

# *An Introduction to Moderated Mediation*

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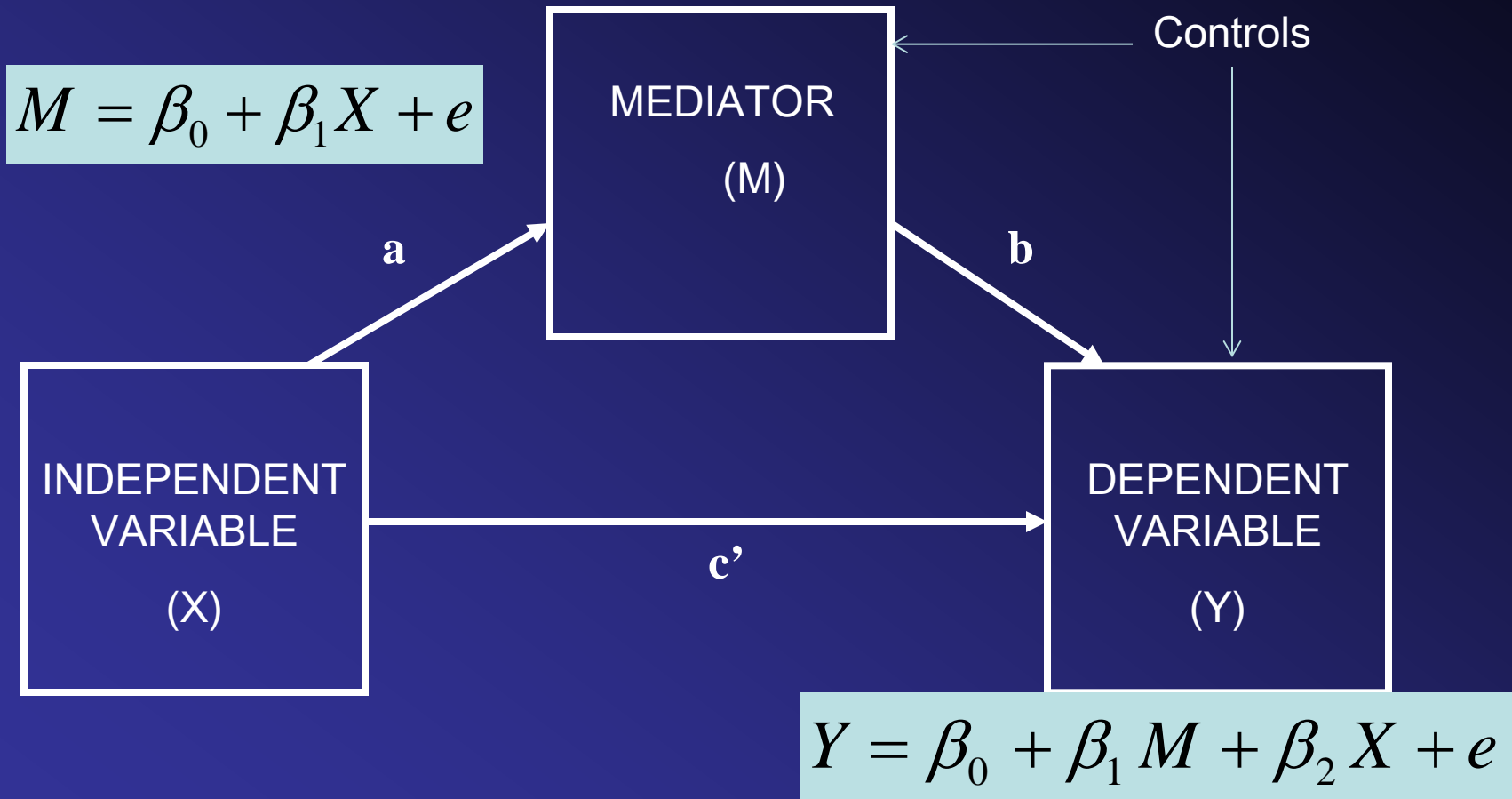
# Mediation and Moderation

- A **mediator** explains how or why an independent variable is related to a dependent variable. Mediation is exemplified by the question “how did it work?” The focus is on understanding the mechanism, causal chain of events, or the underlying process.
- By contrast, a **moderator** shows *when* or under what conditions an independent variable is related to a dependent variable. Moderation is exemplified by the question “Who did it work for?”
- Whether a variable is hypothesised as a mediator or moderator is primarily driven by your research question and theoretical interests.
- Let's first take a closer look at mediation.

# Mediation Analysis

- As shown in Figure 1, in a basic mediation model an independent variable (X) is hypothesized to influence a mediator (M) which, in turn, influences the dependent variable (Y).
- Mediation is also known as an indirect effect of X on Y through M. It answers the question *how does X effect Y?*
- The mediator can be any hypothesised psychological, social or biological variable through which X may influence Y.
- In more complex models there may be more than one mediator but the principles of analysis remain largely the same.

# Figure 1: Basic Mediation Model



Arrows indicate hypothesized effects

Indirect (mediated) effect of X on Y =  $a*b$

Direct (unmediated) effect of X on Y =  $c'$

# The Indirect Effect

- As shown in Fig 1, to test mediation requires estimation of coefficients in two regression equations:
- 1. Run a regression with the IV predicting the mediator. This will give estimate  $a$ .
- 2. Run a regression with the IV and mediator predicting the DV. This will give estimate  $b$ . *Note the IV is controlled in the equation.*
- The indirect effect of  $X$  on  $Y$  through  $M$  is quantified by the product of the  $a$  and  $b$  coefficients ( $ab$ ).
- Note the simple correlation between  $X$  and  $Y$  is not required to claim there is evidence of mediation (see Baron and Kenny, 1986 for discussion).

# Example of Mediation

**Pollack et al. (2012) hypothesized that the relationship between entrepreneurs' economic stress and withdrawal intentions was mediated by depressed effect. In this example (see Figure 3):**

