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GUIDELINES FOR CHOOSING BETWEEN ACOV AND PLS-PM FOR ORDINAL DATA

Nicholas Walker Affiliation: School of Architecture and Design, MIT

Abstract

The accuracy on parameter recovery is compared between Structure Covariance Analysis (ACOV) and Partial Least Squares Path Modeling (PLS-PM), with simulated ordinals data with 5 points, in a simple model. An experimental design is used, controlling the estimation method, sample size, skewness level and model specification. Mean absolute differences are used to assess accuracy for the structural model. ACOV provided more accurate estimates of the structural parameters than PLS-PM in different experimental conditions. With a small sample size, both techniques are equally accurate. Using ACOV against PLS -PM is suggested. PLS choosing ACOV instead based on the use of a small sample size is not recommended.

Keywords: structure covariance analysis; accuracy; structural equation modeling; partial least squares path modeling; parameter recovery; ordinal manifest variables

Introduction

Two approaches to Structural Equation Models (SEM) are usually distinguished: the approach based on covariance, within which is the Covariance Structure Analysis technique ([ACOV]; Jõreskog, 1970, 1979), and the approach based into components, within which is the Partial Least Squares Path Model ([PLS-PM]; Wold, 1977, 1980).

ACOV is the MEE technique that has shown the greatest development and is the most popular to date (López & *López, 2006).* Which, in part, has been favored by being the first technique to be formally proposed and the first to present a statistical computer program that applies it: LISREL, developed by Jõreskog and van Thillo (1972), and which continues to be updated to date. date (Jõreskog & *Sôrbom,*2006). In contrast, PLS-PM has only had the LVPLS computer program, developed by Jan-Bernd Lohmõller, since 1984. Currently, both types of modeling have various specific analysis programs or have been included as routines in analysis packages. of data, among which are: AMOS (Arbuckle, 1994), CALIS (SAS Institute Inc., 2008), EQS (Bentler, 1995), Mplus (Muthén & Muthén, 1998-2010) and R v. 2.14.0 (R Development Core Team, 2011) with the "sem" v. packages. 3.0-0 (Fox, Nie, & Byrne, 2012) and “lavaan” (Rosseel, 2012), for ACOV; and PLS-Graph (Chin, 2001), R v. 2.14.0 (R Development Core Team, 2011) with the packages "plspm" (Sánchez & Trinchera, 2012) and "semPLS" (Monecke & Leisch, 2012), SmartPLS (Ringle, Wende, & Will,

PLS-PM is proposed as an alternative for parameter estimation compared to the normal distribution restrictions presented by ACOV when used with the maximum likelihood method (Jõreskog & Wold, 1982). Both MEE techniques have been purchased on various occasions (Areskoug, 1982; Chin, 1995; Fornell & Bookstein, 1982; Jõreskog & Wold, 1982; Reinartz, Haenlein, & Henseler, 2009; Wold, 1982a). The approaches point out that both techniques are more complementary than competitive, highlighting that the purpose of ACOV is to study the structure of the relationships between variables, reflected in the variance and covariance matrix, while PLS-PM's main objective is to maximize the variance. explained of the dependent variables of the model.

Both MEE techniques share the conventions of graphical representation of the model, the linear formulation of the relationships between indicators and latent variables, and the inclusion of measurement and estimation errors in the model. Among the differences, it is found that ACOV's maximum likelihood estimation method assumes the joint normal distribution, while PLS-PM does not make distributional assumptions.

It should be noted that there are other ACOV estimation methods that do not require compliance with the multivariate normality assumption (e.g., *unweighted least squares, asymptotically free distribution* , and *scale-free least squares).*ACOV estimates in large samples with multivariate normal distribution have turned out to be more efficient than PLS-PM estimates (Fornell & Bookstein, 1982), while PLS-PM estimates do not present problems in model identification, they are efficient in small samples, even estimating complex models and achieve convergence more quickly (Fornell & Bookstein, 1982; Jõreskog & Wold, 1982). On the other hand, it is proposed that PLS-PM parameter estimates present greater efficiency and bias compared to ACOV estimates, tending to underestimate the parameters of the structural model and overestimate the parameters of the measurement model (Chin, 1995; Hulland, Ryan, & Rayner, 2010).

