How to use Stata’s sem command with nonnormal data? A new nonnormality correction for the RMSEA, CFI and TLI

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

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What is the problem? 1

- The Structural Equation Model (SEM) developed by Karl Jöreskog (1970) requires the multivariate normality of indicators using Maximum-Likelihood (ML) or Generalized-Least Squares (GLS) to estimate the parameters
- Instead of the data matrix the SEM uses the covariance matrix of the indicators and the vector of their means
- This reduction to the first and second moments of the indicators is only allowed if strict assumptions about the skewness and kurtosis of the indicators exist

What is the problem? 2

- **The violation of the multivariate normality assumption leads to an inflation of the Likelihood-Ratio-chi^2 test statistics (T_{ML}) for the comparison of actual and saturated or baseline and saturated models respectively when the kurtosis of indicators increases**
- **It has the following effects**
  - **Over-hasty rejection of the actual model**
  - **Severe bias of fit indices using the T_{ML} statistics**
  - **Proposed rules of thumb (Hu & Bentler 1999, Schermelleh-Engel et. al. 2003) to accept a model cannot be applied because they demand the multivariate normality of the indicators**

What are solutions? 1

- **Stata's sem, EQS or MPLUS calculate the Satorra-Bentler (1994) mean-adjusted / rescaled Likelihood-Ratio-chi^2 test statistics (T_{SB}) to correct the inflation of T_{ML}**
  - **They use the T_{SB} values of the actual and base-line models to calculate the Root-Mean-Squared-Error-of Approximation (RMSEA), Comparative-Fit Index (CFI) and Tucker-Lewis Index (TLI)**
- **Simulation studies conducted by Curran, West & Finch (1996), Newitt & Hancock (2000), Yu & Muthén (2002), Lei & Wu (2012) recommend the usage of the T_{SB} for medium-sized and large samples (200 < n < 500 / 1000)**

What are solutions? 2

- **Satorra-Bentler (SB) corrected RMSEA, CFI and TLI implemented in Stata**

$$Satorra-Bentler\ rescaled\ \ T_{SB,M} = \frac{T_{ML,M}}{c_M} \qquad T_{SB,B} = \frac{T_{ML,B}}{c_B}$$

$$RMSEA_{SB} = \sqrt{\frac{T_{SB,M} - df_M}{n \times df_M}}$$

$$CFI_{SB} = 1 - \frac{T_{SB,M} - df_M}{T_{SB,B} - df_B}$$

$$TLI_{SB} = 1 - \frac{T_{SB,M} - df_M}{T_{SB,B} - df_B} \times \frac{df_B}{df_M}$$

What are solutions? 3

- **Brosseau-Liard & Savalei (2012, 2014, 2018) criticize this blind usage of the Satorra-Bentler rescaled T_{SB}.**
  - **They argue that the population values of RMSEA, CFI and TLI differ from those using the T_{ML}-statistics when the sample size grows to infinity. They are a function of the misspecification of the SEM and the violation of the multivariate normality assumption**
  - **Therefore the rules of thumb used to assess the model fit cannot be applied**
  - **They propose an alternative correction leading to the same population values as using the T_{ML} statistics under multivariate normality**

What are solutions? 4

- **To compute the robust fit indices they take the Satorra-Bentler versions of RMSEA, CFI and TLI and the corresponding Satorra-Bentler rescaling factors for the actual model c_M and the baseline model c_B calculated by Stata**

$$Robust\ RMSEA = \sqrt{\frac{T_{ML,M}}{T_{SB,M}}} \times RMSEA_{SB} = \sqrt{c_M} \times RMSEA_{SB}$$

$$Robust\ CFI = 1 - \frac{T_{ML,M} \times T_{SB,B}}{T_{ML,B} \times T_{SB,M}} \times \left(1 - CFI_{SB}\right) = 1 - \frac{c_M}{c_B} \times \left(1 - CFI_{SB}\right)$$

$$Robust\ TLI = 1 - \frac{T_{ML,M} \times T_{SB,B}}{T_{ML,B} \times T_{SB,M}} \times \left(1 - TLI_{SB}\right) = 1 - \frac{c_M}{c_B} \times \left(1 - TLI_{SB}\right)$$

