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A MONTE CARLO INVESTIGATION OF PARTIAL LEAST SQUARES, WITH IMPLICATIONS FOR BOTH STRUCTURAL AND MEASUREMENT MODELS

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ABSTRACT

Partial Least Squares (PLS) is a popular technique with extensive adoption within the Information Systems research community. However, the statistical performance of PLS has not been extensively studied, and recent research has questioned some of its purported advantages. The simulation study reported here analyzed the performance of PLS with regards to the recovery and estimation accuracy of both structural and measurement parameters. Somewhat surprisingly, the effects of estimation bias on the latter and their implications for the evaluation of measurement models have not been the focus of past research. Results show the existence of an important degree of bias in both sets of estimates, and the conflicting effect of increased sample size with additional indicators per composite variable.

Keywords

Partial least squares, Monte Carlo simulation, parameter bias, statistical power, measurement models

INTRODUCTION

In a recent editorial in MIS Quarterly, Marcoulides and Saunders (2006) called for a more careful and critical consideration of the properties and techniques underlying the rather popular PLS approach to structural equation modeling. Given recent research by Goodhue and colleagues (Goodhue, Lewis and Thompson, 2006, 2007), as well as the fundamental nature of the questions posed by the editor-in-chief of a premier IS journal, it appears that PLS is more extensively used than understood in IS research. It is rather surprising that, at least until recently, the performance and properties of this popular statistical technique have not been subjected to extensive examination. Part of the issue lies at the core of the technique. As described by McDonald (1996):

> *"The PLS methods are difficult to describe and extremely difficult to evaluate, partly because PLS constitutes a set of ad hoc algorithms that have generally not been formally analyzed, or shown to possess any clear global optimizing properties (except in the well understood case of just two composites), and partly because these devices are represented as a form of path analysis with latent variables, and it can be difficult to determine what properties of latent variable models they possess, if any." (p. 240)*

The PLS algorithm generates estimates for three different sets of parameters in a model: the block structure (also called outer relations), the inner relations, and the weight relations. The block structure relates indicators to latent variables such that each indicator is subject to predictor specification, and estimates a loading for each indicator. The inner relations specify path coefficients between the latent variables, according to the theoretical model proposed by the investigator. Weight relations help provide explicit estimates for each latent variable, as a weighted aggregate of its indicators. In all cases both latent and manifest variables are scaled to zero means and unit variances to eliminate constant terms from the equations. PLS arrives at estimates for these parameters by means of a three-stage procedure, which is depicted in Figure 1 and described in more detail below. The description of PLS provided in this Figure is adapted from Wold (1982) and Lohmöller (1989); see also Chin (1998) for a more accessible narrative account of this procedure.

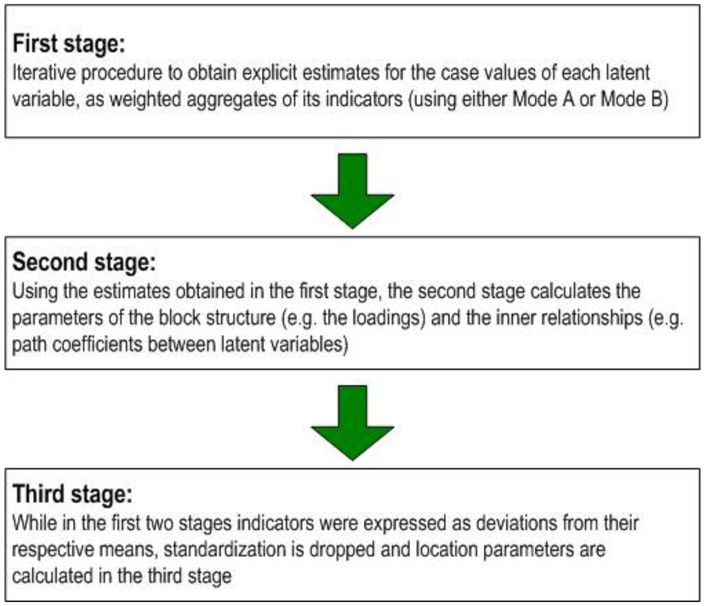


Figure 1 – Stages of the PLS Algorithm (adapted from Wold, 1982 and Lohmöller, 1989)