Economic stress is the independent variable X,

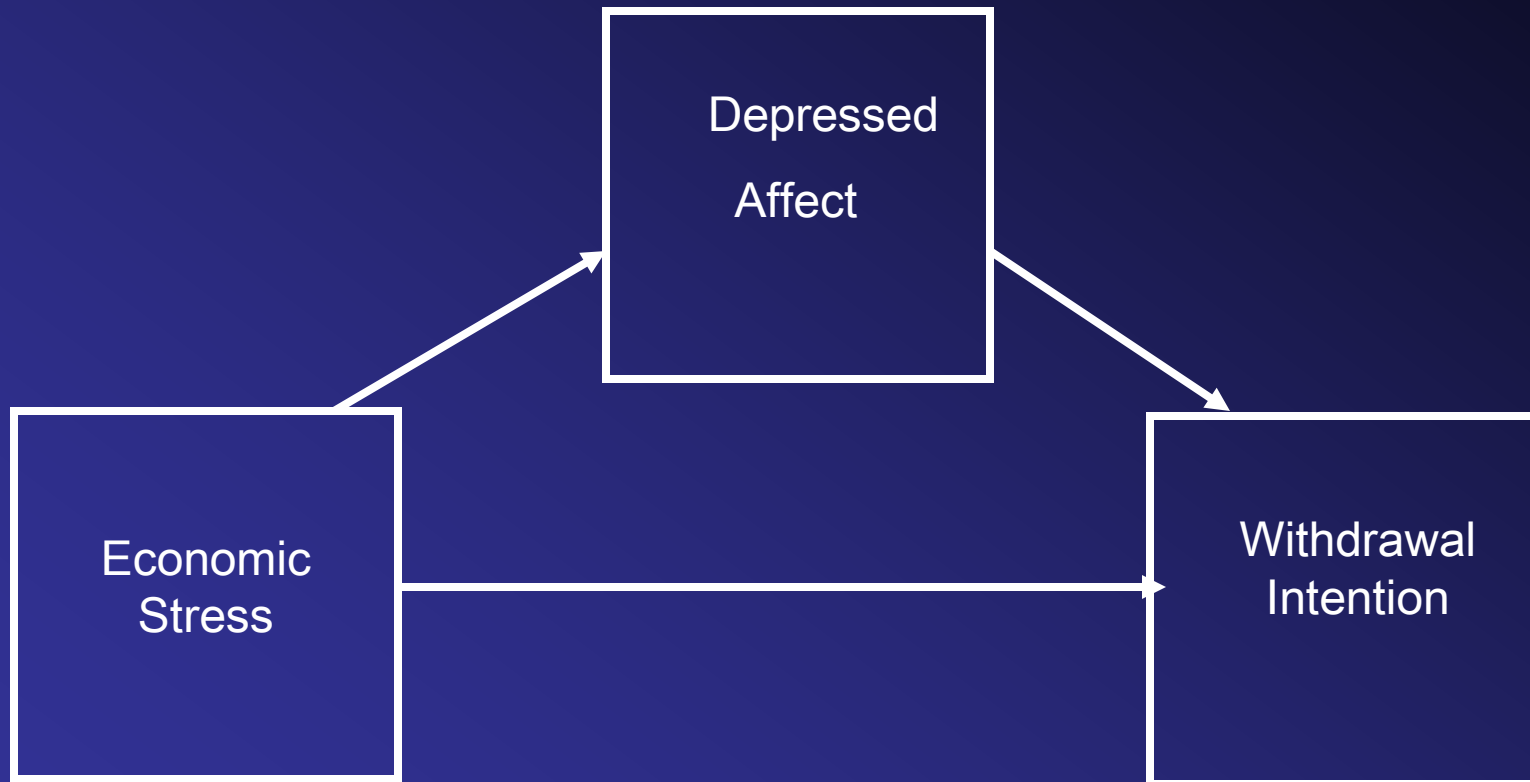
Withdrawal intention is the dependent or outcome variable Y,

Depressed affect is the mediator M.

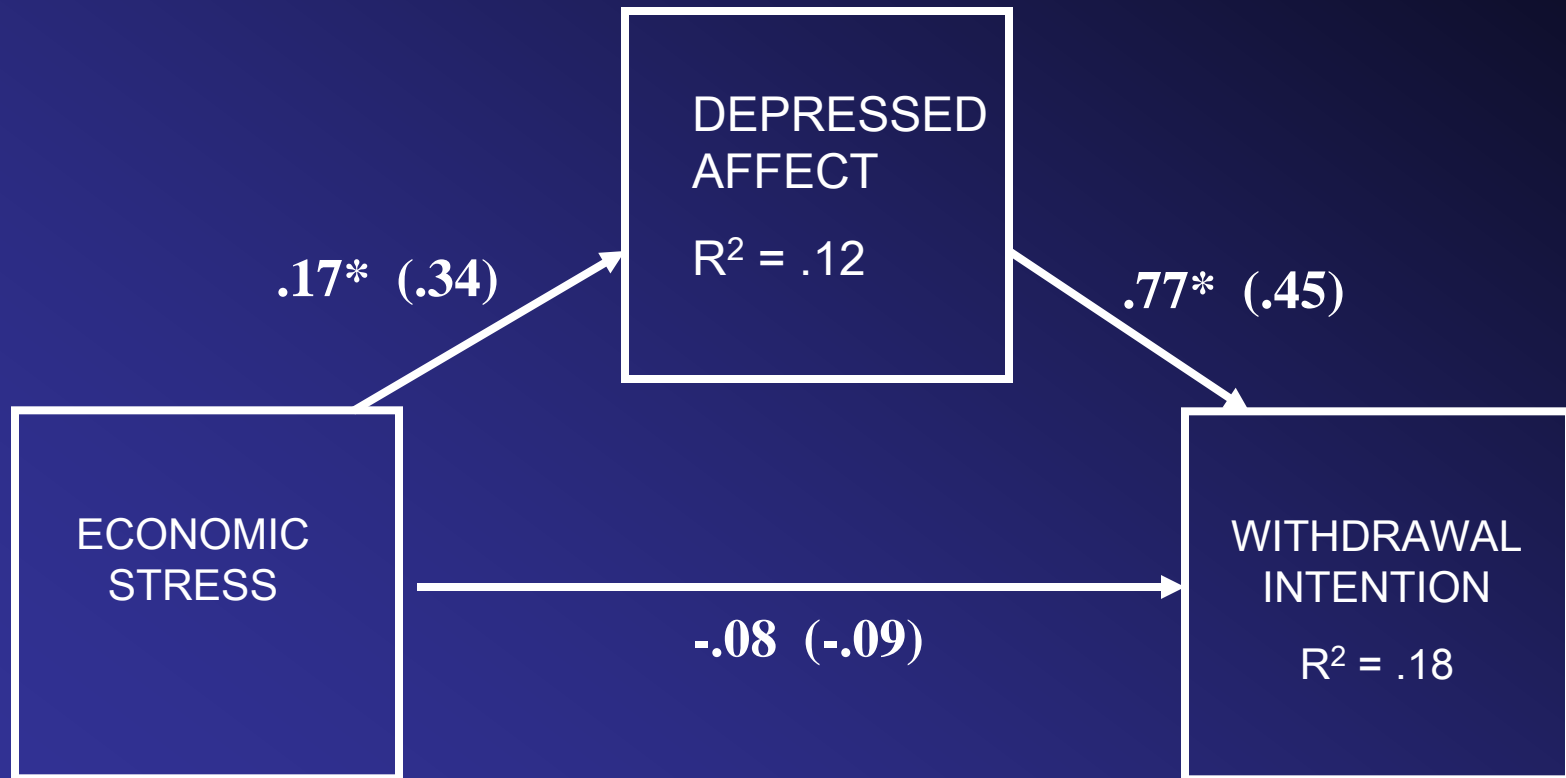
*Note age and gender were included as control variables.*

*Pollack, J., VanEpps, E. M., & Hayes, A. F. (2012). The moderating role of social ties on entrepreneurs' depressed affect and withdrawal intentions in response to economic stress. Journal of Organizational Behavior, 33, 789-810.*

## Figure 2: Example Mediation Model



# Figure 3: Results of Mediation Model



Indirect Effect =  $.17 \times .77 = .13$

Standardized Indirect Effect:  $.34 \times .45 = .15$

\*  $p < .05$ . Standardized coefficients in parentheses.



