Improvements to PLSc: Remaining problems and simple solutions

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Abstract

The recent article by Dijkstra and Henseler (2015b) presents a consistent partial least squares (PLSc) estimator that corrects for measurement error attenuation and provides evidence showing that, generally, PLSc performs comparably to a wide variety of more conventional estimators for structural equation models (SEM) with latent variables. However, PLSc does not adjust for other limitations of conventional PLS, namely: (1) bias in estimates of regression coefficients due to capitalization on chance; and (2) overestimation of composite reliability due to the proportionality relation between factor loadings and indicator weights. In this article, we illustrate these problems and then propose a simple solution: the use of unit-weighted composites, rather than those constructed from PLS results, combined with errors-in-variables regression (EIV) by using reliabilities obtained from factor analysis. Our simulations show that these two improvements perform as well as or better than PLSc. We also provide examples of how our proposed estimator can be easily implemented in various proprietary and open source software packages.

Keywords: partial least squares, structural equation modeling, composite variables, latent variables, measurement error, reliability, correction for attenuation, capitalization on chance, errors-in-variables regression

1. Introduction

Partial least squares (PLS) is currently one of the most popular techniques for the estimation of structural equation models in Information Systems (IS) research (Ringle, Sarstedt, & Straub, 2012). Although appealing due to their lower computational demands relative to conventional maximum-likelihood (ML) approaches, the traditional PLS methods are inconsistent and biased estimators of latent variable models (Dijkstra, 2010). These biases occur because composite loadings overestimate factor loadings (McDonald, 1996), and approximating latent variables with composites leads to the well-known measurement error bias in estimates of structural relationships (Bollen, 1989, Chapter 5).

To address these long-standing issues, Dijkstra and Henseler (2015b) build on the classical correction for measurement error and present a new consistent PLS (PLSc) estimator. The results of their simulation study show that PLSc performs comparably to ML and a wide variety of other SEM estimators. Although these findings seem promising, earlier research (Goodhue, Lewis, & Thompson, 2012; Huang, 2013) showed that corrected PLS may not always work well. Particularly – although using a slightly different correction – Goodhue, Lewis, and Thompson (2012) demonstrated that when adjusted for measurement error, PLS path estimates may actually be positively biased. To clarify these concepts further, a consistent estimator is one that converges in probability to the true population value as the sample size approaches infinity. On the other hand, unbiasedness means that the expected value of the estimator (i.e., average after repeated samples from the same population) is the true population value, and this concept applies regardless of the sample size (Bollen, 2011). Therefore, it is possible to have a consistent but biased estimator, that is, one that tends to over or underestimate the true population parameter in finite samples, but which still approaches the true value as the sample size increases toward infinity.

Due to several issues that we explain in this article, and illustrate via simulated datasets, PLSc can be characterized as a consistent but biased estimator. First, we demonstrate that the PLS weights are susceptible to a small-sample bias, which inflates the correlations between adjacent composites (Rönkkö, 2014; see also Goodhue, Lewis, & Thompson, 2015). Second, we show that the reliability indices used in PLSc, although consistent, only partially address the issues in the estimation of composite reliability in PLS when using sample data (Aguirre-Urreta, Marakas, & Ellis, 2013), leading to a positive bias in these estimates. Third, we build on ideas presented in various prior works (Aguirre-Urreta et al., 2013; Dijkstra, 2010; Dijkstra & Schermelleh-Engel, 2014; Lu, Kwan, Thomas, & Cedzynski, 2011) to propose further corrections to PLSc, in order to overcome the tripartite problems of measurement error, capitalization on chance, and positively biased reliability estimates. These corrections lead to errors-in-variables regression (EIV) with unit-weighted composites and reliabilities obtained from factor analysis. Although factor models can be estimated in a number of ways, we focus on the maximum likelihood confirmatory factor analysis (ML-CFA) and minres approaches because these follow logically from applying the recommendations in the existing literature to the PLSc factor loading correction. Fourth, we replicate Dijkstra and Henseler's (2015b) simulation study, comparing EIV with PLSc and maximum likelihood estimation of the full structural equation model (ML-SEM). Further, we extend the simulation study to conditions with weaker nomological networks, thus providing a direct answer to the call for future research by Dijkstra and Henseler (2015b, p. 17). We conclude our work with a discussion of our findings and recommendations for researchers and provide examples on how to apply the proposed techniques using different statistical software.

Our research is directly relevant for readers of *MIS Quarterly* for two reasons. First, although PLS is commonly used in the IS discipline, it is largely ignored by the leading research methods journals (Rönkkö & Evermann, 2013); consequently, a large share of current methodological writings on PLS have appeared in *MIS Quarterly* (Rönkkö, 2014). In addition to providing a direct answer to a call for future research by Dijkstra and Henseler (2015b, p. 17), we contribute to the methodological discussion by explaining the reason why the PLSc results obtained by Dijkstra and Henseler (2015b) differ from the positively biased results for disattenuated PLS presented by Goodhue et al. (2012). Second, and more importantly, IS researchers rely on composite-based approximations of factor models perhaps more than practitioners in any other discipline. Therefore, it is important that they use composites that are robust, as well as estimation techniques that take measurement error into account. We thus contribute to applied practice by outlining a more robust estimation approach, which can be used immediately with either existing commercial statistical packages or freely available software.

2. Issue 1: Capitalization on chance by PLS weights

A number of recent studies have shown that traditional PLS is highly susceptible to capitalization on chance in finite samples (Goodhue et al., 2015; Goodhue, Thompson, & Lewis, 2013; Rönkkö, 2014; Rönkkö & Evermann, 2013). We explain this issue using the simple structural equation model shown in Figure 1. When applied to data produced by this model, the PLS algorithm produces two composites (weighted sums) of the indicators. The correlation between these composites, which serves as the starting point for the PLSc path estimate, depends on both the indicator weights as well as the between-block indicator correlations. In finite samples, these correlations vary around the population values due to natural sampling variability. This creates a problem because the weights also depend on these correlations: if a correlation between indicators a_i and b_j happens to be large simply by chance, both indicators receive larger weights. Conversely, small correlations lead to decreased weights. This overweighting of highly correlated indicators at the expense of indicators with smaller correlations leads to an overall positive bias in the composite correlation (Rönkkö, 2014; Rönkkö & Ylitalo, 2010). To be sure, sampling error affects other types of correlational and multiple regression-based analyses (including ML-SEM and regression with unit-weighted summed scales), but only by increasing the variance of the estimates, and not their bias (Charles, 2005; Rönkkö, 2014; Stanley & Spence, 2014). In the case of PLS, however, sample fluctuations in the raw data-based correlations lead to both bias *and* increased variance of the estimates (Goodhue et al., 2015; Rönkkö, 2014).

----- Insert Figure 1 about here -----

We will next provide two numerical examples to demonstrate this issue. In the population model, all between-block correlations are 0.147 but, as stated above, the sample correlations, from which the PLS estimates are calculated, are never at the exact population values, and their variance depends on the sample size. When the sample size is 100, the standard error of the correlation is 0.100, which means that an observed between-block correlation falls outside the 0.147 ± 0.1 range about one third of the time. To demonstrate the effects that these small sample fluctuations have on PLS weights, we increase one between-block item correlation by 0.1 and decrease another by 0.1(that is, one standard error). These manipulations are marked with dashed lines in Figure 1. Because all other elements of the correlation matrix are exactly at their population values, the two small departures represent controlled conditions that can be used to demonstrate the issues occasioned by the natural sampling variability that arises in any real dataset. We then used the correlation matrix thus modified to calculate the PLS Mode A weights and the disattenuated correlation between the composites[2] using the *matrixpls* package for R (Rönkkö, 2015) because, unlike most other PLS software implementations, the *matrixpls* package can obtain estimates directly from a correlation matrix without recourse to raw data.

The PLS Mode A algorithm converged in six iterations. Table 1 shows the weight calculation history and the PLSc estimates of both the factor loadings and the path coefficient for each set of weights. The table also shows the PLSc-specific correction factors (*c*'s) used to rescale the indicator weights to factor loadings, and both Dijkstra and Henseler's (2015b) ρ_A coefficient as well as the true reliabilities (R's) for the composite variables. Because all indicators were equally reliable, unit weights, which are used as starting values in the PLS algorithm, produce the most reliable composites. In this scenario, the two manipulated correlations also cancel each other out exactly and all estimates using the starting weights are exactly correct. However, with the PLS indicator weighting system, the indicators with larger correlations receive higher weights and those with smaller correlations receive lower weights (Rönkkö, 2014), leading to a positive estimation error in the PLSc parameter estimates, as shown in Table 1.

