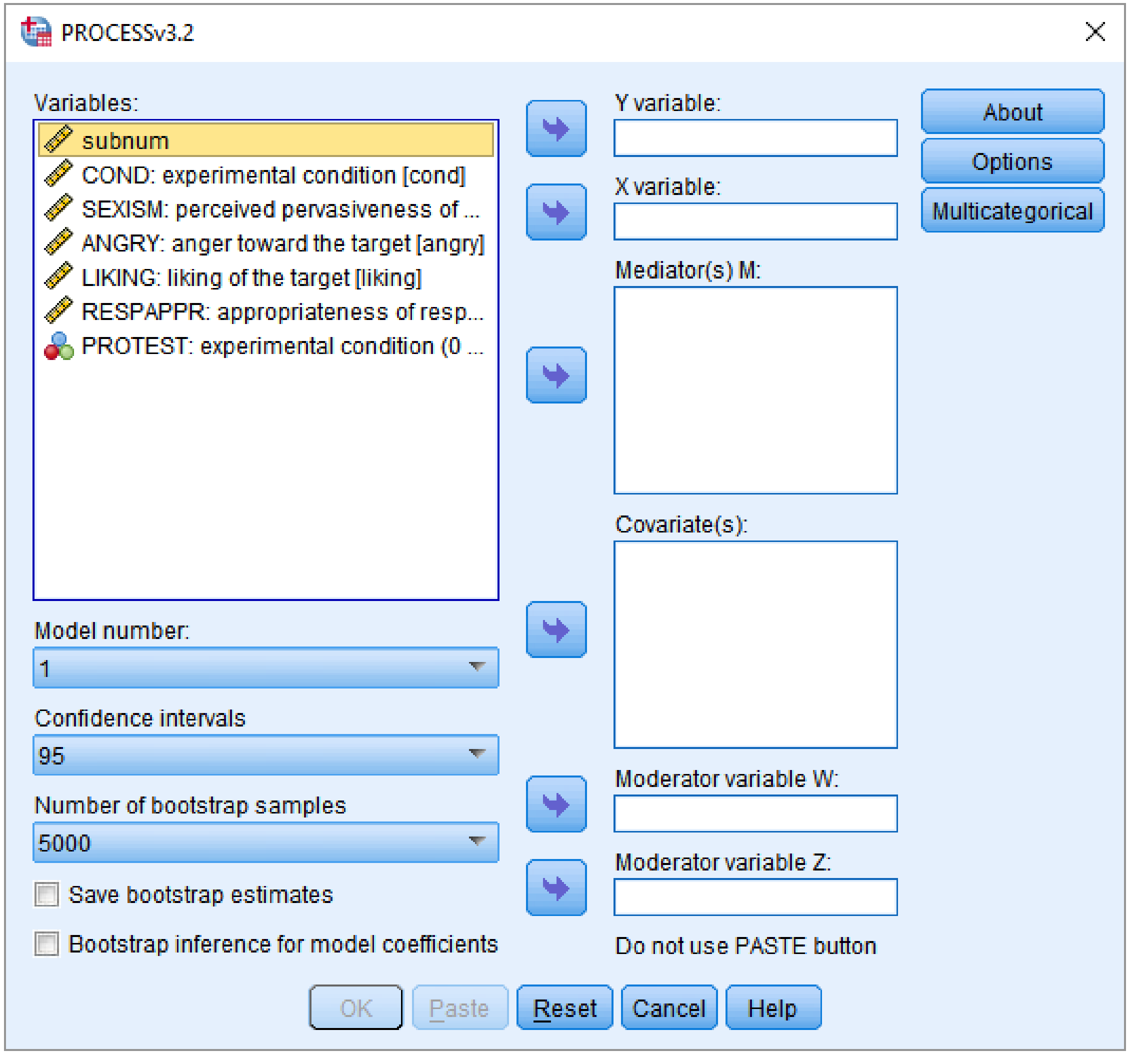
Right click SPSS to select



When installed, PROCESS can be found under "Analyze"→"Regression"

In SPSS24, look under "Extensions" for the Utilities option

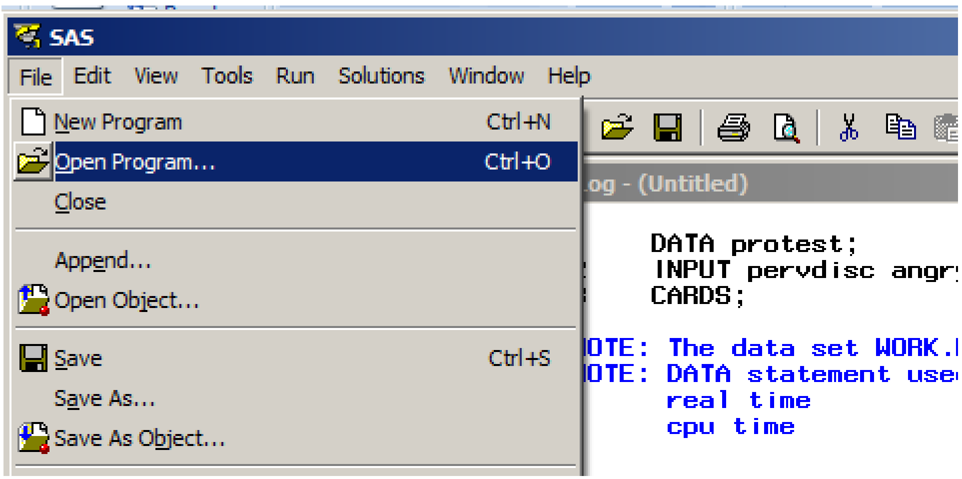
PROCESS "Custom Dialog"

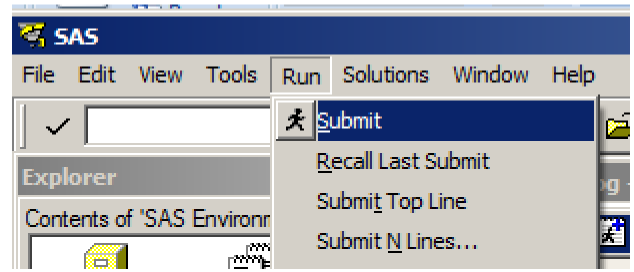


Installing the dialog box does not eliminate the need to run the PROCESS code if you plan on executing with syntax. And don't use the PASTE button.

PROCESS for SAS

In SAS, open process.sas and submit the entire program **exactly as is.** This produces a new SAS command called %PROCESS. The syntax structure is described in the documentation.



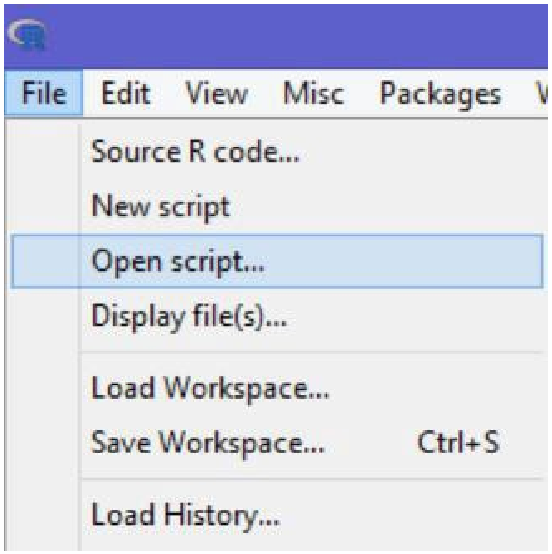


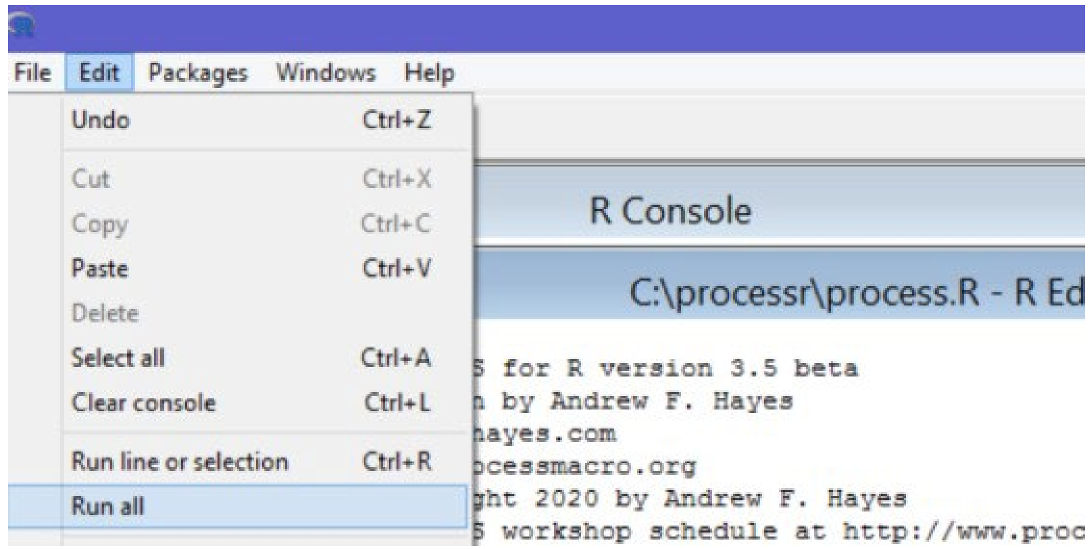
Once PROCESS is defined, you can run a properly-formatted PROCESS command in a new syntax window. Such a command might look something like below. Not all of the arguments below are required.

```
%process(data=protest,y=liking,x=protest,m=respappr,total=1,
          normal=1,boot=10000,model=4);
```

PROCESS for R

PROCESS for R is a script, not a package. Execute the script by opening process.r and running as below. This can be done with or without Rstudio. RStudio may be slower.





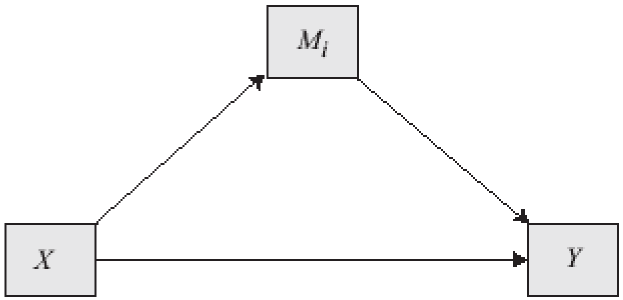
The script will scroll past you on the screen as it runs. It will take a few minutes before PROCESS will be ready to use. Save the workspace to avoid having to run the script again next time you open R. If you save the workspace, you can use R like a package next time. In Rstudio, you can turn it into a package if you want and know how. Consult many sources online for instructions on creating a package.

PROCESS is not available on CRAN. PROCESSR, which is available on CRAN, is not the same as PROCESS. Hayes didn't create PROCESS and we cannot attest to its accuracy or quality.

Model template system

PROCESS has 56 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

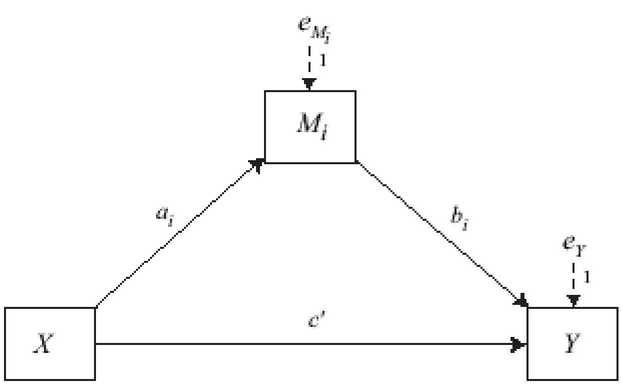
Conceptual diagram



Example #1:

Model 4 is a simple or parallel multiple mediator model, which estimates the direct and indirect effect(s) of *X* on *Y* through one or more mediators (*M*) (up to 10 mediators at once)

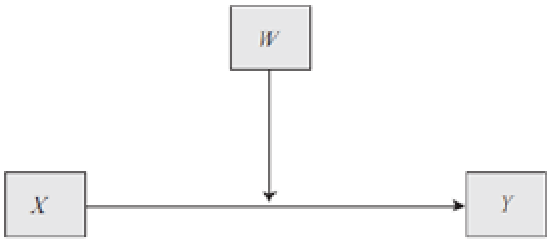
Statistical diagram



Model template system

PROCESS has 56 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

Conceptual diagram

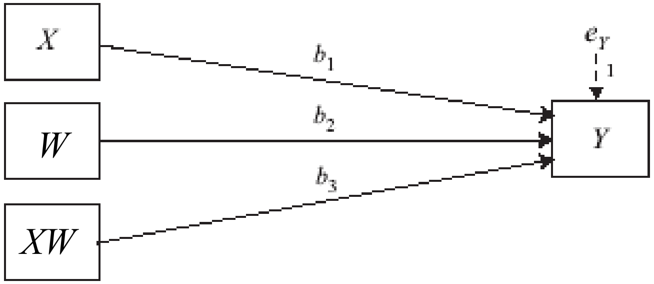


Example #2:

Model 1 is a simple moderation model, with *W* moderating the effect of *X* on *Y*.

The statistical diagram shows the model in the form of a path diagram. This is the form in which the model is estimated.

Statistical diagram



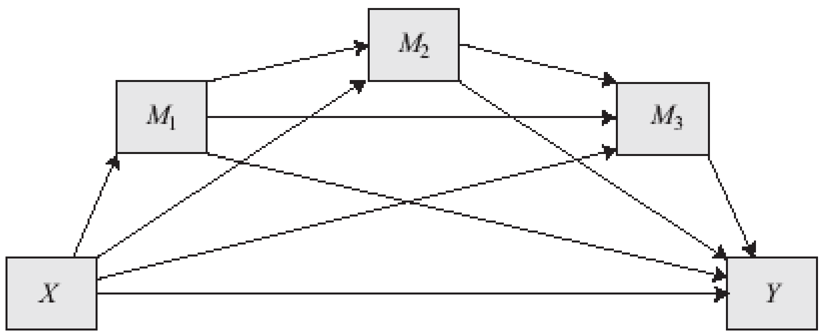
Model template system

PROCESS has 56 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

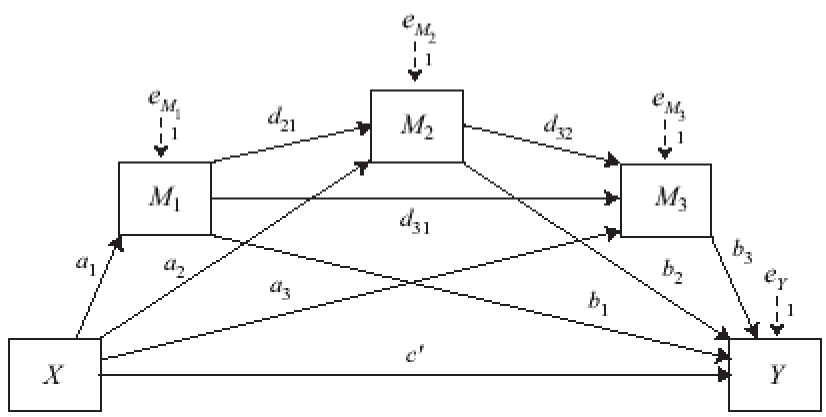
Example #3:

Model 6 is a serial multiple mediator model, which estimates the direct and indirect effect(s) of *X* on *Y* through up to 4 mediators (*M*) chained together in serial. An example with **three** mediators is depicted to the right.

Conceptual diagram



Statistical diagram



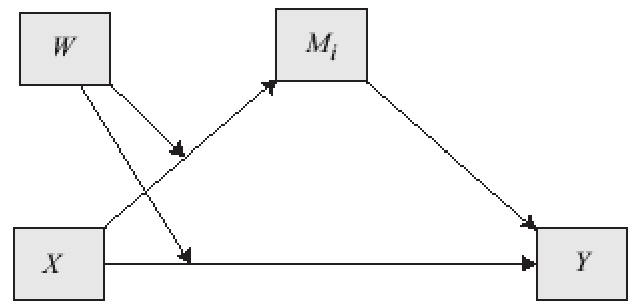
Model template system

PROCESS has 56 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

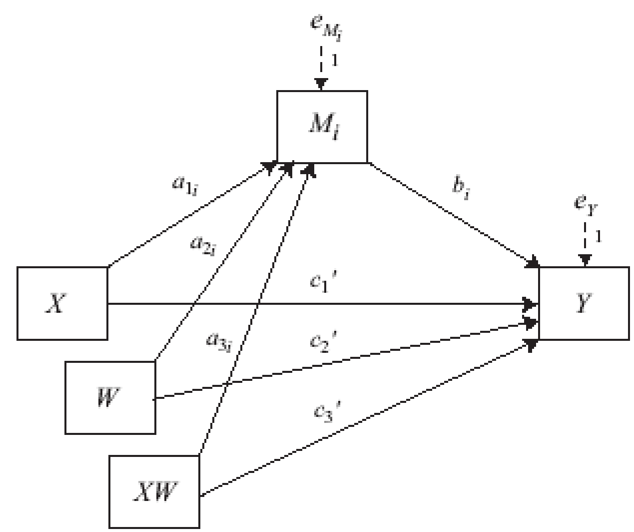
Example #4:

Model 8 is a conditional process model which estimates the conditional direct and indirect effects of *X* on *Y* through *M*, with direct effect and "first stage" moderation by *W*.

Conceptual diagram



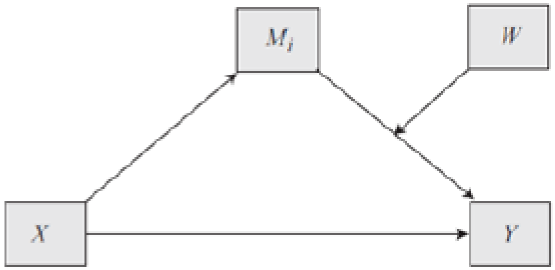
Statistical diagram



Model template system

PROCESS has 56 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

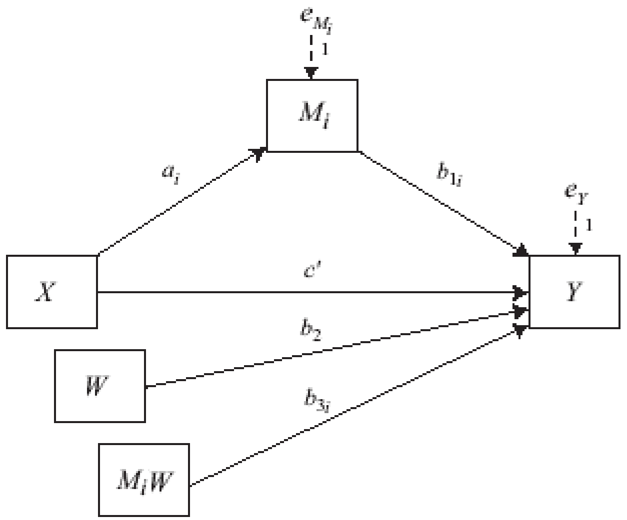
Conceptual diagram



Example #5:

Model 14 is a conditional process model which estimates the direct effect of *X* on *Y* and conditional indirect effects of *X* on *Y* through *M*, with "second stage" moderation by *W*.

Statistical diagram



Model template system

PROCESS has 56 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

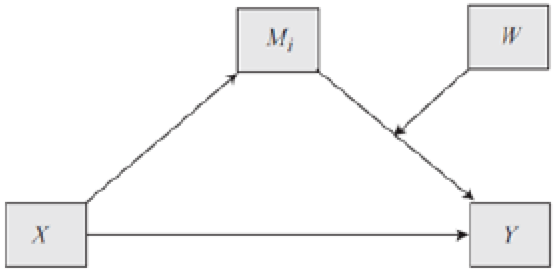
Minimum required specifications

• Which variables play which role in the model (**y= x= m= w =** and so forth)

• Model number (**model=**)

• SAS and R: Data file (**data=**)

Conceptual diagram



SPSS

```
PROCESS y=yvar/x=xvar/m=mvlist/w=wvar/model=14.
```

SAS

```
%process (data=filename,y=yvar,x=xvar,m=mvlist,w=wvar,model=14);
```

R

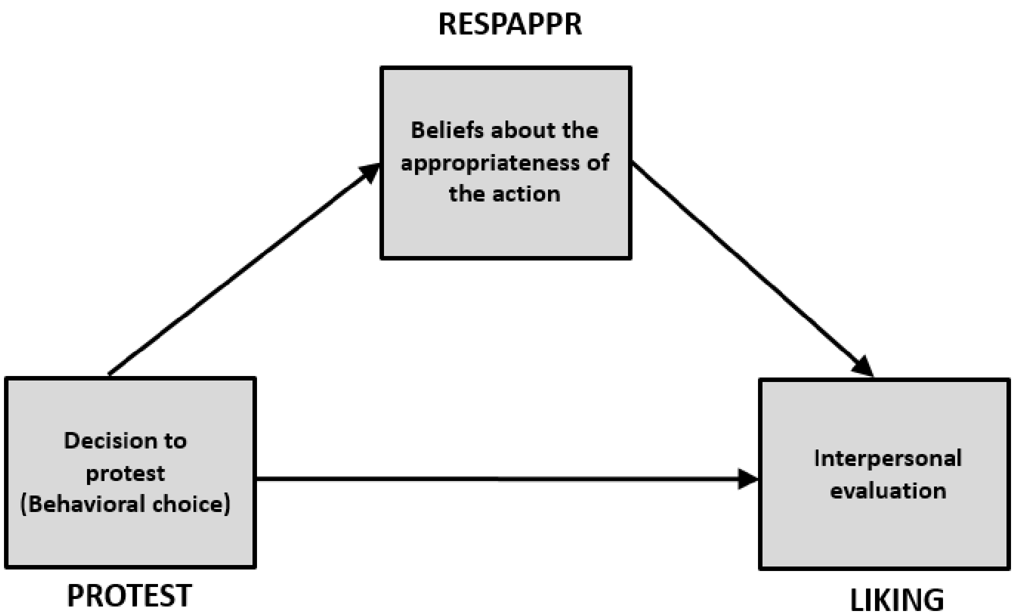
```
process(data=filename,y="yvar",x="xvar",m="mvlist",w="wvar",model=14)
```

Limitations and constraints

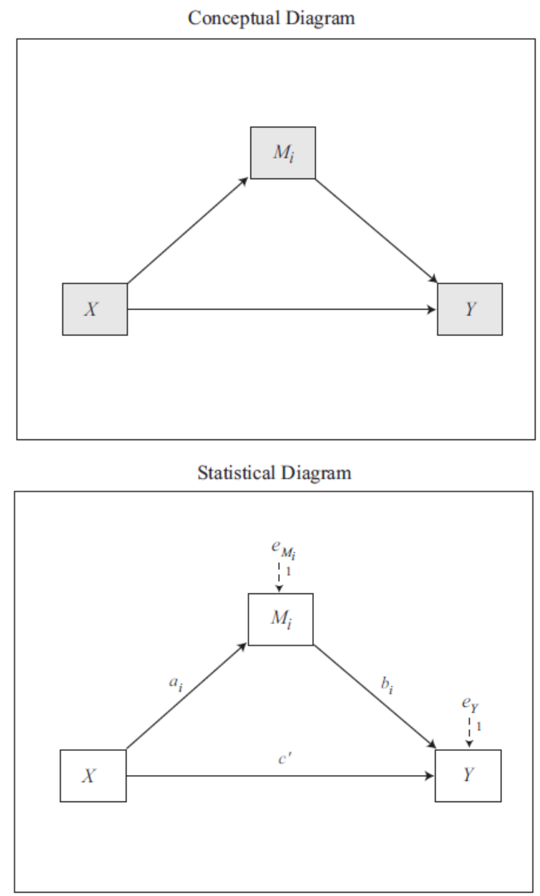
- Only one *X* and one *Y* allowed in a model.
- PROCESS is an OLS or logistic regression modeling tool. Categorical mediators are not allowed.
- Up to 10 mediators in numbered models, 6 in custom models.
- No more than two moderators can be used in any model.
- Most variables can play only one role in the model. Except, a variable can be both a moderator and a covariate in separate equations.
- PROCESS is a single-level observed variable modeling system. No multilevel problems can be analyzed with PROCESS.
- PROCESS requires complete data. Listwise deletion is used for cases missing on any variable in the model.
- Although PROCESS will accept them, it is safer to restrict variable names to eight characters or fewer.

Estimation of the PROTEST model in PROCESS

PROCESS Model 4



Model 4



What should the PROCESS command look like?

Red text not required.

```
process y=liking/x=protest/m=respappr/model=4/boot=10000/normal=1/total=1.
```

```
%process (data=protest, y=liking,x=protest,m=respappr,model=4,boot=10000,normal=1,total=1);
```

```
process(data=protest,y="liking",m="respappr",x="protest",model=4,boot=10000,normal=1,total=1)
```

PROCESS output

```
**************** PROCESS Procedure for SPSS Version 3.00 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : liking
    X  : protest
    M  : respappr

Sample
Size:  129

**************************************************************************
OUTCOME VARIABLE:
 respappr

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4992      .2492     1.3753    42.1550     1.0000   127.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.8841      .1831    21.2078      .0000     3.5217     4.2466
protest      1.4397      .2217     6.4927      .0000     1.0009     1.8785

**************************************************************************
```

$$\widehat{M_i} = 3.884 + 1.440X_i$$

path *a*

PROCESS output

```
**************************************************************************
Outcome: liking

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4959      .2459      .8441    20.5483     2.0000   126.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.7473      .3058    12.2553      .0000     3.1422     4.3524
respappr      .4024      .0695     5.7884      .0000      .2648      .5400
protest      -.1007      .2005     -.5023      .6163     -.4975      .2960

************************** TOTAL EFFECT MODEL ****************************
Outcome: liking

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2131      .0454     1.0601     6.0439     1.0000   127.0000      .0153

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.3102      .1608    33.0244      .0000     4.9921     5.6284
protest       .4786      .1947     2.4584      .0153      .0934      .8639

**************************************************************************
```

$$\widehat{Y}_i = 3.747 - 0.101X_i + 0.402M_i$$

path *b*

path *c′*

$$\widehat{Y}_i = 5.310 + 0.479X_i$$

path *c*

PROCESS output

```
***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .4786      .1947     2.4584      .0153      .0934      .8639

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
     -.1007      .2005     -.5023      .6163     -.4975      .2960

Indirect effect of X on Y
             Effect    Boot SE   BootLLCI   BootULCI
respappr      .5793      .1519      .3113      .9067

Normal theory tests for indirect effect
     Effect         se          Z          p
      .5793      .1350     4.2924      .0000
```

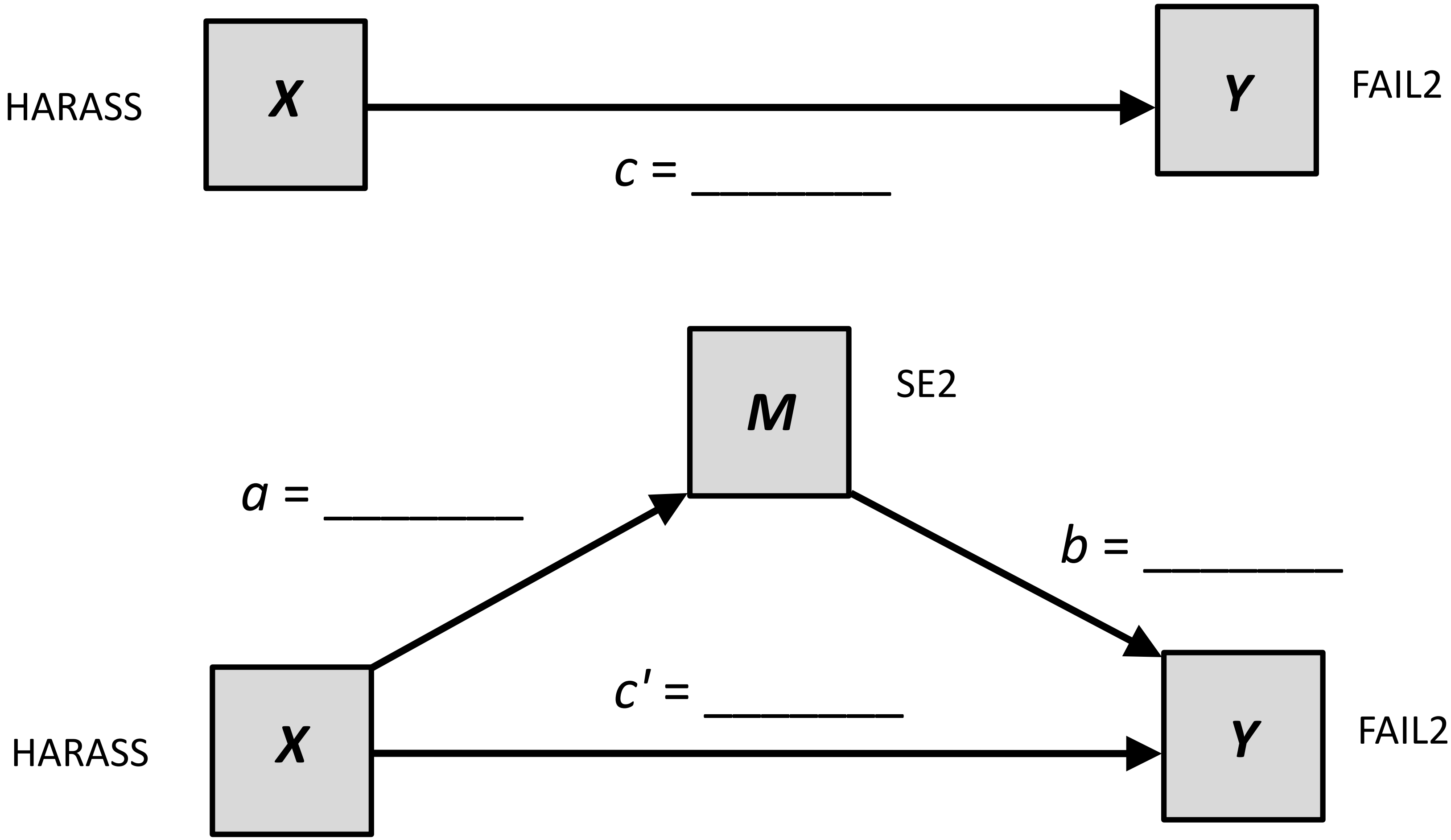
path *c*

path *c′*

ab with 95% bootstrap confidence interval

Sobel test

Her behavior was perceived as more appropriate if she protested relative to when she did not (a = 1.440), and the more appropriate her behavior, the more positively she was perceived (b = 0.402). Her choice to protest had a positive effect on how favorably she was perceived indirectly through perceived appropriateness of the response (point estimate: 0.579, 95% CI = 0.311 to 0.907). After accounting for this mechanism, there was no significant effect of her choice to protest on how she was evaluated (direct effect = -0.101, p = 0.62)

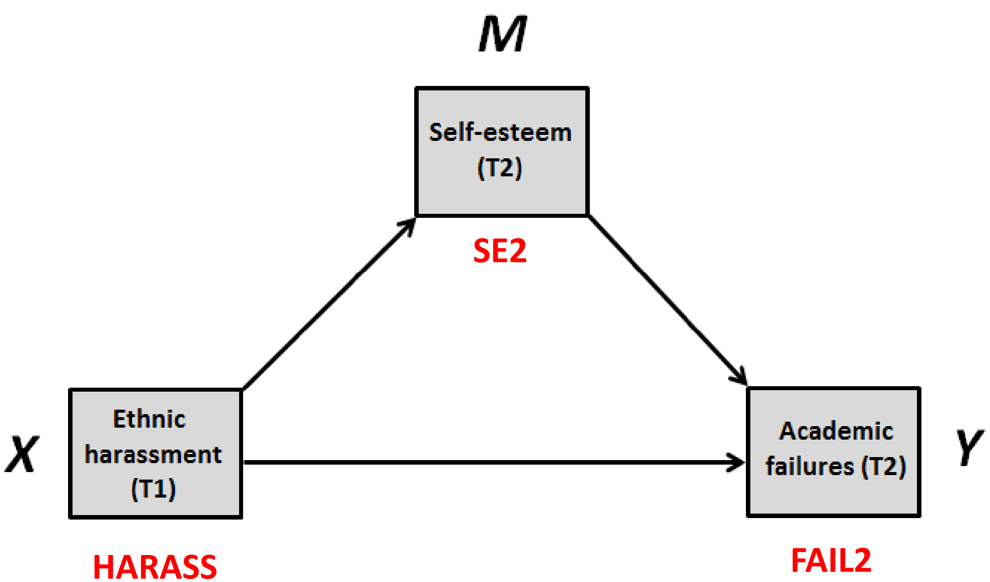


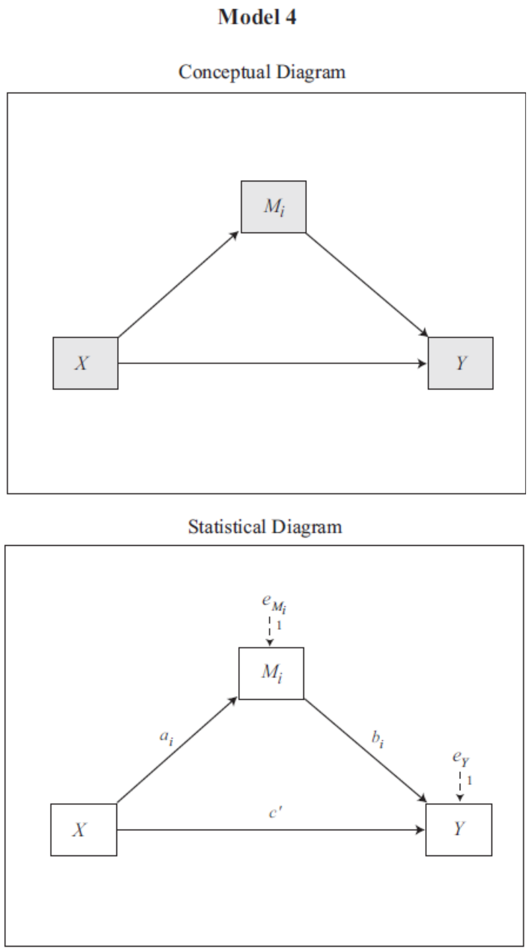
Indirect effect = _______, 95% bootstrap CI = _____________

Your CI will not exactly match. Why?

Estimation of the harassment model in PROCESS

PROCESS Model 4






```
process y=fail2/x=harass/m=se2/model=4/boot=10000
/normal=1 /total=1.
```

```
%process (data=harass,y=fail2,x=harass,m=se2,model=4,
          boot=10000,normal=1,percent=1,total=1);
```

```
process(data=harass,y="fail2",x="harass",m="se2",model=
4,boot=10000,normal=1,total=1)
```

PROCESS output

```
**************** PROCESS Procedure for SPSS Version 3.00 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : fail2
    X  : harass
    M  : se2

Sample
Size:  330

**************************************************************************
OUTCOME VARIABLE:
 se2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2764      .0764      .2905    27.1349     1.0000   328.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.5966      .1235    29.1227      .0000     3.3536     3.8395
harass       -.4156      .0798    -5.2091      .0000     -.5725     -.2586
```

$$\widehat{M_i} = 3.597 - 0.416X_i$$

$\boxed{\text{harass} \quad -.4156 \quad .0798 \quad -5.2091 \quad .0000 \quad -.5725 \quad -.2586}$ path a

PROCESS output

```
**************************************************************************
Outcome: fail2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3397      .1154      .2215    21.3247     2.0000   327.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.3845      .2042    11.6757      .0000     1.9827     2.7863
se2          -.2887      .0482    -5.9879      .0000     -.3836     -.1939
harass        .0616      .0725      .8499      .3960     -.0810      .2042

************************** TOTAL EFFECT MODEL ****************************
Outcome: fail2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1356      .0184      .2451     6.1419     1.0000   328.0000      .0137

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.3460      .1134    11.8660      .0000     1.1229     1.5692
harass        .1816      .0733     2.4783      .0137      .0374      .3257

**************************************************************************
```

$$\widehat{Y}_i = 2.385 + 0.062X_i - 0.289M_i$$

path *b*

path *c′*

$$\widehat{Y}_i = 1.346 + 0.182X_i$$

path *c*

PROCESS output

```
***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .1816      .0733     2.4783      .0137      .0374      .3257

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .0616      .0725      .8499      .3960     -.0810      .2042

Indirect effect of X on Y
        Effect    Boot SE   BootLLCI   BootULCI
se2      .1200      .0321      .0629      .1899

Normal theory tests for indirect effect
     Effect         se          Z          p
      .1200      .0308     3.8993      .0001
```

path c

path c'

ab with 95% bootstrap confidence interval

Sobel test

Kids one unit higher in harassment frequency were 0.416 units lower in self esteem one year later (a = -0.416), and lower self-esteem was related to higher perceived academic failure (b = -0.289). So harassment indirectly affected perceived academic failure (point estimate: 0.120, 95% bootstrap CI = 0.063 to 0.190). After accounting for this mechanism, there was no evidence of an effect of harassment on perceived academic failure (direct effect = 0.062, p = 0.396, 95% CI = -0.081 to 0.204)

Some additional options

SPSS

```
process y=liking/x=protest/m=respappr/model=4/boot=10000/normal=1/total=1/
         effsize=1/conf=99/save=1/seed=25545.
```

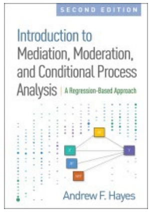
SAS

```
%process (data=protest, y=liking,x=protest,m=respappr,model=4,boot=10000,
         normal=1,total=1,effsize=1,conf=99,save=boots,seed=25545);
```

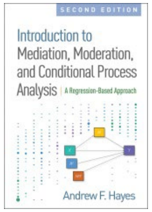
R

```
process (data=protest, y=“liking”,x=“protest”,m=“respappr”,model=4,boot=10000,
         normal=1,total=1,effsize=1,conf=99,save=1,seed=25545);
```

EFFSIZE=1:	Generates various effect size measures for the indirect effect.
MC=1:	Generates Monte Carlo confidence intervals for indirect effect.
CONF=z:	Changes level of confidence to z% for confidence intervals.
SAVE=1	in SPSS, produces a file of all bootstrap estimates of all regression coefficients in the model.
OR	
SAVE=fn	In SAS, saves bootstrap estimates to file named “fn”
SEED=xxxx:	Seeds the random number generator for replication of resamples over repeated runs of PROCESS.



See the documentation in Appendix A of IMMCPA for details.



Effect Sizes in Mediation

There have been multiple proposed effect sizes for mediation analysis. Some of which are generated in PROCESS.

Partially and Completely Standardized Indirect Effects

$$ab_{ps} = \frac{ab}{SD_Y}$$ Recommended for dichotomous X and continuous Y

$$ab_{cs} = \frac{SD_X ab}{SD_Y}$$ Recommended for continuous X and continuous Y

Both generated in PROCESS with `effsize=1`

ν seems to perform well, but isn't available in most software (Lachowicz, Preacher, and Kelley, 2018)

Not Recommended Measures

$$P_M = \frac{ab}{c}$$ "Proportion of total effect that is mediated". Can be > 1 or < 0 (not a proportion). High sampling variability

$$R_M = \frac{ab}{c'}$$ "Ratio of indirect to direct." When c' is small, effect size will be huge (not because ab is large). High sampling variability

R^2_{med} and κ^2 are also not recommended, but hard to calculate without software

What about Baron & Kenny?

Also called the "causal steps" approach, it was popularized by Baron and Kenny (1986) as a test of mediation.

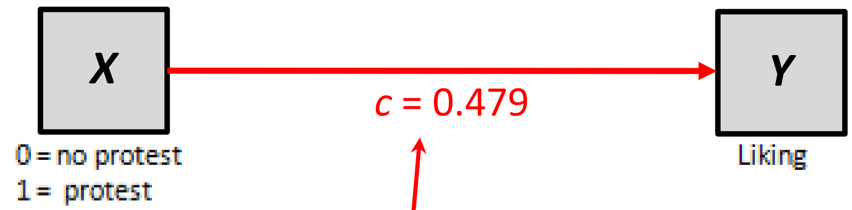
Conditions required to claim *M* functions as a mediator of the relationship between *X* and *Y*:

(1) Does *X* affect *Y?*
(2) Does *X* affect *M* ?
(3) Does *M* affect *Y* holding *X* constant ?

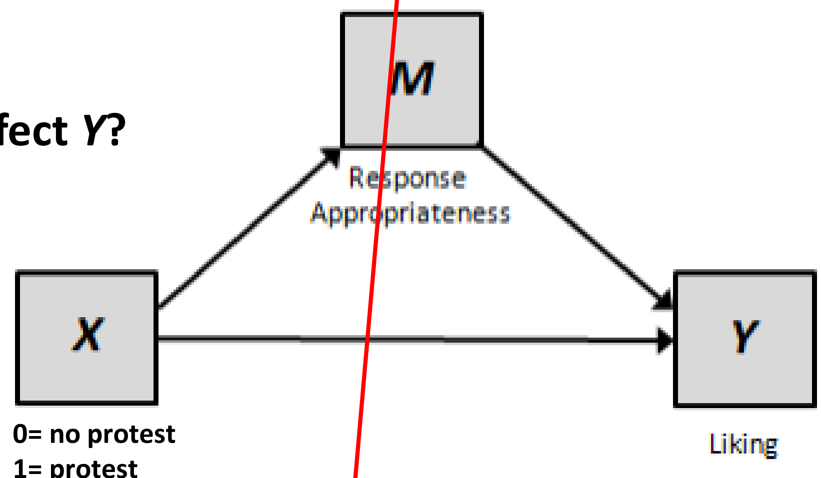
..as gauged by a hypothesis test.

(4) Is the direct effect of *X* closer to zero than the total effect?
  (i) If direct effect is closer to zero than total effect but statistically different from zero, claim "partial mediation"
  (ii) If direct effect is closer to zero than total effect and not statistically different from zero, claim "complete mediation"
  (iii) Otherwise:

Using a set of OLS regression analyses



Condition 1: Does *X* affect *Y*?



Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.313	.161		33.055	.000
	X: experimental condition (0 = no protest, 1 = protest)	.479	.195	.213	2.460	.015

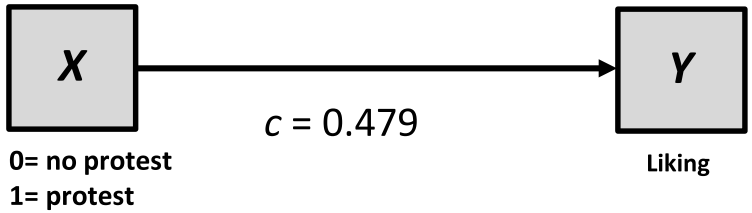
a. Dependent Variable: Y: liking of the target

SPSS:
```
regression/dep=liking/method=enter protest.
```

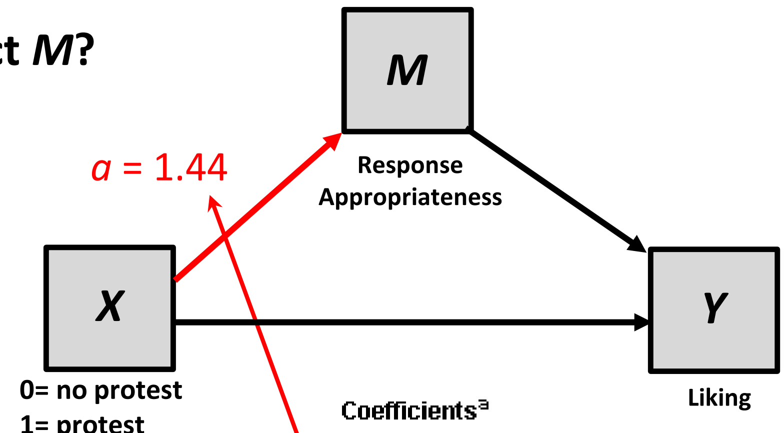
SAS:
```
proc reg data=protest;model liking=protest;run;
```

R:
```
lm(liking~protest, data = protest)
```

Using a set of OLS regression analyses



Condition 2: Does *X* affect *M*?



Coefficients[a]

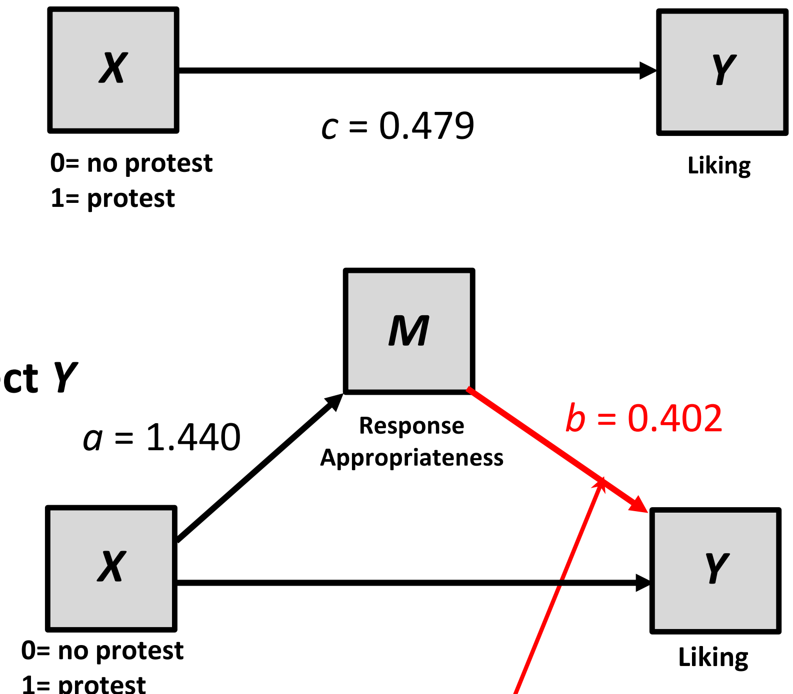
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.884	.183		21.208	.000
	X: experimental condition (0 = no protest, 1 = protest)	1.440	.222	.499	6.493	.000

```
regression/dep=respappr/method=enter protest.
```

```
proc reg data=protest;model respappr=protest;run;
```

```
lm(respappr~protest, data = protest)
```

Using a set of OLS regression analyses



Condition 3: Does *M* affect *Y* holding *X* constant?

Coefficients[a]

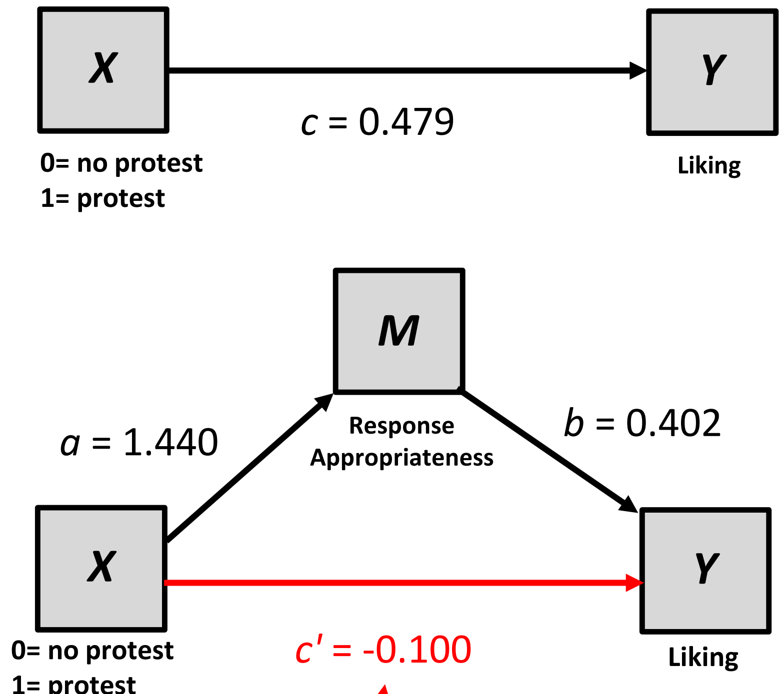
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.751	.306		12.271	.000
	M: appropriateness of response	.402	.069	.517	5.789	.000
	X: experimental condition (0 = no protest, 1 = protest)	-.100	.200	-.045	-.501	.617

```
regression/dep=liking/method=enter respappr protest.
```

```
proc reg data=protest;model liking=respappr protest;run;
```

```
lm(liking~respappr+protest, data = protest)
```

Using a set of OLS regression analyses



4. **Qualitatively compare *c* to *c'***

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.751	.306		12.271	.000
	M: appropriateness of response	.402	.069	.517	5.789	.000
	X: experimental condition (0 = no protest, 1 = protest)	-.100	.200	-.045	-.501	.617

```
regression/dep=liking/method=enter respappr protest.
```

```
proc reg data=protest;model liking=respappr protest;run;
```

```
lm(liking~respappr+protest, data = protest)
```

Problems with the causal steps approach

- ❑ Indirect effect is logically inferred rather than directly estimated

But typically, we make inferences from data using estimates of quantities pertinent to the question. Why should inferences about indirect effects be any different?

A fallacious rebuttal: if *a* and *b* are both different from zero (as established by rejection of the null hypothesis) so too must their product, so no estimate or test of indirect effect is needed.

a) Although this is true at the population level, it isn't necessarily true at the sample level.
b) An indirect effect may be different from zero even in the absence of evidence that both paths *a* and *b* are.

- ❑ If data fail to meet a single criterion, **game over--no indirect effect through *M*.**

The use of multiple, fallible hypothesis tests gives this approach the **lowest power** among competing methods for testing intervening variable effects. **Tests or claims of mediation should not be based on the significance of individual paths in the model.**

Problems with the causal steps approach

- If total effect (path *c*) is not detectably different from zero, the **game doesn't even begin.**

  This is logically sensible if you accept one definition of a mediator variable – a variable that is causally between *X* and *Y* and that **accounts for their association**.

  - By this definition, an effect that does not exist can't be mediated. But the significance of *c* neither constrains nor determines the size of the product of paths *a* and *b*, nor does it tell us whether that product is different from zero.
  - Kenny and Judd (2014, *Psychological Science*) illustrate that a hypothesis test about the total effect is generally less powerful than a hypothesis test about the indirect effect.

- Because the indirect effect is not quantified, this method does not lend itself well to comparisons between indirect effects in multiple mediators models, or to modeling of the size of indirect effects ('conditional process analysis')

“Complete”/”full” and “partial” mediation

The causal steps strategy is often used as a means of labeling a process as “complete” or “partial mediation”.   There is little value to this semantic labeling exercise.

- ❑ What if there is no evidence of a total effect (i.e., c non-significant)? This can happen, and actually does more often than people probably realize. Thus, these concepts don’t have a place much of the time.

- ❑ The reliance on statistical significance criteria means that when power is high for the test on c' partial mediation is the best you can hope for, and when power is relatively low, complete mediation is more likely. So if establishing complete mediation is your goal, <u>you should intentionally limit the size of your sample to as small as necessary</u>

- ❑ Establishing complete mediation by your favored mediator does not preclude others from being able to make the same claim with their own favored mediator.

- ❑ “Direct effects” don’t exist in reality. All effects are mediated by something. Thus, a claim of ‘partial mediation’ is a claim that one has not specified the model correctly.

Experts in mediation analysis have abandoned these concepts, and so should you. They are of historical interest only these days.

Mediation analysis summary thus far

- Mediators are variables which are causally located between two variables *X* and *Y* and that explain, in part, the effect of *X* on *Y*. *X* affects *M* which in turn affects *Y*.

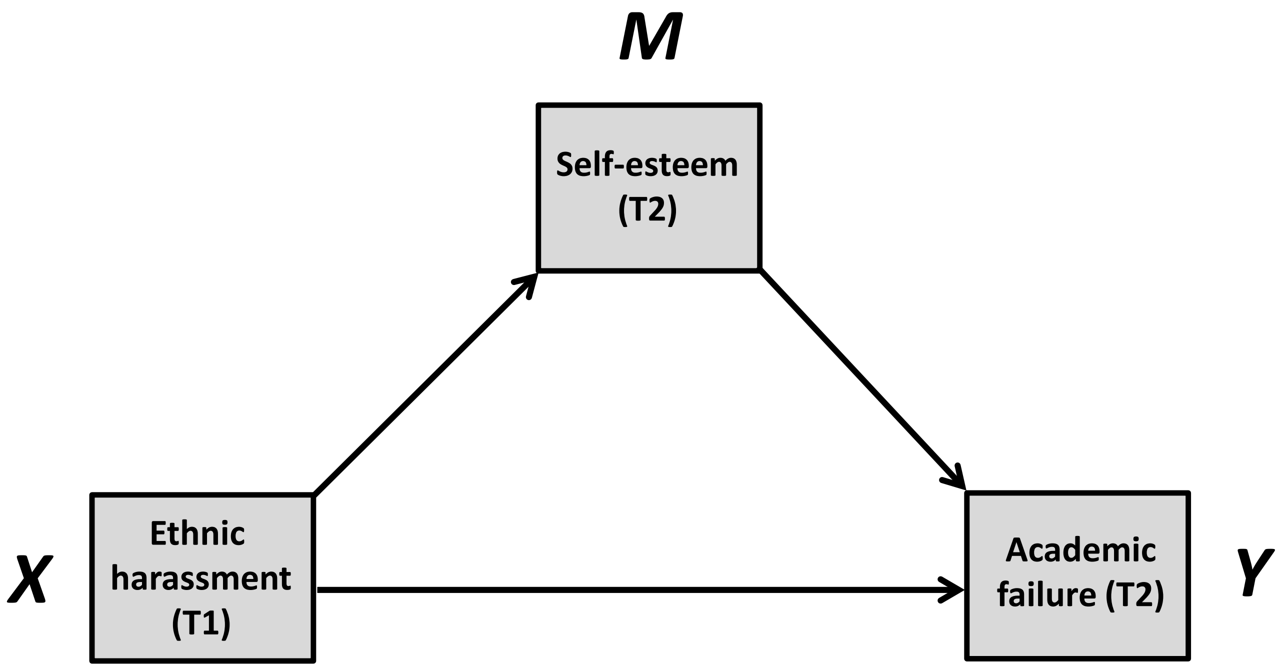
- The causal steps strategy popularized by Baron and Kenny (1986) remains a popular method for mediation analysis.
  - Yet it is among the lowest in power, in some circumstances, massively so.
  - It is not consistent with modern thinking about mediation analysis.
  - Its use is not recommended. Soon you won't be able to get away with it.

- Tests of mediation should be based on an estimate of the indirect effect.
  - Sobel test for inference in large samples only, but we don't know how large is large enough.
  - Bootstrap or Monte Carlo confidence intervals in a sample of any size.

- There is no need to condition the hunt for an indirect effect on a statistically significant total effect (path *c*).

- Focus interpretation on the size and sign of the indirect effect. Tests of significance for the individual paths ($X \rightarrow M$ and $M \rightarrow Y$) are useful as supplemental information but need not be part of the story.

Our question



Does ethnic harassment influence school performance by affecting self-esteem which in turn affects performance.

Asking this question does not require evidence that there is a bivariate relationship between *X* (ethnic harassment) and *Y* (performance)

Confounding

Kids who reported greater harassment earlier reported lower in self-esteem later, but they also reported lower self-esteem earlier (r = -0.18), and self-esteem was temporally consistent over time (r = 0.51). Furthermore, students who reported lower self esteem later reported greater academic failure later, but these low self-esteem students at time 2 also reported greater academic failure earlier (r = -0.26), and academic failure was temporally consistent (r = 0.30)

Correlations

		harass	se1	fail1	se2	fail2
harass	Pearson Correlation	1	-.176	.196	-.276	.136
	Sig. (2-tailed)		.001	.000	.000	.014
	N	330	330	330	330	330
se1	Pearson Correlation	-.176	1	-.306	.505	-.259
	Sig. (2-tailed)	.001		.000	.000	.000
	N	330	330	330	330	330
fail1	Pearson Correlation	.196	-.306	1	-.255	.297
	Sig. (2-tailed)	.000	.000		.000	.000
	N	330	330	330	330	330
se2	Pearson Correlation	-.276	.505	-.255	1	-.337
	Sig. (2-tailed)	.000	.000	.000		.000
	N	330	330	330	330	330
fail2	Pearson Correlation	.136	-.259	.297	-.337	1
	Sig. (2-tailed)	.014	.000	.000	.000	
	N	330	330	330	330	330

Pre-existing self-esteem and failure confound the relationships we believe to be causal. We want to know whether later self-esteem and academic failure are related to ethnic harassment frequency after accounting for initial self-esteem and failure.

Confounding

Some effects in a mediation model are subject to 'confounding' even when *X* is based on random assignment, making causality harder to establish. Partialing out various confounders can help though won't solve the problem entirely.

$$\hat{Y}_i = c_0 + cX_i + c_2U_i$$

$$\hat{M}_i = a_0 + aX_i + a_2U_i$$

$$\hat{Y}_i = c'_0 + c'X_i + bM_i + c'_2U_i$$

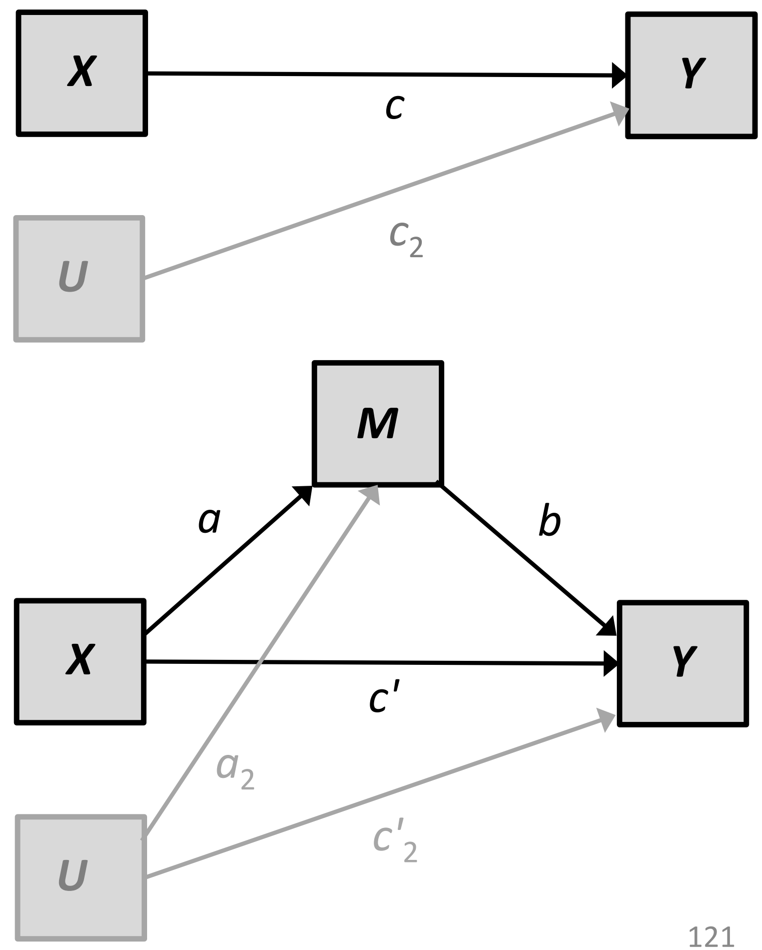
total effect = direct effect + indirect effect

c = c' + $(a \times b)$

indirect effect = total effect – direct effect

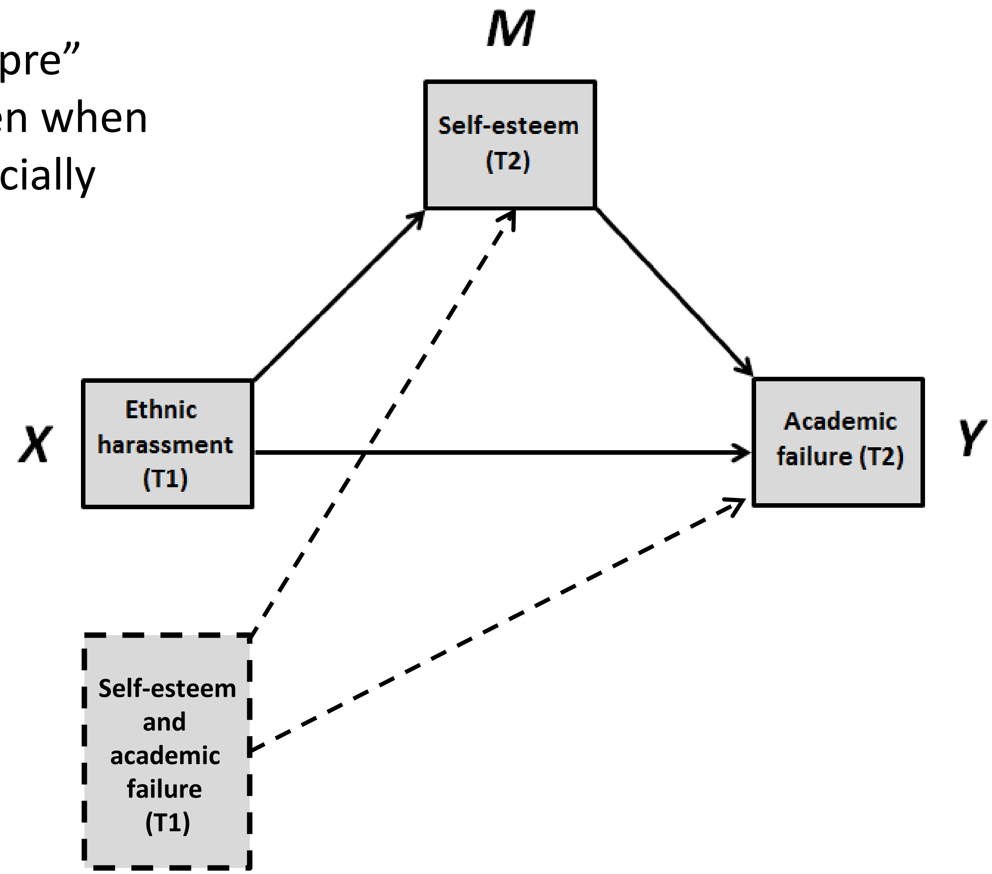
$a \times b$ = c – c'

A simple mediation model, adjusting for a potential confounding variable (*U*)



Some rationales for adjusting for prior state

When available, it is desirable to include "pre" measures of *M* and/or *Y* as covariates, even when *X* is experimentally manipulated, but especially when it is not.

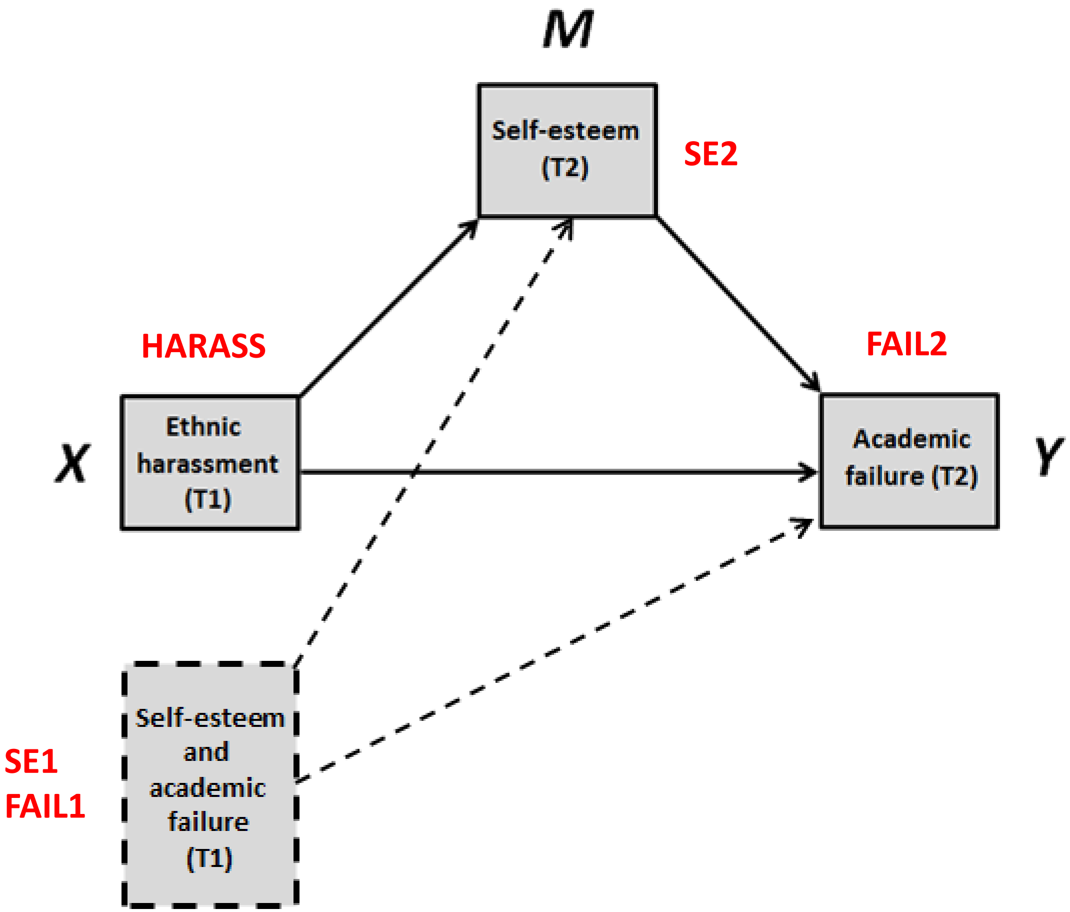


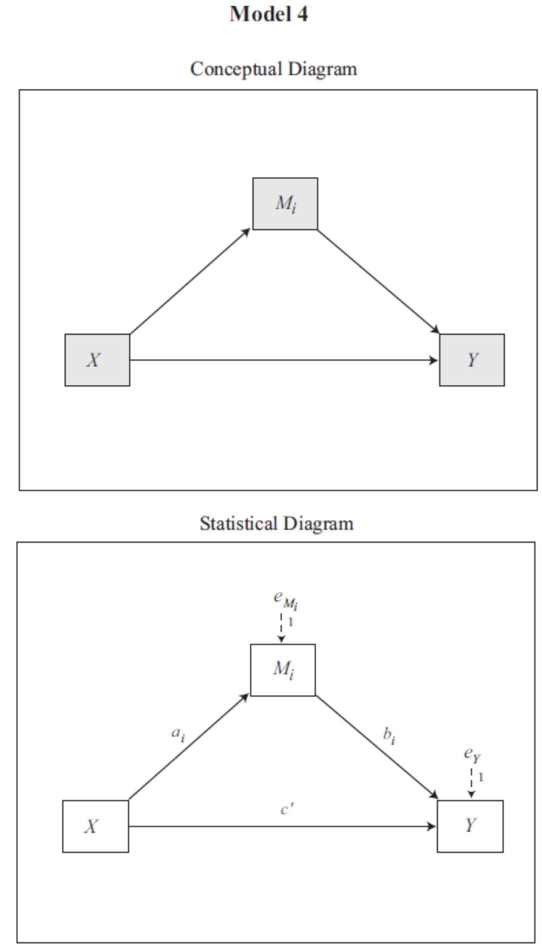
(a) Doing so can **increase precision** in the estimation of *X*'s effect on *M* and/or *Y* if pre-measures are correlated with later measures (as they typically are).

