A Comparative Study on Parameter Recovery of Three Approaches to Structural Equation Modeling: A Rejoinder

Jörg Henseler[a]

[a]*Institute for Management Research, Radboud University Nijmegen, Nijmegen, The Netherlands*

Abstract

Hwang and Takane (2004) introduced generalized structured component analysis (GSCA) as an alternative structural equation modeling technique. In a recent JMR article, Hwang et al. (forthcoming) claim to have analyzed the performance of GSCA relative to covariance-based structural equation modeling and partial least squares path modeling. This article shows that these authors have not analyzed GSCA, but a different method, and that the differences between their method and GSCA are not negligible. Hence, their empirical findings regarding GSCA are invalid.

Keywords: Generalized Structured Component Analysis, GeSCA, VisualGSCA, Structural Equation Modeling

---

Jörg Henseler
Assistant Professor of Marketing
Radboud University Nijmegen
Institute for Management Research
Thomas van Aquinostraat 3, 6525 GD Nijmegen, The Netherlands
Phone: +31 24 361 1854
Fax: +31 24 361 1933
E-Mail: j.henseler@fm.ru.nl

A Comparative Study on Parameter Recovery of Three Approaches to Structural Equation Modeling: A Rejoinder

INTRODUCTION

Structural Equation Modeling (SEM) has become the sine qua non of survey-based research. Researchers embrace its idiosyncratic advantages, such as modeling latent variables, correcting for measurement error, and the simultaneous estimation of entire theories. Until now, two techniques have prevailed (Fornell and Bookstein 1982): covariance-based structural equation modeling (CBSEM) developed by Jöreskog (1969) and partial least squares path modeling (PLS developed by Wold (1974). Owing to a large number of conceptual, empirical, and simulation-based comparisons of both techniques (e.g., Dijkstra 1983; Fornell and Bookstein 1982; Reinartz et al. 2009), researchers in marketing research and other disciplines of business and social sciences have ample support to make a deliberate choice between structural equation modeling techniques.

Recently, Hwang and Takane (2004) proposed a third structural equation modeling technique: generalized structured component analysis (GSCA). GSCA shares characteristics with both CBSEM and PLS. Similar to PLS, GSCA determines latent variables as the weighted sum of their indicators; however, similar to CBSEM, GSCA describes the model in a closed form and has a defined global optimization criterion. In a forthcoming JMR article, Hwang et al. claim to have assessed the relative performance of GSCA with respect to PLS and CBSEM by means of simulated data. They conclude that in general, GSCA should be preferred to PLS, because "generalized structured component analysis generally performed better than or as well as partial least squares in parameter recovery," while it "maintains all the advantages of partial least squares as component-based structural equation modeling methodology" (Hwang et al. forthcoming, p. 25). With regard to CBSEM, Hwang et al. (forthcoming) conclude that "if correct model specification cannot be ensured, the researcher should use generalized structured component analysis" instead of CBSEM. As the condition is rather rhetoric, since virtually all models can be considered biased (Browne and Cudeck 1993), GSCA would always be the method of choice under normal circumstances.

Not only may researchers feel uncomfortable about any one-size-fits-all recommendation in terms of a rigorous choice among structural equation modeling techniques, but also too little – if anything at all – is known about the behavior of GSCA under various modeling conditions. In their recent JMR article, Hwang et al. (forthcoming) intended to fill this gap in the literature. As we will show, these authors did not apply GSCA at all, but only a reduced form of GSCA that ignores the structural model. This reduced form of GSCA provides estimates that differ substantially from those of GSCA. Consequently, these authors' empirical findings and conclusions are invalid and should be ignored.

A REDUCED FORM OF GSCA

The reduced form of GSCA differs from GSCA in that it does not take the sums of squares of the endogenous latent variables in the structural equation model into account – neither during the estimation phase nor to calculate the GSCA-specific model statistic FIT. Compared to GSCA, the reduced form of GSCA has a different matrix $\mathbf{T}$ (referring to equation (5) in Hwang et al. (forthcoming)): $\mathbf{T}_{\text{reduced}} = \begin{bmatrix} \mathbf{0} & \mathbf{C} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}$ in contrast to $\mathbf{T}_{\text{GSCA}} = \begin{bmatrix} \mathbf{0} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{bmatrix}$. This also has implications for the FIT: it means that instead of the formula being calculated that these authors provide (forthcoming, p. 8), the average communality of all the reflective indicators is calculated.