----- Insert Table 1 about here -----

In the second example, we further illustrate the effect of small-sample idiosyncrasies by using a different approach. Instead of taking the population correlation matrix and manipulating it directly, we drew 10000 multivariate normal samples of 100 observations from the unaltered, correct population matrix. Next, the model in Figure 1 was estimated using PLSc under two

[2] In a simple univariate regression such as that used in this demonstration, the correlation is equivalent to the standardized regression coefficient.

distinct scenarios: (1) the usual case where the indicator weights are calculated and the regression coefficient estimated within the same sample; and (2) a case where the PLS weights are first computed from a calibration sample, and are then applied to an independent or "hold-out" sample to calculate the PLSc regression coefficient. Figure 2 shows that these two approaches produce markedly different distributions for the estimates: When the PLS weights and the PLSc regression coefficients are estimated from the same sample, the regression coefficients are biased away from zero and have a small secondary mode on the negative side of the x-axis, as also documented in prior IS research (Goodhue, Lewis, & Thompson, 2007; Goodhue et al., 2012). Contrarily, when these weights are applied to a new sample, the effect disappears and the resulting coefficient estimates are approximately normally distributed, but negatively biased, due to bias in the reliability estimates that we discuss in the next section. In both scenarios, the weights are based on estimated indicator reliabilities, but in the first scenario those weights also capitalize on idiosyncratic variation present in the sample from which the weights were calculated. In the second scenario, this does not happen because the characteristics of the hold-out sample are not the same as in the sample that was originally used to calculate the weights. If the weights were not affected by small-sample idiosyncrasies under the first scenario, then we would expect the two approaches to estimating the regression coefficient to yield identical distributions, which is clearly not the case. Through a different approach than before, this second example also clearly demonstrates that PLS weights capitalize on the idiosyncratic features of a given sample (e.g., correlations that are large by chance only), and that these affect the accuracy of the resulting estimates. In the interest of allowing for the replication of our results, the R source code for both examples is available in Appendix D.

----- Insert Figure 2 about here -----

3. Issue 2: Biasedness of reliability estimates

An unbiased correction for measurement error attenuation in correlational and regression analyses requires unbiased reliability estimates for the variables involved (cf., Borneman, 2010; Muchinsky, 1996). In PLS analyses, these reliability estimates are typically calculated with the composite reliability (CR_U[3]) index – a measure of reliability of unweighted composites historically associated with latent variable SEM (Fornell & Larcker, 1981; Raykov, 1997; Werts, Linn, & Jöreskog, 1974). However, as pointed out by Dijkstra and Henseler (2015b), the CR_U index is inconsistent when calculated from PLS estimates because the well-known overestimation of factor loadings by composite loadings will in turn inflate CR_U. Therefore, they propose an alternative reliability coefficient, ρ_A, where the subscript A refers to the fact that Mode A estimation is used to generate the weights required for calculating the index. Although Dijkstra and Henseler do provide evidence of the consistency of ρ_A in their Figure 3, they do not provide evidence of unbiasedness – recall our earlier discussion on the difference between these two properties. Moreover, Dijkstra and Henseler address only some of the problems associated with the use of the CR_U in a PLS analysis. As recently pointed out by Aguirre-Urreta, Marakas, and Ellis (2013), there are three issues with the way composite reliability is typically estimated following a PLS analysis.

The first problem in using the CR_U with PLS analysis is that the formula for the composite reliability statistic reported in the output of PLS analyses is the one given by Fornell and Larcker (1981; see also Chin, 1998) for equally-weighted composites. In the case of PLS analyses, however, the composites involved in the estimates are not equally-weighted combinations of individual indicators, but are rather created using weights derived with the PLS

[3] We use the acronym CR_U for the unweighted version of composite reliability and CR_W for a weighted version that we will introduce later. The acronyms CR_W and CR_U are not conventional terms from the psychometric literature, but were used here to make a simple distinction between reliability indices for the weighted and unweighted case, respectively.

algorithm. As a result, the composite reliability formula that is commonly employed is biased. For an unbiased estimation, an alternative version that does take into account the particular weights used to construct the composite is necessary (CR_W; c.f. Aguirre-Urreta et al., 2013).

Given that the CR_W index is not as well-known as CR_U, some further elaboration is warranted here. The most general version of CR_W was developed over 70 years ago by Mosier (1943, Equation 5, p. 162; for other variants, see Rozeboom, 1989; Webb, Shavelson, & Haertel, 2006), and can be expressed as follows for the unstandardized case:

$$\mathrm{CR}_W = 1 - \frac{\sum w_i^2\sigma_i^2 - \sum w_i^2\sigma_i^2\lambda_i^2}{\sum_i^n w_i^2\sigma_i^2 + 2\sum_{i=1}^{n-1}\sum_{j=2}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij}} \text{ (with } i{\neq}j\text{)}, \qquad [1]$$

where for a given weighted composite, $w_i, \sigma_i^2, \sigma_i$ and λ_i^2 are, respectively, the weight, variance, standard deviation and reliability of the *i*th indicator (a squared standardized factor loading is the indicator reliability); w_j and σ_j are the weight and standard deviation of the *j*th indicator; and ρ_{ij} is the correlation between the *i*th and *j*th indicators ($i \neq j$). Therefore, the CR_W index is essentially a modified version of the CR_U that takes differential indicator weights into account, whatever their origin. Like the CR_U index, CR_W is an estimate of the ratio of true score variance in the composite to the total variance of the composite. It is evident from Equation [1] that CR_W is the more appropriate measure of composite reliability for PLS-based analyses, which rest on a differential indicator weighting scheme (cf., Aguirre-Urreta et al., 2013). Another difference between these two indices is that CR_U uses the estimated variance of a composite in the denominator, conditional on indicator error terms being exactly uncorrelated in the sample, whereas CR_W uses the variance of the actual composite. Therefore, for standardized composites, which are always the case in the PLS context, CR_W reduces to the square of the sum of products of the loadings and weights for the composite, that is:

$$\mathrm{CR}_w = (\sum w_i \lambda_i)^2. \quad [2]$$

When the indicator weights and loadings originate from a PLSc analysis, CR_W is equivalent to the ρ_A index presented by Dijkstra and Henseler (2015b).

The second concern expressed by Aguirre-Urreta et al. (2013), which was also noted by Dijkstra and Henseler (2015b), is that in traditional PLS analysis the loadings are estimated with correlations between the individual items and the composite of which they are a part, leading to biased estimation. To solve this second issue, the PLSc correction does not use the correlations between indicators and composites as loading estimates, rather, the loadings are consistenly estimated by scaling the weights as follows (Dijkstra, 2010):

$$\hat{\boldsymbol{\lambda}}_i = c_i \cdot \mathbf{w}_i, \quad [3]$$

where $\mathbf{w}_i$ is the weight vector for the *i*th block of indicators, $\hat{\boldsymbol{\lambda}}_i$ is a parallel vector of estimated factor loadings, and c_i is the scaling factor.[4] Unfortunately, consistency does not guarantee unbiasedness in finite samples, and the study by Huang (2013) demonstrates that the PLSc loading estimates are biased, mostly negatively. The same effect can be seen in our second example, where the mean PLSc corrected factor loading over 10 000 replications was 0.653, a -7% bias compared to the population value of 0.7[5].

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[4] Our notation differs from that used by Dijkstra and Henseler (2015b), who deviate from other papers on PLSc (e.g., Dijkstra & Henseler, 2015a; Dijkstra & Schermelleh-Engel, 2014) in that they do not refer directly to the scaling factor *c* in the adjustment formulas. We follow the approach from earlier papers on PLSc of using *c*, given that it simplifies the presentation of the formulas and also directly sets the stage for our improved estimator. However, we follow Dijkstra and Henseler (2015b) in using ρ_A to denote the PLSc reliability coefficient rather than the less intuitive *q* index used in other PLSc studies.

[5] Huang (2013) does not provide an explanation for the bias. Two mechanisms may lead to bias in the factor loading estimates obtained using Equation 3. First, the indicators with loadings having positive estimation error are over-weighted at the expense of other indicators, a phenomenon which is illustrated by our first example model from the previous section. It would intuitively appear that if two pairs of indicators (e.g. a_1, b_1 and a_2, b_2) are affected by error with the same magnitude but different directions, and the third pair (a_3, b_3) is unaffected by the error, the weights assigned to the third pair would remain at the original values, but this is not the case: The variance of a weighted sum depends on the squares of all weights, and therefore increasing one weight while decreasing another by the same amount leads to increasing the variance of the composite. To compensate for this increase, the standardization step must downscale all weights, leading to an overall decrease in the mean standardized weight. Second, the same mechanism affects the factor loading correction factors (c's), which also depend on squares of weights and therefore further downscale the loading estimates. More methodological research addressing the small sample properties of the weights and the correction factor is clearly needed.

