Multiple Regression: Mediation and Conditional Process Analysis

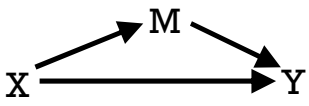
PSY 5102: Advanced Statistics for Psychological and Behavioral Research 2

Goals

- Introduce the idea of mediation
  - Assumptions
  - Additional variables
- Introduce the idea of conditional process analysis
  - Various forms of this analysis

What is Mediation?

- Mediation is a hypothesized causal chain in which one variable (X) affects a second variable (M) which, in turn, affects a third variable (Y)

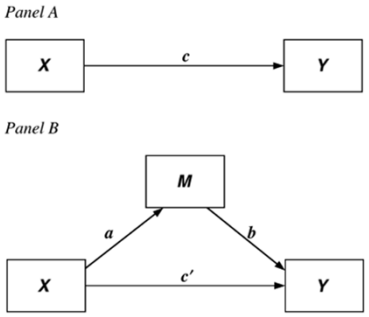


- M "mediates" the relationship between X and Y
- Mediation implies a **causal hypothesis** whereby an independent variable **causes** a mediator which, in turn, **causes** a dependent variable

Interest in Mediation

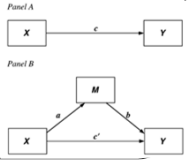
- Dramatic increase in mentions of "mediation" or "mediator" in psychology abstracts during the past few decades
- Why such interest in mediation?
  - Desire to understand the mechanisms or processes underlying behavior
    - Theoretical concerns
  - Find more proximal endpoints
  - Attempt to understand why an intervention did not work
    - Missing links
    - Compensatory processes

The Mediation Model



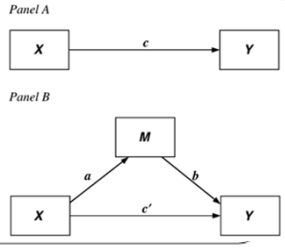
The Four Paths

- X → Y: Path *c*
- X → M: Path *a*
- M → Y (controlling for X): Path *b*
- X → Y (controlling for M): Path *c′*



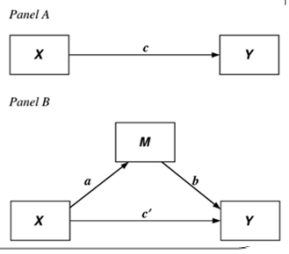
The Four Paths

- Path c (X → Y) is the **<u>total effect</u>** of X on Y



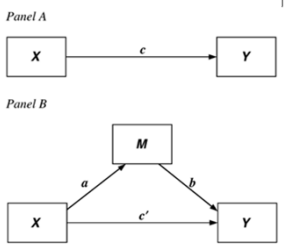
The Four Paths

- Path c' (X → Y) is the **<u>direct effect</u>** of X on Y controlling for M



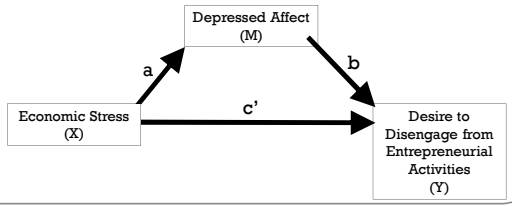
The Four Paths

- The product of Path a (X → M) and Path b (M → Y) is the **<u>indirect effect</u>** of X on Y through M (i.e., a*b)



Example

- Pollack et al. (2012) proposed that economic stress (X) leads to a desire to disengage from entrepreneurial activities (Y) as a result of depressed affect (M)

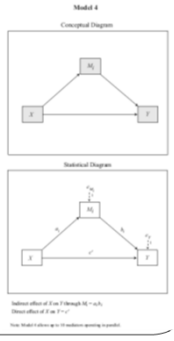


Examining Mediation Using Process

- PROCESS is a computational tool for path analysis-based moderation, mediation, and conditional process analysis (which is a combination of moderation and mediation)
- PROCESS can be downloaded from www.afhayes.com (it is free) and it can be used in conjunction with SPSS

