

The background of the slide features a wide-angle photograph of the Swiss Alps under a clear blue sky. In the foreground, a small town with white buildings and red roofs is nestled at the base of the mountains. A church with a tall, light-colored steeple stands prominently on the right side of the town. The overall atmosphere is bright and airy.

Mediation, Moderation, and Conditional Process Analysis I

Instructor: Amanda K. Montoya



Global School in Empirical Research Methods, St. Gallen, Switzerland

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 per-

ceptions. 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

*Henrik Hagtvedt is a doctoral student in Marketing (e-mail: hhagtvedt@yahoo.com), and Vanessa M. Patrick is Assistant Professor of Marketing (e-mail: vpatrick@uga.edu), Terry College of Business, University of Georgia. Both authors contributed equally to this research. They express their appreciation to the anonymous *JMR* reviewers for their invaluable comments and encouragement. They also thank the University of Georgia for their support of this research. They also thank Reisdar Hagtvedt, John Mowen, Gavan Fitzsimons, Shashi Matta, Piyush Kumar, and Seinivkar K. Reddy for their input and Nicole Patrick, Simone Patrick, and Colin Heacock for their help in creating some of the stimuli used in this article. Chris Janiszewski served as associate editor for this article.

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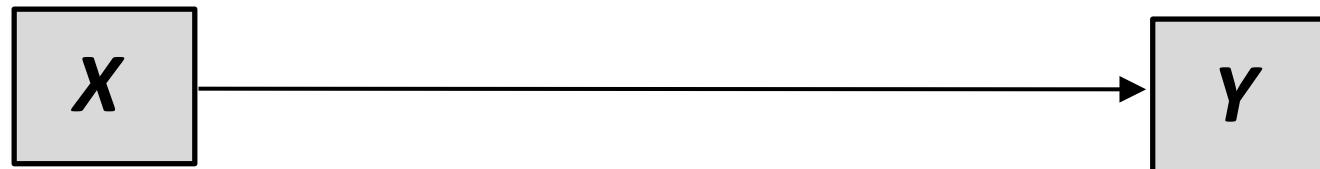


PHOTO or PAINTING

PRODUCT
EVALUATION

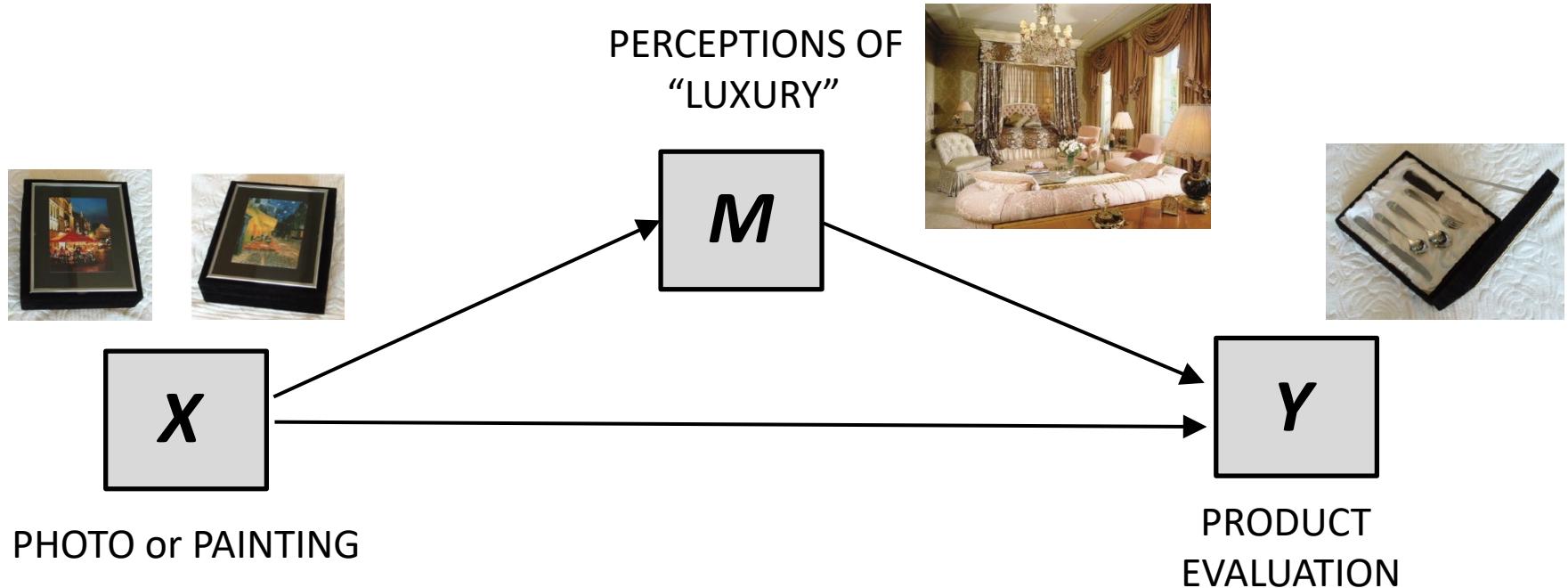
The product with the impressionist painting on the box was evaluated more favorably than the product with a photograph of a similar scene.

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!

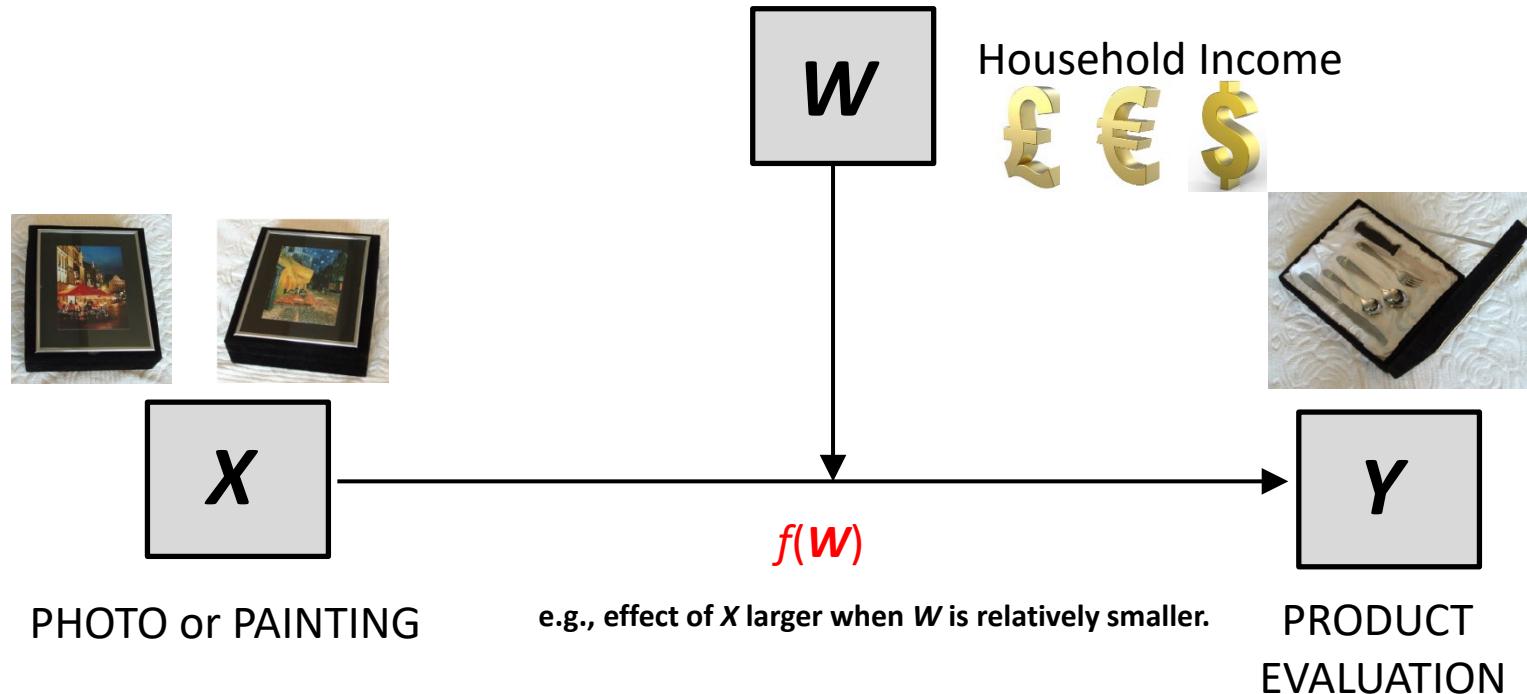
A simple mediation model



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*.

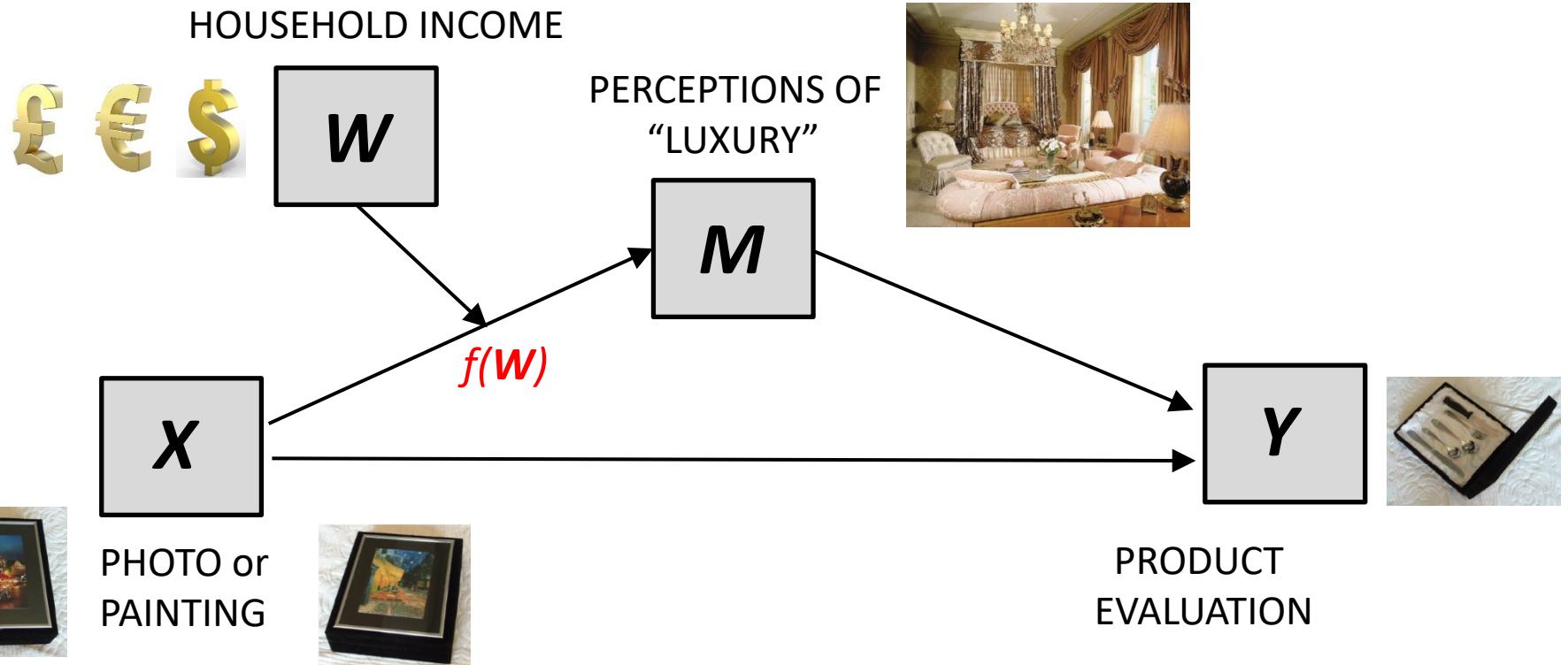
Moderation



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 27+ or SAS 9.1+ with PROC IML. If not, that is ok. You'll still benefit.

SPSS Code

SAS Code

R Code

- ❑ Various files available on GitHub.

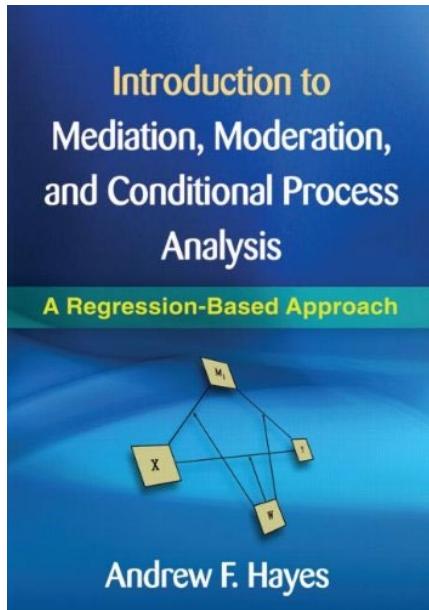
- ❑ SPSS, SAS, and R data folders. SPSS data files are ready to go. SAS files are programs thus must be executed to make them “work” files. R files are CSV and need to be read into R.
- ❑ SPSS, SAS, and R PROCESS folders. This contains the PROCESS macro we'll heavily rely on, and some documents related 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

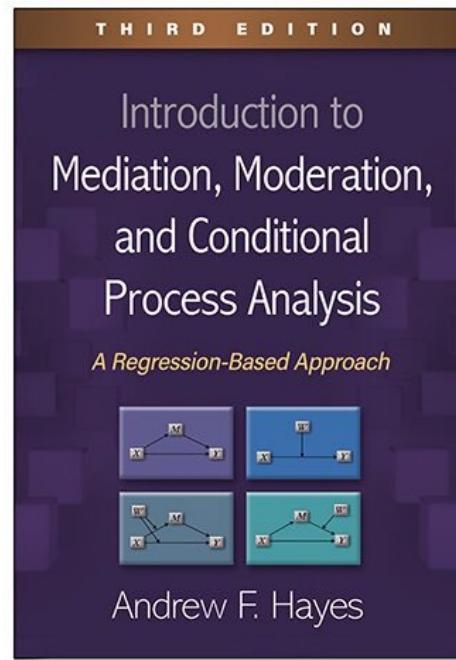
- We will stick with fairly simple models to cover basic principles, with continuous outcomes, and cross-sectional or experimental data.
- Statistical mediation analysis. No discussion of counterfactuals, “potential outcomes,” directed graphs, or other approaches to thinking about cause.
- Everything 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.

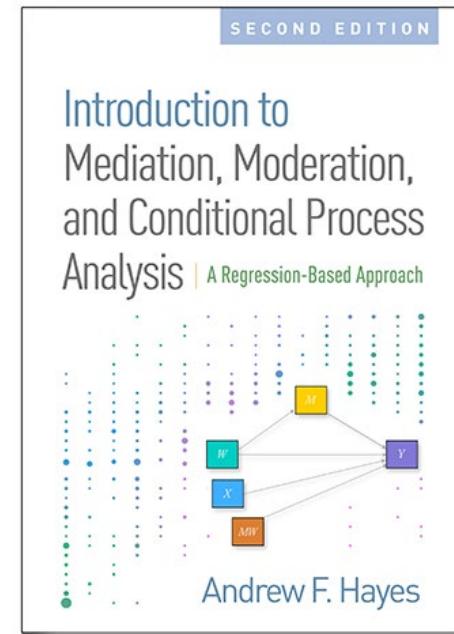
This course is a companion to...



2013



3rd Ed. 2022
(Contains all documentation for PROCESS for R)



2017

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
© Springer Science+Business Media New York 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., Hunyadi and Fulgini 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

S. Bayram Özdemir (✉) · H. Stattin
Center for Developmental Research, School of Law, Psychology
and Social Work, Örebro University, Örebro, Sweden
e-mail: sevgi.bayram-ozdemir@oru.se;
sevgiozdemir1@gmail.com

H. Stattin
e-mail: hakan.stattin@oru.se

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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.

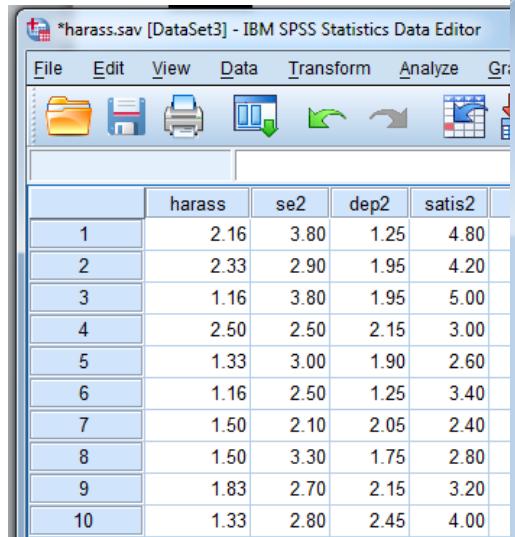
FAIL: 4-item measure of perceived academic failure at school (scaled 1 to 4). T1 and T2.

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

All are continuous variables scaled such that higher = more.

The Data: HARASS

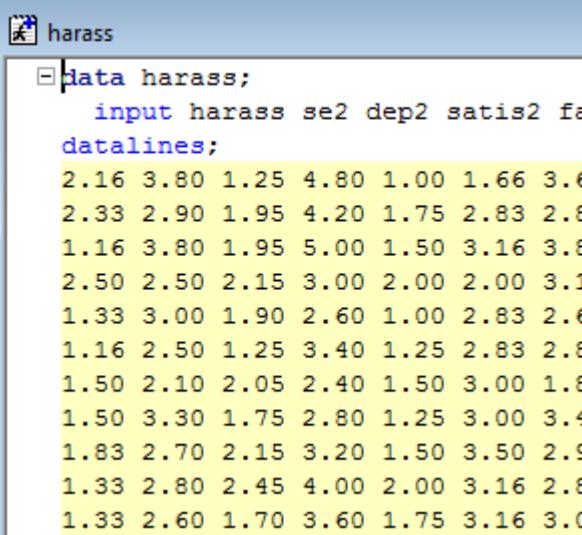
SPSS



	harass	se2	dep2	satis2	posrel
1	2.16	3.80	1.25	4.80	1.66
2	2.33	2.90	1.95	4.20	2.83
3	1.16	3.80	1.95	5.00	3.16
4	2.50	2.50	2.15	3.00	2.00
5	1.33	3.00	1.90	2.60	3.1
6	1.16	2.50	1.25	3.40	1.50
7	1.50	2.10	2.05	2.40	2.83
8	1.50	3.30	1.75	2.80	2.00
9	1.83	2.70	2.15	3.20	1.75
10	1.33	2.80	2.45	4.00	1.00

The SPSS file is ready for analysis.

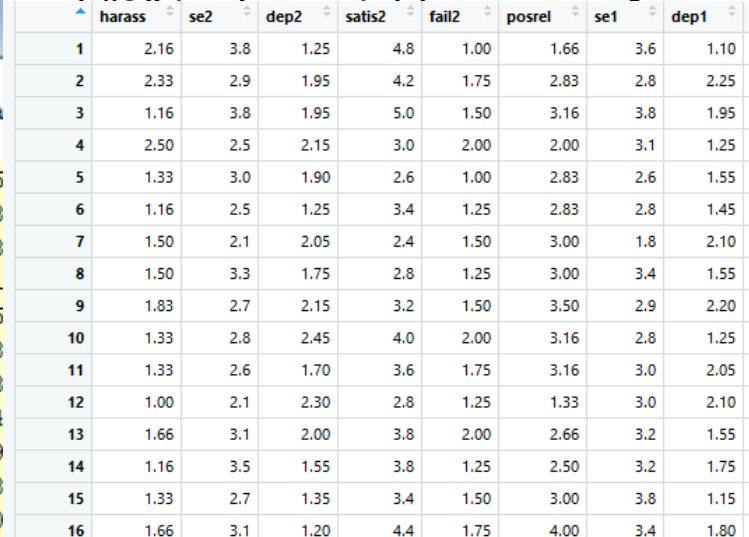
SAS



```
data harass;
  input harass se2 dep2 satis2 fail2 posrel;
  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
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:

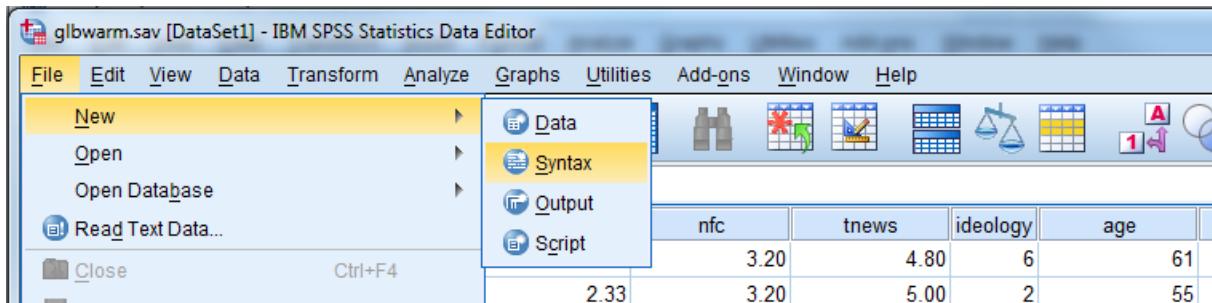
```
filelocation <- "C:\\Your\\Path\\Here\\harass.csv"
harass <- read.csv(filelocation, header = TRUE)
```

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.

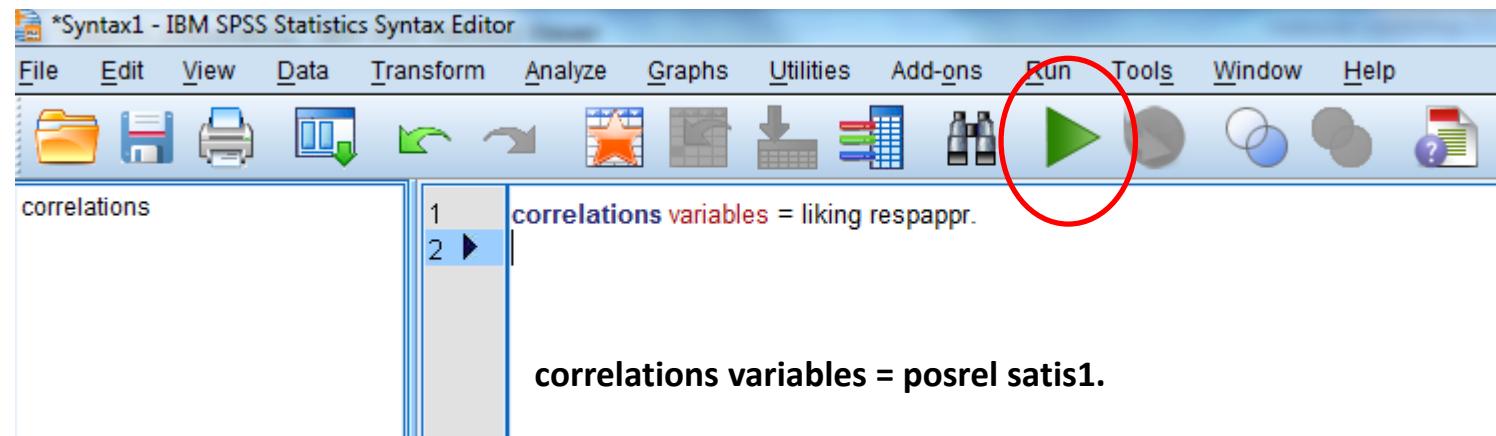
Using SPSS syntax

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



(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			
		harass	fail2
harass	Pearson Correlation	1	.136
	Sig. (2-tailed)		.014
	N	330	330
fail2	Pearson Correlation	.136	1
	Sig. (2-tailed)	.014	
	N	330	330

Pearson's product-moment correlation

```
data: harass and fail2
t = 2.4783, df = 328, p-value = 0.0137
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.0280229 0.2400270
sample estimates:
cor
0.1355765
```

SPSS code in black box

```
correlations variables = harass fail2.
```

R code in grey box

```
cor.test(harass~fail2, data = harass)
```

SAS code in white box

```
proc corr data=harass;var harass fail2;run;
```

Interpretation of Correlation Coefficient

Interpretation is a translation of a numerical result to contextualize it's meaning with the example/data set/ analysis in which it has been estimated

Interpretations are specific to the numerical result (not just sign, magnitude, or statistical significance)

Pearson's product-moment correlation

```
data: harass and fail2
t = 2.4783, df = 328, p-value = 0.0137
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.0280229 0.2400270
sample estimates:
      cor
0.1355765
```

Good Example of Interpretation:

For two kids who differ by one standard deviation on harassment, the kid with the higher harassment is expected to be 0.14 standard deviations higher on perceived academic failure.

Bad Examples:

The correlation between harass and fail2 is 0.14.

Harassment is positively correlated with perceived academic failure.

Harassment is significantly correlated with perceived academic failure.

A scatterplot

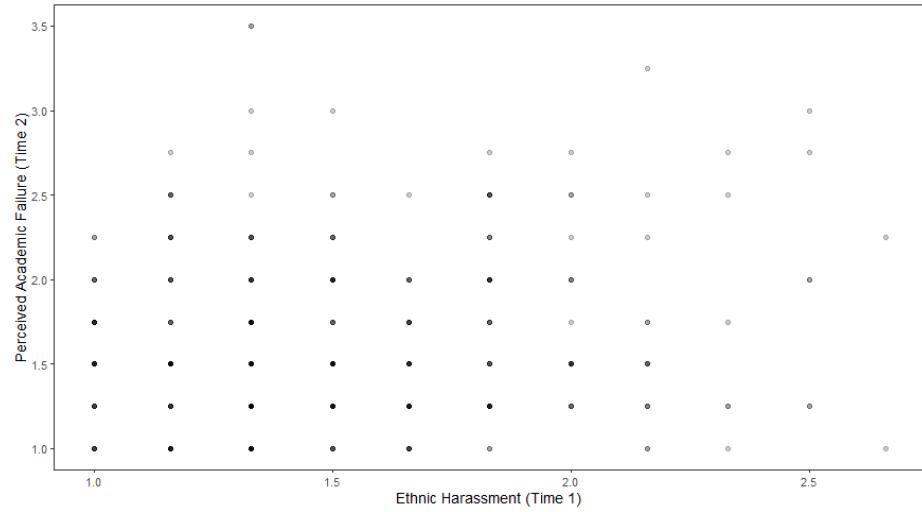
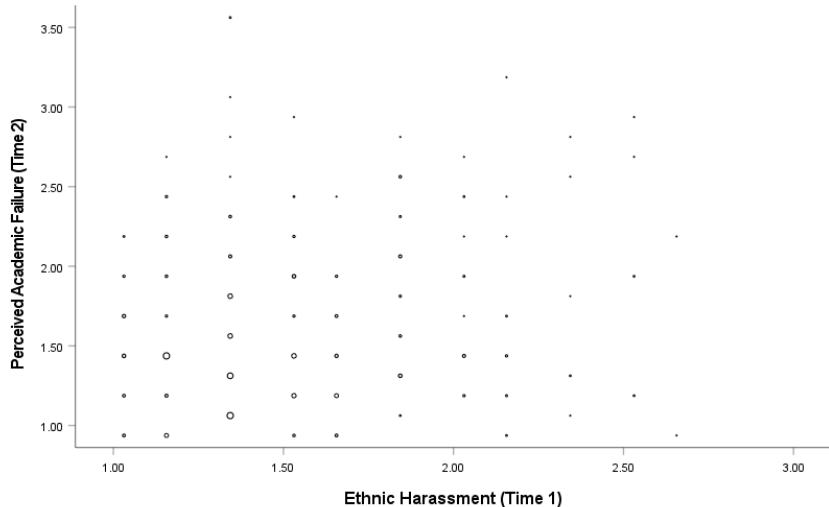
Consider a scatterplot visually depicting this relationship:

```
graph/scatterplot=harass with fail2.
```

```
proc sgscatter data=harass;plot fail2*harass;run;
```

```
gf_point(fail2~harass, data = harass, alpha = .2, xlab = "Ethnic Harassment (Time 1)",  
ylab = "Perceived Academic Failure (Time 2)")+theme_apa()
```

After “binning” to see the overlap:



[Video for SPSS Editing](#)

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 ordinary least squares criterion, there is only one line described by the function

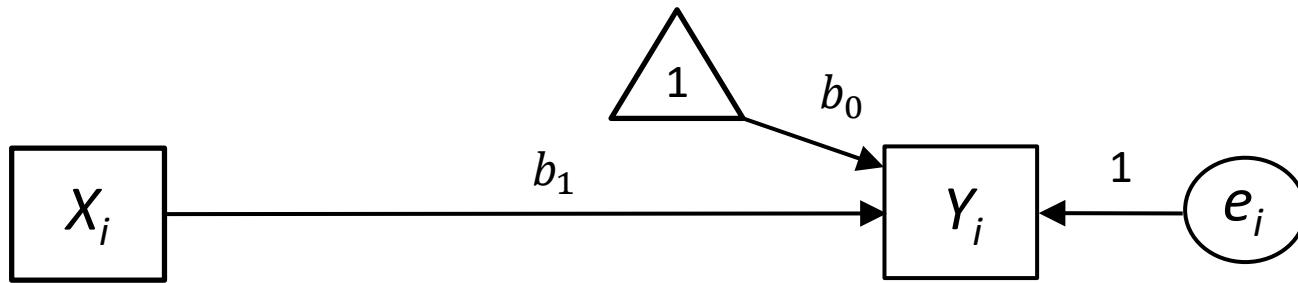
$$\hat{Y}_i = b_0 + b_1 X_i \quad e_i = Y_i - \hat{Y}_i$$

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.

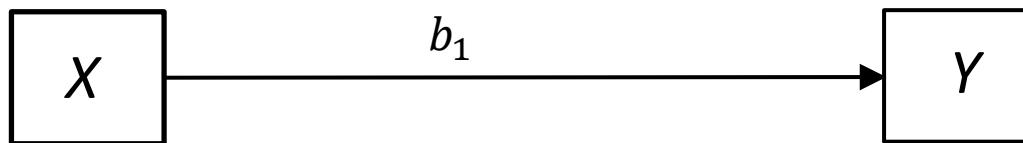
$$SS_{\text{residual}} = \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 = \sum_{i=1}^n e_i^2$$

A visual representation

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



or, in shorthand,



In a diagram such as this, \rightarrow 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 = HARASS (ethnic harassment), Y = FAIL2 (perceived academic failure at Time 2).

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.136 ^a	.018	.015	.49506

a. Predictors: (Constant), harass

ANOVA ^a					
Model		Sum of Squares	df	Mean Square	F
1	Regression	1.505	1	1.505	6.142
	Residual	80.389	328	.245	
	Total	81.894	329		

a. Dependent Variable: fail2

b. Predictors: (Constant), harass

Coefficients ^a						
Model		Unstandardized Coefficients		t	Sig.	95.0% Confidence Interval for B
		B	Std. Error			
1	(Constant)	1.346	.113	11.866	<.001	1.123
X	harass	.182	.073	.136	.014	.037

a. Dependent Variable: fail2

```
regression/statistics defaults ci/dep=fail2/method=enter harass .
```

```
proc reg data=harass;model fail2 = harass/stb clb;run;
```

$$SS_{\text{residual}} = 80.389$$

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

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

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

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

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 = HARASS (ethnic harassment), Y = FAIL2 (perceived academic failure at Time 2).

Analysis of Variance Table

Response: fail2
Df Sum Sq Mean Sq F value Pr(>F)
harass 1 1.505 1.50530 6.1419 0.0137 *
Residuals 328 80.389 0.24509

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

call:
`lm(formula = fail2 ~ harass, data = harass)`

Residuals:
Min 1Q Median 3Q Max
-0.82909 -0.36844 -0.08757 0.32163 1.91243

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.34604	0.11344	11.866	<2e-16 ***
harass	0.18160	0.07327	2.478	0.0137 *

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

Residual standard error: 0.4951 on 328 degrees of freedom
Multiple R-squared: 0.01838, Adjusted R-squared: 0.01539
F-statistic: 6.142 on 1 and 328 DF, p-value: 0.0137

```
model <- lm(fail2~harass, data = harass)
anova(model)
summary(model)
```

$$SS_{\text{residual}} = 80.389$$

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

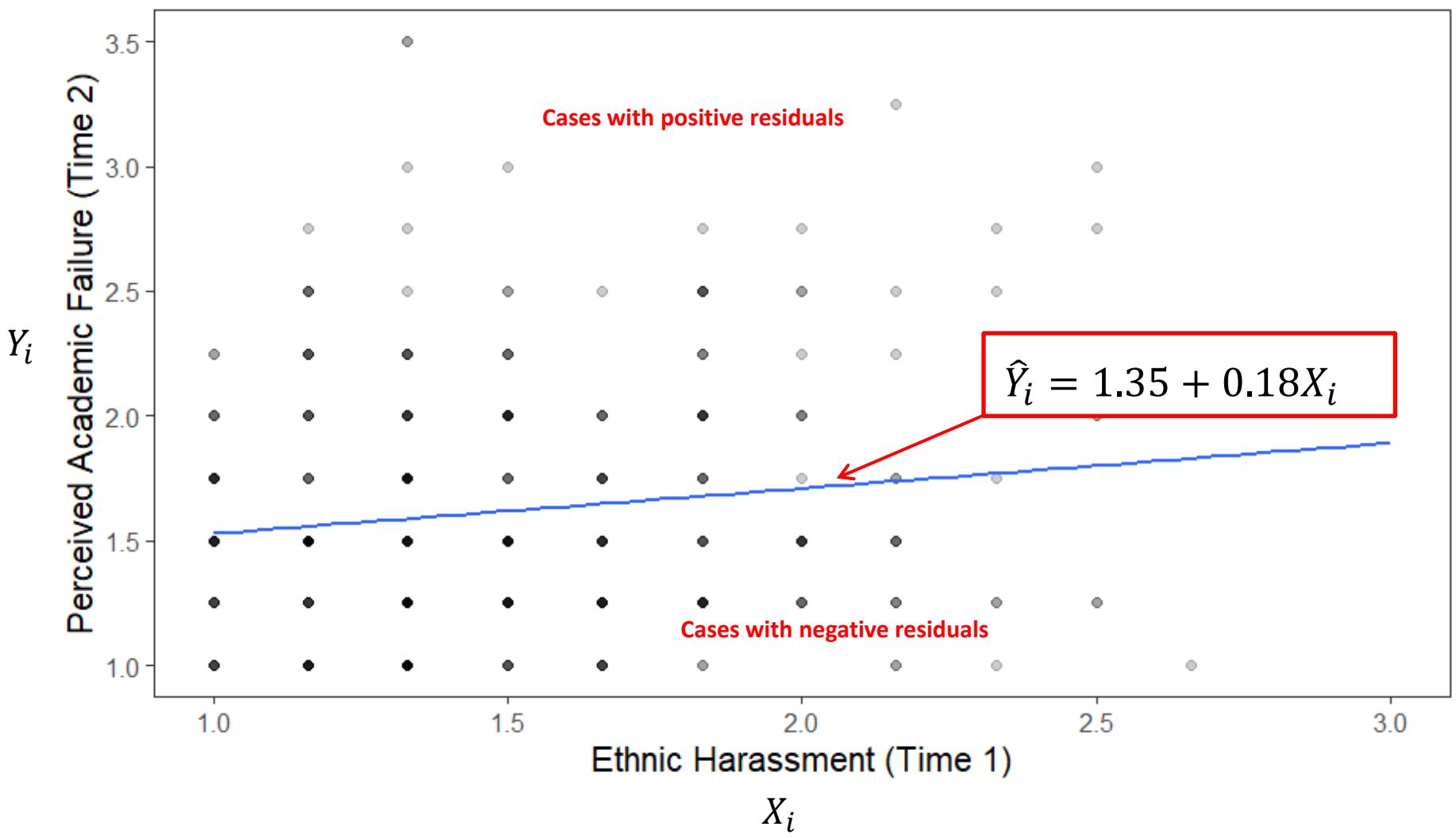
$$\hat{Y}_i = b_0 + b_1 X_i$$

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

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

X

The model in visual form



Interpretation of b_0 and b_1

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

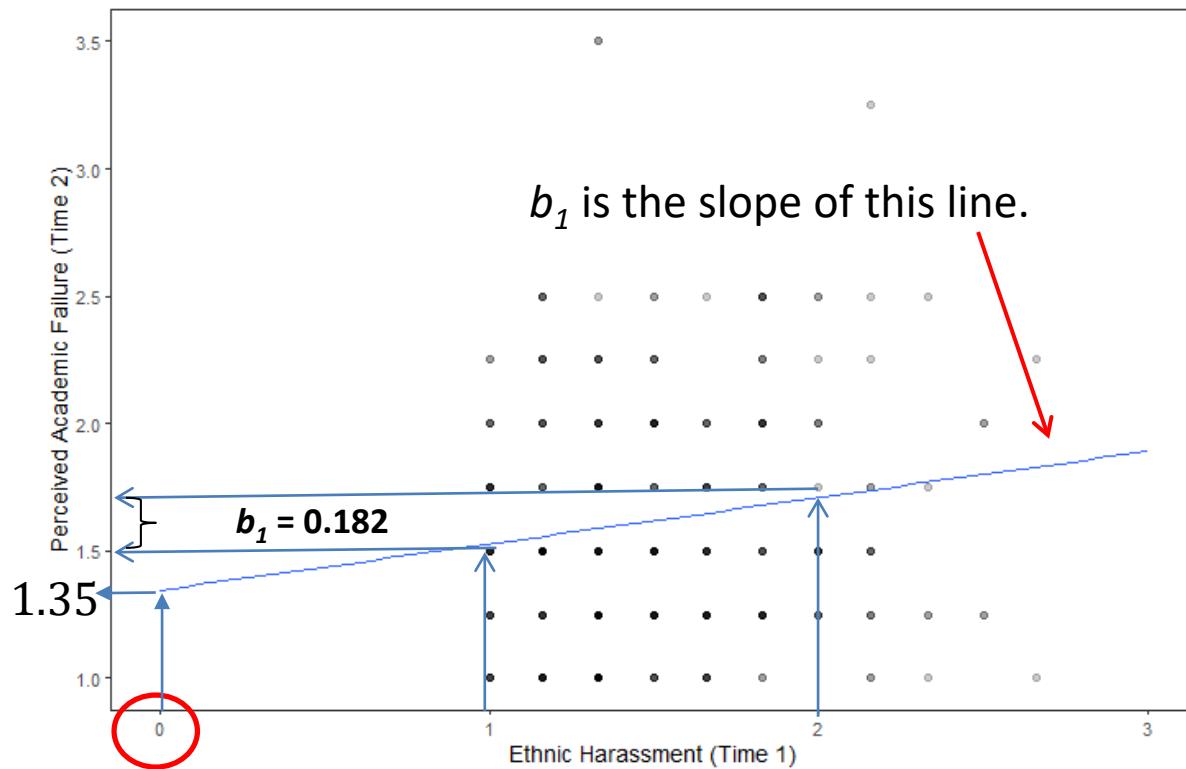
$$\hat{Y}_i = 1.346 + 0.182 X_i$$

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

$$\begin{aligned}\hat{Y} &= 1.346 + 0.182(0) \\ &= 1.346 = b_0\end{aligned}$$

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 .

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



Two kids that differ by one unit ethnic harassment are estimated to differ by $b_1 = 0.182$ units in perceived academic failure at Time 2. The kid that is **higher** in harassment is estimated to be *higher* on perceived failure (because b_1 is positive).

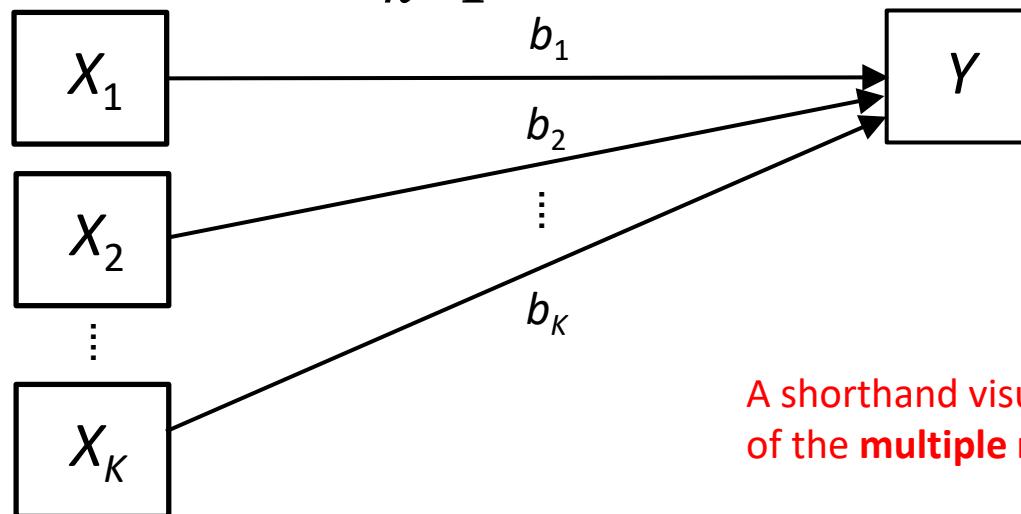
Multiple predictors

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

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

or, more concisely,

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



A multiple regression model (SPSS)

```
regression/statistics defaults ci/dep=fail2/method=enter harass fail1 sel.
```

```
proc reg data=harass;model fail2 = harass fail1 sel/stb clb;run;
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.351 ^a	.123	.115	.46941

a. Predictors: (Constant), se1, harass, fail1

$$SS_{\text{residual}} = 71.832$$

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

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.062	3	3.354	15.222	<.001 ^b
	Residual	71.832	326	.220		
	Total	81.894	329			

a. Dependent Variable: fail2

X_1 = harassment frequency

X_2 = perceived failure (T1)

X_3 = self-esteem (T1)

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error				Lower Bound	Upper Bound
1	(Constant)	1.652	.240	6.884	<.001	1.180	2.124
	harass	.079	.071	.059	1.106	.270	-.061
	fail1	.253	.060	.231	4.189	<.001	.134
	se1	-.173	.053	-.179	-3.251	.001	-.278

a. Dependent Variable: fail2

$$\widehat{Y}_i = 1.652 + 0.079X_{1i} + 0.253X_{2i} - 0.173X_{3i}$$

A multiple regression model (R)

```
mult.model <- lm(fail2~harass+fail1+sel, data = harass)
anova(mult.model)
summary(mult.model)
```

Analysis of Variance Table

Response: fail2

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
harass	1	1.505	1.5053	6.8316	0.009371 **
fail1	1	6.228	6.2276	28.2632	1.969e-07 ***
sel	1	2.329	2.3292	10.5708	0.001269 **
Residuals	326	71.832	0.2203		

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

Call:
lm(formula = fail2 ~ harass + fail1 + sel, data = harass)

Residuals:

Min	1Q	Median	3Q	Max
-0.79072	-0.35927	-0.08593	0.27426	1.99896

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.65229	0.24001	6.884	2.99e-11 ***
harass	0.07898	0.07140	1.106	0.26952
fail1	0.25261	0.06031	4.189	3.62e-05 ***
sel	-0.17335	0.05332	-3.251	0.00127 **

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

Residual standard error: 0.4694 on 326 degrees of freedom
Multiple R-squared: 0.1229, Adjusted R-squared: 0.1148
F-statistic: 15.22 on 3 and 326 DF, p-value: 2.711e-09

$$SS_{\text{residual}} = 71.832$$

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

X_1 = harassment frequency
 X_2 = perceived failure (T1)
 X_3 = self-esteem (T1)

$$\widehat{Y}_i = 1.652 + 0.079X_{1i} + 0.253X_{2i} - 0.173X_{3i}$$

Interpretations of Coefficients

$$\hat{Y}_i = 1.652 + 0.079X_{1i} + 0.253X_{2i} - 0.173X_{3i}$$

Failure (T2) Harass (T1) Failure (T1) Self-esteem (T1)

Two kids *with the same levels of perceived academic failure and self-esteem at Time 1, but who differ by one unit in ethnic harassment frequency* are expected to differ by $b_1 = 0.079$ units in estimated perceived academic failure one year later (\hat{Y}), where more harassment corresponds to greater perceived failure.

Two kids *with the same levels of perceived harassment and academic failure at Time 1, but who differ by one unit in self esteem at Time 1* are expected to differ by $b_3 = -0.173$ units in estimated perceived academic failure one year later (\hat{Y}), where higher self-esteem corresponds to lower perceived failure.

Elements of interpretations:

- One unit difference on X corresponds to b unit difference on Y
- Control for all other predictors in the model
- Difference is **estimated**
- Avoid implying causality unless it is valid based on design

Statistical inference

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

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

$$Y_i = \widetilde{b}_0 + \widetilde{b}_1 X_{1i} + \widetilde{b}_2 X_{2i} + \widetilde{b}_3 X_{3i} + \dots + \widetilde{b}_K X_{Ki} + \widetilde{e}_i$$

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 \tilde{b}

$$Y_i = \tilde{b}_0 + \tilde{b}_1 X_{1i} + \tilde{b}_2 X_{2i} + \tilde{b}_3 X_{3i} + \dots + \tilde{b}_K X_{Ki} + \tilde{e}_i$$

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

e.g., Null hypothesis test about \tilde{b}_j :

Assume \tilde{b}_1 equals some specific value. Typically, we assume $\tilde{b}_1 = 0$ under the **null hypothesis** (i.e., X_1 is unrelated to Y when all other variables in the model are held constant).

$$\begin{aligned} H_0: \tilde{b}_1 &= 0 \\ H_a: \tilde{b}_1 &\neq 0 \end{aligned}$$

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	10.062	3	3.354	15.222	<.001 ^b
Residual	71.832	326	.220		
Total	81.894	329			

a. Dependent Variable: fail2

Coefficients ^a					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	1.652	.240		6.884	<.001
harass	.079	.071	.059	1.106	.270
fail1	.253	.060	.231	4.189	<.001
se1	-.173	.053	-.179	-3.251	.001

a. Dependent Variable: fail2

$$H_0: \tilde{b}_1 = 0$$

$$H_a: \tilde{b}_1 \neq 0$$

$$b_1 = 0.079, se(b_1) = 0.071,$$

$$t(326) = 1.106, p = .27$$

Fail to Reject H_0

$$H_0: \tilde{b}_2 = 0$$

$$H_a: \tilde{b}_2 \neq 0$$

$$b_2 = 0.253, se(b_2) = 0.06,$$

$$t(326) = 4.189, p < .001$$

Reject H_0 in favor of H_a

Two kids equal in perceived academic failure and self esteem at Time 1 but who differ in the perceived ethnic harassment differ from each other in perceived academic failure at Time 2 *no more than can be explained by chance*.

Two kids equal in perceived ethnic harassment and self esteem at Time 1 but who differ in the perceived academic failure differ from each other in perceived academic failure at Time 2 *more can be explained by chance*.

Interval estimation (SPSS and SAS)

```
regression/statistics defaults ci/dep=fail2/method=enter harass fail1 sel.
```

```
proc reg data=harass; model fail2 = harass fail1 sel/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 about 2 standard errors of the obtained estimate.

$$b_j - 2s_{b_j} \leq \tilde{b}_j \leq b_j + 2s_{b_j}$$

Model		Unstandardized Coefficients		Standardized Coefficients		t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta				Lower Bound	Upper Bound
		(Constant)	.240						
1	harass	.079	.071	.059	1.106	.270		-.061	.219
	fail1	.253	.060	.231	4.189	<.001		.134	.371
	sel	-.173	.053	-.179	-3.251	.001		-.278	-.068

a. Dependent Variable: fail2

We can be 95% confident \tilde{b}_1 is somewhere between -0.061 and 0.219
We can be 95% confident \tilde{b}_2 is somewhere between 0.134 and 0.371.

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 about 2 standard errors of the obtained estimate.

$$b_j - 2s_{b_j} \leq \tilde{b}_j \leq b_j + 2s_{b_j}$$

	2.5 %	97.5 %
(Intercept)	1.18012495	2.12445300
harass	-0.06149407	0.21944522
fail1	0.13396626	0.37125511
sel	-0.27823616	-0.06845946

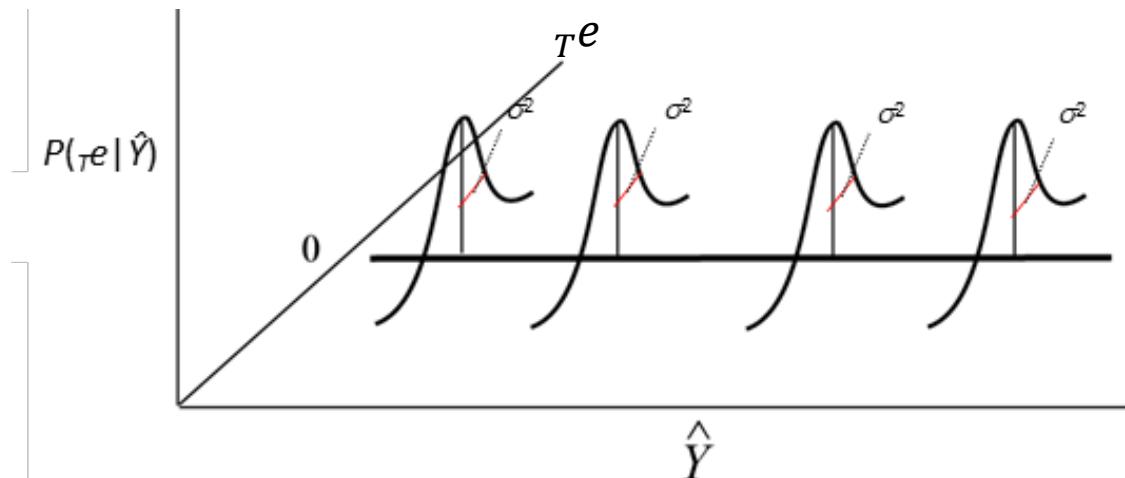
95.0% Confidence Interval for B	
Lower Bound	Upper Bound
1.180	2.124
-.061	.219
.134	.371
-.278	-.068

We can be 95% confident \tilde{b}_1 is somewhere between -0.061 and 0.219
We can be 95% confident \tilde{b}_2 is somewhere between 0.134 and 0.371.

Assumptions in Linear Regression

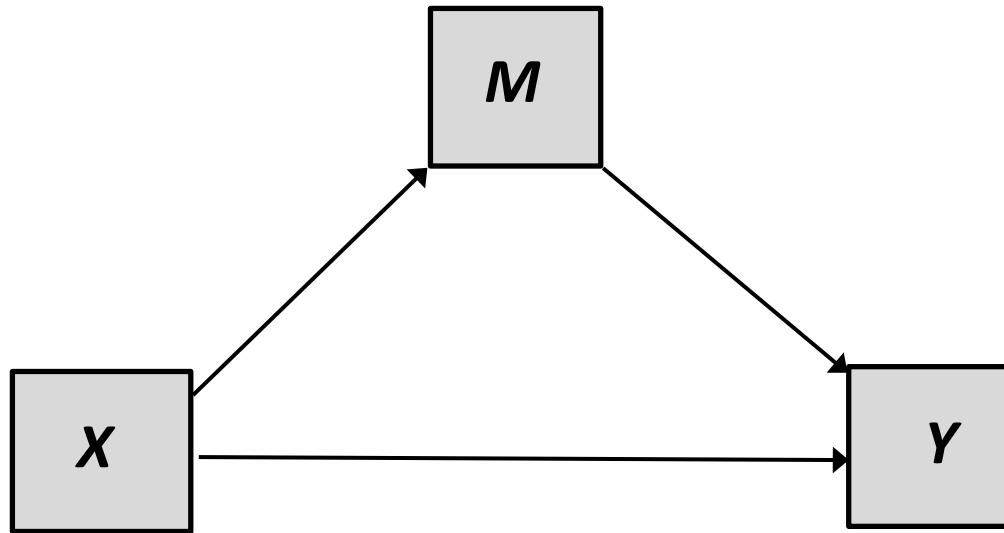
We assume that the distribution of τe is **normal** with a **mean of zero** and **constant variance σ^2 (homoskedasticity)** for all values and patterns of the explanatory variables, and the values of τe are **mutually independent**.

Because the values and patterns of the explanatory variables generate \hat{Y}_i it is convenient and easier (even if not strictly correct) to think about the assumption of the errors as conditioned on \hat{Y}_i



When these conditions are met, we say that the errors in estimation are *independently and identically distributed* (iid) with mean 0 and variance σ^2

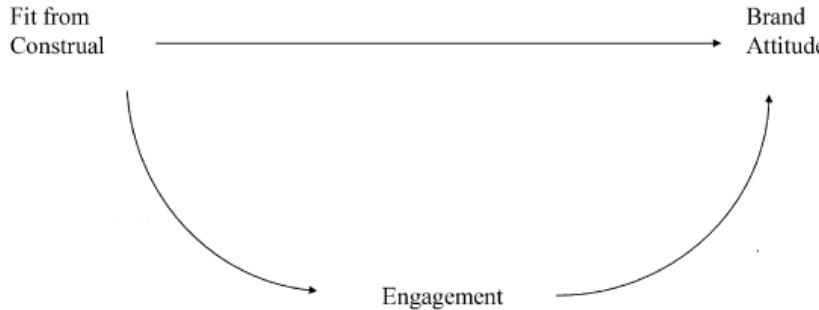
Statistical mediation analysis



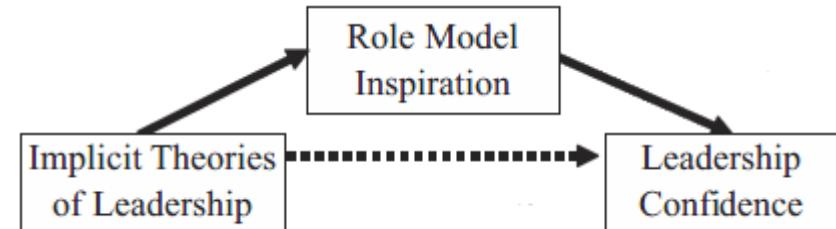
The “simple mediation” model

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 .

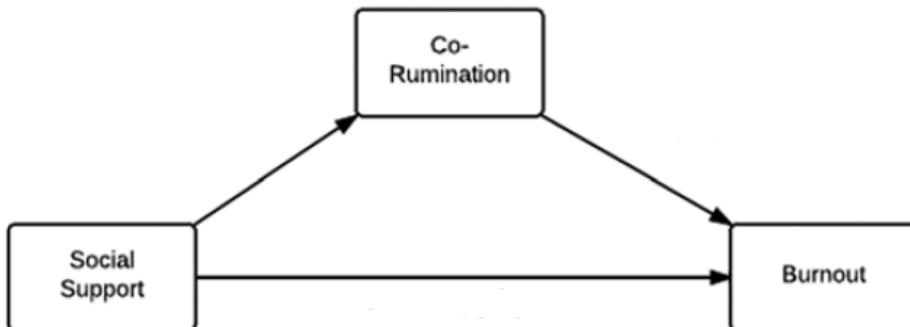
Some examples in the literature



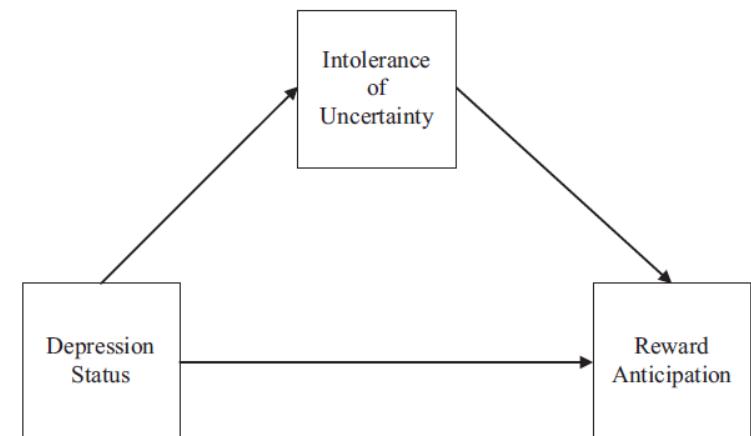
Lee, A. Y., Keller, P. A., & Sternthal, B. (2010). Value from regulatory construal fit: Persuasive impact of fit between consumer goals and message concreteness. *Journal of Consumer Research*, 36, 735-747.



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.

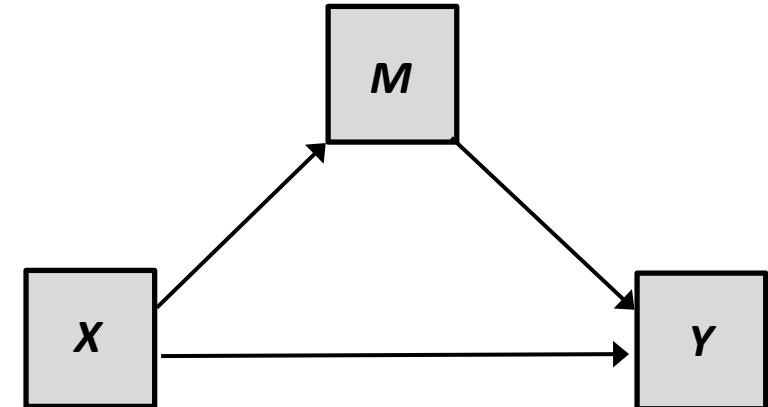


Nelson, B. D., Shankman, S. A., & Proudfit, G. H. (2014). Intolerance of uncertainty mediates reduced reward anticipation in major depressive disorder. *Journal of Affective Disorders*, 158, 108-113.

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?

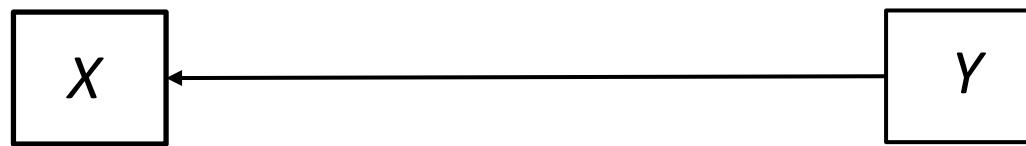
Experimental Manipulation:

Longitudinal Studies:

Cross-sectional Data Collection analyzed using Linear Regression:

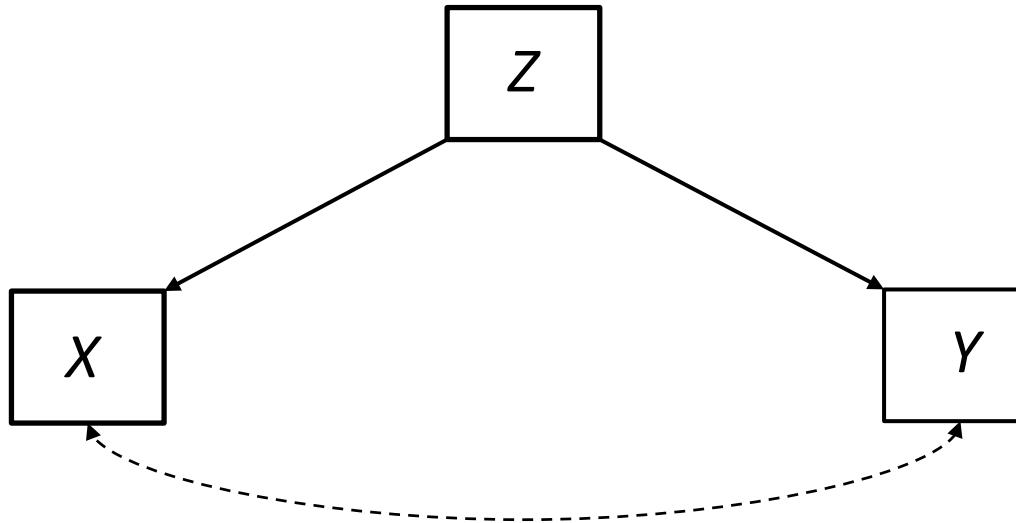
If it's not cause, what is it?

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.

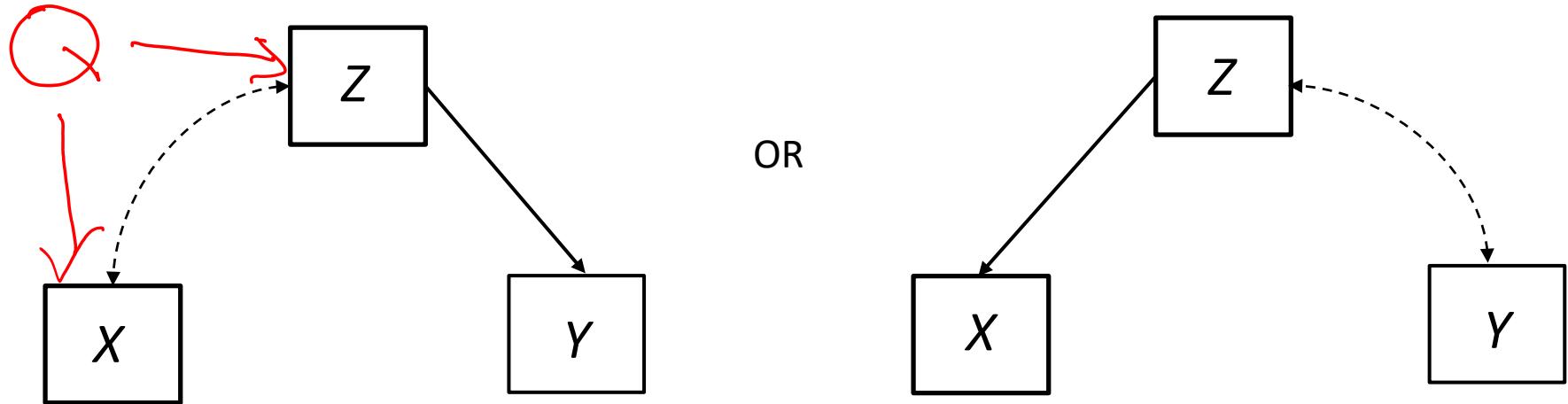


Example: [Skirt length theory](#) is one that suggests that skirt lengths predict the stock market (short skirt → market going up). Likely this is not a causal relationship but rather both skirt length and market trends are influenced by other larger cultural/economic trends.

Controlling for Z helps us eliminate spurious explanations.

If it's not cause, what is it?

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

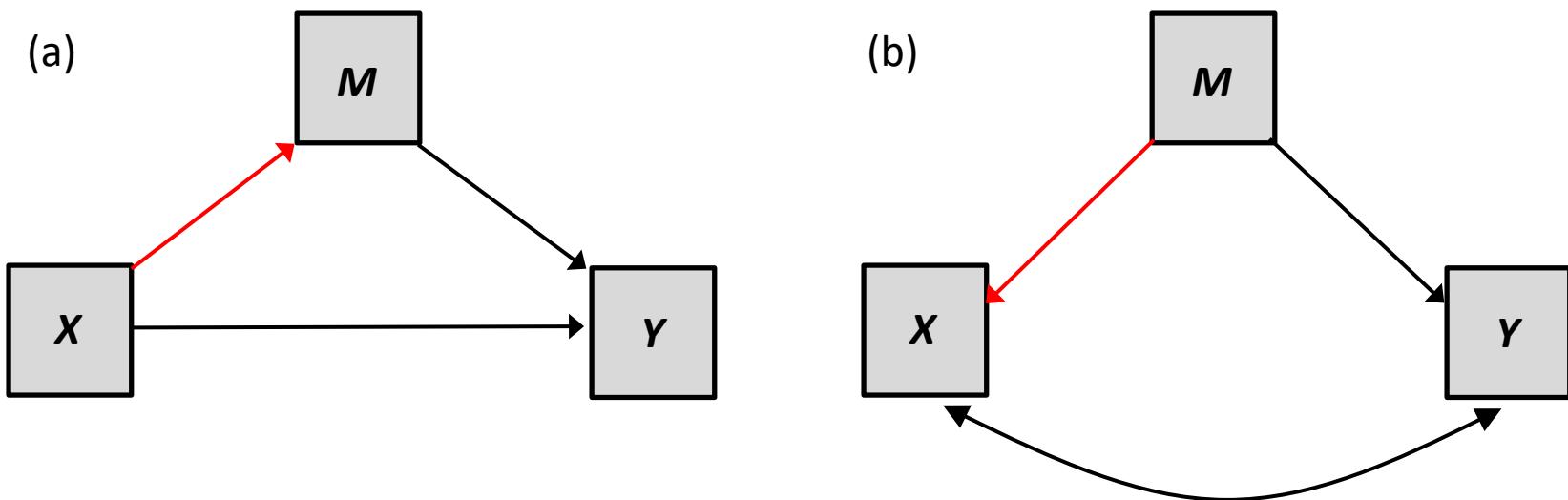


Example: Having an increased risk of breast cancer (Y) concurrent with taking an antibiotic is an **epiphenomenon**. It is not the antibiotic that is causing the increased risk, but the increased inflammation associated with the bacterial infection (Z) that prompted the taking of an antibiotic (X).

Controlling for Z helps us eliminate epiphenomenal explanations.

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.

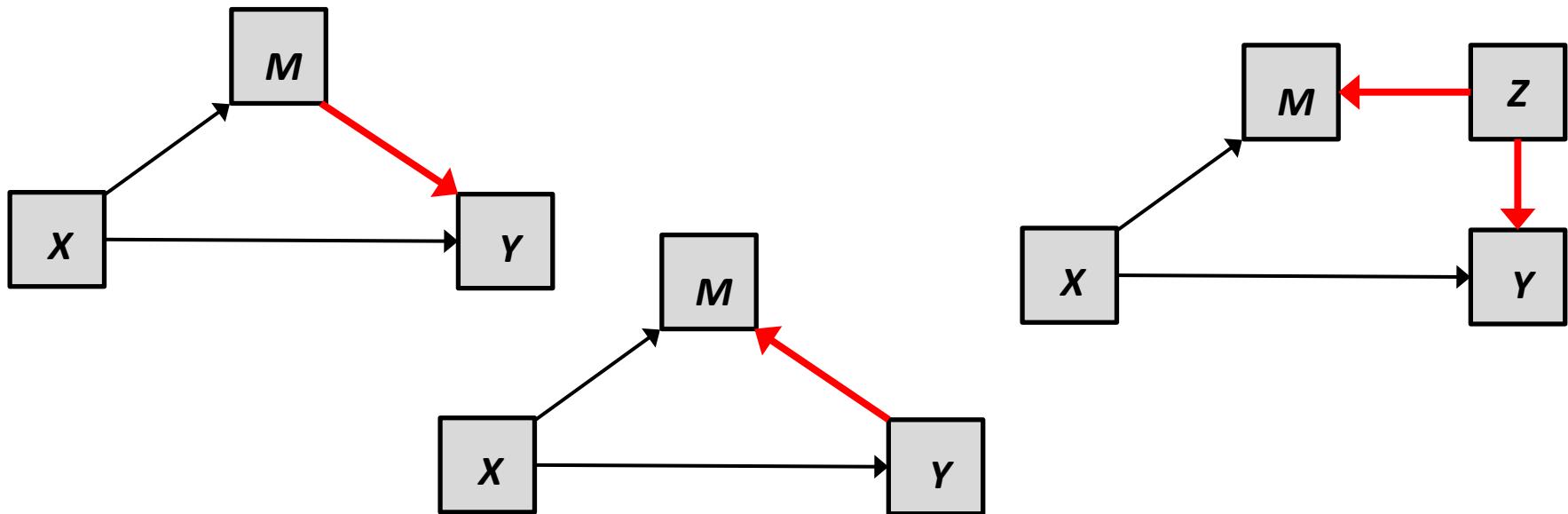


Inferences are always design-bound.

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

Manipulation of X

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 or confounding.

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.

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Psychological Science
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Inferring Whether Officials Are Corruptible From Looking at Their Faces



Chujun Lin, Ralph Adolphs, and R. Michael Alvarez

Division of Humanities and Social Sciences, California Institute of Technology

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

Received 9/25/17; Revision accepted 6/3/18

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, Duchaene, 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 (Genesky & Knutson, 2015; Hamermesh, 2011; Ravina, 2012), science communication (Gheorghiu, Callan, & Skylark, 2017), sentencing decisions (Berry & Zebowitz-McArthur, 1988; Blair, Judd, & Chapleau, 2004; Wilson & Rule, 2015; Zebowitz

& 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

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

Trait	Aggregate-level accuracy			Average individual-level accuracy ^a					
	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.

^aAll p s for this variable are less than .001.

Corresponding Author:

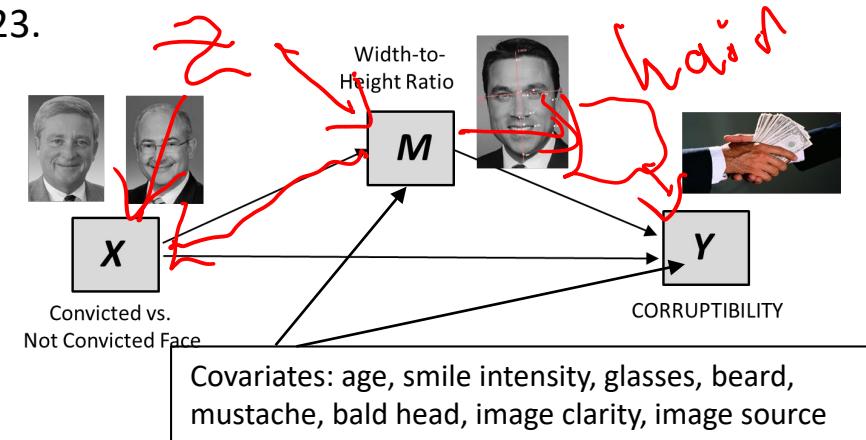
Chujun Lin, California Institute of Technology, Division of Humanities and Social Sciences, 1200 E. California Blvd., Pasadena, CA 91125
E-mail: clin7@caltech.edu

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?

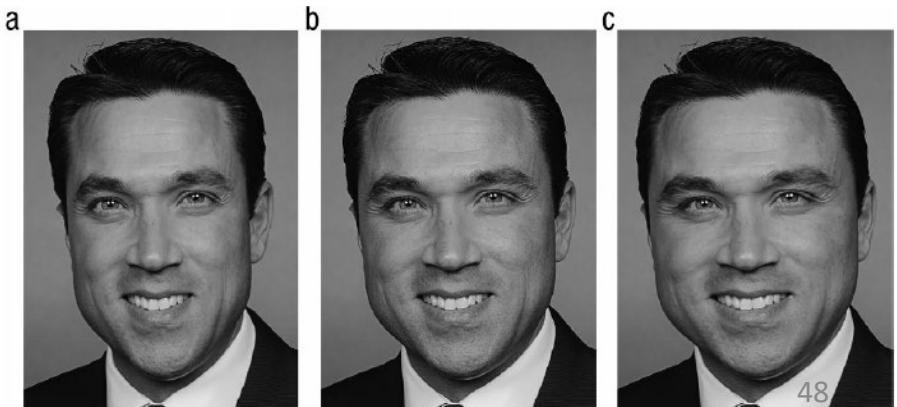


Fig. 6. Example of the same face in (a) slim, (b) original, and (c) fat versions.

Path analysis: Total, direct, and indirect effects

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)

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

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

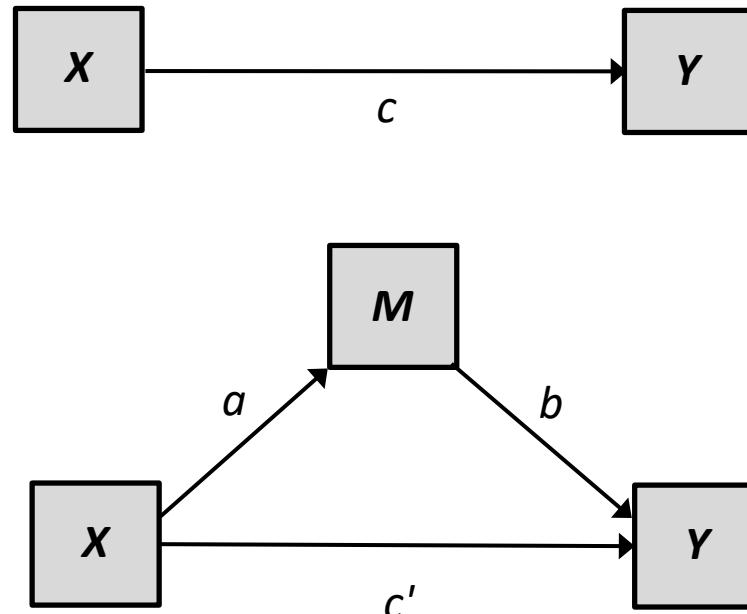
$$\widehat{Y}_i = c'_0 + c'X_i + bM_i$$

c = “total effect” of X on Y

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

c' = “direct effect” of X on Y

A “simple mediation” model



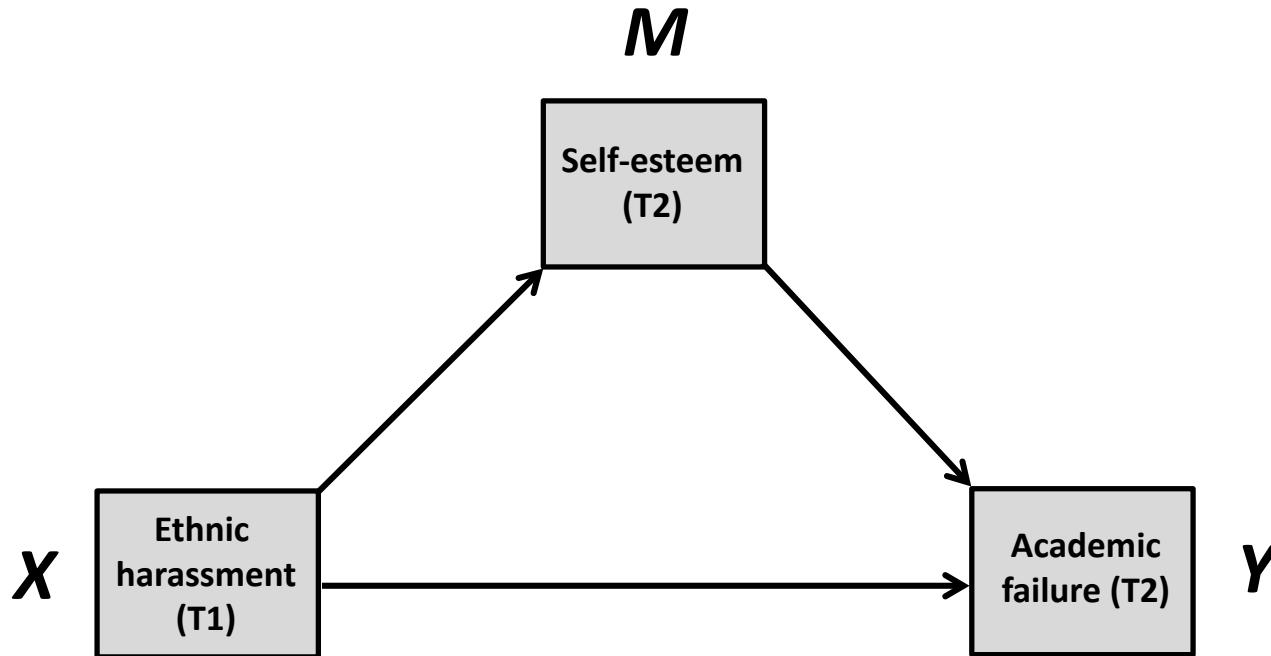
total effect = direct effect + indirect effect

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

indirect effect = total effect – direct effect

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

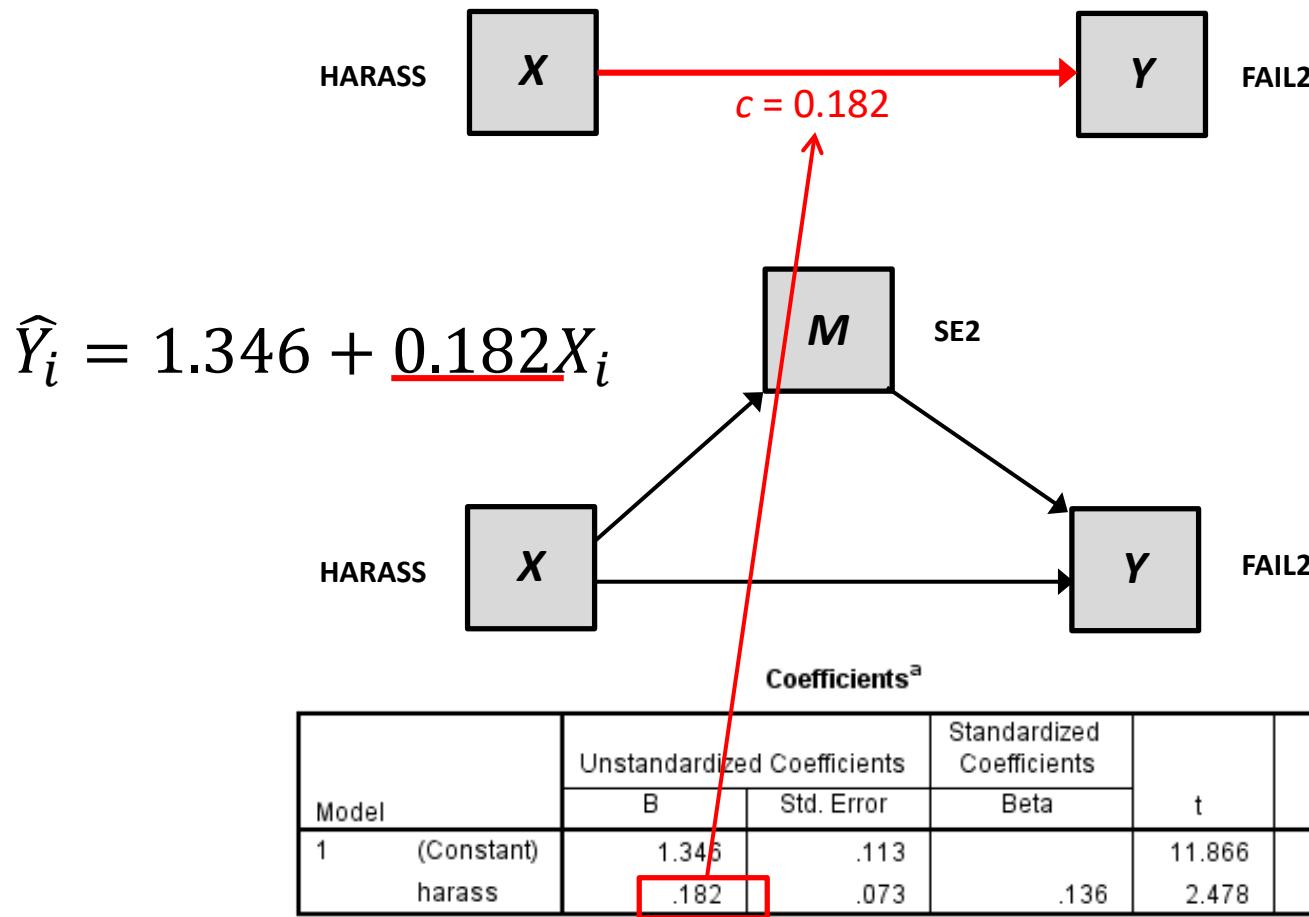
Our question



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



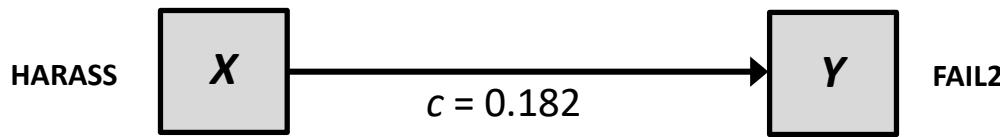
a. Dependent Variable: fail2

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

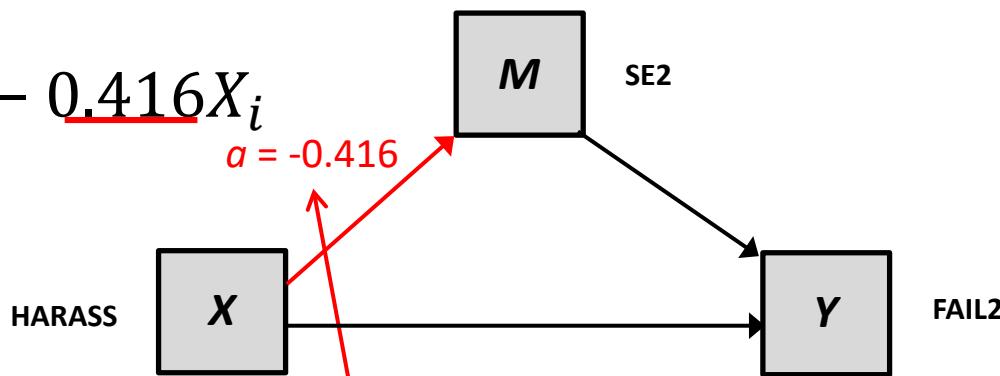
SAS: `proc reg data=harass;model fail2=harass;run;`

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		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1	3.597	.123		29.123	.000
harass	-416	.080	-.276	-5.209	.000

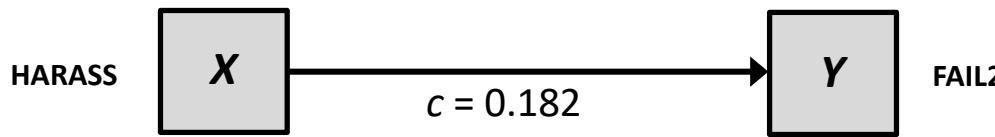
a. Dependent Variable: se2

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

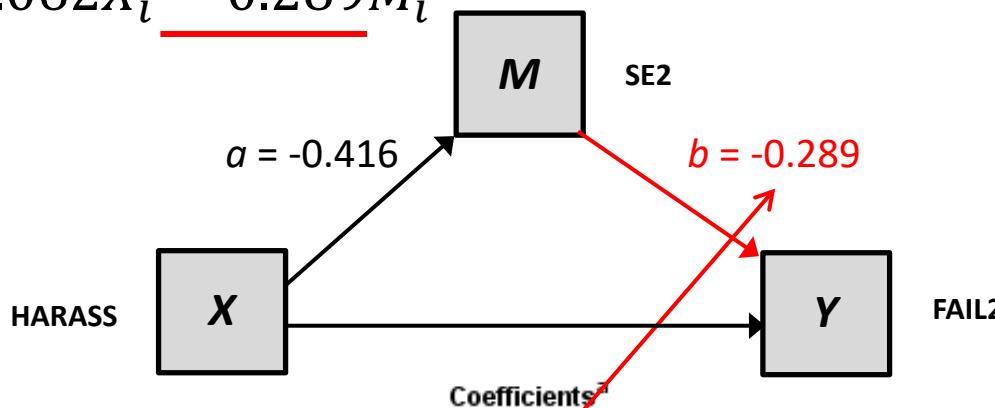
`proc reg data=harass;model se2=harass;run;`

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

Using a set of OLS regression analyses



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



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

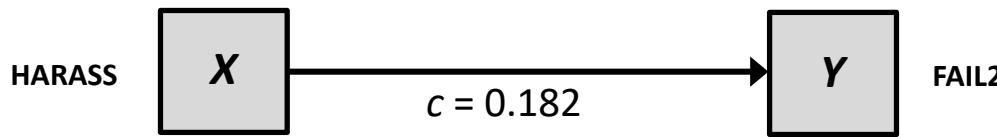
a. Dependent Variable: fail2

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

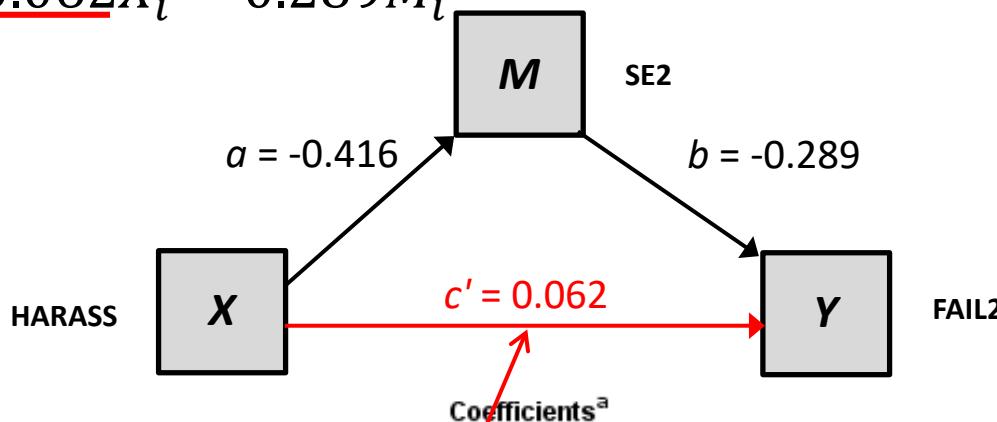
```
proc reg data=harass;model fail2=harass se2;run;
```

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

Using a set of OLS regression analyses



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



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

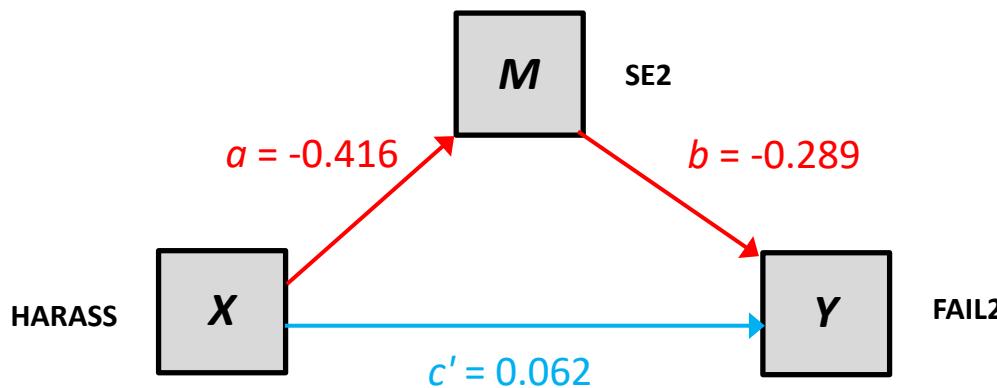
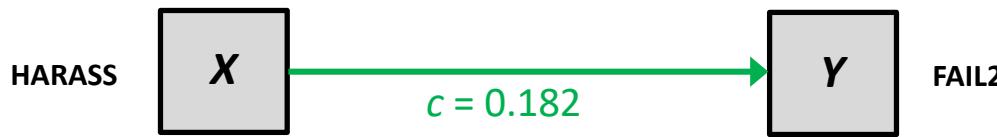
a. Dependent Variable: fail2

```
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.

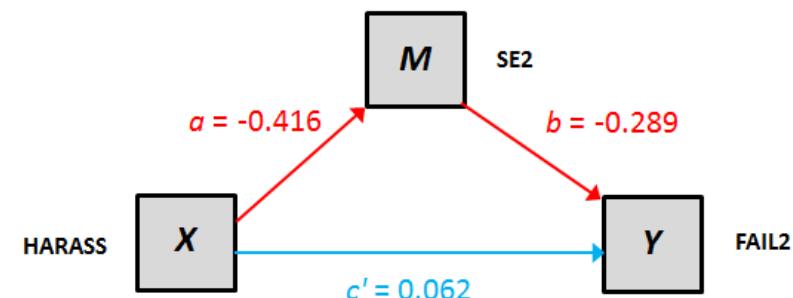
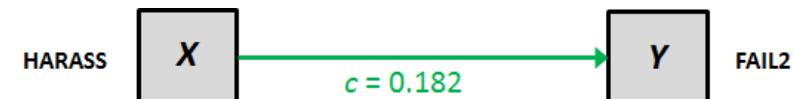
Indirect: They differ by ab units on average as a result of the effect of X on M which in turn affects Y .