The key difference of PLS-PM with respect to ACOV is the explicit definition of the latent variables, as a weighted combination of its indicators by the former (Wold, 1982b), in a similar way to how the Principal Components model is defined (Chin , 1995), which has led to it being called component-based MEE, sometimes also called variance-based MEE. For its part, ACOV proposes the definition of indicators as a combination of latent variables and, in addition, raises the need to estimate communalities as in the Common Factor model

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(Chin, 1995), which has led to it being called Factor-based MEE, sometimes also called covariance-based MEE.

A notable work, on which this study is based, is that carried out by Hwang, Malhotra, Kim, Tomiuk and Hong (2010). In their study, they performed a simulation comparing the efficiency of three MEE techniques: ACOV, PLS-PM and Generalized Structural Component Analysis, with simulated data with interval scale, in a model that included cross effects. The authors found that the *only determining condition in the* adequate recovery of the parameters was the correct specification of the model. Specifically, when the model was correctly specified, ACOV recovered the parameters without bias and *recovered*better parameters than PLS-PM. However, when the model was incorrectly specified, PLS-PM recovered the parameters better, even though both approaches presented bias in their estimates. ACOV overestimated the parameters: those of the structural model at the limit of the acceptable range (10%) and those of the measurement model outside the acceptable range, while PLS-PM underestimated the parameters of the structural model within the acceptable range and overestimated the parameters of the model measurement outside the acceptable range.

In studies comparing ACOV with PLS-PM, interval-scaled simulated data are often used (e.g., Fornell & Bookstein, 1982; Reinartz et al., 2009). Although studies have currently been carried out with variables on an ordinal scale (e.g., Barroso, Cepeda, & Roldán, 2010; Hulland et al., 2010), these have used ACOV with the Maximum Likelihood (ML) estimation method, Despite the approach of Fornell and Bookstein (1982) and Forero, Maydeu-Olivares and Gallardo-Pujol (2009) on the convenience of using the Unweighted Least Squares (ULS) estimation method on the polychoric correlation matrix, when the Manifest variables are measured on an ordinal scale. A study that compares both MEE techniques, using ACOV with the ULS estimation method is the one carried out by Tenenhaus, Mauger and Guinot (2010). However, the manifest variables used are on a dichotomous scale.

The present study seeks to deepen the comparison of the most used MEE techniques, ACOV and PLS-PM, using extreme conditions of asymmetry and sample size, which exceed those used by Hwang et al. (2010); In addition, manifest variables with an ordinal scale are used, a condition that is considered common in the field of applied research in behavioral and health sciences. At the same time, the estimation method that has been proposed as most efficient for estimates with ACOV when ordinal variables are used is used, overcoming the limitations of previous studies. It should be noted that two levels of model specification will be used in the present study: more specified and less specified.

Method

A parameter recovery study was designed through simulation of synthetic samples. It was considered pertinent to assess the joint effect of four factors: MEE definition technique, with two levels: ACOV and PLS-PM; Model specification with two levels: more specified and less specified; Asymmetry with three levels: null (0), medium (1.25) and high (2) and Sample size with four levels: very small (50), small (100), medium (300) and large (500). These levels of asymmetry and sample sizes include the levels used by Hwang et al. (2010), seeking to overcome the limitations indicated by the authors in this regard, incorporating a higher level for asymmetry (2) and a smaller sample size (50). A complete design was proposed for the combination of factor levels.

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The population model used (Figure 1) includes three latent variables (one exogenous and two endogenous) and nine reflective manifest variables (three for each latent variable). The exogenous latent variable (e) has a direct effect on one of the endogenous latent variables (η_1), which in turn has a direct effect on the other endogenous latent variable (η_2). This model is a variation of the model used by Bollen, Kirby, Curran, Paxton, and Chen (2007) and Hwang et al. (2010), to evaluate the recovery of parameters with different estimation methods using manifest variables with interval scale. Cross-loadings from the latent variables to the manifest variables were excluded to consider the simplest possible structure for the measurement model.

