## Replicating Simulation Research: A Case Study

By: Tristan Tibbe

#### Overview

- RepliSims Project
- MacKinnon et al. (2004)
- Replication Process
- Factors that Hindered Replication
- Factors that Facilitated Replication
- Recommendations to Improve Replicability

### RepliSims Project

Published in Royal Society Open Science (Luijken et al., 2024)

8 teams of researchers

8 replicated studies

Criteria:

Published after 2000

Greater than 1000 citations



### MacKinnon et al. (2004)

Compared confidence intervals (CIs) for the indirect effect constructed using 9 methods:

z critical values

M critical values

Empirical M method

Jackknife

Percentile bootstrap

Bias-corrected bootstrap

Bootstrap-t

Boostrap-Q

Monte Carlo



#### NIH Public Access

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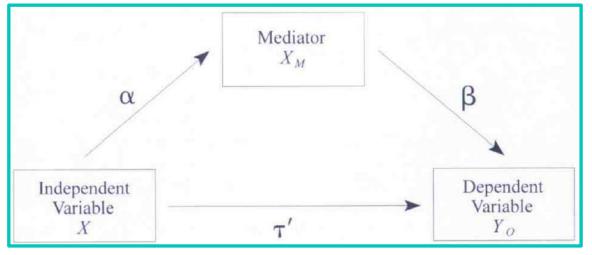
Multivariate Behav Res. Author manuscript; available in PMC 2010 February 12.

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Multivariate Behav Res. 2004 January 1; 39(1): 99. doi:10.1207/s15327906mbr3901\_4.

#### Confidence Limits for the Indirect Effect: Distribution of the Product and Resampling Methods

**David P. MacKinnon**, **Chondra M. Lockwood**, and **Jason Williams** Arizona State University



4

#### MacKinnon et al. (2004)

#### Outcomes:

Type I error rate/power

CI balance/width

#### Findings:

M critical values result in more balanced Cls than z critical values

In order of increasing type I error rate/power and decreasing CI width:

z critical values

Bootstrap-t
Monte Carlo

M critical values
Empirical M method
Bootstrap-Q

Bias-corrected
bootstrap

#### Replication Process

- 1.) Recreate data generating process
- 2.) Recreate methods
- 3.) Rerun simulation
- 4.) Compare results to original findings

#### 1.) Recreate Data Generating Process

with current time as the seed for each simulation. Five different sample sizes corresponding to sample sizes in the social sciences were simulated: 50, 100, 200, 500, and 1000. The

Manipulated Factors
Sample sizes
Effect sizes
Fixed Factors

demands of simulation studies of resampling methods. The ten combinations were 
$$\alpha = 0$$
  $\beta = 0$ ,  $\alpha = 0$   $\beta = .14$ ,  $\alpha = 0$   $\beta = .39$ ,  $\alpha = 0$   $\beta = .59$ ,  $\alpha = \beta = .14$ ,  $\alpha = \beta = .39$ ,  $\alpha = \beta = .59$ , and  $\alpha = .39$   $\beta = .59$ . These ten parameter combinations are the ones presented

simulations indicated no difference in power calculations as the direct effect ( $\tau'$ ) increased, so for simplicity the direct effect was always set equal to zero.

the statistical simulations. The data were simulated using Equations 2 and 3, with sample values of X,  $\varepsilon_2$ , and  $\varepsilon_3$  generated from a standard normal distribution using the SAS RANNOR function

#### 2.) Recreate Methods

$$s_{jackknife} = \sqrt{\frac{N-1}{N}} \sum_{i} [\theta_{(i)} - \theta_{(\cdot)}]^2$$
(8)

Equations

**Programs** 

Specific Settings

Confidence levels

in increments of .2. These additional values were obtained with a FORTRAN algorithm written by Alan Miller which is a minor modification of the method in Meeker and Escobar (1994)

standard error were used to compute confidence limits as described below. Confidence limits for the indirect effect were calculated for 80%, 90%, and 95% intervals. The proportion of

	No.lev-	
Study 2: Simulation factor	els	Levels
Varied		
Confidence interval method	9	$z \ method, M \ method, empirical\text{-}M \ method, jackknife, percentile$
		${\it bootstrap, bias-corrected\ bootstrap, bootstrap-} t, {\it bootstrap-} Q,$
		Monte Carlo method
Sample size	4	25, 50, 100, 200
$\alpha$ effect size	4	0, .14, .39, .59
$\beta$ effect size	4	0, .14, .39, .59
Confidence level	3	95%, 90%, 80%
Fixed		
Direct effect size		0
Intercepts		0
Randomly Sampled		
X values		sampledfromN(0,1)
Error terms		sampledfromN(0,1)