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

$$\text{Direct effect} = c' = 0.062$$

$$\text{Indirect effect} = ab = -0.416(-0.289) = 0.120$$

$$\text{Total effect} = c = 0.062 + 0.120 = 0.182$$



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 \rightarrow FAIL2 (Total Effect):

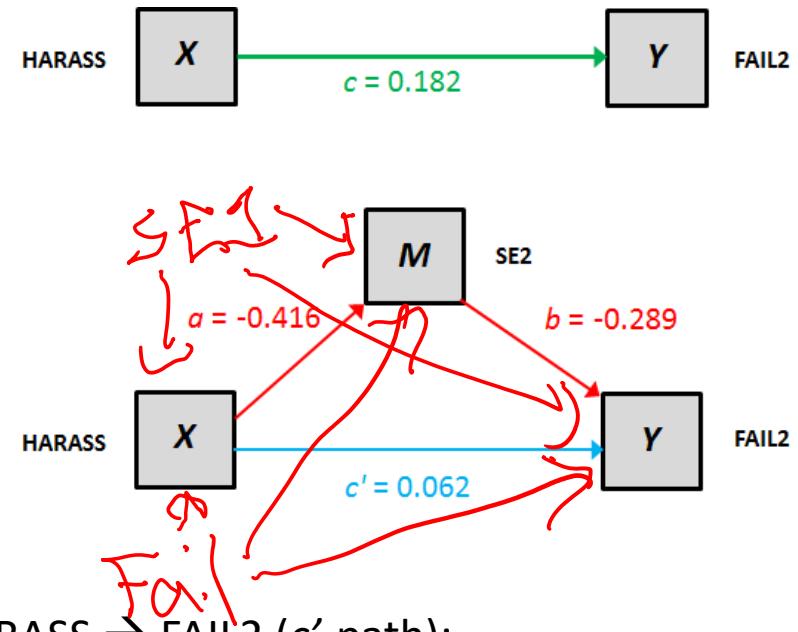
- Covariation ✓
- Temporal Ordering ✓
- Elimination of competing explanations ✗

HARASS \rightarrow SE2 (a -path):

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

SE2 \rightarrow FAIL2 (b -path):

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



HARASS \rightarrow 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

DONNA M. GARCIA^{1*}, MICHAEL T. SCHMITT²,

NYLA R. BRANSCOMBE³ AND NAOMI ELLEMERS⁴

¹University of Guelph, Canada

²Simon Fraser University, Canada

³University of Kansas, USA

⁴Leiden 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.
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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. Mentor Savings Bank vs. Vinson, 477 US 57, 1986; Dekker vs. VIV-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

*Correspondence to: Donna M. Garcia, Department of Psychology, University of Guelph Ontario, Guelph, Ontario, N1G 2W1 Canada.
E-mail: donnagarcia3@gmail.com

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

The screenshot shows the IBM SPSS Statistics Data Editor window. The title bar reads "*protest.sav [DataSet1] - IBM SPSS Statistics Data Editor". The menu bar includes File, Edit, View, Data, Transform, Analyze, Graphs, Utilities, Add-ons, Window, and Help. Below the menu is a toolbar with various icons. The data view shows 14 rows of data across 8 columns. The columns are labeled: subnum, cond, sexism, angry, liking, respappr, and protest. The data values range from 0 to 209.

	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.

The screenshot shows a SAS code editor window titled "protest". The code defines a dataset "protest" with variables: subnum, cond, sexism, angry, liking, respappr, and protest. It uses the "cards" statement to input the data from the previous SPSS screenshot. The data is displayed in a yellow-highlighted area.

```
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

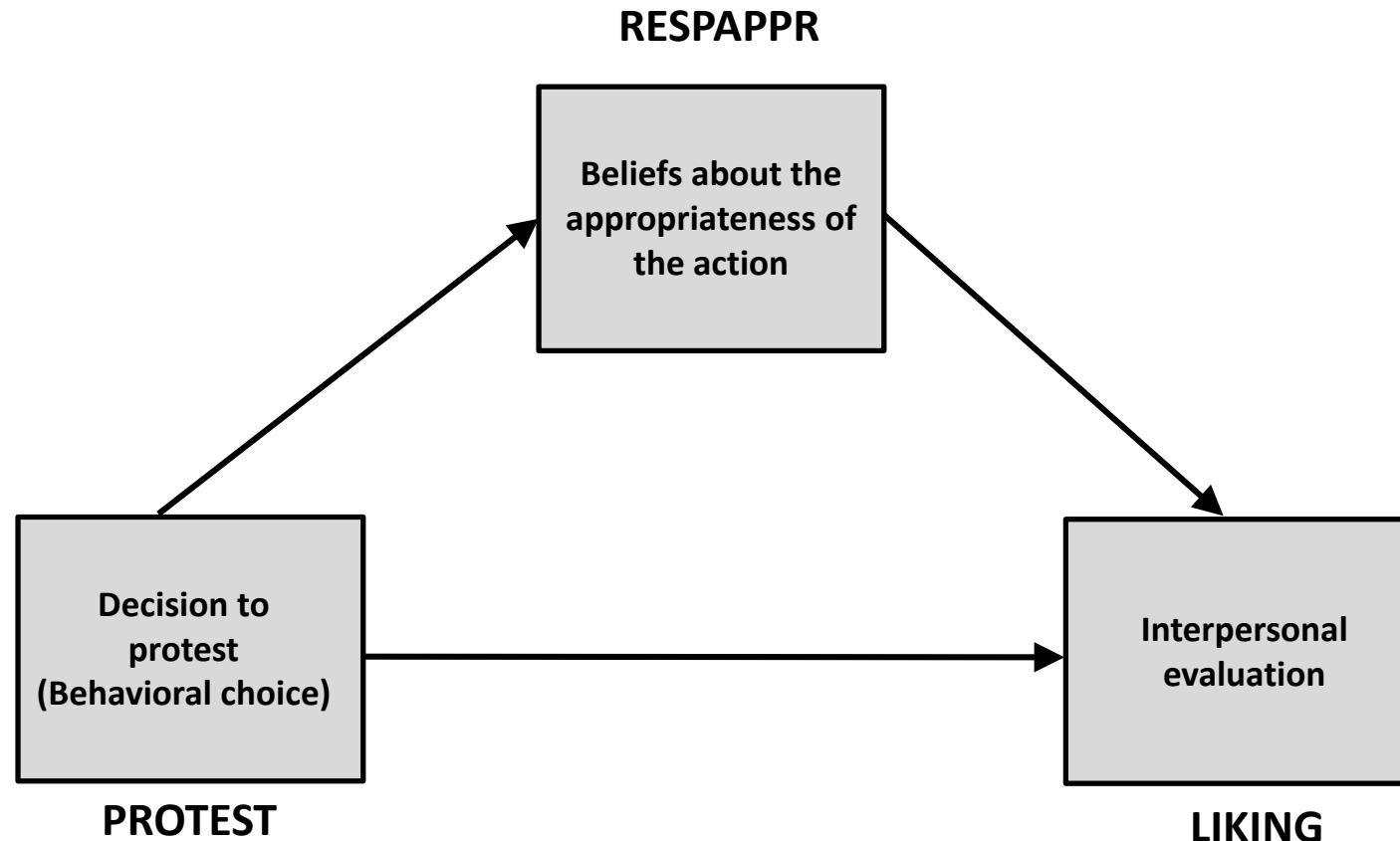
```

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)

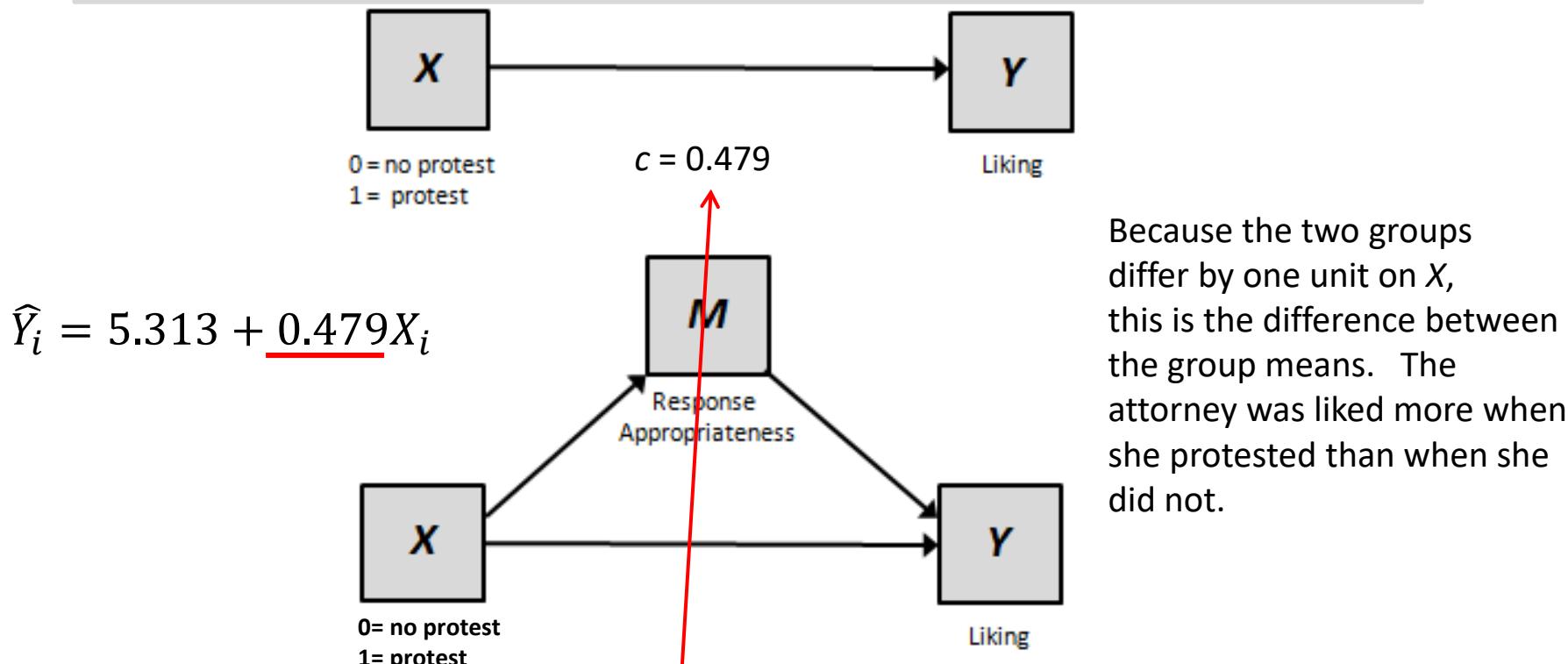
Our question



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



Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
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)**

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

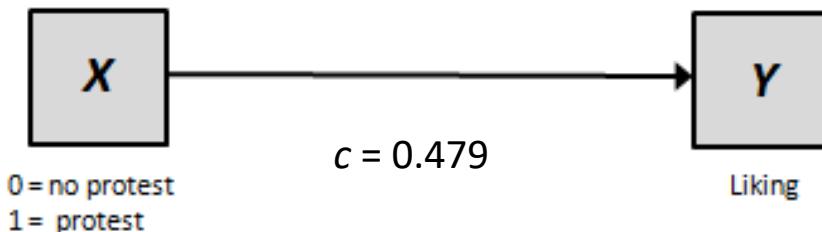
Notice that with X coded 0 and 1, the model yields the group means, b is the difference between the group means, and *the regression constant* is the mean for the group coded $X = 0$ (no protest condition).

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,

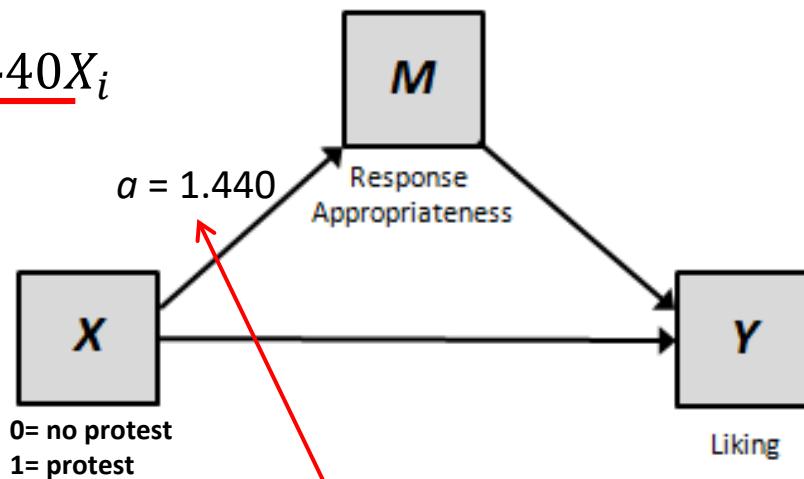
$$c = (\bar{Y}_1 - \bar{Y}_2)/\lambda$$

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.

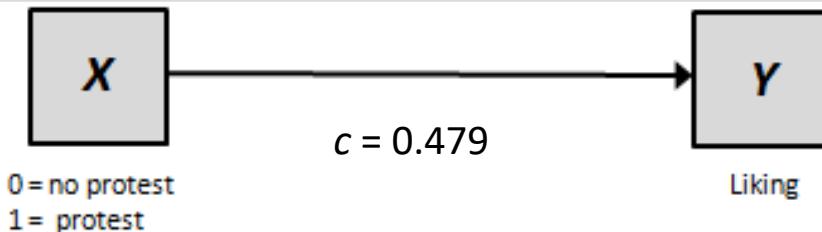
Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
1 (Constant)	3.884	.183		21.208	.000
X: experimental condition (0 = no protest, 1 = protest)	1.440	.222	.499	6.493	.000

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

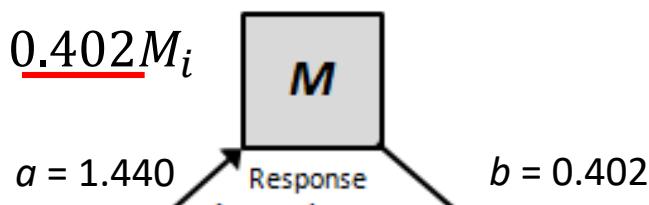
```
proc reg data=protest;model respappr=protest;run;
```

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

Using a set of OLS regression analyses



$$\hat{Y}_i = 3.751 - 0.100X_i + \underline{0.402M_i}$$



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

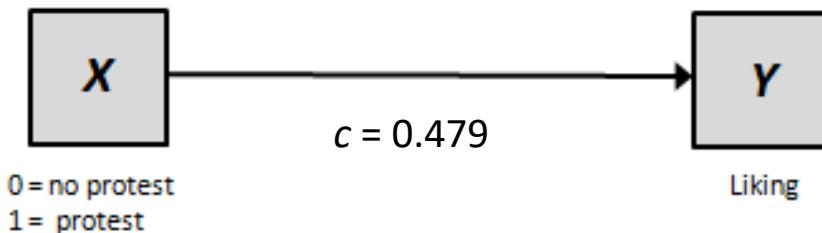
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error			
1 (Constant)	3.751	.306		12.271	.000
M: appropriateness of response	.402	.069	.517	5.789	.000
X: experimental condition (0 = no protest, 1 = protest)	-.100	.200	-.045	-.501	.617

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

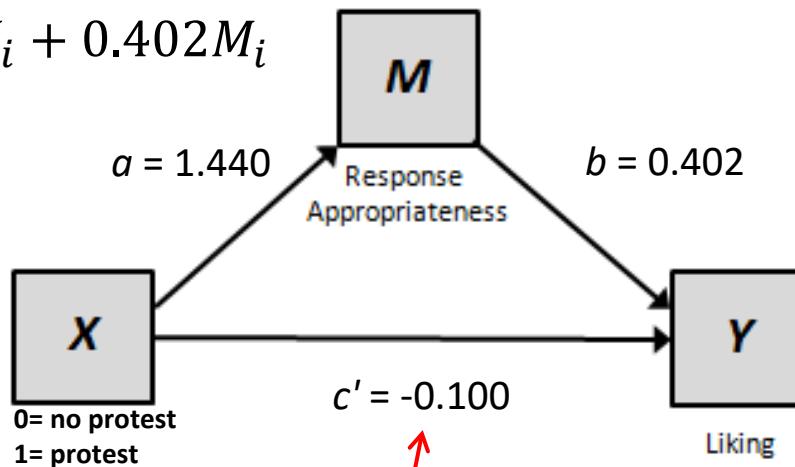
`proc reg data=protest;model liking=respappr protest;run;`

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

Using a set of OLS regression analyses



$$\hat{Y}_i = 3.751 - 0.100X_i + 0.402M_i$$



Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
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)
```

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)

Interpretation of 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 .

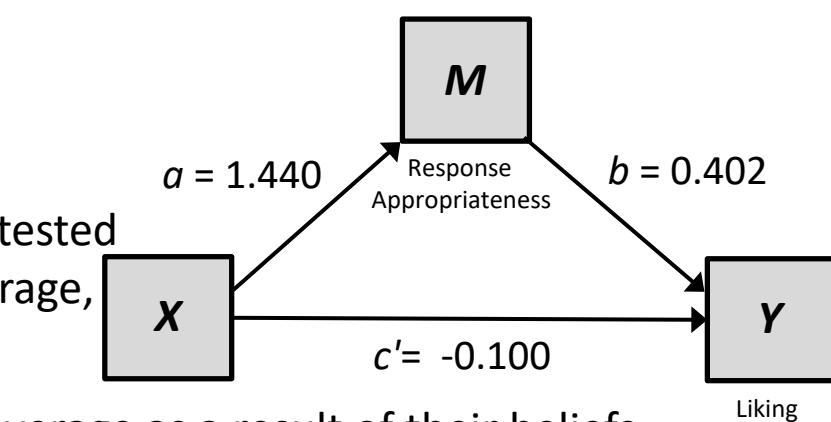
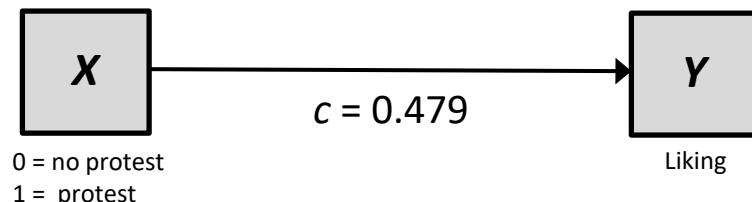
Specific

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.

Direct effect = -0.100

Indirect Effect = $1.440(0.402) = 0.579$

Total effect = $-0.100 + 0.579 = 0.479$



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 \rightarrow LIKING (Total Effect):

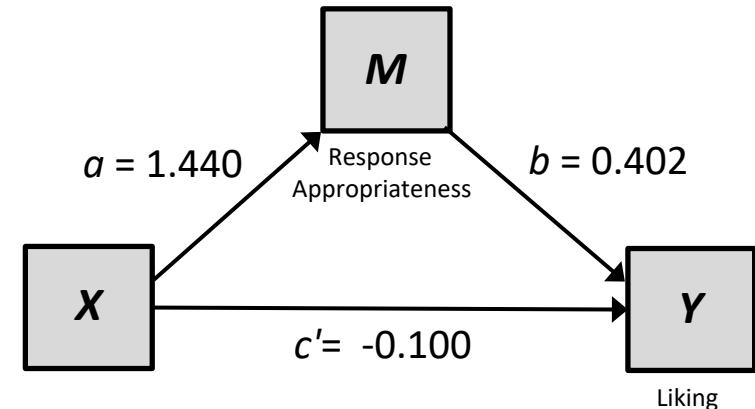
- Covariation ✓
- Temporal Ordering ✓
- Elimination of competing explanations ✓

PROTEST \rightarrow RESPAPPR (a -path):

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

RESPAPPR \rightarrow LIKING (b -path):

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



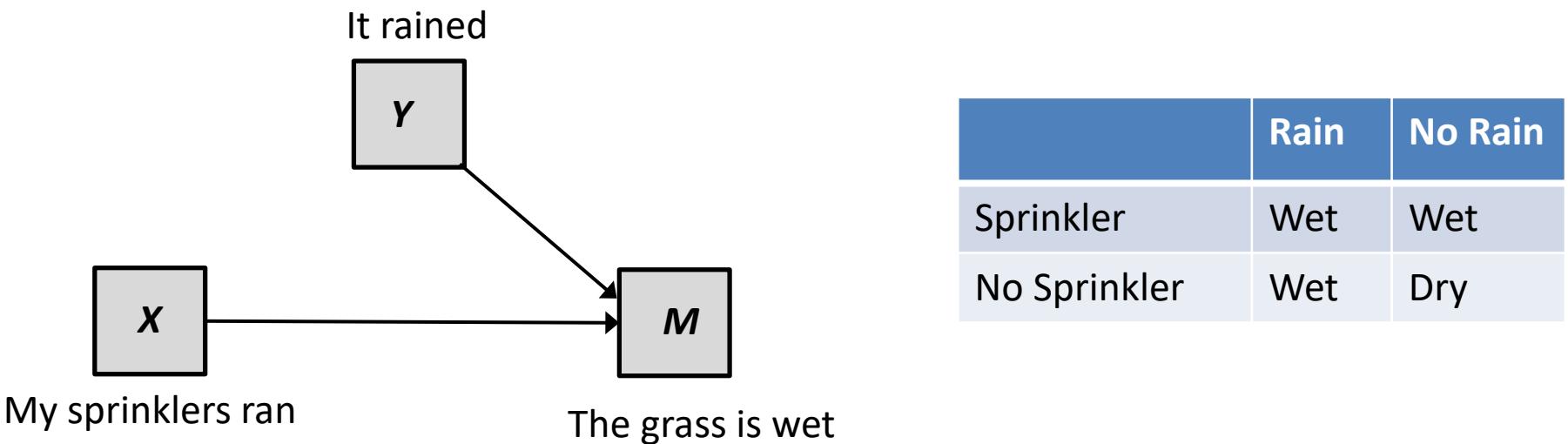
PROTEST \rightarrow LIKING (c' -path):

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

Aside: Conditioning on a Collider

It may not be immediately apparent why conditioning on the mediator impacts causal inference for the total vs. direct effect

If the mediator is a collider, then the direct effect may be inaccurate, even for an experiment.



X and Y are independent (without any controls)

If I control for M in a model of Y, then X is related to Y (which is an incorrect estimate of the causal effect of X on Y)

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 $M \rightarrow Y$ relationship, none is needed for $X \rightarrow M$, and $X \rightarrow Y$ because of randomization

Statistical Inference

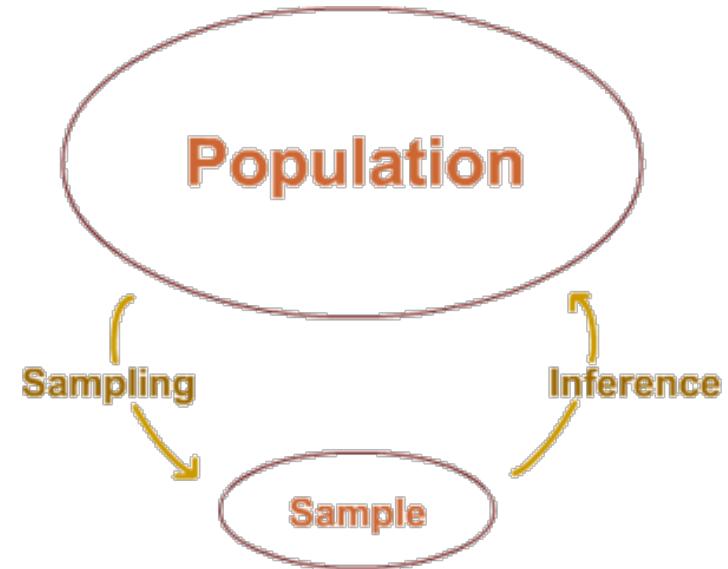
Statistical inference: The indirect effect

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.

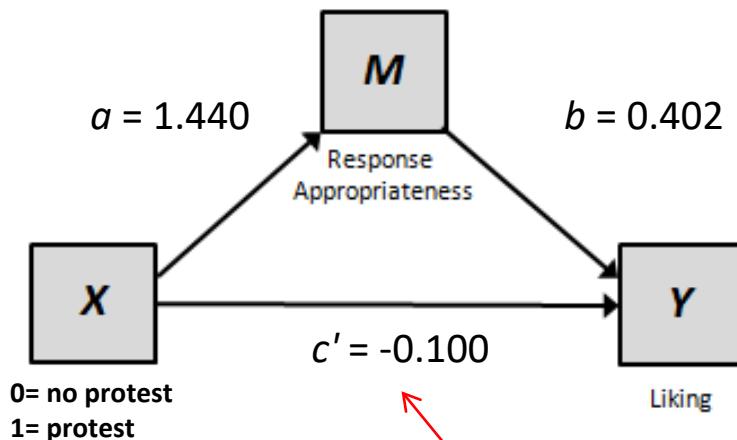
Methods of inference:

- 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 Beta	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error				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

^a Dependent Variable: LIKING: Liking of the target

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

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

Indirect effect → ab

“Second order” estimator of the standard error of ab → $\sqrt{b^2 s_a^2 + a^2 s_b^2 + S_a^2 S_b^2}$

One version eliminates this term (“first order” estimator), $S_a^2 S_b^2$

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

$$a = 1.440 \quad s_a = 0.222$$

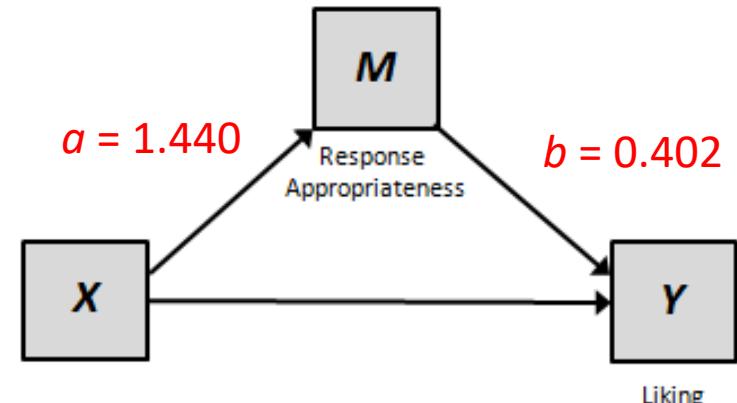
Model	Unstandardized Coefficients		Standardized Coefficients		t	Sig.
	B	Std. Error	Beta			
1	(Constant) 3.984	.183			21.208	.000
	X: Protest 1.440	.222	.499		6.493	.000

a. Dependent Variable: RESPAPPR: appropriateness of response

Model	Unstandardized Coefficients		Standardized Coefficients		t	Sig.
	B	Std. Error	Beta			
1	(Constant) 3.747	.306			12.255	.000
	RESPAPPR: appropriateness of response .402	.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

$$b = 0.402 \quad s_b = 0.070$$



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

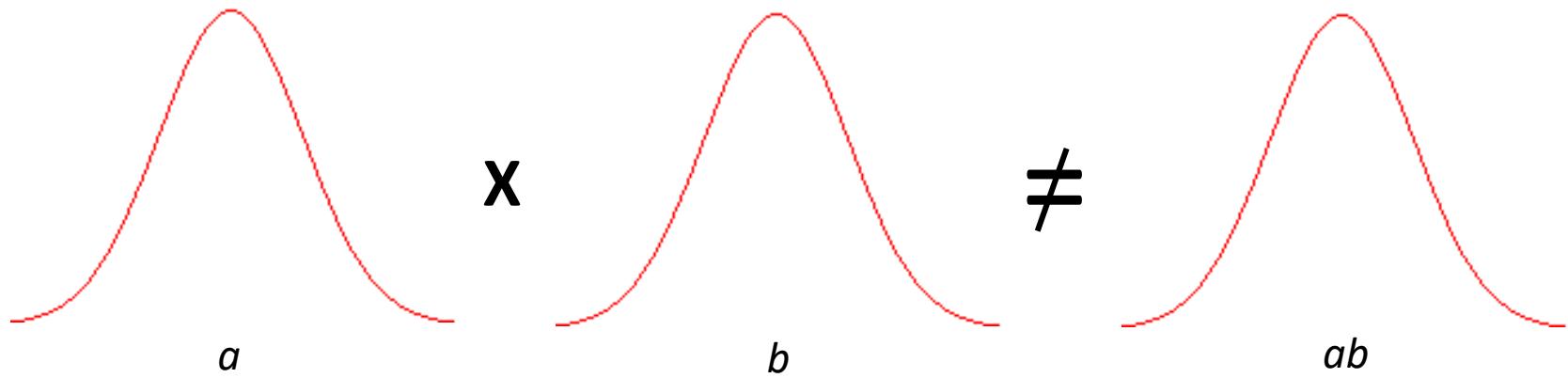
$$(1.440)(0.402)$$

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

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 large sample theory.



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 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

$$a = -0.051 \quad b = -0.844$$

$$ab = 0.043$$

$$a = 0.020 \quad b = -0.921$$

$$ab = -0.018$$

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

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

$$a = -0.051 \quad b = -0.844$$

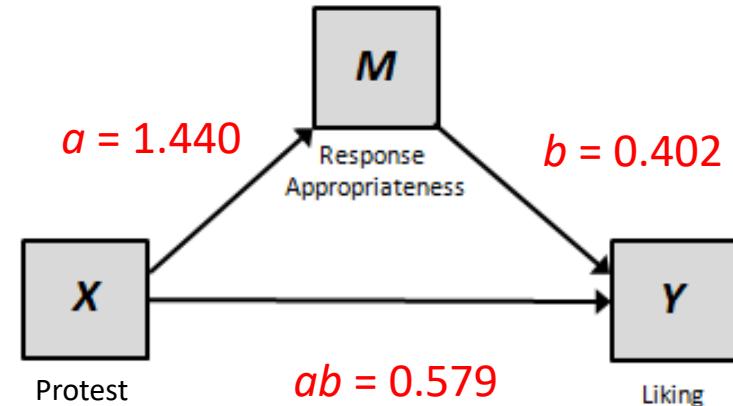
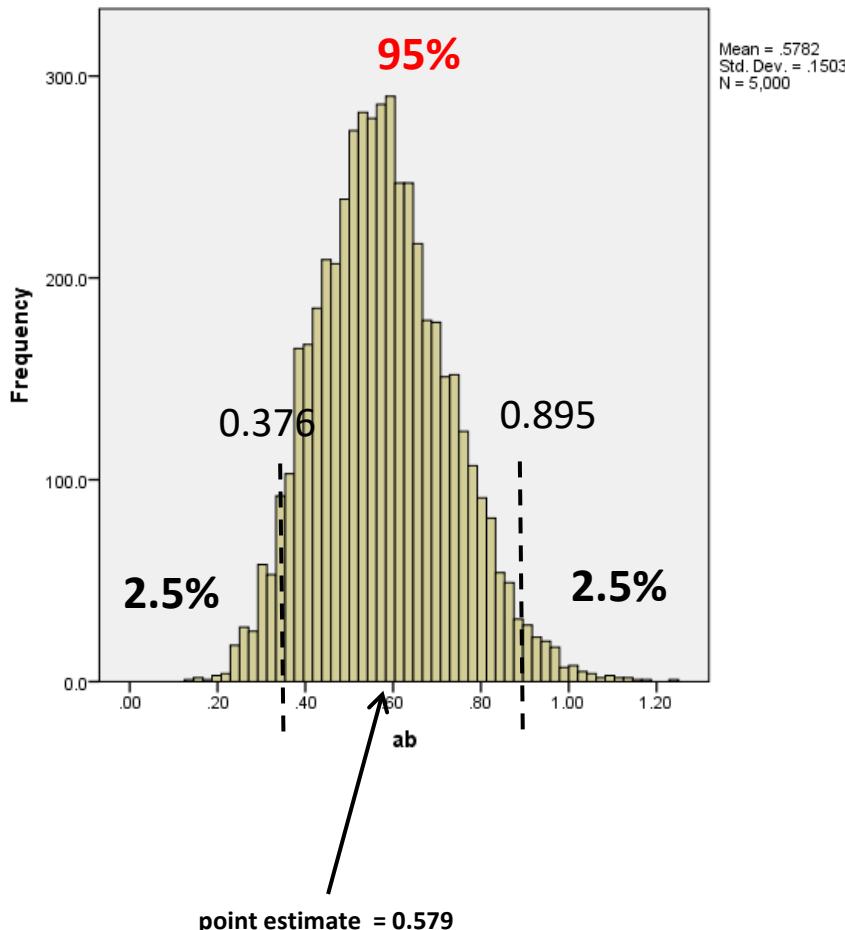
$$ab = 0.043$$

$$a = -0.034 \quad b = 0.523$$

$$ab = -0.017$$

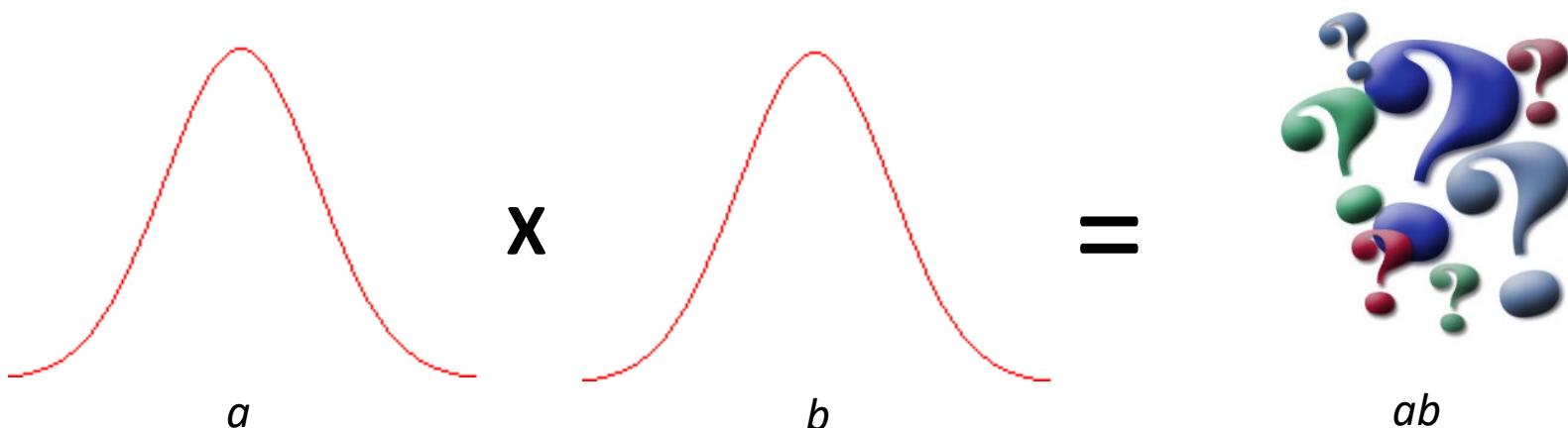
5,000 bootstrap estimates of the indirect effect

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 $\alpha = 0.05$ 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.

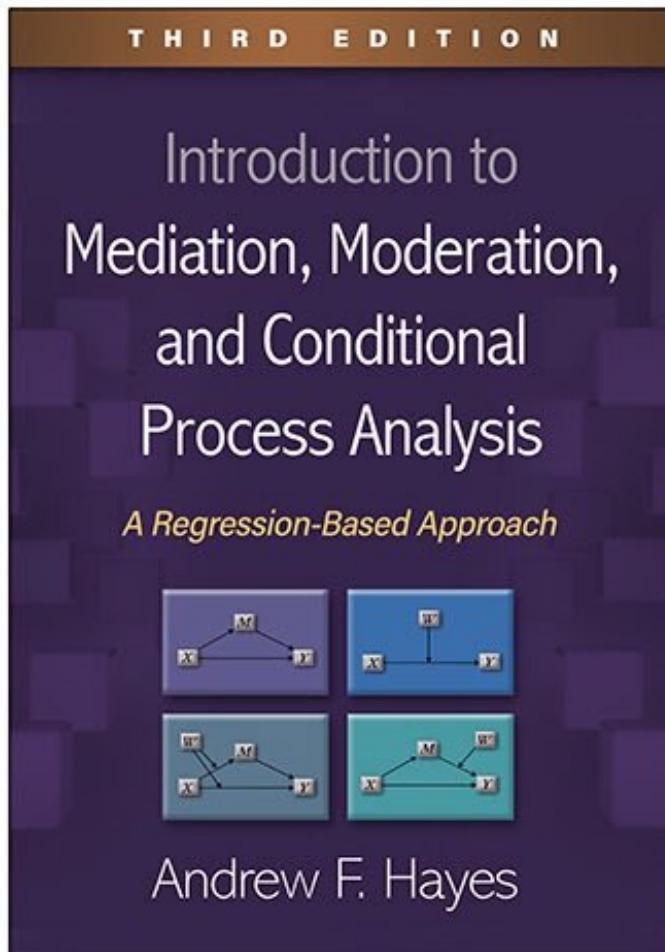
This method makes stronger assumptions than bootstrapping, but does not result in great power.

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 both SPSS (in macro and “custom dialog” form) and SAS.
- 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

[HOME](#)[DOWNLOAD](#)[WORKSHOPS](#)[PAPERS](#)[FAQ](#)[VERSION HISTORY](#)

The PROCESS macro for SPSS, SAS, and R



PROCESS operates on both Windows and Mac versions of SPSS and SAS. PROCESS for SPSS requires SPSS version 19 or later but works best on versions 22 and above. PROCESS for SAS requires PROC IML. PROCESS for R was written in R base 3.6.1 and requires no additional packages. Downloading this software implies you have familiarized yourself with and understand the copyright notice and disclaimer below and will comply. This notice is available in the zip archive.

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.

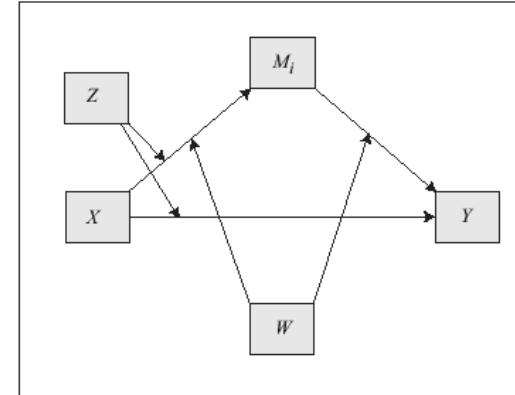
This documentation focuses on the SPSS version of PROCESS. All features and functions described below are available in the SAS version as well and work as described here, with minor modifications to the syntax. At the end of this documentation (see page 438), a special section devoted to SAS describes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

Overview

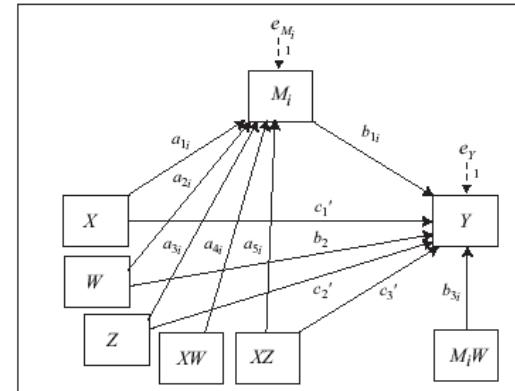
PROCESS is a computational tool for path analysis-based moderation and mediation analysis as well as their integration in the form of a conditional process model. In addition to estimating unstandardized model coefficients, standard errors, *t* and *p*-values, and confidence intervals using either OLS 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-

Model 62

Conceptual Diagram

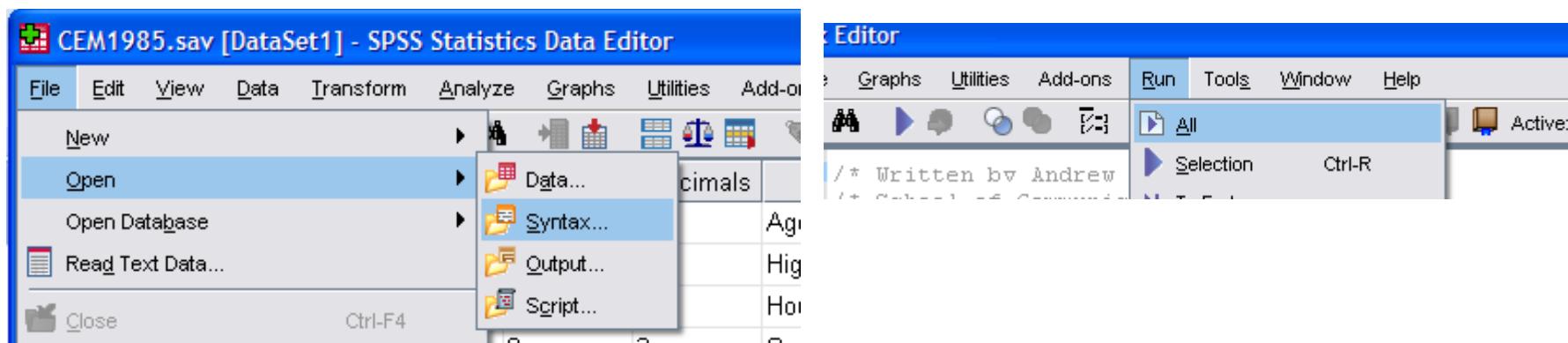


Statistical Diagram



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.

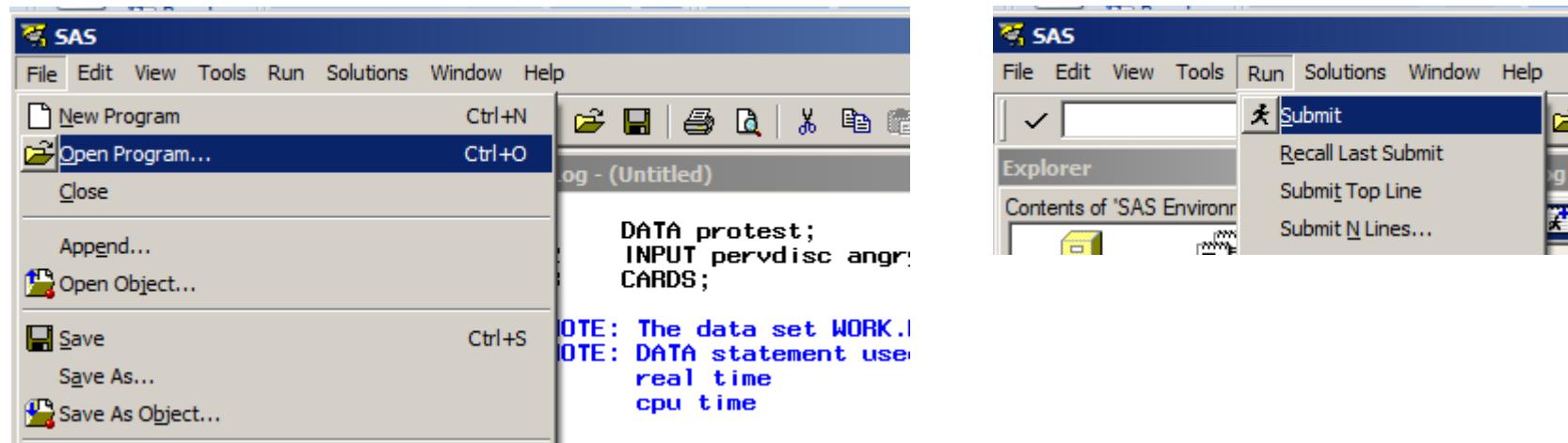


Once PROCESS is defined, you can run a properly-formatted PROCESS command in a new syntax window. Such a command might look something like below. Not all of the arguments below are required.

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

PROCESS 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.



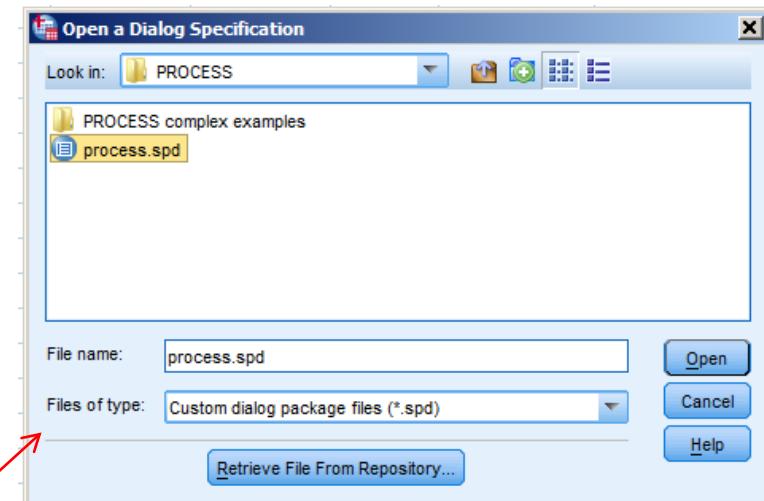
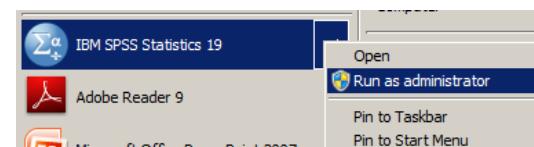
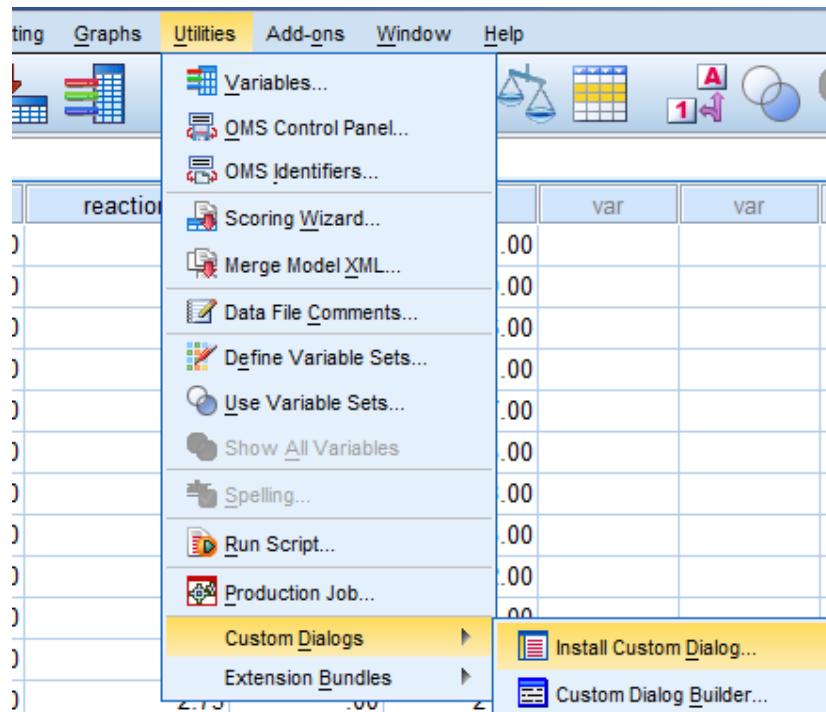
Once PROCESS is defined, you can run a properly-formatted PROCESS command in a new syntax window. Such a command might look something like below. Not all of the arguments below are required.

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

PROCESS “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.**

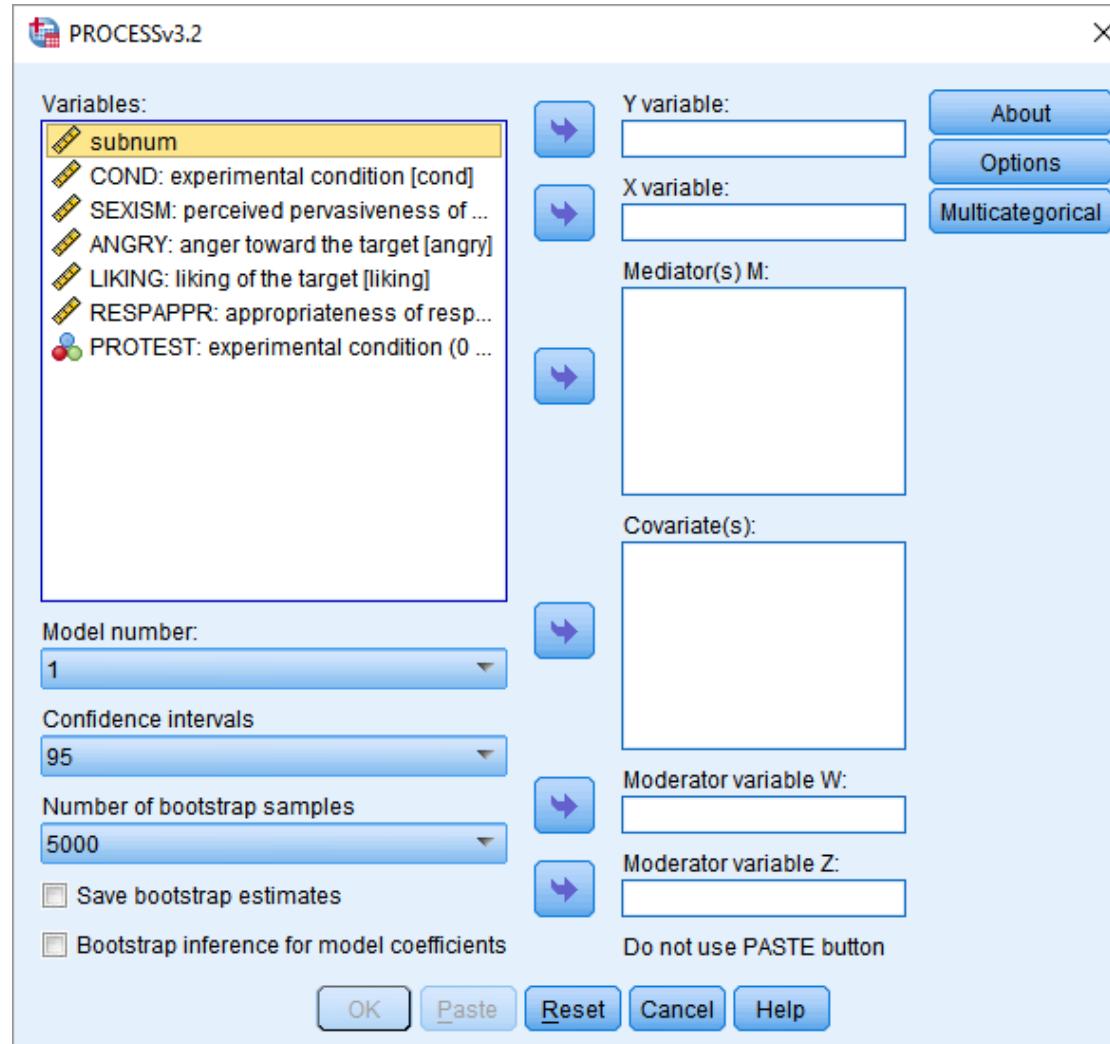
In SPSS 23 and earlier:



When installed, PROCESS can be found under “Analyze”→“Regression”

In SPSS24, look under “Extensions” for the Utilities option

PROCESS “Custom Dialog”

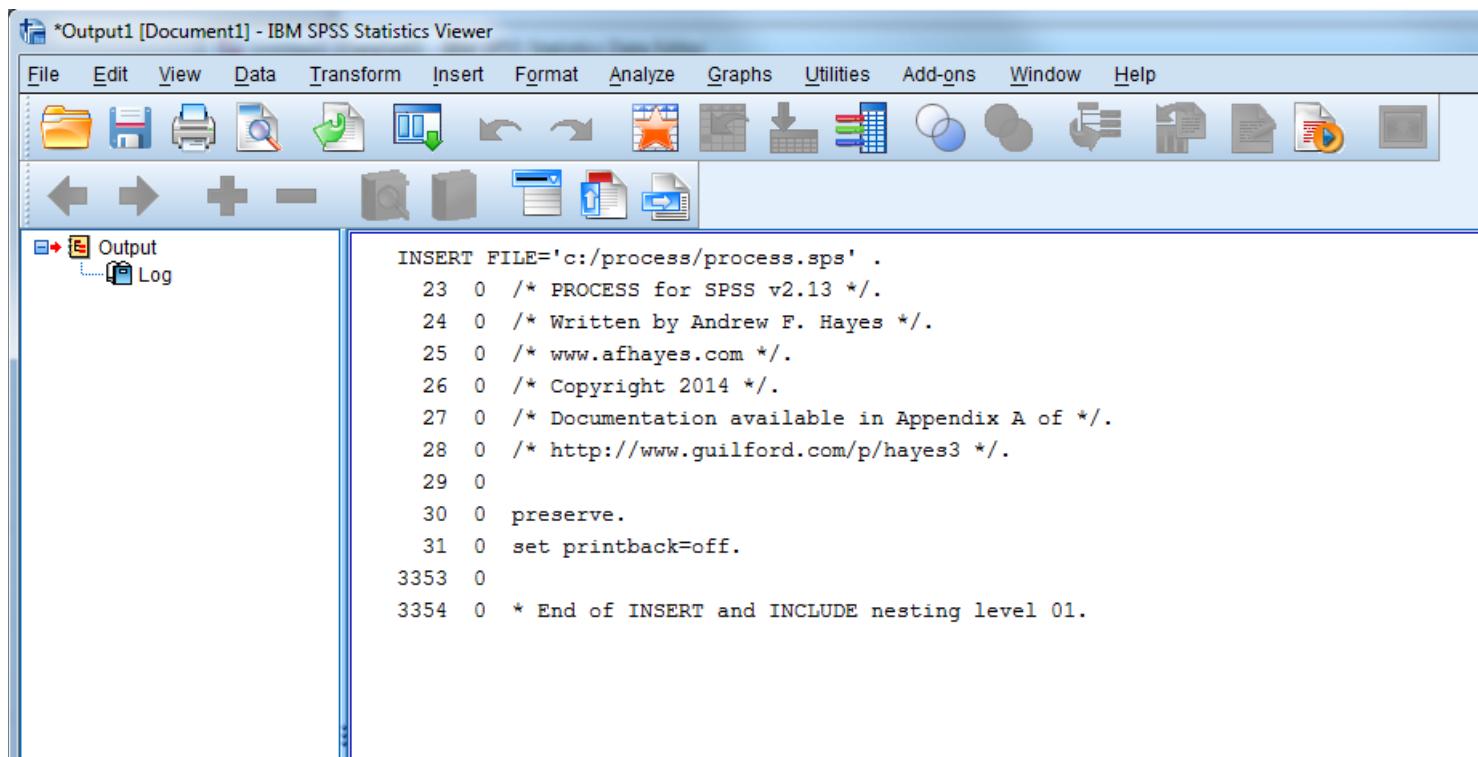


Installing the dialog box does not eliminate the need to run the PROCESS code if you plan on executing with syntax. And don't use the PASTE button.

Autoexecution

It is possible to get SPSS to execute the PROCESS code on its own when SAS/SPSS executes. A document is provided to you with the course files that provides instructions for SPSS for Windows and Mac.

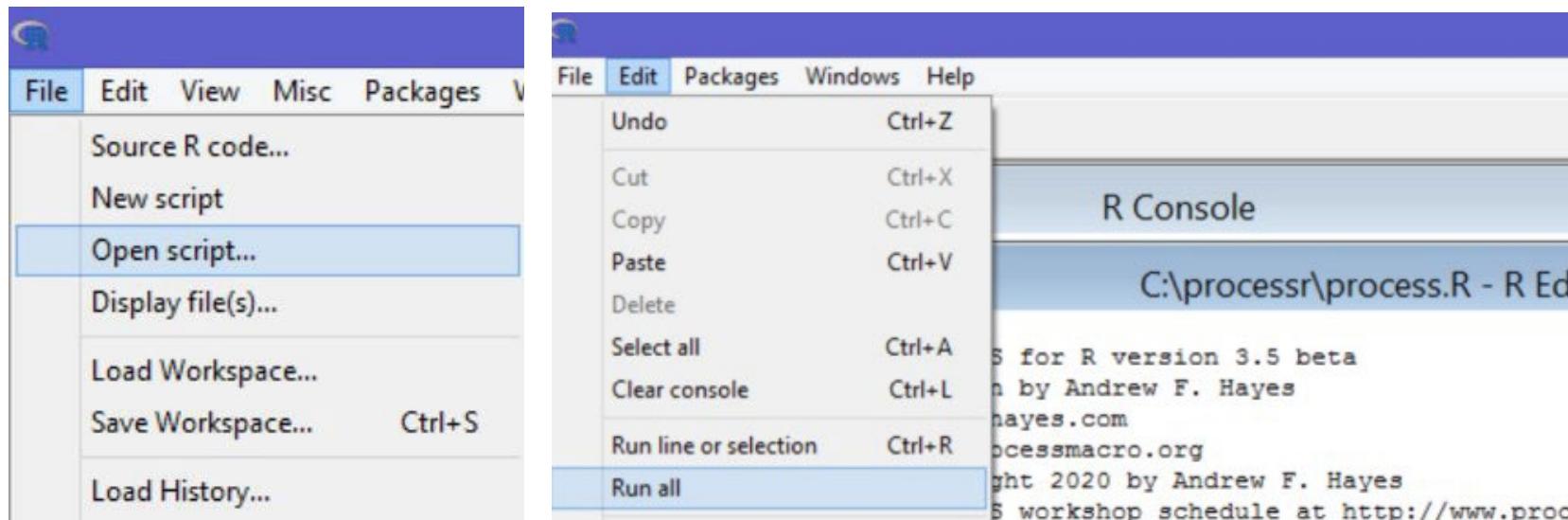
When successful, SPSS for Windows users typically see something like the following in the output window when SPSS is opened:



```
INSERT FILE='c:/process/process.sps'.
23 0 /* PROCESS for SPSS v2.13 */.
24 0 /* Written by Andrew F. Hayes */.
25 0 /* www.afhayes.com */.
26 0 /* Copyright 2014 */.
27 0 /* Documentation available in Appendix A of */.
28 0 /* http://www.guilford.com/p/hayes3 */.
29 0
30 0 preserve.
31 0 set printback=off.
3353 0
3354 0 * End of INSERT and INCLUDE nesting level 01.
```

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.

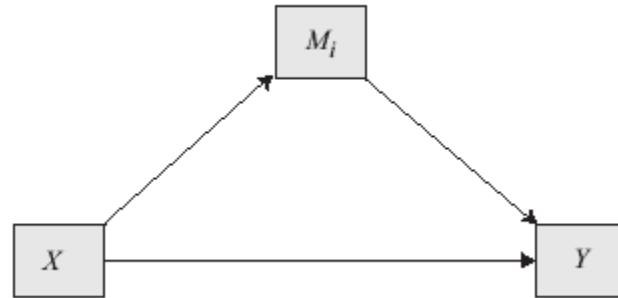
Model template system

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.

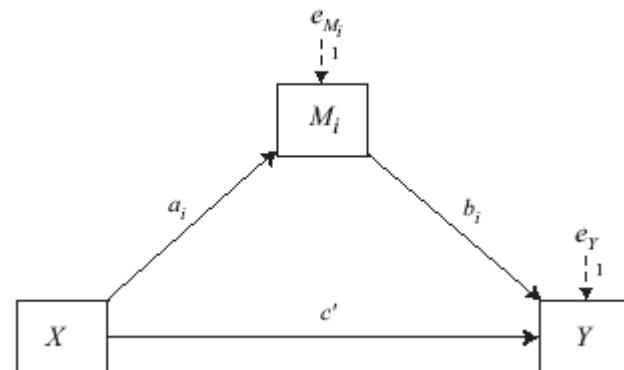
Example #1:

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)

Conceptual diagram



Statistical diagram



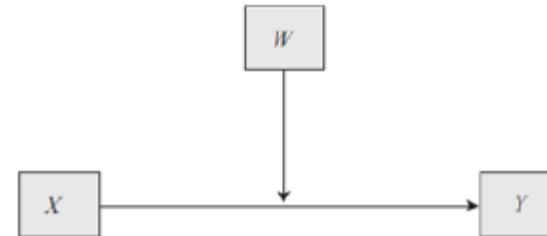
Model template system

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

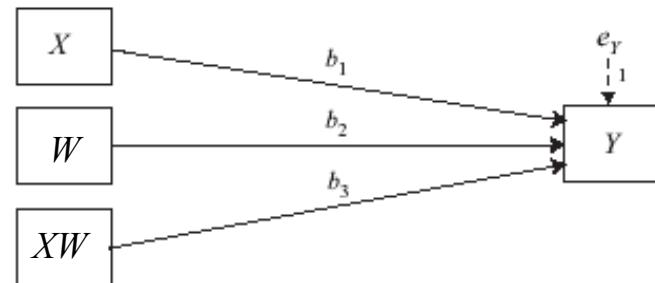
Example #2:

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



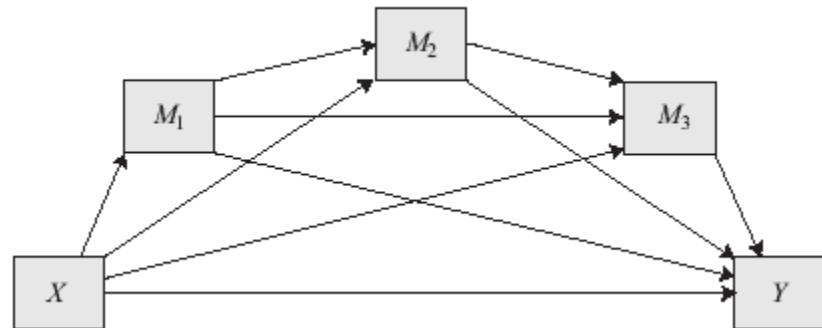
Model template system

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.

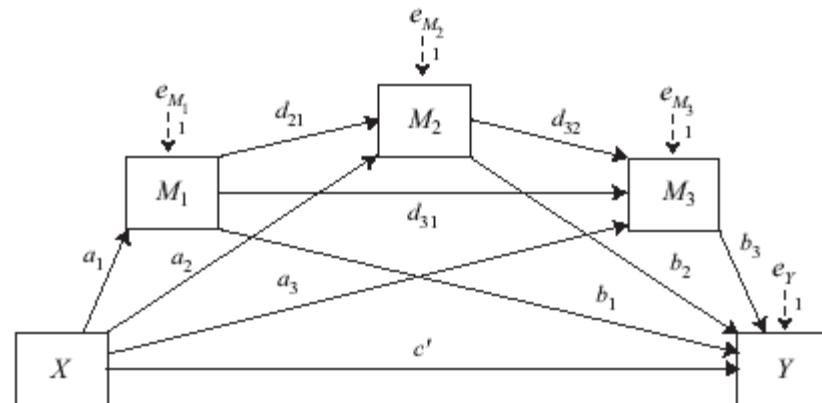
Example #3:

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



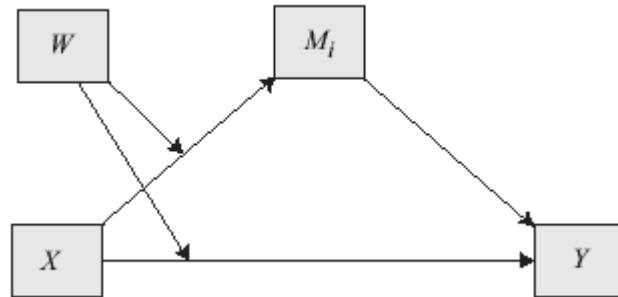
Model template system

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.

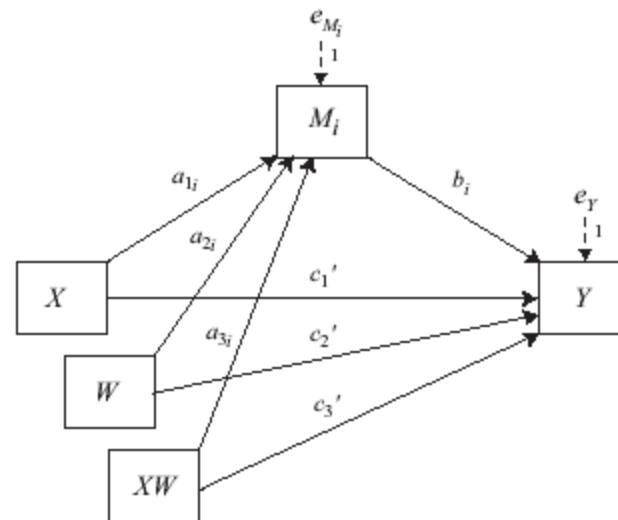
Example #4:

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



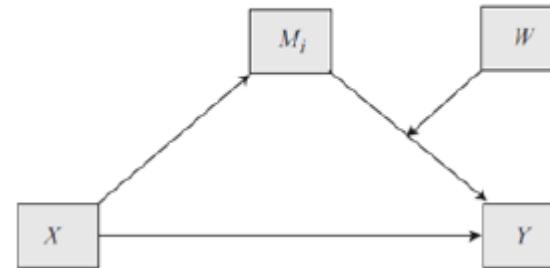
Statistical diagram



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.

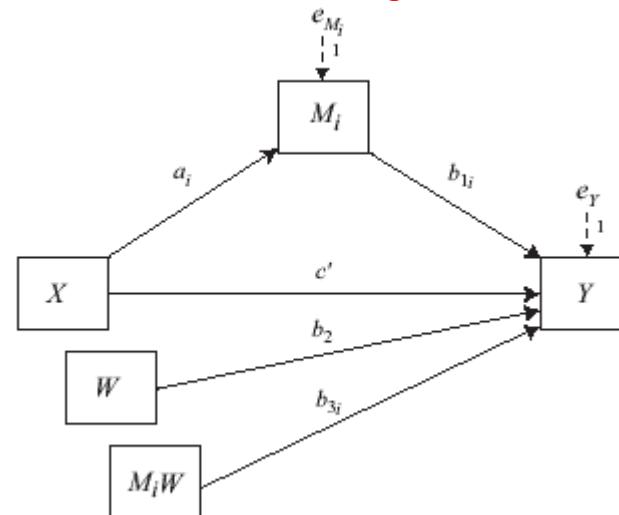
Conceptual diagram



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



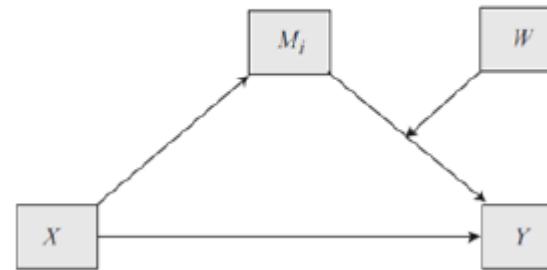
Model template system

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.

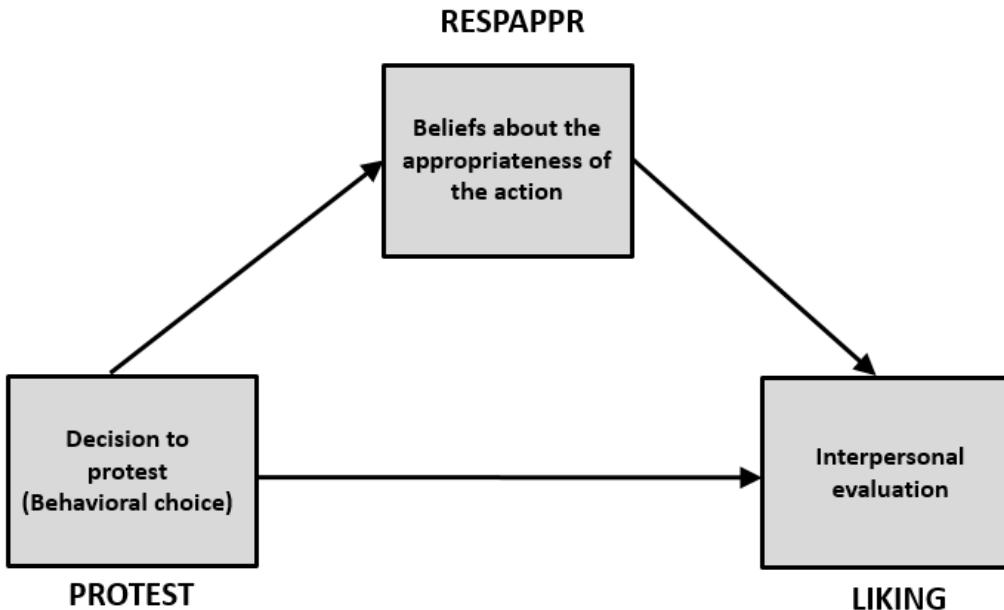
If you are familiar with PROCESS v2, see the “What’s new in PROCESS 3” pages in your course book.

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

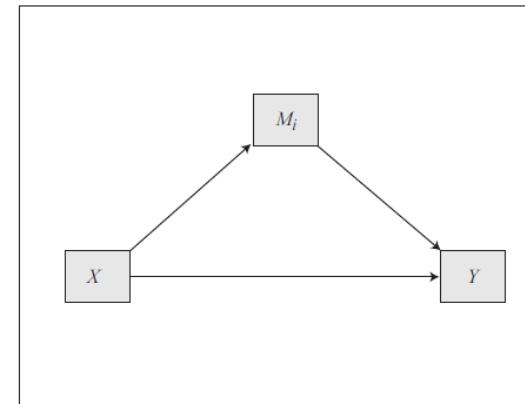
PROCESS Model 4



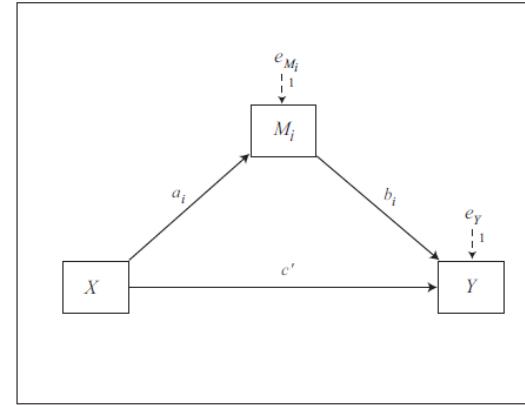
What should the PROCESS command look like?

Model 4

Conceptual Diagram



Statistical Diagram



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

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

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

path a

PROCESS output

Outcome: liking

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

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

path b
path c'

***** TOTAL EFFECT MODEL *****

Outcome: liking

$$\hat{Y} = 5.310 + 0.479X$$

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

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

path c

Direct effect of X on Y

Effect	SE	t	p	LLCI	ULCI
-.1007	.2005	-.5023	.6163	-.4975	.2960

path c'

Indirect effect of X on Y

Effect	Boot SE	BootLLCI	BootULCI
respappr	.1519	.3113	.9067

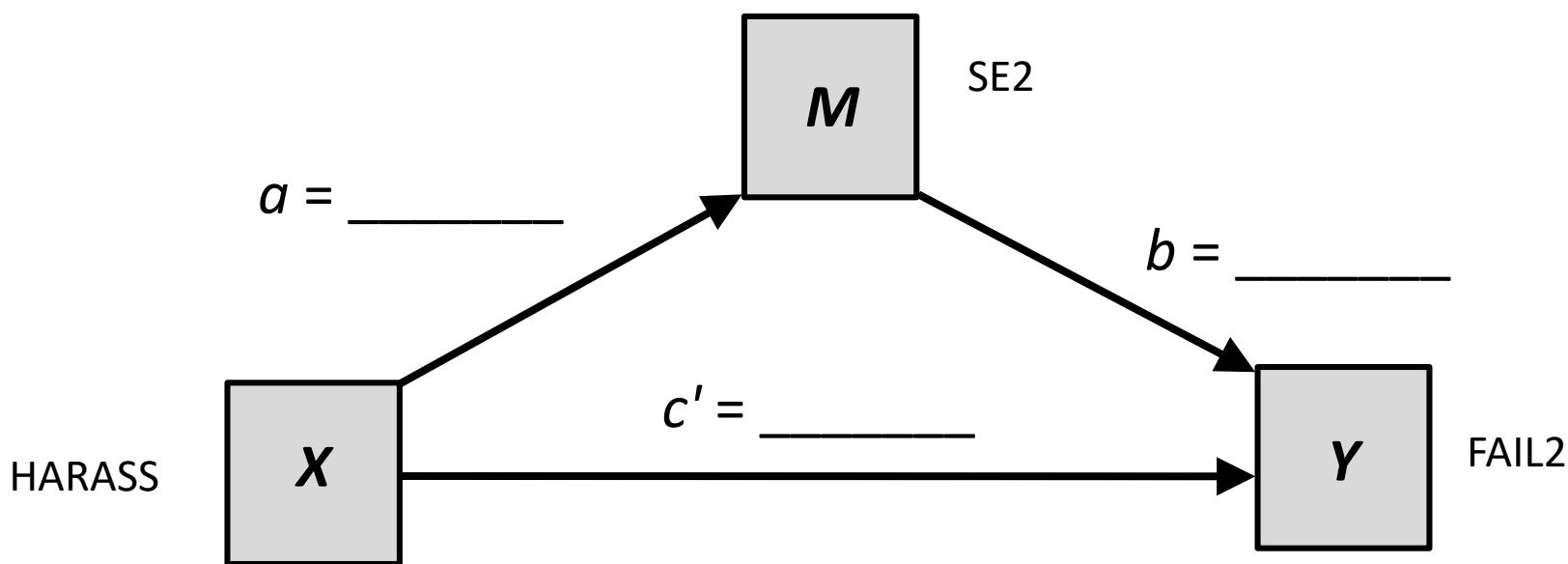
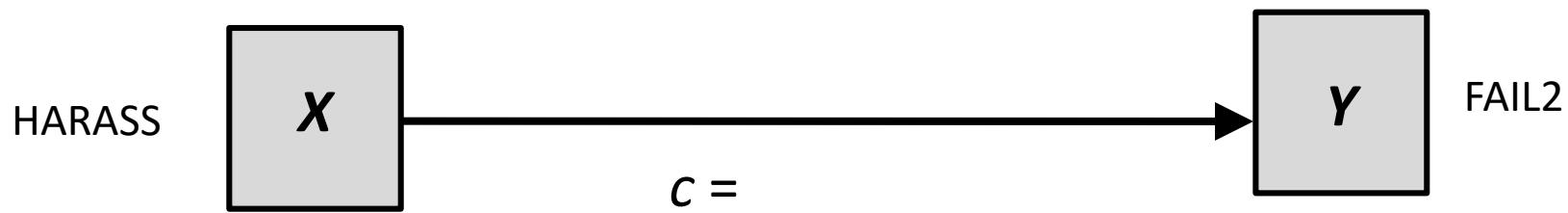
ab with 95% bootstrap
confidence interval

Normal theory tests for indirect effect

Effect	se	z	p
.5793	.1350	4.2924	.0000

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, $p = 0.62$)

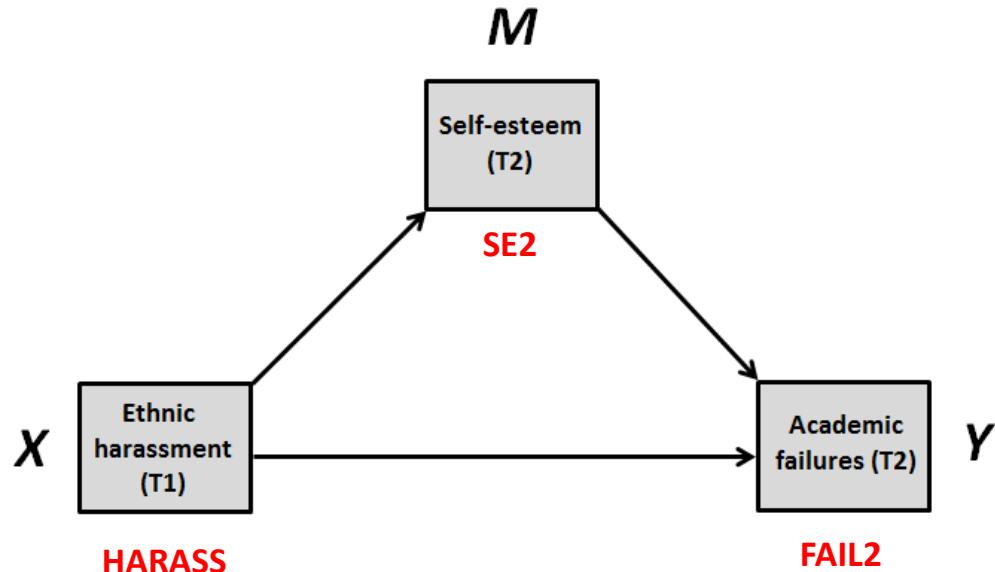


Indirect effect = , 95% bootstrap CI =

Your CI will not
exactly match. Why?

Estimation of the harassment model in PROCESS

PROCESS Model 4



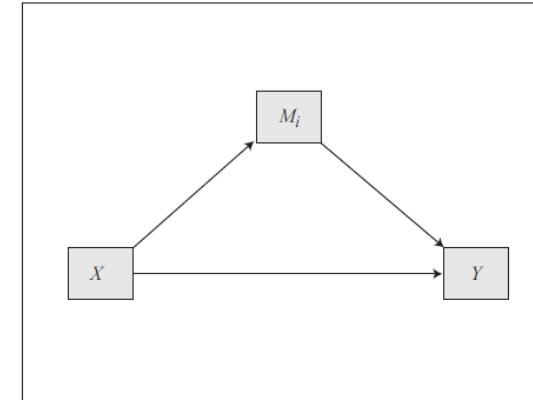
```
process y=fail2/x=harass/m=se2/model=4/boot=10000
/normal=1 /total=1.
```

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

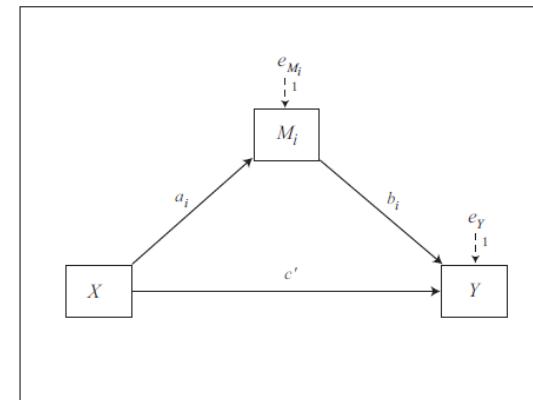
```
process(data=harass,y="fail2",x="harass",m="se2",model=
4,boot=10000,normal=1,total=1)
```

Model 4

Conceptual Diagram



Statistical Diagram



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

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

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

path a
107

PROCESS output

Outcome: fail2

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

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

path b
path c'

***** TOTAL EFFECT MODEL *****

Outcome: fail2

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

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

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

path c

Direct effect of X on Y

Effect	SE	t	p	LLCI	ULCI
.0616	.0725	.8499	.3960	-.0810	.2042

path c'

Indirect effect of X on Y

Effect	Boot SE	BootLLCI	BootULCI
se2	.1200	.0321	.0629 .1899

ab with 95% bootstrap confidence interval

Normal theory tests for indirect effect

Effect	se	z	p
.1200	.0308	3.8993	.0001

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/conf=99/save=1/seed=25545/decimal = F10.2.
```

SAS

```
%process (data=protest, y=liking,x=protest,m=respappr,model=4,boot=10000,
          normal=1,total=1,conf=99,save=boots,seed=25545, decimal = F10.2);
```

R

```
process (data=protest, y="liking",x="protest",m="respappr",model=4,boot=10000,
          normal=1,total=1,conf=99,save=1,seed=25545, decimal=F10.2);
```

- STAND=1:** Generates standardized coefficients for all models.
- 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.
- SAVE=fn** In SAS or R, saves bootstrap estimates to file named “fn”
- SEED=xxxx:** Seeds the random number generator for replication of resamples over repeated runs of PROCESS.
- DECIMAL=F10.XX:** XX is the number of decimal places you want to print in the output

See the documentation in Appendix A of IMCPA for details.

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.

$$\hat{Y} = c_0 + cX + c_2U$$

$$\hat{M} = a_0 + aX + a_2U$$

$$\hat{Y} = c'_0 + c'X + bM + c'_2U$$

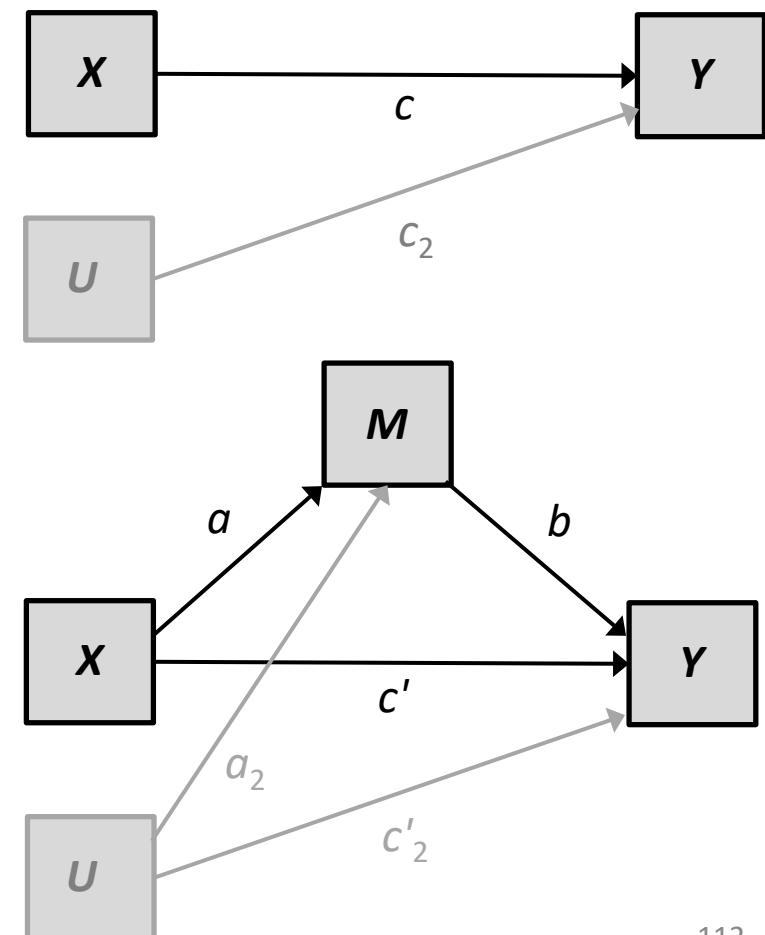
total effect = direct effect + indirect effect

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

indirect effect = total effect – direct effect

$$a \times b = c - c'$$

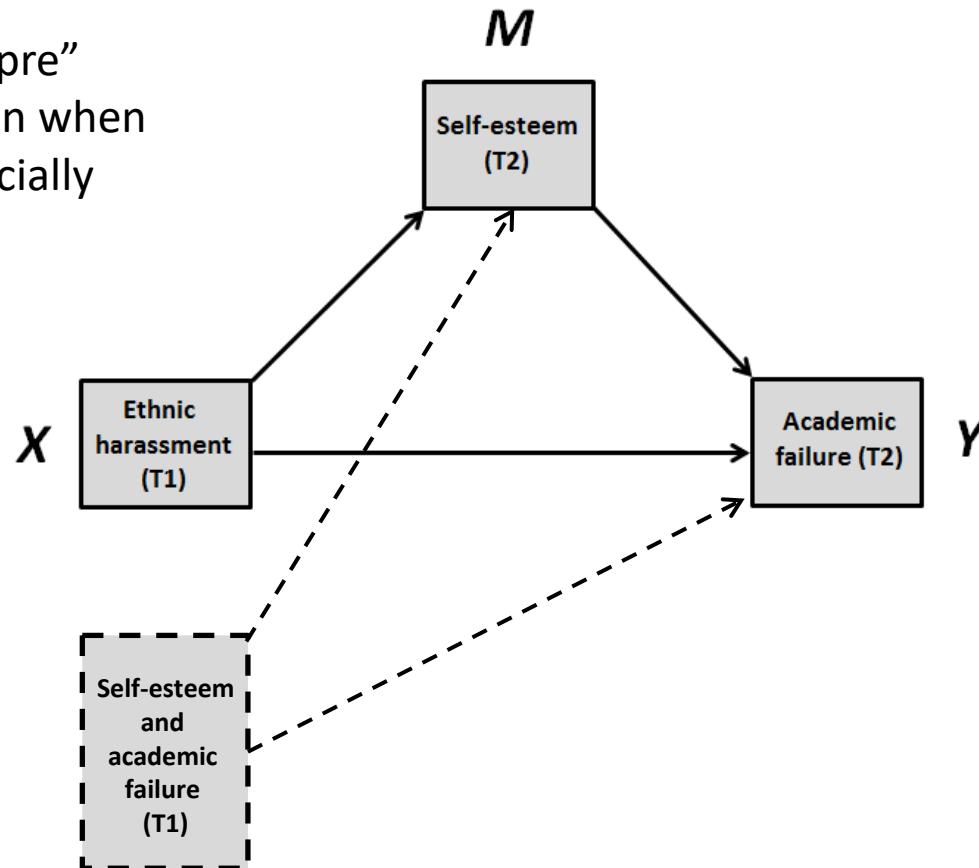
A simple mediation model, adjusting for a potential confounding variable (U)



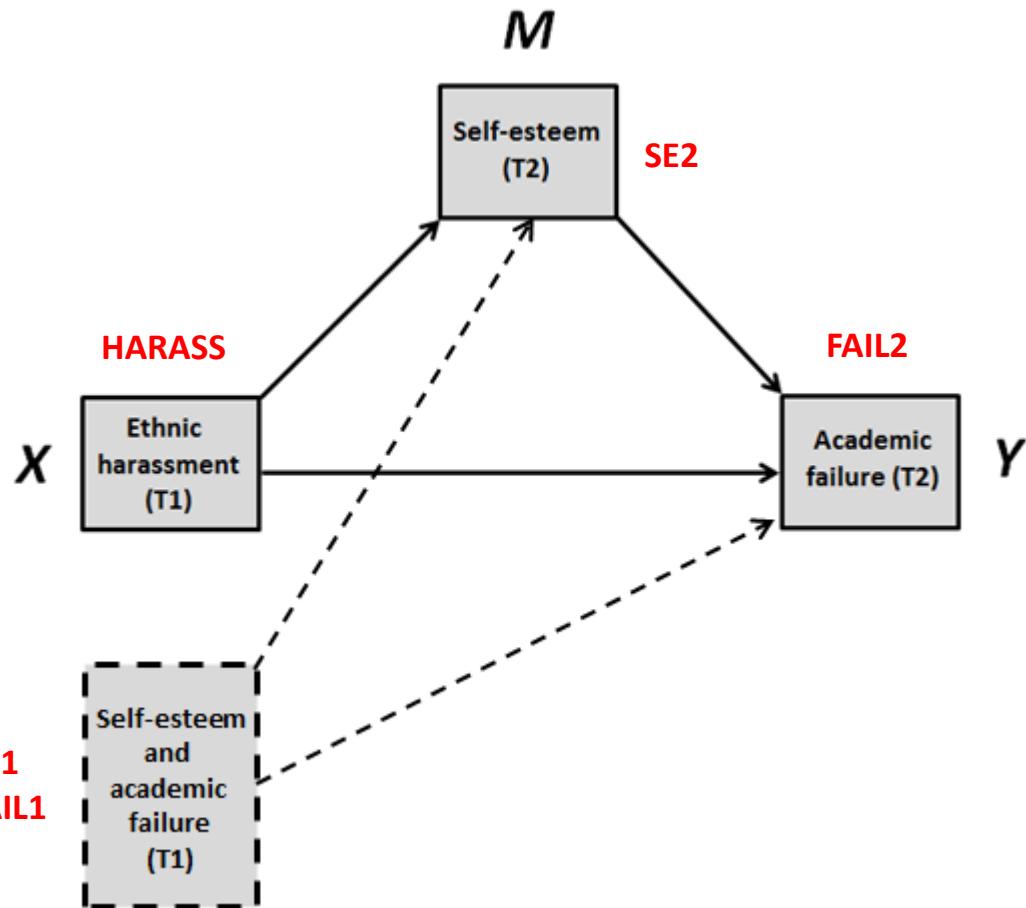
Some rationales for adjusting for prior state

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.