What do we know from M.C. studies? 1

- **Brosseau-Liard & Savalei (2012, 2014) made two Monte-Carlo-simulation studies (M.C.) with 1,000 replications per combination of their study design**
- **They have investigated the effects of**
  - **Sample size**
    - **n = 100, 200, 300, 500, 1000**
  - **Extent of nonnormality of indicators**
    - **Normal (skewness=0, kurtosis=0)**
    - **Moderate nonnormal (skewness=2, kurtosis=7)**
    - **Extreme nonnormal (skewness=3, kurtosis=21)**
  - **Extent of misspecification of the SEM**
    - **10 different population models varying the model fit**

What do we know from M.C. studies? 2

- **Brosseau-Liard & Savalei (2012, 2014) compare the performance of ML-based, Satorra-Bentler rescaled and robust fit indices**
  - **Results concerning RMSEA**
    - **Robust RMSEA correctly estimates for n ≥ 200 the given population values even under moderate or extreme deviation from multivariate normality**
    - **Therefore the robust RMSEA can be interpreted as if multivariate normality is given**
    - **The deviation of the SB-rescaled RMSEA from the given population value increases with the magnitude of nonnormality. It underestimates the true RMSEA which leads very often to the confirmation of the model structure**

What do we know ... ? 3a

- **Results concerning CFI and TLI**
  - **If normality is given, the means of robust CFI and TLI converge towards the given population values and the uncorrected fit indices**
  - **With increasing nonnormality the uncorrected CFI and TLI underestimate the given population values**
  - **Even with increasing nonnormality the robust CFI and TLI estimate very precisely the population values for sample sizes greater or equal 300**
  - **For sample sizes lower 300 the robust CFI and TLI underestimate the given population value to a minor degree as the uncorrected or Satorra-Bentler corrected fit indices**

What do we know ... ? 3b

- **Results concerning Satorra-Bentler corrected CFI and TLI**
  - **The Satorra-Bentler corrected CFI and TLI severely underestimate the given population values if nonnormality increases**

- **Conclusion:**
  - **Brosseau-Liard & Savalei recommend the use of the robust RMSEA, CFI and TLI instead of their Satorra-Bentler corrected versions to assess the model fit if the multivariate normality assumption is violated**

How to implement it in Stata ?

- **I wrote my robust_gof.ado which computes the robust RMSEA, CFI und TLI**

- **Steps of procedure:**

  - **1. Estimate your Structural Equation Model with the vce(sbentler) option of Stata’s sem**
  - **2. Use the estat gof, stats(all) postestimation command**
  - **3. Start the robust_gof.ado**

Empirical example of Islamophobia

- **SEM to explain Islamophobia**
  - **Data set: General Social Survey (ALLBUS) 2016 published by GESIS 2017. Subsample Western Germany: n=1.690**
- **Presentation of used indicators**
- **Test of multivariate normality (mvtest of Stata)**
- **Estimated results from sembuilder**
- **Output of my robust_gof.ado**

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**
  - **lp01: We should be grateful for leaders who can tell us exactly what to do [1;7]**
  - **lp02: It will be of benefit for a child in later life if he or she is forced to conform to his or her parents' ideas [1;7]**
- **Single indicator pa01: left-right self-rating [1;10]**

Used indicators

- **Factor Islamophobia**
  - **Six items [1;7]**
    - **mm01 The exercise of Islamic faith should be restricted in Germany**
    - **mm02r The Islam does not fit to Germany**
    - **mm03 The presence of Muslims in Germany leads to conflicts**
    - **mm04 The Islamic communities should be subject to surveillance by the state**
    - **mm05r I would have objection to having a Muslim mayor in our town / village**
    - **mm06 I have the impression that there are many religious fanatics among Muslims living in Germany**

Test of multivariate normality (mvtest)

Test for univariate normality

Variable	Pr(Skewness)	Pr(Kurtosis)	joint adj chi2(2)	joint Prob>chi2
mm01	0.0006	0.0000	.	.
mm02r	0.0000	0.0000	.	0.0000
mm03	0.0000	0.0000	.	0.0000
mm04	0.0000	0.0000	.	0.0000
mm05r	0.0217	.	.	.
mm06	0.0205	0.0000	.	.
lp01	0.0000	0.0000	.	0.0000
lp02	0.0000	0.0000	.	0.0000
pa01	0.0035	0.6244	8.70	0.0129
id02	0.0236	0.0135	10.82	0.0045
educ2	0.0091	.	.	.
incc	0.0001	0.0000	.	0.0000