#### 3.) Rerun Simulation

**Simulation Description**—The SAS® (1989) programming language was used to conduct the statistical simulations. The data were simulated using Equations 2 and 3, with sample values

Software
Iterations
Seed Values

in the Tables for Study 1. Third, one thousand replications were conducted for each of the 40 combinations of sample size and parameters. Fourth, for each of the 40,000 (4 combinations

of X,  $\varepsilon_2$ , and  $\varepsilon_3$  generated from a standard normal distribution using the SAS RANNOR function with current time as the seed for each simulation. Five different sample sizes corresponding to

### 4.) Compare Results to Original Findings

Recreate tables/figures

Find metrics to compare results/identify differences

Bradley's (1978) Liberal Robustness Criterion (0.0125 – 0.0375)

Proportion of True Value to the Left and Right of 95% Confidence Intervals, study 2

Indirect Effect		Sample Size								
	Method	25		50		100		200		
		left	right	left	right	left	right	left	right	
Null Models	z	0.0020*	0.0028*	0.0055*	0.0043*	0.0090*	0.0083*	0.0098*	0.0078*	
	M	0.0103*	0.0140	0.0113*	0.0145	0.0180	0.0188	0.0183	0.0130	
	Empirical-M	0.0098*	0.0140	0.0128	0.0150	0.0188	0.0195	0.0188	0.0140	
	Jackknife	0.0033*	0.0033*	0.0053*	0.0063*	0.0080*	0.0083*	0.0103*	0.0090*	
	Bootstrap percentile	0.0090*	0.0113*	0.0140	0.0150	0.0188	0.0190	0.0195	0.0150	
	Bootstrap Bias-corrected	0.0245	0.0268	0.0255	0.0260	0.0293	0.0330	0.0275	0.0275	
	Bootstrap-t	0.0065*	0.0088*	0.0133	0.0105*	0.0160	0.0180	0.0178	0.0138	
	Bootstrap-Q	0.0075*	0.0103*	0.0125	0.0110*	0.0165	0.0183	0.0175	0.0135	
	Monte Carlo	0.0070*	0.0108*	0.0103*	0.0113*	0.0165	0.0153	0.0160	0.0110*	
Non-zero Models	z	0.0030*	0.0547*	0.0077*	0.0577*	0.0098*	0.0598*	0.0132	0.0480*	
	M	0.0120*	0.0502*	0.0200	0.0467*	0.0192	0.0492*	0.0198	0.0398*	
	Empirical- M	0.0118*	0.0408*	0.0192	0.0473*	0.0190	0.0487*	0.0190	0.0378*	
	Jackknife	0.0057*	0.0528*	0.0072*	0.0570*	0.0125	0.0582*	0.0135	0.0487*	
	Bootstrap percentile	0.0127	0.0438*	0.0187	0.0437*	0.0233	0.0413*	0.0222	0.0400*	
	Bootstrap Bias-corrected	0.0207	0.0553*	0.0268	0.0498*	0.0288	0.0430*	0.0273	0.0340	
	Bootstrap-t	0.0098*	0.0352	0.0177	0.0372	0.0202	0.0357	0.0223	0.0350	
	Bootstrap-Q	0.0185	0.0603*	0.0273	0.0470*	0.0297	0.0470*	0.0265	0.0365	
	Monte Carlo	0.0098*	0.0295	0.0172	0.0317	0.0168	0.0350	0.0182	0.0335	

