The Effect of Model Size on the Root Mean Square Error of Approximation (RMSEA): The Nonnormal Case

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INTRODUCTION

Ideally, the values of RMSEA would only reflect the "effect size" of model misspecification. However, in addition to the level of model misfit, RMSEA can be influenced by other characteristics of the model (*Saris et al., 2009*). The size of the fitted model (*P*) is one important factor to consider when estimating and interpreting the RMSEA (*Shi et al., 2019*). Previous studies have shed light on understanding the effect of *P* on RMSEA under nonnormal cases; the BSL method provided the most accurate RMSEA estimates and CIs (*BSL, Brosseau-Liard et al., 2012; Gao et al., 20*20). However, there are also some limitations.

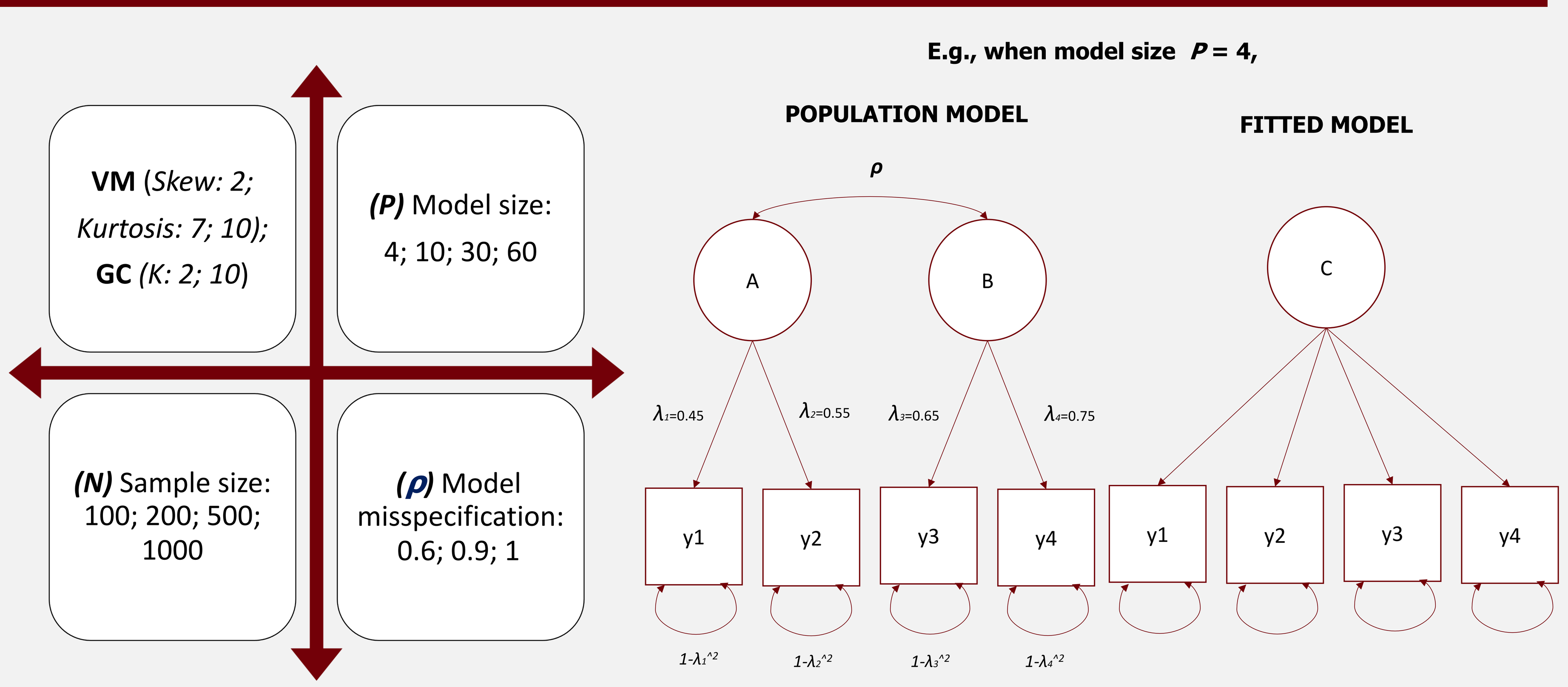
(1) The *P* conditions manipulated are somewhat restricted.

(2) The newest method (Lai, 2020) for estimating RMSEA under nonnormal data was proposed and evaluated in the context of latent growth models only.

(3) Only a singular nonnormal data generation algorithm was considered.