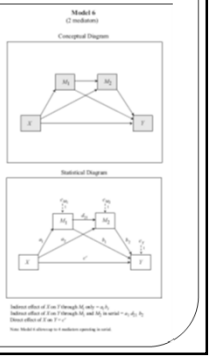
Models from PROCESS

- PROCESS is capable of running a wide variety of analyses (there are nearly 80 models in the current version of PROCESS)
- Model 4: Simple mediation



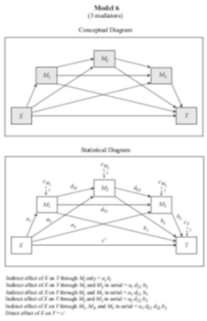
Models from PROCESS

- Model 6: Sequential mediation with two mediators



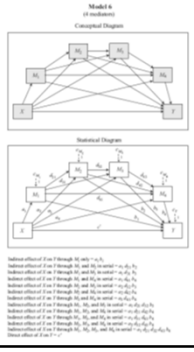
Models from PROCESS

- Model 6: Sequential mediation with three mediators



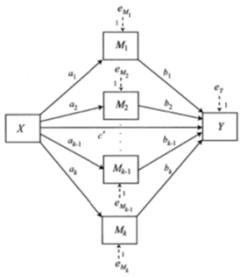
Models from PROCESS

- Model 6: Sequential mediation with four mediators



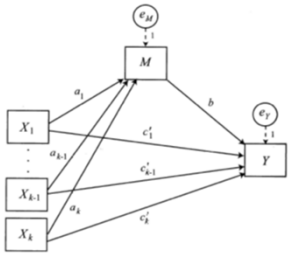
Models from PROCESS

- It is possible to run models involving multiple parallel mediators in PROCESS



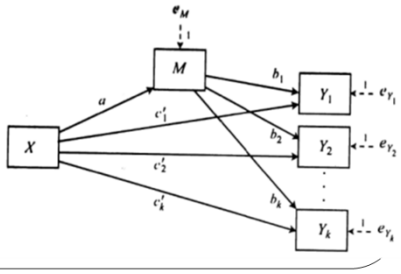
Models from PROCESS

- It is possible to run models involving multiple predictor (X) variables in PROCESS



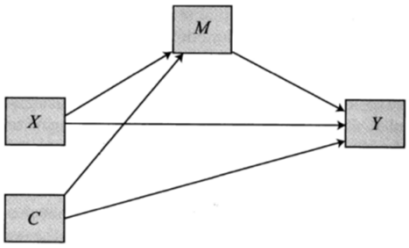
Models from PROCESS

- It is possible to run models involving multiple outcome (Y) variables in PROCESS



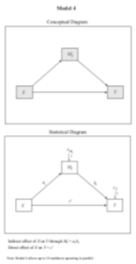
Models from PROCESS

- It is possible to run models that include one or more control (C) variables in PROCESS



Example

- We will start with a relatively simple example
- Model 4: Simple mediation
- Example: economic stress (X) leads to a desire to disengage from entrepreneurial activities (Y) as a result of depressed affect (M)



```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
```

Example

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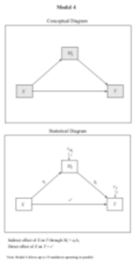
This part of the syntax activates PROCESS



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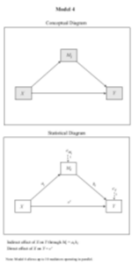

This part of the syntax is the list of the variables that will be included in this analysis

```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
```

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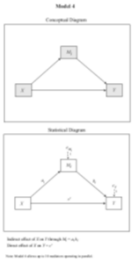

This part of the syntax identifies the outcome variable (Y)

```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
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Example

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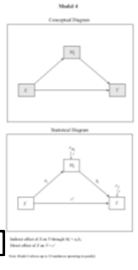

This part of the syntax identifies the predictor variable (X)

```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
```

Example

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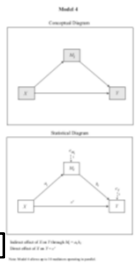

This part of the syntax identifies the mediator variable (M)