Admittedly, we have not had access to the program code that Hwang et al. (forthcoming) used to run their simulation study. However, we have strong evidence for our statement that Hwang et al. (forthcoming) analyzed the reduced form of GSCA instead of GSCA.

To date, two software implementations of GSCA have been launched, both of which were developed by teams associated with Hwang: VisualGSCA and GeSCA. Both software implementations incorrectly calculate the FIT. The documentation of VisualGSCA (Hwang 2007, p. 8) as well as that of GeSCA (Hwang and Park 2009, p. 8-10) report a numerical example with a FIT of .606. If the sum of squares of the endogenous latent variables had been taken into account, the correct value of .557 would have been obtained. In the strict sense, this error in calculating the FIT in both software implementations just implies that the FIT was wrongly programmed. However, as we will show, it stems from a more profound problem, namely calculating the reduced form of GSCA instead of GSCA; that is, ignoring the sum of squares of the endogenous latent variables during the estimation phase. A first indication of this can be found in Tenenhaus (2008): The estimates that he obtained from VisualGSCA are almost equivalent to those stemming from a set of principle component analyses, which – just like the reduced form of GSCA – does not take the structural model into account, either.

We re-analyze the simulation model by Hwang et al. (forthcoming) in order to provide evidence of whether GSCA or the reduced form of GSCA was used. We create population data that exactly fulfill the specification of the simulation model (see Figure 1 in Hwang et al. (forthcoming)). We generate a sufficient number of observations to achieve a positive-definite correlation matrix, which is displayed in Table 1. We refrain from creating replication samples, since we are not interested in the estimates' standard errors, but only their consistency.

– Insert Table 1 about here –

In concordance with Hwang et al. (forthcoming), we estimate two models: Model 1 is parameterized like the population model; Model 2 ignores the cross-loadings and allows for a direct effect between the latent variables η_1 and η_3. We use three methods to obtain estimates: GeSCA (Version as of 9 December 2009, Hwang and Park 2009) as an alleged implementation of GSCA[1], an own implementation of the reduced form of GSCA (rGSCA), and an own implementation of GSCA. The resulting estimates for Model 1 and Model 2 are shown in Table 2.

– Insert Table 2 about here –

Two findings emerge. First, regarding both estimated models, the own implementation of the reduced form almost perfectly recovers the estimates obtained from GeSCA, while the own implementation of GSCA delivers different estimates. This implies that GeSCA is, in fact, an implementation of the reduced form of GSCA. Second, particularly regarding Model 1, we find that the estimates of GSCA differ substantially from those of the reduced form of GSCA. GSCA delivers upward biased path coefficient estimates with a relative bias of ca. +20%. The reduced form of GSCA underestimates the path coefficients with a relative bias of ca. -10%. Regarding

Model 1, Hwang et al. (forthcoming) found that GSCA underestimates the path coefficients (see the right upper plate in Figure 3 in their forthcoming paper). This implies that the authors did not apply GSCA, but the reduced form of GSCA.

CONCLUSIONS

We demonstrated that Hwang et al. (forthcoming), who claimed to have analyzed the performance of GSCA, in fact only analyzed a reduced form of GSCA. We traced back this problem to a wrong implementation of GSCA. As the research group associated with Hwang has been the only provider of statistical GSCA implementations so far, our study strongly suggests that the empirical findings of all extant studies that allegedly analyze the behavior of GSCA are invalid. This applies to the empirical findings of studies based on real data (Hwang 2009; Hwang et al. 2007b; Tenenhaus 2008), as well as to simulation studies (Hwang et al. 2007a; Hwang et al. forthcoming). Also unpublished studies on the behavior of GSCA using VisualGSCA or GeSCA – whether forthcoming, still under review, or close to submission – are invalid with regard to their empirical GSCA findings. Nevertheless, the purely conceptual contributions as well as the empirical findings related to other structural equation modeling techniques than GSCA remain unaffected by the problem.

Since the empirical results by Hwang et al. (forthcoming) are invalid, their implications and recommendations with regard to the use of GSCA are also. As long as empirical evidence of GSCA's superiority to other structural equation modeling techniques is lacking, researchers using structural equation modeling should ignore the findings by Hwang et al. (forthcoming) with regard to GSCA's behavior, and stick to their current heuristics to choose among structural equation modeling techniques.

BIBLIOGRAPHY

Browne, Michael W. and Robert Cudeck (1993), "Alternative Ways of Assessing Model Fit," in Testing structural equation models, K. Bollen and J. Long, Eds. Thousand Oaks, CA: Sage.

