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

Meeting of the German Stata Users Group at the Ludwig-Maximilians Universität, 24th May, 2019

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

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- What do we know from Monte-Carlo simulation studies?
- How to implement the solutions in Stata?
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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.
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 baseline 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

\[
Satorra \text{–} \ Bentler \ rescaled \ T_{SB,M} = \frac{T_{ML,M}}{c_M} \quad T_{SB,B} = \frac{T_{ML,B}}{c_B}
\]

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

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

\[
TLI_{SB} = 1 - \frac{T_{SB,M} - df_M}{T_{SB,B} - df_B} \times \frac{df_B}{df_M}
\]
What are solutions? 3

  - 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

\[
\text{Robust RMSEA} = \sqrt{\frac{T_{ML,M}}{T_{SB,M}}} \times \text{RMSEA}_{SB} = \sqrt{c_M} \times \text{RMSEA}_{SB}
\]

\[
\text{Robust CFI} = 1 - \frac{T_{ML,M} \times T_{SB,B}}{T_{ML,B} \times T_{SB,M}} \times (1 - \text{CFI}_{SB}) = 1 - \frac{c_M}{c_B} \times (1 - \text{CFI}_{SB})
\]

\[
\text{Robust TLI} = 1 - \frac{T_{ML,M} \times T_{SB,B}}{T_{ML,B} \times T_{SB,M}} \times (1 - \text{TLI}_{SB}) = 1 - \frac{c_M}{c_B} \times (1 - \text{TLI}_{SB})
\]
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
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 $n \geq 200$ 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
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.
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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pr(Skewness)</th>
<th>Pr(Kurtosis)</th>
<th>adj chi2(2)</th>
<th>Prob&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>mm01</td>
<td>0.0006</td>
<td>0.0000</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>mm02r</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.</td>
<td>0.0000</td>
</tr>
<tr>
<td>mm03</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.</td>
<td>0.0000</td>
</tr>
<tr>
<td>mm04</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.</td>
<td>0.0000</td>
</tr>
<tr>
<td>mm05r</td>
<td>0.0217</td>
<td>.</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>mm06</td>
<td>0.0205</td>
<td>0.0000</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>lp01</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.</td>
<td>0.0000</td>
</tr>
<tr>
<td>lp02</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.</td>
<td>0.0000</td>
</tr>
<tr>
<td>pa01</td>
<td>0.0035</td>
<td>0.6244</td>
<td>8.70</td>
<td>0.0129</td>
</tr>
<tr>
<td>id02</td>
<td>0.0236</td>
<td>0.0135</td>
<td>10.82</td>
<td>0.0045</td>
</tr>
<tr>
<td>educ2</td>
<td>0.0091</td>
<td>.</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>incc</td>
<td>0.0001</td>
<td>0.0000</td>
<td>.</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Each indicator violates the univariate normality assumption

Test for 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 = 2343.968, Prob>chi2 = 0.0000

All together violate the assumption of multivariate normality
Standardized solution of the SEM (ML)

