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MULTITRAIT-MULTIMETHOD MODELS FOR PROFITABILITY INDICATORS

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Abstract

A 'multitrait-multimethod' (MTMM) model is used when each of a set of traits is measured by each of a set of methods. The multitrait-multimethod model is an example of a highly specialized measurement part of a structural model. In such a model, variables are generated under a systematic design in which certain methods of measurement are fully crossed with the trait variables intended to be measured. That is, each trait is measured by each of several methods. When this design is applied, factors can be hypothesized to separate the various sources of variance, especially, into trait and method factors. Interest is usually on the trait factors, while the method factors provide an important basis for correlations among variables. Based on the goodness-of-fit of the estimated MTMM model this paper aims at testing both convergent and discriminant validity of several microeconomic financial indicators whether they are reliable measures of different traits of economic *profitability* measured by different baseline methods.

Keywords: confirmatory factor analysis, goodness-of-fit, balance-sheet indicators.

1. The MTMM Model

Both *reliability* and *validity* can be investigated by using the MTMM approach: different traits (the latent variables) are measured in different ways, that is, by different methods. According to CAMPBELL and FISKE [6]: 'Reliability is the agreement between two efforts to measure the same trait through maximally similar methods. Validity is represented in the agreement between two methods to measure the same trait through maximally different methods.' A two-trait two-method (correlation or covariance) matrix is illustrated in *Table 1*.

The off-diagonal elements in such a matrix can be classified into three groups:

1. *within-method, cross-trait* (WMCT) correlations,
2. *within trait, cross-method* (WTCM) correlations,
3. *cross-trait, cross-method* (CTCM) correlations.

Statistically significant and sufficiently large within-trait cross-method (WTCM) correlations are evidence of *convergent validity*, the agreement of different methods of measuring the same trait. Low correlations elsewhere give evidence of *discriminant validity*, that the assumed different traits really are distinct. An

Table 1. Multitrait-multimethod matrix for two traits and two methods

Method		M1		M2	
	Trait	T1	T2	T1	T2
M1	T1	1			
	T2	WMCT	1		
M2	T1	WTCM	CTCM	1	
	T2	CTCM	WTCM	WMCT	1

additional requirement for discriminant validity is that the pattern of inter-trait correlations should be the same whether the indicators are from the same or different methods.

An obvious approach to analyze MTMM data is to perform a confirmatory factor analysis (CFA). Although several CFA models can be applied to the MTMM matrix the most widely used and recommended models origin from the so-called *complete model*.

In the CFA specification of the complete model each measured indicator is considered to be a function of trait factors, method factors and unique factors. According to the complete model if we have three traits namely T1, T2, T3 and three methods M1, M2, M3 then there are nine indicators I1-I9 with their unique factors denoted by U1-U9. The *complete* model states that the three indicators of each trait load on a single trait factor yielding three trait factors for this design. In addition, each indicator that uses the same method loads on a single method factor yielding three method factors. If the indicator of a trait is not affected by the method used in its measurement, then the indicator will load only on the common factor for that trait and not on the common factor for the method. If, however, there is an effect of the method of measurement, then each indicator will load on both the common factor for the trait and the factor for the particular method of measurement being used. This model permits to measure the degree of trait effects and method effects as well as various correlations between the trait and method factors and correlations between some unique factors. These parameters can be used to assess convergent and discriminant validity. Because of the large number of parameters and identification problems some appropriate restrictions imposed on the parameters are necessary yielding special cases of the complete model.

2. Indicators of the Financial Profitability

Based on balance-sheet microeconomic indicators characterizing industrial branches of the Hungarian corporations with double-entry book keeping our hypothesis is that *three* types of profitability measured by *three* methods can be described using an MTMM model. Industries are distinguished by a four-digit code of the corporations defined by the Hungarian Standard Industrial Classification of All Economic Activities introduced in 1998. Restricting analysis to the industries for which data are available, finally, 479 industries have been considered in the analysis as observation units. Hence, the microeconomic indicators relate to an industry as a whole and calculated based on the aggregated balance-sheet formed for the industry of interest. The data set corresponds to the economic year of 2002.

