

# Computationally Efficient Power and Sample Size Determination for Mediation Models

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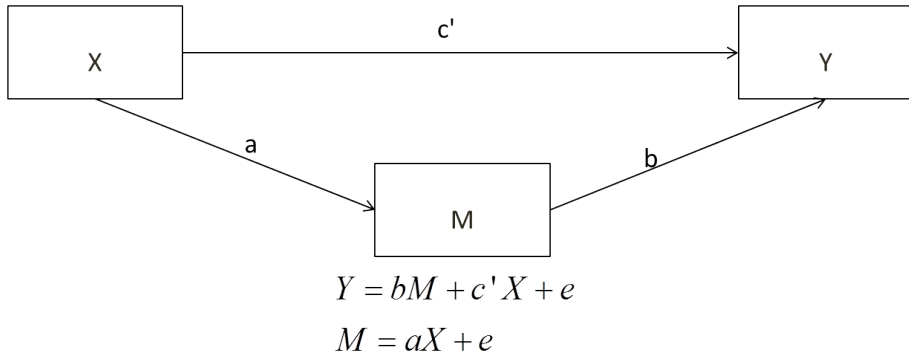
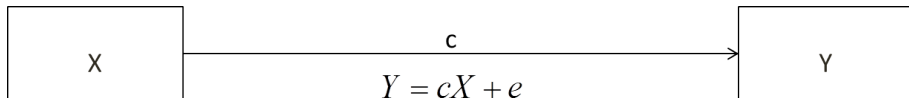
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- Power in Mediation Models
- Monte Carlo Power Analysis
  - Monte Carlo CI for inference
  - Varying N power analysis
  - GUI for computations

# Basic Mediation



# Testing the indirect effect: Power

- Methods of testing the indirect effect have different power for the same data (e.g. Fritz & MacKinnon, 2007, MacKinnon, Lockwood, & Williams, 2004)
  - Difference in coefficients method has extremely low power (especially when  $c$  is small)
  - Distribution of the product, bootstrap CI and Monte Carlo CI have higher power
    - Power for these methods is generally comparable

# Testing the indirect effect: Power

- What else affects power to detect an indirect effect?
  - Sample size
  - Effect size
    - Effect size of both the a and b path

# Determining power for an indirect effect

- Methods of power analysis should match methods of analysis
- No analytic method of power analysis for distribution of the product, bootstrap CI or Monte Carlo CI!
- We need to use a Monte Carlo power analysis

# Monte Carlo Power Analysis

- General steps in a Monte Carlo Power Analysis
  - 1 Specify all population parameters
  - 2 Create a sample of size  $N$ , based on population parameters
  - 3 Analyze sample data from Step 2 with chosen statistical method(s)
  - 4 Repeat steps 2 and 3 for each of  $r$  replications (often  $r > 1000$ )
  - 5 The proportion of replications with a significant parameter is an estimate of power (for all parameters not equal to 0)

# Monte Carlo Power Analysis

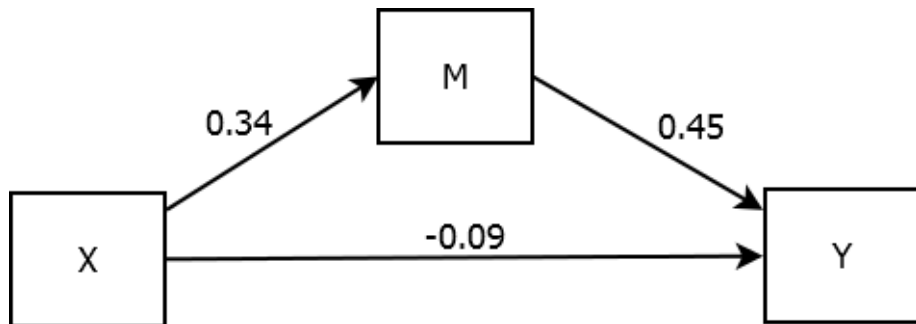
- Best practice approach for assessing power in mediation models (Zhang, 2014)
  - Can utilize any method of testing the indirect effect
- Two main limitations to Monte Carlo Power Analysis for mediation models
  - Limited, user friendly software (e.g. Mplus, bmem, simsem)
  - Very time consuming (especially with bootstrapping!)



