How to use Stata's sem with small samples? New corrections for the L. R. χ^2 statistics and fit indices

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"All models are false, but some are useful." (George E. P. Box)

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What is the problem?

- In empirical research more and more people estimate their SEM using a small sample (n<100) in psychology, marketing or business research
- When working with small samples we are confronted with a severe problem
 - The traditional Likelihood-Ratio x² goodness-of-fit test and all fit-indices basing on it tend to overreject acceptable models. They are too conservative!
 - This is caused by the pure approximation of the χ² test statistics to the noncentral χ² distribution

What are solutions for it?

- Several correction procedures have been developed to improve the approximation of the L.R.χ²-test statistics (T_{ML}) to the noncentral χ² distribution
 - The Bartlett correction
 - The Yuan correction
 - The Swain correction

The Bartlett correction

 Bartlett developed a small-sample correction to test the exact fit of exploratory factor models (1937, 1950, 1954) estimated by ML

$$b = 1 - \frac{4k + 2p + 5}{6n}$$

Bartlett – corrected $T_{MLb} = b \cdot T_{ML}$ Legend :

- k: number of latent variables (factors)
- *p*: number of observed variables (indicators)
- n: sample size N + 1

The Yuan correction

 Yuan (2005) proposed an "ad hoc" simplification of a Bartlett like correction formula developed by Wakaki, Eguchi & Fujikoshi (1990) for covariance structure models

$$y = 1 - \frac{2k + 2p + 7}{6n}$$

Yuan – corrected
$$T_{MLy} = y \cdot T_{ML}$$

The Swain correction

Swain (1975) proposed the following correction of the test statistics T_{ML}

$$s = 1 - \frac{p \times (2p^{2} + 3p - 1) - q(2q^{2} + 3q - 1)}{12d \times n}$$

with $q = \frac{\sqrt{1 + 4p(p + 1) - 8d} - 1}{2}$

Swain-corrected $T_{MLs} = s \times T_{ML}$

Legend :

- *p*: number of observed variables (indicators)
- d: degrees of freedom of actual model
- n: sample size N + 1

What do we know from M. C. studies?

- A lot of Monte-Carlo simulation studies with small samples have been made to evaluate the shown corrections. They test systematically
 - Violations of the multivariate normal distribution assumption
 - Sample size
 - Number of indicators
 - Extend of model misspecification

What do we know ... ?

- Fouladi (2000) and Newitt & Hancock (2004) recommended the Bartlett correction of the T_{ML} for normal data. For not normal distributed data they proposed the Bartlett correction of the Satorra-Bentler adjusted T_{ML}
- Herzog, Boomsma & Reinecke (2007) and Herzog
 & Boomsma (2009/13) showed that
 - Both Bartlett and Yuan corrections overestimate the type-I-error rate when sample size decreases
 - The Swain correction is the winner for small sample sizes and large models with many indicators
 - It reduces to a high extend the type-I-error rate
 - It works even to a sample size to estimated parameter ratio of 2:1

What do we know ... ?

- Herzog, Boomsma & Reinecke (2007) and Herzog & Boomsma (2009/13) also developed and tested a modified version of Tucker-Lewis-Index (TLI or NNFI) using the Swain-rescaled T_{ML} for the target model and usual T_{ML} for the baseline model
 - It clearly outperforms the TLI calculated by standard programs like MPLUS, EQS, LISREL
 - It reports correctly the misspecification of the SEM
 - They recommended this correction also for the Comparativ Fit Index developed by Bentler (1990) and Steiger's Root-Mean-Squared-Error of Approximation (RMSEA)

Swain corrected Tucker-Lewis Index

Formulas

For normal distributed data:

$$TLI = \frac{\frac{T_{ML_{bs}}}{df_{bs}} - \frac{s \cdot T_{ML_{ms}}}{df_{ms}}}{\frac{T_{ML_{bs}}}{df_{bs}} - 1}$$

For not normal distributed data:

$$TLI = \frac{\frac{sb \cdot T_{ML_{bs}}}{df_{bs}} - \frac{s \cdot sb \cdot T_{ML_{ms}}}{df_{ms}}}{\frac{sb \cdot T_{ML_{bs}}}{df_{bs}} - 1}$$

Swain corrected Comparative-Fit Index

Formulas

For normal distributed data:

$$CFI = \frac{\left(T_{ML_{bs}} - df_{bs}\right) - \left(s \cdot T_{ML_{ms}} - df_{ms}\right)}{\left(T_{ML_{bs}} - df_{bs}\right)}$$

For not normal distributed data:

$$CFI = \frac{\left(sb \cdot T_{ML_{bs}} - df_{bs}\right) - \left(s \cdot sb \cdot T_{ML_{ms}} - df_{ms}\right)}{\left(sb \cdot T_{ML_{bs}} - df_{bs}\right)}$$

Swain corrected RMSEA

Formulas

For normal distributed data:

$$RMSEA = \sqrt{\frac{s \cdot T_{ML_{ms}} - df_{ms}}{n \cdot df_{ms}}}$$

For not normal distributed data:

$$RMSEA = \sqrt{\frac{s \cdot sb \cdot T_{ML_{ms}} - df_{ms}}{n \cdot df_{ms}}}$$

How to implement it in Stata?

