

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

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Abstract

Traditionally, two distinct approaches have been employed for structural equation modeling: covariance structure analysis and partial least squares. A third alternative called generalized structured component analysis was introduced recently in the psychometric literature. A simulation study is carried out to evaluate the relative performance of these three approaches in terms of parameter recovery under different experimental conditions of sample size, data distribution, and model specification. In this study, model specification was found to be the only meaningful condition in differentiating the performance of the three approaches in parameter recovery. Specifically, when the model was correctly specified, covariance structure analysis generally recovered parameters better than generalized structured component analysis and partial least squares. On the other hand, when the model was misspecified, generalized structured component analysis tended to recover parameters better than the two traditional approaches. Additionally, partial least squares exhibited relatively inferior performance in parameter recovery in comparison to the other approaches. In particular, this tendency became salient when the model involved cross-loadings. As a result, generalized structured component analysis may be regarded as a good alternative to partial least squares for structural equation modeling. Moreover, this novel and recent approach may be recommended over covariance structure analysis unless

correct model specification is ensured.

Keywords: Structural equation modeling, covariance structure analysis, partial least squares, generalized structured component analysis, Monte Carlo simulations.

DO NOT PRINT

Structural equation modeling, also known as path analysis with latent variables, is used for the specification and analysis of interdependencies among observed variables and underlying theoretical constructs, often called latent variables. Since its introduction to marketing (Bagozzi 1980), structural equation modeling has become a remarkably popular tool for many reasons including the analytic flexibility and generality imparted by the procedure (Baumgartner and Homburg 1996; Steenkamp and Baumgartner 2000).

Traditionally, two approaches have been used for structural equation modeling (Anderson and Gerbing 1988; Fornell and Bookstein 1982; Jöreskog and Wold 1982): One is covariance structure analysis (Jöreskog 1973). The other is partial least squares (Lohmöller 1989; Wold 1975). Covariance structure analysis is exemplified by many available software programs including LISREL (Jöreskog and Sörbom 1993), AMOS (Arbuckle 1994), EQS (Bentler 1995), and Mplus (Muthén and Muthén 1994) whereas partial least squares can be implemented by the software programs LVPLS (Lohmöller 1984), PLS-Graph (Chin 2001), SmartPLS (Ringle, Wende, and Will 2005), and VisualPLS (Fu 2006). Recently, a third approach, namely generalized structured component analysis, was published in the psychometric literature (Hwang and Takane 2004). Generalized structured component analysis was implemented by the software program GeSCA (Hwang 2009).

However, no study has been carried out to investigate the relative performance of these three approaches to structural equation modeling. Therefore, the objective of this paper is to evaluate the three approaches in terms of parameter recovery capability based on a Monte Carlo simulation study.

The structure of this paper is as follows: First, we briefly review generalized

structured component analysis, and discuss theoretical differences and similarities among the three approaches. Subsequently, we describe the design of our simulation study, and report results. Finally, we discuss the implications of the present study and also provide recommendations for marketing/applied researchers on the basis of parameter recovery capability of the three approaches.

BACKGROUND

There exists a vast literature providing the technical underpinnings of covariance structure analysis (e.g., Bollen 1989; Kaplan 2000) and partial least squares (e.g., Lohmöller 1989; Tenenhaus et al. 2005). On the other hand, generalized structured component analysis is still novel to marketing researchers. Thus, a brief description of generalized structured component analysis is first presented, followed by a discussion about theoretical characteristics among the three approaches.

Generalized Structured Component Analysis

As its name explicitly suggests, generalized structured component analysis represents a component-based approach to structural equation modeling (Tenenhaus 2008). Thus, this approach defines latent variables as components or weighted composites of observed variables as follows:

$$(1) \quad \boldsymbol{\gamma}_i = \mathbf{W}\mathbf{z}_i,$$

where \mathbf{z}_i denotes a vector of observed variables for a respondent i ($i = 1, \dots, N$), $\boldsymbol{\gamma}_i$ is a vector of latent variables for a respondent i , and \mathbf{W} is a matrix consisting of component weights assigned to observed variables. Moreover, generalized structured component analysis

involves two additional equations for model specifications: One is for the measurement or outer model which specifies the relationships between observed and latent variables; and the other is for the structural or inner model which expresses the relationships among latent variables. Specifically, in generalized structured component analysis, the measurement model is given by:

$$(2) \quad \mathbf{z}_i = \mathbf{C}\boldsymbol{\gamma}_i + \boldsymbol{\varepsilon}_i,$$

where \mathbf{C} is a matrix of loadings relating latent variables to observed variables and $\boldsymbol{\varepsilon}_i$ is a vector of residuals for \mathbf{z}_i . The structural model is defined by:

$$(3) \quad \boldsymbol{\gamma}_i = \mathbf{B}\boldsymbol{\gamma}_i + \boldsymbol{\xi}_i,$$

where \mathbf{B} is a matrix of path coefficients connecting latent variables among themselves and $\boldsymbol{\xi}_i$ is a vector of residuals for $\boldsymbol{\gamma}_i$.

Then, the generalized structured component analysis model is derived from combining these three equations into a single equation as follows:

$$(4) \quad \begin{aligned} \begin{bmatrix} \mathbf{z}_i \\ \boldsymbol{\gamma}_i \end{bmatrix} &= \begin{bmatrix} \mathbf{C} \\ \mathbf{B} \end{bmatrix} \boldsymbol{\gamma}_i + \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix} \\ \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix} \mathbf{z}_i &= \begin{bmatrix} \mathbf{C} \\ \mathbf{B} \end{bmatrix} \mathbf{W}\mathbf{z}_i + \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix} \\ \mathbf{V}\mathbf{z}_i &= \mathbf{A}\mathbf{W}\mathbf{z}_i + \mathbf{e}_i, \end{aligned}$$

where $\mathbf{V} = \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix}$, $\mathbf{A} = \begin{bmatrix} \mathbf{C} \\ \mathbf{B} \end{bmatrix}$, $\mathbf{e}_i = \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix}$, and \mathbf{I} is an identity matrix (Hwang and Takane

2004; Hwang, DeSarbo, and Takane 2007). Although Equation 4 represents the original generalized structured component analysis model proposed in Hwang and Takane (2004), this model can also be expressed as:

$$\begin{aligned}
& \begin{bmatrix} \mathbf{z}_i \\ \boldsymbol{\gamma}_i \end{bmatrix} = \begin{bmatrix} \mathbf{C} \\ \mathbf{B} \end{bmatrix} \boldsymbol{\gamma}_i + \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix} \\
(5) \quad & \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix} \mathbf{z}_i = \begin{bmatrix} \mathbf{0} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{bmatrix} \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix} \mathbf{z}_i + \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix} \\
& \mathbf{u}_i = \mathbf{T} \mathbf{u}_i + \mathbf{e}_i
\end{aligned}$$

where $\mathbf{u}_i = \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix} \mathbf{z}_i$, and $\mathbf{T} = \begin{bmatrix} \mathbf{0} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{bmatrix}$. As shown above, thus, the generalized structured component analysis model is essentially of the same form as the reticular action model (McArdle and McDonald 1984), which is mathematically the most compact specification amongst various formations of covariance structure analysis. With respect to the reticular action model, the only difference in model specification is that generalized structured component analysis defines latent variables as components, i.e., $\boldsymbol{\gamma}_i = \mathbf{W} \mathbf{z}_i$.