In our analysis, the *traits* are the following types of profitability:

- OP: Operating profitability,
- NP: Net (after-tax) profitability,
- BP: Balance-sheet (book value) profitability.

On the other hand, the *methods* applied to each of the traits are as follows:

- S: Net sales revenues,
- A: Assets (total),
- E: Owners' equity.

In order to remove the effect of the various sizes of the several industries profitability is measured by some comparable ratios formed as: *profit level/baseline method*. Based on this customary approach we expect the following indicators to reflect the movements in profitability:

- OP_S = Operating profit/Net sales revenues
- NP_S = After-tax profit/Net sales revenues
- BP_S = Balance-sheet profit/Net sales revenues
- OP_A = Operating profit/Assets, total
- NP_A = After-tax profit/Assets, total
- BP_A = Balance-sheet profit/Assets, total
- OP_E = Operating profit/Owners' equity
- NP_E = After-tax profit/Owners' equity
- BP_E = Balance-sheet profit/Owners' equity

The correlation matrix of the indicators is shown in *Table 2*.

An example for the WMCT correlation is the value of 0.689 in the BP_S row and NP_S column, the correlation between BP and NP both assessed by S. An example for the WTCM correlation is the value of 0.641 in the OP_A row and OP_S column, the correlation between OP assessed by A and OP assessed by S.

We use two approaches in order to impose restrictions on the complete MTMM model:

Table 2. Correlation matrix of the financial indicators

Indicator	OP_S	NP_S	BP_S	OP_A	NP_A	BP_A	OP_E	NP_E
OP_S	1							
NP_S	0.406	1						
BP_S	0.371	0.689	1					
OP_A	0.641	0.218	0.281	1				
NP_A	0.601	0.405	0.351	0.897	1			
BP_A	0.538	0.243	0.371	0.828	0.894	1		
OP_E	−0.050	−0.043	−0.121	0.128	0.066	−0.017	1	
NP_E	−0.100	0.016	−0.101	0.051	0.072	−0.017	0.971	1
BP_E	−0.155	−0.054	−0.116	−0.028	−0.022	−0.033	0.952	0.981

Included Method Factors – Uncorrelated Uniqueness

This model is defined by the path-diagram shown in *Fig. 1*.[1] According to the model correlated trait and correlated method factors are also postulated but no correlations are allowed across trait and method factors and the unique „U" factors are also assumed to be uncorrelated. In addition, the variances of the unique factors are estimated under the model. The model contains 33 free parameters. Assuming the model fits the data, convergent validation is assessed by significant loadings on the trait factors, discriminant validity by low correlations between the trait factors and method effects by significant loadings on the method factors.

Excluded Method Factors – Correlated Uniqueness

Under this model no method factors are created. Instead, the *standardized* unique factors are allowed to be correlated across indicators using the same method. Now, method effects are assessed by highly correlated unique factors. This type of model is defined by the path diagram in *Fig. 2*. This simpler model contains only 30 free parameters.

[1]Coefficients of directed effects are represented by arrows while the indirected wires stand for variances, covariances and correlations. The figure shows that extending the number of traits and methods the number of parameters to be estimated increases substantially.