# Testing the Indirect Effect

- To test for mediation we can examine the statistical significance of the indirect effect (ie.  $H_0 : ab = 0$ ).
- There are many statistical tests of the indirect effect (see Hayes & Scharkow, 2013 for a review). Some of these tests (eg. the Sobel Z test) assume the indirect effect is normally distributed.
- Unfortunately, the indirect effect is rarely normally distributed.
- Non-parametric bootstrapping (with confidence intervals) has been recommended for testing mediation as it does assume the indirect effect is normally distributed and yields the most accurate results.

# What is Bootstrapping?

- Take a random sample of size  $N$  with replacement from the data (note each bootstrap sample is thus the same size as the original sample).
- Using the bootstrap sample calculate the desired estimates (eg. calculate  $ab$ ).
- Repeat the above  $k$  times (usually at least 1,000 times).
- The result is an *empirical sampling distribution* from the bootstrapped samples.
- We can then take the 2.5 and 97.5 percentiles of the empirical sampling distribution to form a 95% confidence interval (CI) for the estimate. This is called a *percentile bootstrap*.
- The confidence interval gives a range of plausible values for the estimate. *If the 95% confidence interval does not contain zero at the selected level of confidence the result is statistically significant ( $p < .05$ ).*
- It is recommended to use *bias-corrected (BC)* confidence intervals as they have slightly better accuracy than percentile intervals.

# Full or Partial Mediation

- If there is evidence of mediation and the direct effect (path  $c'$ ) is non-significant, then we can infer **full mediation**. This suggests that all of the relationship between X and Y is transmitted through the mediator.
- If there is evidence of mediation and the direct effect (path  $c'$ ) is statistically significant then this indicates **partial mediation**.
- Partial mediation is more commonly observed than full mediation. In other words, it is less likely a mediator will explain all of the variation between X and Y. This suggests there may be additional mediators to be discovered.

# PROCESS Macro

- PROCESS is an easy to use add-on to SPSS or SAS for estimating mediation, moderation, and moderated mediation models with **multiple regression** (for continuous outcomes) or **logistic regression** (for dichotomous outcomes).
- Link: <http://afhayes.com/introduction-to-mediation-moderation-and-conditional-process-analysis.html>
- **Reference:** Hayes, A. (2013). *Introduction to mediation, moderation, and conditional process analysis*. New York: Guilford Press.

# Example of Bootstrapping

- Refer back to the mediation analysis shown in Figure 3.
- The *a* & *b* path coefficients are both statistically significant and in the direction predicted. This provides some evidence in favor of mediation.
- Using bias-corrected bootstrapping with 1,000 resamples the indirect effect is .13 with a 95% CI: .08 to .21.
- Since the 95% CI does not include 0, the indirect effect is statistically significant (ie. mediation is supported).
- Note the example in Figure 3 shows that the direct effect (-.08) is not statistically significant at  $p > .05$ . Hence, we infer full mediation.

R	R-sq	F	df1	df2	p
.3425	.1173	11.4267	3.0000	258.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.9151	.2240	4.0850	.0001	.4740	1.3562
estress	.1740	.0300	5.7895	.0000	.1148	.2331
gender	.0062	.0880	.0701	.9442	-.1671	.1795
age	-.0028	.0041	-.6926	.4892	-.0109	.0052

\*\*\*\*\*

Outcome: withdraw

Model Summary

R	R-sq	F	df1	df2	p
.4274	.1827	14.3608	4.0000	257.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.5278	.3839	3.9792	.0001	.7717	2.2838
affect	.7671	.1034	7.4178	.0000	.5634	.9707
estress	-.0801	.0531	-1.5104	.1322	-.1846	.0243
gender	.1119	.1462	.7655	.4447	-.1760	.3997
age	-.0030	.0068	-.4396	.6606	-.0164	.0104

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

Direct effect of X on Y

Effect	SE	t	p	LLCI	ULCI
-.0801	.0531	-1.5104	.1322	-.1846	.0243

Indirect effect of X on Y

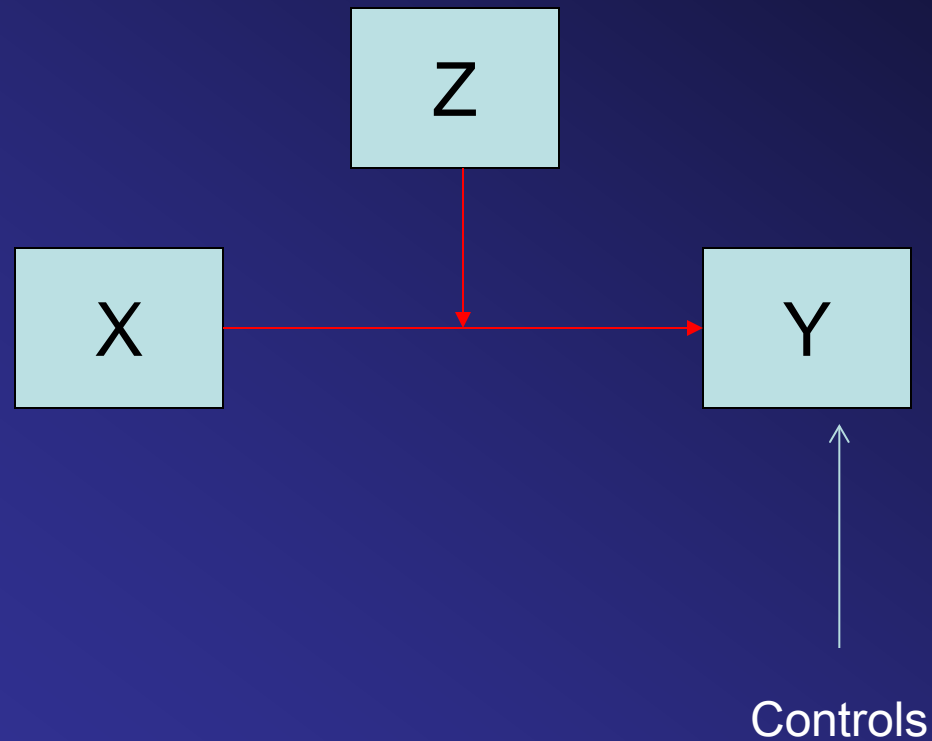
	Effect	Boot SE	BootLLCI	BootULCI
affect	.1334	.0329	.0790	.2100

\*\*\*\*\* ANALYSIS NOTES AND WARNINGS \*\*\*\*\*

# Testing Interactions: Moderated Regression

- A moderator (Z) is a variable that affects the strength and/or direction of the relationship between an independent variable (X) and a dependent variable (Y).
- Moderation is also known as an interaction.
- Linear regression is the most common way to test for moderation.
- To test for moderation we first construct a new variable defined as the product of scores on X and Z. This is called an interaction or product term.
- We then include this interaction term as a predictor in a regression model along with both X and Z as predictors. By including the product of X and Z in the equation we allow the regression coefficient for X to vary as a linear function of Z.
- If the interaction term is significantly different from zero there is evidence of moderation – that is, the effect of X on Y depends on the values of Z.