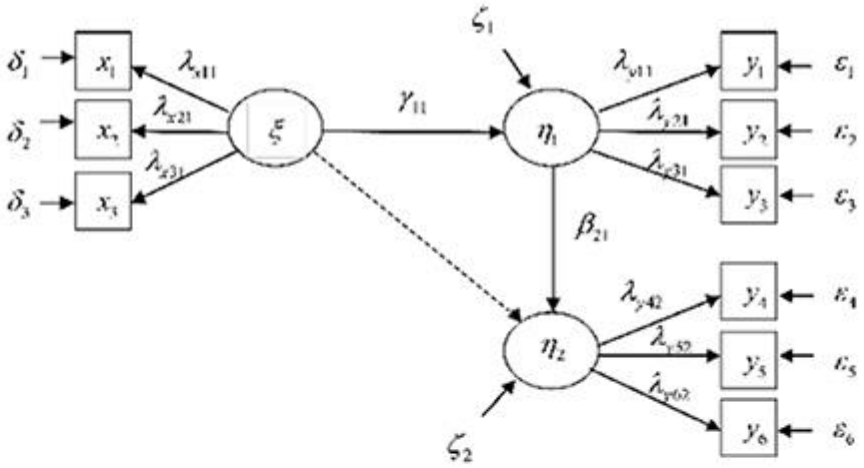

Figura 1. Diagrama de rutas del modelo poblacional.
Fuente: elaboración propia

Two levels of model specification were assessed in the estimable parameters: more specified (the population model is specified) and less specified (the parameter y 21 is also estimated , and which has not been specified in the generation of the samples, see Figure 1). This factor was defined as an intragroup effect.

Both intragroup factors were combined within the four possible intergroup combinations. Therefore, the four factors are combined in a design (2x2x3x4),

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with the first two factors being intergroups and the second two being intragroups.

For each of the simulated samples, the theoretical parameters of the model are estimated. From the estimates obtained, the percentage of solutions that converge and the percentage of improper solutions are assessed, for each of the experimental conditions considered and for the total number of samples generated. A maximum of 100 iterations was determined for the convergence of the solutions, and a solution was considered improper when one or more variances are negative or when one or more estimated parameters have values greater than 1 in absolute value, according to the verification. technique proposed by Bollen (1989). Samples that present solutions that do not converge or improper solutions are excluded from subsequent analyzes of the study because they are considered invalid, as in the study by Forero et al. (2009).

To assess the distance between the estimated parameters and the population parameters expressed on the same scale as the parameters (precision), the Mean Absolute Differences (MAD) was calculated between the estimated parameter and the population parameter, for the Structural Model and the Measurement Model, in accordance with:

$$MAD(\hat{\square}_{k}) = \frac{\square_{j=1}^{J} \left| \hat{\square}_{jk} \; \square\square_{jk} \right|}{J} \quad (5)$$

Then, through a repeated measures ANOVA, the means of the MAD of the Structural Model are compared, in the valid replications per experimental condition. Lower values of MAD imply a smaller distance between the parameter estimate and the population parameter value.

Analysis

To estimate parameters with ACOV, the LISREL v.8.8 program (Jõreskog & Sõrbom, 2006) is used, calculating the polychoric correlation matrix with PRELIS and using Unweighted Least Squares as the estimation method, in accordance with what was proposed by Forero et al. to the. (2009).

For the analysis with PLS-PM, the R v statistical analysis programming environment is used. 2.14.0 (R Development Core Team, 2011), with the "plspm" package (Sánchez & Trinchera, 2012). Considering that previous studies (Tenenhaus, Esposito Vinzi, Chatelin, & Lauro, 2005; Ringle, Gõtz, Wetzels, & Wilson, 2009) have verified the absence of differences in parameter estimates when using the different schemes for estimating parameters of PLS-PM and the approach of Esposito Vinzi, Trinchera and Amato (2010), we choose to use the route scheme, as it is the only one that considers the direction of the relationships as they have been established in the predictive route model.

To automate the analyzes in all conditions, the Visual Fox Pro 9.0 program is used, through which the LISREL and R analysis statements are executed, and the standardized estimates of the parameters are also extracted from the results files. of each program.