- In 2013 John Antonakis and Nicolas Bastardoz, both from University of Lausanne, Switzerland, published their "swain.ado" calculating only the Swain-corrected T_{ML} value for comparison of the actual vs. saturated model
- I have modified this ado-file calculating now Swain-corrected T_{ML}, TLI, CFI and RMSEA
 - Under the assumption of multivariate normality (Jöreskog 1970, p. 239)
 - Under violation of the multivariate normality assumption (not normal distributed data) using the Satorra-Bentler-corrected T_{ML}
 - All calculated scalars are displayed and returned in r-containers

Empirical example of Islamophobia

- SEM explaining Islamophobia in West Germany 2016
- 5% sample of the German General Social Survey 2016, subsample west: n=84
- Presentation of used indicators
- Test of multivariate normal distribution of observed indicators (mvtest in Stata)
- Estimated results from sembuilder
- Results of estat gof, stats(all)
- Output of my swain_gof.ado

SEM to explain Islamophobia



Used indicators

- Factor SES: Socio-economic status
 - id02: Self rating of social class
 - Underclass to upperclass [1;5]
 - educ2: educational degree
 - Without degree to grammar school [1;5]
 - incc: income class (quintiles) [1;5]
- **Factor Authoritu: authoritarian submission**
 - Ip01: Thank to the leading heads saying us what to do [1;7]
 - Ip02: It is good for a child to learn to obey its parents [1;7]
- Single indicator pa01: left-right self-rating
 1) left .. 10) right

Used indicators

- **Factor Islamophobia**
 - Six items [1;7]
 - mm01 The religious practice of Islam should be restricted in Germany
 - mm02r The Islam does not belong to Germany
 - mm03 The presence of Muslims leads to conflicts
 - mm04 The Islamic communities should be supervised by the state
 - mm05r I object to have an Islamic mayor in my town
 - mm06 There are a lot of religious fanatics in the Islamic community

Test of multivariate normality (n = 84)

. mvtest normality mm01 mm02r mm03 mm04 mm05r mm06 lp01 lp02 pa01 id02 educ2 incc, uni stats(all)

Test for univariate normality

				ioint		
	Variable	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2	
	mm01	0.4475	0.0000	44.17	0.0000	Excont id02 all
	mm02r	0.0086	0.4302	6.91	0.0317	
	mm03	0.4600	0.0040	7.89	0.0194	indicators violate the
	mm04	0.1012	0.0002	13.43	0.0012	assumption of
	mm05r	0.4737	0.0000	•	0.0000	
	mm06	0.5839	0.0000	24.28	0.0000	univariate nomality!
	lp01	0.1037	0.0827	5.47	0.0648	
	lp02	0.0000	0.0174	19.23	0.0001	
	pa01	0.0280	0.9034	4.83	0.0893	
	id02	0.9191	0.4762	0.53	0.7685	
	educ2	0.0255	0.0142	9.47	0.0088	
	incc	0.8780	0.0000	20.93	0.0000	
						All together violate
						the assumption of
Test	: for multivari	late normality				
						multivariate normality!
Mardia mSkewness = 31.04157			chi2(364) =	452.560 Prob	>chi2 = 0.0	0011
Mardia mKurtosis =		sis = 173.1796	chi2(1) =	1.677 Prob	>chi2 = 0.2	1954
	Henze-Zirkler	= 1.034168	chi2(1) =	40.558 Prob	>chi2 = 0.0	0000
	Doornik-Hansen	1	chi2(24) =	118.558 Prob	>chi2 = 0.0	0000

Standardized solution of the SEM with Satorra-Bentler corrections: vce(sbentler)



	Fit statistic	Value	Description		
Goodness	Likelihood ratio				
	$chi2_ms(51)$	67.723	model vs. saturated		
of fit	p > chi2	0.058			
OTIN	chi2_bs(66)	264.488	baseline vs. saturated		
	p > chi2	0.000			
STATISTICS:	Satorra-Bentler				
	chi2sb_ms(51)	65.876			
ton tetee	p > chi2	0.079			
Usiai yu	chi2sb_bs(66)	253.809			
	p > chi2	0.000			
	Population error				
	RMSEA	0.062	Root mean squared error of approximation		
	90% CI, lower bound	0.000			
	upper bound	0.099			
	pclose	0.292	Probability RMSEA <= 0.05		
	Satorra-Bentler				
	RMSEA_SB	0.059	Root mean squared error of approximation		
	Baseline comparison				
	CFI	0.916	Comparative fit index		
	TLI	0.891	Tucker-Lewis index		
	Satorra-Bentler				
	CFI_SB	0.921	Comparative fit index		
	TLI_SB	0.897	Tucker-Lewis index		
	Size of residuals				
	SRMR	0.083	Standardized root mean squared residual		
	CD	0.884	Coefficient of determination		