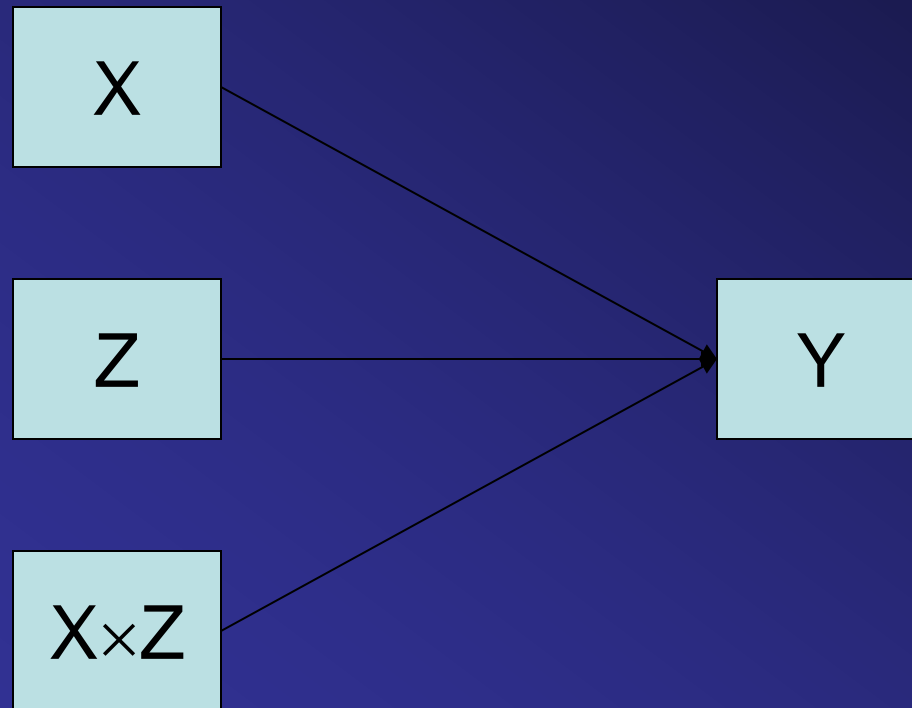
# Basic Moderation Model



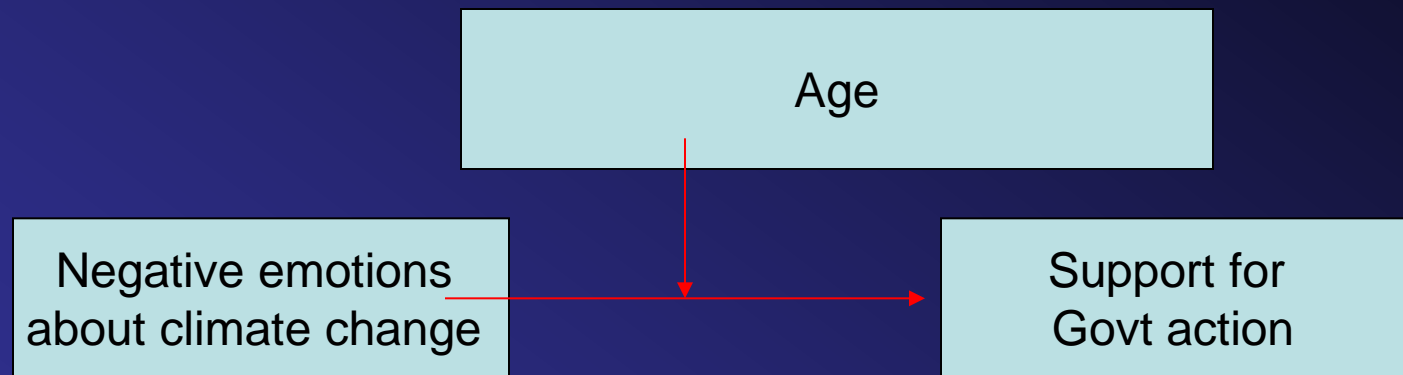


# Moderated Regression Equation

$$Y = B_0 + B_1X + B_2Z + B_3XZ + e$$



# Example of Moderation



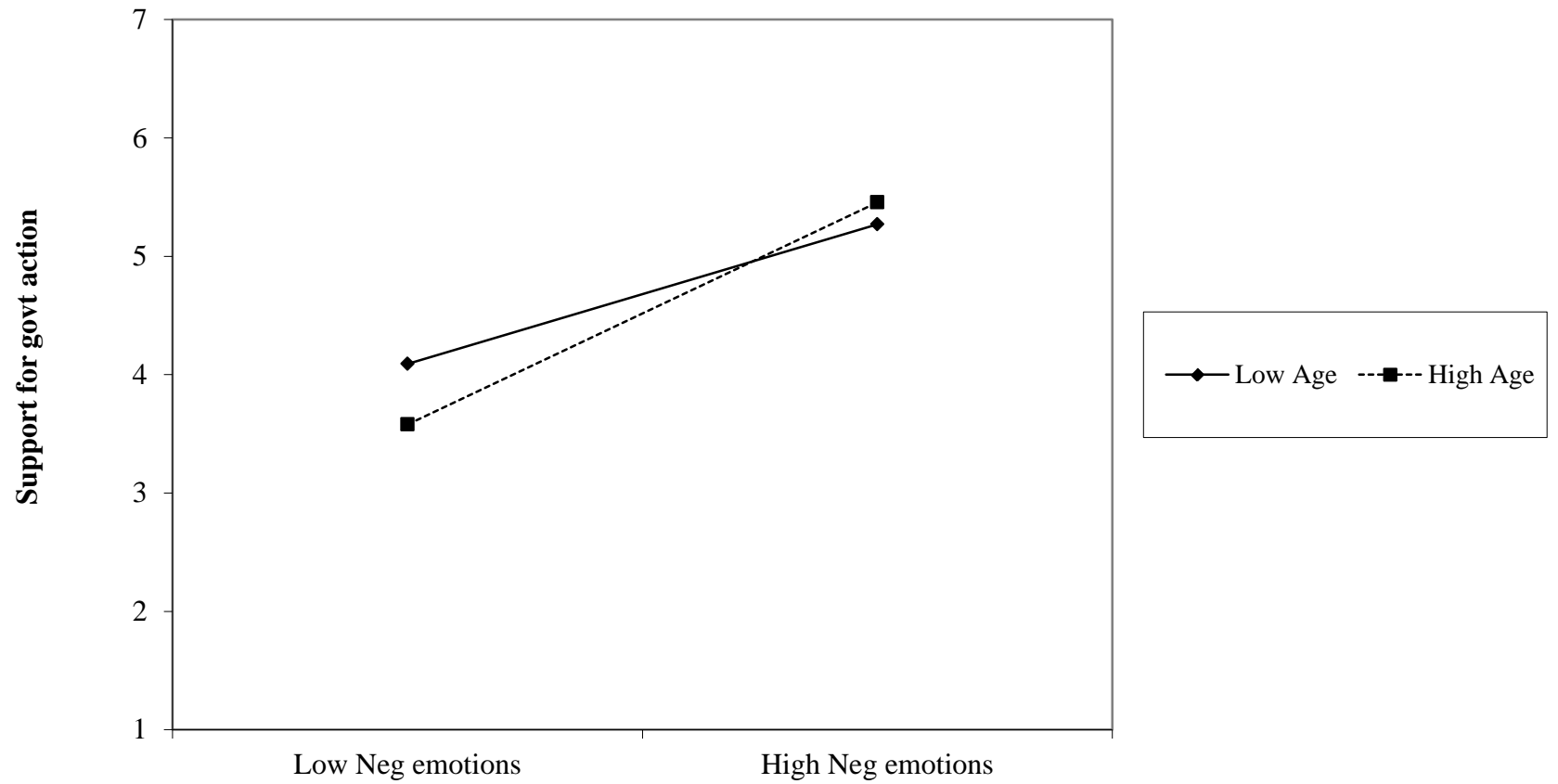
**Example hypothesis:** We hypothesize that the relationship between negative emotions about climate change and support for government action on climate change will be stronger among older people.