```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
```

Example

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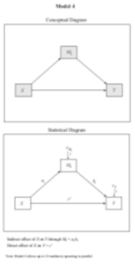

This part of the syntax requests that PROCESS generate the total effect of X on Y

```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
```

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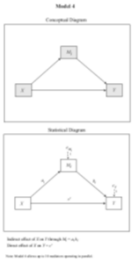

This part of the syntax requests that PROCESS generate 10,000 bootstrap samples

```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
```

Example

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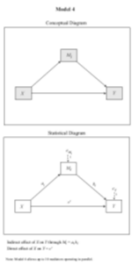

This part of the syntax requests that PROCESS generate the normal theory-based Sobel test for the indirect effect

```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
```

Example

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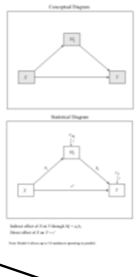
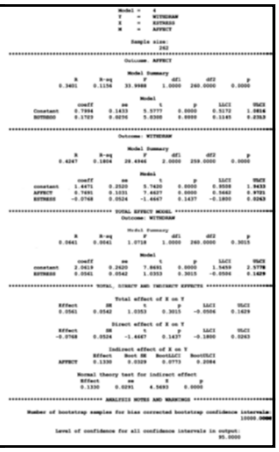


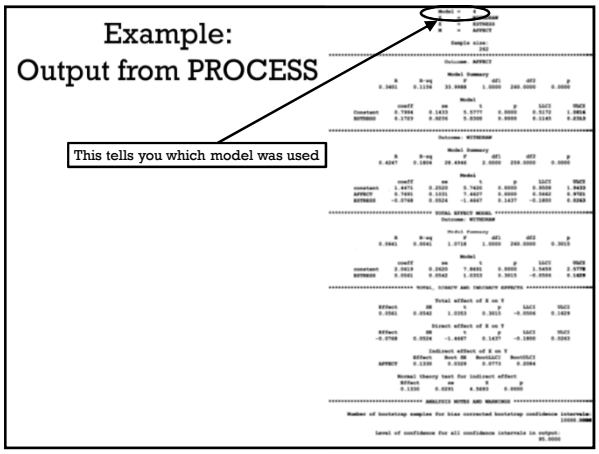
This part of the syntax tells PROCESS to run Model 4