(b) Prior states often are correlated with *X*, *M*, or *Y*, introducing a **"self-selection" threat** to causal claims. Including prior state helps to reduce that threat.

(c) It gives an interpretation to paths that are **closer to a "change" interpretation** without regression artifacts that can be introduced with the use of difference scores. In this example, the *b* path estimates the relationship between later self-esteem and how much higher or lower a student's failure is given expected later failure from prior self-esteem and failure. Path *a* estimates the relationship between ethnic harassment frequency and how much lower or higher a student's self-esteem is later relative to what would be expected given his or her earlier self-esteem and academic failure.

Adding covariates to a model using PROCESS






```
process cov=se1 fail1/y=fail2/x=harass/m=se2/model=4/
  boot=10000/total=1.
```

```
%process (data=harass, cov=se1 fail1,y=fail2,x=harass,m=se2,
  model=4,boot=10000,total=1);
```

```
process (data=harass, cov=c("se1", "fail1"),y="fail2",x="harass",m="se2",
  model=4,boot=10000,total=1)
```

PROCESS output

```
**************** PROCESS Procedure for SPSS Version 3.00 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : fail2
    X  : harass
    M  : se2

Covariates:
 se1       fail1

Sample
Size:  330

**************************************************************************
OUTCOME VARIABLE:
 se2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5450      .2971      .2224    45.9259     3.0000   326.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.0280      .2412     8.4095      .0000     1.5536     2.5024
harass       -.2728      .0717    -3.8025      .0002     -.4139     -.1317
se1           .4879      .0536     9.1081      .0000      .3825      .5933
fail1        -.1010      .0606    -1.6661      .0967     -.2202      .0182

**************************************************************************
```

path *a*

PROCESS output

****
Outcome: fail2

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4059	.1648	.2105	16.0276	4.0000	325.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI	
constant	2.0934	.2588	8.0900	.0000	1.5843	2.6025	
se2	-.2175	.0539	-4.0375	.0001	-.3235	-.1115	path *b*
harass	.0196	.0713	.2754	.7832	-.1207	.1599	path *c'*
se1	-.0672	.0584	-1.1517	.2503	-.1820	.0476	
fail1	.2307	.0592	3.8966	.0001	.1142	.3471	

************************* TOTAL EFFECT MODEL ****************************
Outcome: fail2

Model Summary

R	R-sq	MSE	F	df1	df2	p
.3505	.1229	.2203	15.2219	3.0000	326.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI	
constant	1.6523	.2400	6.8842	.0000	1.1801	2.1245	
harass	.0790	.0714	1.1060	.2695	-.0615	.2194	path *c*
se1	-.1733	.0533	-3.2513	.0013	-.2782	-.0685	
fail1	.2526	.0603	4.1886	.0000	.1340	.3713	

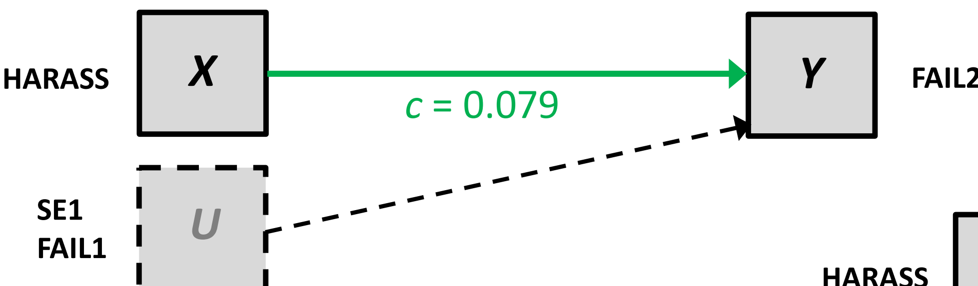
PROCESS output

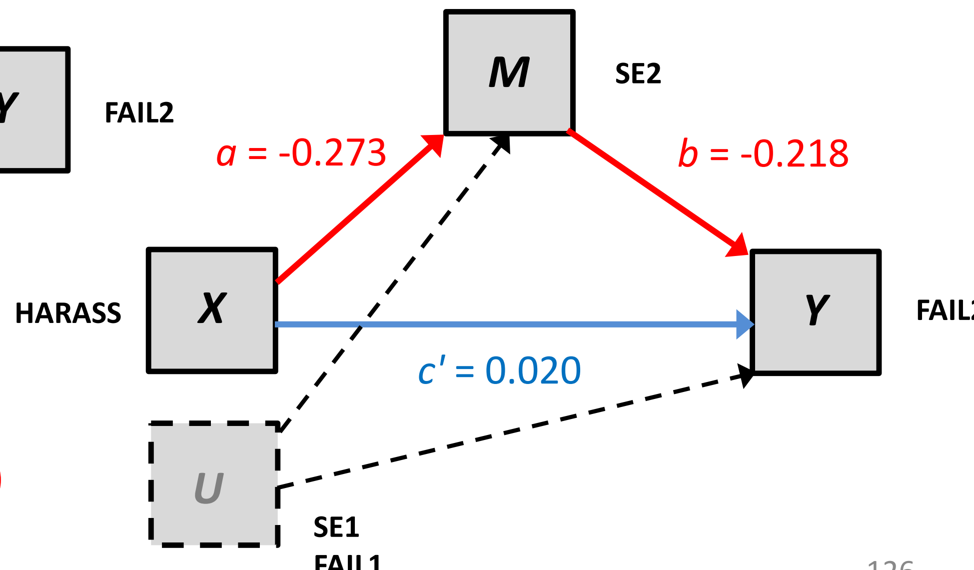
```
**************** TOTAL, DIRECT, AND INDIRECT EFFECTS *******************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .0790      .0714     1.1060      .2695     -.0615      .2194

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .0196      .0713      .2754      .7832     -.1207      .1599

Indirect effect of X on Y
        Effect    Boot SE   BootLLCI   BootULCI
se2      .0593      .0229      .0203      .1089
```

path *c*

path *c*′

ab with 95% bootstrap confidence interval

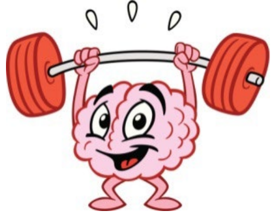




$$c \quad = \quad c' \quad + \quad a \quad \times \quad b$$

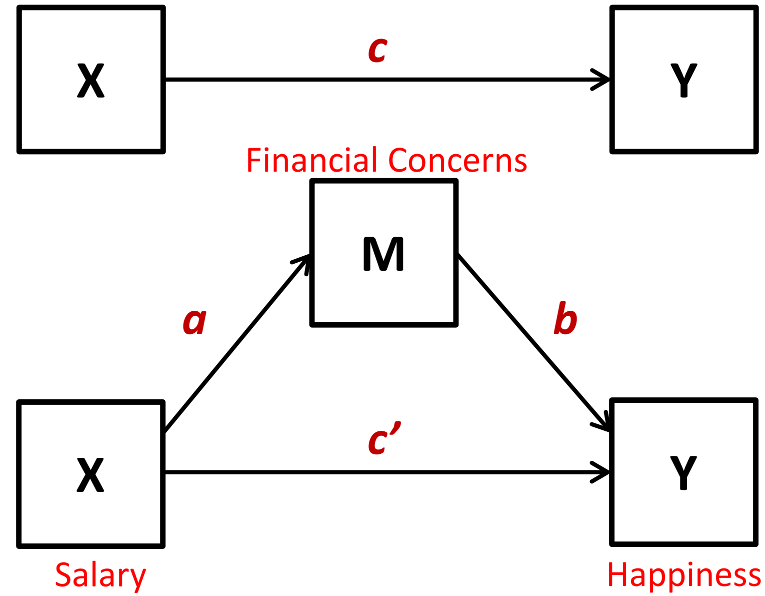
$$0.079 = 0.020 + (-0.273)(-0.218)$$

$$0.079 = 0.020 + 0.059$$



Path Analysis: Exercise Example

Suppose the true state of the world is such, and salary is measured in thousands of dollars per year (i.e. a one unit increase in salary corresponds to a $1000 increase in salary/year): An increase in salary of **$2,000/year** is associated with an overall increase in happiness of **3**. Suppose also that an increase in salary of **$1,000/year** is associated with a decrease in financial concerns by **2**. It is known that increasing financial concerns by **1** decreases happiness by **.5** when controlling for salary.



$$Y_i = i_{Y*} + cX_i + e_{Y_i^*}$$

$$M_i = i_M + aX_i + e_{M_i}$$

$$Y_i = i_Y + c'X_i + bM_i + e_{Y_i}$$

What are the values for:

a = ____________ total = ______________

b = ____________ direct = ______________

c = ____________ indirect = _________________

c′ = ____________

Direct effect of X on Y (not through M) = *c′*

Indirect effect of X on Y (through M) = $a \times b$

Total effect = direct effect + indirect effect

$c = c' + a \times b$

Indirect effect = total effect - direct effect

$a \times b = c - c'$

Moderation

Moderation. The effect of X on Y can be said to be *moderated* if its size or direction is dependent on some third variable W. It tells us about the conditions that facilitate, enhance, or inhibit the effect, or for whom or what the effect is large vs. small, present vs. absent, positive vs. negative vs. zero.

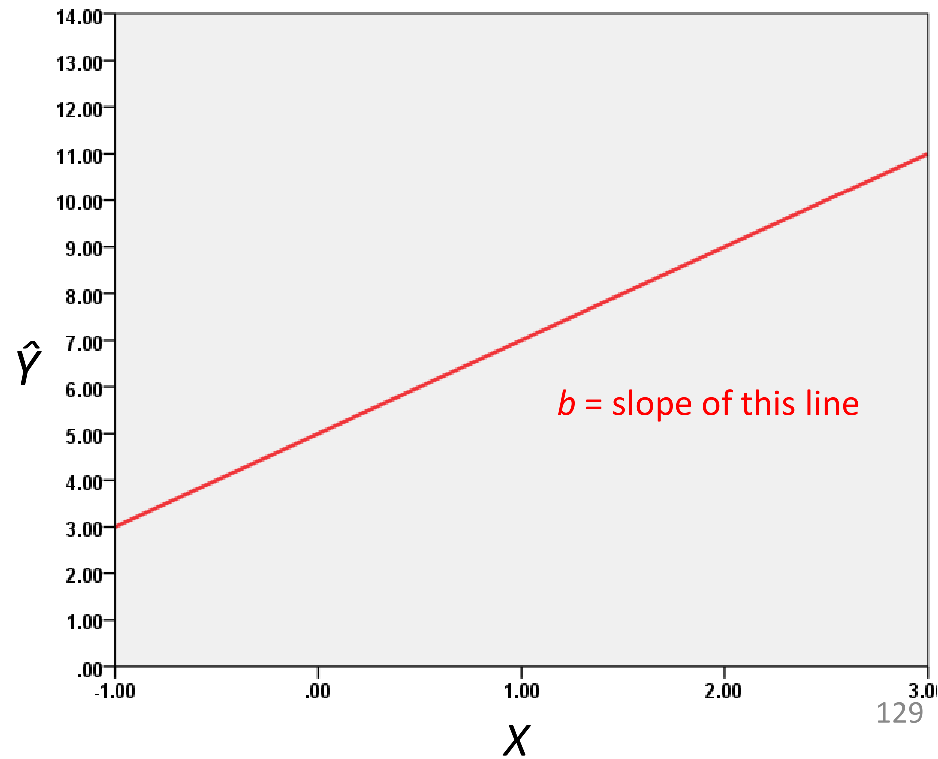
The simple regression coefficient

Consider a simple regression model with predictor variable *X*.

$$\widehat{Y}_i = b_0 + bX_i \quad \text{such as} \quad \widehat{Y}_i = 5.00 + 2.00X_i$$

Two cases that differ by one unit on *X* are estimated to differ by *b* = 2.00 units on *Y*. *b* is a "global property" of the model, in that makes no difference which value of *X* you start at---*b* is the estimated difference in *Y* between two cases who differ by a unit on *X*. Most generally, $b = \hat{Y}|(X = \omega + 1) - \hat{Y}|(X = \omega)$ for all ω.

X	$\hat{Y}$
-1	3.00
0	5.00
1	7.00
2	9.00
3	11.00



Partial regression coefficients as unconditional effects

Consider a multiple regression model with two predictors, *X* and *W*.

$$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i \text{ such as } \widehat{Y}_i = 4.50 + 2.00 X_i + 0.50 W_i$$

Regardless of *W*, a one unit difference in *X* is associated with the same expected difference on *Y*. And regardless of the value of *X*, a one unit difference in *W* is associated with the same expected difference on *Y*. This is true regardless of which value of *X* or *W* you choose. b_1 and b_2 are global properties of the model.

X	W	$\hat{Y}$
-1	0	2.50
-1	1	3.00
-1	2	3.50
0	0	4.50
0	1	5.00
0	2	5.50
1	0	6.50
1	1	7.00
1	2	7.50
2	0	8.50
2	1	9.00
2	2	9.50

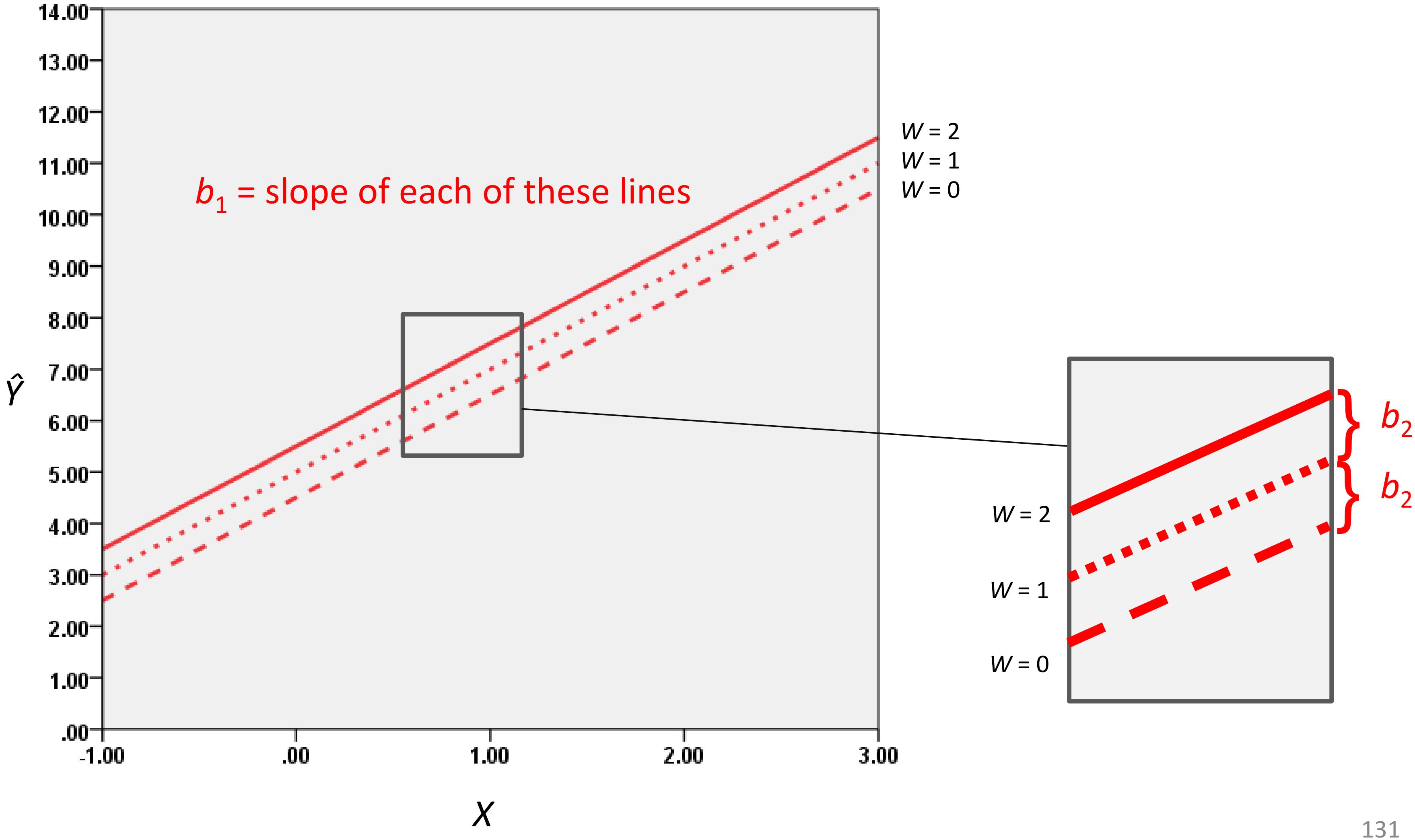
Most generally,

$b_1 = \hat{Y} | (X = \omega + 1, W = \lambda) - \hat{Y} | (X = \omega, W = \lambda)$ for all ω, λ

$b_2 = \hat{Y} | (W = \lambda + 1, X = \omega) - \hat{Y} | (W = \lambda, X = \omega)$ for all λ, ω

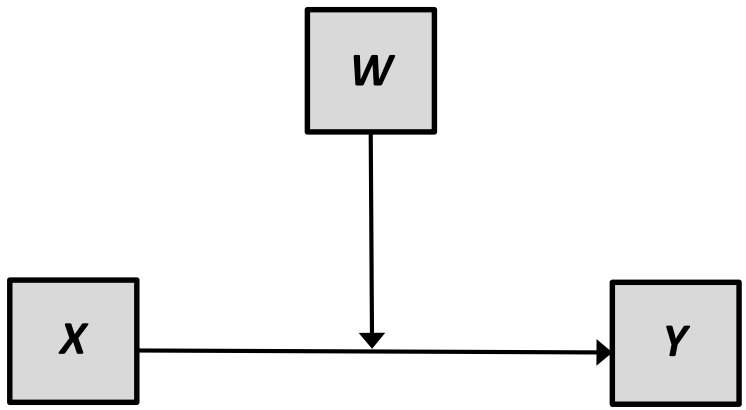
Partial regression coefficients as unconditional effects

$$\hat{Y}_i = 4.50 + 2.00X_i + 0.50W_i$$



Moderation

Moderation. The effect of *X* on *Y* can be said to be *moderated* if its size or direction is dependent on some third variable *W*. It tells us about the conditions that facilitate, enhance, or inhibit the effect, or for whom or what the effect is large vs. small, present vs. absent, positive vs. negative vs. zero.



In this diagram, *W* is depicted to *moderate* the size of the effect of *X* on *Y*, meaning that the size of the effect of *X* on *Y* depends on *W*. In such a case, we say *W* is the *moderator* of the $X \rightarrow Y$ relationship, or that *X* and *W* *interact* in their influence on *Y*. *X* is sometimes called the focal predictor, and *W* the moderator.

Releasing this constraint on the model

Suppose we let *X*'s effect be a function of *W*, *f*(*W*), as in

$$\widehat{Y}_i = b_0 + f(W_i)X_i + b_2W_i$$

For instance, let *f*(*W*) be a linear function of *W*, $b_1 + b_3W$. Thus,

$$\widehat{Y}_i = b_0 + (b_1 + b_3W_i)X_i + b_2W_i$$

This can be rewritten in an equivalent form as

$$\widehat{Y}_i = b_0 + b_1X_i + b_2W_i + b_3X_iW_i$$

This model, the "simple moderation model," allows *X*'s effect on *Y* to depend linearly on *W*. Other forms of moderation are possible, but this form is the one most frequently estimated.

Moderation

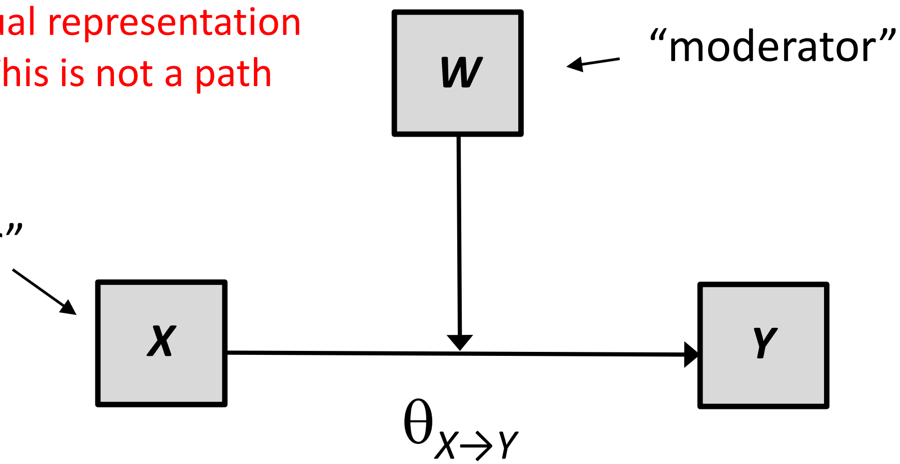
$$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$$

can be written as

$$\widehat{Y}_i = b_0 + (b_1 + b_3 W_i) X_i + b_2 W_i$$

This is a conceptual representation of moderation. This is not a path diagram.

"focal predictor"



$\theta_{X \rightarrow Y} = b_1 + b_3 W$

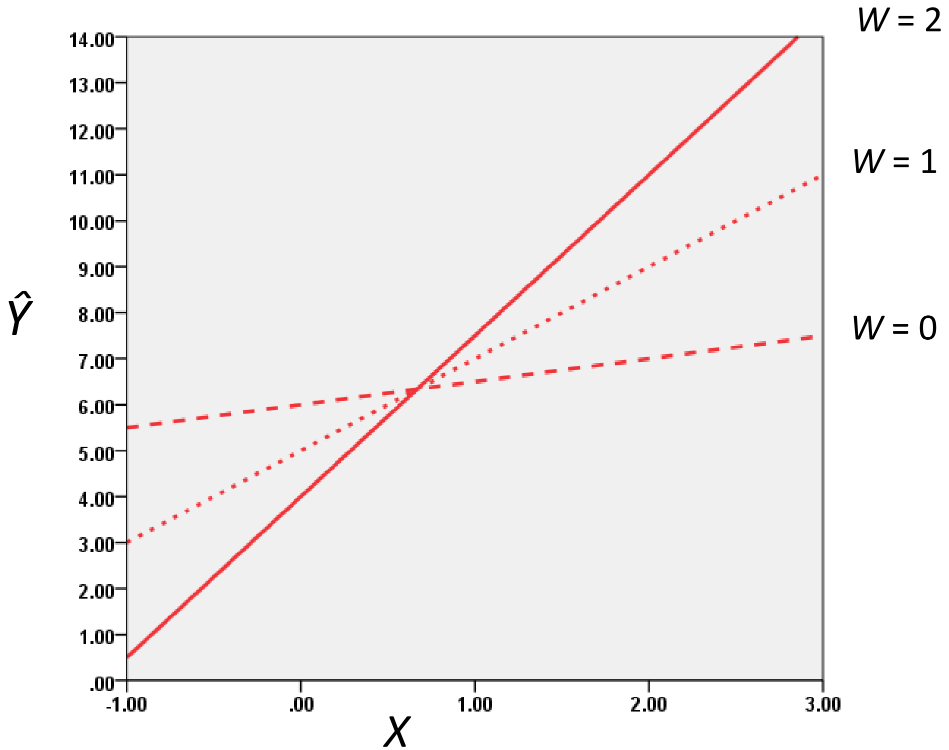
$\theta_{X \rightarrow Y}$ is the "conditional effect of *X*" defined by the function $b_1 + b_3 W$

X's effect as a function of *W*

b_0 = 6.00
b_1 = 0.50
b_2 = -1.00
b_3 = 1.50

$$\widehat{Y}_i = 6.00 + 0.50X_i - 1.00W_i + 1.50X_iW_i$$

Observe that the amount by which two cases that differ by one unit on *X* are estimated to differ on *Y* **depends on** *W*.



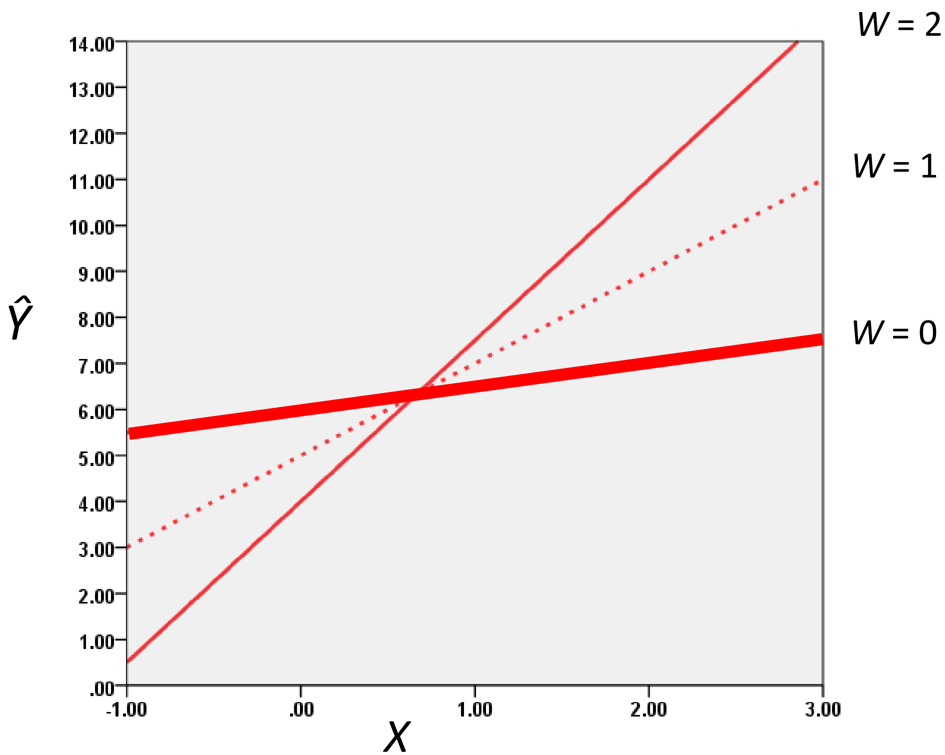
X	W	$\hat{Y}$
-1	0	5.50
-1	1	3.00
-1	2	0.50
0	0	6.00
0	1	5.00
0	2	4.00
1	0	6.50
1	1	7.00
1	2	7.50
2	0	7.00
2	1	9.00
2	2	11.00

X's effect as a function of *W*

b_0 = 6.00
b_1 = 0.50
b_2 = -1.00
b_3 = 1.50

$$\hat{Y}_i = 6.00 + 0.50X_i - 1.00W_i + 1.50X_iW_i$$

Observe that the amount by which two cases that differ by one unit on *X* are estimated to differ on *Y* **depends on** *W*.



X	W	$\hat{Y}$
-1	0	5.50
-1	1	3.00
-1	2	0.50
0	0	6.00
0	1	5.00
0	2	4.00
1	0	6.50
1	1	7.00
1	2	7.50
2	0	7.00
2	1	9.00
2	2	11.00

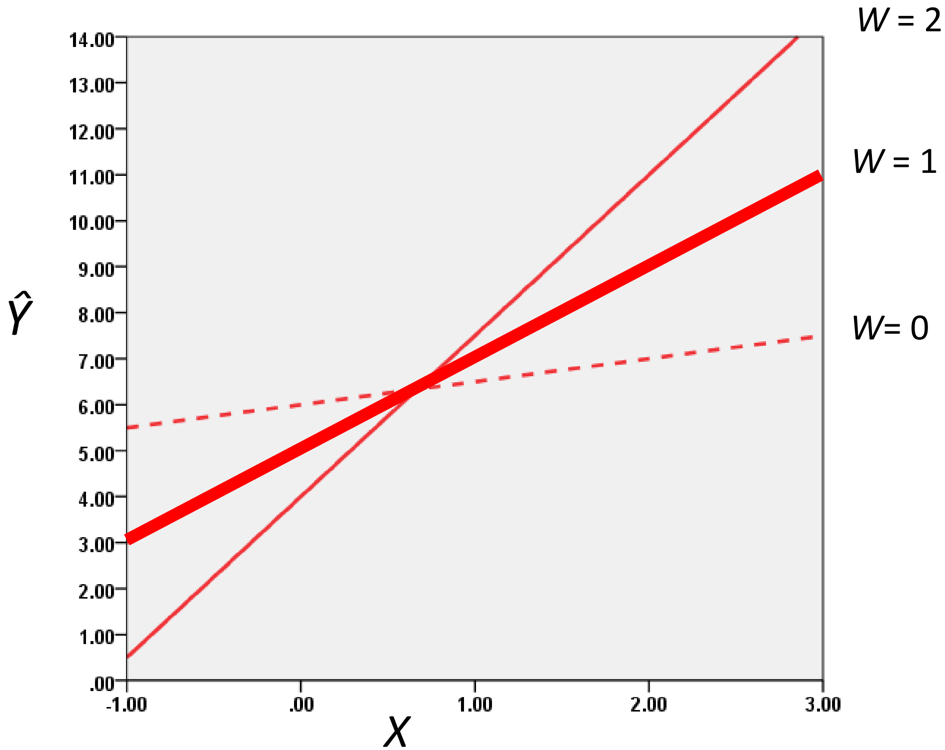
$$\theta_{X\to Y} = b_1 + b_3W$$
$$= 0.50 + 1.50W$$
$$= 0.50 + 1.50(0) = 0.50$$

X's effect as a function of W

$b_0 = 6.00$
$b_1 = 0.50$
$b_2 = -1.00$
$b_3 = 1.50$

$$\hat{Y}_i = 6.00 + 0.50X_i - 1.00W_i + 1.50X_iW_i$$

Observe that the amount by which two cases that differ by one unit on X are estimated to differ on Y **depends on** W.



X	W	$\hat{Y}$
-1	0	5.50
-1	1	3.00
-1	2	0.50
0	0	6.00
0	1	5.00
0	2	4.00
1	0	6.50
1	1	7.00
1	2	7.50
2	0	7.00
2	1	9.00
2	2	11.00

$$\theta_{X\rightarrow Y} = b_1 + b_3W$$
$$= 0.50 + 1.50W$$
$$= 0.50 + 1.50(1) = 2.00$$

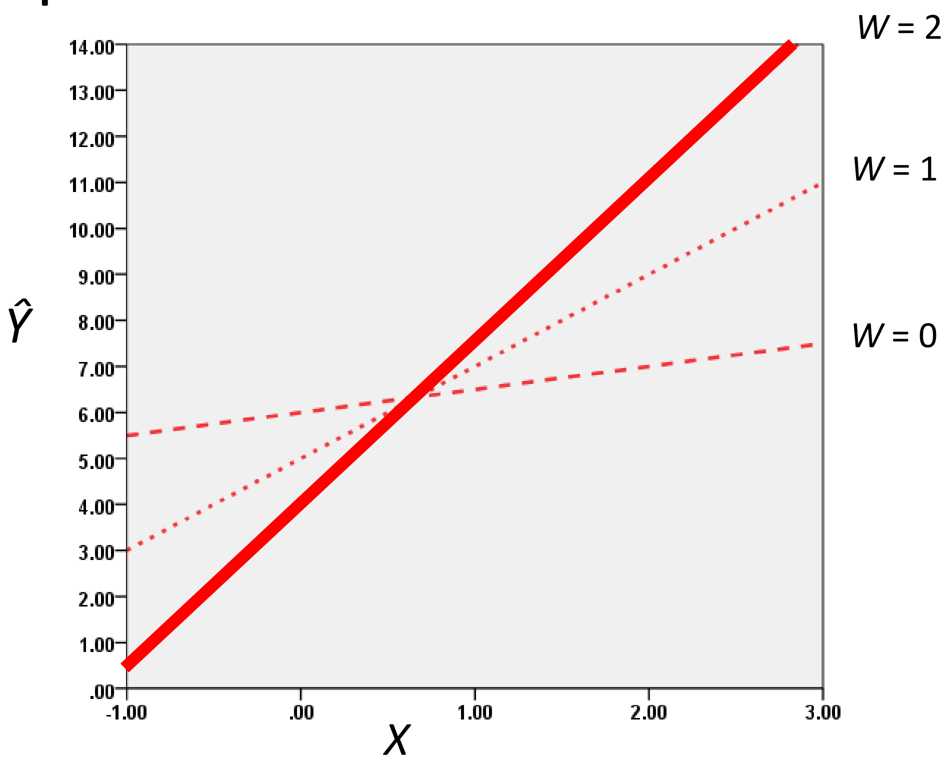
X's effect as a function of *W*

b_0 = 6.00
b_1 = 0.50
b_2 = -1.00
b_3 = 1.50

$$\hat{Y}_i = 6.00 + 0.50X_i - 1.00W_i + 1.50X_iW_i$$

X	W	$\hat{Y}$
-1	0	5.50
-1	1	3.00
-1	2	0.50
0	0	6.00
0	1	5.00
0	2	4.00
1	0	6.50
1	1	7.00
1	2	7.50
2	0	7.00
2	1	9.00
2	2	11.00

Observe that the amount by which two cases that differ by one unit on *X* are estimated to differ on *Y* **depends on** *W*.



$$\theta_{X \to Y} = b_1 + b_3W$$
$$= 0.50 + 1.50W$$
$$= 0.50 + 1.50(2) = 3.50$$

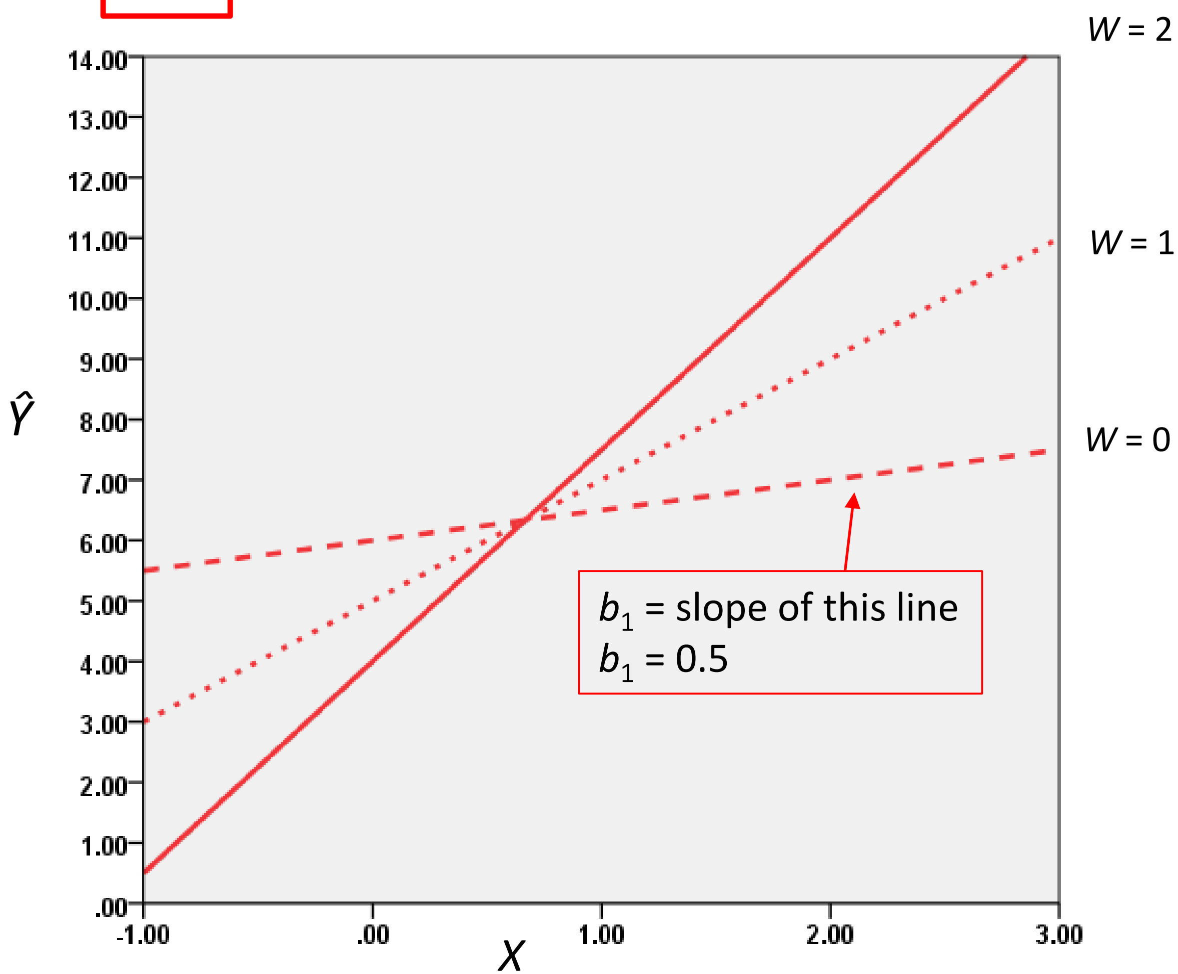
Interpretation of b_1 as a conditional effect

$b_0 = 6.00$
$b_1 = 0.50$
$b_2 = -1.00$
$b_3 = 1.50$

$$\widehat{Y}_i = 6.00 + \boxed{0.50}X_i - 1.00W_i + 1.50X_iW_i$$

b_1 is the effect of *X* on *Y* when *W* = 0. It quantifies how much two cases that differ by one unit on *X* but with *W* = 0 are estimated to differ on *Y*.

b_1 is a local property of the model. It characterizes the association between *X* and *Y* only when *W* = 0.



$b_1 = \hat{Y}|(X = \omega + 1, W = 0) - \hat{Y}|(X = \omega, W = 0)$ for all ω.

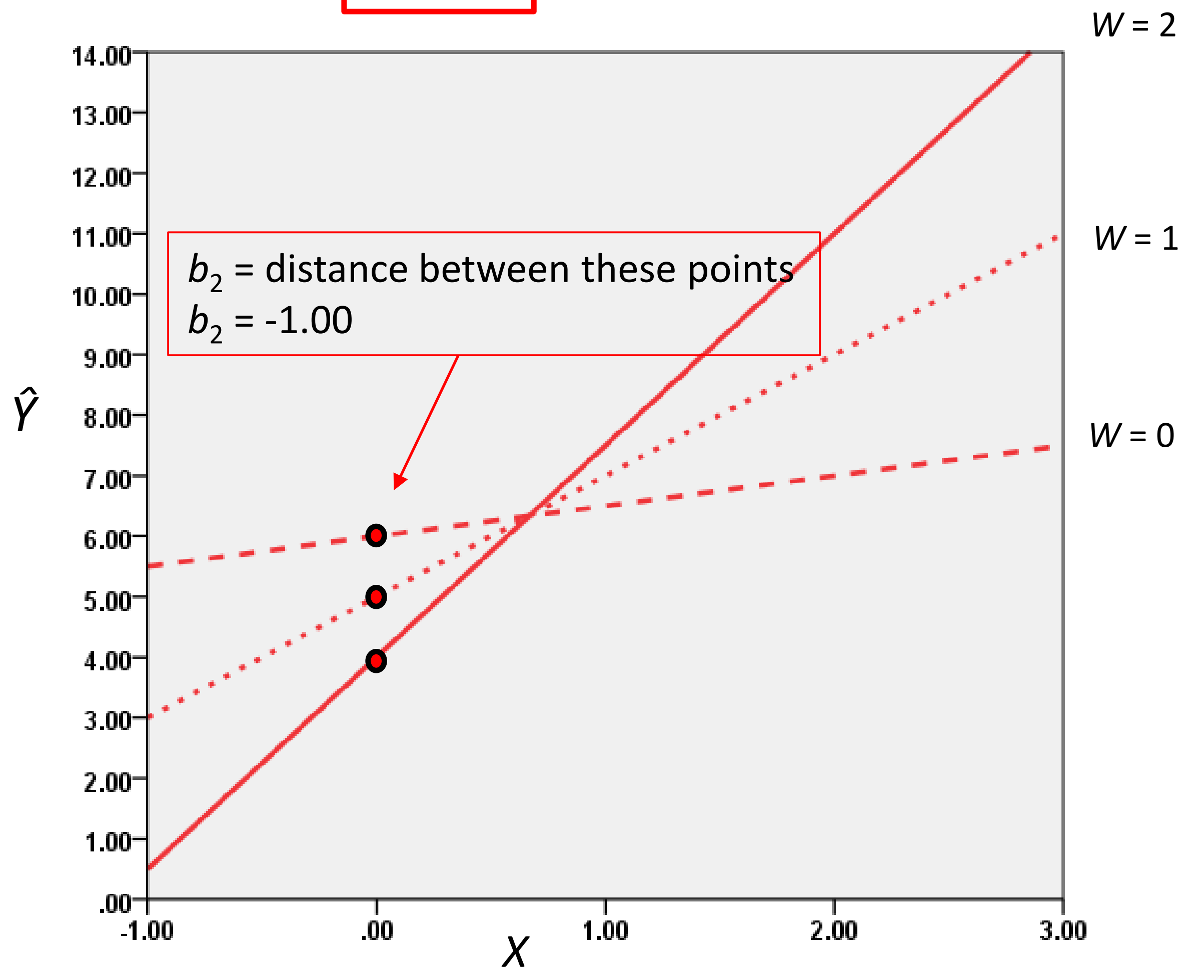
Interpretation of b_2 as a conditional effect

$b_0 = 6.00$
$b_1 = 0.50$
$b_2 = -1.00$
$b_3 = 1.50$

$$\widehat{Y}_i = 6.00 + 0.50X_i \boxed{-\ 1.00} W_i + 1.50X_iW_i$$

b_2 is the effect of W when $X = 0$. It quantifies how much two cases that differ by one unit on W but with $X = 0$ are estimated to differ on Y.

b_2 is a local property of the model. It characterizes the association between W and Y only when $X = 0$.



$$\boxed{b_2 = \hat{Y}|(W = \lambda + 1, X = 0) - \hat{Y}|(W = \lambda, X = 0) \text{ for all } \lambda}$$

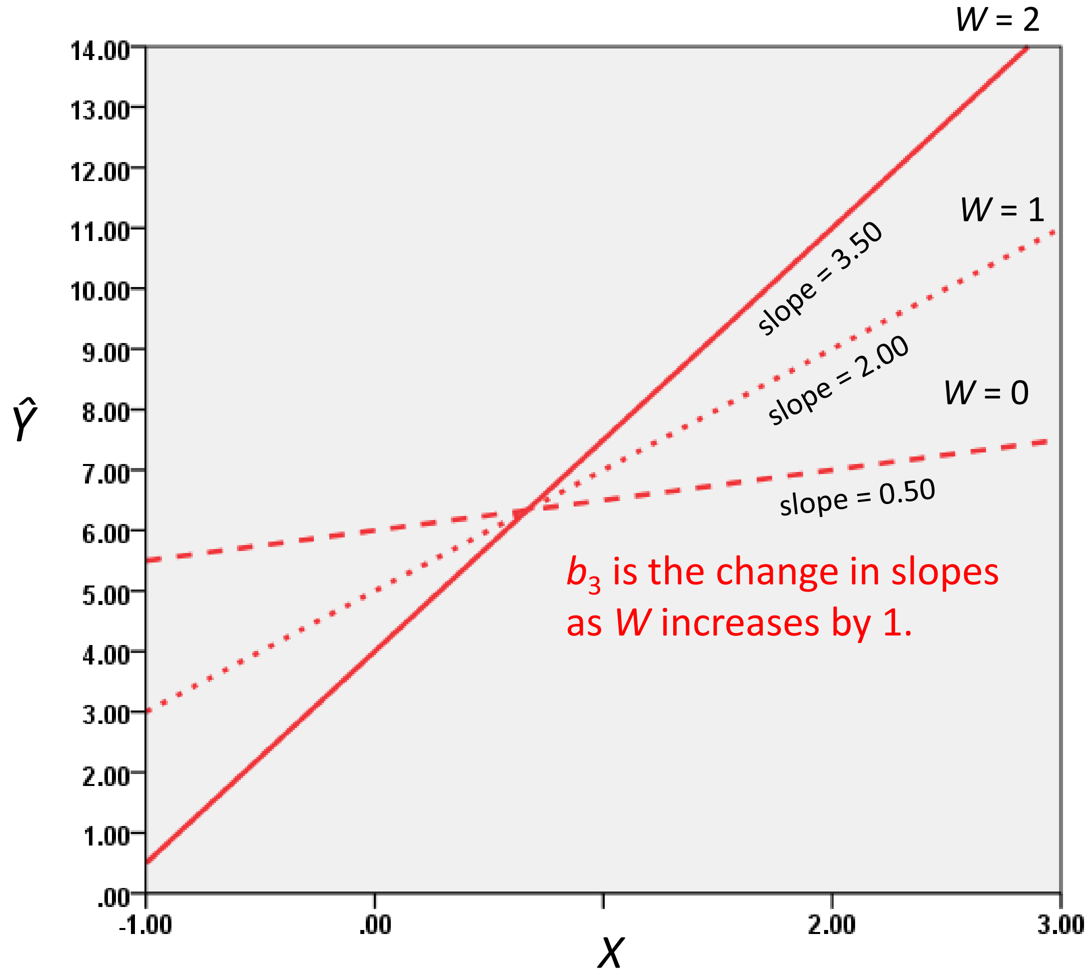
Interpretation of b_3

$$\widehat{Y}_i = 6.00 + 0.50X_i - 1.00W_i + \boxed{1.50}X_iW_i$$

b_3 is the amount by which the conditional effect of X changes as W changes by one unit.

$$\theta_{X\rightarrow Y} = b_1 + b_3W$$
$$= 0.50 + 1.50W$$

$\theta_{X\rightarrow Y}$	W
0.50	0
2.00	1
3.50	2



$$b_3 = (\theta_{X\rightarrow Y} | W = \lambda + 1) - (\theta_{X\rightarrow Y} | W = \lambda) \text{ for all } \lambda$$

Differences in interpretation

	$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i$	$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$
b_0	The estimated value of *Y* when *X* and *W* = 0.	The estimated value of *Y* when *X* and *W* = 0.
b_1	The effect of *X* on *Y* holding *W* constant. This is a *partial* effect.	The effect of *X* on *Y* when *W* = 0. This is a *conditional* effect. It is Not a “main effect” or “average effect” of *X*.
b_2	The effect of *W* on *Y* holding *X* constant. This is a *partial* effect.	The effect of *W* on *Y* when *X* = 0. This is a *conditional* effect. It is not a “main effect” or “average effect” of *W*.
b_3		How much the effect of *X* on *Y* changes as *W* changes by 1 unit.

Symmetry in moderation

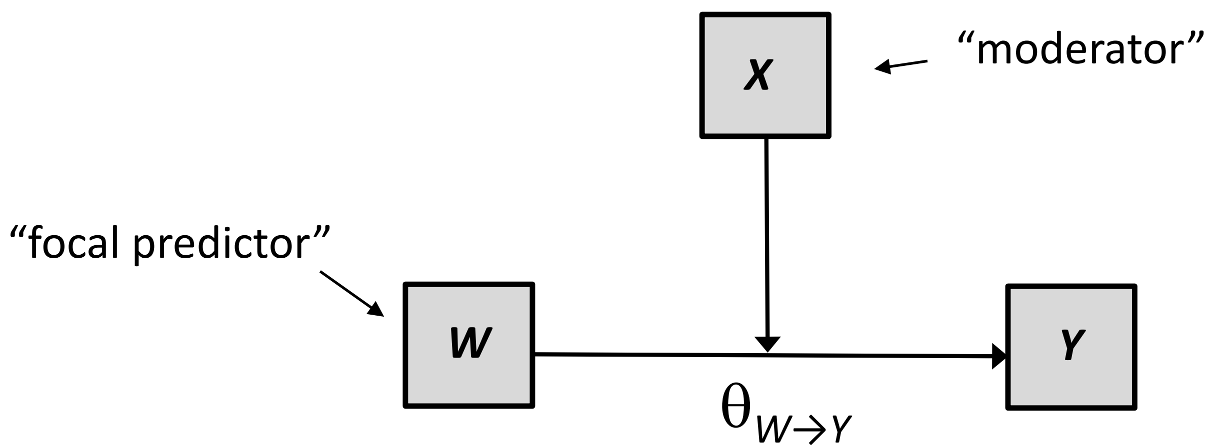
$$\boxed{\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i}$$

We saw that this is alternative representation of

$$\widehat{Y}_i = b_0 + (b_1 + b_3 W_i) X_i + b_2 W_i$$

But it is also an alternative representation of

$$\widehat{Y}_i = b_0 + (b_2 + b_3 X_i) W_i + b_1 X_i$$

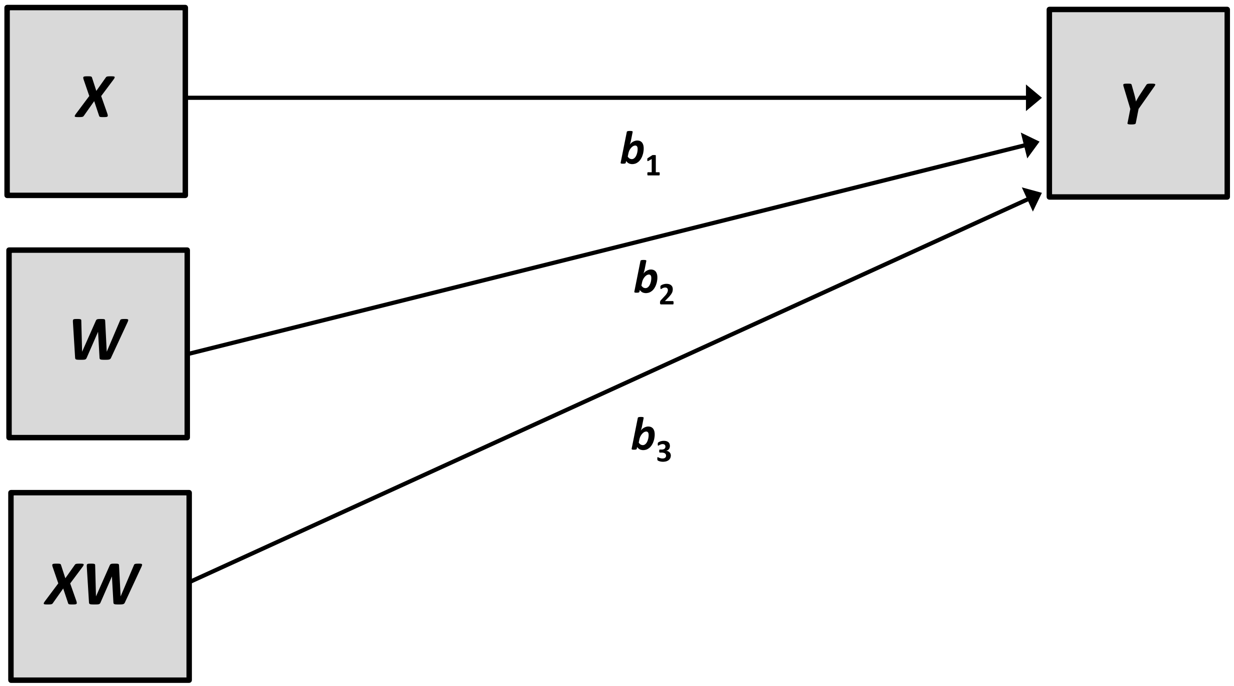


$$\theta_{W \to Y} = b_2 + b_3 X$$

Here, *X* moderates the size of the effect of *W* on *Y*. Now *X* is the moderator. Ultimately, which variable *X* or *W* we think of as the moderator depends on substantive concerns. Statistically, it makes no difference as they are mathematically equivalent models.

In path diagram form

$$\hat{Y}_1 = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$$

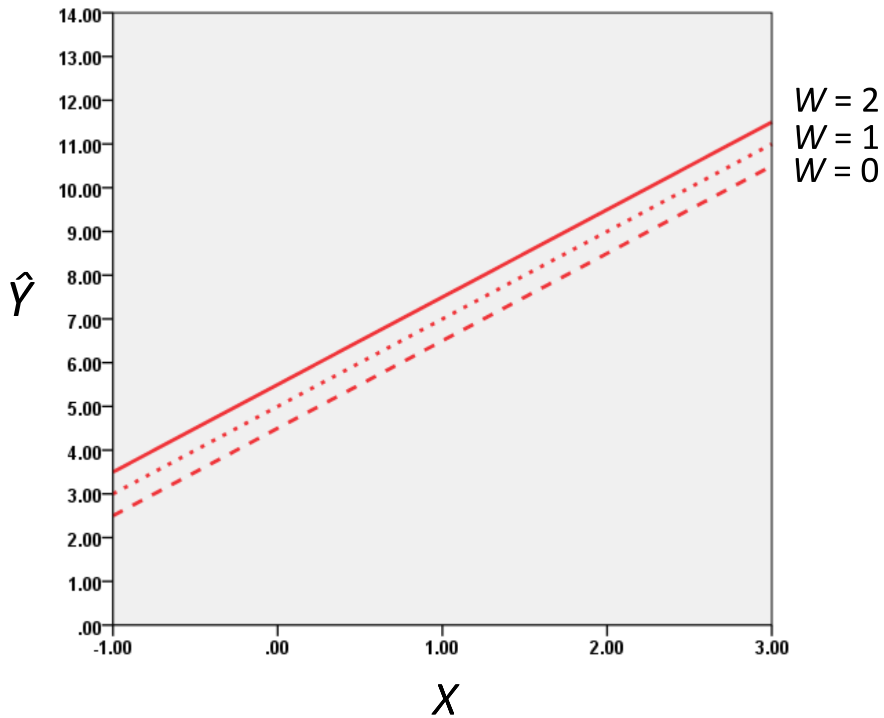


Remember

b_1 is NOT the effect of *X* on *Y*. The effect of *X* is $b_1 + b_3W$
b_2 is NOT the effect of *W* on *Y*. The effect of *W* is $b_2 + b_3X$

The importance of b_3 when testing a moderation hypothesis

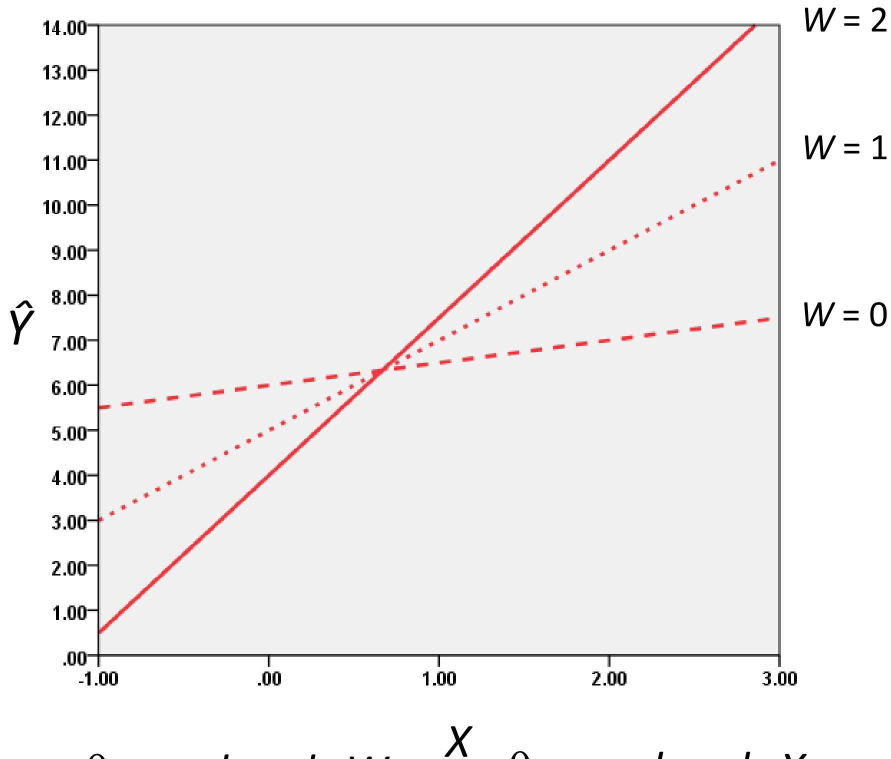
$\widehat{Y}_i = 4.50 + 2.00X_i + 0.50W_i + 0X_iW_i$



$\theta_{X\rightarrow Y} = b_1 + b_3W$
$= 2.00 + 0W$

$\theta_{W\rightarrow Y} = b_2 + b_3X$
$= 0.50 + 0X$

$\widehat{Y}_i = 6.00 + 0.50X_i - 1.00W_i + 1.50X_iW_i$



$\theta_{X\rightarrow Y} = b_1 + b_3W$
$= 0.50 + 1.50W$

$\theta_{W\rightarrow Y} = b_2 + b_3X$
$= -1.00 + 1.50X$

When $b_3 = 0$, a one unit change in X has the same effect on Y regardless of W, and a one unit change in W has the same effect on Y regardless of X. When $b_3 \neq 0$, the effect of a change in X on Y depends on W, and the effect of a change in W on Y depends on X. So we test a moderation hypothesis by testing whether b_3 is different from zero.

Example inspired by …

Witkiewitz, K., & Bowen, S. (2010). Depression, craving, and substance use following a randomized trial of mindfulness-based relapse prevention. ***Journal of Consulting and Clinical Psychology, 78***, 362-374.

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2010, Vol. 78, No. 3, 362–374

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Depression, Craving, and Substance Use Following a Randomized Trial of Mindfulness-Based Relapse Prevention

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University of Washington

Objective: A strong relation between negative affect and craving has been demonstrated in laboratory and clinical studies, with depressive symptomatology showing particularly strong links to craving and substance abuse relapse. Mindfulness-based relapse prevention (MBRP), shown to be efficacious for reduction of substance use, uses mindfulness-based practices to teach alternative responses to emotional discomfort and lessen the conditioned response of craving in the presence of depressive symptoms. The goal in the current study was to examine the relation between measures of depressive symptoms, craving, and substance use following MBRP. ***Method:*** Individuals with substance use disorders (N = 168; mean age 40.45 years, SD = 10.28; 36.3% female; 46.4% non-White) were recruited after intensive stabilization, then randomly assigned to either 8 weekly sessions of MBRP or a treatment-as-usual control group. Approximately 73% of the sample was retained at the final 4-month follow-up assessment. ***Results:*** Results confirmed a moderated-mediation effect, whereby craving mediated the relation between depressive symptoms (Beck Depression Inventory) and substance use (Timeline Follow-Back) among the treatment-as-usual group but not among MBRP participants. MBRP attenuated the relation between postintervention depressive symptoms and craving (Penn Alcohol Craving Scale) 2 months following the intervention (f^2 = .21). This moderation effect predicted substance use 4 months following the intervention (f^2 = .18). ***Conclusion:*** MBRP appears to influence cognitive and behavioral responses to depressive symptoms, partially explaining reductions in postintervention substance use among the MBRP group. Although results are preliminary, the current study provides evidence for the value of incorporating mindfulness practice into substance abuse treatment and identifies a potential mechanism of change following MBRP.

Keywords: mindfulness based relapse prevention, substance use, craving, negative affect, depression

Addiction has generally been characterized as a chronic and relapsing condition (Connors, Maisto, & Zywiak, 1996; Leshner, 1999). Research on the relapse process has implicated numerous risk factors that appear to be the most robust and immediate predictors of posttreatment substance use, including negative affect, craving or urges, interpersonal stress, motivation, self-efficacy, and ineffective coping skills in high-risk situations (Connors et al., 1996; Witkiewitz & Marlatt, 2004). Targeting these risk factors during treatment, either pharmacologically (e.g., naltrexone to reduce alcohol craving; Richardson et al., 2008) or behaviorally (e.g., coping skills training; Monti et al., 2001), has become a priority for substance abuse researchers and clinicians.

Depression, Craving, and Relapse

The significant roles of negative affective states and craving in the substance use relapse process have been described for over 30 years (e.g., Ludwig & Wikler, 1974; Solomon & Corbit, 1974). Craving, the subjective experience of an urge or desire to use substances (Kozlowski & Wilkinson, 1987), has been shown to strongly predict reinstatement of substance use for all major drugs of abuse (e.g., Hartz, Frederick-Osborne, & Galloway, 2001; Hopper et al., 2006; Shiffman et al., 2002). Negative affect has been shown to be a prominent cue for craving in both laboratory and clinical studies (e.g., Cooney, Litt, Morse, Bauer, & Gaupp, 1997; Perkins & Grobe, 1992; Shiffman & Waters, 2004; Sinha & O'Malley, 1999; Stewart, 2000; Wheeler et al., 2008), and both the experience of negative affective states and the desire to avoid these aversive states have been described as primary motives for substance use (e.g., Wikler, 1948). Depressive symptomatology has been linked to reinitiation of drug use following periods of abstinence (e.g., Curran, Booth, Kirchner, & Deneke, 2007; Witkiewitz & Villarroel, 2009), and self-reported depression has been shown to predict substance use treatment outcomes (e.g., Cornelius et al., 2004; Greenfield et al., 1998; Hodgins, el-Guebaly, & Armstrong, 1995).

The relation between depression and substance use is also evident in the disproportionately higher rates of substance use relapse in individuals with affective disorders (Conner, Sorensen, & Leonard, 2005; Hasin & Grant, 2002; Kodl et al., 2008).

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168 clients of a public service agency providing treatment for alcohol and substance use disorders.

MBRP : Randomly assigned to treatment as usual (0) or mindfulness-based relapse prevention therapy (1)

BDI0: Beck Depression Inventory at start of therapy (0 to 3; multiply by 21 to see BDI in its original 0 to 63 metric). This is also available at the termination of therapy (**BDIP**)

CRAVE2: Score on the Penn Alcohol Craving Scale at 2 month follow-up (0 to 6). Also available at baseline, prior to start of therapy (**CRAVE0**)

USE4: Alcohol and other substance use at 4-month follow-up. (0 to 5)

TREATHRS: Hours of therapy administered.