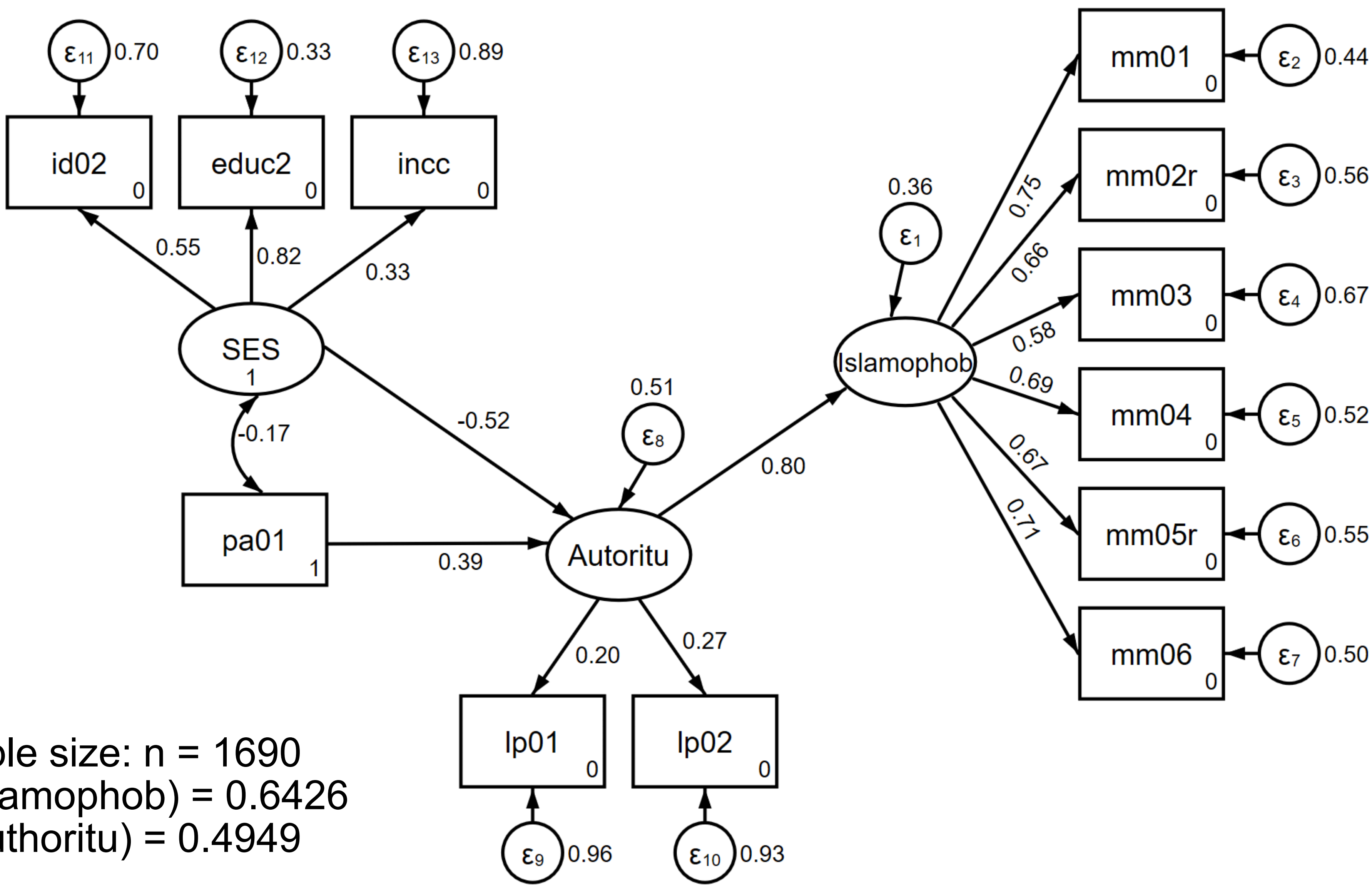
Each indicator violates the univariate normality assumption

Test for multivariate normality

All together violate the assumption of multivariate normality

Mardia mSkewness = 6.24481	chi2(364) = 1762.558	Prob>chi2 =	0.0000
Mardia mKurtosis = 176.6351	chi2(1) = 93.761	Prob>chi2 =	0.0000
Henze-Zirkler = 1.353375	chi2(1) = 8686.420	Prob>chi2 =	0.0000
Doornik-Hansen	chi2(24) = 2343.968	Prob>chi2 =	0.0000

Standardized solution of the SEM (ML)