			Sample Size								
	Method	25			50		100		200		
Indirect Effect		left	right	left	right	left	right	left	right		
Null Models	Z	0.0018*	0.0023*	0.0033*	0.0050*	0.0078*	0.0083*	0.0133	0.0108*		
	M	0.013	0.0128	0.0125	0.0158	0.016	0.0155	0.0193	0.0158		
	Jackknife	0.0048*	0.0045*	0.0043*	0.0035*	0.0085*	0.0085*	0.0120*	0.0108*		
	Bootstrap percentile	0.0113*	0.0088*	0.0125	0.0148	0.014	0.0143	0.0178	0.0163		
	Bootstrap Bias-										
	corrected	0.0195	0.0175	0.0243	0.0268	0.0235	0.0255	0.0245	0.023		
	Bootstrap-t	0.019	0.0198	0.022	0.024	0.0233	0.0255	0.0263	0.0228		
	Bootstrap-Q	0.019	0.0198	0.022	0.024	0.0233	0.0255	0.0263	0.0228		
	Monte Carlo	0.0095*	0.0090*	0.0095*	0.0128	0.0135	0.0145	0.019	0.0138		
Non-zero											
Models	Z	0.0058*	0.0595*	0.0077*	0.0552*	0.0103*	0.0553*	0.0103*	0.0483*		
	M	0.0142	0.0575*	0.0152	0.0482*	0.0173	0.0487*	0.0173	0.0363		
	Jackknife	0.0093*	0.0605*	0.0093*	0.0550*	0.0117*	0.0577*	0.0108*	0.0487*		
	Bootstrap percentile	0.0142	0.0375	0.0158	0.0397*	0.0187	0.0362	0.0173	0.0338		
	Bootstrap Bias-										
	corrected	0.0228	0.0468*	0.0235	0.0428*	0.0243	0.0378*	0.0228	0.0277		
	Bootstrap-t	0.025	0.1012*	0.022	0.0818*	0.0242	0.0667*	0.0233	0.0435*		
	Bootstrap-Q	0.025	0.1012*	0.022	0.0818*	0.0242	0.0667*	0.0233	0.0435*		
	Monte Carlo	0.0117*	0.0308	0.0128	0.0333	0.0167	0.0313	0.0167	0.0312		

#### Findings:

M critical values result in more balanced Cls than z critical values

In order of increasing type I error rate/power and decreasing CI width:

z critical values

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Bias-corrected

bootstrap

#### Findings:

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In order of increasing type I error rate/power and decreasing CI width:

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Percentile bootstrap
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Monte Carlo

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Monte Carlo

#### Findings:

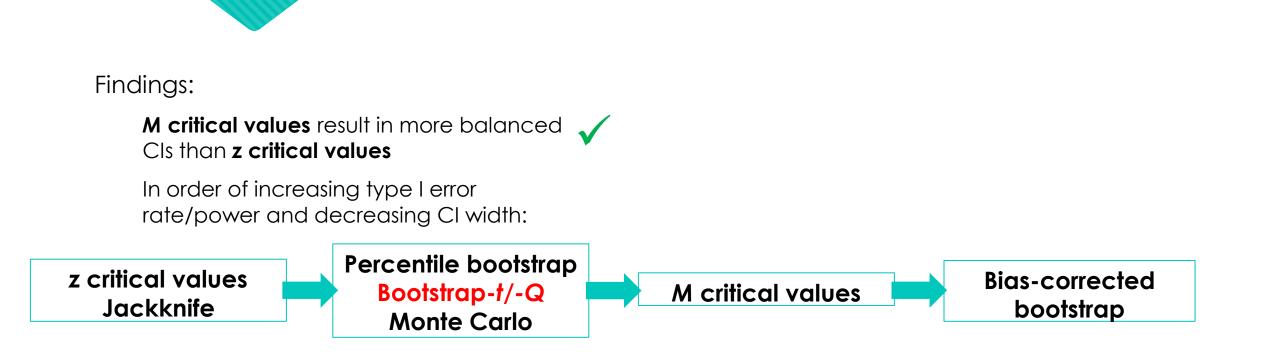
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Bootstrap-t
Monte Carlo

M critical values
Bootstrap-Q

Bias-corrected bootstrap



#### Factors that Hindered Replication

<sup>2</sup>The empirical-*M* critical values are given at our website given in Footnote 1.

Broken/Outdated Links

**Unclear Information** 

Methods Implementation

**Error Handling** 

**Paywalls** 

Equations 6 and 7 were used to calculate the *M* confidence limits. The upper and lower critical values were obtained from the table in Meeker et al. (1981) for percentiles of .025 and .975.