The final concern expressed by Aguirre-Urreta et al. (2013) is the non-independence of weights and loading estimates. In a traditional PLS estimation, loadings are obtained as correlations between the indicators and composites. Because loading estimates depend on the weights, choosing different weights (e.g. Mode A vs. Mode B) leads to different loading estimates. Because loadings are fixed population parameters that are estimated, the estimates should not depend on the way a researcher chooses to form the composites. To break the explicit dependency between loadings and weights, Aguirre-Urreta et al. (2013) recommended that loadings be obtained through alternative procedures, such as maximum likelihood estimates from a confirmatory factor analysis of each set of items separately, following Raykov (1997). This final concern, in the form presented by Aguirre-Urreta et al. (2013), is not directly applicable to PLSc because weights are always calculated by Mode A and are thus proportional to estimated loadings, and because just one weight algorithm is allowed there is no choice of weights involved.

Unfortunately, the non-independence of weights and loadings leads to an additional but slightly different problem in small samples for the case of PLSc. Assume an ideal scenario where the estimated loadings are unbiased, normally distributed, and independent from one another. In this case, the estimation error associated with a single loading estimate can be either positive or negative. A negative estimation error leads to a weight that is smaller than the “correct” weight, whereas a positive error leads to a weight that is larger. Therefore, indicators with overestimated loadings are over-weighted and those with underestimated loadings are under-weighted, leading to an overall positive bias in the composite reliability estimates (i.e., ρ_A) by inflating the effects of positive estimation error and reducing the effects of negative estimation error so that they no longer cancel out as would be expected if the weights were independent of the reliability estimates. The effect is clearly seen in our example in Table 1 where the reliabilities are over estimated by 0.039, or by +5%.

Thus, although the composite reliabilities are estimated with an appropriate formula in PLS, the issues of biased loading estimates and non-independence of weights and loadings remain. Because the effect of the two biases – negative bias of loadings and positive bias due to proportionality of loadings and weights – are in opposing directions, their net effect on the estimated reliabilities (ρ_A) is not obvious. However, it is safe to say that these two biases would only cancel each other out exactly by chance, and that is not something on which researchers should be willing to rely. In the next section, therefore, we propose further corrections to the new PLSc estimator that address these issues and later pit our corrected estimator against PLSc to compare their performance in a study that replicates the simulation done by Dijkstra and Henseler (2015b).

4. Proposed corrections to PLSc

In order to resolve the issues presented above, we now propose some simple improvements to PLSc, beginning with the factor loading estimation. The first correction is to estimate the factor loadings using traditional factor analysis techniques instead of by rescaling the indicator weights[6]. This leads to general confirmatory factor analysis-based techniques for disattenuation (e.g., Croon, 2002; Lu et al., 2011). The proposed technique has three advantages over the per-block correction proposed by Dijkstra, namely, it: (1) breaks the explicit dependency between weights and loadings; (2) does not depend on the initial indicator weights,

[6] This improvement can be motivated in at least two different ways. First, the scaling factor c_i should be estimated to minimize the Euclidean distance between the sample and model-implied correlation matrices for the ith block of indicators. However, we can get closer to the minimum by replacing the single scalar c_i, which is applied to an entire block of indicators, with a vector $\mathbf{c}$, such that each loading is corrected separately. Estimating the corrections for each indicator block separately essentially leads to minimum residuals or *minres* (cf., Nunnally, 1978, Chapter 11) estimates of loadings for multiple single-factor models. Second, the PLSc factor loading estimator can be considered as a special case of minres estimator, constrained to produce loadings proportional to PLS weights. All corrections can also be estimated simultaneously and, with appropriate weighting of the distance function, lead to maximum likelihood confirmatory factor analysis. See Appendix B for how these corrections can be derived.

and is therefore more general and can also be applied to other composite-based SEM estimators (e.g. PLS Mode B), which may not have the same asymptotic properties for weights as PLS Mode A; and (3) is a full-information estimator in the scenario where all loadings are estimated simultaneously, and would therefore be expected to estimate the factor loadings more efficiently, that is, the estimates should be more precise.

Although estimating the loadings with factor analysis breaks the explicit dependency between loadings and weights, this change is insufficient to make weights and loadings independent. To completely sever this connection, we introduce a second correction, which entails constructing the composites with unit weights (i.e., sums of standardized indicators, e.g., Bobko, Roth, & Buster, 2007; Cohen, 1990; Cohen, Cohen, West, & Aiken, 2003, pp. 97–98) scaled to produce standardized composites, instead of using PLS weights to construct the composites. Even though there may be some situations where this choice leads to a marginal decrease in the reliability of the composites (Henseler et al., 2014), unit-weighted composites have been shown to be robust in a broad range of scenarios (e.g., Bobko et al., 2007; Cohen, 1990; Cohen et al., 2003, pp. 97–98; Raju, Bilgic, Edwards, & Fleer, 1999). Moreover, regardless of how the indicators are weighted, the correction for attenuation should eliminate any effect that indicator weights have on the estimated composite correlation matrix, and therefore there is little if any loss in estimation accuracy[7]. Another advantage of this second correction is that it eliminates the biasing effects of chance correlations from the results, as unit-weighted composites do not exhibit the same sensitivity for these correlations as PLS weights do (Rönkkö, 2014).

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[7] We note that starting with less reliable composites may have an effect on the estimates because less reliable composites require a higher disattenuation coefficient, and this same coefficient is also used to multiply sample imperfections such as chance fluctuations in indicator correlations. We will address the overall effect of the correction on estimation accuracy later in the paper.

Our more refined correction obviates the need for calculating the PLS weights as the initial step during estimation, but follows the remaining steps used in PLSc, that is, disattenuation of the composite correlation matrix using estimated composite reliabilities, followed by applying regression analysis to estimate the structural coefficients. This technique is equivalent to errors-in-variables (EIV) regression (Fuller & Hidiroglou, 1978; Warren, White, & Fuller, 1974), and also better known by this name[8]. Reliability can be estimated using either of the CR indices presented above, or any other model-based formulas appropriate for unit-weighted composites (Cho & Kim, 2015; Green & Yang, 2009). In the remainder of this research we will focus on two estimators of this class, namely EIV regression using unit-weighted composites with reliability estimates from maximum likelihood factor analysis ($EIV_{ML\text{-}CFA}$) and per-block minres factor analysis (EIV_{minres}), which is closer to PLSc, but requires at least three indicators per block[9].

5. Replication of Dijkstra and Henseler

In the simulations that follow, we compare $EIV_{ML\text{-}CFA}$ and EIV_{minres} with PLSc as well as simultaneous maximum likelihood estimation of the full structural equation model (ML-SEM). As explained in the previous section, our corrections to PLSc focus on unbiased reliability estimation and eliminating the small sample bias due to PLS weights from the initial composite correlations. Therefore, in addition to focusing on the bias, efficiency, and power of the estimators themselves, we also analyzed the performance of the three different reliability estimates discussed so far (Cronbach's alpha, CR_U, and CR_W) for both PLS and unit-weighted composites as well as designed the simulation to isolate the effects of capitalization on chance by

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[8] These techniques are sometimes referred to as the "bias correcting" (Croon, 2002) or "two-step" (Oberski & Satorra, 2013) method in the SEM literature.

[9] We also studied a number of other confirmatory factor analysis estimators including GLS, WLS, DWLS, and ULS. Because these estimators are rarely used in IS research and did not show any advantage over the ML estimator in our simulations, these results are omitted from the article, but are available upon request from the first author.

the PLS weights. The true population model for the simulation is taken directly from Figure 4 in Dijkstra and Henseler's (2015b) study, and is comprised of the following set of structural equations:

$$\begin{aligned}\eta_3 &= \gamma_{23}\xi_2 + \zeta_3 \\ \eta_4 &= \gamma_{14}\xi_1 + \gamma_{24}\xi_2 + \zeta_4 \\ \eta_5 &= \gamma_{15}\xi_1 + \gamma_{25}\xi_2 + \beta_{35}\eta_3 + \zeta_5,\end{aligned} \qquad [3]$$

where $\phi_{12} = 0.70$, γ_{23}= 0.0, γ_{14}= 0.0, γ_{24}= 0.70, γ_{15}= 0.22, γ_{25}= -0.70, and β_{35}= 0.35. All measurement equations were of the form $y = \lambda\eta + \delta$ and $x = \lambda\xi + \varepsilon$, with λ's ranging widely in value from 0.40 to 0.94. The number of indicators also varied considerably. Both ξ_1 and η_4 were only measured by two indicators each; ξ_1 and η_4 by six indicators each; and η_4 by four indicators.