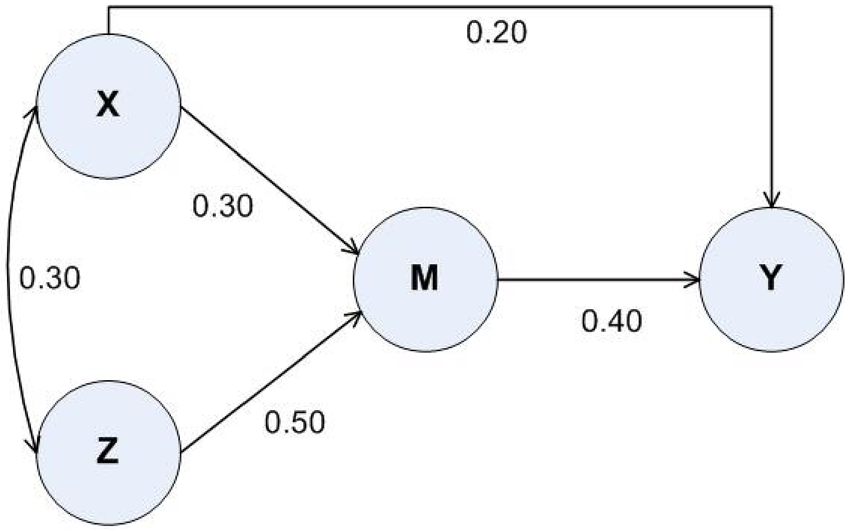
The research presented here reports on a Monte Carlo simulation designed to assess the performance of PLS against a known population model, for a variety of sample sizes and number of indicators for each composite variable. In particular, this paper has two major objectives: a) to contribute to the growing literature[1] analyzing the properties and bias of PLS estimates, with particular interest in models depicting partial mediation of effects , and b) to examine the extent to which known bias present in indicator loadings (Chin, Marcolin and Newsted, 2003) affects two important statistics involved in the evaluation of the measurement relations in structural equation models, namely Composite Reliability (CR) and Average Variance Extracted (AVE) (Fornell and Larcker, 1981).

Given that the latter are commonly used as cutoffs to judge the acceptability of the relationship between indicators and posited latent variables (Gefen and Straub, 2005; Gefen, Straub and Boudreau, 2000), assessing the extent to which these are biased and may be providing researchers with a false sense of confidence is deemed to be of significant relevance. To the best of our knowledge this is the first study that has investigated this issue.

RESEARCH DESIGN AND DATA GENERATION

Figure 2 depicts the population model for data generation used in this study (although not shown, all loadings were set at 0.80, well above commonly accepted cutoffs). Although much of the simulation research that employed multiple independent variables generated data as if they were statistically independent (i.e., not correlated with each other), we chose to design the population model with a medium size (Cohen, 1988) correlation of 0.30 to better reflect scenarios encountered in actual research, where non-correlated variables are extremely rare.

[1] Space limitations preclude a comprehensive literature review of extant research in this area. Past research, however, has exclusively focused on models with just one causal link, i.e., from one or more independent variables to a single dependent variable. A table comparing these studies is available from the first author upon request



Note: Single-headed arrows depict standardized path coefficients, double-headed arrows show correlations between variables

Figure 2. Population Model for Monte Carlo Simulation

Data for this research were generated[2] using Mplus 3.0 (Muthén and Muthén, 1998-2004). This software package allows researchers to completely specify all parameters in a latent variable model, and then take samples as if they were obtained from that population. Two simulation parameters were varied: sample size, with seven different conditions (40, 80, 120, 160, 200, 260 and 320), and the number of indicators per composite variable, with five different conditions (3, 5, 7, 9 and 11). All latent factors were modeled as reflective. Sample size and number of manifest indicators for each construct were deemed to be of theoretical interest given that estimates in PLS are asymptotically correct only under the joint conditions of consistency (sample size becomes large) and consistency-at-large (the number of indicators per latent variable becomes large) (Anderson and Gerbing, 1988; Jöreskorg and Wold, 1982). The thirty five different conditions simulated (seven for sample size and five for number of indicators) are taken to be representative of current research practice. In each of the cells, five hundred replications were conducted with five hundred bootstrap samples. All variables (latent and manifest) were modeled as normal and standardized to have a mean of zero and variance of one.

STRUCTURAL MODEL RESULTS

Results for the structural part of the model (i.e., the path coefficients linking the composite variables) are reported in Tables 1, 2 and 3. Table 1 shows the average of the estimated path coefficients over the replications together with the estimated population standard errors. The pattern of significance shows that the two higher paths in Figure 2, from Z to M (population value 0.50) and from M to Y (population value 0.40) were significantly different from zero for all combinations of sample size and number of indicators. The next highest path, from X to M (population value 0.30), was significantly different from zero in all indicator and sample size conditions except for the smallest sample size of 40. The partially mediated path from X to Y (population value 0.20) did not reach significance over the replications until the cell with a sample size of 160 and 9 indicators per composite variable.

Table 2 reports the power to detect significant path coefficients for each path and simulation condition. While for the two larger paths power was above conventionally acceptable levels (i.e., 0.80; Cohen, 1988) for any sample size of 80 or above, power did not reach this threshold for the X → M path (population value 0.30) for samples of 160 or more. For the smallest path, power remained below 0.80 until the sample size reached 320, and only with 5 or more indicators per construct. For Table 2 both the sample size and the number of indicators resulted in increasing levels of power, with the effect of sample size being of a larger magnitude. These results are consistent with those reported by Goodhue, et al. (2007).

Table 3 shows the Mean Relative Bias (MRB) for the four paths in the model, for each simulated condition. The MRB is a measure of the mean bias of each path with respect to their population values. An examination of these results shows some

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[2] Sample code for the data generation portion of this research is available from the first author upon request

interesting patterns. First, the degree of bias is not the same for the four different paths. The two paths into the mediator variable M are the most highly biased, the partially mediated path from M to Y somewhat less, and the path from M to Y shows notably less bias than any other. Second, while bias ***decreases*** as each composite variable is represented by more indictors, bias ***increases*** with larger sample sizes. This is indeed a puzzling result; however, an examination of the results published by Chin, et al. (2003) and Goodhue, et al. (2007) show a similar pattern. Together with the results shown in Table 1, this means that while the path coefficients tend to become more stable and clustered around a mean value, as evidenced by decreasing standard errors and increased significance over five hundred replications, the value that these coefficients cluster around becomes somewhat more distant from the population parameter as sample size increases. Given that the above cited studies and this study used different statistical packages to simulate data it does not seem likely this may be the cause of these findings. Clearly more research is needed to tease out the reasons behind this phenomenon.