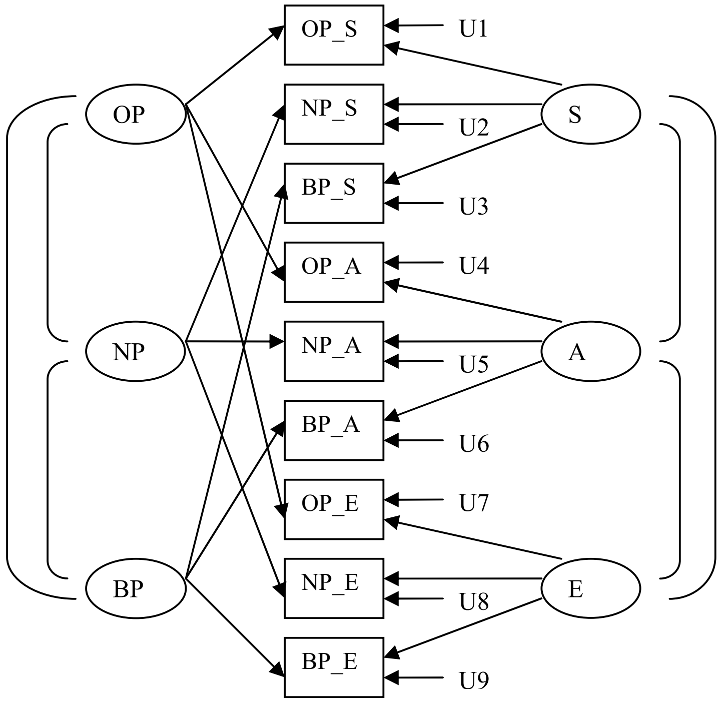

Fig. 1. Path diagram with 3 correlated trait factors and 3 correlated method factors

3. Parameter Estimation and the Goodness-of-fit

According to the *confirmatory* factor model let us consider the null hypothesis that the reproduced covariance matrix $\Sigma(\theta)$ expressed by the $\theta = (\theta_1, \theta_2, \ldots, \theta_q)$ freely estimated parameters holds for the population covariance matrix Σ against the alternative that it does not hold:

$$H_0 : \Sigma = \Sigma(\theta), \qquad H_1 : \Sigma \neq \Sigma(\theta).$$

In other words, the H_1 hypothesis states that a significant improvement is expected in the discrepancy between H_0 and H_1 due to a simple switch from $\Sigma(\theta)$ to Σ.

Based on a sample of size N, parameter estimates are obtained by the *iteratively weighted least squares* method (IWLS) which minimizes the discrepancy between the *saturated* model – defined as the sample covariance matrix of the indicators – and the estimated reproduced covariance matrix $\hat{\Sigma} = \Sigma(\hat{\theta})$.[2] The *fitting*

[2] In general, the so-called saturated model means the most complex model that contains as many free parameters to be estimated as many sample statistics are intended to be predicted. In our case the sample correlation matrix has $9 \cdot 10/2 = 45$ distinct elements including the entries on the main diagonal as well.

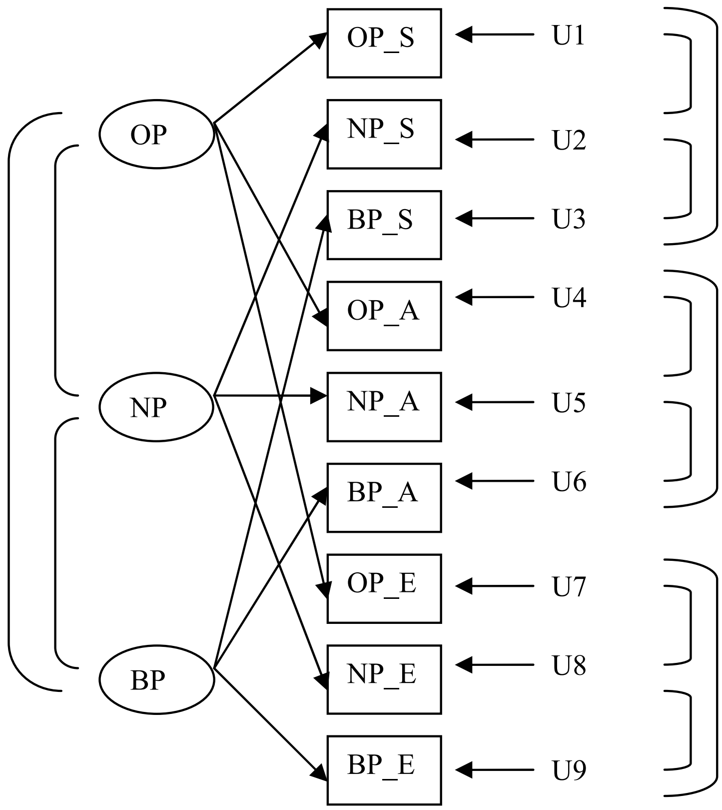

Fig. 2. Path diagram with 3 correlated trait factors and correlated unique factors