The data file is MBRP

The Data: MBRP

SPSS

mbrp.sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Add-ons Window

	mbrp	bdi0	bdip	crave0	crave2	use4	tr
1	0	1.28	1.09	4.0	.8	.95	
2	0	1.47	1.52	2.4	3.8	1.30	
3	0	.66	1.14	2.2	1.4	1.09	
4	1	1.66	1.23	2.2	2.4	1.17	
5	0						
6	1						
7	0						
8	0						
9	0						
10	1						
11	1						
12	0						
13	1						
14	1						

SAS

mbrp *

```
data mbrp;
  input mbrp bdi0 bdip crave0 crave2 use4 treathrs;
  datalines;
  0 1.28 1.09 4.0 .8 .95 32
  0 1.47 1.52 2.4 3.8 1.30 36
  0 .66 1.14 2.2 1.4 1.09 34
  .23 2.2 2.4 1.17 37
  35 4.2 2.4 .91 27
  04 1.0 1.0 1.31 32
  35 2.0 .8 .36 38
  95 3.2 2.0 .83 26
  1 3.0 1.2 .57 42
  .14 1.2 1.6 1.24 32
  .00 2.4 2.6 1.54 25
  51 1.0 .6 .63 24
  .66 3.8 1.2 .54 35
  95 1.8 1.2 1.81 34
```

R

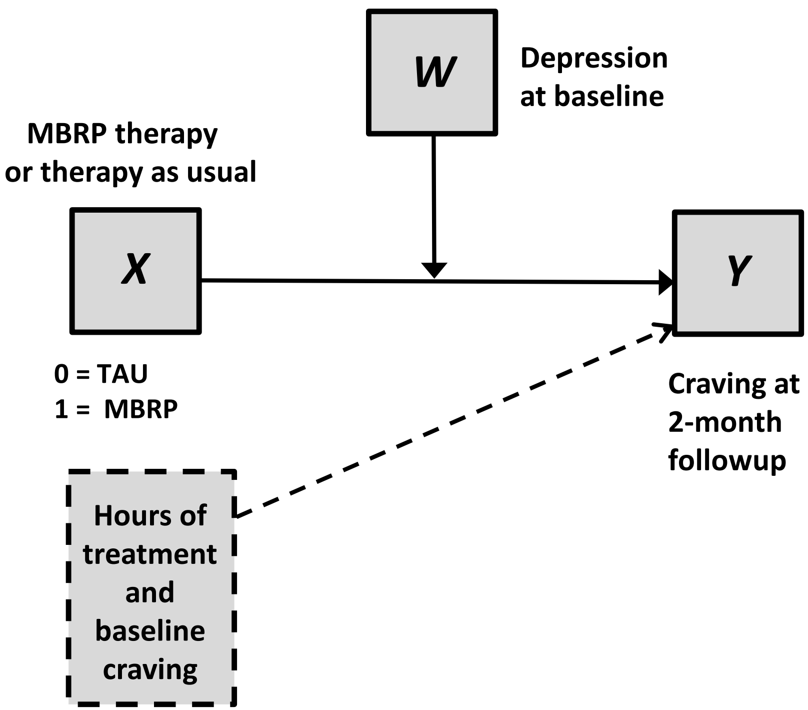
	mbrp	bdi0	bdip	crave0	crave2	use4	treathrs
1	0	1.28	1.09	4.0	0.8	0.95	32
2	0	1.47	1.52	2.4	3.8	1.30	36
3	0	0.66	1.14	2.2	1.4	1.09	34
4	1	1.66	1.23	2.2	2.4	1.17	37
5	0	1.28	0.85	4.2	2.4	0.91	27
6	1	0.95	1.04	1.0	1.0	1.31	32
7	0	1.38	0.85	2.0	0.8	0.36	38
8	0	1.76	0.95	3.2	2.0	0.83	26
9	0	0.80	0.71	3.0	1.2	0.57	42
10	1	1.47	1.14	1.2	1.6	1.24	32
11	1	1.38	2.00	2.4	2.6	1.54	25
12	0	1.00	0.61	1.0	0.6	0.63	24
13	1	1.38	1.66	3.8	1.2	0.54	35
14	1	1.09	0.95	1.8	1.2	1.81	34
15	1	1.52	2.33	3.8	2.8	1.34	30

Showing 1 to 16 of 168 entries

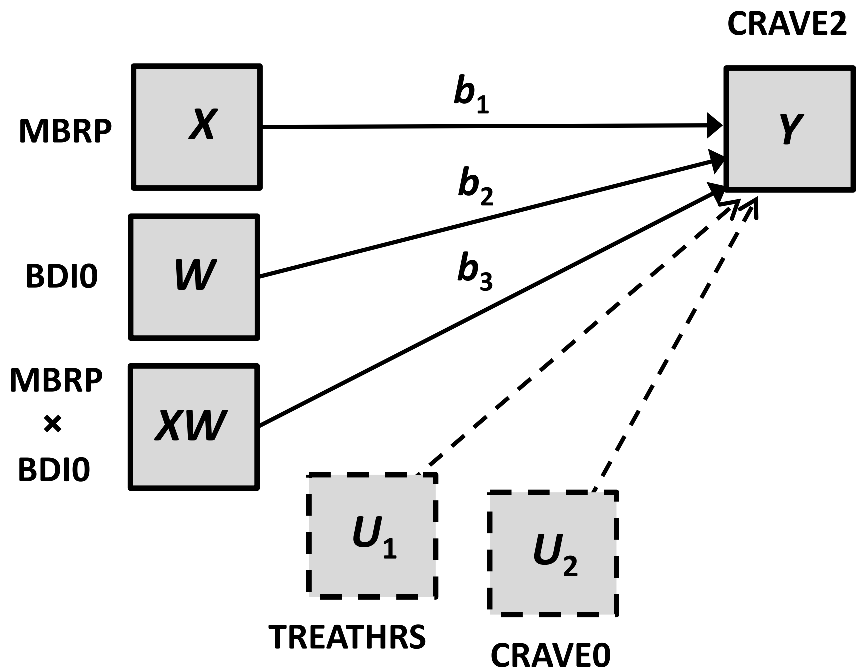
These aren't the actual data. But the analyses we do yield similar results to what they report.

Example

Conceptual diagram



Statistical model



Does the effect of MBRP therapy relative to therapy as usual on craving depend on initial depression? That is, is the therapy more or less effective as a function of depression prior to start of therapy?

Estimation using OLS regression

```
compute mbrpdep = mbrp*bdi0.
regression/dep = crave2/method = enter mbrp bdi0 mbrpdep treathrs crave0.
```

```
data mbrp;set mbrp;mbrpdep=mbrp*bdi0;run;
proc reg data=mbrp;model crave2=mbrp bdi0 mbrpdep treathrs crave0;run;
```

```
summary(lm(crave2~mbrp*bdi0+treathrs+crave0, data = mbrp))
```

X **= MBRP**
W **= BDI0**
Y **= CRAVE2**

$$\widehat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.038	.470		2.209	.029
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.587	.524	.299	1.120	.264
	BDI0: Beck Depression Inventory baseline	1.122	.276	.366	4.063	.000
	mbrpdep	-.948	.423	-.598	-2.240	.026
	TREATHRS: Hours of therapy	-.018	.010	-.120	-1.719	.088
	CRAVE0: Baseline craving	.192	.073	.183	2.614	.010

a. Dependent Variable: CRAVE2: Craving at two month follow-up

"conditional effects", not "main effects"

$b_1 = 0.587$
$b_2 = 1.122$
$b_3 = -0.948$

The coefficient for the product is statistically different from zero. This means that the effect of MBRP therapy on craving depends on the person's level of depression at the start of therapy. But to really understand what is happening, we need a picture.

Visualizing the model

Rejecting the null hypothesis that "true b_3" is equal to zero tells you that the focal predictor's effect is indeed moderated by the proposed moderator. But moderation can take many different forms. We need to visualize the effect in order to interpret the result.

Step 1: Select various combinations of values of the focal predictor and moderator. The selection is sometimes arbitrary, but it may not be. Just make sure the values chosen are within the range of the data.

Step 2: Using the model, generate the estimates of Y using your selected values of the focal predictor and moderator. If your model includes covariates, use the sample mean for each of those.

Step 3: Graph, using whatever graphics program you prefer.

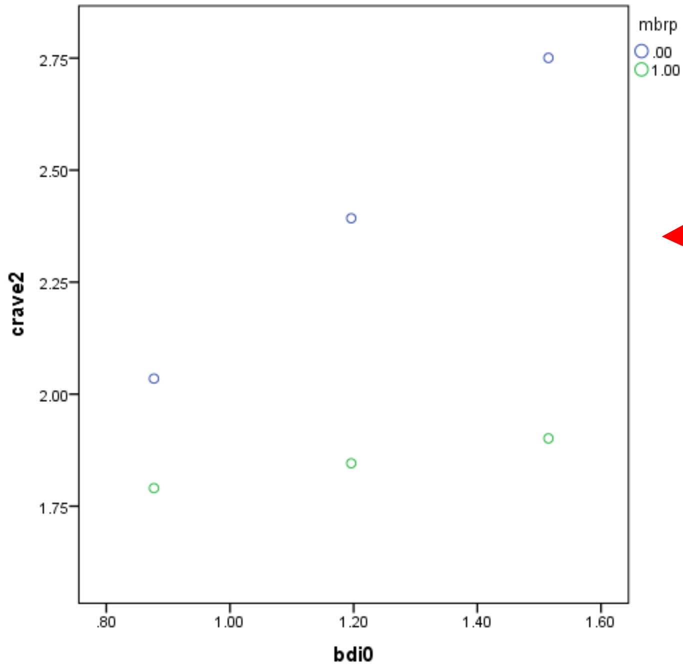
$$\widehat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i - 0.018U_{1i} + 0.192U_{2i}$$

MBRP (X)	**BDI0** (W)	**TREATHRS** (U_1)	**CRAVE0**(U_2)	$\hat{Y}$
0	0.877	30.685	2.943	2.035
0	1.196	30.685	2.943	2.393
0	1.515	30.685	2.943	2.751
1	0.877	30.685	2.943	1.790
1	1.196	30.685	2.943	1.846
1	1.515	30.685	2.943	1.901

I used one standard deviation below the mean, the mean, and one standard deviation above the mean. It really makes no difference what you choose, except you want to make sure that your resulting graph is not extrapolating beyond the available data.

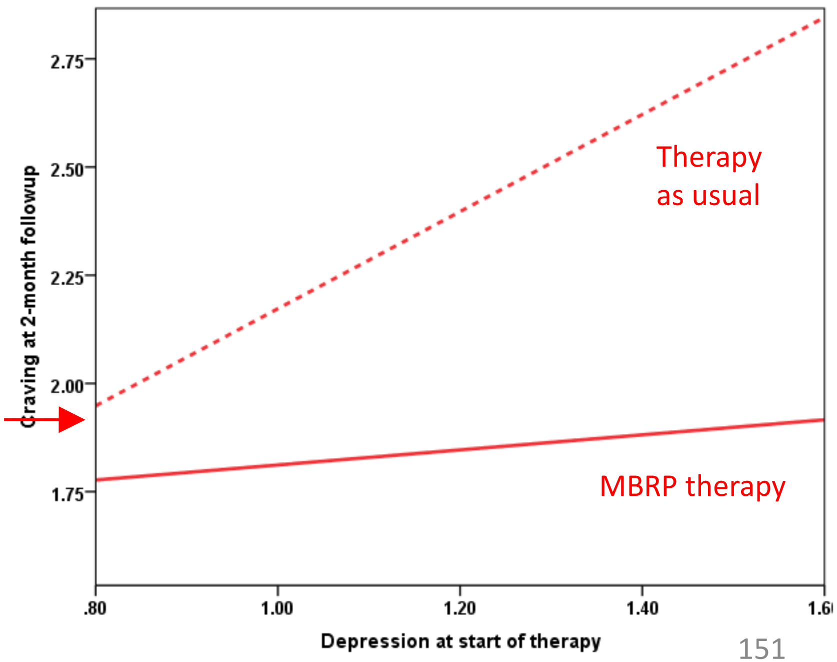
Example code in SPSS

```
data list free/mbrp bdi0.
begin data.
 0  0.877
 0  1.196
 0  1.515
 1  0.877
 1  1.196
 1  1.515
end data.
compute crave2=1.038+0.587*mbrp+1.122*bdi0-0.948*mbrp*bdi0-0.018*30.685+0.192*2.943.
graph/scatterplot = bdi0 with crave2 by mbrp.
```



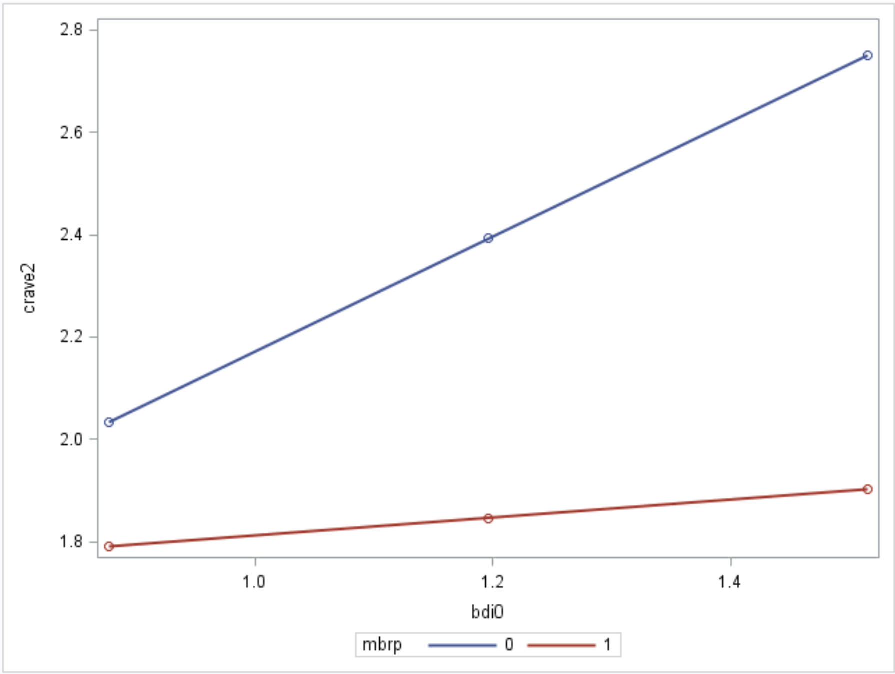
Before editing

After editing



Example code in SAS

```
data;
input mbrp bdi0;
crave2=1.038+0.587*mbrp+1.122*bdi0-0.948*mbrp*bdi0-0.018*30.685+0.192*2.943;
datalines;
0  0.877
0  1.196
0  1.515
1  0.877
1  1.196
1  1.515
run;
proc sgplot;reg x=bdi0 y=crave2/group=mbrp;run;
```



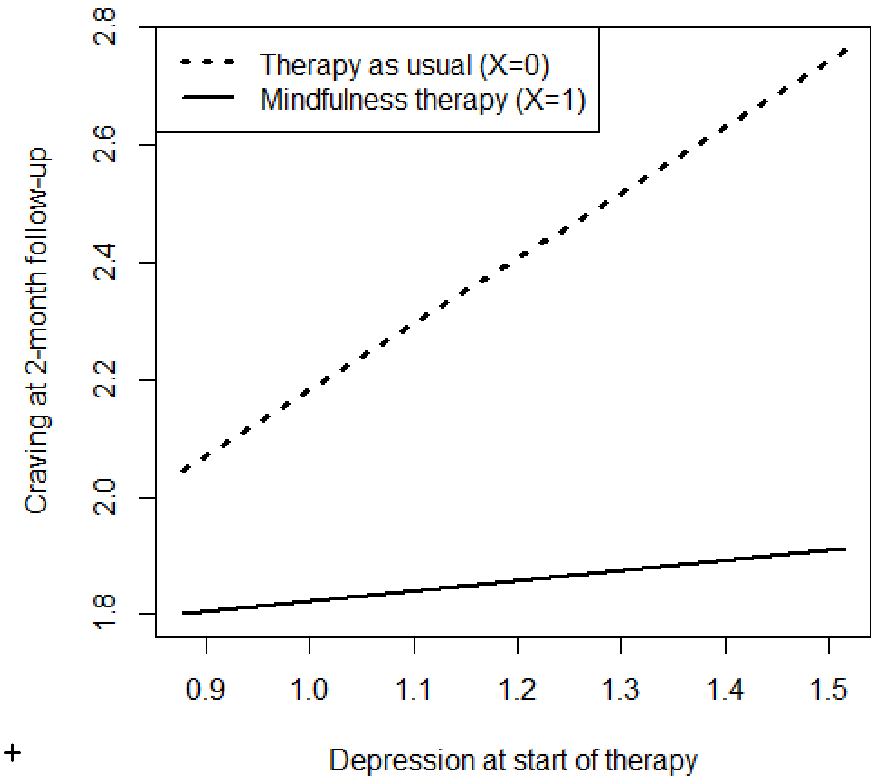
Example code in R

Although hard to learn at first, once you learn how to use R, you will find it very helpful In the construction of visual depictions of models.

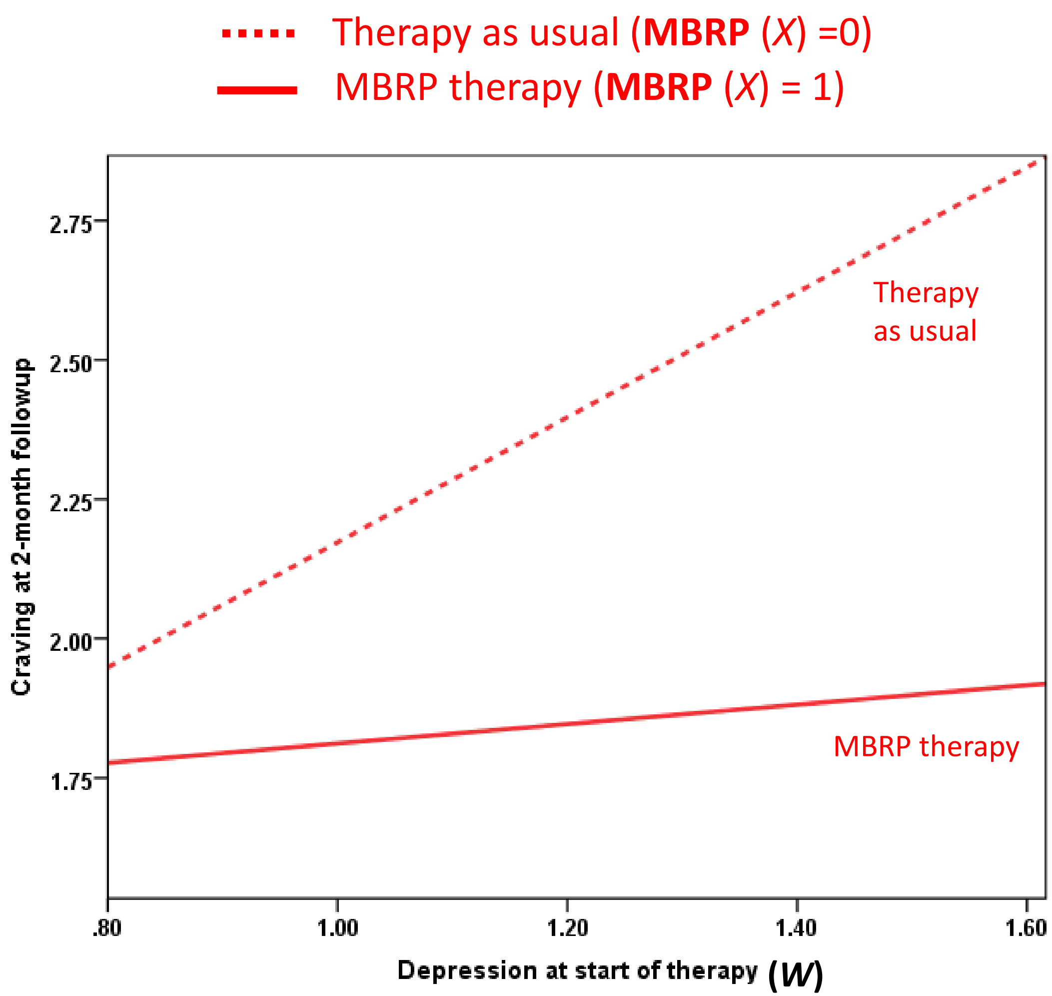
```
x<-c(0,1,0,1,0,1)
w<-c(0.877,0.877,1.196,1.196,1.515,1.515)
y<-1.038+0.587*x+1.122*w-0.948*x*w-0.018*30.685+0.192*2.943
plot(y=y,x=w,pch=15,col="white",
xlab="Depression at start of therapy",
ylab="Craving at 2-month follow-up")
legend.txt<-c("Therapy as usual (X=0)",
"Mindfulness therapy (X=1)")
legend("topleft",legend=legend.txt,
lty=c(3,1),lwd=c(3,2))
lines(m[x==0],y[x==0],lwd=3,lty=3)
lines(m[x==1],y[x==1],lwd=2,lty=1)
```

OR

```
library(ggplot2)
qplot(x = w, y = y, linetype = as.factor(x),
      geom = "line")+
  xlab("Depression at start of therapy")+
  ylab("Craving at 2-month follow-up")+
  scale_linetype_discrete(name=element_blank(),
        breaks=c("0", "1"),
        labels=c("Therapy as Usual (X = 0)",
                 "Mindfulness Therapy (X = 1)"))+
  theme(legend.justification=c(-0.1,1.1),
         legend.position=c(0,1),
        panel.background = element_rect("white", "black"),
        panel.grid.major = element_blank())
```



Substantive interpretation of the pattern



Those who receive MBRP therapy crave substances less than those who receive therapy as usual, but this difference is larger among those more depressed at the start of therapy.

A graphical depiction of the model

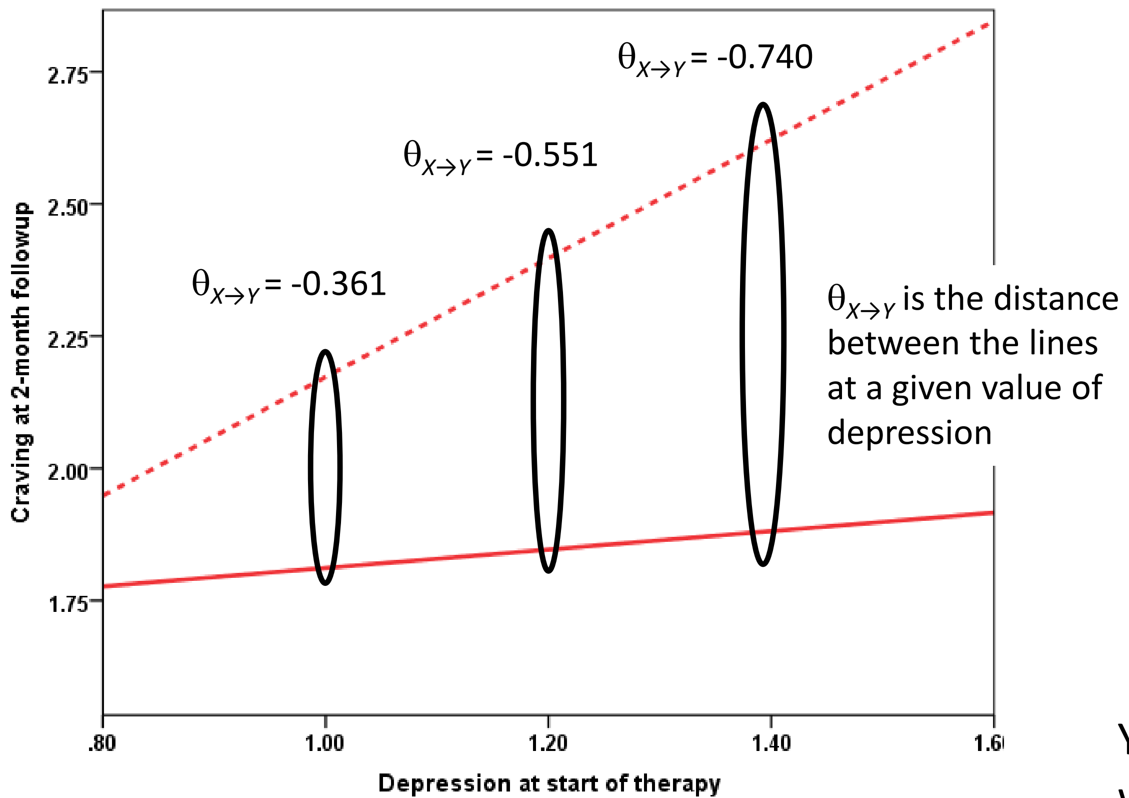
$$\widehat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

or, equivalently,

$$\widehat{Y}_i = 1.038 + (0.587 - 0.948W_i)X_i + 1.122W_i + \ldots$$

Therapy as usual (**MBRP** (X) =0)

MBRP therapy (**MBRP** (X) = 1)



The conditional effect of MBRP therapy ($\theta_{X\rightarrow Y}$) is defined by the function

$$\boldsymbol{\theta_{X\rightarrow Y} = 0.587 - 0.948W}$$

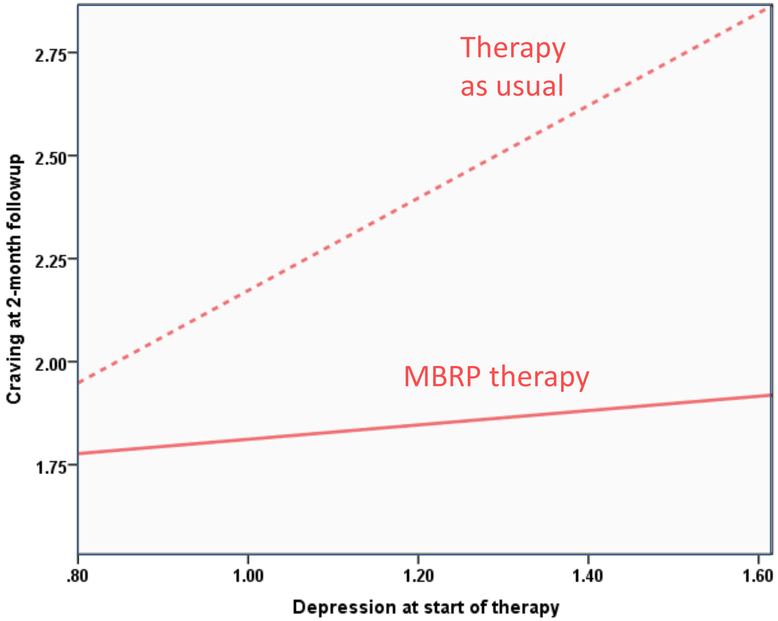
BDI0 (*W*)	$\theta_{X\rightarrow Y}$
1.00	-0.361
1.20	-0.551
1.40	-0.740

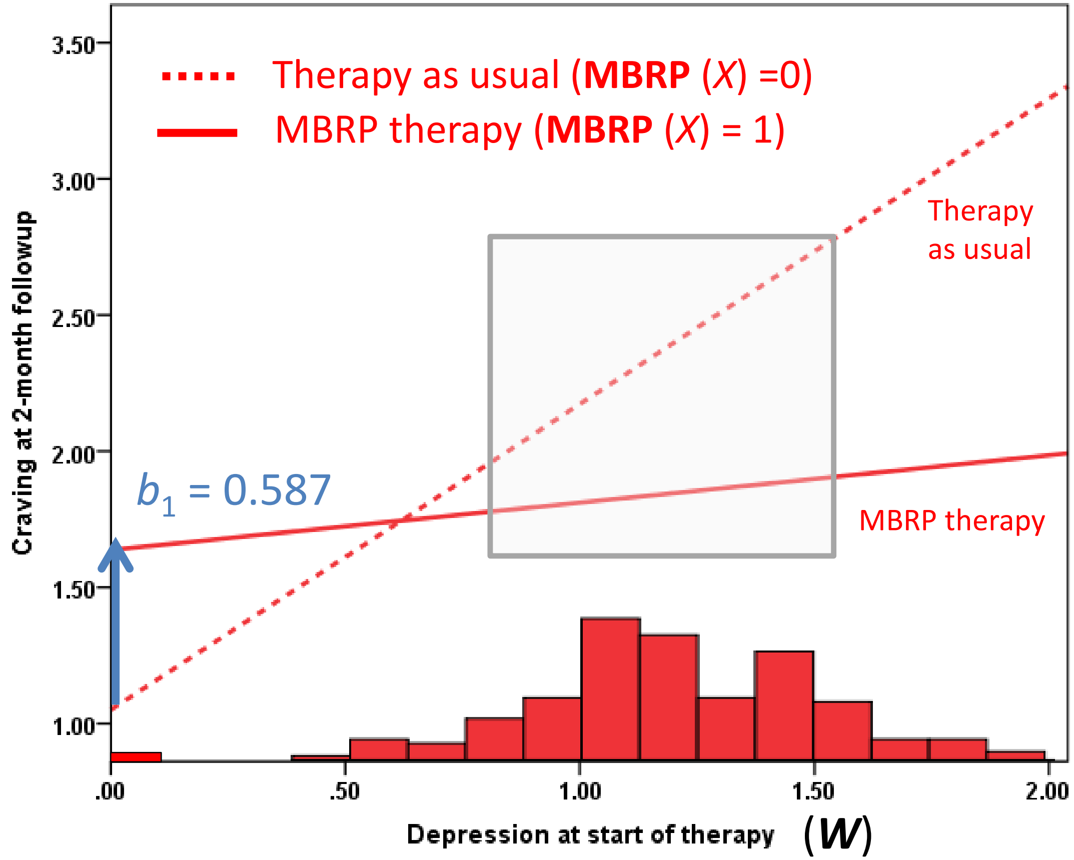
You can plug any value of BDI0 you want into the function to get the conditional effect of MBRP therapy

Interpretation of b_1

$b_1 = 0.587$

$$\widehat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$





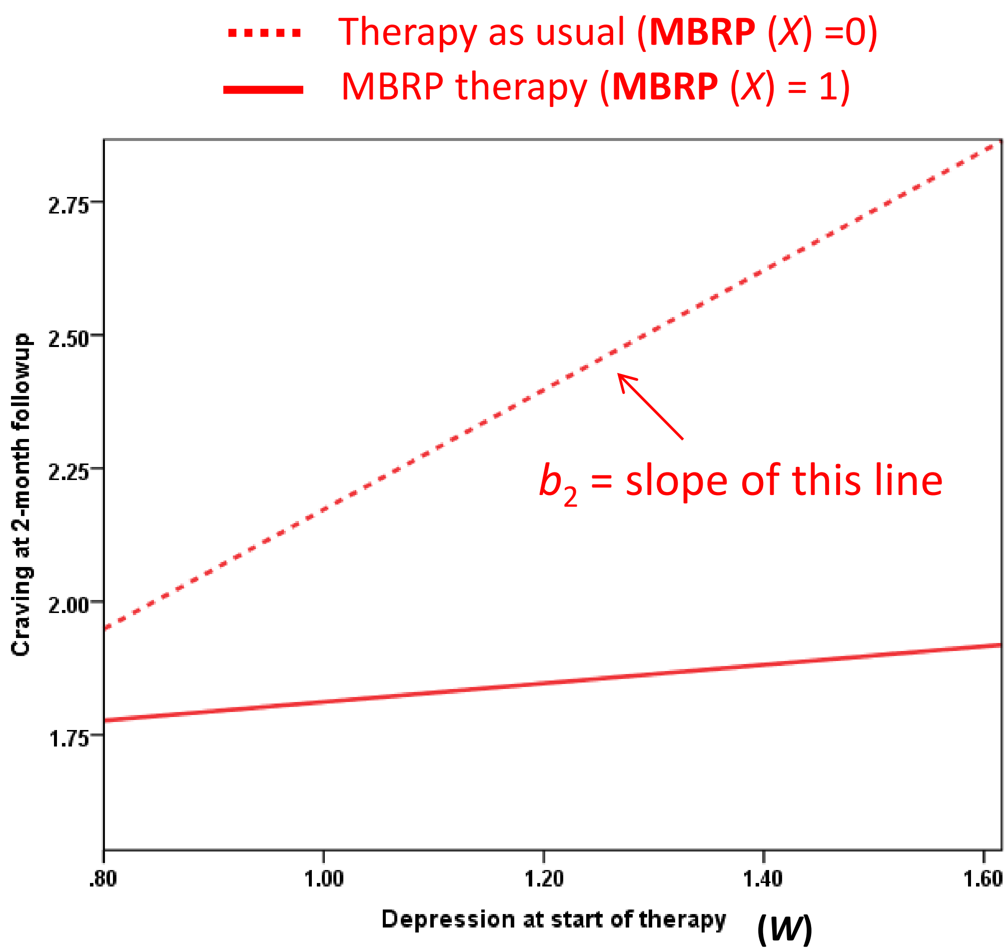
b_1 is the effect of X on Y when $W = 0$. It is a conditional effect, and a local term of the model.

Interpretation of b_2

b_2 = 1.122 $\hat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$

b_2 is the conditional effect of W when X = 0. It is a conditional effect and a local term of the model.

Among those given therapy as usual, those who were relatively more depressed at the start of therapy had relatively higher craving at two months follow-up



Interpretation of b_3

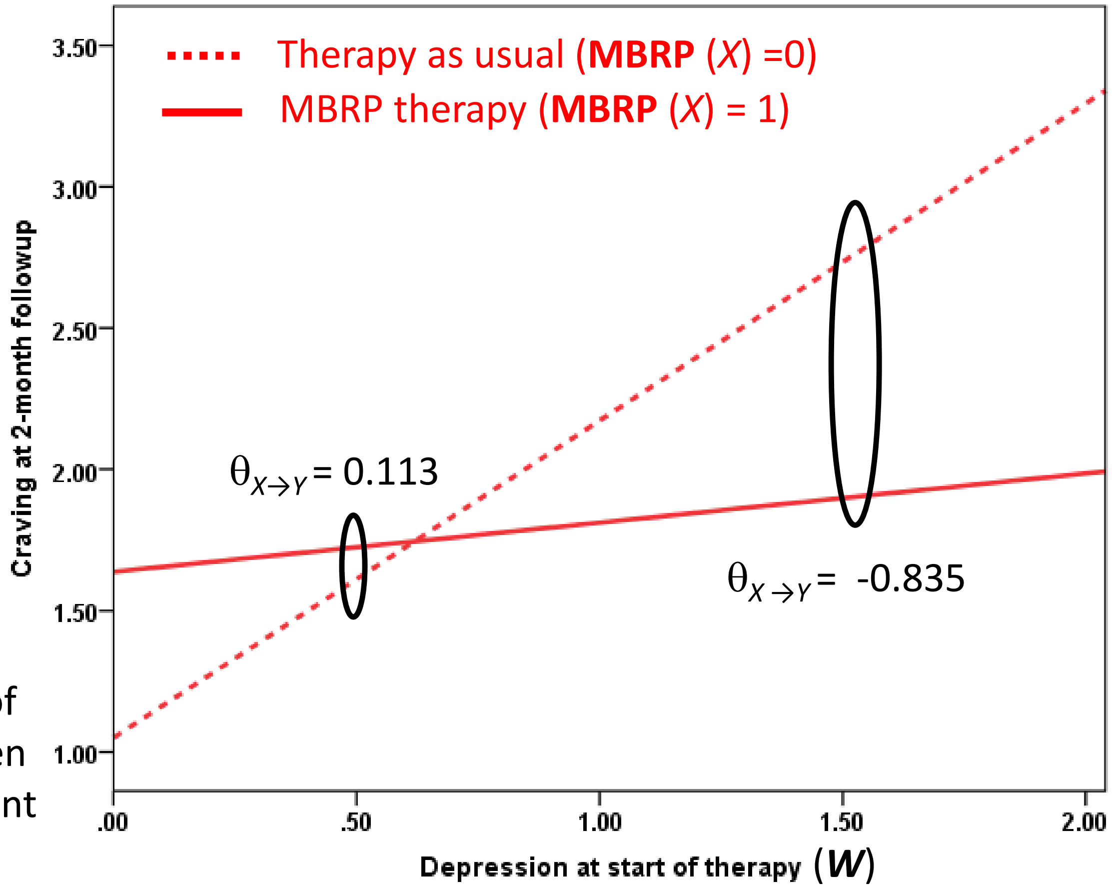
b_3 = -0.948

$$\hat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

$\theta_{X \to Y} = \mathbf{0.587 - 0.948}W$

W	$\theta_{X \to Y}$
0.50	**0.113**
1.00	-0.361
1.50	**-0.835**
2.00	-1.309

-0.835 – (0.113) = -0.948 = b_3
-1.309 – (-0.361) = -0.948 = b_3



b_3 is the difference in the effect of MBRP therapy on craving between those who differ by one scale point in their pre-therapy depression.

$$\theta_{X \to Y} | (W = \lambda + 1) - \theta_{X \to Y} | (W = \lambda) = -0.948, \text{ for all } \lambda$$

Interpretation of b_3

b_3 = -0.948

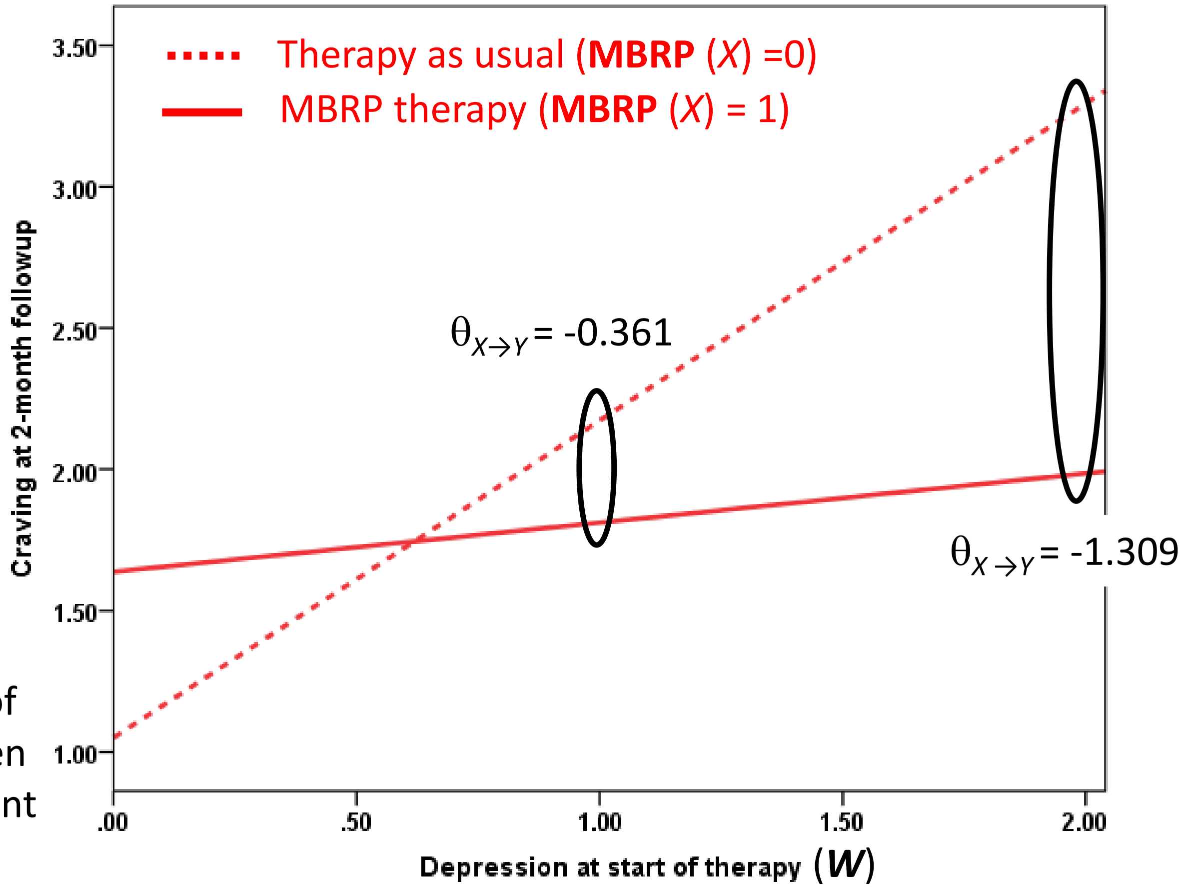
$$\widehat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

$\theta_{X \to Y} = 0.587 - 0.948W$

W	$\theta_{X \to Y}$
0.50	0.113
1.00	**-0.361**
1.50	-0.835
2.00	**-1.309**

-0.835 – (0.113) = -0.948 = b_3

-1.309 – (-0.361) = -0.948 = b_3

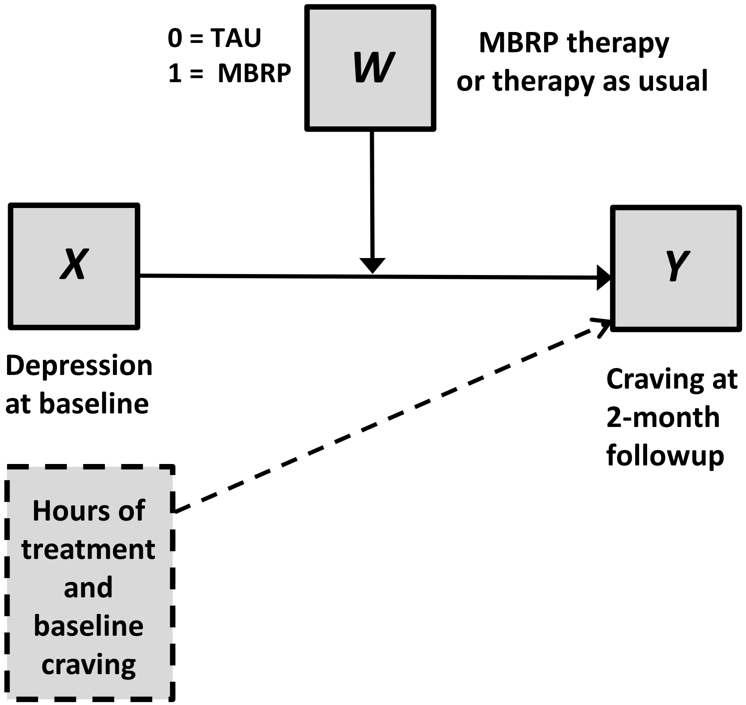


b_3 is the difference in the effect of MBRP therapy on craving between those who differ by one scale point in their pre-therapy depression.

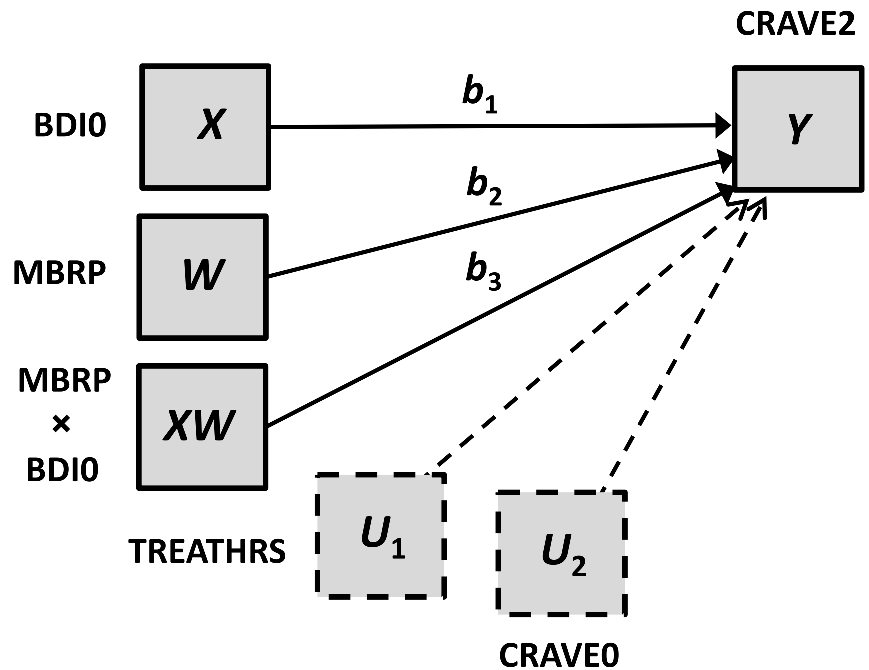
$$\boxed{\theta_{X \to Y} | (W = \lambda + 1) - \theta_{X \to Y} | (W = \lambda) = -0.948, \text{ for all } \lambda}$$

A Dichotomous Moderator

Conceptual diagram



Statistical model

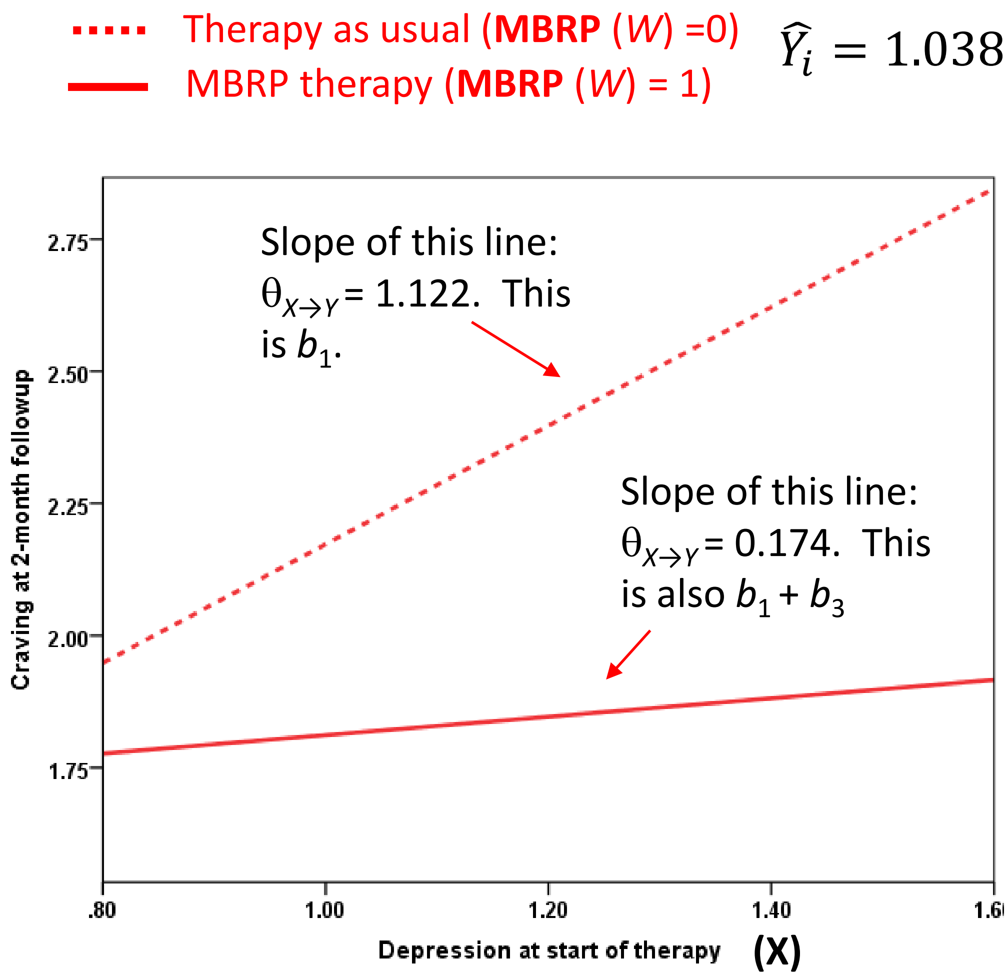


Does the association between pre-treatment depression and later craving differ between those who receive MBRP therapy versus therapy as usual?

A graphical depiction of the model

$\hat{Y}_i = 1.038 + 1.122X_i + 0.587W_i - 0.948X_iW_i + \ldots$ or, equivalently,

$\hat{Y}_i = 1.038 + (1.122 - 0.948W_i)X_i + 0.587W_i + \ldots$



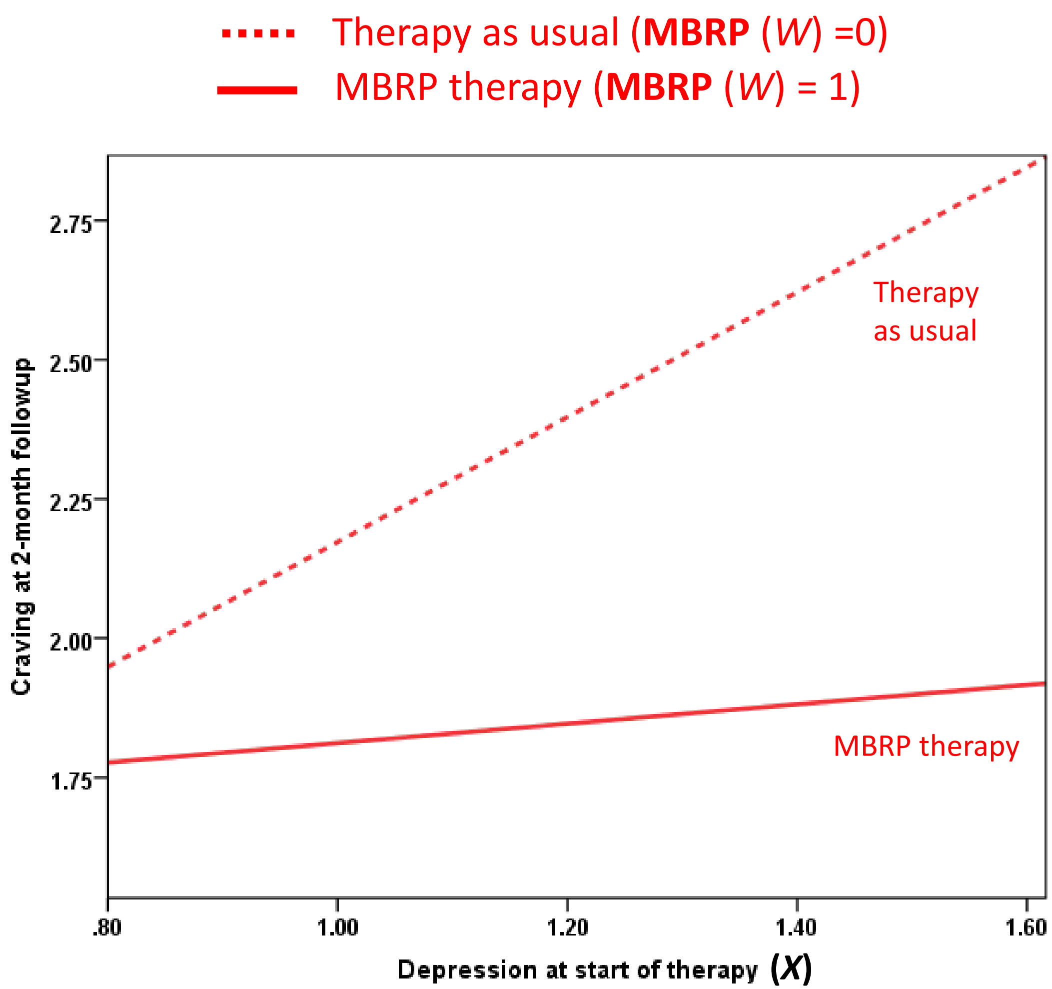
The conditional effect of pre-therapy depression ($\theta_{X\to Y}$) is defined by the function

$$\boldsymbol{\theta_{X\to Y} = b_1 + b_3W}$$
$$\boldsymbol{= 1.122 - 0.948W}$$

MBRP (*W*)	$\theta_{X\to Y}$
0	1.122
1	0.174

Two cases that differ by one unit on *W* are estimated to differ by $\theta_{X\to Y}$ units on *Y*. $\theta_{X\to Y}$ depends on *W*.

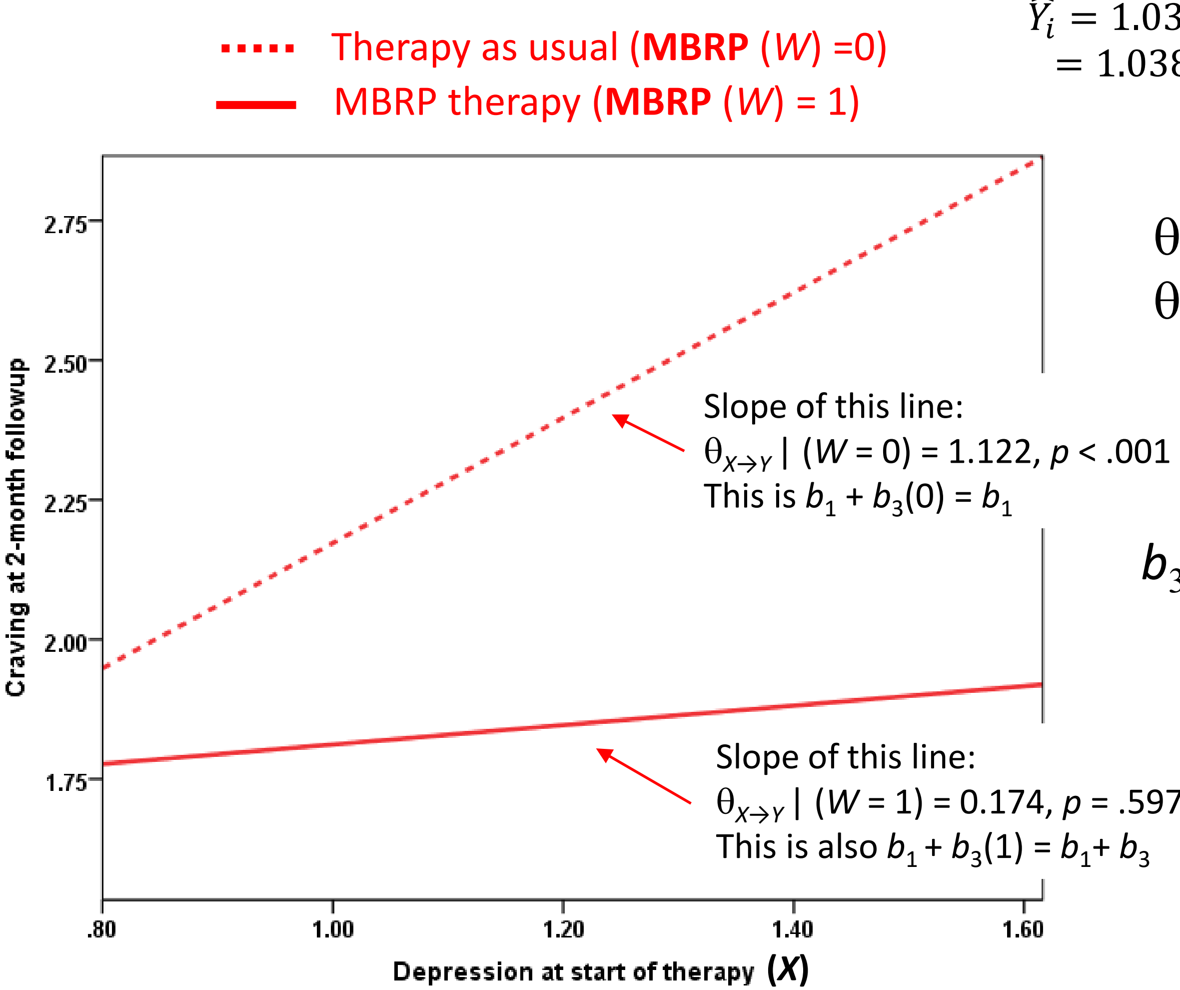
Substantive interpretation of the pattern



A larger effect of pre-therapy depression on later craving among those who experienced therapy as usual compared to those who received mindfulness behavioral relapse prevention therapy. MBRP therapy seems to have disrupted the link between depression and craving.

Interpreting b_3

$$\hat{Y}_i = 1.038 + 1.122X_i + 0.587W_i - 0.948X_iW_i$$
$$= 1.038 + (1.122 - 0.948W_i)X_i + 0.587W_i + \ldots$$



$$\theta_{X\to Y} | W = b_1 + b_3W$$
$$\theta_{X\to Y} | W = 1.122 - 0.948W$$

$$\begin{aligned} b_3 &= \theta_{X\to Y} | (W = 1) - \theta_{X\to Y} | (W = 0) \\ &= (b_1 + b_3) - (b_1) \\ &= (0.174) - (1.122) \\ &= -0.948 \end{aligned}$$

So b_3 is the difference in the slopes of these two lines. As W increases by one unit, $\theta_{X\to Y}$ decreases by 0.948 units. This difference is statistically different from zero.

Probing an interaction

The coefficient for the product term carries information about how changes in one variable are related to changes in the effect of the other. A picture helps to understand how the focal variable's effect changes as a function of the moderator variable.

It is typically desirable to conduct statistical tests of the focal predictor variable's effect at values of the moderator. This allows you to make more definitive claims about where the focal predictor variables effect is zero versus where it is not.

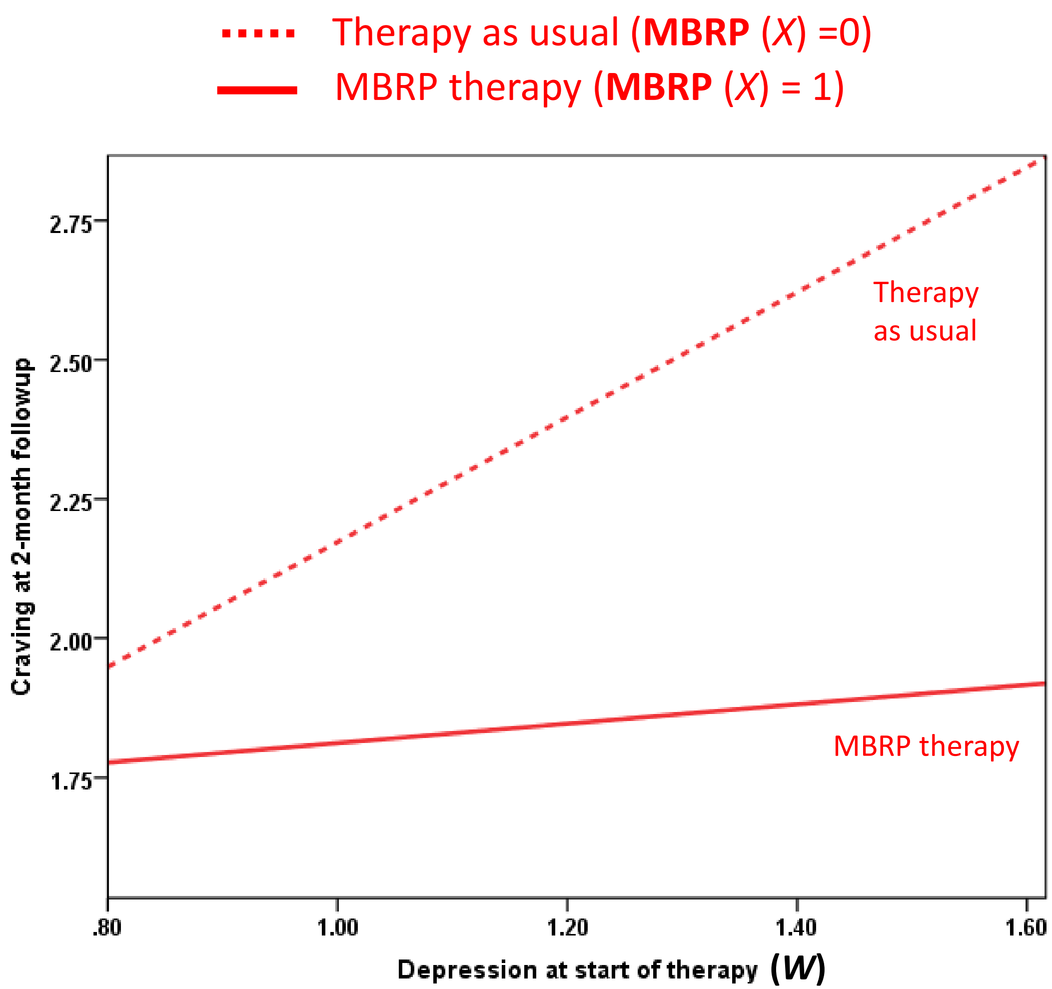
"Pick-a-Point" Approach

Select values of the moderator and estimate the conditional effect of the focal predictor at those values of the moderator, along with a hypothesis test or confidence interval.

Johnson-Neyman Technique

Derive mathematically where on the moderator variable continuum the focal variable's effect transitions between statistically significant and nonsignificant.

Substantive interpretation of the pattern



Those who receive MBRP therapy crave substances less than those who receive therapy as usual, and this difference is larger among those more depressed at the start of therapy.

Pick-a-point approach

$$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$$

Select a value of the moderator (*W*) at which you'd like to have an estimate of $\theta_{X \to Y}$, the focal predictor variable's (*X*) effect. Then derive its standard error. The ratio of the effect to its standard error is distributed as $t(df_{residual})$ under the null hypothesis that the effect of the focal predictor is zero at that moderator value, where df_{residual} is the residual degrees of freedom from the regression model.

We already know that $\theta_{X \to Y} = b_1 + b_3 W$

The estimated standard error of $\theta_{X \to Y}$ is

$$s_{\theta_{X \to Y}} = \sqrt{s_{b_1}^2 + 2W s_{b_1 b_3} + W^2 s_{b_3}^2}$$

Squared standard error of b_1

Covariance of b_1 and b_3

Squared standard error of b_3

You could do this by hand, and instructions are available in various books on regression analysis (e.g., Aiken and West, 1991; Cohen et al., 2003). But there is no reason to, and the potential for mistakes is high. It is made easier using "**regression centering**."

Pick-a-point: Regression centering approach

$$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$$

In the above model, b_1 estimates the conditional effect of X when W = 0. If we desire the conditional effect of X when W equals some value λ, we can produce a new variable W' that is W centered around λ, such that W' = 0 when $W = \lambda$. Then substitute W' for W in the model above. That is, we will estimate

$$\widehat{Y}_i = b_0 + b_1 X_i + b_2 (W_i - \lambda) + b_3 X_i (W_i - \lambda)$$

as

$$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i' + b_3 X_i W_i'$$ where $$W_i' = W_i - \lambda$$

In this model, b_1 is the conditional effect of X when W' = 0. But W' = 0 when $W = \lambda$. So b_1 estimates the conditional effect of X when $W = \lambda$. A common (but arbitrary) convention is to use $\lambda = \overline{W}$, $\lambda = \overline{W} - SD_W$, and $\lambda = \overline{W} + SD_W$

Pick-a-point: Regression centering approach

```
compute bdi0_p = bdi0-1.196.
compute interact = bdi0_p*mbrp.
regression/dep = crave2/method = enter mbrp bdi0_p interact treathrs crave0.
```

λ= 1.196
(the sample mean)

```
data mbrp;set mbrp;
bdi0_p=bdi0-1.196;
interact=bdi0_p*mbrp;
proc reg data=mbrp;model crave2=mbrp bdi0_p interact treathrs crave0;run;
```

```
mbrp <- transform(mbrp, bdi0_p = bdi0-1.196)
summary(lm(crave2~mbrp*bdi0_p+treathrs+crave0, data = mbrp))
```

Coefficients[a]

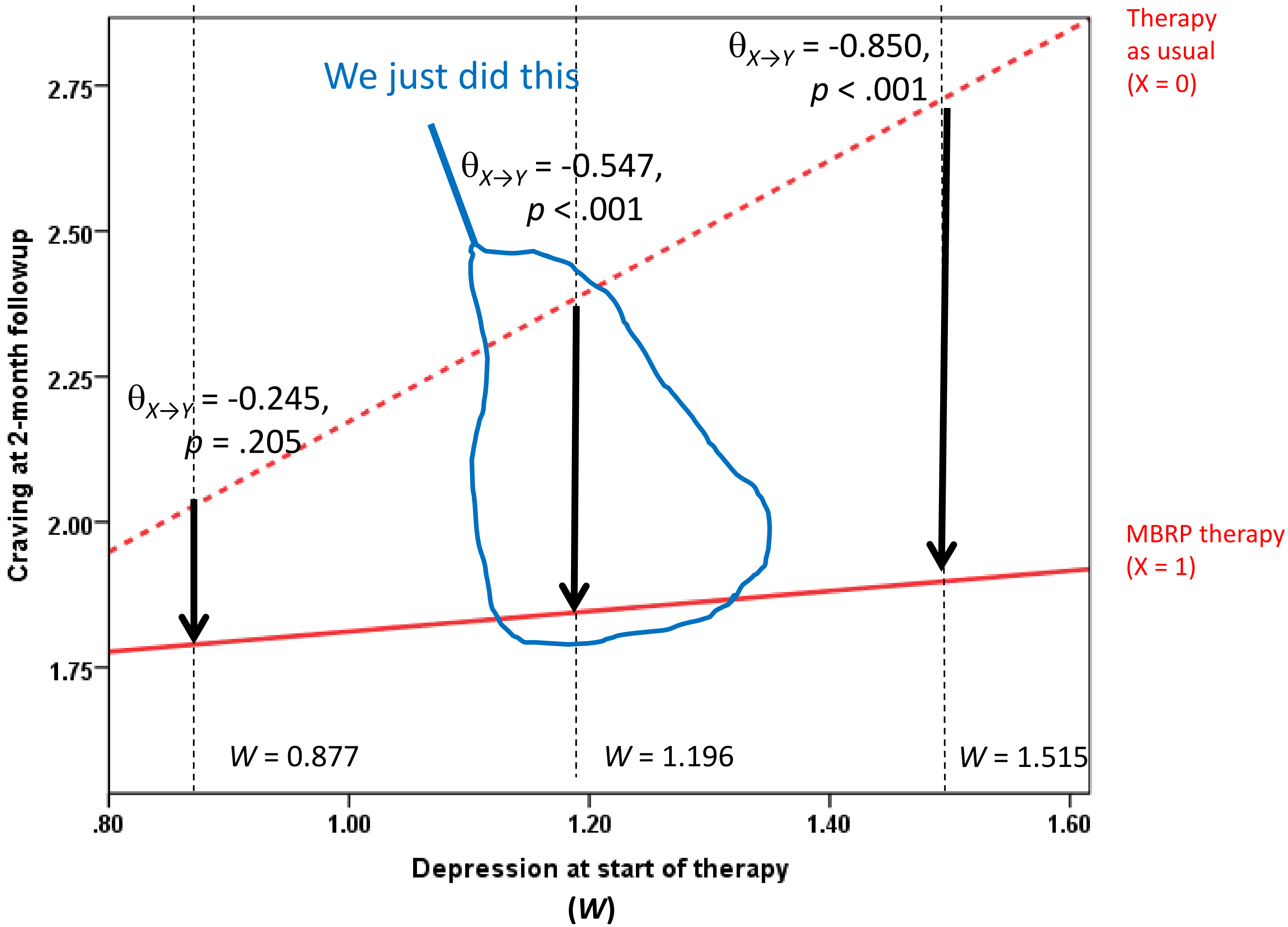
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.380	.364		6.534	.000
	MBRP: Therapy as usual (0) or MBRP therapy (1)	-.547	.137	-.279	-3.980	.000
	bdi0_p	1.122	.276	.366	4.063	.000
	interact	-.948	.423	-.197	-2.240	.026
	TREATHRS: Hours of therapy	-.018	.010	-.120	-1.719	.088
	CRAVE0: Baseline craving	.192	.073	.183	2.614	.010

a. Dependent Variable: CRAVE2: Craving at two month follow-up

$\theta_{X\to Y} | (W = 1.196)$ $\quad s_{\theta_{X\to Y}}$

MBRP therapy reduces craving relative to therapy as usual among people "average" in pre-therapy depression, $\theta_{X\to Y}$ = -0.547, p < .001.