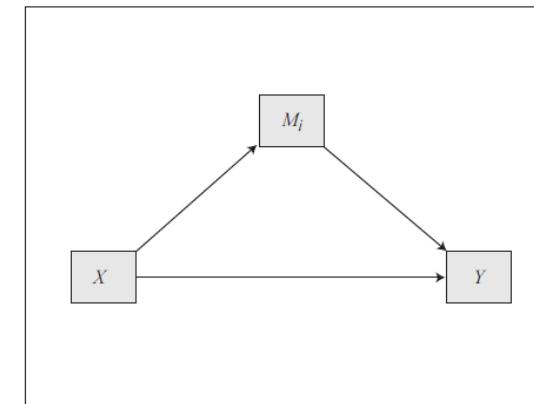


Adding covariates to a model using PROCESS

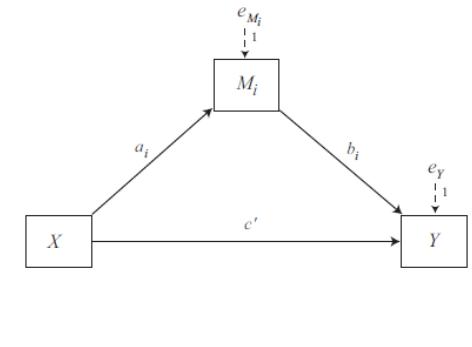


Model 4

Conceptual Diagram



Statistical Diagram



```
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:
sel 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
sel	.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
harass	.0196	.0713	.2754	.7832	-.1207	.1599
sel	-.0672	.0584	-1.1517	.2503	-.1820	.0476
fail1	.2307	.0592	3.8966	.0001	.1142	.3471

path b
path c'

***** 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
sel	-.1733	.0533	-3.2513	.0013	-.2782	-.0685
fail1	.2526	.0603	4.1886	.0000	.1340	.3713

path c

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

path c

Direct effect of X on Y

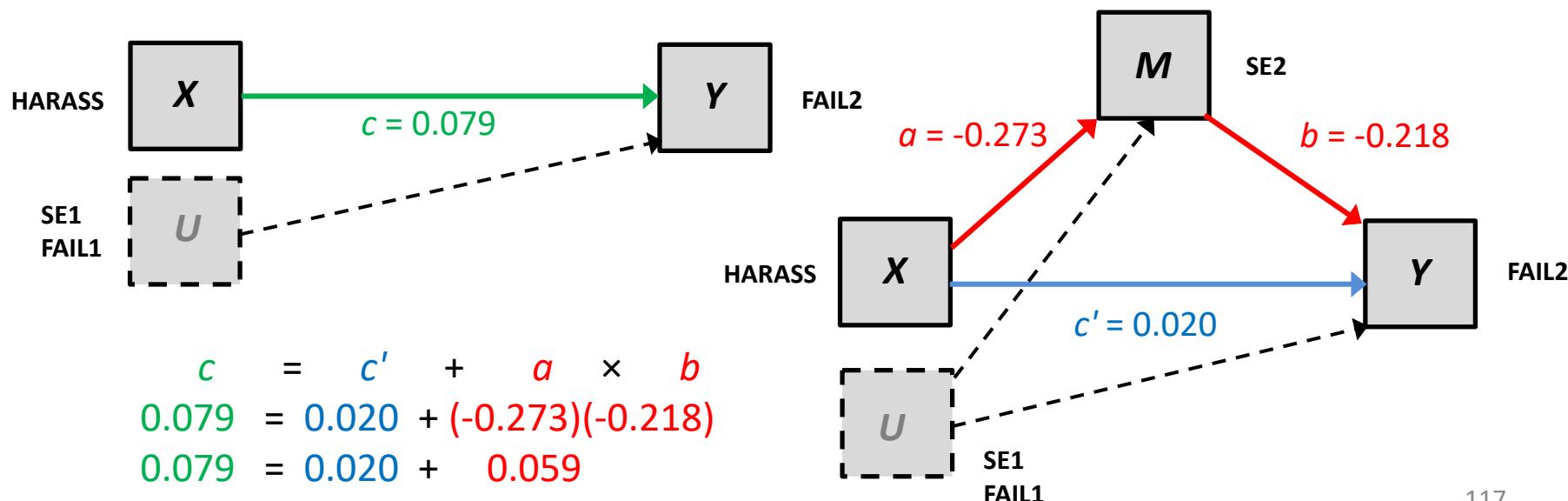
Effect	SE	t	p	LLCI	ULCI
.0196	.0713	.2754	.7832	-.1207	.1599

path c'

Indirect effect of X on Y

Effect	Boot SE	BootLLCI	BootULCI
se2	.0593	.0229	.0203

ab with 95% bootstrap
confidence interval



Discussion: Comparing Results

We ran the mediation analysis with the harass data twice. Once without covariates and once with covariates.

- What are some key differences between the results?
- Which analysis do you think best approximates the “truth”?
- If the results had not changed while including the covariates, what would that mean?

What about Baron & Kenny?

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

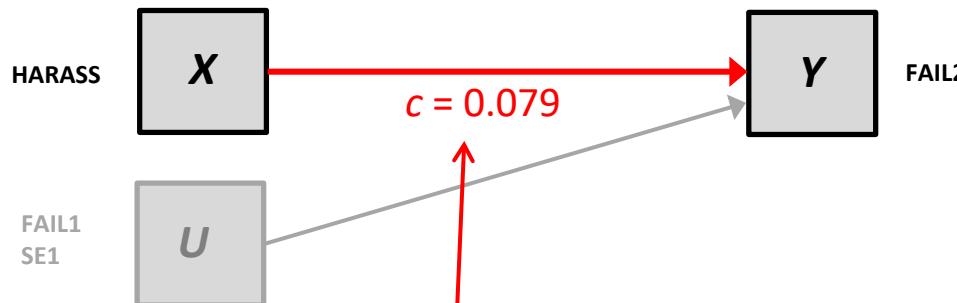
Conditions required to claim M functions as a mediator of the relationship between X and Y :

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

} ..as gauged by a hypothesis test.

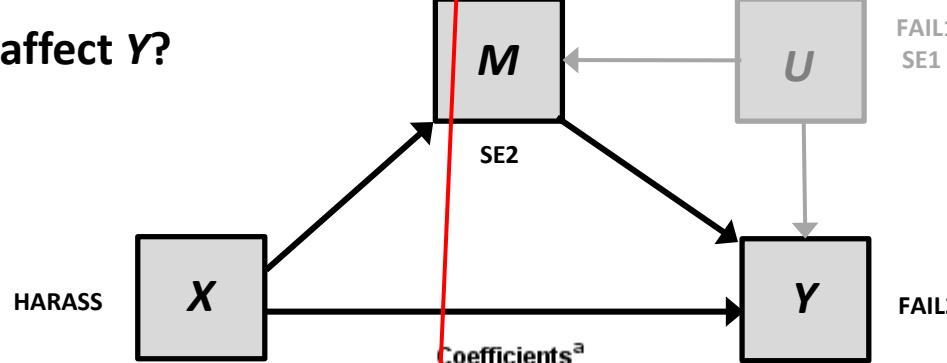


Using a set of OLS regression analyses



Condition 1: Does X affect Y ?

**NO. THUS, NO
MEDIATION BY
THE CAUSAL
STEPS STRATEGY**



Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1	(Constant)	1.652	.240	6.884	.000
	harass	.079	.071	.059	.270
	fail1	.253	.060	.231	4.189
	se1	-.173	.053	-.179	-3.251

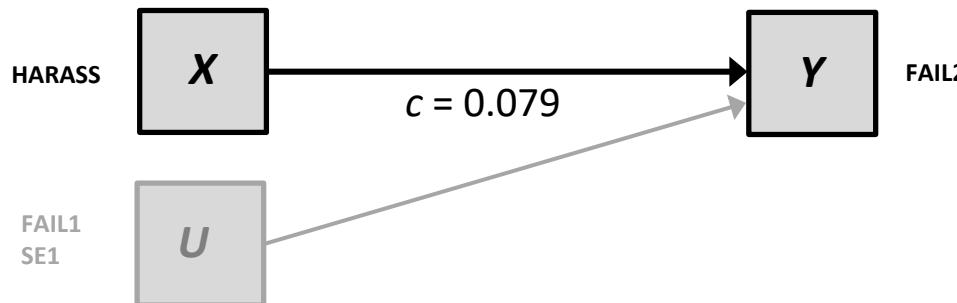
a. Dependent Variable: fail2

```
lm(fail2~harass+fail1+sel, data = harass)
```

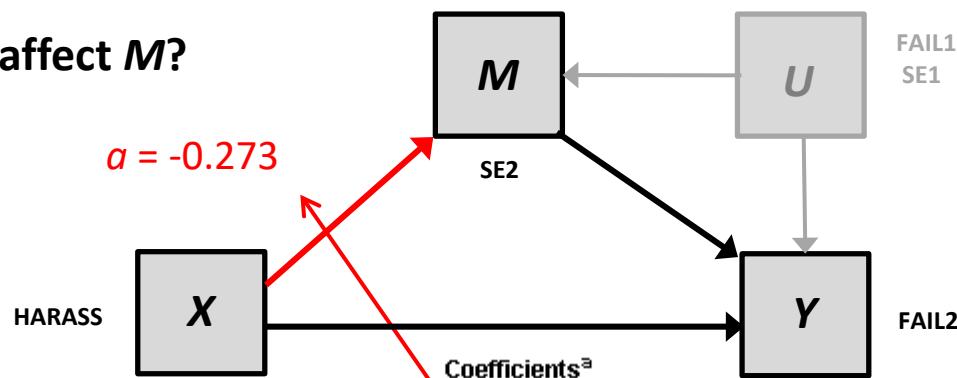
```
regression/dep=fail2/method=enter harass fail1 sel.
```

```
proc reg data=harass;model fail2=harass fail1 sel;run;
```

Using a set of OLS regression analyses



Condition 2: Does X affect M?



Model	Unstandardized Coefficients			t	Sig.
	B	Std. Error	Beta		
1 (Constant)	2.028	.241		8.410	.000
harass	-.273	.072	-.181	-3.802	.000
se1	.488	.054	.448	9.108	.000
fail1	-.101	.061	-.082	-1.666	.097

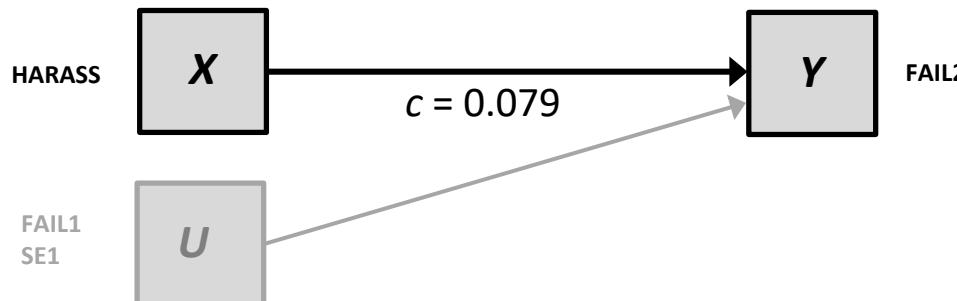
a. Dependent Variable: se2

```
lm(se2~harass+fail1+se1, data = harass)
```

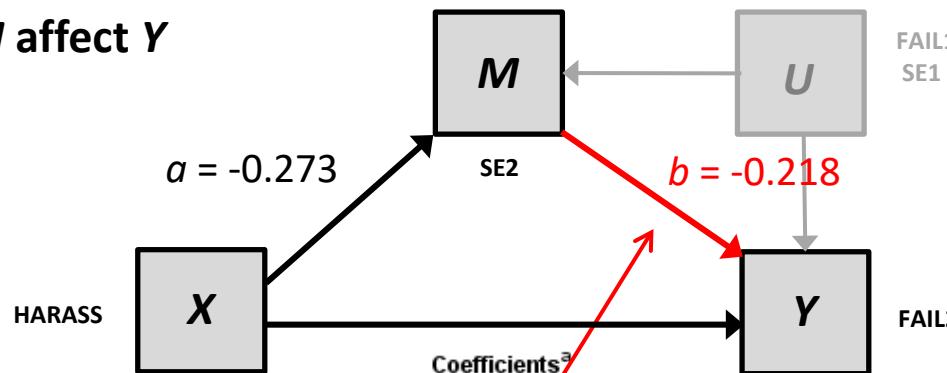
```
regression/dep=se2/method=enter harass se1 fail1.
```

```
proc reg data=harass;model se2=harass se1 fail1;run;
```

Using a set of OLS regression analyses



Condition 3: Does M affect Y holding X constant?



Model	Unstandardized Coefficients		Beta	t	Sig.
	B	Std. Error			
1 (Constant)	2.093	.259		8.090	.000
harass	.020	.071	.015	.275	.783
se2	-.218	.054	-.244	-4.038	.000
fail1	.231	.059	.211	3.697	.000
se1	-.067	.058	-.069	-1.152	.250

a. Dependent Variable: fail2

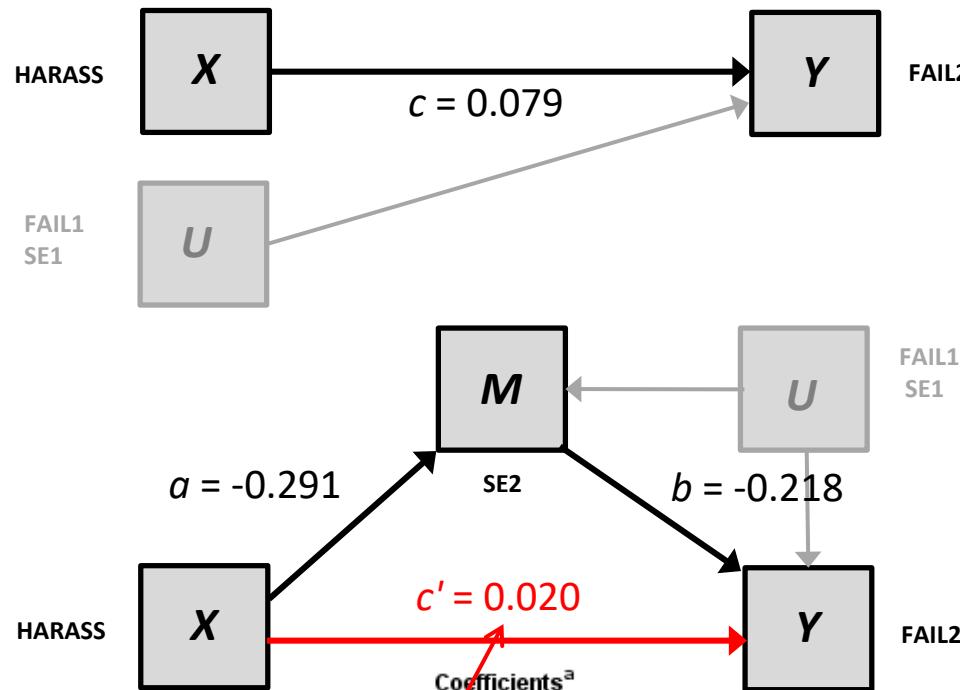
```
lm(fail2~harass+se2+fail1+se1, data = harass)
```

```
regression/dep=fail2/method=enter harass se2 fail1 se1.
```

```
proc reg data=harass;model fail2=harass se2 fail1 se1;run;
```

Using a set of OLS regression analyses

4. Qualitatively compare c to c'



Direct effect (c') is closer to zero than the total effect (c) and is not statistically different from zero. But can we really call this 'complete mediation' given that there was no total effect of X in the first place by commonly-used inferential rules?

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1	(Constant)	2.093	.259	8.090	.000
	harass	.020	.071	.015	.275
	se2	-.218	.054	-.244	-4.038
	fail1	.231	.059	.211	3.897
	se1	-.067	.058	-.069	-1.152

a. Dependent Variable: fail2

```
lm(fail2~harass+se2+fail1+sel, data = harass)
```

```
regression/dep=fail2/method=enter harass se2 fail1 sel.
```

```
proc reg data=harass;model fail2=harass se2 fail1 sel;run;
```

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, you should intentionally limit the size of your sample to as small as necessary
- ❑ 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

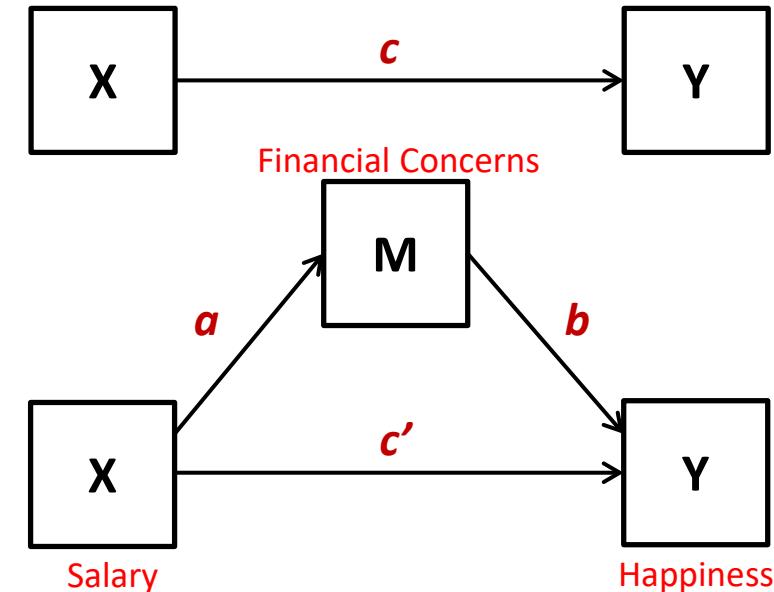
- ❑ Mediators are variables which are causally located between two variables X and Y and that explain, in part, the effect of X on Y . X affects M which in turn affects Y .
- ❑ The causal steps strategy popularized by Baron and Kenny (1986) remains a popular method for mediation analysis.
 - Yet it is 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.



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.



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

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

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

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

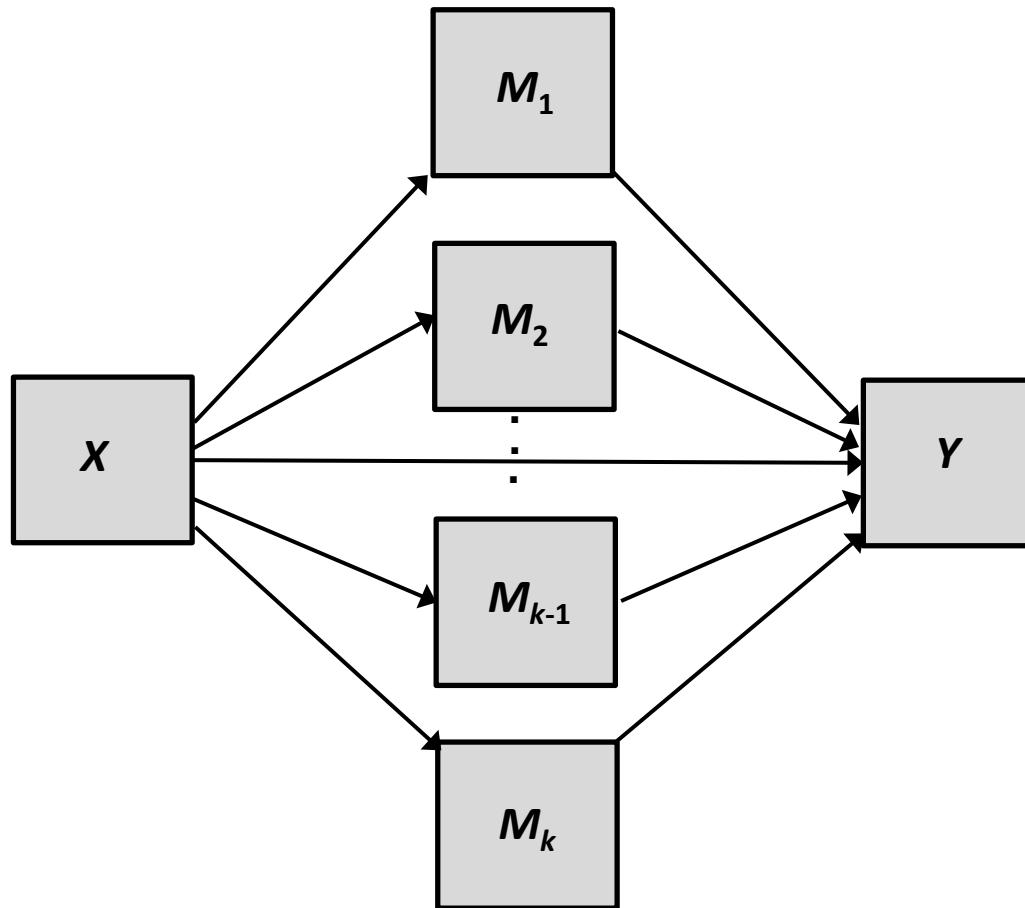
Indirect effect of X on Y (through M) = **$a \times b$**

Total effect = direct effect + indirect effect

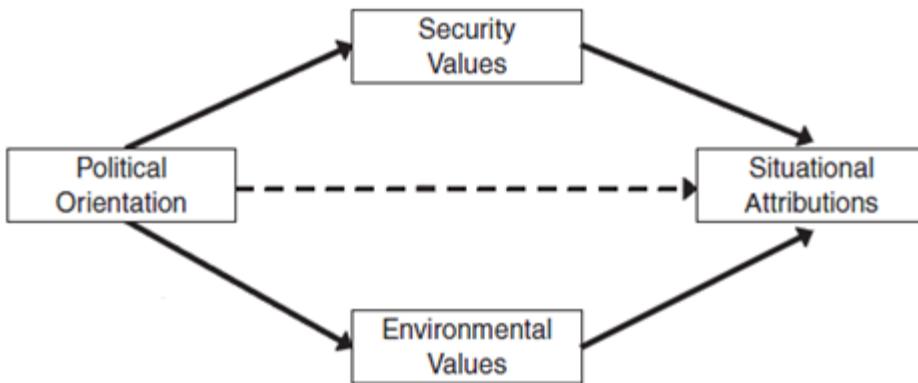
$$\begin{aligned} \text{Indirect effect} &= \text{Total effect} - \text{Direct effect} \\ c \times b &= c' + a \times b \\ &= c - c' \end{aligned}$$

Models with More Than One Mediator

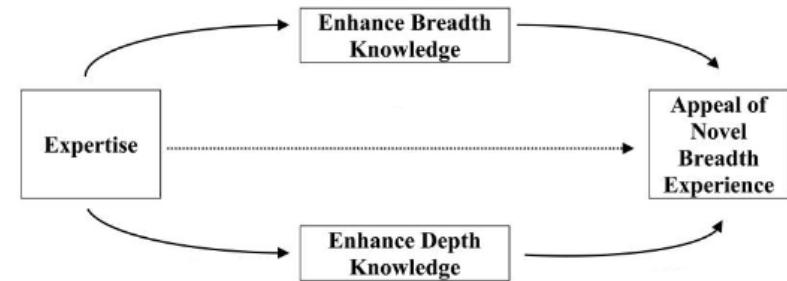
A parallel multiple mediator model



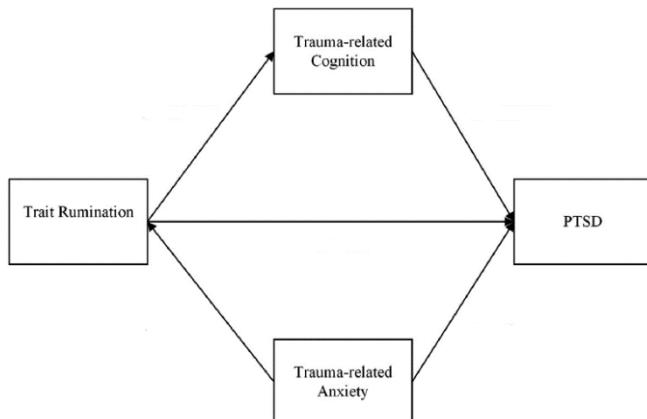
Some examples From the literature with 2 mediators



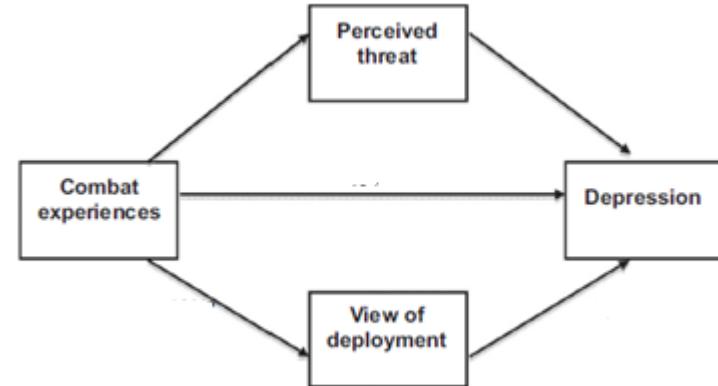
Morgan, G. S., Mullen, E., & Skitka, L. J. (2010). When values and attributions collide: Liberals' and conservatives' values motivate attributions for alleged misdeeds. *Personality and Social Psychology Bulletin*, 36, 1241-1254.



Clarkson, J. J., Janiszewski, C., & Cinelli, M. D. (2013). The desire for consumption knowledge. *Journal of Consumer Research*, 39, 1313-1329.

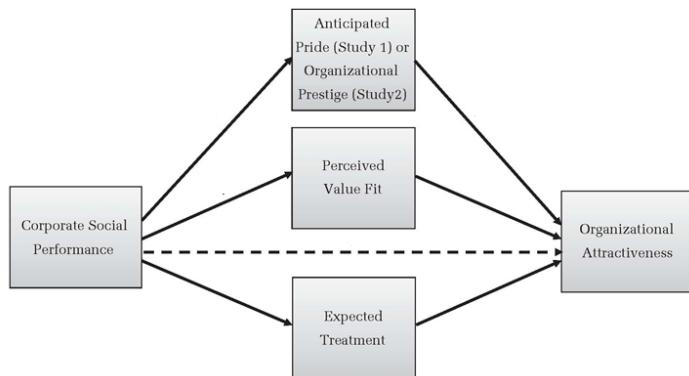


Spinhoven, P., Penninx, B. W., Krempeniou, A., et al. (2015). Trait rumination predicts onset of post-traumatic stress disorder through trauma-related cognitive appraisals: A 4-year longitudinal study. *Behaviour Research and Therapy*, 71, 101-109.

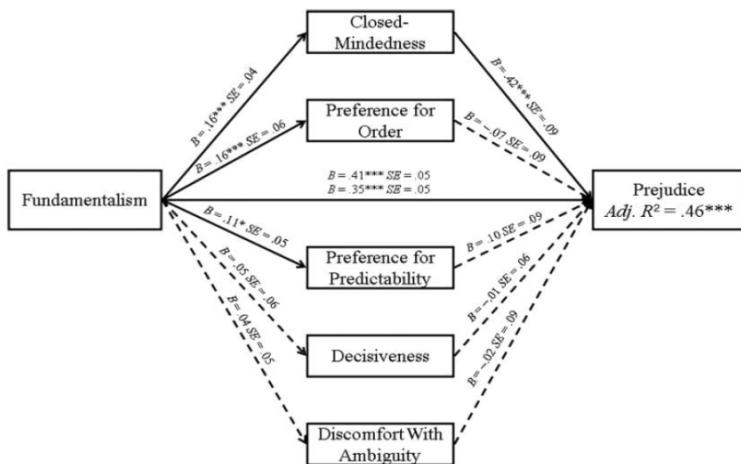


Pitts, B. L., & Safer, M. A. (2016). Retrospective appraisals mediate the effect of combat experiences on PTS and depression symptoms in U.S. Army medics. *Journal of Traumatic Stress*, 29, 65-71.

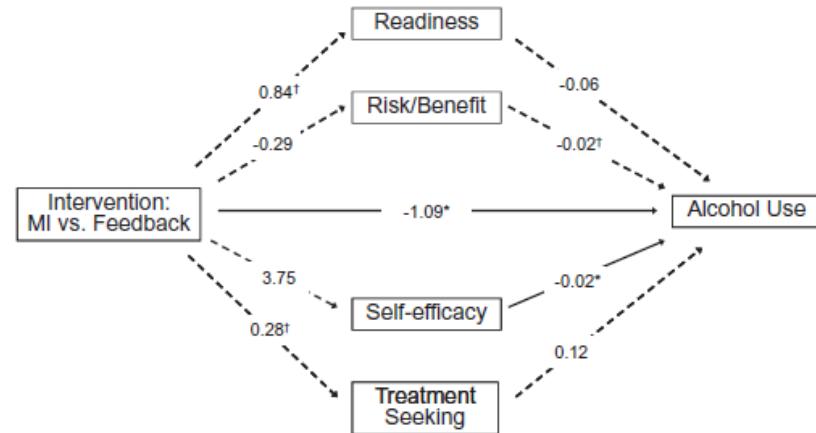
Some examples from the literature with several mediators



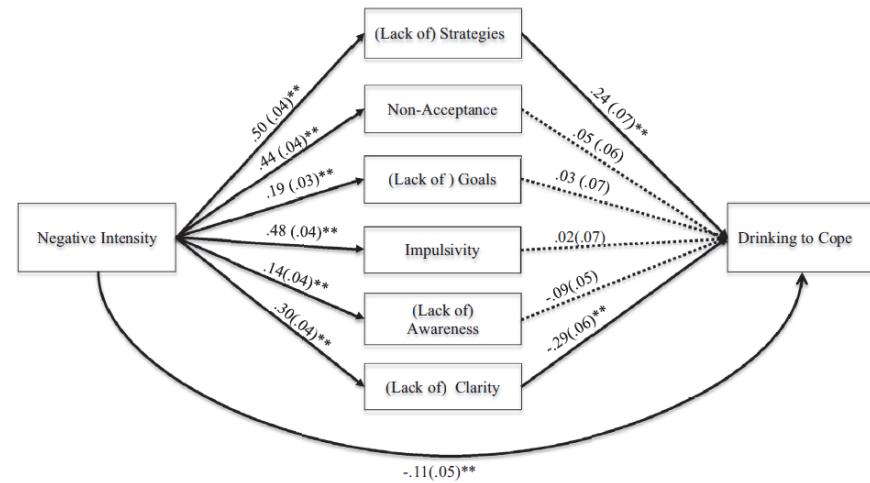
Jones, D. A., Willness, C. R., & Madey, S. (2014). Why are job seekers attracted by corporate social performance? Experimental and field tests of three signal-based mechanisms. *Academy of Management Journal*, 57, 383-404.



Brandt, M. J., & Reyna, C. (2010). The role of prejudice and the need for closure in religious fundamentalism. *Personality and Social Psychology Bulletin*, 36, 715-725.



Barnett, N. P., Apodaca, T. R., et al. (2010). Moderators and mediators of two brief interventions for alcohol in the emergency department. *Addiction*, 105, 452-465.



Veilleux, J. C., Skinner, K. D., Reese, E. D., & Shaver, J. A. (2014). Negative affect intensity influences drinking to cope through facets of emotion dysregulation. *Personality and Individual Differences*, 49, 96-101.

Why estimate such a model?

- Many causal effects probably operate through multiple mechanisms simultaneously. Better to estimate a model **consistent with such real-world complexities**.
- If your proposed mediator is correlated with the real mediator but not caused by the independent variable, a model with only your proposed mediator in it will be a **misspecification** and will potentially misattribute the process to your proposed mediator rather than the real mediator—“epiphenomenality.”
- Different theories may postulate different mediators as mechanisms. Including them all in a model simultaneously allows for a formal statistical comparison of indirect effects **representing different theoretical mechanisms**.

Path Analysis: Total, Direct, and Indirect Effects

$$\hat{Y} = c_0 + cX$$

$$\widehat{M}_j = a_{0j} + a_j X$$

$$\hat{Y} = c'_0 + c'X + \sum_{j=1}^K b_j M_j$$

c = “total effect” of X on Y

$a_j \times b_j$ = “specific indirect effect” of X on Y through M_i

$\sum (a_j \times b_j)$ = “total indirect effect” of X on Y

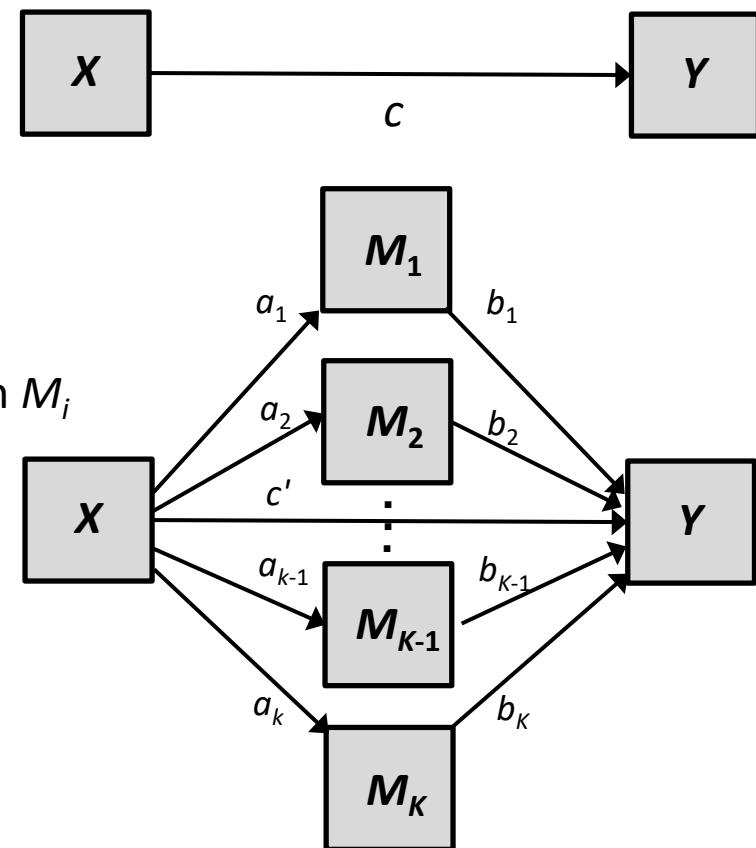
c' = “direct effect” of X on Y

total effect = direct effect + total indirect effect

$$c = c' + \sum (a_j \times b_j)$$

total indirect effect = total effect – direct effect

$$\sum (a_j \times b_j) = c - c'$$



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
1.00	3.00	5	2.7

data science;

```
input Subject Cond sex ProNo comm diff interest;
```

datalines;

106	1	1	1	5.2	5	6
109	1	1	1	1	4	2.25
112	1	1	1	4	4	2.5
114	1	1	1	4	2	3.5
115	1	1	1	7	7	7
121	1	1	1	6	1	6
131	1	1	1	4	7	2.75
132	1	1	1	3.4	6	4.25
148	1	1	1	4.2	3	3.5
161	1	1	1	4.6	6	1.5
162	1	1	1	4.2	5	2
164	1	1	1	4.4	5	1
174	1	1	1	5.4	3	7
176	1	1	1	5	4	2.25
177	1	1	1	4.6	6	2.75
178	1	1	1	3.4	4	1.25
190	1	1	1	3.8	5	2.75
206	1	1	1	4.2	6	1.75
216	1	1	1	7	7	6
217	1	1	1	5	4	4.75

ProNo: Experimental condition (1 = procollaboration, 0 = no collaboration)

interest : interest in class (higher = greater interest)

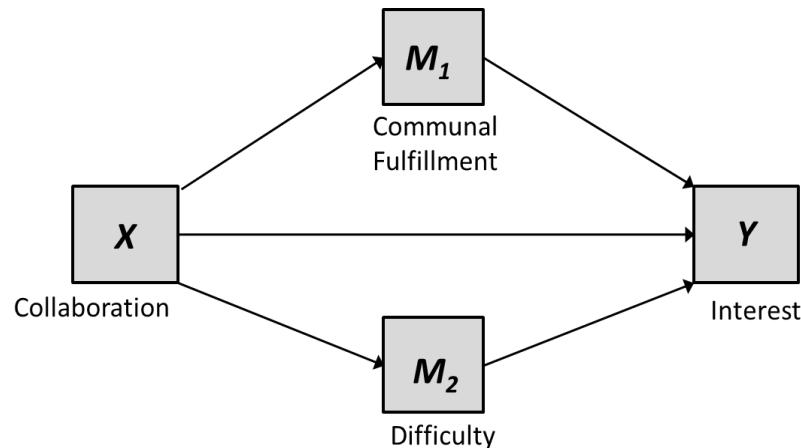
comm: Perceived fulfillment of communal goals (higher = more fulfillment)

diff: Perceived difficulty of the class (higher = more difficult)

gender: 1 = Male, 2 = Female

Estimation and inference using PROCESS

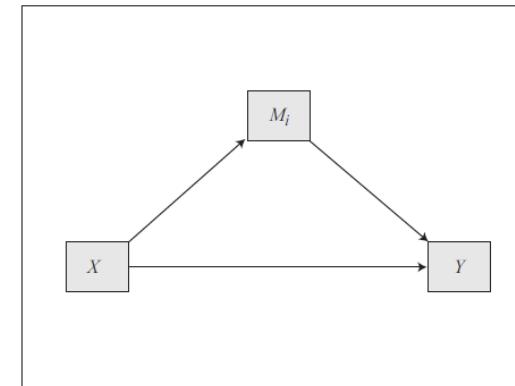
PROCESS model 4 is used for the parallel multiple mediator model.



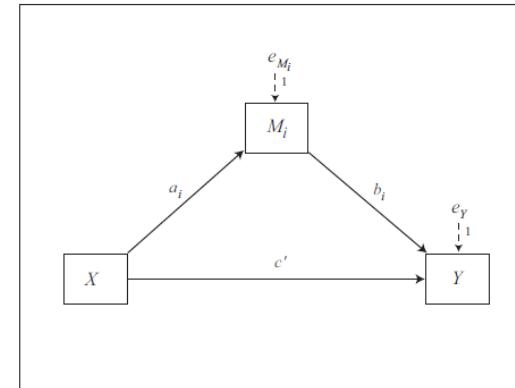
Up to 10 mediators can be listed in the “m =” list. Order does not matter.

Model 4

Conceptual Diagram



Statistical Diagram



```
process y=interest/x=ProNo/m=comm diff/total=1/boot=10000/model=4/normal=1/contrast=1.
```

```
%process (data=science,y=interest,x=ProNo,m=comm diff,total=1,boot=10000,model=4,  
normal=1,contrast=1);
```

```
process(data=science, y = "interest", x = "ProNo", m = c("comm", "diff"), total = 1,  
boot = 10000, model = 4, normal = 1, contrast = 1)
```

PROCESS output

Model : 4
 Y : interest
 X : ProNo
 M1 : comm
 M2 : diff
 Sample Size: 232

OUTCOME VARIABLE:

comm

$$\widehat{M}_{1i} = 3.12 + 0.78X_i$$

Model Summary

R	R-sq	MSE	F	df1	df2	p
.3031	.0919	1.5279	23.2670	1.0000	230.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	3.1160	.1133	27.4994	.0000	2.8927	3.3392
ProNo	.7831	.1624	4.8236	.0000	.4632	1.1030

← a_1 path

OUTCOME VARIABLE:

diff

$$\widehat{M}_{2i} = 4.94 - 0.15X_i$$

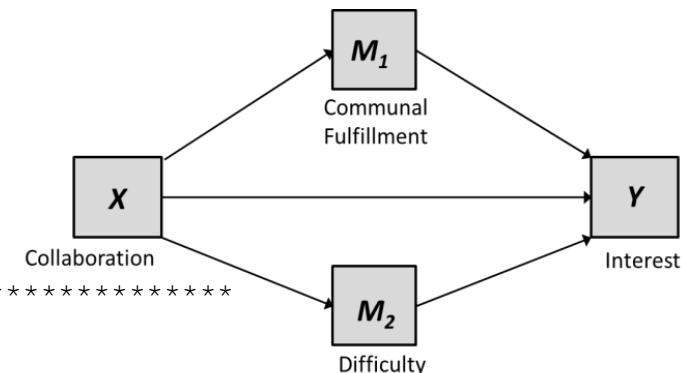
Model Summary

R	R-sq	MSE	F	df1	df2	p
.0594	.0035	1.6760	.8155	1.0000	230.0000	.3674

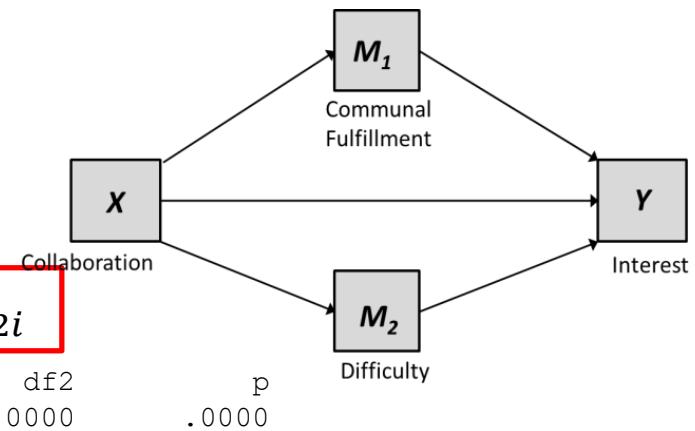
Model

	coeff	se	t	p	LLCI	ULCI
constant	4.9412	.1187	41.6352	.0000	4.7073	5.1750
ProNo	-.1536	.1700	-.9031	.3674	-.4886	.1815

← a_2 path



PROCESS output



OUTCOME VARIABLE:

interest

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4418	.1952	1.9659	18.4348	3.0000	228.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.4898	.4618	1.0607	.2899	-.4201	1.3996
ProNo	-.0895	.1933	-.4630	.6438	-.4705	.2914
comm	.5367	.0752	7.1418	.0000	.3886	.6848
diff	.1364	.0718	1.9008	.0586	-.0050	.2778

***** TOTAL EFFECT MODEL *****

OUTCOME VARIABLE:

interest

$$\hat{Y}_i = 2.84 + 0.31X_i$$

Model Summary

R	R-sq	MSE	F	df1	df2	p
.1000	.0100	2.3974	2.3217	1.0000	230.0000	.1290

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.8361	.1419	19.9817	.0000	2.5565	3.1158
ProNo	.3099	.2034	1.5237	.1290	-.0908	.7106

c' path
b₁ path
b₂ path

c path

PROCESS output

***** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y *****

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
.3099	.2034	1.5237	.1290	-.0908	.7106

c path

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
-.0895	.1933	-.4630	.6438	-.4705	.2914

c' path

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	.3994	.1135	.1950	.6399
comm	.4203	.1128	.2171	.6594
diff	-.0209	.0282	-.0858	.0280
(C1)	.4413	.1189	.2251	.6927

$a_1 b_1 + a_2 b_2$ with bootstrap CI

$a_1 b_1$ with bootstrap CI

$a_2 b_2$ with bootstrap CI

Normal theory test for indirect effect(s):

	Effect	se	Z	p
comm	.4203	.1059	3.9706	.0001
diff	-.0209	.0284	-.7367	.4613

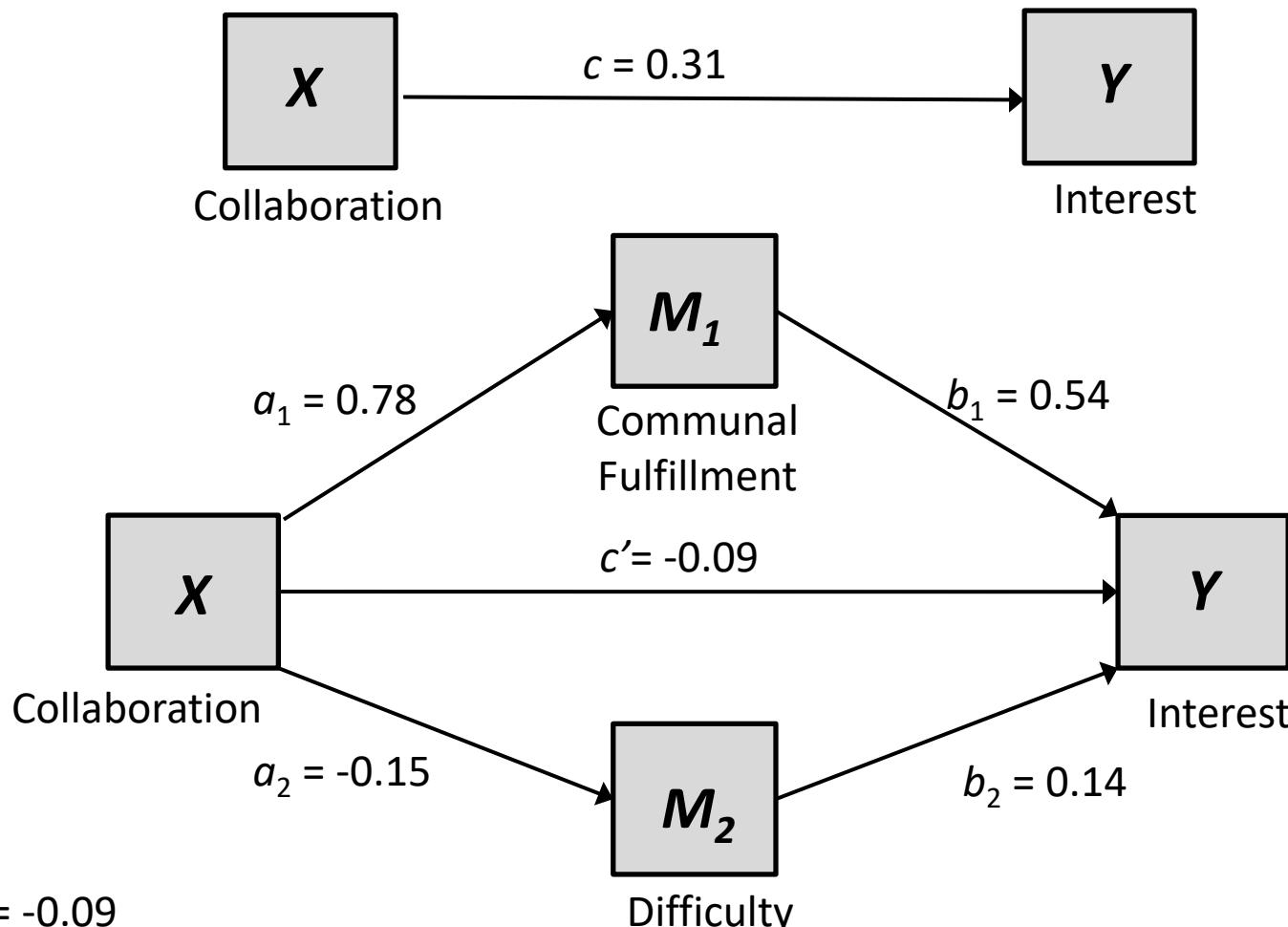
Sobel tests (less trustworthy than bootstrap CIs)

Specific indirect effect contrast definition(s):

(C1) comm minus diff

The data are consistent with the claim that group work influences interest indirectly through communal goal fulfillment controlling for difficulty (0.420; 95% CI = 0.217 to 0.659) but not through difficulty controlling for goal fulfillment (-0.0209; 95% CI = -0.086 to 0.028).

Example: Science



Direct effect = -0.09

Specific indirect effect via Comm: $0.78(0.54) = 0.42$

Specific indirect effect via Diff: $-0.15(0.14) = -0.02$

Total indirect effect = $0.42 - 0.02 = 0.40$

Total effect = $-0.09 + .42 - 0.02 = 0.31$

Reflecting on Causality in Science Analysis

Necessary Conditions for Cause:

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

Must consider each path separately:

Collaboration \rightarrow Interest (Total Effect):

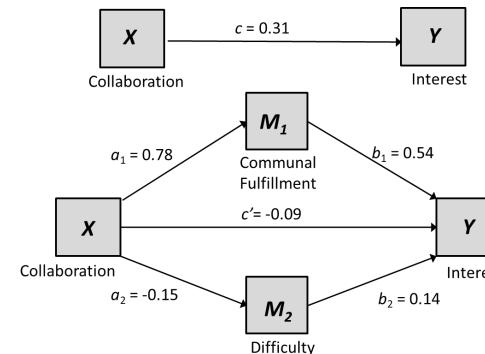
- Covariation X
- Temporal Ordering ✓
- Elimination of competing explanations ✓

Collaboration \rightarrow Communal Fulfillment (a_1 -path):

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

Collaboration \rightarrow Difficulty (a_2 -path):

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



Communal Fulfillment \rightarrow Interest (b_1 -path):

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

Difficulty \rightarrow Interest (b_2 -path):

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

Collaboration \rightarrow Interest (c' -path):

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

Things to consider

- (1) In a multiple mediator model, the specific indirect effect through M_k quantifies the component of the total indirect effect that is unique to M_k . Each specific indirect effect is estimated **controlling for all other mediators**.

M_k may function as a mediator variable when considered in isolation but not when considered with other mediator variables in the same model. If the intervening variables are highly intercorrelated, they can “cancel out” each others’ effects.

- (2) It is possible for a total indirect effect to be not detectably different from zero even when one or more specific indirect effects is.

total indirect effect = sum of specific indirect effects

$$\Sigma (a_i b_i) = a_1 b_1 + a_2 b_2 + \dots a_k b_k.$$

Scenario (a): A single large specific indirect combined with several tiny ones.

Scenario (b): Specific indirect effects that have different signs and add to near zero.

In multiple mediator models, the total indirect effect is not always of great interest.₁₄₂

Comparing specific indirect effects

Indirect effects quantify how Y changes as X changes by one unit through a mediator. **They are free of the scale of measurement of the mediators.** So in multiple mediator models, indirect effects linking the same X to the same Y are directly comparable even if the mediators are measured on different scales. We can statistically compare them if so desired. No standardization or other arithmetic gymnastics is required.

Approach #1: Calculate the ratio of the difference between the indirect effect through M_i and the indirect effect through M_j to its standard error. Assuming a normally distributed sampling distribution of the difference, a p -value for the null hypothesis that the difference equals zero can be derived from the standard normal distribution.

$$Z = \frac{a_i b_i - a_j b_j}{se_{a_i b_i - a_j b_j}}$$

Approach #2: Bootstrap a confidence interval for the $a_i b_i - a_j b_j$ and ascertain whether 0 is in the confidence interval as a pseudo null hypothesis test that the difference is zero.

PROCESS can generate a bootstrap confidence interval for all possible pairwise comparisons between specific indirect effects

PROCESS output

```
process y=interest/x=prono/m=comm diff/total=1/boot=10000/model=4/normal=1/contrast=1.
```

```
%process (data=science,y=interest,x=prono,m=comm diff, total=1,boot=10000,model=4,  
normal=1,contrast=1);
```

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
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(C1)	.4413	.1189	.2251	.6927

$$a_1b_1 - a_2b_2$$

Normal theory test for indirect effect(s) :

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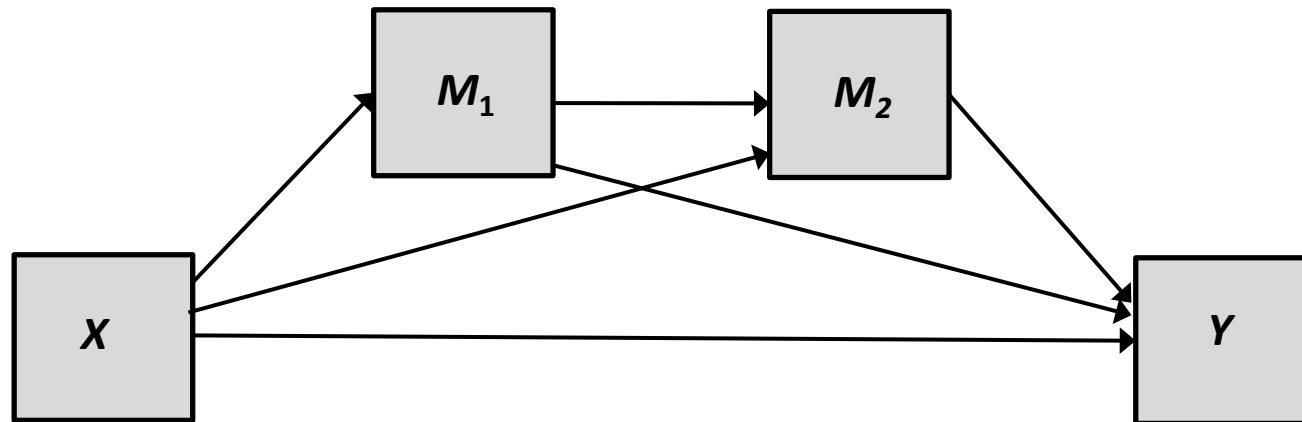
Specific indirect effect contrast definition(s) :

(C1) comm minus diff

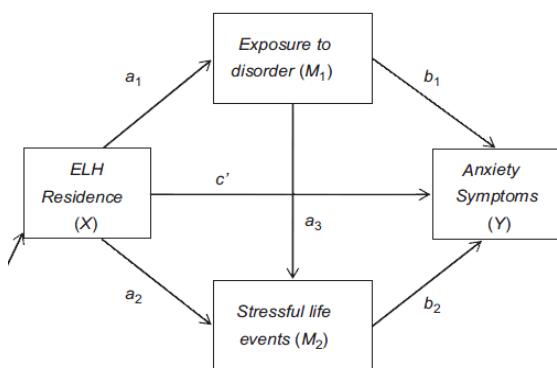
The specific indirect effect of collaboration on interest through perceived Communal goal fulfillment is different from the specific indirect effect through perceived class difficulty (difference = 0.441; 95% CI = 0.225 to .6927).

The serial multiple mediator model

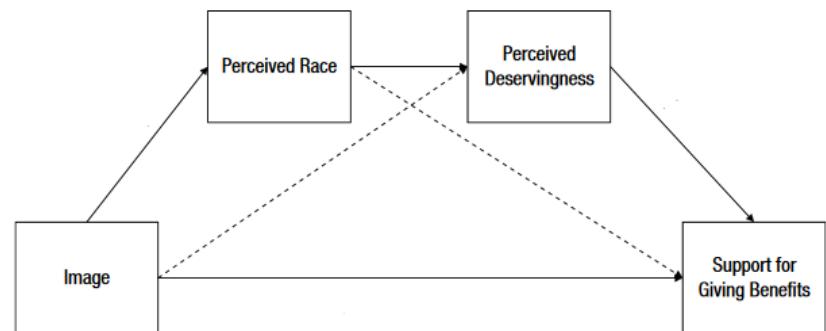
A serial multiple mediator model with two mediators and all possible direct and indirect effects freely estimated.



Some examples in the literature:

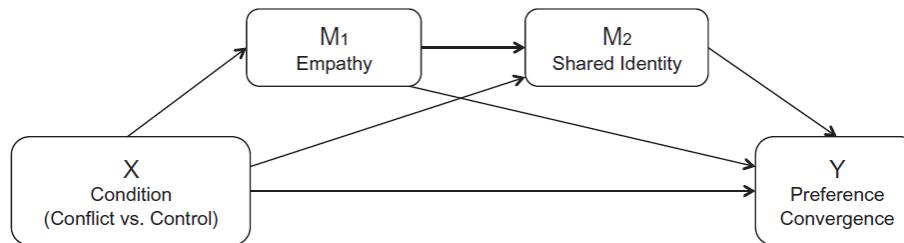


Casciano, R., & Massey, D. S. (2012). Neighborhood disorder and anxiety symptoms: New evidence from a quasiexperimental study. *Health and Place*, 18, 180-190.

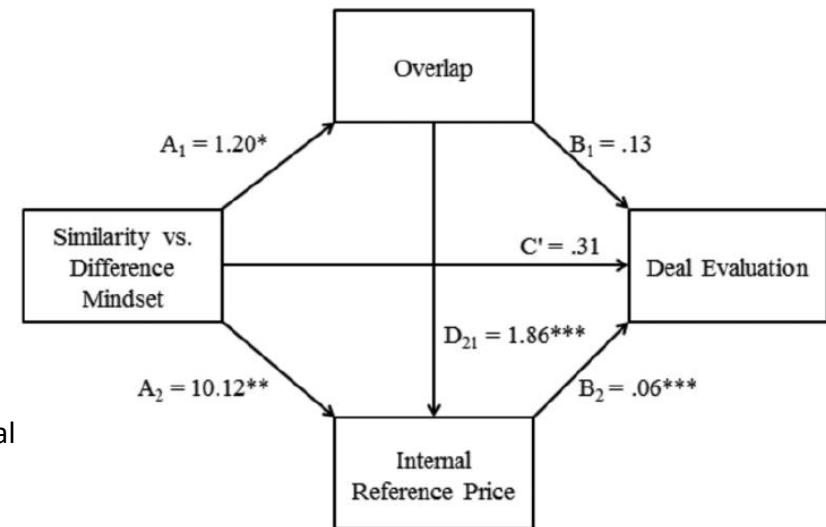


Brown-Iannuzzi, J. L., Dotsch, R., Cooley, E., & Payne, B. K. (2017). The relationship between mental representations of welfare recipients and attitudes toward welfare. *Psychological Science*, 28, 92-103.

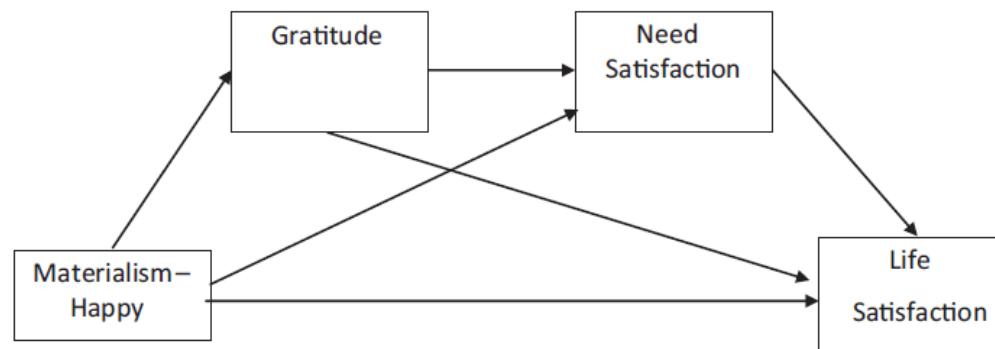
More examples from the literature



Schrift, R. Y., & Moty, A. (2015). Pain and preferences: Observed decisional conflict and the convergence of preferences. *Journal of Consumer Research*, 42, 515-534..

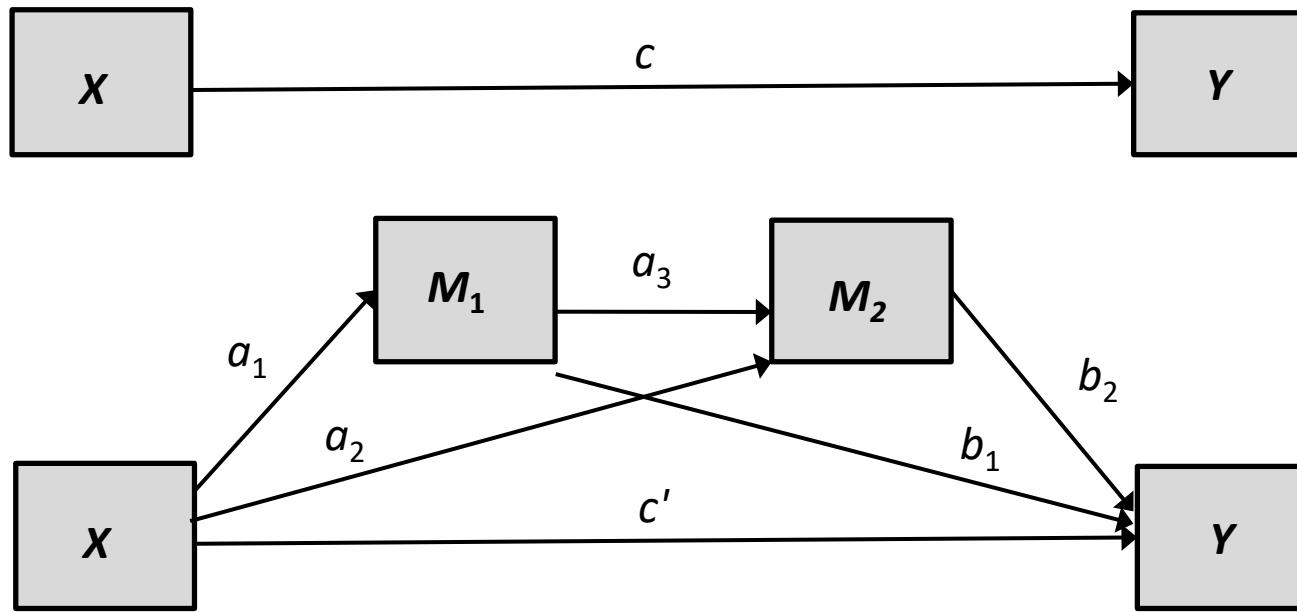


Kan, C., Lichtenstein, D. R., Grant, S. J., & Janiszewski, C. (2014). Strengthening the influence of advertised reference prices through information priming. *Journal of Consumer Research*, 40, 1078-1096.



Tsang, J-A., Carpenter, T. P., Roberts, J. A., Frisch, M. B., & Carlisle, R. D. (2014). Why are materialists less happy? The role of gratitude and need satisfaction in the relationship between materialism and life satisfaction. *Personality and Individual Differences*, 64, 62-66.

Serial mediation: Path analysis rules



The total effect of X on Y is equal to the direct effect of X plus the sum of all specific indirect effects (there are three of them here).

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

$$\widehat{M}_{1i} = a_{01} + a_1X_i$$

$$\widehat{M}_{2i} = a_{02} + a_2X_i + a_3M_{1i}$$

$$\widehat{Y}_i = c'_0 + c'X_i + b_1M_{1i} + b_2M_{2i}$$

Direct effect of X : c'

Specific indirect effect of X through M_1 : a_1b_1

Specific indirect effect of X through M_2 : a_2b_2

Specific indirect effect of X through M_1 and M_2 : $a_1a_3b_2$

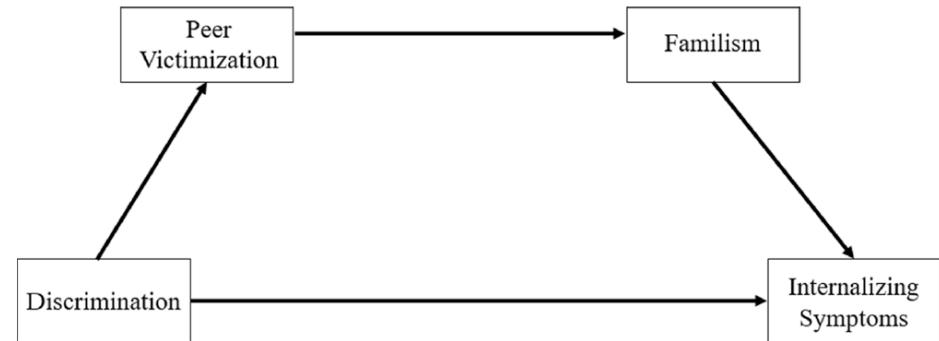
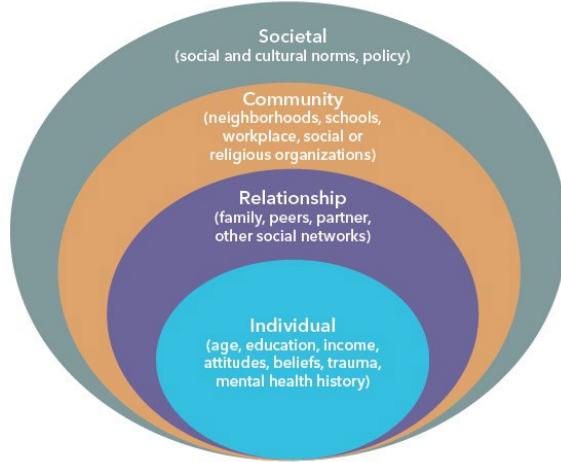
Total indirect effect of X : $a_1b_1 + a_2b_2 + a_1a_3b_2$

Total effect of X : $c = c' + a_1b_1 + a_2b_2 + a_1a_3b_2$

Example: LatinoMentalHealth

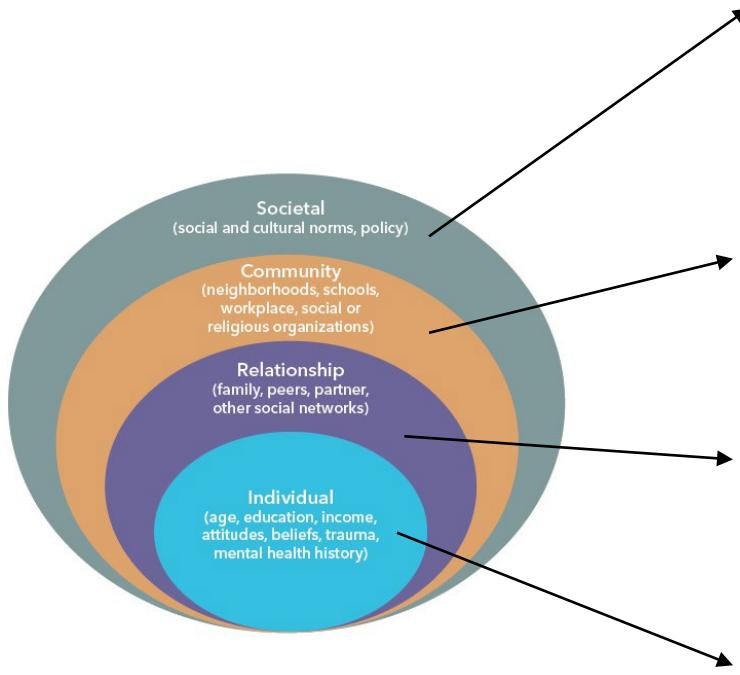
Discrimination and internalizing symptoms in rural Latinx adolescents: An ecological model of etiology

Giovanni Ramos ^{a,* ,1}, Desiree Delgadillo ^{a,* ,1}, Jessica Fossum ^a, Amanda K. Montoya ^a, Hardian Thamrin ^b, Amy Rapp ^a, Emily Escovar ^a, Denise April Chavira ^a



It has long been demonstrated that discrimination leads to poor mental health outcomes, especially for Latino youth, but the process is not well understood.

Example: LatinoMentalHealth



Discrimination

Subscale of the Society, Attitudinal, Familial, and Environmental Acculturative Stress – Child Scale

"Many people have stereotypes about Latinxs and treat me as if those were true."

10 items, rated 1 (Not at all True) to 4 (Very True), Mean score

Peer Victimization

Subscale of the Illinois Bullying Scale

"I got hit and pushed by other students."

4 items, rated 1 (Never) to 4 (7 or more times), Sum score

Familism

Familism Scale

"Family members feel loyal to the family."

7 items, rated 1 (Not at all True) to 5 (Very much true), Sum score

Internalizing Symptoms

Youth Self-Report subscales: anxious/depressed, withdrawn/depressed, somatic complaints

"Feels worried" "Feels sad" "Feels nausea"

31 items, rated 0 (Not True) to 2 (Very true), Sum score

Researchers hypothesized that discrimination leads to higher peer victimization, which leads to lower familism, which leads to higher internalizing symptoms

The Data: LatinoMentalHealth

LatinoMentalHealth.sav

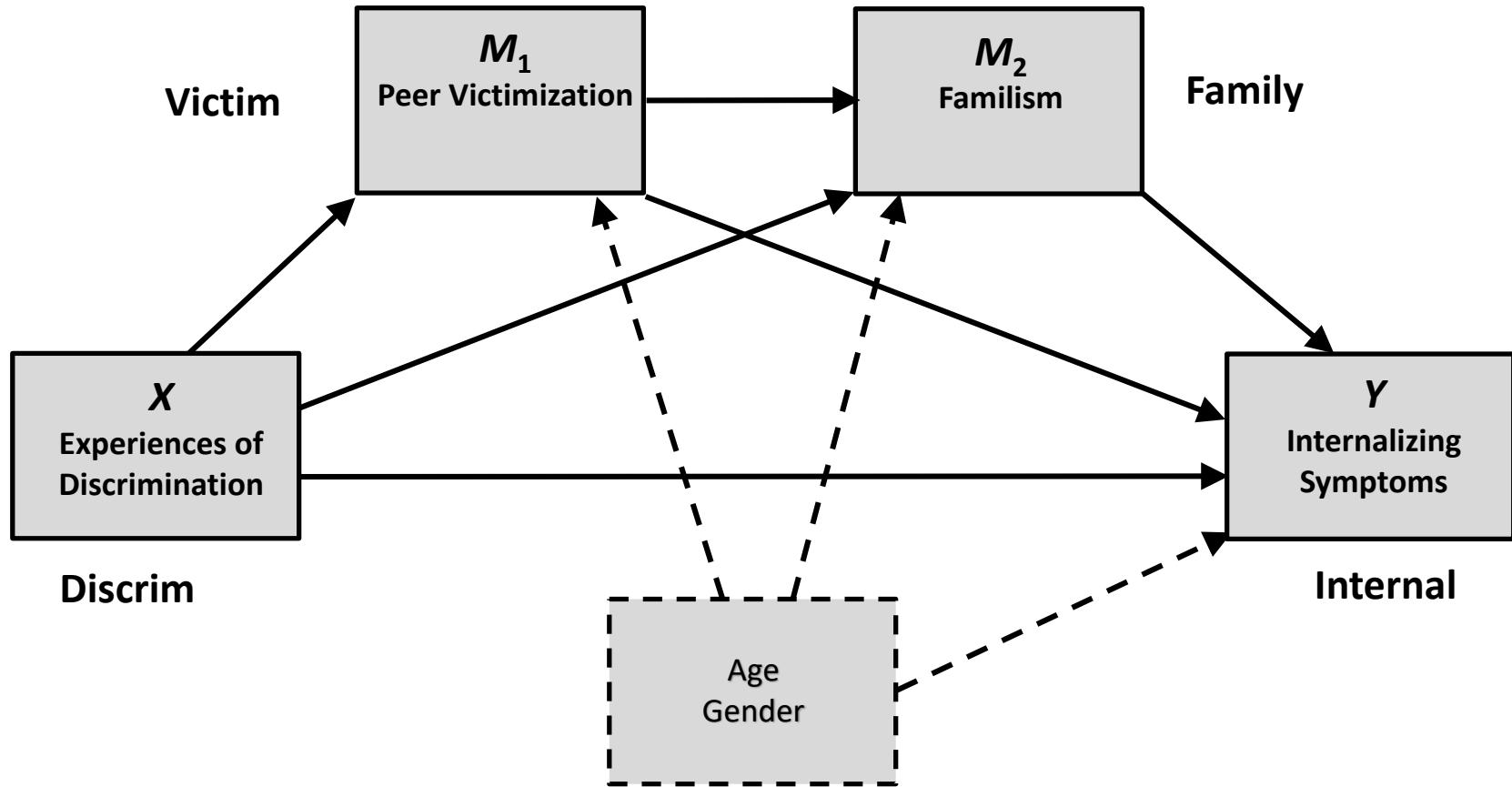
ID	Age	Gender	Discrim	Victim	Family	Internal
1005	14	2	1.44	.00	31.00	21.0
1008	14	2	1.89	3.00	35.00	14.0
1013	14	2	1.11	.00	35.00	1.0
1014	18	2	1.11	.00	19.00	22.0
1023	18	1	1.56	4.00	24.00	14.0
1026	17	1	1.67	.00	24.00	9.0
1029	18	1	1.33	3.00	18.00	17.0
1035	16	2	1.89	2.00	31.00	
2003	16	2	2.33	12.00	15.00	
2005	15	2	2.11	.00	29.00	
2006	16	2	1.22	.00	25.00	
2007	18	1	1.22	.00	31.00	
2008	17	1	1.00	.00	35.00	
2009	18	2	2.89	4.00	19.00	
2011	17	1	1.56	.00	30.00	
2013	17	2	1.11	5.00	15.00	
2014	17	2	1.89	1.00	25.00	

LatinoMentalHealth.csv

ID	Age	Gender	Discrim	Victim	Family	Internal
1005	14	2	1.444444	0.000000	31	21
1008	14	2	1.888889	3.000000	35	14
1013	14	2	1.111111	0.000000	35	1
1014	18	2	1.111111	0.000000	19	22
1023	18	1	1.555556	4.000000	24	14
1026	17	1	1.666667	0.000000	24	9
1029	18	1	1.333333	3.000000	18	17
1035	16	2	1.888889	2.000000	31	24
2003	16	2	2.333333	12.000000	15	31
2005	15	2	2.111111	0.000000	29	21
2006	16	2	1.222222	0.000000	25	11
2007	18	1	1.222222	0.000000	31	9
2008	17	1	1.000000	0.000000	35	7
2009	18	2	2.888889	4.000000	19	42
2011	17	1	1.555556	0.000000	30	17
2013	17	2	1.111111	5.000000	15	41
2014	17	2	1.888889	1.000000	25	44

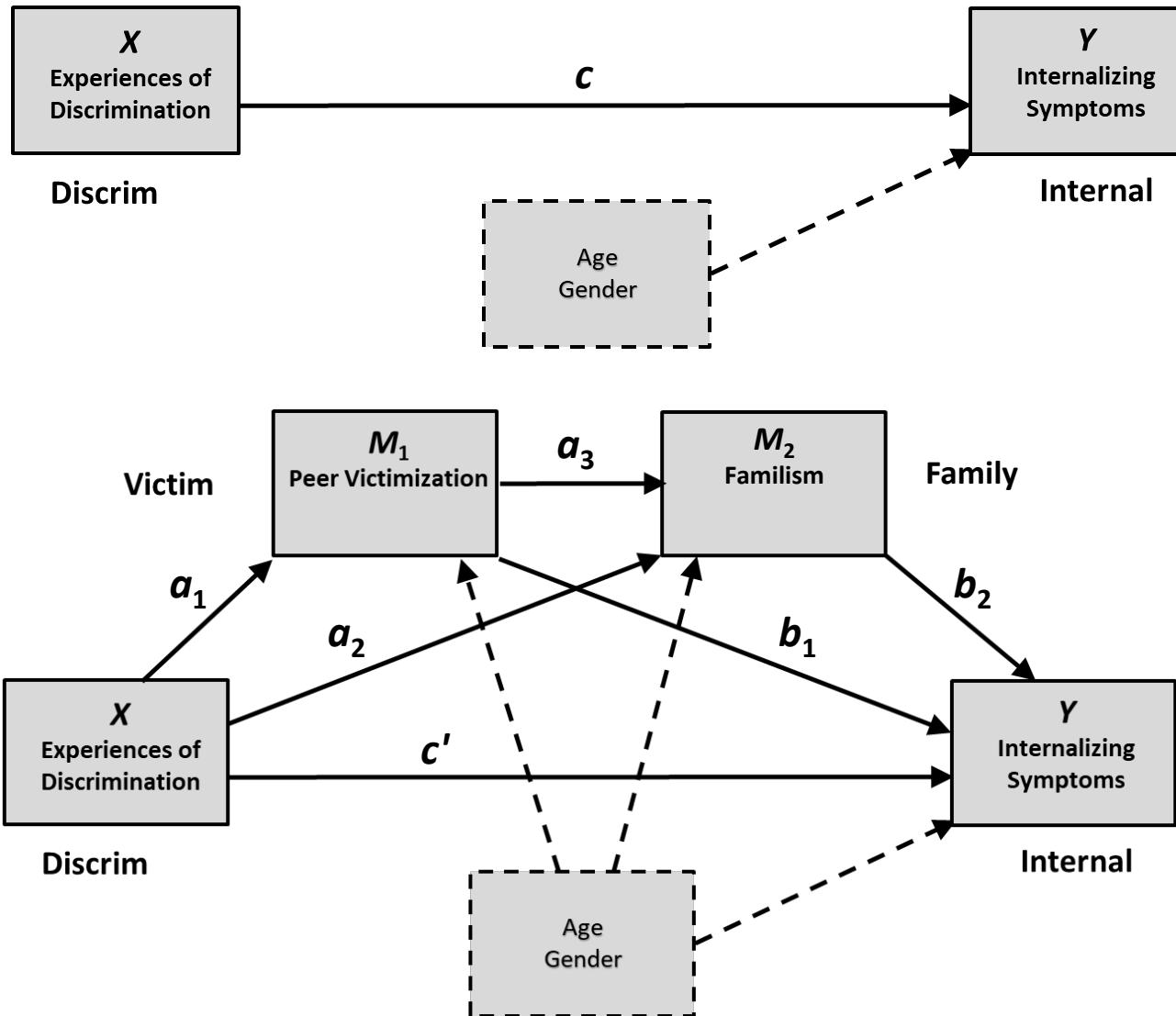
Also included in the data file are respondent **age** and **gender** (2 = female, 1 = male).

Example

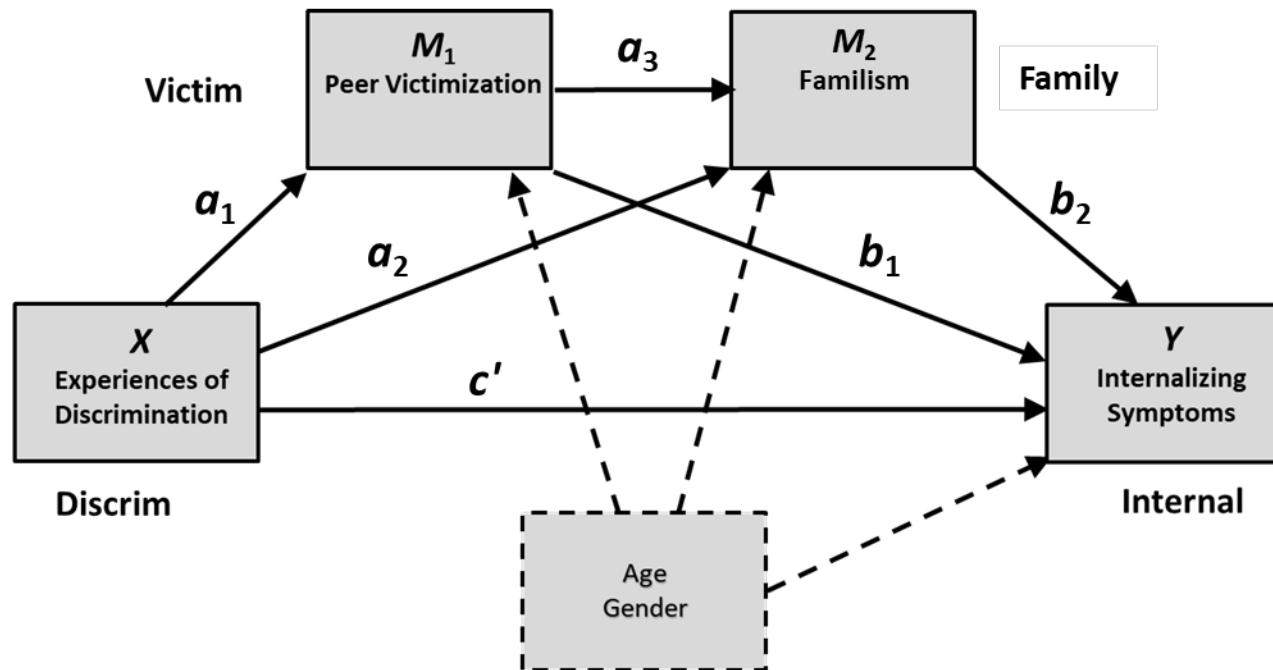


This model includes four pathways of influence of discrimination, two through a single mediator, one through both mediators in serial, and one direct.

Example



Example



Direct effect = c'

Specific indirect effect via peer victimization: $a_1 b_1$

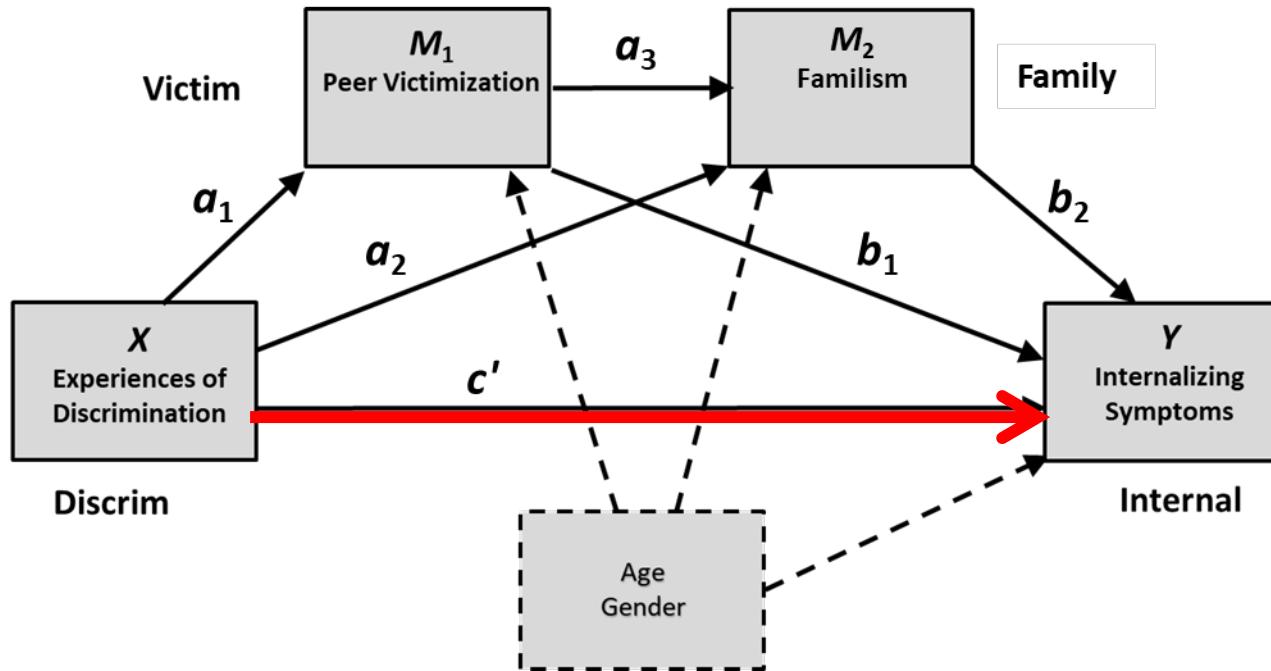
Specific indirect effect via familism: $a_2 b_2$

Specific indirect effect via peer victimization and familism: $a_1 a_3 b_2$

Total indirect effect = $a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Total effect = $c' + a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Example



Direct effect = c'

Specific indirect effect via peer victimization: $a_1 b_1$

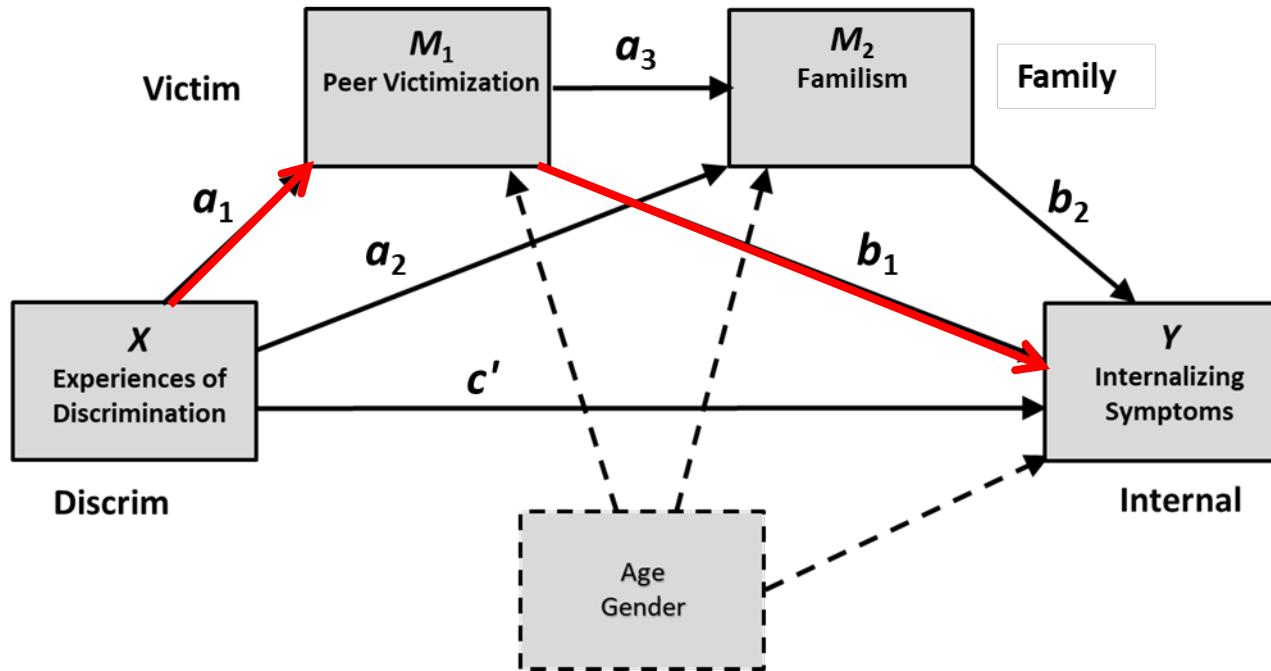
Specific indirect effect via familism: $a_2 b_2$

Specific indirect effect via peer victimization and familism: $a_1 a_3 b_2$

Total indirect effect = $a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Total effect = $c' + a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Example



Direct effect = c'

Specific indirect effect via peer victimization: $a_1 b_1$

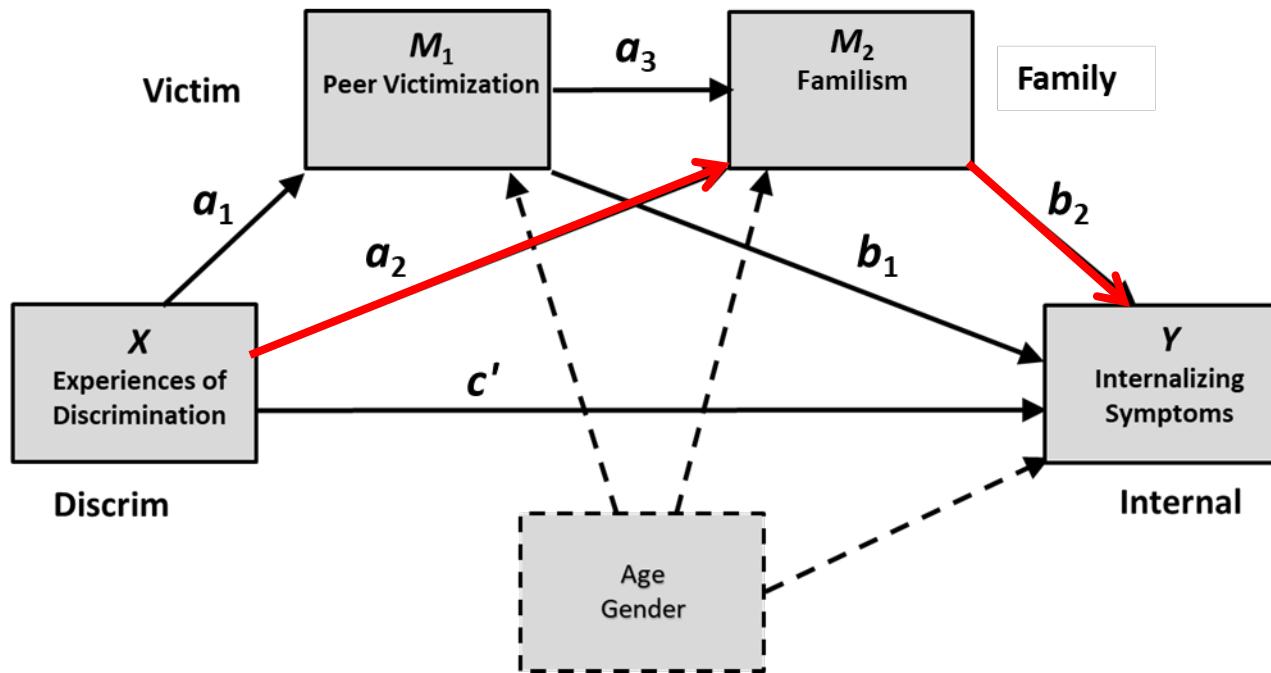
Specific indirect effect via familism: $a_2 b_2$

Specific indirect effect via peer victimization and familism: $a_1 a_3 b_2$

Total indirect effect = $a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Total effect = $c' + a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Example



Direct effect = c'

Specific indirect effect via peer victimization: $a_1 b_1$

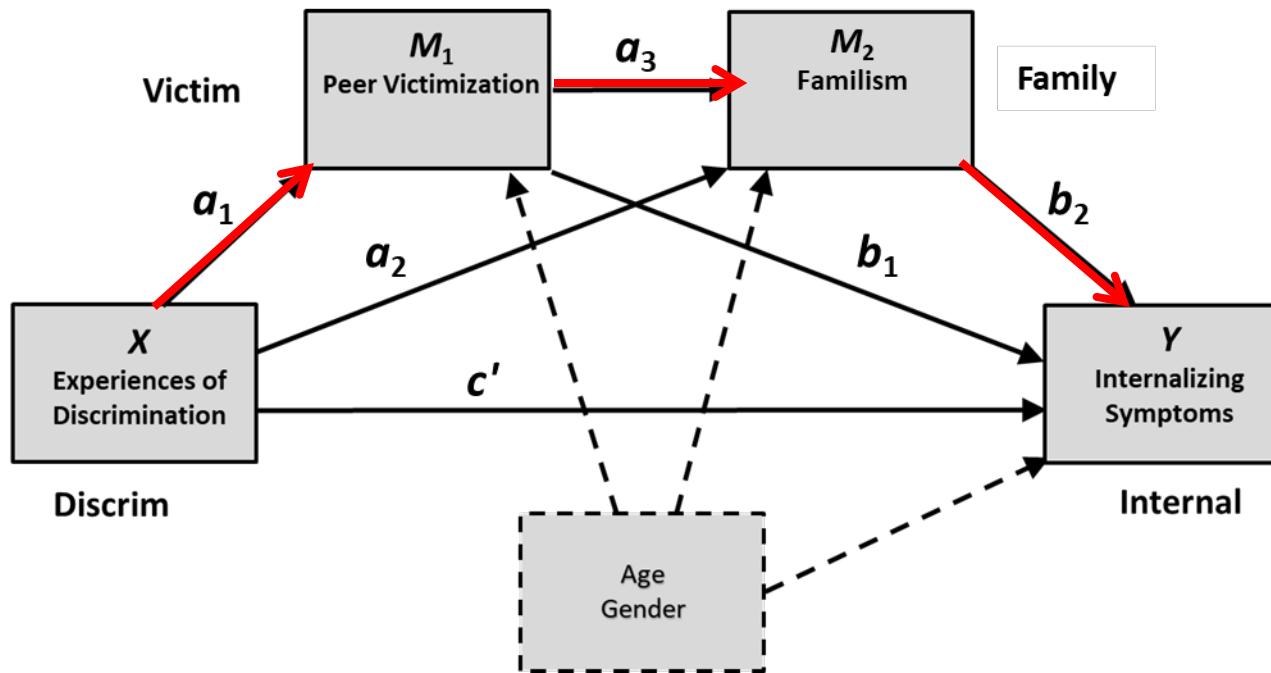
Specific indirect effect via familism: $a_2 b_2$

Specific indirect effect via peer victimization and familism: $a_1 a_3 b_2$

Total indirect effect = $a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Total effect = $c' + a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Example



Direct effect = c'

Specific indirect effect via peer victimization: $a_1 b_1$

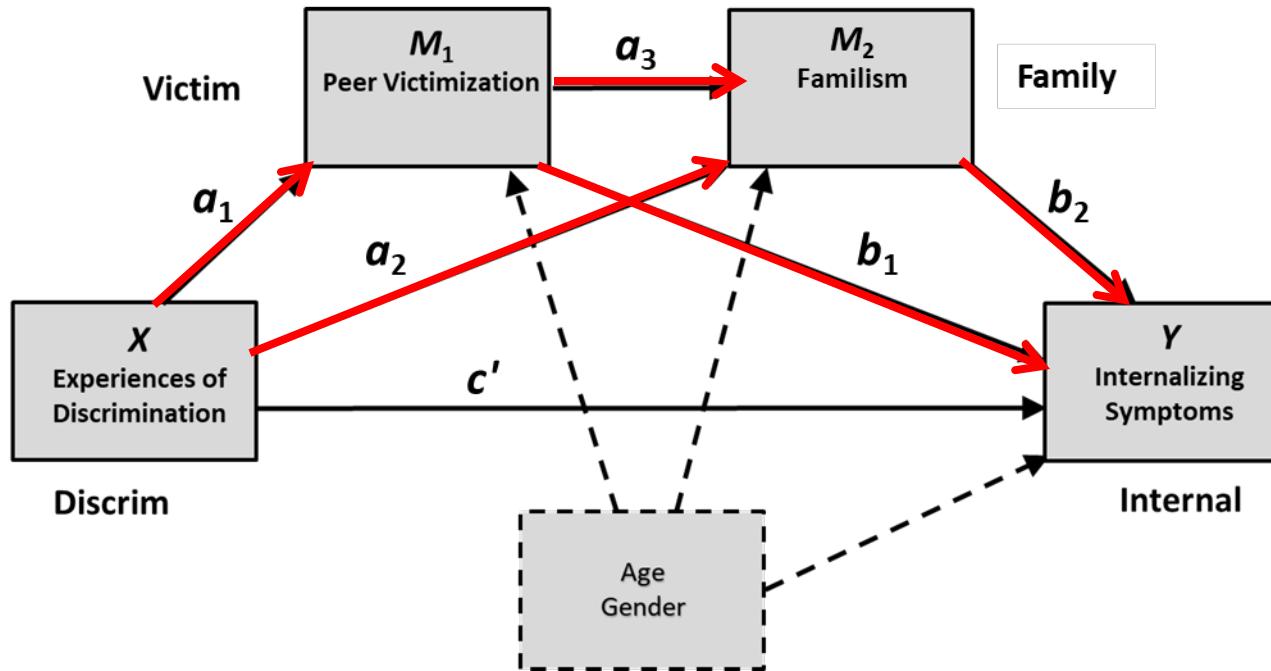
Specific indirect effect via familism: $a_2 b_2$

Specific indirect effect via peer victimization and familism: $a_1 a_3 b_2$

Total indirect effect = $a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Total effect = $c' + a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Example



Direct effect = c'

Specific indirect effect via peer victimization: $a_1 b_1$

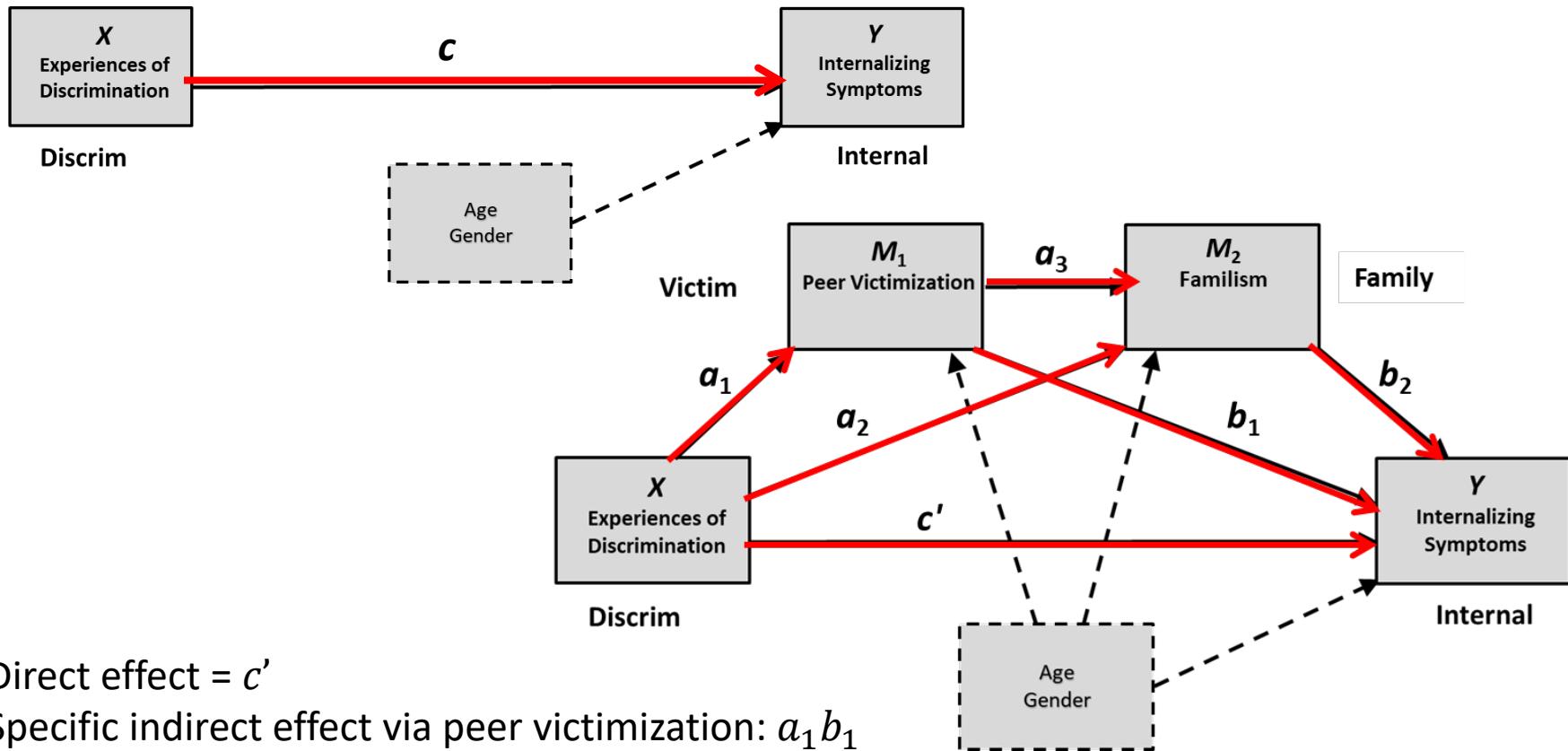
Specific indirect effect via familism: $a_2 b_2$

Specific indirect effect via peer victimization and familism: $a_1 a_3 b_2$

Total indirect effect = $a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Total effect = $c' + a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Example



Direct effect = c'

Specific indirect effect via peer victimization: $a_1 b_1$

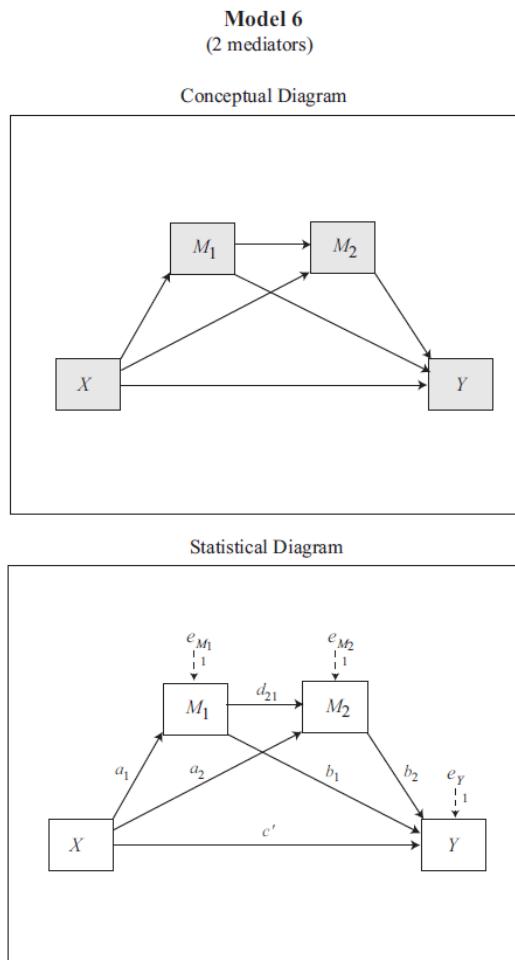
Specific indirect effect via familism: $a_2 b_2$

Specific indirect effect via peer victimization and familism: $a_1 a_3 b_2$

Total indirect effect = $a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Total effect = $c' + a_1 b_1 + a_2 b_2 + a_1 a_3 b_2$

Estimation and inference using PROCESS



PROCESS model 6 is the serial multiple mediator model.

In model 6, order of the variables in the "m=" list matters. Variables listed earlier are causally prior to those listed later. PROCESS allows up to four mediators to be linked in a causal chain. All possible indirect and direct effects are estimated.