Dijkstra, Theo K. (1983), "Some Comments on Maximum Likelihood and Partial Least Squares Methods," Journal of Econometrics, 22 (1-2), 67-90.

Fornell, Claes and Fred L. Bookstein (1982), "Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-voice Theory," Journal of Marketing Research, 19 (4), 440-52.

Hwang, Heungsun (2009), "Regularized Generalized Structured Component Analysis," Psychometrika, 74 (3), 517-30.

---- (2007), VisualGSCA 1.0, A Graphical User Interface Software Program for Generalized Structured Component Analysis. Montreal: Department of Psychology, McGill University.

Hwang, Heungsun, Wayne S. Desarbo, and Yoshio Takane (2007a), "Fuzzy Clusterwise Generalized Structured Component Analysis," Psychometrika, 72 (2), 181-98.

Hwang, Heungsun, Naresh K. Malhotra, Youngchan Kim, Marc A. Tomiuk, and Sungjin Hong (forthcoming), "A Comparative Study on Parameter Recovery of Three Approaches to Structural Equation Modeling," Journal of Marketing Research.

Hwang, Heungsun and Sunyoung Park (2009), GeSCA, Version as of 9 December 2009. Montreal: McGill University, http://www.sem-gesca.org.

Hwang, Heungsun and Yoshio Takane (2004), "Generalized Structured Component Analysis," Psychometrika, 69 (1), 81-99.

Hwang, Heungsun, Yoshio Takane, and Naresh K. Malhotra (2007b), "Multilevel Generalized Structured Component Analysis," Behaviormetrika, 34 (2), 95-109.

Jöreskog, Karl G. (1969), "A General Approach to Confirmatory Maximum Likelihood Factor Analysis," Psychometrika, 34 (2), 183-202.

Reinartz, Werner J., Michael Haenlein, and Jörg Henseler (2009), "An Empirical Comparison of the Efficacy of Covariance-Based and Variance-Based SEM," International Journal of Research in Marketing, 26 (4), 332-44.

Tenenhaus, Michel (2008), "Component-based Structural Equation Modelling," Total Quality Management & Business Excellence, 19 (7), 871-86.

Wold, Herman O.A. (1974), "Causal Flows with Latent Variables: Partings of the Ways in the Light of NIPALS Modelling," European Economic Review, 5 (1), 67-86.

TABLES

Table 1: Correlation matrix of Hwang et al.'s (forthcoming) population model

	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9
Z1	1.0000								
Z2	.4900	1.0000							
Z3	.4900	.4900	1.0000						
Z4	.4410	.4410	.4410	1.0000					
Z5	.2940	.2940	.2940	.5782	1.0000				
Z6	.3469	.3469	.3469	.6823	.5782	1.0000			
Z7	.2646	.2646	.2646	.5204	.4410	.6145	1.0000		
Z8	.1764	.1764	.1764	.3469	.2940	.4410	.5782	1.0000	
Z9	.1764	.1764	.1764	.3469	.2940	.4410	.5782	.4900	1.0000

Table 2: Parameter estimates per method depending on model specification

POPULATION MODEL			MODEL 1 measurement correct structural model correct			MODEL 2 cross-loadings ignored direct effect added		
Parameter		**value**	**GeSCA**	**rGSCA**	**GSCA**	**GeSCA**	**rGSCA**	**GSCA**
λ_{11}	loading	.700	.812	.812	.790	.812	.812	.812
λ_{12}	loading	.700	.812	.812	.790	.812	.812	.812
λ_{13}	loading	.700	.812	.812	.790	.812	.812	.812
λ_{14}	cross-loading	.210	.147	.146	.260	—	—	—
λ_{24}	loading	.700	.787	.788	.698	.878	.878	.890
λ_{25}	loading	.700	.845	.845	.787	.827	.828	.795
λ_{26}	loading	.700	.813	.813	.813	.878	.878	.893
λ_{27}	cross-loading	.210	.235	.235	.090	—	—	—
λ_{36}	cross-loading	.210	.111	.111	.101	—	—	—
λ_{37}	loading	.700	.701	.701	.819	.865	.865	.896
λ_{38}	loading	.700	.837	.837	.788	.822	.822	.803
λ_{39}	loading	.700	.837	.837	.788	.822	.822	.803
β_1	path coefficient	.600	.527	.526	.666	.517	.517	.522
β_2	path coefficient	.600	.549	.546	.778	.578	.578	.601
β_3	path coefficient	.000	—	—	—	.005	.006	-.002

FOOTNOTES

[1] VisualGSCA 1.0 (Hwang 2007) was not used because it does not allow for cross-loadings.