Results in this section illustrate the relatively poor performance of the technique when considering the partially mediated path from X to Y (population value 0.20). However, since this is also the path with the smallest coefficient in the model, it is not clear whether the lack of significance and low power is due only to its low strength, or whether the position in the research model also has an effect. For instance, the second smallest path from X to M (population value 0.30) was recovered by PLS an order of magnitude better if one were to consider the outcomes shown in Tables 1 and 2.

To gain some insight into the relative importance of these two effects in bringing about the observed performance, one cell was re-run with a modified population model where the path from X to Y took the value of 0.40, the same value as the path from M to Y. Given that these two paths had the same dependent variable and strength in the population model, any differential effects can then be attributed to the different positioning of these variables in the model. Table 4 provides a comparison of the cell with 7 indicators and a sample size of 160 for all parameters of interest. The results show a large increase in power (from 49% to 97%, with $p < 0.01$), which is balanced by an increase in bias for both the M $\rightarrow$ Y as well as the X $\rightarrow$ Y path coefficients. In the former, bias increased from 0% to -7%, whereas in the latter the MRB went from -16% to -23%. In addition, loadings in the model with the higher structural path were slightly more biased than in the baseline model, which impacted the AVE (bias went from +16% to +20%).

MEASUREMENT MODEL RESULTS

Average loading bias was calculated following Chin, et al. (2003) and is shown in Table 5 for each composite in all simulated conditions. Average bias tends to decrease as more indicators are used to represent constructs, while sample size has no noticeable effect. It has long been known that PLS tends to underestimate path coefficients and overestimate loadings (Hui and Wold, 1982); however, the impact of the latter effect on CR and AVE has not been previously examined. Recall these two statistics are a function of the loadings for each construct (Fornell and Larcker, 1981):

$$CR = \frac{\left(\sum_{i=1}^{p} \lambda_{yi}\right)^2}{\left(\sum_{i=1}^{p} \lambda_{yi}\right)^2 + \sum_{i=1}^{p} Var(\varepsilon_i)} \qquad AVE = \frac{\sum_{i=1}^{p} \lambda_{yi}^2}{\sum_{i=1}^{p} \lambda_{yi}^2 + \sum_{i=1}^{p} Var(\varepsilon_i)}$$

Tables 6 and 7 show the AVE and CR calculated from PLS (averaged over 500 replications in each condition). Whereas the population AVE equals 0.64 in all cases (given loadings of 0.80 and standardized indicators), the population CR varies with the number of indicators in each construct. An examination of Table 6 reveals three distinct effects on AVE: first, bias is reduced as the number of indicator per composite increases; second, sample size has essentially no effect on bias; and finally, the amount of bias is markedly different for variables that emit paths as opposed to those that receive them, the estimate of AVE being quite more biased upward for the latter, as much as 26% when only employing 3 indicators. While as stated above bias decreases as the number of indicators increases, it remains relatively high for variables receiving paths, up to 16% even when 11 indicators are employed. This is consistent with the differential pattern of loading bias depicted in Table 5 for these constructs.

Table 7 shows a similar pattern of results for CR in all conditions, with bias for this important statistic remaining unchanged with increasing sample size, but shrinking as more indicators are added to the construct. Consistent with the results for AVE and the differential loading bias shown in Table 5, CR for path-receiving variables is always more biased than for path-emitting ones; however, these differences are small and become negligible as the number of indicators increases. In general CR does not exhibit the same amount of bias as AVE, for practical purposes becoming unbiased when seven or more indicators per construct are employed. The importance of studying the performance of PLS with regards to these statistics lies in the important role they play in the evaluation and validation of reflective constructs, where the literature has proposed minimum cutoffs such as 0.70 for CR and 0.50 for AVE (Straub, Boudreau and Gefen, 2004).

CONCLUSION AND DIRECTIONS FOR FUTURE RESEARCH

This research contributes to the growing literature on PLS performance and bias through the use of Monte Carlo simulations to examine structural and measurement aspects of a research model that consists of direct and partially mediated paths of varying strengths in models where all variables are specified as reflective. Two theoretically interesting parameters, sample size and number of indicators per composite variable, were systematically varied to study their effect on the ability of PLS to accurately recover population parameters from a known model, depicted in Figure 2. Other important conditions, such as deviations from normality and misspecification were not considered in order to keep the scope of this research manageable, although there is a clear need of further research to understand how the results presented here would be affected by these issues, among others. A systematic examination of type I error and misspecification is also needed.

Results show that power to detect significant structural parameters (i.e., path coefficients), which are the main focus of interest in applied research, improves as both the number of indicators per variable and sample size increase, with the latter effect being more marked. The degree of bias in path coefficients, on the other hand, is reduced with additional indicators per composite, but estimated parameters are more biased as the sample size increases. Reconciliation of these two effects is quite straightforward. Increased sample size results in smaller standard errors and thus more stable path coefficients, leading to increased statistical power. However, path coefficients stabilize at a value that is consistently, and increasingly with larger samples, smaller than the population parameter. There seems to be a tradeoff for researchers between increased significance of the estimates and increased bias; the effect of increasing the number of indicators is always beneficial.