**Bootstrap-Q:** The bootstrap-Q is a transformation of the bootstrap-t that makes the distribution more closely follow the t distribution (Manly, 1997). The bootstrap-Q is obtained by transforming the bootstrap-t using Equation 9 shown below where t is skewness in each bootstrap distribution of t, t is the bootstrap-t value in each individual bootstrap sample, and t is the sample size (Manly, 1997).

$$Q(T) = T + (sT^2)/3 + (s^2T^3)/27 + s/(6N)$$
(9)

#### Factors that Facilitated Replication

Explicitly stated simulation conditions

Provided equations or instructions for many methods used

Simulation Description—The simulation procedure in Study 1 was used in Study 2 with four exceptions: sample size, parameter combinations, number of replications, and resampling methods. First, only four sample sizes were simulated: 25, 50, 100, and 200. Because resampling methods are particularly useful when sample sizes are small, the two largest sample sizes from Study 1 were dropped and a sample size of 25 was added. Second, a subset of the combinations of parameter values were simulated to reduce the considerable computational demands of simulation studies of resampling methods. The ten combinations were  $\alpha = 0$   $\beta = 0$  $0, \alpha = 0 \beta = .14, \alpha = 0 \beta = .39, \alpha = 0 \beta = .59, \alpha = \beta = .14, \alpha = \beta = .39, \alpha = \beta = .59, \alpha = .14 \beta = .$ 39.  $\alpha = .14 \beta = .59$ , and  $\alpha = .39 \beta = .59$ . These ten parameter combinations are the ones presented in the Tables for Study 1. Third, one thousand replications were conducted for each of the 40 combinations of sample size and parameters. Fourth, for each of the 40,000 (4 combinations of sample size times 10 parameter value combinations times 1000 replications) different data sets, six resampling methods were applied. For the bootstrap methods, a total of 1000 resampled data sets from each of the 40,000 data sets were used. That is, each bootstrap method entailed 1,000,000 (1000 replications times 1000 bootstrap samples) data sets for each of the 40 combinations of sample size and parameter values. For the jackknife method, the number of samples was the same as the sample size (N), Each of the resampling methods are described in more detail in the next section.

# Recommendations to Improve Replicability

Be Specific/Explicit About:

Data generation

Method implementation

Error handling

Results

Use supplemental material if necessary

Use Permanent Links:

Upload materials/code to repository (e.g., OSF)

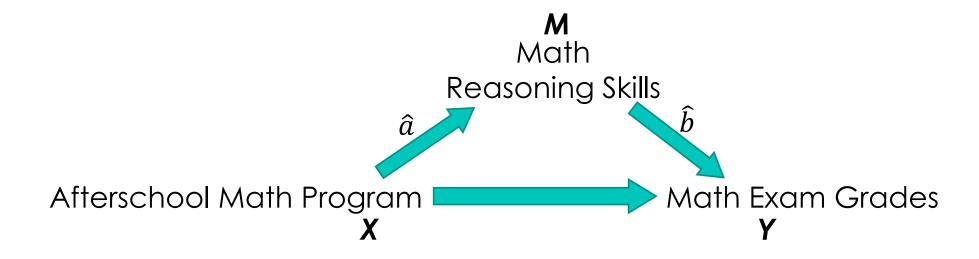
### Questions?

#### References

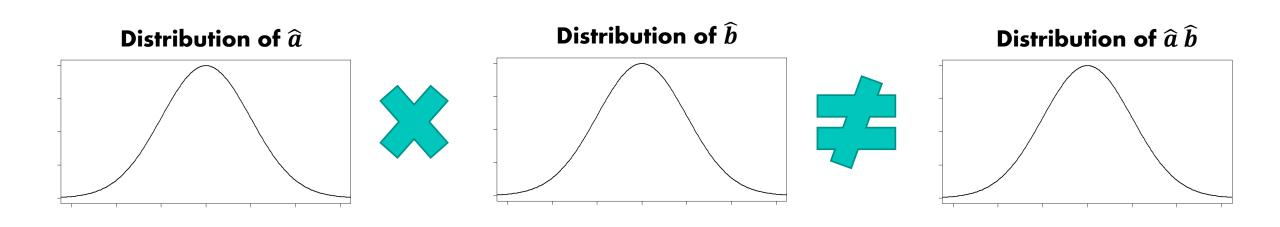
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#### **Mediation Analysis**



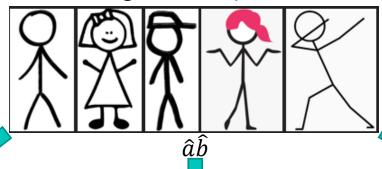


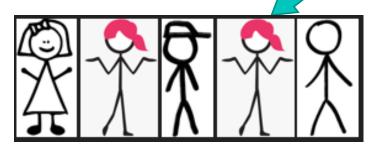
### Indirect Effect in Mediation Analysis



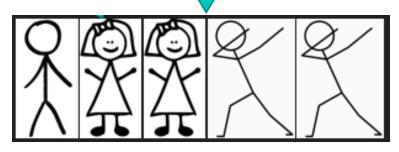
How to test indirect effect for statistical significance?