The unknown parameters of generalized structured component analysis (\mathbf{W} and \mathbf{A}) are estimated such that the sum of squares of all residuals (\mathbf{e}_i) is as small as possible across all respondents. This problem is equivalent to minimizing the following least squares criterion:

$$(6) \quad \phi = \sum_{i=1}^N (\mathbf{V} \mathbf{z}_i - \mathbf{A} \mathbf{W} \mathbf{z}_i)' (\mathbf{V} \mathbf{z}_i - \mathbf{A} \mathbf{W} \mathbf{z}_i),$$

with respect to \mathbf{W} and \mathbf{A} , subject to $\sum_{i=1}^N \gamma_{id}^2 = 1$, where γ_{id} is the d -th element of $\boldsymbol{\gamma}_i$. An alternating least squares algorithm (de Leeuw, Young, and Takane 1976) was developed to minimize this criterion. This algorithm alternates two main steps until convergence: In the first step, for fixed \mathbf{W} , \mathbf{A} is updated in the least squares sense, and in the second, \mathbf{W} is updated in the least squares sense for fixed \mathbf{A} (refer to Hwang and Takane, 2004, for a detailed description of the algorithm).

Generalized structured component analysis estimates model parameters by consistently minimizing the global optimization criterion. This enables the provision of measures of overall model fit. Specifically, generalized structured component analysis offers an overall measure of fit, called FIT, which is the proportion of the total variance of all endogenous variables explained by a given particular model specification. It is given by

$$\text{FIT} = 1 - \left[\frac{\sum_{i=1}^N (\mathbf{V}\mathbf{z}_i - \mathbf{A}\mathbf{W}\mathbf{z}_i)'(\mathbf{V}\mathbf{z}_i - \mathbf{A}\mathbf{W}\mathbf{z}_i)}{\sum_{i=1}^N \mathbf{z}_i' \mathbf{V}' \mathbf{V} \mathbf{z}_i} \right].$$

The values of FIT range from 0 to 1. The larger this value, the more variance in the variables is accounted for by the specified model. FIT is a function of the sum of the squared residuals that summarizes the discrepancies between the model and the data. However, FIT is obviously affected by model complexity, i.e., the more parameters the larger the value of FIT. Thus, another index of fit was developed which takes this contingency into account. It is referred to as Adjusted FIT or AFIT (Hwang, DeSarbo, and Takane 2007), given by AFIT

$$= 1 - (1 - \text{FIT}) \frac{d_0}{d_1},$$

where $d_0 = NJ$ is the degrees of freedom for the null model ($\mathbf{W} = \mathbf{0}$ and $\mathbf{A} = \mathbf{0}$) and $d_1 = NJ - G$ is the degrees of freedom for the model being tested, where J is the number of observed variables and G is the number of free parameters. The model that maximizes AFIT is regarded as the most appropriate among competing models.

In generalized structured component analysis, the bootstrap method (Efron 1982) is employed to calculate the standard errors of parameter estimates without recourse to the assumption of multivariate normality of observed variables. The bootstrapped standard errors or confidence intervals can be used for assessing the reliability of the parameter estimates.

Similarities and Dissimilarities among the Three Approaches

In this section, the theoretical characteristics of generalized structured component analysis are compared to those of covariance structure analysis and partial least squares. Table 1 provides a summary of the comparisons among the three approaches in terms of model specification and parameter estimation.

Insert Table 1 about here

Comparisons in model specification. With respect to model specification, generalized structured component analysis defines latent variables as components or weighted sums of observed variables as shown in Equation 1. This is similar to partial least squares in which latent variables are also regarded as components. On the other hand, in covariance structure analysis, latent variables are equivalent to common factors. Thus, generalized structured component analysis and partial least squares are viewed as a component-based approach to structural equation modeling whereas covariance structure analysis as a factor-based approach (Chin 1998; Velicer and Jackson 1990). In turn, this implies that latent variables in covariance structure analysis are random whereas in partial least squares and generalized structured component analysis, they are fixed. Consequently, this leads to the specification of different sets of model parameters for latent variables (i.e., factor means and/or variances in covariance structure analysis vs. component weights in partial least squares and generalized structured component analysis).

Another point of comparison in model specification rests in the number of equations to be used in specifying models. As shown in Equations 2 and 3, generalized structured component analysis entails the specifications of measurement and structural

models. This is the case in both covariance structure analysis and partial least squares. However, covariance structure analysis and generalized structured component analysis integrate the two sub-models into a unified algebraic formulation (i.e., a single equation) such as the reticular action model in covariance structure analysis and Equation 4 in generalized structured component analysis. On the other hand, partial least squares does not combine the two sub-models into a single equation and thus addresses the two equations separately. This difference in the number of equations for the specification of structural equation models contributes to characterizing the parameter estimation procedures of the three approaches as will be discussed shortly.

Comparisons in parameter estimation. As the name suggests, covariance structure analysis is run on covariances or correlations among observed variables as input data. Specifically, in covariance structure analysis, the population covariance matrix of observed variables is modeled as a function of the parameters of a hypothesized structural equation model. This modeled population covariance matrix is often referred to as the implied population covariance matrix. If the model is correct and the population covariance matrix is known, the parameters can be estimated by minimizing the difference between the population and the implied covariance matrices. In practice, the population covariance matrix is substituted for by the sample covariance matrix because the population covariance matrix is usually unknown (Bollen 1989). Under the assumption of multivariate normality of observed variables, Jöreskog (1973) developed a maximum likelihood method for parameter estimation for covariance structure analysis. This procedure is by far the most widely used (Bollen 1989); although there are alternate estimation methods which include generalized least squares and unweighted least squares.

On the other hand, partial least squares and generalized structured component analysis employ individual-level raw data as input data for parameter estimation. Moreover, the two approaches estimate parameters based on a least squares estimation method: the fixed point algorithm for partial least squares (Wold 1965) and the alternating least squares algorithm for generalized structured component analysis. Due to the adoption of a least squares estimation method, partial least squares and generalized structured component analysis do not require the normality assumption for parameter estimation. Note that in covariance structure analysis, this distributional assumption can also be relaxed through the use of unweighted least squares or asymptotically distribution-free estimators (e.g., Browne 1982, 1984).

Despite that covariance structure analysis and generalized structured component analysis utilize differing estimation methods (maximum likelihood vs. least squares), they remain comparable in the sense that both approaches aim to optimize a single optimization function for parameter estimation. Specifically, maximum likelihood estimates parameters by consistently maximizing a single likelihood function which, in turn, is derived from a single formulation of structural equation modeling. Similarly, the alternating least squares algorithm of generalized structured component analysis also estimates parameters by consistently minimizing a single least squares optimization function which, in turn, is directly derived from a single equation. On the other hand, due to the absence of such a global optimization function stemming from a unified formulation of the two sub-models, the fixed point algorithm inherent to partial least squares involves minimizing separate local optimization functions by solving a series of ordinary regression analyses. Consequently, covariance structure analysis and generalized structured component

analysis define convergence as the increase or decrease in the function value beyond a certain threshold. In contrast, partial least squares defines convergence as a sort of equilibrium, i.e., the point at which no substantial difference occurs between the previous and current estimates of component weights. Thus, the algebraic formulations underlying the three approaches seem to result in substantial differences in the procedures of parameter estimation.

