Determining Power and Sample size for Mediation Models

Alexander M. Schoemann ¹ Aaron J. Boulton ²

¹East Carolina University

²University of North Carolina - Chapel Hill

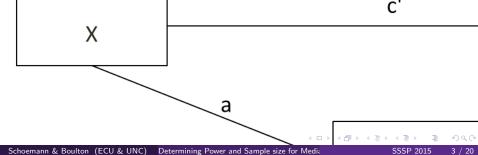
SSSP 2015

Basic Mediation

- Three variable system
 - Predictor variable X
 - Outcome variable Y
 - Mediator variable M
- M (partially) explains the relationship between X and Y

Mediation Vocabulary

Y = cX + e



How do we get estimates of a, b, and c?

- We get estimates of the slopes through a series of separate regression models:
 - Y = cX + e
 - Y = bM + c'X + e
 - M = aX + e

what do that paths tell us about mediation?

- When investigating mediation we are interested in if strength of the relationship between X and Y is reduced when M is included in the regression equation
 - Is the direct effect (c') less than the total effect (c)?
 - Does c c' = 0?
- c c' is also called the indirect effect
- The indirect effect can also be estimated by multiplying a*b
- a*b and c c' should provide the same value

Testing the indirect effect

- When we test for mediation we test if the indirect effect is different from zero.
 - If the indirect effect does not differ from zero there is no evidence of mediation
 - If the indirect effect differs from zero there is evidence of mediation

Testing the indirect effect

- There have been many methods developed to assess the indirect effect:
 - Difference in coefficients (Baron & Kenny, 1984)
 - Sobel test
 - Distribution of the product method
 - Bootstrap confidence intervals
 - Monte Carlo confidence intervals

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

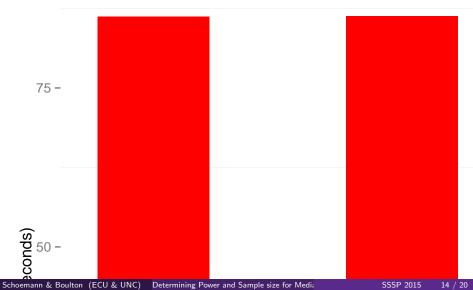
Determing power for an indirect effect

- 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

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

- Best practice approach for assessing power in mediation models (Zhang, 2014)
 - Can utilize bootstrapping, distribution of the product method, or Monte Carlo CI
- 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 boostrapping!)

- Overcoming limitations
 - Use Monte Carlo CI to test indirect effects
 - Faster than bootstrapping
 - Estimates of power are extremely similar (r = .99)



- Overcoming limitations
 - Use Monte Carlo CI to test indirect effects
 - Faster than bootstrapping
 - Estimates of power are extremely similar (r = .99)
 - Create user friendly software
 - Shiny app for simple mediation models

Power estimation app

- Available from MARlab.org
- Web based or run locally on your computer
 - Requires R is installed on a computer (it helps if RStudio is too)
- ullet Population parameters can be entered as correlations or r^2 for each path

Power estimation app

shinyapps.io

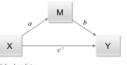




Monte Carlo Power Analysis for Indirect Effects

Written by Aaron Boulton & Alexander M. Schoemann





- X: focal predictor M: mediator Y: outcome
- a: effect of focal predictor on mediator
- b: effect of mediator on outcome, controlling for focal c': effect of focal predictor on mediator, controlling for
- mediator
- Indirect Effect (IE): $a \times b$ Total Effect(TE): $e' + a \times b$

0.6	
correla	tion between X and Y
0.2	
Correla	tion between M and Y
0.6	
Variano	e of X variable
1	
Variano	e of M variable
1	
	e of Y variable

Future directions

- Expansion of models available in app
 - 2 and 3 mediator models
 - Conditional process models
- Integration of other methods of sample size determination
 - Accuracy in parameter estimation (Kelly & Maxwell, 2003)
 - Varying N Monte Carlo simulations (Schoemann, Pornprasermanit, Miller, & Wu, 2014)

Thank you!

- Questions?
- Slides and shiny app from today at: http://http://MARlab.org/Supplemental_Materials/
- email: schoemanna@ecu.edu

References

- Fritz, M. S., & MacKinnon, D. P. (2007). Required Sample Size to Detect the Mediated Effect. Psychological Science, 18, 233-239.
- Kelley K., & Maxwell S. E. (2003). Sample size for multiple regression: Obtaining regression coefficients that are accurate, not simply significant. *Psychological Methods* 8, 305-321.
- MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004).
 Confidence Limits for the Indirect Effect: Distribution of the Product and Resampling Methods. *Multivariate Behavioral Research*, 39, 99-128.
- Schoemann, A. M., Miller, P. R., Pornprasertmanit, S., & Wu, W. (2014). Using Monte Carlo simulations to determine power and sample size in planned missing data designs. *International Journal of Behavioral Development*, 38, 471-479.
- Zhang, Z. (2014). Monte Carlo based statistical power analysis for mediation models: Methods and software. Behavior Research Methods, 46, 1184-1198.