function then to be minimized is

$$F = \frac{1}{2}\mathrm{tr}\left\{\left([\mathbf{S} - \hat{\Sigma}]\hat{\Sigma}^{-1}\right)^2\right\} \to \min$$

where $\mathrm{tr}(.)$ denotes the *trace* operator and the sample covariance matrix $\mathbf{S}_{(p,\,p)}$ of the p indicators is the sample counterpart of Σ. In addition, $\hat{\Sigma}^{-1}$ is used iteratively as a positive-definite weight matrix. As it is well-known, for large samples the IWLS method simultaneously leads to the maximum likelihood (ML) estimator which maximizes the likelihood of the sample by the minimization of the minus log of the likelihood function:

$$F = \log|\hat{\Sigma}| + \mathrm{tr}\left[\mathbf{S}\hat{\Sigma}^{-1}\right] - \log|\mathbf{S}| - p \to \min .$$

Hereafter, F stands for both the IWLS and the ML fitting functions. Finally, the goodness-of-fit *chi-square statistic* is

$$\chi^2 = (N-1)F.$$

Namely, χ^2 is the *distance* of the currently estimated model from the saturated one. The *degree of freedom* of this chi-square is $p(p+1)/2 - q$.[3] Notice that the value of the chi-square statistic depends on the sample size N whereas its degree of freedom is independent on N. In general, comparing a nested (simpler) and a more complex model the degree of freedom to be applied is the difference on the numbers of their free parameters.

Model estimates based on the sample *correlation matrix* (rather than the covariance matrix) are shown in *Table 3* for the models with and without method factors. Since these models contain 33 and 30 parameters to be estimated the respective degrees of freedom are $df = 45 - 33 = 12$ and $df = 45 - 30 = 15$ because the sample correlation matrix has 45 distinct elements. The *free* parameters are termed by the following scheme: (.) contains latent variable, [.] includes measured indicator, the numbered $-\# \rightarrow$ arrow represents directed coefficients and the numbered $-\#-$ wire represents undirected variance or correlation.

Considering the model including method factors, based on the values of the t-statistic (parameter/standard error) we can conclude that the measurements are statistically determined by both the trait factors and the method factors with the only exception of the indicator OP_S loaded on the method of S. The indicators are somewhat less determined by the methods S and A, while, the loadings on method E are extremely large. The factor correlations and variances are all significant at a 5% level with the exceptions of the variance of U6 and the correlation between methods E and A. Notice that the variances of the unique factors U4, U5 and U8 do not differ from zero.

Based on the significant loadings of the trait factors convergent validity of the profitability indicators holds. Besides, because of the high inter-trait factor correlations discriminant validation is rejected. Finally, according to the significant method factor loadings method effects also influence the indicators.

Considering now the more parsimonious model defined without method factors, only the correlation between the unique terms U1 and U2 is not significant using a 5% level. In addition to the conclusions made above the high unique factor correlations also suggest accepting the evidence of method effects.

Two further aspects arise at this stage. First, the question is how good the model fits the data. The answer is always based on the *chi-square distance* of the current model from the *saturated* model. Several goodness-of-fit measures are available to evaluate the goodness-of-fit. One way is to test statistically whether the estimated value of the χ^2 statistic is small enough.[4] Other fit indices are *heuristic* and *descriptive* without any probabilistic assumption.

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[3] For the Satorra-Bentler correction to the goodness-of-fit statistic in the case of non-normality see SATORRA–BENTLER [16].

[4] The *small value* of the goodness-of-fit chi-square statistic is preferred because it indicates that the current model is close to the model with perfect predictions.