The 24,000 estimation analyzes are performed (6,000 samples x 2 MEE approximations x 2 model specifications). The resulting data were analyzed using SPSS version 15. The analysis model used was a repeated measures Analysis of Variance (ANOVA) with 2 intragroup factors (MEE techniques and model specification) and with 2 intergroup factors (level of asymmetry). and sample size), using as the dependent variable the average of the absolute differences by condition for the parameters of the structural model.

To evaluate the statistical relevance of the results, the use of the observed statistical significance value (p value) was rejected due to the large number of replications used and the influence that the sample size has on the *p value*. For these reasons, it was decided to consider the effect size as a comparison value, taking into account only the effects corresponding to an effect size of at least medium (η = 0.06), according to Cohen (1988). The value of Eta square that assumes sphericity is reported, considering that this is the same value that was obtained for Greenhouse-Geisser, Huynh-Feldt and Lower-Limit.

Results

The percentage of convergent estimates in the total number of replicates was very high for both the ACOV technique (97.35%) and the PLS-PM technique (98.24%). The lowest percentage of convergence by condition was 79.2% for ACOV with the least specified model, asymmetry of 2 and sample size of 50; condition in which PLS-PM presented 86.8% of solutions that converged. 4% of the total replicas had to be discarded due to lack of convergence.

PLS-PM presented 0.2% of improper solutions, while ACOV presented 15.2% of improper solutions of the total number of replicates. The highest percentage of improper solutions (62.2%) was presented by ACOV in the less specified model condition, with asymmetry of 2 and a sample size of 50, an instance in which PLS-PM presented 0.8% of improper solutions.

Replicas that presented improper solutions were not considered in subsequent analyses. In total, the use of 17.7% of the replicates was rejected, considering the 4,938 replicates valid for subsequent analyses.

Precision

In the repeated measures ANOVA (2x2x3x4) that assessed the MAD of the standardized estimates of the parameters of the Structural Model (Table 1), no

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third-order interactions with medium or higher effect sizes were evident. The following second-order interaction effect was found.

TABLA 1

Pruebas de efectos intragrupo e intergrupo para el MAD de las estimaciones estandarizadas de los parámetros del modelo estructural y del modelo de medida

		(A) Modelo Estructural		
Fuente	gl	F	Sig.	η^2
Técnica de MEE (Técnica)	1	8162	<0.01	0.62*
Especificación del modelo (Espec)	1	217.9	<0.01	0.04
Nivel de Asimetría (Asim)	2	243.2	<0.01	0.09*
Tamaño muestral (n)	3	325.5	<0.01	0.17*
Técnica x Espec	1	1153.5	<0.01	0.19*
Técnica x Asim	2	11.1	<0.01	0
Técnica x n	3	1180.3	<0.01	0.42*
Espec x Asim	2	132.4	<0.01	0.05
Espec x n	3	62.3	<0.01	0.04
Asim x n	6	6.9	<0.01	0.01
Técnica x Espec x Asim	2	216.8	<0.01	0.08*
Técnica x Espec x n	3	30.6	<0.01	0.02
Técnica x Asim x n	6	31.2	<0.01	0.04
Espec x Asim x n	6	9.4	<0.01	0.01
Técnica x Espec x Asim x n	6	6.7	<0.01	0.01

* Tamaño del efecto al menos mediano ($\eta^2 = 0.06$)

Fuente: elaboración propia

Interaction between the MEE technique, the model specification and the level of asymmetry ($\eta^2 = 0.08$). The ACOV estimates presented a lower average MAD than the PLS-PM estimates, in the two model specification modalities, when the different levels of asymmetry were used. The difference between the MAD of ACOV and PLS-PM was smaller with the less specified model and this difference decreased as the level of asymmetry increased. The difference between the MAD of the techniques with the most specified model increased as the level of asymmetry increased (Figures 2 , 3 and 4).