Sample size: $n = 1690$

$R^2(\text{Islamophob}) = 0.6426$

$R^2(\text{Authoritu}) = 0.4949$
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) =  .0662884724781481
```
The presented Monte-Carlo simulation studies prove the advantage of the robust RMSEA, CFI and TLI using medium sized and great samples (n ≥ 200 / 300)

My robust_gof.ado computes the robust fit indices using the individual data set, the Satorra-Bentler-rescaled Likelihood-Ratio-chi² 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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  Institute of Sociology
  D 06099 Halle (Saale)

- Email:
  – wolfgang.langer@soziologie.uni-halle.de
References

References 2

References 3

References 4

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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:

<table>
<thead>
<tr>
<th>Fit Measure</th>
<th>Good Fit</th>
<th>Acceptable Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$</td>
<td>$0 \leq \chi^2 \leq 2df$</td>
<td>$2df &lt; \chi^2 \leq 3df$</td>
</tr>
<tr>
<td>$p$ value</td>
<td>$0.05 &lt; p \leq 1.00$</td>
<td>$0.01 \leq p &lt; 0.05$</td>
</tr>
<tr>
<td>$\chi^2 / df$</td>
<td>$0 \leq \chi^2 / df \leq 2$</td>
<td>$2 &lt; \chi^2 / df \leq 3$</td>
</tr>
<tr>
<td>RMSEA</td>
<td>$0 \leq RMSEA \leq 0.05$</td>
<td>$0.05 &lt; RMSEA \leq 0.08$</td>
</tr>
<tr>
<td>$p$ value for test of close fit (RMSEA &lt; 0.05)</td>
<td>$0.10 &lt; p \leq 1.00$</td>
<td>$0.05 \leq p \leq 0.10$</td>
</tr>
<tr>
<td>Confidence interval (CI)</td>
<td>close to RMSEA, left boundary of CI = 0.00</td>
<td>close to RMSEA</td>
</tr>
<tr>
<td>SRMR</td>
<td>$0 \leq SRMR \leq 0.05$</td>
<td>$0.05 \leq SRMR \leq 0.10$</td>
</tr>
<tr>
<td>NFI</td>
<td>$0.95 \leq NFI \leq 1.00$</td>
<td>$0.90 \leq NFI &lt; 0.95$</td>
</tr>
<tr>
<td>NNFI / TLI</td>
<td>$0.97 \leq NNFI \leq 1.00$</td>
<td>$0.95 \leq NNFI &lt; 0.97$</td>
</tr>
<tr>
<td>CFI</td>
<td>$0.97 \leq CFI \leq 1.00$</td>
<td>$0.95 \leq CFI &lt; 0.97$</td>
</tr>
<tr>
<td>GFI</td>
<td>$0.95 \leq GFI \leq 1.00$</td>
<td>$0.90 \leq GFI &lt; 0.95$</td>
</tr>
<tr>
<td>AGFI</td>
<td>$0.90 \leq AGFI \leq 1.00$, close to GFI</td>
<td>$0.85 \leq AGFI &lt; 0.90$, close to GFI</td>
</tr>
<tr>
<td>AIC</td>
<td>smaller than AIC for comparison model</td>
<td></td>
</tr>
<tr>
<td>CAIC</td>
<td>smaller than CAIC for comparison model</td>
<td></td>
</tr>
<tr>
<td>ECVI</td>
<td>smaller than ECVI for comparison model</td>
<td></td>
</tr>
</tbody>
</table>
### Sample and population values of RMSEA under ML and robust ML

<table>
<thead>
<tr>
<th>Estimator name</th>
<th>Test statistic</th>
<th>Sample formula</th>
<th>Population value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ML</strong></td>
<td>$T_{ML,M}$</td>
<td>$RMSEA_{ML,n} = \sqrt{\frac{T_{ML,M} - df_M}{n \times df_M}}$</td>
<td>$RMSEA_{ML} = \sqrt{\frac{\hat{F}_{ML,M}}{df_M}}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$n \rightarrow \infty$</td>
<td></td>
</tr>
<tr>
<td>$E(T_{ML,M})$</td>
<td>$df$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{var}(T_{ML,M})$</td>
<td>$2 \times df$</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Roboust ML</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satorra – Bentler</td>
<td>$T_{SB,M} = \frac{T_{ML,M}}{c_M}$</td>
<td>$RMSEA_{SB,n} = \sqrt{\frac{T_{SB,M} - df_M}{n \times df_M}}$</td>
<td>$RMSEA_{SB} = \sqrt{\frac{\hat{F}_{ML,M}}{c_M \times df}}$</td>
</tr>
<tr>
<td>rescaled</td>
<td>$E(T_{SB,M}) = df$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Borsseau – Liard &amp; Savalei</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$RMSEA_{ML\text{Robust},n} = \sqrt{\frac{(T_{ML,M} - c_M \times df_M)}{n \times df_M}}$</td>
<td>$RMSEA_{ML\text{Robust,Pop}} = \sqrt{\frac{\hat{F}_{ML,M}}{df_M}}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>or</td>
<td>$RMSEA_{SB\text{Robust},n} = \sqrt{\frac{c_M \times (T_{SB,M} - df_M)}{n \times df_M}}$</td>
<td>$RMSEA_{SB\text{Robust,Pop}} = \sqrt{\frac{\hat{F}_{ML,M}}{df_M}}$</td>
<td></td>
</tr>
</tbody>
</table>
## Sample and population values of CFI

<table>
<thead>
<tr>
<th>Estimator Name</th>
<th>Sample formula</th>
<th>Population Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ML</strong></td>
<td>$CFI_{ML,n} = 1 - \frac{T_{ML,M} - df_M}{T_{ML,B} - df_B}$</td>