Table 3. IWLS (ML) model estimates of θ

Included Method Factors – Uncorrelated Uniqueness				Excluded Method Factors – Correlated Uniqueness			
Term	Parameter	t-value	Tail prob.	Term	Parameter	t-value	Tail prob.
(OP)−1→[OP_S]	0.686	28.465	0	(OP)−1→[OP_S]	0.730	23.466	0
(OP)−2→[OP_A]	0.897	38.493	0	(OP)−2→[OP_A]	0.831	31.171	0
(OP)−3→[OP_E]	0.343	19.656	0	(OP)−3→[OP_E]	0.331	18.142	0
(NP)−4→[NP_S]	0.732	19.084	0	(NP)−4→[NP_S]	0.567	16.547	0
(NP)−5→[NP_A]	0.916	40.766	0	(NP)−5→[NP_A]	0.842	31.846	0
(NP)−6→[NP_E]	0.330	19.696	0	(NP)−6→[NP_E]	0.301	18.021	0
(BP)−7→[BP_S]	0.635	19.768	0	(BP)−7→[BP_S]	0.541	12.959	0
(BP)−8→[BP_A]	0.868	28.994	0	(BP)−8→[BP_A]	0.771	21.708	0
(BP)−9→[BP_E]	0.277	18.227	0	(BP)−9→[BP_E]	0.244	15.168	0
(S)−10→[OP_S]	**0.005**	**0.109**	**0.913**	(U1)−10→[OP_S]	0.683	20.556	0
(S)−11→[NP_S]	0.681	16.528	0	(U2)−11→[NP_S]	0.824	34.895	0
(S)−12→[BP_S]	0.408	8.561	0	(U3)−12→[BP_S]	0.841	31.308	0
(A)−13→[OP_A]	0.442	9.347	0	(U4)−13→[OP_A]	0.556	13.977	0
(A)−14→[NP_A]	0.402	7.862	0	(U5)−14→[NP_A]	0.540	13.122	0
(A)−15→[BP_A]	0.496	9.457	0	(U6)−15→[BP_A]	0.636	14.780	0
(E)−16→[OP_E]	0.928	135.742	0	(U7)−16→[OP_E]	0.944	147.840	0
(E)−17→[NP_E]	0.944	161.202	0	(U8)−17→[NP_E]	0.954	180.500	0
(E)−18→[BP_E]	0.958	213.462	0	(U9)−18→[BP_E]	0.970	239.684	0
(U1)−19−(U1)	0.529	16.002	0	(NP)−19−(BP)	0.838	44.649	0
(U2)−20−(U2)	0.000			(OP)−20−(BP)	0.720	22.892	0
(U3)−21−(U3)	0.021	11.050	0	(OP)−21−(NP)	0.843	49.395	0
(U4)−22−(U4)	0.000			(U2)−22−(U1)	0.253	4.690	0
(U5)−23−(U5)	0.000			**(U3)−23−(U1)**	**0.116**	**1.851**	**0.064**
(U6)−24−(U6)	**0.000**	**0.370**	**0.711**	(U3)−24−(U2)	0.673	23.907	0
(U7)−25−(U7)	0.430	14.511	0	(U5)−25−(U4)	1.000		
(U8)−26−(U8)	0.000			(U6)−26−(U4)	0.993	81.476	0
(U9)−27−(U9)	0.005	7.629	0	(U6)−27−(U5)	1.000		
(NP)−28−(OP)	0.869	67.146	0	(U8)−28−(U7)	0.989	938.565	0
(BP)−29−(OP)	0.758	33.074	0	(U9)−29−(U7)	0.986	697.943	0
(BP)−30−(NP)	0.867	63.083	0	(U9)−30−(U8)	0.997	3645.225	0
(A)−31−(S)	−1.000						
(E)−32−(S)	−0.118	−2.036	0.042				
(E)−33−(A)	**−0.136**	**−1.585**	**0.113**				

Some of the fit indices compensate also for the model *parsimony* (i.e. prefer models with fewer parameters) while others prefer models simply closer to the sample data points. The widely used heuristic indices are listed in Table 6 in the Appendix. Their meanings obviously follow from their definitions. (For a detailed discussion of these indices see for instance HAJDU [9] or MULAIK et al. [12].