While space limitations preclude a comprehensive discussion about the recovery of the correlation between the independent variables X and Z, the following observations can be made (full results are available from the first author upon request): estimation is always negatively biased, ranging from -15/17% with three indicators to -3/6% with eleven indicators and sample size has not discernable effect on this; and power to detect a correlation significantly different from zero at $p < 0.01$ increases with both sample size and number of indicators, going over 0.80 with a sample size of 120 and seven or more indicators, and for any larger sample size regardless of the number of indicators.

Turning to the measurement model, loadings are always biased upwards, to varying degree depending on both sample size (larger samples have a slightly negative effect on loading bias, that is they are more upwardly biased) and the number of indicators per variable, which leads to decreasing bias as more are employed. This positive bias in loadings leads to the consistent overestimation of two important statistics, Average Variance Extracted and Composite Reliability. Given the role these play in assessing the appropriateness of measurement models, researchers are advised to be suspect of borderline values which, depending on the position of the variable in the structural model, may be significantly biased. This point was recognized by Straub, et al. (2004); however, the degree of bias had not been subject to quantification, nor had it been recognized that it is dependent on the form of the research model.

Given these results, one final (and quite important) consideration is the degree to which use of PLS is advised. Even in situations with a large number of indicators per variable and a sample size that is above average for IS research, the performance of PLS is still largely biased with respect to known population parameters (as much as 17% downwards for path coefficients). In addition, Table 3 shows that the degree of bias in the estimation is dependent on the structure of the research model. Given the limited amount of research involving models with multiple causal links, it is not clear what performance can be expected in more complex models, but this is clearly not a desirable property in a statistical technique. As a point of comparison, Table 8 reports the analysis of the raw data in the cell with 11 indicators and a sample size of 320 with PLS versus covariance-based SEM. The results are notably superior, in every respect, for the latter. While convergence problems are likely to arise with smaller samples and data that less cleanly conforms to the assumptions of SEM, the value in using PLS when covariance-based techniques are an alternative appears circumspect.

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Table 1. Path Coefficients from Monte Carlo Simulation (500 runs per cell)

	Indicators									
Sample Size	**3**		**5**		**7**		**9**		**11**	
40	0.246 (0.142)	**0.376 (0.144)**	0.252 (0.142)	**0.384 (0.153)**	0.255 (0.141)	**0.408 (0.144)**	0.265 (0.141)	**0.406 (0.137)**	0.263 (0.133)	**0.417 (0.132)**
	0.377 (0.131)	0.157 (0.173)	**0.394 (0.129)**	0.190 (0.157)	**0.411 (0.126)**	0.178 (0.161)	**0.417 (0.126)**	0.171 (0.158)	**0.422 (0.123)**	0.180 (0.158)
80	**0.236 (0.096)**	**0.370 (0.097)**	**0.246 (0.097)**	**0.394 (0.100)**	**0.247 (0.096)**	**0.392 (0.097)**	**0.255 (0.096)**	**0.399 (0.102)**	**0.262 (0.094)**	**0.408 (0.094)**
	0.368 (0.094)	0.160 (0.109)	**0.389 (0.093)**	0.171 (0.109)	**0.401 (0.095)**	0.182 (0.105)	**0.415 (0.095)**	0.175 (0.105)	**0.403 (0.092)**	0.172 (0.107)
120	**0.237 (0.078)**	**0.366 (0.085)**	**0.253 (0.081)**	**0.387 (0.082)**	**0.249 (0.079)**	**0.392 (0.081)**	**0.256 (0.079)**	**0.397 (0.080)**	**0.240 (0.079)**	**0.403 (0.082)**
	0.374 (0.080)	0.167 (0.086)	**0.390 (0.075)**	0.177 (0.089)	**0.398 (0.076)**	0.179 (0.087)	**0.406 (0.077)**	0.170 (0.088)	**0.409 (0.080)**	0.175 (0.083)
160	**0.236 (0.069)**	**0.368 (0.069)**	**0.251 (0.068)**	**0.384 (0.069)**	**0.243 (0.066)**	**0.399 (0.070)**	**0.247 (0.062)**	**0.397 (0.068)**	**0.251 (0.066)**	**0.396 (0.071)**
	0.370 (0.064)	0.170 (0.074)	**0.384 (0.065)**	0.172 (0.076)	**0.403 (0.064)**	0.168 (0.075)	**0.402 (0.062)**	**0.177 (0.073)**	**0.404 (0.067)**	**0.176 (0.073)**
200	**0.233 (0.061)**	**0.367 (0.061)**	**0.250 (0.062)**	**0.384 (0.066)**	**0.239 (0.064)**	**0.389 (0.063)**	**0.245 (0.064)**	**0.399 (0.062)**	**0.246 (0.063)**	**0.402 (0.059)**
	0.366 (0.060)	**0.164 (0.069)**	**0.383 (0.058)**	**0.170 (0.064)**	**0.398 (0.059)**	**0.174 (0.061)**	**0.405 (0.059)**	**0.171 (0.065)**	**0.404 (0.057)**	**0.173 (0.066)**
260	**0.235 (0.054)**	**0.370 (0.054)**	**0.244 (0.055)**	**0.386 (0.055)**	**0.243 (0.054)**	**0.390 (0.056)**	**0.252 (0.056)**	**0.397 (0.054)**	**0.250 (0.051)**	**0.401 (0.055)**
	0.368 (0.052)	**0.159 (0.059)**	**0.389 (0.054)**	**0.165 (0.060)**	**0.396 (0.050)**	**0.176 (0.058)**	**0.400 (0.053)**	**0.170 (0.056)**	**0.403 (0.050)**	**0.172 (0.055)**
320	**0.234 (0.052)**	**0.369 (0.050)**	**0.241 (0.051)**	**0.385 (0.049)**	**0.242 (0.046)**	**0.394 (0.050)**	**0.250 (0.050)**	**0.399 (0.047)**	**0.247 (0.047)**	**0.404 (0.047)**
	0.369 (0.049)	**0.164 (0.052)**	**0.390 (0.048)**	**0.169 (0.050)**	**0.396 (0.046)**	**0.170 (0.055)**	**0.397 (0.048)**	**0.168 (0.050)**	**0.405 (0.043)**	**0.166 (0.051)**