Sample size: n = 1690
R^2(Islamophob) = 0.6426
R^2(Authoritu) = 0.4949

Output of my robust_gof.ado

```
. robust_gof
Root-Mean-Squared-Error-of-Approximation:

MVN-based RMSEA = 0.0666
90% Confidence Interval for MNV-based RMSEA:
MVN-based Lower Bound (5%)  = 0.0609
MVN-based Upper Bound (95%) = 0.0725

Satorra-Bentler corrected RMSEA = 0.0638

Robust-RMSEA = 0.0663

Incremental Fit-Indices:

MVN-based Tucker-Lewis-Index(TLI) = 0.8947
Satorra-Bentler corrected TLI     = 0.8983
Robust Tucker-Lewis-Index(TLI)    = 0.8958

MVN-based Comparative Fit Index (CFI) = 0.9187
Satorra-Bentler-corrected CFI         = 0.9214
Robust Comparative Fit Index(CFI)     = 0.9195
```

r-containers of the robust_gof.ado

- **The robust_gof.ado returns the following r-containers**

```
. return list

scalars:
          r(robust_tli) =  .895787959581779
          r(robust_cfi) =  .919472514222837
        r(robust_rmsea) =  .066288472478148
```

Conclusions

- **The presented Monte-Carlo simulation studies prove the advantage of the robust RMSEA, CFI and TLI using medium sized and great samples (n $\geq$ 200 / 300)**
- **My robust_gof.ado computes the robust fit indices using the individual data set, the Satorra-Bentler-rescaled Likelihood-Ratio-chi^2 test statistics (T_{SB}) and scaling factors c_M and c_B**
- **For small sample sizes I recommend the Swain-correction of T_{ML} and my swain_gof.ado presented at the German Stata Users Group Meeting last year in Konstanz**

Closing words

- **Thank you for your attention**
- **Do you have some questions?**

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Appendix

Rules of thumb for evaluation of fit

- **Schermelleh-Engel et. al. (2003, p. 53) recommend the following rules of thumb**

Fit Measure	Good Fit	Acceptable Fit
χ^2	$0 \leq \chi^2 \leq 2df$	$2df < \chi^2 \leq 3df$
p value	$.05 < p \leq 1.00$	$.01 \leq p \leq .05$
χ^2/df	$0 \leq \chi^2/df \leq 2$	$2 < \chi^2/df \leq 3$
$RMSEA$	$0 \leq RMSEA \leq .05$	$.05 < RMSEA \leq .08$
p value for test of close fit ($RMSEA < .05$)	$.10 < p \leq 1.00$	$.05 \leq p \leq .10$
Confidence interval (CI)	close to $RMSEA$, left boundary of CI $= .00$	close to $RMSEA$
$SRMR$	$0 \leq SRMR \leq .05$	$.05 < SRMR \leq .10$
NFI	$.95 \leq NFI \leq 1.00$[a]	$.90 \leq NFI < .95$
$NNFI$ / TLI	$.97 \leq NNFI \leq 1.00$[b]	$.95 \leq NNFI < .97$[c]
CFI	$.97 \leq CFI \leq 1.00$	$.95 \leq CFI < .97$[c]
GFI	$.95 \leq GFI \leq 1.00$	$.90 \leq GFI < .95$
$AGFI$	$.90 \leq AGFI \leq 1.00$, close to GFI	$.85 \leq AGFI < .90$, close to GFI
AIC	smaller than AIC for comparison model	
$CAIC$	smaller than $CAIC$ for comparison model	
$ECVI$	smaller than $ECVI$ for comparison model	