On the other hand, the question is whether the model contains relevant information from the sample. In this context the model is accepted to be relevant if it is far enough from the *null* model in a chi-square distance sense. The null model is the simplest model defined with the unique factors only. In our case, the distance of the model with method factors from the null model is 6642.6 with degree of freedom $33 - 9 = 24$ and the distance of the model without method factors from the null model is 6569.7 with degree of freedom $30 - 9 = 21$. This indicates that both of them are relevant.

Returning to the problem of the goodness-of-fit – in the case of the model defined with method factors – the chi-square statistic equals 142.959 with degree of freedom 12 producing zero tail-probability level. The discrepancy fitting function equals 0.299. Similarly, in the case of the model defined without method factors the chi-square statistic equals 215.947 with degree of freedom 15 yielding also a zero tail-probability level. The discrepancy fitting function here equals 0.452. Hence, based on the small tail-probability values the chi-square statistics suggest that both models seem to exhibit a poor fit.

Nevertheless, this badness-of-fit may be resulted from the relatively large sample size. As mentioned earlier, given a specified model the value of the chi-square statistic increasingly depends on the N sample size, whereas its degree of freedom is independent on N (it depends only on the number of indicators i.e. the size of the sample correlation matrix). Obviously, choosing a sample size large enough any models can be rejected in the favour of the saturated model. For this reason in our case the model goodness-of-fit must be evaluated in a descriptive way as well. The computed values of some heuristic indices are summarized in *Table 4* and other ones for which confidence intervals can be produced are given in *Table 5*.[5] The indices indicated by an asterisk show a better fit with smaller values close to 0 whereas the other ones indicate a better fit with larger values close to 1. Some indices reflect not only the improvement in the fitting function but also the number of the estimated parameters spent to achieve a good model fit.

Table 4. Heuristic goodness-of-fit indices

Index	Method Factors Included	Method Factors Excluded
Jöreskog-Sörbom GFI	0.939	0.910
Jöreskog-Sörbom AGFI	0.773	0.729
Akaike Information Criterion	0.437	0.577
Schwarz's Bayesian Criterion	0.725	0.839
Browne-Cudeck Cross Validation Index	0.440	0.580
Null Model Chi-Square (df)	6785.5 (36)	6785.5 (36)
Bentler-Bonett Normed Fit Index	0.979	0.968
Bentler-Bonett Non-Normed Fit Index	0.942	0.929
Bentler Comparative Fit Index	0.981	0.970
James-Mulaik-Brett Parsimonious Fit Index	**0.326**	**0.403**
Bollen's Rho	0.937	0.924
Bollen's Delta	0.981	0.970

[5] Confidence intervals are computed at a 90% percentage confidence level.

Table 5. Confidence intervals at 90% level

Index	Lower	Point	Upper	Lower	Point	Upper
	Method Factors Included			Method Factors Excluded		
Population Noncentrality Index	0.193	0.265	0.352	0.324	0.415	0.522
Steiger-Lind RMSE Index	0.127	0.149	0.171	0.147	0.166	0.186
McDonald Noncentrality Index	0.839	0.876	0.908	0.770	0.813	0.851
Population Gamma Index	0.927	0.944	0.959	0.896	0.916	0.933
Adjusted Population Gamma Index	0.728	0.792	0.846	0.688	0.747	0.799

The goodness-of-fit summary indicates that despite the chi-square test results both models exhibit an excellent goodness-of-fit. This is apparent especially from the Bentler-type and the Bollen-type normed indices of Table 4 because these measures would indicate a perfect fit with a value of 1. The 90% confidence upper bound of the population gamma index also measures an outstanding fit. Almost all indices even the parsimonious ones prefer the more complex model against the simpler one but the differences are negligible. The only exception is the James et al. Parsimonious Fit Index which prefers the simpler model with a greater degree of freedom and suffers only a small loss in the fitting function.