Importantly, the availability of measures of overall model fit relies on whether or not some global optimization criterion is present. In fact, because generalized structured component analysis and covariance structure analysis involve a global optimization criterion, they can provide measures of overall and local model fit. In contrast, partial least squares entails the estimation of two different sub-models in order to capture the same relationships and each is linked to a separate local optimization criterion. Hence, partial least squares is incapable of providing a measure of overall model fit. This forces partial least squares users to rely solely on local fit measures for the evaluation of a model. Despite the importance of measures of local fit in evaluating the suitability of models (Bollen 1989), they provide little information on how well a model fits to the data as a whole. Moreover, they are of little use for comparisons of a focal model to alternative model specifications.

SIMULATION DESIGN

The experimental conditions considered in the present simulation study were as follows: approach (covariance structure analysis, partial least squares, and generalized structured component analysis), sample size ($N = 100, 200, 300, 400$ and 500), model

specification (correctly specified vs. misspecified), and data distribution (normal vs. non-normal). These experimental conditions are commonly encountered in simulations based on structural equation modeling (Paxton et al. 2001).

A structural equation model was specified for this study, which involved three latent variables and four observed variables per latent variable. This model was essentially the same as that specified in Paxton et al. (2000) in their simulations. Figure 1 displays the correct specification and a misspecification of the model along with their unstandardized and standardized parameter values. In the misspecified model, cross-loadings are omitted and an additional path coefficient is specified, as indicated by dashed lines in Figure 1.

Insert Figure 1 about here

Individual-level multivariate normal data were drawn from $N(\mathbf{0}, \Sigma)$, where Σ is the implied population covariance matrix derived from a covariance structure analysis formulation (i.e., the reticular action model) using the unstandardized parameter values. For a non-normal distribution, we adopted skewness = 1.25 and kurtosis = 3.75. These levels of skewness and kurtosis were used in order to closely reflect a non-normal condition typically encountered in marketing research (e.g., Hulland, Ryan and Rayner 2005). To generate the intended non-normality (i.e., the intended skewness and kurtosis values), Fleishman's (1978) power transformation approach was applied to normal data. Five hundred samples were generated at each level of the experimental conditions. Subsequently, all 10000 samples (5 sample sizes \times 2 distributions \times 2 model specifications \times 500 replications) were fitted by the three approaches.

SIMULATION RESULTS

To evaluate the recovery of parameter estimates under the three approaches, we computed the mean absolute differences (MAD) of parameters and their estimates given by:

$$(7) \quad \text{MAD} = \frac{\sum_{j=1}^P |\hat{\theta}_j - \theta_j|}{P},$$

where $\hat{\theta}_j$ and θ_j are an estimate and its parameter, respectively, and P is the number of parameters (e.g., Mason and Perreault 1991). Any simulated sample involving non-convergence within 100 iterations or convergence to improper solutions was removed from the calculation of the absolute differences.

As discussed earlier, the three approaches estimate different sets of model parameters. Thus, in this study, we evaluate and report the recovery of the estimates of a common set of parameters (i.e., loadings and path coefficients) and the recovery of the standard errors of those parameter estimates. Covariance structure analysis typically provides unstandardized parameter estimates and their standard errors, whereas generalized structured component analysis and partial least squares result in standardized parameter estimates and their standard errors. Thus, all estimates were rescaled by dividing them by the corresponding (unstandardized or standardized) parameters so as to ensure equal-scale comparisons across the three approaches.

Recovery of Parameters

An ANOVA test for examining the recovery of parameters. An analysis of variance (ANOVA) test was performed that included the mean absolute differences of the estimates

of loadings and path coefficients as the dependent variable and the four experimental conditions as design factors. Table 2 presents the results of the ANOVA test. A number of the main and interaction effects of the design factors were statistically significant. However, this may be largely due to the enormously large number of observations stemming from a number of replications under multiple conditions (the total number of observations was 28267). Thus, it is important to report and interpret the meaningfulness of such effects using an effect size (Paxton et al., 2001). We focus only on those effects whose sizes were at least medium (i.e., $\eta^2 \geq .06$) (Cohen 1988).

Insert Table 2 about here

First, *model specification* ($\eta^2 = .08$) and *approach* ($\eta^2 = .14$) had a medium and large main effect, respectively. Thus, it is likely that the levels of the mean absolute differences of parameter estimates were higher when the model was correctly specified (.31) compared to when the model was misspecified (.15). Moreover, there are likely meaningful differences in the mean absolute differences among the three approaches. It appears that there were little differences in the mean absolute differences between covariance structure analysis (.16) and generalized structured component analysis (.15), whereas partial least squares was associated with a higher level of the mean absolute differences (.38).

Second, the two-way interaction effect between *model specification* and *approach* was large ($\eta^2 = .16$). Figure 2 displays the average values of the mean absolute differences of the three approaches under the two different levels of model specification (correct vs.

misspecified). When the model was correctly specified, covariance structure analysis was associated with the smallest level of the mean absolute differences (.15); generalized structured component analysis was with the second smallest (.16); and partial least squares was with the largest (.62). On the other hand, when the model was misspecified, generalized structured component analysis involved the smallest level of the mean absolute differences (.13); partial least squares had the second smallest (.14); and covariance structure analysis yielded the largest (.18). Thus, the somewhat counterintuitive nature of the main effect of model specification may be due to the poor parameter recovery of partial least squares under correct specification.

Insert Figure 2 about here

Overall finite-sample properties of parameter estimates under model specification levels. The above ANOVA test showed that the parameter recovery of the three approaches was distinct between the two different levels of model specification. To obtain a greater understanding of how differently they behave under this condition, we further investigated the overall finite-sample properties of the parameter estimates of the three approaches across the model specification levels. Figures 3 and 4 display the average relative biases, standard deviations, and mean square errors of parameter estimates obtained from the three approaches under the two model specifications. Among these properties, in particular, the mean square error is the average squared difference between a parameter and its estimate, thereby indicating how far an estimate is, on average, from its parameter, i.e., the smaller the mean square error, the closer the estimate is to the parameter. Specifically, the mean

square error (MSE) is given by:

$$(8) \quad \text{MSE}(\hat{\theta}_j) = E[(\hat{\theta}_j - \theta_j)^2] = E[(\hat{\theta}_j - E(\hat{\theta}_j))^2] + (E(\hat{\theta}_j) - \theta_j)^2.$$

As shown in Equation 8, the mean square error of an estimate is the sum of its variance and squared bias. Thus, the mean square error entails information on both bias and variability of the estimate (Mood, Graybill and Boes 1974).

In the present study, absolute values of relative bias greater than 10 percent are regarded as indicative of an unacceptable degree of bias (Lei in press; Muthén, du Toit, and Spisic 1997; Bollen et al. 2007). As displayed in Figure 3, under correct model specification, covariance structure analysis on average yielded unbiased estimates of loadings and path coefficients across all sample sizes. Generalized structured component analysis led to unbiased loading estimates while it yielded negatively biased path coefficient estimates, regardless of sample size. Partial least squares showed a very high level of positive bias in loading estimates, which appeared to increase with sample size. This approach also tended to result in positively biased path coefficient estimates as sample size increased. When the model was correctly specified, overall, the parameter estimates of generalized structured component analysis were consistently associated with smaller standard deviations than those via the two traditional approaches. The estimates of partial least squares involved larger standard deviations than those under covariance structure analysis. As sample size increased, these standard deviations tended to decrease across all approaches.