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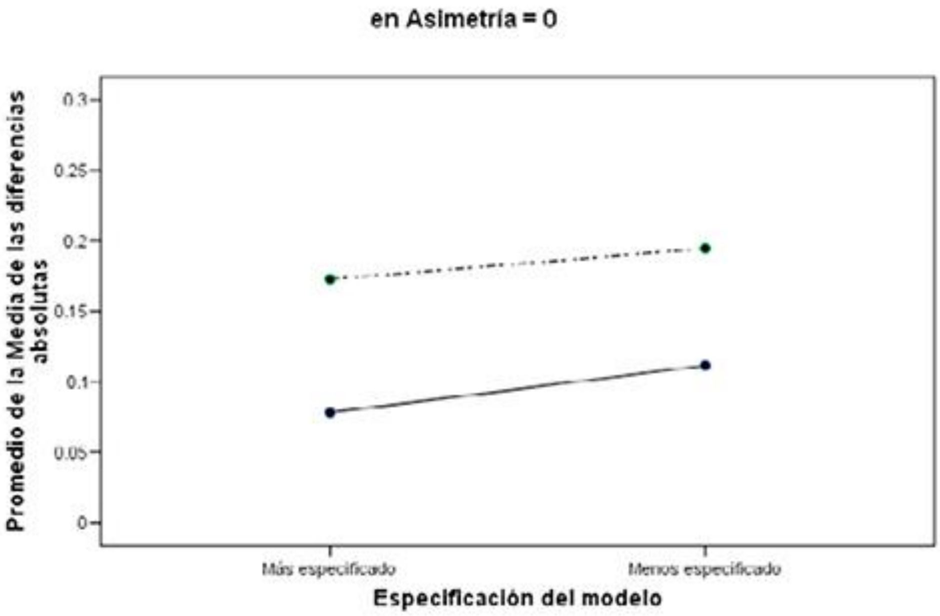

Figura 2. Medias del MAD de las estimaciones del modelo estructural de ACOV y PLS-PM, de acuerdo a la especificación del modelo, en asimetría nula.

Fuente: elaboración propia

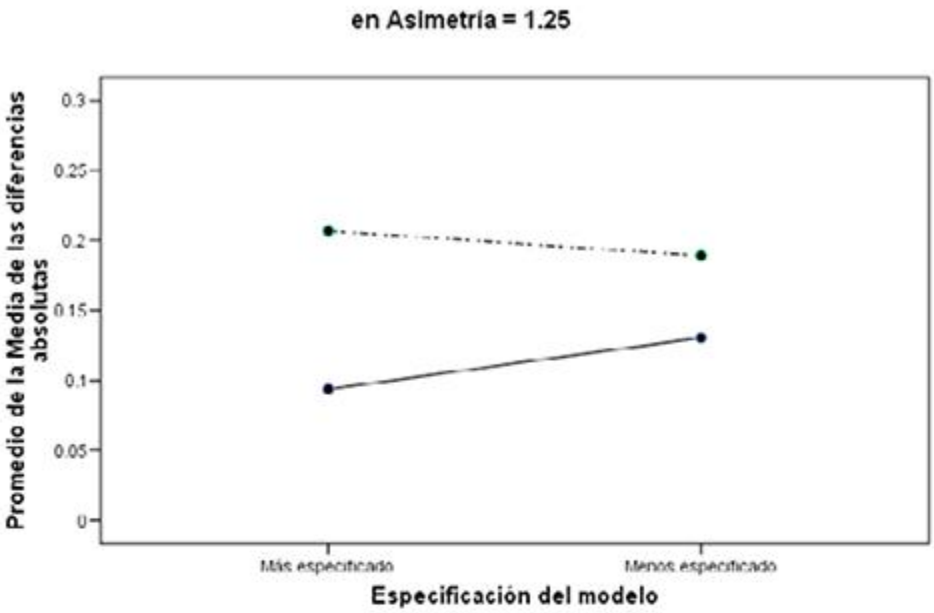

Figura 3. Medias del MAD de las estimaciones del modelo estructural de ACOV y PLS-PM, de acuerdo a la especificación del modelo, en asimetría media.