To be able to analyze the performance (i.e., bias and efficiency) of reliability estimates, we constructed our datasets sequentially by first generating all latent variables and then calculating the indicators as weighted sums of their respective latent variables and random error terms. This approach is similar to past research on PLS (e.g., Goodhue et al., 2007, 2012), and was used here because it allows for straightforward calculation of true composite reliabilities, that is, the squared correlations between the latent variables and their respective composite proxies, which can then be compared to the estimated reliabilities in order to assess the performance of different reliability indices. In the rare cases where a composite correlated negatively with the latent variable, we coded the reliability as negative.

For the conventional multivariate-normal scenario, it was assumed that all exogenous latent variables (i.e., factors and errors) were joint-normally distributed, and that measurement and structural errors were mutually independent; factors were also assumed to be independent of all error vectors. In line with Dijkstra and Henseler (2015b), sample sizes were set at *N* = 100, *N* = 200, and *N* = 500. The non-normal data condition was constructed using the method described by Vale and Maurelli (1983), as implemented in the R package *simsem* (version 0.5-9, Pornprasertmanit, Miller, & Schoemann, 2014). Because the data were generated sequentially rather than drawing samples from a covariance matrix as in Dijkstra and Henseler's (2015b) study, we could not directly specify the degree of excess kurtosis in the observed variables; rather, only the distributions of the exogenous latent variables could be manipulated directly, followed by generating the indicators as weighted sums of the non-normal latent variables. However, a sum of leptokurtic variables generally has smaller excess kurtosis than the raw variables. Therefore, to ensure that our observed data were sufficiently non-normal to be comparable with the datasets used by Dijkstra and Henseler, we set all exogenous latent variables to have excess kurtosis of 5.

In addition to replicating past research, we also introduced two additional experimental conditions. The first involved the use of three different scaling factors (0, 0.5, 1) for the true parameter values, in order to examine the behavior of the estimators with respect to each model structure when the population effect sizes for the relationships between the latent variables are weaker or non-existent. This is a relevant experimental manipulation because the PLSc estimator requires the latent variables to be correlated in the population in order to calibrate the indicator weights (Dijkstra & Henseler, 2015b), but this requirement may not always be fulfilled in real datasets. Moreover, this strategy allowed us to examine the null distribution of the estimates, which will help shed further light on the appropriateness of assuming a reference distribution based on normality – the current practice in PLS – to obtain *p*-values for parameter estimates (Rönkkö & Evermann, 2013).

However, one complication with applying the scaling factor of 0 to Dijkstra and Henseler's (2015b) population model is that there are two factors (ξ_1 and η_4) with only two indicators each. As is well known, a common factor model with only two indicators is identified only if the factor is embedded in a larger system of non-zero relationships (Bollen, 1989, pp. 238–246). Therefore, setting all factors to be uncorrelated leads to empirically underidentified measurement models for both ξ_1 and η_4 (Rindskopf, 1984; see e.g., Kline, 2011, p. 147). Resolving this identification problem by imposing equality constraints on loadings was not a viable option, as such a modification would deviate too much from the original model. Therefore, to solve this issue, we followed the example by Huang (2013) and implemented the simulations also using an alternative, larger model where the indicators x_{11}, x_{12}, y_{41}, and y_{42} were each included twice in the population model such that all latent variables had at least four indicators, rendering each factor individually overidentified.

As the second additional experimental condition, we implemented a manipulation aimed at quantifying the effects of capitalization on chance across the different estimators. Rönkkö (2014) argues that the effect is mostly caused by chance correlations between the measurement errors in the indicator variables. Following his approach, we created two versions of each dataset, which we refer to here as *original* and *manipulated* data. The original data were generated using the sequential data generation approach described above, which entailed first generating the latent variable values and then generating the indicators based on these values. For each generated dataset, the corresponding *manipulated* data were constructed by orthogonalizing the error terms in the original data (but maintaining their variances), and then calculating a new set of indicators using the original latent variable values and error terms that were artificially restricted to be uncorrelated in the sample, thereby removing any chance correlations between measurement errors. Similarly to the recent study by Rönkkö (2014) and the second example presented above, when estimating the model with *manipulated* data we always used the *original* data for calculating the indicator weights and then used the *manipulated* data for the estimation of the structural paths. This design allowed us to quantify the extent to which chance correlations inflated the estimates of the relationships between the latent variables, which are the effects of primary substantive interest. This comparison was done only for PLSc and the EIV estimators, which are the main focus of the paper, but not for ML-SEM because the estimator does not use indicator weights that could be retained from one sample to another.

For the PLSc and EIV estimators, all simulations were conducted within the R statistical programming environment (version 3.1.0, R Core Team, 2015) using the *matrixpls* package (version 0.6.0, Rönkkö, 2015). In line with the approach of Dijkstra and Henseler (2015b), the factor weighting scheme was used for inner estimation and Mode A for outer estimation. ML-SEM estimations were performed with the *lavaan* package (version 0.5-17, Rosseel, 2014). The number of Monte Carlo replications was set at 1000 for all simulation conditions.

5.1. Experiment results

We compared the composite-based PLSc, $EIV_{ML\text{-}CFA}$, and EIV_{minres} estimators, and ML-SEM, in terms of their ability to estimate factor loadings, composite reliabilities, and path coefficients, as well as accuracy of confidence intervals and their statistical power. These results are further disaggregated by the experimental manipulations: (1) Dijkstra and Henseler's (2015b) original model (Small Model) vs. a model with duplicated indicators for each of ξ_1 and η_4 (Large Model); (2) scaling factors (0, 0.5, 1) for effect sizes; (3) original vs. orthogonalized measurement errors; and (4) sample size. Given that the results for the normal and non-normal data conditions were virtually identical, only the results for normal data are presented here (see Appendix A for comprehensive results tables, including those for the non-normal condition).

5.1.1. Inadmissible values

In contrast to Dijkstra and Henseler (2015b), who studied only conditions where all estimators are expected to perform well, we also included conditions where the estimators can be expected to encounter difficulties. Particularly, the two-indicator measurement model is empirically underidentified in the scenario where the latent variables are uncorrelated in the population. In these scenarios, the data do not provide sufficient information to estimate the loadings, resulting in arbitrary estimates with a large number of inadmissible values for all estimators, as shown in Table 2 below. For the Small Model (where EIV_{minres} cannot be used because a factor analysis requires at least three observed variables), the number of replications with inadmissible loadings exceeded 90% for all estimation techniques at all three sample sizes when the population path coefficients were set to zero. The number of replications showing inadmissible loadings declined with increased effect and sample size for all four of the above estimators, but this effect was weaker for PLSc than for the other estimators. In the original, unscaled model, PLSc always produced more than 2.5 times as many inadmissible loadings than any of the competing techniques. These findings are also consistent with prior research showing that having only two indicators per factor leads to increased rates of inadmissible solutions (Ding, Velicer, & Harlow, 1995; Gagne & Hancock, 2006; Jackson, Voth, & Frey, 2013; Marsh, Hau, Balla, & Grayson, 1998). Highly similar patterns of inadmissible results were found under the Small Model for the composite reliability indices, which are only relevant for PLSc and $EIV_{ML\text{-}CFA}$ because the latent variable-based ML-SEM estimation technique does not use composites.

--- Insert Table 2 about here ----

With respect to factor correlations under the Small Model, inadmissible solutions were much less frequent, which is the expected result; model underidentification does not necessarily mean that all model parameters are not identified and, in these models, the factor correlations remain identified. Inadmissible correlations were produced in two scenarios. First, when the factors were uncorrelated in the population, the uncorrected correlations between PLS composites were strongly biased away from zero due to the capitalization on chance effect discussed earlier. At the same time some of the reliability estimates were very small, producing larger correction factors. The combination of these two issues leads to inadmissible correlation estimates (i.e., greater than 1.0)[10]. The second scenario that produced inadmissible correlations involved the original, unscaled model. In this scenario, inadmissibility of correlations is a consequence of the fact that some of the population correlations were very large, which in situations where estimates are normally distributed and have large variances, inevitably leads to some estimates that exceed the range of admissible values. The latent variable-based ML-SEM technique resulted in a slightly smaller number of inadmissible estimates in the unscaled models because the technique is generally more efficient than the traditional correction for attenuation (Charles, 2005; Kline, 2011, pp. 70–71; Muchinsky, 1996; Schmidt & Hunter, 1996; Schumacker, 2010, sec. 3.2.5).