On average, covariance structure analysis showed the smallest mean square errors of loading estimates and generalized structured component analysis involved the second smallest mean square errors of loading estimates, although they showed similar levels of

the mean square errors until $N = 300$. On the other hand, partial least squares exhibited the largest mean square errors of loading estimates across all sample sizes. Lastly, generalized structured component analysis involved the smallest mean square errors of path coefficient estimates until $N = 400$ whereas covariance structure analysis resulted in the smallest mean square error of path coefficient estimate at $N = 500$, although the differences in the mean square errors between generalized structured component analysis and covariance structure analysis became quite small as $N > 100$. On the other hand, partial least squares was associated with the largest mean square errors of path coefficient estimates across all sample sizes.

Insert Figure 3 about here

As shown in Figure 4, under model misspecification, all three approaches yielded positively biased loading estimates across sample sizes, although the amount of bias tended to decrease with sample size in covariance structure analysis. On the other hand, generalized structured component analysis and partial least squares led to a negatively yet tolerable degree of bias for path coefficient estimates, whereas covariance structure analysis yielded positively biased path coefficient estimates that were slightly less than 10% of relative bias. Additionally, under misspecification, the parameter estimates under generalized structured component analysis were consistently associated with smaller standard deviations than those via the other approaches, although the differences between generalized structured component analysis and partial least squares were very small. The parameter estimates from covariance structure analysis showed the largest levels of

standard deviations over sample size.

On average, generalized structured component analysis had the smallest mean square errors of both loading and path coefficient estimates across all sample sizes. However, the differences in the mean square errors of the parameter estimates were negligibly small between generalized structured component analysis and partial least squares. On the other hand, covariance structure analysis resulted in the parameter estimates having the largest mean square errors over sample size, although the mean squares errors of the loading estimates appeared to close to those of generalized structured component analysis and partial least squares, when sample size increased.

Insert Figure 4 about here

Recovery of Standard Errors

An ANOVA test for examining the recovery of standard errors. To evaluate the recovery of the standard errors of parameter estimates, we first obtained the true standard errors empirically as follows:

$$(9) \quad SE(\hat{\theta}_j) = \sqrt{\frac{\sum_{i=1}^B (\hat{\theta}_j - \bar{\hat{\theta}}_j)^2}{B-1}},$$

where $\bar{\hat{\theta}}_j$ is the mean of a parameter estimate across B replications (e.g., B = 500)

(Srinivasan and Mason 1986; Sharma, Durvasula and Dillon 1989). We then calculated the mean absolute differences of the standard errors of loading and path coefficient estimates across different experimental conditions. In covariance structure analysis, the standard

errors were obtained from the asymptotic covariance matrix of parameter estimates under asymptotic normal theory (e.g., Bollen 1989), whereas in generalized structured component analysis and partial least squares, they were estimated based on the bootstrap method with 100 bootstrap samples.

An ANOVA test was performed to examine the main and interaction effects of the design factors on the mean absolute differences of the standard error estimates. Table 3 shows the results of the ANOVA test. As before, most of the main and interaction effects of the design factors turned out to be statistically significant. Nonetheless, only two design factors showed sufficiently large main effects - *model specification* ($\eta^2 = .14$) and *approach* ($\eta^2 = .27$). Thus, these suggest meaningful differences in the mean absolute differences of standard errors between the two model specifications (correct = .03 and misspecified = .01) and the three approaches (generalized structured component analysis = .00, covariance structure analysis = .02, partial least squares = .04).

Moreover, the two-way interaction between *model specification* and *approach* had a quite large effect size ($\eta^2 = .36$). Figure 2 displays the average values of the mean absolute differences of the three approaches under the two different levels of model specification. Under both levels, generalized structured component analysis resulted in the smallest level of the mean absolute differences of standard errors (correct = .00 and misspecified = .00). On the other hand, covariance structure analysis provided a smaller level of the mean absolute differences than partial least squares under correct specification (covariance structure analysis = .02 and partial least squares = .07), whereas partial least squares yielded a smaller level of the mean absolute differences than covariance structure analysis under misspecification (covariance structure analysis = .02 and partial least

squares = .00). In particular, there seemed to be a large difference in the mean absolute differences of the standard errors of partial least squares across the two specifications. Again, this may explain why the level of the mean absolute differences was on average lower under misspecification, as concluded with respect to the main effect of model specification.

Insert Table 3 about here

Overall finite-sample properties of standard error estimates under model specification levels. Figures 5 and 6 show the average relative biases, standard deviations, and mean square errors of the standard errors estimated from the three approaches under the two different model specifications over sample size. As seen in Figure 5, when the model was correctly specified, on average, generalized structured component analysis yielded unbiased standard errors of both loading and path coefficient estimates across all sample sizes. Covariance structure analysis led to positively biased standard errors of the parameter estimates. Partial least squares resulted in unbiased standard errors of loading estimates, while providing biased standard errors of path coefficients when $N \leq 200$. Under correct specification, the standard errors of loading and path coefficient estimates under generalized structured component analysis were associated with the smallest levels of standard deviations, except for those of loading estimates at $N \geq 300$. On the other hand, the standard errors of both sets of parameter estimates obtained from partial least squares had the largest levels of standard deviations over sample size.

On average, generalized structured component analysis showed the smallest mean

square errors of the standard errors of loading and path coefficient estimates over sample size. Covariance structure analysis involved smaller mean square errors of both sets of estimates than those under partial least squares when $N \geq 200$. However, the differences in the mean squares errors of the standard errors of path coefficient estimates appeared negligibly small among the three approaches, as sample size increased.

As shown in Figure 6, under model misspecification, the standard errors for covariance structure analysis and generalized structured component analysis seemed to possess similar properties to those under correct specification. On the other hand, the standard errors for partial least squares under misspecification appeared to have smaller biases, standard deviation, and mean square errors, compared to those under correct specification. Moreover, under misspecification, the standard errors obtained from partial least squares and generalized structured component analysis behaved quite comparably.

Insert Figures 5 and 6 about here

CONCLUSIONS AND RECOMMENDATIONS

This paper undertook investigations of the performance of three approaches to structural equation modeling (covariance structure analysis, partial least squares, and generalized structured component analysis) via analyses of simulated data under diverse experimental conditions. The present study represents the first effort toward providing systematic comparisons between the performances of three different approaches to structural equation modeling, including a very recent development in the area - generalized

structured component analysis.

The major findings of the present study are two-fold as follows.

Only the model specification factor led to differences in parameter recovery among the approaches. Whether or not the model is correctly specified was the only meaningful factor in differentiating the performance of the three approaches in parameter recovery. Specifically, when the model was correctly specified, covariance structure analysis generally recovered loadings and path coefficients better than generalized structured component analysis and partial least squares. On the other hand, when the model was misspecified, generalized structured component analysis resulted in more accurate estimates of these parameters than covariance structure analysis and partial least squares. However, generalized structured component analysis appeared to estimate standard errors more precisely under both levels of model specification. The relatively poor performance of covariance structure analysis under misspecification has been previously reported in the literature (e.g., Hoogland and Boomsma 1998; Bollen et al. 2007). What is novel in this present study rests in the demonstration of the superior performance of generalized structured component analysis over covariance structure analysis under misspecification.

Similarly, the overall finite-sample properties of the three approaches were shown to be distinct between the two levels of model specification. In particular, covariance structure analysis and generalized structured component analysis tended to result in parameter estimates having relatively small mean square errors (i.e., close to their parameters), when the model was correctly specified. On the other hand, generalized structured component analysis and partial least squares tended to yield parameter estimates having relatively small mean square errors when the model was misspecified. In addition,

generalized structured component analysis produced standard error estimates having the smallest mean square errors regardless of model specification. This suggests that the bootstrap method adopted by generalized structured component analysis performed well in the estimation of standard errors of the parameter estimates.