To fill these gaps, we investigate the effect of *P* on RMSEA by conducting a more comprehensive simulation study that not only compares the performance of different methods (*i.e., BSL, Lai, and Normal theory [NT] method*) in estimating point RMSEA and CIs under a variety of simulation conditions, but also considers the impact of nonnormal data generation (*i.e., VM and Gumbel Copula [GC]*)

METHODS (240 CONDITIONS)



CONCLUSION

Results indicated that the normal theory RMSEA should not be used under nonnormal data unless the model size is very small. In the presence of nonnormal data, researchers should consider using either the BSL or the Lai method to estimate RMSEA and its CIs. **The Lai method is recommended when very large models are fit under nonnormal data.**

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Saris, W. E., et al. (2009). Testing structural equation models or detection of misspecifications? *Structural equation modeling*, 16(4), 561-582.

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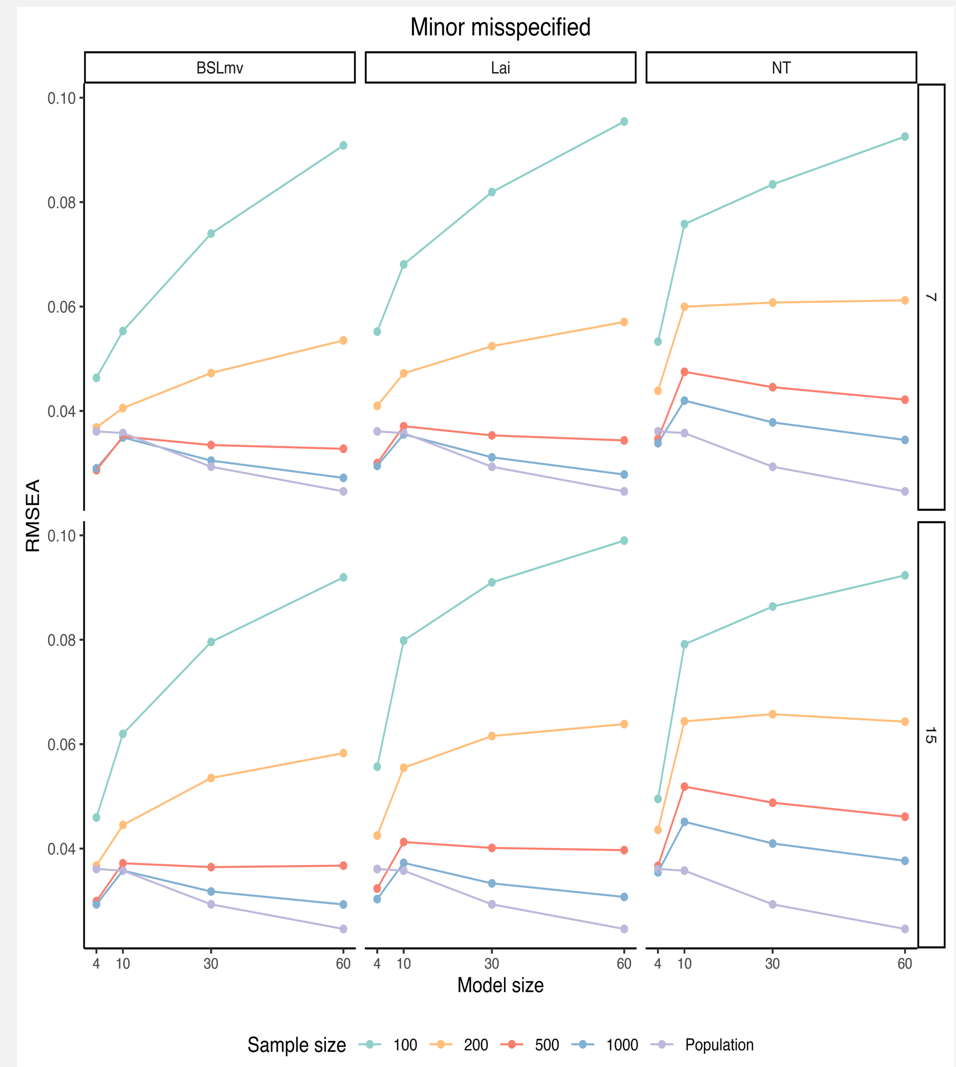
RESULTS (1) Average of sample RMSEA estimated across replications (*VM*)