4. Conclusions

There are several aspects to interpret and several methods to measure the level of financial profitability of an economic activity. The paper investigates standard ratio-type microeconomic profitability indicators based on appropriate balance-sheet items. The numerator of an indicator gives the trait of profitability whereas the denominator gives the method how to evaluate its level. The paper uses the so-called ‘multitrait-multimethod’ (MTMM) model to test whether the financial ratios considered are valid indicators of the phenomenon. Convergent validity and discriminant validity are discussed based on two model types. Because of the large sample size, the model goodness-of-fit is evaluated on the basis of heuristic measures rather than a chi-square statistic. As a result, based on the significant trait factor loadings convergent validity of the profitability indicators holds, while, because of the high inter-trait factor correlations discriminant validation is rejected. Finally, according to the significant method factor loadings method effects are also found to govern the indicators.

Appendix

Table 6. Heuristic goodness-of-fit indices

Index name	Index formula
Population Noncentrality Index*	$\mathrm{NCI} = \dfrac{\chi^2 - df}{N-1}$
Steiger-Lind Root Mean Square Error*	$\mathrm{RMSE} = \sqrt{\dfrac{1}{df}\max\{\mathrm{NCI}, 0\}}$
McDonald Noncentrality Index	$\mathrm{MDNI} = \exp\{-0.5\max(\mathrm{NCI}, 0)\}$
Population Gamma Index	$\Gamma_1 = \dfrac{p}{2\mathrm{NCI} + p}$
Adjusted Population Gamma Index	$\Gamma_2 = 1 - \dfrac{p(p+1)}{2df}(1 - \Gamma_1)$
Jöreskog–Sörbom GFI	$\mathrm{GFI} = 1 - \frac{2F}{\mathrm{tr}\,([\mathbf{S}\hat{\Sigma}^{-1}]^2)}$
Adjusted Jöreskog–Sörbom	$\mathrm{AGFI} = 1 - \dfrac{p(p+1)}{2df}(1 - \mathrm{GFI})$
Akaike Information Criterion*	$\mathrm{AC} = F + \dfrac{2q}{N-1}$
Schwarz's Bayesian Criterion*	$\mathrm{SC} = F + \dfrac{q\ln(N)}{N-1}$
Browne-Cudeck Cross Validation Index*	$\mathrm{C} = F + \dfrac{2q}{N-p-2}$
Bentler–Bonett Normed Fit Index	$\mathrm{NFI}_{t/b} = 1 - \dfrac{\chi_t^2}{\chi_b^2}$
Bentler–Bonett, Tucker–Lewis Non-Normed Fit Index	$\mathrm{NNFI}_{t/b} = 1 - \dfrac{df_b}{df_t}\dfrac{\chi_t^2 - df_t}{\chi_b^2 - df_b}$
Bentler Comparative Fit Index	$\mathrm{BCF}I_{t/b} = 1 - \dfrac{\chi_t^2 - df_t}{\chi_b^2 - df_b}$
James–Mulaik–Brett Parsimonious Fit Index	$\mathrm{PI} = \dfrac{df_t}{df_b}\mathrm{NFI}_t$
Bollen's Rho	$\rho_{t/b} = 1 - \dfrac{df_b}{df_t}\dfrac{\chi_t^2}{\chi_b^2}$
Bollen's Delta	$\Delta_{t/b} = \dfrac{\chi_b^2 - \chi_t^2}{\chi_b^2 - df_t}$

Note: Sample size equals N, p denotes the number of indicators and q stands for the number of free parameters.
Subscription t indicates the target (more complex) model and b stands for the simpler baseline (now the null) model.
$F = \chi^2/(N-1)$ is the converged value of the '*fitting function*'.
*The indices indicated by an asterisk select the preferred model at their minimized values.