#### Original Sample

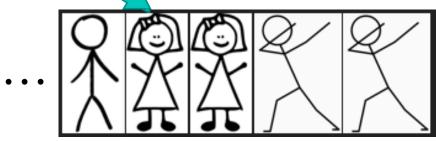




Bootstrap Sample 1  $\hat{a}\hat{b}_1^*$ 



Bootstrap Sample 2  $\hat{a}\hat{b}_2^*$ 



Bootstrap Sample B  $\hat{a}\hat{b}_{B}^{*}$ 



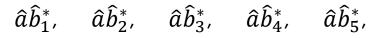








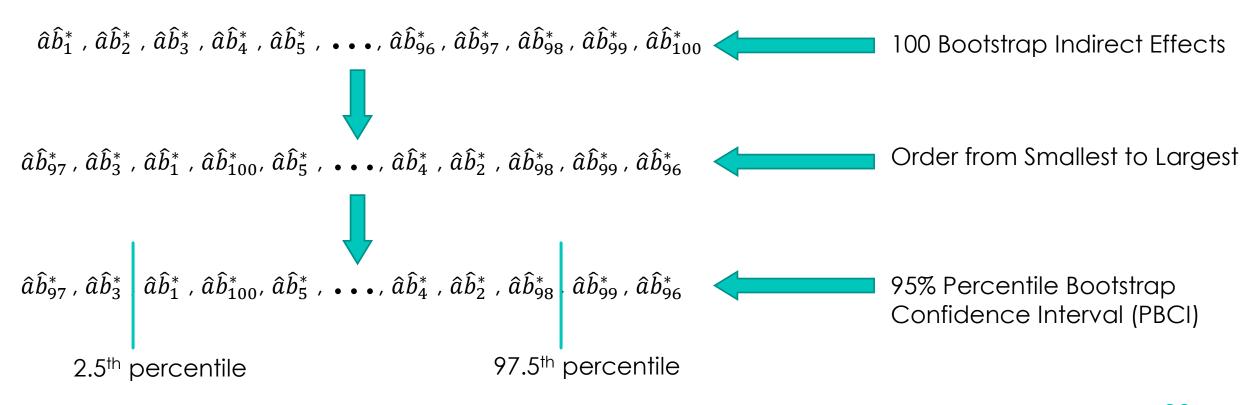


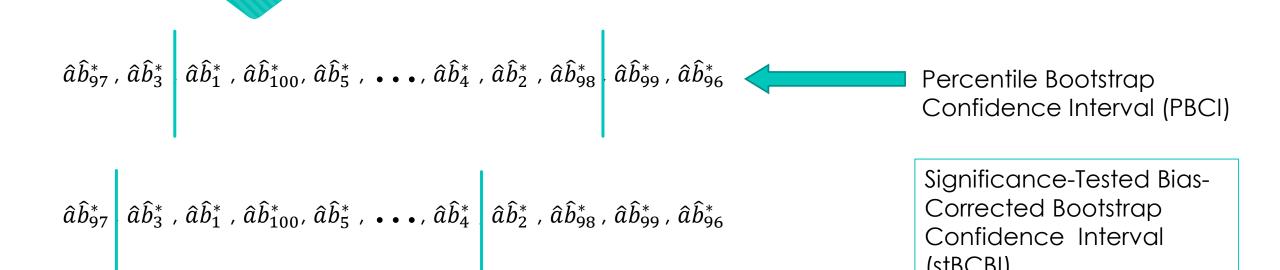




$$\hat{a}\hat{b}_{97}^{*}$$
,

$$\hat{a}\hat{b}_{98}^*$$
,  $\hat{a}\hat{b}_{99}^*$ ,





Bias-Corrected Bootstrap Confidence Interval (BCBI)

30% Winsorized Bias-Corrected Bootstrap Confidence Interval (WBCBI)

Reduced Bias-Corrected Bootstrap Confidence Interval (rBCBI)

(Efron & Tibshirani, 1993) (Chen & Fritz, 2021) (Stine, 1989) 30 (Tibbe & Montoya, 2022)

Confidence Interval

(stBCBI)