<td>$CFI_{ML,Pop} = 1 - \frac{\hat{F}<em>{ML,M}}{\hat{F}</em>{ML,B}}$</td>
</tr>
<tr>
<td><strong>Robust ML</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Satorra – Bentler</strong></td>
<td>$CFI_{SB,n} = 1 - \frac{T_{SB,M} - df_M}{T_{SB,B} - df_B}$</td>
<td>$CFI_{SB,Pop} = 1 - \frac{c_B \times \hat{F}<em>{ML,M}}{c_M \times \hat{F}</em>{ML,B}}$</td>
</tr>
<tr>
<td><strong>Borsseau – Liard &amp; Savalei</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$CFI_{MLRobust,n} = 1 - \frac{T_{ML,M} - c_M \times df_M}{T_{ML,B} - c_B \times df_B}$</td>
<td>$CFI_{MLRobust,Pop} = 1 - \frac{\hat{F}<em>{ML,M} - c_M \times df_M}{\hat{F}</em>{ML,B} - c_B \times df_B}$</td>
</tr>
</tbody>
</table>
Sample and population values of TLI

<table>
<thead>
<tr>
<th>Estimator name</th>
<th>Sample formula</th>
<th>Population value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ML</td>
<td>(T_{ML,n} = 1 - \frac{T_{ML,M} - \text{df}<em>M}{T</em>{ML,B} - \text{df}<em>B} \times \frac{\text{df}<em>B}{\text{df}<em>M} \rightarrow T</em>{ML,Pop} = 1 - \frac{\hat{F}</em>{ML,M}}{\hat{F}</em>{ML,B}} \times \frac{\text{df}_B}{\text{df}_M} )</td>
<td></td>
</tr>
<tr>
<td>Robust ML</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satorra–Bentler</td>
<td>(T_{SB,n} = 1 - \frac{T_{SB,M} - \text{df}<em>M}{T</em>{SB,B} - \text{df}<em>B} \times \frac{\text{df}<em>B}{\text{df}<em>M} \rightarrow T</em>{SB,Pop} = 1 - \frac{c_B \times \hat{F}</em>{ML,M}}{c_M \times \hat{F}</em>{ML,B}} \times \frac{\text{df}_B}{\text{df}_M} )</td>
<td></td>
</tr>
<tr>
<td>Borsseau–Liard &amp; Savalei</td>
<td>(T_{ML,Robust,n} = 1 - \frac{T_{ML,M} - c_M \times \text{df}<em>M}{T</em>{ML,B} - c_B \times \text{df}_B} \times \frac{\text{df}<em>B}{\text{df}<em>M} \rightarrow T</em>{ML,Robust,Pop} = 1 - \frac{\hat{F}</em>{ML,M} - c_M \times \text{df}<em>M}{\hat{F}</em>{ML,B} - c_B \times \text{df}_B} \times \frac{\text{df}_B}{\text{df}_M} )</td>
<td></td>
</tr>
</tbody>
</table>
# Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSEA</td>
<td>Root-Mean-Squared-Error-of Approximation using $T_{ML,M}$, $df_M$</td>
</tr>
<tr>
<td>RMSEA$_{SB}$</td>
<td>Root-Mean-Squared-Error-of Approximation using $T_{SB,M}$, $df_M$</td>
</tr>
<tr>
<td>CFI</td>
<td>Comparative-Fit Index using $T_{ML,M}$, $df_M$, $T_{ML,B}$, $df_B$</td>
</tr>
<tr>
<td>CFI$_{SB}$</td>
<td>Comparative-Fit Index using $T_{SB,M}$, $df_M$, $T_{SB,B}$, $df_B$</td>
</tr>
<tr>
<td>TLI</td>
<td>Tucker-Lewis Index / Non-Normed-Fit Index using $T_{ML,M}$, $df_M$, $T_{ML,B}$, $df_B$</td>
</tr>
<tr>
<td>TLI$_{SB}$</td>
<td>Tucker-Lewis Index / Non-Normed-Fit Index using $T_{SB,M}$, $df_M$, $T_{SB,B}$, $df_B$</td>
</tr>
<tr>
<td>$T_{ML,M}$</td>
<td>Likelihood-Ratio-$\chi^2_{MS}$ test statistic for comparison target model against saturated model</td>
</tr>
<tr>
<td>$T_{SB,M}$</td>
<td>Satorra-Bentler-rescaled Likelihood-Ratio-$\chi^2_{MS}$ test statistic</td>
</tr>
<tr>
<td>$df_M$</td>
<td>Degrees of freedom target model (M)</td>
</tr>
<tr>
<td>$n$</td>
<td>Sample size</td>
</tr>
<tr>
<td>$c_M$</td>
<td>Satorra-Bentler-scaling constant for the target model (M)</td>
</tr>
<tr>
<td>$T_{ML,B}$</td>
<td>Likelihood-Ratio-$\chi^2_{BS}$ test statistic for comparison baseline model against saturated model</td>
</tr>
<tr>
<td>$T_{SB,B}$</td>
<td>Satorra-Bentler-rescaled Likelihood-Ratio-$\chi^2_{BS}$ test statistic</td>
</tr>
<tr>
<td>$df_B$</td>
<td>Degrees of freedom baseline model (B)</td>
</tr>
<tr>
<td>$c_B$</td>
<td>Satorra-Bentler-scaling constant for the baseline model (B)</td>
</tr>
<tr>
<td>$\hat{F}_{ML,M}$</td>
<td>Minimum value of the Maximum-Likelihood Fit-Function for the target model</td>
</tr>
<tr>
<td>$\hat{F}_{ML,B}$</td>
<td>Minimum value of the Maximum-Likelihood Fit-Function for the baseline model</td>
</tr>
</tbody>
</table>
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.

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

Ip01

Ip02

(GESIS 2017, Liste 34)
<table>
<thead>
<tr>
<th>Links</th>
<th>F</th>
<th>A</th>
<th>M</th>
<th>O</th>
<th>G</th>
<th>Z</th>
<th>E</th>
<th>Y</th>
<th>I</th>
<th>P</th>
</tr>
</thead>
</table>
| Rechts

(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)

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