```
process cov=age gender/y=internal/x=discrim/m=victim family/boot=10000/model=6/total=1.
```

```
%process (data=LatinoMentalHealth,cov=age gender,y=internal,x=discrim,m=victim family,boot=10000,model=6,total=1);
```

```
process(data=LatinoMentalHealth,cov=c("Age", "Gender"),y="Internal",x="Discrim" ,m=c("Victim", "Family"), boot=10000,model=6,total=1)
```

PROCESS output

***** PROCESS Procedure for R Version 5.0 *****

Written by Andrew F. Hayes, Ph.D. www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

Model: 6

Y: Internal

X: Discrim

M1: Victim

M2: Family

Covariates:

Age Gender

Sample size: 186

Random seed: 433165

Outcome Variable: Victim

$$\hat{M}_{1i} = 2.37 + 3.22X_i + \dots$$

Model Summary:

R	R-sq	MSE	F	df1	df2	p
0.4379	0.1918	9.9004	14.3940	3.0000	182.0000	0.0000

Model:

	coeff	se	t	p	LLCI	ULCI
constant	2.3723	3.7124	0.6390	0.5236	-4.9525	9.6972
Discrim	3.2185	0.5153	6.2465	0.0000	2.2019	4.2352
Age	-0.2926	0.2020	-1.4484	0.1492	-0.6912	0.1060
Gender	-0.0750	0.4759	-0.1576	0.8750	-1.0140	0.8640

a_1 path

For two children who are the same age and gender, but differ by 1 unit on discrimination, the child experiencing more discrimination is expected to experience 3.21 units more peer victimization.

PROCESS output

$$\hat{M}_{2i} = 38.77 - 2.68X_i - 0.44M_{1i} + \dots$$

Outcome Variable: Family

Model Summary:

R	R-sq	MSE	F	df1	df2	p
0.3962	0.1570	34.9067	8.4257	4.0000	181.0000	0.0000

Model:

	coeff	se	t	p	LLCI	ULCI
constant	38.7705	6.9786	5.5556	0.0000	25.0007	52.5404
Discrim	-2.6826	1.0662	-2.5161	0.0127	-4.7863	0.5789
Victim	-0.4405	0.1392	-3.1650	0.0018	-0.7152	-0.1659
Age	-0.2175	0.3815	-0.5701	0.5693	-0.9704	0.5353
Gender	-2.0614	0.8937	-2.3067	0.0222	-3.8248	-0.2981

For two children who are the same age and gender and experience the same level of victimization, but differ by 1 unit on discrimination, the child experiencing more discrimination is expected to endorse 2.68 units less familismo.

For two children who are the same age and gender and experience the same level of discrimination, but differ by 1 unit on peer victimization, the child experiencing more victimization is expected to endorse 0.44 units less familismo.

a_2 path
 a_3 path

PROCESS output

Outcome Variable: Internal

$$\hat{Y}_i = 13.25 + 9.17X_i + 0.19M_{1i} - 0.62M_{2i} + \dots$$

Model Summary:

R	R-sq	MSE	F	df1	df2	p
0.6734	0.4535	70.8521	29.8740	5.0000	180.0000	0.0000

Model:

	coeff	se	t	p	LLCI	ULCI
constant	13.2471	10.7567	1.2315	0.2197	-7.9784	34.4726
Discrim	9.1686	1.5453	5.9332	0.0000	6.1193	12.2178
Victim	0.1854	0.2037	0.9101	0.3640	-0.2166	0.5874
Family	-0.6188	0.1059	-5.8439	0.0000	-0.8278	-0.4099
Age	-0.1575	0.5441	-0.2896	0.7725	-1.2311	0.9160
Gender	5.0603	1.2918	3.9173	0.0001	2.5113	7.6092

c' path

For two children who are the same age and gender and experience the same level of victimization and familism, but differ by 1 unit on discrimination, the child experiencing more discrimination is expected to endorse 9.18 more internalizing symptoms.

PROCESS output

Outcome Variable: Internal

$$\hat{Y}_i = 13.25 + 9.17X_i + 0.19M_{1i} - 0.62M_{2i} + \dots$$

Model Summary:

R	R-sq	MSE	F	df1	df2	p
0.6734	0.4535	70.8521	29.8740	5.0000	180.0000	0.0000

Model:

	coeff	se	t	p	LLCI	ULCI
constant	13.2471	10.7567	1.2315	0.2197	-7.9784	34.4726
Discrim	9.1686	1.5453	5.9332	0.0000	6.1193	12.2178
Victim	0.1854	0.2037	0.9101	0.3640	-0.2166	0.5874
Family	-0.6188	0.1059	-5.8439	0.0000	-0.8278	-0.4099
Age	-0.1575	0.5441	-0.2896	0.7725	-1.2311	0.9160
Gender	5.0603	1.2918	3.9173	0.0001	2.5113	7.6092

b_1 path
 b_2 path

For two children who are the same age and gender and experience the same level of discrimination and familism, but differ by 1 unit on peer victimization, the child experiencing more victimization is expected to endorse 0.19 more internalizing symptoms.

For two children who are the same age and gender and experience the same level of discrimination and peer victimization, but differ by 1 unit on familism, the child endorsing more familism is expected to endorse 0.62 fewer internalizing symptoms.

PROCESS output

***** TOTAL EFFECT MODEL *****

Outcome Variable: Internal

$$\hat{Y}_i = -9.66 + 12.30X_i + \dots$$

Model Summary:

R	R-sq	MSE	F	df1	df2	p
0.5776	0.3336	85.4452	30.3724	3.0000	182.0000	0.0000

Model:

	coeff	se	t	p	LLCI	ULCI
constant	-9.6595	10.9061	-0.8857	0.3770	-31.1782	11.8592
Discrim	12.3028	1.5137	8.1277	0.0000	9.3162	15.2894
Age	-0.1569	0.5935	-0.2644	0.7917	-1.3280	1.0141
Gender	6.3016	1.3981	4.5074	0.0000	3.5431	9.0601

c path

For two children who are the same age and gender, but differ by 1 unit on discrimination, the child experiencing more discrimination is expected to endorse 12.30 more internalizing symptoms.

PROCESS output

***** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y *****

Total effect of X on Y:

effect	se	t	p	LLCI	ULCI
12.3028	1.5137	8.1277	0.0000	9.3162	15.2894

← c path

Direct effect of X on Y:

effect	se	t	p	LLCI	ULCI
9.1686	1.5453	5.9332	0.0000	6.1193	12.2178

← c' path

Indirect effect(s) of X on Y:

Effect	BootSE	BootLLCI	BootULCI
TOTAL	3.1342	1.2582	0.9412
Ind1	0.5967	0.8784	-1.0034
Ind2	1.6601	0.7944	0.2549
Ind3	0.8774	0.4486	0.1272
			5.7836
		2.4832	
		3.3700	
		1.8815	

$a_1b_1 + a_2b_2 + a_1a_3b_2$

a_1b_1

a_2b_2

and bootstrap CIs

$a_1a_3b_2$

Indirect effect key:

Ind1 Discrim	->	Victim	->	Internal		
Ind2 Discrim	->	Family	->	Internal		
Ind3 Discrim	->	Victim	->	Family	->	Internal

The data are consistent with the claim that discrimination increased internalizing symptoms serially through peer victimization and familism (0.88, 95% CI=0.13 to 1.88) and through familism independent of victimization (1.66, 95% = 0.25 to 3.37) but not through victimization independent of familism (0.60, 95% CI =-1.00 to 2.48). There is also evidence of a direct effect of discrimination independent of these pathways of influence (9.17, SE = 1.55, p <.001).

Causality in Serial Mediation

In a simple mediation model with no random assignment there are 6 possible orderings of the variables in the model.

$X \rightarrow M \rightarrow Y$, $X \rightarrow Y \rightarrow M$, $M \rightarrow X \rightarrow Y$, $M \rightarrow Y \rightarrow X$, $Y \rightarrow X \rightarrow M$, $Y \rightarrow M \rightarrow X$

With randomization of X , you can eliminate many of these, and are left with 2 possible orders. But also any of these could be confounded as well.

$X \rightarrow M \rightarrow Y$, $X \rightarrow Y \rightarrow M$,

Serial mediation with 2 mediators and no random assignment there are $6 \times 4 = 24$ possible orderings of the variables in the model.

$X \rightarrow M_1 \rightarrow M_2 \rightarrow Y$, $X \rightarrow M_1 \rightarrow Y \rightarrow M_2$, $X \rightarrow M_2 \rightarrow M_1 \rightarrow Y$, $X \rightarrow M_2 \rightarrow Y \rightarrow M_1$, $X \rightarrow Y \rightarrow M_1 \rightarrow M_2$, $X \rightarrow Y \rightarrow M_2 \rightarrow M_1$

$M_1 \rightarrow M_2 \rightarrow X \rightarrow Y$, $M_1 \rightarrow M_2 \rightarrow Y \rightarrow X$, $M_1 \rightarrow X \rightarrow M_2 \rightarrow Y$, $M_1 \rightarrow X \rightarrow Y \rightarrow M_2$, $M_1 \rightarrow Y \rightarrow M_2 \rightarrow X$, $M_1 \rightarrow Y \rightarrow X \rightarrow M_2$

$M_2 \rightarrow M_1 \rightarrow X \rightarrow Y$, $M_2 \rightarrow M_1 \rightarrow Y \rightarrow X$, $M_2 \rightarrow X \rightarrow M_1 \rightarrow Y$, $M_2 \rightarrow X \rightarrow Y \rightarrow M_1$, $M_2 \rightarrow Y \rightarrow M_1 \rightarrow X$, $M_2 \rightarrow Y \rightarrow X \rightarrow M_1$

$Y \rightarrow X \rightarrow M_1 \rightarrow M_2$, $Y \rightarrow X \rightarrow M_2 \rightarrow M_1$, $Y \rightarrow M_1 \rightarrow M_2 \rightarrow X$, $Y \rightarrow M_1 \rightarrow X \rightarrow M_2$, $Y \rightarrow M_2 \rightarrow M_1 \rightarrow X$, $Y \rightarrow M_2 \rightarrow X \rightarrow M_1$

With randomization of X you limit to 6 but also confounding. This number continues to increase as you add mediators.

Planning a Mediation Analysis

There are many choices to be made in a mediation analysis, and these choices become even more plentiful as you add more complexity to your models

- Moderated mediation
- Multiple moderators
- Complex outcomes

Increasing criticism of mediation analysis, means researchers need to provide transparent plans for their analysis prior to conducting data collection and analysis.

You must think through the assumptions in advance:

- Select design characteristics to minimize assumptions
- Measure potential confounders of each relationship in your model

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., $SE \leq 0.5$)

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 than 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

Test	Condition															
	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 Simulations:

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.

WebPower R package, Schoemann, et al., 2017

bmem R package (uses lavaan) allows for non-normal distributions and missing data

<https://davidakenny.shinyapps.io/MedPower/> simple mediation only

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 or path coefficients, 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://schoemann.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

Power Analysis Examples

medjs function in the **pwr2ppl** R package

<https://cran.r-project.org/web/packages/pwr2ppl/pwr2ppl.pdf>

Assume we want to replicate the protest study assuming no XM interaction,
what sample size should we use to have 80% to detect an effect?

```
cor(protest$protest, protest$respappr)
cor(protest$protest, protest$liking)
cor(protest$respappr, protest$liking)

for (i in seq(36,50,2)){
  medjs(rx1m1=0.50, rx1y=0.21, rym1=0.49,mvars=1,n=i)
}
```

Output:

```
> for (i in seq(36,50,2)){
+   medjs(rx1m1=0.50, rx1y=0.21, rym1=0.49,mvars=1,n=i)
+ }
Sample size is 36
Power is 0.718
Sample size is 38
Power is 0.755
Sample size is 40
Power is 0.761
Sample size is 42
Power is 0.796
Sample size is 44
Power is 0.818
Sample size is 46
Power is 0.873
Sample size is 48
Power is 0.881
Sample size is 50
Power is 0.889
```

It appears we will
need a sample size
of about 44 to
have 80% power.

Preregistration

Preregistration: A process where you create a time-stamped, publicly accessible record of your plan for a specific study.

Current preregistrations of mediation analysis are light on the details: "We plan to conduct mediation tests (including multiple mediation) using the MEMORE macro (Montoya & Hayes, 2017) and the PROCESS macro (Hayes, 2017)."

- Planned sample size
- α -level/CI-level for each test
- Role of different variables in the analysis (e.g., independent variable, mediator, outcome, covariate), and how they are computed
- Estimation Method
- Inferential method and any important specifications for that method (e.g., how many bootstraps, seed number)
- Tools and specifications

Example Preregistration

We will estimate a simple mediation analysis where protest condition (X) affects liking (Y) through response appropriateness (M) using a sample of 500 participants. Protest condition is randomly assigned to individuals where 50% will be assigned to the protest condition and 50% to the no protest condition. Liking is measured using 4 Likert type items evaluating the lawyers positive characteristics. We will check the reliability of our scale prior to analysis and if the reliability (alpha) is greater than 0.7, we will proceed. If it is not we may consider dropping items. Similarly, response appropriateness is measured using 5 Likert type items. We will use the same procedure for measurement evaluation as with liking. In our analysis we will not control for any covariates.

We will use the **PROCESS function for R (version 4.2)** to estimate our model, which uses ordinary least squares regression and generates percentile bootstrap confidence intervals for the indirect effect. We will use 5,000 bootstraps. *We will test hypothesis 1 by examining whether the 95% bootstrap confidence interval for the indirect effect includes zero.*

Reporting Mediation Analysis

Mediation analysis should be reported thoroughly throughout the paper, and is not just something to consider in your methods/results. The analysis will have implications for the way you craft every part of your paper.

Intro:

- Build a theoretical argument for your causal model
- What evidence is there from prior studies that the pathways you are examining are causal?
- Research that suggests potential confounders should be discussed

Methods:

- Study designs should sufficiently described so that readers can evaluate validity of causal claims
- Measures should be sufficiently described so that readers can evaluate reliability and interpret regression coefficients
- Sample size planning/rationale
- Analysis approach should be sufficiently describe to allow for reproduction using the original data
 - Role of variables, OLS vs. ML, covariates, inferential method, levels of tests, software (with version info)

Reporting Mediation Analysis

Results:

- Estimates and inferential statistics for important paths in the mediation
 - Report a , b , and ab
- Provide information for all paths in table or supplement

Discussion:

- Balance evidence and limitations
- Be careful about making unfounded causal claims
- Limitations: discuss each assumption in turn, evidence for meeting or not meeting, hypotheses, suggested future directions

Other Things:

- Include a figure that shows the role of each variable and includes all covariates
- Post your data & code openly
- Post your materials openly

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

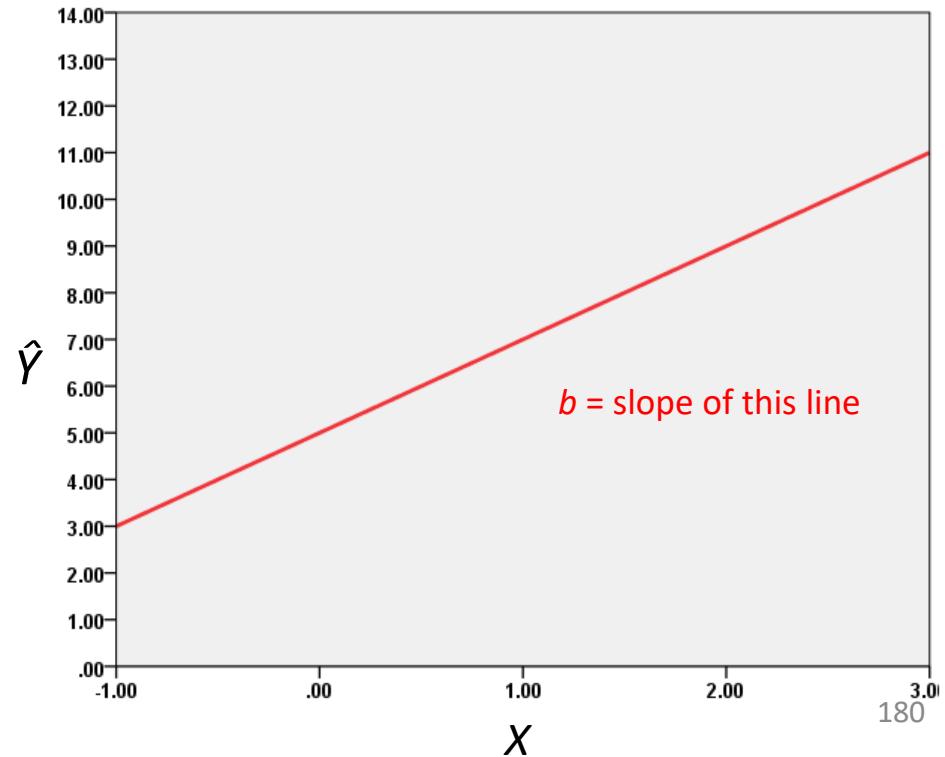
Consider a simple regression model with predictor variable X .

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

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 .

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

Regardless of W , a one unit difference in X is associated with the same expected difference on \hat{Y} . And regardless of the value of X , a one unit difference in W is associated with the same expected difference on \hat{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.

Most generally,

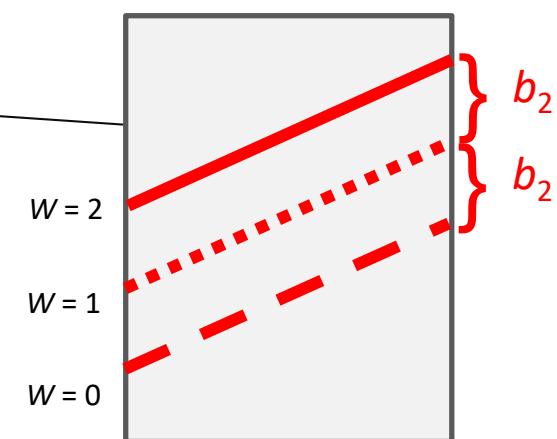
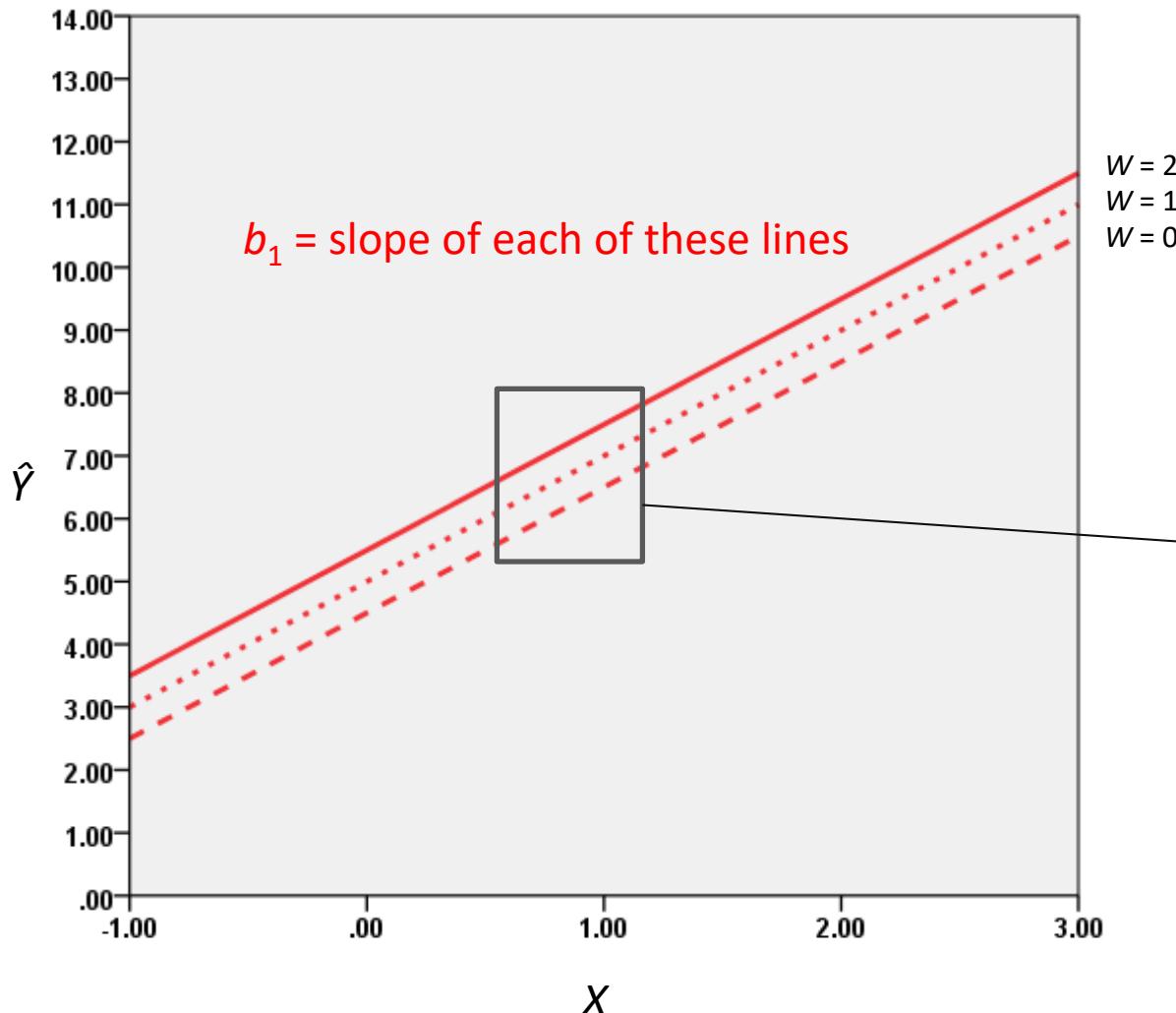
$$b_1 = \hat{Y}|(X = \omega + 1, W = \lambda) - \hat{Y}|(X = \omega, W = \lambda) \text{ for all } \omega, \lambda$$

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

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

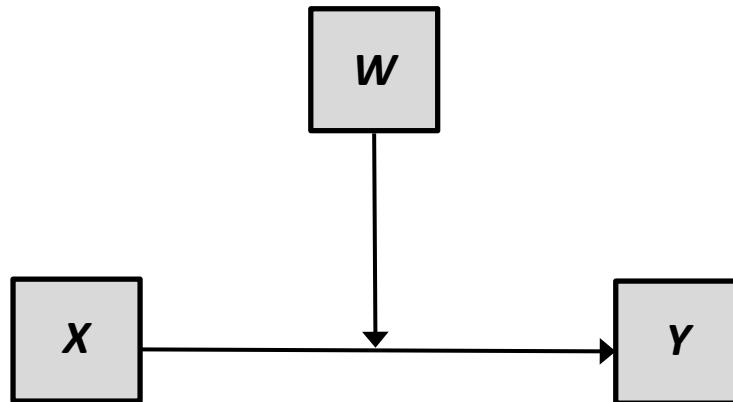
Partial regression coefficients as **unconditional** effects

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



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

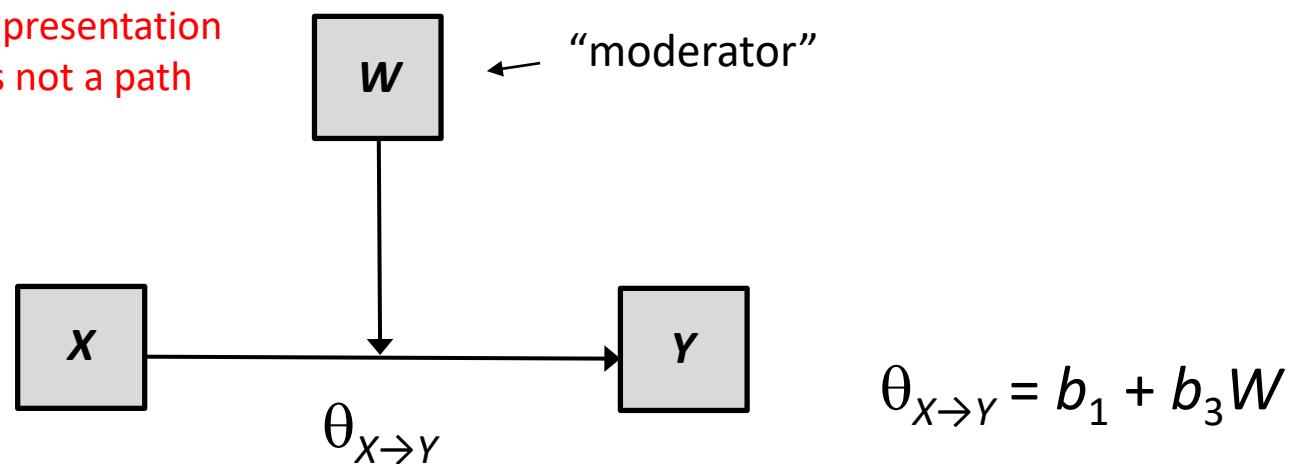
$$\hat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$$

can be written as

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

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

“focal predictor”



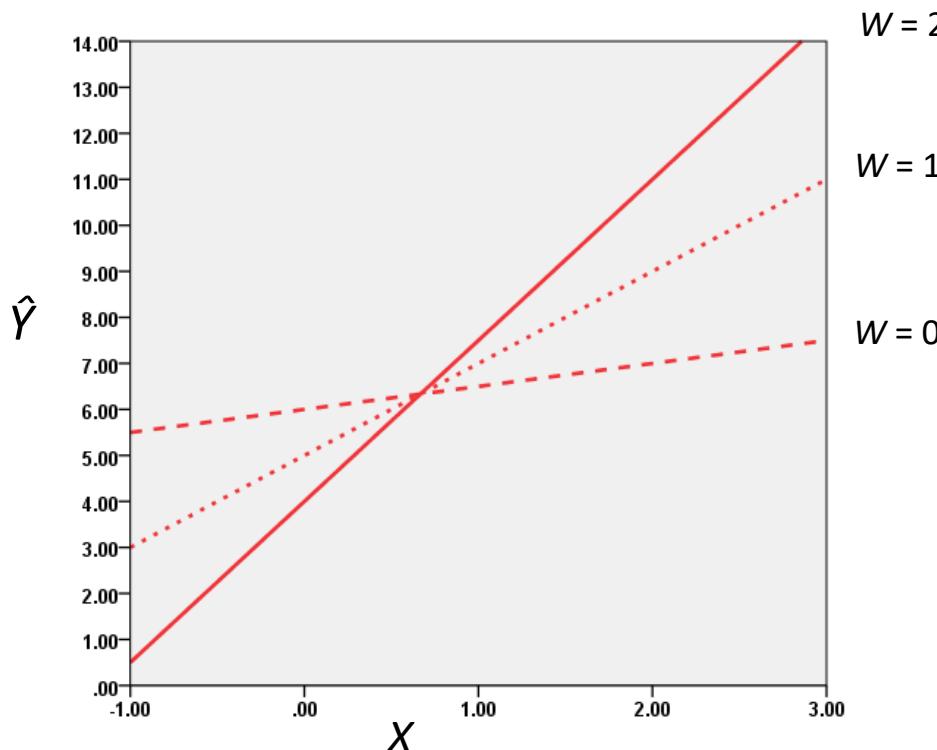
$\theta_{X \rightarrow Y}$ is the “conditional effect of X ” defined by the function $b_1 + b_3 W$

X 's effect as a function of W

$$\begin{aligned}b_0 &= 6.00 \\b_1 &= 0.50 \\b_2 &= -1.00 \\b_3 &= 1.50\end{aligned}$$

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

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



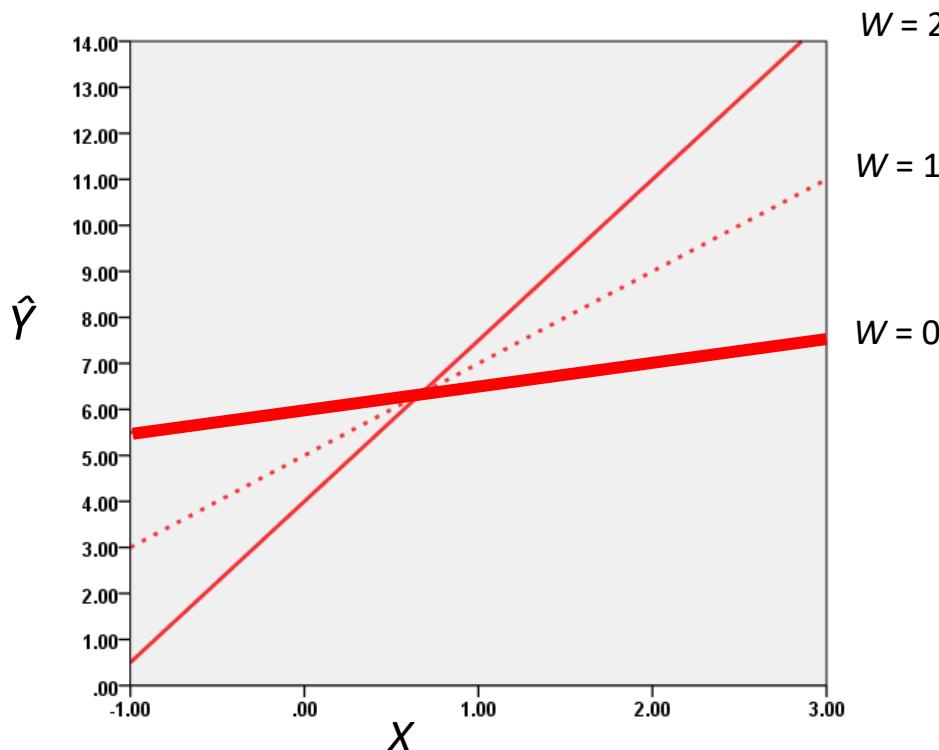
X	W	\hat{Y}
-1	0	5.50
-1	1	3.00
-1	2	0.50
0	0	6.00
0	1	5.00
0	2	4.00
1	0	6.50
1	1	7.00
1	2	7.50
2	0	7.00
2	1	9.00
2	2	11.00

X's effect as a function of W

$$\begin{aligned}b_0 &= 6.00 \\b_1 &= 0.50 \\b_2 &= -1.00 \\b_3 &= 1.50\end{aligned}$$

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

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

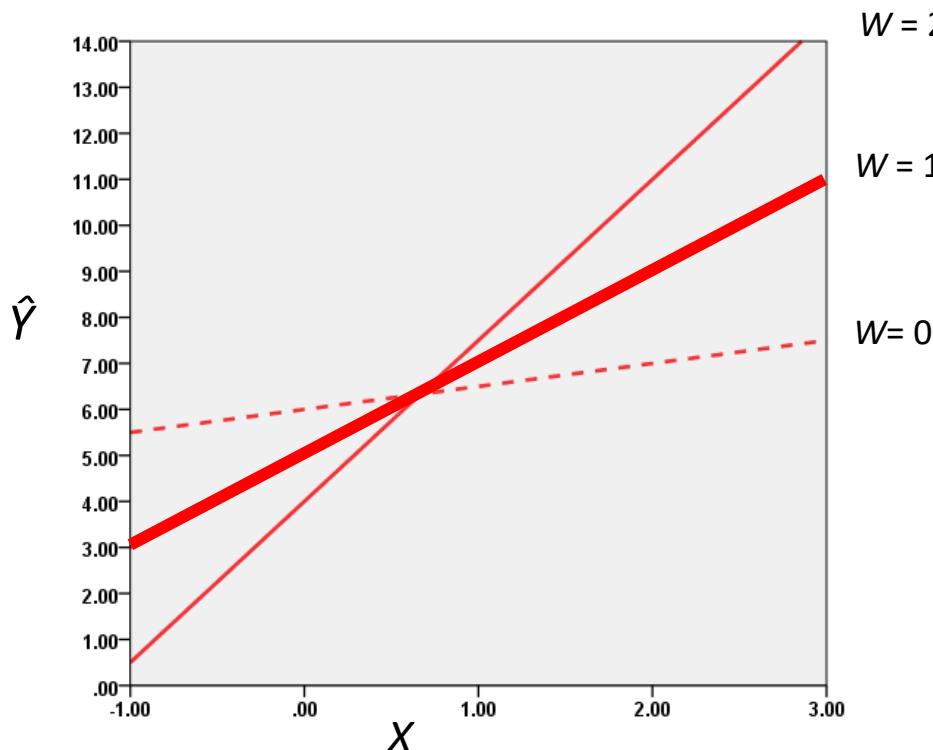
$$\begin{aligned}\theta_{X \rightarrow Y} &= b_1 + b_3 W \\&= 0.50 + 1.50W \\&= 0.50 + 1.50(0) = 0.50\end{aligned}$$

X's effect as a function of W

$$\begin{aligned}b_0 &= 6.00 \\b_1 &= 0.50 \\b_2 &= -1.00 \\b_3 &= 1.50\end{aligned}$$

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

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

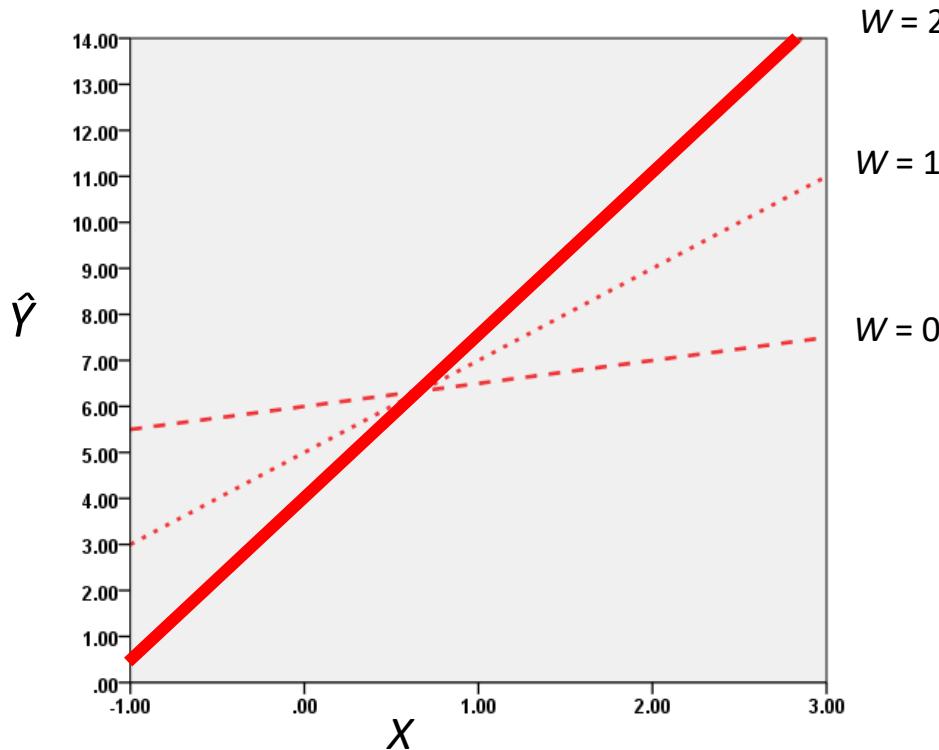
$$\begin{aligned}\theta_{X \rightarrow Y} &= b_1 + b_3 W \\&= 0.50 + 1.50W \\&= 0.50 + 1.50(1) = 2.00\end{aligned}$$

X's effect as a function of W

$$\begin{aligned}b_0 &= 6.00 \\b_1 &= 0.50 \\b_2 &= -1.00 \\b_3 &= 1.50\end{aligned}$$

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

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

$$\begin{aligned}\theta_{X \rightarrow Y} &= b_1 + b_3 W \\&= 0.50 + 1.50W \\&= 0.50 + 1.50(2) = 3.50\end{aligned}$$

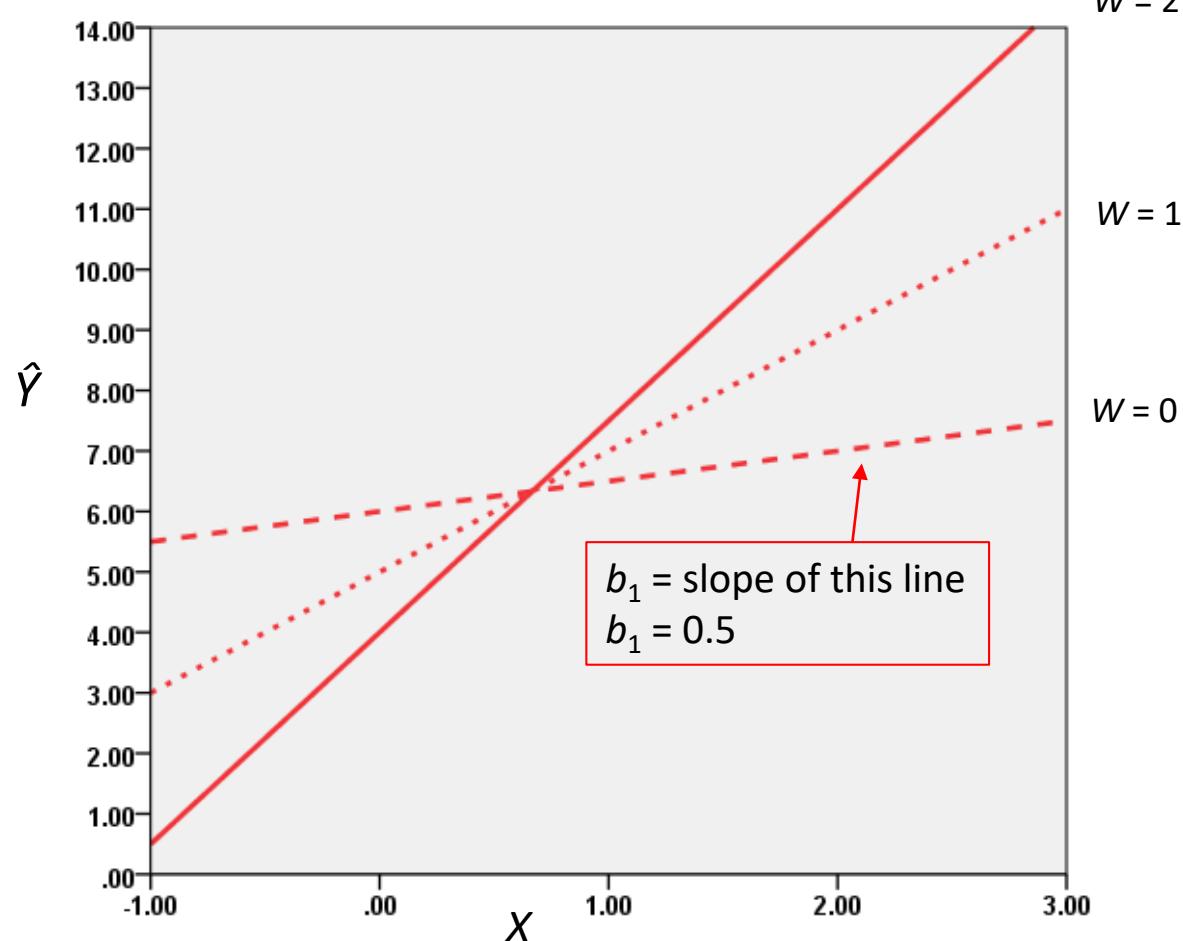
Interpretation of b_1 as a conditional effect

$$\begin{aligned}b_0 &= 6.00 \\b_1 &= 0.50 \\b_2 &= -1.00 \\b_3 &= 1.50\end{aligned}$$

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 $W = 0$.

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



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

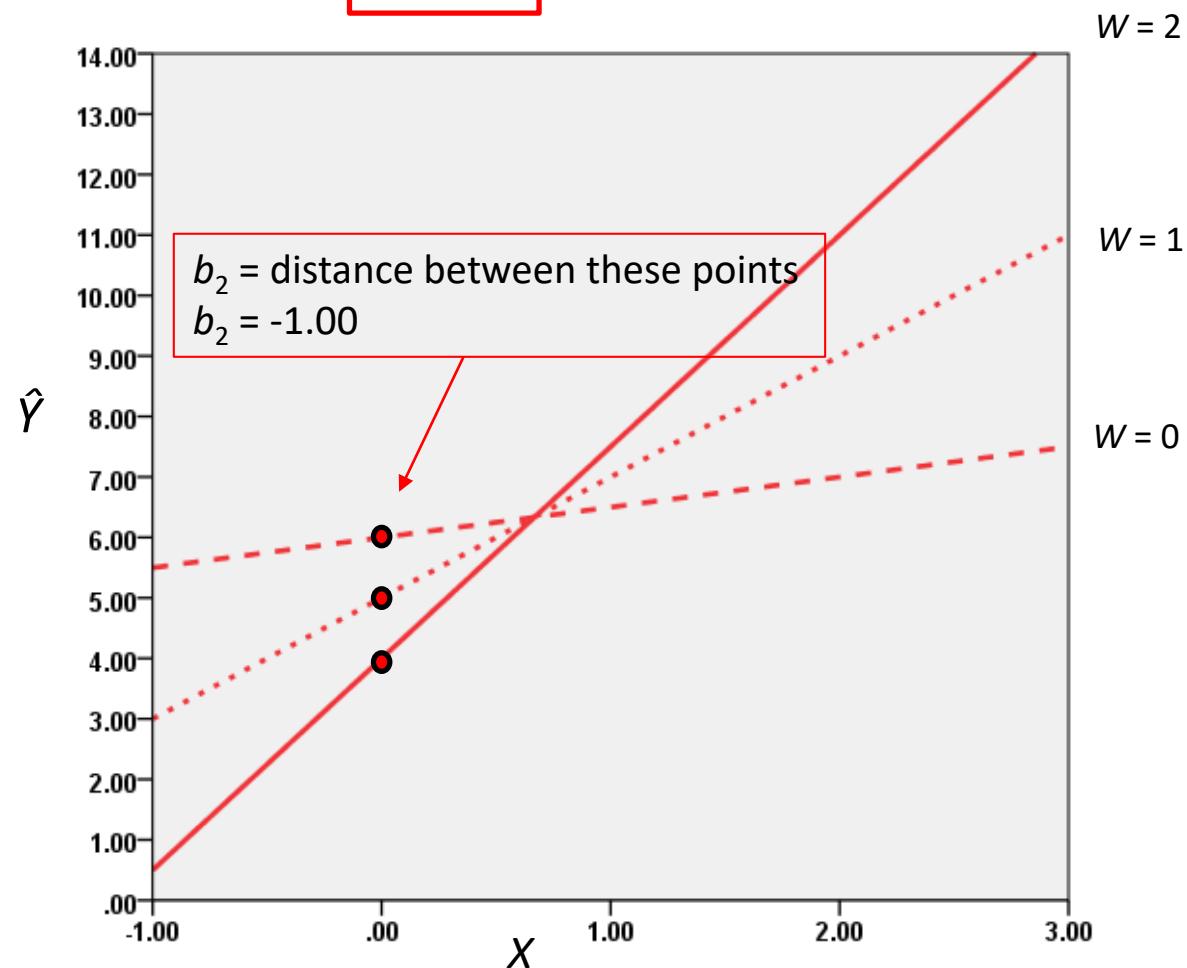
Interpretation of b_2 as a conditional effect

$$\begin{aligned}b_0 &= 6.00 \\b_1 &= 0.50 \\b_2 &= -1.00 \\b_3 &= 1.50\end{aligned}$$

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 $X = 0$.

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



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

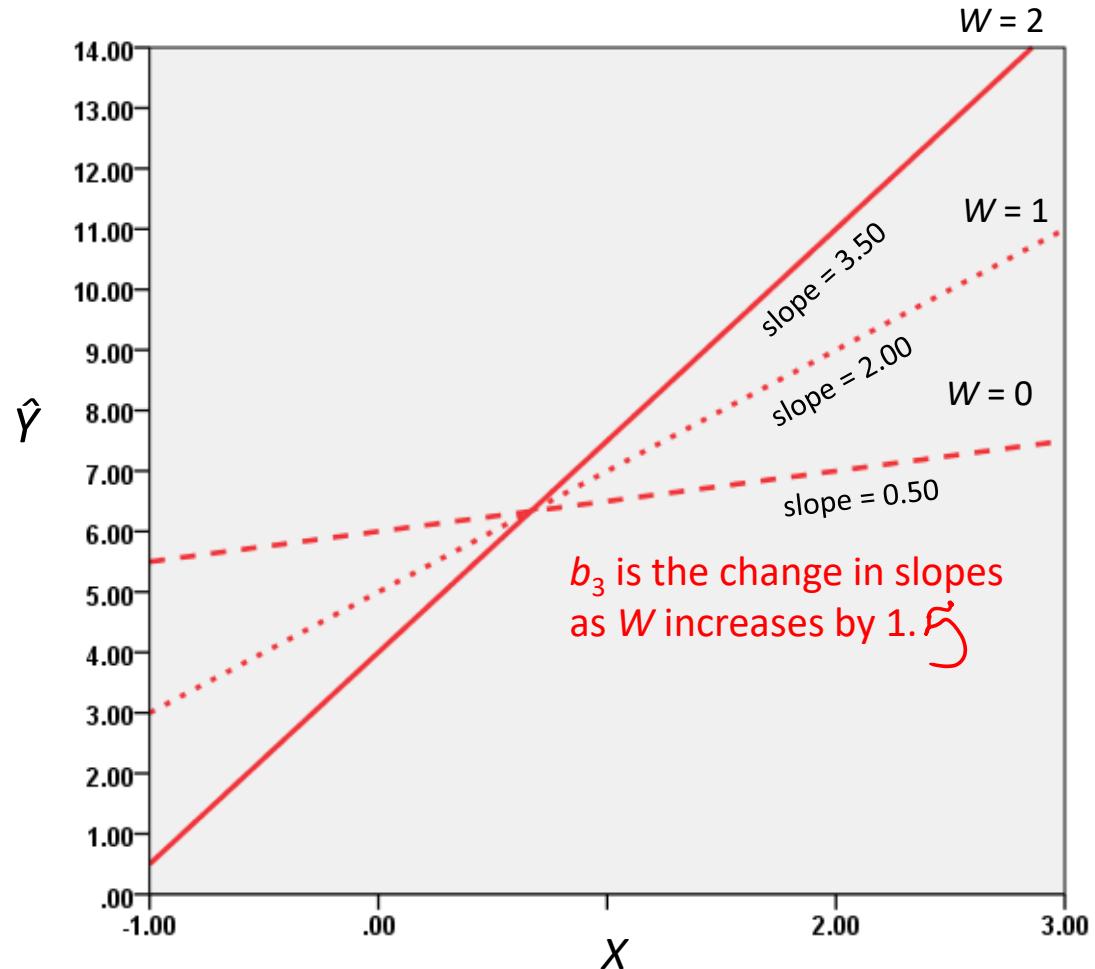
Interpretation of b_3

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

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

$$\theta_{X \rightarrow Y} = b_1 + b_3 W \\ = 0.50 + 1.50W$$

$\theta_{X \rightarrow Y}$	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

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

b_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.

b_2

The effect of W on Y holding X constant. This is a *partial* effect.

b_3

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

The estimated value of Y when X and $W = 0$.

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 .

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 .

How much the effect of X on Y changes as W changes by 1 unit.

Symmetry in moderation

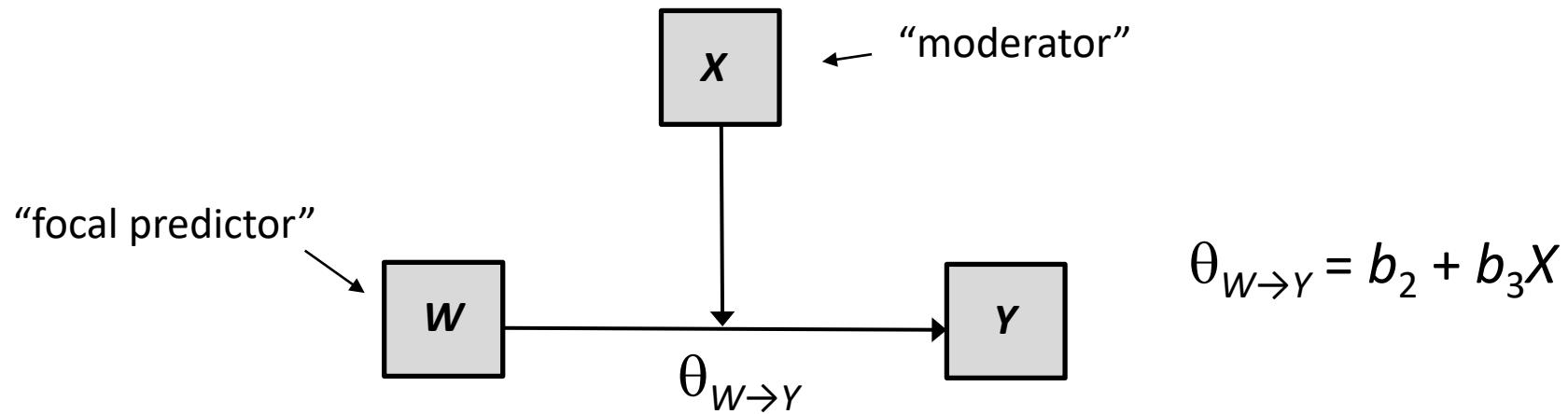
$$\hat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$$

We saw that this is alternative representation of

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

But it is also an alternative representation of

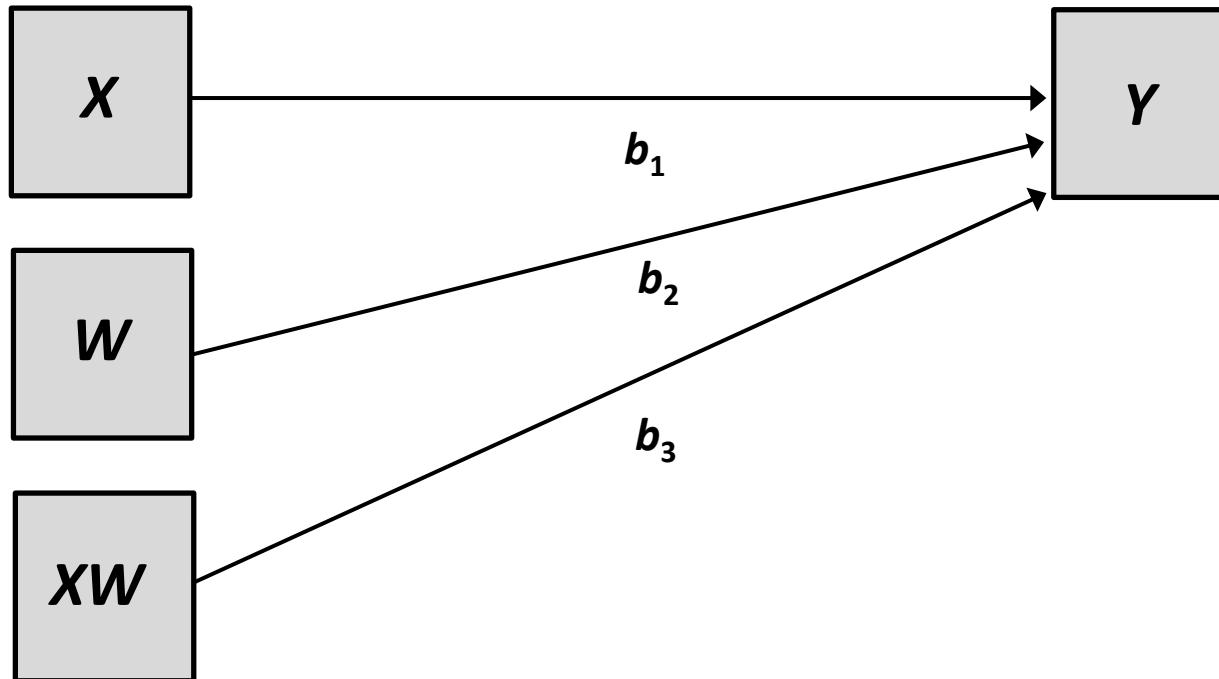
$$\hat{Y}_i = b_0 + (b_2 + b_3 X_i) W_i + b_1 X_i$$



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

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

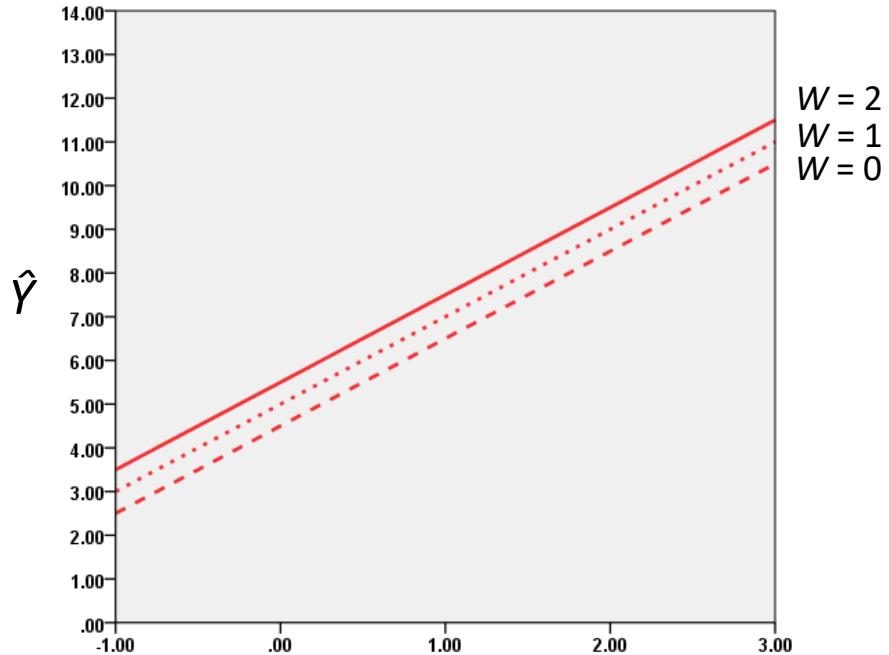


Remember

b_1 is NOT the effect of X on Y . The effect of X is $b_1 + b_3 W$
 b_2 is NOT the effect of W on Y . The effect of W is $b_2 + b_3 X$

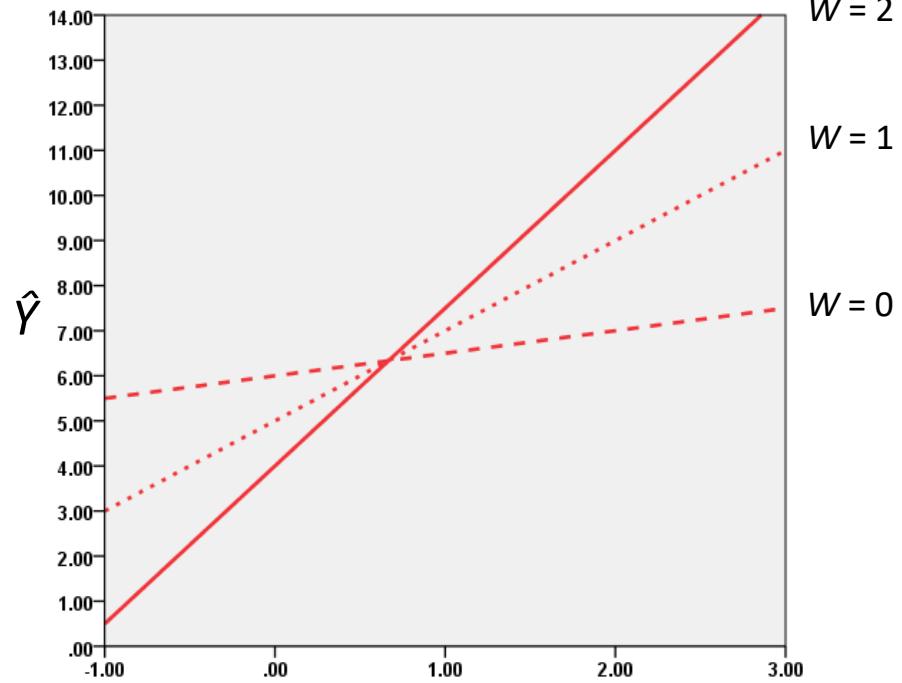
The importance of b_3 when testing a moderation hypothesis

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



$$\begin{aligned}\theta_{X \rightarrow Y} &= b_1 + b_3 W & X \\ &= 2.00 + 0W & \theta_{W \rightarrow Y} = b_2 + b_3 X \\ &&= 0.50 + 0X\end{aligned}$$

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



$$\begin{aligned}\theta_{X \rightarrow Y} &= b_1 + b_3 W & X \\ &= 0.50 + 1.50W & \theta_{W \rightarrow Y} = b_2 + b_3 X \\ &&= -1.00 + 1.50X\end{aligned}$$

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.

Adding covariates to the model

If we want to add covariates to the model, we add in additional terms:

$$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i + b_4 U_i$$

The new covariate does not interact with any of the other variables in the model, so none of the relationships between other variables and the outcome **depend on the value** of the covariate.

Differences in interpretation

$$\hat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i + b_4 U_i$$

b_0

The estimated value of Y when $X_1 = \cancel{X_2} = \cancel{X_3} = 0$.

b_1

The effect of X_1 on Y when $\cancel{X_2} = 0$, and $\cancel{X_3}$ is held constant (at any value).

b_2

The effect of \cancel{W} on Y when $X_1 = 0$, and $\cancel{X_3}$ is held constant (at any value)

b_3

How much the effect of X_1 on Y changes as \cancel{W} changes by 1 unit, holding $\cancel{X_3}$ constant (at any value)

b_4

The effect of \cancel{U} on Y holding X_1 and \cancel{W} constant at any values (this is a *partial effect*)

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

The estimated value of Y when $X_1 = \cancel{W} = 0$.

The effect of X_1 on Y when $\cancel{W} = 0$.

The effect of \cancel{W} on Y when $X_1 = 0$.

How much the effect of X_1 on Y changes as \cancel{W} changes by 1 unit.

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.

Journal of Consulting and Clinical Psychology
2010, Vol. 78, No. 3, 362-374

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0022-006X/10/\$12.00 DOI: 10.1037/a0019172

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

Katie Witkiewitz
Washington State University Vancouver

Sarah Bowen
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 posttreatment depressive symptoms and craving (Penn Alcohol Craving Scale) 2 months following the intervention ($\beta^2 = .21$). This moderation effect predicted substance use 4 months following the intervention ($\beta^2 = .18$). **Conclusion:** MBRP appears to influence cognitive and behavioral responses to depressive symptoms, partially explaining reductions in posttreatment 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, Maiso, & Zwykai, 1996; Lester, 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.

Katie Witkiewitz, Department of Psychology, Washington State University Vancouver; Sarah Bowen, Department of Psychology, University of Washington.

This research was supported by National Institute on Drug Abuse Grant R21 DA010562 (G. Alan Marlatt, principal investigator). We gratefully acknowledge G. Alan Marlatt for his leadership and support and the mindfulness-based relapse prevention research team for its dedication to this project. Without these efforts and talents, this project would not have been possible.

Correspondence concerning this article should be addressed to Sarah Bowen, University of Washington, Department of Psychology, Box 351629, Seattle, WA 98195-1525. E-mail: swbowen@u.washington.edu

362

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 reinstitution of drug use following periods of abstinence (e.g., Curran, Booth, Kirchner, & Denke, 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; Kool et al., 2008).

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

	mbrp	bdi0	bdip	crave0	crave2	use4	treathrs
1	0	1.28	1.09	4.0	.8	.95	32
2	0	1.47	1.52	2.4	3.8	1.30	36
3	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						
6	1						
7	0						
8	0						
9	0						
10	1						
11	1						
12	0						
13	1						
14	1						
15	0						
16	0	1.05	2.05	2.0	1.0	1.34	30

Showing 1 to 16 of 168 entries

SAS

```
mbrp *
```

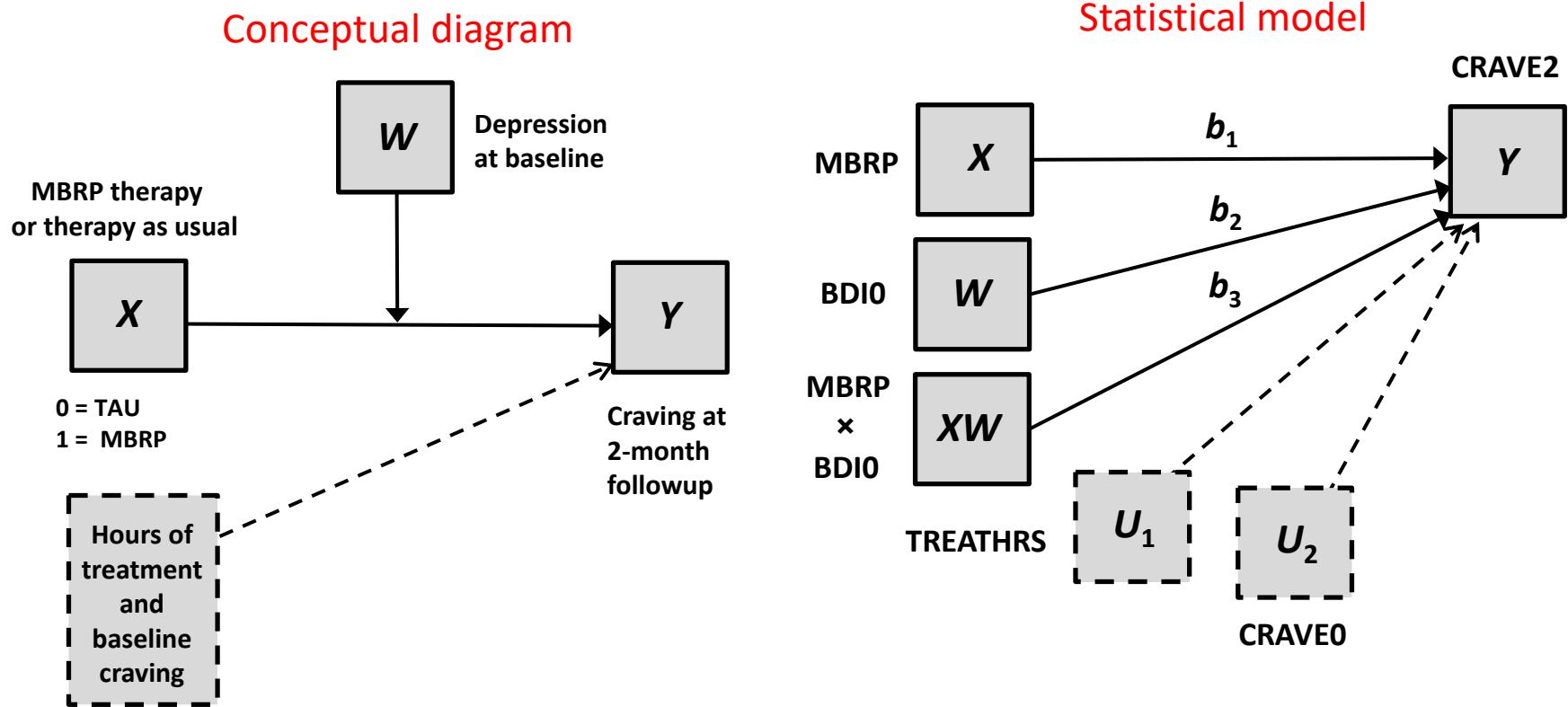
```
data mbrp;
input mbrp bdi0 bdip crave0 crave2 use4 treathrs;
datalines;
0 1.28 1.09 4.0 .8 .95 32
0 1.47 1.52 2.4 3.8 1.30 36
0 .66 1.14 2.2 1.4 1.09 34
1 1.66 1.23 2.2 2.4 1.17 37
1 0 1.28 1.09 4.0 0.8 0.95 32
2 0 1.47 1.52 2.4 3.8 1.30 36
3 0 0.66 1.14 2.2 1.4 1.09 34
4 1 1.66 1.23 2.2 2.4 1.17 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
16 0 1.05 2.05 2.0 1.0 1.34 30

```

R

These aren't the actual data. But the analyses we do yield similar results to what they report.²⁰⁰

Example



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

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

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
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”

$$\begin{aligned}b_1 &= 0.587 \\b_2 &= 1.122 \\b_3 &= -0.948\end{aligned}$$

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.

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

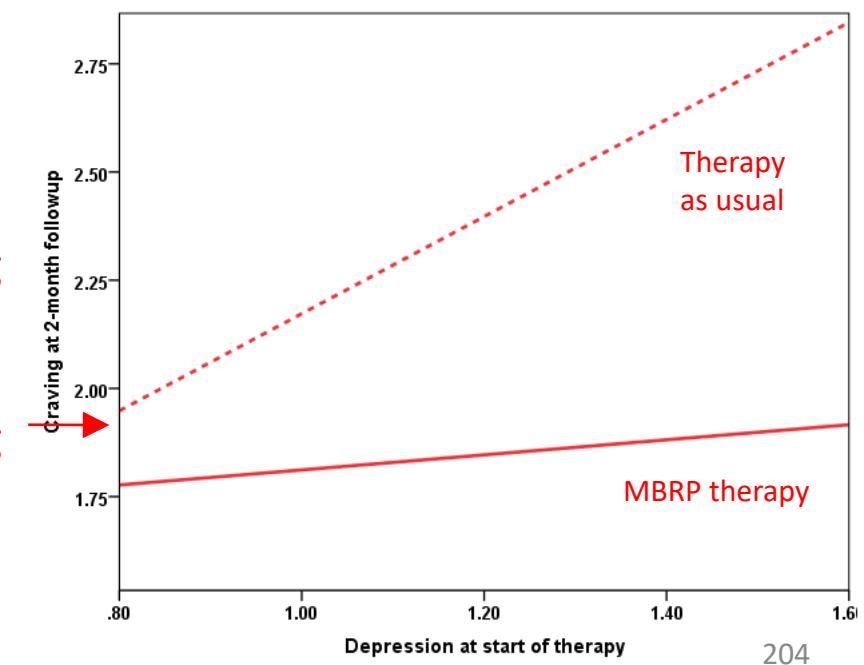
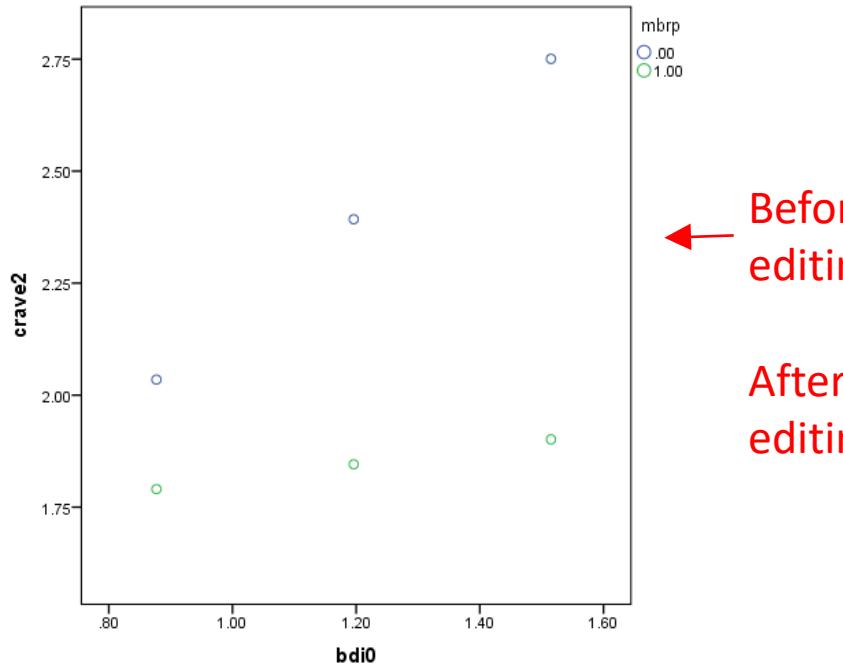
MBRP (X)	BDI0 (W)	TREATHRS (U_1)	CRAVE0(U_2)	\hat{Y}
0	0.877	30.685	2.943	2.035
0	1.196	30.685	2.943	2.393
0	1.515	30.685	2.943	2.751
1	0.877	30.685	2.943	1.790
1	1.196	30.685	2.943	1.846
1	1.515	30.685	2.943	1.901

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.



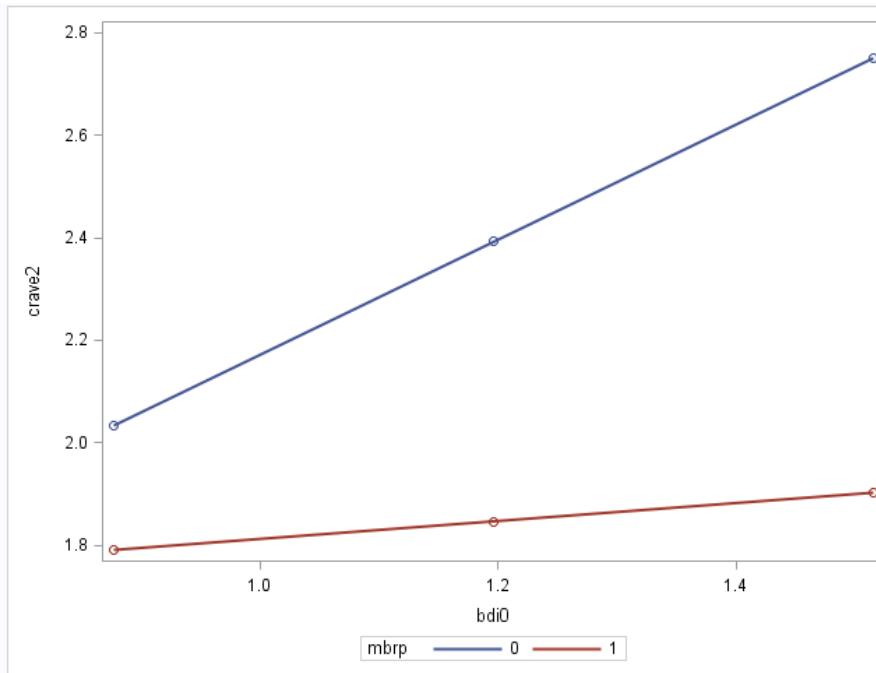
Example code in SPSS

```
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.
```



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;
```



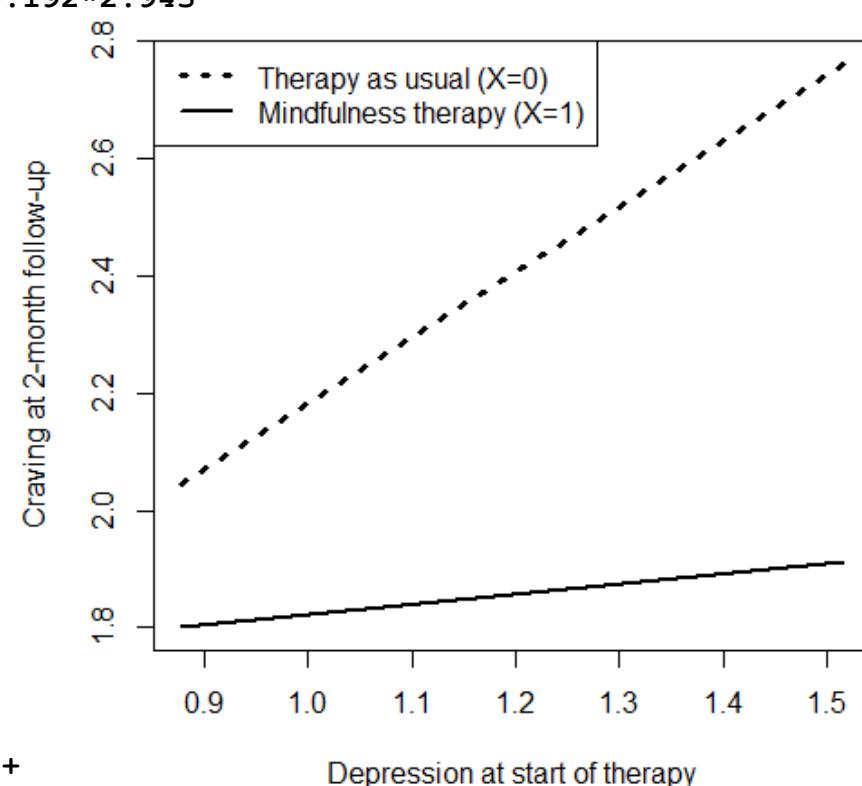
Example code in R

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.