# Steps in Moderated Regression

1. **First Z-standardize or mean-centre X and Z.** *Although not essential this step can assist in estimating and interpreting the regression equation.*
2. **Multiply the (mean-centred/standardized) scores on X and Z to create the product term.**
3. **Run the regression with X, Z and the product term as predictors.**
4. **If the interaction term statistically significant, plot the interaction to assist in interpretation (Aiken & West, 1991)**

# Plotting Interactions

- How do we make sense of the interaction? One way is to solve the regression equation at selected values of the moderator. These are called conditional effects or simple slopes.
- Referring back to slide 18, the conditional effect of X on Y at a given value of Z can be expressed as:  $Y = B_1 + B_3Z$
- Typically, we plot the relationship between X and Y at high and low values of Z.
- Any plausible “high” and “low” values of the moderator can be plotted.
- Aiken & West (1991) define high and low values as +/- 1 SD from the mean for a continuous moderator. Values for dichotomous moderators are simply the two coded values of the moderator.
- Link to a useful tool for plotting interactions:  
<http://www.jeremydawson.co.uk/slopes.htm>



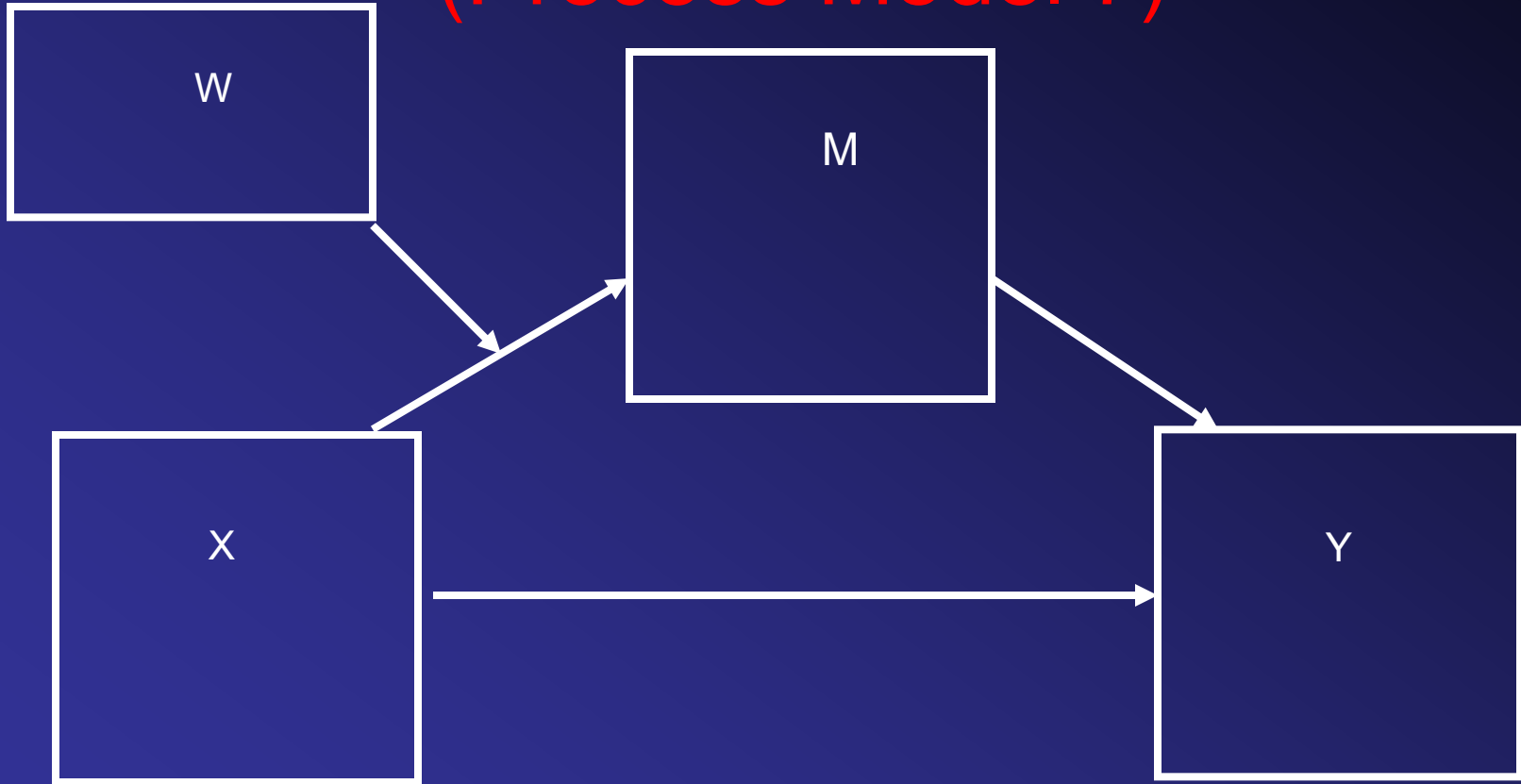
# Combining Mediation and Moderation

Indirect effects can be moderated. This implies that the indirect or mediated effect is itself contingent or conditional. This is also known as *moderated mediation* or a *conditional process*.