```
process vars=estress affect withdraw/y=withdraw/x=estress/m=affect/total=1/boot=10000/normal=1/model=4
```

Example: Output from PROCESS

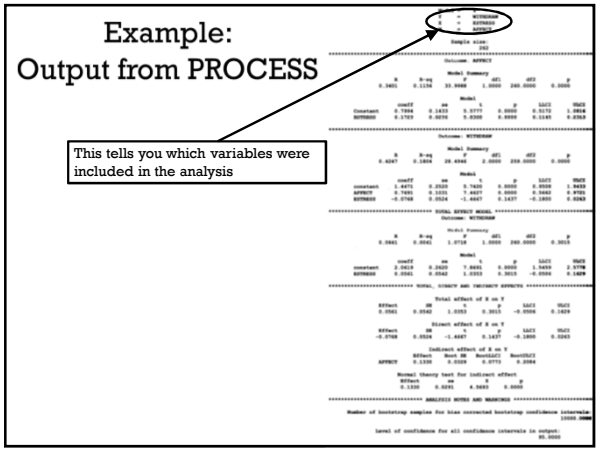


Example: Output from PROCESS



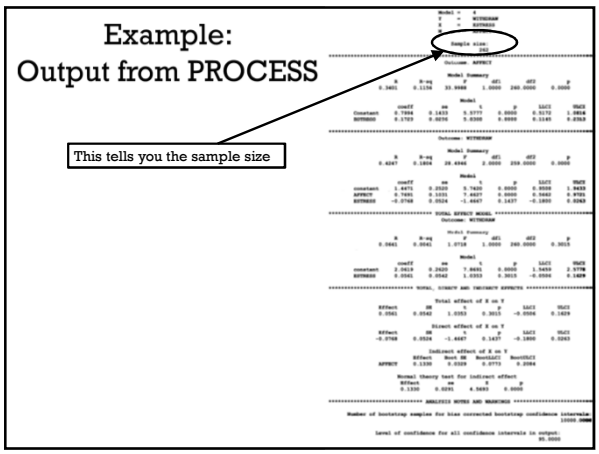
This tells you which model was used

Example: Output from PROCESS



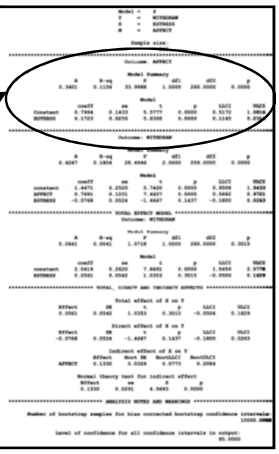
This tells you which variables were included in the analysis

Example: Output from PROCESS



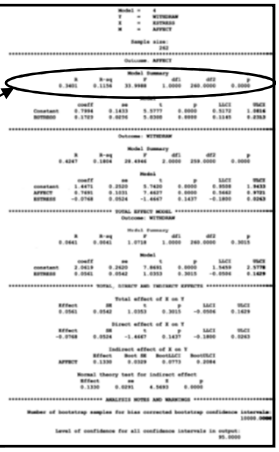
This tells you the sample size

Example: Output from PROCESS



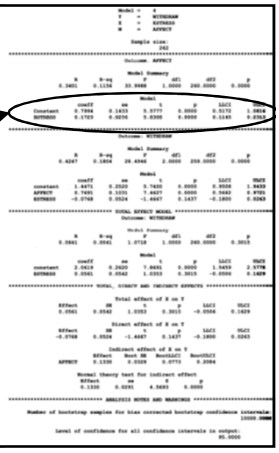
This tells you about Path a (X → M).

Example: Output from PROCESS



R^2 for AFFECT (M) represents the amount of variance in AFFECT (M) that is explained by ESTRESS (X). To express this value as a percentage, you should multiply this value by 100.

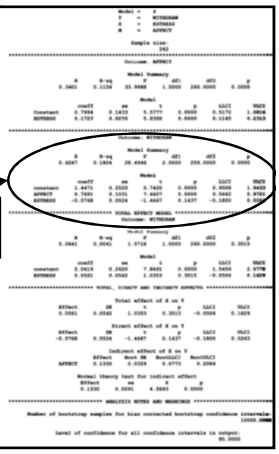
Example: Output from PROCESS



Constant is the Y-intercept for this model.

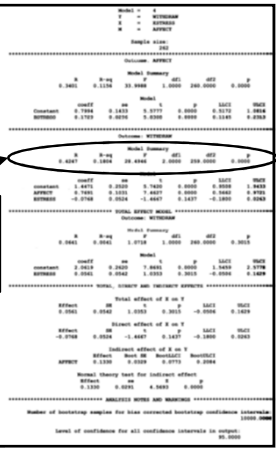
The row for ESTRESS represents the association between ESTRESS (X) and AFFECT (M). The coefficient is .1729 with a t-value of 5.8308 and a p-value of 0.0000 which means that ESTRESS (X) has a significant positive association with AFFECT (M).

Example: Output from PROCESS



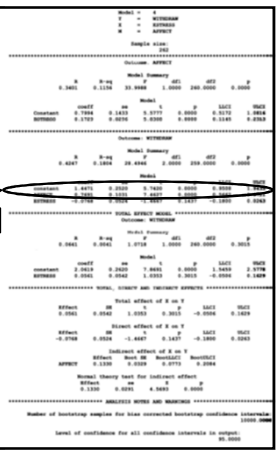
This tells you about Path c' (X → Y when M is included in the model) and Path b (M → Y) which both involve WITHDRAW (Y).

Example: Output from PROCESS



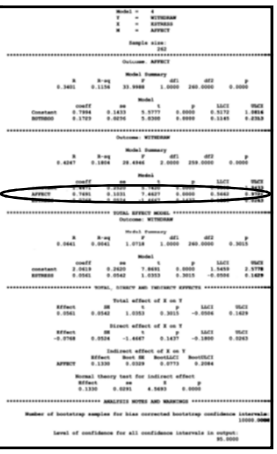
R^2 for WITHDRAW (Y) represents the amount of variance in WITHDRAW (Y) that is explained by ESTRESS (X) and AFFECT (M). To express this value as a percentage, you should multiply this value by 100.

Example: Output from PROCESS



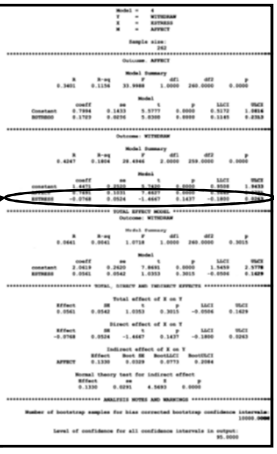
Constant is the Y-intercept for this model.

Example: Output from PROCESS



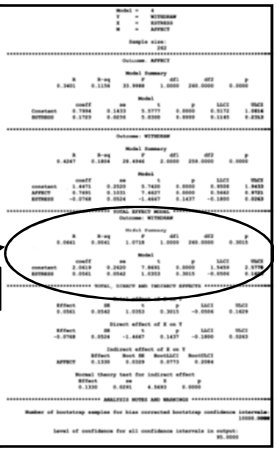
The row for AFFECT represents the association between AFFECT (M) and WITHDRAW (Y). The coefficient is .7691 with a t-value of 7.4627 and a p-value of 0.0000 which means that AFFECT (M) has a significant positive association with WITHDRAW (Y).

Example: Output from PROCESS



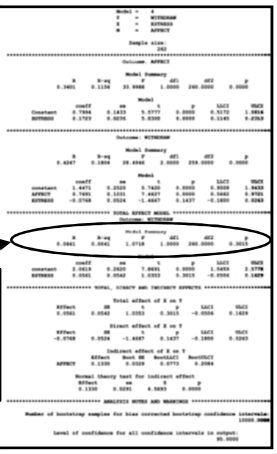
The row for ESTRESS represents the association between ESTRESS (X) and WITHDRAW (Y). The coefficient is -0.0768 with a t-value of -1.4667 and a p-value of 0.1437 which means that ESTRESS (X) does not have a significant association with WITHDRAW (Y) when AFFECT (M) is included in the model.