Sample and population values of RMSEA

- **Sample and population values of RMSEA under ML and robust ML**

Estimator name	Test statistic	Sample formula	$\xrightarrow{n\to\infty}$	Population value
ML	$T_{ML,M}$	$RMSEA_{ML,n} = \sqrt{\dfrac{T_{ML,M} - df_M}{n \times df_M}}$	$\to$	$RMSEA_{ML} = \sqrt{\dfrac{\widehat{F}_{ML,M}}{df_M}}$
	$E(T_{ML,M}) = df$			
	$\operatorname{var}(T_{ML,M}) = 2 \times df$			
$Roboust\ ML:$				
$Satorra - Bentler$	$T_{SB,M} = \dfrac{T_{ML,M}}{c_M}$	$RMSEA_{SB,n} = \sqrt{\dfrac{T_{SB,M} - df_M}{n \times df_M}}$	$\to$	$RMSEA_{SB} = \sqrt{\dfrac{\widehat{F}_{ML,M}}{c_M \times df}}$
$rescaled$	$E(T_{SB,M}) = df$			
$Borsseau - Liard\ \&\ Savalei:$		$RMSEA_{ML\,Robust,n} = \sqrt{\dfrac{\left(T_{ML,M} - c_M \times df_M\right)}{n \times df_M}}$		
	or	$RMSEA_{SB\,Robust,n} = \sqrt{\dfrac{c_M \times \left(T_{SB,M} - df_M\right)}{n \times df_M}}$	$\to$	$RMSEA_{Robust,Pop} = \sqrt{\dfrac{\widehat{F}_{ML,M}}{df_M}}$

Sample and population values of CFI

- **Sample and population values of CFI**

Estimator name — *Sample formula* $\xrightarrow{n \to \infty}$ *Population value*

ML

$$CFI_{ML,n} = 1 - \frac{T_{ML,M} - df_M}{T_{ML,B} - df_B} \rightarrow CFI_{ML,Pop} = 1 - \frac{\widehat{F}_{ML,M}}{\widehat{F}_{ML,B}}$$

Roboust ML :

Satorra – Bentler

$$CFI_{SB,n} = 1 - \frac{T_{SB,M} - df_M}{T_{SB,B} - df_B} \rightarrow CFI_{SB,Pop} = 1 - \frac{c_B \times \widehat{F}_{ML,M}}{c_M \times \widehat{F}_{ML,B}}$$

Borsseau – Liard & Savalei :

$$CFI_{ML\,Robust,n=}1 - \frac{T_{ML,M} - c_M \times df_M}{T_{ML,B} - c_B \times df_B} \rightarrow CFI_{ML\,Robust,POP} = 1 - \frac{\widehat{F}_{ML,M} - \frac{c_M \times df_M}{n-1}}{\widehat{F}_{ML,B} - \frac{c_B \times df_B}{n-1}}$$

Sample and population values of TLI

- **Sample and population values of TLI**

$$\textit{Estimator name} \qquad \textit{Sample formula} \xrightarrow{n\to\infty} \textit{Population value}$$

$$ML \qquad TLI_{ML,n} = 1 - \frac{T_{ML,M} - df_M}{T_{ML,B} - df_B} \times \frac{df_B}{df_M} \rightarrow TLI_{ML,Pop} = 1 - \frac{\widehat{F}_{ML,M}}{\widehat{F}_{ML,B}} \times \frac{df_B}{df_M}$$

Roboust ML:

$$Satorra-Bentler \qquad TLI_{SB,n} = 1 - \frac{T_{SB,M} - df_M}{T_{SB,B} - df_B} \times \frac{df_B}{df_M} \rightarrow TLI_{SB,Pop} = 1 - \frac{c_B \times \widehat{F}_{ML,M}}{c_M \times \widehat{F}_{ML,B}} \times \frac{df_B}{df_M}$$

Borsseau – Liard & Savalei:

$$TLI_{ML\,Robust,n=}1 - \frac{T_{ML,M} - c_M \times df_M}{T_{ML,B} - c_B \times df_B} \times \frac{df_B}{df_M} \rightarrow TLI_{ML\,Robust,POP} = 1 - \frac{\widehat{F}_{ML,M} - \frac{c_M \times df_M}{n-1}}{\widehat{F}_{ML,B} - \frac{c_B \times df_B}{n-1}} \times \frac{df_B}{df_M}$$