Bias in parameter estimates and standard errors under the three approaches also appeared to differ between the two levels of model specification. For instance, when the model was correctly specified, covariance structure analysis generally resulted in unbiased parameter estimates, whereas the other two approaches tended to provide biased parameter estimates. On the other hand, when the model was misspecified, all three approaches tended to yield biased parameter estimates. Bias represents an important piece of information regarding the finite-sample behavior of a parameter estimate (i.e., how close the mean of an estimate is to the parameter). Nonetheless, as implied in Equation 8, bias *per se* may not be of serious concern unless it increases mean square error in combination with variance, thereby making an estimate far from its true value on average (cf. Hastie, Tibshirani and Friedman 2001).

Additionally, it is noticeable that the violation of normality, to the extent which was frequently faced in practice, did not seem to greatly affect parameter recovery among the three approaches. This appears to be consistent with Hullah, Ryan, and Rayner (2005), where the recovery of path coefficients between covariance structure analysis and partial least squares was compared with simulated data.

The performance of partial least squares was relatively poor in parameter recovery in comparison to the two other approaches. Partial least squares showed relatively inferior

performance in parameter recovery compared to the two other approaches. In particular, this tendency was prominent when the model was correctly specified. This may hinge on the fact that the correct model in our study was composed of cross-loadings. Partial least squares was found to perform similarly to generalized structured component analysis when the model was misspecified to exclude cross-loadings. This suggests that the performance of partial least squares may be affected by how the model is specified, not by whether or not the model is correct. This result is somewhat unexpected because partial least squares has been regarded and presented as a model-free or soft-modeling approach requiring minimal demands on prior assumptions for structural equation modeling (Wold 1982). It is unclear which technical mechanism underlying partial least squares is related to our finding. A further study may thus be warranted to more fully investigate this issue.

Recommendations

At the risk of generalizing from the results of the present simulation study, we venture to provide some recommendations for the marketing/applied researcher. First, the adoption of generalized structured component analysis is recommended as a sensible alternative to partial least squares. As demonstrated in our analyses, generalized structured component analysis generally performed better than or as well as partial least squares in parameter recovery. In addition, generalized structured component analysis maintains all the advantages of partial least squares as a component-based structural equation modeling methodology. However, simultaneously, it offers additional benefits such as overall measures of model fit (Hwang and Takane 2004).

Second, if correct model specification is ensured, the use of covariance structure

analysis is recommended. This approach resulted in more accurate parameter estimates than generalized structured component analysis under correct model specification.

Lastly, if correct model specification cannot be ensured, the researcher should use generalized structured component analysis because it outperformed covariance structure analysis in the recovery of parameters under misspecification. This may have a practical implication in that virtually all models are to be considered biased (Hastie, Tibshirani, and Friedman 2001).

It should be noted that our recommendations are given based on the capability of parameter recovery among the three approaches in this simulation study. In practice, however, what may be also important to the researcher is the data analytic flexibility of the three approaches. Although generalized structured component analysis has been rapidly extended and refined to enhance its generality and versatility (e.g., Hwang in press; Hwang, DeSarbo, and Takane 2007; Hwang and Takane 2008; Hwang, Takane, and Malhotra 2007; Takane, Hunter, and Hwang 2004), covariance structure analysis still appears more versatile because it has been extended by a great number of researchers over several decades. For instance, since the seminal work reported in Kenny and Judd (1984), many researchers have elaborated covariance structure analysis to accommodate nonlinear latent variables such as quadratic and interaction terms of latent variables (e.g., Klein and Muthén 2007; March, Wen and Hau 2004; Schumacker and Marcoulides 1998; Wall and Amemiya 2001). As in partial least squares, generalized structured component analysis may readily address a two-way interaction of latent variables by adopting the so-called product-indicator procedure (Chin, Marcolin and Newsted 1996) whereby new product terms of observed variables taken to underlie two latent variables are computed in advance

and are subsequently used as the indicators for the two-way interaction. Nonetheless, no formal study has been yet carried out to deal with such nonlinear latent variables in generalized structured component analysis. In addition, the product-indicator procedure is mainly limited to examine a two-way interaction of latent variables since it is difficult to decide which and how many observed variables should be selected to form product indicators for higher-way latent interactions. Thus, covariance structure analysis may remain more flexible in accounting for nonlinear latent variables.

Limitations and Contributions

Like other simulation studies, the present study has limitations. First, the present study generated simulated data based on covariance structure analysis. This data generation procedure may have had an unfavorable effect on the performance of partial least squares and generalized structured component analysis. The procedure was adopted because it was rather difficult to arrive at an impartial way of generating synthetic data for all three different approaches. Nevertheless, the same procedure has been used in other studies in which the performance of covariance structure analysis was compared to that of partial least squares (e.g., Hulland, Ryan, and Rayner 2005). In any case, it appears necessary in future studies to investigate whether or not a particular data generation procedure may influence the relative performance of the different approaches.

Second, as stated earlier, this study analyzed only converged samples without improper solutions for covariance structure analysis. Nonconvergence or improper solutions are likely to lead to outliers or suboptimal estimates for covariance structure analysis. The purposeful exclusion of such solutions may thus render covariance structure

analysis solutions biased by enhancing the differences between the distributions of the sample and population covariance matrices (Hoogland and Boomsma 1998). On the other hand, no such manipulation was carried out for generalized structured component analysis and partial least squares, as they did not involve any convergence problems. This may have led to results that were more favorable for covariance structure analysis.

Lastly, our simulation study took into account diverse experimental conditions that are frequently considered in simulations based on structural equation modeling. Nonetheless, as with all simulation studies, the range of conditions in this study may still be limited in scope. Thus, it may be necessary to consider a greater variety of experimental levels/conditions, e.g., a wider range of skewness and kurtosis and different models, for more thorough investigations of the relative performance of the three approaches.

Notwithstanding these limitations, our research makes a number of contributions. We present the technical underpinnings of generalized structured component analysis to marketing researchers. Moreover, we compare generalized structured component analysis to the two traditional approaches to structural equation modeling in order to highlight their similarities and differences and to assess its relative performance with respect to the traditional approaches using simulated data. Overall, the results of the Monte Carlo analysis provide rather clear guidelines with respect to the conditions under which generalized structured component analysis is to be preferred over the two traditional approaches. We hope that our study will provide a greater understanding of the three currently available approaches to structural equation modeling and lead marketing researchers to adopt generalized structured component analysis for use in many situations, and particularly those in which they have little confidence that their models are correctly

specified.

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Table 1. Similarities and Dissimilarities among the Three Approaches to Structural Equation Modeling.

		Covariance Structure Analysis	Partial Least Squares	Generalized Structured Component Analysis
Model Specification	Latent variables	Factors	Components	Components
	Number of equations	One	Two	One
	Model parameters	Loadings, path coefficients, error variances, factor means and/or variances	Loadings, path coefficients, component weights	Loadings, path coefficients, component weights
Parameter Estimation	Input data	Covariances/Correlations	Individual-level raw data	Individual-level raw data
	Estimation method	Maximum likelihood (mainly)	Least squares	Least squares
	Global optimization function	Yes	No	Yes
	Normality assumption	Required for maximum likelihood	Not required	Not required
	Model fit measures	Overall and local	Local	Overall and local

Table 2. The Results of an ANOVA Test for the Mean Absolute Differences of Parameter Estimates.