For the Large Model, which simply duplicates each of the original indicators for ξ_1 and η_4, the proportions of inadmissible results under PLSc closely paralleled those of the Small Model for all three types of statistics (i.e., loadings, factor correlations, and composite reliabilities). However, there was a large difference in the performance of $EIV_{ML\text{-}CFA}$ and ML-SEM in estimating loadings and reliabilities, which results from the fact that a latent variable

[10] The disattenuation correction is known to produce inadmissible correlations when the observed composite correlation is greater than the square root of the product of the two composite reliabilities (cf., Charles, 2005; Nimon, Zientek, & Henson, 2012)

with three or more indicators is identified without requiring any information from the larger model, and therefore empirical underidentification is no longer an issue. The PLSc results are largely unaffected by increasing the number of indicators because only the between-block correlations are used to estimate the proportionalities of the indicator weights, and therefore the new information that the added indicators bring to model estimation is underutilized. The pattern of results is very similar to the results by Huang (2013). That EIV_{minres} never produced any inadmissible loadings is explained by the fact that the minres implementation we used (the fa function in the psych package of R; Revelle, 2015) is constrained to always yield admissible loadings.

We will next focus on the performance of the parameter estimates. In doing so, we chose to include the inadmissible estimates in the computation of our descriptive statistics. The reason for this is two-fold. First, Dijkstra and Henseler (2015b) did not report dropping inadmissible estimates and we prefer our study to be as comparable to theirs as possible. Second, because the model contained a few very large loadings or correlations, dropping inadmissible estimates would have effectively truncated their sampling distributions, causing artificial bias in estimates that would be otherwise unbiased.

5.1.2. Factor loadings

Because the models examined here contained large numbers of factor loadings, results needed to be reported selectively. Therefore, in order to make the analysis of patterns in the results more manageable, we focus on examining six loading estimates. Of the two underidentified factors, ξ_1 and η_4, we chose to focus on the latter because the indicator loadings have larger variances, and thus the results may be more generalizable than in the case of ξ_1, which had two exceptionally reliable indicators. Of the remaining three identified factors, we chose to focus on η_3 and η_5, which are, respectively, the least and most correlated with the other factors. Therefore we expect to see large differences here between PLSc estimates – whose proportionality depends solely on the between-block correlations – and other factor loadings estimates, which are either completely unaffected (minres) or relatively less affected (ML-CFA) by the between-block correlations. With these two factors, we chose to focus on the largest and smallest (i.e., first and last) factor loadings. Table 3 shows the results for the selected loadings. (The full table of estimated loadings is presented in Appendix A). Because both estimation strategies that relied on ML estimation of the full factor model ($EIV_{ML\text{-}CFA}$ and ML-SEM) produced nearly identical estimates, we only report results for $EIV_{ML\text{-}CFA}$.

--- Insert Table 3 about here ---

As shown in Table 3, the $EIV_{ML\text{-}CFA}$ estimates were unbiased and more efficient than the PLSc estimates, across all conditions and both Models 1 and 2 for those factors that were identified (i.e., had 3 or more indicators); under the Large Model, the EIV_{minres} estimates and SDs were virtually identical to those of $EIV_{ML\text{-}CFA}$. $EIV_{ML\text{-}CFA}$ faced serious difficulties with the empirically underidentified loadings in the Small Model. However, the same problem arose in PLSc where all loading estimates were biased and varied widely from sample to sample.

When discussing the three problems in estimation of composite reliabilities in PLSc (i.e., assumption of equal weights, biased estimates of loadings, and dependencies between weights and loadings; see Aguirre-Urreta et al., 2013). Except for the non-identified factors, all PLSc loading estimates are negatively biased and the magnitude of the bias depends on the strength of the correlations between the factors. The pattern of results is again very similar to the results by

Huang (2013), where the PLSc loadings were negatively biased except for doublet factors where the bias was positive[11].

5.1.3. Reliabilities

We analyzed the performance of several different reliability statistics for all composite-based techniques: (1) the classical Cronbach's alpha; (2) the composite reliability index (CR_U) for the unweighted case, commonly used in PLS studies; and (3) the CR_W index, designed specifically for the case of weighted composites. With the CR_U index, we estimated the variance of the composite assuming uncorrelated errors in the sample, in keeping with how the index has been used in the PLS literature; whereas with the CR_W index, we use the real composite variance so that the index is equivalent to the ρ_A used by Dijkstra and Henseler (2015b). Both CR_U and CR_W indices were calculated using the corrected loading estimates instead of using the indicator composite correlations, which Dijkstra and Henseler used for the CR_U (labeled as Jöreskog's ρ or ρ_c in their article).

Table 4 shows the estimation errors of the reliabilities calculated as differences between reliability estimates and the true reliabilities (i.e., squared correlations between the composites and the latent variable scores used to generate the data). Because the results for reliability estimates calculated with minres loading estimates were identical to the third decimal place with the reliability indices calculated with ML-CFA, only the latter are reported. We focus on the Small Model, because it is expected to show the largest discrepancies among the different reliability estimates. This approach also allowed us to compare the reliability results for the doublet factors (ξ_1 and η_4) to those with 4+ indicators. For the two doublet factors (where minres

[11] The positive bias in the two-indicator case may be an outcome of the PLSc correction, stemming from the fact that the scaling factor c_i reduces to the square root of the indicator correlation divided by the product of the two weights. Because the weights are scaled so that the resulting composite is standardized, this can lead to an effect where larger weights are scaled up less than smaller weights, leading to an overall positive bias in the loadings. As noted in footnote 5, more research on the small sample characteristics of the weights and the PLSc corrections is required before any definite statements about the source of the bias in the loadings can be made.

estimation was not possible), both PLSc and $EIV_{ML\text{-}CFA}$ yielded large numbers of inadmissible values for CR_U and CR_W. For both estimators, the values for CR_U and CR_W in the doublet case improved appreciably as the scaling factor and sample size increased, and ultimately achieved less bias under $EIV_{ML\text{-}CFA}$ than PLSc.

For the remaining composites, which corresponded to identified factors with 4 or more indicators, the $EIV_{ML\text{-}CFA}$-based CR_U and CR_W outperformed those obtained under PLSc by a wide margin, being unbiased and more efficient in all scenarios. As would be expected, Cronbach's alpha tended to underestimate reliability, given that it is a lower bound on reliability when the assumption of tau-equivalency (i.e., equal loadings) is violated (Green & Hershberger, 2000), as in the present case. However, this underestimation was not severe, with the bias still being substantially less than in the case of CR_U and CR_W under PLSc. Interestingly, in scenarios where the latent variables were uncorrelated, alpha overestimated reliability. This result is due to the fact that alpha is an estimate of reliability for equally weighted composites, which are more reliable than PLS composites in some scenarios (Rönkkö & Evermann, 2013). The CR_U and CR_W produce differing results for the empirically-weighted PLS composites and show an interesting pattern. Consistent with our expectations, the unweighted CR_U index is negatively biased because the effects of indicator weights are ignored. A more interesting finding – but one that is expected because weights depend on the reliability estimates – is that the CR_W indices are always positively biased.

--- Insert Table 4 about here ---

The results show that estimating the reliability of empirically-weighted composites used by PLSc is substantially more difficult than estimating the reliabilities of unit-weighted composites used by the EIV estimators. This can be intuitively explained by considering that with PLSc, there are two sources of sampling variability, namely the variance of the weights and the variance of the loadings estimates, whereas with unit-weighted composites, only the variance of the loading estimates affects the results.

5.1.4. Path coefficients

Table 5 and Table 6 show the estimates for both the Small Model and Large Model with normally distributed data, under all modeling conditions. We start by comparing the estimates obtained with the original data to estimates obtained with manipulated data, where the correlations between the indicator error terms were artificially restricted to be zero in the sample, because the comparison reveals important differences between the estimators. As explained earlier, this manipulation was not performed for ML-SEM because the estimator does not use weighted composites. The tables demonstrate that, generally and across all conditions, the differences in the estimated path coefficients (and their SDs) across the original and manipulated data were greatest for PLSc, as compared to $EIV_{ML\text{-}CFA}$ and EIV_{minres}. When the population value was different from zero, estimates with original data were generally further from zero than with the manipulated data. The effect can be seen most clearly for β_{35} and γ_{24}, which are correlations in the population[12], and γ_{25}, which is the strongest predictor of η_4. This effect is caused by PLS weights capitalizing on chance, as discussed earlier in Section 2, which is a source of bias that remains unaddressed by the PLSc correction. The differences between estimates using the manipulated and normal data with the EIV estimators are small and non-systematic, demonstrating that using unit weights instead of PLS weights in the estimator corrects for this bias. The only effect of using unit weights is a decrease in the variance of the estimates

[12] A standardized regression coefficient equals the zero-order correlation between the predictor and the crierion, if a predictor is uncorrelated with all other predictors in the model (β_{35}). The same applies if a given predictor is the only predictor with a non-zero regression coefficient (γ_{24}).