Repeat for other values of the moderator



Pick-a-point: Regression centering approach

```
compute bdi0_p = bdi0-0.877.
compute interact = bdi0_p*mbrp.
regression/dep = crave2/method = enter mbrp bdi0_p interact treathrs crave0.
```

λ= 0.877
(One SD below the sample mean)

```
data mbrp;set mbrp;
bdi0_p=bdi0-0.877;
interact=bdi0_p*mbrp;
proc reg data=mbrp;model crave2=mbrp bdi0_p interact treathrs crave0;run;
```

```
mbrp <- transform(mbrp, bdi0_p = bdi0-0.877)
summary(lm(crave2~mbrp*bdi0_p+treathrs+crave0, data = mbrp))
```

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.023	.367		5.506	.000
	MBRP: Therapy as usual (0) or MBRP therapy (1)	-.245	.192	-.124	-1.272	.205
	bdi0_p	1.122	.276	.366	4.063	.000
	interact	-.948	.423	-.242	-2.240	.026
	TREATHRS: Hours of therapy	-.018	.010	-.120	-1.719	.088
	CRAVE0: Baseline craving	.192	.073	.183	2.614	.010

a. Dependent Variable: CRAVE2: Craving at two month follow-up

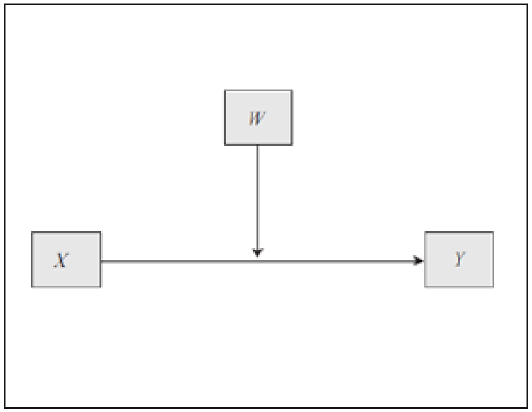
$\theta_{X \to Y} \mid (W = 0.877)$ $\quad s_{\theta_{X \to Y}}$

MBRP therapy does not reduce craving relative to therapy as usual among people "relatively low" in pre-therapy depression, $\theta_{X \to Y}$ = -0.245, p = .21.

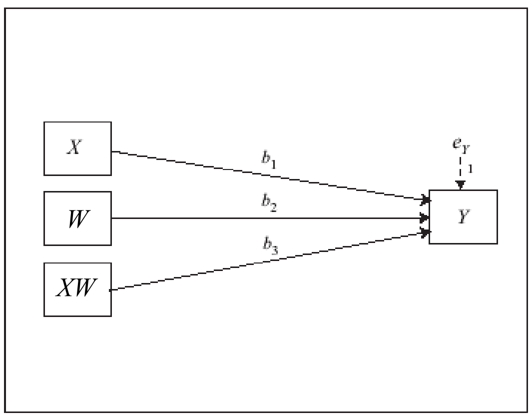
Using PROCESS

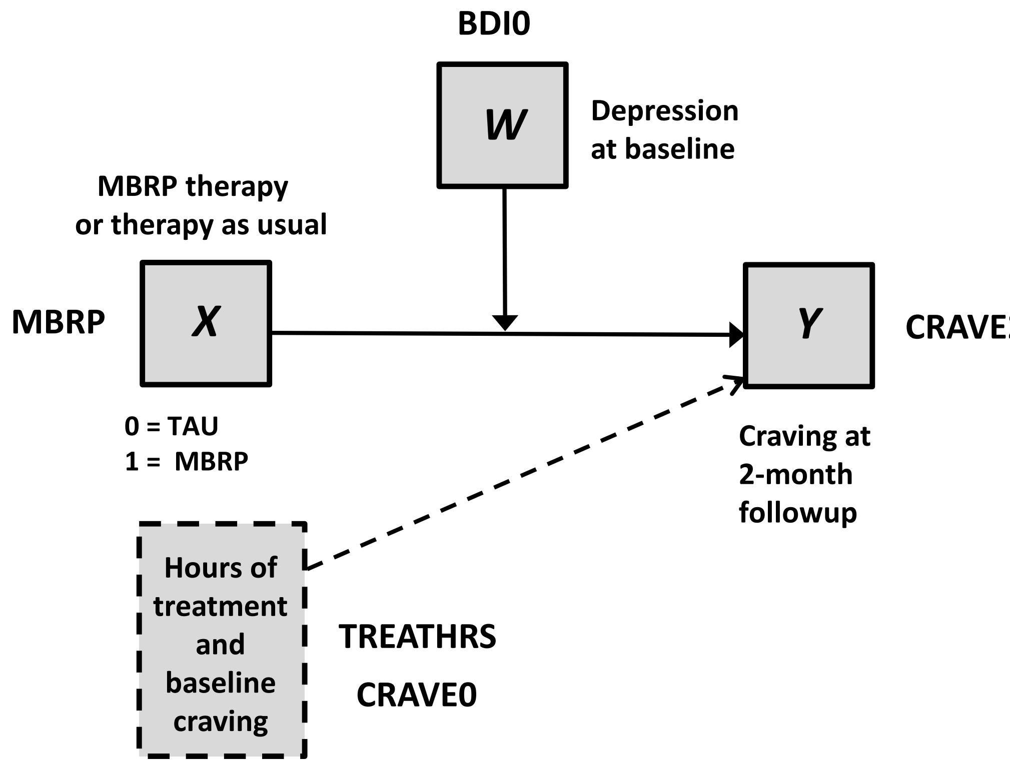
Model 1

Conceptual Diagram



Statistical Diagram






```
process cov = treathrs crave0/y=crave2/x=mbrp/w=bdi0/model=1/jn=1/plot=1/moments=1/intprobe=1.
```

```
%process(data=mbrp,cov=treathrs crave0,y=crave2,x=mbrp,w=bdi0,model=1,jn=1,plot=1,moments=1,
         intprobe=1);
```

```
process(data=mbrp, cov=c("treathrs", "crave0"), y="crave2", x="mbrp", w="bdi0", model=1, jn=1,
        plot=1, moments=1, intprobe=1)
```

PROCESS output

```
Model  : 1
    Y  : crave2
    X  : mbrp
    W  : bdi0

Covariates:
 treathrs crave0

Sample
Size:  168

***************************************************************************
OUTCOME VARIABLE:
 crave2
```

$$\widehat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

PROCESS generates the product term for you.

```
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5140      .2642      .7277    11.6319     5.0000   162.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.0385      .4701     2.2090      .0286      .1102     1.9668
mbrp          .5872      .5241     1.1204      .2642     -.4478     1.6222
bdi0         1.1221      .2762     4.0625      .0001      .5767     1.6675
Int_1        -.9485      .4235    -2.2398      .0265    -1.7847     -.1122
treathrs     -.0177      .0103    -1.7190      .0875     -.0380      .0026
crave0        .1920      .0735     2.6138      .0098      .0470      .3371

Product terms key:
 Int_1    :        mbrp     x        bdi0

Test(s) of highest order unconditional interaction(s):
       R2-chng         F        df1        df2          p
X*W      .0228    5.0166     1.0000   162.0000      .0265
```

PROCESS output

PROCESS sees that the moderator is quantitative (because it has more than 2 values) so it automatically implements the pick-a-point procedure. When `moments = 1` moderator values equal to the mean of the moderator as well as ± one SD from the mean.

```
*************************************************************************

Conditional effect of X on Y at values of the moderator(s):
       bdi0     Effect         se          t          p       LLCI       ULCI
      .8772     -.2447      .1922    -1.2733      .2047     -.6243      .1348
     1.1963     -.5473      .1375    -3.9818      .0001     -.8188     -.2759
     1.5153     -.8500      .1933    -4.3973      .0000    -1.2317     -.4683

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

*************************************************************************
```

$$\theta_{X \rightarrow Y} = 0.587 - 0.948W$$

MBRP therapy resulted in lower craving than did therapy as usual among those relatively “moderate” ($\theta_{X \rightarrow Y|W=1.196}$ = -0.547, p < .001) or “relatively high” ($\theta_{X \rightarrow Y|W=1.515}$ = -0.850, p < .001) in pre-therapy depression. Among those “relatively low” in pre-therapy depression, MBRP therapy had no statistically significant effect on craving relative to therapy as usual. ($\theta_{X \rightarrow Y|W=0.877}$ = -0.245, p = .205)

PROCESS output: PLOT option

```
process cov = treathrs crave0/y=crave2/x=mbrp/w=bdi0
  /model=1/jn=1/plot=1/moments=1.
```

```
%process (data=mbrp,cov=treathrs crave0,y=crave2,x=mbrp,
   w=bdi0,model=1,jn=1,plot=1,moments=1);
```

```
process(data=mbrp, cov=c("treathrs", "crave0"), y="crave2", x="mbrp",
        w="bdi0", model=1, jn=1, plot=1, moments=1, intprobe=1)
```

SPSS, SAS, and R versions produce a table of estimated values of *Y* for different combinations of *X* and *W*. Plug these into your preferred graphing program to generate a plot, or use SPSS, SAS, or R's graphics features. SPSS writes the code for you. Just cut and paste this into an SPSS syntax file and execute:

```
DATA LIST FREE/mbrp bdi0 crave2.
BEGIN DATA.
      .0000      .8772     2.0456
     1.0000      .8772     1.8009
      .0000     1.1963     2.4037
     1.0000     1.1963     1.8563
      .0000     1.5153     2.7617
     1.0000     1.5153     1.9117
END DATA.
GRAPH/SCATTERPLOT=bdi0 WITH crave2 BY mbrp.
```

Generating a graph from PROCESS "PLOT" option: SAS

```
data;
input mbrp bdi0 crave2;
datalines;
 .0000       .8772     2.0456
1.0000       .8772     1.8009
 .0000      1.1963     2.4037
1.0000      1.1963     1.8563
 .0000      1.5153     2.7617
1.0000      1.5153     1.9117
run;
proc sgplot;reg x=bdi0 y=crave2/group=mbrp;run;
```

Output generated
by the PLOT option.

Generating a graph from PROCESS "PLOT" option: R

```
x<-c(0,1,0,1,0,1)
w<-c(0.877,0.877,1.196,1.196,1.515,1.515)
y<-c(2.046,1.801,2.404,1.856,2.762,1.912)
plot(y=y,x=w,pch=15,col="white",
xlab="Depression at start of therapy",
ylab="Craving at 2-month follow-up")
legend.txt<-c("Therapy as usual (X=0)","Mindfulness therapy (X=1)")
legend("topleft",legend=legend.txt,
lty=c(3,1),lwd=c(3,2))
lines(w[x==0],y[x==0],lwd=3,lty=3)
lines(w[x==1],y[x==1],lwd=2,lty=1)
```

From the PLOT option in PROCESS.

Additional probing options: moments

Setting `moments = 0` or leaving it out, produces estimates of the conditional effect of *X* at the 16th, 50th, and 84th percentiles of the moderator rather than the mean and plus/minus one standard deviation. Or use the `wmodval` option to request a specific value of the moderator at which you'd like the conditional effect of *X*.

```
process y=.../moments=0.
```

```
%process(data=... ,moments=0);
```

```
process(data=... ,moments=0)
```

```
Conditional effects of the focal predictor at values of the moderator(s):

      bdi0      Effect         se          t          p       LLCI       ULCI
     .9020     -.2683      .1850    -1.4500      .1490     -.6336      .0971
    1.1900     -.5414      .1375    -3.9384      .0001     -.8129     -.2699
    1.5180     -.8525      .1941    -4.3923      .0000    -1.2358     -.4692

W values in conditional tables are the 16th, 50th, and 84th percentiles.
```

```
process y=.../wmodval=1.5.
```

```
%process(data=... ,wmodval=1.5);
```

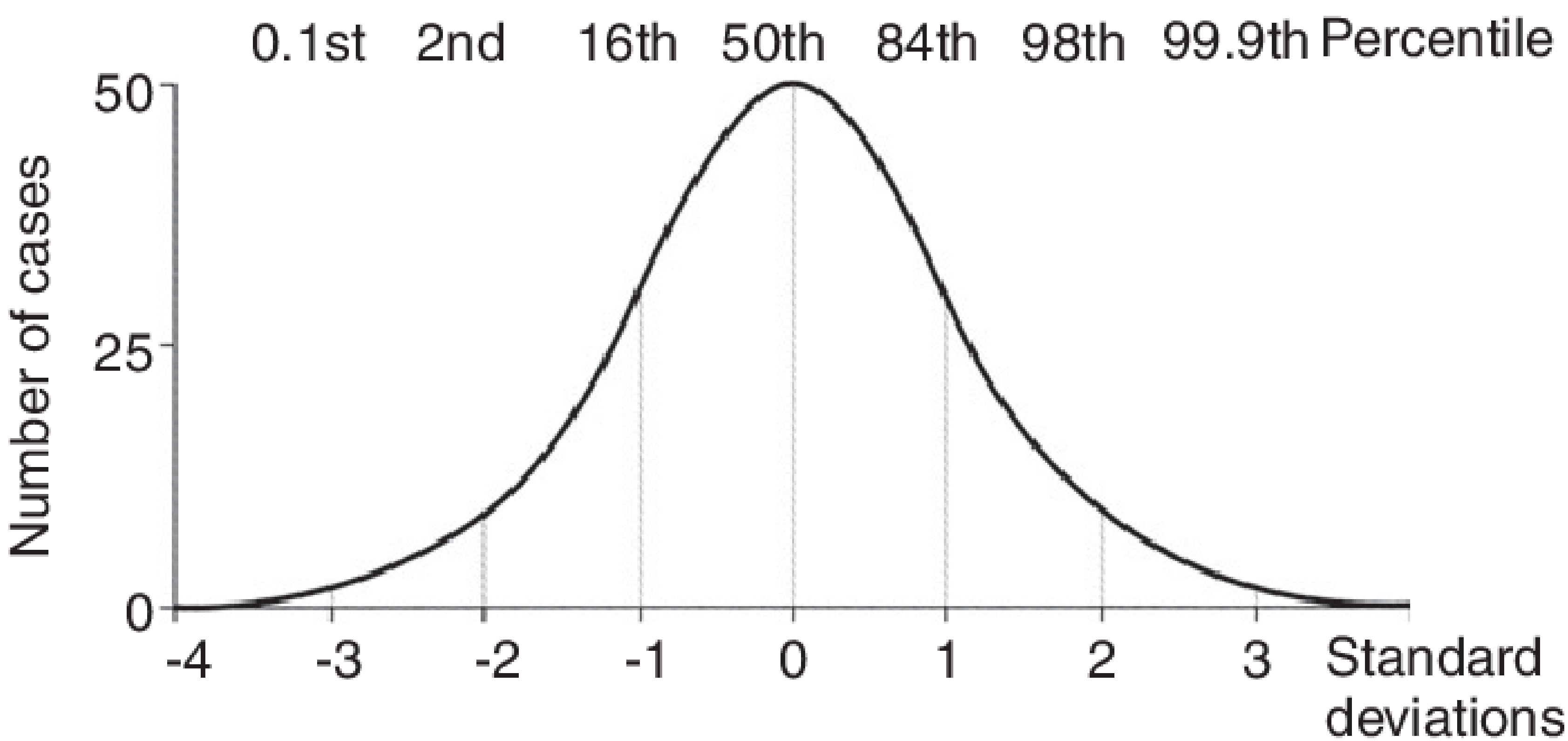
```
process(data=... ,wmodval=1.5)
```

```
               Conditional effect of X on Y at values of the moderators(s)
      bdi0     Effect         se          t          p       LLCI       ULCI
    1.5000     -.8354      .1888    -4.4253      .0000    -1.2082     -.4626
```

Why the 16th, 50th, and 84th Percentile?

The 16th, 50th, and 84th percentiles of a normal distribution correspond to the Mean $\pm$ 1SD.

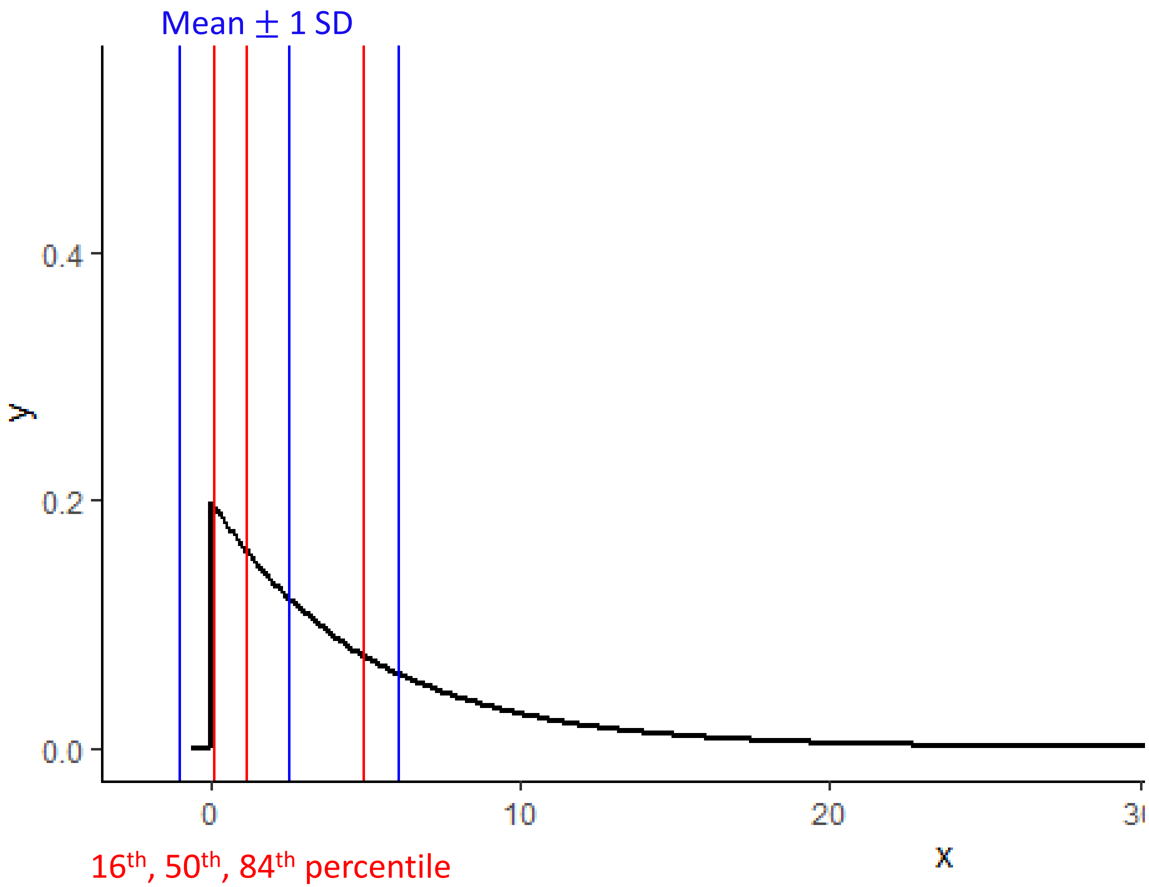
So **assuming your moderator is normally distributed, you would get the same answer either way**, and if the moderator is not normally distributed probing at percentiles guarantees they are within the range of the observed data.



Why the 16th, 50th, and 84th Percentile?

The 16th, 50th, and 84th percentiles of a normal distribution correspond to the Mean $\pm$ 1SD.

So assuming your moderator is normally distributed, you would get the same answer either way, and **if the moderator is not normally distributed probing at percentiles guarantees they are within the range of the observed data**.



Additional probing options: `intprobe`

You may not want to probe all interactions, especially if they're not significant. The `intprobe` option lets you set a threshold for the p-value of an interaction in order to probe it. The default is 0.10. Interactions that are significant at the 0.10 level will be probed by default. If you set `intprobe` to be 1, it will probe all interaction (because *p*-values are always less than 1). This can help reduce the busyness of the output, especially when we get to moderated mediation.

```
process y=... /intprobe=0.1.
```

```
%process(dat =... ,intprobe=0.1);
```

```
process(data=...,intprobe=0.1);
```

Same as leaving `intprobe` out of command

```
process y=... /intprobe=0.05.
```

```
%process(dat =... ,intprobe=0.05);
```

```
process(data=...,intprobe=0.05);
```

Probes all interactions in the model **significant at .05**

```
process y=... /intprobe=1.
```

```
%process(dat =... ,intprobe=1);
```

```
process(data=...,intprobe=1);
```

Probes **all interactions**

The Johnson-Neyman technique

The Johnson-Neyman technique seeks to find the value or values of the moderator *(W)* within the data, if they exist, such that the *p*-value for the ratio of the conditional effect of the focal predictor at that value or values of *W* is exactly equal to some chosen level of significance α

To do so, we ask what value of *W* produces a ratio exactly equal to the critical *t* value (t_{crit}) required to reject the null hypothesis that the conditional effect of *X* is equal to zero?

$$t_{crit} = \frac{b_1 + b_3 W}{\sqrt{s_{b_1}^2 + 2W s_{b_1 b_3}^2 + W^2 s_{b_3}^2}}$$

Isolate *W* and solve the polynomial that results. The quadratic formula finds the solutions:

$$W = \frac{-2(t_{crit}^2 s_{b_1 b_3}^{-} - b_1 b_3) \pm \sqrt{(2t_{crit}^2 s_{b_1 b_3} - 2b_1 b_3)^2 - 4(t_{crit}^2 s_{b_3}^2 - b_3^2)(t_{crit}^2 s_{b_1}^2 - b_1^2)}}{2(t_{crit}^2 s_{b_3}^2 - b_3^2)}$$

The Johnson-Neyman technique

This will produce no values, one value, or two values of *W* that are within the range of the moderator variable data.

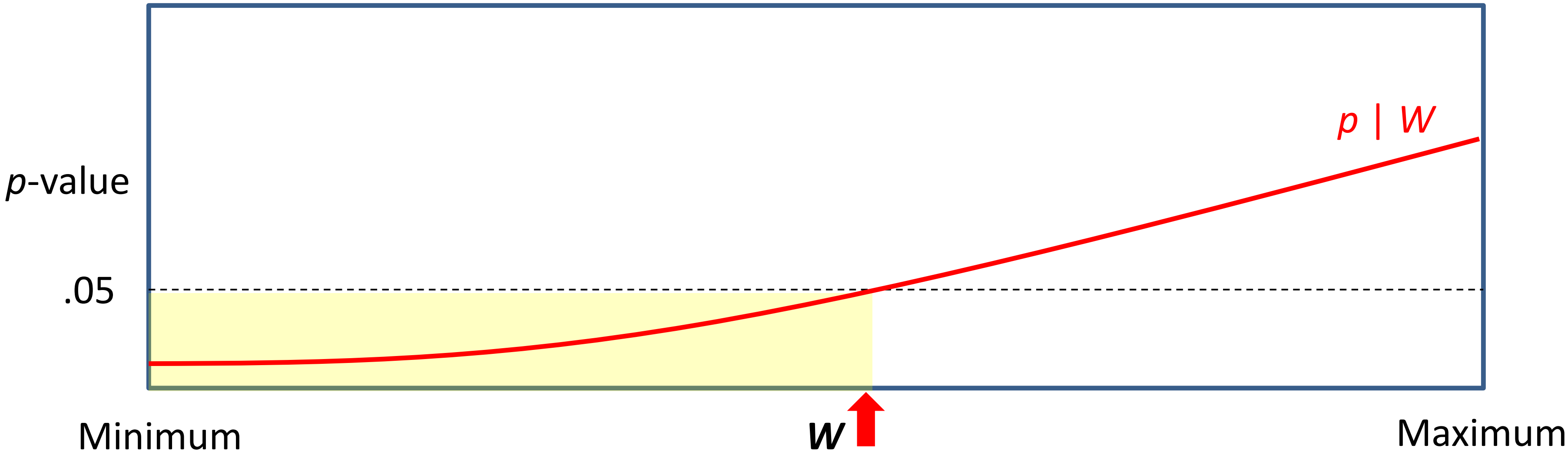
- If one value, this defines a single point of transition between a statistically significant and a statistically nonsignificant conditional effect of the focal predictor, such that $p \leq .05$ for either values of the moderator (1) equal to above *W* or (2) equal to and below *W*.

- If two values, this defines the two points of transition between a statistically significant and a statistically nonsignificant conditional effect of the focal predictor, such that the conditional effect is statistically significant for either (1) values of the moderator between the two values of *W*, or (2) values of the moderator at least as large as the larger *W* and at least as small as the smaller *W*.

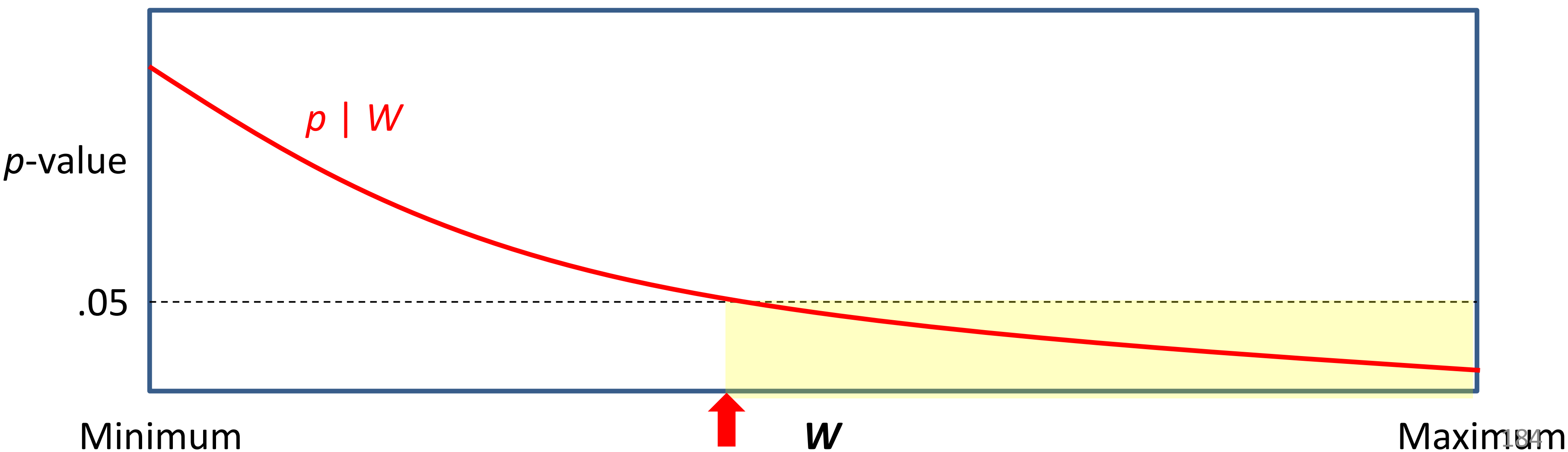
- If no values, that means the conditional effect is statistically significant for ALL values of the moderator within the range of the data, or it NEVER is.

We would not attempt to do this by hand

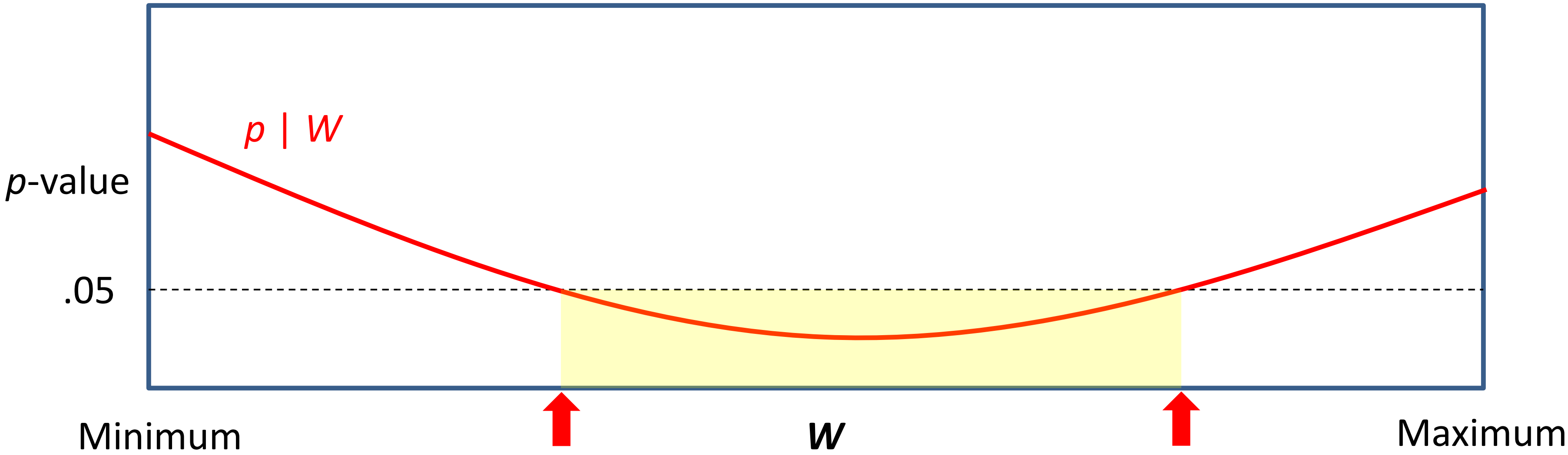
Examples of one solution



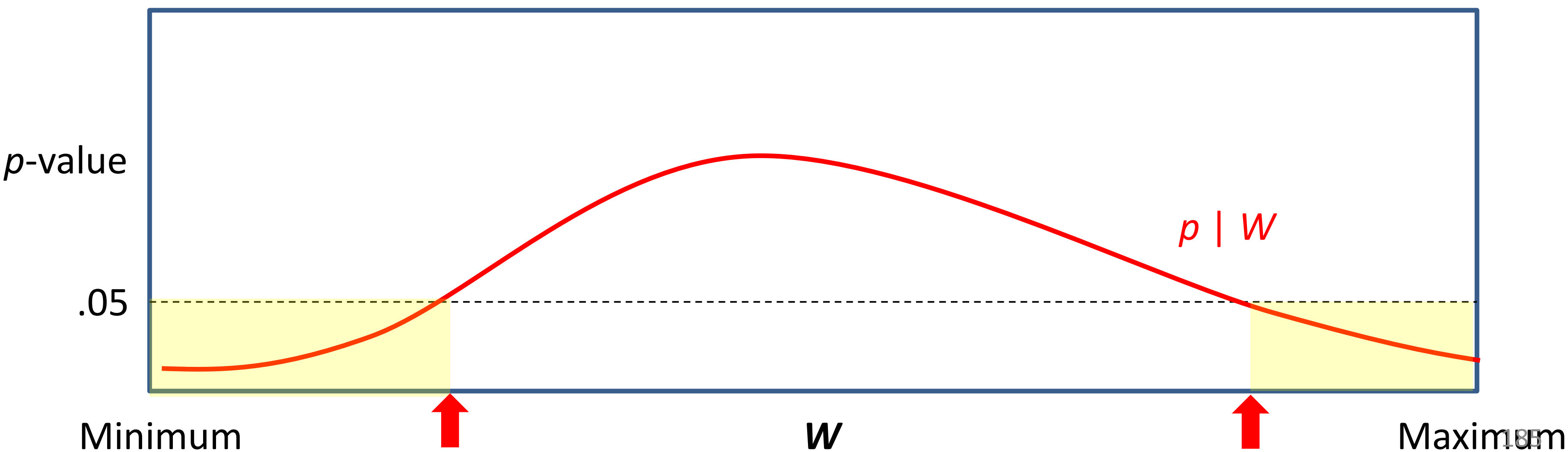
OR



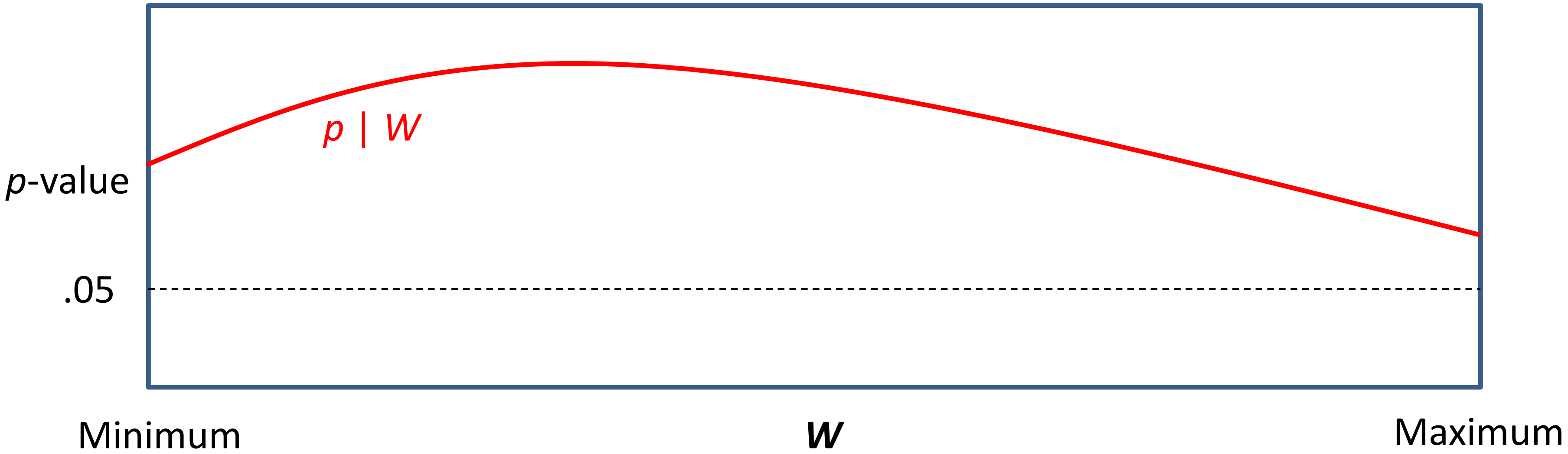
Examples of two solutions



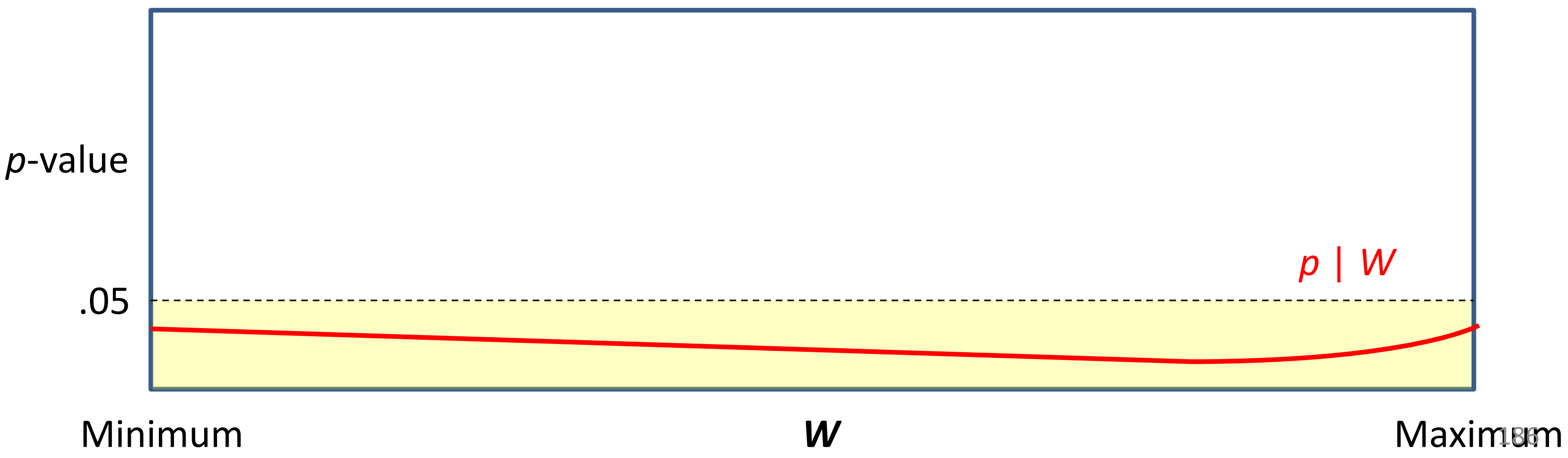
OR



Examples of no solutions



OR



Johnson-Neyman output from PROCESS

```
process cov = treathrs crave0/y=crave2/x=mbrp/w=bdi0
  /model=1/jn=1/plot=1/moments=1.
```

```
%process (data=mbrp,cov=treathrs crave0,y=crave2,x=mbrp,
   w=bdi0,model=1,jn=1,plot=1,moments=1);
```

```
process(data=mbrp, cov=c("treathrs", "crave0"), y="crave2", x="mbrp",
        w="bdi0", model=1, jn=1, plot=1, moments=1, intprobe=1)
```

Moderator value(s) defining Johnson-Neyman significance region(s)

Value	% below	% above
.9681	21.4286	78.5714

$\theta_{X \rightarrow Y} | W$

W

Conditional effect of X on Y at values of the moderator:

bdi0	Effect	se	t	p	LLCI	ULCI
.0000	.5872	.5241	1.1204	.2642	-.4478	1.6222
.1070	.4858	.4806	1.0108	.3136	-.4632	1.4347
.2140	.3843	.4373	.8787	.3809	-.4793	1.2479
.3210	.2828	.3946	.7167	.4746	-.4964	1.0620
.4280	.1813	.3525	.5144	.6077	-.5147	.8773
.5350	.0798	.3112	.2565	.7979	-.5348	.6944
.6420	-.0217	.2713	-.0798	.9365	-.5574	.5141
.7490	-.1231	.2334	-.5276	.5985	-.5840	.3377
.8560	-.2246	.1986	-1.1312	.2596	-.6167	.1675
.9630	-.3261	.1688	-1.9318	.0551	-.6595	.0072
.9681	-.3309	.1676	-1.9747	.0500	-.6618	.0000
1.0700	-.4276	.1472	-2.9047	.0042	-.7183	-.1369
1.1770	-.5291	.1377	-3.8435	.0002	-.8009	-.2573
1.2840	-.6306	.1426	-4.4220	.0000	-.9122	-.3490
1.3910	-.7321	.1607	-4.5553	.0000	-1.0494	-.4147
1.4980	-.8335	.1882	-4.4288	.0000	-1.2052	-.4619
1.6050	-.9350	.2216	-4.2186	.0000	-1.3727	-.4973
1.7120	-1.0365	.2587	-4.0063	.0001	-1.5474	-.5256
1.8190	-1.1380	.2981	-3.8178	.0002	-1.7266	-.5494
1.9260	-1.2395	.3389	-3.6571	.0003	-1.9088	-.5702
2.0330	-1.3410	.3808	-3.5216	.0006	-2.0929	-.5890
2.1400	-1.4424	.4234	-3.4072	.0008	-2.2784	-.6064

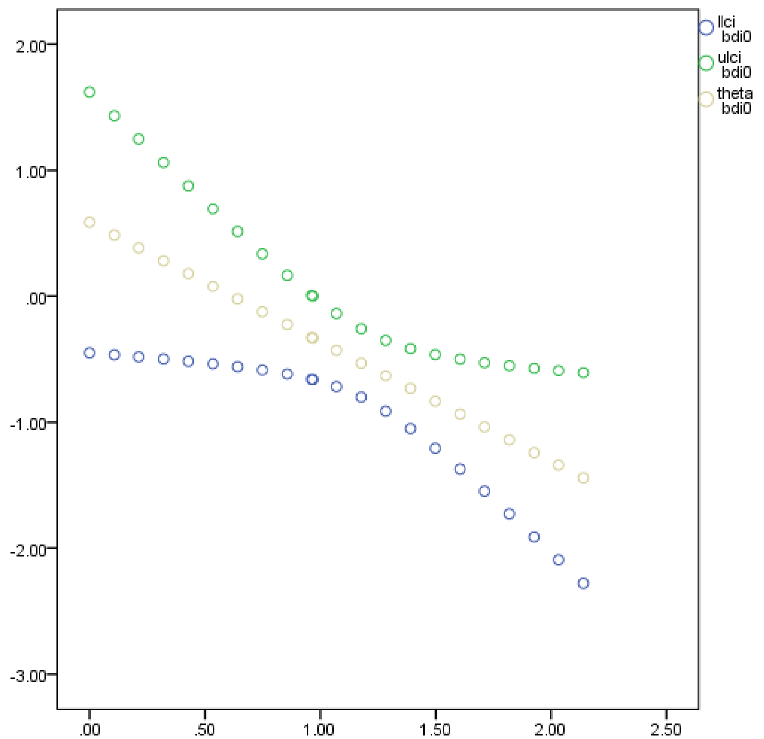
78.6% of the data are up here

A visual representation (SPSS)

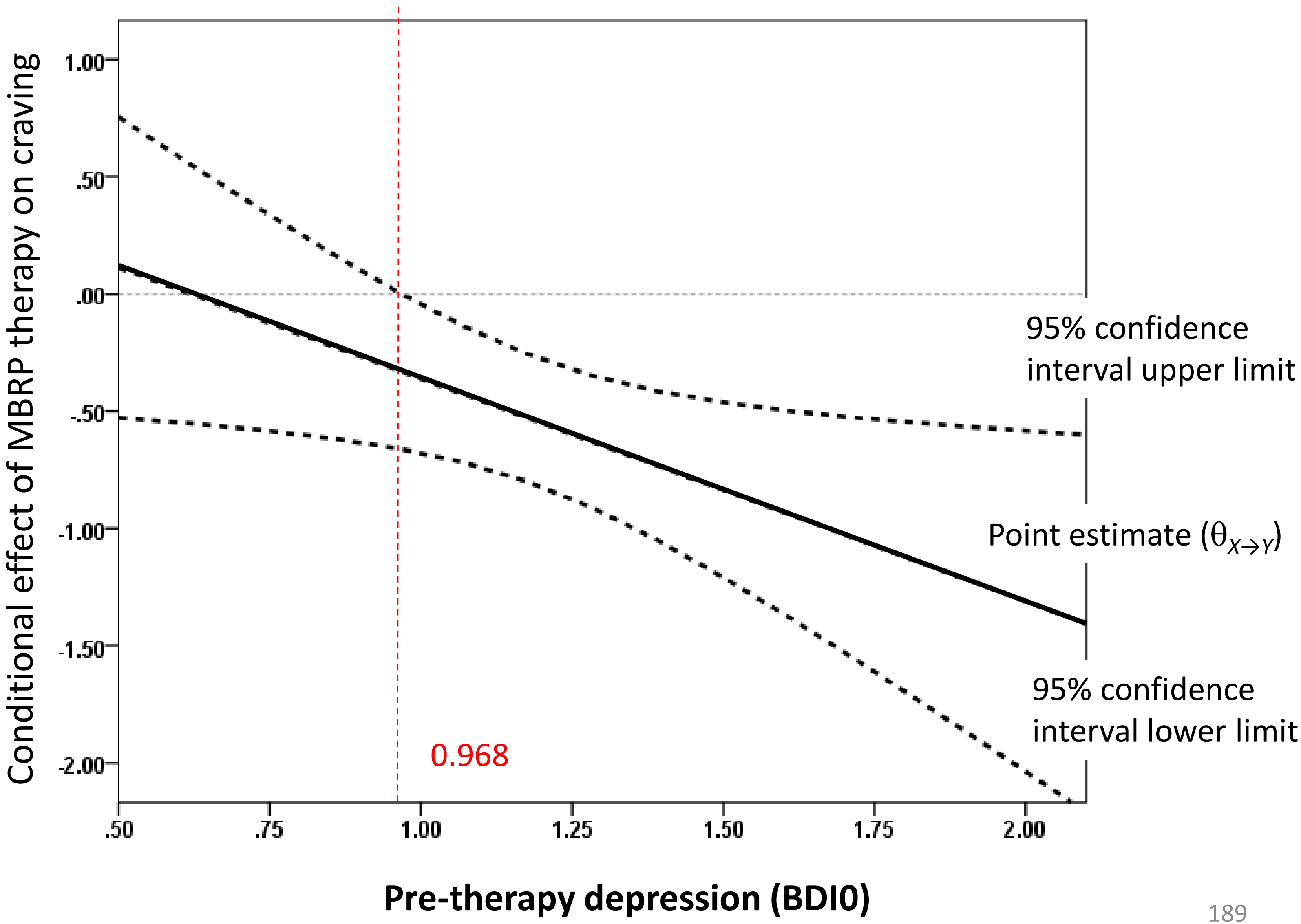
bdi0 effect LLCI ULCI (from PROCESS JN output)

```
data list free/bdi0 theta llci ulci.
begin data.
 .0000      .5872     -.4478    1.6222
 .1070      .4858     -.4632    1.4347
 .2140      .3843     -.4793    1.2479
 .3210      .2828     -.4964    1.0620
 .4280      .1813     -.5147     .8773
 .5350      .0798     -.5348     .6944
 .6420     -.0217     -.5574     .5141
 .7490     -.1231     -.5840     .3377
 .8560     -.2246     -.6167     .1675
 .9630     -.3261     -.6595     .0072
 .9681     -.3309     -.6618     .0000
1.0700     -.4276     -.7183    -.1369
1.1770     -.5291     -.8009    -.2573
1.2840     -.6306     -.9122    -.3490
1.3910     -.7321    -1.0494    -.4147
1.4980     -.8335    -1.2052    -.4619
1.6050     -.9350    -1.3727    -.4973
1.7120    -1.0365    -1.5474    -.5256
1.8190    -1.1380    -1.7266    -.5494
1.9260    -1.2395    -1.9088    -.5702
2.0330    -1.3410    -2.0929    -.5890
2.1400    -1.4424    -2.2784    -.6064
end data.
graph
  /scatterplot(overlay)=bdi0 bdi0 bdi0 WITH llci ulci theta (pair).
```

Before editing

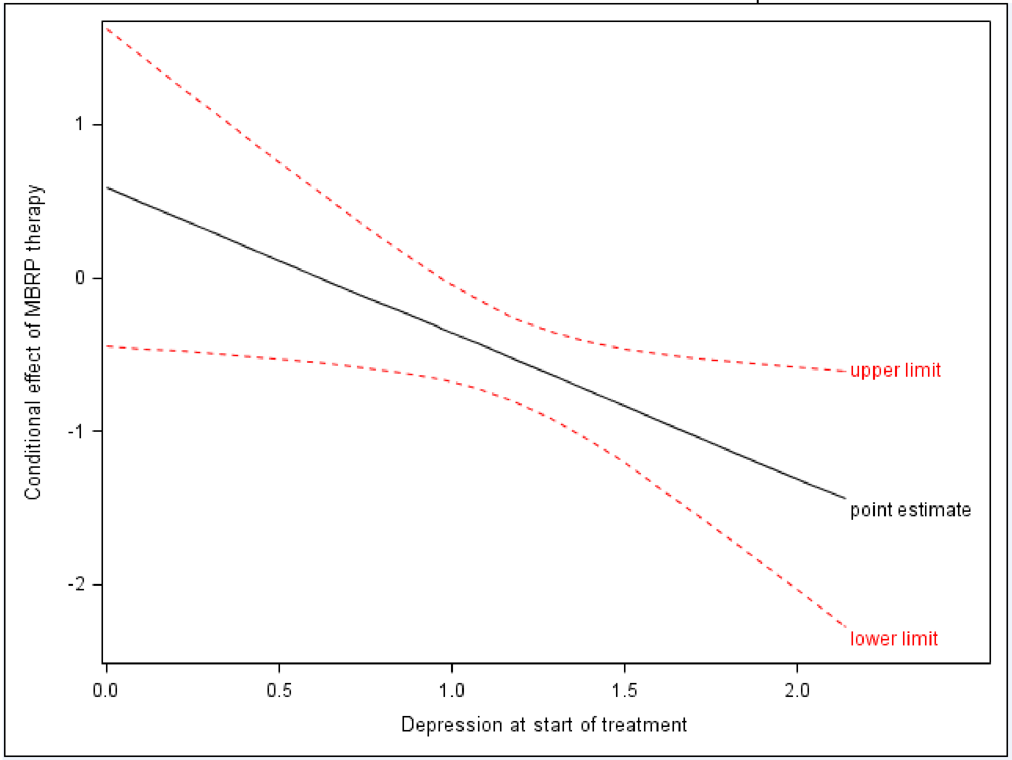


After some editing in SPSS



A visual representation (SAS)

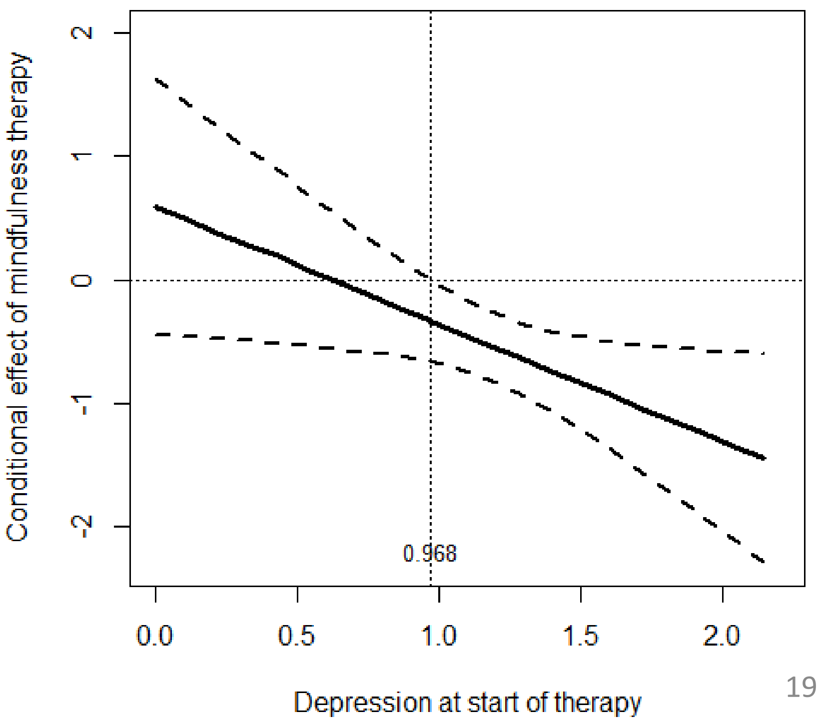
```
data;
input bdi0 effect llci ulci;
datalines;
 .0000       .5872      -.4478     1.6222
 .1070       .4858      -.4632     1.4347
 .2140       .3843      -.4793     1.2479
 .3210       .2828      -.4964     1.0620
 .4280       .1813      -.5147      .8773
 .5350       .0798      -.5348      .6944
 .6420      -.0217      -.5574      .5141
 .7490      -.1231      -.5840      .3377
 .8560      -.2246      -.6167      .1675
 .9630      -.3261      -.6595      .0072
 .9681      -.3309      -.6618      .0000
1.0700      -.4276      -.7183     -.1369
1.1770      -.5291      -.8009     -.2573
1.2840      -.6306      -.9122     -.3490
1.3910      -.7321     -1.0494     -.4147
1.4980      -.8335     -1.2052     -.4619
1.6050      -.9350     -1.3727     -.4973
1.7120     -1.0365     -1.5474     -.5256
1.8190     -1.1380     -1.7266     -.5494
1.9260     -1.2395     -1.9088     -.5702
2.0330     -1.3410     -2.0929     -.5890
2.1400     -1.4424     -2.2784     -.6064
run;
proc sgplot;
  series x=bdi0 y=ulci/curvelabel = "upper limit" lineattrs=(color=red pattern=ShortDash);
  series x=bdi0 y=effect/curvelabel = "point estimate" lineattrs=(color=black pattern=Solid);
  series x=bdi0 y=llci/curvelabel = "lower limit" lineattrs=(color=red pattern=ShortDash);
  yaxis label = "Conditional effect of MBRP therapy";
  xaxis label = "Depression at start of treatment";
run;
```



A visual representation (R)

```
bdi0<-c(0,.107,.214,.321,.438,.535,.642,.749,.856,.963,.968,1.070,1.177,
  1.284,1.391,1.498,1.605,1.712,1.819,1.926,2.033,2.140)
effect<-c(.587,.486,.384,.283,.181,.080,-.022,-.123,-.225,-.326,-.331,-.428,
  -.529,-.631,-.732,-.834,-.935,-1.037,-1.138,-1.240,-1.341,-1.442)
llci<-c(-.448,-.463,-.479,-.496,-.515,-.535,-.557,-.584,-.617,-.660,-.662,
  -.718,-.801,-.912,-1.049,-1.205,-1.373,-1.547,-1.727,-1.909,-2.092,-2.278)
ulci<-c(1.622,1.435,1.248,1.062,.877,.684,.515,.338,.168,.007,0,-.137,
  -.257,-.349,-.415,-.462,-.497,-.526,-.549,-.571,-.589,-.606)
plot(x=bdi0,y=effect,type="l",pch=19,ylim=c(-2.3,2),xlim=c(0,2.2),lwd=3,
ylab="Conditional effect of mindfulness therapy",
xlab="Depression at start of therapy")
points(bdi0,llci,lwd=2,lty=2,type="l")
points(bdi0,ulci,lwd=2,lty=2,type="l")
abline(h=0,untf = FALSE,lty=3,lwd=1)
abline(v=0.968,untf=FALSE,lty=3,lwd=1)
text(0.968,-2.2,"0.968",cex=0.8)
```

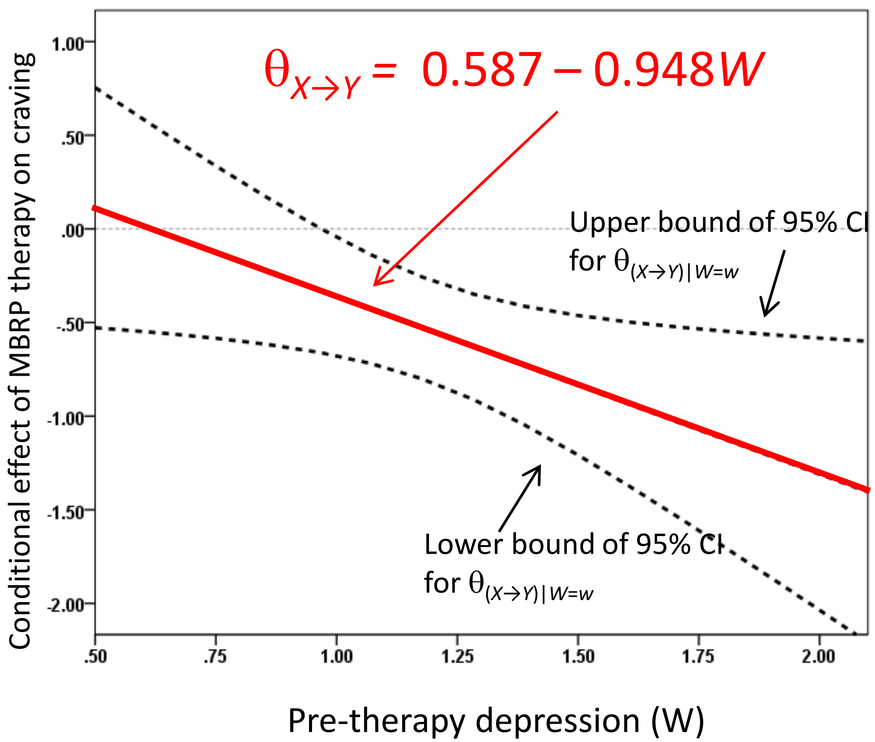
From the JN option in PROCESS.



Testing moderation versus testing a conditional effect

A test of moderation is a test as to whether the size of the effect of *X* on *Y* is related to the proposed moderator. This is different than asking whether a conditional effect is different from zero.

$$\hat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$



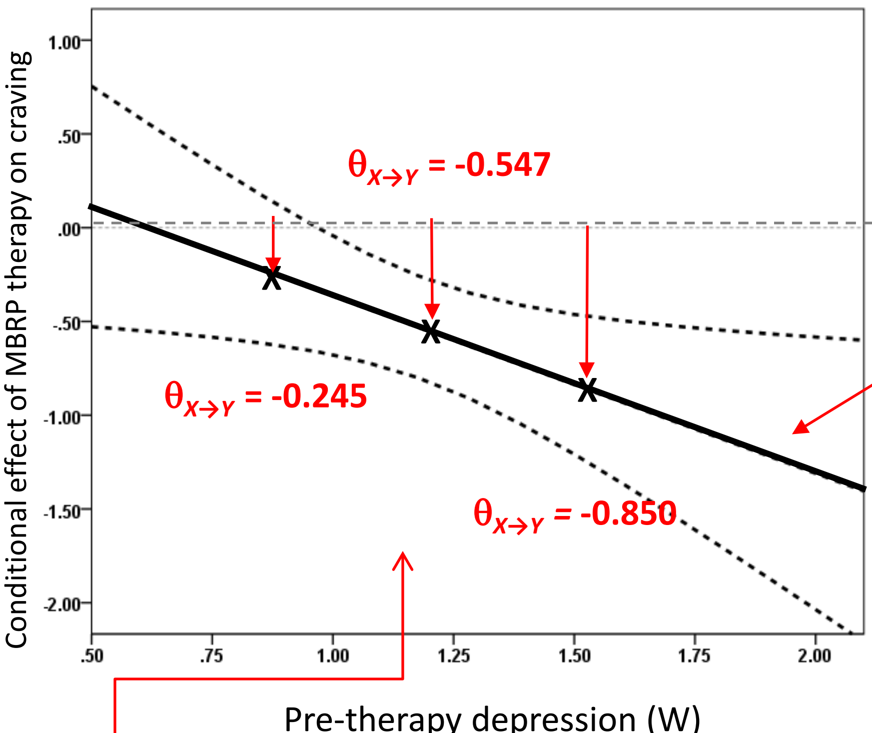
$\theta_{X\rightarrow Y} = b_1 + b_3W = 0.587 - 0.948W$

b_3 is the slope of this line. It is statistically different from zero, meaning that the effect of *X* depends on *W*---moderation.

Moderation does **not** imply that the conditional effect of *X* is different from zero at some, any, or all specific values of the moderator that you choose. Often it will be, perhaps for some values of the moderator but not others. But this is not a requirement of moderation.

Testing moderation versus testing a conditional effect

A test of moderation is a test as to whether the size of the effect of *X* on *Y* is related to the proposed moderator. This is different than asking whether a conditional effect is different from zero.



When testing a conditional effect, we are asking whether the effect of *X* on Y at a specific value of *W* is statistically different from zero. This is the difference between the point estimate of $\theta_{X\to Y}$ and zero.

$$\theta_{X\to Y} = b_1 + b_3W = 0.587 - 0.948W$$

Difference in significance does not imply significantly different. The pattern of significance or lack thereof across values of *M* does not say anything about moderation.

Conditional effect of X on Y at values of the moderator(s):

bdi0	Effect	se	t	p	LLCI	ULCI
.8772	-.2447	.1922	-1.2733	.2047	-.6243	.1348
1.1963	-.5473	.1375	-3.9818	.0001	-.8188	-.2759
1.5153	-.8500	.1933	-4.3973	.0000	-1.2317	-.4683

Comparing conditional effects

We want to know whether the conditional effect of X on Y when $W = w_1$ is different from the conditional effect of X on Y when $W = w_2$.

$$\theta_{(X \rightarrow Y)|W=w_2} - \theta_{(X \rightarrow Y)|W=w_1} = (b_1 + b_3 w_2) - (b_1 + b_3 w_1)$$
$$= (w_2 - w_1) b_3$$

and the standard error of the difference is $(w_2 - w_1) \times$ standard error of b_3. Under the null hypothesis that the difference in conditional effects is zero, the ratio

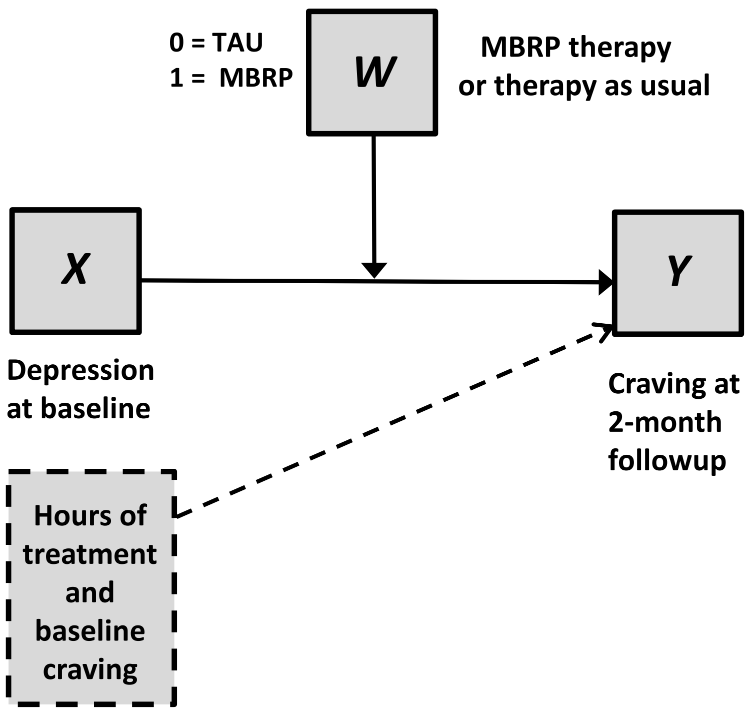
$$\frac{(w_2 - w_1) b_3}{(w_2 - w_1) se_{b_3}}$$

is distributed as $t(df_{residual})$. But notice that *regardless of the values of w_1 and w_2*, this ratio simplifies to b_3 / se_{b_3}. **We already have the *p*-value for this**. It is the p-value for b_3 from the regression model.

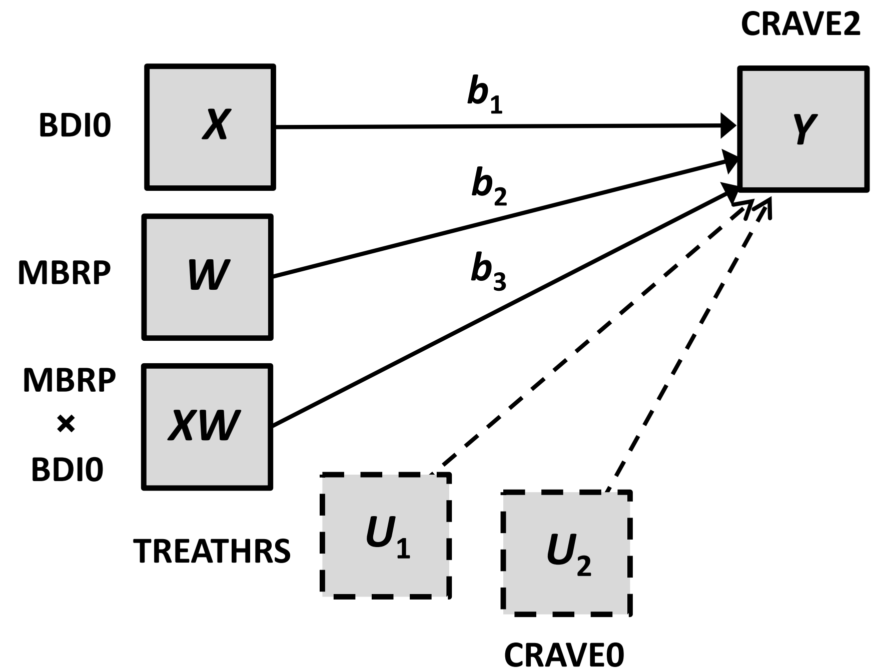
A test of linear moderation of *X*'s effect on *Y* by *W* is equivalent to a test of the difference between *any* two conditional effects of *X*. Moderation = any two conditional effects of *X* are different from each other. No moderation = no two conditional effects of *X* are different from each other. It doesn't matter what values of w_1 and w_2 you choose.

A Dichotomous Moderator

Conceptual diagram



Statistical model



Does the association between pre-treatment depression and later craving differ between those who receive MBRP therapy versus therapy as usual?