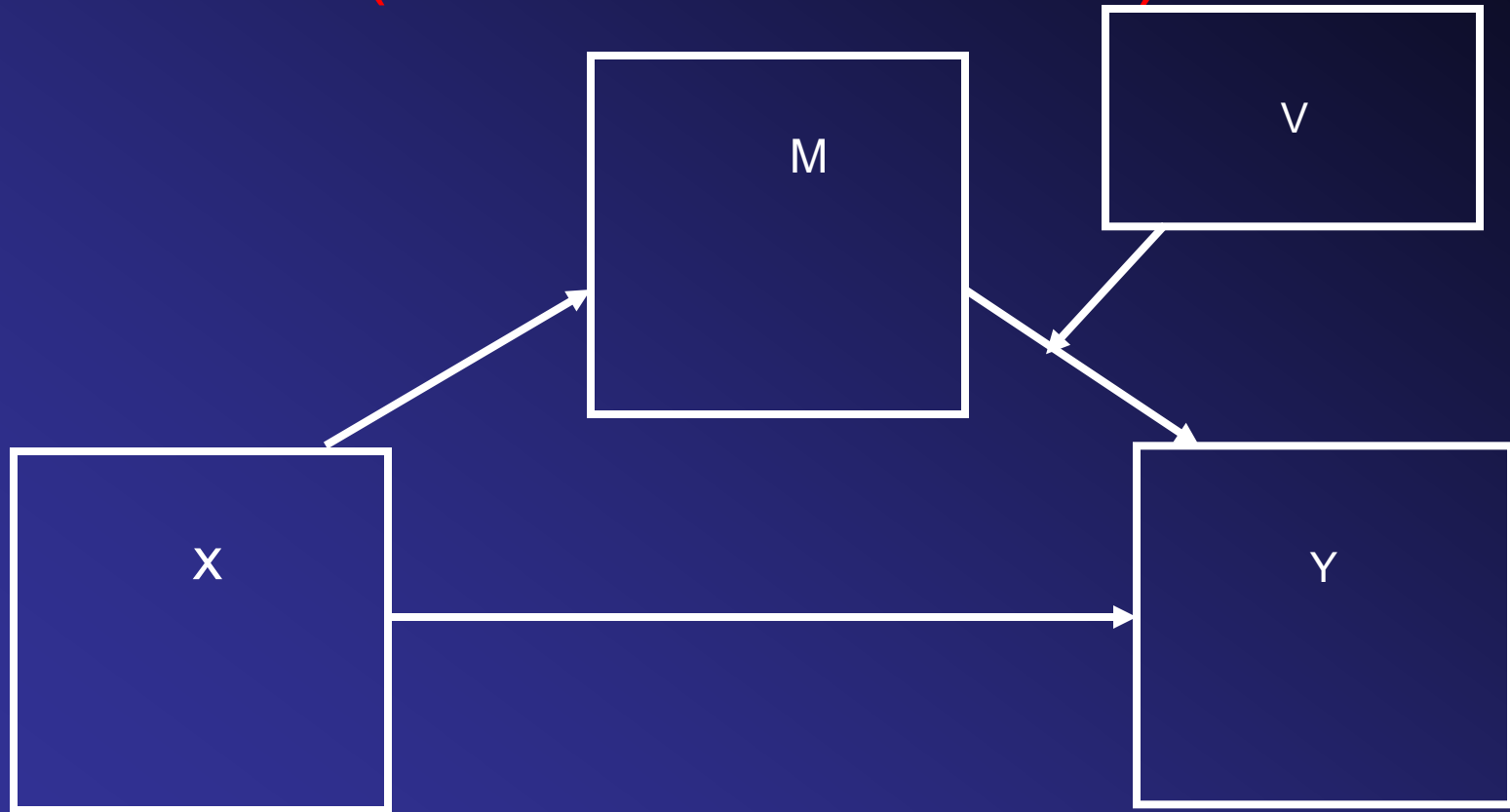
Following Preacher et al. (2007) there are many ways in which the magnitude of an indirect effect may be dependent upon one or more moderators. We will consider the following cases:

1. A fourth variable ( $W$ ) affects the  $a$  path. *First stage moderation*
2. A fourth variable ( $V$ ) affects the  $b$  path. *Second stage moderation*
3.  $W$  affects  $a$  whereas yet another variable ( $V$ ) affects  $b$ .
4.  $W$  affects both  $a$  and  $b$ .