(particularly in small samples), which is consistent with earlier results using the same manipulation (Rönkkö, 2014).

Overall, the ML-SEM estimator is the most efficient across both models and both normal and non-normal data (See Appendix A for the results tables for non-normal data). For γ_{23} and γ_{14}, which were both zero in the population, none of the estimators produced mean estimates that deviated markedly from the true value; however, PLSc was less efficient than $EIV_{ML\text{-}CFA}$ or ML-SEM. A closer inspection of the distribution diagrams revealed that this difference was largely attributed to the bimodal shape of the PLSc estimates for these paths with two peaks on both sides of zero, and only a few estimates were very close to zero (Rönkkö & Evermann, 2013). The same effect is clearly visible in the results that were obtained after scaling the latent variable paths to half or zero.

--- Insert Table 5 and Table 6 about here ---

Generally, the PLSc estimates where chance correlations between the error terms were removed were biased toward zero in nearly all scenarios. The result is expected because positively biased reliability estimates lead to undercorrecting for attenuation. However, when chance correlations were not eliminated from the data, the results were most often slightly biased away from zero. Therefore, in this case, the positive bias due to chance correlations happened to yield close to optimal recovery of the true value by compensating for the biases in reliability estimates, but of course one would not be able to rely routinely on this type of effect (Rönkkö, 2014).

5.1.5. Statistical inference

Because the sampling distribution of the PLS weights is unknown (Dijkstra, 1983), null hypothesis significance testing using a known, theoretical distribution is not possible with PLSc (see McIntosh, Edwards, & Antonakis, 2014; Rönkkö & Evermann, 2013; Rönkkö, McIntosh, & Antonakis, 2015). Therefore, following Dijkstra and Henseler (2015b), we assess the performance of bootstrapped confidence intervals as a tool for statistical inference. Table 7 and Table 8 show the bootstrapped 95% percentile confidence intervals for PLSc, EIV_{minres}, and $EIV_{ML\text{-}CFA}$. Each cell in Tables 7 and 8 represents 1000 replications with 1000 bootstrap samples each, for a total of more than a million estimations each. Because of the extent of the required computational effort, we did not bootstrap the ML-SEM estimates. Given that the ML estimator has known closed-form solutions for standard errors, ML estimates are rarely bootstrapped in research practice.

Instead of focusing solely on whether zero was included in the confidence intervals, we also addressed the validity of the confidence intervals themselves by including statistics on coverage and balance of the intervals (DiCiccio & Efron, 1996): A well-constructed confidence interval should contain the population value at the stated degree of confidence and fall above and below the confidence limits in a balanced way. For the 95% intervals used here, the coverage should be close to 95% and the population value should be below or above the confidence limits for 2.5% of the time. There are no notable differences between the normal and non-normal condition or the Small Model and Large Model. The mean coverage statistics over all scenarios are .021/.962/.014[13] for PLSc, .029/.946/.026 for $EIV_{ML\text{-}CFA}$ and .030/.944/.026 for EIV_{minres}. The coverage values of the EIV estimator confidence intervals are closer to their nominal values and also better-balanced. These very small differences are explained by the fact that capitalization on chance by the PLS weights often created a small secondary mode in the bootstrap replications (See Figure 2), leading to skewed bootstrap distributions, which are known to cause problems for

[13] % replications with population value under lower limit of CI/% replications with population value within CI/% replications with population value over upper limit of CI. The balance values of the negative path γ_{25} are reversed. Because of rounding, the proportions do not sum to 1 exactly.

the simple percentile method (Davison & Hinkley, 1997, Chapter 5). This is an issue that can potentially be resolved by using more advanced methods for calculating the confidence intervals such as the BCa intervals which Henseler, Dijkstra, and colleagues (2014) have experimented with.

--- Insert Table 7 and Table 8 about here ---

We also assessed the false positive rates and statistical power of the confidence intervals of the three techniques by inspecting how frequently zero was not included within the confidence interval when an effect was zero or non-zero in the population, respectively. The mean false positive rates for the three techniques over both distribution conditions and models were .021 for PLSc, .055 for $EIV_{ML\text{-}CFA}$, and .056 for EIV_{minres}. The EIV estimators were only slightly over the nominal 5% level, whereas the confidence intervals for PLSc were clearly too wide compared to their nominal coverage when no effects existed in the population. The difference in statistical power over all conditions was .720 for PLSc, .770 for $EIV_{ML\text{-}CFA}$, and .778 for EIV_{minres}. Because all techniques can reliably detect the largest paths, the difference is attributed to PLSc having smaller power to detect weaker effects. These patterns in statistical power are similar to the results presented by Dijkstra and Henseler (2015b).

6. Conclusions

Ever since its introduction into mainstream IS research more than twenty years ago, PLS has become one of the most commonly employed techniques for the estimation of structural equation models in the discipline. However, the technique is not without its weaknesses. Some of these, such as the biased and inconsistent estimation of factor loadings and structural parameters unless the limiting condition of ‘consistency-at-large’ (an infinitely large number of indicators measuring each construct and an infinitely large sample size) applies, have been well-known since the technique was originally developed (Wold, 1982b). Other problems, such as bias due to between-block chance correlations that are present in finite samples, have only been recently recognized (Goodhue et al., 2015; Rönkkö, 2014).

Given the increased recognition of the presence of a number of unresolved issues in the PLS approach (McIntosh et al., 2014; Rönkkö et al., 2015), researchers are left with essentially three alternatives. First, they could continue employing the technique while acknowledging that the results obtained would be biased and inaccurate, which leads to questioning their validity altogether. Second, researchers could opt to stop using the approach for the estimation of structural equation models, which would limit those to the conditions that can be examined with conventional latent variable approaches, and such a position has also been advocated in the literature (e.g., Antonakis, Bendahan, Jacquart, & Lalive, 2010). Finally, PLS could be further developed and enhanced in order to do away with, or at the very least mitigate, these issues (Dijkstra & Henseler, 2015b). A pivotal step in this direction was taken by Dijkstra and colleagues (Dijkstra & Henseler, 2015a, 2015b; Dijkstra & Schermelleh-Engel, 2014) in the form of consistent PLS.

Though certainly an important development in this literature, and one that addresses the best-known issues with PLS outlined above, the procedure proposed by Dijkstra and colleagues suffers from two important limitations. First, PLSc fails to consider bias due to capitalization on between-block chance correlations in finite samples, which result in composites that over-weight those items that, in a given sample, happened to be more strongly correlated with items in a different block, even if those correlations are solely the result of natural sampling variability (Rönkkö, 2014). Because the weights resulting from a PLS analysis are the starting point in the PLSc algorithm, any resulting biases carry over to PLSc as well. Second, the reliability estimates employed in the PLSc procedure to correct for the effects of measurement error are biased due to biases in loading estimates and a dependency between the indicator weights and loading estimates. As a result, any adjustments made based on biased reliability statistics will also affect the resulting estimates (e.g., path coefficients).

Fortunately, both of these issues can be resolved. While developing new innovations or reusing existing, well-known results to refine our estimation techniques, we should also avoid dogmatically following past research practices. In the present research, we have shown that PLSc can be further improved by eliminating the PLS indicator weighting system from the estimator by using unit weights to form the composites (e.g., Bobko et al., 2007; Cohen, 1990; Cohen et al., 2003, pp. 97–98), and by estimating the indicator loadings directly with well-known factor analytical techniques without constraining the loadings to be proportional to the indicator weights. In doing this, we also derived an estimator that is more general than PLSc. As explained by Dijkstra and Henseler (2015b), the PLS indicator weighting system requires a strong nomological network for accurate weight calibration. What this means is that to apply PLSc or any other estimator that uses PLS weights, a researcher must have a strong theory that the constructs represented by the latent variables in the model are highly correlated. However, the need for highly correlated latent variables seems to be at odds with current PLS practice. In particular, PLS is most commonly used to test whether relationships between latent variables are non-zero (Rönkkö & Evermann, 2013), and is often recommended for exploratory research (Gefen, Rigdon, & Straub, 2011; Ringle et al., 2012), which is defined by Hair et al as the *"search for latent patterns in the data in case there is no or only little prior knowledge on how the variables are related"* (2014, p. 3). Moreover, the review by Goodhue et al (2015) revealed that models estimated with PLS and published in *MIS Quarterly* often contained composites that were calibrated based on just one path that was also tested and therefore cannot be assumed to be non-zero. Considering that EIV techniques presented in this article do not assume highly correlated latent variables (provided that at least three indicators are available for each factor), these estimation techniques are generally more useful for the purposes and scenarios where IS researchers typically use composite-based SEM estimation.