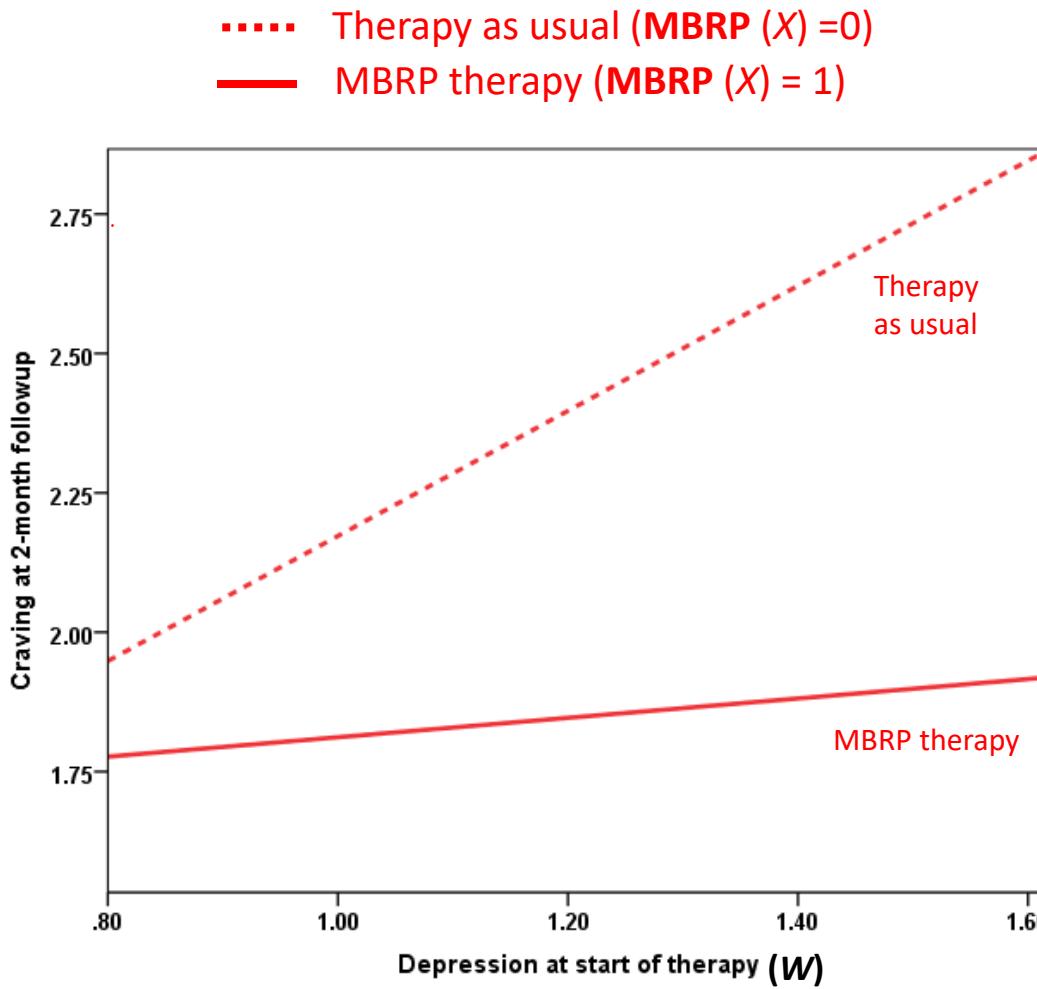
```
x<-c(0,1,0,1,0,1)
w<-c(0.877,0.877,1.196,1.196,1.515,1.515)
y<-1.038+0.587*x+1.122*w-0.948*x*w-0.018*30.685+0.192*2.943
plot(y=y,x=w,pch=15,col="white",
xlab="Depression at start of therapy",
ylab="Craving at 2-month follow-up")
legend.txt<-c("Therapy as usual (X=0)",
"Mindfulness therapy (X=1)")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



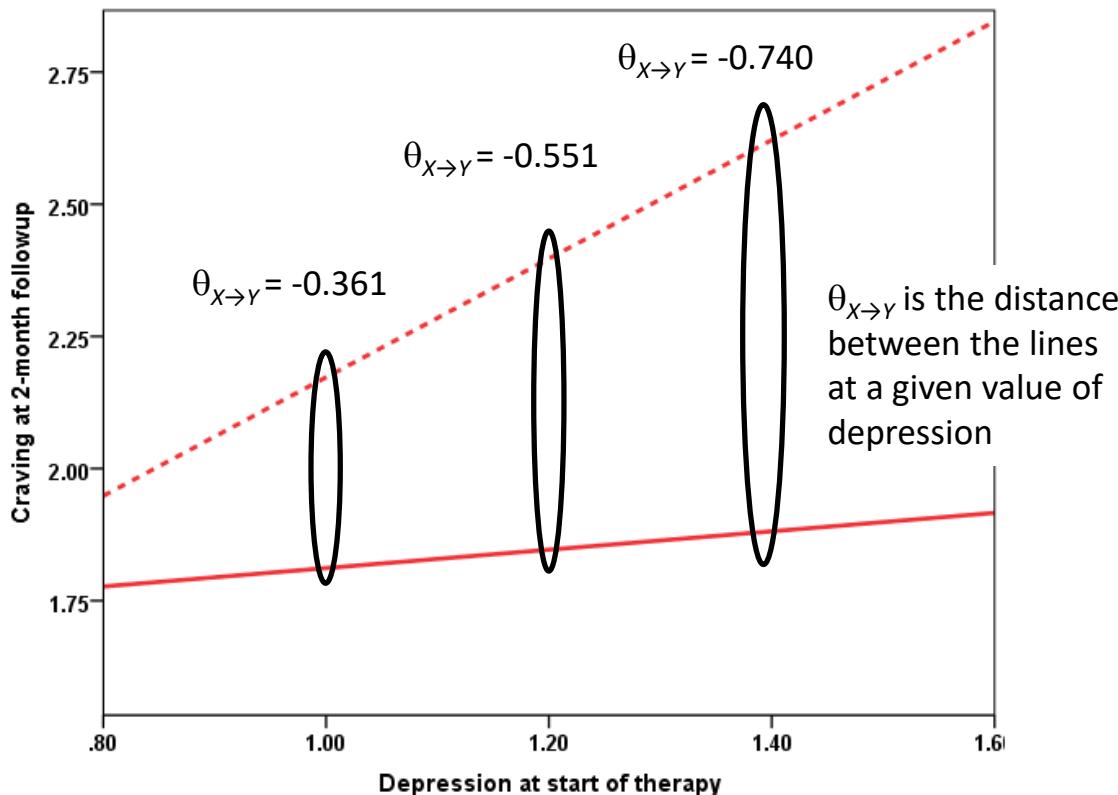
Those who receive MBRP therapy crave substances less than those who receive therapy as usual, but this difference is larger among those more depressed at the start of therapy.

A graphical depiction of the model

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

Therapy as usual (MBRP ($X=0$)
MBRP therapy (MBRP ($X=1$)

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



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

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

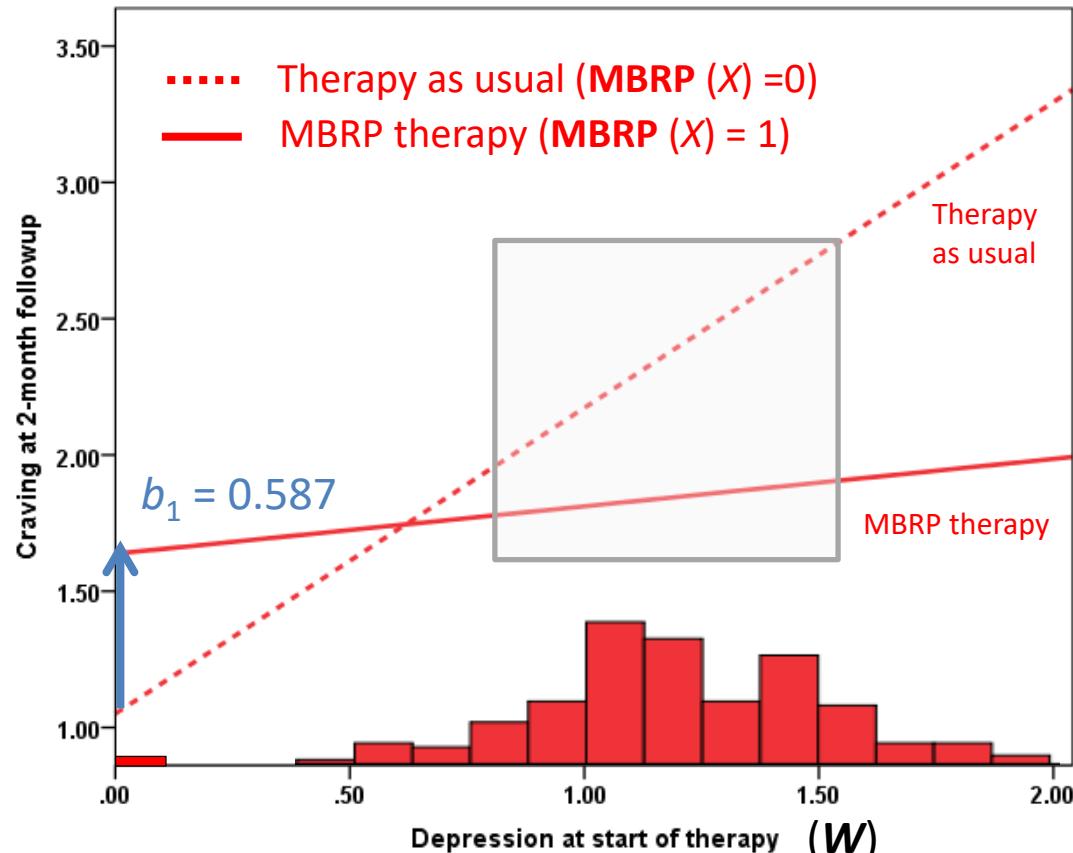
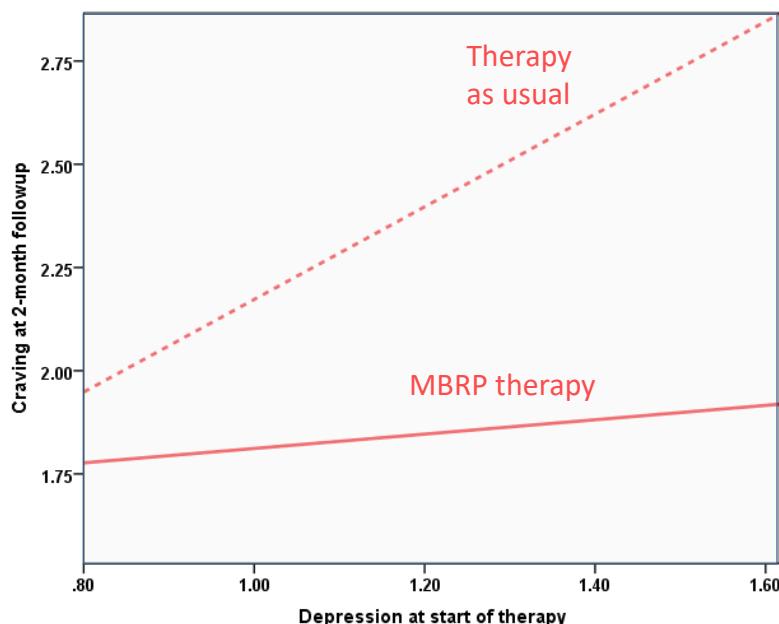
BDI0 (W)	$\theta_{X \rightarrow Y}$
1.00	-0.361
1.20	-0.551
1.40	-0.740

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

Interpretation of b_1

$$b_1 = 0.587$$

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



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: For people with a score of 0 on depression (BDI), we would predict that those in the MBRP treatment ($X = 1$) would have .587 units more cravings on average compared to those in the treatment as usual condition ($X = 0$).

Interpretation of b_2

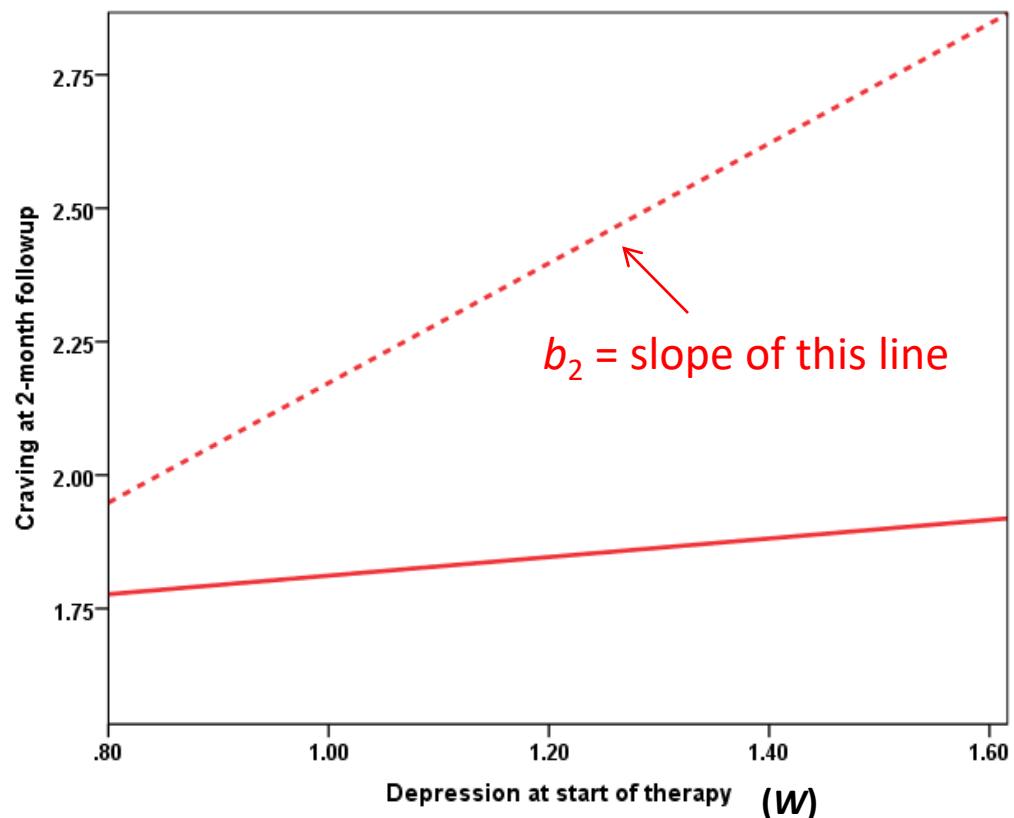
$$b_2 = 1.122$$

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

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

- Therapy as usual (MBRP (X) = 0)
- MBRP therapy (MBRP (X) = 1)



Interpretation of b_3

$$b_3 = -0.948$$

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

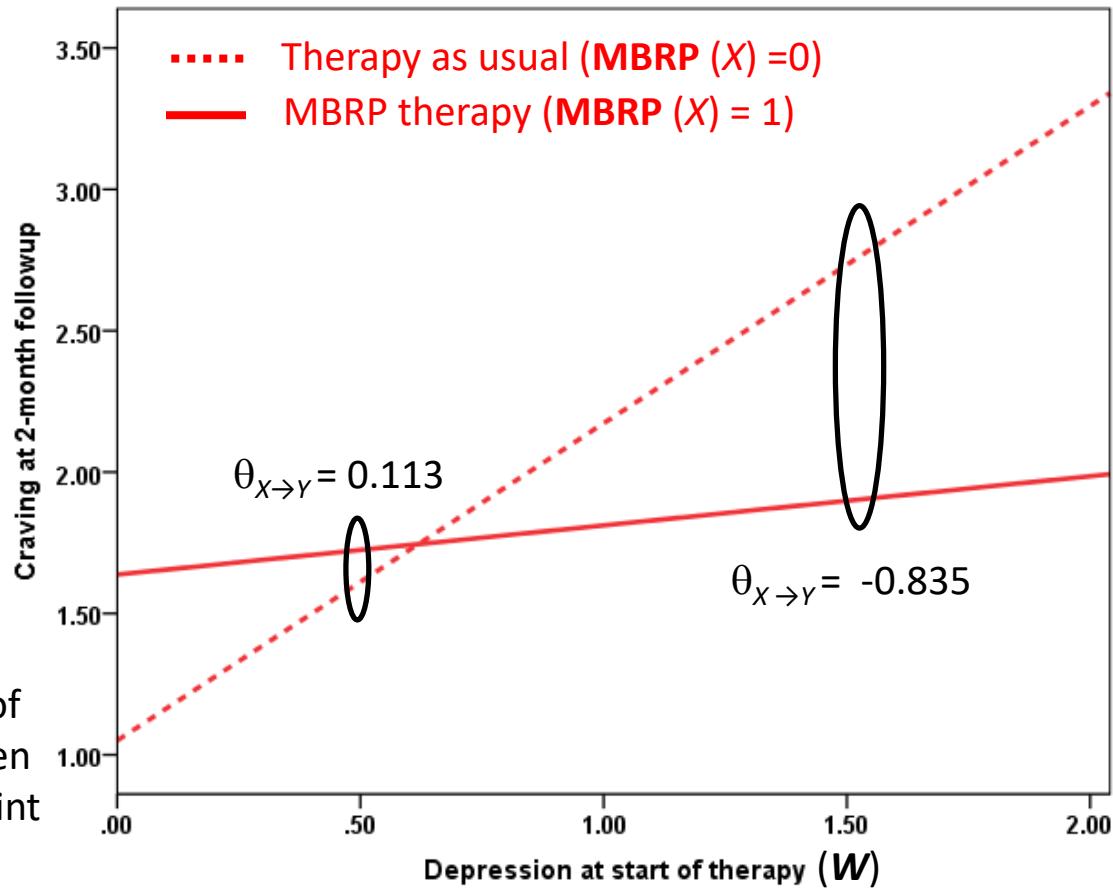
$$\theta_{X \rightarrow Y} = 0.587 - 0.948W$$

W	$\theta_{X \rightarrow Y}$
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.



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

Interpretation of b_3

$$b_3 = -0.948$$

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

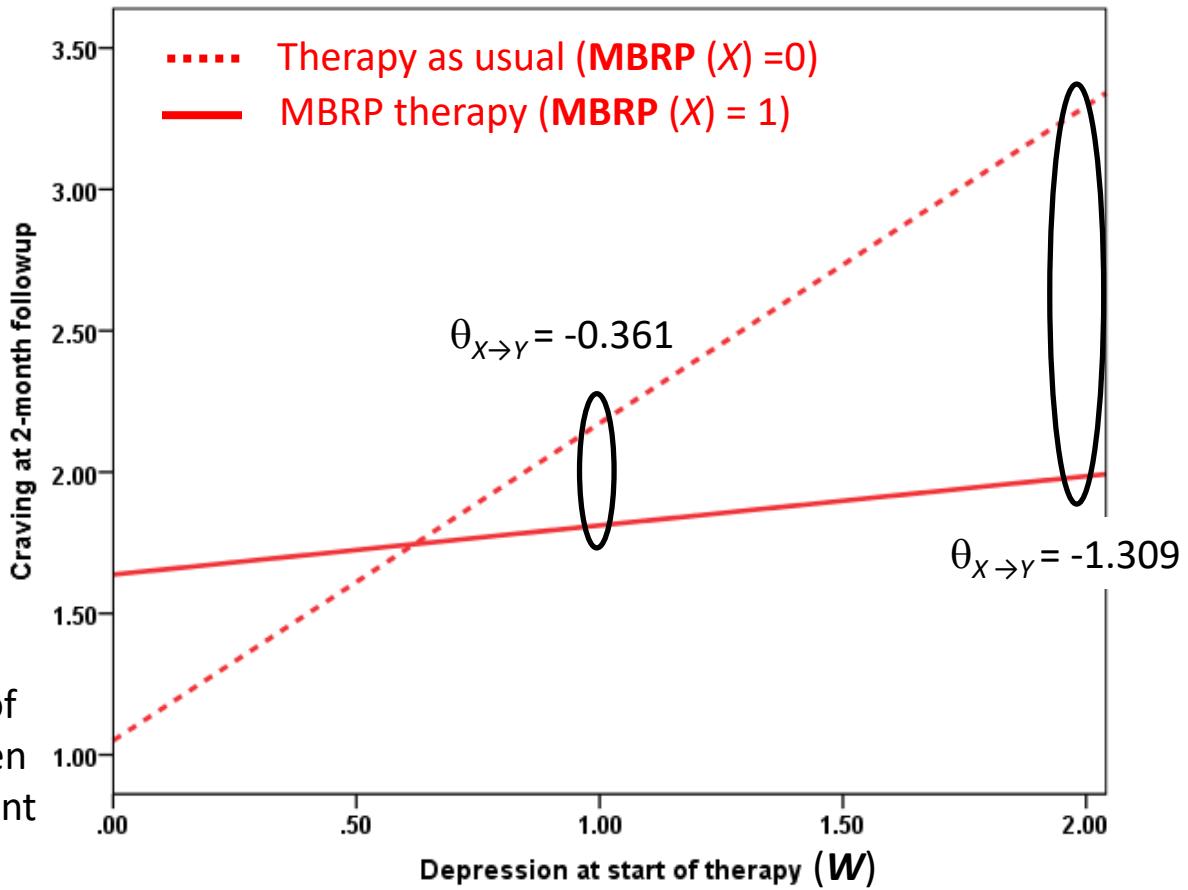
$$\theta_{X \rightarrow Y} = 0.587 - 0.948W$$

W	$\theta_{X \rightarrow Y}$
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.



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

Interpretation of b_3

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

$$b_3 = -0.948$$

$$\theta_{x \rightarrow y} = 0.587 - 0.948W$$

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.

$$\theta_{x \rightarrow y}|(W=\lambda) - \theta_{x \rightarrow y}|(W = \lambda - 1) = -0.948, \text{ for all } \lambda$$

Select a value of λ then calculate the conditional effect of X on Y at $\lambda-1$, λ , and the difference between the two. Then answer the questions below.

λ	$\theta_{x \rightarrow y} (W=\lambda)$	$\theta_{x \rightarrow y} (W = \lambda - 1)$	$\theta_{x \rightarrow y} (W=\lambda) - \theta_{x \rightarrow y} (W = \lambda - 1)$

1. Write an interpretation for $\theta_{x \rightarrow y}|(W=\lambda)$ given your specific value of λ .
2. Write an interpretation for $\theta_{x \rightarrow y}|(W = \lambda - 1)$ given your specific value of λ .
3. Write an interpretation for $\theta_{x \rightarrow y}|(W=\lambda) - \theta_{x \rightarrow y}|(W = \lambda - 1)$ given your specific value of λ .
4. Use your own words to describe what it means that $\theta_{x \rightarrow y}|(W=\lambda) - \theta_{x \rightarrow y}|(W = \lambda - 1) = -0.948$ for all λ .

λ	$\theta_{x \rightarrow y} (W=\lambda)$	$\theta_{x \rightarrow y} (W = \lambda-1)$	$\theta_{x \rightarrow y} (W=\lambda) - \theta_{x \rightarrow y} (W = \lambda-1)$
3	0.587 – 0.948(3) =-2.257	0.587-.948(2) = -1.309	-2.257-(-1.309) = -.948

Write an interpretation for $\theta_{x \rightarrow y}|(W=\lambda)$ given your specific value of λ .

Cravings are 2.257 units lower in the MPBR therapy condition compared to the TAU condition, when pre-therapy depression level is 3.

Write an interpretation for $\theta_{x \rightarrow y}|(W = \lambda-1)$ given your specific value of λ .

Cravings are 1.309 units lower in the MPBR therapy condition compared to the TAU condition, when pre-therapy depression level is 2.

Write an interpretation for $\theta_{x \rightarrow y}|(W=\lambda) - \theta_{x \rightarrow y}|(W = \lambda-1)$ given your specific value of λ .

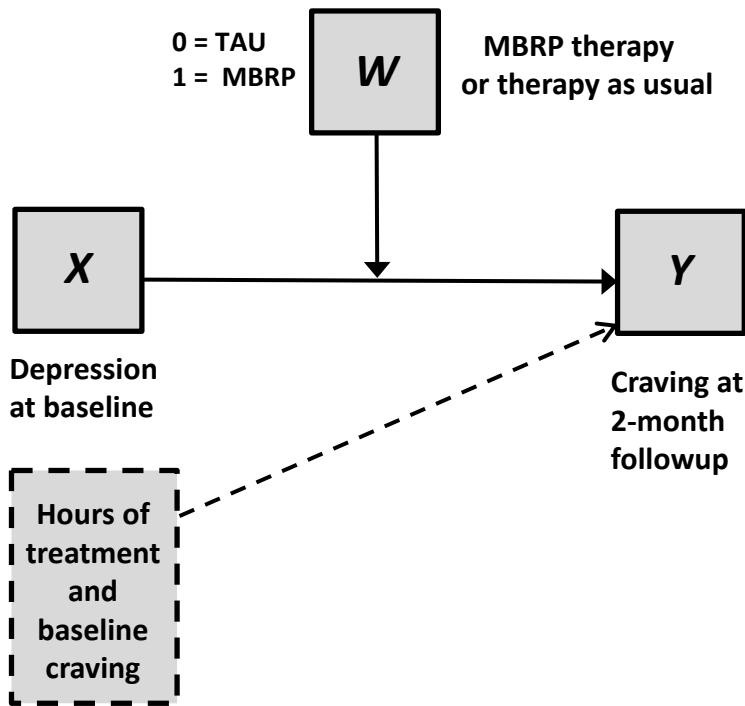
The effect of MBRP therapy (relative to TAU) is 0.948 units more effective at decreasing cravings for the pretherapy depression group with score 3 compared to those with score 2.

Use your own words to describe what it means that $\theta_{x \rightarrow y}|(W=\lambda) - \theta_{x \rightarrow y}|(W = \lambda-1) = -0.948$ for all λ .

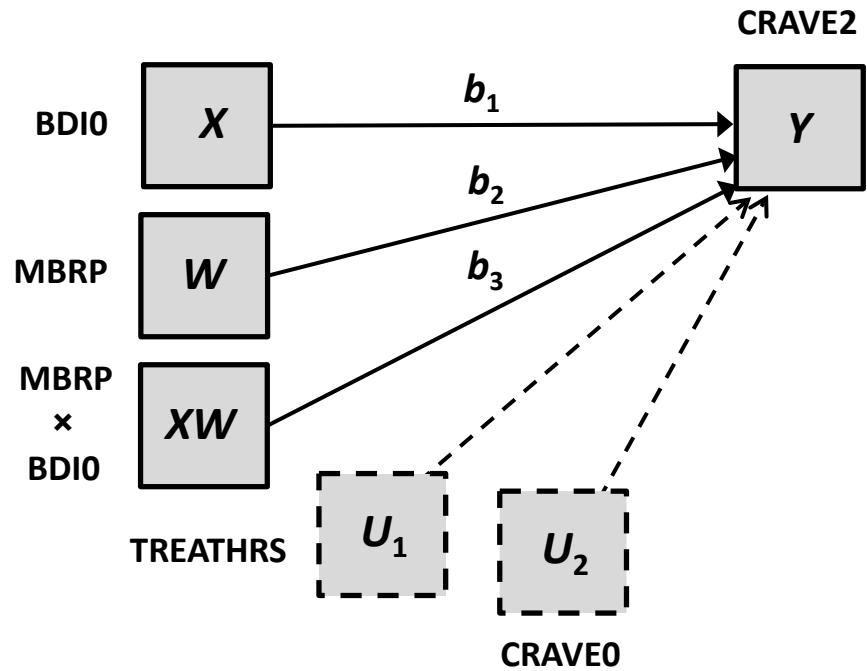
The effect of MBRP therapy (relative to TAU) is 0.948 units more effective at decreasing cravings for the pretherapy depression group with a one unit higher score than another group.

A Dichotomous Moderator

Conceptual diagram



Statistical model



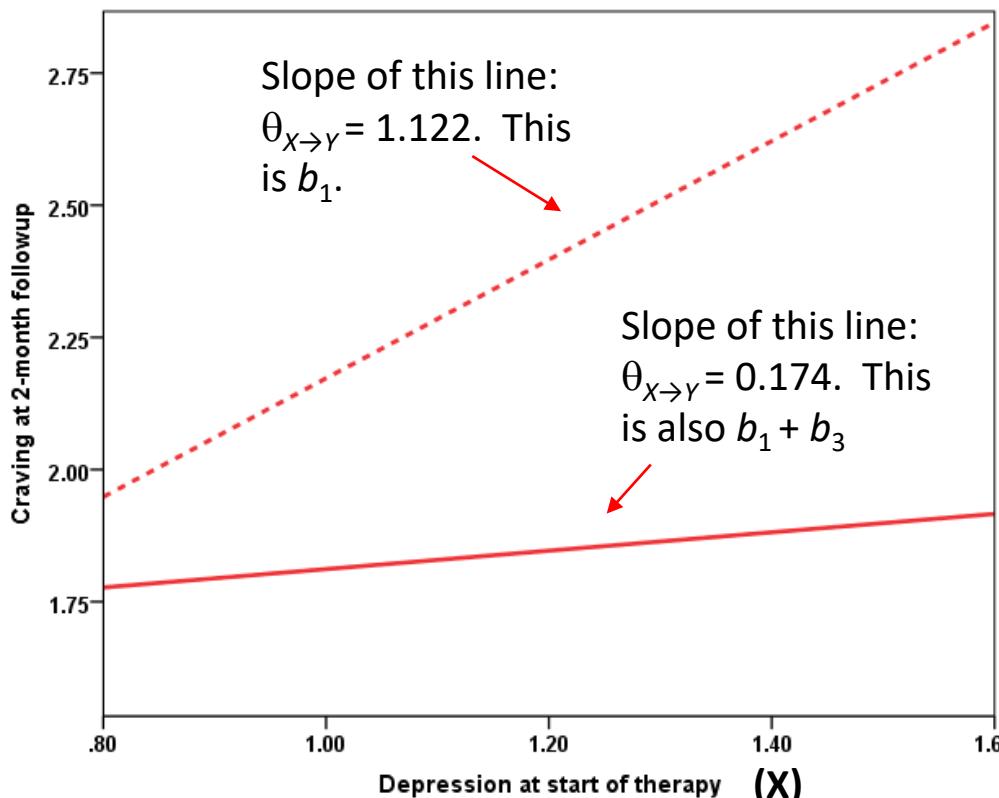
Does the association between pre-treatment depression and later craving differ between those who receive MBRP therapy versus therapy as usual?

A graphical depiction of the model

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

Therapy as usual (MBRP ($W=0$))
MBRP therapy (MBRP ($W=1$))

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



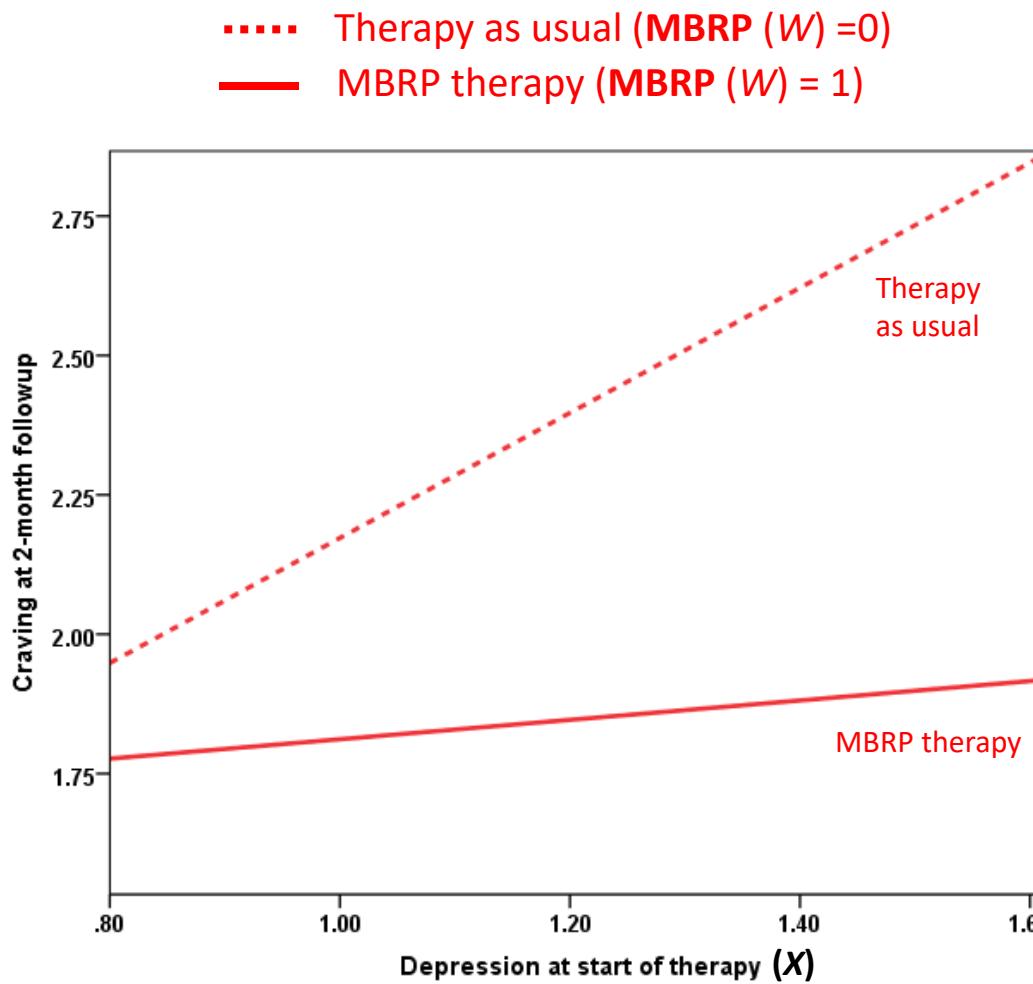
The conditional effect of pre-therapy depression ($\theta_{X \rightarrow Y}$) is defined by the function

$$\begin{aligned}\theta_{X \rightarrow Y} &= b_1 + b_3 W \\ &= 1.122 - 0.948 W\end{aligned}$$

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

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

Substantive interpretation of the pattern

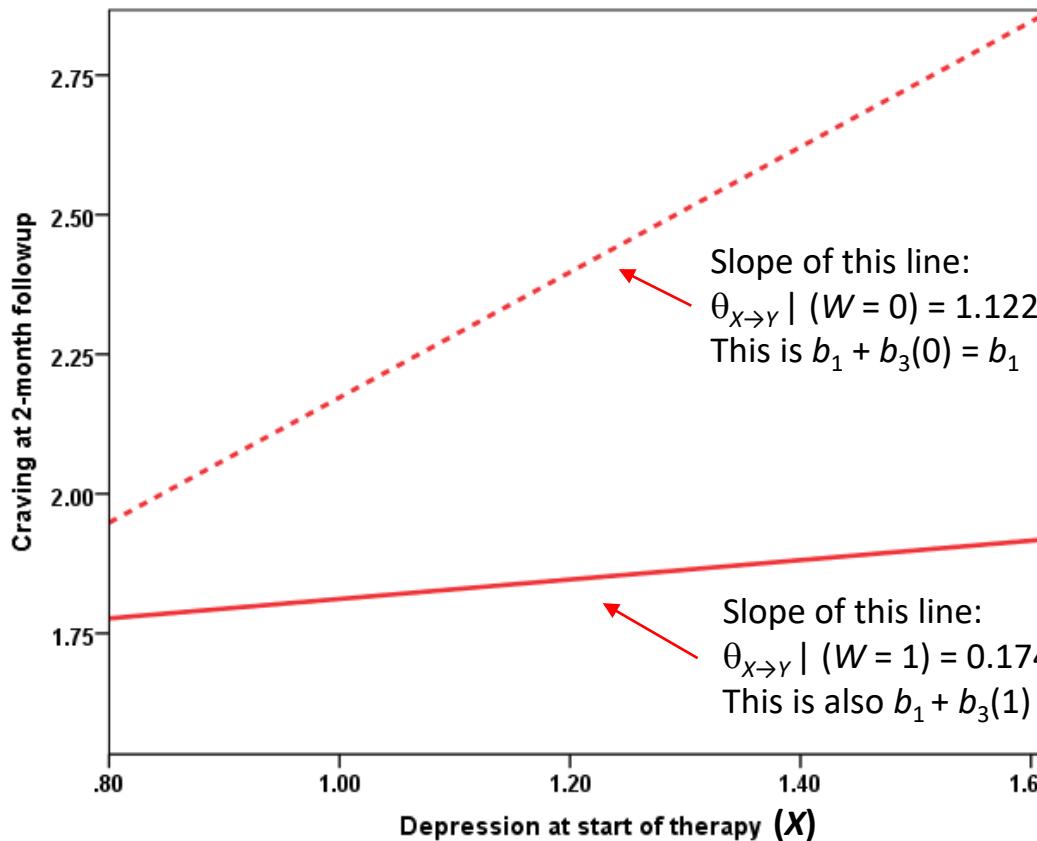


A larger effect of pre-therapy depression on later craving among those who experienced therapy as usual compared to those who received mindfulness behavioral relapse prevention therapy. MBRP therapy seems to have disrupted the link between depression and craving.

Interpreting b_3

- Therapy as usual (MBRP ($W = 0$)
- MBRP therapy (MBRP ($W = 1$)

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



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

$$b_3 = \theta_{X \rightarrow Y} | (W = 1) - \theta_{X \rightarrow Y} | (W = 0) \\ = (b_1 + b_3) - (b_1) \\ = (0.174) - (1.122) \\ = -0.948$$

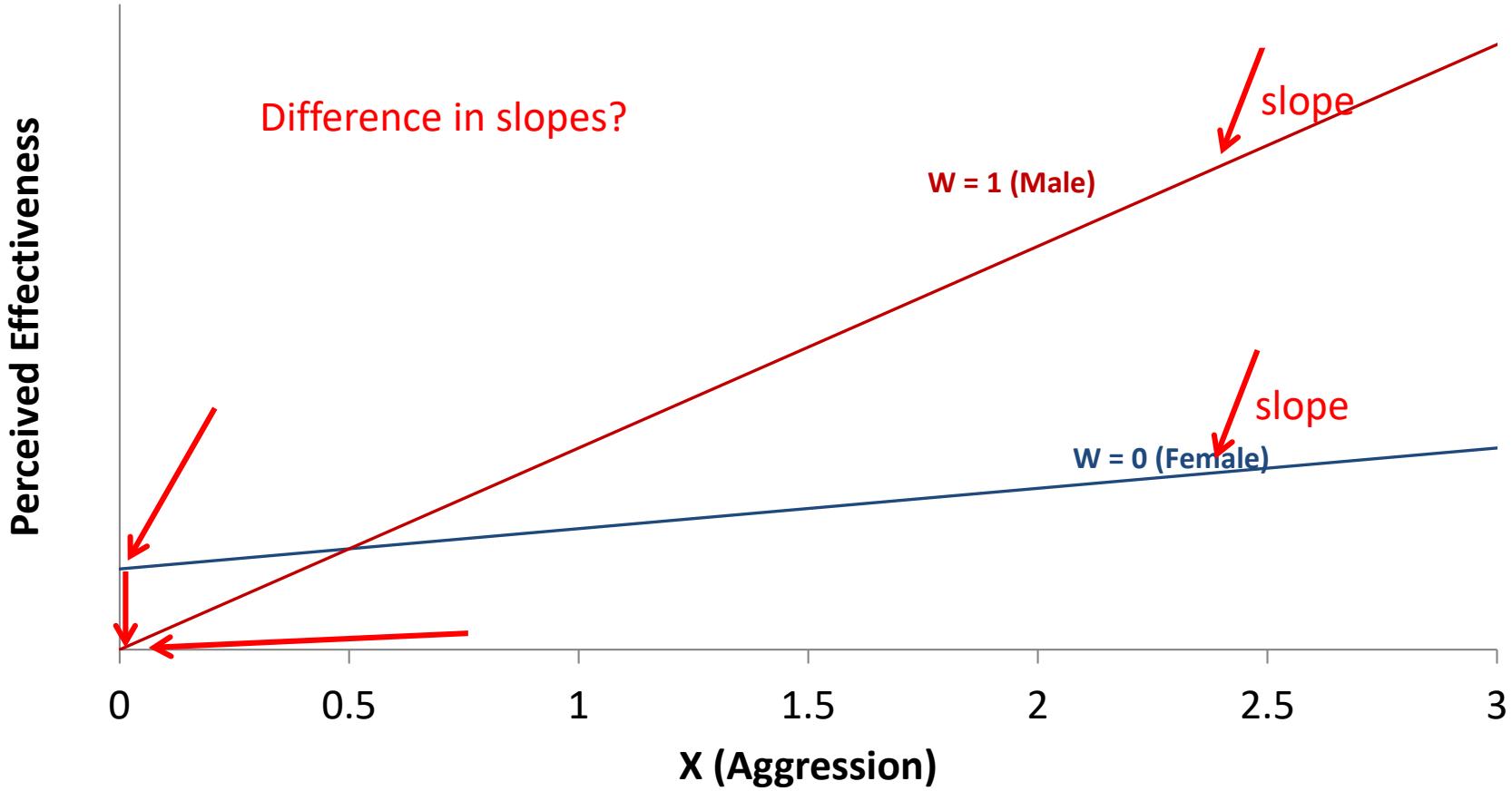
So b_3 is the difference in the slopes of these two lines. As W increases by one unit, $\theta_{X \rightarrow Y}$ decreases by 0.948 units. This difference is statistically different from zero.¹⁸

Practice Interpreting Coefficients



Among upper level managers, does the relationship between aggression and perceived effectiveness depends on gender?

$$\hat{Y}_i = 1 + (.5 + 2W_i)X_i - 1W_i$$



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.

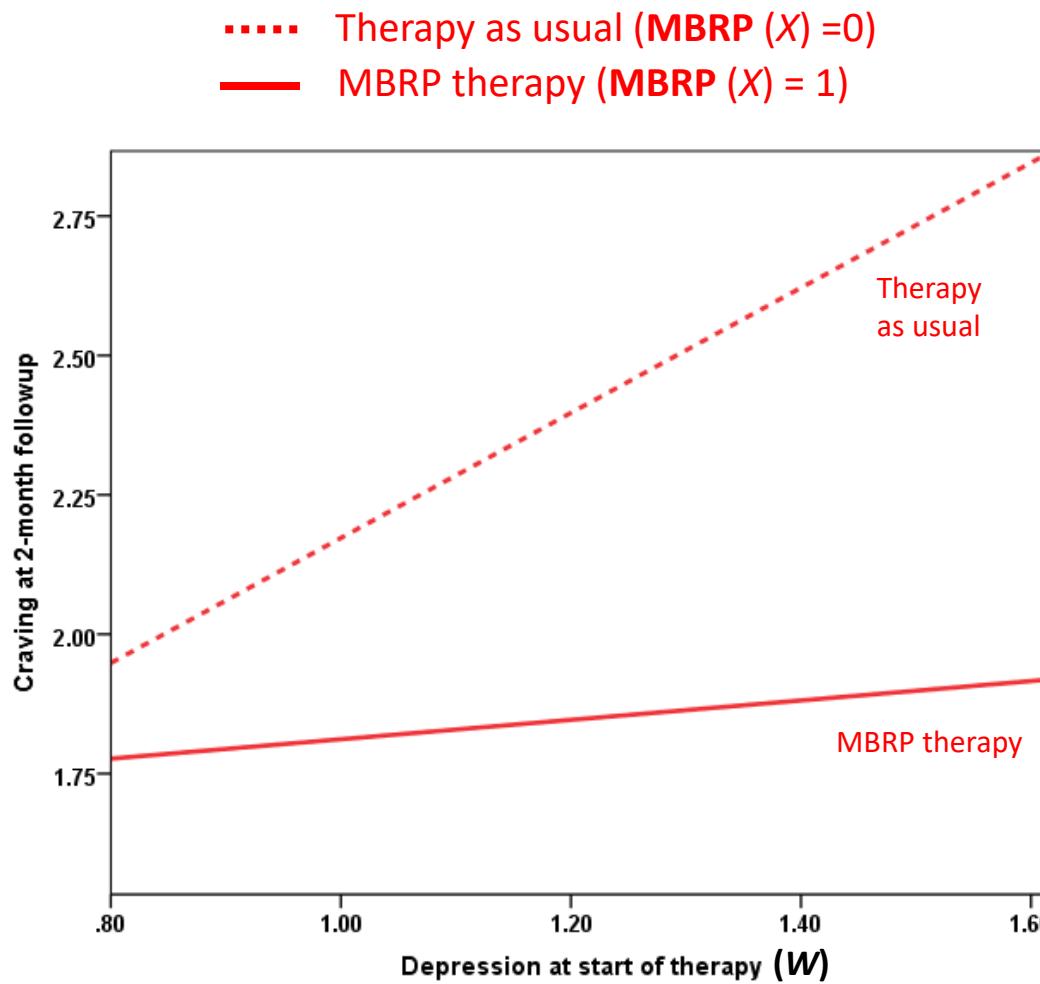
“Pick-a-Point” Approach

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

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

Select a value of the moderator (W) at which you'd like to have an estimate of $\theta_{X \rightarrow Y}$, the focal predictor variable's (X) effect. Then derive its standard error. The ratio of the effect to its standard error is distributed as $t(df_{\text{residual}})$ 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

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

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

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

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

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

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

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

as

$$\hat{Y}_i = b_0 + b_1 X_i + b_2 W'_i + b_3 X_i W'_i \quad \text{where} \quad W'_i = W_i - \lambda$$

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 $\lambda = \bar{W}$, $\lambda = \bar{W} - SD_W$, and $\lambda = \bar{W} + SD_W$

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.
```

$\lambda = 1.196$
(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))
```

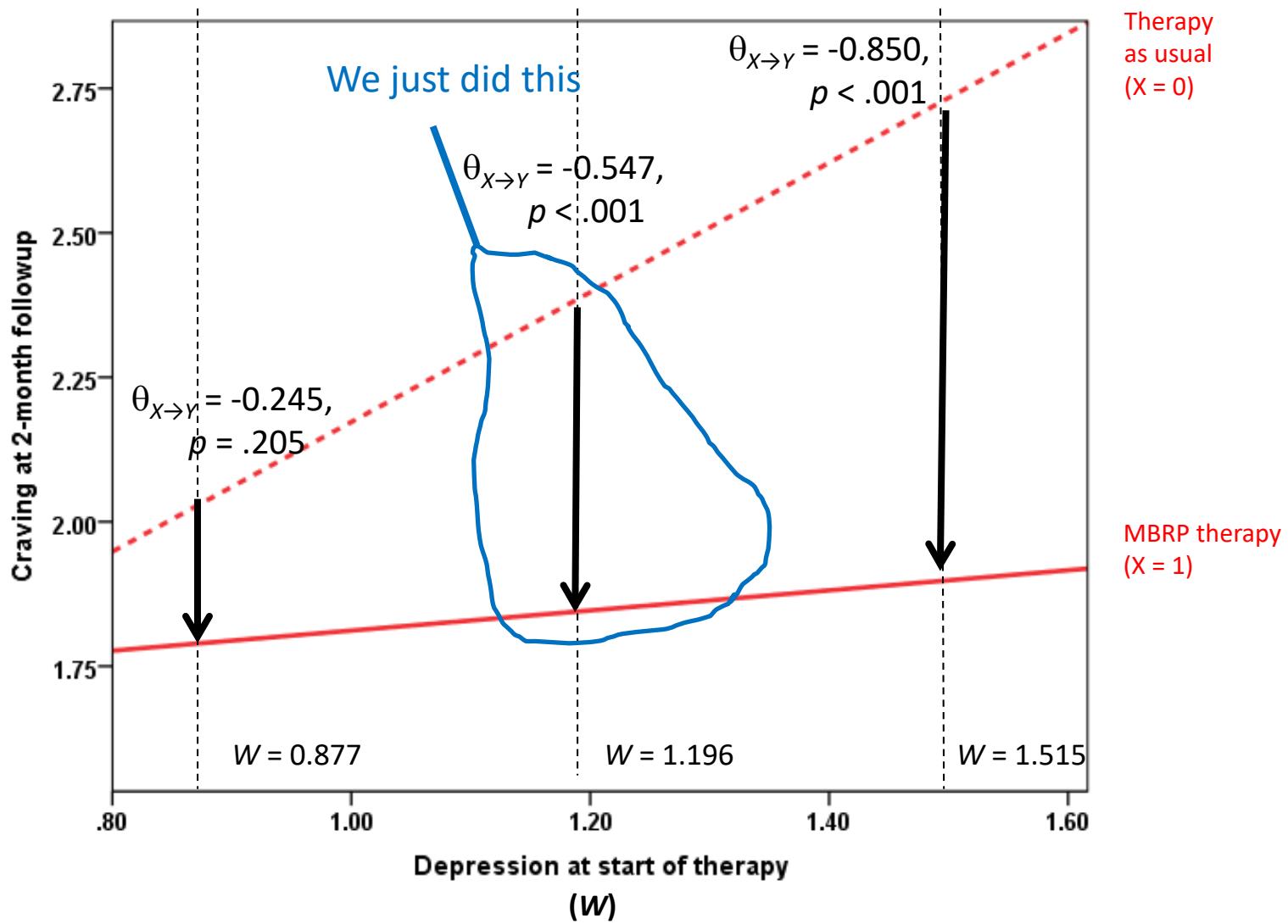
Model	Coefficients ^a					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	
	B	Std. Error	Beta			
1 (Constant)	2.380	.364		6.534	.000	
MBRP: Therapy as usual (0) or MBRP therapy (1)	-0.547	.137	-.279	-3.980	.000	
bdi0_p	1.122	.276	.366	4.063	.000	
interact	-.948	.423	-.197	-2.240	.026	
TREATRS: 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

$$\theta_{X \rightarrow Y} |(W = 1.196) \quad S_{\theta_{X \rightarrow Y}}$$

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

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.
```

```
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))
```

$\lambda = 0.877$
(One SD below the sample mean)

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
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

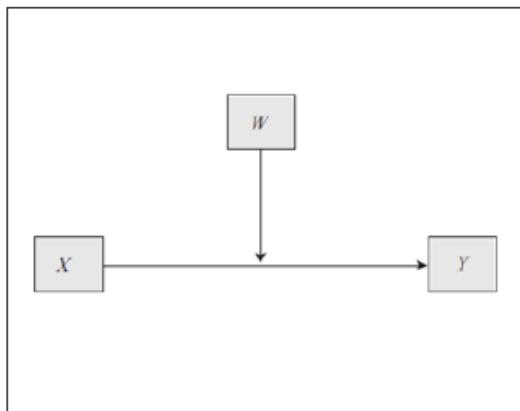
$$\theta_{X \rightarrow Y} |(W = 0.877) \quad S_{\theta_{X \rightarrow Y}}$$

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

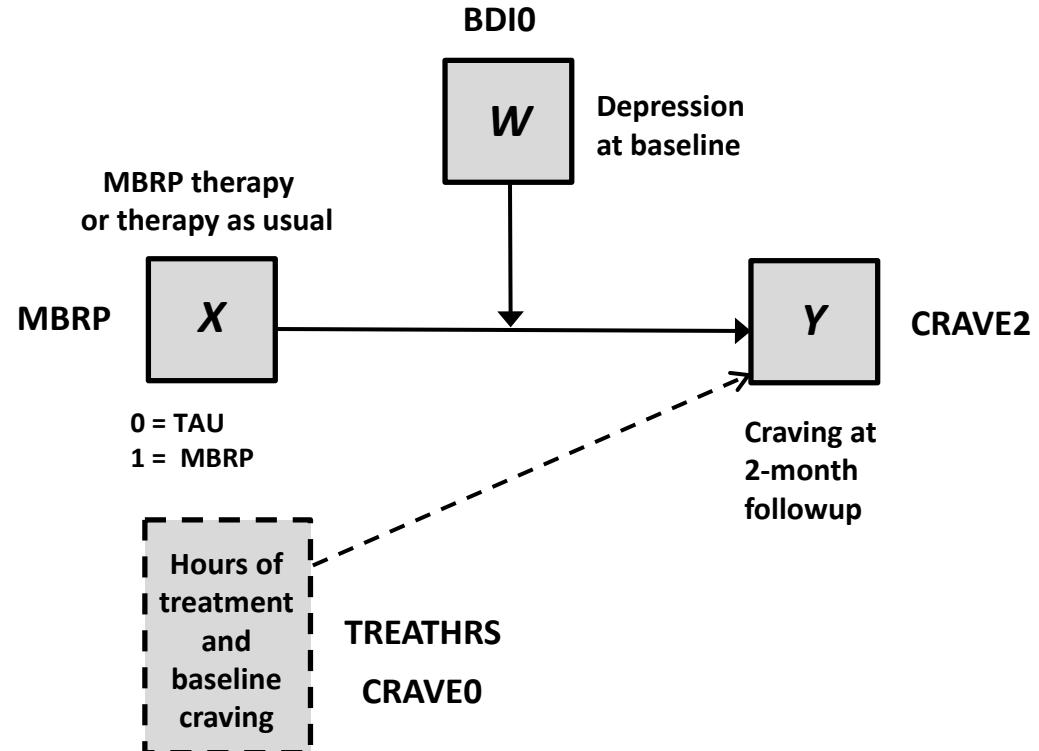
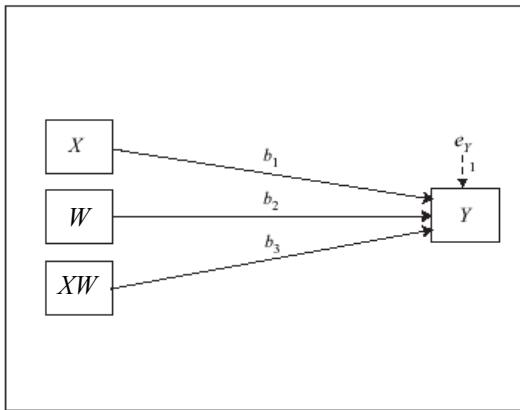
Using PROCESS

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

Schö'

 OUTCOME VARIABLE:
 crave2 $\hat{Y} = 1.038 + 0.587X + 1.122M - 0.948XM + \dots$

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 \pm 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)
```

Both the 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 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)
```

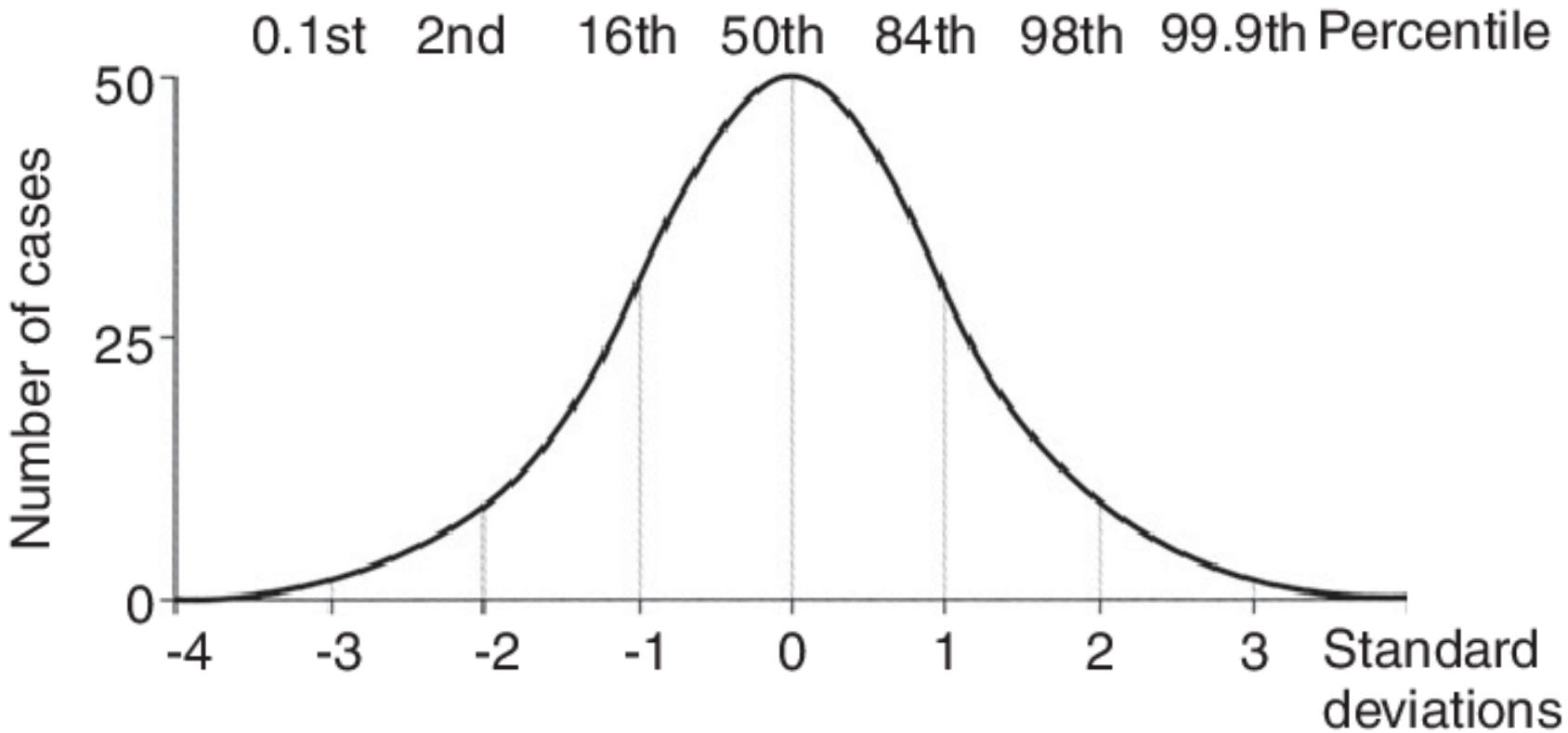
Conditional effect of X on Y at values of the moderators(s)

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.

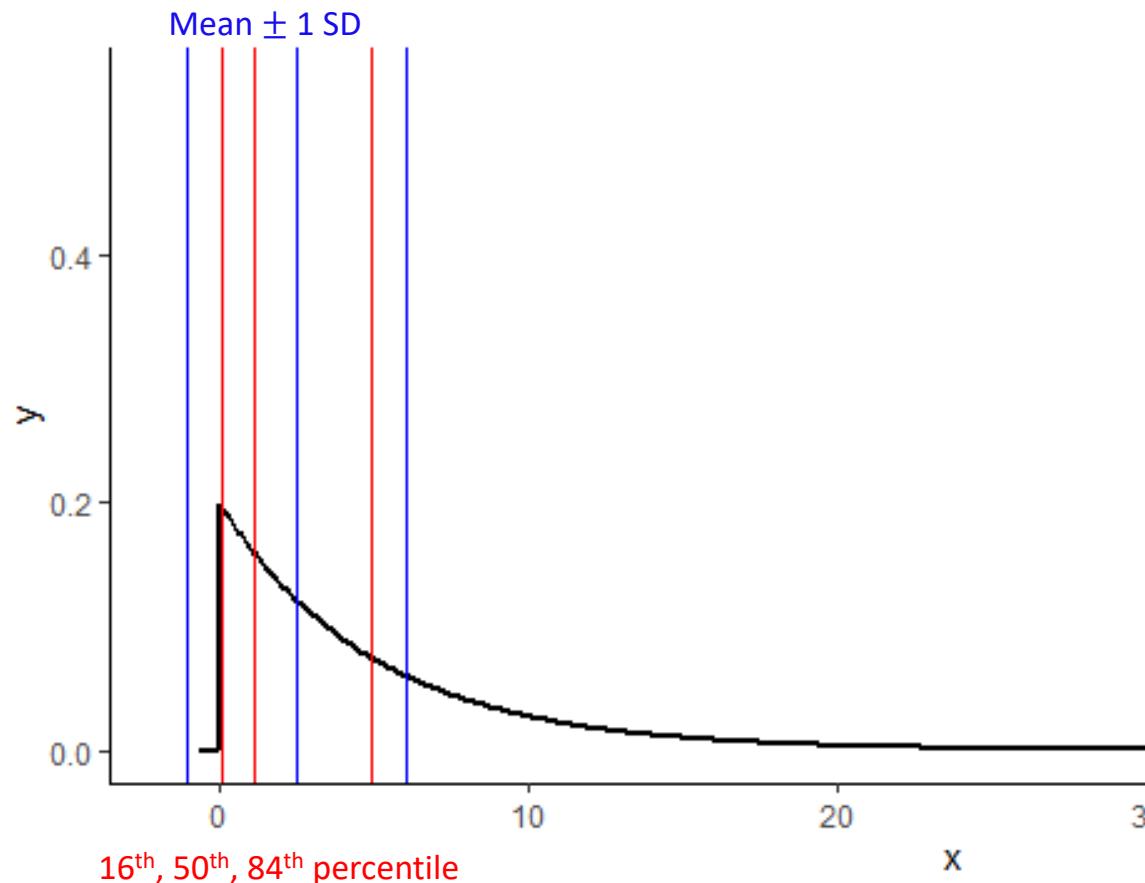
So **assuming your moderator is normally distributed, you would get the same answer either way**, and if the moderator is not normally distributed probing at percentiles guarantees they are within the range of the observed data.



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:

$$W = \frac{-2(t_{crit}^2 s_{b_1 b_3}^2 - b_1 b_3) \pm \sqrt{(2t_{crit}^2 s_{b_1 b_3}^2 - 2b_1 b_3)^2 - 4(t_{crit}^2 s_{b_3}^2 - b_3^2)(t_{crit}^2 s_{b_1}^2 - b_1^2)}}{2(t_{crit}^2 s_{b_3}^2 - b_3^2)}$$

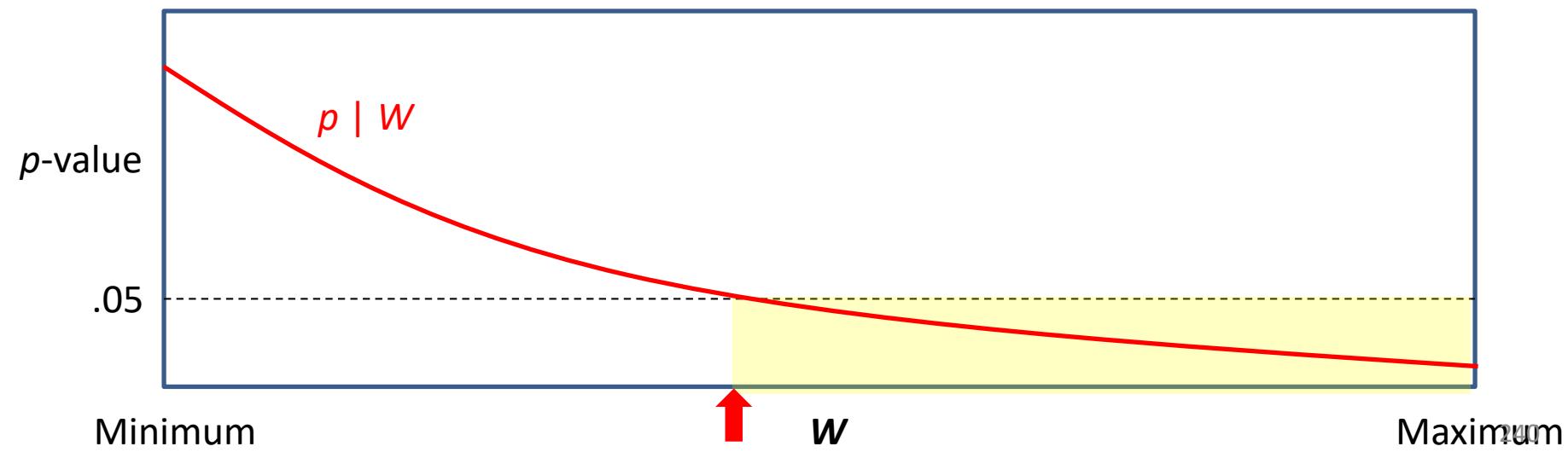
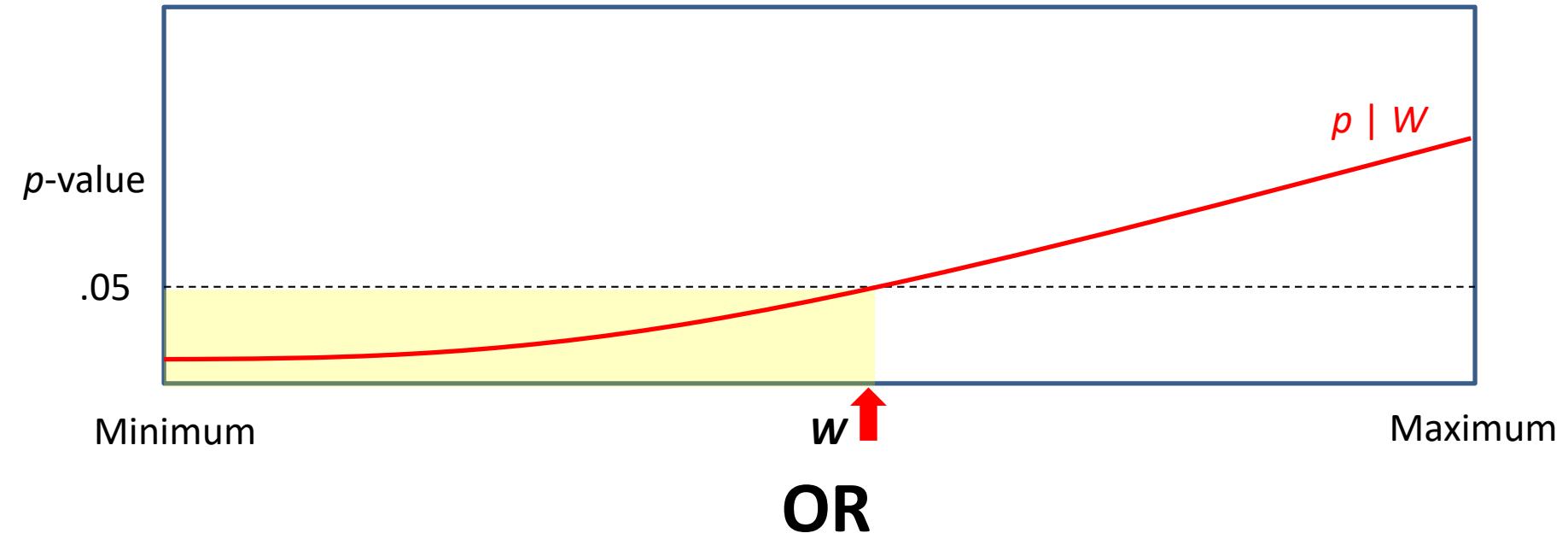
The Johnson-Neyman technique

This will produce no values, one value, or two values of W that are within the range of the moderator variable data.

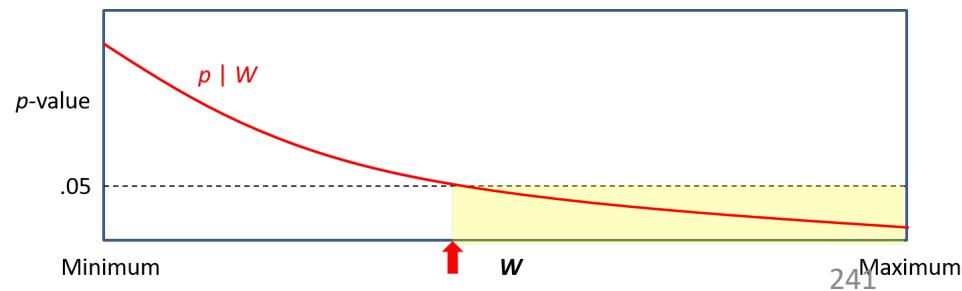
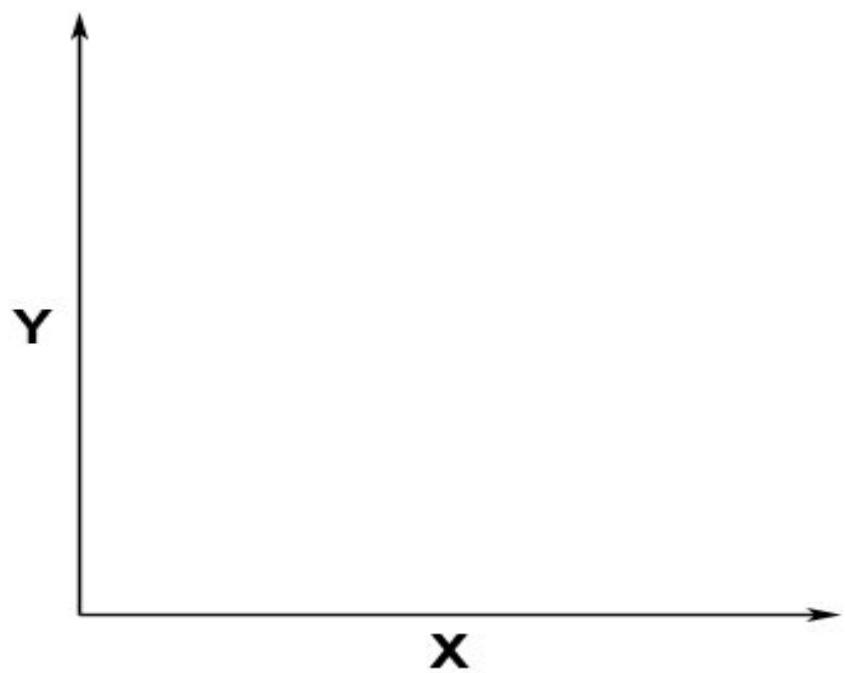
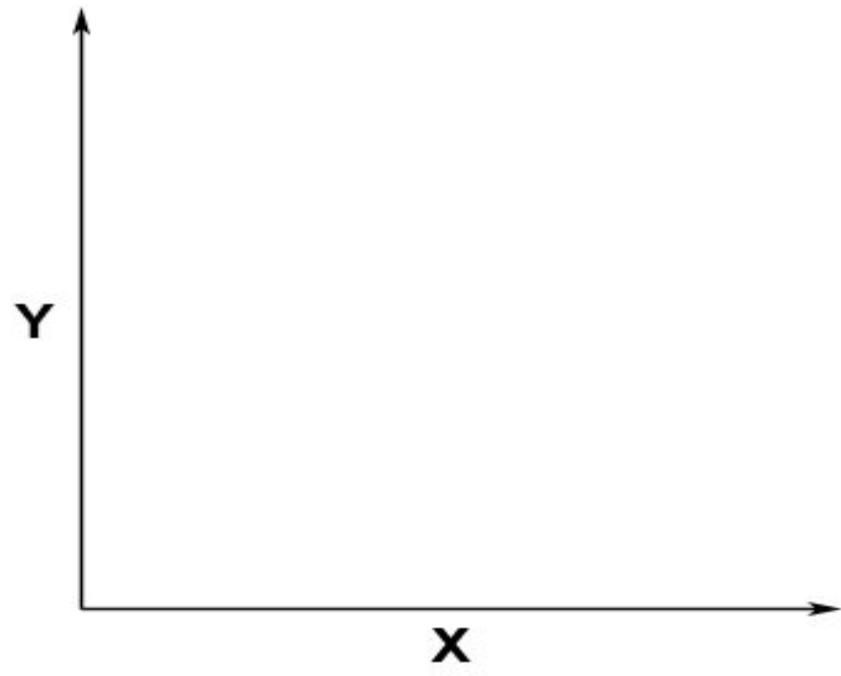
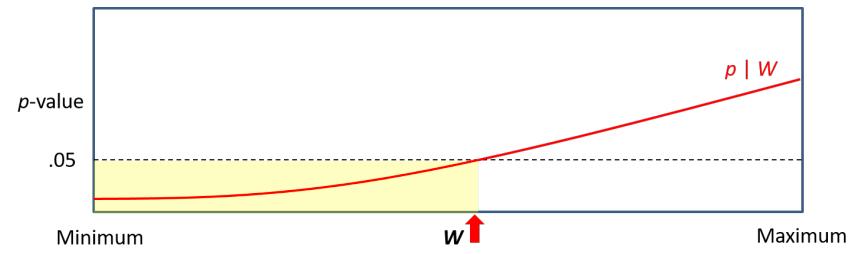
- If one value, this defines a single point of transition between a statistically significant and a statistically nonsignificant conditional effect of the focal predictor, such that $p \leq .05$ for either values of the moderator (1) equal to above W or (2) equal to and below W .
- If two values, this 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

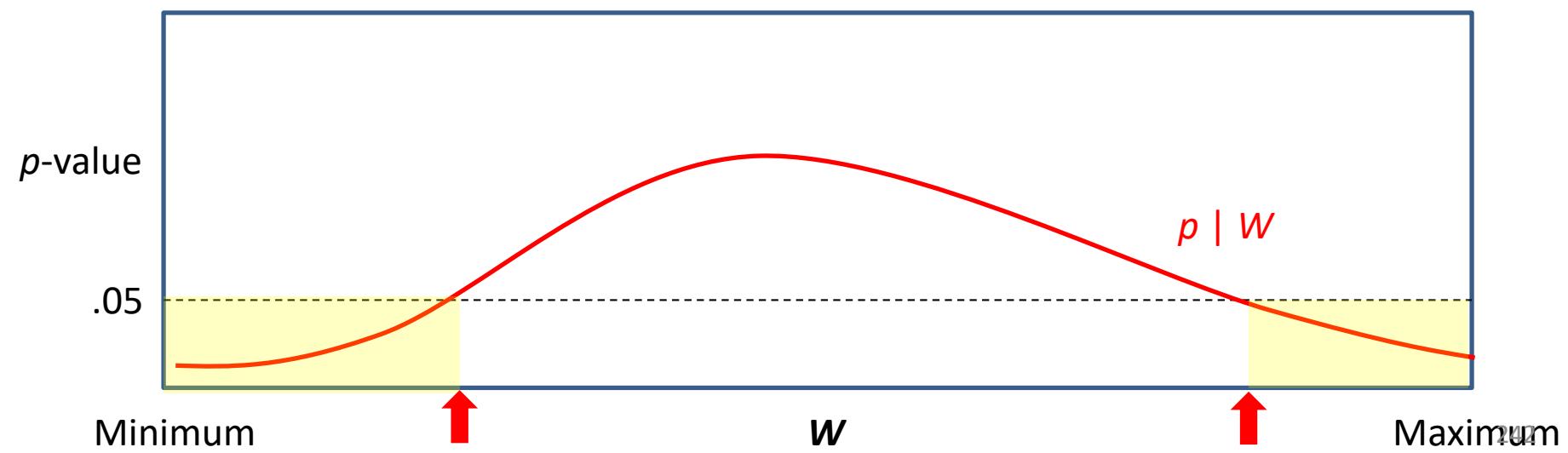
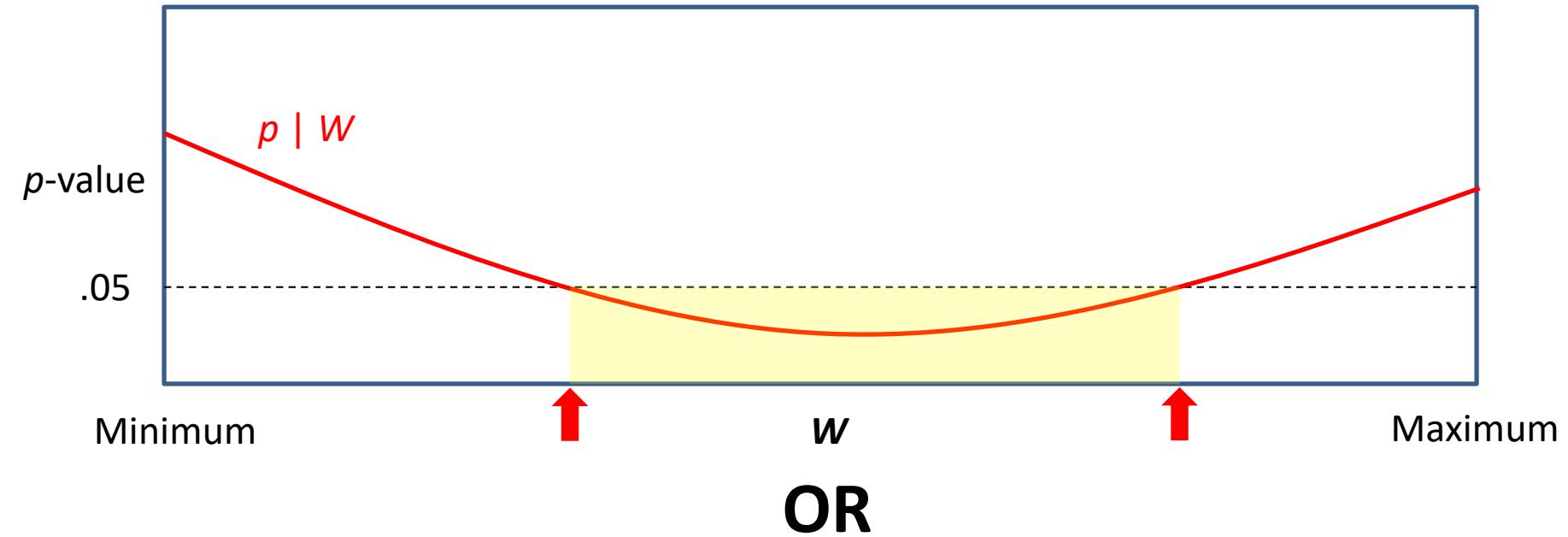
Examples of one solution



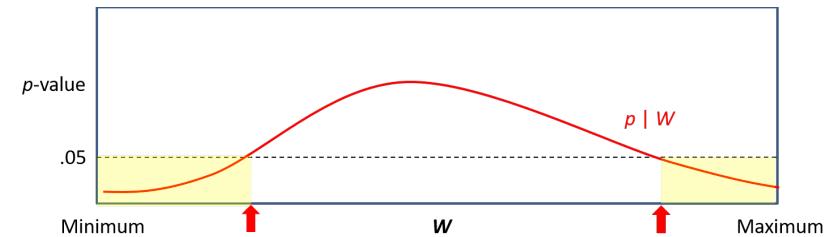
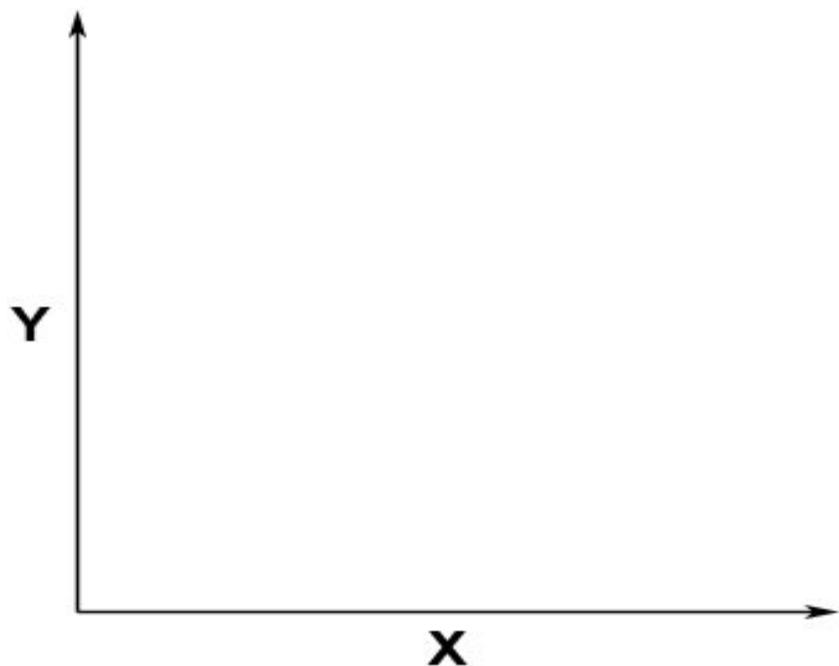
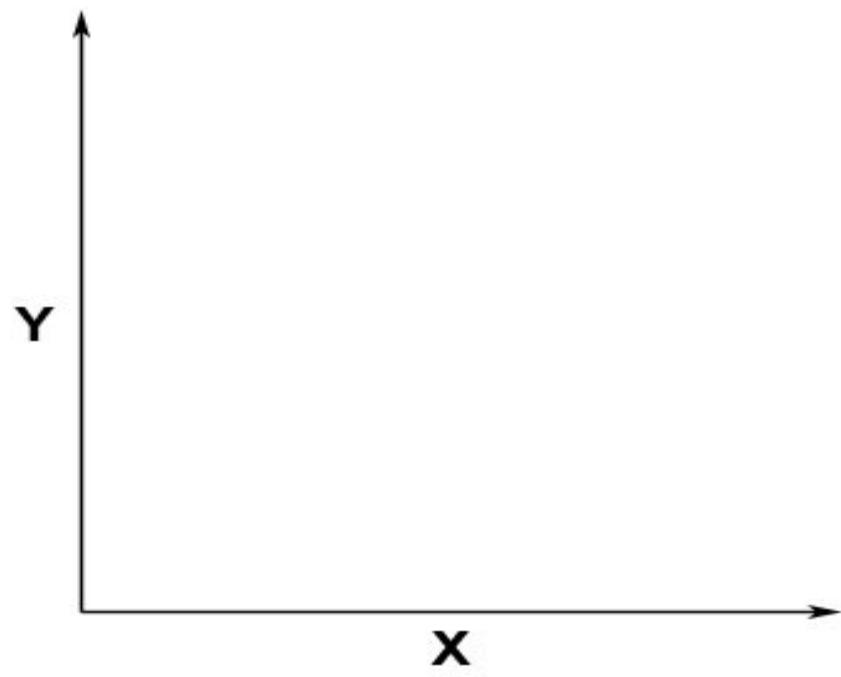
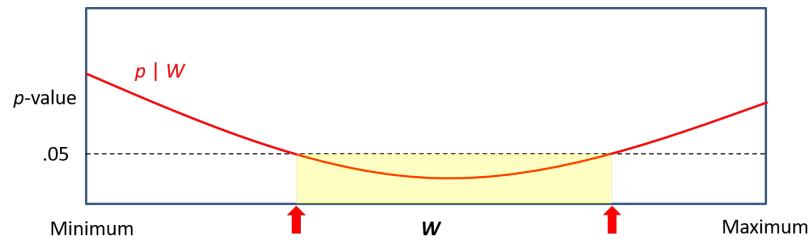
One Solution: What could graphs look like?