Fuente: elaboración propia

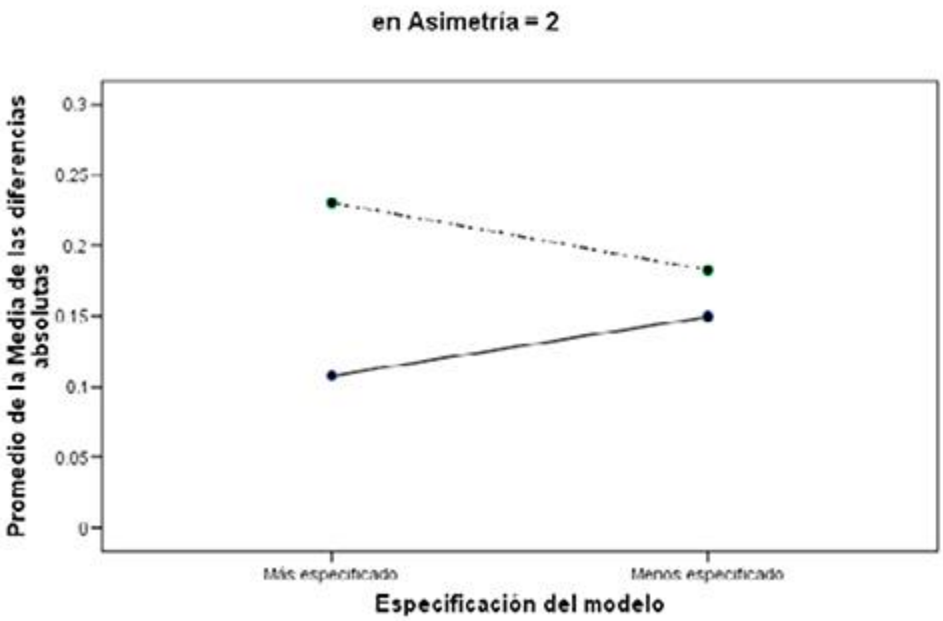

Figura 4. Medias del MAD de las estimaciones del modelo estructural de ACOV y PLS-PM, de acuerdo a la especificación del modelo, en asimetría alta.

Fuente: elaboración propia

In addition, the first-order interaction effect was found between the MEE Technique and sample size ($\eta^2 = 0.42$). The average MAD of the ACOV estimates was lower than the average MAD of PLS-PM when very large, large, and medium sample sizes were used. The average MAD of PLS-PM tended to increase as the sample size decreased, and the average MAD of ACOV tended to increase as the sample size decreased, reaching levels similar to those presented by PLS. -PM when the sample size was small. Thus, the differences between the averages of the MAD decreased as the sample size decreased (Figure 5).

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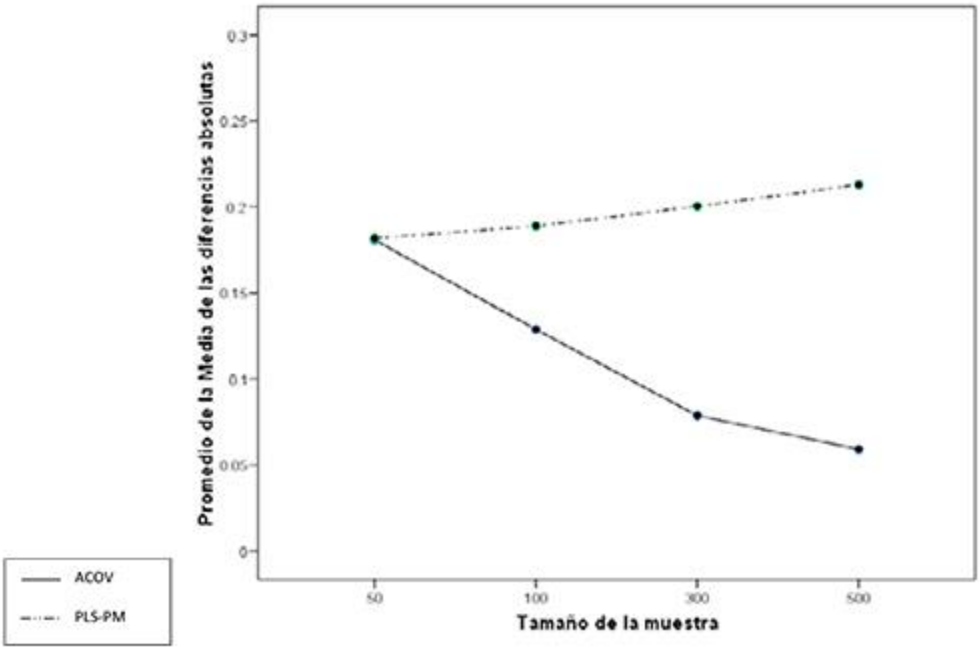

Figura 5. Promedios del MAD de las estimaciones del Modelo Estructural con ACOV y PLS-PM, de acuerdo al tamaño de la muestra.