Source	SS	DF	MS	F	Sig.	η^2
Distribution (A)	.41	1	.41	8.13	.00	.00
Model specification (B)	179.20	1	179.20	3521.36	.00	.08
Sample size (C)	8.70	4	2.17	42.72	.00	.00
Approach (D)	325.05	2	162.53	3193.77	.00	.14
A*B	.75	1	.75	14.80	.00	.00
A*C	.13	4	.03	.62	.65	.00
A*D	.10	2	.05	.96	.38	.00
B*C	.25	4	.06	1.23	.30	.00
B*D	391.09	2	195.54	3842.60	.00	.16
C*D	6.80	8	.85	16.71	.00	.00
A*B*C	.39	4	.10	1.89	.11	.00
A*B*D	.35	2	.17	3.40	.03	.00
A*C*D	.28	8	.04	.69	.71	.00
B*C*D	1.09	8	.14	2.67	.01	.00
A*B*C*D	.73	8	.09	1.78	.08	.00
Error	1435.40	28207	.05			

Table 3. The Results of an ANOVA Test for the Mean Absolute Differences of Standard Error Estimates.

Source	SS	DF	MS	F	Sig.	η^2
Distribution (A)	.00	1	.00	.16	.69	.00
Model specification (B)	2.99	1	2.99	38820.93	.00	.14
Sample size (C)	.63	4	.16	2040.47	.00	.03
Approach (D)	5.68	2	2.84	36932.50	.00	.27
A*B	.04	1	.04	524.39	.00	.00
A*C	.01	4	.00	28.48	.00	.00
A*D	.39	2	.20	2551.00	.00	.02
B*C	.09	4	.02	295.41	.00	.00
B*D	7.54	2	3.77	49004.23	.00	.36
C*D	.50	8	.06	815.28	.00	.02
A*B*C	.01	4	.00	21.49	.00	.00
A*B*D	.09	2	.05	603.77	.00	.01
A*C*D	.03	8	.00	43.44	.00	.00
B*C*D	.23	8	.03	375.65	.00	.01
A*B*C*D	.01	8	.00	20.76	.00	.00
Error	2.17	28207	.00			

Figure 1: The Specified Model for the Simulation Study along with Standardized Parameters in Parentheses. The Model Misspecification Indicates Omission of Dashed Loadings and Inclusion of the Dashed Path Coefficient.

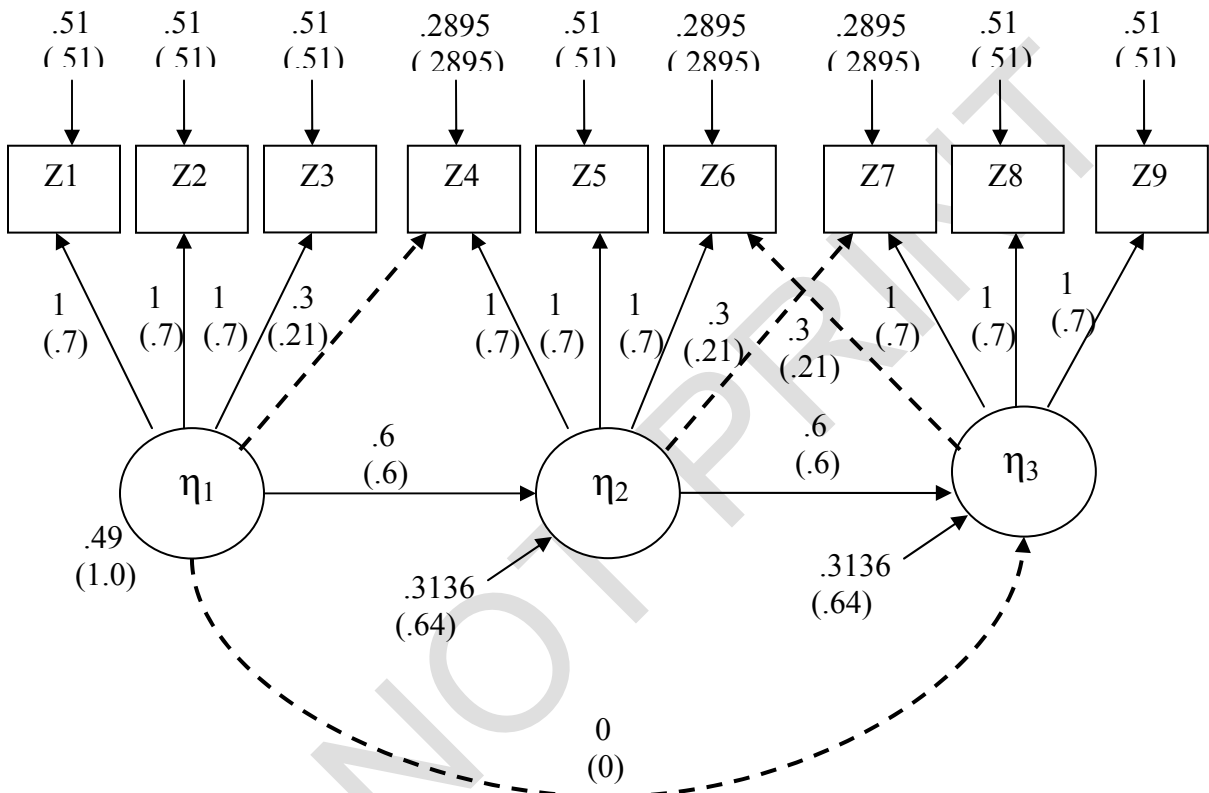


Figure 2: The Average Values of the Mean Absolute Differences of the Estimates of Parameters and Standard Errors Obtained from the Three Approaches across Two Levels of Model Specification.