Note: For each individual cell top-left values (and associated standard error within parentheses) refer to the X → M path (population value = 0.30), bottom-left to the Z → M path (population value = 0.50), top-right to the M → Y path (population value = 0.40), and bottom-right ones to the X → Y path (population value = 0.20).

Bolded values are significant at $p < 0.01$.

Table 2. Power to Detect Significant Effects (500 runs per cell)

	Indicators				
Sample Size	**3**	**5**	**7**	**9**	**11**
40	30% 56% 65% 12%	33% 60% 68% 16%	33% 64% 75% 17%	40% 66% 76% 14%	38% 66% 78% 15%
80	55% 87% 91% 21%	59% 89% 95% 26%	59% 90% 94% 28%	64% 89% 96% 24%	66% 93% 96% 27%
120	74% 95% 97% 35%	77% 98% 100% 41%	79% 98% 100% 41%	81% 98% 100% 38%	75% 98% 99% 41%
160	84% 100% 100% 48%	88% 99% 100% 49%	89% 100% 100% 49%	92% 100% 100% 54%	91% 100% 100% 50%
200	92% 100% 100% 52%	95% 100% 100% 59%	92% 100% 100% 63%	93% 100% 100% 57%	93% 100% 100% 62%
260	97% 100% 100% 63%	98% 100% 100% 66%	98% 100% 100% 74%	98% 100% 100% 71%	99% 100% 100% 74%
320	98% 100% 100% 77%	99% 100% 100% 80%	100% 100% 100% 80%	100% 100% 100% 81%	100% 100% 100% 81%

<u>Note</u>: For each individual cell top-left values refer to the X → M path (population value = 0.30), bottom-left to the Z → M path (population value = 0.50), top-right to the M → Y path (population value = 0.40), and bottom-right ones to the X → Y path (population value = 0.20).

Power to detect significant effects at $p < 0.01$ (t-stat ≥ 2.36)

Table 3. Mean Relative Bias for Path Coefficients (500 runs per cell)

	Indicators									
Sample Size	**3**		**5**		**7**		**9**		**11**	
40	-18%	- 6%	-16%	- 4%	-15%	2%	-12%	2%	-12%	4%
	-25%	-21%	-21%	- 5%	-18%	-11%	-17%	-15%	-16%	-10%
80	-20%	- 8%	-18%	- 1%	-18%	- 2%	-15%	0%	-13%	2%
	-26%	-20%	-22%	-14%	-20%	- 9%	-17%	-13%	-19%	-14%
120	-21%	-9%	-16%	- 3%	-17%	- 2%	-15%	- 1%	-20%	1%
	-25%	-16%	-22%	-11%	-20%	-11%	-19%	-15%	-18%	-12%
160	-21%	- 8%	-16%	- 4%	-19%	0%	-18%	- 1%	-16%	- 1%
	-26%	-15%	-23%	-14%	-19%	-16%	-20%	-11%	-19%	-12%
200	-22%	- 8%	-17%	- 4%	-20%	- 3%	-18%	0%	-18%	0%
	-27%	-18%	-23%	-15%	-20%	-13%	-19%	-15%	-19%	-14%
260	-22%	- 7%	-19%	- 4%	-19%	- 3%	-16%	- 1%	-17%	0%
	-26%	-20%	-22%	-18%	-21%	-12%	-20%	-15%	-19%	-14%
320	-22%	- 8%	-20%	- 4%	-19%	- 2%	-17%	0%	-18%	1%
	-26%	-18%	-22%	-15%	-21%	-15%	-21%	-16%	-19%	-17%

Note: For each individual cell top-left values refer to the mean relative bias of the X → M path (population value = 0.30), bottom-left to the Z → M path (population value = 0.50), top-right to the M → Y path (population value = 0.40), and bottom-right ones to the X → Y path (population value = 0.20).