Fuente: elaboración propia

Finally, when analyzing the estimates obtained from each of the parameters of the Structural Model, when the less specified model is used. Regarding the parameter γ_{21} PLS-PM presents higher estimates (x = 0.11; dt = 0.10; ET = 0.001) than the ACOV estimates (x = 0.02; dt = 0.19; ET = 0.003), with η 2 = $^{0.27}$. The PLS-PM estimates of the parameter γ_{11} presented a negative bias in the range of 28% to 38%, whereas ACOV presented a bias within the acceptable range (η^2 = 0.18). The PLS-PM estimates of the parameter β_{21} presented a negative bias in the range of 33% to 42%, whereas ACOV presented a bias within the acceptable range $\eta^2 = 0.13$.

Discussion

The present study evaluates the accuracy in parameter recovery of the two most widespread MEE techniques: ACOV and PLS-PM. When analyzing a model defined by manifest variables measured on an ordinal scale, under different conditions of model specification, sample size and level of asymmetry.

The main contribution of the present study is found in the inclusion of manifest variables on an ordinal scale and the use of the method that has proven to be most efficient for estimating parameters for ACOV under these conditions: ULS on the polychoric correlation matrix (Forero et al. ., 2009), an instance little investigated in the field of comparison of MEE techniques; and if it has been studied, the estimation method specified in the default statistical programs (Maximum Likelihood) has been used. This study overcomes this deficiency. Furthermore, some of the limitations pointed out by Hwang et al. are overcome. (2010), regarding the levels of asymmetry and sample size,

The results show that about one sixth of the total parameter estimates made with ACOV present improper solutions, compared to 0.2% for PLS-PM.

Regarding the precision in parameter estimation, the results show effects of asymmetry and sample size, unlike the findings of Hwang et al. (2010), in which only an effect of model specification was evident. In the Structural Model, ACOV presented a lower average absolute difference between estimates and population parameters (MAD), than PLS-PM in both model specification modalities, at the three levels of asymmetry. Likewise, the average MAD of the ACOV estimates was lower than the average MAD of PLS-PM when very large, large, and medium sample sizes were used. When a small sample size was used, both techniques obtained similar MAD values.

In the Measurement Model, ACOV presented a smaller average absolute difference between estimates and population parameters (MAD) than PLS-PM in the condition of null asymmetry and large (n = 300) *and* very large sample sizes (n = 500). By increasing the level of asymmetry, the MAD values of PLS-

PM resemble the MAD values of ACOV. With medium and small sample sizes, both techniques present similar average differences in the different levels of asymmetry used in this study.

The tendency of PLS-PM to overestimate the parameter of the Structural Model that was set to 0 in the population model, that is, the tendency to identify direct effects where there are none, and to present a negative bias in the other parameters of the Structural Model, is mean the tendency to indicate that the relationship between latent variables is less intense than it really is. It will have negative effects when carrying out a mediation analysis. Therefore, for this type of analysis it is suggested to choose ACOV.

In conclusion, it is proposed that the ACOV parameter estimation presents fewer differences between the estimated parameters and the population parameters (MAD) than PLS-PM, when large, medium and small sample sizes are used. Thus, it is proposed that ACOV estimates are more precise than PLS-PM estimates. However, with a very small sample size, both techniques present similar values. Therefore, the tendency to use PLS-PM, based on the use of a small sample size (Hair et al., 2012; Gefen, Straub, & Boudreau, 2000; Marcoulides, 2006), is not supported by the results of this study. study and is inadvisable.

The main limitations of the present study are the use of a model that is too simple, with high and invariant values for the parameters, which, being unusual in applied research, may limit the generalization of the results found. Furthermore, it seems advisable to use higher effect sizes to determine a relevant effect.

As a suggestion for future studies on this topic, it is suggested to incorporate different levels for the ordinal scale, and may also incorporate different

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measurement scales for the manifest variables (e.g., ordinal and interval), models with different levels of complexity, different values of population parameters and/or training indicators.

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