# When the *a* Path is Moderated by *W* (Process Model 7)

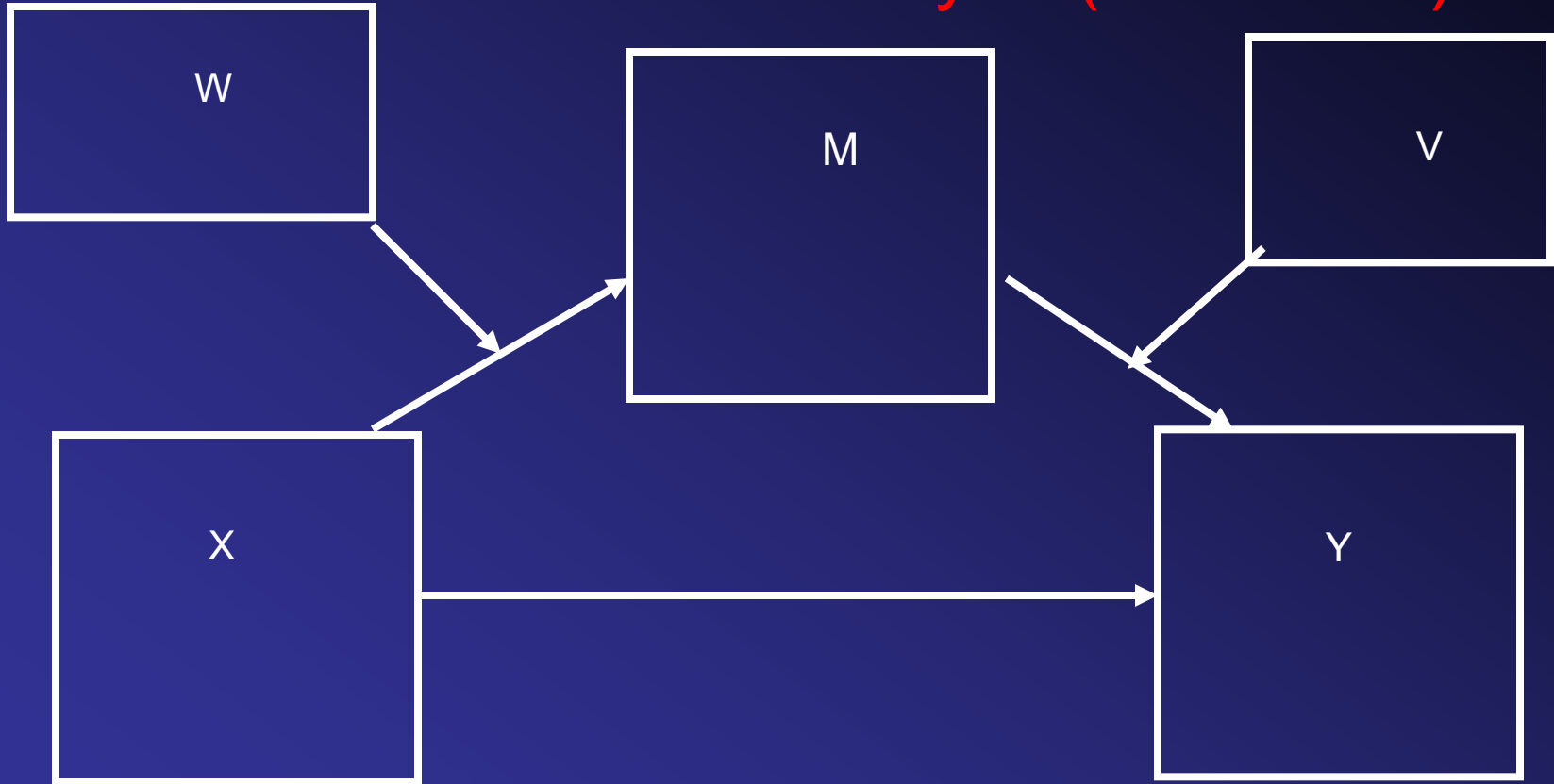


# When the *b* Path is Moderated by *V* (Process Model 14)

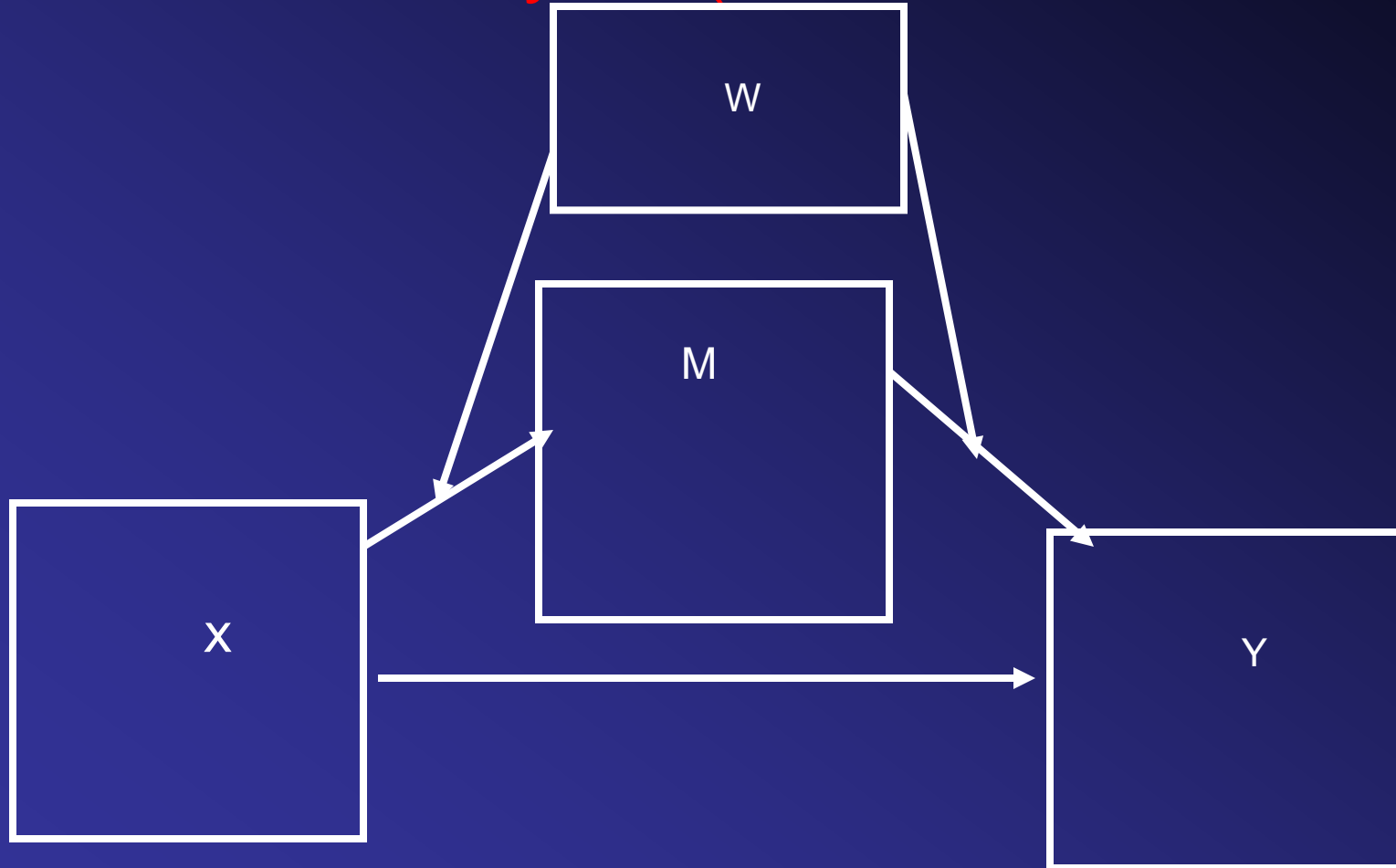




# When the *a* Path is Moderated by *W* and the *b* Path is Moderated by *V* (Model 21)



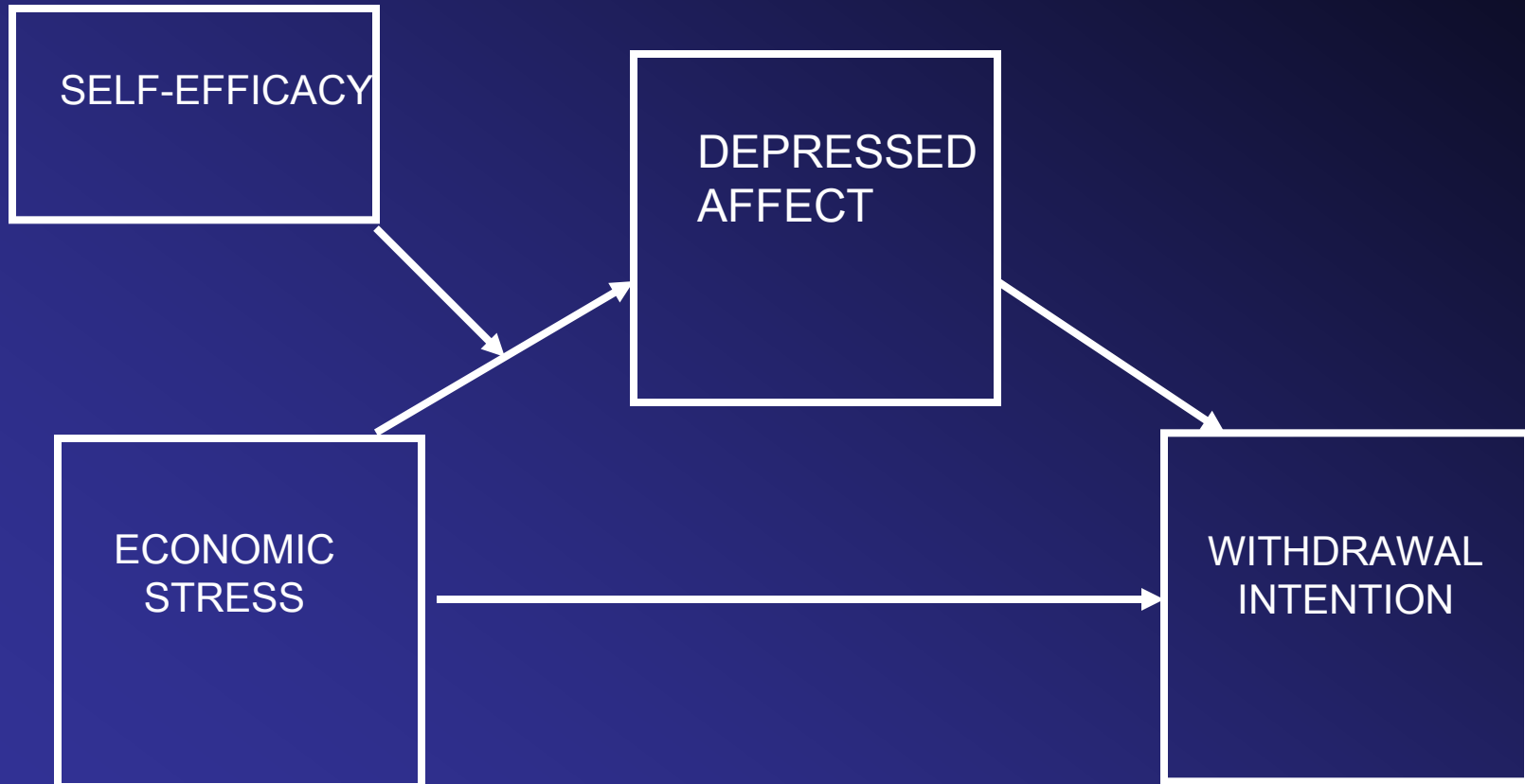
# When the *a* and *b* Paths Are Both Moderated by *W* (Process Model 58)