Probing the Interaction

When the moderator is dichotomous, the pick-a-point procedure is the only option available, as the Johnson-Neyman technique is meaningful only with a quantitative moderator. Typically, you'd want to estimate the effect of the focal predictor at the two values of the moderator and conduct an inferential test for each conditional effect.

$$\hat{Y}_i = 1.038 + 1.122X_i + 0.587W_i - 0.948X_iW_i \ldots$$
$$= 1.038 + (1.122 - 0.948W_i)X_i + 0.587W_i + \ldots$$

$$\theta_{X \rightarrow Y} = b_1 + b_3W = 1.122 - 0.948W$$

When one of the moderator categories is coded 0, we already have an estimate of $\theta_{X \rightarrow Y}$ when $W = 0$. That estimate is b_1. And the regression output provides a test of significance.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.038	.470		2.209	.029
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.587	.524	.299	1.120	.264
	BDI0: Beck Depression Inventory baseline	1.122	.276	.366	4.063	.000
	mbrpdep	-.948	.423	-.598	-2.240	.026
	TREATHRS: Hours of therapy	-.018	.010	-.120	-1.719	.088
	CRAVE0: Baseline craving	.192	.073	.183	2.614	.010

a. Dependent Variable: CRAVE2: Craving at two month follow-up

Among those given therapy as usual, those who were relatively more depressed at the start of therapy had relatively higher craving at two months follow-up, $\theta_{X \rightarrow Y} = 1.122$, $t(162) = 4.063$, $p < .001$

Probing the Interaction

We already know effect of pre-therapy depression on later craving among those given MBRP therapy. That is 1.122 – 0.948(1) = 0.174. We can use the regression centering approach, constructing $W' = W - 1$ and re-estimating the model in order to get a test of significance.

```
compute mbrp_p = mbrp-1.
compute mbrpdep = mbrp_p*bdi0.
regression/dep = crave2/method = enter mbrp_p bdi0 mbrpdep treathrs crave0.
```

```
data mbrp;set mbrp;mbrp_p=mbrp-1;mbrpdep=mbrp_p*bdi0;
proc reg data=mbrp;model crave2=mbrp_p bdi0 mbrpdep treathrs crave0;run;
```

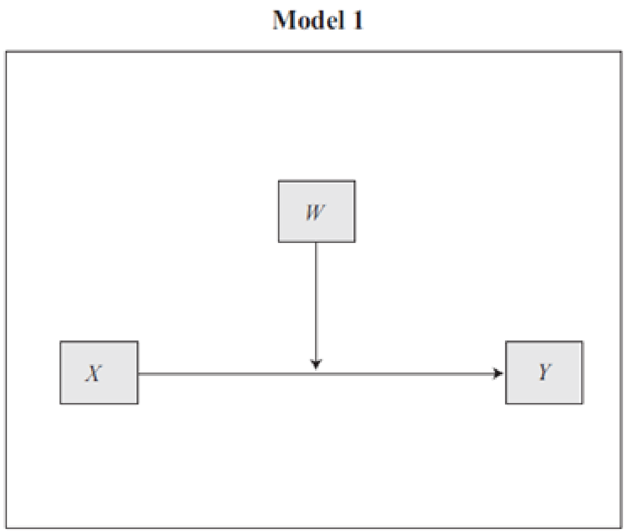
```
mbrp <- transform(mbrp, mbrp_p = mbrp-1)
summary(lm(crave2~mbrp_p*bdi0+treathrs+crave0, data = mbrp))
```

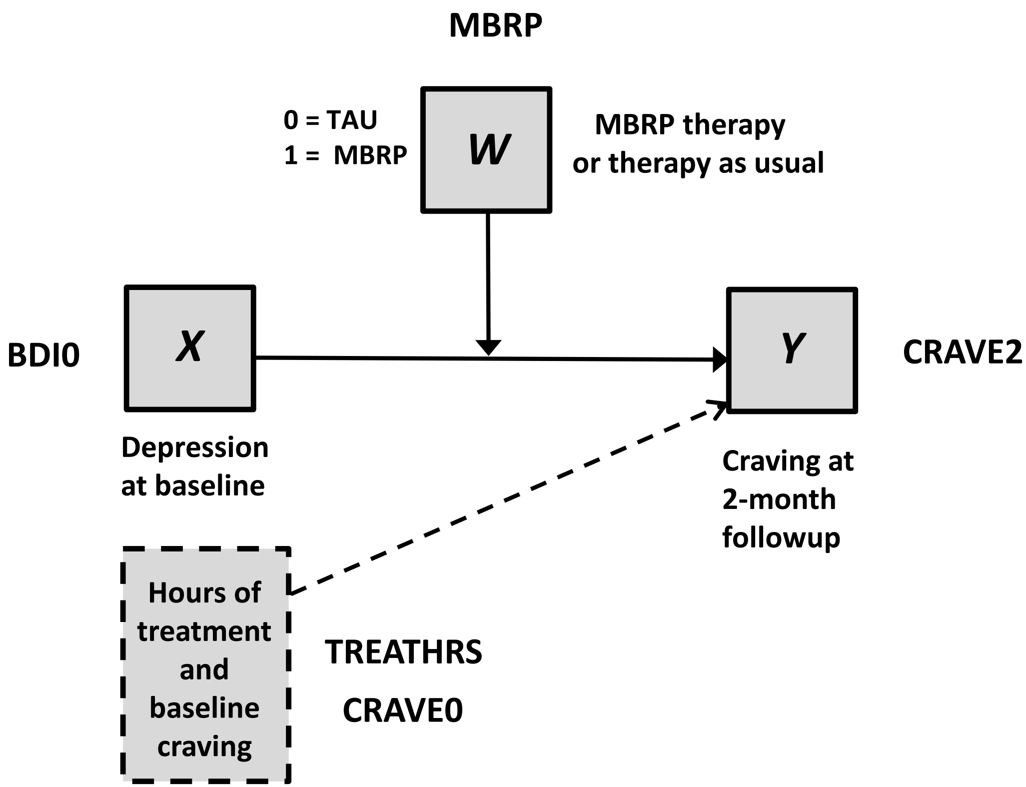
Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.626	.535		3.041	.003
	mbrp_p	.587	.524	.299	1.120	.264
	BDI0: Beck Depression Inventory baseline	.174	.328	.057	.529	.597
	mbrpdep	-.948	.423	-.639	-2.240	.026
	TREATHRS: Hours of therapy	-.018	.010	-.120	-1.719	.088
	CRAVE0: Baseline craving	.192	.073	.183	2.614	.010

a. Dependent Variable: CRAVE2: Craving at two month follow-up

Among those given MBRP therapy, there was no statistically significant relationship between pre-therapy depression and later craving, $\theta_{X \to Y} = 0.174$, $t(162) = 0.529$, $p = .597$

Estimation Using PROCESS






```
process cov = treathrs crave0/y=crave2/x=bdi0/w=mbrp/model=1.
```

```
%process (data=mbrp,cov=treathrs crave0,y=crave2,x=bdi0,w=mbrp,model=1);
```

```
process(data=mbrp, cov=c("treathrs", "crave0"), y="crave2", x="bdi0", w="mbrp", model=1)
```

Notice we did not include `jn` or `moments`, because the moderator is dichotomous

PROCESS Output

```
Model = 1
    Y = crave2
    X = bdi0
    M = mbrp

Statistical Controls:
CONTROL= treathrs crave0

Sample size
        168

**************************************************************************
Outcome: crave2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5140      .2642      .7277    11.6319     5.0000   162.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.0385      .4701     2.2090      .0286      .1102     1.9668
mbrp          .5872      .5241     1.1204      .2642     -.4478     1.6222
bdi0         1.1221      .2762     4.0625      .0001      .5767     1.6675
int_1        -.9485      .4235    -2.2398      .0265    -1.7847     -.1122
treathrs     -.0177      .0103    -1.7190      .0875     -.0380      .0026
crave0        .1920      .0735     2.6138      .0098      .0470      .3371

Interactions:

 int_1    bdi0        X     mbrp

R-square increase due to interaction(s):
         R2-chng          F        df1        df2          p
int_1      .0228     5.0166     1.0000   162.0000      .0265

*************************************************************************

Conditional effect of X on Y at values of the moderator(s):
       mbrp     Effect         se          t          p       LLCI       ULCI
      .0000     1.1221      .2762     4.0625      .0001      .5767     1.6675
     1.0000      .1736      .3281      .5291      .5974     -.4744      .8216
```

PROCESS detects that the moderator is dichotomous and generates the conditional effect of the focal predictor at the two values of the moderator.

Myths and truths about mean centering

In a model such as

$$\hat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$$

there is much ado in the literature about the need to mean center *X* and *W* first, thereby estimating the following model instead:

$$\hat{Y}_i = b'_0 + b'_1(X_i - \bar{X}) + b'_2(W_i - \bar{W}) + b_3(X_i - \bar{X})(W_i - \bar{W})$$

There are three reasons commonly offered for why this should be done.

(1) Estimation accuracy and statistical power is increased by reducing collinearity. **A MYTH!**
(2) The interpretations of b_1 and b_2 are more meaningful. **TYPICALLY TRUE!**
(3) Rounding error is less likely to affect computations. **NOT TYPICALLY A CONCERN WITH MODERN COMPUTING**

There is no need to mean center in this fashion, although you may do so if you choose. As standardization is a form of mean centering (combined with a rescaling), all these arguments apply to standardization as well.

Illustration

Without mean centering

```
compute mbrpdep = mbrp*bdi0.
regression/dep = crave2/method = enter mbrp bdi0 mbrpdep treathrs crave0.
```

```
data mbrp;set mbrp;mbrpdep=mbrp*bdi0;run;
proc reg data=mbrp;model crave2=mbrp bdi0 mbrpdep treathrs crave0;run;
```

```
summary(lm(crave2~mbrp*bdi0+treathrs+crave0, data = mbrp))
```

$$\widehat{Y}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ ...$$

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.038	.470		2.209	.029
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.587	.524	.299	1.120	.264
	BDI0: Beck Depression Inventory baseline	1.122	.276	.366	4.063	.000
	mbrpdep	-.948	.423	-.598	-2.240	.026
	TREATHRS: Hours of therapy	-.018	.010	-.120	-1.719	.088
	CRAVE0: Baseline craving	.192	.073	.183	2.614	.010

a. Dependent Variable: CRAVE2: Craving at two month follow-up

b_3 = -0.948
se_{b3} = 0.423
t = -2.240,
p = 0.026

b_1 = 0.587. This is the effect of X (MBRP) when W (pre-therapy depression) = 0.

b_2 = 1.122. This is the effect of W (Pre-therapy depression) when X = 0 (therapy-as-usual condition)

Illustration

With mean centering

```
compute mbrp_c = mbrp-0.554.
compute bdi0_c = bdi0-1.196.
compute mbrpdep_c = mbrp_c*bdi0_c.
regression/dep = crave2/method = enter mbrp_c bdi0_c mbrpdep_c treathrs crave0.
```

```
data mbrp;set mbrp;bdi0_c=bdi0-1.196;mbrp_c=mbrp-0.554;mbrpdep_c=mbrp_c*bdi0_c;run;
proc reg data=mbrp;model crave2=mbrp_c bdi0_c mbrpdep_c treathrs crave0;run;
```

```
mbrp <- transform(mbrp, mbrp_c = mbrp-0.554, bdi0_c = bdi0-1.196)
summary(lm(crave2~mbrp_c*bdi0_c+treathrs+crave0, data = mbrp))
```

$$\widehat{Y}_i = 2.077 \ - 0.547X_i + 0.597W_i \ - 0.948X_iW_i \ldots$$

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.077	.369		5.635	.000
	mbrp_c	-.547	.137	-.279	-3.980	.000
	bdi0_c	.597	.222	.194	2.685	.008
	mbrpdep_c	-.948	.423	-.158	-2.240	.026
	TREATHRS: Hours of therapy	-.018	.010	-.120	-1.719	.088
	CRAVE0: Baseline craving	.192	.073	.183	2.614	.010

a. Dependent Variable: CRAVE2: Craving at two month follow-up

b_3 = -0.948
se_{b_3} = 0.423
t = -2.240,
p = 0.026

Mean centering has had no effect on b_3.

b_1 = -0.547. This is the effect of *X* (MBRP) among people average in *W* (pre-therapy depression)

b_2 = 0.597. This is the group-weighted average effect of *W* (Pre-therapy depression)

The interaction is unaffected by centering. b_1 and b_2 have changed because the meaning of "0" changes when *X* and *W* are mean centered. This change has nothing to do with multicollinearity being reduced by mean centering.

Collinearity and regression standard errors

The estimated standard error (s_{b_j}) for predictor variable *j* is

$$s_{b_j} = \sqrt{\frac{1}{1-R_j^2}}\sqrt{\frac{MS_{residual}}{n(s_j^2)}} = \sqrt{\frac{MS_{residual}(VIF)}{n(s_j^2)}}$$

where R^2_j is the squared multiple correlation in a model estimating predictor variable *j* from the other predictor variables and s^2_j is the variance of predictor *j*.

- $1 - R^2_j$ is called predictor variable *j*'s **tolerance**. It quantifies the proportion of the variance in variable *j* unexplained by the other predictor variables. Larger is better.

- The inverse of a variable's tolerance is its **variance inflation factor** (VIF). It quantifies how much the sampling variance of predictor *j*'s regression coefficient is affected by the correlation between it and the other predictor variables (larger is worse)

In general, the weaker the correlation between predictor variables, the larger a variable's tolerance, the smaller its variation inflation factor, the smaller the standard error, and the more power the hypothesis test for that predictor. Thus, anything you can do to reduce the correlation between predictors would seem to be a good thing.

Collinearity and regression standard errors

In moderated multiple regression, some therefore argue that you should mean center *X* and *W* prior to computing their product, because this will lower the intercorrelation between *X*, *W*, and their product, reduce the standard error for the regression coefficient for the product, and therefore increase the power of the hypothesis test for interaction.

Correlations between variables in their original metric:

Correlations

		MBRP: Therapy as usual (0) or MBRP therapy (1)	BDI0: Beck Depression Inventory baseline	mbrpdep
MBRP: Therapy as usual (0) or MBRP therapy (1)	Pearson Correlation	1	-.091	.945
	Sig. (2-tailed)		.242	.000
	N	168	168	168
BDI0: Beck Depression Inventory baseline	Pearson Correlation	-.091	1	.123
	Sig. (2-tailed)	.242		.113
	N	168	168	168
mbrpdep	Pearson Correlation	.945	.123	1
	Sig. (2-tailed)	.000	.113	
	N	168	168	168

Tolerance	**VIF**
0.064	15.674
0.561	1.782
0.064	15.704

Some say you should NEVER include two predictors in a model that are so highly correlated.

Collinearity and regression standard errors

In moderated multiple regression, some therefore argue that you should mean center *X* and *W* prior to computing their product, because this will lower the intercorrelation between *X*, *W*, and their product, reduce the standard error for the regression coefficient for the product, and therefore increase the power of the hypothesis test for interaction.

Correlations between variables after mean centering *X* and *M:*

Correlations

		mbrp_c	bdi0_c	mbrpdep_c
mbrp_c	Pearson Correlation	1	-.091	.020
	Sig. (2-tailed)		.242	.798
	N	168	168	168
bdi0_c	Pearson Correlation	-.091	1	-.287
	Sig. (2-tailed)	.242		.000
	N	168	168	168
mbrpdep_c	Pearson Correlation	.020	-.287	1
	Sig. (2-tailed)	.798	.000	
	N	168	168	168

Tol.	VIF
0.928	1.078
0.867	1.154
0.915	1.093

The offensively large correlation has been reduced to near zero, and all the VIFs are near the minimum possible value of 1. Certainly this is a good thing, right?

But other things have changed too.

$$s_{b_j} = \sqrt{\frac{MS_{residual}(VIF)}{n(s_j^2)}}$$

Descriptive Statistics

	N	Variance
mbrpdep	168	.3816
mbrpdep_c	168	.0266
Valid N (listwise)	168	

Without mean centering

$$s_{b_3} = \sqrt{\frac{MS_{residual}(15.704)}{n(0.3816)}}$$

$$= \sqrt{\frac{15.704}{0.3816}}\sqrt{\frac{MS_{residual}}{n}}$$

$$= \sqrt{41.1}\sqrt{\frac{MS_{residual}}{n}}$$

With mean centering

$$s_{b_3} = \sqrt{\frac{MS_{residual}(1.093)}{n(0.0266)}}$$

$$= \sqrt{\frac{1.093}{0.0266}}\sqrt{\frac{MS_{residual}}{n}}$$

$$= \sqrt{41.1}\sqrt{\frac{MS_{residual}}{n}}$$

The variance of the product changes by the same factor as the variance inflation factor is changed after mean centering. The result is no change in the standard error of the interaction. (The mean squared residual and sample size are unaffected by mean centering)

To mean center or not to mean center

- The choice is yours to make. It is not required for the purpose of estimation.

- Mean centering does nothing to the test of the interaction. Although mean centering does reduce multicollinearity, this has no consequence on the estimate of the interaction or its statistical test.

- If you mean center, you run no risk of interpreting the coefficients for the predictor and the moderator when they estimate quantities beyond the range of the data. <u>This is a good reason for doing it</u>.

- Mean centering does change the coefficient for the focal predictor and moderator. But this has nothing to do with reducing multi-collinearity. Mean centering changes the conditioning from "0" to the sample mean.

All these arguments apply to standardization as well.

Mean centering in PROCESS

You can mean center variables before using PROCESS. But PROCESS has an option built in which does it for you. Use the **`center = 1`** option to automatically mean center variables which define product terms.

```
process cov = treathrs crave0
  /y=crave2/x=mbrp /w=bdi0/model=1
  /moments = 1/center=1.
```

```
%process (data=mbrp,cov=treathrs
  crave0,y=crave2, x=mbrp,m=bdi0,
  model=1, momens = 1, center=1);
```

```
process(data=mbrp, cov=c("treathrs",
  "crave0"), y="crave2", x="bdi0",
  w="mbrp", model=1, center=1)
```

Use the `center = 2` option to automatically mean center variables only continuous variables which define product terms. Dichotomous variables will be left in their original metric.

```
**************************************************************************
Outcome: crave2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5140      .2642      .7277    11.6319     5.0000   162.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.0778      .3686     5.6363      .0000     1.3498     2.8057
bdi0          .5970      .2221     2.6876      .0079      .1584     1.0357
mbrp         -.5473      .1375    -3.9818      .0001     -.8188     -.2759
int_1        -.9485      .4235    -2.2398      .0265    -1.7847     -.1122
treathrs     -.0177      .0103    -1.7190      .0875     -.0380      .0026
crave0        .1920      .0735     2.6138      .0098      .0470      .3371

Interactions:

 int_1    mbrp        X     bdi0

R-square increase due to interaction(s):
         R2-chng          F        df1        df2          p
int_1      .0228     5.0166     1.0000   162.0000      .0265

*************************************************************************

Conditional effect of X on Y at values of the moderator(s):
       bdi0     Effect         se          t          p       LLCI       ULCI
     -.3191     -.2447      .1922    -1.2733      .2047     -.6243      .1348
      .0000     -.5473      .1375    -3.9818      .0001     -.8188     -.2759
      .3191     -.8500      .1933    -4.3973      .0000    -1.2317     -.4683

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

******************** ANALYSIS NOTES AND WARNINGS *************************

Level of confidence for all confidence intervals in output:
    95.00

NOTE: The following variables were mean centered prior to analysis:
 mbrp     bdi0
```

Moderation analysis summary

- A moderator of the effect of *X* on *Y* is a variable which influences or otherwise is related to the size of *X*'s effect on *Y*.

- Including a variable defined as the product *X* of *W* to a regression model that includes *X* and *W* allows *X*'s effect on *Y* to be a linear function of *W*.

- The regression coefficient for *XW* in such a model is hard to interpret without a picture. Draw a picture of your model before attempting to interpret.

- We can dissect or "probe" interactions in a few different ways:

  - The pick-a-point approach requires us to select values of *W* at which to estimate the conditional effect of *X* on *Y*. Usually the selection is arbitrary.
  - The Johnson-Neyman technique avoids the need to choose values of the moderator arbitrarily.

- Care must be taken when interpreting the regression coefficients for *X* and *W* in a model that includes *XW*. They are not "main effects" and they may not have any substantive interpretation. Their interpretation will be influenced by their scaling and whether a value of zero is meaningful on the measurement scale. We can make it meaningful by centering.

Example: Science

Participants read a syllabus for a computer science class. The syllabus one of two policies: **procollaboration** or **no collaboration**. Participants were randomly assigned to condition.

Participants completed questionnaire (Higher = greater):

(1) interest in the class (this is the primary DV).
(2) how much they felt the class would help them in achieving **communal goals** (helping others, working with others)
(3) how **difficult** they expected the class to be.


Girls who Code

Question: Does group work in computer science classes increase interest in the class indirectly through perceived communal goal fulfillment, through class difficulty, or both?

Would people who read about the procollaboration policy think the class is more communal and would that communality then predict greater interest? Would the procollaboration policy make students think the course is easier, and this would increase interest?

The data: Science

ProNo	comm	diff	interest
1.00	5.20	5	6.0
1.00	1.00	4	2.2
1.00	4.00	4	2.5
1.00	4.00	2	3.5
1.00	7.00	7	7.0
1.00	6.00	1	6.0
1.00	4.00	7	2.7
1.00	3.40	6	4.2
1.00	4.20	3	3.5
1.00	4.60	6	1.5
1.00	4.20	5	2.0
1.00	4.40	5	1.0
1.00	5.40	3	7.0
1.00	5.00	4	2.2
1.00	4.60	6	2.7
1.00	3.40	4	1.2

```
data science;
    input Subject Cond sex ProNo comm diff interest;
    datalines;
    106     1     1     1     5.2     5
    109     1     1     1     1       4
    112     1     1     1     4       4
    114     1     1     1     4       2
    115     1     1     1     7       7
    121     1     1     1     6       1
    131     1     1     1     4       7
    132     1     1     1     3.4     6
    148     1     1     1     4.2     3
    161     1     1     1     4.6     6
    162     1     1     1     4.2     5
    164     1     1     1     4.4     5
    174     1     1     1     5.4     3
    176     1     1     1     5       4
    177     1     1     1     4.6     6
    178     1     1     1     3.4     4
    190     1     1     1     3.8     5
    206     1     1     1     4.2     6
    216     1     1     1     7       7
```

ProNo: Experimental condition (1 = procollaboration, 0 = no collaboration)

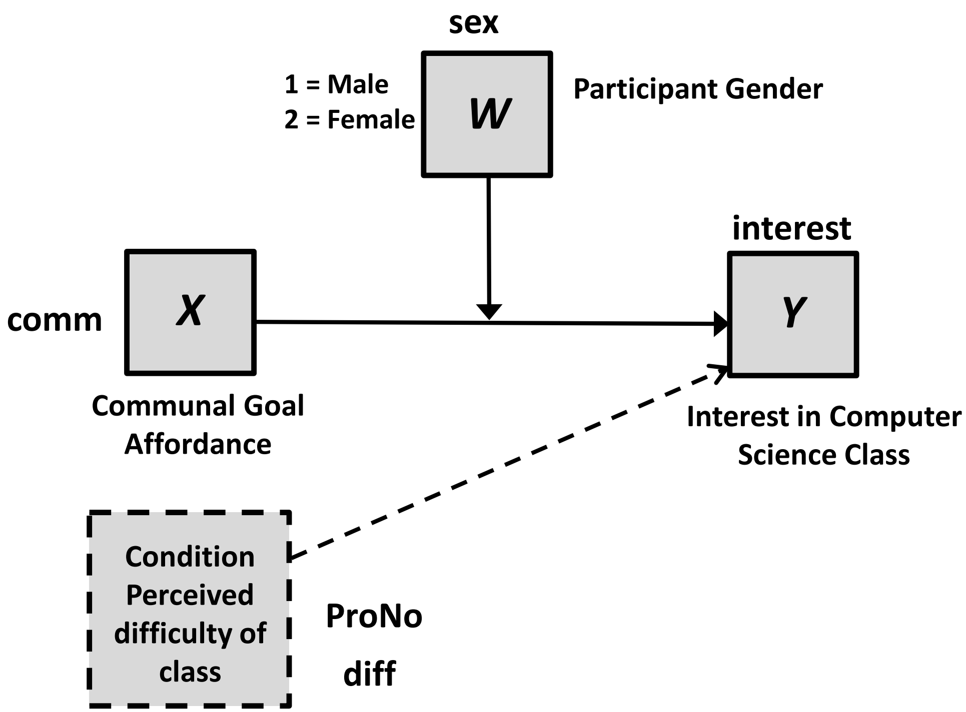
interest : interest in class (higher = greater interest)

comm: Perceived fulfillment of communal goals (higher = more fulfillment)

diff: Perceived difficulty of the class (higher = more difficult)

gender: 1 = Male, 2 = Female

Moderation Activity: Science



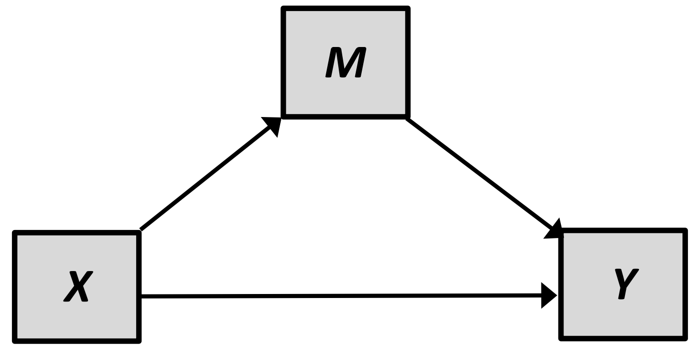
1) Estimate this model using both the base regression functions and PROCESS. Confirm your models are the same.
2) Is the effect of communal goal affordance on interest moderated by gender?
3) Probe the interaction: We expect a positive relationship for women and near zero relationship for men. Is this confirmed?
4) Swap the interaction and re-estimate, probe (use JN).
5) Visualize the interaction using PROCESS
6) Try mean-centering the predictors and seeing how this changes the regression results
7) Try writing a results section for this analysis.

Combining moderation and mediation
"Conditional Process Analysis"

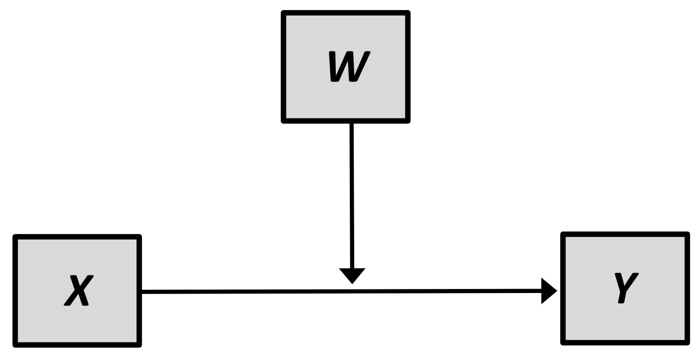
"Conditional process analysis" is a general modeling strategy undertaken with the goal of describing the *conditional* nature of the *mechanism*(*s*) by which a variable transmits its effect on another, and testing hypotheses about such contingent effects.

A merging of two ideas conceptually and analytically:

"**Process analysis**", used to quantify and examine the direct and indirect pathways through which an antecedent variable *X* transmits its effect on a consequent variable *Y* through an intermediary *M*. Better known as "mediation analysis" these days.



"**Moderation analysis**" used to examine how the effect of an antecedent *X* on an consequent *Y* depends on a third moderator variable *W* (a.k.a. "interaction")



History

Idea is not new (e.g., Judd & Kenny, 1981; James & Brett, 1984; Baron and Kenny, 1986). It goes by various names that often confuse, including "moderated mediation" and "mediated moderation."

More recently:

Muller, Judd, and Yzerbyt (2005): Describe analytical models and steps for assessing when "mediation is moderated" and "moderation is mediated."

Edwards and Lambert (2007): Take a path analysis perspective and show how various effects in a simple mediation model can be conditioned on a third variable.

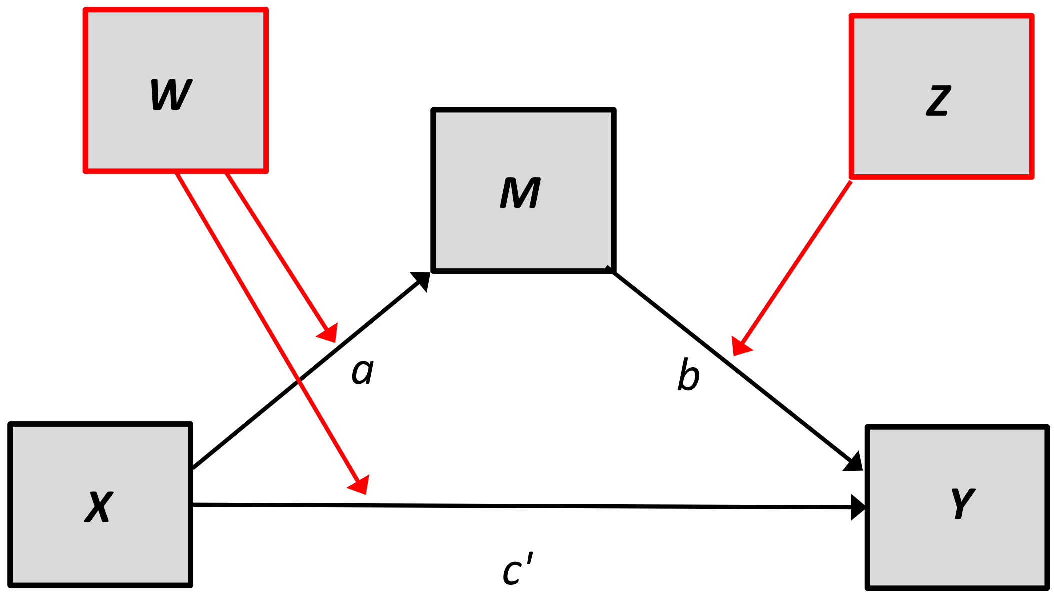
Preacher, Rucker, and Hayes (2007): Provide a formal definition of the *conditional indirect effect* and give formulas, standard errors, and a bootstrap approach for estimating and testing hypotheses about moderated mediation in five different models.

MacKinnon and colleagues (e.g., Fairchild & MacKinnon, 2009): Explicate various analytical approaches to testing hypotheses about mediated moderation and moderated mediation.

Hayes (2013). Introduces the term "conditional process modeling" (also see Hayes and Preacher, 2013) and provides tools for SPSS and SAS to make it easy to do.

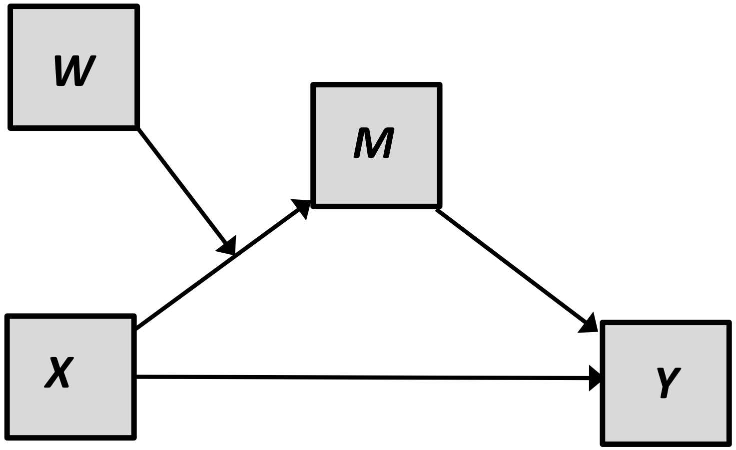
Hayes (2015): Introduces the *index of moderated mediation* which provides a formal test for moderated mediation in a variety of models.

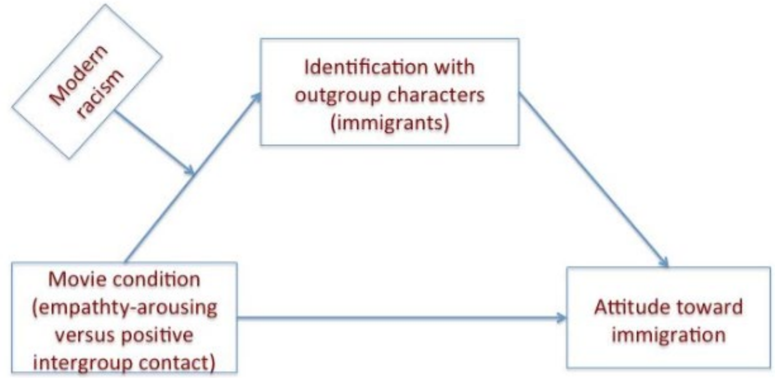
“Moderated mediation”



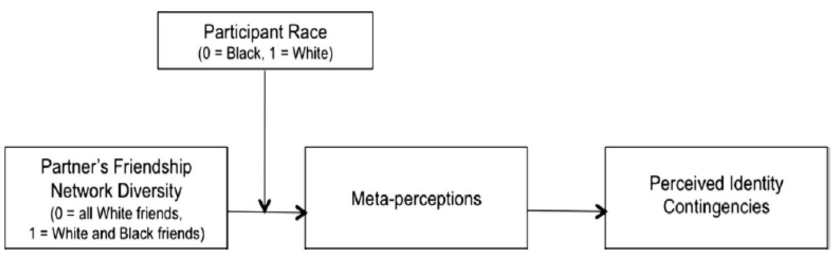
- The indirect effect of *X* on *Y* through *M* is estimated as the product of the *a* and *b* paths
- But what if the size of *a* or *b* (or both) depends on another variable (i.e., is moderated)?
- If so, then the magnitude of the indirect effect therefore depends on a third variable, meaning that “mediation is moderated”.
- When *a* or *b* is moderated, it is sensible then to estimate “conditional indirect effects”—values of indirect effect conditioned on values of the moderator variable that moderates *a* and/or *b*.
- Direct effects can also be conditional. For instance, above, *W* moderates *X*’s direct effect on *Y*.

Examples: *X* to *M* path moderated by *W*

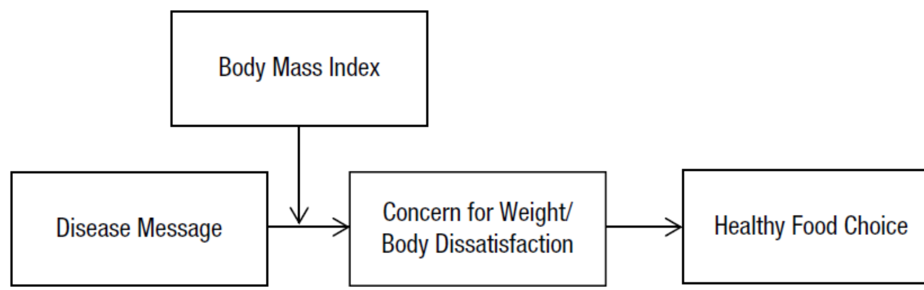




Igartua, J-J., & Frutos, F. J. (2017). Enhancing attitudes toward stigmatized groups with movies. Mediating and moderating processes of narrative persuasion. *International Journal of Communication, 11*, 158-`77.

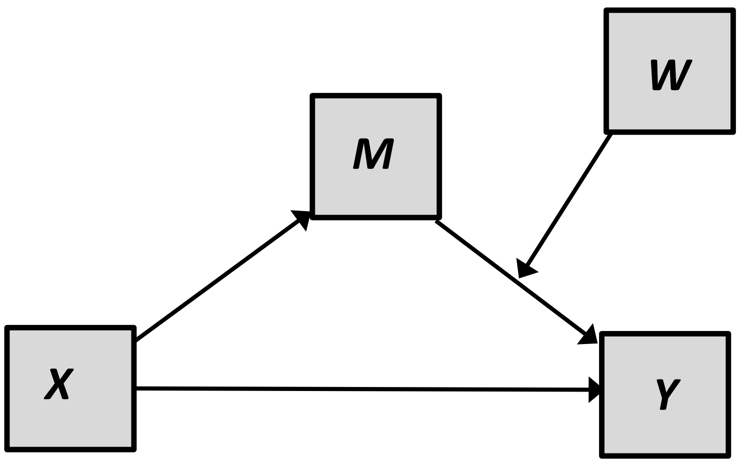


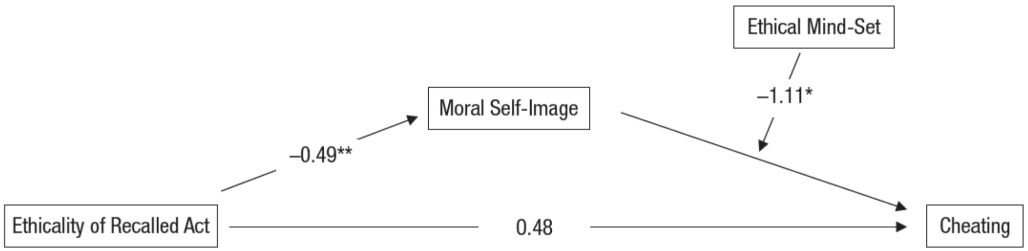
Wout, D. A., Murphy, M. C., & Steele, C. M. (2010). When your friends matter: The effect of White students' racial friendship networks on meta-perceptions and Perceived identity contingencies. ***Journal of Experimental Social Psychology**, 46*, 1035-1041.



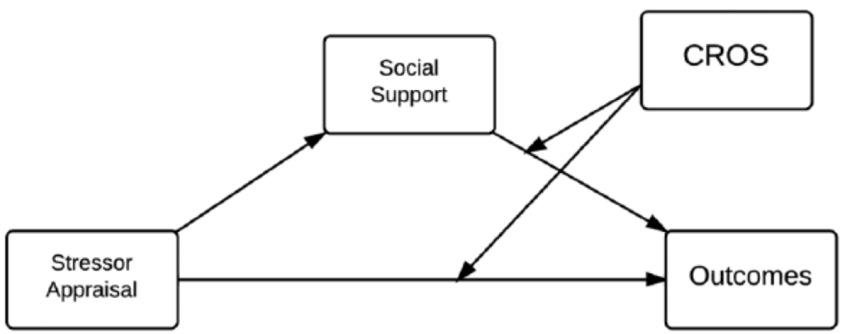
Hoyt, C. L., Burnette, J. L., & Auster-Gussman, L. (2014). "Obesity is a disease": Examining the self-regulatory impact of this public-health message. ***Psychological Science**, 25*, 997-1002.

Examples: *M* to *Y* path moderated by *W*

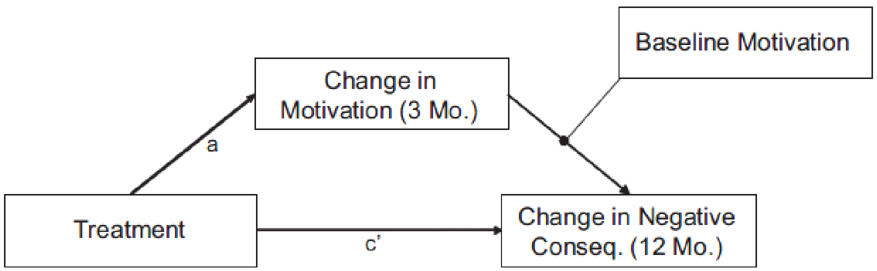




Cornelissen, G., Bashshur, M. R., Rode, J., & Le Menestrel, M. (2013). Rules or consequences? The role of ethical mind-sets in moral dynamics. ***Psychological Science, 24,*** 492-488.

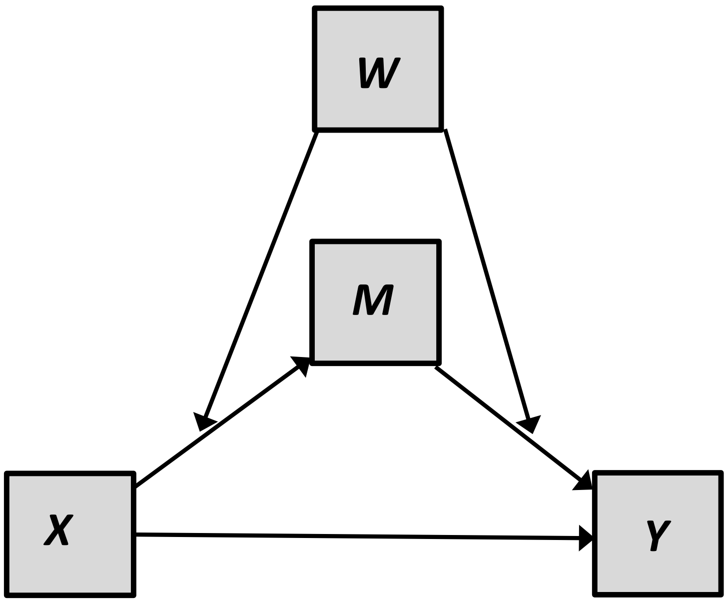


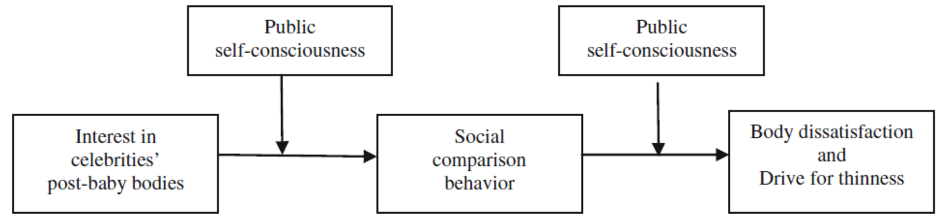
Boren, J. P., & Veksler, A. E. (2015). Communicatively restricted organizational stress (CROS) I: Conceptualization and overview. ***Management Communication Quarterly,*** *29*, 28-55.



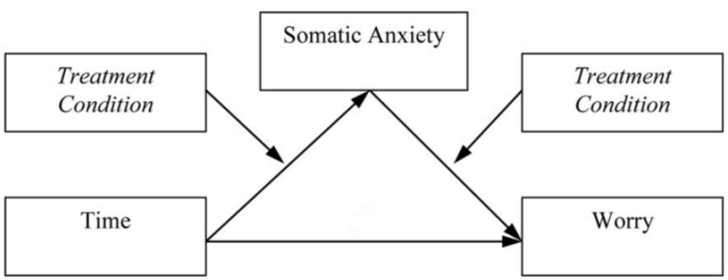
Stein, L. A. R., Minugh, P. A. et al. (2009). Readiness to change as a mediator of the effect of a brief motivational intervention on posttreatment alcohol-related consequences of injured emergency department hazardous drinkers. ***Psychology of Addictive Behaviors, 23***, 185-195.

Examples: *X* to *M* and *M* to *Y* path moderated by *W*

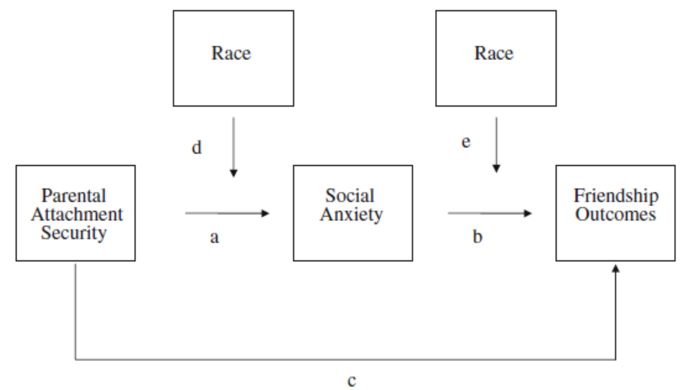




Chae, J. (2014). Interest in celebrities' post-baby bodies and Korean women's body image disturbance after childhood. ***Sex Roles**, 71*, 419-435.



Donegan, E., & Dugas, M. (2012). Generalized anxiety disorder: A comparison of symptom change in adults receiving cognitive-behavioral therapy or applied relaxation. ***Journal of Consulting and Clinical Psychology**, 80*, 490-496.



Parade, S. H., Leerkes, E. M., & Blankson, A. (2010). Attachment to parents, social anxiety, and close relationships of female students over the transition to college**. *Journal of Youth and Adolescence***, *39*, 127-137.

“Conditional direct effect”

In a mediation model, the direct effect of *X* on *Y* quantifies *X*’s effect independent of the intervening variable or variables. If that direct effect is moderated, then the direct effect is conditional on the variable that moderates *X*’s effect. For example,

$$\widehat{M_i} = a_0 + aX_i$$

$$\hat{Y}_i = c_0' + c_1'X_i + c_2'W_i + c_3'X_iW_i + bM_i$$

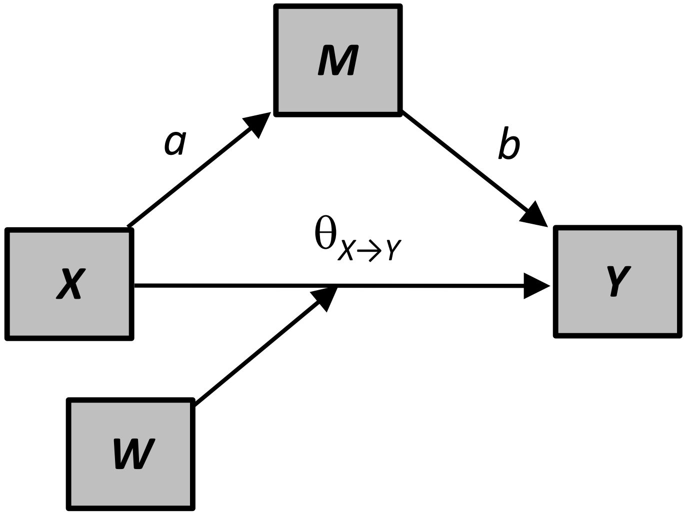
or, equivalently,

$$\hat{Y}_i = c_0' + (c_1' + c_3'W_i)X_i + c_2'W_i + bM_i$$

or, equivalently,

$$\hat{Y}_i = c_0' + \theta_{X\to Y}X_i + c_2'W_i + bM_i$$

where $\theta_{X\to Y} = (c_1' + c_3'W_i)$



In this model, $\theta_{X\to Y}$ is the conditional direct effect of *X*, which is defined by the function $c'_1 + c'_3W$. Holding *M* constant, two cases that differ by one unit on *X* are estimated to differ by $c'_1 + c'_3W$ units on *Y*.

This is a very basic conditional process model. It models two pathways through which *X* affects *Y*. One is unconditional and indirect via *M*, and the other is direct but conditional—the size of the direct effect depends on *W*.

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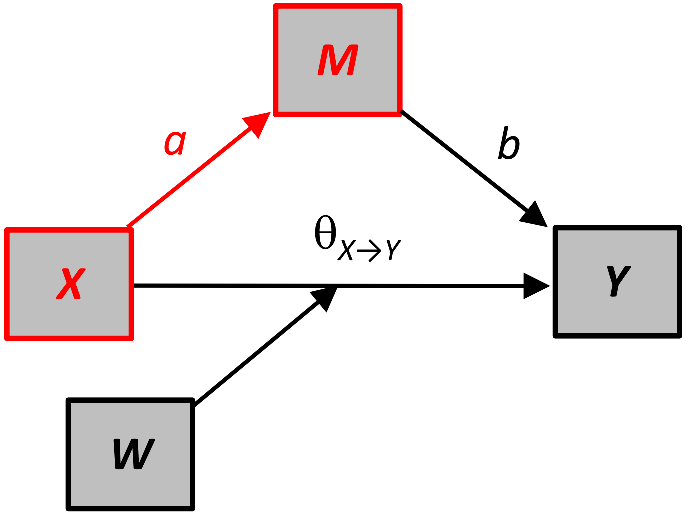

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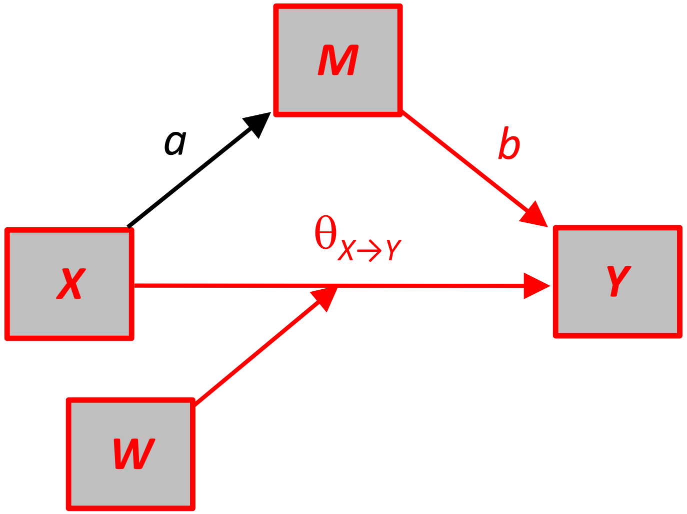

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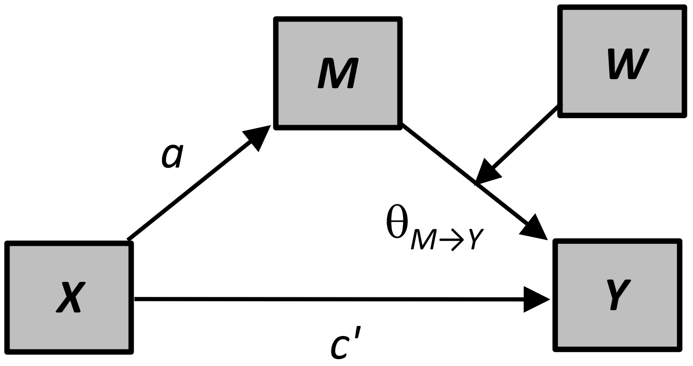

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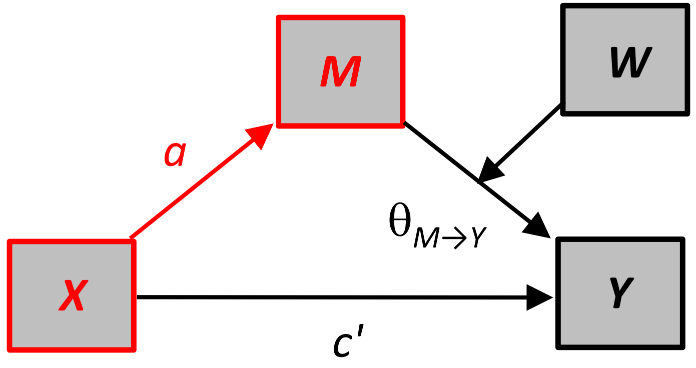

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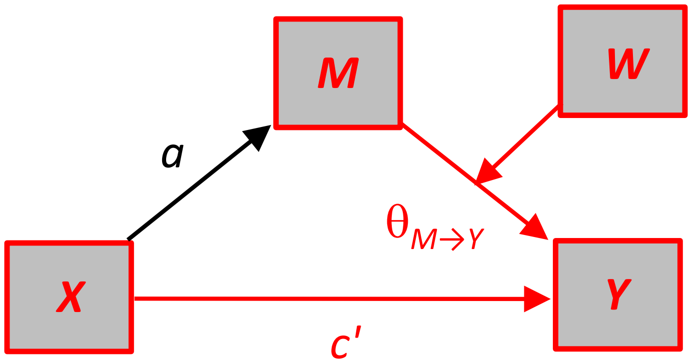

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Condition process analysis: Example 1

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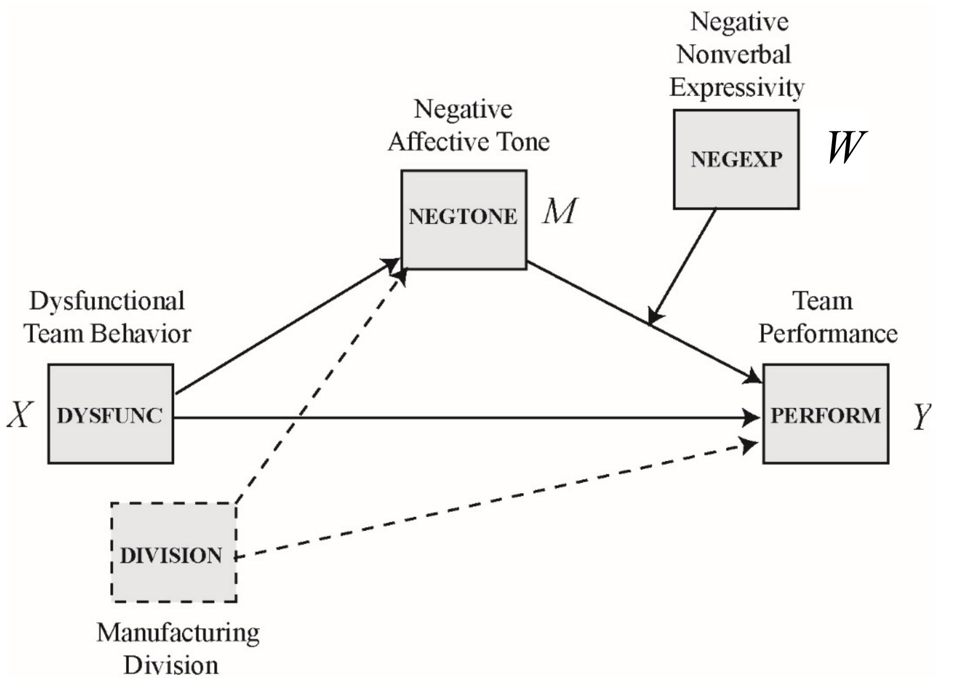

This is a model of **negative affective tone (*M*)** as the mechanism by which **dysfunctional team behavior (*X*)** influences **performance *(Y*)*,*** with that mechanism being contingent on the extent to which **team members hide their negative feelings (*W*)** from the team. This "nonverbal expressivity" is postulated as moderating the effect of negative tone on performance. This is a "second stage" moderated mediation model.

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Affective Mechanisms Linking Dysfunctional Behavior to Performance in Work Teams: A Moderated Mediation Study

Michael S. Cole
Texas Christian University

Frank Walter
University of Groningen

Heike Bruch
University of St. Gallen

The present study examines the association between dysfunctional team behavior and team performance. Data included measures of teams' dysfunctional behavior and negative affective tone as well as supervisors' ratings of teams' (nonverbal) negative emotional expressivity and performance. Utilizing a field sample of 61 work teams, the authors tested the proposed relationships with robust data analytic techniques. Results were consistent with the hypothesized conceptual scheme, in that negative team affective tone mediated the relationship between dysfunctional team behavior and performance when teams' nonverbal negative expressivity was high but not when nonverbal expressivity was low. On the basis of the findings, the authors conclude that the connection between dysfunctional behavior and performance in team situations is more complex than was previously believed—thereby yielding a pattern of moderated mediation. In sum, the findings demonstrated that team members' collective emotions and emotional processing represent key mechanisms in determining how dysfunctional team behavior is associated with team performance.

Keywords: work teams, dysfunctional behavior, emotion, emotion regulation, performance

A body of research has recently emerged with an emphasis on "bad" employee behavior (e.g., Dunlop & Lee, 2004; Felps, Mitchell, & Byington, 2006; Griffin & Lopez, 2005; Robinson & O'Leary-Kelly, 1998). According to Griffin and Lopez (2005), bad employee behavior refers to any form of intentional act that has the potential to adversely affect organizations and their employees. In other words, bad behavior reflects employee conduct that an organization would otherwise prefer not to have displayed by its employees. Exemplars of these behaviors can range from employee theft and sabotage to social undermining and antisocial activity.

In their review on employee "bad" behavior, Lawrence and Robinson (2007) remarked that the prevalence and costs of such misconduct "make its study imperative" (p. 378). In the present instance, we focus on bad behavior occurring within a team context (cf. Robinson & O'Leary-Kelly, 1998) and, as recommended by Griffin and Lopez (2005), dub these behaviors *dysfunctional team behavior*. As we suggested earlier, there is a range of possible forms that dysfunctional team behavior might take; however, we chose to focus on the readily observable but not illegal types. For our purposes, *dysfunctional team behavior* is defined as any observable, motivated (but not illegal) behavior by an employee or group of employees that is intended to impair team functioning. In accordance with this operational definition, dysfunctional behaviors within teams should encumber team processes and goals (Robinson & O'Leary-Kelly, 1998), violate norms that are necessary for effective team performance (Felps et al., 2006), and thus hold strong negative connotations for team members (Griffin & Lopez, 2005).

Whereas scholars have exerted considerable effort toward understanding the determinants of dysfunctional behavior (e.g., Diefendorff & Mehta, 2007; Duffy, Ganster, Shaw, Johnson, & Pagon, 2006; Mitchell & Ambrose, 2007), they have not devoted much attention to the associated consequences. Further, researchers have conducted the majority of existing studies at the individual level of analysis. Nevertheless, with the increasing use of teams in organizations (Kozlowski & Ilgen, 2006), there is mounting interest in dysfunctional behavior as a team-level construct (e.g., Felps et al., 2006). Research on this issue, however, is generally limited to investigating how individuals' team context shapes their dysfunc-

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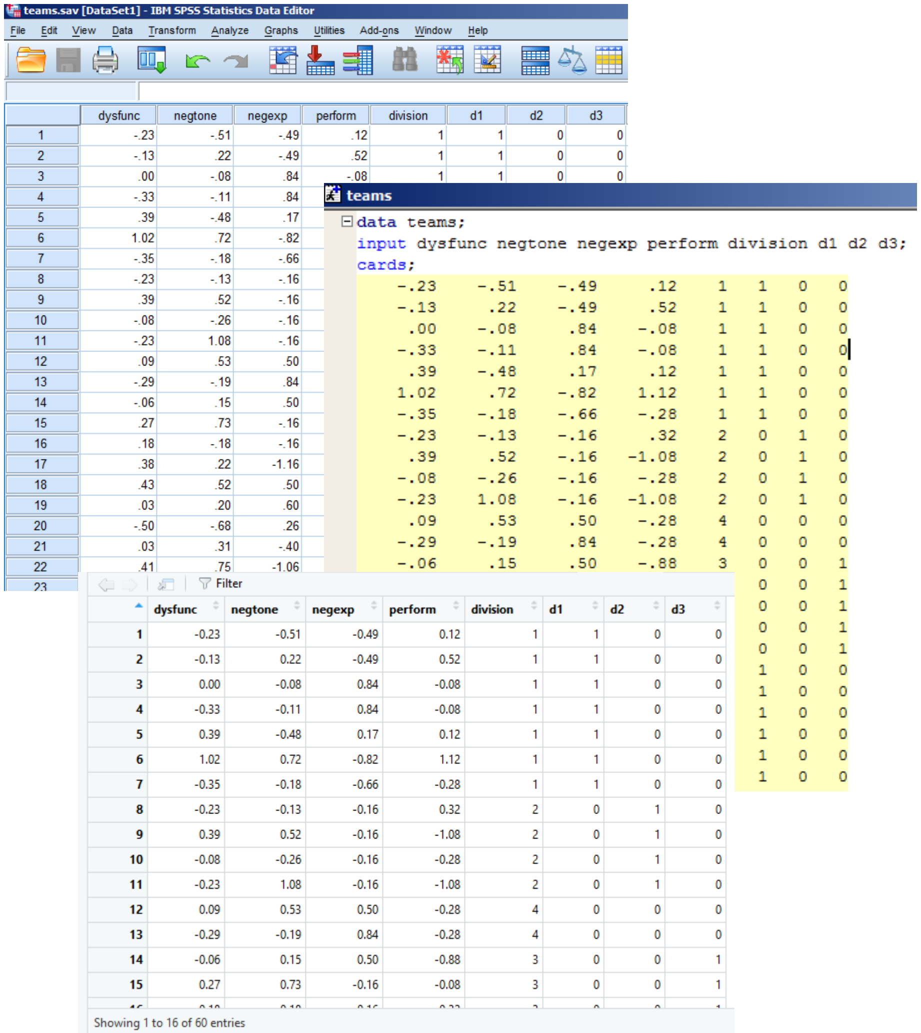
We thank Steven Brown, Hubert Feild, and Jochen Menges for vetting a draft manuscript and Silja Drack for her assistance with data collection.

The Data: TEAMS



	dysfunc	negtone	negexp	perform	division	d1	d2	d3
1	-.23	-.51	-.49	.12	1	1	0	0
2	-.13	.22	-.49	.52	1	1	0	0
3	.00	-.08	.84	-.08	1	1	0	0
4	-.33	-.11	.84					
5	.39	-.48	.17					
6	1.02	.72	-.82					
7	-.35	-.18	-.66					
8	-.23	-.13	-.16					
9	.39	.52	-.16					
10	-.08	-.26	-.16					
11	-.23	1.08	-.16					
12	.09	.53	.50					
13	-.29	-.19	.84					
14	-.06	.15	.50					
15	.27	.73	-.16					
16	.18	-.18	-.16					
17	.38	.22	-1.16					
18	.43	.52	.50					
19	.03	.20	.60					
20	-.50	-.68	.26					
21	.03	.31	-.40					
22	.41	.75	-1.06					

teams

```
data teams;
input dysfunc negtone negexp perform division d1 d2 d3;
cards;
  -.23   -.51   -.49    .12   1   1   0   0
  -.13    .22   -.49    .52   1   1   0   0
   .00   -.08    .84   -.08   1   1   0   0
  -.33   -.11    .84   -.08   1   1   0   0
   .39   -.48    .17    .12   1   1   0   0
  1.02    .72   -.82   1.12   1   1   0   0
  -.35   -.18   -.66   -.28   1   1   0   0
  -.23   -.13   -.16    .32   2   0   1   0
   .39    .52   -.16  -1.08   2   0   1   0
  -.08   -.26   -.16   -.28   2   0   1   0
  -.23   1.08   -.16  -1.08   2   0   1   0
   .09    .53    .50   -.28   4   0   0   0
  -.29   -.19    .84   -.28   4   0   0   0
  -.06    .15    .50   -.88   3   0   0   1
                                  0   0   1
                                  0   0   1
                                  0   0   1
                                  0   0   1
                                  1   0   0
                                  1   0   0
                                  1   0   0
                                  1   0   0
                                  1   0   0
                                  1   0   0
```

Filter

	dysfunc	negtone	negexp	perform	division	d1	d2	d3
1	-0.23	-0.51	-0.49	0.12	1	1	0	0
2	-0.13	0.22	-0.49	0.52	1	1	0	0
3	0.00	-0.08	0.84	-0.08	1	1	0	0
4	-0.33	-0.11	0.84	-0.08	1	1	0	0
5	0.39	-0.48	0.17	0.12	1	1	0	0
6	1.02	0.72	-0.82	1.12	1	1	0	0
7	-0.35	-0.18	-0.66	-0.28	1	1	0	0
8	-0.23	-0.13	-0.16	0.32	2	0	1	0
9	0.39	0.52	-0.16	-1.08	2	0	1	0
10	-0.08	-0.26	-0.16	-0.28	2	0	1	0
11	-0.23	1.08	-0.16	-1.08	2	0	1	0
12	0.09	0.53	0.50	-0.28	4	0	0	0
13	-0.29	-0.19	0.84	-0.28	4	0	0	0
14	-0.06	0.15	0.50	-0.88	3	0	0	1
15	0.27	0.73	-0.16	-0.08	3	0	0	1

Showing 1 to 16 of 60 entries

60 teams working in an automobile parts manufacturing facility.

DYSFUNC: Dysfunctional team behavior, i.e., How often members of the team do things to weaken the work of others or hinder change and innovation.

NEGTONE: Negative affective group tone. How often team members report feeling negative emotions at work such as "angry", "disgust", etc.

NEGEXP: Negative nonverbal expressivity. Supervisor's perception as to how easy it is to tell how team members are feeling.

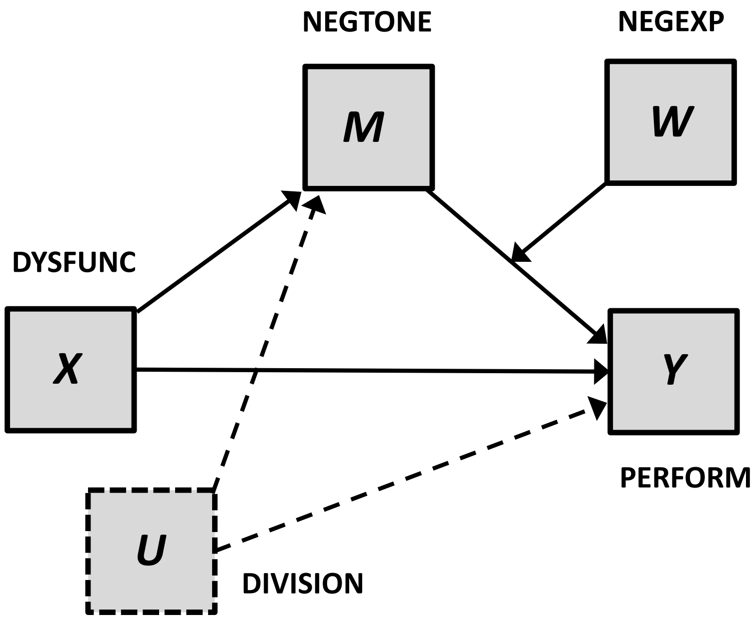
PERFORM: Team performance. Supervisor's judgment as to the team's efficiency, ability to get task done in a timely fashion, etc.

All variables are scaled arbitrarily, but higher = "more"

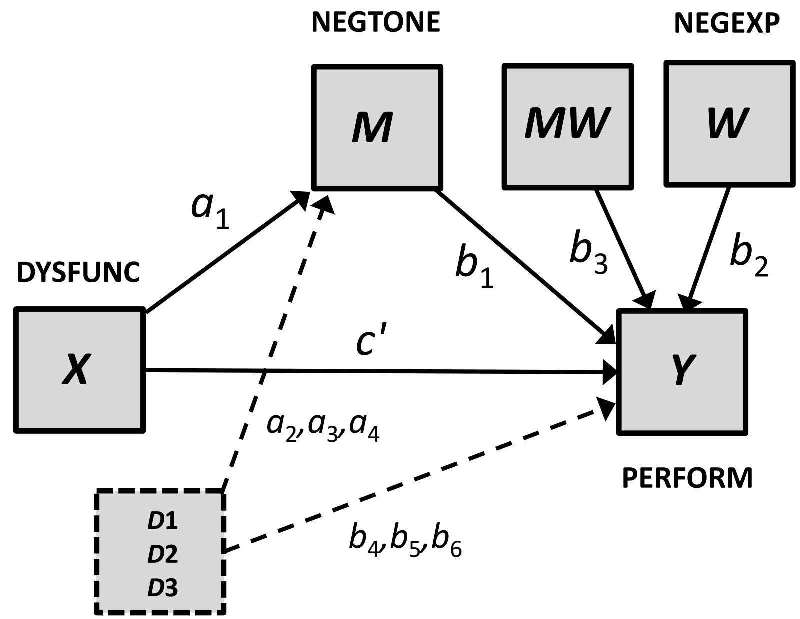
Also available is which of four parts divisions the team worked in, as a single categorical variable (division) as well as three dummy variables (d1, d2, d3).