Example: Output from PROCESS



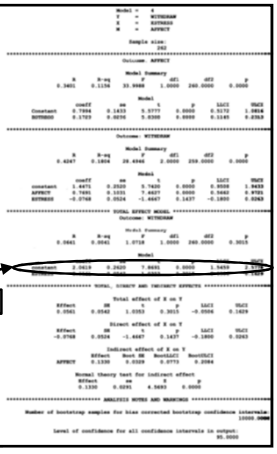
This tells you about Path c (X → Y when M is not included in the model).

Example: Output from PROCESS



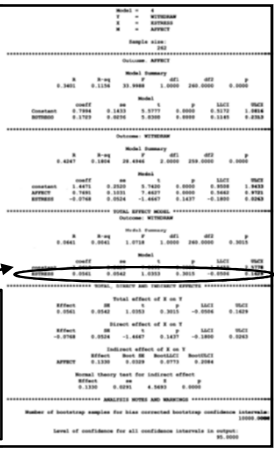
R^2 for the TOTAL EFFECT MODEL represents the amount of variance in WITHDRAW (Y) that is explained by ESTRESS (X) when AFFECT (M) is not included in the model. To express this value as a percentage, you should multiply this value by 100.

Example: Output from PROCESS



Constant is the Y-intercept for this model.

Example: Output from PROCESS



The row for ESTRESS represents the association between ESTRESS (X) and WITHDRAW (Y). The coefficient is 0.0561 with a t-value of 1.0353 and a p-value of 0.3015 which means that ESTRESS (X) does not have a significant association with WITHDRAW (Y) even when AFFECT (M) is NOT included in the model.

Example: Output from PROCESS

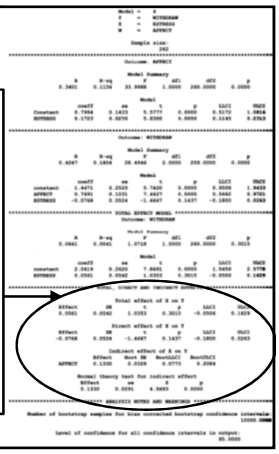
This provides a summary of the TOTAL EFFECT of X on Y (c), the DIRECT EFFECT of X on Y (c'), and the INDIRECT EFFECT of X on Y (a*b).

TOTAL EFFECT
Path c (X → Y without M in model) = .0561

DIRECT EFFECT
Path c' (X → Y with M in model) = -.0768

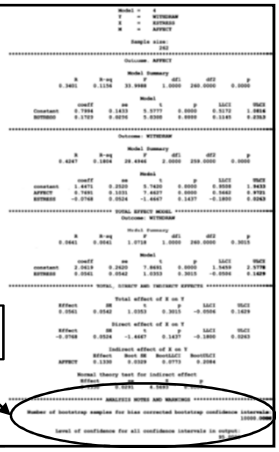
INDIRECT EFFECT
Path a (X → M) = .1729
Path b (M → Y) = .7691
Path a*b = (.1729)(.7691) = .1330

The INDIRECT EFFECT is significant because it has a 95% confidence interval that does not contain 0 (BootLLCI = .0773, Boot ULCI = .2084) which is consistent with the normal theory-based Sobel test (Z = 4.5693, p = .0000).



Example: Output from PROCESS

This tells you that PROCESS used 10,000 bootstrap samples to estimate the 95% confident intervals for the indirect effect of X on Y.



Reporting the Results of a Mediational Analysis

- From a simple mediation analysis conducted using ordinary least squares path analysis, economic stress indirectly influenced the desire to disengage from entrepreneurial activities through its association with depressive affect. Participants who reported higher levels of economic stress reported higher levels of depressive affect ($a = 0.17$, $p < .001$) and participants who experienced higher levels of depressive affect also reported a greater desire to disengage from entrepreneurial activities ($b = .77$, $p < .001$). A