Mean Relative Bias (MRB) = (mean path coefficient across replications – population value) / population value

Table 4. Partially Mediated Path with 0.40 Coefficient

	Original Population Model	X → Y Path at 0.40
Path Estimates (Standard Errors)		
X → M	0.243 (0.066)	0.243 (0.072)
Z → M	0.403 (0.064)	0.400 (0.068)
M → Y	0.399 (0.070)	0.373 (0.069)
X → Y	0.168 (0.075)	0.308 (0.068)
Power		
X → M	89%	86%
Z → M	100%	100%
M → Y	100%	99%
X → Y	49%	97%
MRB for Path Coefficients		
X → M	-19%	-19%
Z → M	-19%	-20%
M → Y	0%	-7%
X → Y	-16%	-23%
Average Loading Bias		
X	0.830 [+ 4%]	0.831 [+ 4%]
Z	0.831 [+ 4%]	0.829 [+ 4%]
M	0.870 [+ 9%]	0.870 [+ 9%]
Y	0.863 [+ 8%]	0.876 [+10%]
AVE and MRB		
X	0.689 [+ 8%]	0.691 [+ 8%]
Z	0.692 [+ 8%]	0.688 [+ 8%]
M	0.757 [+18%]	0.757 [+18%]
Y	0.745 [+16%]	0.768 [+20%]
CR and MRB		
X	0.939 [+ 1%]	0.940 [+ 1%]
Z	0.940 [+ 2%]	0.939 [+ 1%]
M	0.956 [+ 3%]	0.956 [+ 3%]
Y	0.953 [+ 3%]	0.959 [+ 4%]

Table 5. Average Loading Bias (500 runs per cell)

	Indicators				
Sample Size	**3**	**5**	**7**	**9**	**11**
40	0.859 0.897 [+ 7%] [+12%] 0.860 0.890 [+ 7%] [+11%]	0.832 0.875 [+ 4%] [+ 9%] 0.835 0.868 [+ 4%] [+ 8%]	0.822 0.867 [+ 3%] [+ 8%] 0.827 0.860 [+ 3%] [+ 8%]	0.817 0.859 [+ 2%] [+ 7%] 0.815 0.853 [+ 2%] [+ 7%]	0.812 0.860 [+ 2%] [+ 7%] 0.812 0.851 [+ 2%] [+ 6%]
80	0.867 0.899 [+ 8%] [+12%] 0.868 0.893 [+ 8%] [+12%]	0.840 0.877 [+ 5%] [+10%] 0.839 0.873 [+ 5%] [+ 9%]	0.828 0.868 [+ 3%] [+ 9%] 0.829 0.863 [+ 4%] [+ 8%]	0.822 0.864 [+ 3%] [+ 8%] 0.824 0.857 [+ 3%] [+ 7%]	0.815 0.860 [+ 2%] [+ 8%] 0.817 0.853 [+ 2%] [+ 7%]
120	0.869 0.900 [+ 9%] [+13%] 0.871 0.895 [+ 9%] [+12%]	0.842 0.880 [+ 5%] [+10%] 0.842 0.873 [+ 5%] [+ 9%]	0.829 0.870 [+ 4%] [+ 9%] 0.831 0.863 [+ 4%] [+ 8%]	0.824 0.864 [+ 3%] [+ 8%] 0.824 0.858 [+ 3%] [+ 7%]	0.817 0.861 [+ 2%] [+ 8%] 0.818 0.854 [+ 2%] [+ 7%]
160	0.870 0.901 [+ 9%] [+13%] 0.871 0.895 [+ 9%] [+12%]	0.842 0.879 [+ 5%] [+10%] 0.842 0.873 [+ 5%] [+ 9%]	0.830 0.870 [+ 4%] [+ 9%] 0.831 0.863 [+ 4%] [+ 8%]	0.823 0.864 [+ 3%] [+ 8%] 0.824 0.859 [+ 3%] [+ 7%]	0.819 0.862 [+ 2%] [+ 8%] 0.818 0.854 [+ 2%] [+ 7%]
200	0.870 0.900 [+ 9%] [+12%] 0.870 0.896 [+ 9%] [+12%]	0.842 0.878 [+ 5%] [+10%] 0.843 0.872 [+ 5%] [+ 9%]	0.830 0.870 [+ 4%] [+ 9%] 0.829 0.862 [+ 4%] [+ 8%]	0.823 0.865 [+ 3%] [+ 8%] 0.823 0.858 [+ 3%] [+ 7%]	0.819 0.862 [+ 2%] [+ 8%] 0.819 0.854 [+ 2%] [+ 7%]
260	0.871 0.901 [+ 9%] [+13%] 0.870 0.895 [+ 9%] [+12%]	0.842 0.879 [+ 5%] [+10%] 0.843 0.873 [+ 5%] [+ 9%]	0.830 0.870 [+ 4%] [+ 9%] 0.831 0.863 [+ 4%] [+ 8%]	0.825 0.865 [+ 3%] [+ 8%] 0.824 0.858 [+ 3%] [+ 7%]	0.819 0.861 [+ 2%] [+ 8%] 0.820 0.855 [+ 2%] [+ 7%]
320	0.871 0.900 [+ 9%] [+13%] 0.871 0.896 [+ 9%] [+12%]	0.843 0.879 [+ 5%] [+10%] 0.843 0.873 [+ 5%] [+ 9%]	0.831 0.870 [+ 4%] [+ 9%] 0.831 0.864 [+ 4%] [+ 8%]	0.823 0.865 [+ 3%] [+ 8%] 0.823 0.859 [+ 3%] [+ 7%]	0.819 0.861 [+ 2%] [+ 8%] 0.820 0.855 [+ 2%] [+ 7%]

Note: For each individual cell top-left values (and associated mean relative bias within brackets) refer to average loadings for the X variable, bottom-left to those for the Z variable, top-right values to M, and bottom-right ones to the Y variable. In all cases loadings were set at 0.8 in the model used to generate the data (see Figure 1).