Conceptual and statistical models

Conceptual Model



Statistical Model



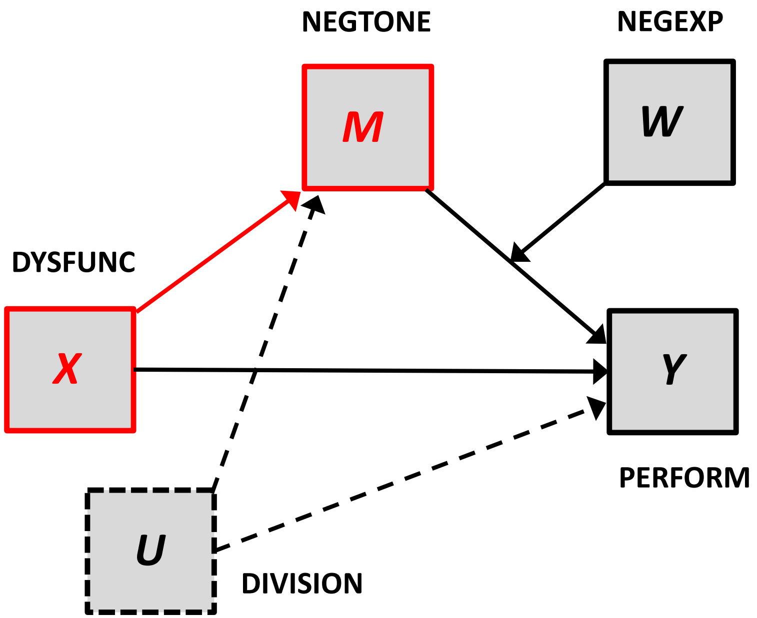
$$\widehat{M_i} = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

$$\widehat{Y_i} = c'_0 + c' X_i + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

The number of equations needed is equal to the number of variables with arrows pointing **at** them in the conceptual or statistical diagram.

Conceptual and statistical models

Conceptual Model



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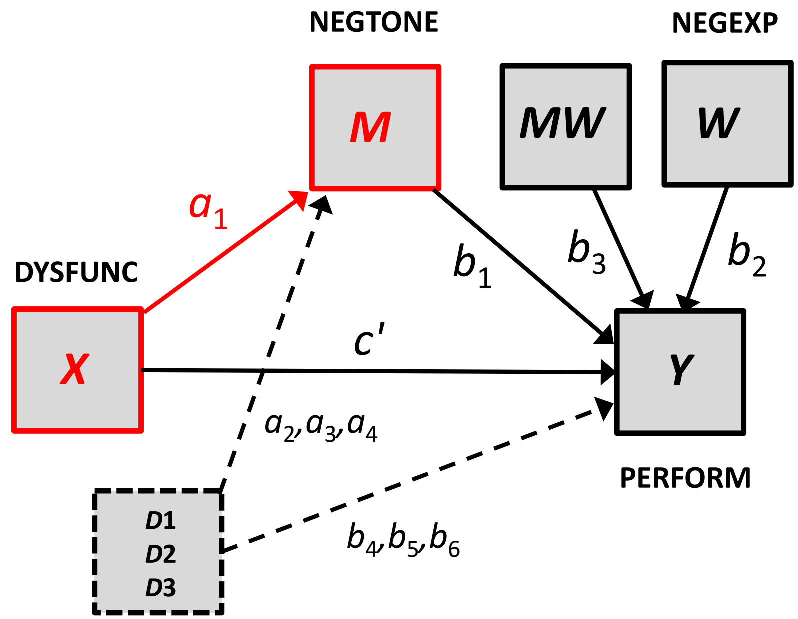
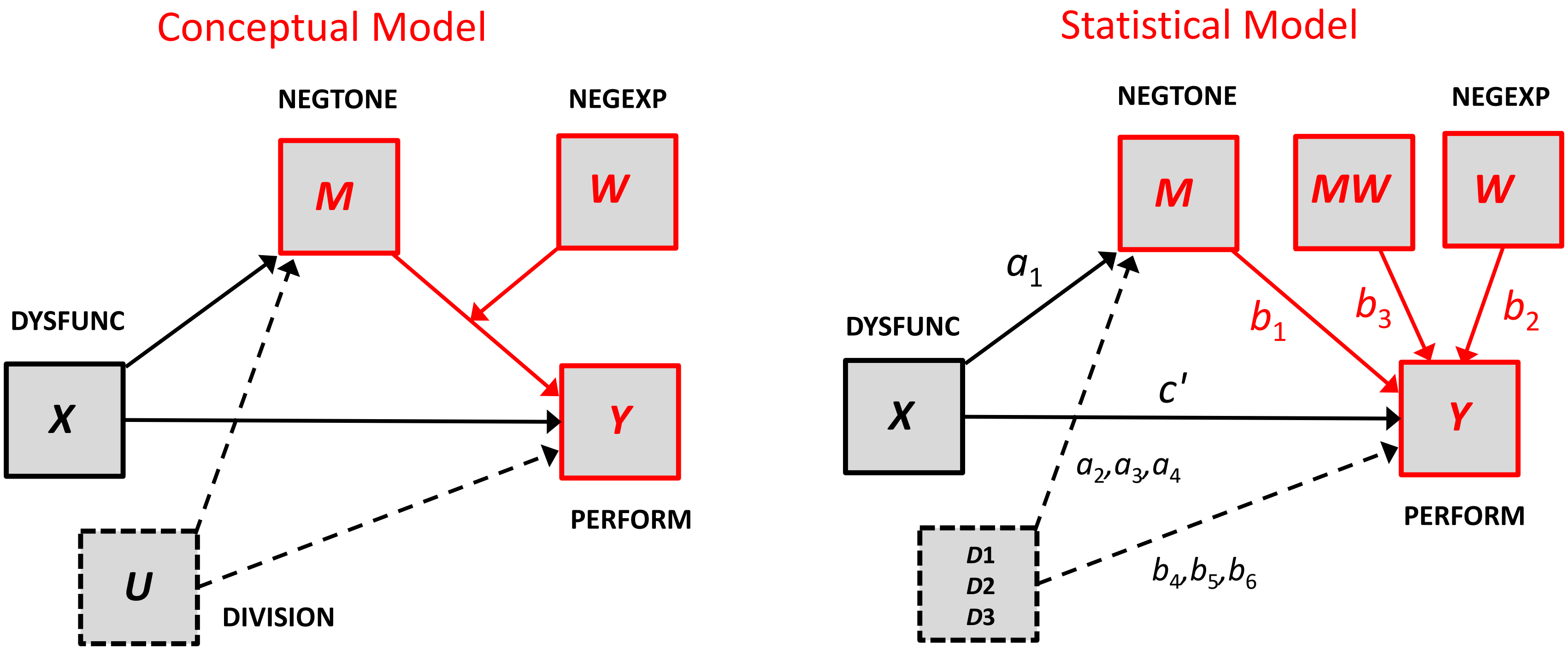


$$\widehat{M}_i = a_0 \boxed{+ a_1 X_i} + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

$$\widehat{Y}_i = c'_0 + c' X_i + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

The effect of dysfunctional team behavior (*X*) on negative affective tone of the work environment (*M*).

Conceptual and statistical models



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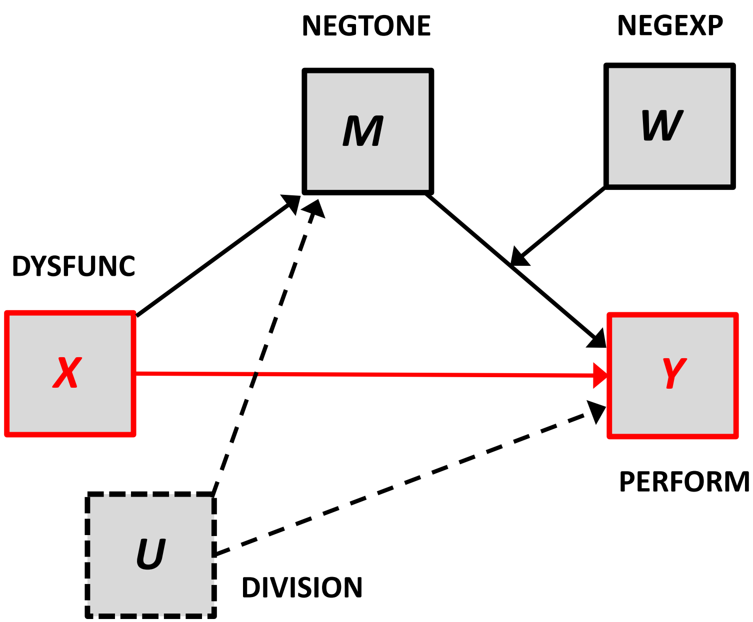
$$\widehat{Y_i} = c'_0 + c' X_i + \boxed{b_1 M_i + b_2 W_i + b_3 M_i W_i} + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

The moderation of the effect of the negative affective tone of the work environment (*M*) on team performance (*Y*) by negative nonverbal expressivity (*W*).

Conceptual and statistical models

Conceptual Model



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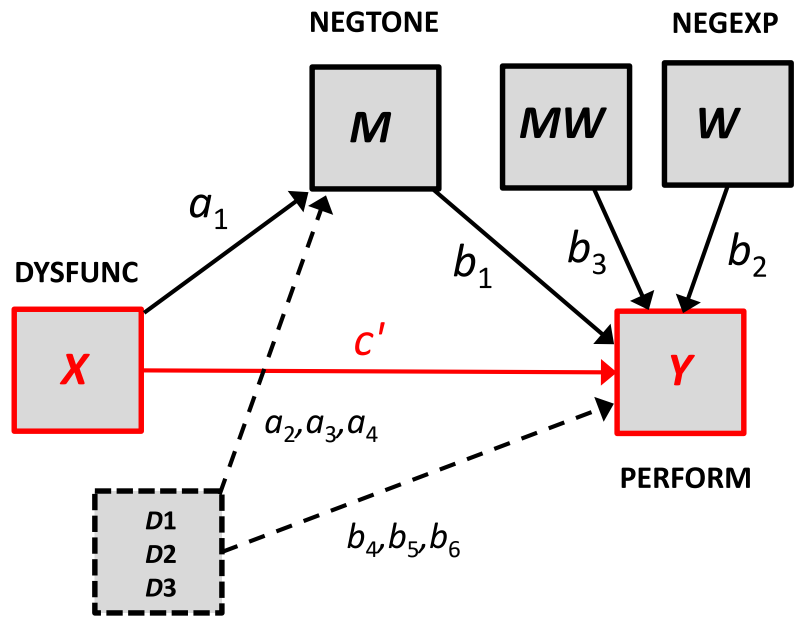

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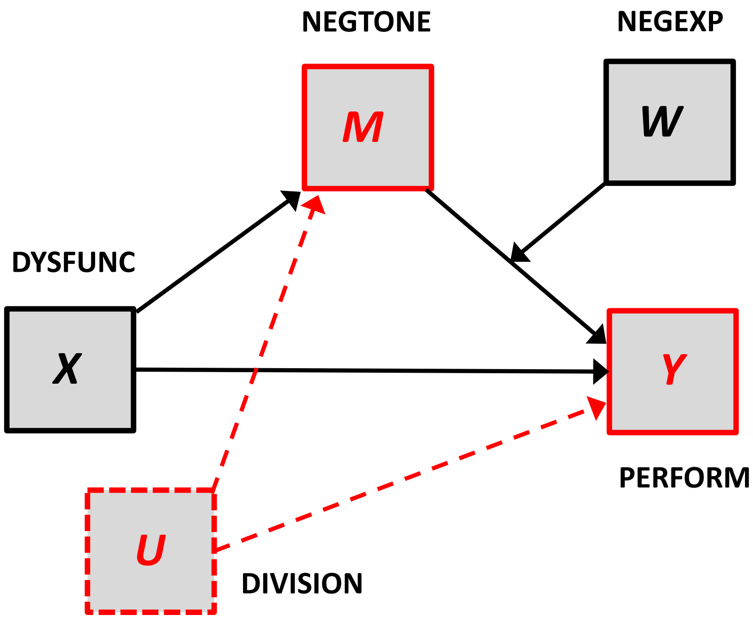
$$\widehat{Y_i} = c'_0 \boxed{+ c' X_i} + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

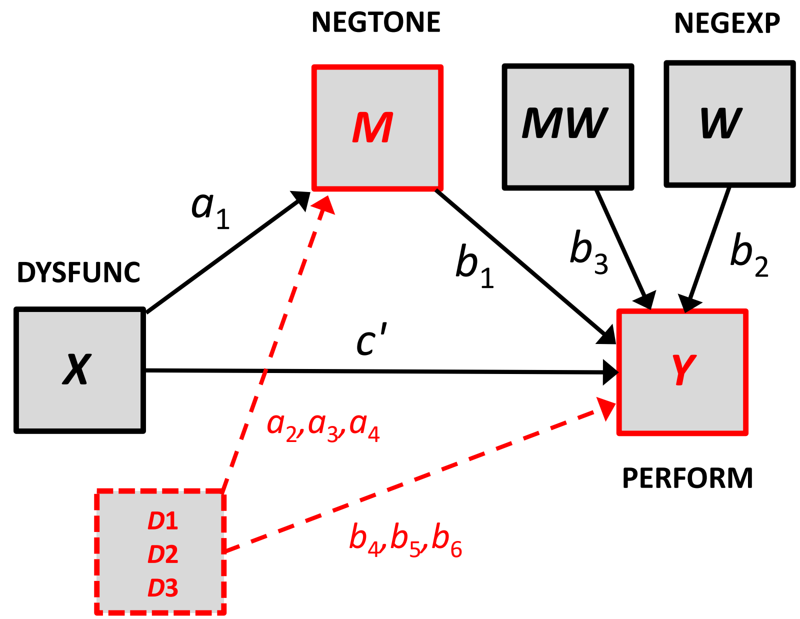
The direct effect of dysfunctional team behavior (*X*) on team performance (*Y*).

Conceptual and statistical models

Conceptual Model



Statistical Model



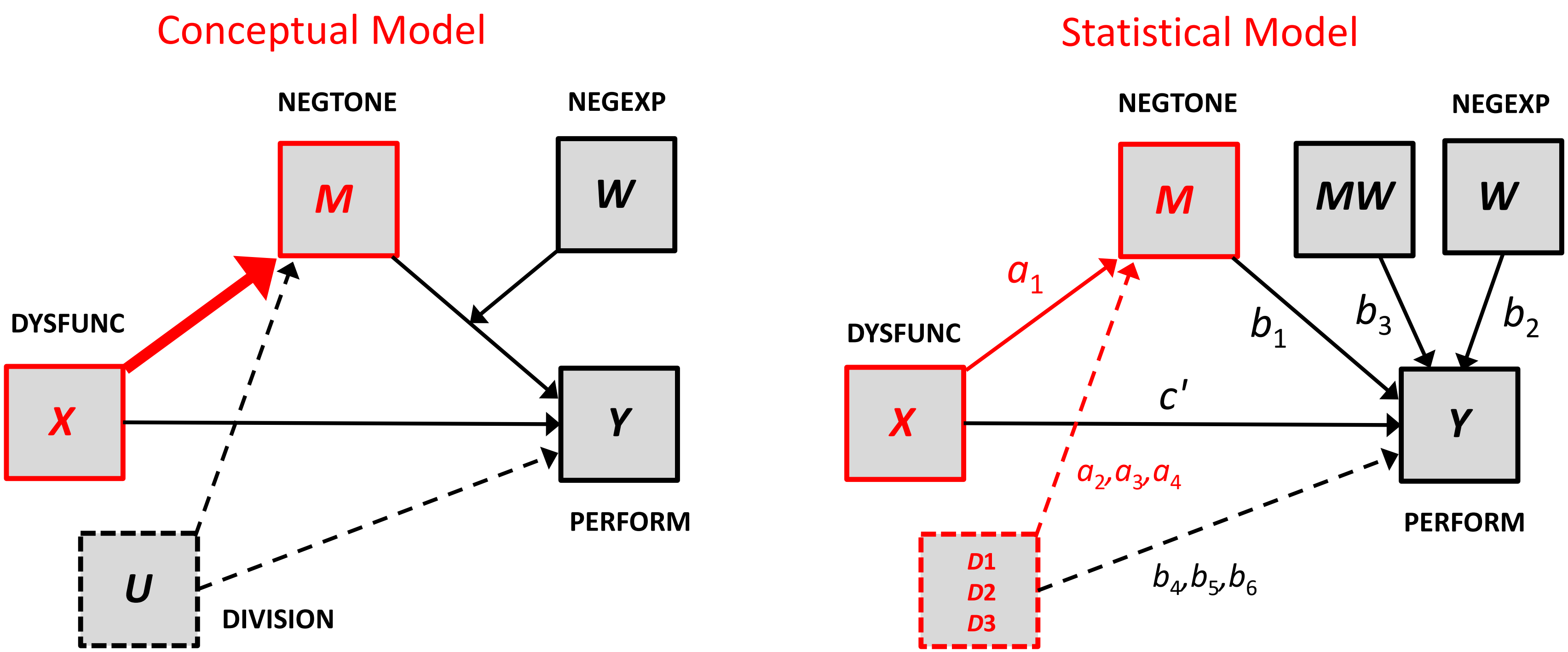
$$\widehat{M}_i = a_0 + a_1 X_i + \boxed{a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}}$$

$$\widehat{Y}_i = c'_0 + c' X_i + b_1 M_i + b_2 W_i + b_3 M_i W_i + \boxed{b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}}$$

Covariates to account for potential confounding by divisional differences (*U*) in negative tone of the work environment (*M*) and performance (*Y*)

Estimating the a_1 path

Let's first estimate the effect of dysfunctional team behavior on the negative affective tone of the team environment: Path a_1 in the statistical model.



$$\widehat{M_i} = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

Emphasis in not on statistical significance, as neither the direct or indirect effects of X are defined entirely in terms of a_1.

Estimating the a_1 path

```
regression/dep=negtone/method=enter dysfunc d1 d2 d3.
```

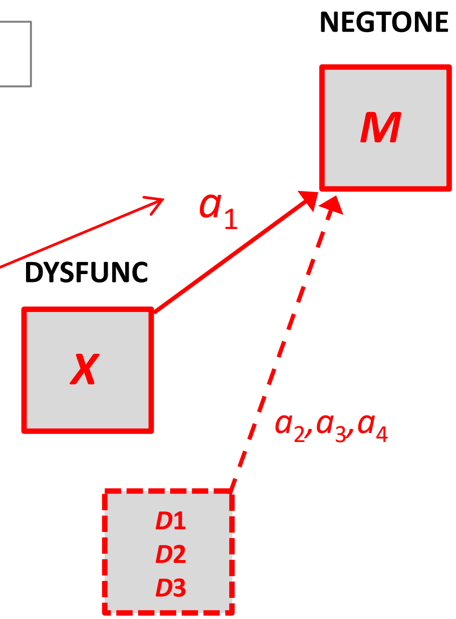
```
proc reg data=teams;model negtone=dysfunc d1 d2 d3;run;
```

```
summary(lm(negtone~dysfunc+d1+d2+d3, data = teams))
```

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.206	.130		-1.576	.121
	Dysfunctional team behavior	.609	.167	.431	3.655	.001
	d1	.349	.171	.307	2.033	.047
	d2	.295	.212	.193	1.391	.170
	d3	.251	.166	.230	1.508	.137

a. Dependent Variable: Negative affective tone



$$\boxed{a_1 = 0.609}$$

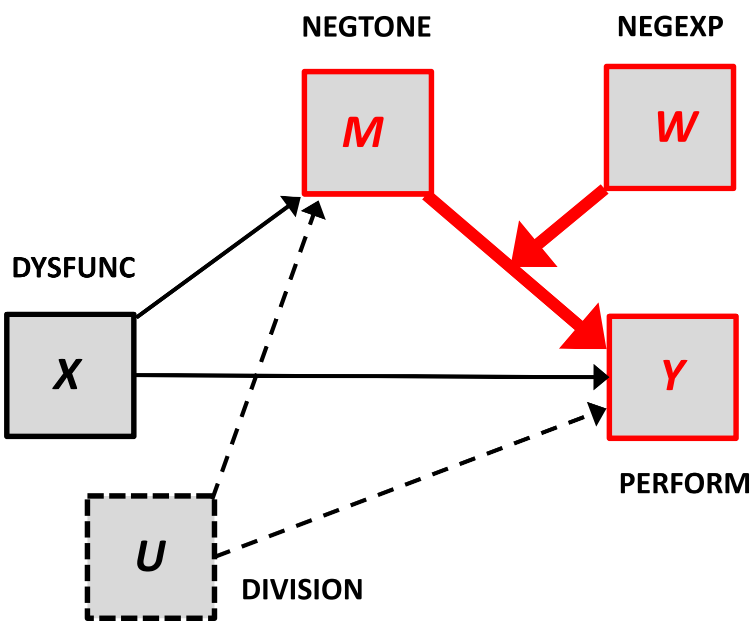
$$\widehat{M_i} = -0.206 + 0.609X_i + 0.349D_{1i} + 0.295D_{2i} + 0.251D_{3i}$$

Teams whose members exhibit relatively more dysfunctional behavior tend to operate in a work environment characterized by relatively more negative affective tone (i.e., members report more negative affect)

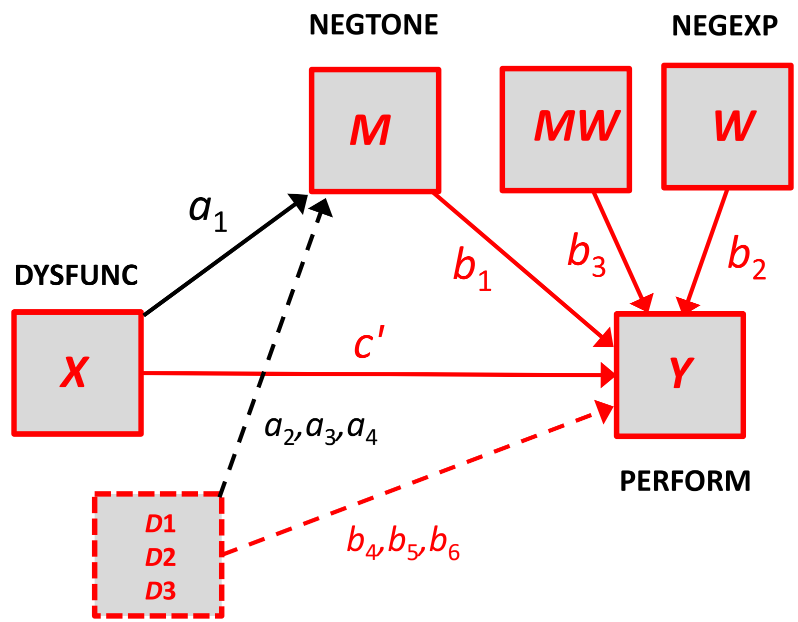
Estimating the moderation component of the model

The conceptual model proposes that the effect of negative work tone on performance depends on negative nonverbal expressivity. Let's see whether there is evidence of this.

Conceptual Model



Statistical Model



$$\widehat{Y}_i = c'_0 + c'X_i + \boxed{b_1M_i + b_2W_i + b_3M_iW_i} + b_4D_{1i} + b_5D_{2i} + b_6D_{3i}$$

We most care about the moderation components of the model of Y: b_1, b_2, and b_3. But these must be estimated in the context of the complete model of Y, which includes X as well.

Estimating the moderation component of the model

```
compute toneexp=negtone*negexp.
regression/dep=perform/method=enter dysfunc negtone negexp toneexp d1 d2 d3.
```

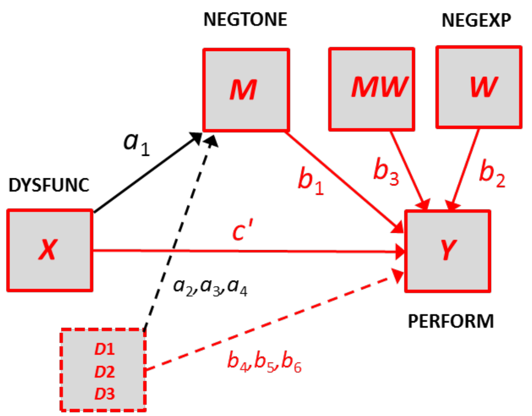
```
data teams;set teams;toneexp=negtone*negexp;run;
proc reg data=teams;model perform=dysfunc negtone negexp toneexp d1 d2 d3;run;
```

```
summary(lm(perform~dysfunc+negtone*negexp+d1+d2+d3, data = teams))
```

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.175	.130		-1.344	.185
	Dysfunctional team behavior	.373	.181	.265	2.062	.044
	Negative affective tone	-.489	.138	-.491	-3.549	.001
	Negative expressivity	-.022	.118	-.023	-.188	.852
	toneexp	-.450	.245	-.240	-1.835	.072
	d1	.182	.172	.161	1.056	.296
	d2	.084	.210	.055	.400	.690
	d3	.282	.165	.259	1.709	.093

a. Dependent Variable: Team performance



b_1 = -0.489, b_2=-0.022, b_3 = -0.450

$$\hat{Y}_i = -0.175 + 0.373X_i - 0.489M_i - 0.022W_i - 0.450M_iW_i + 0.182D_{1i} + 0.084D_{2i} + 0.282D_{3i}$$

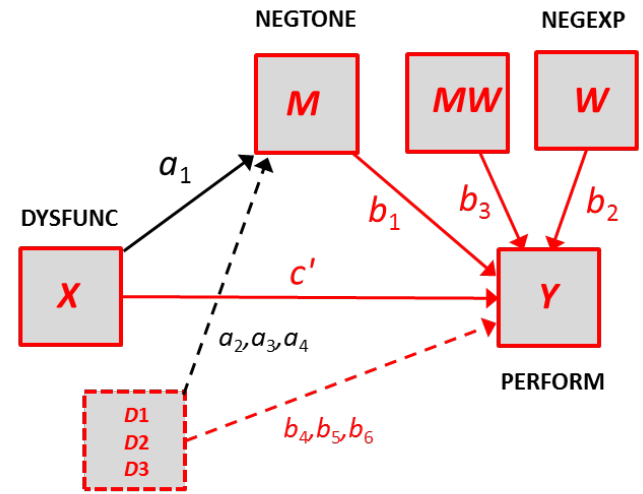
"Marginally significant" evidence that the effect of negative tone of the work environment on team performance depends on the negative nonverbal expressivity of team members. To better understand this, dissect this model.

Estimating the moderation component of the model

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.175	.130		-1.344	.185
	Dysfunctional team behavior	.373	.181	.265	2.062	.044
	Negative affective tone	-.489	.138	-.491	-3.549	.001
	Negative expressivity	-.022	.118	-.023	-.188	.852
	toneexp	-.450	.245	-.240	-1.835	.072
	d1	.182	.172	.161	1.056	.296
	d2	.084	.210	.055	.400	.690
	d3	.282	.165	.259	1.709	.093

a. Dependent Variable: Team performance



b_1 = -0.489, b_3 = -0.450

$$\hat{Y}_i = -0.175 + 0.373X_i - 0.489M_i - 0.022W_i - 0.450M_iW_i + 0.182D_{1i} + 0.084D_{2i} + 0.282D_{3i}$$

which can be written as

$$\hat{Y}_i = -0.175 + 0.373X_i + (-0.489 - 0.450W_i)M_i - 0.022W_i + 0.182D_{1i} + 0.084D_{2i} + 0.282D_{3i}$$

or

$$\hat{Y}_i = -0.175 + 0.373X_i + \theta_{M \to Y}M_i - 0.022W_i + 0.182D_{1i} + 0.084D_{2i} + 0.282D_{3i}$$

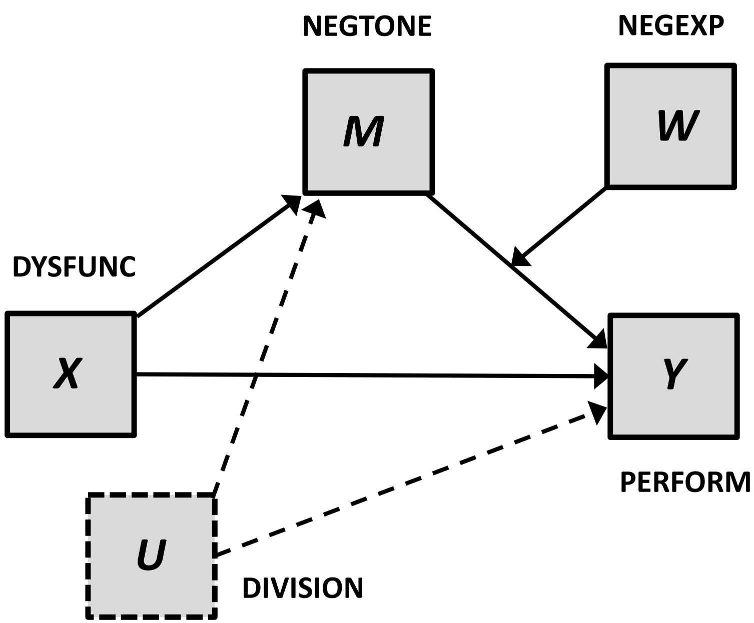
where

$$\theta_{M \to Y} = -0.489 - 0.450W_i = b_1 + b_3W_i$$

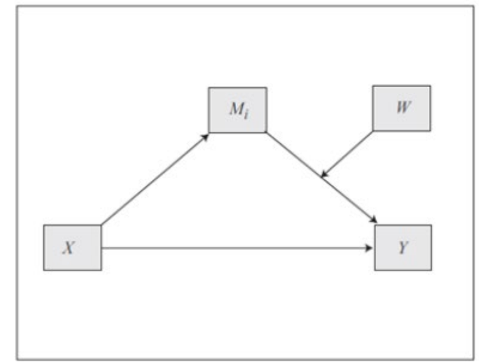
Let's visualize and probe this. PROCESS will take the work out of it.

Estimation of the model in PROCESS

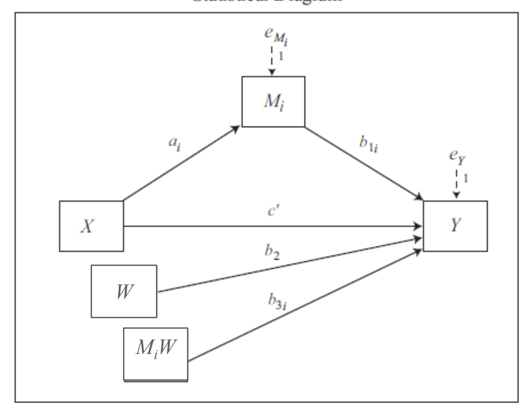
PROCESS takes most of the computational burden off our shoulders.



Model 14



Statistical Diagram



This is PROCESS model 14

```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000/model=14/
        plot = 1.
```

```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,
          boot=10000,model=14, plot = 1);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform",
        w="negexp", boot=10000, model=14, plot=1)
```

PROCESS output

```
OUTCOME VARIABLE:
 perform

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5937      .3524      .2006     4.0428     7.0000    52.0000      .0013

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.1754      .1305    -1.3444      .1847     -.4373      .0864
dysfunc       .3729      .1808     2.0622      .0442      .0100      .7357
negtone      -.4886      .1377    -3.5485      .0008     -.7649     -.2123
negexp       -.0221      .1176     -.1875      .8520     -.2581      .2140
Int_1        -.4498      .2451    -1.8353      .0722     -.9417      .0420
d1            .1815      .1720     1.0556      .2960     -.1635      .5266
d2            .0841      .2099      .4004      .6905     -.3372      .5053
d3            .2816      .1648     1.7087      .0935     -.0491      .6123

Product terms key:
 Int_1    :        negtone   x        negexp

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      .0419     3.3684     1.0000    52.0000      .0722
```

b_1 = -0.489

b_2 = -0.022

b_3 = -0.450

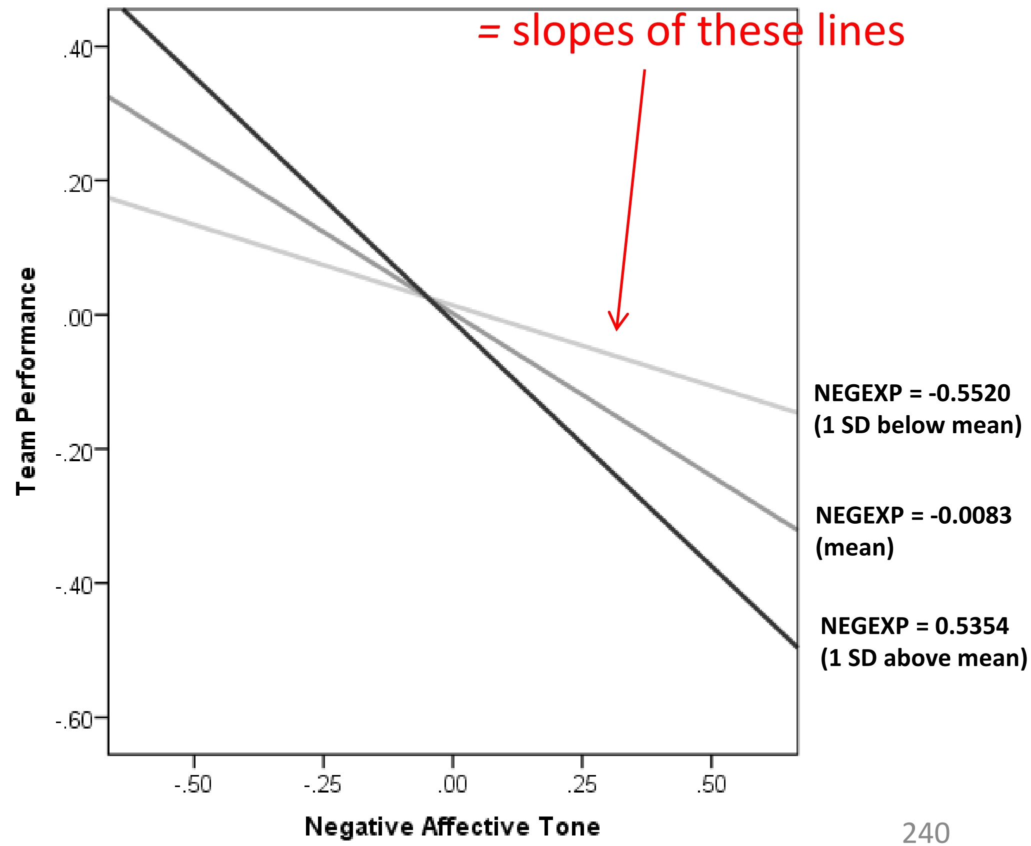
Visualizing the interaction

Use of the PLOT option in SPSS (**`plot=1`**) produces a table of estimated values of the outcome for various combinations of the focal predictor and moderator, and an SPSS program to generate a skeleton of the plot that can be edited.

M *W* $\hat{Y}$

```
DATA LIST FREE/negtone negexp perform.
BEGIN DATA.
     -.4782      -.5520       .1288
      .0472      -.5520       .0026
      .5726      -.5520      -.1237
     -.4782      -.0083       .2338
      .0472      -.0083      -.0210
      .5726      -.0083      -.2757
     -.4782       .5354       .3387
      .0472       .5354      -.0445
      .5726       .5354      -.4278
END DATA.
GRAPH/SCATTERPLOT=negtone WITH perform
   BY negexp.
```

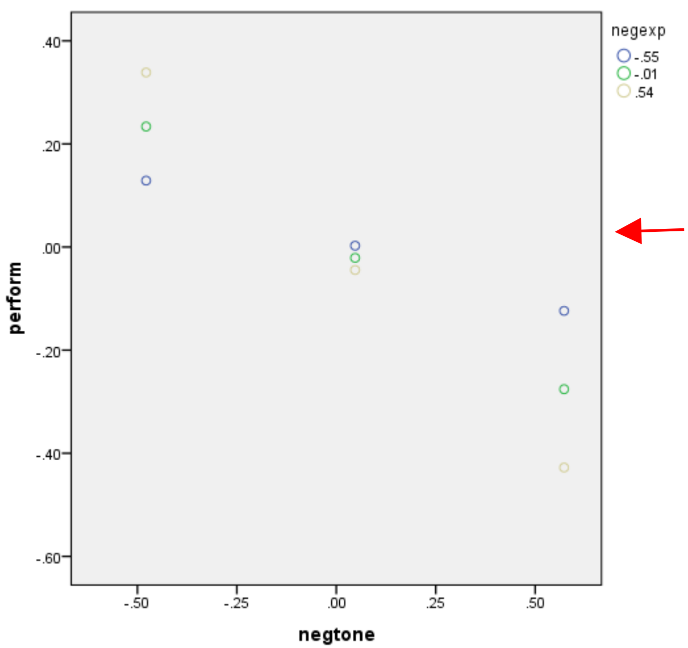
$\theta_{M \rightarrow Y} = b_1 + b_3 W =$
$= -0.489 - 0.450W$
= slopes of these lines



Visualizing the interaction

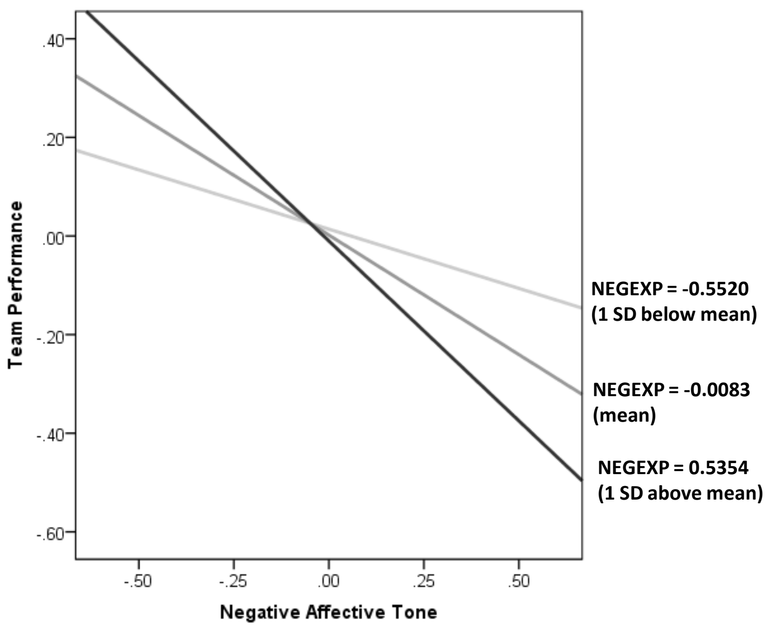
```
DATA LIST FREE/negtone negexp perform.
BEGIN DATA.
     -.4782      -.5520       .1288
      .0472      -.5520       .0026
      .5726      -.5520      -.1237
     -.4782      -.0083       .2338
      .0472      -.0083      -.0210
      .5726      -.0083      -.2757
     -.4782       .5354       .3387
      .0472       .5354      -.0445
      .5726       .5354      -.4278
END DATA.
GRAPH/SCATTERPLOT=negtone WITH perform BY negexp.
```

Use of the PLOT option (**`plot=1`**) produces a table of estimated values of the outcome for various combinations of the focal predictor and moderator.



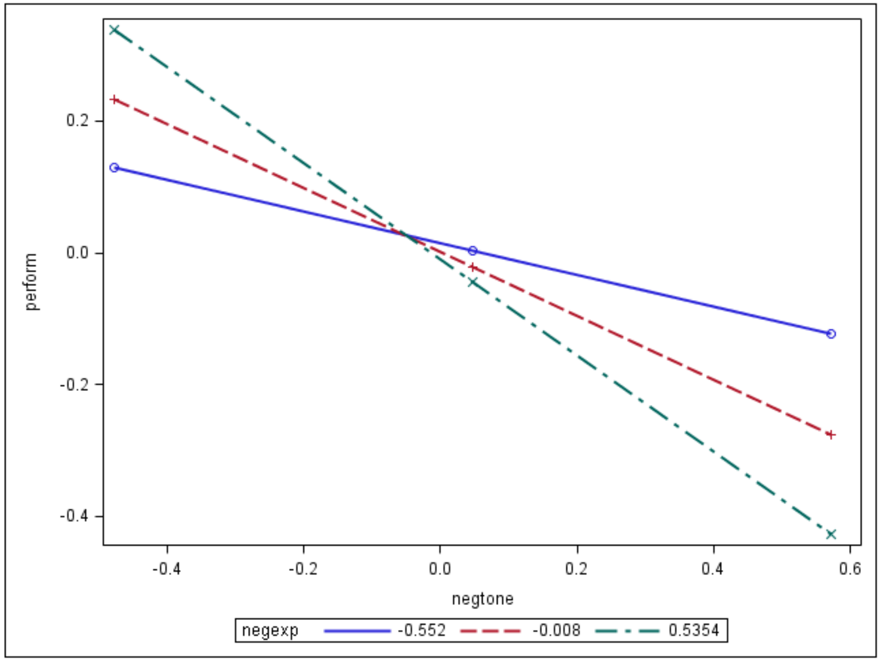
Before editing

After editing



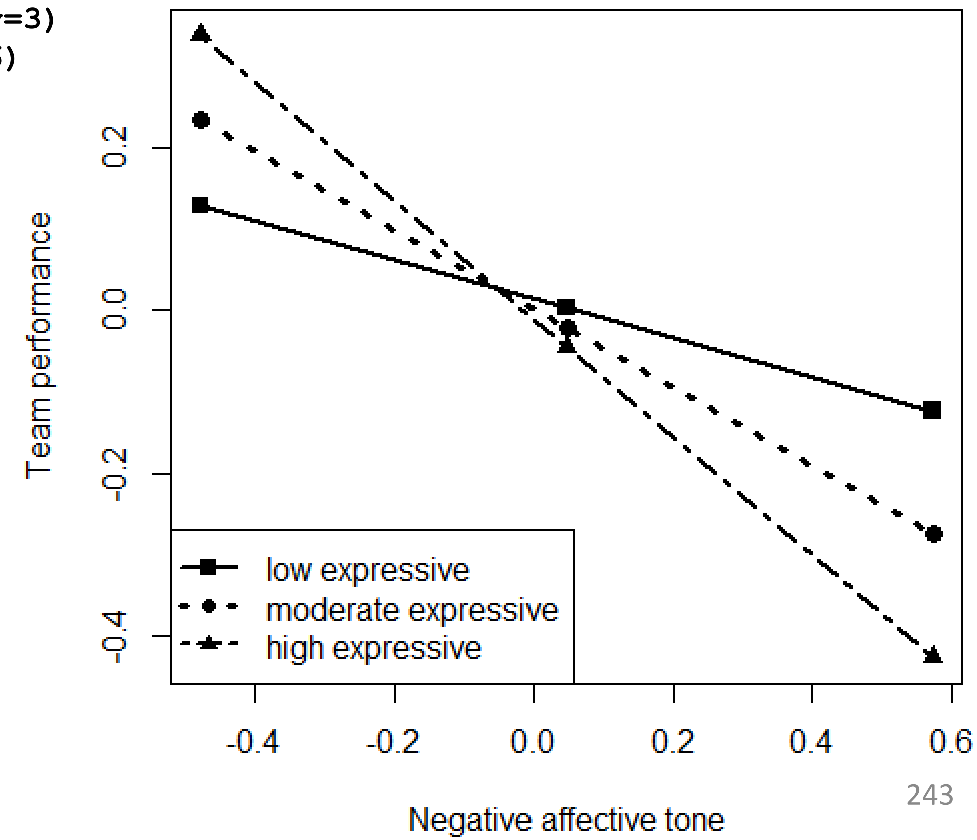
Example code in SAS

```
data;
input negtone negexp perform;
cards;
-.4782     -.5520      .1288
 .0472     -.5520      .0026
 .5726     -.5520     -.1237
-.4782     -.0083      .2338
 .0472     -.0083     -.0210
 .5726     -.0083     -.2757
-.4782      .5354      .3387
 .0472      .5354     -.0445
 .5726      .5354     -.4278
run;
proc sgplot;reg x=negtone y=perform/group=negexp;run;
```



Example code in R

```
m<-c(-.478,.047,.573,-.478,.047,.573,-.478,.047,.573)
w<-c(-.552,-.552,-.552,-.008,-.008,-.008,.535,.535,.535)
y<-c(.129,.003,-.124,.234,-.021,-.276,.339,-.045,-.428)
wmarker<-c(15,15,15,16,16,16,17,17,17)
plot(y=y,x=m,cex=1.2,pch=wmarker,xlab="Negative affective tone",
ylab="Team performance")
legend.txt<-c("low expressive","moderate expressive","high expressive")
legend("bottomleft", legend = legend.txt,cex=1,lty=c(1,3,6),lwd=c(2,3,2),pch=c(15,16,17))
lines(m[w==-.552],y[w==-.552],lwd=2)
lines(m[w==-.008],y[w==-.008],lwd=3,lty=3)
lines(m[w==.535],y[w==.535],lwd=2,lty=6)
```



Probing the interaction: Pick-a-point

PROCESS sees that the moderator is quantitative (i.e., it has more than 2 values) so it implements the pick-a-point procedure with moderator values equal to 16th, 50th, and 84th percentile.

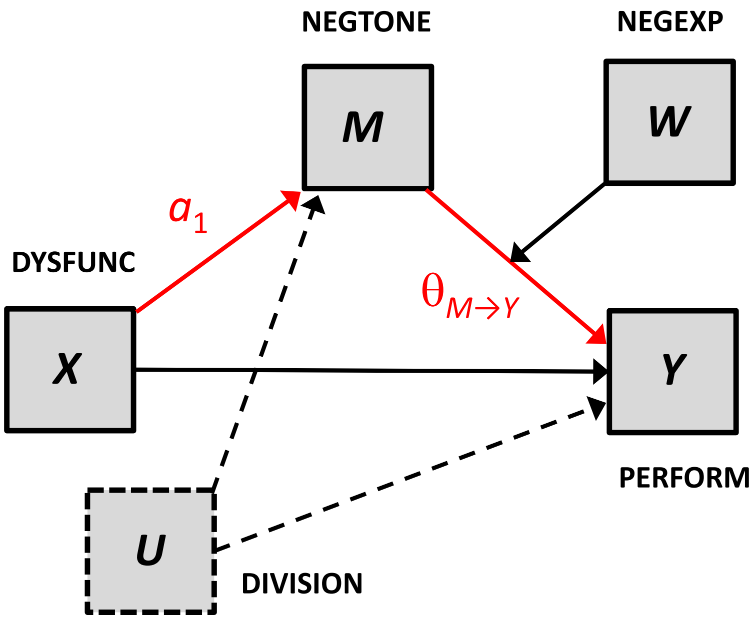
$$\theta_{M \rightarrow Y} = b_1 + b_3 W = -0.489 - 0.450W$$

```
*************************************************************************
 Focal predict: negtone  (M)
       Mod var: negexp   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     negexp     Effect         se          t          p       LLCI       ULCI
     -.5308     -.2498      .2196    -1.1379      .2604     -.6904      .1907
     -.0600     -.4616      .1434    -3.2188      .0022     -.7494     -.1738
      .6000     -.7585      .1633    -4.6451      .0000    -1.0862     -.4308
```

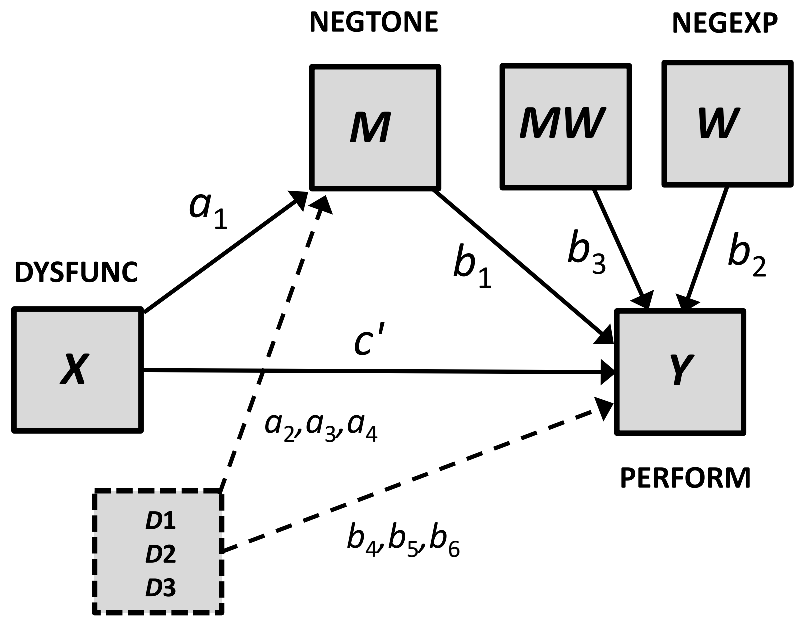
Negative affective tone is significantly negatively related to performance among teams relatively “moderate” and “relatively high” in negative nonverbal expressivity but not among teams “relatively low” in negative nonverbal expressivity.

The conditional indirect effect of *X*

Conceptual Model



Statistical Model

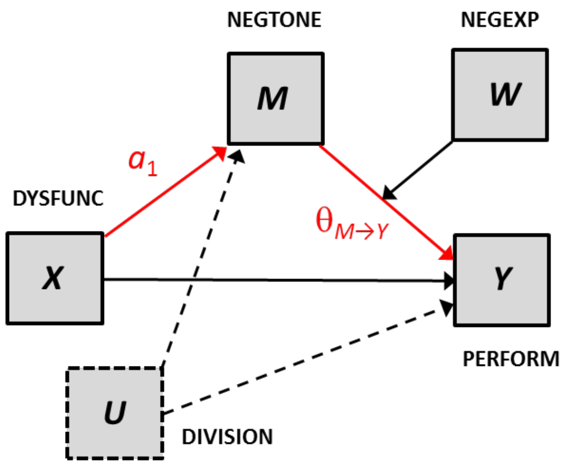


The conditional indirect effect of *X* on *Y* through *M* is the product of the effect of X on *M* (a_1) and the conditional effect of *M* on *Y* given *W* ($\theta_{M\rightarrow Y} = b_1 + b_3W$):

$$a_1\theta_{M\rightarrow Y} = a_1(b_1 + b_3W) = 0.610(-0.489 - 0.450W)$$

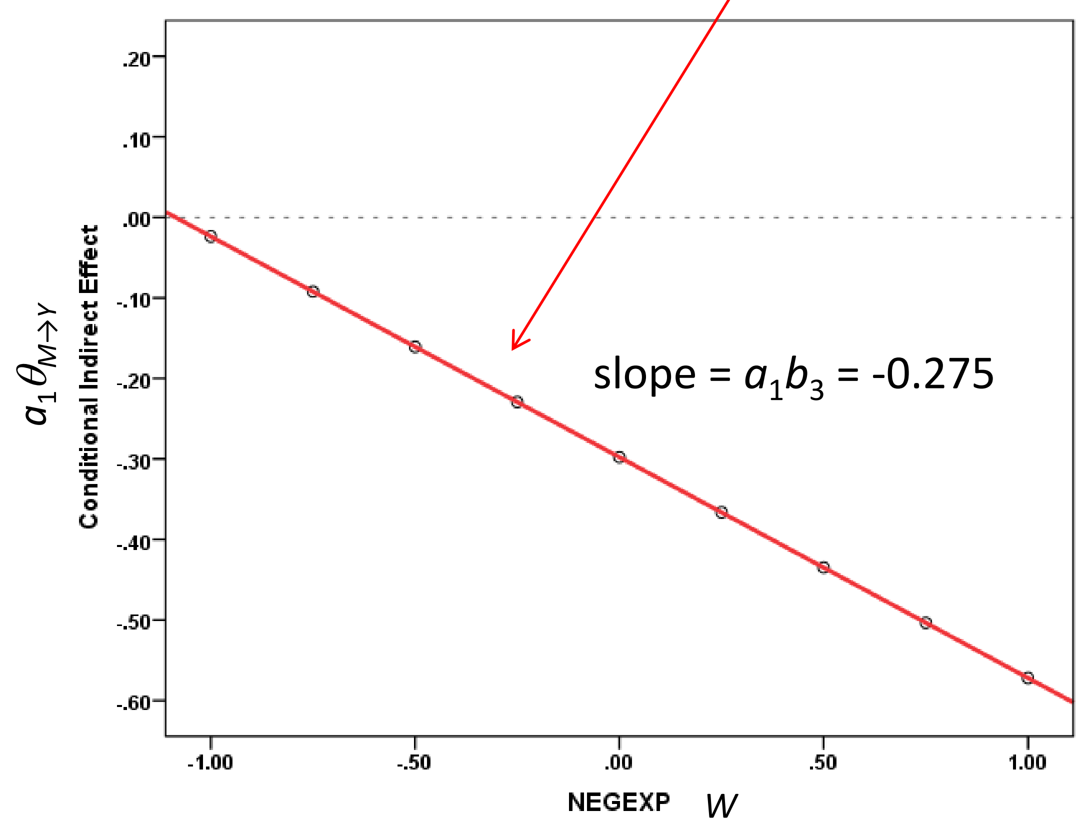
The indirect effect of dysfunctional team behavior on team performance through negative tone is allowed to be a function of negative nonverbal expressivity.

A visual representation of the indirect effect



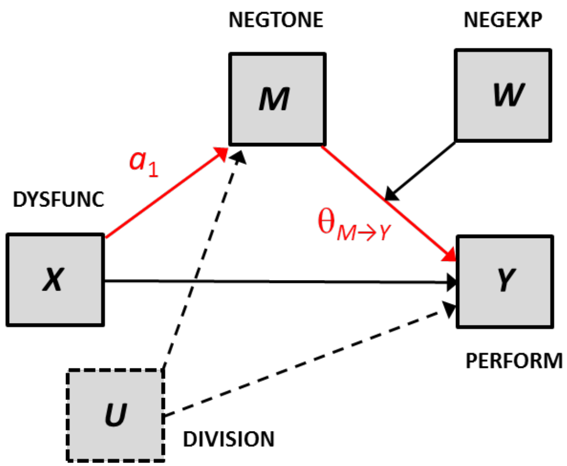
$$a_1\theta_{M\to Y} = a_1(b_1 + b_3W) = 0.610(-0.489 - 0.450W)$$
$$= a_1b_1 + a_1b_3W = -0.298 - 0.275W$$

The indirect effect is more negative as negative nonverbal expressivity increases. The "**index of moderated mediation**" is a_1b_3 = -0.275. It quantifies the relationship between the moderator and the indirect effect in this model.



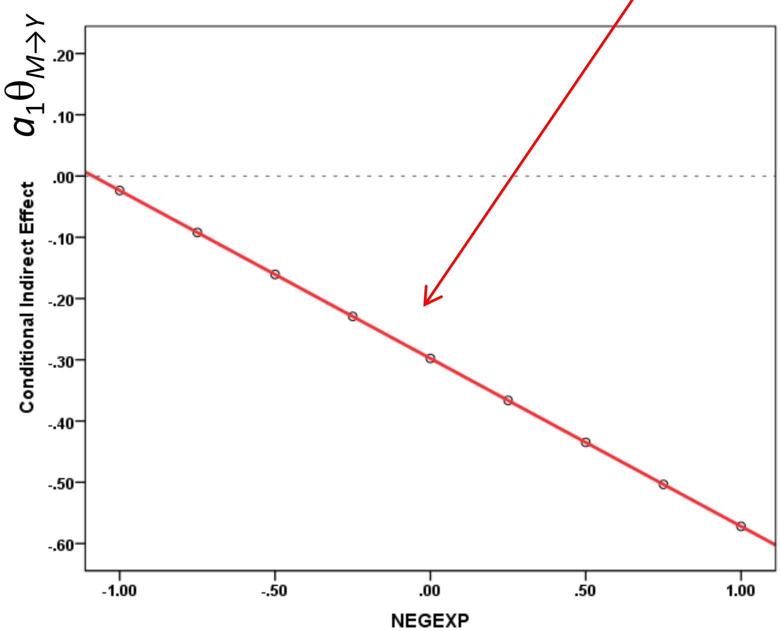
As will be seen, a hypothesis test that the slope of this function is equal to 0 is a formal test of moderated mediation….moderation of the indirect effect.

The conditional indirect effect of *X*



$$a_1\theta_{M\to Y} = a_1(b_1 + b_3W) = 0.610(-0.489 - 0.450W)$$
$$= a_1b_1 + a_1b_3W = -0.298 - 0.275W$$

The indirect effect is more negative as negative nonverbal expressivity increases.



Using this function, we can estimate the indirect effect for any value of the moderator we choose:

If we had used `moments = 1`

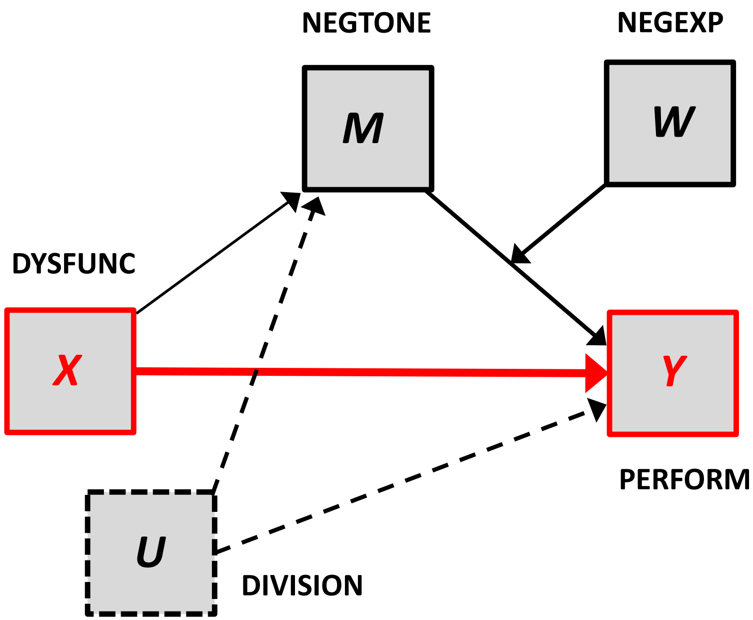
	NEGEXP (*W*)	a_1	$\theta_{M\to Y}$	$a_1\theta_{M\to Y}$
$\bar{W} - SD_W$	-0.552	0.610	-0.240	-0.146
$\bar{W}$	-0.008	0.610	-0.485	-0.296
$\bar{W} + SD_W$	0.535	0.610	-0.730	-0.445

Conditional indirect effects

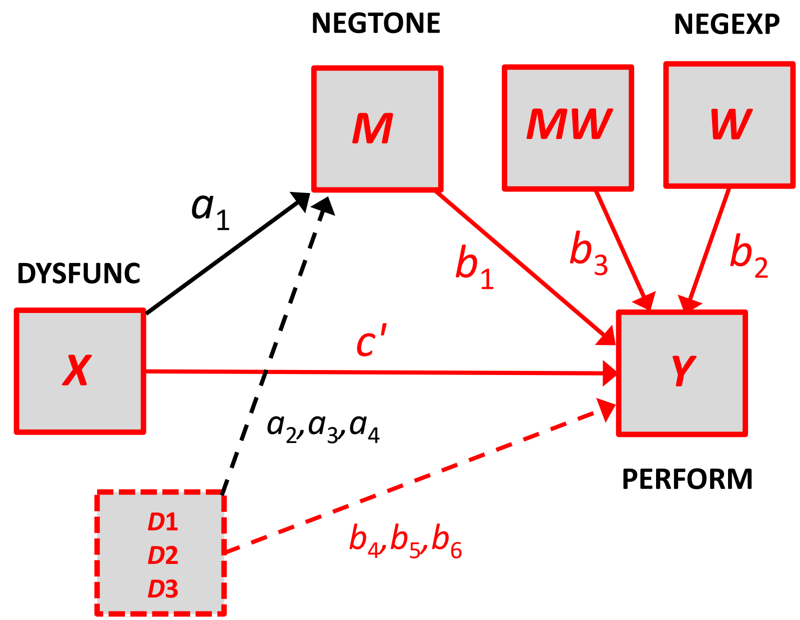
The direct effect of *X*

The direct effect of *X* is the effect of *X* of *Y* that does not operate through *M.*

Conceptual Model



Statistical Model



$$\widehat{Y}_i = i_1 + \boxed{c' X_i} + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

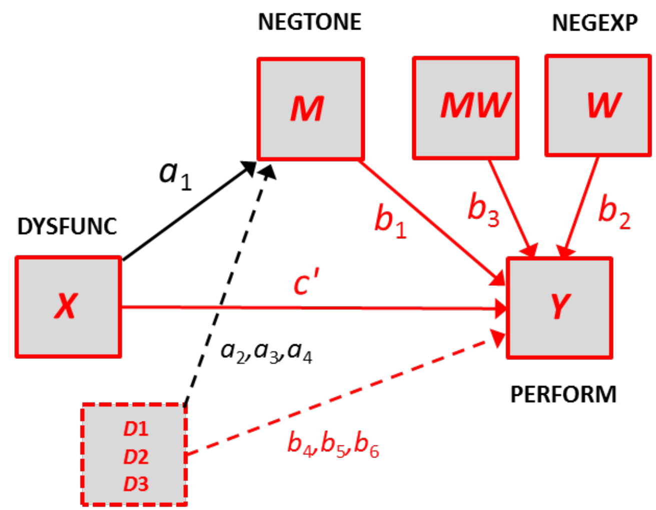
In this model, the direct effect is fixed to be unmoderated. It is a constant rather than a function of another variable in the model.

The direct effect of *X* (we estimated earlier)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.175	.130		-1.344	.185
	Dysfunctional team behavior	.373	.181	.265	2.062	.044
	Negative affective tone	-.489	.138	-.491	-3.549	.001
	Negative expressivity	-.022	.118	-.023	-.188	.852
	toneexp	-.450	.245	-.240	-1.835	.072
	d1	.182	.172	.161	1.056	.296
	d2	.084	.210	.055	.400	.690
	d3	.282	.165	.259	1.709	.093

a. Dependent Variable: Team performance



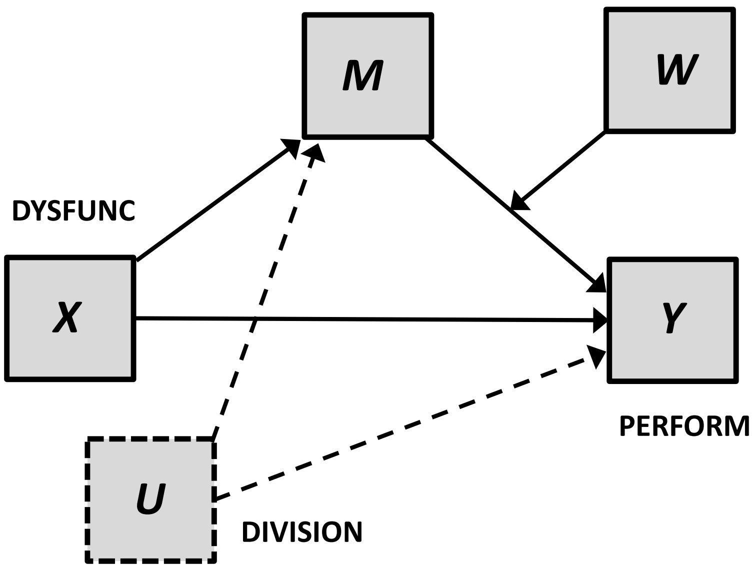
c' = 0.373, $t(55)$ = 2.062, $p < .05$.

$$\hat{Y}_i = -0.175 + 0.373X_i - 0.489M_i - 0.022W_i - 0.450M_iW_i + 0.182D_{1i} + 0.084D_{2i} + 0.282D_{3i}$$

Holding constant negative affective tone and negative nonverbal expressivity, teams that exhibit more dysfunctional behavior perform *better*.

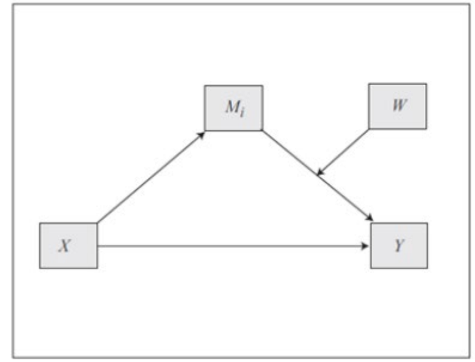
Estimation of the model in PROCESS

PROCESS takes most of the computational burden off our shoulders.