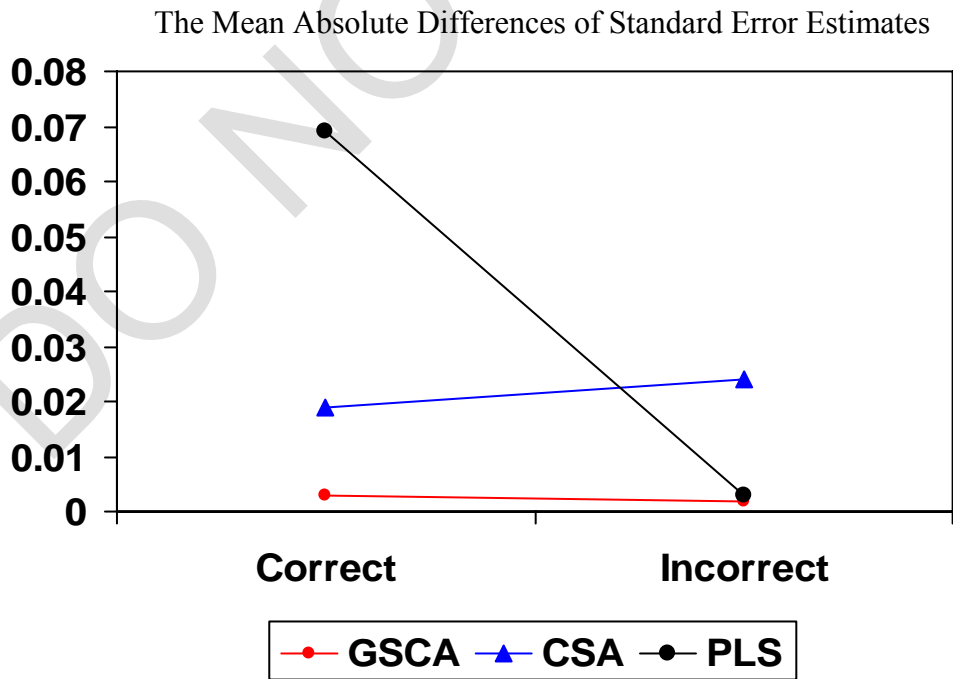
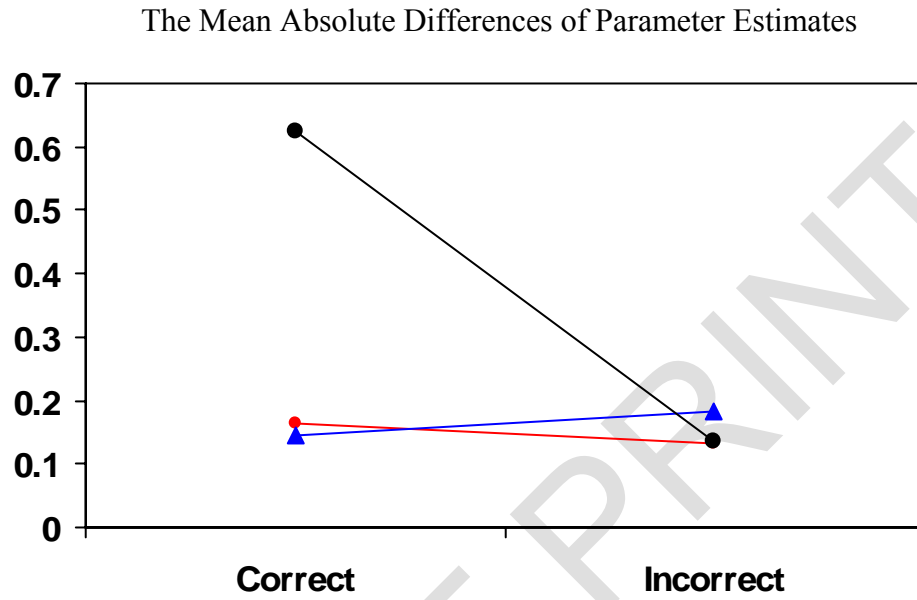


Figure 3: Overall Finite-Sample Properties of the Parameter Estimates of the Three Approaches under Correct Specification across Different Sample Sizes (RB = Relative Bias, SD = Standard Deviation, MSE = Mean Square Error). A Dotted Line Indicates No Relative Bias.

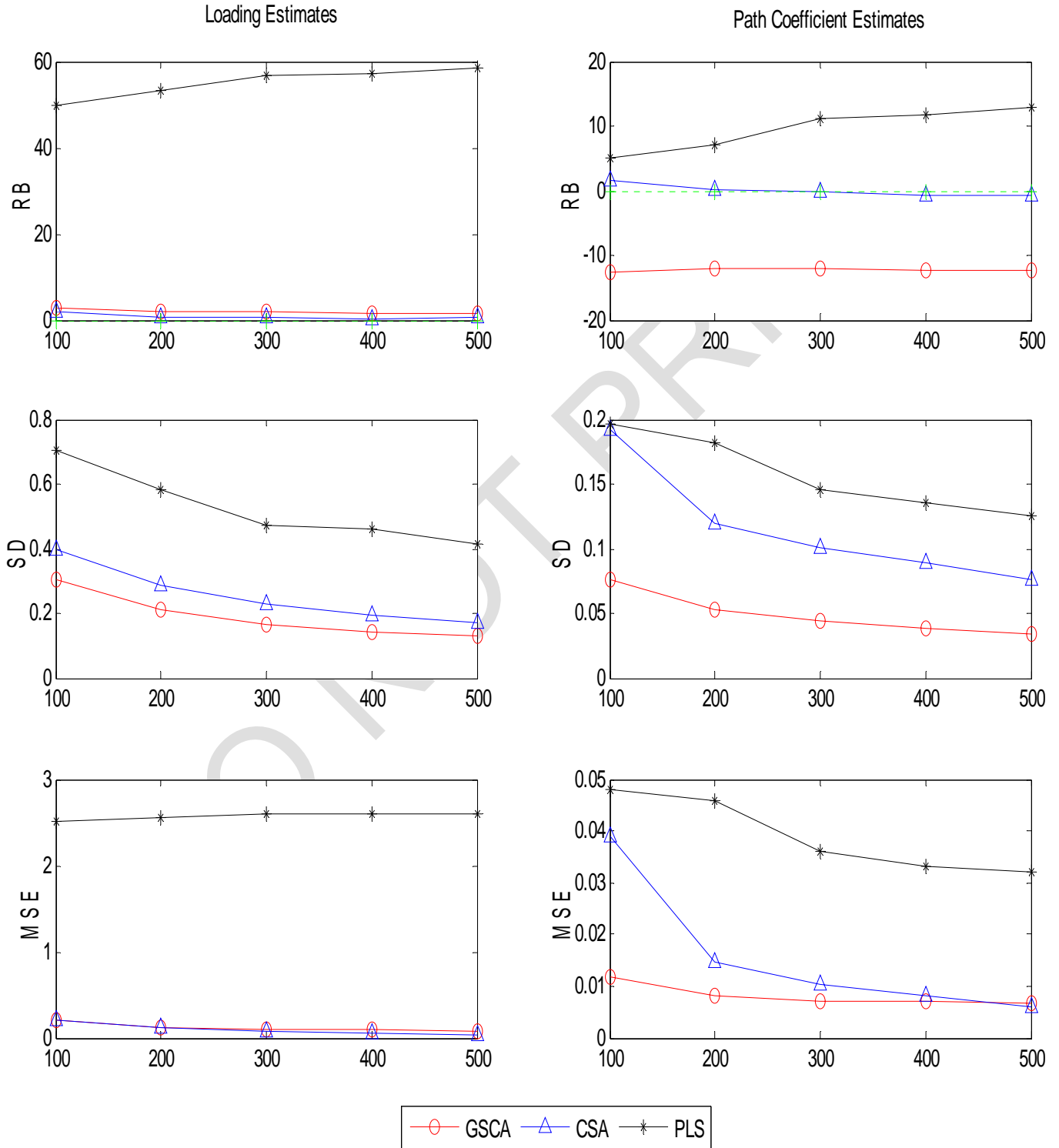


Figure 4: Overall Finite-Sample Properties of the Parameter Estimates of the Three Approaches under Misspecification across Different Sample Sizes (RB = Relative Bias, SD = Standard Deviation, MSE = Mean Square Error). A Dotted Line Indicates No Relative Bias.

