Estimation of Indirect Effects in Structural Equation Models Under Violation of Model Assumptions

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Abbreviated abstract: The indirect effect of an exposure on an outcome of interest through a mediator can be estimated in several ways within the context of structural equation models (SEM) considering some standard assumptions, which includes multivariate normality and independence. In this work, the usual approaches for the point and interval estimation of indirect effects in SEM are presented.

Related publications:

Cheung et al (2008) Testing mediation and suppression effects of latent variables: Bootstrapping with structural equation models. *Organizational research methods.* 11: 296-325.

Finch *et al* (1997) Effects of sample size and nonnormality on the estimation of mediated effects in latent variable models, *Structural Equation Modeling: A Multidisciplinary Journal* ,4: 87-107.

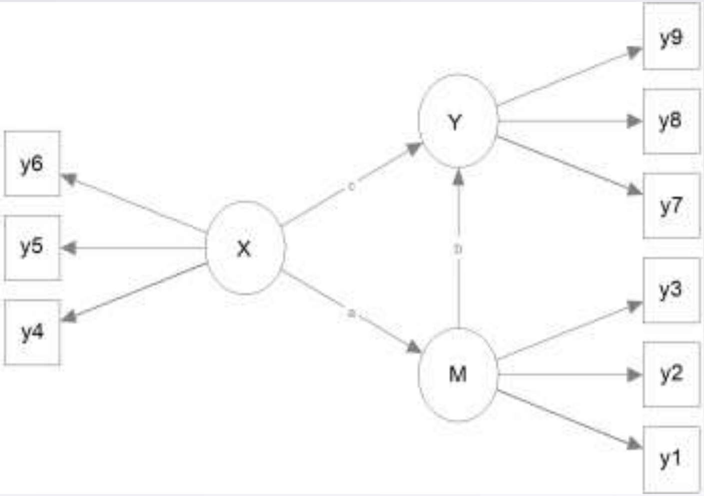
Rosseel Y. (2012) lavaan: An R package for structural equation modeling, *Journal of statistical software.* 48:1-36.

Introduction

- The indirect/mediated effect of an exposure on an outcome is usually estimated within the context of structural equation models (SEM) considering standard assumptions, including (Finch et al, 1997):
  - multivariate normality
  - independence.

- Limited literature about the estimation of indirect effects in SEM under violation of model assumptions (Cheung et al, 2008)

- Goal: to assess, via simulation studies, the robustness of SEM to deviations from these assumptions.



Methods

Setups

Data Generation (package: *simsem*)

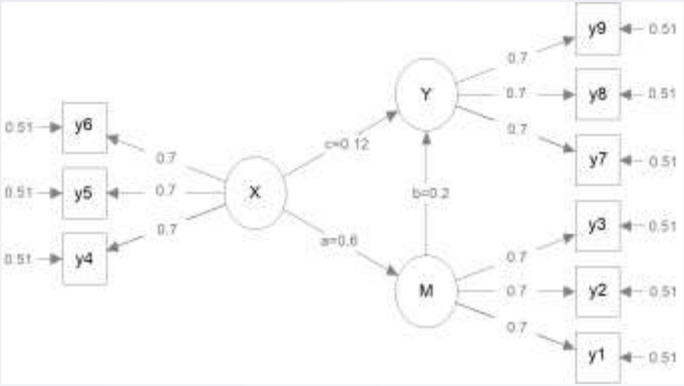
- **Factor loadings**= 0,7
- **Mediated Effect** = 0,12
- **Residual correlation**= 0,51
- **Variance**: fixed at 1

Configurations

- **Monte Carlo**: 2,000 simulations
- **Sample size**: 100, 200, 500 and 1,000
- **Normality**: symmetry, moderate skewness, severe skewness.

Estimation (package: *lavaan*)

- **Estimator**: ML
- **Standard error estimation procedures**
  - Inverse of information matrix,
  - Huber-White robust se,
  - Bootstrap methods: basic, percentile, normal approximation, and bias-corrected approach (Rosseel, 2012).



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Results and Conclusions

- Main conclusions:
    - Underestimation of standard errors for mediation effect using inverse of information matrix, specially for smaller sample sizes.
    - Bootstrap methods provide improved results (higher CPs)
- Future work: extension of simulations to further evaluate the performance of methods for estimation of the indirect effects in SEM :
    - Varying the number of indicators and factor loadings,
    - Including violation of Independence.

Table 1: Estimation of mediated effects using different methods in SEM (True value: 0,12).

Method	Symmetry			Moderate Asymmetry		Severe Asymmetry	
	n=100	n=200	n=500	n=200	n=500	n=200	n=500
$\hat{a}\hat{b}$	0,1244	0,1165	0,1118	0,1143	0,1150	0,1235	0,1133
$\sqrt{\mathrm{Var}(\hat{a}\hat{b})}$	0,1593	0,0979	0,0664	0,1201	0,0792	0,1410	0,0820
$RB\%(\hat{a}\hat{b})$	3,66	-2,94	-6,87	-4,73	-4,14	2,90	-5,59
$\lvert AB(\hat{a}\hat{b})\rvert$	0,11	0,08	0,05	0,09	0,06	0,10	0,06
RMSE	0,16	0,10	0,07	0,12	0,08	0,14	0,08
Huber-White robust							
$s_{\hat{a}\hat{b}}$	0,1439	0,0896	0,0538	0,1053	0,0613	0,1266	0,0675
$CP\%\ (s_{\hat{a}\hat{b}})$	94,9	92,8	87,6	90,5	88,8	90,9	86,5
Inverse of information matrix							
$s_{\hat{a}\hat{b}}$	0,1316	0,0843	0,0509	0,0890	0,0525	0,0957	0,0530
$CP\%\ (s_{\hat{a}\hat{b}})$	93,8	92,1	86,9	86,6	82,6	85,6	79,5
Bootstrap conventional							
$s_{\hat{a}\hat{b}\ basic}$	0,2877	0,1061	0,0563	0,1418	0,0657	0,2263	0,0781
$CP\%\ (s_{\hat{a}\hat{b}\ basic})$	98,2	96,5	90,4	94,4	91,4	96,0	89,6
$s_{\hat{a}\hat{b}\ percentile}$	0,2877	0,1061	0,0563	0,1418	0,0657	0,2263	0,0781
$CP\%\ (s_{\hat{a}\hat{b}\ percentile})$	95,9	93,6	88,6	91,9	89,0	94,6	88,7
$s_{\hat{a}\hat{b}\ normal}$	0,2877	0,1061	0,0563	0,1418	0,0657	0,2263	0,0781
$CP\%\left(s_{\hat{a}\hat{b}\ normal}\right)$	98,4	96,0	89,6	93,7	91,0	96,5	89,2
$s_{\hat{a}\hat{b}\ bias}$	0,2877	0,1061	0,0563	0,1418	0,0657	0,2263	0,0781
$CP\%\ (s_{\hat{a}\hat{b}\ bias})$	93,5	92,8	88,2	91,3	89,0	92,3	87,6

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