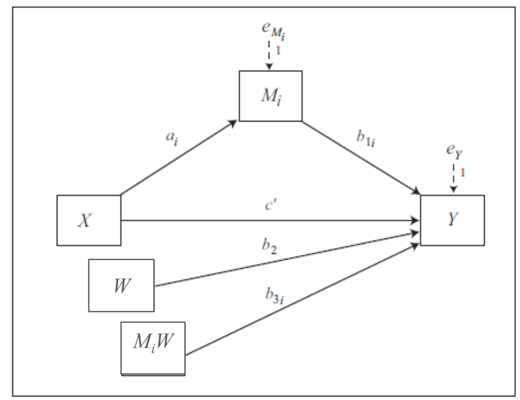


This is PROCESS model 14

Model 14



Statistical Diagram



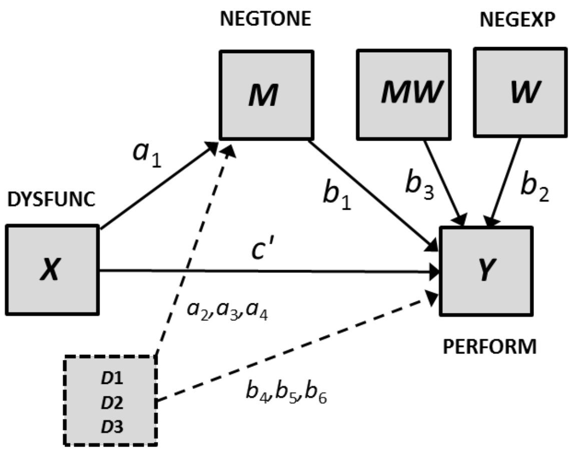

```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000/model=14/
        plot = 1.
```

```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,
         boot=10000,model=14, plot = 1);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform",
        w="negexp", boot=1000, model=14, plot=1)
```

PROCESS output

```
Model = 14
    Y = perform
    X = dysfunc
    M = negtone
    W = negexp

Statistical Controls:
CONTROL= d1       d2       d3

Sample size
         60
```




```
**************************************************************************
Outcome: negtone
```

$$\boxed{\widehat{M_i} = -0.206 + 0.610X_i + \cdots}$$

Model Summary

R	R-sq	MSE	F	df1	df2	p
.5026	.2526	.2213	4.6462	4.0000	55.0000	.0027

Model

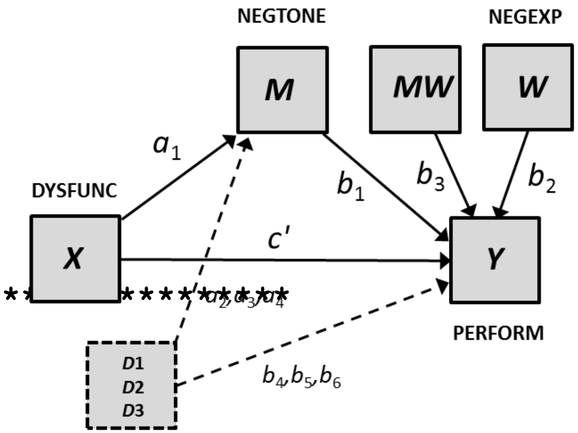
	coeff	se	t	p	LLCI	ULCI
constant	-.2057	.1305	-1.5760	.1208	-.4672	.0559
dysfunc	.6095	.1668	3.6546	.0006	.2753	.9437
d1	.3487	.1715	2.0332	.0469	.0050	.6923
d2	.2951	.2122	1.3906	.1700	-.1302	.7204
d3	.2507	.1663	1.5078	.1373	-.0825	.5840

$a_1 = 0.610$

```
**************************************************************************
```

PROCESS output

$$\widehat{Y}_i = -0.175 + 0.373X_i - 0.489M_i - 0.022W_i - 0.450M_iW_i + \cdots$$




```
**************************************************************************

Outcome: perform

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5937      .3524      .2006     4.0428     7.0000    52.0000      .0013

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.1754      .1305    -1.3444      .1847     -.4373      .0864
negtone      -.4886      .1377    -3.5485      .0008     -.7649     -.2123
dysfunc       .3729      .1808     2.0622      .0442      .0100      .7357
negexp       -.0221      .1176     -.1875      .8520     -.2581      .2140
int_1        -.4498      .2451    -1.8353      .0722     -.9417      .0420
d1            .1815      .1720     1.0556      .2960     -.1635      .5266
d2            .0841      .2099      .4004      .6905     -.3372      .5053
d3            .2816      .1648     1.7087      .0935     -.0491      .6123

Interactions:

 int_1    negtone       X     negexp

**************************************************************************
```

b_1 = -0.489
c' = 0.373
b_2 = -0.022
b_3 = -0.450

PROCESS output

```
******************** DIRECT AND INDIRECT EFFECTS *************************

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .3729      .1808     2.0622      .0442      .0100      .7357

INDIRECT EFFECT:
 dysfunc     ->    negtone     ->    perform

     negexp     Effect     BootSE   BootLLCI   BootULCI
     -.5308     -.1523      .1540     -.4335      .1943
     -.0600     -.2813      .1249     -.5432     -.0549
      .6000     -.4623      .1678     -.8095     -.1503

      Index of moderated mediation:
           Index     BootSE   BootLLCI   BootULCI
negexp     -.2742      .1791     -.7172     -.0234

W values in conditional tables are the 16th, 50th, and 84th percentiles.
```

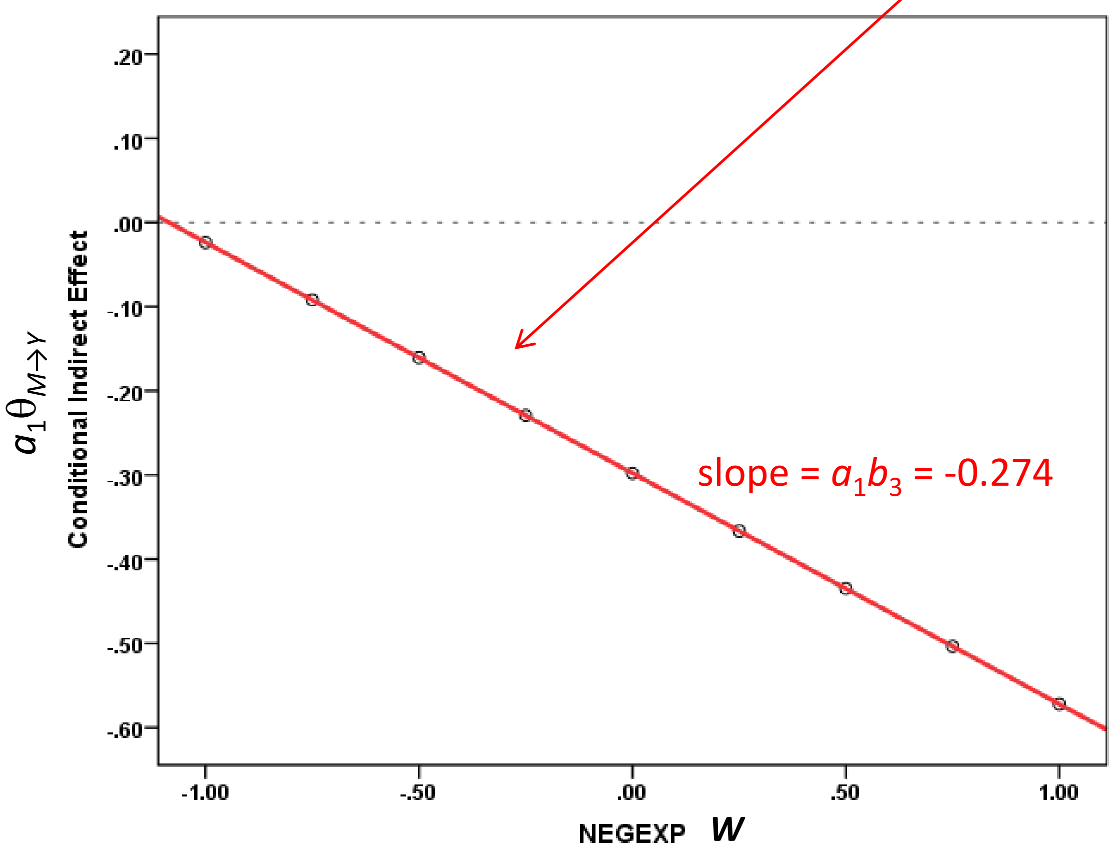
Direct effect
$c' = .373$, $p < .05$

$$a_1\theta_{M \to Y} = a_1(b_1 + b_3W)$$
$$= 0.610(-0.489 - 0.450W)$$
$$= a_1b_1 + a_1b_3W$$
$$= -0.298 - 0.274W$$

PROCESS sees that the moderator is continuous so, without instruction otherwise, prints the conditional indirect effect at the 16th, 50th, and 84th percentiles. For the mean +/- 1 SD add `moments = 1` to the command line.

A statistical test of moderated mediation
in the second stage moderated mediation model

$$a_1\theta_{M\rightarrow Y} = a_1(b_1 + b_3W) = 0.610(-0.489 - 0.450W)$$
$$= a_1b_1 + a_1b_3W = -0.298 - 0.274W$$



The indirect effect is a function of W (negative nonverbal expressivity) in our model. This function is a line.

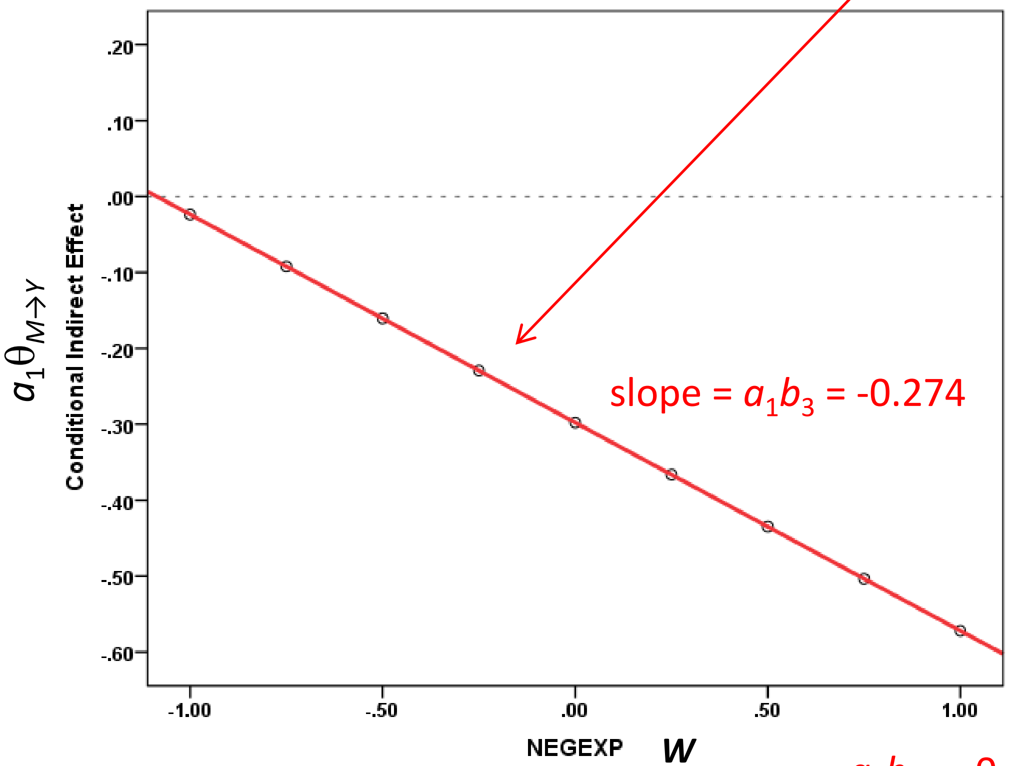
$$a_1\theta_{M\rightarrow Y} = a_1(b_1 + b_3W)$$
$$= a_1b_1 + a_1b_3W$$
$$= -0.298 - 0.274W$$

An inference about the slope of this line—the "index of moderated mediation"—is an inference about whether the indirect effect is moderated: Is this slope significantly different from zero? If so, that supports a claim of "moderated mediation."

As a_1b_3 is a product of regression coefficients, an inferential test should respect the nonnormality of the sampling distribution of the product. A bootstrap confidence interval is a good choice.

This test is provided automatically by PROCESS

$$a_1\theta_{M\rightarrow Y} = a_1(b_1 + b_3W) = 0.610(-0.489 - 0.450W)$$
$$= a_1b_1 + a_1b_3W = -0.298 - 0.274W$$



The indirect effect is a function of V (negative nonverbal expressivity) in our model. This function is a line.

$$a\theta_{M\rightarrow Y} = a_1(b_1 + b_3W)$$
$$= a_1b_1 + a_1b_3W$$
$$= -0.298 - 0.274W$$

a_1b_3 = -0.274, 95% bootstrap CI = -0.683 to -0.024

```
******************* INDEX OF MODERATED MEDIATION ***********************

            Index    SE(Boot)    BootLLCI    BootULCI
Negexp     -.2742       .1727      -.6833      -.0243
```

This slope is statistically different from zero. The indirect effect depends on negative nonverbal expressivity…. The mediation is moderated.

Where is this test discussed?

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Taylor & Francis Group

An Index and Test of Linear Moderated Mediation

Andrew F. Hayes
The Ohio State University

I describe a test of linear moderated mediation in path analysis based on an interval estimate of the parameter of a function linking the indirect effect to values of a moderator—a parameter that I call the *index of moderated mediation*. This test can be used for models that integrate moderation and mediation in which the relationship between the indirect effect and the moderator is estimated as linear, including many of the models described by Edwards and Lambert (2007) and Preacher, Rucker, and Hayes (2007) as well as extensions of these models to processes involving multiple mediators operating in parallel or in serial. Generalization of the method to latent variable models is straightforward. Three empirical examples describe the computation of the index and the test, and its implementation is illustrated using Mplus and the PROCESS macro for SPSS and SAS.

AN INDEX AND TEST OF LINEAR MODERATED MEDIATION

Empirically substantiating the boundary conditions of one variable's causal effect on another and the mechanism(s) by which that effect operates are recognized as markers of deeper understanding than merely establishing that X affects Y. Successfully answering such questions as "Under what circumstance does X affect Y?" and "How does X affect Y?" adds much merit to one's science and can enhance its impact on a field.

Questions about the contingencies of an effect are often answered statistically through moderation analysis. Assuming continuous Y and dichotomous and/or continuous X and W (the only case considered in this paper), moderation of the effect of X on Y by W is popularly tested by estimating a linear model of the form

$$Y = i_Y + b_1X + b_2W + b_3XW + e_Y$$

where b_1, b_2, and b_3 are estimated regression coefficients, e_Y is an error in estimation, and i_Y is a regression intercept. X's effect on Y is linearly moderated by W if the regression coefficient for XW is different from zero by an inferential test or confidence interval.[1]

Questions about the mechanism by which an effect operates are frequently answered with mediation analysis. In a mediation analysis, focus is on the estimation of the indirect effect of X on Y through an intermediary *mediator* variable M causally located between X and Y (i.e., a model of the form $X \rightarrow M \rightarrow Y$). Assuming continuous Y and M, the indirect effect of X on Y through M can be derived using two linear models:

$$M = i_M + aX + e_M$$
$$Y = i_Y + c'X + bM + e_Y$$

where a, b, and c' are estimated regression coefficients, i_M and i_Y are regression intercepts, and e_M and e_Y are errors in estimation. The product of a and b quantifies the indirect effect of X on Y and estimates how much two cases that differ by one unit on X are estimated to differ on Y through the effect of X on M which in turn influences Y. Evidence that the indirect effect is different from zero by an inferential test or confidence interval bolsters a claim that the effect of X on Y is mediated at least in part by M.

Mediation and moderation analysis can be analytically integrated into a unified statistical model. Although not a new idea by any means—such terms as "mediated moderation" and "moderated mediation" appeared in the literature decades ago (e.g., Baron & Kenny, 1986; James & Brett, 1984; Judd & Kenny, 1981)—it is only recently that a handful of articles in the methodology literature have provided researchers the tools and systematic procedures for answering questions focused on the "when of the how" or the "how of the when." Hayes (2013) introduces the term

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[1] Unless otherwise stated, assume that all regression coefficients and functions thereof in my notation are estimates based on the data available.

Provided with your materials

in the causal model in order to claim M is a mediator. In addition, Kraemer et al. (2002, 2008) don't discuss formally quantifying the indirect effect. In this model, M's effect on Y is not b but, rather, $b + c_2'X$. Thus, the indirect effect of X on Y through M is $a(b + c_2'M)$, meaning it is a function of X (see, e.g., Preacher et al., 2007).

In the model they recommend using to test for mediation, X is estimated to affect Y indirectly through M, as well as directly independent of M. But the direct effect of X in this model is not c_1' as it might seem. Grouping terms in equation 12.2 involving X and then factoring out X yields the direct effect of X on Y:

$$\theta_{X\rightarrow Y} = c_1' + c_2'M$$

So the direct effect of X is conditioned on M. In other words, if c_2' in equation 12.2 is statistically different from zero, M moderates X's direct effect on Y. The MacArthur camp would reject this as a possibility, as a moderator can't be correlated with X. By their criteria, M *can* be deemed a mediator of X's effect if a and c_2' are both statistically different from zero, but that very circumstance implies that M is *not* uncorrelated with X. At the same time, a statistically significant c_2' means that X's direct effect on Y is moderated by M. Thus, in the model Kraemer et al. (2002, 2008) recommend as the best approach to testing mediation, meeting one subset of their criteria for establishing M as a mediator also means that M could be construed as a moderator of X's effect, at least statistically or mathematically so.

Just because something is mathematically possible doesn't mean that it is sensible theoretically or substantively interpretable when it happens (as it does, as evidenced in some of the example studies cited on page 332). I will not take a firm position on whether construing M as a simultaneous mediator and moderator of a variable's effect could ever make substantive or theoretical sense. I am uncomfortable categorically ruling out the possibility that M could be a moderator just because it is correlated with X. My guess is that there are many real-life processes in which things caused by X also influence the size of the effect of X on Y measured well after X. But M would have to be causally prior to Y in order for this to be possible, implying that M could also be construed as a mediator if M is caused in part by X but also influences Y in some fashion.

12.3 Comparing Conditional Indirect Effects and a Formal Test of Moderated Mediation

If the indirect effect of X on Y through M depends on a particular moderator, that means that the indirect effect is a function of that moderator. A sensible question to ask is whether the conditional indirect effect when the

Chapter 12 of IMMCPA

PROCESS output

We need an inferential test for these conditional indirect effects. Bootstrap confidence intervals are perfect for the job. PROCESS does this for us automatically.

```
******************** DIRECT AND INDIRECT EFFECTS *************************

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .3729      .1808     2.0622      .0442      .0100      .7357

INDIRECT EFFECT:
 dysfunc     ->    negtone     ->    perform

     negexp     Effect     BootSE   BootLLCI   BootULCI
     -.5308     -.1523      .1540     -.4335      .1943
     -.0600     -.2813      .1249     -.5432     -.0549
      .6000     -.4623      .1678     -.8095     -.1503

      Index of moderated mediation:
            Index     BootSE   BootLLCI   BootULCI
negexp     -.2742      .1791     -.7172     -.0234
```

Conditional indirect effects with 95% bootstrap CIs based on 10,000 bootstrap samples.

The indirect effect of dysfunctional behavior on performance through negative tone is negative among teams relatively moderate (point estimate: -0.28, 95% CI from -0.54 to -0.05) and relatively high (point estimate: -0.46, 95% CI from -0.81 to -0.14) in negative nonverbal expressivity but not different from zero among those low in negative nonverbal expressivity (point estimate: -0.15, 95% CI from -0.43 to 0.19).

Comparing conditional indirect effects (2nd stage model)

A seemingly sensible question to ask is whether the conditional indirect effect of X when the moderator equals some value $W = w_1$ is different than the conditional indirect effect of X when the moderator is some different value $W = w_2$. For example, is the indirect effect among teams low in negative nonverbal expressivity different from the indirect effect among teams high in negative nonverbal expressivity?

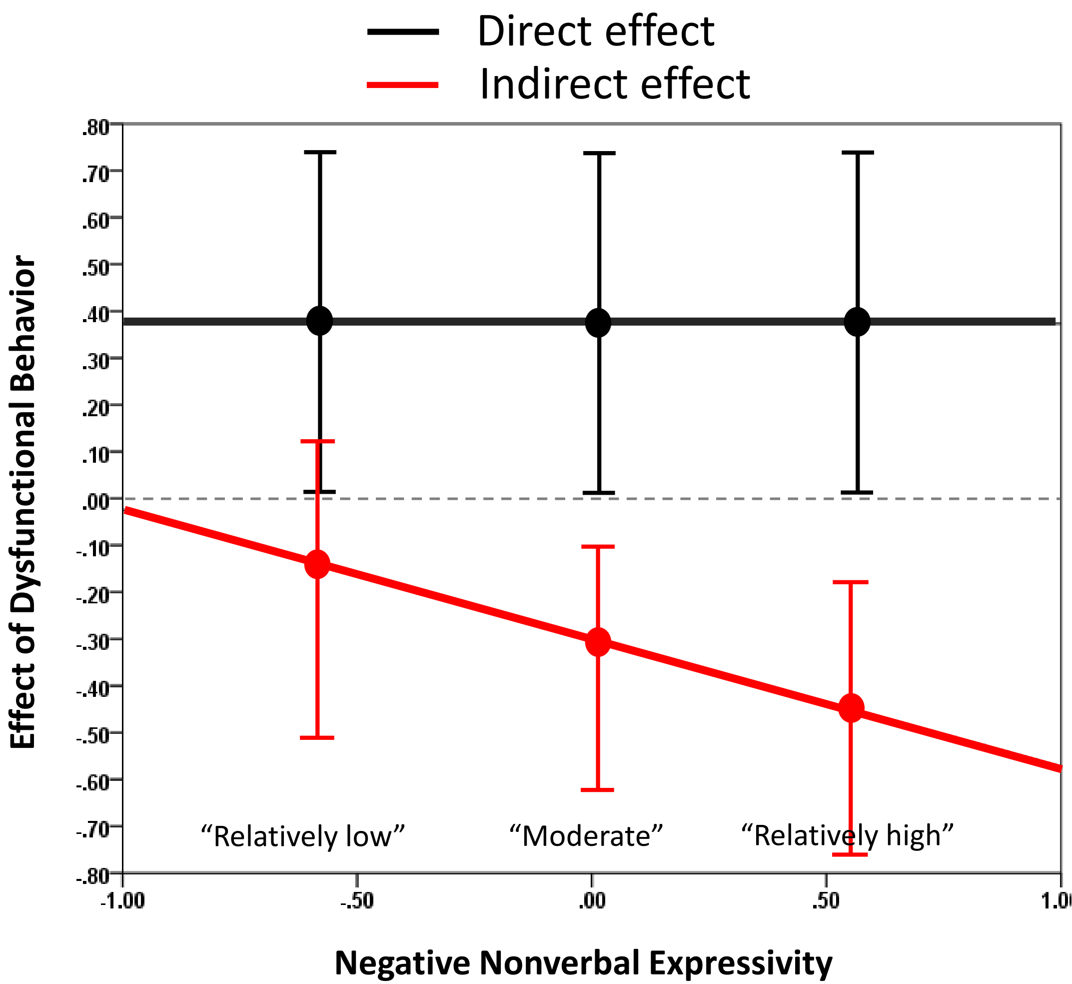
Rejection of the null hypothesis of no moderated mediation based on the index of moderated mediation implies that **any** two conditional indirect effects are different! No additional test is needed.

For example, for the second stage moderated mediation model just estimated:

$$
\begin{aligned}
a_1(b_1+b_3w_1) - a_1(b_1+b_3w_2) &= a_1(b_1+b_3w_1) - a_1(b_1+b_3w_2) \\
&= a_1b_1+a_1b_3w_1 - a_1b_1 - a_1b_3w_2 \\
&= a_1b_3w_1 - a_1b_3w_2 \\
&= a_1b_3(w_1 - w_2)
\end{aligned}
$$

If a bootstrap confidence interval for a_1b_3 does not contain zero, then neither will a confidence interval for $a_1b_3(w_1 - w_2)$, ***regardless*** of values of w_1 and w_2 chosen, so long as $w_1 \neq w_2$. And if a bootstrap confidence interval for a_1b_3 contains zero, then so too will a confidence interval for $a_1b_3(w_1 - w_2)$, ***for any two values*** of w_1 and w_2, ($w_1 \neq w_2$).

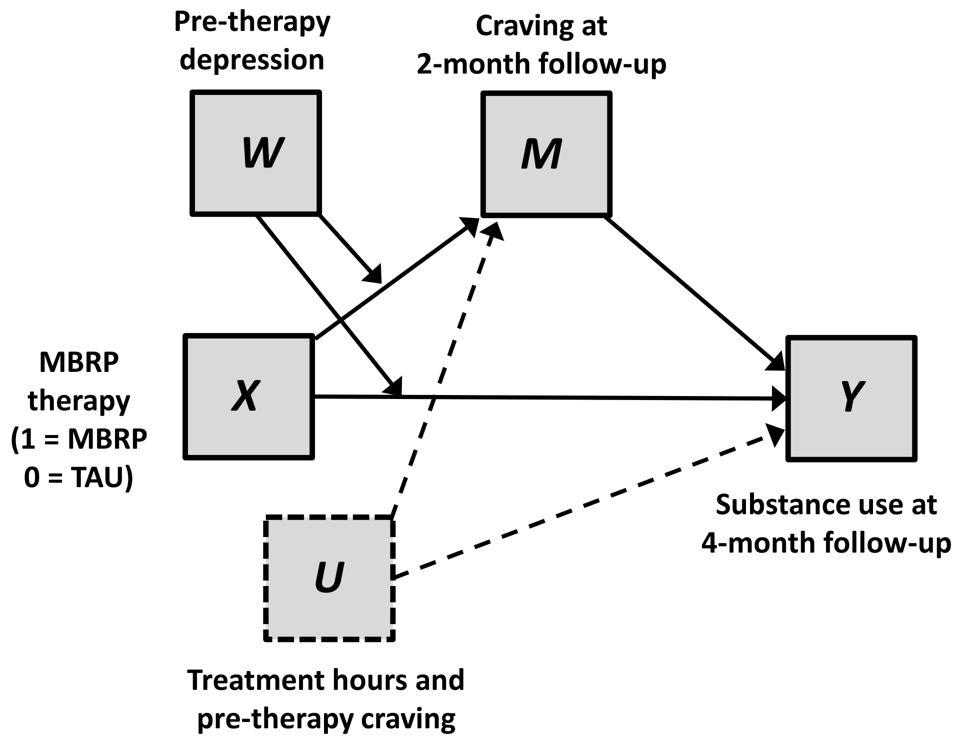
Putting it all together



Point estimates with 95% confidence intervals (OLS confidence intervals for direct effects, bootstrap confidence intervals for indirect effects).

More dysfunctional behavior tends to lead to more negative affective tone, yet this negative affective tone seems to lower performance only among teams that are more demonstrative of their negative feelings. Such a process does not operate among teams that hide their feelings. Independent of differences between teams in the negative affective tone of the work environment, teams that exhibit more dysfunctional behavior otherwise perform *better*.

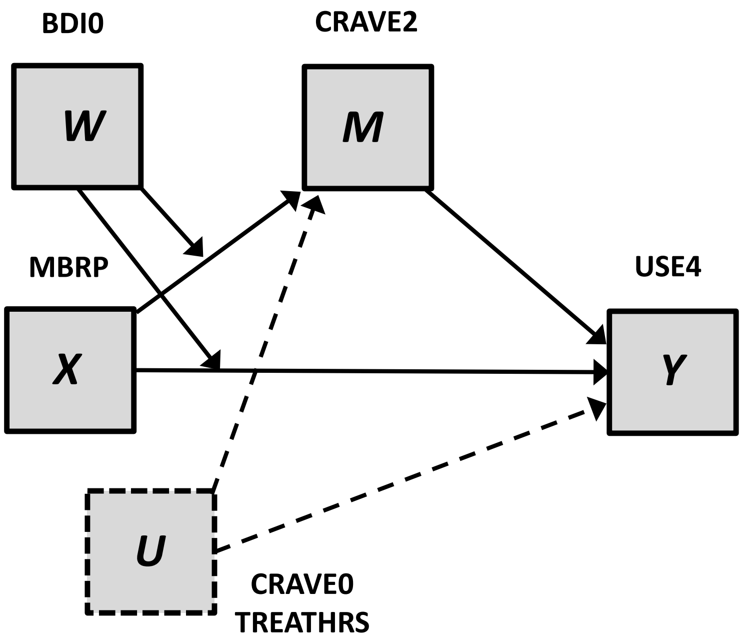
Conditional Process Modeling Example #2



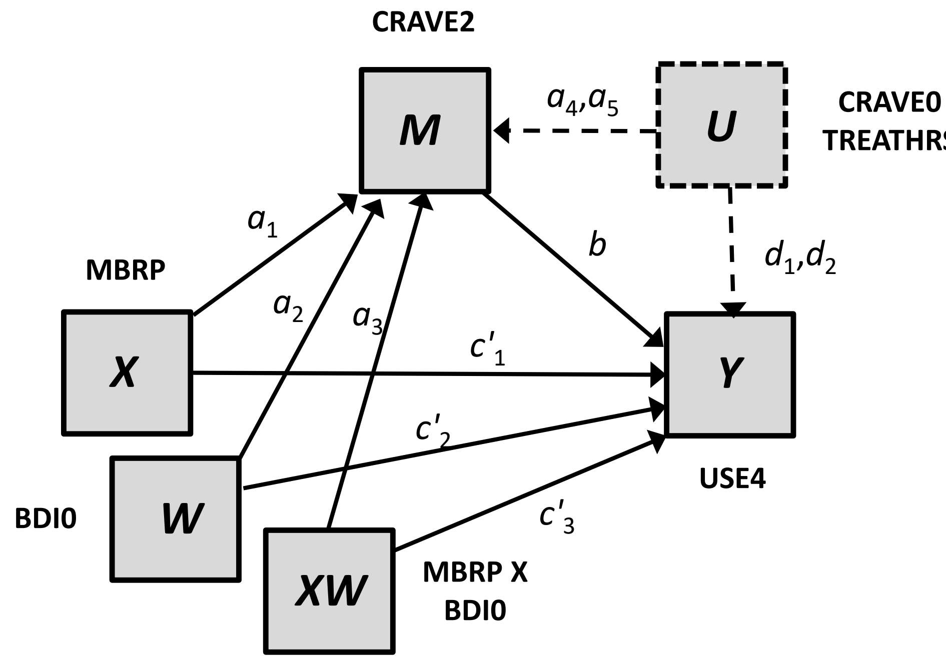
This is a model of **craving (*M*)** as the mechanism by which **mindfulness relapse prevention therapy (*X*)** affects **substance use (*Y*)** relative to therapy as usual. In this model, moderation of the mechanism is proposed as operating in the "first stage" of the mediation process via the moderation of the effect of MBRP therapy on craving and on the "direct effect" via moderation of the effect of MBRP therapy on substance use at 4 month follow up by **pre-therapy depression level (*W*),**.

Conceptual and Statistical Models

Conceptual model



Statistical model



Try writing out the equations for *M* and *Y*

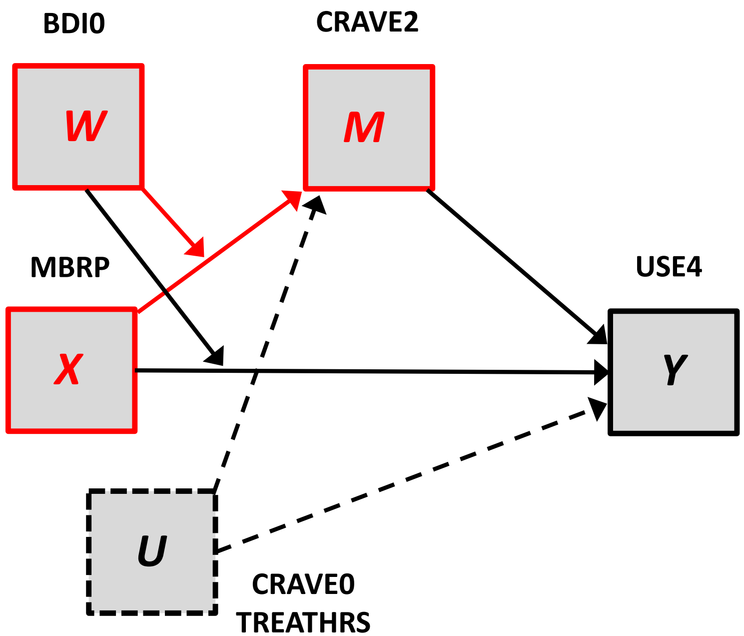
$$\widehat{M_i} =$$

$$\widehat{Y_i} =$$

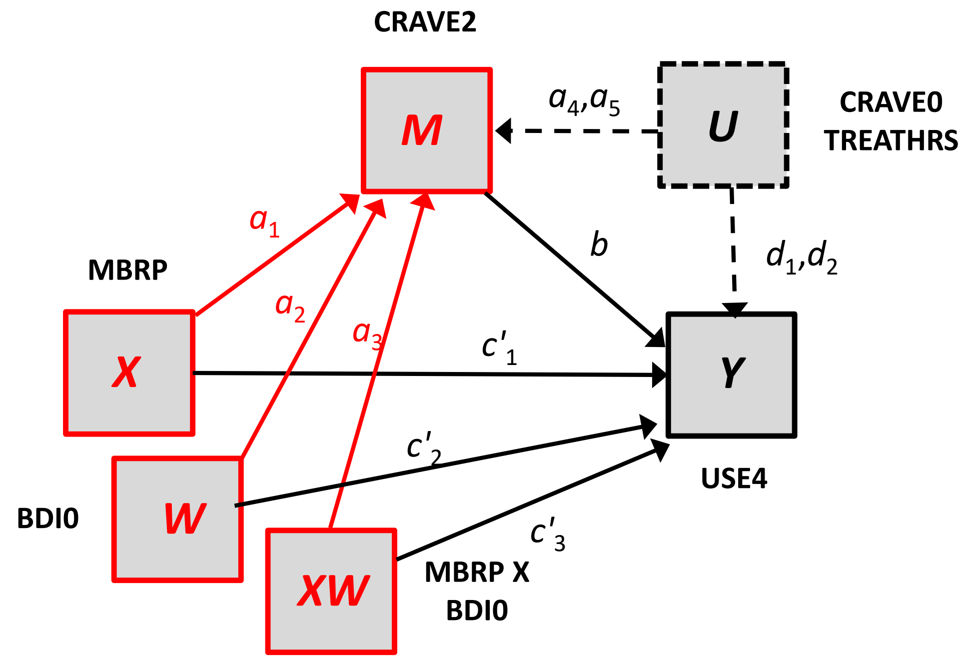
The number of equations needed is equal to the number of variables with arrows pointing at them in the conceptual or statistical diagram.

Conceptual and Statistical Models

Conceptual model



Statistical model



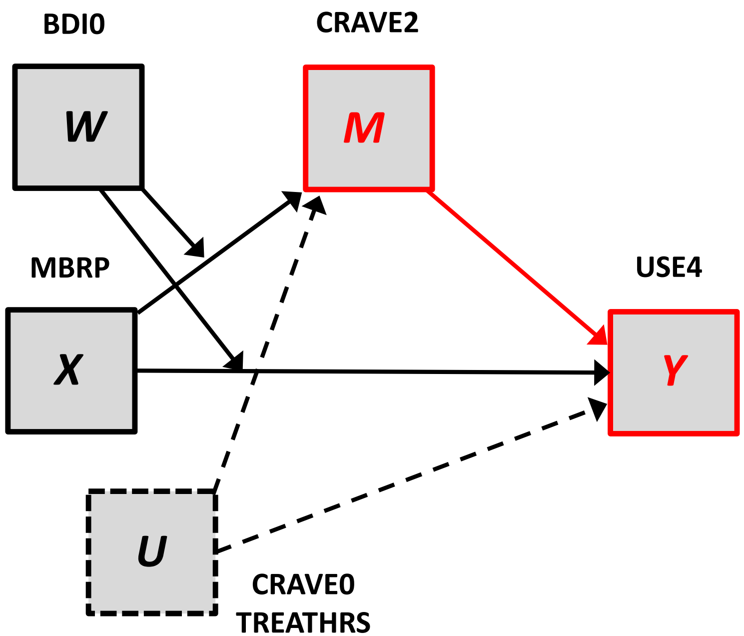
$$\widehat{M_i} = a_0 + \boxed{a_1 X_i + a_2 W_i + a_3 X_i W_i} + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y_i} = c'_0 + c'_1 X_i + c'_2 W_i + c'_3 X_i W_i + bM_i + d_1 U_{1i} + d_2 U_{2i}$$

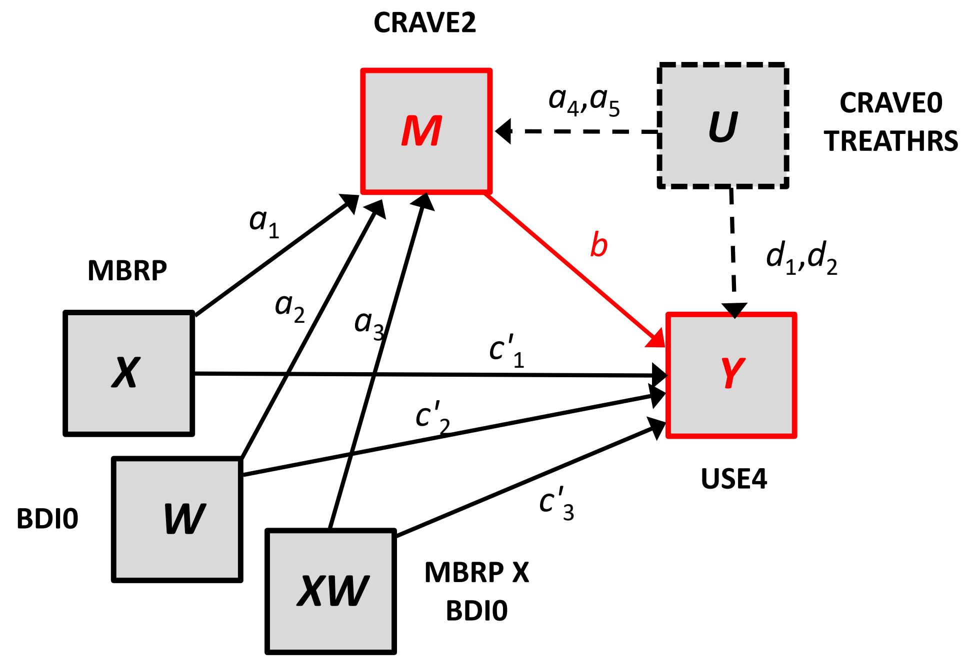
The moderation of the effect of mindfulness behavioral relapse prevention therapy relative to therapy as usual on craving by pre-therapy depression level.

Conceptual and Statistical Models

Conceptual model



Statistical model



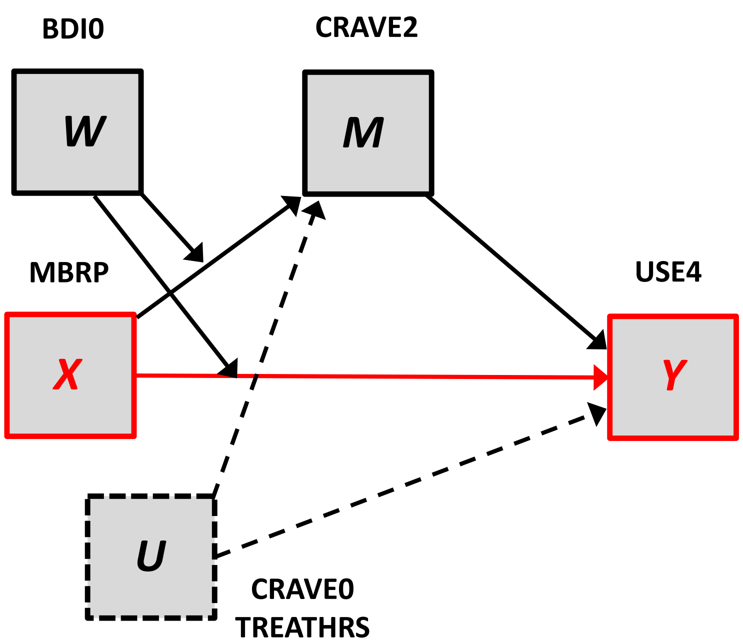
$$\widehat{M_i} = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y_i} = c_0' + c_1' X_i + c_2' W_i + c_3' X_i W_i + \boxed{bM_i} + d_1 U_{1i} + d_2 U_{2i}$$

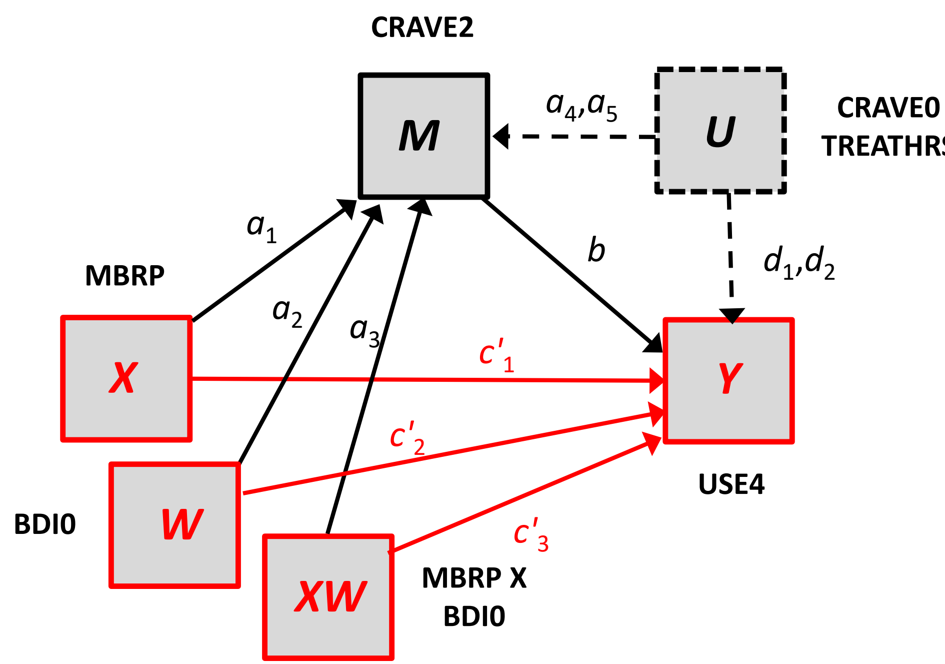
The effect of craving at two month follow-up on substance use after 4 months.

Conceptual and Statistical Models

Conceptual model



Statistical model



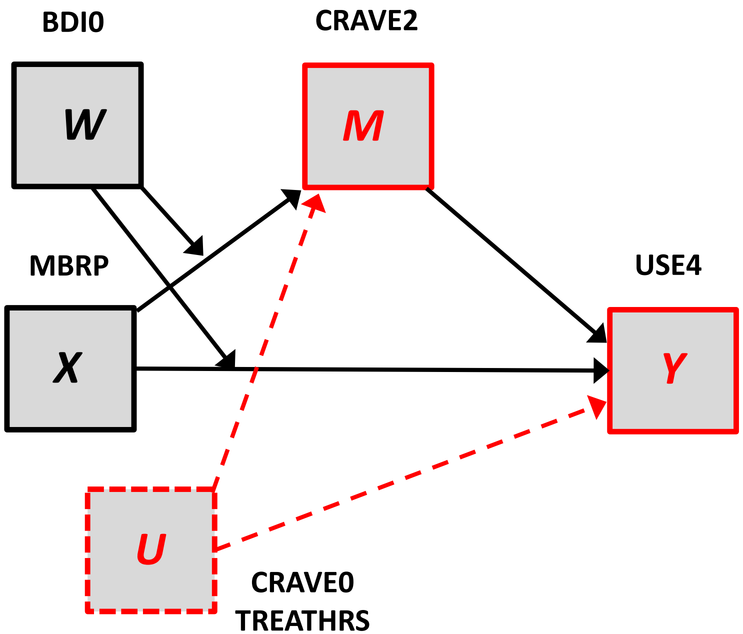
$$\widehat{M_i} = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y_i} = c'_0 + \boxed{c'_1 X_i + c'_2 W_i + c'_3 X_i W_i} + b M_i + d_1 U_{1i} + d_2 U_{2i}$$

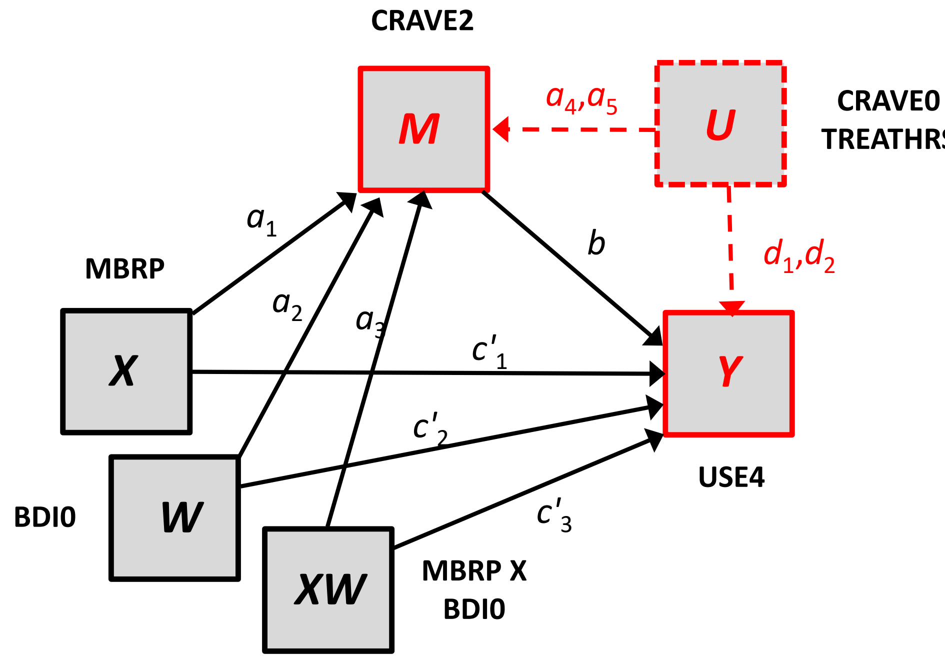
The moderation of the effect of mindfulness behavioral relapse prevention therapy relative to therapy as usual on substance use at 4 month follow up by pre-therapy depression level controlling for craving at time 2.

Conceptual and Statistical Models

Conceptual model



Statistical model



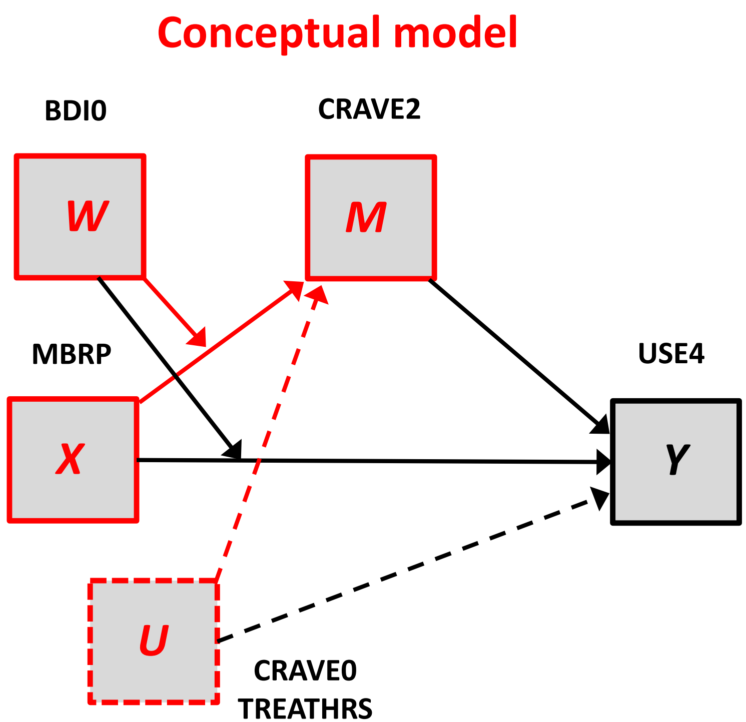
$$\widehat{M_i} = a_0 + a_1X_i + a_2W_i + a_3X_iW_i + \boxed{a_4U_{1i} + a_5U_{2i}}$$

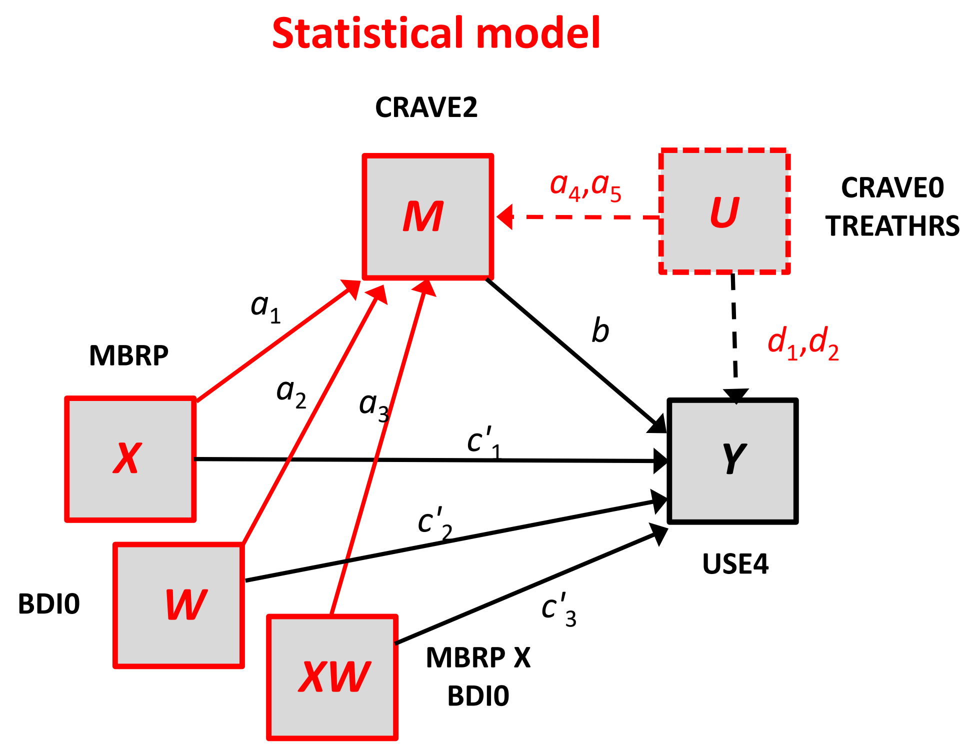
$$\widehat{Y_i} = c'_0 + c'_1X_i + c'_2W_i + c'_3X_iW_i + bM_i + \boxed{d_1U_{1i} + d_2U_{2i}}$$

Covariates to account for potential confounding by treatment hours and pre-therapy craving.

Estimating the moderation component of the model

The conceptual model proposes that the effect of mindfulness behavioral relapse prevention therapy depends on pre-therapy depression.





$$\widehat{M_i} = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

We most care about the moderation components of the model of *M*: a_1 and a_3

We did this already

```
compute mbrpdep = mbrp*bdi0.
regression/dep = crave2/method = enter mbrp bdi0 mbrpdep treathrs crave0.
```

```
data mbrp;set mbrp;mbrpdep=mbrp*bdi0;run;
proc reg data=mbrp;model crave2=mbrp bdi0 mbrpdep treathrs crave0;run;
```

```
summary(lm(crave2~mbrp*bdi0+treathrs+crave0, data = mbrp))
```

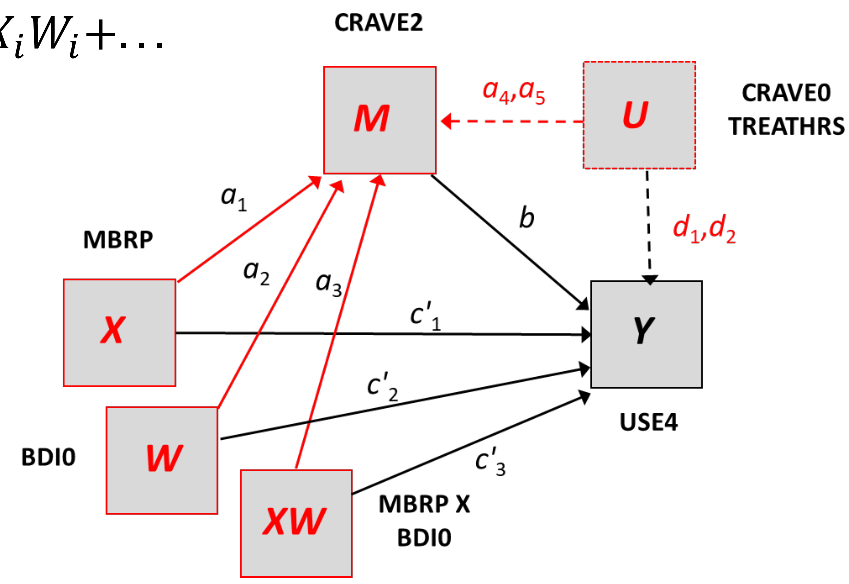
X = MBRP
W = BDI0
Y = CRAVE2

$$\widehat{M_i} = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.038	.470		2.209	.029
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.587	.524	.299	1.120	.264
	BDI0: Beck Depression Inventory baseline	1.122	.276	.366	4.063	.000
	mbrpdep	-.948	.423	-.598	-2.240	.026
	TREATHRS: Hours of therapy	-.018	.010	-.120	-1.719	.088
	CRAVE0: Baseline craving	.192	.073	.183	2.614	.010

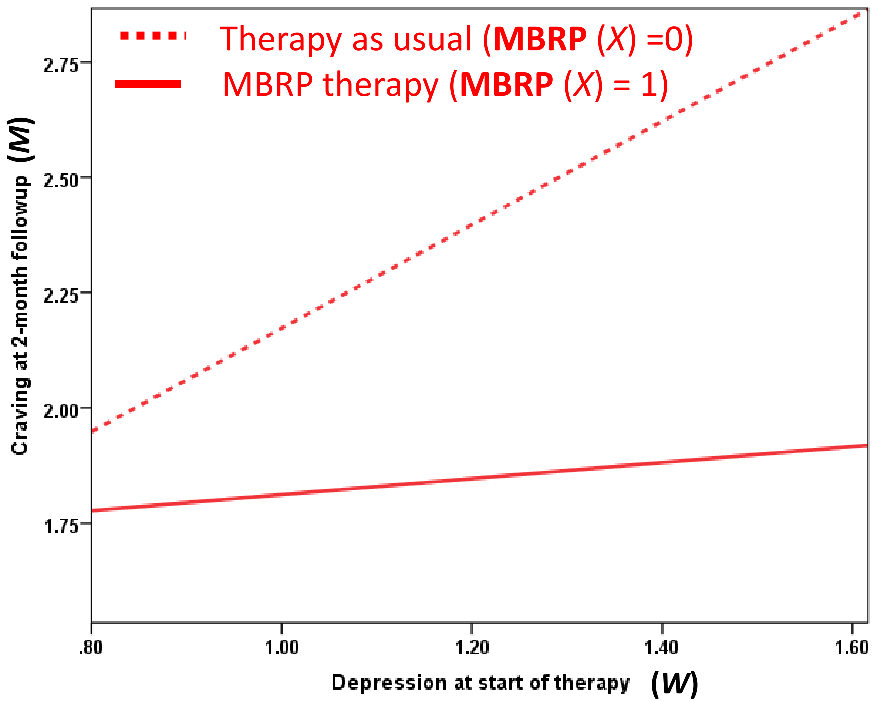
a. Dependent Variable: CRAVE2: Craving at two month follow-up



$a_1 = 0.587$, $a_3 = -0.948$

Pre-therapy depression moderates the effect of mindfulness behavioral relapse prevention therapy on craving. We can say that this moderation/interaction is statistically significant, but this doesn't matter for our purposes because neither the direct nor indirect effects in this model are determined entirely by a_3, and it is the direct and indirect effects we care about. We need a_1 and a_3 to estimate the indirect effects.

Recall the pattern from the earlier analysis



The conditional effect of MBRP therapy ($\theta_{X\rightarrow M}$) is defined by the function

$$\theta_{X\rightarrow M} = 0.587 - 0.948W$$

BDI0 (*W*)	$\theta_{X\rightarrow M}$
0.877	-0.245
1.196	-0.547
1.515	-0.850

Recall these from our Implementation of the pick-a-point approach.

$$\widehat{M}_i = 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

which can be written as

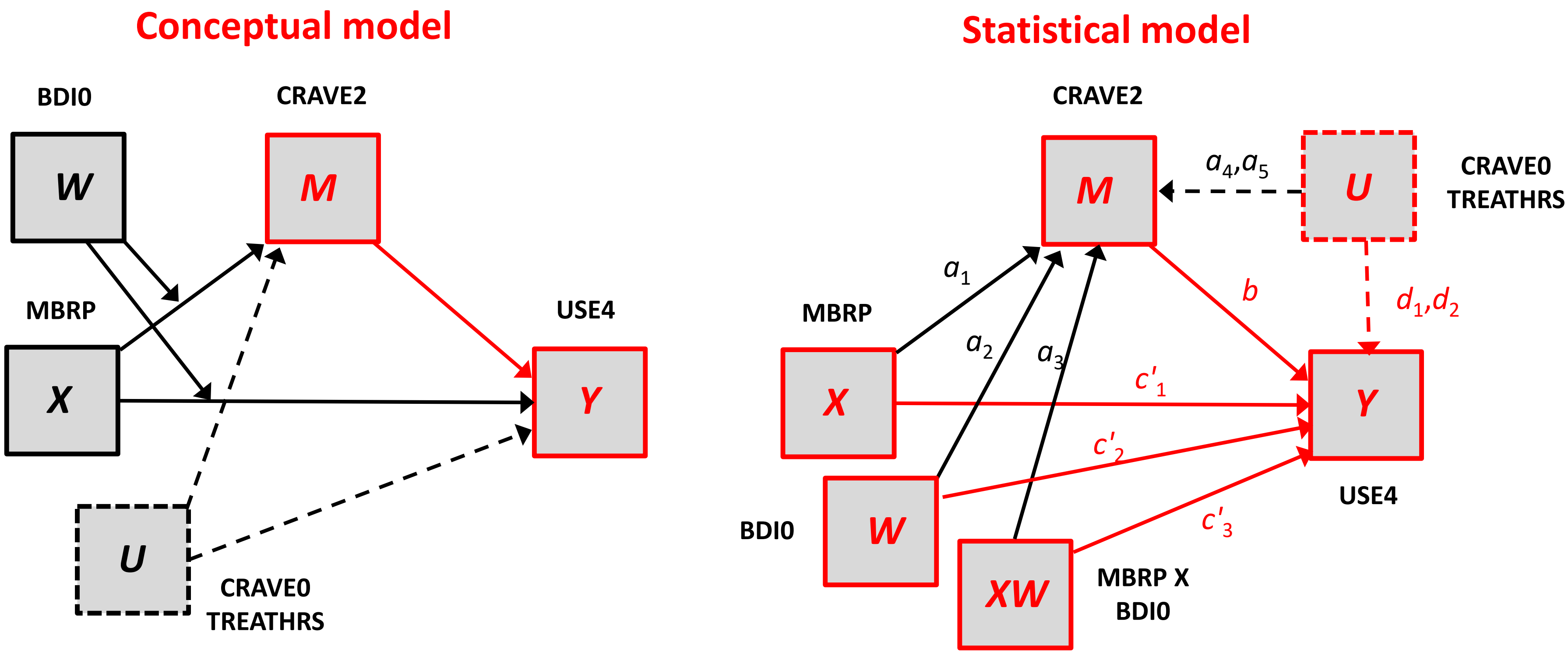
$$\widehat{M}_i = 1.038 + (0.587 - 0.948W_i)X_i + 1.122W_i + \ldots$$

or

$$\widehat{M}_i = 1.038 + \theta_{X\rightarrow M}X_i + 1.122W_i + \ldots.$$

where $\theta_{X\rightarrow M} = 0.587 - 0.948W = a_1 + a_3W$

Estimating the b and c' paths



$$\widehat{M_i} = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y_i} = c_0' + \boxed{c_1' X_i + c_2' W_i + c_3' X_i W_i + b M_i} + d_1 U_{1i} + d_2 U_{2i}$$

Estimating the b and c' paths

```
regression/dep=use4/method=enter crave2 mbrp mbrpdep bdi0 crave0 treathrs.
```

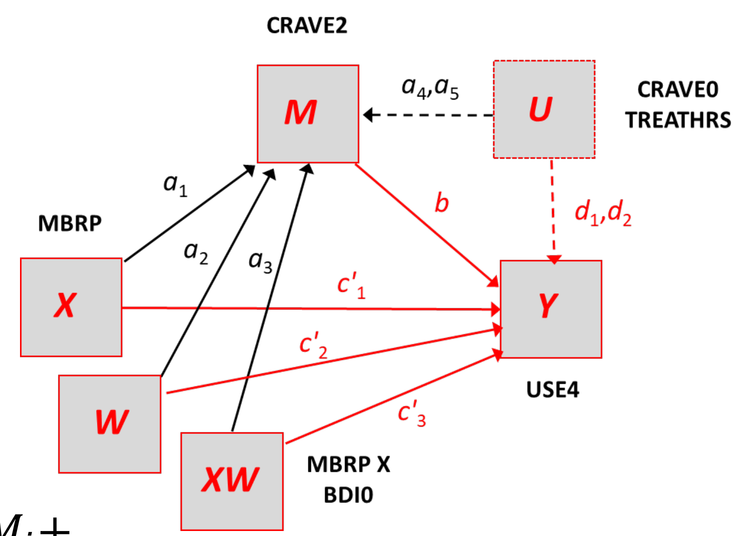
```
proc reg data=mbrp;model use4 = crave2 mbrp mbrpdep bdi0 crave0 treathrs;run;
```

```
summary(lm(use4~crave2+mbrp*bdi0+crave0+treathrs, data = mbrp))
```

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.374	.251		5.479	<.001
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.256	.276	.192	.926	.356
	BDI0: Beck Depression Inventory baseline	-.298	.152	-.143	-1.953	.053
	mbrpdep	-.135	.226	-.125	-.597	.552
	CRAVE2: Craving at two month follow-up	.509	.041	.751	12.318	<.001
	CRAVE0: Baseline craving	-.068	.039	-.095	-1.719	.088
	TREATHRS: Hours of therapy	-.020	.005	-.203	-3.712	<.001

a. Dependent Variable: USE4: Substance use at four month follow-up

Statistical model

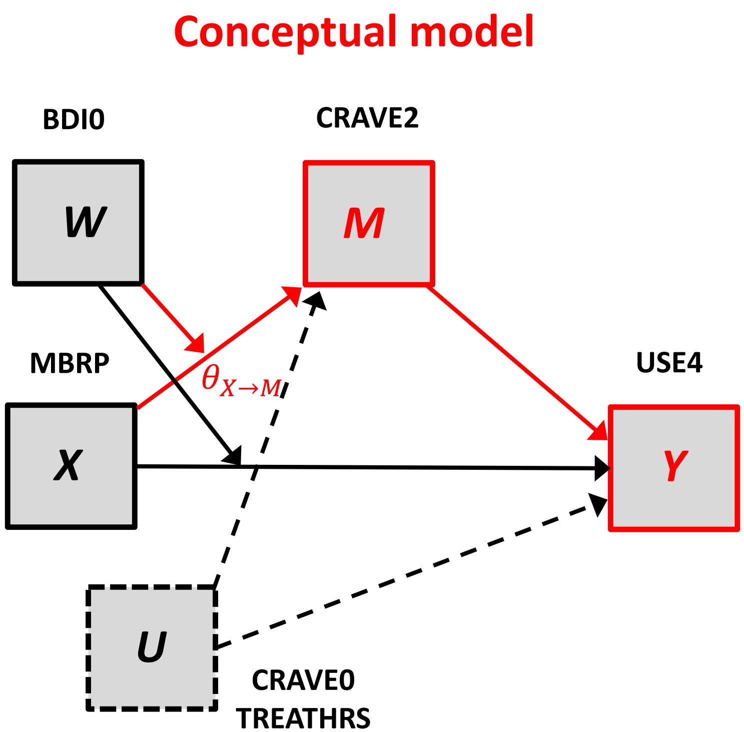


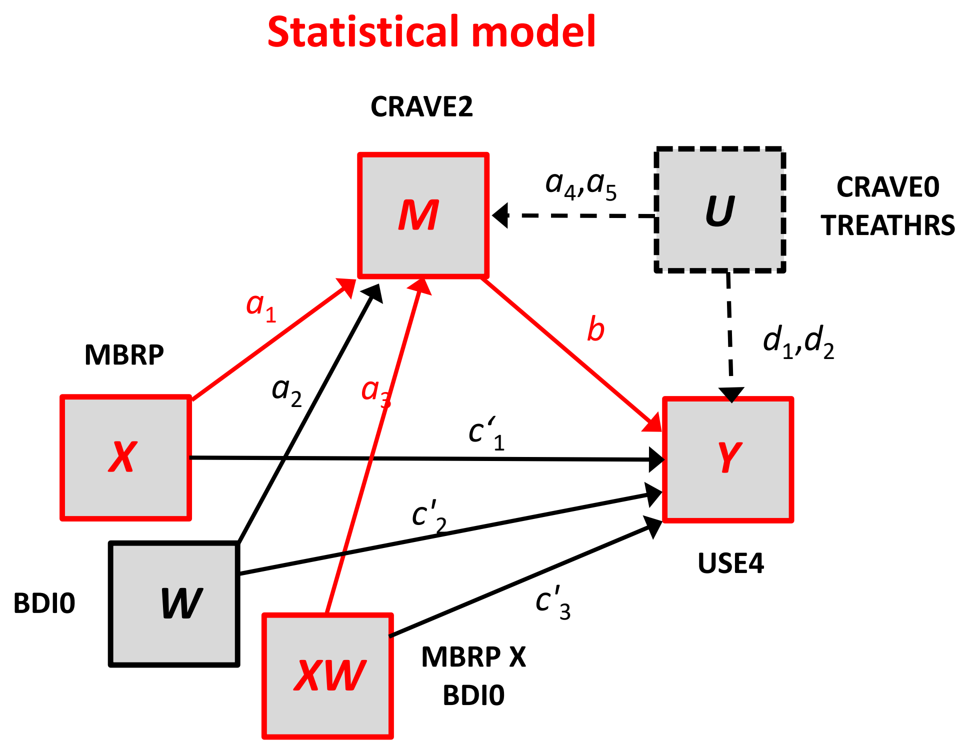
$$\widehat{Y}_i = 1.374 + 0.256X_i - .298W_i - .135X_iW_i + 0.509M_i + \ldots$$

$$\boxed{b \;=\; 0.509,\, c'_1 \;=\; 0.256,\, c'_3 = -.135}$$

Emphasis in not on statistical significance of the b-path, as the indirect effect of X is not defined entirely in terms of b. $c'_1 + c'_3W$ is the conditional direct effect (discussed in a bit).