Abbreviations

RMSEA	Root-Mean-Squared-Error-of Approximation using $T_{ML,M}$, df_M
$RMSEA_{SB}$	Root-Mean-Squared-Error-of Approximation using $T_{SB,M}$, df_M
CFI	Comparative-Fit Index using $T_{ML,M}$, df_M, $T_{ML,B}$, df_B
CFI_{SB}	Comparative-Fit Index using $T_{SB,M}$, df_M, $T_{SB,B}$, df_B
TLI	Tucker-Lewis Index / Non-Normed-Fit Index using $T_{ML,M}$, df_M, $T_{ML,B}$, df_B
TLI_{SB}	Tucker-Lewis Index / Non-Normed-Fit Index using $T_{SB,M}$, df_M, $T_{SB,B}$, df_B
$T_{ML,M}$	Likelihood-Ratio-χ^2_{MS} test statistic for comparison target model against saturated model
$T_{SB,M}$	Satorra-Bentler-rescaled Likelihood-Ratio-χ^2_{MS} test statistic
df_M	Degrees of freedom target model (M)
n	sample size
c_M	Satorra-Bentler-scaling constant for the target model (M)
$T_{ML,B}$	Likelihood-Ratio-χ^2_{BS} test statistic for comparison baseline model against saturated model
$T_{SB,B}$	Satorra-Bentler-rescaled Likelihood-Ratio-χ^2_{BS} test statistic
df_B	Degrees of freedom baseline model (B)
c_B	Satorra-Bentler-scaling constant for the baseline model (B)
$\widehat{F}_{ML,M}$	Minimum value of the Maximum-Likelihood Fit-Function for the target model
$\widehat{F}_{ML,B}$	Minimum value of the Maximum-Likelihood Fit-Function for the baseline model

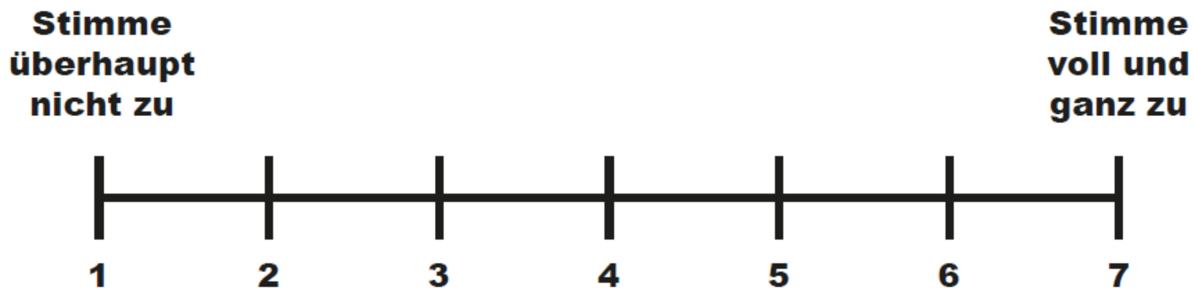
My robust_gof.ado

```
program define robust_gof, rclass
 version 15

   if "`e(cmd)'"!="sem" {
  di in red "This command only works after sem"
  exit 198
  }

  if "`e(vce)'"!="sbentler" {
  di in red "This command only works with sem,vce(sbentler) option"
  exit 198
  }

 * Satorra-Bentler-corrected statistics

 local chi2_ms=`r(chi2_ms)'

 local chi2_bs=`r(chi2_bs)'

 local chi2sb_ms = `r(chi2sb_ms)'

 local chi2sb_bs = `r(chi2sb_bs)'

 local df_bs = `r(df_bs)'

 local df_ms = `r(df_ms)'

 local nobs=`e(N)'
```

```
local lb90_rmsea=`r(lb90_rmsea)'

local ub90_rmsea=`r(ub90_rmsea)'

* Calculation of Satorra-Bentler correction factor c_ms und c_bs

local c_ms = `e(sbc_ms)'

local c_bs = `e(sbc_bs)'

* Calculation of robust CFI, TLI, RMSEA

local cfi=`r(cfi)'

local tli=`r(tli)'

local cfi_sb=`r(cfi_sb)'

local tli_sb=`r(tli_sb)'

local rmsea=`r(rmsea)'

local rmsea_sb=`r(rmsea_sb)'

local robust_cfi = 1 - ((`c_ms' / `c_bs')*(1 - `cfi_sb'))

local robust_tli = 1 - ((`c_ms' / `c_bs')*(1 - `tli_sb'))

local robust_rmsea = sqrt(`c_ms')*`rmsea_sb'
```

```
  *stores saved results in r()
  return scalar robust_rmsea = `robust_rmsea'
  return scalar robust_cfi = `robust_cfi'
  return scalar robust_tli = `robust_tli'

  * Display robust Fit indices
  dis as text "Root-Mean-Squared-Error-of-Approximation: "
  dis ""
  dis as text "MVN-based RMSEA = " as result %6.4f `rmsea'
  dis as text "90% Confidence Interval for MNV-based RMSEA: "
  dis as text "MVN-based Lower Bound (5%)  = " as result %6.4f `lb90_rmsea'
  dis as text "MVN-based Upper Bound (95%) = " as result %6.4f `ub90_rmsea'
  dis ""
  dis as text "Satorra-Bentler corrected RMSEA = " as result %6.4f `rmsea_sb'
  dis ""
  dis as text "Robust-RMSEA = " as result %6.4f `robust_rmsea'
  * dis as text "90% Confidence Interval for robust RMSEA: "
  * dis as text "Robust Lower Bound (5%)  = " as result %6.4f `rob_rmsea_lb90'
  * dis as text "Robust Upper Bound (95%) = " as result %6.4f `rob_rmsea_ub90'
  dis ""
  dis as text "Incremental Fit-Indices: "
  dis ""
  dis as text "MVN-based Tucker-Lewis-Index(TLI) = " as result %6.4f `tli'
  dis as text "Satorra-Bentler corrected TLI     = " as result %6.4f `tli_sb'
  dis as text "Robust Tucker-Lewis-Index(TLI)    = " as result %6.4f `robust_tli'
  dis ""
  dis as text "MVN-based Comparative Fit Index (CFI) = " as result %6.4f `cfi'
  dis as text "Satorra-Bentler-corrected CFI         = " as result %6.4f `cfi_sb'
  dis as text "Robust Comparative Fit Index(CFI)     = " as result %6.4f `robust_cfi'
  dis ""
end
exit
```