bootstrap confidence interval for the indirect effect ($ab = .13$) based on 10,000 bootstrap samples was entirely above zero (.08 to .21) which indicates that depressive affect mediated the association between economic stress and the desire to disengage from entrepreneurial activities ($Z = 4.57$, $p < .001$). There was no evidence that economic stress was associated with the desire to disengage from entrepreneurial activities independent of its association with depressive affect ($c' = .06$, $p = .30$).

Bootstrap Confidence Interval

- PROCESS uses a bootstrapping approach to estimate the confidence interval for the indirect effect
- Steps for constructing the bootstrap confidence interval
  1. Take a random sample of *n* cases from the original sample (sampled with replacement) where *n* is the size of the original sample. This is called a bootstrap sample.
  2. Estimate the indirect effect (a*b) in this bootstrap sample.
  3. Repeat Steps 1 and 2 a total of k times (k is usually a large number such as 10,000) saving the value of a*b for each bootstrap sample.
  4. Sort the k indirect effects (a*b) from each bootstrap sample from low to high.
  5. Find the lower bound and upper bound of the 95% confidence interval.
  6. If the 95% confidence interval does not contain 0, then the indirect effect is significant (i.e., mediation is supported).

Previous Approaches to Mediation

- The most popular approach to mediation in the past was **the causal steps approach** which is also referred to as **the Baron and Kenny approach**
- Problems with the Baron and Kenny approach…

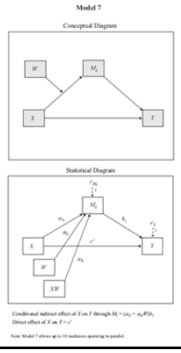
1. It does not formally quantify the indirect effect nor does it require an inferential test about the indirect effect.
2. The ability to claim that M is a mediator depends of rejecting three null hypotheses (Path c, Path a, and Path b) which makes it a relatively low power approach for detecting indirect effects.
3. The failure to find a significant Path c (X → Y) is a stopping point (i.e., this approach argues that it is impossible to mediate an association that is not significant) but this logic if flawed. There are many situations in which mediation may occur even when the total effect (X → Y) appears to be 0. For example, if there are two mediators where the association through one mediator is positive and the association through the other mediator is negative, then it may lead to a situation where the total effect is 0.