Table 6. Average Variance Extracted and Mean Relative Bias (500 runs per cell)

	Indicators									
Sample Size	**3**		**5**		**7**		**9**		**11**	
40	0.745 [+16%]	0.806 [+26%]	0.698 [+ 9%]	0.768 [+20%]	0.680 [+ 6%]	0.754 [+18%]	0.671 [+ 5%]	0.740 [+16%]	0.663 [+ 4%]	0.741 [+16%]
	0.746 [+16%]	0.795 [+24%]	0.701 [+10%]	0.756 [+18%]	0.688 [+ 7%]	0.743 [+16%]	0.668 [+ 4%]	0.731 [+14%]	0.664 [+ 4%]	0.727 [+14%]
80	0.754 [+18%]	0.809 [+26%]	0.708 [+11%]	0.771 [+20%]	0.687 [+ 7%]	0.755 [+18%]	0.678 [+ 6%]	0.748 [+17%]	0.665 [+ 4%]	0.741 [+16%]
	0.755 [+18%]	0.798 [+25%]	0.706 [+10%]	0.763 [+19%]	0.688 [+ 8%]	0.745 [+16%]	0.680 [+ 6%]	0.735 [+15%]	0.669 [+ 5%]	0.729 [+14%]
120	0.757 [+18%]	0.811 [+27%]	0.709 [+11%]	0.775 [+21%]	0.688 [+ 8%]	0.758 [+18%]	0.680 [+ 6%]	0.747 [+17%]	0.669 [+ 5%]	0.742 [+16%]
	0.759 [+19%]	0.802 [+25%]	0.710 [+11%]	0.763 [+19%]	0.691 [+ 8%]	0.746 [+17%]	0.679 [+ 6%]	0.736 [+15%]	0.671 [+ 5%]	0.730 [+14%]
160	0.757 [+18%]	0.811 [+27%]	0.710 [+11%]	0.773 [+21%]	0.689 [+ 8%]	0.757 [+18%]	0.678 [+ 6%]	0.747 [+17%]	0.672 [+ 5%]	0.743 [+16%]
	0.759 [+19%]	0.802 [+25%]	0.710 [+11%]	0.762 [+19%]	0.692 [+ 8%]	0.745 [+16%]	0.679 [+ 6%]	0.738 [+15%]	0.671 [+ 5%]	0.729 [+14%]
200	0.758 [+18%]	0.810 [+27%]	0.710 [+11%]	0.772 [+21%]	0.690 [+ 8%]	0.757 [+18%]	0.677 [+ 6%]	0.749 [+17%]	0.671 [+ 5%]	0.744 [+16%]
	0.757 [+18%]	0.803 [+26%]	0.711 [+11%]	0.761 [+19%]	0.688 [+ 8%]	0.744 [+16%]	0.678 [+ 6%]	0.737 [+15%]	0.672 [+ 5%]	0.729 [+14%]
260	0.759 [+19%]	0.811 [+27%]	0.710 [+11%]	0.773 [+21%]	0.689 [+ 8%]	0.756 [+18%]	0.680 [+ 6%]	0.748 [+17%]	0.671 [+ 5%]	0.742 [+16%]
	0.758 [+18%]	0.802 [+25%]	0.711 [+11%]	0.763 [+19%]	0.691 [+ 8%]	0.745 [+16%]	0.680 [+ 6%]	0.737 [+15%]	0.672 [+ 5%]	0.731 [+14%]
320	0.760 [+19%]	0.811 [+27%]	0.711 [+11%]	0.772 [+21%]	0.691 [+ 8%]	0.758 [+18%]	0.678 [+ 6%]	0.748 [+17%]	0.671 [+ 5%]	0.742 [+16%]
	0.759 [+19%]	0.803 [+25%]	0.710 [+11%]	0.763 [+19%]	0.691 [+ 8%]	0.746 [+17%]	0.678 [+ 6%]	0.737 [+15%]	0.673 [+ 5%]	0.730 [+14%]

Note: For each individual cell top-left values (and associated mean relative bias within brackets) refer to AVE for the X variable, bottom-left for that of the Z variable, top-right values to M, and bottom-right ones to the Y variable. In all cases the population AVE equals 0.64.