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

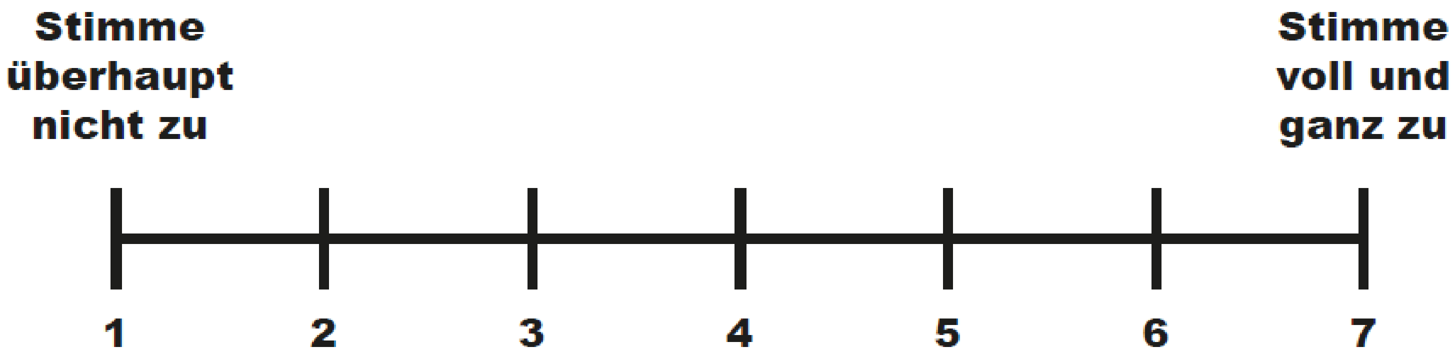
D Islamische Gemeinschaften sollten vom Staat beobachtet werden. +) mm04

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.

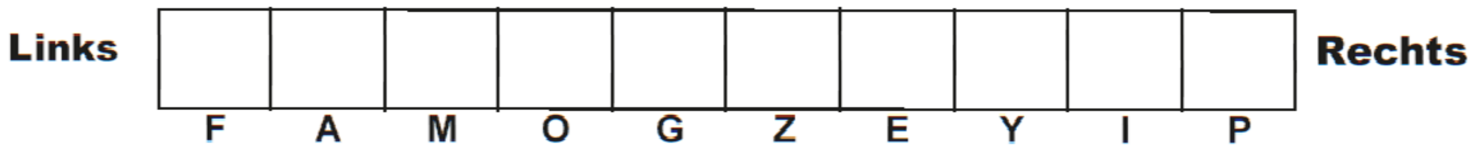
Ip01

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

Ip02

(GESIS 2017, Liste 34)