The conditional indirect effect of *X*



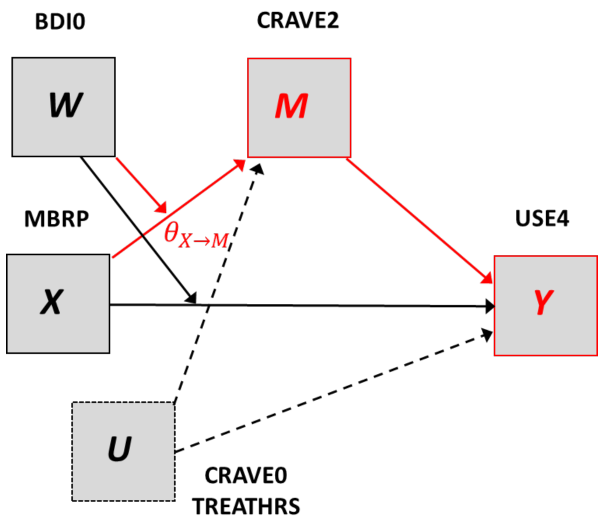


The conditional indirect effect of X on Y through M is the product of the conditional effect of X on M ($\theta_{X\to M} = a_1 + a_3 W$) and effect of M on Y (b):

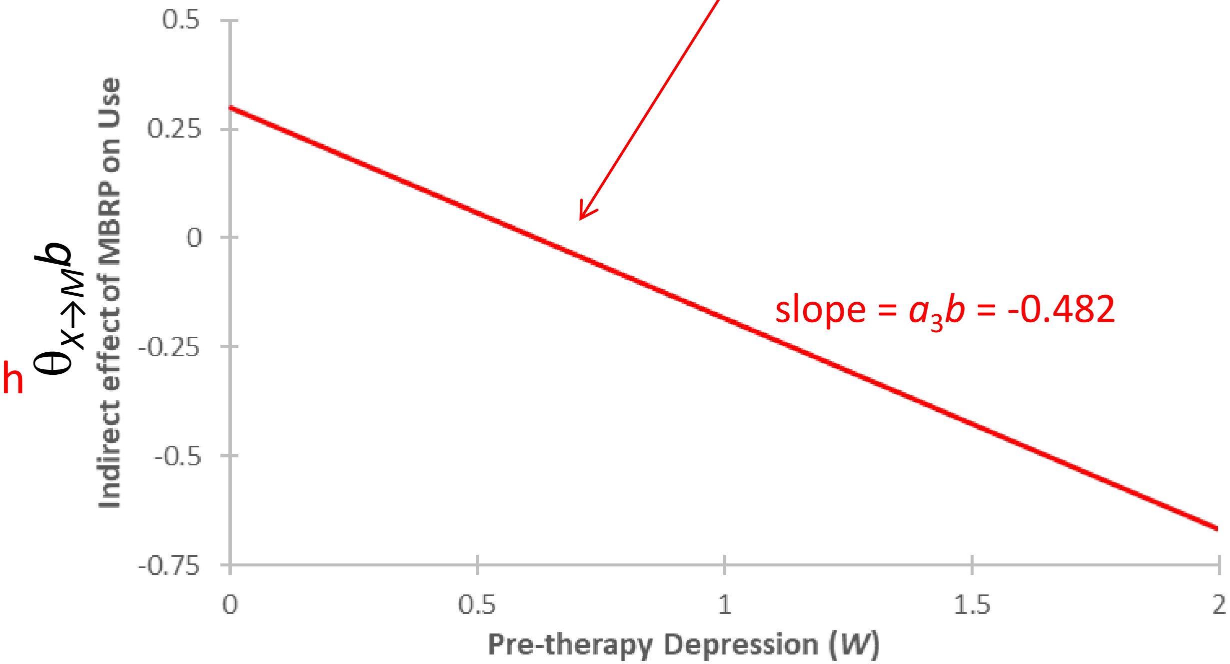
$$\theta_{X\to M}\, b = (a_1 + a_3 W)b = (0.587 - 0.948W)(0.509)$$

The indirect effect of MBRP therapy relative to therapy as usual on later substance use through craving is a function of pre-therapy depression.

A visual representation of the indirect effect



$$\theta_{X \to M}\, b = (a_1 + a_3 W) b = (0.587 - 0.948W)(0.509)$$
$$= a_1 b + a_3 b W = 0.299 - 0.482W$$

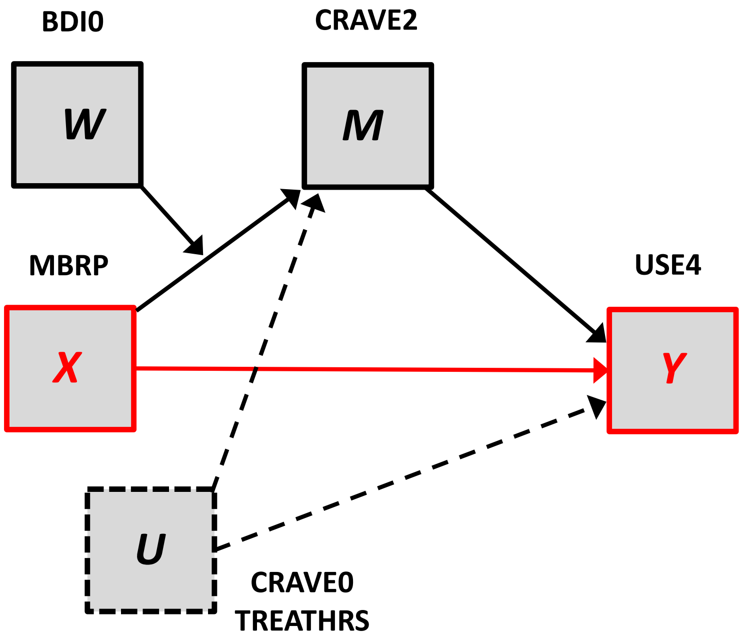


The indirect effect declines with increasing pre-therapy depression. The "**index of moderated mediation**" is $a_3 b$ = -0.482. It quantifies the relationship between the moderator and the indirect effect in this model.

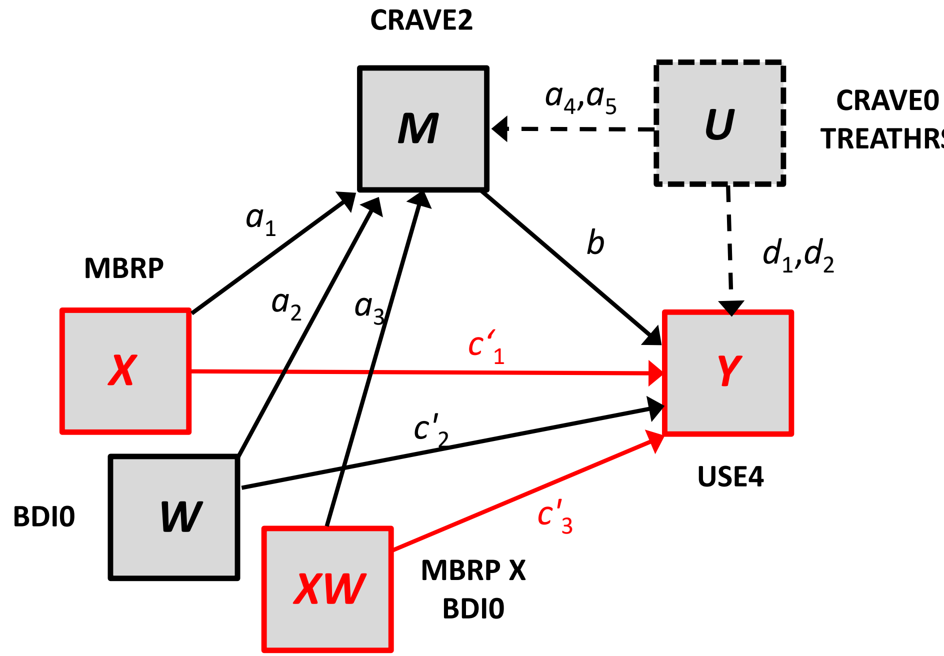
As will be seen, a hypothesis test that the slope of this function is equal to 0 is a formal test of moderated mediation….moderation of the indirect effect.

The conditional direct effect of *X*

Conceptual model



Statistical model



$$\widehat{M}_i = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y}_i = c'_0 + \boxed{c'_1 X_i} + c'_2 W_i + \boxed{c'_3 X_i W_i} + b M_i + d_1 U_{1i} + d_2 U_{2i}$$

In this model, the direct effect is moderated. It is a function of another variable in the model (W). This is a modeling or theoretical decision, not a requirement.

The direct effect of *X* (estimated earlier)

```
regression/dep=use4/method=enter crave2 mbrp mbrpdep bdi0 crave0 treathrs.
```

```
proc reg data=mbrp;model use4 = crave2 mbrp mbrpdep bdi0 crave0 treathrs;run;
```

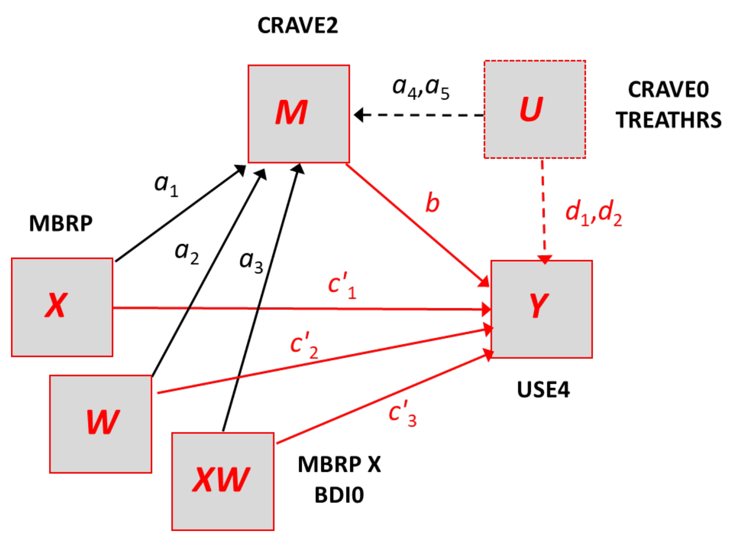
```
summary(lm(use4~crave2+mbrp*bdi0+crave0+treathrs, data = mbrp))
```

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.374	.251		5.479	<.001
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.256	.276	.192	.926	.356
	BDI0: Beck Depression Inventory baseline	-.298	.152	-.143	-1.953	.053
	mbrpdep	-.135	.226	-.125	-.597	.552
	CRAVE2: Craving at two month follow-up	.509	.041	.751	12.318	<.001
	CRAVE0: Baseline craving	-.068	.039	-.095	-1.719	.088
	TREATHRS: Hours of therapy	-.020	.005	-.203	-3.712	<.001

a. Dependent Variable: USE4: Substance use at four month follow-up

$$c'_1 = 0.256, p = .356$$
$$c'_3 = -.135, p = .552$$

Statistical model



The direct effect when for those with a depression score of zero is not statistically significant (c'_1), nor is the direct effect significantly moderated (c'_3). However, we should not take this to mean that all conditional direct effects are not significant, especially because zero is on the outer edge of our data.

What to do when there is not significant moderation?

Two options for when we find non-significant moderation of the **direct effect**:

1) Continue with model as estimated
2) Drop moderated direct effect

What are some pros and cons of these approaches?

1) Continue on with the model as estimated, and examine the conditional direct effects in order to make an overall statement about the direct effect.

Conditional direct effect(s) of X on Y:

bdi0	Effect	se	t	p	LLCI	ULCI
.9020	.1344	.0978	1.3734	.1715	-.0588	.3276
1.1900	.0956	.0756	1.2637	.2082	-.0538	.2449
1.5180	.0513	.1079	.4758	.6349	-.1617	.2644

PROS: Does not require estimating multiple models and potentially impacting the estimate of the indirect effect.
CONS: Can find seemingly contradictory results (change in sign or significance)

What to do when there is not significant moderation?

What are some pros and cons of these approaches?

2) Re-estimate the model by dropping the moderated direct effect.

```
regression/dep=use4/method=enter crave2 mbrp crave0 treathrs.
```

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.130	.215		5.254	.000
	CRAVE2: Craving at two month follow-up	.481	.040	.710	11.955	.000
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.093	.077	.070	1.198	.233
	CRAVE0: Baseline craving	-.088	.040	-.124	-2.225	.027
	TREATHRS: Hours of therapy	-.020	.006	-.200	-3.572	.000

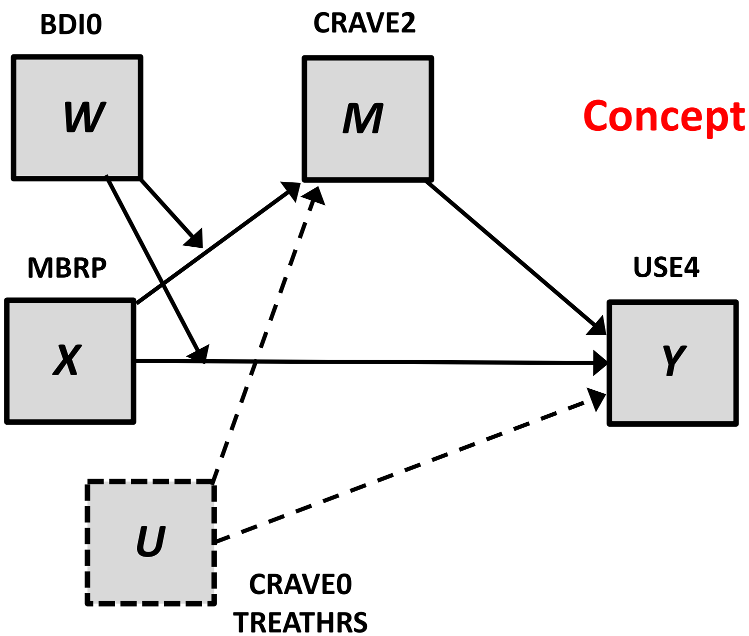
a. Dependent Variable: USE4: Substance use at four month follow-up

PROS: Results in a more parsimonious model, and more concrete conclusions about the direct effect.
CONS: Can find seemingly contradictory results (change in sign or significance). If we drop the moderation we no longer include bdi0 in the model for Y, but should we keep it in as a covariate? Each of these choices can impact the indirect effect.

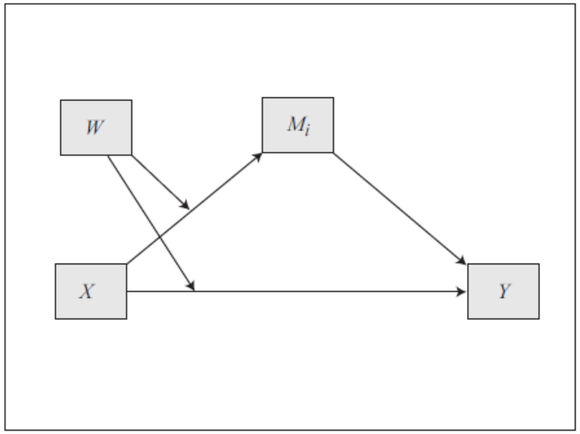
Either way, report transparently the process you used

Estimation of the model in PROCESS

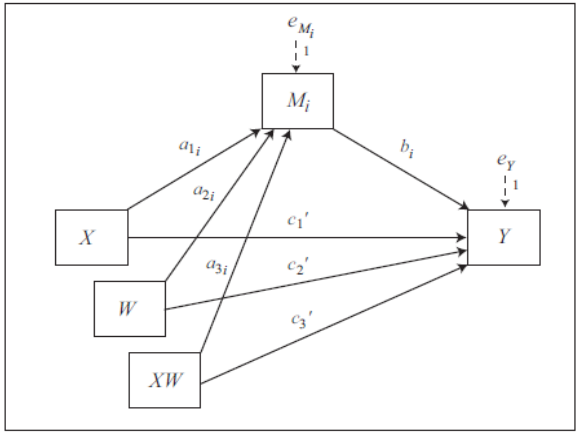
PROCESS takes most of the computational burden off our shoulders.



Conceptual model



Statistical Diagram



This is PROCESS model 8

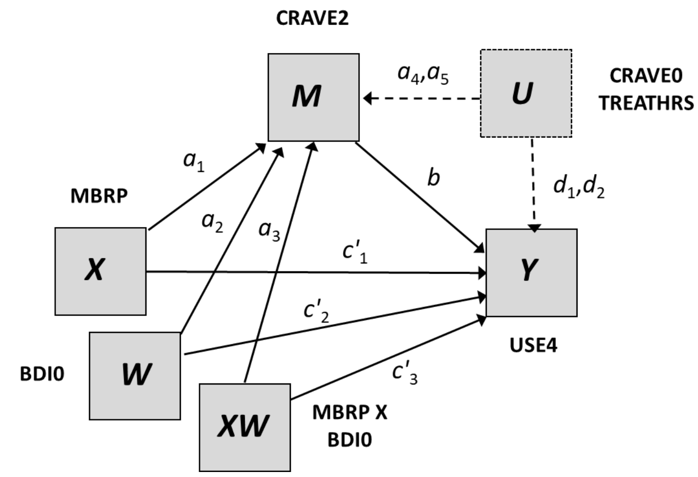
```
process cov = crave0 treathrs/x=mbrp/m=crave2/y=use4/w=bdi0/boot=10000/model=8.
```

```
%process (data=mbrp,cov=crave0 treathrs,x=mbrp,m=crave2,y=use4,w=bdi0, boot=10000,model=8);
```

```
process(data=mbrp,cov=c("crave0","treathrs"),x="mbrp",m="crave2",y="use4",w="bdi0",
       boot=10000,model=8)
```

PROCESS output

```
***************** PROCESS Procedure for SPSS Version 3.4 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 8
    Y  : use4
    X  : mbrp
    M  : crave2
    W  : bdi0

Covariates:
 crave0    treathrs

Sample
Size:  168

**************************************************************************
OUTCOME VARIABLE:
 crave2

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5140      .2642      .7277    11.6319     5.0000   162.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.0385      .4701     2.2090      .0286      .1102     1.9668
mbrp          .5872      .5241     1.1204      .2642     -.4478     1.6222
bdi0         1.1221      .2762     4.0625      .0001      .5767     1.6675
Int_1        -.9485      .4235    -2.2398      .0265    -1.7847     -.1122
crave0        .1920      .0735     2.6138      .0098      .0470      .3371
treathrs     -.0177      .0103    -1.7190      .0875     -.0380      .0026
```



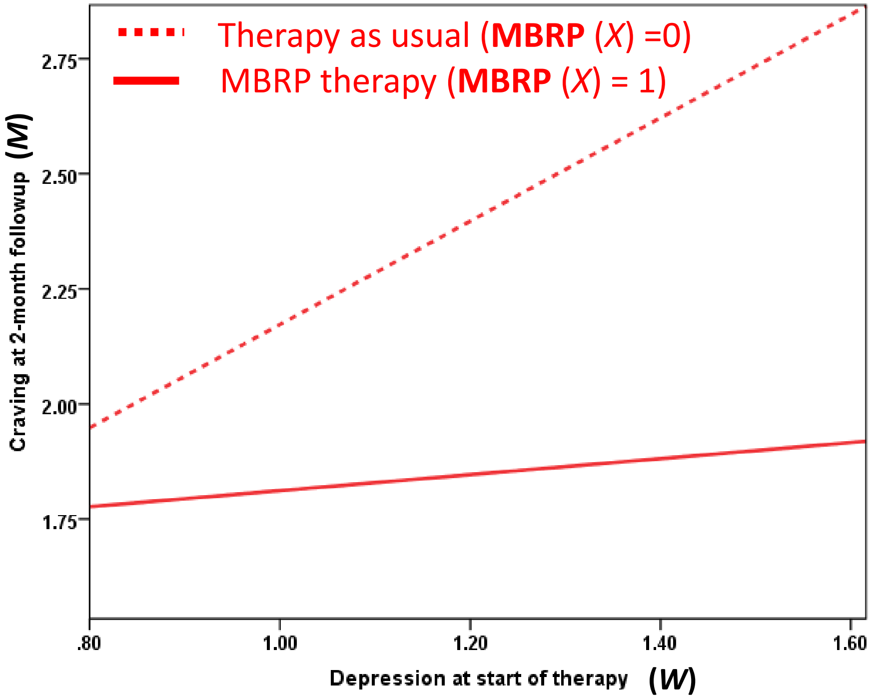
$$\widehat{M_i} = 1.039 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

$a_1 = 0.587$

$a_2 = 1.122$

$a_3 = -0.948$

PROCESS output



$$\Theta_{X \to M} = 0.587 + 1.122W$$

```
Test(s) of highest order unconditional interaction(s):
       R2-chng         F        df1        df2          p
X*W      .0228    5.0166     1.0000   162.0000      .0265
----------
    Focal predict: mbrp      (X)
          Mod var: bdi0      (W)
```

$$\widehat{M_i} = 1.039 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \ldots$$

```
Conditional effects of the focal predictor at values of the moderator(s):

       bdi0     Effect         se          t          p       LLCI       ULCI
      .9020     -.2683      .1850    -1.4500      .1490     -.6336      .0971
     1.1900     -.5414      .1375    -3.9384      .0001     -.8129     -.2699
     1.5180     -.8525      .1941    -4.3923      .0000    -1.2358     -.4692
```

$$\Theta_{X \to M} = 0.587 + 1.122W$$

PROCESS output

```
**************************************************************************
OUTCOME VARIABLE:
 use4

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7484      .5601      .2009    34.1716     6.0000   161.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.3736      .2507     5.4786      .0000      .8785     1.8687
mbrp          .2560      .2765      .9259      .3559     -.2900      .8020
crave2        .5086      .0413    12.3179      .0000      .4270      .5901
bdi0         -.2976      .1524    -1.9533      .0525     -.5985      .0033
Int_1        -.1348      .2259     -.5967      .5516     -.5810      .3114
crave0       -.0678      .0394    -1.7192      .0875     -.1456      .0101
treathrs     -.0202      .0055    -3.7117      .0003     -.0310     -.0095

Product terms key:
 Int_1    :        mbrp      x        bdi0

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0010      .3560     1.0000   161.0000      .5516
```

$c'_1 = 0.2560$

$b = 0.509$

$c'_3 = -0.1348$

$$\widehat{Y}_i = 1.374 + 0.256X_i - 0.298W_i - 0.135X_iW_i + 0.509M_i \ldots$$

PROCESS output

```
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Conditional direct effect(s) of X on Y:
      bdi0      Effect        se         t          p       LLCI       ULCI
     .9020       .1344     .0978    1.3734      .1715     -.0588      .3276
    1.1900       .0956     .0756    1.2637      .2082     -.0538      .2449
    1.5180       .0513     .1079     .4758      .6349     -.1617      .2644

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 mbrp         ->     crave2       ->     use4

      bdi0      Effect    BootSE  BootLLCI   BootULCI
     .9020      -.1364     .0799    -.2977      .0154
    1.1900      -.2753     .0872    -.4604     -.1194
    1.5180      -.4335     .1374    -.7232     -.1926
```

W

W

$\theta_{X\rightarrow Y} = 0.256 - 0.135W$

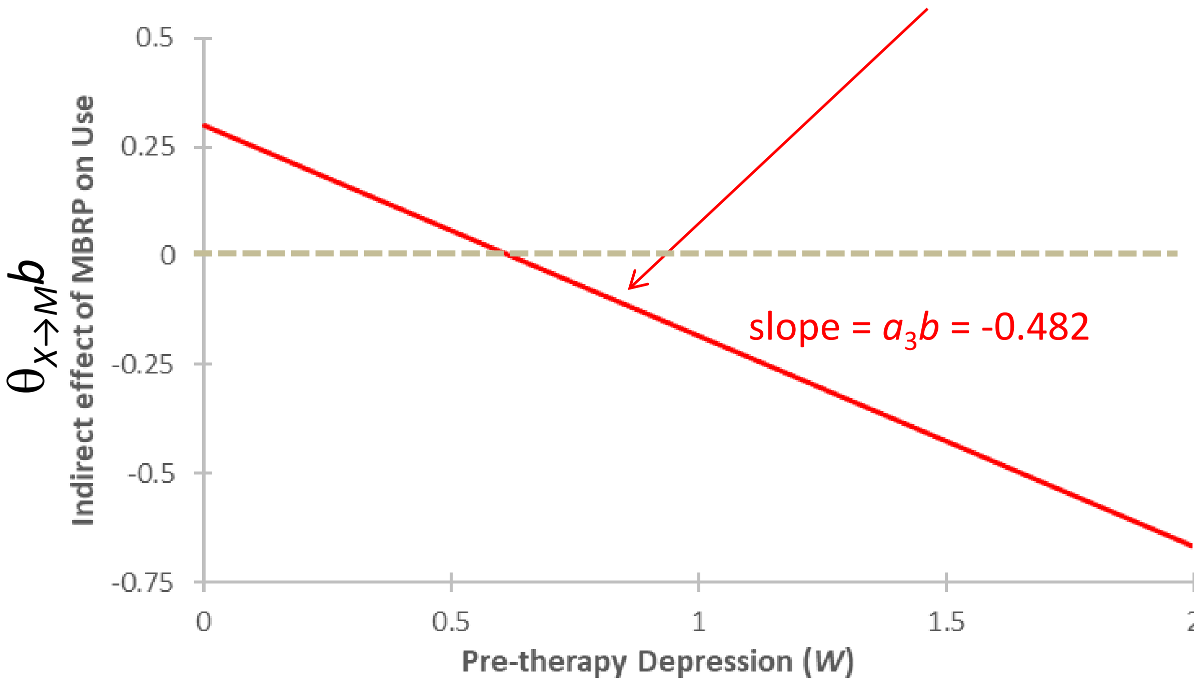
$$\theta_{X\rightarrow M}\, b = (a_1 + a_3W)b = (0.587 - 0.948W)(0.509)$$
$$= a_1b + a_3bW = 0.299 - 0.482W$$

PROCESS sees that the moderator is continuous so, without instruction otherwise, prints the conditional indirect effect at 16th, 50th, and 84th percentile of the moderator.

A statistical test of moderated mediation

in the first stage moderated mediation model

$$\theta_{X\rightarrow M}\, b = (a_1 + a_3W)b = (0.587 - 0.948W)(0.509)$$
$$= a_1b + a_3bW = 0.299 - 0.482W$$



The indirect effect is a function of W (pre-therapy depression) in our model. This function is a line.

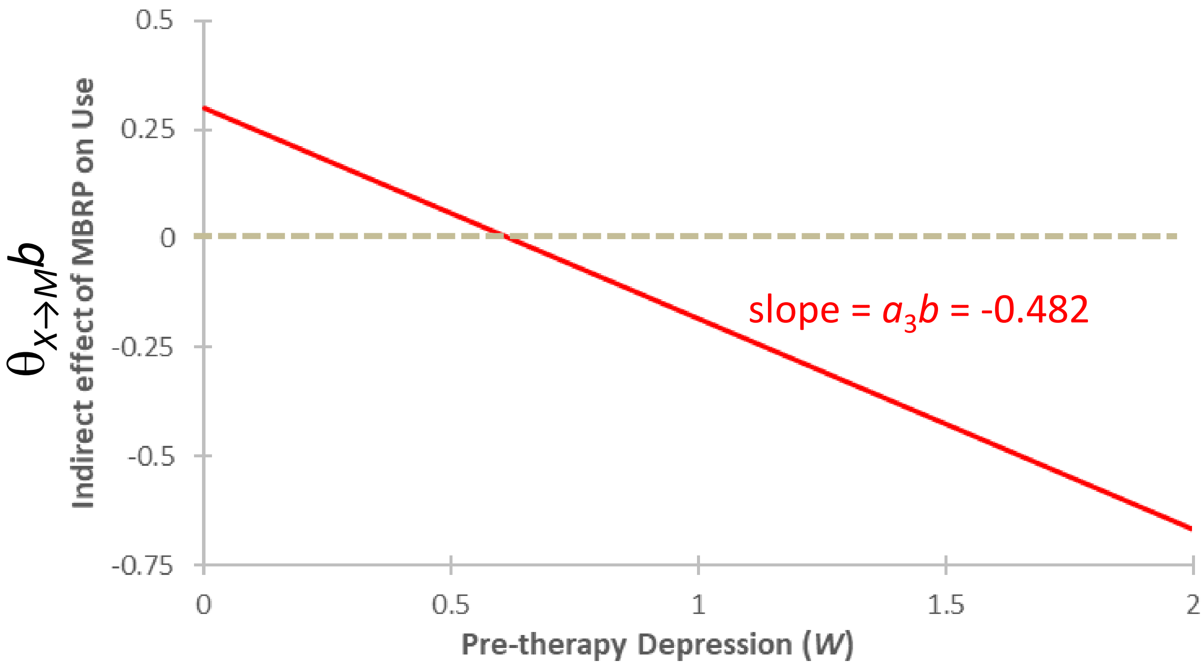
$$\theta_{X\rightarrow M}\, b = (a_1 + a_3W)b$$
$$= a_1b + a_3bW$$
$$= 0.299 - 0.482W$$

An inference about the slope of this line—the "index of moderated mediation"—is an inference about whether the indirect effect is moderated: Is this slope significantly different from zero? If so, that supports a claim of "moderated mediation."

As a_3b is a product of regression coefficients, an inferential test should respect the nonnormality of the sampling distribution of the product. A bootstrap confidence interval is a good choice.

This test is provided automatically by PROCESS

$$\theta_{X \to M} b = (a_1 + a_3 W)b = (0.587 - 0.948W)(0.509)$$
$$= a_1 b + a_3 bW = 0.299 - 0.482W$$



The indirect effect is a function of W (pre-therapy depression) in our model. This function is a line.

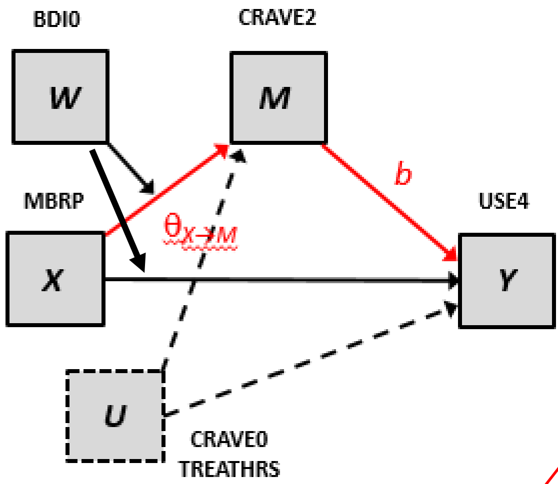
$$\theta_{X \to M} b = (a_1 + a_3 W)b$$
$$= a_1 b + a_3 bW$$
$$= 0.299 - 0.482W$$

(W) $a_3 b$ = -0.486, 95% bootstrap CI = -0.967 to -0.104

```
Index of moderated mediation:
          Index     BootSE    BootLLCI   BootULCI
bdi0      -.4823    .2213     -.9665     -.1041
---
```

This slope is statistically different from zero. The indirect effect depends on pre-therapy depression….the mediation is moderated.

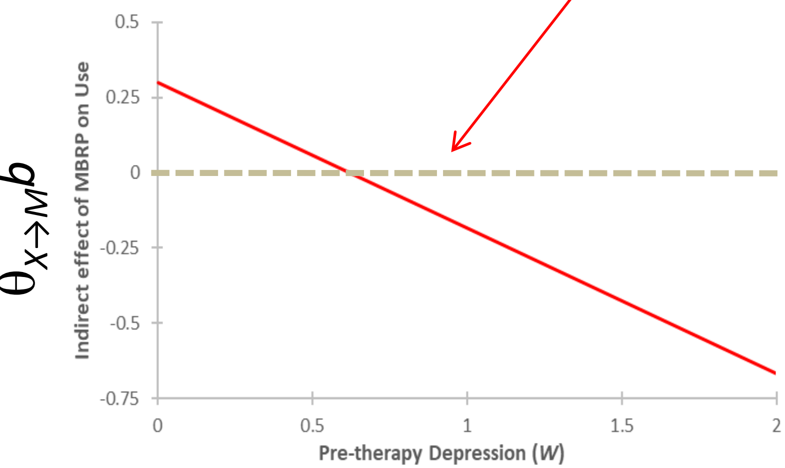
Probing the moderation of mediation



$\theta_{X\rightarrow M}\, b = (a_1 + a_3W)b = (0.587 - 0.948W)(0.481)$

The indirect effect decreases with increased pre-therapy depression.

With evidence of moderation of the indirect effect, we can now probe this moderation of mediation through an analogue of the pick-a-point approach used in moderation analysis.



	Pre-therapy depression (W)	$\theta_{X\rightarrow M}$	b	$\theta_{X\rightarrow M}\, b$
16th %	.9020	-.2683	0.509	-0.136
50th %	1.1900	-.5414	0.509	-0.275
84th %	1.5180	-.8525	0.509	-0.433

Conditional indirect effects

We need an inferential test for these conditional indirect effects. Bootstrap confidence intervals are perfect for the job. PROCESS does this for us automatically.

PROCESS output

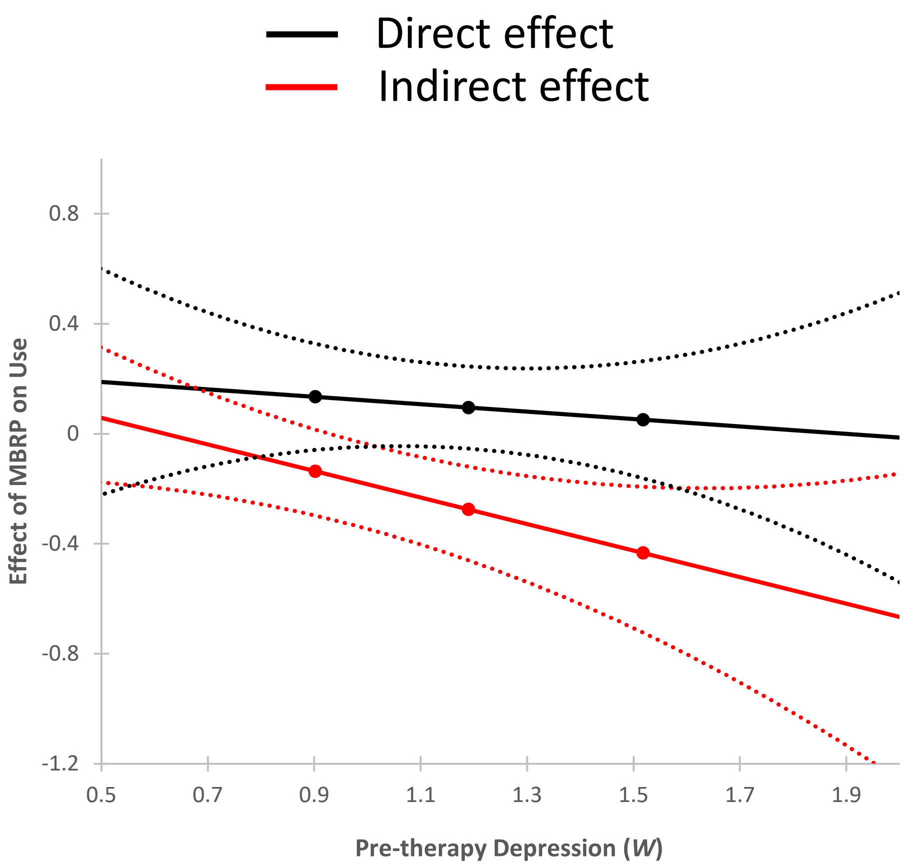
```
Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 mbrp        ->    crave2      ->    use4
```

bdi0	Effect	BootSE	BootLLCI	BootULCI
.9020	-.1364	.0799	-.2977	.0154
1.1900	-.2753	.0872	-.4604	-.1194
1.5180	-.4335	.1374	-.7232	-.1926

Conditional indirect effects with 95% bootstrap CIs based on 10,000 bootstrap samples.

The indirect effect of MBRP therapy relative to therapy as usual on substance use through craving is negative among the relatively moderate (point estimate: -0.275, 95% CI from -0.460 to -0.119) and relatively highly depressed (point estimate: -0.434, 95% CI from -0.723 to -0.193) but not different from zero among the relatively less depressed (point estimate: -0.136, 95% CI from -0.298 to 0.015).

Putting it all together



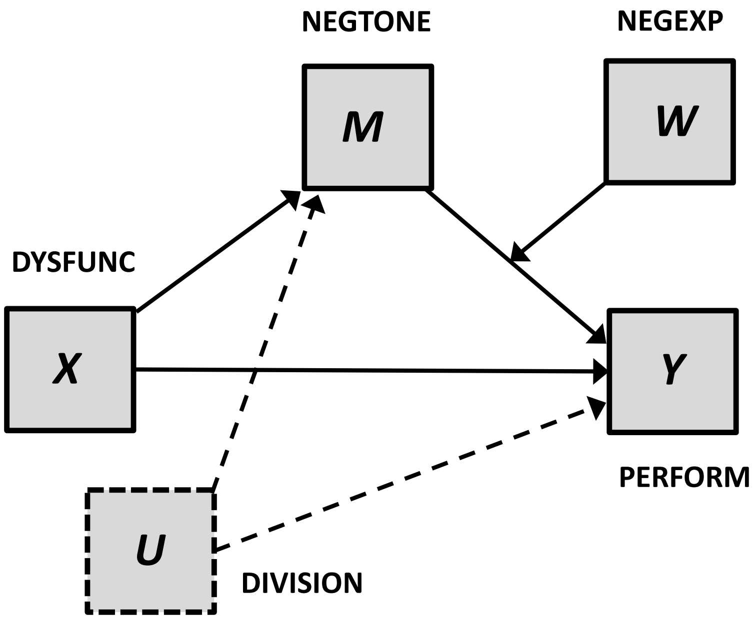
MBRP seems to reduce substance use through a reduction in craving which in turn lowers use, but more so among those who are more depressed at the start of therapy. Among those relatively lower in depression, we cannot say definitively that this mechanism is in operation. Independent of this mechanism, there is no evidence of an effect of MBRP therapy on later substance use.

Pre-therapy depression

Relatively least depressed”	Relatively average In depression	Relatively most depressed

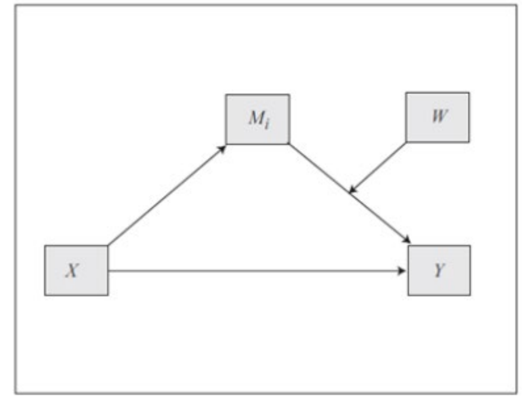
Point estimates with 95% confidence intervals (OLS confidence intervals for direct effects, bootstrap confidence intervals for indirect effects).

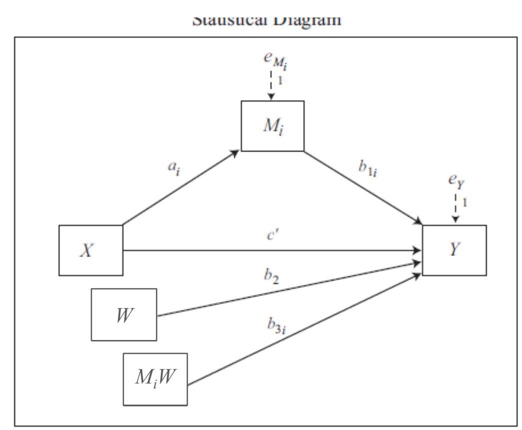
PROCESS versus SEM



This is PROCESS model 14

Model 14






```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000
         /model=14/plot = 1.
```

```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,
         boot=10000,model=14, plot = 1);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform",
        w="negexp", boot=1000, model=14, plot=1)
```

In Mplus

```
DATA:
  file is 'c:\mplus\teams.csv';
VARIABLE:
  names are dysfunc negtone negexp perform division d1 d2 d3;
  usevariables are dysfunc negexp negtone perform d1 d2 d3 toneexp;
DEFINE:
  toneexp = negtone*negexp;
ANALYSIS:
  !bootstrap=10000;
MODEL:
  perform ON d1 d2 d3
             dysfunc (cp)
             negtone (b1)
             negexp (b2)
             toneexp (b3);
  negtone ON d1 d2 d3
             dysfunc (a1);
  d1;
  d2;
  d3;
  negexp;
  dysfunc;
  toneexp;
  negtone with negexp;
  negtone with toneexp;
MODEL CONSTRAINT:
  new (a1thetaL a1thetaM a1thetaH a1b3);
  a1thetaL=a1*(b1+b3*(-.5308));
  a1thetaM=a1*(b1+b3*(-0.0600));
  a1thetaH=a1*(b1+b3*(0.6000));
  a1b3=a1*b3;
OUTPUT:
  !cinterval(bootstrap);
```

COMPARE TO OUTPUT THAT PROCESS GENERATES

	Estimate	S.E.	Est./S.E.	P-Value
PERFORM ON				
D1	0.182	0.147	1.231	0.218
D2	0.084	0.252	0.333	0.739
D3	0.282	0.170	1.659	0.097
DYSFUNC	0.373	0.195	1.908	0.056
NEGTONE	-0.489	0.131	-3.728	0.000
NEGEXP	-0.022	0.102	-0.217	0.829
TONEEXP	-0.450	0.243	-1.851	0.064
NEGTONE ON				
D1	0.349	0.167	2.093	0.036
D2	0.295	0.206	1.436	0.151
D3	0.251	0.116	2.167	0.030
DYSFUNC	0.609	0.216	2.822	0.005
Intercepts				
NEGTONE	-0.206	0.087	-2.368	0.018
PERFORM	-0.175	0.127	-1.380	0.167
New/Additional Parameters				
A1THETAL	-0.152	0.152	-1.003	0.316
A1THETAM	-0.281	0.126	-2.235	0.025
A1THETAH	-0.462	0.170	-2.722	0.006
A1B3	-0.274	0.176	-1.557	0.119

In Mplus

Removing exclamation points from the code generates bootstrap confidence intervals for all parameter estimates, including conditional indirect effects.

COMPARE TO OUTPUT THAT PROCESS GENERATES

CONFIDENCE INTERVALS OF MODEL RESULTS

	Lower .5%	Lower 2.5%	Lower 5%	Estimate	Upper 5%	Upper 2.5%	Upper .5%
New/Additional Parameters							
A1THETAL	-0.568	-0.429	-0.377	-0.152	0.113	0.187	0.352
A1THETAM	-0.664	-0.544	-0.488	-0.281	-0.082	-0.052	0.010
A1THETAH	-0.954	-0.816	-0.753	-0.462	-0.194	-0.146	-0.064
A1B3	-0.886	-0.702	-0.617	-0.274	-0.051	-0.022	0.030

Point estimates

End points of a 95% bootstrap confidence intervals
for the conditional indirect effect based on 10,000 bootstrap samples.

Observe that the results using an SEM program are largely the same as the results that PROCESS produces.

Mplus vs. PROCESS output

```
CONFIDENCE INTERVALS OF MODEL RESULTS

                  Lower 2.5%    Estimate    Upper 2.5%

New/Additional Parameters
    A1THETAL        -0.429       -0.152       0.187
    A1THETAM        -0.544       -0.281      -0.052
    A1THETAH        -0.816       -0.462      -0.146
    A1B3            -0.702       -0.274      -0.022
```

Point estimates

```
        INDIRECT EFFECT:
         dysfunc     ->    negtone     ->    perform

             negexp      Effect      BootSE    BootLLCI    BootULCI
             -.5308      -.1523       .1540     -.4335       .1943
             -.0600      -.2813       .1249     -.5432      -.0549
              .6000      -.4623       .1678     -.8095      -.1503

              Index of moderated mediation:
                    Index      BootSE    BootLLCI    BootULCI
        negexp      -.2742       .1791     -.7172      -.0234
```

Observe that the results using an SEM program are largely the same as the results that PROCESS produces.

In Lavaan

```
library(lavaan)
SEM.model <- '#structual model
               negtone ~ a1*dysfunc+d1+d2+d3
               perform ~
b1*negtone+b2*negexp+b3*negtone:negexp+cp*dysfunc+d1+d2+d3

               #indirect effects
               a1thetaL := a1*(b1+b3*(-.5308))
               a1thetaM := a1*(b1+b3*(-.0600))
               a1thetaH := a1*(b1+b3*(0.6000))
               a1b3 := a1*b3'

semfit <- sem(SEM.model, data=teams, se = "bootstrap",
bootstrap = 10000)
summary(semfit)
pes <- parameterEstimates(semfit, boot.ci.type = "perc")
pes
```

Similar to Mplus, you have to find the values to probe at before running the model

```
> summary(semfit)
lavaan 0.6-5 ended normally after 23 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         13

  Number of observations                            60

Model Test User Model:

  Test statistic                                 8.428
  Degrees of freedom                                 2
  P-value (Chi-square)                           0.015

Parameter Estimates:

  Standard errors                            Bootstrap
  Number of requested bootstrap draws            10000
  Number of successful bootstrap draws            9999
```

```
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
  negtone ~
    dysfunc   (a1)    0.609    0.216    2.821    0.005
    d1                0.349    0.164    2.127    0.033
    d2                0.295    0.206    1.430    0.153
    d3                0.251    0.115    2.175    0.030
  perform ~
    negtone   (b1)   -0.489    0.129   -3.777    0.000
    negexp    (b2)   -0.022    0.102   -0.217    0.828
    ngtn:ngxp (b3)   -0.450    0.245   -1.838    0.066
    dysfunc   (cp)    0.373    0.190    1.962    0.050
    d1                0.182    0.144    1.259    0.208
    d2                0.084    0.255    0.330    0.741
    d3                0.282    0.171    1.646    0.100

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)
   .negtone           0.203    0.045    4.539    0.000
   .perform           0.174    0.030    5.874    0.000

Defined Parameters:
                   Estimate  Std.Err  z-value  P(>|z|)
    a1thetaL         -0.152    0.152   -1.001    0.317
    a1thetaM         -0.281    0.126   -2.240    0.025
    a1thetaH         -0.462    0.171   -2.707    0.007
    a1b3             -0.274    0.178   -1.537    0.124
```

In Lavaan

When you ask for bootstraps from lavaan, expect your run time to go up a lot! When I ran this it took 5 min in lavaan (less than 5 seconds in PROCESS)

lavaan

```
> pes[35:38,]
         lhs op                  rhs    label   est    se      z pvalue ci.lower ci.upper
35 a1thetaL := a1*(b1+b3*(-.5308)) a1thetaL -0.152 0.152 -1.001  0.317   -0.436    0.180
36 a1thetaM := a1*(b1+b3*(-.0600)) a1thetaM -0.281 0.126 -2.240  0.025   -0.546   -0.060
37 a1thetaH := a1*(b1+b3*(0.6000)) a1thetaH -0.462 0.171 -2.707  0.007   -0.821   -0.152
38     a1b3 :=                a1*b3     a1b3 -0.274 0.178 -1.537  0.124   -0.702   -0.023
```

Mplus

```
CONFIDENCE INTERVALS OF MODEL RESULTS

                  Lower 2.5%  Estimate  Upper 2.5%

New/Additional Parameters
    A1THETAL         -0.429    -0.152     0.187
    A1THETAM         -0.544    -0.281    -0.052
    A1THETAH         -0.816    -0.462    -0.146
    A1B3             -0.702    -0.274    -0.022
```

PROCESS

```
INDIRECT EFFECT:
 dysfunc     ->    negtone     ->    perform

     negexp     Effect     BootSE   BootLLCI   BootULCI
     -.5308     -.1523      .1540    -.4335      .1943
     -.0600     -.2813      .1249    -.5432     -.0549
      .6000     -.4623      .1678    -.8095     -.1503

      Index of moderated mediation:
            Index     BootSE   BootLLCI   BootULCI
negexp     -.2742      .1791    -.7172     -.0234
```

Observe that the results using an SEM program are largely the same as the results that PROCESS produces.

PROCESS versus Structural Equation Modeling

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Commentary

The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling

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A R T I C L E I N F O

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A B S T R A C T

Marketing, consumer, and organizational behavior researchers interested in studying the mechanisms by which effects operate and the conditions that enhance or inhibit such effects often rely on statistical mediation and conditional process analysis (also known as the analysis of "moderated mediation"). Model estimation is typically undertaken with ordinary least squares regression-based path analysis, such as implemented in the popular PROCESS macro for SPSS and SAS (Hayes, 2013), or using a structural equation modeling program. In this paper we answer a few frequently-asked questions about the difference between PROCESS and structural equation modeling and show by way of example that, for observed variable models, the choice of which to use is inconsequential, as the results are largely identical. We end by discussing considerations to ponder when making the choice between PROCESS and structural equation modeling.

C H I N E S E A B S T R A C T

营销、消费者和组织行为研究人员对研究这种影响经营的机制非常感兴趣，增强或抑制这种影响的条件通常依赖于统计调节和在一定条件下的处理分析（也叫做分析"适度调节"）。模型评估通常采用普通最小乘法基于回归的路径分析（例如，在 SPSS 和 SAS 深受青睐的 PROCESS 宏中实现[Hayes, 2013]）或采用结构方程模型方案。本文回答了一些有关 PROCESS 和结构方程模型之间区别的常见问题，并举例说明，对于观察的变量模型，选择使用哪种模型都无关紧要，因为其结果都大同小异。本文结略讨论了在PROCESS和结构方程模型之间进行选择时应考虑哪些因素。

Marketing researchers and those who study organizational or consumer behavior strive to understand how marketing and other organizational effects operate, meaning the underlying cognitive, social, and biological processes that intervene between a stimulus (e.g., a particular kind of packaging or promotion, or the management style of a leader) and a response (e.g., the evaluation of a product, a decision or timing to purchase, or employee turnover at a company). Mediation analysis is a popular statistical procedure for testing hypotheses about the *mechanisms* by which a causal effect operates. A mediation model contains at least one mediator variable M that is causally between X and Y, such that X's effect on Y is transmitted through the joint causal effect of X on M which in turn affects Y. Fig. 1, panel A, depicts a mediation model with two mediators. Some examples found in the pages of *Australasian Marketing Journal* include Kongarchapatara and Shannon (2016), Baxter and Kleinaltenkamp (2015), and Schiele and Vos (2015). Such models are commonplace in the empirical literature.

Less common but growing in frequency are mediation models that allow for *moderation* of a mechanism, what Hayes (2013) calls a *conditional process model*. Fig. 1, panels B, C, and D, represent a few conditional process models, also known as *moderated mediation* models. Panel A is a *first stage* conditional process model that allows the effect of X on M in a mediation model to depend on variable W. The moderator, W, could be anything that influences or changes the effect of X on M. For some examples, see Voola et al. (2012), White et al. (2016), Shen et al. (2016), and Zenker et al. (2017). But if the moderation operates on the second stage of a mediation process (i.e., on the effect of M on Y), as in Cassar and Briner (2011) and Dubois et al. (2016), the result is a *second stage* conditional process model, as in Fig. 1, panel C. If the same moderator influences the relationship between X and M and M and Y (Fig. 1, panel D), this is a *first and second stage* conditional process model. Examples include Shenu-Fen et al. (2012) and Etkin and Sela (2016). These represent only three of the many ways that mediation and moderation can be integrated into a unified model.

Each of the models depicted in Fig. 1 looks like a path diagram, with variables connected with unidirectional arrows. Such diagrams, for most researchers, bring to mind structural equation

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Hayes, A. F., Montoya, A. K., & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. *Australasian Marketing Journal, 25,* 76-81.

For observed variable models, it makes no difference whether you use SEM or PROCESS. You get the same results and with a lot less effort.

Some reasons you might choose SEM:

- More options for dealing with missing data
- More sophisticated means of managing the effects of measurement error.
- Latent variables and blends of latent and observed variables.
- Greater flexibility for model specification.

Sample Size Planning

How many people/rats/observations do I need to collect for my study?

Two philosophies:

- Avoid making a Type II Error (Power)

  Collect a sample which should have the power to detect a pre-specified effect up to a certain proportion (e.g., 80%, 95%)

  Pros: Aligns with hypothesis testing mentality.
  Cons: Requires an estimate of the effect of interest

- Have a very precise estimate (Precision)

  Collect a sample which should have a precise estimate of the effect of interest (e.g., SE <= 0.5)

  Pros: Does not require an estimate of effect (kind of).
  Cons: Doesn’t necessarily guarantee a “high powered” study

Sample Size Planning

What effect size do I choose?

- Pilot Study
  - This method is often ineffective, because in order to estimate your effect size with enough precision to run a power analysis, you'd likely need to collect a larger sample that what you ultimately need. (See Simonsohn, 2014 for a nice illustration)
- Published research
  - Published examples of "similar studies" can be useful
  - Meta-analyses in fields can be useful
    - Publication bias can cause problems
  - Meta-meta-analyses (if you just feel like you have no idea)
    - Typical effect size in psychology based on published findings is d = .2 (Hemphill (2003), Gignac & Szodorai, 2016; Haase, Waechter, & Solomon (1982)).
    - Doesn't take into account design

- Smallest effect size of interest (see Lakens, Scheel, Isager (2018) *AMPPS)*
  - Determine what size of an effect would be interesting / practically significant and then power for that effect.

Simulations as “Rules of Thumb”

Beware of simulations. Read carefully and understand the situations under which data is simulated.

Typically effect sizes can be interpreted as “standardized effect sizes.”

These simulations typically only reflect “best case scenarios”

Previous simulation work:

Fritz & MacKinnon (2007) – simple mediation
Hayes & Scharkow (2013) – simple mediation
Biesanz, Falk, & Savalei (2016) – mediation with normal and nonnormal data
Williams & MacKinnon (2008) – serial mediation models

TABLE 3

Empirical Estimates of Sample Sizes Needed for .8 Power

	Condition															
Test	**SS**	**SH**	**SM**	**SL**	**HS**	**HH**	**HM**	**HL**	**MS**	**MH**	**MM**	**ML**	**LS**	**LH**	**LM**	**LL**
Percentile bootstrap	558	412	406	398	414	162	126	122	404	124	78	59	401	123	59	36

Simulations for Power

Doing your own simulations:

You will need to make a variety of decisions about what's going on in your data, and those decisions **will definitely have an impact on your results**. If you're not sure about something, simulate under a variety of conditions.

Monte Carlo Simulation Tools:

Thoemmes , MacKinnon & Reiser (2010) – specific to mediation

Sigal & Chalmers (2016) - Really great R package called 'simdesign' which can be used for Monte Carlo Simulations to understand power.

Table: Tools available for power analysis in mediation					
Tool Name	WebPower	WebPower	bmem	MedPower	pwr2ppl
Interface	Online/R	Online/R	R	Online-Shiny	R functions
Reference	Schoemann, Boulton, Short, 2017	Zhang & Yuan (2015)	Zhang, & Wang, 2013)	Kenny, 2017	Aberson
Inputs	Correlations, standard deviations)	Estimates of a and b, variances	Estimates of all paths, skew, kurtosis, N	Estimates of paths or partial correlations	Correlations, N
Outputs	Required N (Given Power), Estimated Power (Given N)	Required N (Given Power), Estimated Power (Given N)	Estimated Power (Given N)	Required N (Given Power), Estimated Power (Given N)	Estimated Power (Given N)
Standardized	No	No	Yes	Yes	No
Method of Estimation	Bootstrap, Monte Carlo	Sobel	Sobel, Bootstrap	Distribution of the Product	Sobel, Joint Significance
Model Complexity	Simple, Parallel, Serial	Simple	Simple, Parallel, Serial	Simple	Simple, Parallel
URL	https://schoemanna.shinyapps.io/mc_power_med/	https://webpower.psychstat.org/models/med01/	https://cran.r-project.org/web/packages/bmem/bmem.pdf	https://davidakenny.shinyapps.io/MedPower/	https://github.com/chrisaberson/pwr2ppl/blob/master/R/med.R

Sample Size Planning: Moderation/CPA

There are a lot of rules of thumbs and some recommendation out there, but I'm not particularly happy with any of them.

Powering an interaction term is more complex that powering for a regression coefficient.

I recommend powering for simple effects (but this requires heavy thinking about what you expect).

CPA: pwr2ppl R package uses Monte Carlo simulation for common models in PROCESS

- One of my graduate students is working on this, so if you find yourself in need of a power analysis, feel free to reach out.

Amanda's Power Rule of Thumb: Collect enough people so that when you get a null result you believe it.

Finding Examples

My AWESOME graduate student, Jessica Fossum, created a database of published examples of moderated mediation model. It's searchable based on PROCESS model number as well as other characteristics.

You can also submit a form to add your paper to the database if you want others to be able to find it!

https://www.jlfossum.com/home/moderated-mediation-article-database

Model Number | Type of Manipulated Variable | Number of Moderators | Number of Mediators | Year

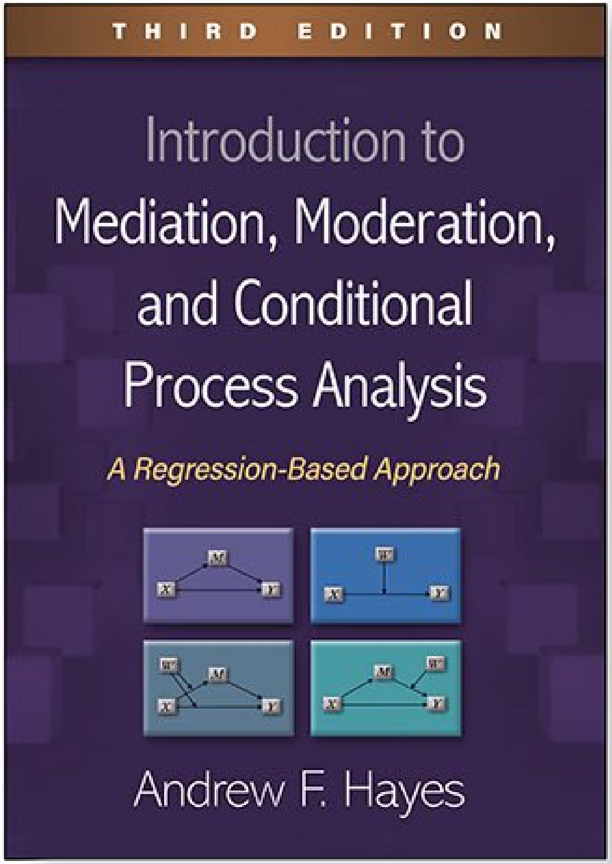
Estimation Procedure | Research Area | Journal | Number of X Variables | Number of Y Variables

Article	Journal	First Author	Research Area	Model Number	Sample Size	Estimation Procedure	Number of X Variables	Type of X Variable	Number of Y Variables	Mediators	Moderators	Covariates
"They've conspired against us": Understanding the role of social identification and conspiracy beliefs in justification of ingroup collective behavior	EUROPEAN JOURNAL OF SOCIAL PSYCHOLOGY	Chayinska, M	Psychology	7	315	Regression	1		1	1	1	0
A Conditional Process Analysis of the Teacher Confirmation-Student Learning Relationship	COMMUNICATION QUARTERLY	Goldman, ZW	Communication	7	208	Regression	1		1	1	1	1
A Latent Growth Moderated Mediation Model of Math Achievement and Postsecondary Attainment: Focusing on Context-Invariant Predictors	JOURNAL OF EDUCATIONAL PSYCHOLOGY	Guglielmi, RS	Psychology		8791	Regression	1		1	3	2	2
A Longitudinal Study of Inhibited Temperament, Effortful Control, Gender, and Anxiety in Early Childhood	CHILD & YOUTH CARE FORUM	Niditch, LA	Psychology	59	1226	SEM	1		1	1	1	4
A Moderated Mediation Model for Board Diversity and Corporate Performance in ASEAN Countries	SUSTAINABILITY	E-Vahdati, S	Science & Technology - Other Topics	58	264	SEM	2		1	1	1	3
A Social Influence Interpretation of Workplace Ostracism and Counterproductive Work Behavior	JOURNAL OF BUSINESS ETHICS	Yang, J	Business & Economics	21	156	Regression	1		1	1	2	4
A genetic variant brain-derived neurotrophic factor (BDNF) polymorphism interacts with hostile parenting to predict error-related brain activity and thereby risk for internalizing disorders in children	DEVELOPMENT AND PSYCHOPATHOLOGY	Meyer, A	Psychology	7	201	Regression	1		1	1	1	2
A pre-event assessment of	TOURISM	Tournois, L	Environmental	9	317	Regression	1		1	1		

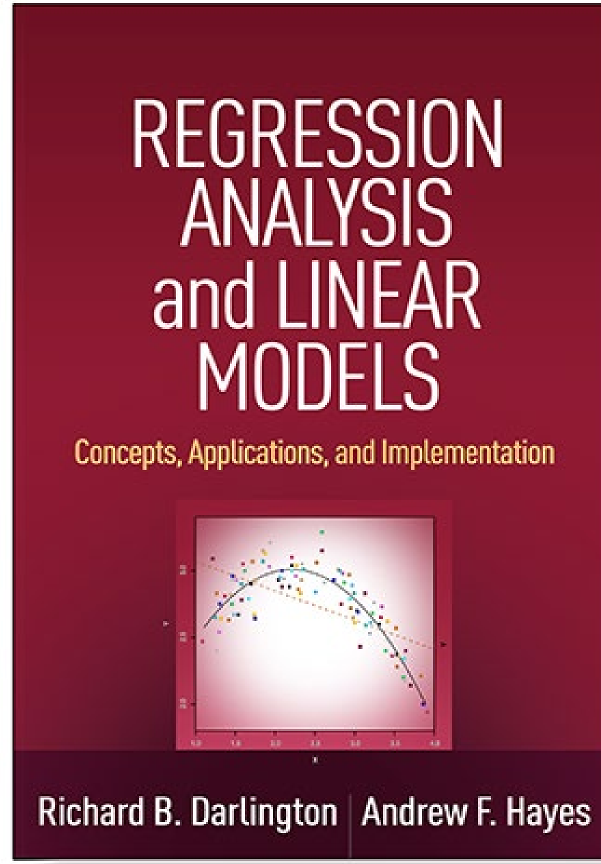
Google Data Studio

Where to learn more

The entire book



Chapters 13, 14, and 15



http://www.guilford.com/

Advanced Courses on MMCPA

- Review of the fundamentals of mediation, moderation, and conditional process analysis.
- Testing whether an indirect effect is moderated and probing moderation of indirect effects.
- Partial and conditional moderated mediation.
- Mediation analysis with a multicategorical independent variable.
- Moderation analysis with a multicategorical (3 or more groups) independent variable or moderator.
- Conditional process analysis with a multicategorical independent variable
- Moderation of indirect effects in the serial mediation model.
- New features available in PROCESS v3.0, such as how to modify a numbered model or customize your own model.

Follow me on Twitter for info about upcoming courses @AmandaKMontoya

Pertinent Publications

Rockwood, N. J., & Hayes, A. F. (2018). Mediation, moderation, and conditional process analysis: Regression-based approaches for clinical research. Draft submitted and to appear in A. G. C. Wright and M. N. Hallquist (Eds.) *Handbook of research methods in clinical psychology.* Cambridge University Press.

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Hayes, A. F., & Rockwood, N. J. (2017). Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. *Behaviour Research and Therapy, 98*, 39-57. [paper and data]

Hayes, A. F., Montoya, A. K., & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. *Australasian Marketing Journal, 25,* 76-81. [PDF and Mplus code]

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Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter? *Psychological Science, 24*, 1918-1927.

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Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*, 879-891.

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