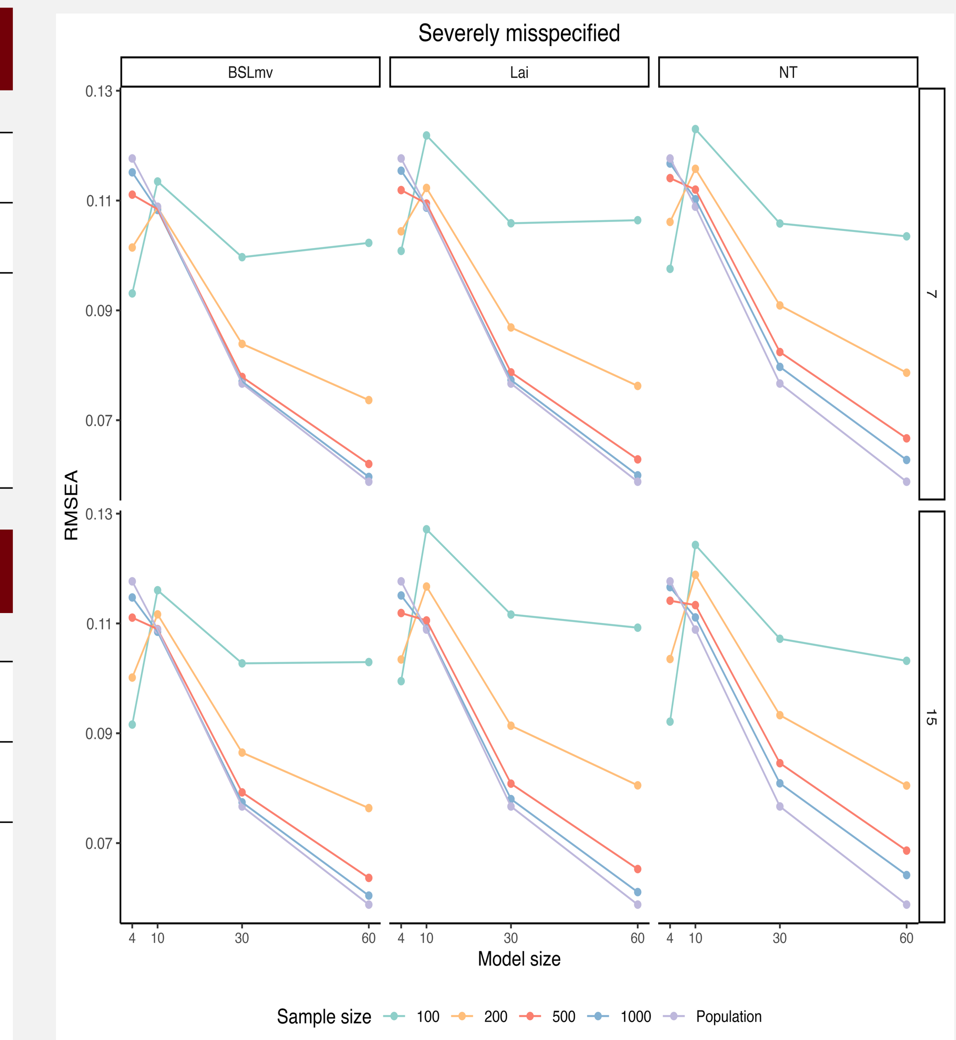


e.g., ρ=0.9, N=500, skew & Kurt=2 & 7

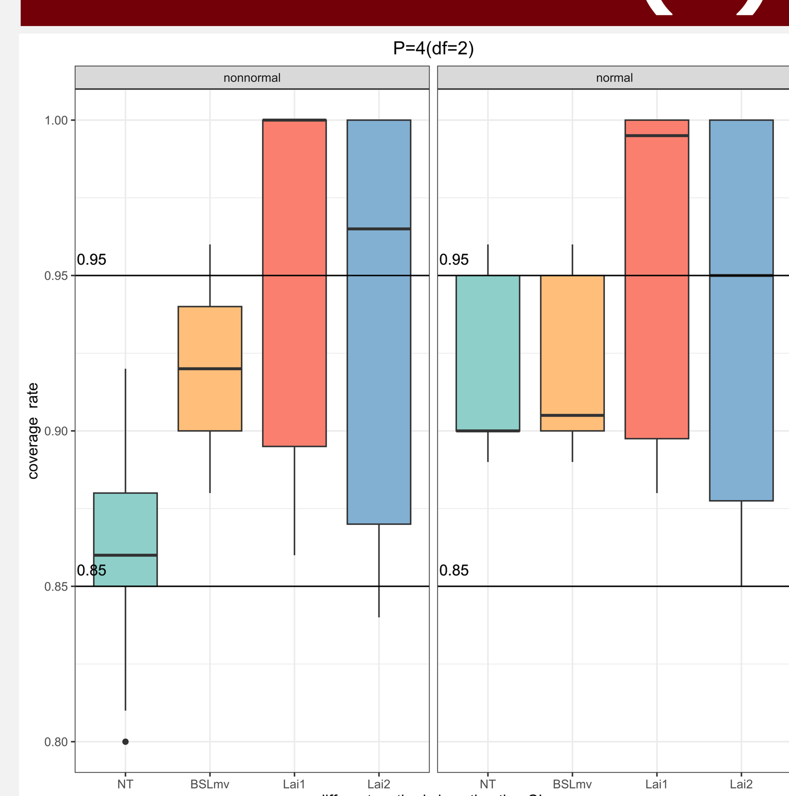
Model size : *P (df)*	POPULATION RMSEA	Pointe estimates RMSEA		
		NT (ML)	BSL_MLMV	Lai
4 (2)	0.036	**0.035**	0.029	0.03
10 (35)	0.036	0.047	**0.035**	**0.037**
30 (405)	0.029	0.045	**0.033**	0.035
60 (1710)	0.025	0.042	**0.033**	0.034