Table 7. Composite Reliability and Mean Relative Bias (500 runs per cell)

	Indicators									
Sample Size	**3**		**5**		**7**		**9**		**11**	
40	0.896 [+ 6%]	0.925 [+10%]	0.918 [+ 2%]	0.942 [+ 5%]	0.935 [+ 1%]	0.955 [+ 3%]	0.947 [+ 1%]	0.962 [+ 2%]	0.954 [0%]	0.969 [+ 2%]
	0.895 [+ 6%]	0.920 [+ 9%]	0.919 [+ 2%]	0.938 [+ 4%]	0.937 [+ 1%]	0.952 [+ 3%]	0.946 [+ 1%]	0.960 [+ 2%]	0.954 [0%]	0.967 [+ 2%]
80	0.901 [+ 7%]	0.927 [+10%]	0.923 [+ 3%]	0.943 [+ 5%]	0.938 [+ 1%]	0.955 [+ 3%]	0.949 [+ 1%]	0.964 [+ 2%]	0.956 [0%]	0.969 [+ 2%]
	0.902 [+ 7%]	0.922 [+ 9%]	0.923 [+ 3%]	0.941 [+ 5%]	0.939 [+ 1%]	0.953 [+ 3%]	0.950 [+ 2%]	0.961 [+ 2%]	0.957 [+ 1%]	0.967 [+ 2%]
120	0.903 [+ 7%]	0.928 [+10%]	0.924 [+ 3%]	0.945 [+ 5%]	0.939 [+ 1%]	0.956 [+ 3%]	0.950 [+ 1%]	0.964 [+ 2%]	0.957 [+ 1%]	0.969 [+ 2%]
	0.904 [+ 7%]	0.924 [+10%]	0.924 [+ 3%]	0.941 [+ 5%]	0.940 [+ 2%]	0.953 [+ 3%]	0.950 [+ 1%]	0.962 [+ 2%]	0.957 [+ 1%]	0.967 [+ 2%]
160	0.903 [+ 7%]	0.928 [+10%]	0.924 [+ 3%]	0.944 [+ 5%]	0.939 [+ 1%]	0.956 [+ 3%]	0.950 [+ 1%]	0.964 [+ 2%]	0.957 [+ 1%]	0.969 [+ 2%]
	0.904 [+ 7%]	0.924 [+10%]	0.924 [+ 3%]	0.941 [+ 5%]	0.940 [+ 2%]	0.953 [+ 3%]	0.950 [+ 1%]	0.962 [+ 2%]	0.957 [+ 1%]	0.967 [+ 2%]
200	0.904 [+ 7%]	0.927 [+10%]	0.924 [+ 3%]	0.944 [+ 5%]	0.939 [+ 1%]	0.956 [+ 3%]	0.950 [+ 1%]	0.964 [+ 2%]	0.957 [+ 1%]	0.970 [+ 2%]
	0.903 [+ 7%]	0.924 [+10%]	0.925 [+ 3%]	0.941 [+ 5%]	0.939 [+ 1%]	0.953 [+ 3%]	0.950 [+ 1%]	0.962 [+ 2%]	0.957 [+ 1%]	0.967 [+ 2%]
260	0.904 [+ 7%]	0.928 [+10%]	0.924 [+ 3%]	0.944 [+ 5%]	0.939 [+ 1%]	0.956 [+ 3%]	0.950 [+ 1%]	0.964 [+ 2%]	0.957 [+ 1%]	0.969 [+ 2%]
	0.904 [+ 7%]	0.924 [+10%]	0.925 [+ 3%]	0.941 [+ 5%]	0.940 [+ 2%]	0.953 [+ 3%]	0.950 [+ 1%]	0.962 [+ 2%]	0.957 [+ 1%]	0.968 [+ 2%]
320	0.904 [+ 7%]	0.928 [+10%]	0.925 [+ 3%]	0.944 [+ 5%]	0.940 [+ 2%]	0.956 [+ 3%]	0.950 [+ 1%]	0.964 [+ 2%]	0.957 [+ 1%]	0.969 [+ 2%]
	0.904 [+ 7%]	0.924 [+10%]	0.925 [+ 3%]	0.941 [+ 5%]	0.940 [+ 2%]	0.954 [+ 3%]	0.950 [+ 1%]	0.962 [+ 2%]	0.958 [+ 1%]	0.967 [+ 2%]

Note: For each individual cell top-left values (and associated mean relative bias within brackets) refer to Composite Reliability for the X variable, bottom-left for that of the Z variable, top-right values to M, and bottom-right ones to the Y variable.

Table 8. Comparison of PLS and CFA-SEM Estimates

	PLS	**CFA-SEM**
Path Estimates (Standard Errors)		
X → M	0.247 (0.047)	0.301 (0.065)
Z → M	0.405 (0.043)	0.503 (0.066)
M → Y	0.404 (0.047)	0.404 (0.062)
X → Y	0.166 (0.051)	0.194 (0.064)
Power		
X → M	100%	100%
Z → M	100%	100%
M → Y	100%	100%
X → Y	81%	85%
MRB for Path Coefficients		
X → M	-18%	0%
Z → M	-19%	1%
M → Y	1%	1%
X → Y	-17%	-3%
Average Loading Bias		
X	0.819 [+ 2%]	0.796 [- 1%]
Z	0.820 [+ 2%]	0.799 [0%]
M	0.861 [+ 8%]	0.794 [- 1%]
Y	0.855 [+ 7%]	0.795 [- 1%]
XZ Correlation		
Estimate (Standard Error)	0.288 (0.053)	0.301 (0.055)
Power	99%	100%
Mean Relative Bias	-4%	0%