References

[1] BENTLER, P. M., Comparative Fit Indexes in Structural Models, *Psychological Bulletin*, **107** No. 2 (1990), pp. 238–246.
[2] BENTLER, P. M. – BONETT, D. G., Significance Tests and Goodness of Fit in the Analysis of Covariance Structures, 1980.
[3] BOLLEN, K. A., *Structural Equations with Latent Variables*, Wiley, New York, 1989.
[4] BROWNE, M. W., Generalized Least Squares Estimators in the Analysis of Covariance Structures, *South African Statistical Journal*, **8** (1974), pp. 1–24.
[5] BROWNE, M. W., Asymptotically Distribution-free Methods for the Analysis of Covariance Structures, *British Journal of Mathematical and Statistical Psychology*, **37** (1984), pp. 62–83.
[6] CAMPBELL, D. T. – FISKE, D. W., Convergent and Discriminant Validation by the Multitrait-Multimethod Matrix, *Psychological Bulletin*, **56** (1959), pp. 81–105.
[7] BROWNE, M. W. – CUDECK, R., Single Sample Cross-validation Indices for Covariance Structures, *Multivariate Behavioral Research*, **24** (1990), pp. 445–455.
[8] CUDECK, R. – HENLY, S. J., Model Selection in Covariance Structures Analysis and the ‘Problem’ of Sample Size: A Clarification, *Psychological Bulletin*, **109** No. 3 (1991), pp. 512–519.
[9] HAJDU, O., Diagnostics of the Error Factor Covariance Structure, *Hungarian Statistical Review*, Special Number, 2004.
[10] KENNY, D. A. – KASHY, D. A., Analysis of the Multitrait-Multimethod Matrix by Confirmatory Factor Analysis, *Psychological Bulletin*, **112** No. 1 (1992), pp. 165–172.
[11] MCDONALD, R. P. – MARSH, H. W., Choosing a Multivariate Model: Noncentrality and Goodness of Fit, *Psychological Bulletin*, **107** No. 2 (1990), pp. 247–255.
[12] MULAIK, S. A. – JAMES, L. R. – VAN ALSTINE, J. – BENNETT, N. – LIND, S. – STILLWELL, C. D., An Evaluation of Goodness of Fit Indices for Structural Equation Models, *Psychological Bulletin*, **105** No. 3. (1989), pp. 430–445.
[13] RAFTERY, A., Bayesian Model Selection in Structural Equation Models, In K. Bollen & J. Long (Eds.), *Testing Structural Equation Models* (pp. 163–180), Newbury Park, California, 1993.
[14] SATORRA, A., Scaled and Adjusted Restricted Tests in Multi-sample Analysis of Moment Structures, In: Heijmans, R. D. H., Pollock, D. S. G. & Satorra, A. (eds.), *Innovations in Multivariate Statistical Analysis*, *A Festschrift for Heinz Neudecker* (pp. 233–247), London: Kluwer Academic Publishers, 2000.
[15] SATORRA, A., Goodness of Fit Testing of Structural Equation Models with Multiple Group Data and Non-normality in Structural Equation Modeling, Present and Future, R. Cudeck, S. Du Toit & D. Sörbom. (Edits.) SSI Scientific Software International, Lincolnwood, IL, 2001.
[16] SATORRA, A. – BENTLER, P. M., A Scaled Difference Chi-square Test Statistic for Moment Structure Analysis, *Psychometrika*, **66**, pp. 507–514.
[17] SCHWARZ, G., Estimating the Dimension of a Model, *Annals of Statistics*, **6** (1978), pp. 461–464.
[18] TANAKA, J. S. – HUBA, G. J., A Fit Index for Covariance Structure Models under Arbitrary GLS Estimation, *British Journal of Mathematical and Statistical Psychology*, **38** (1985), pp. 197–201.
[19] TUCKER, L. R. – LEWIS, C., The Reliability Coefficient for Maximum Likelihood Factor Analysis, *Psychometrika*, **38** (1973), pp. 1–10.
[20] YUAN, K.-H. – BENTLER, P. M., Improving Parameter Tests in Covariance Structure Analysis, *ELSEVIER Computational Statistics & Data Analysis*, **26** (1997), pp. 177–198.