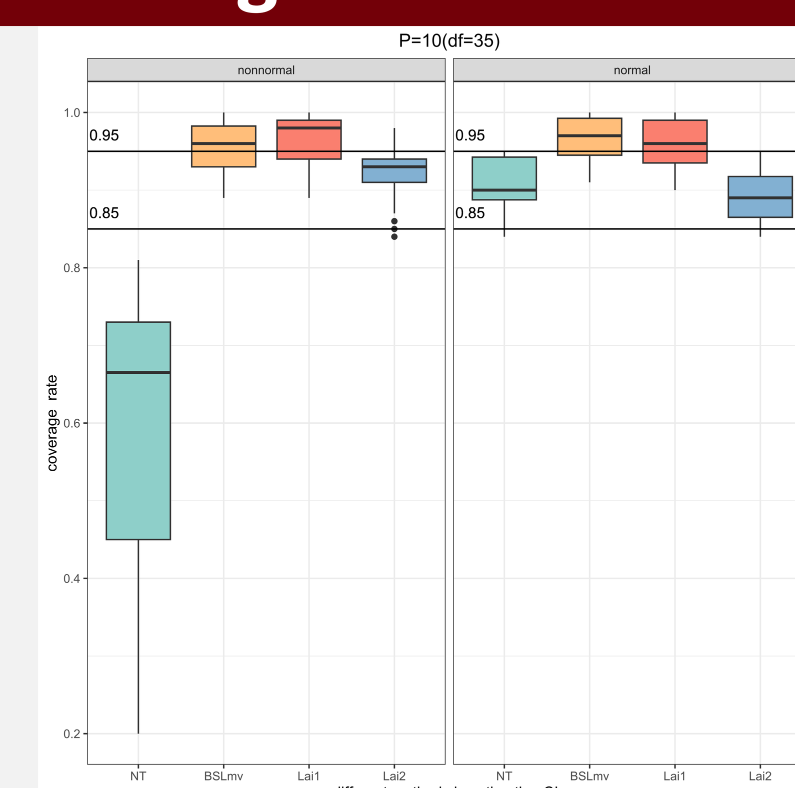
e.g., ρ=0.6, N=500 , skew & Kurt=2 & 7

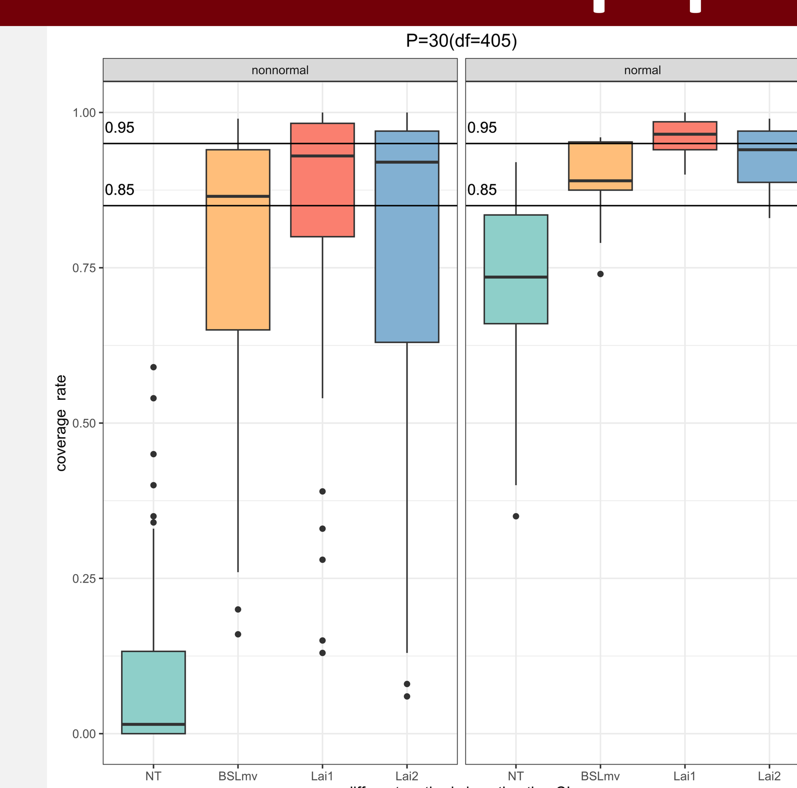
Model size : *P (df)*	POPULATION RMSEA	Pointe estimates RMSEA		
		NT (ML)	BSL_MLMV	Lai
4 (2)	0.118	**0.114**	0.111	0.112
10 (35)	0.109	0.112	0.108	**0.109**
30 (405)	0.077	0.082	**0.078**	0.079
60 (1710)	0.059	0.067	**0.062**	0.063

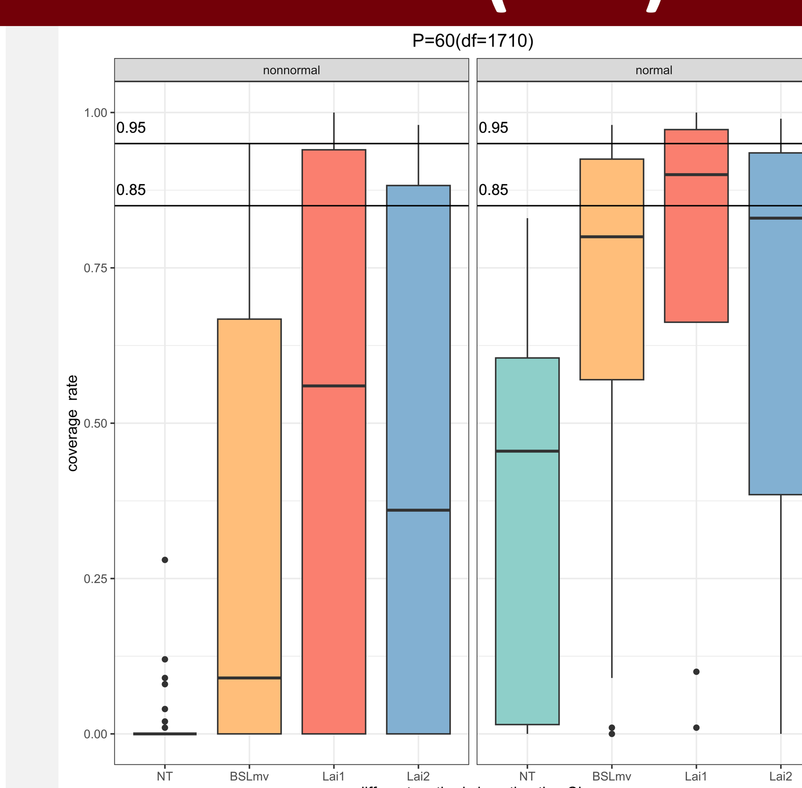


RESULTS (2) Coverage rates for 90% CIs around the population RMSEA (*VM*)









Major findings

The behavior of the sample RMSEAs was very similar across the two data generation methods under nonnormal data conditions.

At the population level, results indicated that under misspecified models, the population RMSEA values decreased as the model size increased.

At the sample level, (1) The normal theory (NT) method ***only yielded unbiased*** sample RMSEA and accurate CIs when the model size is very small.

(2) Both BSL_{MV} and Lai methods ***yielded less biased sample RMSEA*** than those obtained using the normal theory method.

(3) The standard deviations for sample RMSEAs using both the BSL_{MV} and Lai methods increased as the model size decreased, indicating that there were higher levels of uncertainties in terms of the parameter estimates.

(4) A. Both BSL_{MV} and Lai methods yielded ***more accurate CIs*** than those from the normal theory method.

B. The CRs for both BSL_{MV} and Lai methods dropped as the model size and the sample size decreased.

C. The Lai1 CIs yielded the best performance when fitting very large CFA models.

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