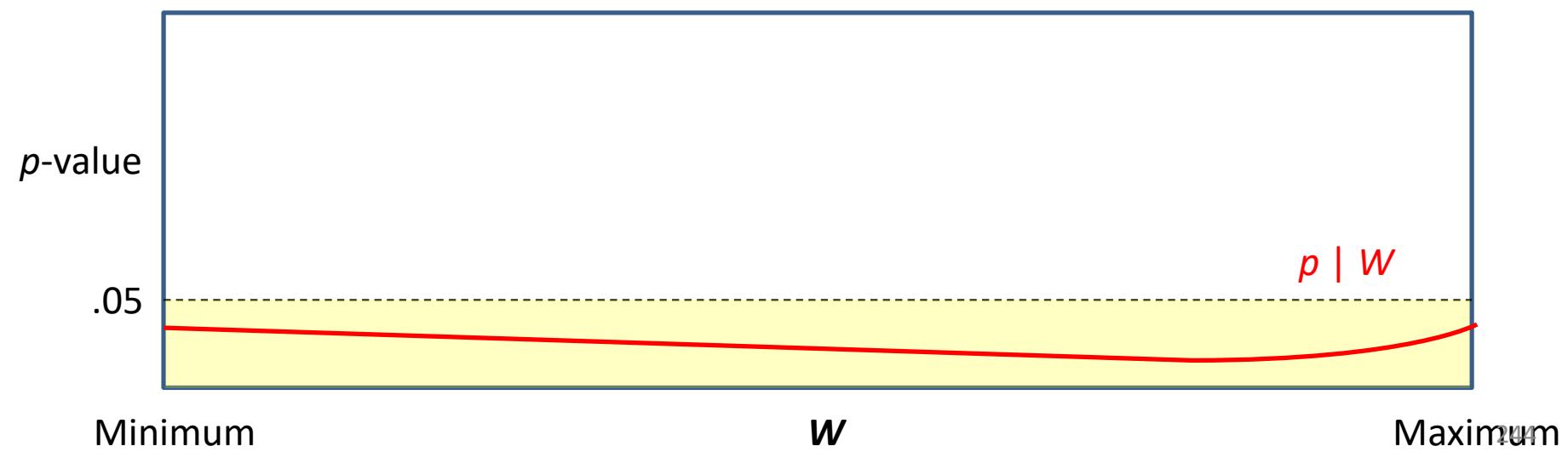
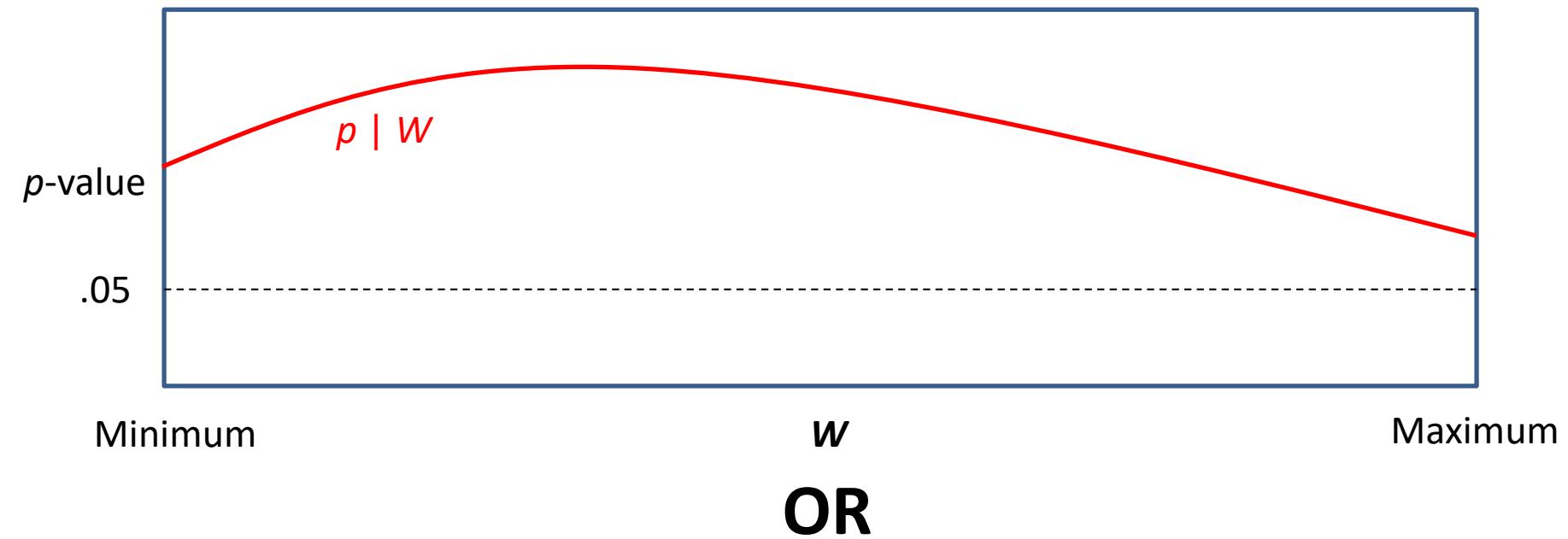
Examples of two solutions



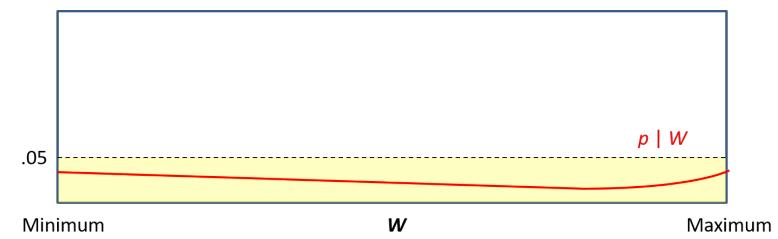
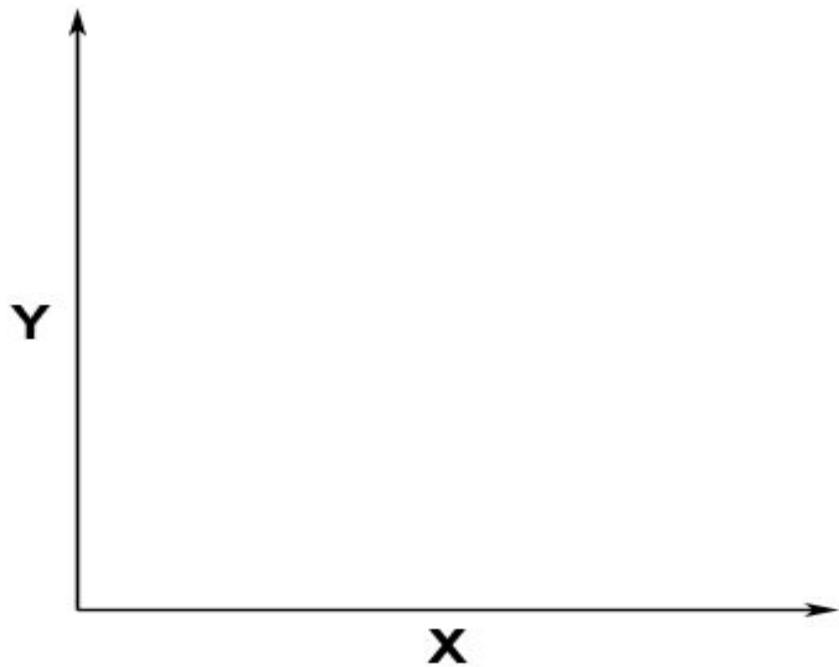
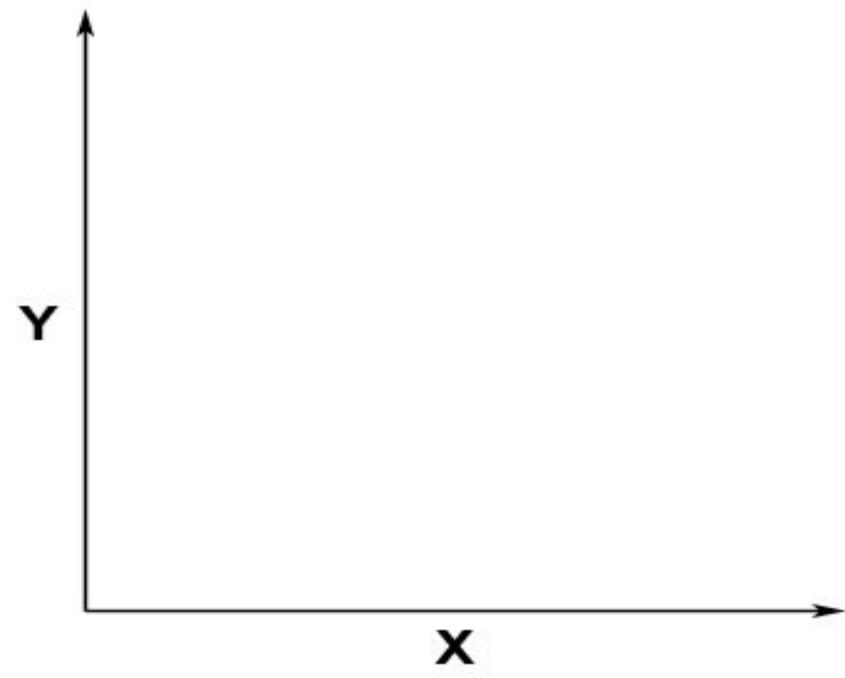
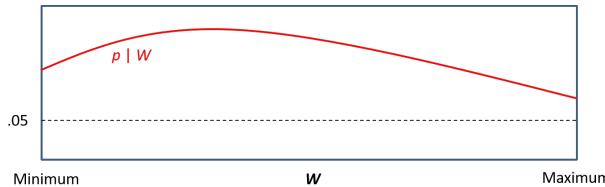
Two solution graphs



Examples of no solutions



No solution graphs



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:

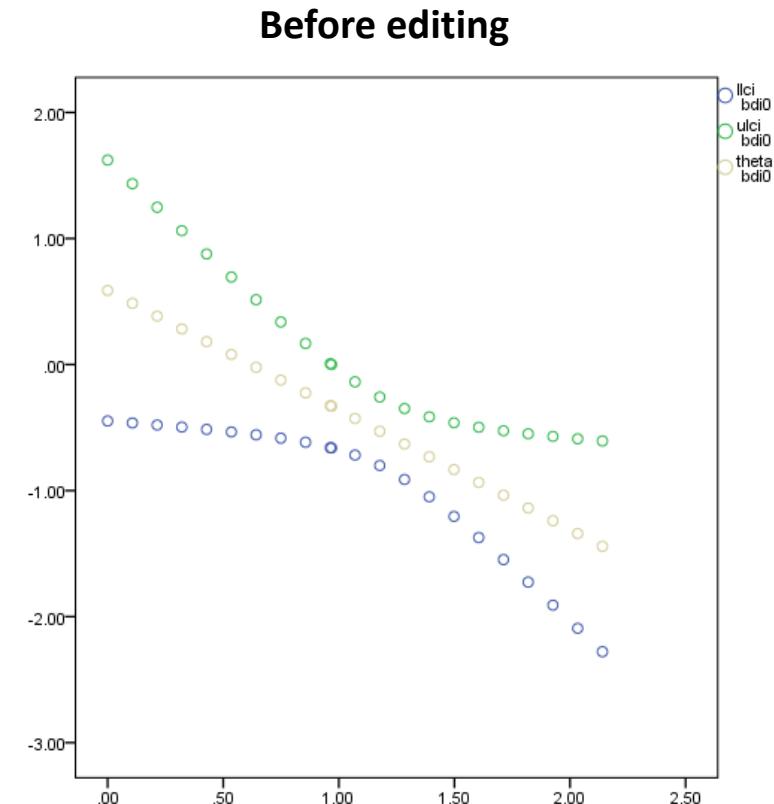
bdi0	Effect	se	t	p	LLCI	ULCI
.0000	.5872	.5241	1.1204	.2642	-.4478	1.6222
.1070	.4858	.4806	1.0108	.3136	-.4632	1.4347
.2140	.3843	.4373	.8787	.3809	-.4793	1.2479
.3210	.2828	.3946	.7167	.4746	-.4964	1.0620
.4280	.1813	.3525	.5144	.6077	-.5147	.8773
.5350	.0798	.3112	.2565	.7979	-.5348	.6944
.6420	-.0217	.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

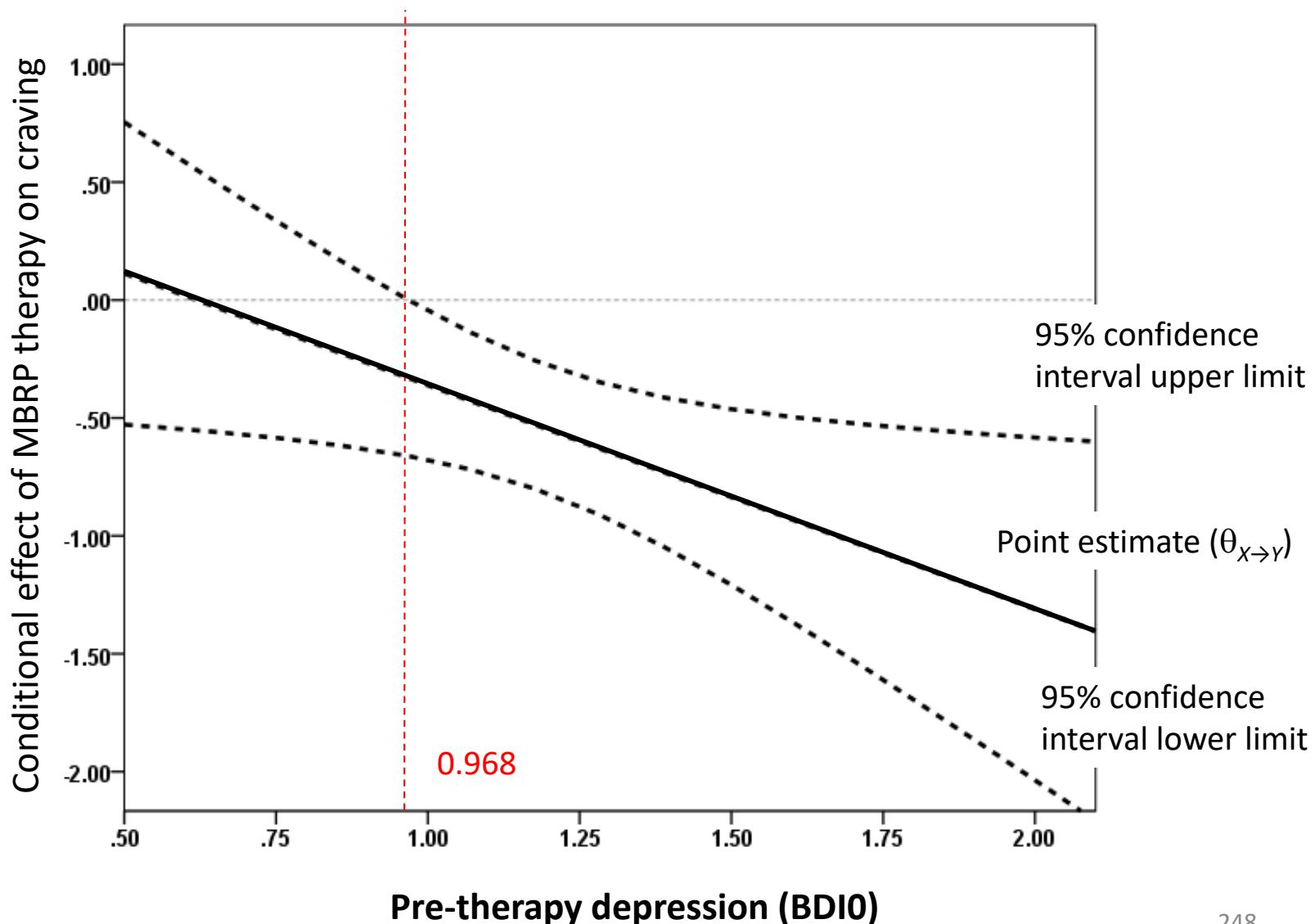
A visual representation (SPSS)

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).
```

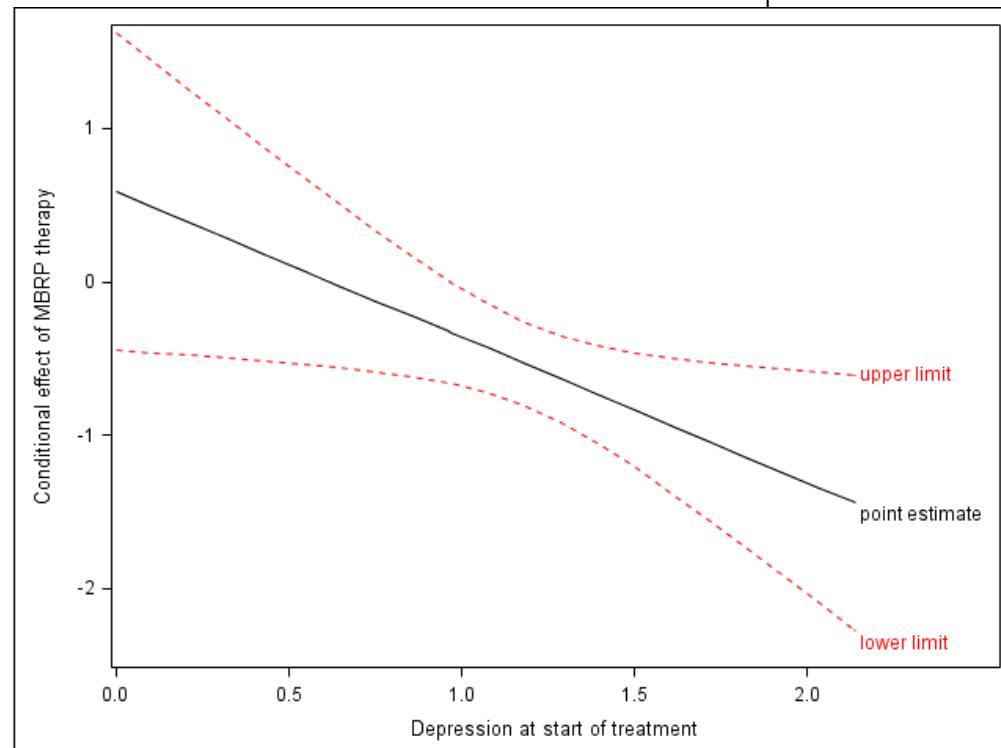


After some editing in SPSS



A visual representation (SAS)

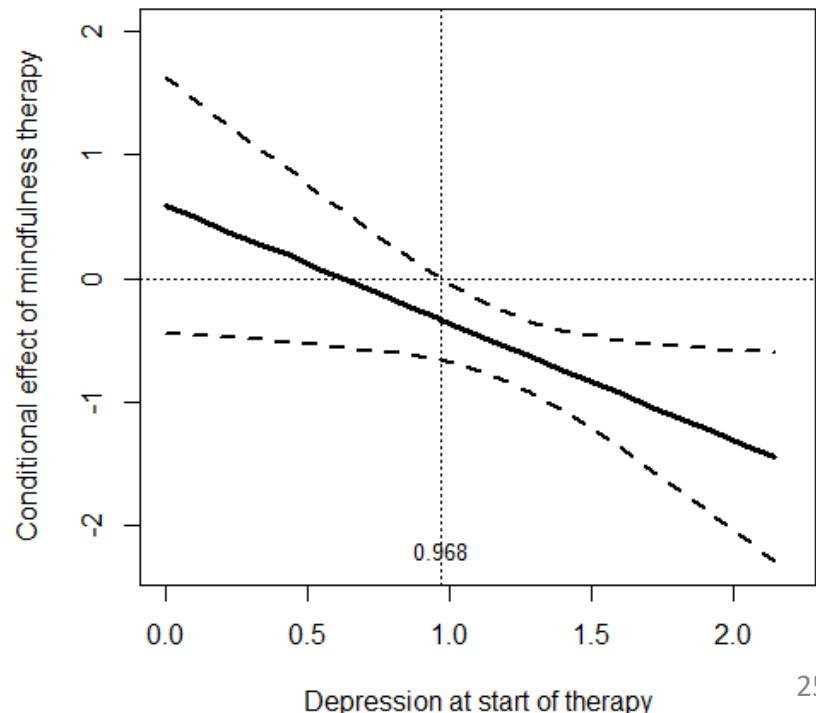
```
data;
input bdi0 effect llci ulci;
datalines;
.0000      .5872      -.4478      1.6222
.1070      .4858      -.4632      1.4347
.2140      .3843      -.4793      1.2479
.3210      .2828      -.4964      1.0620
.4280      .1813      -.5147      .8773
.5350      .0798      -.5348      .6944
.6420     -.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)
```

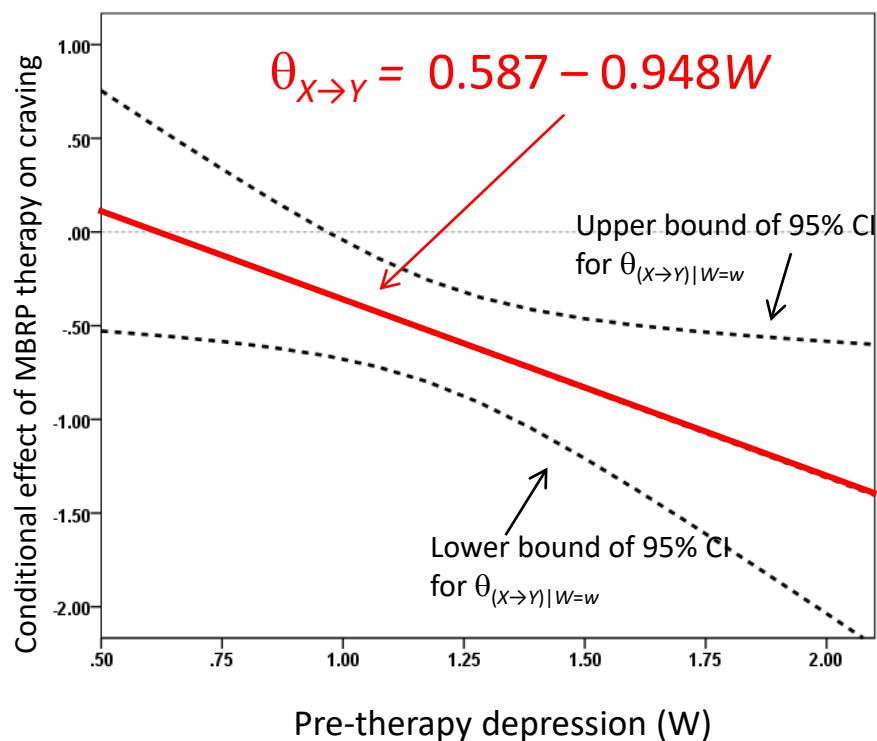
From the
JN option in
PROCESS.



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.

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



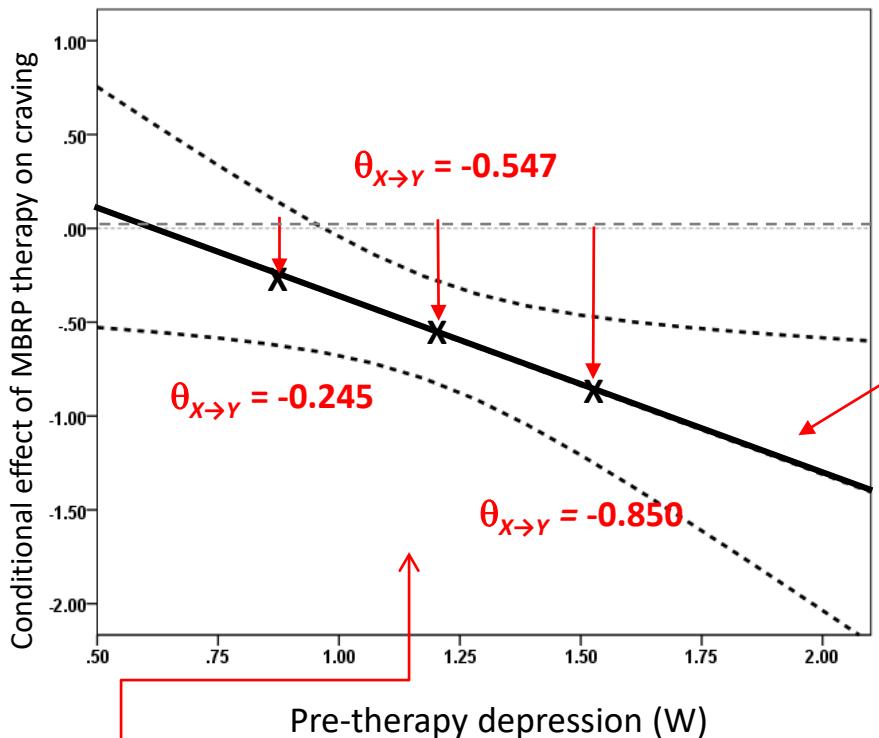
$$\theta_{X \rightarrow Y} = b_1 + b_3 W = 0.587 - 0.948W$$

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 $\theta_{X \rightarrow Y}$ and zero.

$$\theta_{X \rightarrow Y} = b_1 + b_3 W = 0.587 - 0.948W$$

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 $W = w_2$.

$$\begin{aligned}\theta_{(X \rightarrow Y) | W=w_2} - \theta_{(X \rightarrow Y) | W=w_1} &= (b_1 + b_3 w_2) - (b_1 + b_3 w_1) \\ &= (w_2 - w_1)b_3\end{aligned}$$

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

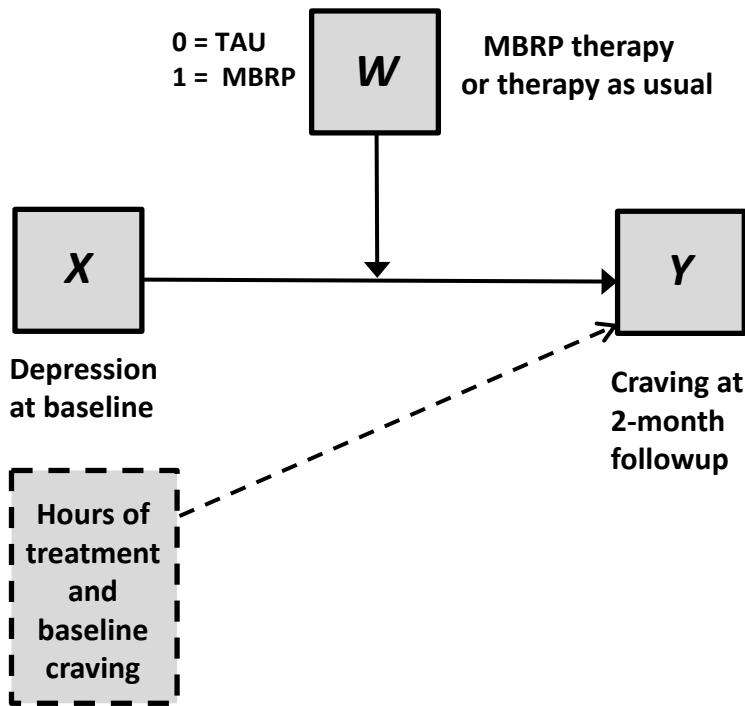
$$\frac{(w_2 - w_1)b_3}{(w_2 - w_1)\text{se}_{b_3}}$$

is distributed as $t(df_{\text{residual}})$. 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.

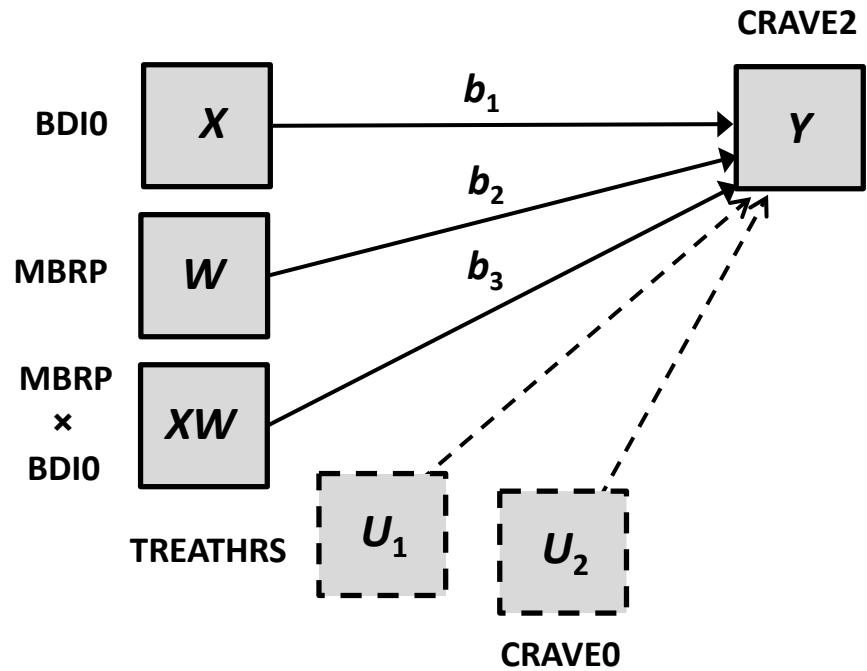
A test of linear moderation of X 's effect on Y by W is equivalent to a test of the difference between *any* two conditional effects of X . Moderation = any two conditional effects of X are different from each other. No moderation = no two conditional effects of X are different from each other. It doesn't 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.

$$\begin{aligned}\hat{Y}_i &= 1.038 + 1.122X_i + 0.587W_i - 0.948X_iW_i \\ &= 1.038 + (1.122 - 0.948W_i)X_i + 0.587W_i + \dots\end{aligned}$$

$$\theta_{X \rightarrow Y} = b_1 + b_3 W = 1.122 - 0.948W$$

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.

Model	Coefficients ^a					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	
	B	Std. Error	Beta			
1	(Constant)	1.038	.470		.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;
```

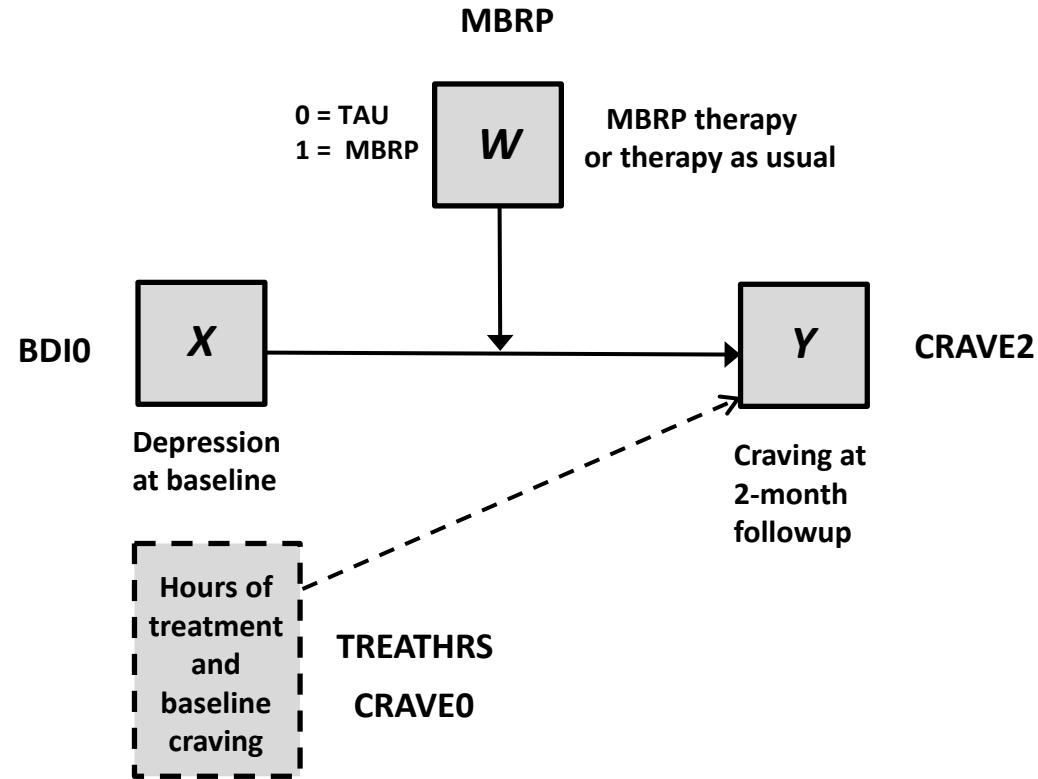
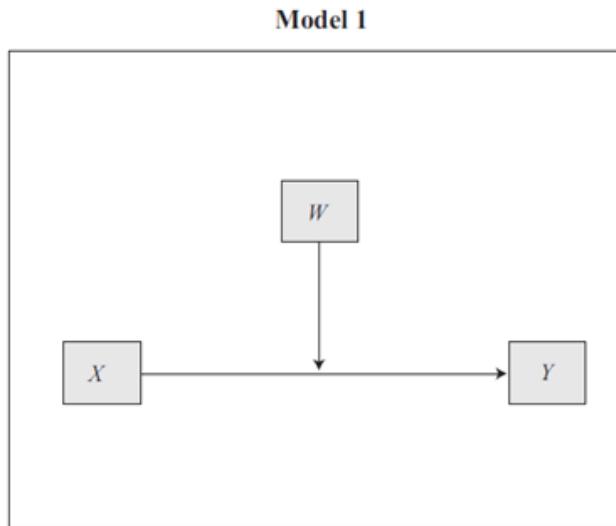
```
mbrp <- transform(mbrp, mbrp_p = mbrp-1)  
summary(lm(crave2~mbrp_p*bdi0+treathrs+crave0, data = mbrp))
```

Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
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
TREATRS: 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, $\theta_{X \rightarrow Y} = 0.174$, $t(162) = 0.529$, $p = .597$

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
W = 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

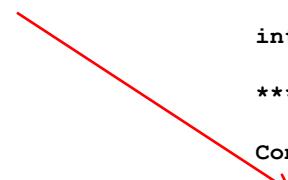
Model
      coeff      se      t      p      LLCI      ULCI
constant  1.0385  .4701  2.2090  .0286   .1102  1.9668
mbrp     .5872  .5241  1.1204  .2642  -.4478  1.6222
bdi0     1.1221  .2762  4.0625  .0001   .5767  1.6675
int_1    -.9485  .4235 -2.2398  .0265  -1.7847 -.1122
treathrs -.0177  .0103 -1.7190  .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

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

there is much ado in the literature about the need to mean center X and W first, thereby estimating the following model instead:

$$\widehat{Y}_i = b'_0 + b'_1(X_i - \bar{X}) + b'_2(W_i - \bar{W}) + b_3(X_i - \bar{X})(W_i - \bar{W})$$

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 A CONCERN THESE DAYS**

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))
```

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

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

$$\begin{aligned}b_3 &= -0.948 \\se_{b3} &= 0.423 \\t &= -2.240, \\p &= 0.026\end{aligned}$$

$b_1 = 0.587$. 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))
```

$$\widehat{Y}_i = 2.077 - 0.547X_i + 0.597W_i - 0.948X_iW_i \dots$$

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
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

$b_3 = -0.948$
 $se_{b_3} = 0.423$
 $t = -2.240,$
 $p = 0.026$

Mean centering has had no effect on b_3 .

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

$b_1 = -0.547$. 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

$$s_{b_j} = \sqrt{\frac{1}{1 - R_j^2}} \sqrt{\frac{MS_{\text{residual}}}{n(s_j^2)}} = \sqrt{\frac{MS_{\text{residual}} (\text{VIF})}{n(s_j^2)}}$$

where R_j^2 is the squared multiple correlation in a model estimating predictor variable j from the other predictor variables and s_j^2 is the variance of predictor j .

- $1 - R_j^2$ 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 M prior to computing their product, because this will lower the intercorrelation between X , M , 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			Tolerance	VIF
		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	0.064	15.674
	Sig. (2-tailed)		.242	.000		
	N	168	168	168		
BDI0: Beck Depression Inventory baseline	Pearson Correlation	-.091	1	.123	0.561	1.782
	Sig. (2-tailed)	.242		.113		
	N	168	168	168		
mbrpdep	Pearson Correlation	.945	.123	1	0.064	15.704
	Sig. (2-tailed)	.000	.113			
	N	168	168	168		

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 M prior to computing their product, because this will lower the intercorrelation between X , M , 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			Tol.	VIF
		mbrp_c	bdi0_c	mbrpdep_c		
mbrp_c	Pearson Correlation	1	-.091	.020	0.928	1.078
	Sig. (2-tailed)		.242	.798		
	N	168	168	168		
bdi0_c	Pearson Correlation	-.091	1	-.287	0.867	1.154
	Sig. (2-tailed)	.242		.000		
	N	168	168	168		
mbrpdep_c	Pearson Correlation	.020	-.287	1	0.915	1.093
	Sig. (2-tailed)	.798	.000			
	N	168	168	168		

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

$$\begin{aligned}s_{b_3} &= \sqrt{\frac{MS_{residual} (15.704)}{n(0.3816)}} \\&= \sqrt{\frac{15.704}{0.3816}} \sqrt{\frac{MS_{residual}}{n}} \\&= \sqrt{41.1} \sqrt{\frac{MS_{residual}}{n}}\end{aligned}$$

With mean centering

$$\begin{aligned}s_{b_3} &= \sqrt{\frac{MS_{residual} (1.093)}{n(0.0266)}} \\&= \sqrt{\frac{1.093}{0.0266}} \sqrt{\frac{MS_{residual}}{n}} \\&= \sqrt{41.1} \sqrt{\frac{MS_{residual}}{n}}\end{aligned}$$

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. This is a good reason for doing it.
- Mean centering does change the coefficient for the focal predictor and moderator. But this has nothing to do with reducing multicollinearity. 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 = treachrs crave0  
 /y=crave2/x=mbrp /w=bdi0/model=1  
 /moments = 1/center=1.
```

```
%process (data=mbrp,cov=treachrs  
 crave0,y=crave2, x=mbrp,m=bdi0,  
 model=1, momens = 1, center=1);
```

```
process(data=mbrp, cov=c("treachrs",  
 "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
treachrs	-.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:

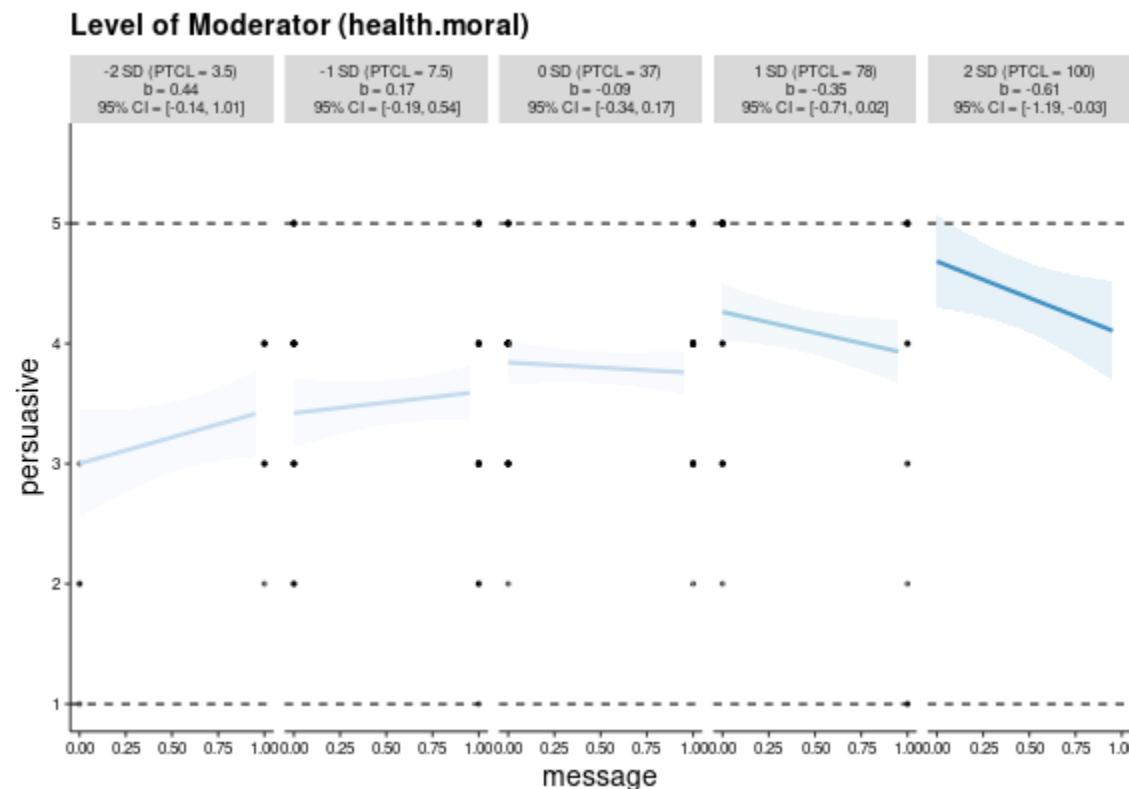
mbrp	bdi0
------	------

Interactive: A tool for visualization

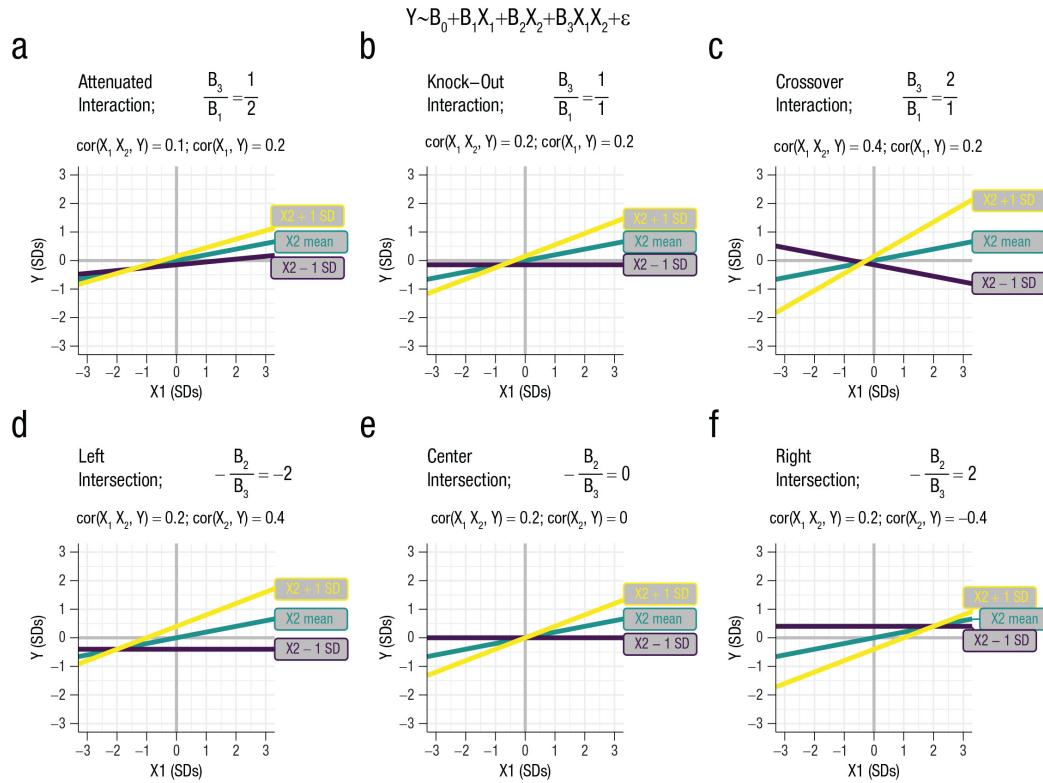
Another tool available for visualizing interactions is a shiny app called interActive by Conor McCabe

McCabe, C., Kim, D., & King, K. (2018). Improving Present Practices in the Visual Display of Interactions. *Advances in Methods and Practices in Psychological Science*, 1(2), 147-165.

<https://connorjmccabe.shinyapps.io/interactive/>



Sample Size Planning: Moderation



Baranger et al., (2023) describes methods for selecting effect sizes in moderation

Powering an interaction term is more complex than powering for a regression coefficient.

See Also [Sommet et al., 2023 AMPPS](#)

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 XW 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.

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
1.00	2.00	5	2.7

```

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
114 1 1 1 4
115 1 1 1 7
121 1 1 1 6
131 1 1 1 4
132 1 1 1 3.4
148 1 1 1 4.2
161 1 1 1 4.6
162 1 1 1 4.2
164 1 1 1 4.4
174 1 1 1 5.4
176 1 1 1 5
177 1 1 1 4.6
178 1 1 1 3.4
190 1 1 1 3.8
206 1 1 1 4.2
216 1 1 1 7
217 1 1 1 5

```

ProNo: Experimental condition (1 = procollaboration, 0 = no collaboration)

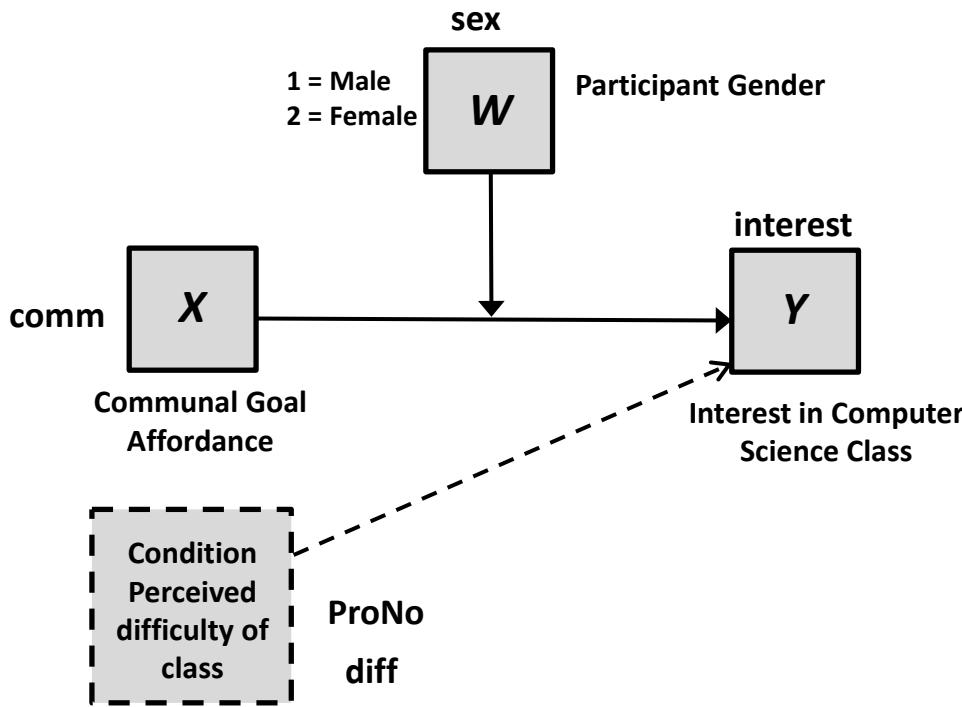
interest : interest in class (higher = greater interest)

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



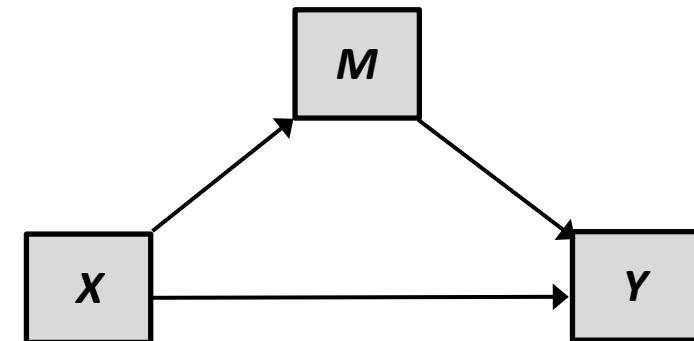
- 1) Estimate this model using both the base regression functions and PROCESS. Confirm your models are the same.
- 2) Is the effect of communal goal affordance on interest moderated by gender?
- 3) Probe the interaction: We expect a positive relationship for women and near zero relationship for men. 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”

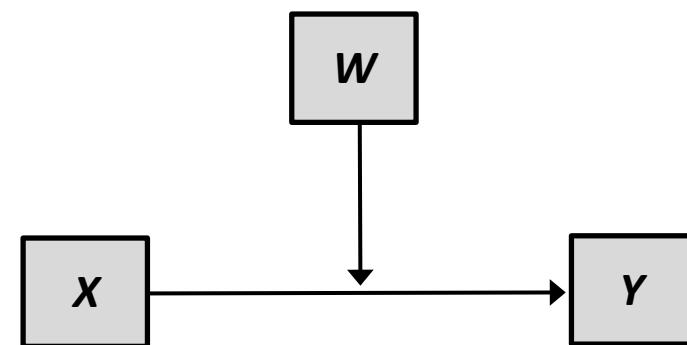
“Conditional process analysis” is a general modeling strategy undertaken with the goal of describing the *conditional* nature of the *mechanism(s)* by which a variable transmits its effect on another, and testing hypotheses about such contingent effects.

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.

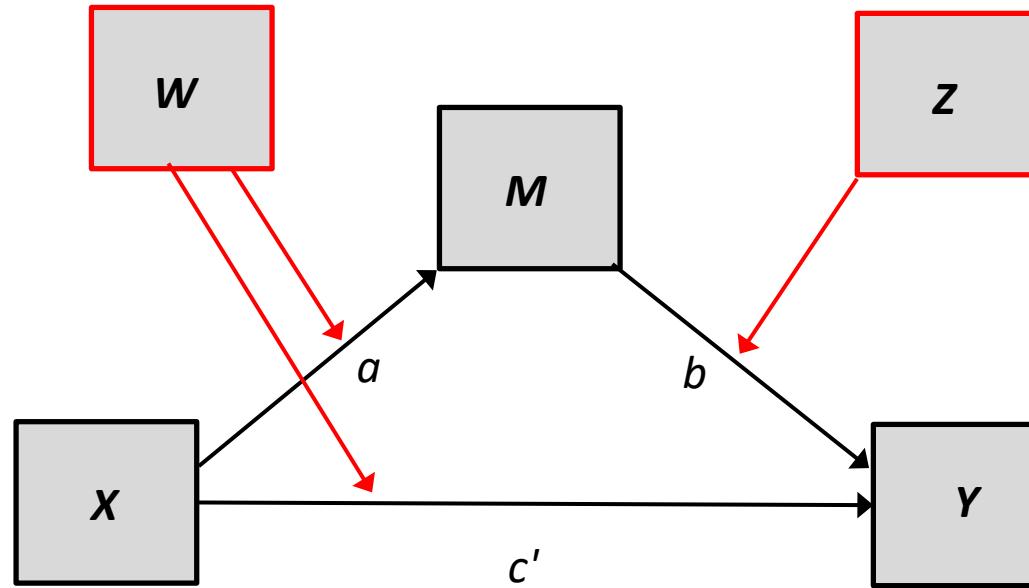
Preacher, Rucker, and Hayes (2007): Provide a formal definition of the *conditional indirect effect* and give formulas, standard errors, and a bootstrap approach for estimating and testing hypotheses about moderated mediation in five different models.

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.

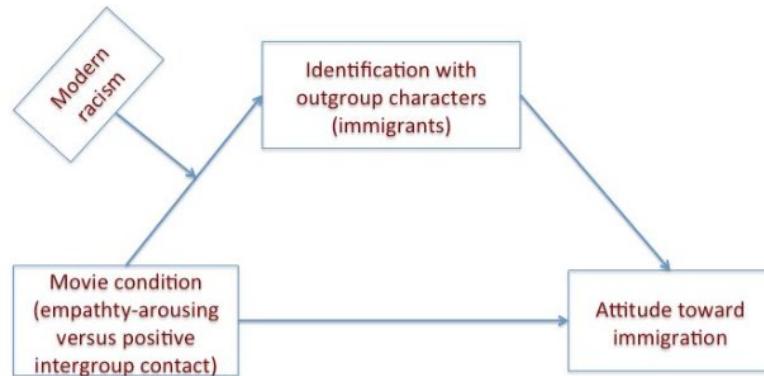
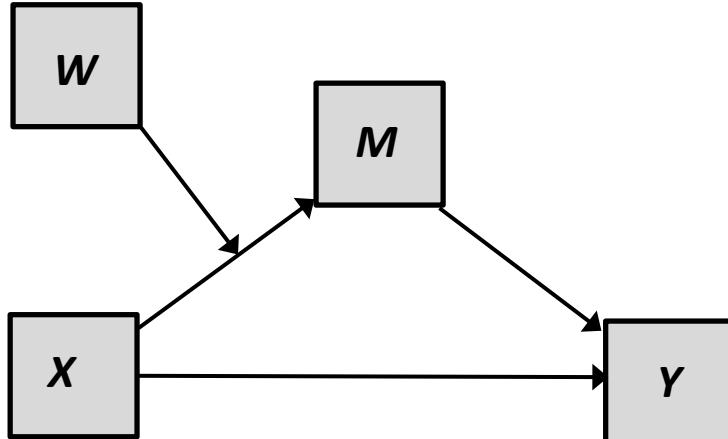
Hayes (2015): Introduces the *index of moderated mediation* which provides a formal test for moderated mediation in a variety of models.

“Moderated mediation”

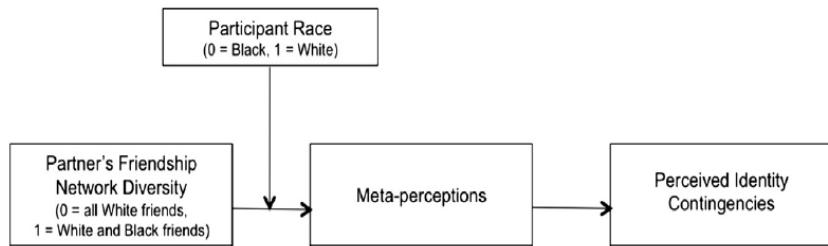


- The indirect effect of *X* on *Y* through *M* is estimated as the product of the *a* and *b* paths
- But what if the size of *a* or *b* (or both) depends on another variable (i.e., is moderated)?
- If so, then the magnitude of the indirect effect therefore depends on a third variable, meaning that “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*.

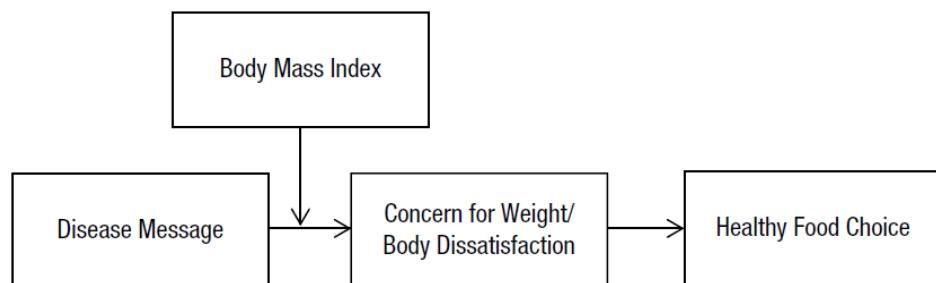
Examples: X to M path moderated by W



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.

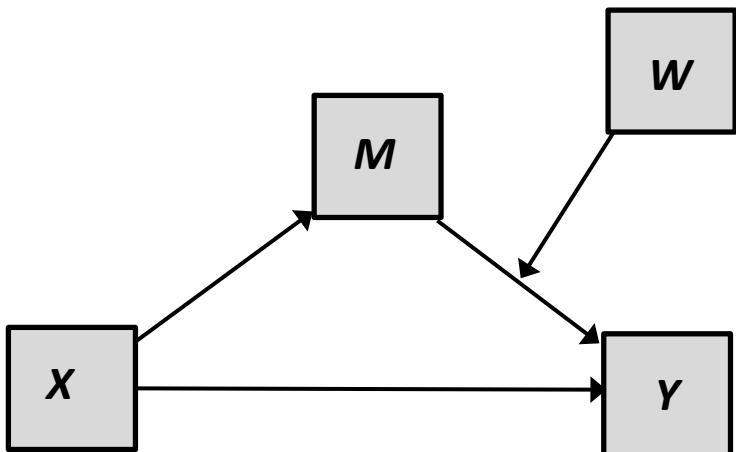


Wout, D. A., Murphy, M. C., & Steele, C. M. (2010). When your friends matter: The effect of White students' racial friendship networks on meta-perceptions and Perceived identity contingencies. *Journal of Experimental Social Psychology*, 46, 1035-1041.

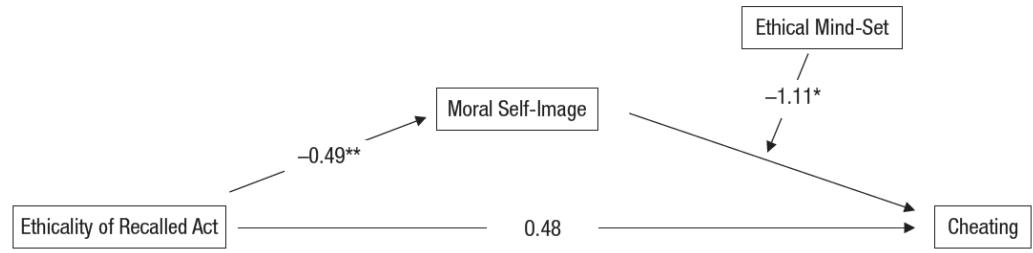


Hoyt, C. L., Burnette, J. L., & Auster-Gussman, L. (2014). "Obesity is a disease": Examining the self-regulatory impact of this public-health message. *Psychological Science*, 25, 997-1002.

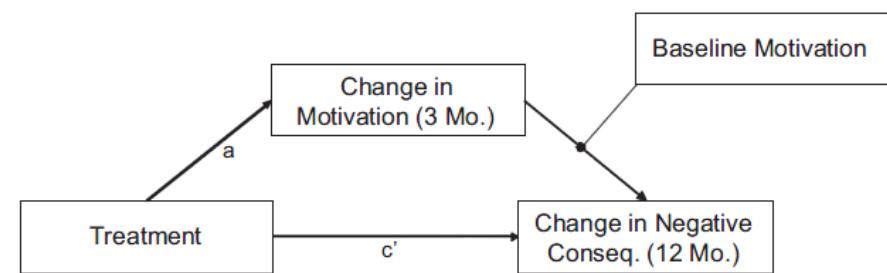
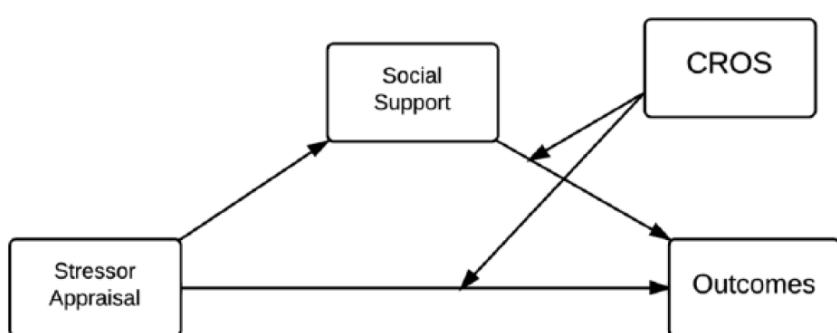
Examples: M to Y path moderated by W



Boren, J. P., & Veksler, A. E. (2015). Communicatively restricted organizational stress (CROS) I: Conceptualization and overview. *Management Communication Quarterly*, 29, 28-55.

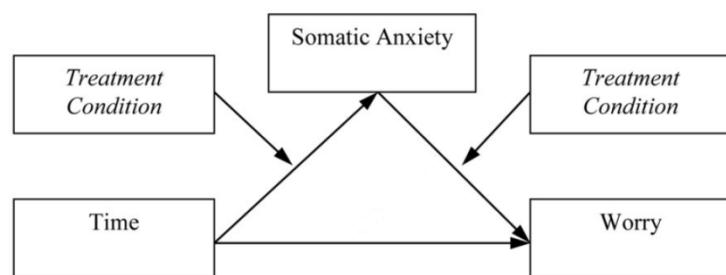
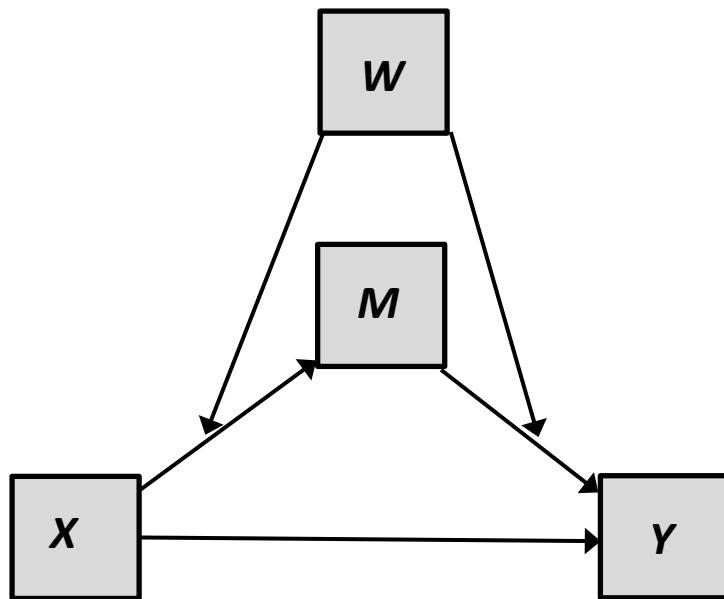


Cornelissen, G., Bashshur, M. R., Rode, J., & Le Menestrel, M. (2013). Rules or consequences? The role of ethical mind-sets in moral dynamics. *Psychological Science*, 24, 492-488.

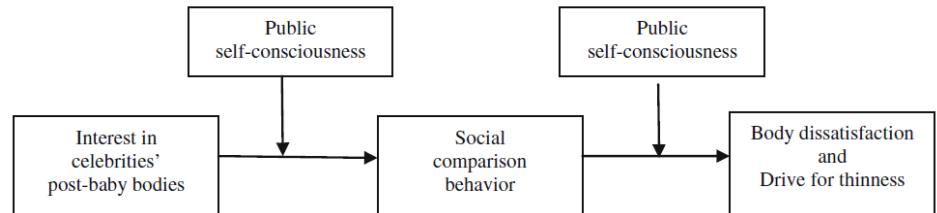


Stein, L. A. R., Minugh, P. A. et al. (2009). Readiness to change as a mediator of the effect of a brief motivational intervention on posttreatment alcohol-related consequences of injured emergency department hazardous drinkers. *Psychology of Addictive Behaviors*, 23, 185-195.

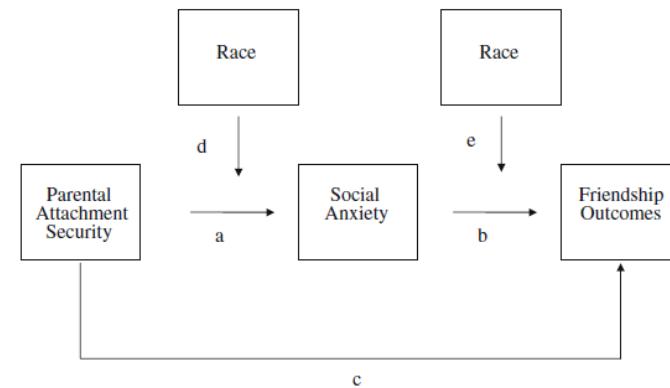
Examples: X to M and M to Y path moderated by W



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.



Chae, J. (2014). Interest in celebrities' post-baby bodies and Korean women's body image disturbance after childhood. *Sex Roles*, 71, 419-435.



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,

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

$$\widehat{Y}_i = c'_0 + c'_1 X_i + c'_2 W_i + c'_3 X_i W_i + bM_i$$

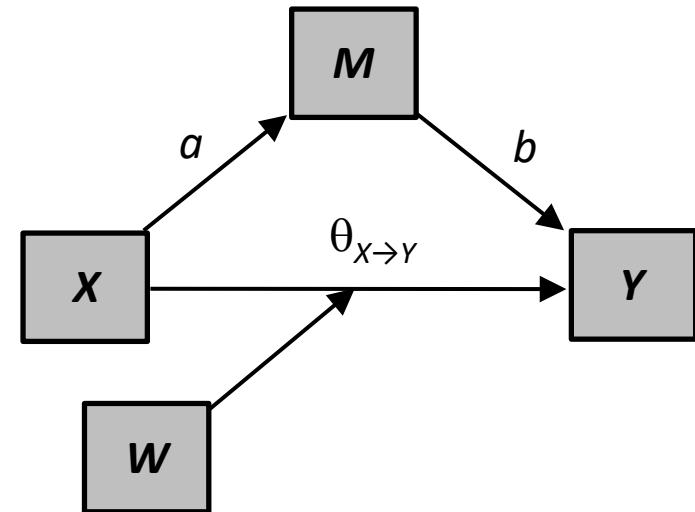
or, equivalently,

$$\widehat{Y}_i = c'_0 + (c'_1 + c'_3 W_i) X_i + c'_2 W_i + bM_i$$

or, equivalently,

$$\widehat{Y}_i = c'_0 + \theta_{X \rightarrow Y} X_i + c'_2 W_i + bM_i$$

$$\text{where } \theta_{X \rightarrow Y} = (c'_1 + c'_3 W_i)$$



In this model, $\theta_{X \rightarrow Y}$ is the **conditional direct effect of X** , which is defined by the function $c'_1 + c'_3 W$. Holding M constant, two cases that differ by one unit on X are estimated to differ by $c'_1 + c'_3 W$ 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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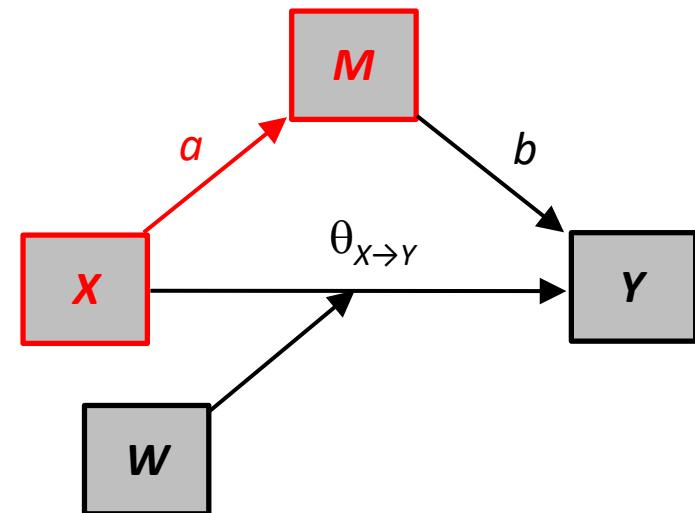
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or, equivalently,

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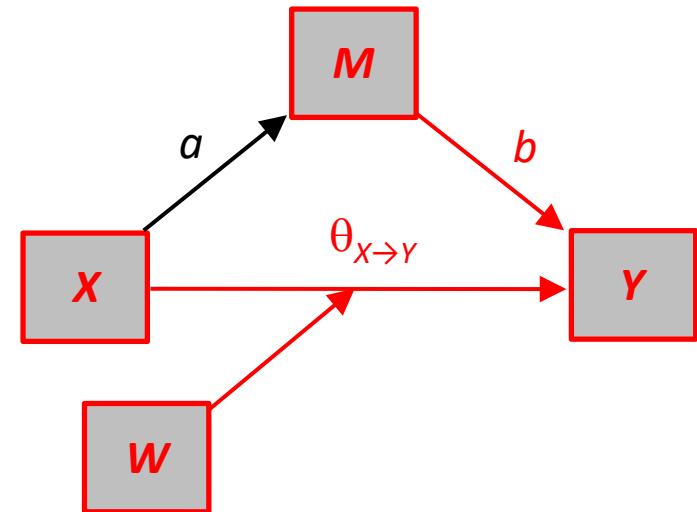
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or, equivalently,

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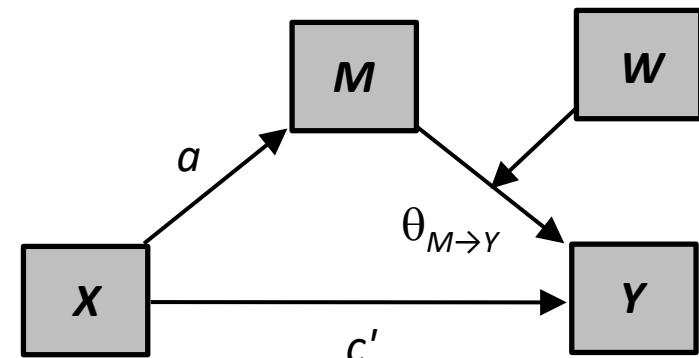
or, equivalently,

$$\widehat{Y}_i = c'_0 + c'_1 X_i + \theta_{M \rightarrow Y} M_i + b_2 W_i$$

$$\text{where } \theta_{M \rightarrow Y} = (b_1 + b_3 W_i)$$

The indirect effect of X on Y via M is $a\theta_{M \rightarrow Y}$, but as $\theta_{M \rightarrow Y}$ is a conditional effect (the conditional effect of M), then $a\theta_{M \rightarrow Y}$ is the *conditional indirect effect* of X on Y via M : $a\theta_{M \rightarrow Y} = a(b_1 + b_3 W) = ab_1 + ab_3 W$. It depends on W .

This is also a basic conditional process model, and potentially more interesting one. It allows for the process or ‘mechanism’ linking X to Y via M to differ systematically as a function of W . This model allows “mediation to be moderated.”



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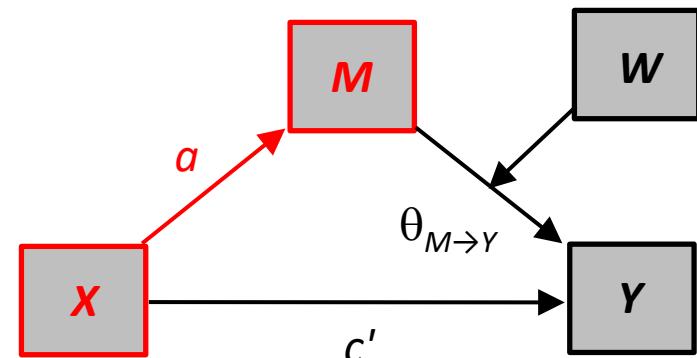
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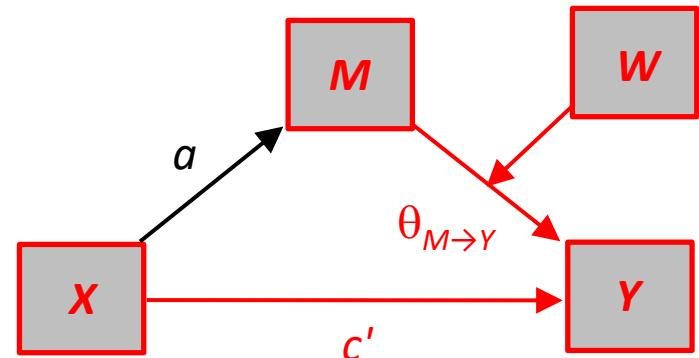
or, equivalently,

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or, equivalently,

$$\widehat{Y}_i = c'_0 + c'_1 X_i + \theta_{M \rightarrow Y} M_i + b_2 W_i$$

where $\theta_{M \rightarrow Y} = (b_1 + b_3 W_i)$



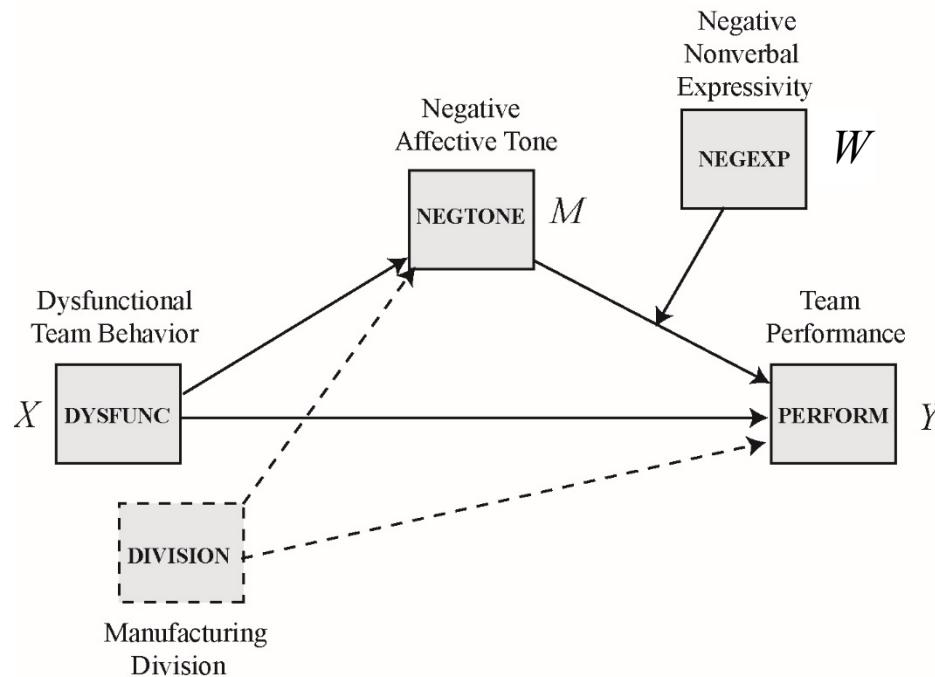
The indirect effect of X on Y via M is $a\theta_{M \rightarrow Y}$, but as $\theta_{M \rightarrow Y}$ is a conditional effect (the conditional effect of M), then $a\theta_{M \rightarrow Y}$ is the *conditional indirect effect* of X on Y via M : $a\theta_{M \rightarrow Y} = a(b_1 + b_3 W) = ab_1 + ab_3 W$. It depends on W .

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Condition process analysis: Example 1



Condition process analysis: Example 1



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.

Journal of Applied Psychology
2008, Vol. 93, No. 5, 945–958

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0021-9010/08/\$12.00 DOI: 10.1037/0021-9010.93.5.945

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., Dieendorff & 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-

Michael S. Cole, Department of Management, M.J. Neely School of Business, Texas Christian University; Frank Walter, Department of Human Resource Management and Organizational Behavior, Faculty of Business and Economics, University of Groningen, Groningen, The Netherlands; Heike Bruch, Institute for Leadership and Human Resource Management, University of St. Gallen, St. Gallen, Switzerland.

We thank Steven Brown, Hubert Feild, and Jochen Menges for vetting a draft manuscript and Silja Drack for her assistance with data collection. We also acknowledge the helpful and constructive feedback provided by Anne

The Data: TEAMS

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

```

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 -.52 -.16 1.02 .72 -.82 1 1 0 0
.09 .53 .50 -.29 -.19 .84 1 1 0 0
.27 .73 -.16 -.06 .15 .50 1 1 0 0
.18 -.18 -.16 -.23 1.08 -.16 1 1 0 0
.38 .22 -.16 -.43 .52 .50 1 1 0 0
.03 .20 .60 -.50 -.68 .26 1 1 0 0
.03 .31 -.40 -.41 .75 -.06 1 1 0 0

```

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.

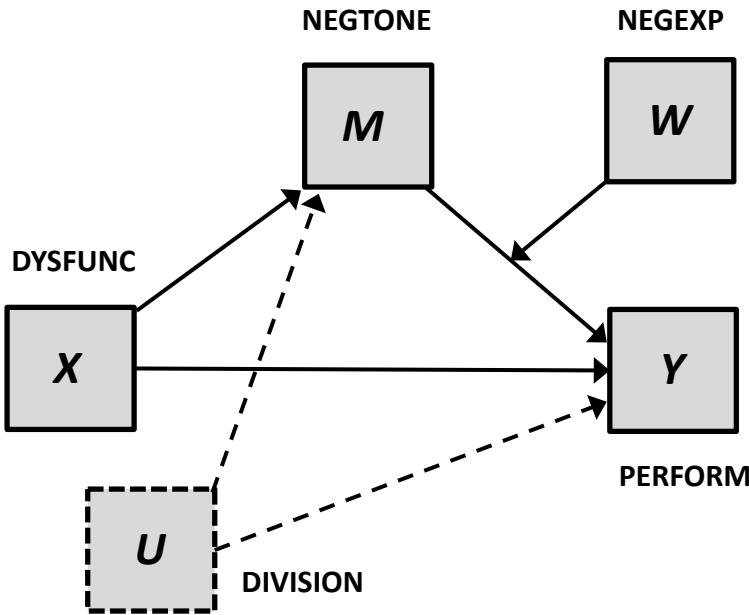
PERFORM: Team performance. Supervisor’s judgment as to the team’s efficiency, ability to get task done in a timely fashion, etc.

All variables are scaled arbitrarily, but higher = “more”

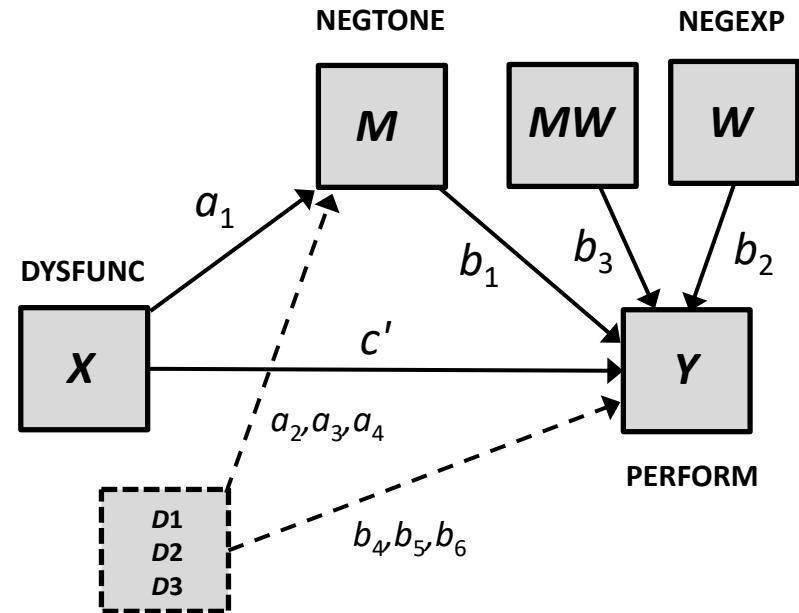
Also available is which of four parts divisions the team worked in, as a single categorical variable (**division**) as well as three dummy variables (**d1, d2, d3**).

Conceptual and statistical models

Conceptual Model



Statistical Model



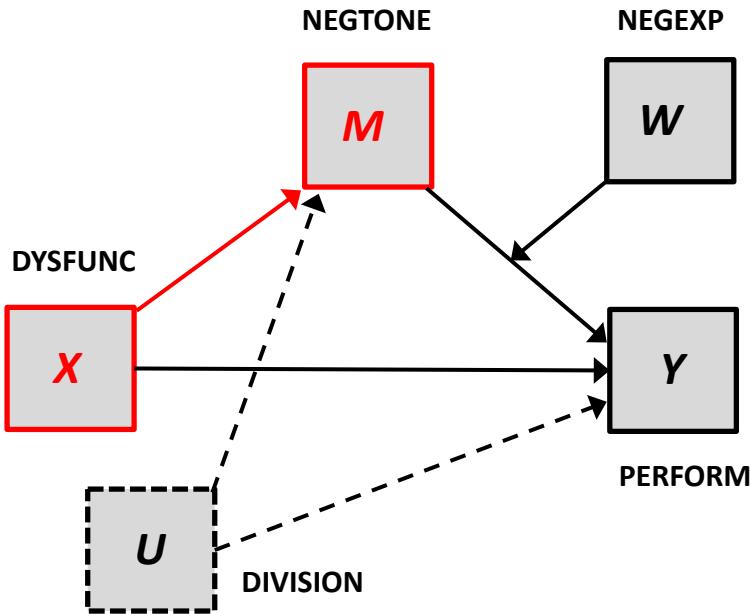
$$\widehat{M}_i = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

$$\widehat{Y}_i = c'_0 + c' X_i + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

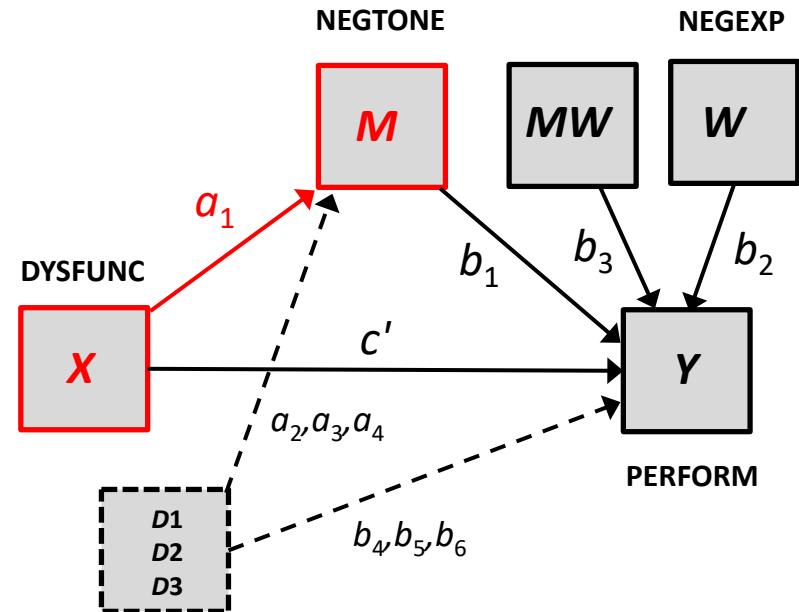
The number of equations needed is equal to the number of variables with arrows pointing at them in the conceptual or statistical diagram.

Conceptual and statistical models

Conceptual Model



Statistical Model



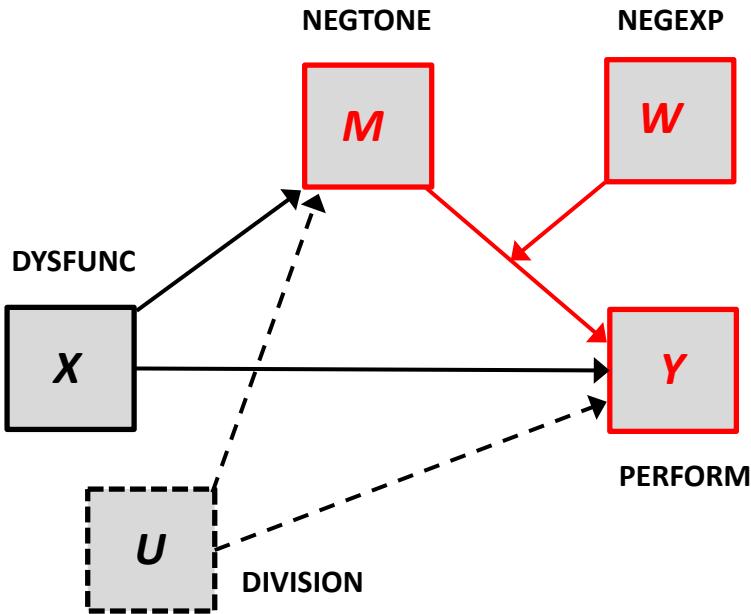
$$\widehat{M}_i = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

$$\widehat{Y}_i = c'_0 + c' X_i + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

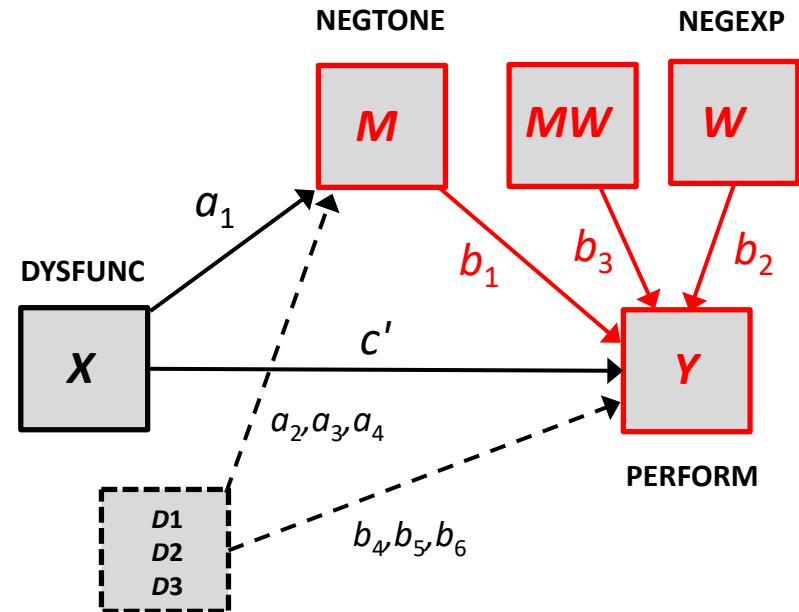
The effect of dysfunctional team behavior (X) on negative affective tone of the work environment (M).

Conceptual and statistical models

Conceptual Model



Statistical Model



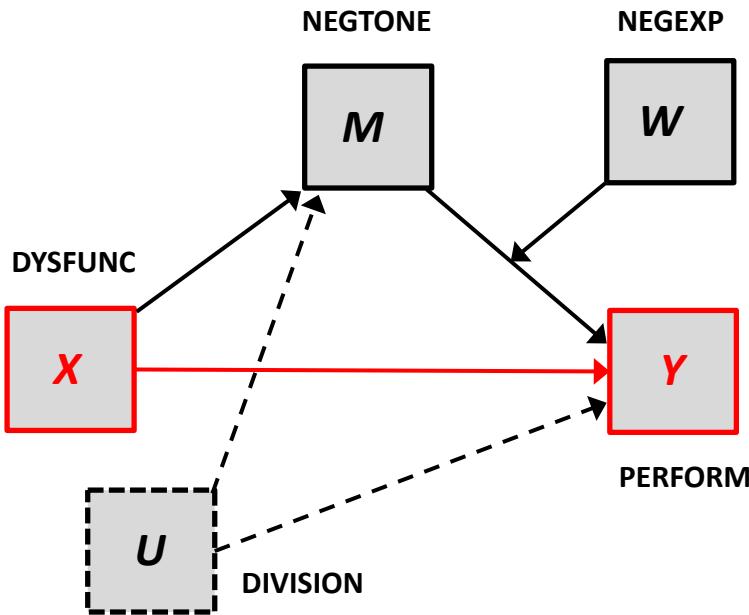
$$\widehat{M}_i = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

$$\widehat{Y}_i = c'_0 + c' X_i + \boxed{b_1 M_i + b_2 W_i + b_3 M_i W_i} + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

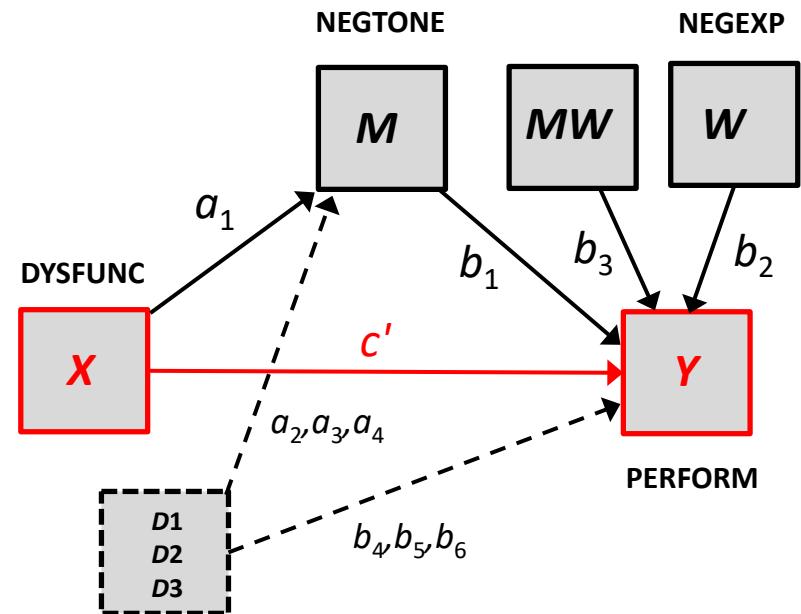
The moderation of the effect of the negative affective tone of the work environment (M) on team performance (Y) by negative nonverbal expressivity (W).

Conceptual and statistical models

Conceptual Model



Statistical Model



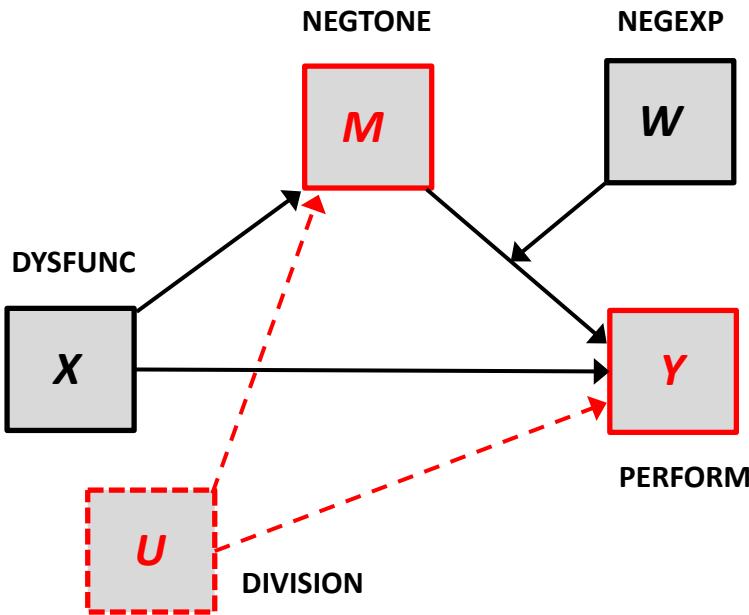
$$\widehat{M}_i = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

$$\widehat{Y}_i = c'_0 + c' X_i + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

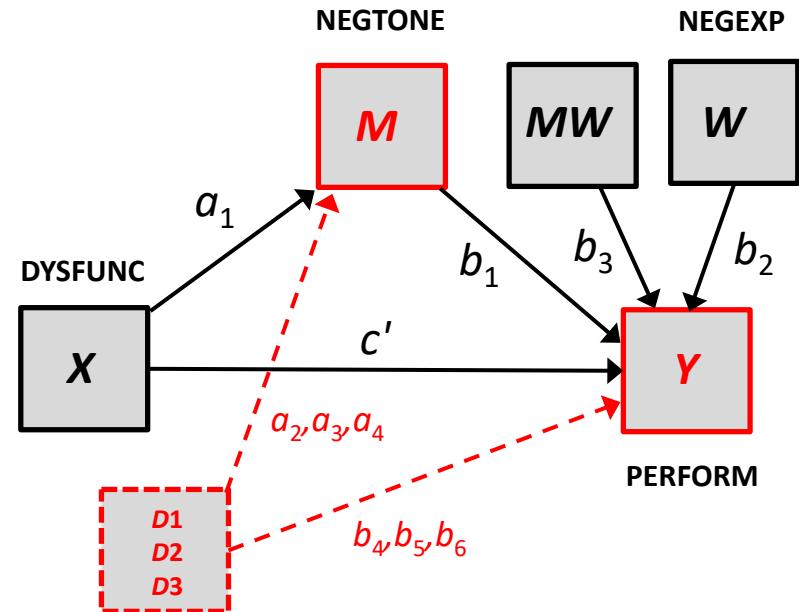
The direct effect of dysfunctional team behavior (X) on team performance (Y).

Conceptual and statistical models

Conceptual Model



Statistical Model



$$\widehat{M}_i = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

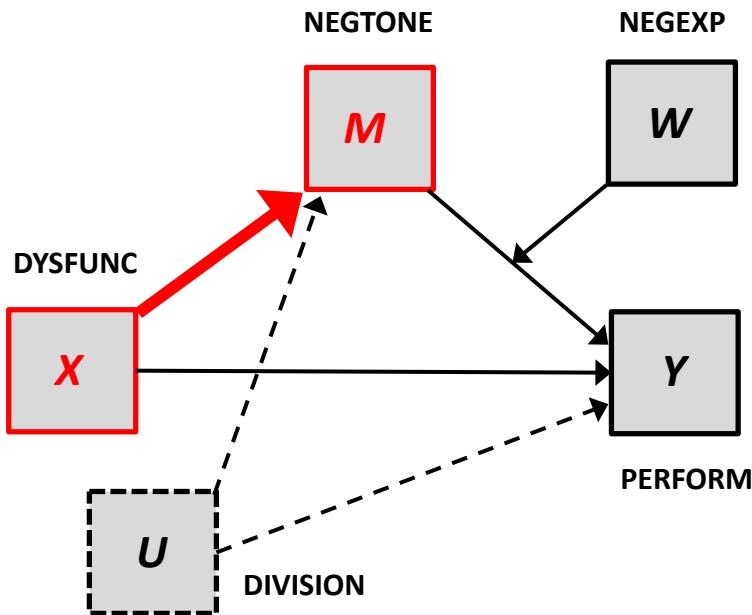
$$\widehat{Y}_i = c'_0 + c' X_i + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

Covariates to account for potential confounding by divisional differences (**U**) in negative tone of the work environment (**M**) and performance (**Y**)

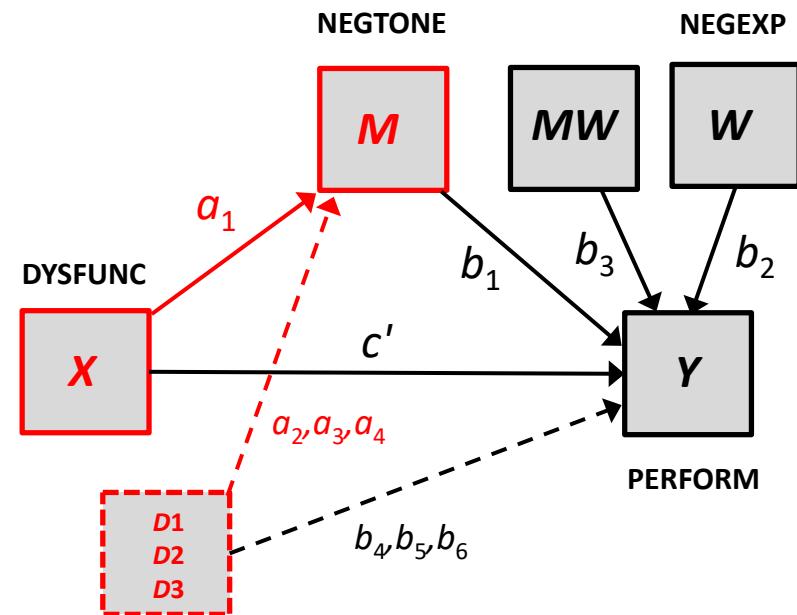
Estimating the a_1 path

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.