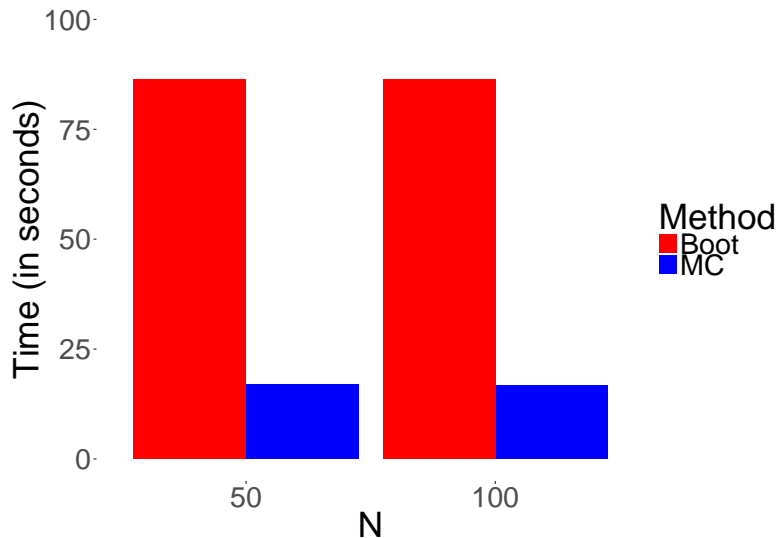
- Overcoming limitations
  - Use Monte Carlo CI to test indirect effects
    - Faster than bootstrapping
    - Estimates of power are similar or slightly higher than bootstrapping (Tofighi & MacKinnon, 2016)
    - Simulation study comparing power analyses. Run 500 power analyses using Monte Carlo CI and Bootstrapped CI for each sample size
    - Sample sizes range from 10 to 200 (in increments of 10)
    - Compare time to completion and estimated power for each method

# Monte Carlo Power Analysis

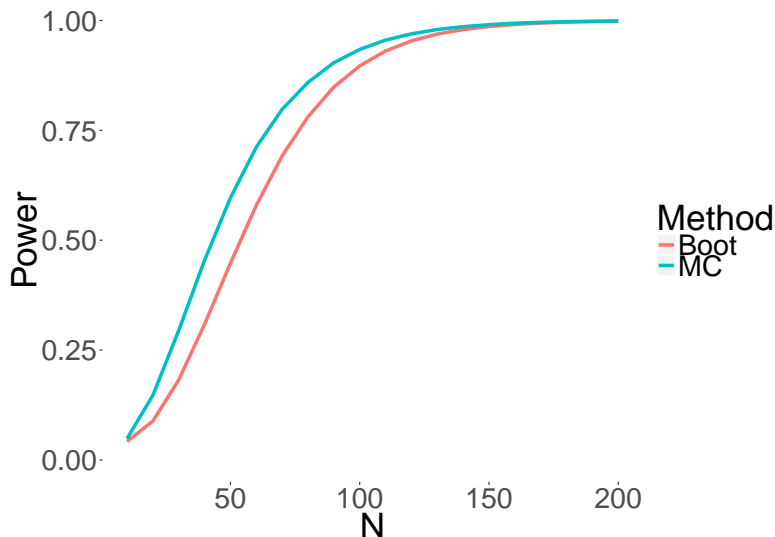
- Example (from Hayes, 2013):