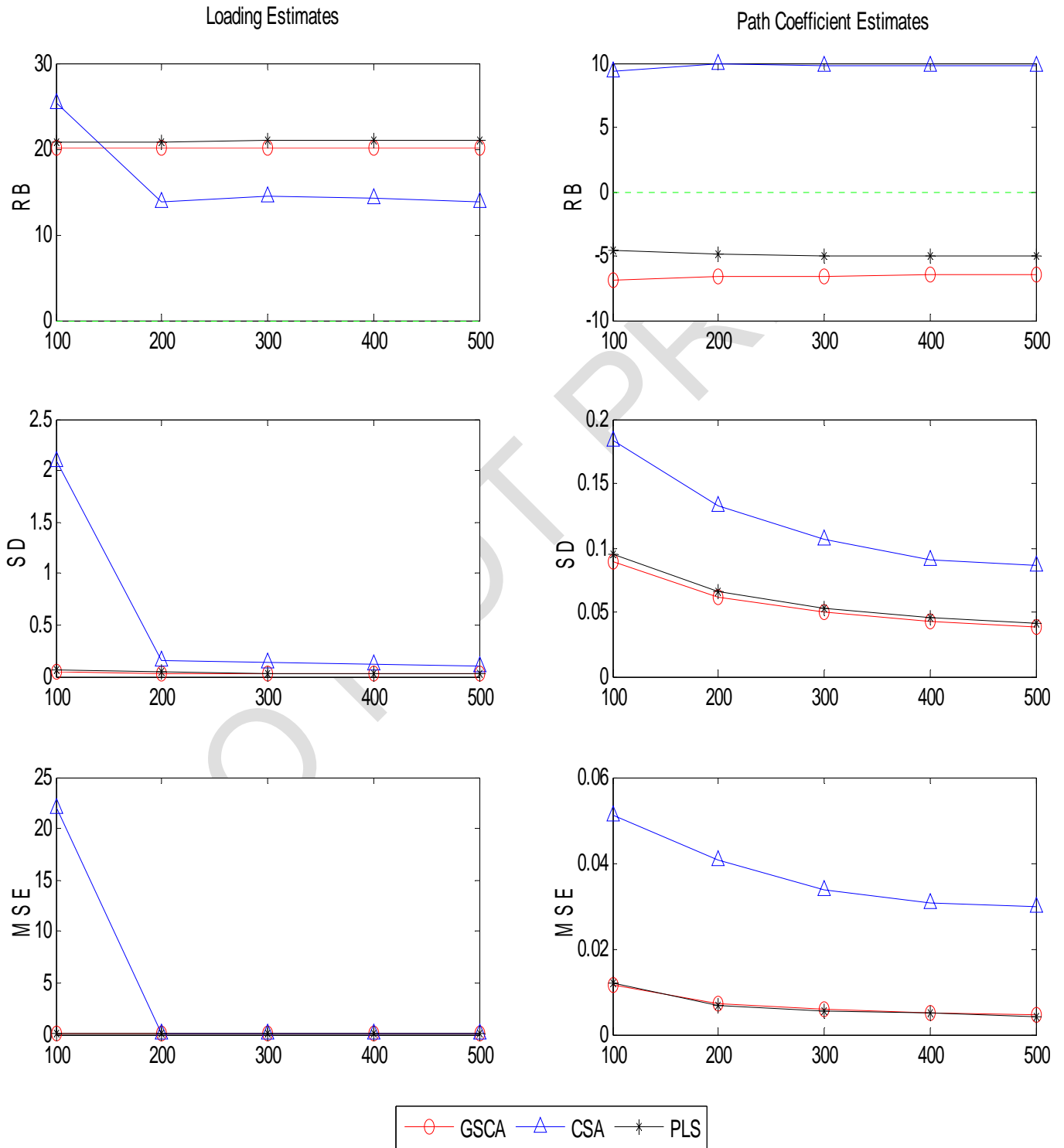


Figure 5. Overall Finite-Sample Properties of the Standard Error Estimates of the Three Approaches under Correct Specification across Different Sample Sizes (RB = Relative Bias, SD = Standard Deviation, MSE = Mean Square Error). A Dotted Line Indicates No Relative Bias.

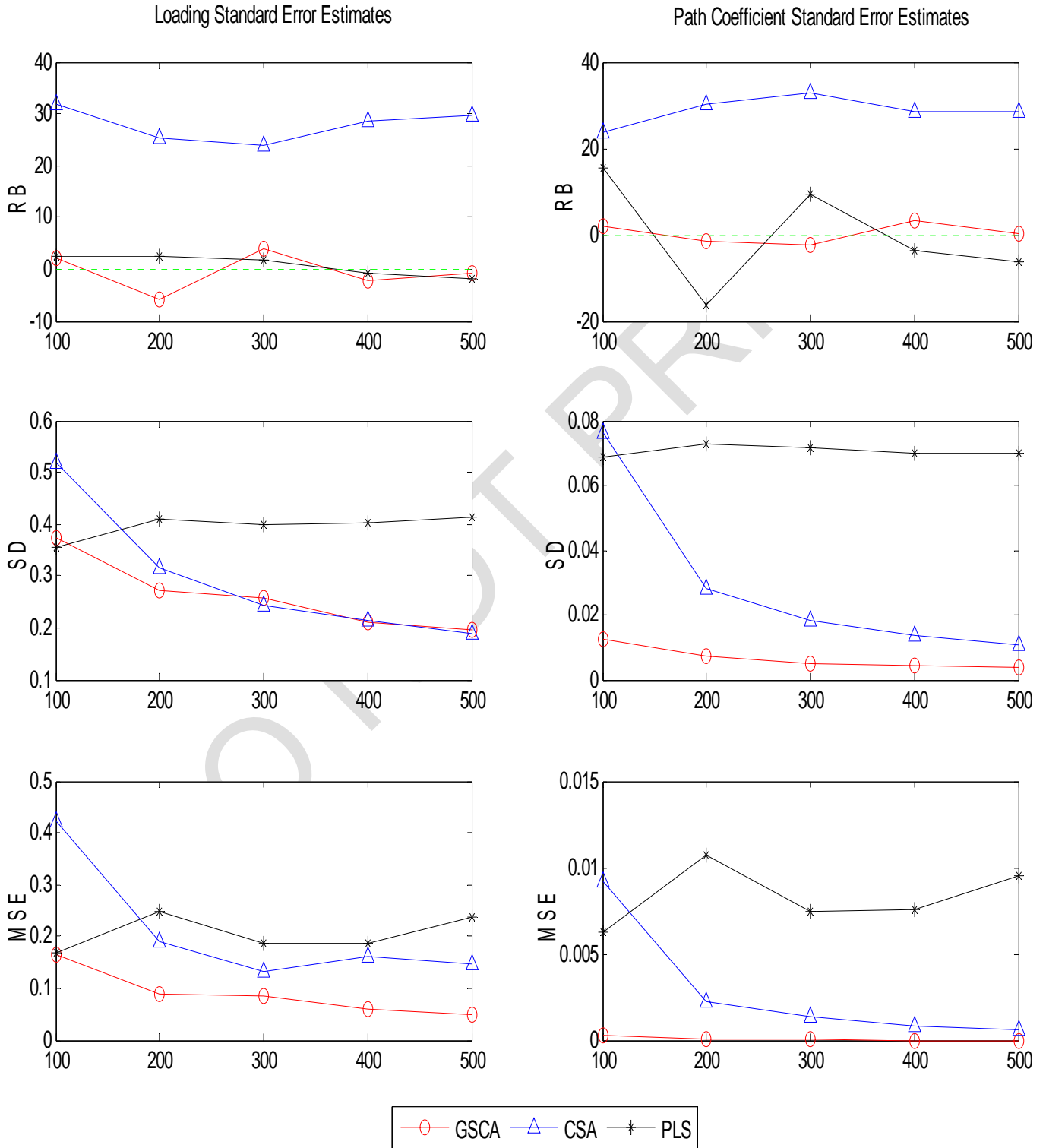


Figure 6: Overall Finite-Sample Properties of the Standard Error Estimates of the Three Approaches under Misspecification across Different Sample Sizes (RB = Relative Bias, SD = Standard Deviation, MSE = Mean Square Error). A Dotted Line Indicates No Relative Bias.