Conceptual Model



Statistical Model



$$\widehat{M}_i = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

Emphasis is 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))
```

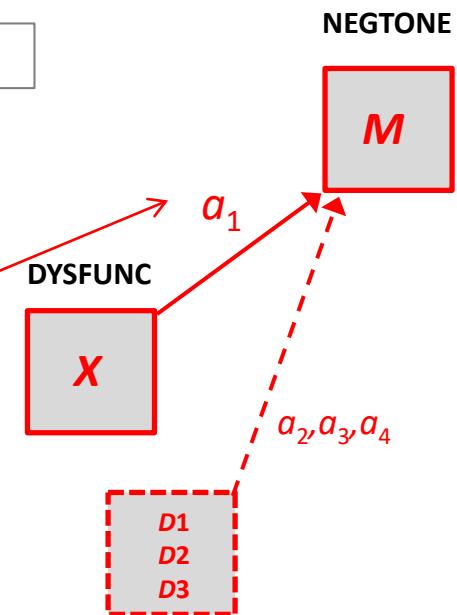
Model	Coefficients ^a				
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	- .206	.130		-1.576	.121
Dysfunctional team behavior	.609	.167	.431	3.655	.001
d1	.349	.171	.307	2.033	.047
d2	.295	.212	.193	1.391	.170
d3	.251	.166	.230	1.508	.137

a. Dependent Variable: Negative affective tone

$$a_1 = 0.609$$

$$\widehat{M}_i = -0.206 + 0.609X_i + 0.349D_{1i} + 0.295D_{2i} + 0.251D_{3i}$$

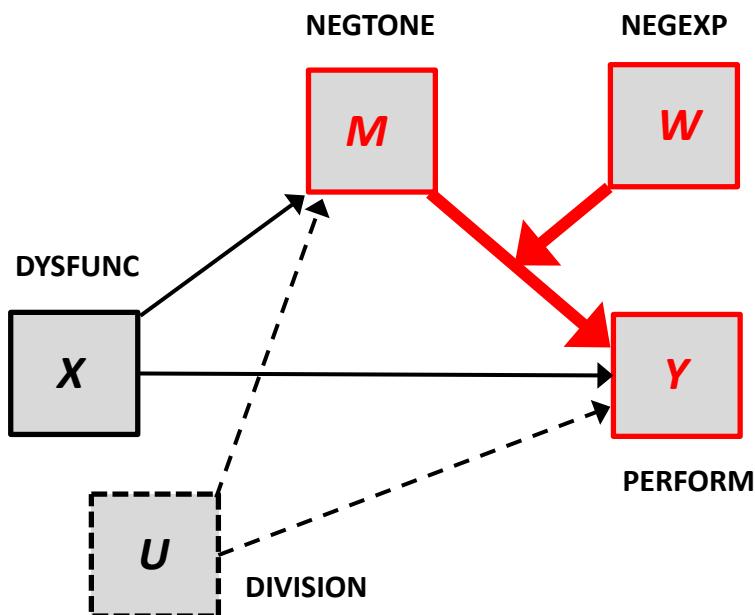
Teams whose members exhibit relatively more dysfunctional behavior tend to operate in a work environment characterized by relatively more negative affective tone (i.e., members report more negative affect)



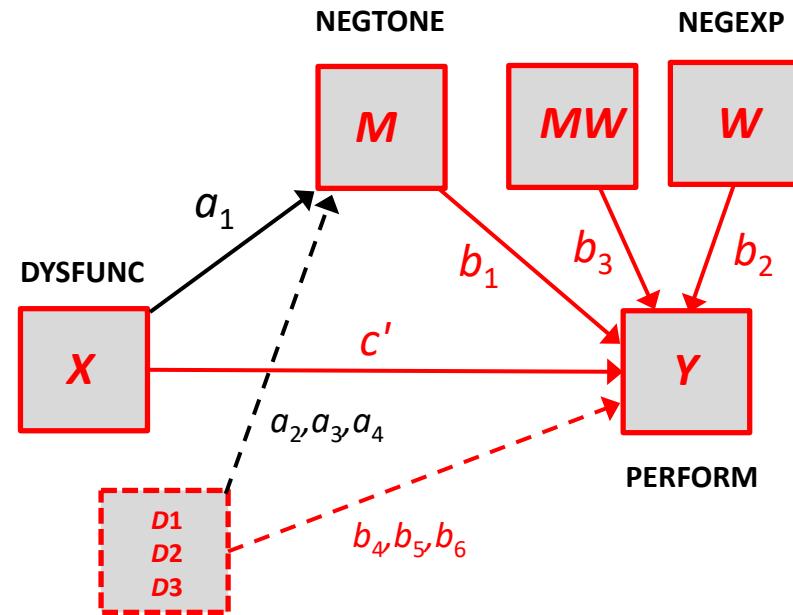
Estimating the moderation component of the model

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;
```

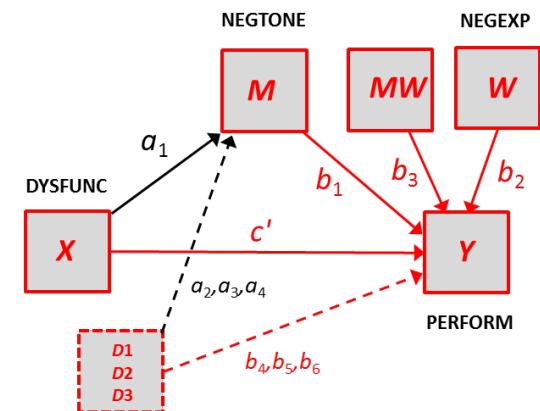
```
summary(lm(perform~dysfunc+negtone*negexp+d1+d2+d3, data = teams))
```

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error			
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

Model	Coefficients ^a				
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	-.175	.130		-1.344	.185
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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

$$\hat{Y}_i = -0.175 + 0.373X_i + (-0.489 - 0.450W_i)M_i - 0.022W_i + 0.182D_{1i} + 0.084D_{2i} + 0.282D_{3i}$$

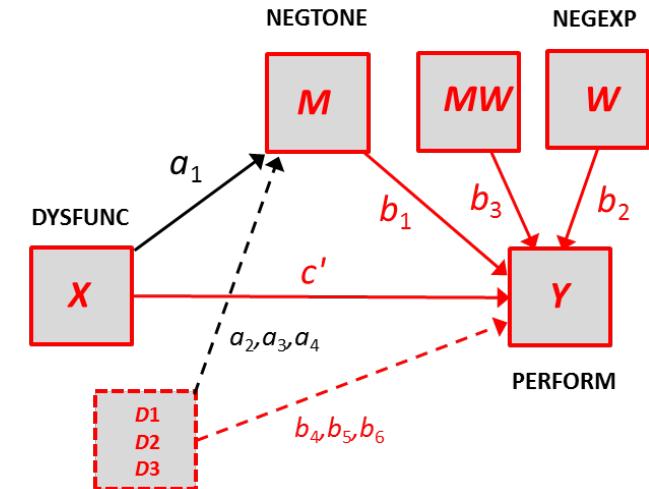
or

$$\hat{Y}_i = -0.175 + 0.373X_i + \theta_{M \rightarrow Y}M_i - 0.022W_i + 0.182D_{1i} + 0.084D_{2i} + 0.282D_{3i}$$

where

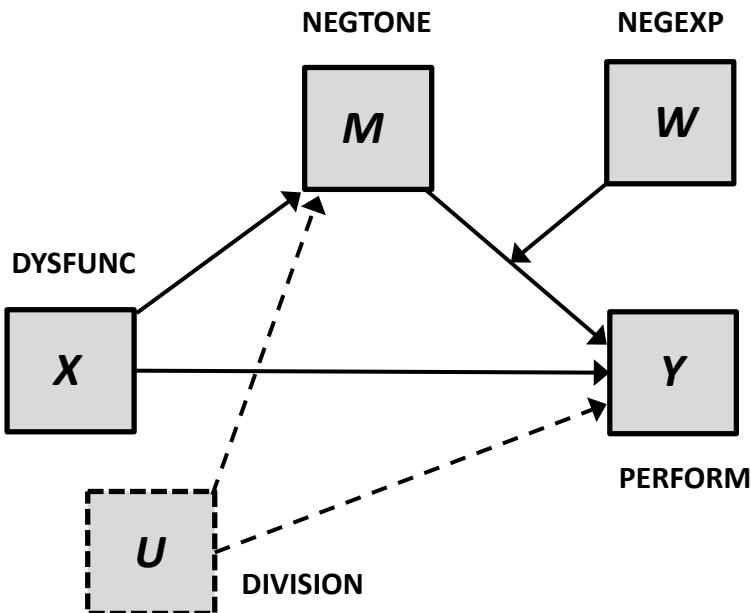
$$\theta_{M \rightarrow Y} = -0.489 - 0.450W_i = b_1 + b_3W_i$$

Let's visualize and probe this. PROCESS will take the work out of it.

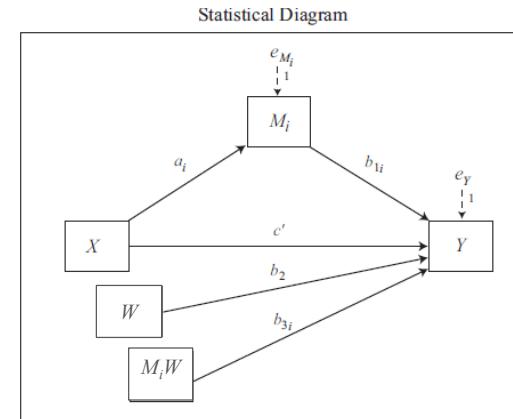
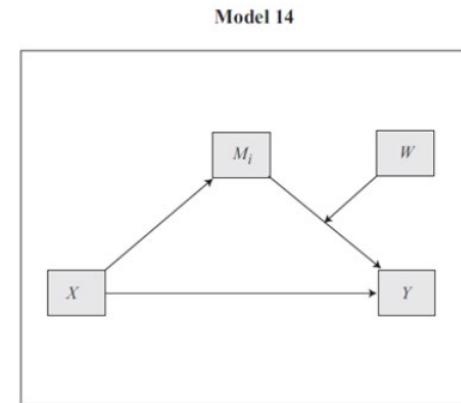


Estimation of the model in PROCESS

PROCESS takes most of the computational burden off our shoulders.



This is PROCESS model 14



```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000/model=14/
plot = 1/moments=1.
```

```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,
boot=10000,model=14, plot = 1,moments=1);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform",
w="negexp", boot=1000, model=14, plot=1,moments=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

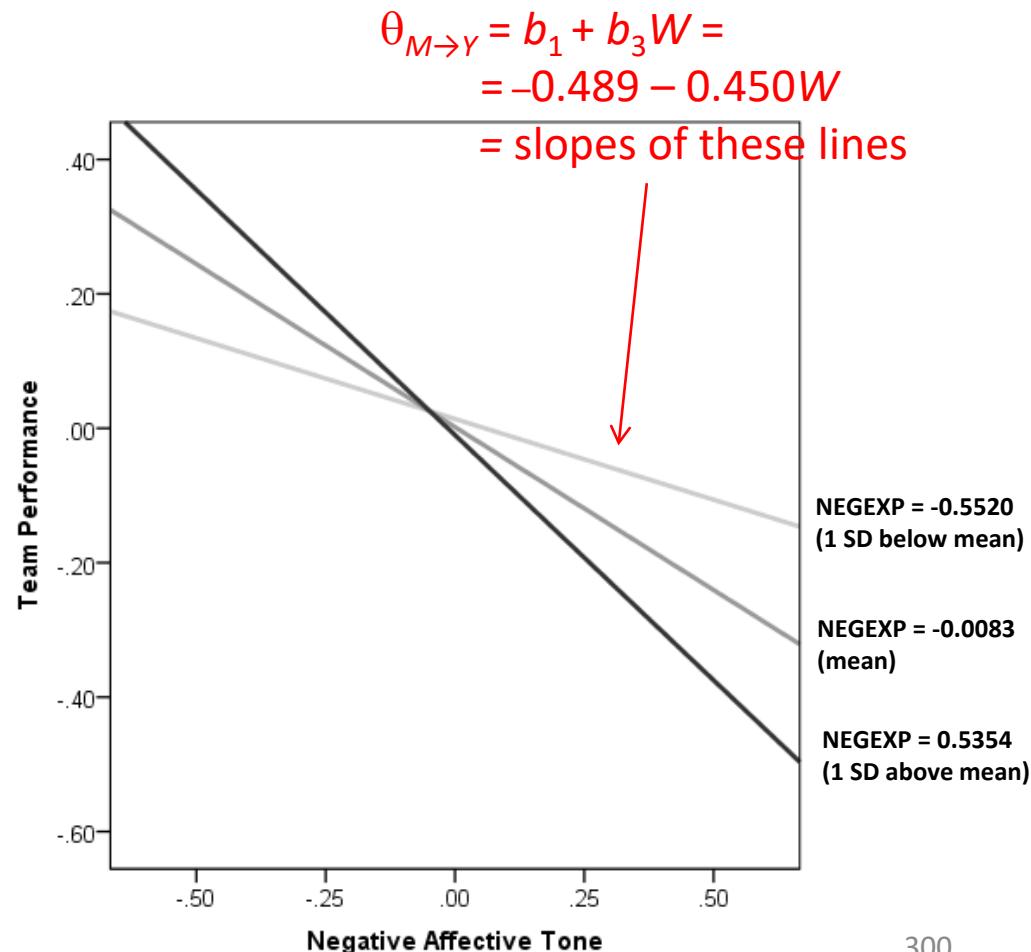
$$\begin{aligned} b_1 &= -0.489 \\ b_2 &= -0.022 \\ b_3 &= -0.450 \end{aligned}$$

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}

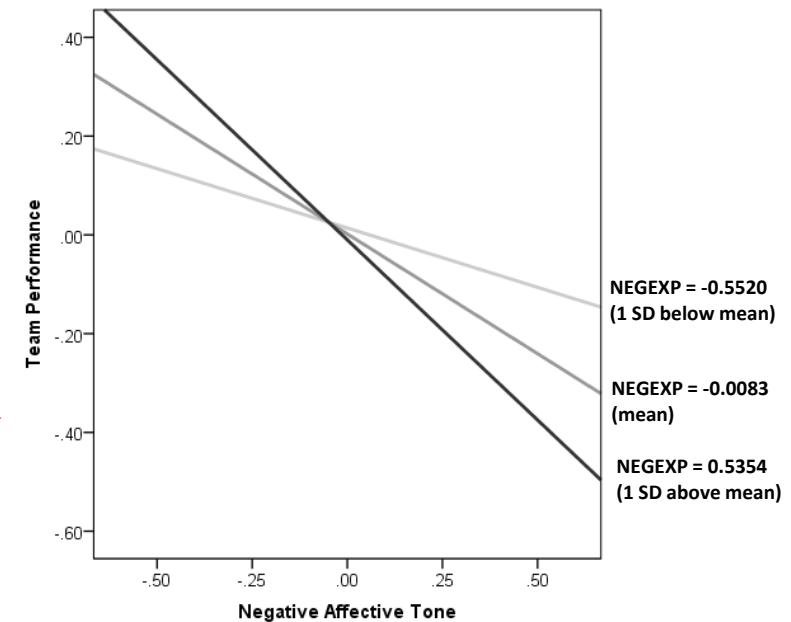
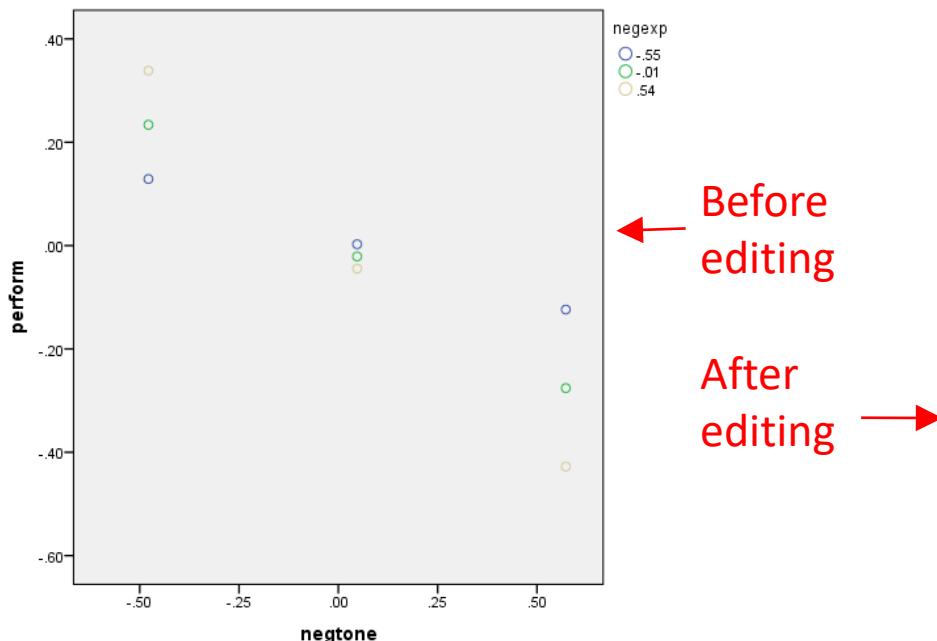
```
DATA LIST FREE/negtone negexp perform.  
BEGIN DATA.  
-.4782 -.5520 .1288  
.0472 -.5520 .0026  
.5726 -.5520 -.1237  
-.4782 -.0083 .2338  
.0472 -.0083 -.0210  
.5726 -.0083 -.2757  
-.4782 .5354 .3387  
.0472 .5354 -.0445  
.5726 .5354 -.4278  
END DATA.  
GRAPH/SCATTERPLOT=negtone WITH perform  
BY negexp.
```



Visualizing the interaction

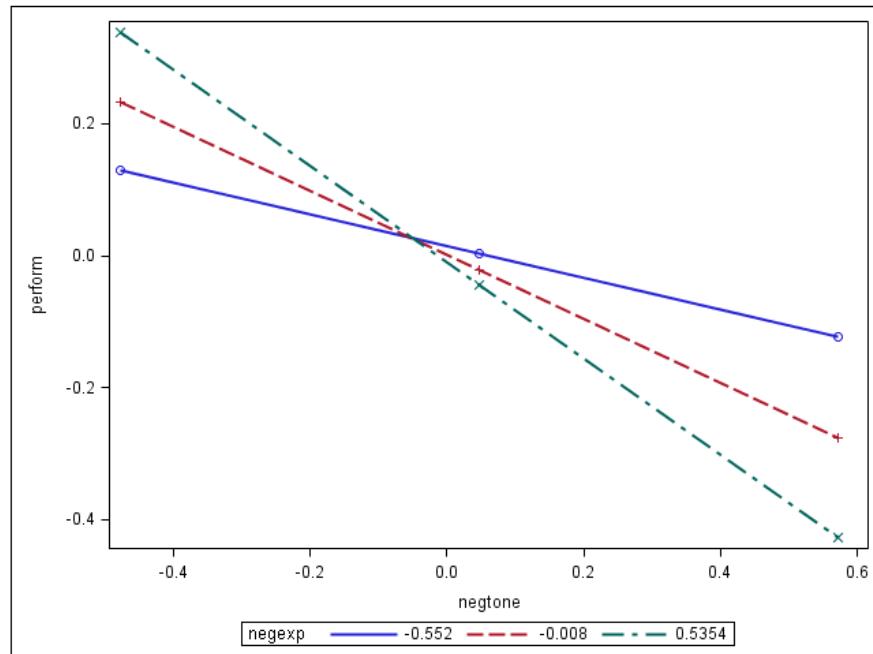
```
DATA LIST FREE/negtone negexp perform.  
BEGIN DATA.  
  -.4782    -.5520     .1288  
   .0472    -.5520     .0026  
   .5726    -.5520    -.1237  
  -.4782    -.0083     .2338  
   .0472    -.0083    -.0210  
   .5726    -.0083    -.2757  
  -.4782     .5354     .3387  
   .0472     .5354    -.0445  
   .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.



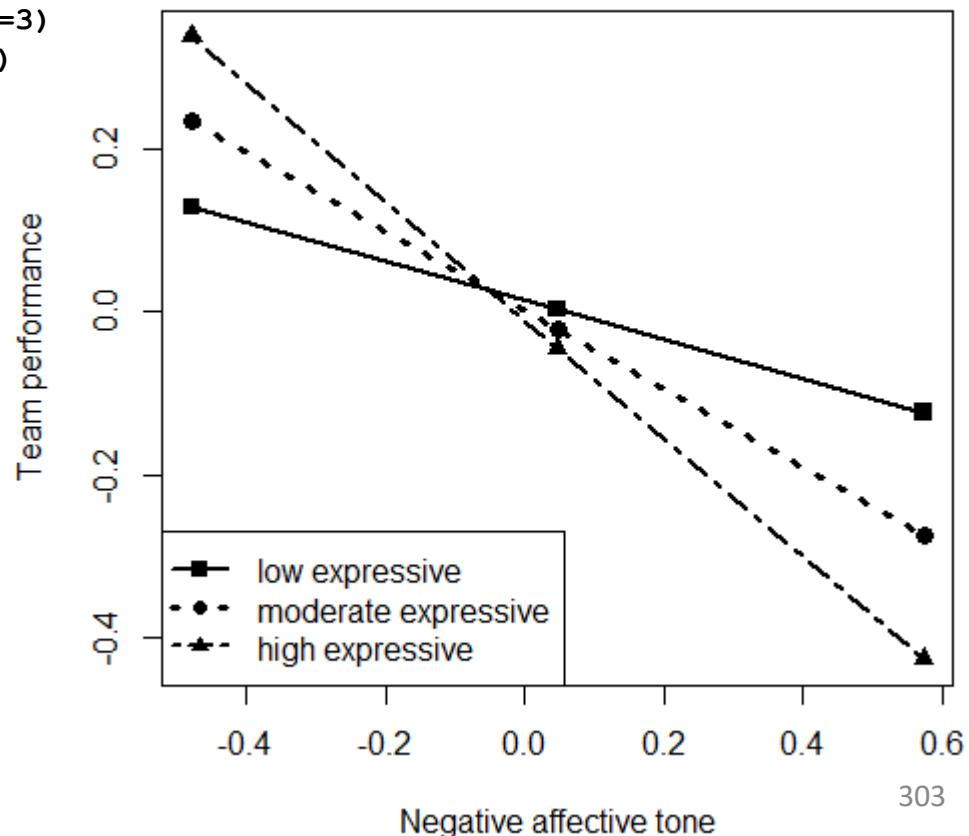
Example code in SAS

```
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)
```



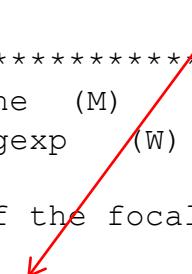
Probing the interaction: Pick-a-point

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) :

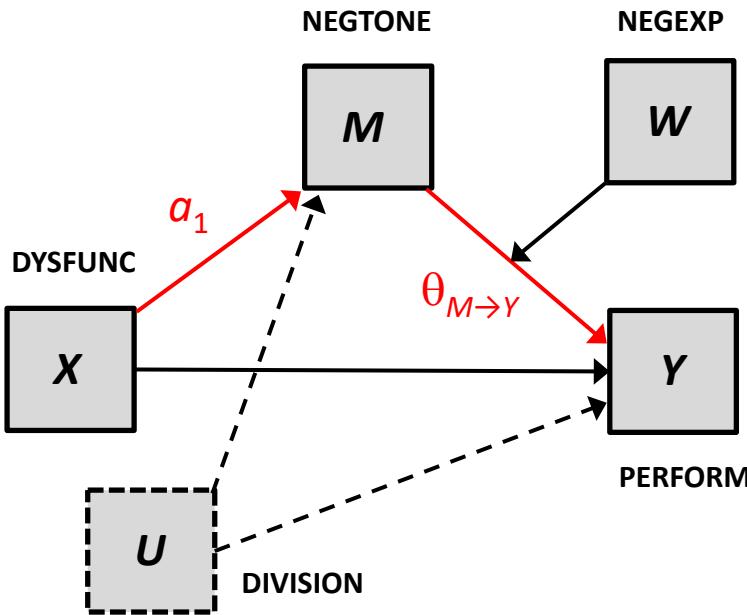


negexp	Effect	se	t	p	LLCI	ULCI
-.5308	-.2498	.2196	-1.1379	.2604	-.6904	.1907
-.0600	-.4616	.1434	-3.2188	.0022	-.7494	-.1738
.6000	-.7585	.1633	-4.6451	.0000	-1.0862	-.4308

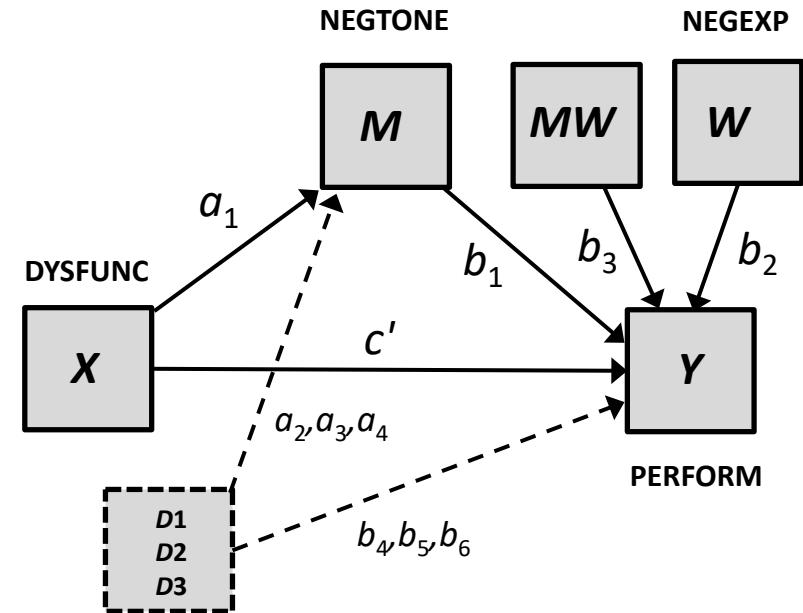
Negative affective tone is significantly negatively related to performance among teams relatively “moderate” and “relatively high” in negative nonverbal expressivity but not among teams “relatively low” in negative nonverbal expressivity.

The conditional indirect effect of X

Conceptual Model



Statistical Model

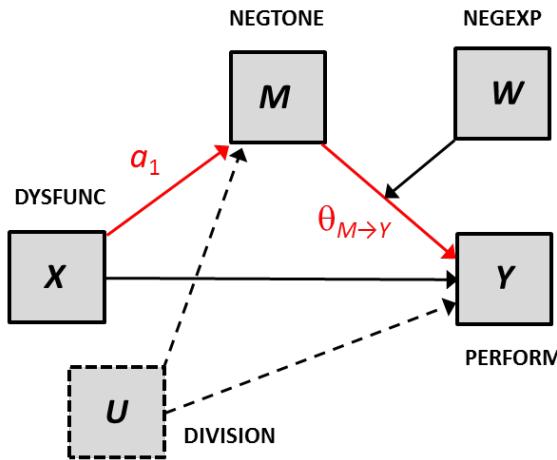


The conditional indirect effect of X on Y through M is the product of the effect of X on M (a_1) and the conditional effect of M on Y given W ($\theta_{M \rightarrow Y} = b_1 + b_3W$):

$$a_1 \theta_{M \rightarrow Y} = a_1(b_1 + b_3W) = 0.610(-0.489 - 0.450W)$$

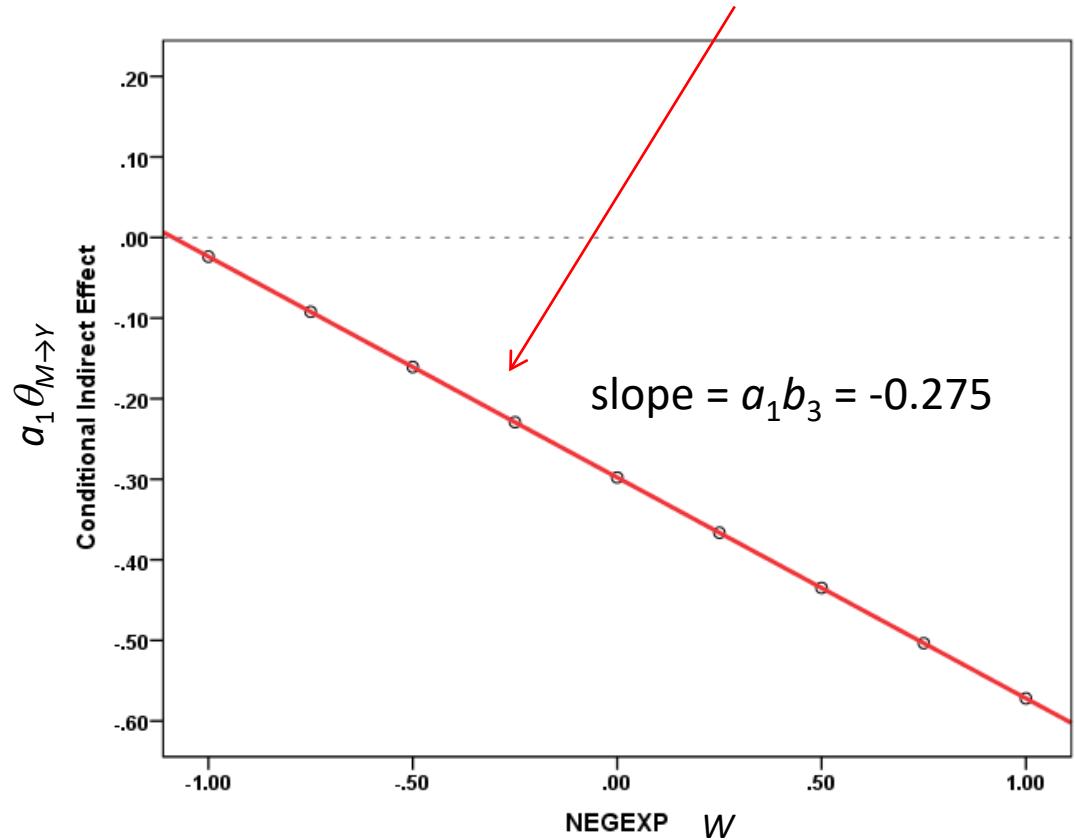
The indirect effect of dysfunctional team behavior on team performance through negative tone is allowed to be a function of negative nonverbal expressivity.

A visual representation of the indirect effect



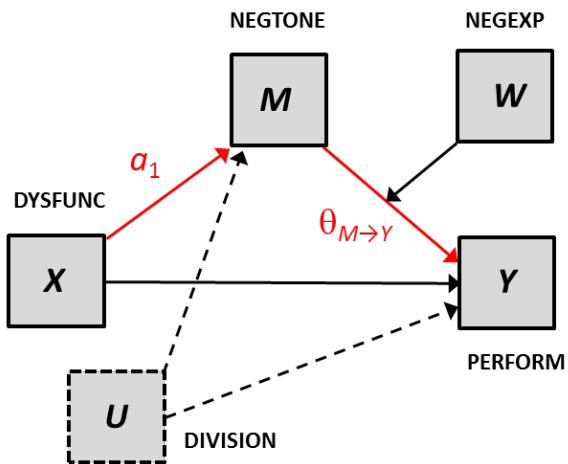
The indirect effect is more negative as negative nonverbal expressivity increases. The “**index of moderated mediation**” is $a_1 b_3 = -0.275$. It quantifies the relationship between the moderator and the indirect effect in this model.

$$a_1 \theta_{M \rightarrow Y} = a_1(b_1 + b_3 W) = 0.610(-0.489 - 0.450W) \\ = a_1 b_1 + a_1 b_3 W = -0.298 - 0.275W$$



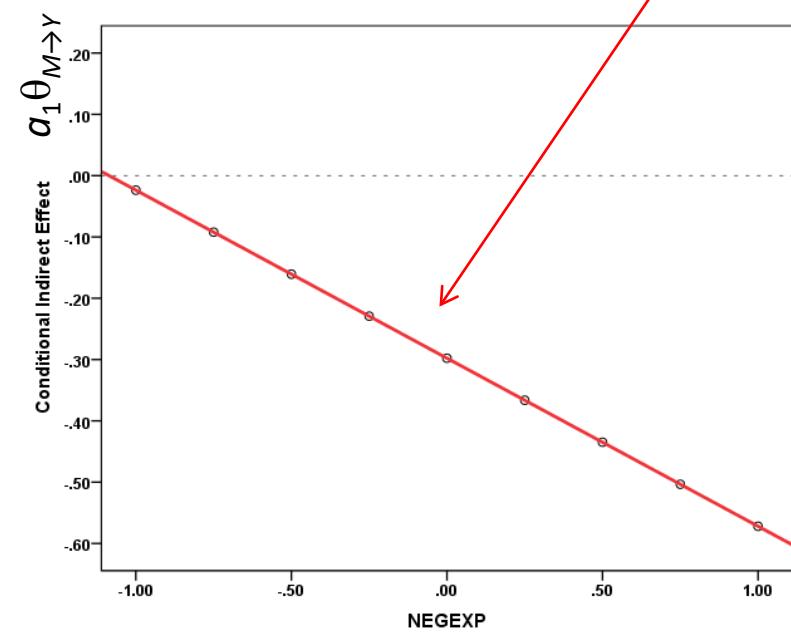
As will be seen, a hypothesis test that the slope of this function is equal to 0 is a formal test of moderated mediation....moderation of the indirect effect.

The conditional indirect effect of X



$$a_1 \theta_{M \rightarrow Y} = a_1(b_1 + b_3 W) = 0.610(-0.489 - 0.450W) \\ = a_1 b_1 + a_1 b_3 W = -0.298 - 0.275W$$

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

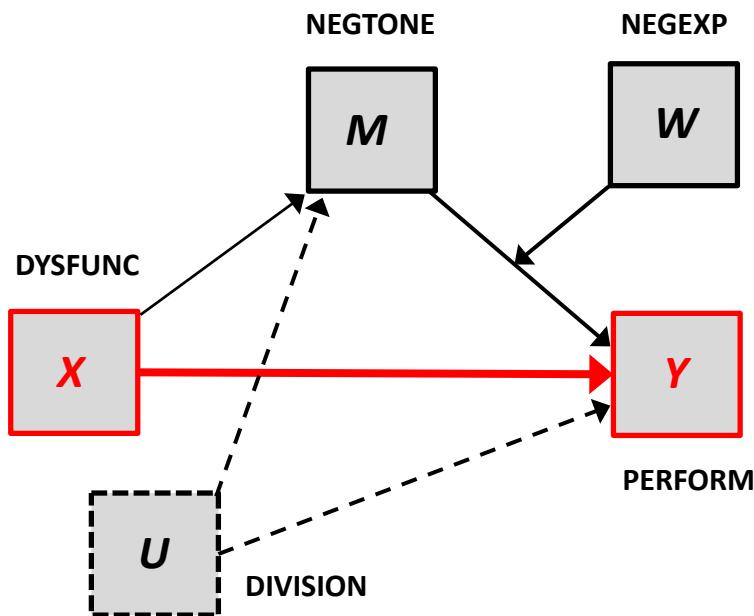
NEGEXP (W)	a_1	$\theta_{M \rightarrow Y}$	$a_1 \theta_{M \rightarrow Y}$
$\bar{W} - SD_w$	0.610	-0.240	-0.146
\bar{W}	0.610	-0.485	-0.296
$\bar{W} + SD_w$	0.610	-0.730	-0.445

Conditional indirect effects

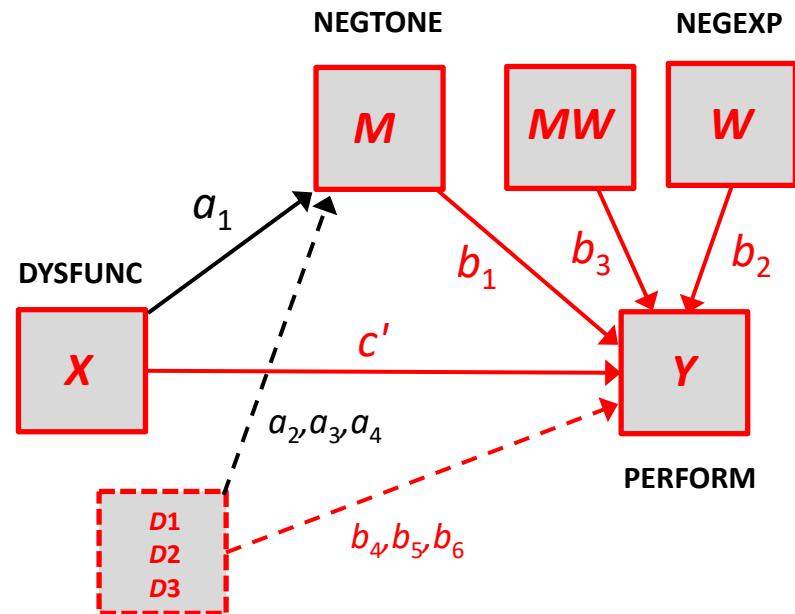
The direct effect of X

The direct effect of X is the effect of X of Y that does not operate through M .

Conceptual Model



Statistical Model



$$\widehat{Y}_i = c'_0 + c'X_i + b_1M_i + b_2W_i + b_3M_iW_i + b_4D_{1i} + b_5D_{2i} + b_6D_{3i}$$

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)

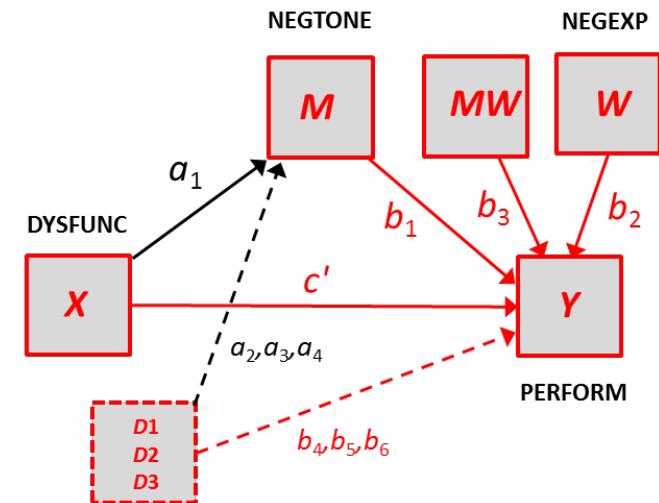
Model	Coefficients ^a				
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	-.175	.130		-1.344	.185
Dysfunctional team behavior	.373	.181	.265	2.062	.044
Negative affective tone	-.489	.138	-.491	-3.549	.001
Negative expressivity	-.022	.118	-.023	-.188	.852
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

$$c' = 0.373, t(55) = 2.062, p < .05.$$

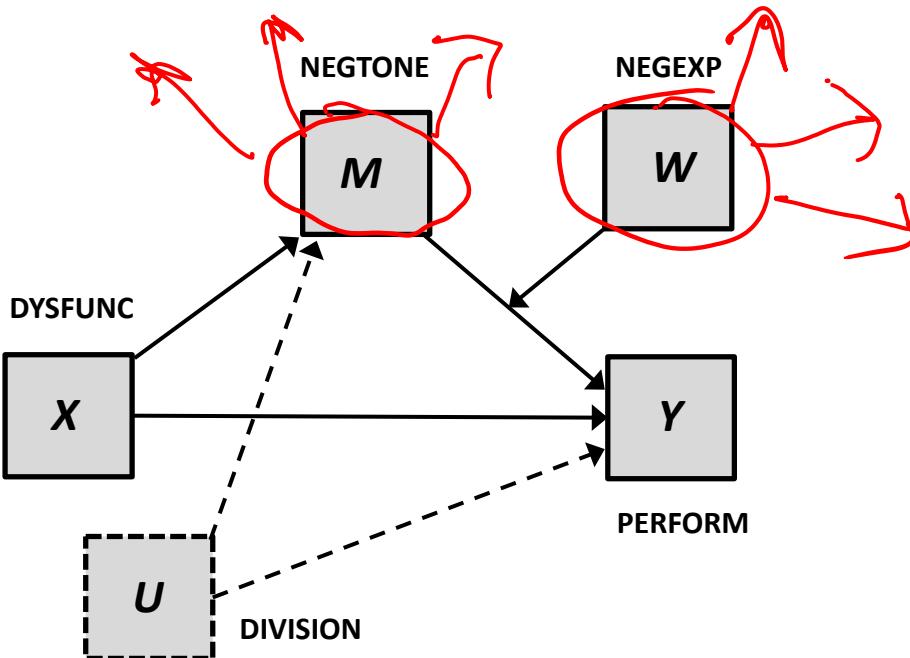
$$\hat{Y} = -0.175 + 0.373X - 0.489M - 0.022W - 0.450MW + 0.182D_1 + 0.084D_2 + 0.282D_3$$

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.



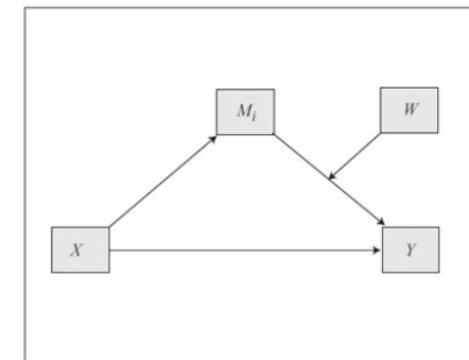
This is PROCESS model 14

```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000/model=14/
plot = 1.
```

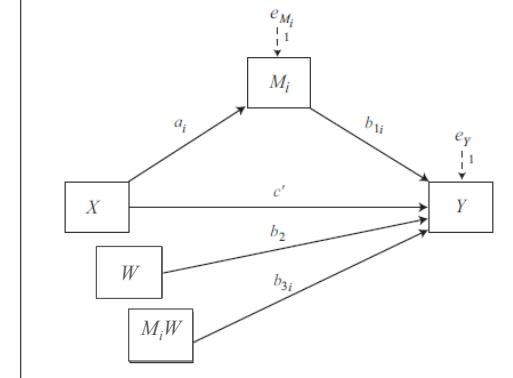
```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,
boot=10000,model=14, plot = 1);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform",
w="negexp", boot=1000, model=14, plot=1)
```

Model 14



Statistical Diagram



PROCESS output

```
Model = 14
Y = perform
X = dysfunc
M = negtone
W = negexp
```

Statistical Controls:

CONTROL= d1 d2 d3

Sample size
60

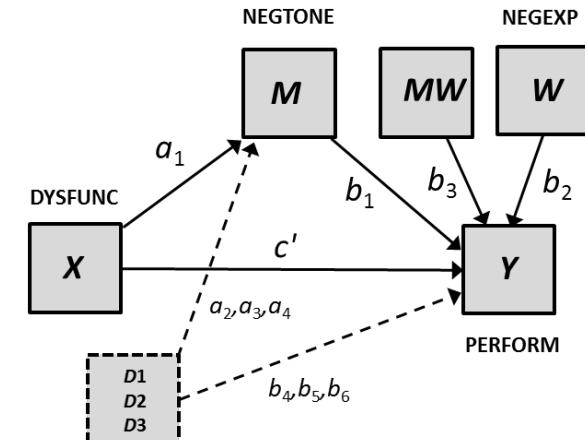
Outcome: negtone

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	$a_1 = 0.610$
d1	.3487	.1715	2.0332	.0469	.0050	.6923	
d2	.2951	.2122	1.3906	.1700	-.1302	.7204	
d3	.2507	.1663	1.5078	.1373	-.0825	.5840	



PROCESS output

$$\hat{Y}_i = -0.175 + 0.373X_i - 0.489M_i - 0.022W_i - 0.450M_iW_i + \dots$$

Outcome: perform

Model Summary

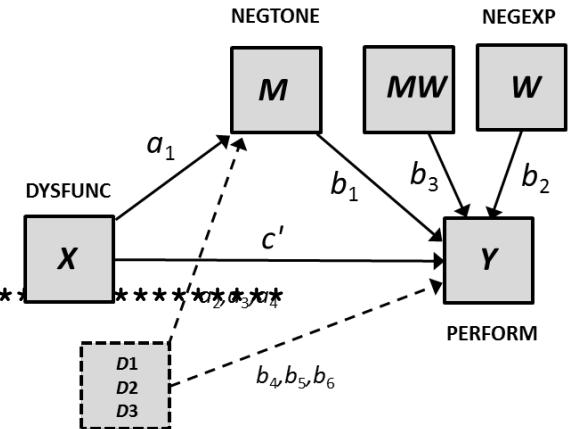
R	R-sq	MSE	F	df1	df2	p
.5937	.3524	.2006	4.0428	7.0000	52.0000	.0013

Model

	coeff	se	t	p	LLCI	ULCI	
constant	-.1754	.1305	-1.3444	.1847	-.4373	.0864	
negtone	-.4886	.1377	-3.5485	.0008	-.7649	-.2123	$b_1 = -0.489$
dysfunc	.3729	.1808	2.0622	.0442	.0100	.7357	$c' = 0.373$
negexp	-.0221	.1176	-.1875	.8520	-.2581	.2140	$b_2 = -0.022$
int_1	-.4498	.2451	-1.8353	.0722	-.9417	.0420	$b_3 = -0.450$
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



PROCESS output

***** DIRECT AND INDIRECT EFFECTS *****

Direct effect of X on Y

Effect	SE	t	p	LLCI	ULCI	Direct effect $c' = .373, p < .05$
.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

$$\begin{aligned}
 a_1\theta_{M \rightarrow Y} &= a_1(b_1 + b_3W) \\
 &= 0.610(-0.489 - 0.450W) \\
 &= a_1b_1 + a_1b_3W \\
 &= -0.298 - 0.274W
 \end{aligned}$$

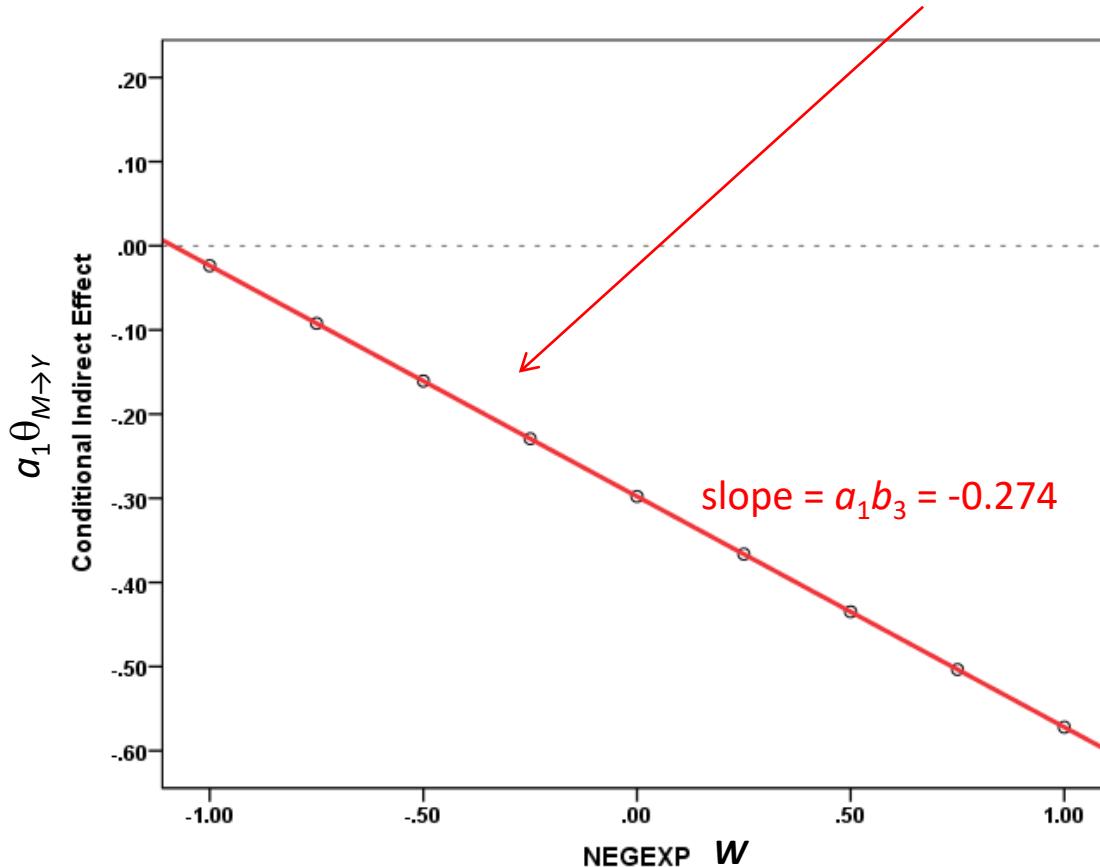
W values in conditional tables are the 16th, 50th, and 84th percentiles.

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

$$a_1 \theta_{M \rightarrow Y} = a_1(b_1 + b_3 W) = 0.610(-0.489 - 0.450W)$$

$$= a_1 b_1 + a_1 b_3 W = -0.298 - 0.274W$$



The indirect effect is a function of W (negative nonverbal expressivity) in our model. This function is a line.

$$a_1 \theta_{M \rightarrow Y} = a_1(b_1 + b_3 W)$$

$$= a_1 b_1 + a_1 b_3 W$$

$$= -0.298 - 0.274W$$

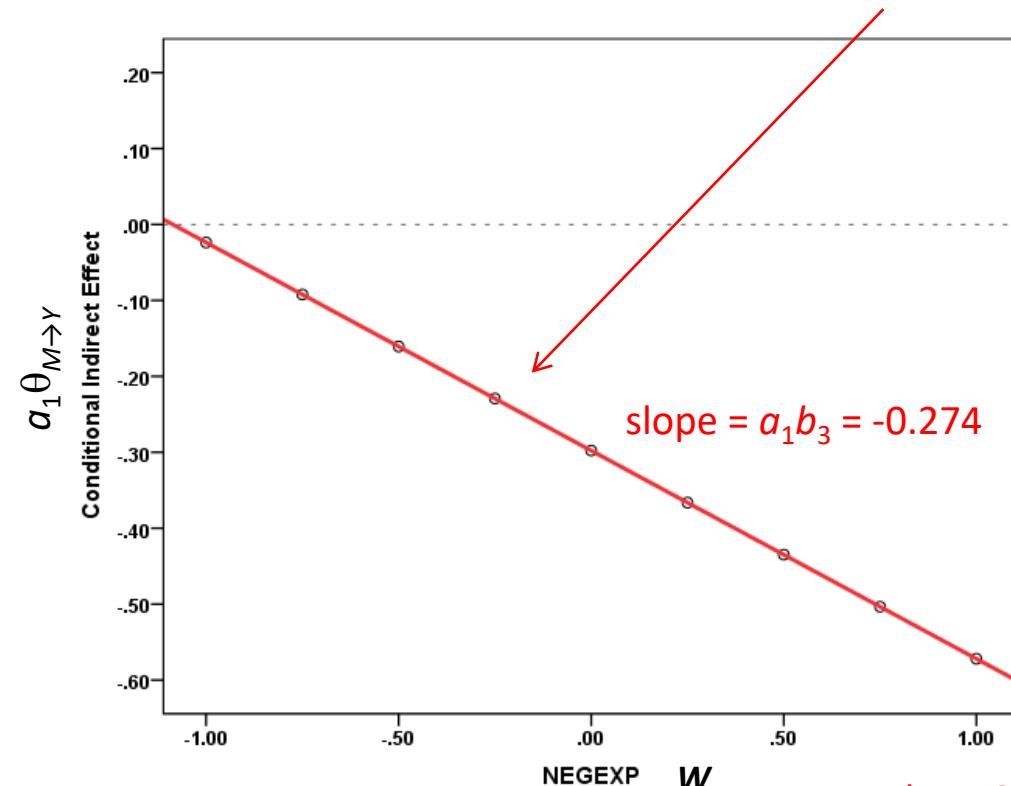
An inference about the slope of this line—the “index of moderated mediation”—is an inference about whether the indirect effect is moderated: Is this slope significantly different from zero? If so, that supports a claim of “moderated mediation.”

As $a_1 b_3$ 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

$$a_1 \theta_{M \rightarrow Y} = a_1(b_1 + b_3 W) = 0.610(-0.489 - 0.450W)$$

$$= a_1 b_1 + a_1 b_3 W = -0.298 - 0.274W$$



The indirect effect is a function of W (negative nonverbal expressivity) in our model. This function is a line.

$$a\theta_{M \rightarrow Y} = a_1(b_1 + b_3 W)$$

$$= a_1 b_1 + a_1 b_3 W$$

$$= -0.298 - 0.274W$$

$a_1 b_3 = -0.274$, 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?

Multivariate Behavioral Research, 0:1–22, 2015
Copyright © Taylor & Francis Group, LLC
ISSN: 0027-3171 print / 1532-7906 online
DOI: 10.1080/00273171.2014.962683



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

$$Y = i_Y + b_1 X + b_2 W + b_3 XW + e_Y$$

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

Correspondence concerning this article should be addressed to Andrew F. Hayes, Department of Psychology, The Ohio State University, Columbus, OH 43210, USA. E-mail: hayes.338@osu.edu, Website: www.ahayes.com

¹Unless otherwise stated, assume that all regression coefficients and functions thereof in my notation are estimates based on the data available.

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:

$$\begin{aligned} M &= i_M + aX + e_M \\ Y &= i_Y + c'X + bM + e_Y \end{aligned}$$

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

402 Mediation, Moderation, and Conditional Process Analysis

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 $a(b + c'_2 X)$, 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 :

$$O_{X \rightarrow Y} = c'_1 + c'_2 M$$

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

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

Conditional indirect effects with 95% bootstrap CIs based on 10,000 bootstrap samples.

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
negexp	-.2742	.1791	-.7172	-.0234

The indirect effect of dysfunctional behavior (X) on performance (Y) through negative tone (M) 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 (W) 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?

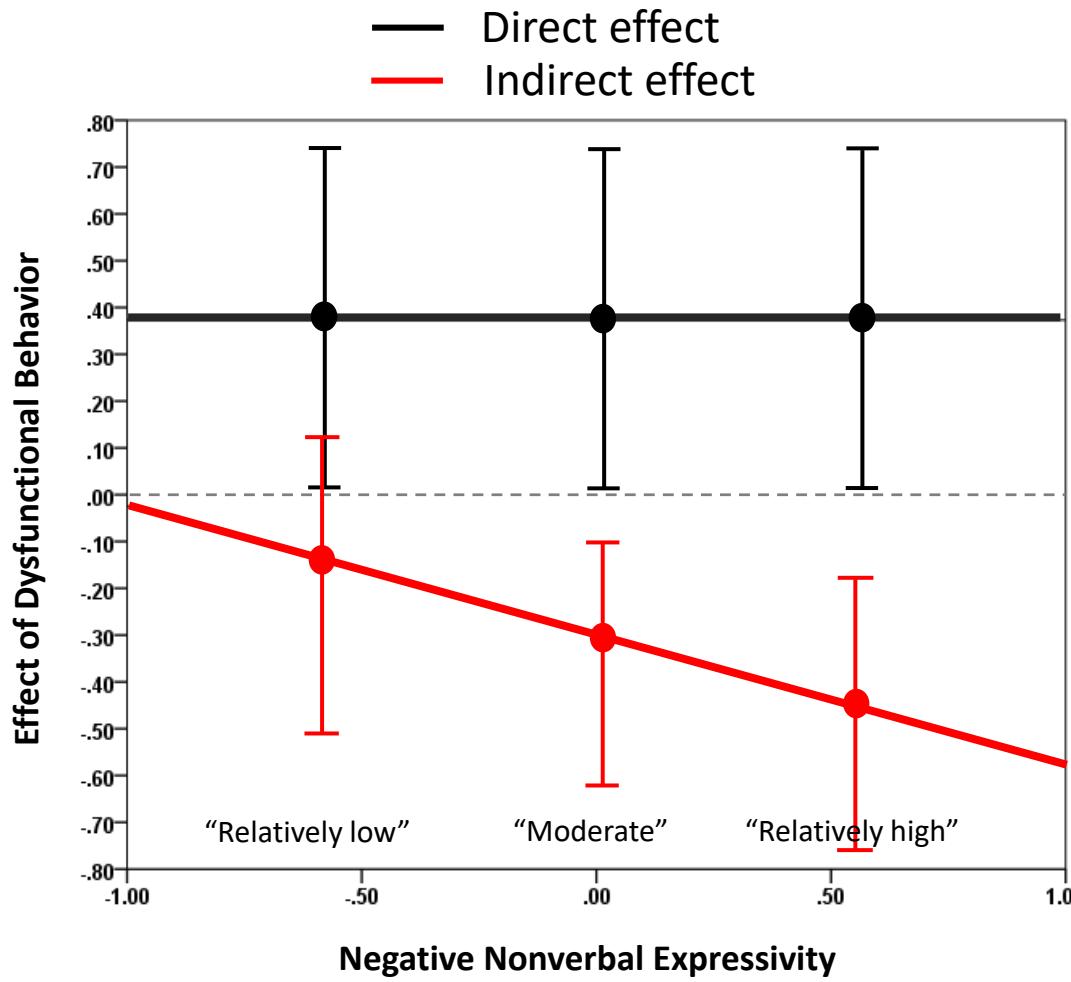
Rejection of the null hypothesis of no moderated mediation based on the index of moderated mediation implies that **any two conditional indirect effects are different!** No additional test is needed.

For example, for the second stage moderated mediation model just estimated:

$$\begin{aligned} a_1(b_1 + b_3 w_1) - a_1(b_1 + b_3 w_2) &= a_1(b_1 + b_3 w_1) - a_1(b_1 + b_3 w_2) \\ &= a_1 b_1 + a_1 b_3 w_1 - a_1 b_1 - a_1 b_3 w_2 \\ &= a_1 b_3 w_1 - a_1 b_3 w_2 \\ &= a_1 b_3 (w_1 - w_2) \end{aligned}$$

If a bootstrap confidence interval for $a_1 b_3$ does not contain zero, then neither will a confidence interval for $a_1 b_3 (w_1 - w_2)$, **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 $a_1 b_3$ contains zero, then so too will a confidence interval for $a_1 b_3 (w_1 - w_2)$, **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, and controlling for division and negative nonverbal expressivity teams that exhibit more dysfunctional behavior otherwise perform *better*.

Exploring some “What ifs...?”

- What if we had not used moments = 1? Would our conclusions change?
- Where is the indirect effect significant? (JN for indirect effects)
- What if the direct effect was moderated?

Probing at Quantiles $\theta_{M \rightarrow Y}$

First, let's consider the conditional effect of M on Y ($\theta_{M \rightarrow Y}$)

When we probe using the `moments = 1` option, we find a significant effect for average (Mean) and relatively high (Mean + 1 SD) individuals, but not among relatively low individuals (Mean – 1SD)

```
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
-0.5520	-0.2403	0.2238	-1.0738	0.2879	-0.6893	0.2088
-0.0083	-0.4849	0.1384	-3.5031	0.0010	-0.7626	-0.2071
0.5354	-0.7295	0.1541	-4.7326	0.0000	-1.0387	-0.4202

What if instead we used `moments = 0` (default)?

```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000/model=14/
plot = 1/moments=0.
```

```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,
boot=10000,model=14, plot = 1, moments=0);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform",
w="negexp", boot=1000, model=14, plot=1, moments=0)
```

Probing at Quantiles $\theta_{M \rightarrow Y}$

When we probe using the moments = 0 option, we find a significant effect for typical (Median/50th Percentile) and relatively high (84th Percentile) individuals, but not among relatively low individuals (16th Percentile)

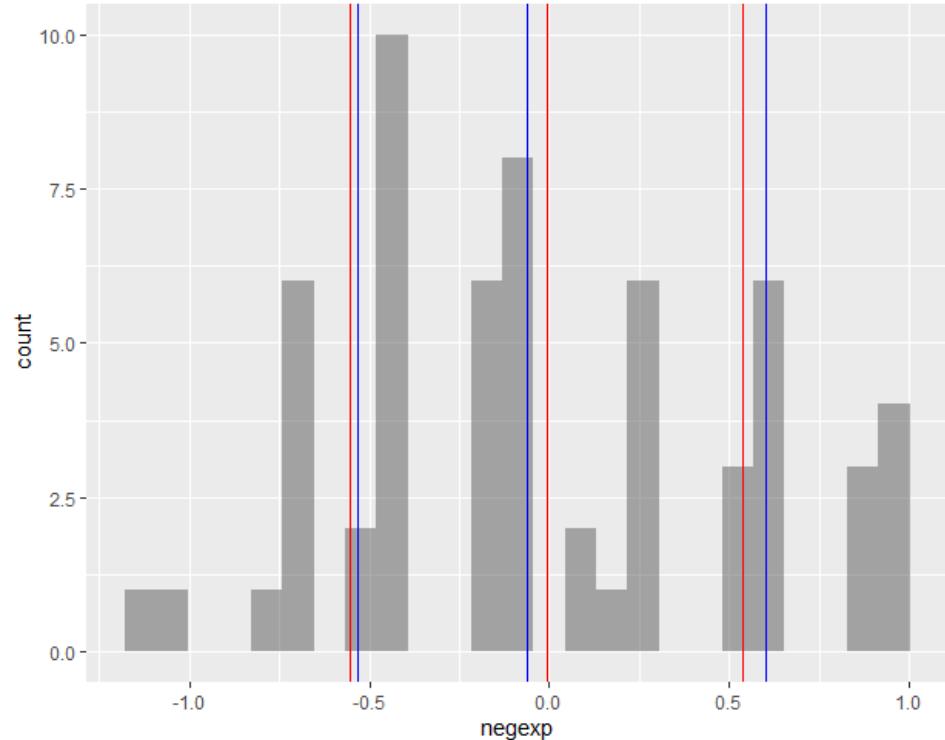
Conditional effects of the focal predictor at values of the moderator(s):

negexp	effect	se	t	p	LLCI	ULCI
-0.5308	-0.2498	0.2196	-1.1379	0.2604	-0.6904	0.1907
-0.0600	-0.4616	0.1434	-3.2188	0.0022	-0.7494	-0.1738
0.6000	-0.7585	0.1633	-4.6451	0.0000	-1.0862	-0.4308

These results are substantively similar regardless of whether we use moments or percentiles for probing.

BUT, this may not always be the case!

Red lines (moments), Blue lines (Percentiles)



Probing at Quantiles $\theta_{M \rightarrow Y}$

When we probe using the moments = 1 option, we find a significant **indirect effect** for average (Mean) and relatively high (Mean + 1 SD) individuals, but not among relatively low individuals (Mean – 1SD)

INDIRECT EFFECT:

dysfunc → negtone → perform

negexp	Effect	BootSE	BootLLCI	BootULCI
-0.5520	-0.1464	0.1504	-0.4479	0.2198
-0.0083	-0.2955	0.1276	-0.5712	-0.0596
0.5354	-0.4446	0.1667	-0.8159	-0.1432

When we probe using the moments = 0 option, we find a significant **indirect effect** for typical (Median/50th Percentile) and relatively high (84th Percentile) individuals, but not among relatively low individuals (16th Percentile)

INDIRECT EFFECT:

dysfunc → negtone → perform

negexp	Effect	BootSE	BootLLCI	BootULCI
-0.5308	-0.1523	0.1501	-0.4462	0.1799
-0.0600	-0.2813	0.1229	-0.5447	-0.0566
0.6000	-0.4623	0.1662	-0.8031	-0.1498

Just as before, these will not always match. I suggest consider which “type” of people you’re interested and using that. Remember to report the exact values probed at to help with replicability.

Johnson-Neyman Technique

We found that among teams who are average/typical and high on negative nonverbal expressivity there is a significant effect of negative tone on performance ($\theta_{M \rightarrow Y}$) and a significant indirect effect of dysfunctional team behavior on performance through negative tone ($\theta_{X \rightarrow M \rightarrow Y}$). But this effect was not significant when we probe at Mean – 1SD or 16th percentile.

So **where** is the point of transition for these two effects?

Is the point of transition **the same** for these two effects?

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

negexp	Effect	se	t	p	LLCI	ULCI
-0.5520	-0.2403	0.2238	-1.0738	0.2879	-0.6893	0.2088
-0.0083	-0.4849	0.1384	-3.5031	0.0010	-0.7626	-0.2071
0.5354	-0.7295	0.1541	-4.7326	0.0000	-1.0387	-0.4202

```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000/model=14/
plot = 1/jn=1.
```

```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,
boot=10000,model=14, plot = 1, jn=1);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform",
w="negexp", boot=1000, model=14, plot=1, jn=1)
```

Johnson-Neyman Technique

```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000/model=14/plot = 1/jn=1.
```

```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,boot=10000,model=14, plot = 1, jn=1);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform", w="negexp", boot=1000, model=14, plot=1, jn=1)
```

Moderator value(s) defining Johnson-Neyman significance region(s):

Value	% below	% above
-0.2981	35.0000	65.0000

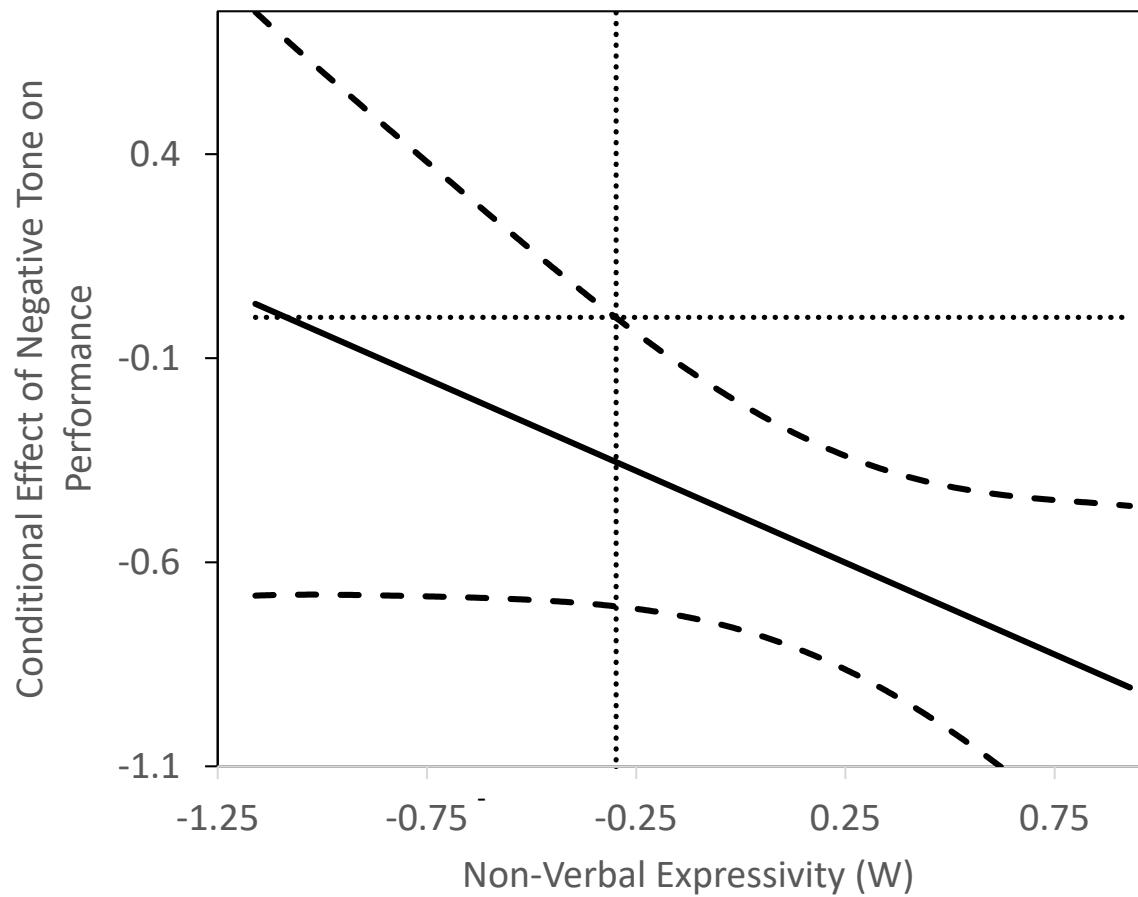
Conditional effect of focal predictor at values of the moderator:

negexp	effect	se	t	p	LLCI	ULCI
-1.1600	0.0332	0.3560	0.0933	0.9260	-0.6811	0.7475
-1.0555	-0.0138	0.3322	-0.0415	0.9670	-0.6805	0.6529
-0.9510	-0.0608	0.3088	-0.1969	0.8447	-0.6805	0.5589
-0.8465	-0.1078	0.2857	-0.3773	0.7075	-0.6812	0.4656
-0.7420	-0.1548	0.2632	-0.5883	0.5588	-0.6829	0.3732
-0.6375	-0.2018	0.2412	-0.8369	0.4065	-0.6858	0.2821
-0.5330	-0.2488	0.2200	-1.1312	0.2632	-0.6903	0.1926
-0.4285	-0.2959	0.1998	-1.4805	0.1448	-0.6969	0.1051
-0.3240	-0.3429	0.1811	-1.8936	0.0638	-0.7062	0.0205
-0.2981	-0.3545	0.1767	-2.0067	0.0500	-0.7091	-0.0000
-0.2195	-0.3899	0.1642	-2.3750	0.0213	-0.7193	-0.0605
-0.1150	-0.4369	0.1497	-2.9176	0.0052	-0.7374	-0.1364
-0.0105	-0.4839	0.1386	-3.4913	0.0010	-0.7620	-0.2058
0.0940	-0.5309	0.1316	-4.0352	0.0002	-0.7949	-0.2669
0.1985	-0.5779	0.1293	-4.4692	0.0000	-0.8374	-0.3184
0.3030	-0.6249	0.1321	-4.7314	0.0000	-0.8900	-0.3599
0.4075	-0.6719	0.1396	-4.8142	0.0000	-0.9520	-0.3919
0.5120	-0.7189	0.1511	-4.7583	0.0000	-1.0221	-0.4157
0.6165	-0.7660	0.1658	-4.6198	0.0000	-1.0987	-0.4332
0.7210	-0.8130	0.1829	-4.4442	0.0000	-1.1800	-0.4459
0.8255	-0.8600	0.2019	-4.2603	0.0001	-1.2650	-0.4549
0.9300	-0.9070	0.2221	-4.0831	0.0002	-1.3527	-0.4612

For teams with a score lower than -.2981, there is not a significant effect of negative affective tone on performance.

For teams with a score lower of -.2981 and higher, there is a significant negative effect of negative affective tone on performance.

Johnson-Neyman Technique



Note: Made in Excel, see example on GitHub

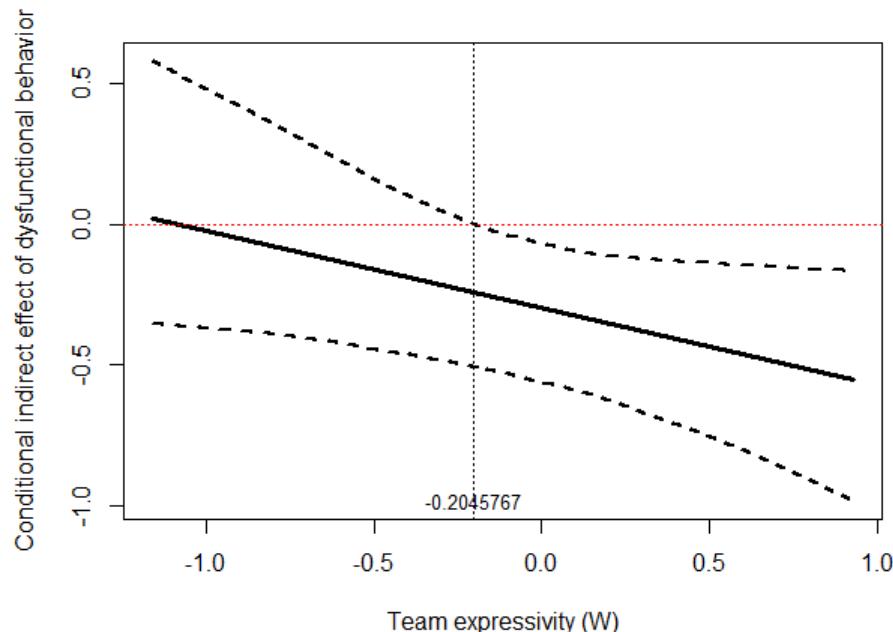
For teams with non-verbal expressivity scores below -0.2981 , the conditional effect of negative tone on performance is not statistically significant. However, for teams with a score of -0.2981 or above, there is a significant negative effect of negative tone on performance, such that more negative tone corresponds to lower predicted performance.

Johnson-Neyman Technique (CIE)

Preacher et al. (2007) showed how to conduct the JN method for conditional indirect effects; however, these are based on standard error estimates which are inaccurate.

Inference for the conditional indirect effect is not done using a Z or t statistic, and so the traditional derivation of the JN technique does not apply. Instead we use bootstrapping which provides more accurate inference.

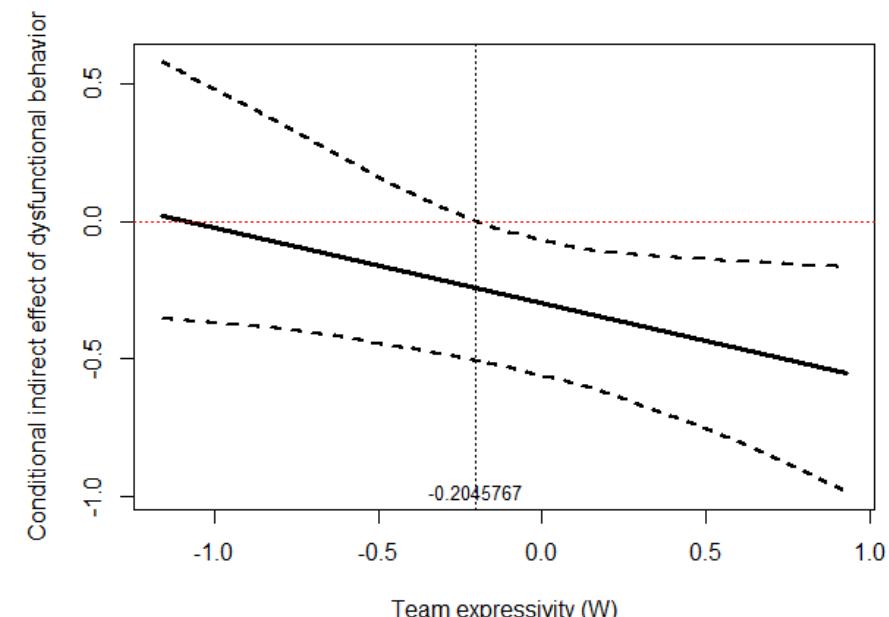
However, the idea of the JN transition point still applies to conditional indirect effects.



Johnson-Neyman Technique (CIE)

The textbook demonstrates a method called the “Pseudo JN”

- Save the bootstrap estimates using the save option in PROCESS
- Try many values of W to hone in on significance range (e.g., we already know a transition point is between $-.06$ and $-.53$).
- Find value(s) of W where conditional indirect effect bootstrap CI bound is **exactly** zero.