# Monte Carlo Power Analysis



# Monte Carlo Power Analysis



- Overcoming limitations
  - Use Monte Carlo CI to test indirect effects
    - Faster than bootstrapping
    - Estimates of power are extremely similar
  - Use varying N for sample size determination (Schoemann, Miller, Pornprasertmanit, & Wu, 2014)

# Monte Carlo Power Analysis: Varying N

- Determine range of samples sizes of interest
- Vary sample size across replications within a single simulation
  - Example: N ranges from 100 to 500 within a simulation with 10 replications at each sample size (4000 total replications)
- Analyze results with logistic regression
  - Regress significance of a parameter on N
  - From this model the predicted probability for a given sample size is the estimate of power.

# Monte Carlo Power Analysis: Varying N

- Example (from Hayes, 2013):
  - Run power analysis varying N between 15 and 300
    - ~ 1000 total replications (1144 actual replications)
    - Predicted probability for a given N:

$$p = \frac{e^{-2.211+0.053N}}{1 + e^{-2.211+0.053N}}$$

# Monte Carlo Power Analysis: Varying N

- Example (from Hayes, 2013):
  - Target N for power of .80 is 68 with estimated power of 0.801
  - Run power analysis (again) with  $N = 68$  and 1000 replications
  - Estimated power is 0.78



- Overcoming limitations
  - Use Monte Carlo CI to test indirect effects
    - Faster than bootstrapping
    - Estimates of power are extremely similar
  - Use varying N for sample size determination
  - Create user friendly software
    - Shiny app for simple mediation models

# Power estimation app

- Available from MARlab.org (soon!)
- Web based or run locally on your computer
  - Requires R is installed on a computer (it helps if RStudio is too)
- Population parameters are entered as correlations

# Power estimation app

## Monte Carlo Power Analysis for Indirect Effects

Written by Alexander M. Schoemann ( [Contact](#) ), Aaron J. Boulton, & Stephen D. Short

Model One Mediator

Objective Set Power, Vary N

Target Power

Minimum N

Maximum N

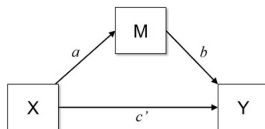
Sample Size Steps

# of Replications

MCMC Draws per Rep

Random Seed

Confidence Level (%)



Input Method Correlation Matrix

	X	M	Y
X	<input type="text" value="1"/>	<input type="text" value="0.4"/>	<input type="text" value="0.1"/>
M	<input type="text" value="0.4"/>	<input type="text" value="1"/>	<input type="text" value="0.3"/>
Y	<input type="text" value="0.1"/>	<input type="text" value="0.3"/>	<input type="text" value="1"/>

### Instructions

To use this app, follow these steps:

- 1. Select Model.** The user should first select the mediation model containing the indirect effect(s) of interest. Models may be selected in the drop-down menu in the left-most column of the app. Note that when a different mediation model is selected, the model graphic and input-value sections in the middle column will be altered.
- 2. Select Objective.** Once the desired model is

### Calculate Power

Parameter	N	LL_pow	pow	UL_pow
ab	50.00	0.42	0.49	0.55
ab	75.00	0.61	0.66	0.70
ab	100.00	0.76	0.80	0.82
ab	125.00	0.86	0.89	0.91

- Best practice recommendations for varying N power analysis
  - Number of recommendations, distribution of N, optimal meta-model
- Extend methods and Shiny app to complex data and mediation models
  - Multiple mediators, longitudinal mediation, moderated mediation
  - Missing data, non-normal data, nested data

# Thank you!

- Slides and Shiny app (soon!) from today at:  
[http://MARlab.org/Supplemental\\_Materials/](http://MARlab.org/Supplemental_Materials/)
- email: [schoemanna@ecu.edu](mailto:schoemanna@ecu.edu)

- Fritz, M. S., & MacKinnon, D. P. (2007). Required Sample Size to Detect the Mediated Effect. *Psychological Science*, 18, 233-239.
- Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Press. Chicago
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