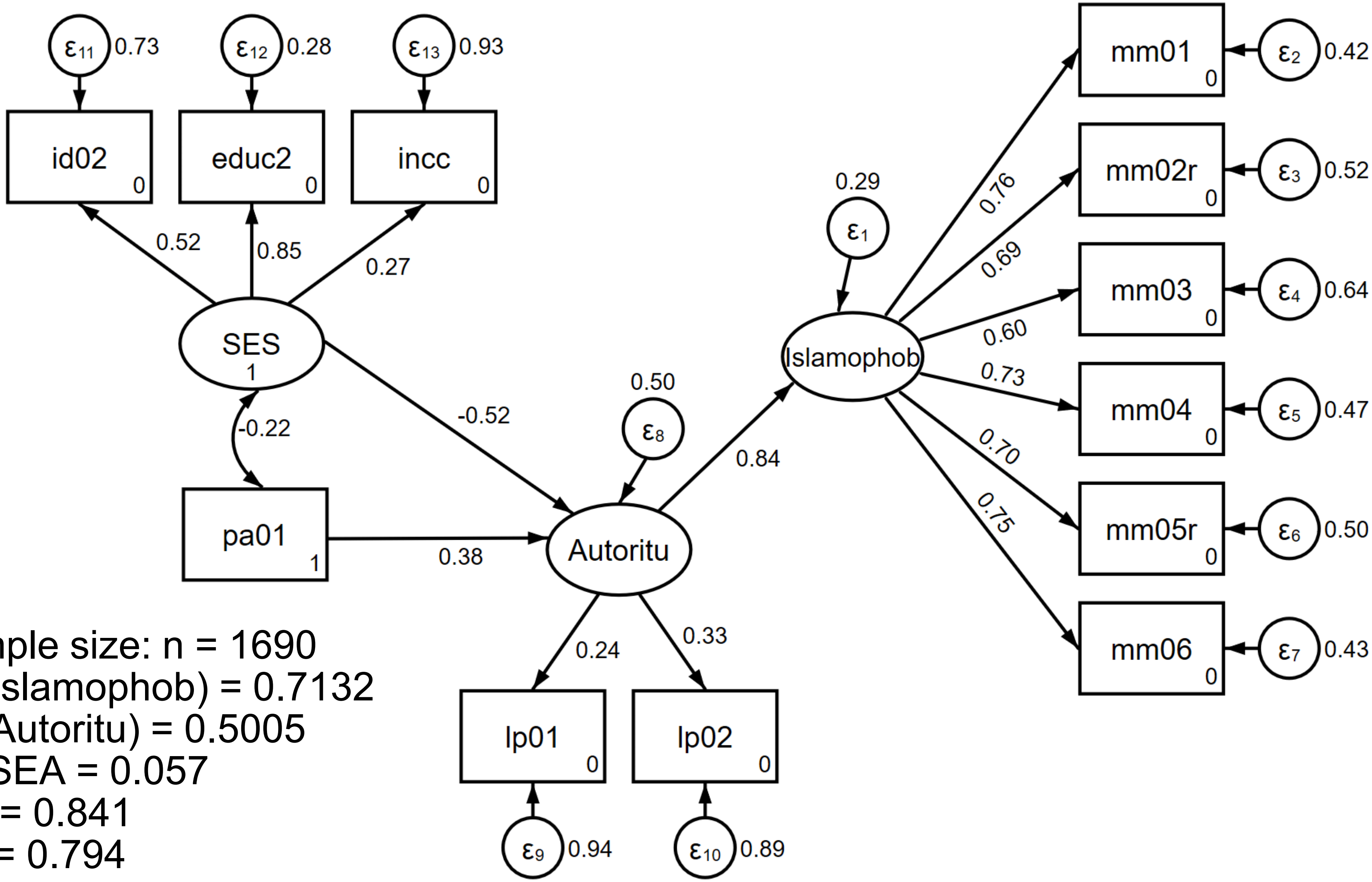
Left-right-self rating



pa01

(GESIS 2017, Liste 46)

Standardized solution of the SEM (ADF)



Sample size: n = 1690

R^2 (Islamophob) = 0.7132

R^2 (Autoritu) = 0.5005

RMSEA = 0.057

CFI = 0.841

TLI = 0.794

Goodness of fit statistics: estat gof (ADF)

Fit statistic	Value	Description
Discrepancy		
chi2_ms(51)	327.481	model vs. saturated
p > chi2	0.000	
chi2_bs(66)	1803.350	baseline vs. saturated
p > chi2	0.000	
Population error		
RMSEA	0.057	Root mean squared error of approximation
90% CI, lower bound	0.051	
upper bound	0.063	
pclose	0.030	Probability RMSEA <= 0.05
Baseline comparison		
CFI	0.841	Comparative fit index
TLI	0.794	Tucker-Lewis index
Size of residuals		
SRMR	0.058	Standardized root mean squared residual
CD	0.827	Coefficient of determination