We compared the proposed two EIV estimators with PLSc and ML-SEM by means of a simulation study, which led to several interesting findings. First, we examined the presence of inadmissible solutions for all estimators and simulation conditions, in the form of loadings greater than one, reliability estimates greater than one, or corrected correlations greater than one. Extending the work of Dijkstra and Henseler (2015b), who focused only on well-behaved scenarios, we followed their suggestion (Dijkstra & Henseler, 2015b, p. 17) and also examined the various estimators under conditions where they were not expected to perform well, such as when all latent variable pathways are null in the population. Our results show that the EIV estimators performed as well as or better than PLSc for the different models, sample sizes, and scaling factors (for effect sizes) that were studied. Second, we examined bias in the estimation of factor loadings. As was the case before with regards to inadmissible estimates, both versions of our proposed estimator performed as well as or better than PLSc for all the conditions examined, and on par with ML-SEM included in the comparison. Considering that the factor loadings from the EIV estimators are estimated directly with well-known factor analysis tools, the result is not very surprising.

Third, given that the disattenuation of structural path coefficients, which are of prime theoretical interest for researchers, is dependent on the accuracy of the reliability estimates used in the process, we compared two composite reliability statistics, CR_W and CR_U (for the weighted and unweighted formulations, respectively; see Aguirre-Urreta et al., 2013) – calculated from the output of ML confirmatory factor analysis, per-block minres factor analysis, and PLSc – with the true reliability of each composite, which was known from the data generation process, and with Cronbach's alpha as an additional benchmark. Our results indicate that both versions of our estimator performed similarly and were superior to PLSc under all conditions. Though it is well-known that Cronbach's alpha would underestimate the true reliability under the conditions examined here (i.e., uncorrelated measurement errors in the population, non-tau-equivalent items), the underestimation observed here was not severe, and bias was nonetheless substantially lower than either the unweighted or weighted composite reliability estimates when those were calculated from PLSc outputs. These results are in agreement with a recent review demonstrating that in practice, the differences between Cronbach's alpha and CR are often small (Peterson & Kim, 2013), which means that alpha may also be a practical option in many research scenarios.

Fourth, our results demonstrated that the path coefficient estimates from the EIV approaches were nearly always less biased and substantially more efficient than PLSc, particularly for weak effects. With regard to statistical inference in particular, the bootstrapped confidence intervals from the EIV estimators also provided slightly more statistical power than PLSc, without deviating from the nominal false positive rates. Given that PLSc was able to reliably detect large paths, its slightly lower statistical power in relation to EIV is due to PLSc being the relatively underpowered approach in the case of weaker effects. Indeed, the suboptimal performance of the bootstrapped CIs under PLSc was especially notable in the case of null pathways among the latent variables, where the CIs were far too wide compared to their nominal coverage.

Given these results, we can now explain the contradictory findings by Goodhue et al (2012, pp. 996–997), who noted that some of their disattenuated PLS results were positively biased, and those from Dijkstra and Henseler (2015b), which did not show a similar effect. Goodhue and colleagues explain the bias by stating that *"when a small effect size is involved [...] the reliability correction sometimes seems to over correct for PLS.*" (2012, p. 996), whereas Dijkstra and Henseler (2015b) attribute the discrepancies in the results to the different disattenuation approaches used in the studies. It is easy to see that neither explanation is complete because the positive bias in the estimates is already present in Figure 8a (Goodhue et al., 2012, p. 997) that shows the uncorrected estimates. This bias is due to the effect of capitalizing on chance discussed in our research, and it is a feature of the PLS weights, not any disattenuation correction. Dijkstra and Henseler (2015b) explain the differences by suggesting that Goodhue et al. used an incorrect formula and claiming that the Cronbach's alpha is a poor estimate of the reliability of PLS composites. However, considering that all paths in the model used by Goodhue et al. were correlations in the population, direct disattenuation of the path estimates using the classical formula is consistent in this scenario. The results of our research suggest that alpha works much better than given credit for, and the partial replication of the study by Goodhue et al. (2012) presented in Appendix E shows that the bias of alpha is negligible. Rather, the differences in the estimates can be attributed to positive bias in the reliability estimates used in disattenuation in PLSc. The same conditions that lead to the positive bias due to chance correlations also lead to positively biased reliability estimates and therefore attenuation is undercorrected, with these two sources of bias nearly canceling each other out in some scenarios, such as the ones studied by Dijkstra and Henseler.

The EIV estimators have a few additional advantages over PLSc that have not been discussed thus far. First, although we only addressed statistical inference with empirical confidence intervals in this study, the EIV estimators can also be used with null hypothesis significance testing. Because the estimates were approximately normal under the null hypothesis of no effects, the parametric one sample *t*-test can be used to calculate *p*-values to be used for inferential purposes. Second, the EIV estimators do not require specialized software because these estimators are available in many commonly used statistical packages such as Stata. Moreover, although we used the *minres* and ML estimators for our factor models, any other well-known factor analysis technique can be used. Considering the availability of both more computationally effective principal axis factoring and more statistically appealing ML, the *minres* technique can be considered obsolete and is no longer included in many statistical packages (Bartholomew, Knott, & Moustaki, 2011, sec. 3.9). Because different factor analysis techniques generally yield highly similar estimates[14], using a different factor analysis technique should not affect the final path estimates. Third, the regression part of the EIV estimator has been thoroughly studied (Fuller, 1987) and the method has known closed-form solutions for estimating standard errors[15], thereby obviating the need for obtaining these with bootstrapping. This does not of course mean that bootstrapping cannot be used, but simply that EIV provides a broader array of inferential tools than are available with PLSc.

Our research provides clear evidence that the EIV estimators should be preferred over PLSc. Our results also show that the performance of EIV in terms of unbiasedness is comparable with ML-SEM, but the estimator is slightly less efficient. Nevertheless, the broader

[14] We note that principal component analysis should not be confused with factor analysis. If the goal is to obtain the parameters of a latent variable model (i.e., factor loadings and intercorrelations), then factor analysis should be used (cf. Widaman, 1993).
[15] The conventional procedures for calculating standard errors for errors-in-variables models may be biased in small samples because they do not take the uncertainty of the reliability estimates into consideration. Although adjustments for this issue have been proposed in the literature (Devlieger, Mayer, & Rosseel, 2015; Oberski & Satorra, 2013), as far as we know, these corrections have not been implemented in any of the commonly used software packages.

methodological literature provides conflicting advice on the usefulness of the technique. On one extreme, Moosbrugger, Schermelleh-Engel, and Klein (1997) declare that the "correction for attenuation […] in multiple regression analysis has become obsolete with the development of structural equation models" (p. 97). However, others still see value in EIV (Antonakis et al., 2010; Oberski & Satorra, 2013) and the composite-approximation followed by disattenuation is presented as a viable estimation option even in some recent SEM textbooks as well (Schumacker, 2010, Chapter 9). These differing opinions are not new, as the various techniques based on the correction for attenuation have been surrounded with controversies since its introduction in the early 20th century (Spearman, 1904; see Charles, 2005; LeBreton, Scherer, & James, 2014; Muchinsky, 1996).