```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform",
        w="negexp", model=14, plot=1, wmodval = -.2045767, seed = 42517)
```

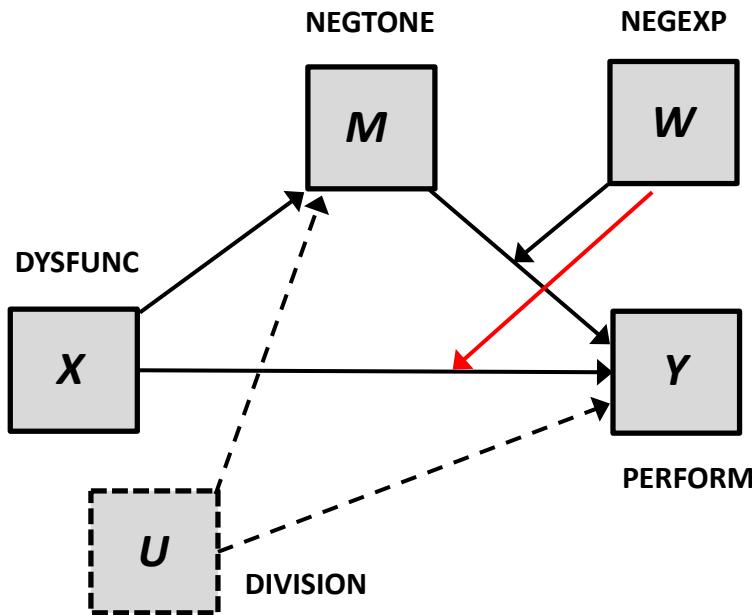
INDIRECT EFFECT:

dysfunc → negtone → perform

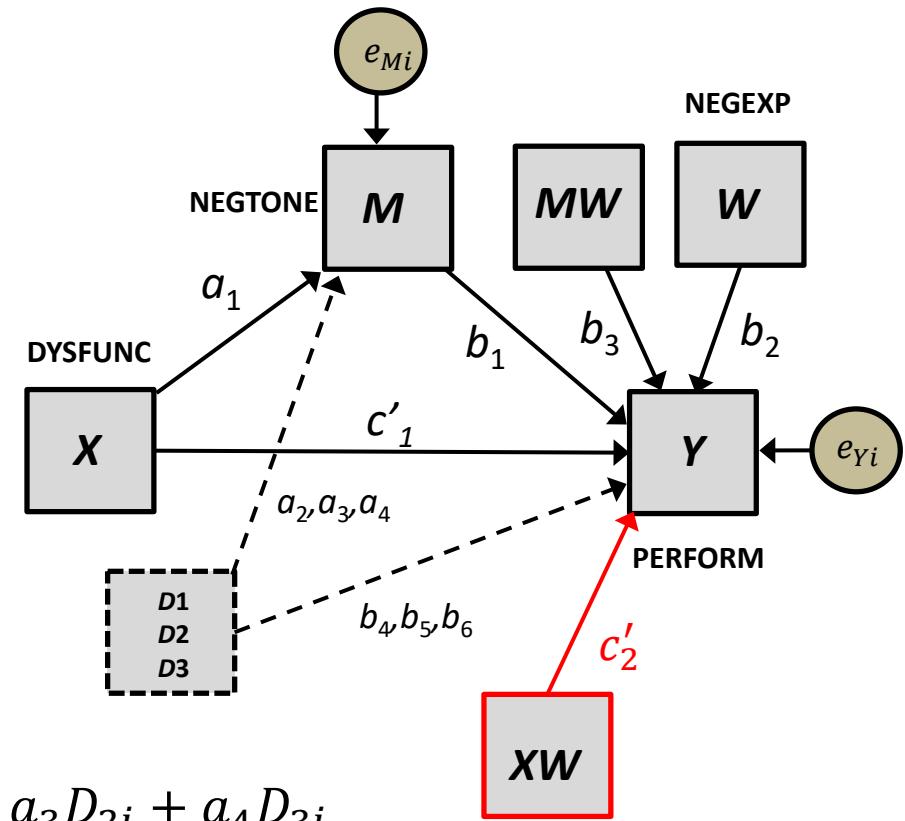
negexp	Effect	BootSE	BootLLCI	BootULCI
-0.2046	-0.2417	0.1295	-0.5081	0.0004

Moderated Direct Effect

Conceptual Model



Statistical Model



$$\widehat{M}_i = a_0 + a_1 X_i + a_2 D_{1i} + a_3 D_{2i} + a_4 D_{3i}$$

$$\widehat{Y}_i = c'_0 + c'_1 X_i + \textcolor{red}{c'_2 X_i W_i} + b_1 M_i + b_2 W_i + b_3 M_i W_i + b_4 D_{1i} + b_5 D_{2i} + b_6 D_{3i}$$

Model for M remains unchanged. Model for Y adds one term, which is the product of X and W . Notice, a single term for W is already in the model as b_2

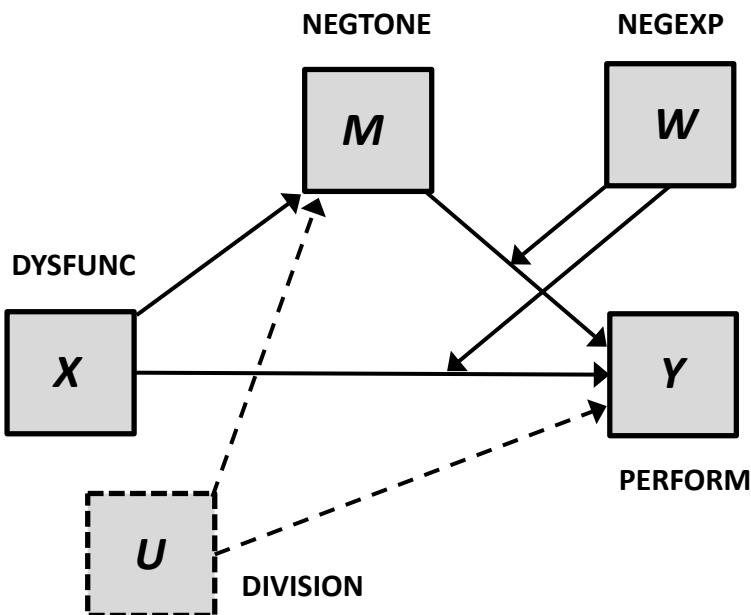
Moderated Direct Effect

Including a moderated direct effect will impact the interpretations of some but not all of the coefficients

Coefficient	Non-moderated Direct Effect	Moderated Direct Effect
a_1	The effect of X on M controlling for covariates.	Same
b_1	The effect of M on Y when W is zero, and controlling for X and covariates	Same
b_2	The effect of W on Y when M is zero , and controlling for X and covariates.	The effect of W on Y when M and X are zero , and controlling for covariates.
b_3	The effect of W on effect of M on Y controlling for X and covariates.	Same
c'/c'_1	The effect of X on Y controlling for M , W , and covariates.	The effect of X on Y when W is zero , and controlling for M and covariates.
c'_2	NA	The effect of W on the effect of X on Y , controlling for M and covariates.

Estimation of the model in PROCESS

PROCESS takes most of the computational burden off our shoulders.



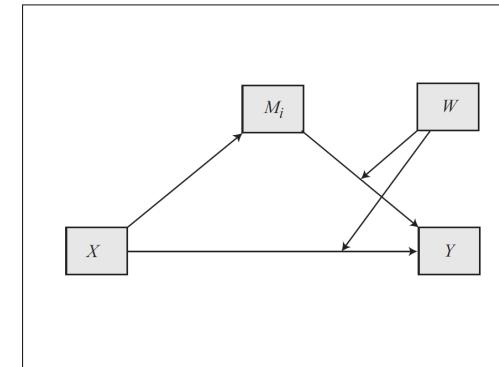
This is PROCESS model 15

```
process cov = d1 d2 d3/x=dysfunc/m=negtone/y=perform/w=negexp/boot=10000/model=15/plot = 1/moments=1.
```

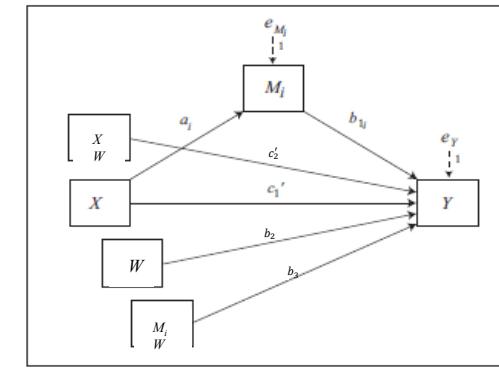
```
%process (data=teams,cov=d1 d2 d3,x=dysfunc,m=negtone,y=perform,w=negexp,boot=10000,model=15, plot = 1, moments=1);
```

```
process(data=teams, cov=c("d1","d2","d3"), x="dysfunc", m="negtone", y="perform", w="negexp", boot=1000, model=15, plot=1, moments =1)
```

Model 15



Statistical Diagram



Moderated Direct Effect

Model : 15

Y : perform
X : dysfunc
M : negtone
W : negexp

Covariates:

d1 d2 d3

Sample size: 60

Random seed: 14958

Outcome Variable: negtone

Model Summary:

R	R-sq	MSE	F	df1	df2	p
0.5026	0.2526	0.2213	4.6462	4.0000	55.0000	0.0027

Model:

	coeff	se	t	p	LLCI	ULCI
constant	-0.2057	0.1305	-1.5760	0.1208	-0.4672	0.0559
dysfunc	0.6095	0.1668	3.6546	0.0006	0.2753	0.9437
d1	0.3487	0.1715	2.0332	0.0469	0.0050	0.6923
d2	0.2951	0.2122	1.3906	0.1700	-0.1302	0.7204
d3	0.2507	0.1663	1.5078	0.1373	-0.0825	0.5840

Model for M is completely unchanged. No differences. Same coefficient estimates and inference!

Moderated Direct Effect

Outcome Variable: perform

Model Summary:

R	R-sq	MSE	F	df1	df2	p
0.5945	0.3534	0.2042	3.4850	8.0000	51.0000	0.0028

Model:

	coeff	se	t	p	LLCI	ULCI
constant	-0.1761	0.1317	-1.3370	0.1871	-0.4404	0.0883
dysfunc	0.3873	0.1894	2.0448	0.0460	0.0071	0.7676
negtone	-0.4980	0.1428	-3.4867	0.0010	-0.7848	-0.2113
negexp	-0.0145	0.1216	-0.1194	0.9054	-0.2587	0.2296
Int_1	-0.0770	0.2712	-0.2838	0.7777	-0.6214	0.4675
Int_2	-0.4217	0.2665	-1.5821	0.1198	-0.9567	0.1134
d1	0.1782	0.1739	1.0246	0.3104	-0.1709	0.5273
d2	0.0895	0.2127	0.4208	0.6757	-0.3375	0.5165
d3	0.2820	0.1663	1.6957	0.0960	-0.0519	0.6158

Product terms key:

Int_1 : dysfunc x negexp
Int_2 : negtone x negexp

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	0.0010	0.0805	1.0000	51.0000	0.7777
M*W	0.0317	2.5030	1.0000	51.0000	0.1198

Model for Y now includes 2 interactions (XW and MW). Including this new interaction changes estimates and inference for other coefficients in the model. The degree of this change will depend on the data.

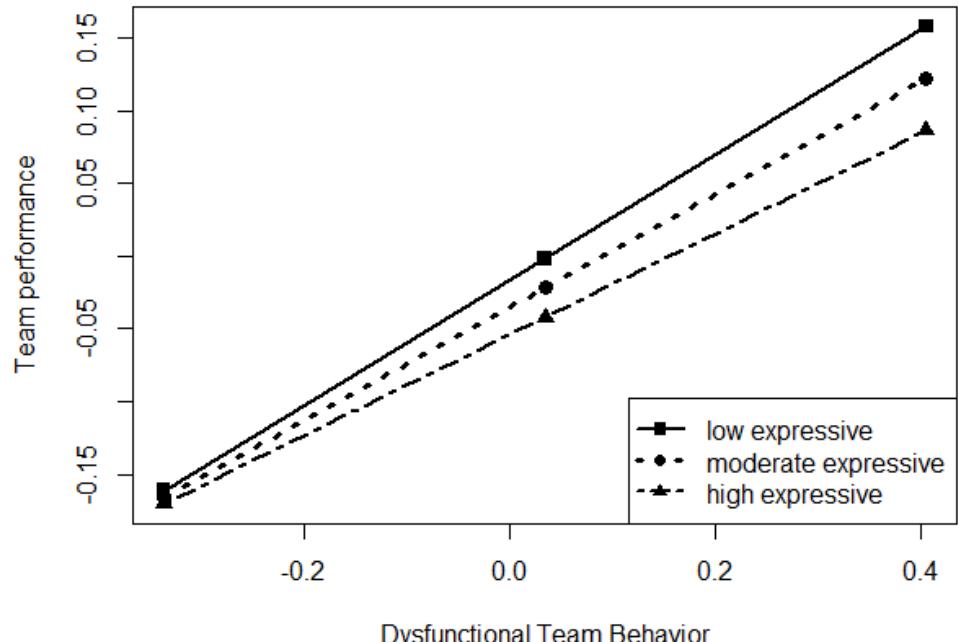
Plotting Conditional Direct Effect

Focal predictor: dysfunc (X)

Moderator: negexp (W)

Data for visualizing the conditional effect of the focal predictor:

dysfunc	negexp	perform
-0.3370	-0.5520	-0.1613
0.0347	-0.5520	-0.0016
0.4063	-0.5520	0.1582
-0.3370	-0.0083	-0.1659
0.0347	-0.0083	-0.0217
0.4063	-0.0083	0.1224
-0.3370	0.5354	-0.1705
0.0347	0.5354	-0.0419
0.4063	0.5354	0.0867



```
x<-c(-0.3370,0.0347,0.4063,-0.3370,0.0347,0.4063,-0.3370,0.0347,0.4063)
w<-c(-.552,-.552,-.552,-.008,-.008,.535,.535,.535)
y<-c(-0.1613,-0.0016,0.1582,-0.1659,-0.0217, 0.1224,-0.1705,-0.0419,0.0867)
wmarker<-c(15,15,15,16,16,16,17,17,17)
plot(y=y,x=x,cex=1.2,pch=wmarker,xlab="Dysfunctional Team Behavior",
      ylab="Team performance")
legend.txt<-c("low expressive","moderate expressive","high expressive")
legend("bottomright", legend =
legend.txt,cex=1,lty=c(1,3,6),lwd=c(2,3,2),pch=c(15,16,17))
lines(x[w==-.552],y[w==-.552],lwd=2)
lines(x[w==-.008],y[w==-.008],lwd=3,lty=3)
lines(x[w==.535],y[w==.535],lwd=2,lty=6)
```

Conditional Direct Effect

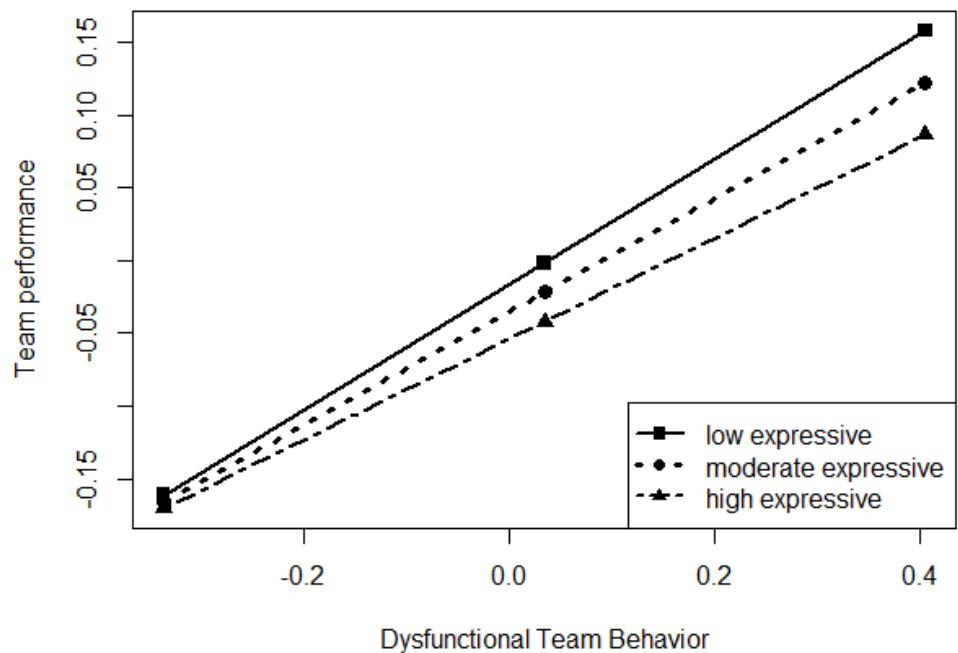
Conditional direct effect(s) of X on Y:

negexp	effect	se	t	p	LLCI	ULCI
-0.5520	0.4298	0.2712	1.5847	0.1192	-0.1147	0.9743
-0.0083	0.3880	0.1900	2.0415	0.0464	0.0064	0.7695
0.5354	0.3461	0.2053	1.6859	0.0979	-0.0660	0.7583

Direct effect is **not significantly moderated**, but conditional direct effect is significant for some values of the moderator and not others.

This is a good example of a case which would be difficult to interpret.

One solution would be to drop the interaction (make sure you report that you did so), and interpret the unconditional direct effect



Index of Moderated Mediation

Including the moderated direct effect actually changes the conclusion about the moderated mediation.

Confidence interval for index of moderated mediation now includes zero.

This suggests that our results are not particularly robust, and should be interpreted with caution.

Conditional indirect effects of X on Y:

INDIRECT EFFECT:

dysfunc → negtone → perform

negexp	Effect	BootSE	BootLLCI	BootULCI
-0.5520	-0.1617	0.1648	-0.4773	0.2007
-0.0083	-0.3014	0.1255	-0.5415	-0.0591
0.5354	-0.4411	0.1515	-0.7172	-0.1278

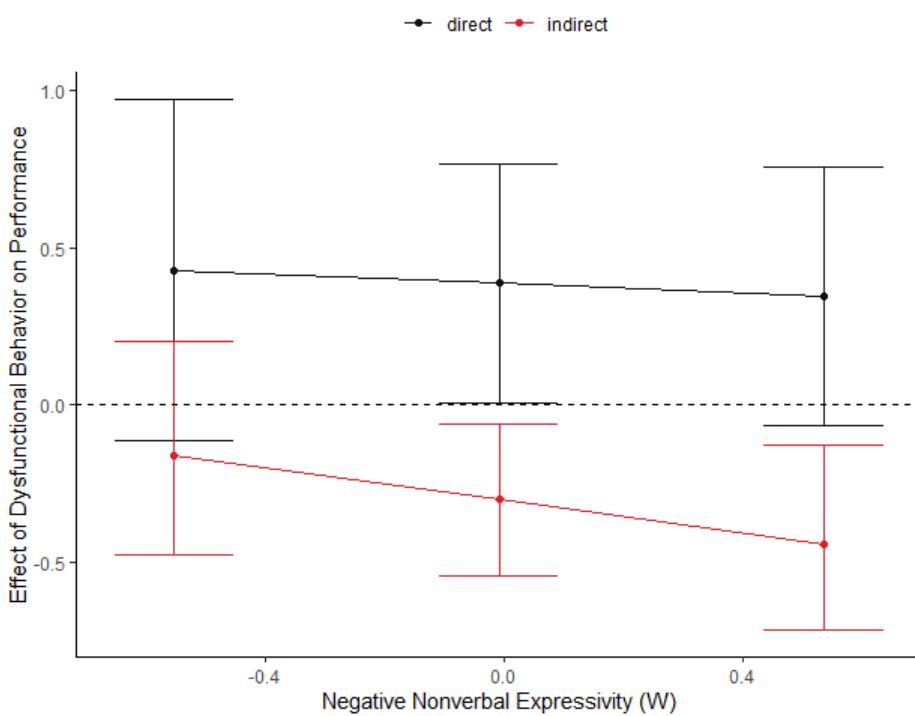
Pattern of significance for conditional indirect effects is the same (though notice estimates are slightly different)

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
negexp	-0.2570	0.1773	-0.6865	0.0411

Index of moderated mediation is slightly different and confidence interval no longer excludes zero.

Putting it all together



Point estimates with 95% confidence intervals (OLS confidence intervals for direct effects, bootstrap confidence intervals for indirect effects).

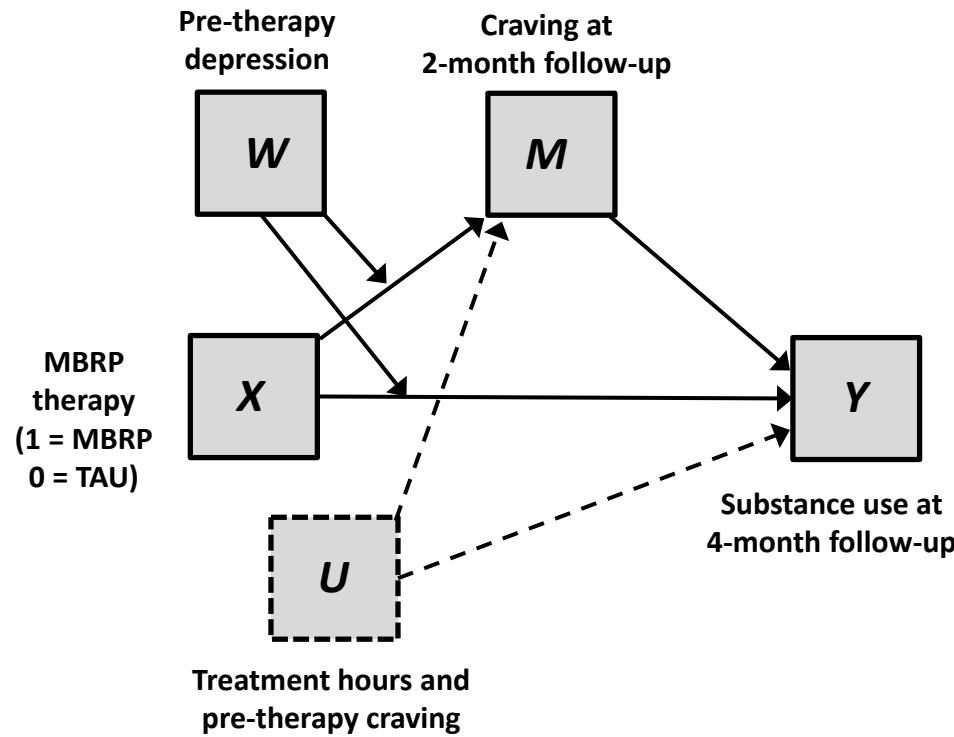
Note: Made in R (See Script for Example Code)

More dysfunctional behavior tends to lead to more negative affective tone (a_1). Negative non-verbal expressivity did not significantly moderate the effect of negative affective tone on performance (b_3). Generally, there is a negative effect of tone on performance, but this is only significant among teams with negative non-verbal expressivity scores above $-.2893$ ($\theta_{M \rightarrow Y}$). The indirect effect of dysfunctional team behavior was not significantly moderated by negative non-verbal expressivity ($a_1 b_3$). The conditional indirect effect tended to be negative, was not significant for the entire observed range of W ($\theta_{X \rightarrow M \rightarrow Y}$). The direct effect was neither moderated by nonverbal expressivity (c'_2), nor consistently significant ($\theta_{X \rightarrow Y, M}$).

Should I allow the direct effect to be moderated?

- There are differing opinions on this issue, and no clear “correct answer”
- If your theory suggests the direct effect is moderated: include it
 - Alternative mediators not included in the model which could be moderated
 - Previous literature found significant moderated direct effect
- Pros of allowing for moderation
 - If interaction between XW is a confounder of MW interaction, including it will reduce bias in estimation of MW coefficient.
 - Can increase explained variance in outcome, increasing power to detect other effects.
- Cons of allowing for moderation
 - Can increase multicollinearity with other coefficients and reduce power to detect other effects.
 - Uses up a degree of freedom, reducing power to detect all effects (equivalent to throwing out one case).
- An opinion from A.F. Hayes: “In the case of moderation, we usually assume its absence unless we expect it or theorize it (most every regression analysis without an interaction assumes its absence) so to assume it present is inconsistent with typical practice.”

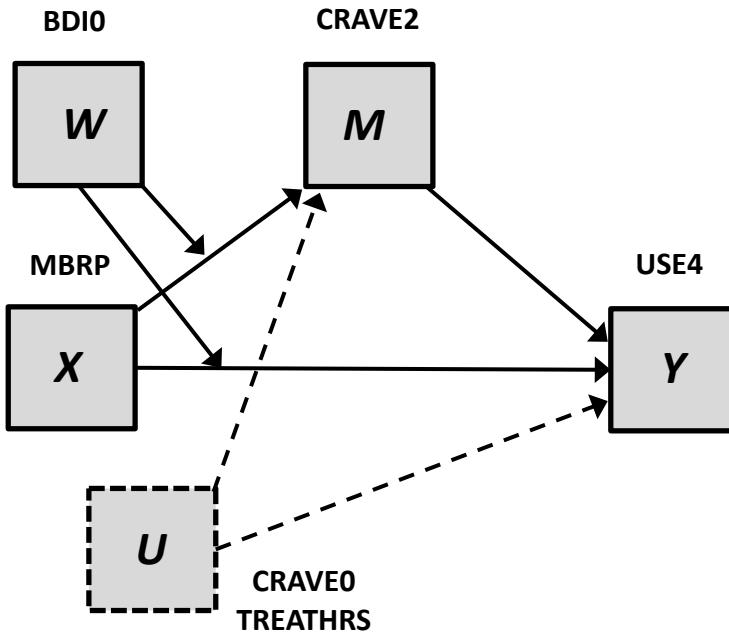
Conditional Process Modeling Example #2



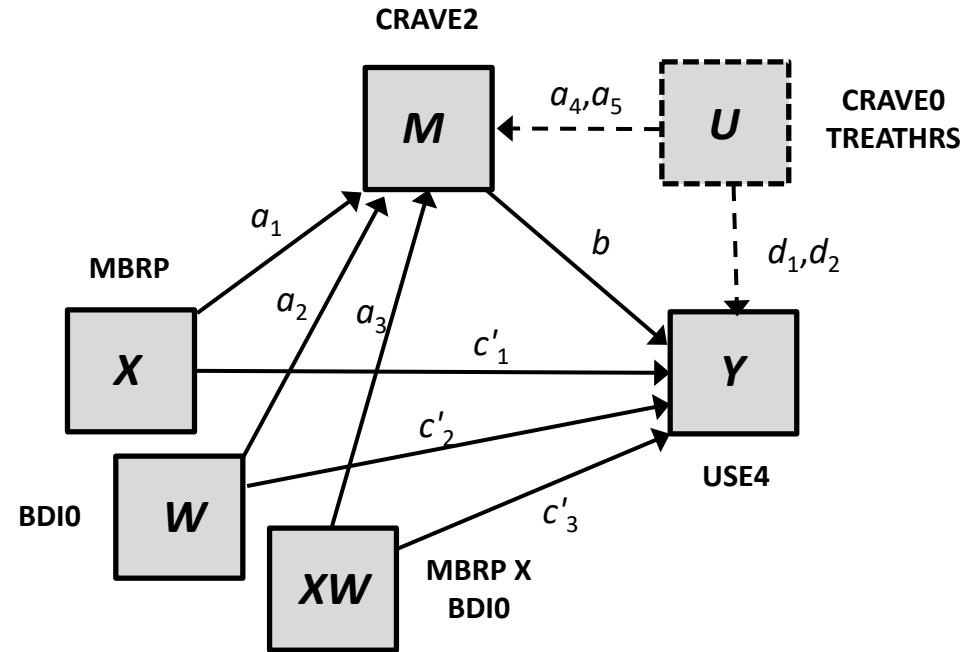
This is a model of **craving (M)** as the mechanism by which **mindfulness relapse prevention therapy (X)** affects **substance use (Y)** relative to therapy as usual. In this model, moderation of the mechanism is proposed as operating in the “first stage” of the mediation process via the moderation 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**

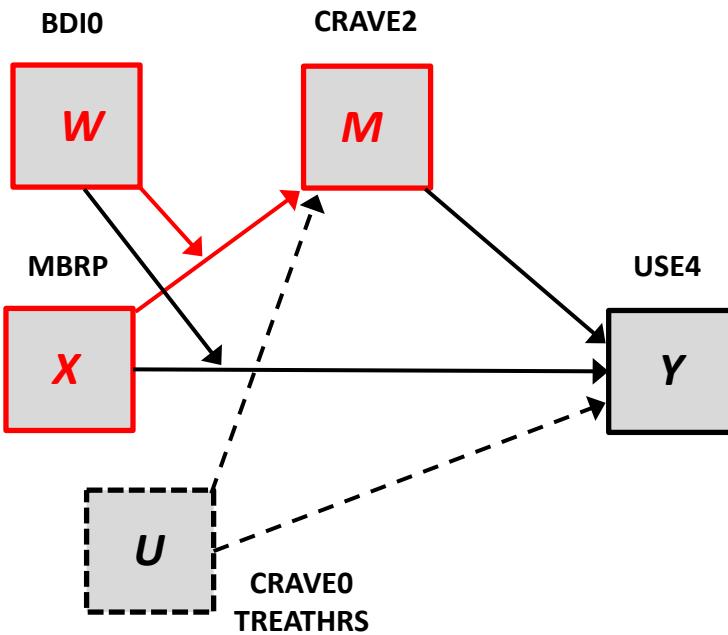
$$\widehat{M}_i =$$

$$\widehat{Y}_i =$$

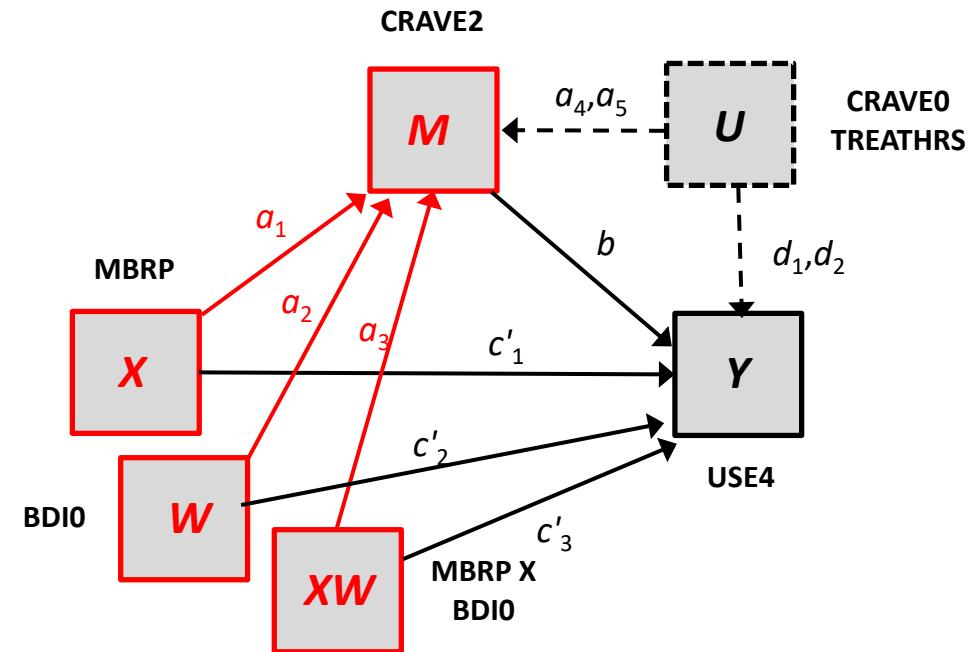
The number of equations needed is equal to the number of variables with arrows pointing at them in the conceptual or statistical diagram.

Conceptual and Statistical Models

Conceptual model



Statistical model



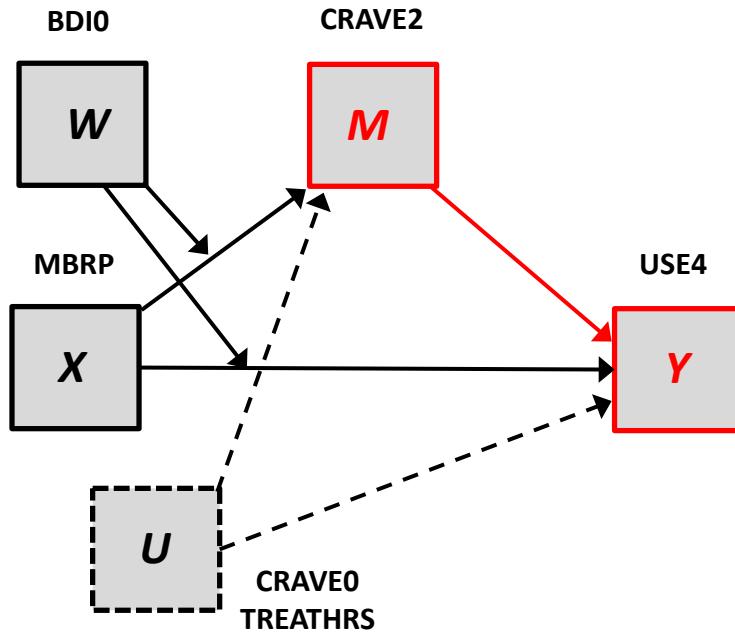
$$\widehat{M}_i = a_0 + \boxed{a_1 X_i + a_2 W_i + a_3 X_i W_i} + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y}_i = c'_0 + c'_1 X_i + c'_2 W_i + c'_3 X_i W_i + b M_i + d_1 U_{1i} + d_2 U_{2i}$$

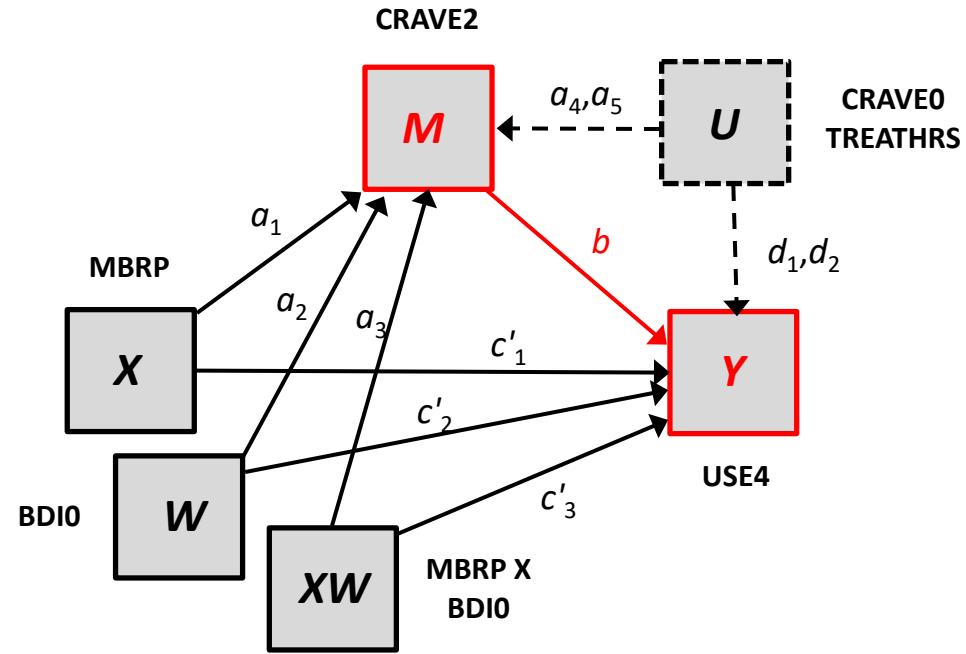
The moderation of the effect of mindfulness behavioral relapse prevention therapy relative to therapy as usual on craving by pre-therapy depression level.

Conceptual and Statistical Models

Conceptual model



Statistical model



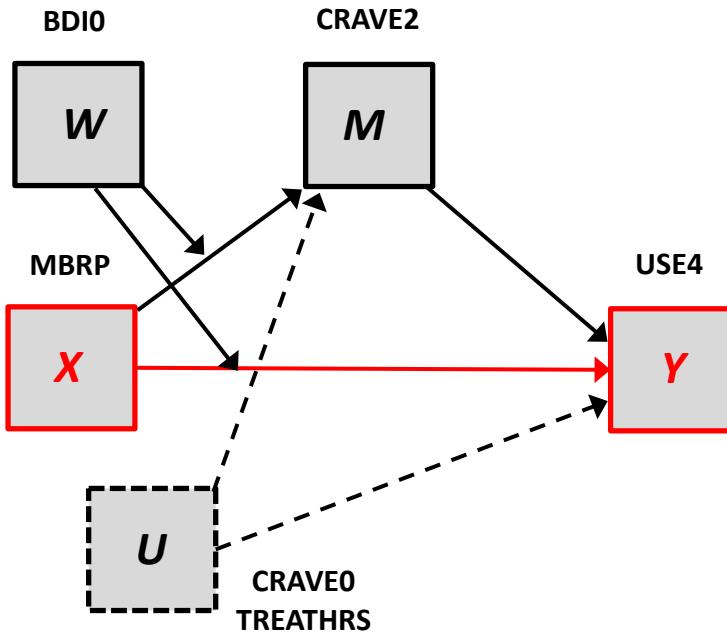
$$\widehat{M}_i = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y}_i = c'_0 + c'_1 X_i + c'_2 W_i + c'_3 X_i W_i + b \boxed{M_i} + d_1 U_{1i} + d_2 U_{2i}$$

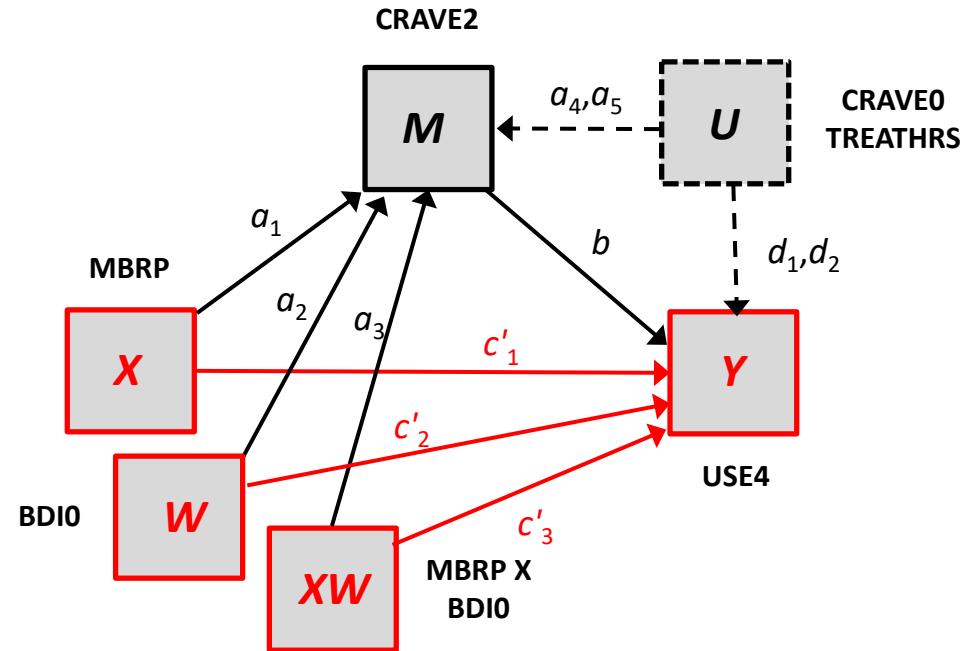
The effect of craving at two month follow-up on substance use after 4 months.

Conceptual and Statistical Models

Conceptual model



Statistical model



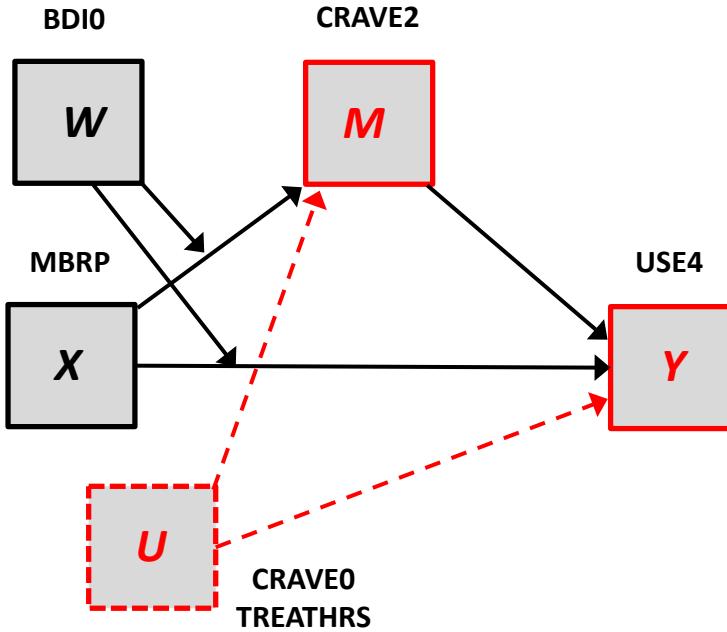
$$\widehat{M}_i = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y}_i = c'_0 + c'_1 X_i + c'_2 W_i + c'_3 X_i W_i + b M_i + d_1 U_{1i} + d_2 U_{2i}$$

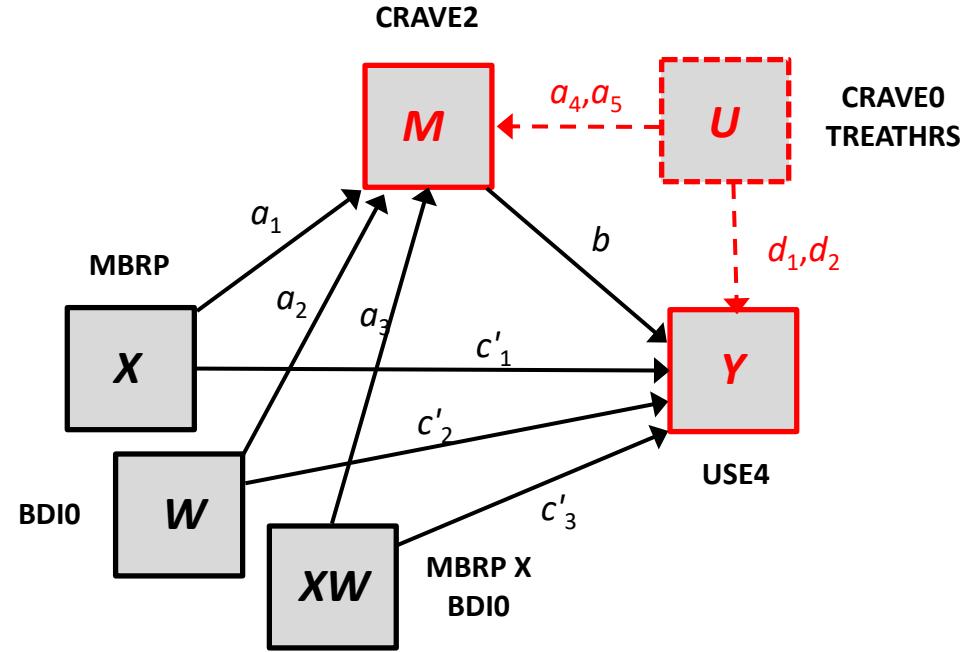
The moderation of the effect of mindfulness behavioral relapse prevention therapy relative to therapy as usual on substance use at 4 month follow up by pre-therapy depression level controlling for craving at time 2.

Conceptual and Statistical Models

Conceptual model



Statistical model



$$\widehat{M}_i = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

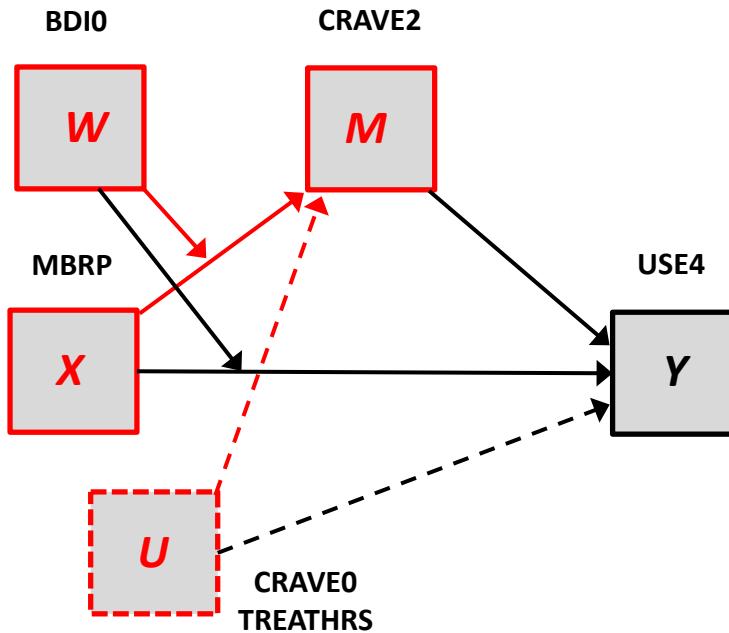
$$\widehat{Y}_i = c'_0 + c'_1 X_i + c'_2 W_i + c'_3 X_i W_i + b M_i + d_1 U_{1i} + d_2 U_{2i}$$

Covariates to account for potential confounding by treatment hours and pre-therapy craving.

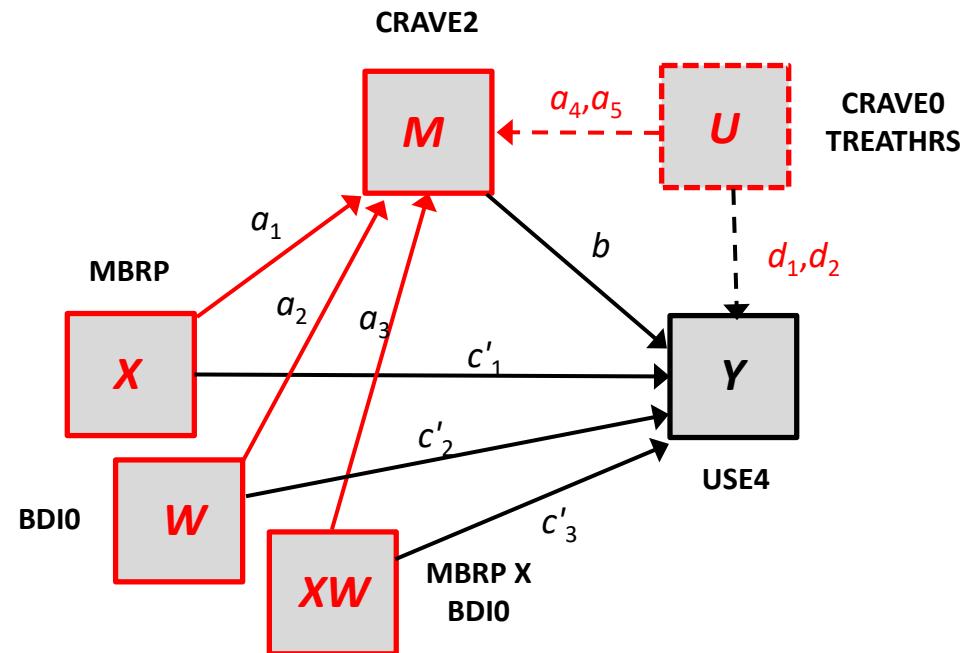
Estimating the moderation component of the model

The conceptual model proposes that the effect of mindfulness behavioral relapse prevention therapy depends on pre-therapy depression.

Conceptual model



Statistical model



$$\widehat{M}_i = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

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))
```

$X = \text{MBRP}$
 $W = \text{BDI0}$
 $Y = \text{CRAVE2}$

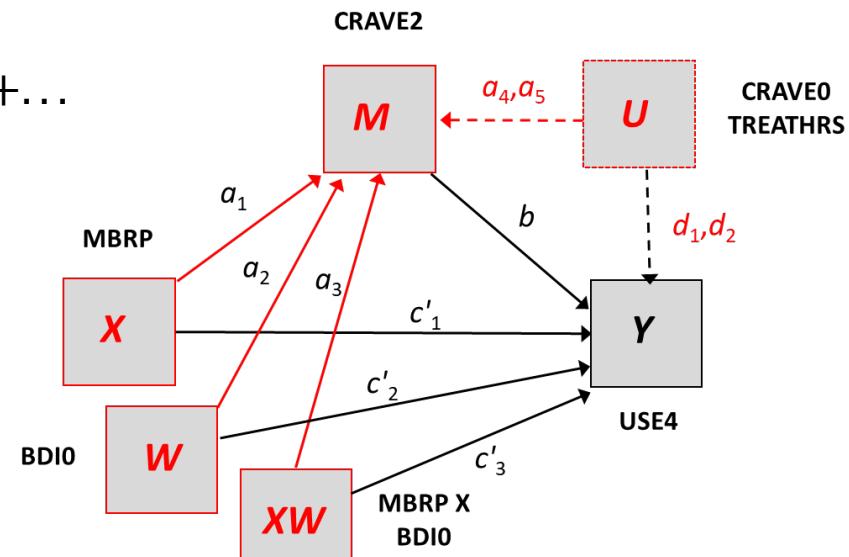
\widehat{M}_i

$$= 1.038 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \dots$$

Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
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

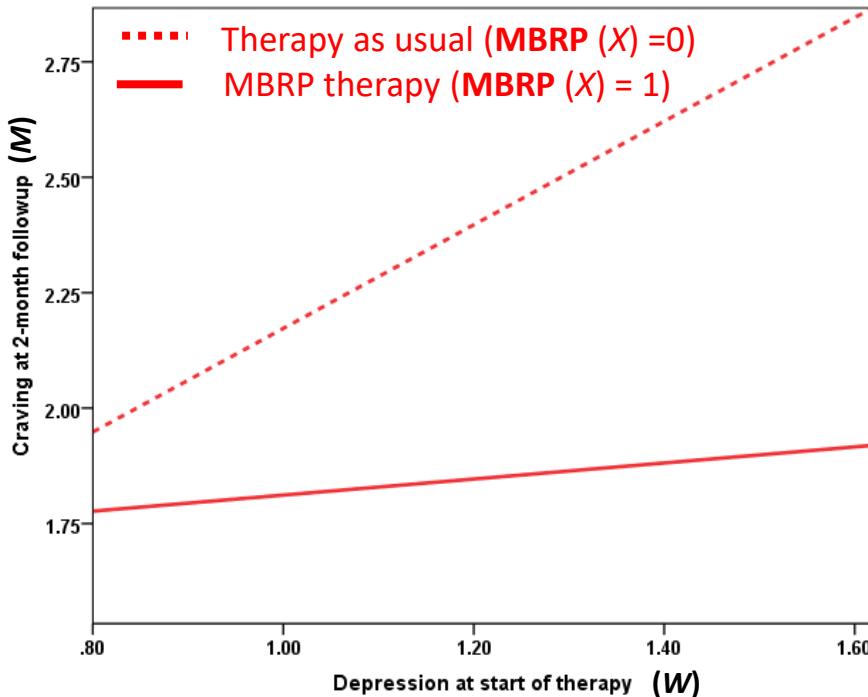
a. Dependent Variable: CRAVE2: Craving at two month follow-up

$$a_1 = 0.587, a_3 = -0.948$$



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



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

which can be written as

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

or

$$\begin{aligned} \widehat{M}_i \\ = 1.038 + \theta_{X \rightarrow M} X_i + 1.122W_i + \dots \end{aligned}$$

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

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

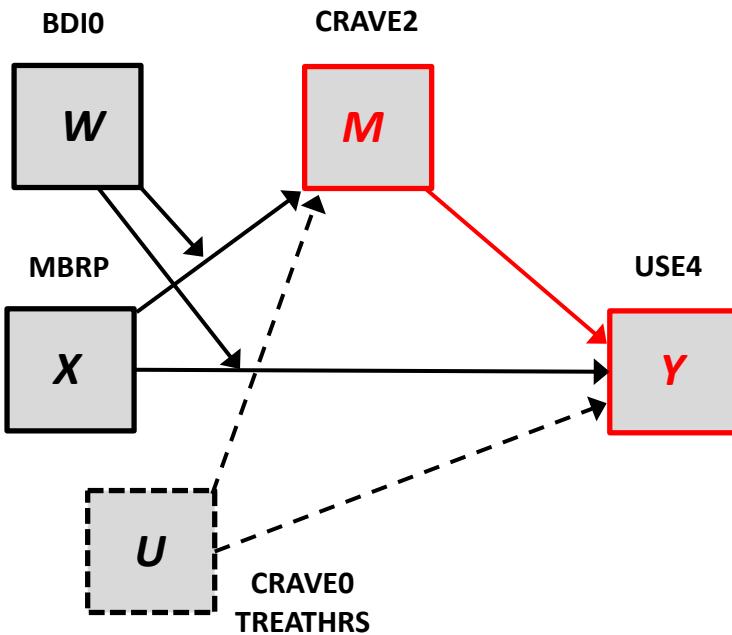
BDI0 (W)	$\theta_{X \rightarrow M}$
0.877	-0.245
1.196	-0.547
1.515	-0.850

Recall these from our implementation of the pick-a-point approach.

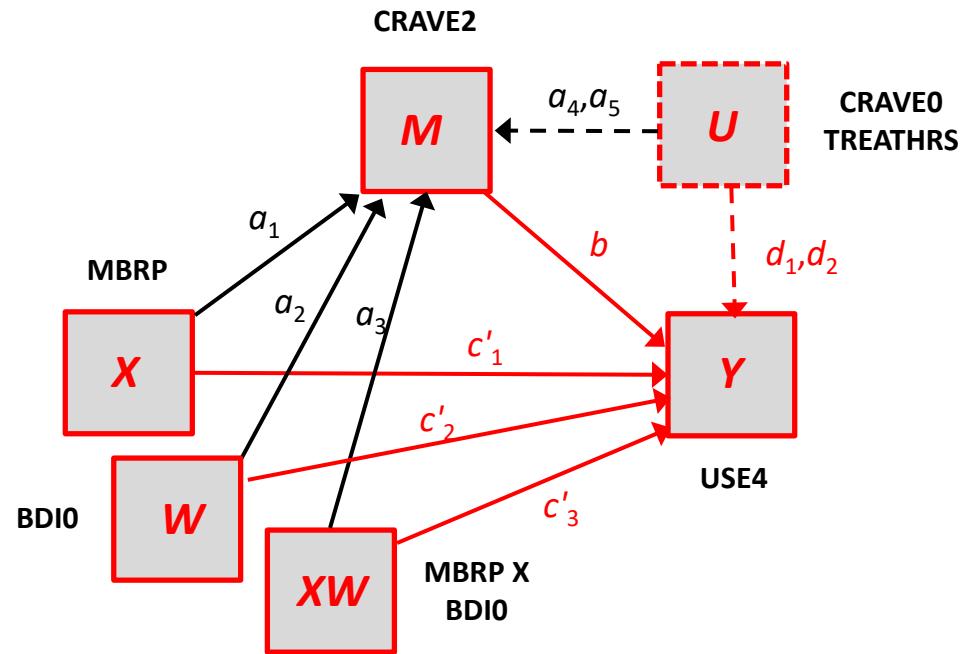
where $\theta_{X \rightarrow M} = 0.587 - 0.948W = a_1 + a_3W$

Estimating the b and c' paths

Conceptual model



Statistical model



$$\widehat{M}_i = a_0 + a_1 X_i + a_2 W_i + a_3 X_i W_i + a_4 U_{1i} + a_5 U_{2i}$$

$$\widehat{Y}_i = c'_0 + c'_1 X_i + c'_2 W_i + c'_3 X_i W_i + b M_i + d_1 U_{1i} + d_2 U_{2i}$$

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))
```

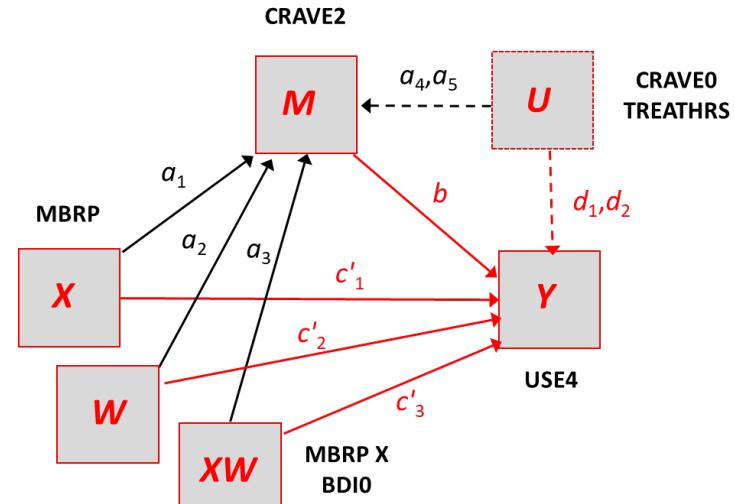
Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
1	(Constant)	1.374	.251	5.479	<.001
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.256	.276	.192	.926
	BDI0: Beck Depression Inventory baseline	-.298	.152	-.143	-1.953
	mbrpdep	-.135	.226	-.125	-.597
	CRAVE2: Craving at two month follow-up	.509	.041	.751	12.318
	CRAVE0: Baseline craving	-.068	.039	-.095	-1.719
	TREATHRS: Hours of therapy	-.020	.005	-.203	-3.712

a. Dependent Variable: USE4: Substance use at four month follow-up

$$\hat{Y}_i = 1.374 + 0.256X_i - .298W_i - .135X_iW_i + 0.509M_i + \dots$$

$b = 0.509, c'_1 = 0.256, c'_3 = -.135$

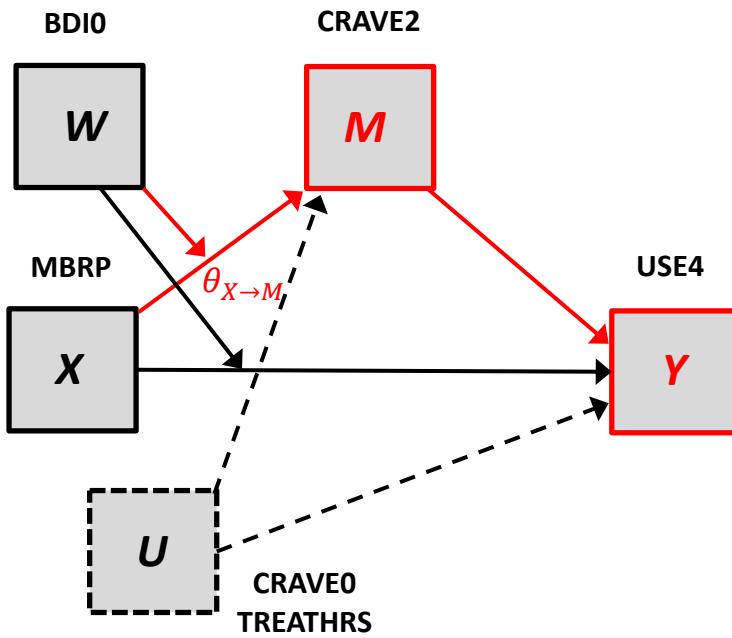
Statistical model



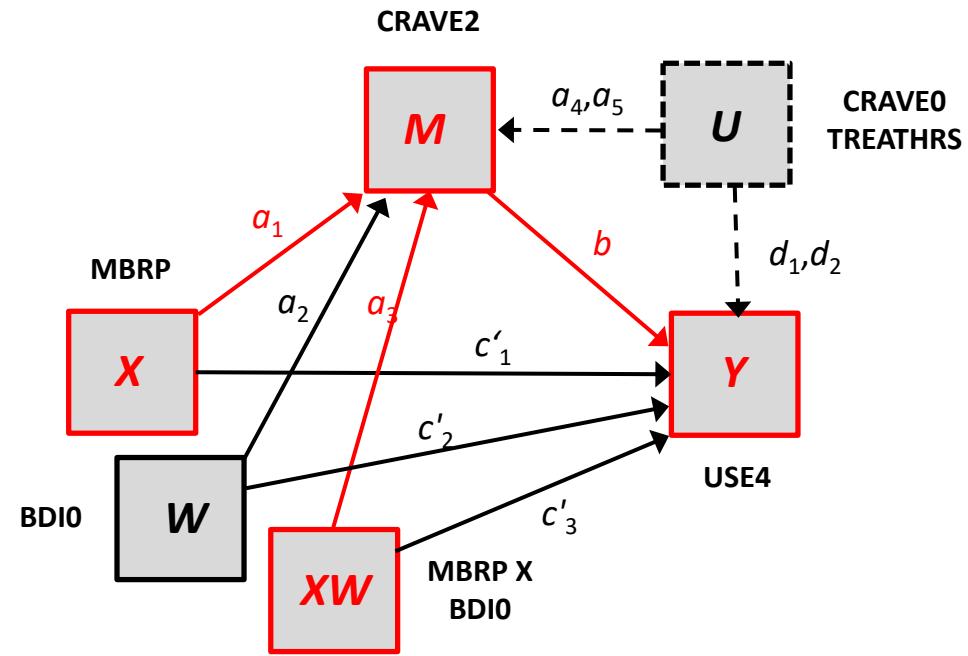
Emphasis is not on statistical significance of the b -path, as the indirect effect of X is not defined entirely in terms of b . $c'_1 + c'_3W$ is the conditional direct effect (discussed in a bit).

The conditional indirect effect of X

Conceptual model



Statistical model

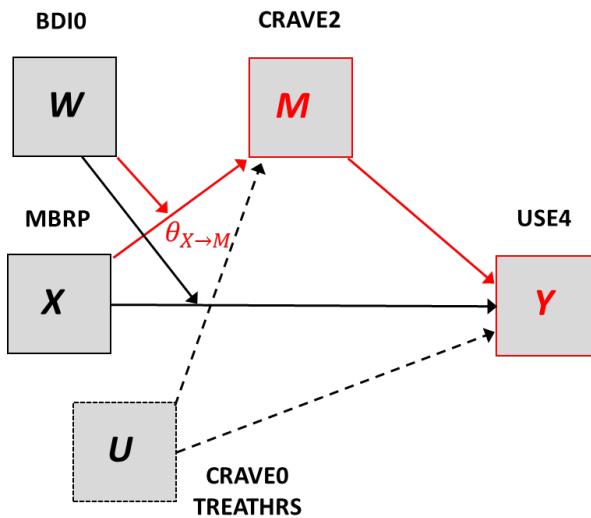


The conditional indirect effect of X on Y through M is the product of the conditional effect of X on M ($\theta_{X \rightarrow M} = a_1 + a_3 W$) and effect of M on Y (b):

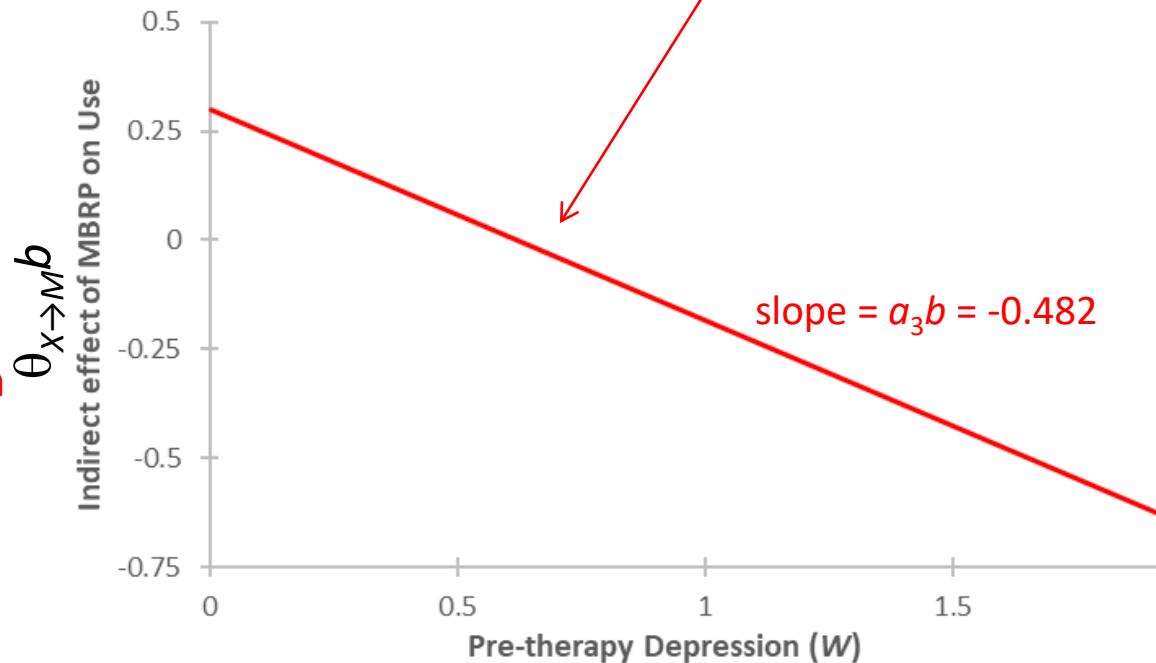
$$\theta_{X \rightarrow M} b = (a_1 + a_3 W)b = (0.587 - 0.948W)(0.509)$$

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



$$\begin{aligned}\theta_{X \rightarrow M} b &= (a_1 + a_3 W)b = (0.587 - 0.948W)(0.509) \\ &= a_1 b + a_3 b W = 0.299 - 0.482W\end{aligned}$$

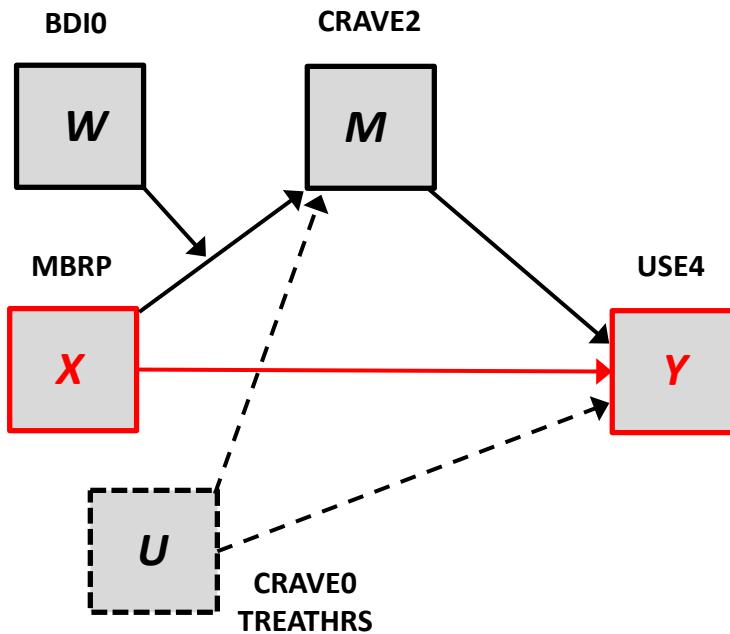


The indirect effect declines with increasing pre-therapy depression. The “**index of moderated mediation**” is $a_3 b = -0.482$. It quantifies the relationship between the moderator and the indirect effect in this model.

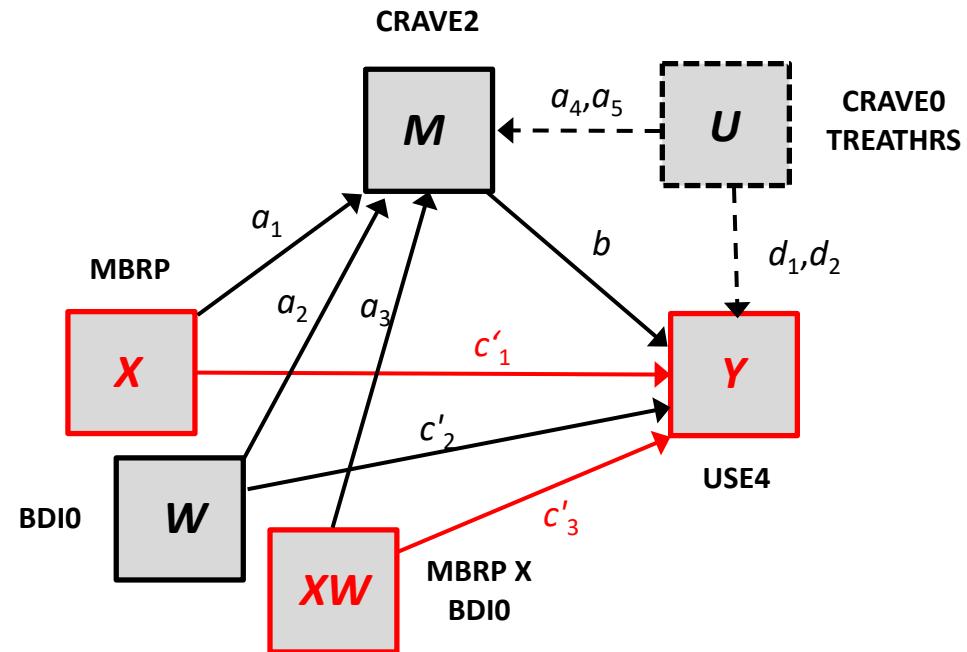
As will be seen, a hypothesis test that the slope of this function is equal to 0 is a formal test of moderated mediation....moderation of the indirect effect.

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 crave0 treathrs.
```

```
proc reg data=mbrp;model use4 = crave2 mbrp crave0 treathrs;run;
```

```
summary(lm(use4~crave2+mbrp+crave0+treathrs, data = mbrp))
```

Coefficients^a

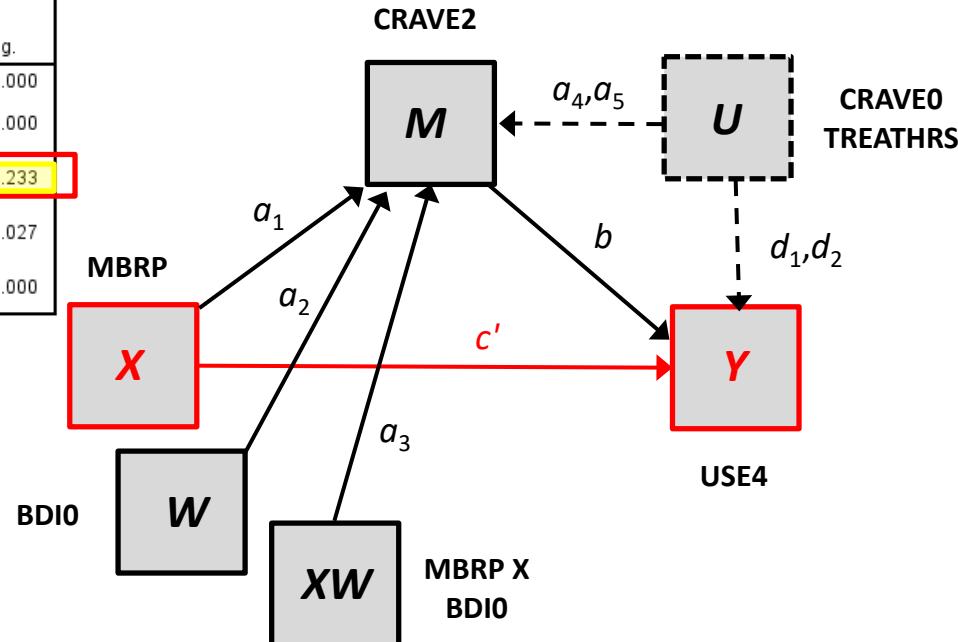
Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
1 (Constant)	1.130	.215		5.254	.000
CRAVE2: Craving at two month follow-up	.481	.040	.710	11.955	.000
MBRP: Therapy as usual (0) or MBRP therapy (1)	.093	.077	.070	1.198	.233
CRAVE0: Baseline craving	-.088	.040	-.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

$$\hat{Y}_i = 1.130 + 0.093X_i + 0.481M_i + \dots$$

$$c' = 0.093, t(163) = 1.198, p = 0.233$$

Statistical model



Mindfulness behavioral relapse prevention therapy has no apparent effect on later substance use relative to therapy as usual after accounting for the mechanism through craving.

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))
```

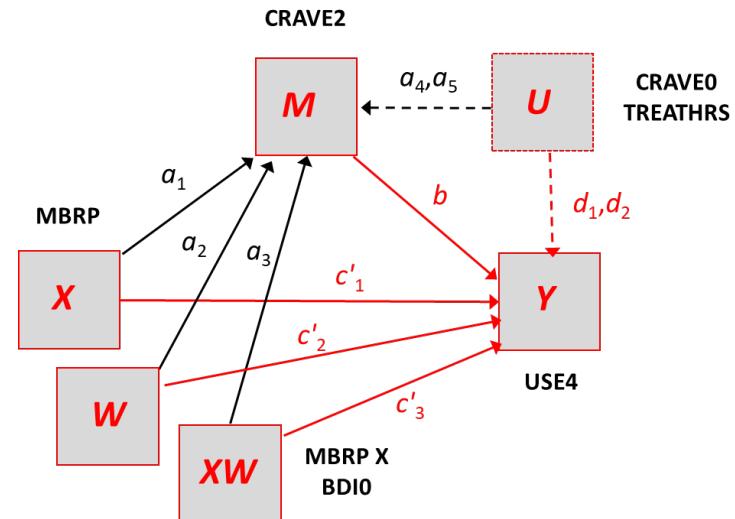
Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
	B	Std. Error			
1	(Constant)	1.374	.251	5.479	<.001
	MBRP: Therapy as usual (0) or MBRP therapy (1)	.256	.276	.192	.926
	BDI0: Beck Depression Inventory baseline	-.298	.152	-.143	-1.953
	mbrpdep	-.135	.226	-.125	-.597
	CRAVE2: Craving at two month follow-up	.509	.041	.751	12.318
	CRAVE0: Baseline craving	-.068	.039	-.095	-1.719
	TREATHRS: Hours of therapy	-.020	.005	-.203	-3.712

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		Standardized Coefficients		
		B	Std. Error	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

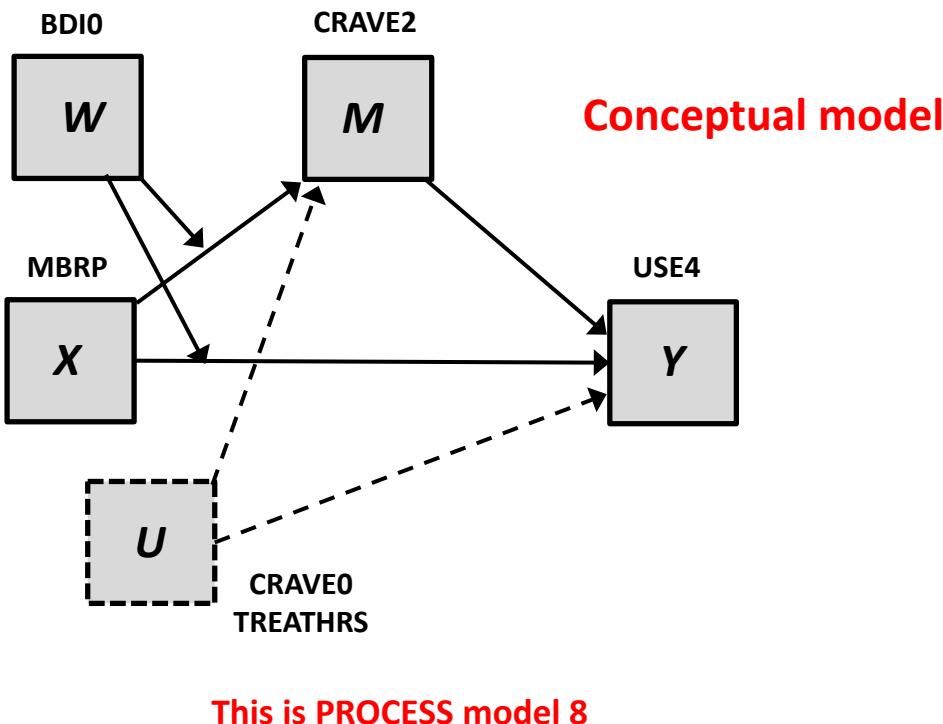
PROS: Results in a more parsimonious model, and more concrete conclusions about the direct effect.

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

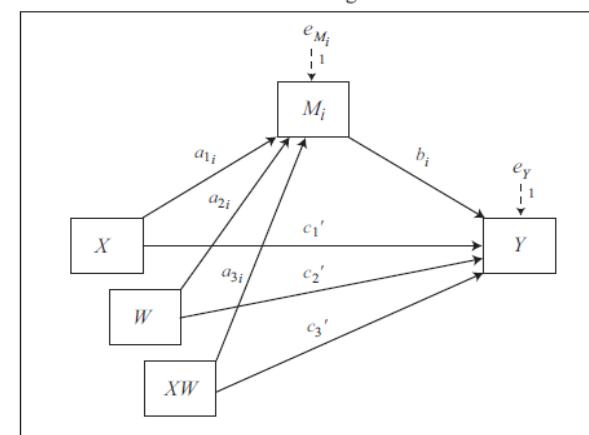
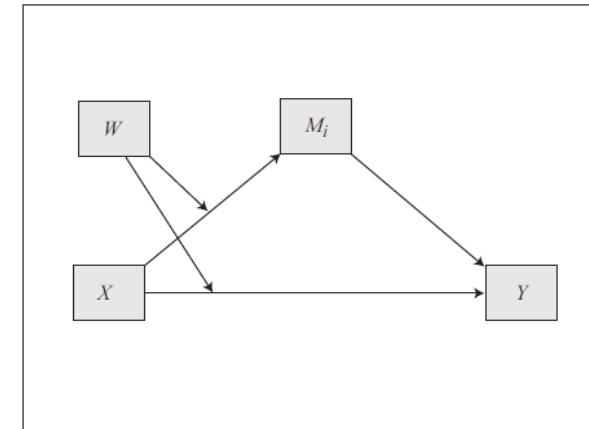
PROCESS takes most of the computational burden off our shoulders.



```
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

$$\widehat{M}_i = 1.039 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \dots$$

OUTCOME VARIABLE:

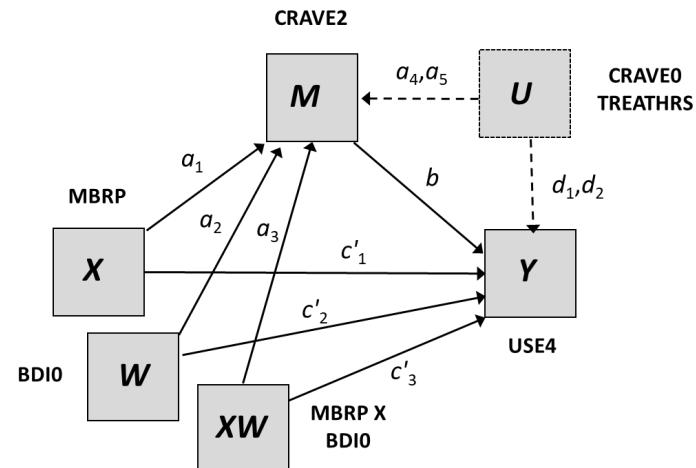
crave2

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

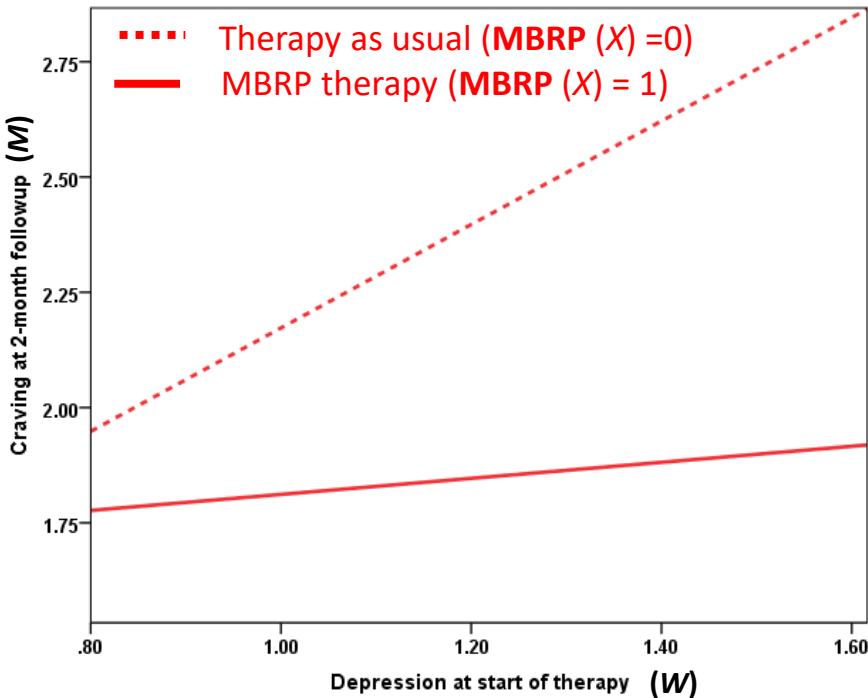


$$a_1 = 0.587$$

$$a_2 = 1.122$$

$$a_3 = -0.948$$

PROCESS output



$$\Theta_{X \rightarrow M} = 0.587 + 1.122W$$

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: mbzp (X)
Mod var: bdi0 (W)

$$\widehat{M}_i = 1.039 + 0.587X_i + 1.122W_i - 0.948X_iW_i + \dots$$

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

$$\Theta_{X \rightarrow M} = 0.587 + 1.122W$$

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

$$c'_1 = 0.2560$$

$$b = 0.509$$

$$c'_3 = -0.1348$$

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

$$\widehat{Y}_i = 1.374 + 0.256X_i - 0.298W_i - 0.135X_iW_i + 0.509M_i \dots$$

PROCESS output

***** DIRECT AND INDIRECT EFFECTS OF X ON Y *****

Conditional direct effect(s) of X on Y:

<i>W</i>	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

$$\theta_{X \rightarrow Y} = 0.256 - 0.135W$$

Conditional indirect effects of X on Y:

INDIRECT EFFECT:

mbrp → crave2 → use4

<i>W</i>	bdi0	Effect	BootSE	BootLLCI	BootULCI
	.9020	-.1364	.0799	-.2977	.0154
	1.1900	-.2753	.0872	-.4604	-.1194
	1.5180	-.4335	.1374	-.7232	-.1926

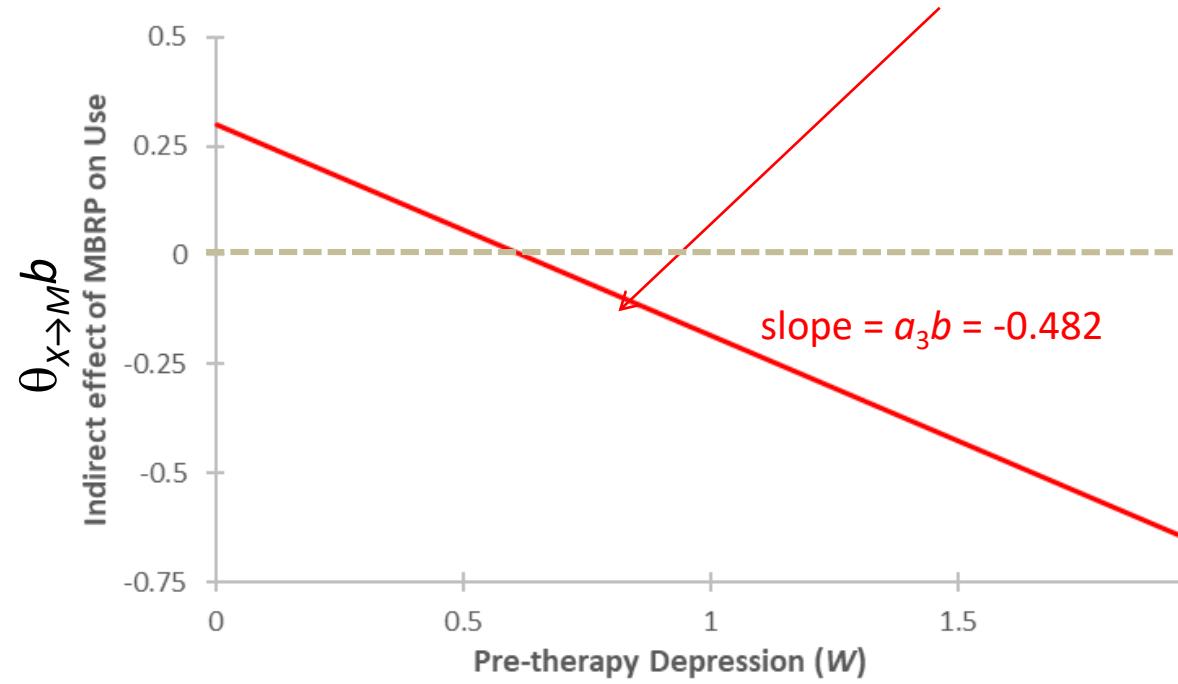
$$\begin{aligned}\theta_{X \rightarrow M} b &= (a_1 + a_3 W)b = (0.587 - 0.948W)(0.509) \\ &= a_1 b + a_3 b W = 0.299 - 0.482W\end{aligned}$$

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

$$\begin{aligned}\theta_{X \rightarrow M} b &= (a_1 + a_3 W)b = (0.587 - 0.948W)(0.509) \\ &= a_1 b + a_3 b W = 0.299 - 0.482W\end{aligned}$$



The indirect effect is a function of W (pre-therapy depression) in our model. This function is a line.

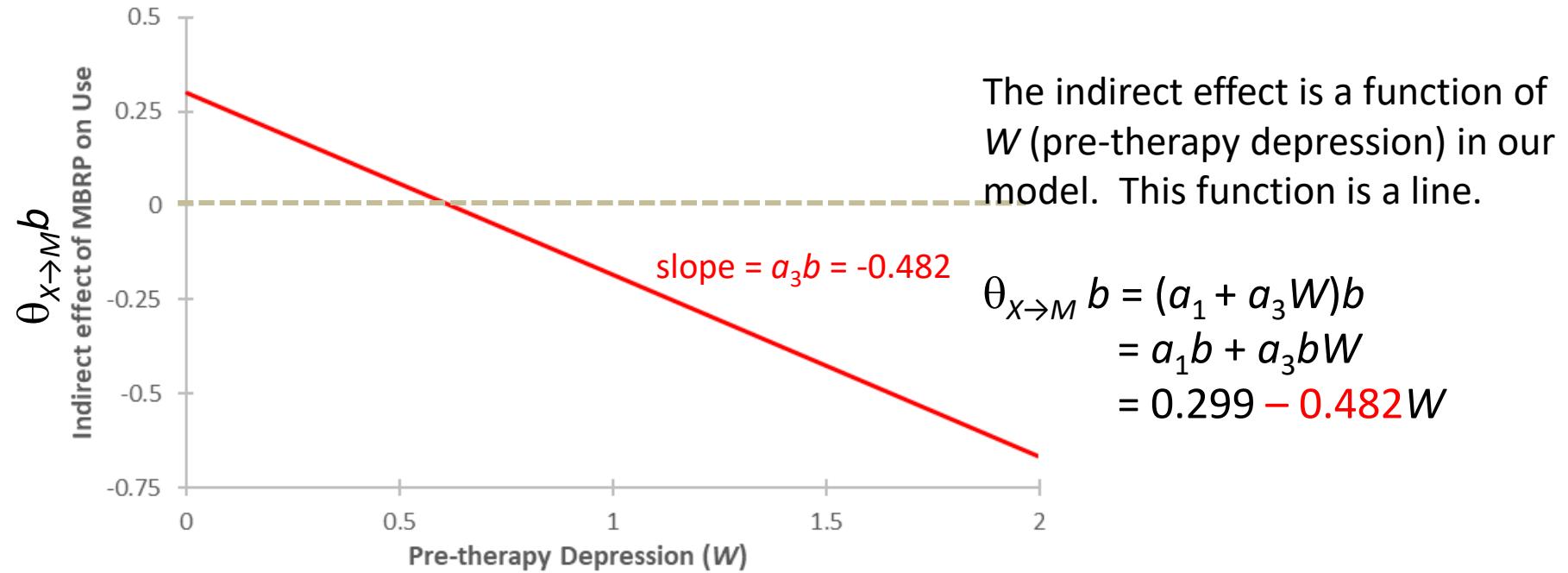
$$\begin{aligned}\theta_{X \rightarrow M} b &= (a_1 + a_3 W)b \\ &= a_1 b + a_3 b W \\ &= 0.299 - 0.482W\end{aligned}$$

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 $a_3 b$ 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

$$\begin{aligned}\theta_{X \rightarrow M} b &= (a_1 + a_3 W)b = (0.587 - 0.948W)(0.509) \\ &= a_1 b + a_3 b W = 0.299 - 0.482W\end{aligned}$$



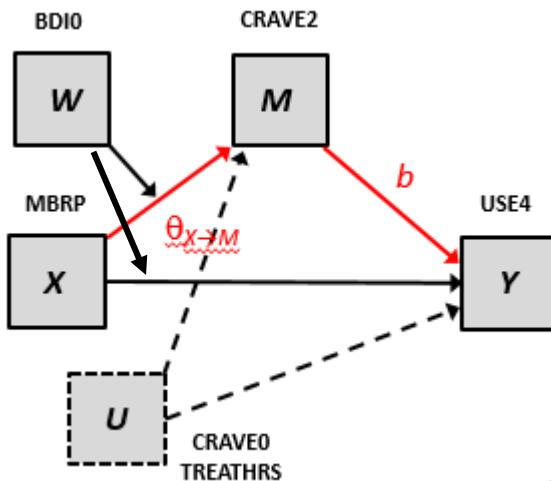
$$(W) \quad a_3 b = -0.486, 95\% \text{ bootstrap CI} = -0.967 \text{ to } -0.104$$

~~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.

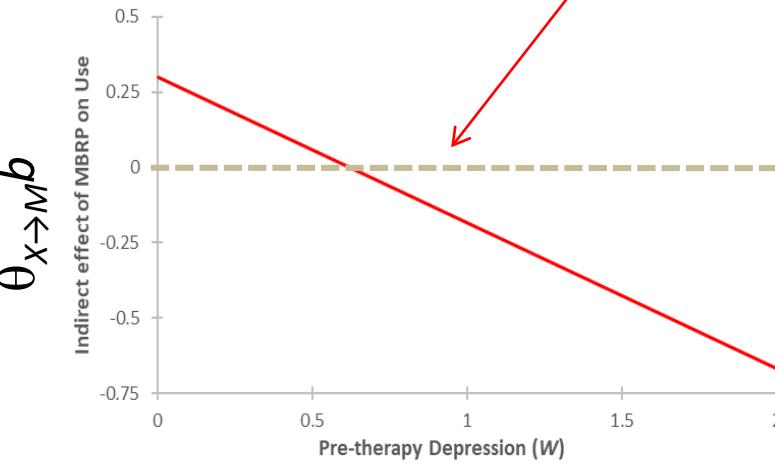
Probing the moderation of mediation



$$\theta_{X \rightarrow M} b = (a_1 + a_3 W)b = (0.587 - 0.948W)(0.481)$$

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	$\theta_{X \rightarrow M} b$
16 th %	.9020	- .2683	0.509
50 th %	1.1900	- .5414	0.509
84 th %	1.5180	- .8525	0.509

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).

Comparing conditional indirect effects (1st 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 of MBRP therapy through craving different for those relatively low in pre-therapy depression relative to those relatively high?

For this model, the difference between any two conditional indirect effects defined by different values of W equal to w_1 and w_2 is

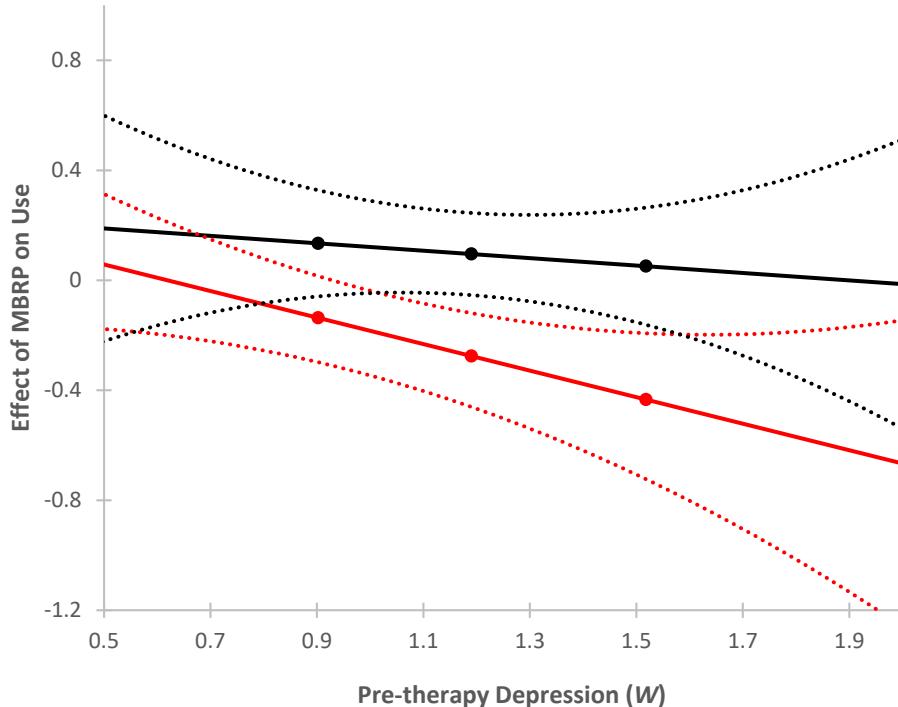
$$\begin{aligned}(a_1 + a_3 w_1)b - (a_1 + a_3 w_2)b &= a_1 b + a_3 b w_1 - a_1 b - a_3 b w_2 \\&= a_3 b w_1 - a_3 b w_2 \\&= a_3 b (w_1 - w_2)\end{aligned}$$

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.

If a bootstrap confidence interval for $a_3 b$ does not contain zero, then neither will a confidence interval for $a_3 b (w_1 - w_2)$, **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 $a_3 b$ contains zero, then so too will a confidence interval for $a_3 b (w_1 - w_2)$, **for any two values** of w_1 and w_2 , ($w_1 \neq w_2$).

Putting it all together

— Direct effect
— Indirect effect



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 depression	Relatively most depressed
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Point estimates with 95% confidence intervals (OLS confidence intervals for direct effects, bootstrap confidence intervals for indirect effects).

CPA Wrap Up

Conditional process analysis can be used to answer questions about the contingencies of mechanisms

These models are fit by adding moderation to any of the paths in a mediation analysis

- First-stage
- Second-stage
- Direct effect
- More complex also possible

In these models indirect and direct effects can be moderated (i.e., conditional on the moderator)

To test whether the mediation is moderated, the inference on the Index of Moderated Mediation is needed

Sample Size Planning: CPA

pwr2ppl R package uses Monte Carlo simulation for common models in PROCESS

Models 7 & 14

WebPower: <https://webpower.psychstat.org/wiki/>

Calculates power...

Conditional indirect effect when $W = 0$

Each pathway or moderation of that pathway

Models: 7, 8, 14, 15, 58

If you find yourself in need of a power analysis for a different model, feel free to contact me

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.

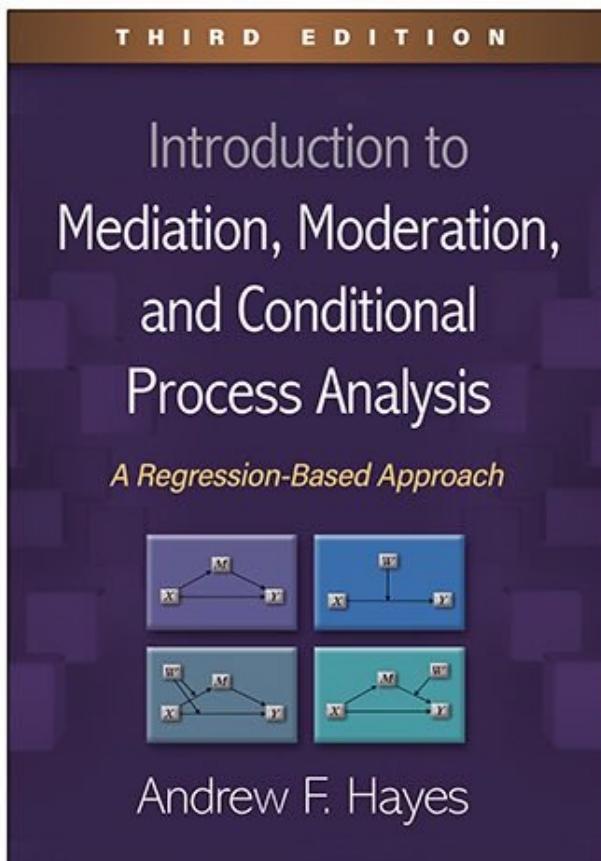
You can also submit a form to add your paper to the database if you want others to be able to find it!

<https://www.jlfossum.com/home/moderated-mediation-article-database>

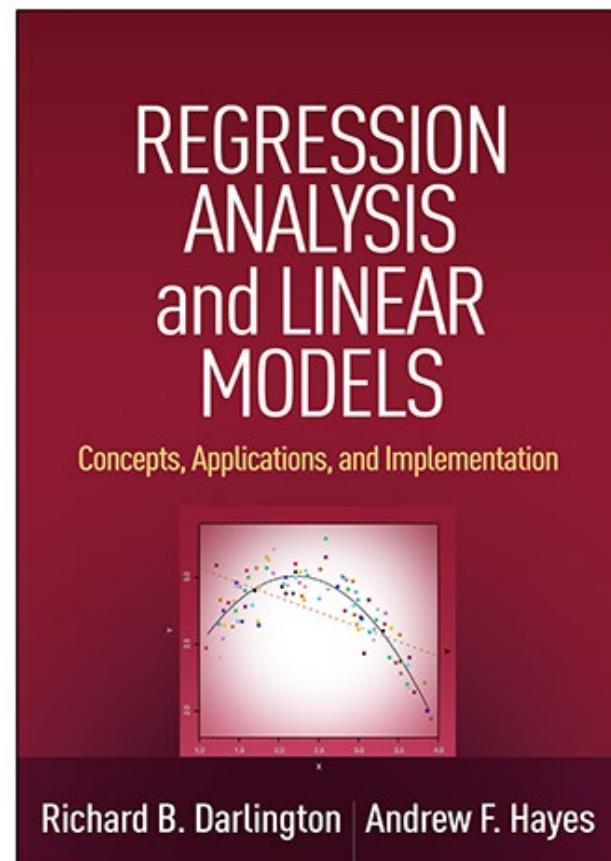
Model Number	Type of Manipulated Variable	Number of Moderators	Number of Mediators	Year								
Estimation Procedure	Research Area	Journal	Number of X Variables	Number of Y Variables								
Article	Journal	First Author	Research Area	Model Number	Sample Size	Estimation Procedure	Number of X Variables	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	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	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	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	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	1	2

Where to learn more

The entire book



Chapters 13, 14, and 15



<http://www.guilford.com/>

MMCIIA

Typically Taught in GSERM St. Gallen Summer

- 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 mult categorial independent variable.
- Moderation analysis with a mult categorial (3 or more groups) independent variable or moderator.
- Conditional process analysis with a mult categorial 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.