Output of my swain_gof.ado

. swain_gof

```
Swain correction factor = 0.9391
Swain corrected chi-square = 63.597864
p-value of Swain corrected chi-square = 0.1108
```

```
Satorra-Bentler-corrected statistics:
Swain-Satorra-Bentler corrected chi-square = 61.863491
p-value of Swain-Satorra-Bentler corrected chi-square = 0.1417
```

Fit indices under assumption of multivariate normal distribution

```
Swain-corrected Tucker-Lewis-Index = 0.9179
Swain-corrected Comparative-Fit-Index = 0.9365
Swain-correct RMSEA = 0.0542
```

Fit indices under violation of multivariate normal distribution

```
Swain-Satorra-Bentler-corrected Tucker-Lewis-Index = 0.9251
Swain-Satorra-Bentler-corrected Comparative-Fit-Index = 0.9422
Swain-Satorra-Bentler-correct RMSEA = 0.0504
```

r-containers of the swain_gof.ado

The swain_gof.ado returns the following r-containers

. return list

```
scalars:
```

r(swain_rmsea_sb)		.0503570145572617
r(swain_cfi_sb)	=	.9421565802285176
r(swain_tli_sb)	=	.9251438097074932
r(swain_rmsea)	=	.0542280184201118
r(swain_cfi)	=	.936530799932064
r(swain_tli)	=	.917863388147377
r(swain_sb_p)	=	.1417421175619517
r(swain_chi_sb)	=	61.86349107237523
r(swain_corr)	=	.9390845490337976
r(swain_chi)	=	63.59786447391117
r(swain_p)	=	.1108283705582046

What do we see ?

- Violation of the multivariate normality assumption. Therefore we look at the Satorra & Bentler (SB) corrected statistics of Stata
 - SB T_{ML} (Stata) = 65.876 df=51 p=0.079
 - ► Swain SB T_{ML} = 61.863 df=51 p=0.142 ☺
 - SB TLI (Stata) = 0.891
 - ► Swain SB TLI = 0.925 ☺
 - SB CFI (Stata) = 0.921
 - ► Swain SB CFI = 0.942 ☺
 - SB RMSEA (Stata) = 0.059
 - Swain SB RMSEA = 0.050 ②
- The SB T_{ML} statistics is reduced by the Swain correction. Therefore all fit indices are improved!

Conclusions

The Monte-Carlo studies presented have proofed the advantage of the Swain correction for the SEM with small samples and many indicators

It works just to a sample size-parameter ratio of 2:1

- My swain_gof.ado calculates easily the Swaincorrected T_{ML} statistics and the fit indices TLI, CFI and RMSEA basing on it
 - Under the assumption of multivariate normality
 - Under violation of multivariate normality
- Therefore I recommend my swain_gof.ado to assess the fit of SEMs using small samples



Thank you for your attention

Do you have some questions?

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Appendix

Assumption of multivariate normality 1

 Karl G. Jöreskog (1970) formulated this assumption in his article "A general method for analysis of covariance structures". Biometrika, 57 (2), p. 239-251

"It is assumed that observations on a set of variables have a multivariate normal distribution with a general parametric form of the mean vector and the variancecovariance parameters. Any parameter of the model may be fixed, free or constrained to be equal to other parameters. The free and constrained parameters are estimated by maximum likelihood." (p. 239)

Assumption of multivariate normality 2

- Jöreskog had reduced the whole data matrix X to the first and second moments of the observed variables ignoring the third and forth moments - their skewness and kurtosis. Therefore he needed a strict assumption of their distribution.
- That's why he introduced the multivariate normality assumption of the observed variables.

Items measuring Islamophobia



- A Die Ausübung des islamischen Glaubens in Deutschland sollte eingeschränkt werden.
 +) mm01
- B Der Islam passt in die deutsche Gesellschaft. -) mm02r
- C Die Anwesenheit von Muslimen in Deutschland führt zu Konflikten. +) mm03
- D Islamische Gemeinschaften sollten vom Staat beobachtet werden. +) mm04
- E Ich hätte nichts gegen einen muslimischen Bürgermeister in meiner Gemeinde. -) mm05r
- F Ich habe den Eindruck, dass unter den in Deutschland lebenden Muslimen viele religiöse Fanatiker sind. +) mm06

(GESIS 2017, Liste 54)

Items measuring authoritarian submission



A Wir sollten dankbar sein für führende Köpfe, die uns genau sagen können, was wir tun sollen und wie.

lp01

B Im allgemeinen ist es einem Kind im späteren Leben nützlich, wenn es gezwungen wird, sich den Vorstellungen seiner Eltern anzupassen.

lp02

(GESIS 2017, Liste 34)

Left-right-self rating



(GESIS 2017, Liste 46)