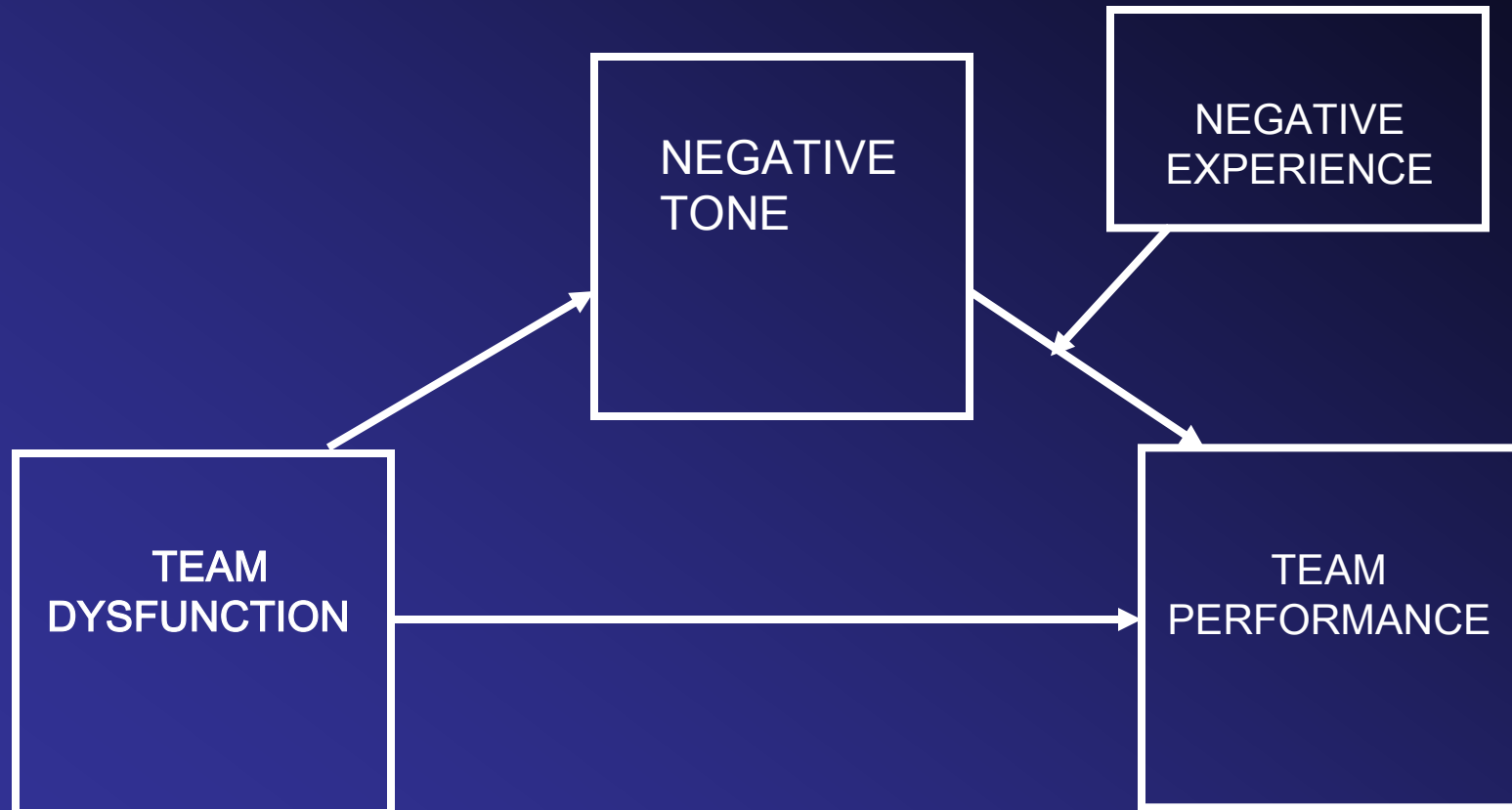
# Index of Moderated Mediation

- Hayes (2015) has developed an “Index of Moderation Mediation”. This index provides the most direct test for evidence of moderated mediation.
- This test is available for some moderated mediation models.
- Example. Recall from Model 7, the conditional indirect effect of X on Y through M is  $b(a_1 + a_3W)$ .
- The Index of Moderated Mediation for Model 7 is defined as:  $a_3bW$ . It quantifies the effect of W on the indirect effect of X on Y through M.
- The Index of Moderated Mediation can be tested for statistical significance using either parametric or non-parametric tests. Hayes (2015) recommends use of bias-corrected bootstrapping for statistical inference.

# Example: Path a Moderation



## Example 2: Path *b* Moderation



# Model Inferences

- **Correct specification.** Pay attention to including possible confounders of the relationships between  $X$  and  $Y$ . Statistical models are biased if not correctly specified. Control variables appear in the PROCESS macro as 'covariates'.
- **Multiple mediators.** Different theories may hypothesize alternative mechanisms or processes involving two or more mediators. PROCESS allows up to 10 mediators in parallel to be simultaneously tested and calculates *specific indirect effects for each mediator*. This is useful for comparing the effects of different mediators.
- **Causal inferences.** Be careful of making causal interpretations with cross-sectional data. Experimental manipulation or longitudinal data offers stronger causal inferences.

# PROCESS TIPS

- ***Missing data.*** PROCESS requires complete data. If missing data is an issue, it can be imputed prior to using the macro. Mplus offers further options for handling missing data.
- ***Dichotomous outcome variables.*** PROCESS automatically handles binary dependent variables by using logistic regression. More complex models with categorical mediators can be estimated using software such as Mplus.

# PROCESS TIPS

- ***Multiple independent variables.*** If you have multiple IVs, run PROCESS each time with one of the predictors as the focal IV and the others as covariates. PROCESS will control (partial out) the other IVs.
- ***Multiple moderating variables.*** If desired PROCESS can estimate three-way interactions (ie. two moderators of an IV).
- ***Multiple dependent variables.*** With multiple DVs, simply run PROCESS for each DV in turn.
- ***Categorical independent variables.*** The easiest approach is to dummy code the categorical IV. If your IV has  $k$  categories, construct  $k-1$  dummy variables and then run PROCESS using the approach outlined above. This is similar to an ANOVA.



# PROCESS TIPS

- **Standardized coefficients.** PROCESS coefficients are unstandardized. Variables may be Z-scored prior to the use of the macro to generate standardized (Beta) coefficients. However, in PROCESS bootstrap confidence intervals for the indirect effect should not be interpreted as properly standardized. See Preacher & Kelley (2011).

**Latent variables and multi-level models.** Moderated mediation models with latent variables require advanced software such as Mplus, which can also handle multi-level data structures. However, these require complex programming.

# References

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