4. This approach does not quantify the indirect effect so it encourages researchers to think about indirect effects in qualitative terms (e.g., no mediation, partial mediation, full mediation).

Conditional Process Analysis

- Conditional process analysis is used when the analytical goal is to describe and understand the conditional nature of the mechanism (or mechanisms) by which a variable transmits its effect on another
  - This is a blend of **moderation** ("conditional nature") and **mediation** ("the mechanism [or mechanisms] by which a variable transmits its effect on another")
  - This has been referred to by labels such as **moderated mediation** and **mediated moderation**
- The mechanism linking X to Y can be said to be conditional if the indirect effect of X on Y through M is contingent on a moderator

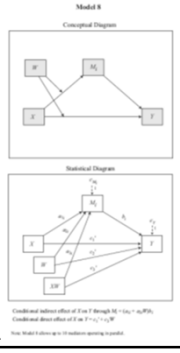
Models from PROCESS

- PROCESS is capable of running a wide variety of conditional process analyses
- Model 7: Moderator of X → M



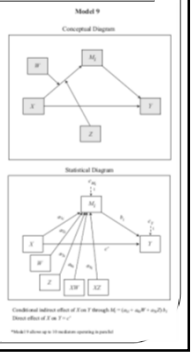
Models from PROCESS

- Model 8: Moderator of X → M and X → Y



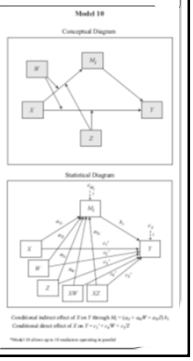
Models from PROCESS

- Model 9: Two moderators of X → M



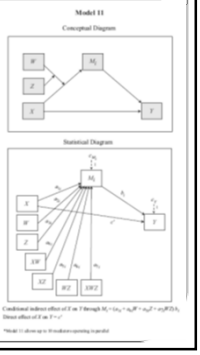
Models from PROCESS

- Model 10: Two moderators of X → M and X → Y



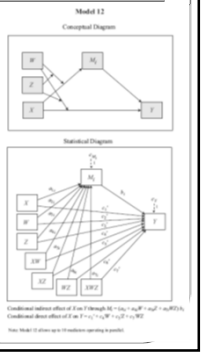
Models from PROCESS

- Model 11: Two moderators of X → M that include the three-way interaction (X*W*Z)



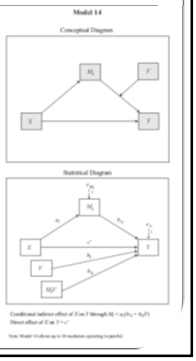
Models from PROCESS

- Model 12: Two moderators of X → M and X → Y that include the three-way interactions (X*W*Z)



Models from PROCESS

- Model 14: Moderators of M → Y

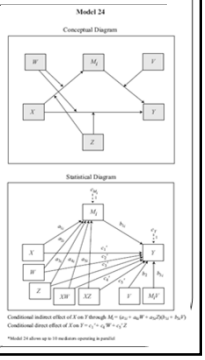


Models from PROCESS

- Model 17: Two moderators of M → Y and X → Y

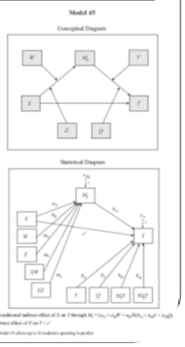
Models from PROCESS

- Model 24: Two moderators of X → M and X → Y and a third moderator of M → Y



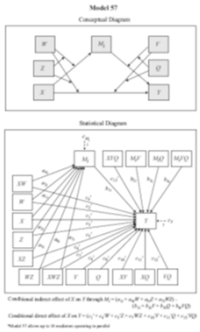
Models from PROCESS

- Model 45: Two moderators of X → M and two moderators of M → Y



Models from PROCESS

- Model 57: Two moderators of X → M and X → Y that include the three-way interactions (X*W*Z) and two moderators of M → Y and X → Y that include the three-way interactions (X*V*Q)



Models from PROCESS

- Model 59: A moderator of X → M, M → Y, and X → Y