However, despite the availability of full ML-SEM, which is the most unbiased and efficient estimator of latent variable models, there are a number of reasons why the EIV techniques should still have a place in the statistical toolbox of IS researchers. First, it is clear that IS researchers have a long history of estimating factor models by composite approximations, and this is unlikely to change overnight. Therefore, introducing new and better composite-based techniques to the discipline is valuable; two critical requirements for these techniques are the ability to correct for measurement error and to produce robust composites that do not capitalize on sample idiosyncrasies. Another pragmatic reason to apply EIV instead if ML-SEM is that techniques based on composites are intuitively easier to understand and sometimes easier to apply (Oberski & Satorra, 2013), as well as more computationally feasible. Therefore, EIV may provide a simple and accurate alternative in cases where ML may be too computationally intensive to be practical, for example, with large models containing high numbers of observed indicators and latent variables. As a composite-approximation, the EIV technique also provides straightforward diagnostics of observational residuals (e.g., Cohen et al., 2003, Chapter 4), a useful set of techniques that are more complex to implement with latent variable techniques (Bollen & Arminger, 1991); these techniques remain underutilized in the current PLS literature as well. The EIV estimators are also limited information techniques, which means that the effects of model misspecification are local and do not spread through the model, as might occur when using full information estimators (Antonakis et al., 2010). However, rather than immediately resorting to estimators that may be more robust to model misspecification, we strongly recommend that researchers first strive for correct model specification (cf., Kline, 2011, Chapter 8). Also, small sample size is not a good reason to resort to EIV over ML-SEM. The EIV techniques have been shown to perform poorly in small samples and when used with composites with poor reliabilities, and are therefore not recommended for these scenarios. For example, Zimmerman and Williams (1997) suggest a reliability cutoff of .7 and a minimum sample size of 100. On the other hand, ML-SEM has been shown to be fairly robust in small samples (e.g., Goodhue et al., 2012). Nonetheless, simulation studies on the EIV techniques demonstrate that the techniques work well, as long as both the sample sizes and composite reliabilities are reasonable (e.g., Devlieger, Mayer, & Rosseel, 2015). Thus, on balance, EIV methods should not be viewed as a routine replacement for full ML-SEM, but rather as pragmatic alternatives in certain modeling situations.

Furthermore, in order to use the EIV techniques effectively, researchers require a set of model quality statistics. Although EIV does not provide the overall model tests that ML-SEM does, there is still a large portfolio of statistics that can be used. For instance, the factor analyses used for calculating the indicator reliabilities can also be used to assess scale dimensionality, and the CR and AVE statistics used in the Fornell-Larcker (1981) testing system can be readily calculated from the factor loadings and compared against the disattenuated correlations between the composites. The new HTMT discriminant validity statistic (Henseler, Ringle, & Sarstedt, 2015) is similarly applicable because it is calculated from raw data correlations, and therefore does not depend on any particular way of estimation. Finally, the bootstrap-based model tests suggested by Dijkstra and Henseler (2015a) should work well for evaluating model specification, although this is something to be tested in future research.

To encourage the adoption of the EIV techniques presented in this research, we have made these techniques available in the free and open source *matrixpls* (Rönkkö, 2015) package for R, which also provides an implementation of the PLSc estimator and Monte Carlo features to facilitate future comparisons (for a tutorial for using *matrixpls*, see Aguirre-Urreta & Rönkkö, 2015). The package also calculates all the model quality statistics listed in the previous paragraph. Additionally, we have included several examples of how to specify an EIV analysis with several popular statistical software packages in Appendix C.

7. References

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8. Tables and Figures

Table 1 Estimation history of two LV model with two chance correlations

	γ	λ_1, λ_4	λ_2, λ_5	λ_3, λ_6	w_1, w_4	w_2, w_5	w_3, w_6	c_1, c_2	ρ_{A1}, ρ_{A2}	R_1, R_2
Start	.300	.700	.700	.700	.410	.410	.410	1.706	.742	.742
1	.305	.537	.851	.694	.316	.501	.409	1.698	.773	.736
2	.305	.554	.859	.672	.326	.505	.395	1.701	.774	.736
3	.304	.551	.861	.673	.324	.506	.395	1.701	.775	.736
4	.304	.551	.861	.672	.324	.506	.395	1.701	.775	.736
5	.304	.551	.861	.672	.324	.506	.395	1.701	.775	.736
6	.304	.551	.861	.672	.324	.506	.395	1.701	.775	.736

Note: The model is symmetric for the latent variables.

Table 2 Inadmissible replications over 1000 replications for normal data

			Inadmissible loadings				Inadmissible reliabilities			Inadmissible factor correlations			
Model	Scale	N	PLSc	$EIV_{ML\text{-}CFA}$	EIV_{minres}	ML-SEM	PLSc	$EIV_{ML\text{-}CFA}$	EIV_{minres}	PLSc	$EIV_{ML\text{-}CFA}$	EIV_{minres}	ML-SEM
Small Model	0	100	944	935	N/A	941	762	741	N/A	93	0	N/A	2
		200	936	938	N/A	937	769	749	N/A	44	0	N/A	0
		500	957	939	N/A	936	754	746	N/A	22	0	N/A	0
	.5	100	855	673	N/A	650	537	243	N/A	11	0	N/A	0
		200	780	446	N/A	429	448	73	N/A	3	0	N/A	0
		500	612	187	N/A	184	250	2	N/A	0	0	N/A	0
	1	100	438	166	N/A	152	72	2	N/A	27	19	N/A	15
		200	268	44	N/A	45	11	0	N/A	0	0	N/A	0
		500	54	1	N/A	1	0	0	N/A	0	0	N/A	0
Large Model	0	100	964	43	0	40	580	0	0	144	0	0	0
		200	968	4	0	4	570	0	0	52	0	0	0
		500	975	0	0	0	598	0	0	28	0	0	0
	.5	100	943	42	0	42	398	0	0	24	0	0	1
		200	904	3	0	3	364	0	0	3	0	0	0
		500	817	0	0	0	143	0	0	1	0	0	0
	1	100	554	21	0	20	21	0	0	10	9	9	5
		200	311	0	0	0	2	0	0	0	0	0	0
		500	79	0	0	0	0	0	0	0	0	0	0

Note: Loadings and reliabilities are invalid if any value in a replication exceeds one in absolute value. Factor correlations are inadmissible if any disattenuated composite correlation matrix exceeds one in absolute value. Small Model: Original model, Large Model: Model with duplicated indicators for ξ1 and η4. N/A = not estimated.

Table 3 Loadings over 1000 replications for normal data

Param.	Scale	N	Small Model				Large Model					
			PLSc		$EIV_{ML\text{-}CFA}$		PLSc		$EIV_{ML\text{-}CFA}$		EIV_{minres}	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{31}	0	100	-.059	.398	-.003	.087	-.096	.413	-.005	.084	-.003	.083
		200	-.047	.397	-.001	.061	-.041	.410	.000	.059	.001	.059
.490		500	-.064	.387	-.000	.039	-.083	.402	-.000	.037	-.000	.037
	.5	100	-.065	.346	-.003	.089	-.070	.351	-.001	.087	.000	.086
		200	-.028	.302	-.002	.060	-.021	.291	-.001	.058	-.001	.058
		500	-.021	.212	-.000	.037	-.010	.205	.001	.037	.001	.037
	1	100	-.027	.241	-.003	.088	-.014	.242	-.000	.087	.000	.086
		200	-.014	.167	-.002	.060	-.016	.160	-.002	.058	-.001	.058
		500	-.006	.101	-.000	.037	-.009	.107	.001	.037	.001	.037
λ_{34}	0	100	-.354	.361	.000	.056	-.341	.345	.004	.055	.000	.049
		200	-.336	.344	.001	.037	-.328	.342	.001	.035	-.000	.034
.900		500	-.340	.362	-.001	.022	-.327	.346	-.000	.023	-.001	.023
	.5	100	-.217	.314	-.000	.055	-.220	.314	.004	.053	.001	.049
		200	-.122	.238	.001	.036	-.137	.248	-.000	.035	-.001	.035
		500	-.045	.144	-.000	.022	-.043	.135	-.000	.023	-.001	.023
	1	100	-.060	.160	-.000	.052	-.059	.158	.002	.048	.001	.049
		200	-.019	.099	.001	.034	-.018	.100	-.000	.033	-.001	.035
		500	-.008	.063	-.000	.020	-.006	.064	-.000	.022	-.001	.023
λ_{41}	0	100	.218	1.507	4.880	11.634	-.107	.397	-.005	.070	-.005	.070
		200	.188	1.104	4.668	10.970	-.103	.399	-.001	.049	-.001	.049
.630		500	.195	1.258	4.252	9.601	-.100	.402	-.002	.031	-.002	.031
	.5	100	.018	.245	.633	4.785	-.033	.227	-.004	.072	-.004	.072
		200	.008	.132	.075	1.636	-.016	.159	.001	.048	.001	.049
		500	-.001	.075	-.004	.078	-.006	.101	-.002	.032	-.002	.032
	1	100	-.001	.089	-.005	.090	-.010	.109	-.002	.070	-.002	.071
		200	-.001	.064	-.001	.064	-.005	.074	-.002	.049	-.002	.050
		500	-.001	.039	-.001	.038	-.002	.046	-.001	.031	-.002	.032
λ_{42}	0	100	-.073	.768	4.594	11.563	-.273	.366	-.002	.050	-.001	.049
		200	.118	4.488	4.314	10.964	-.258	.346	-.000	.034	.000	.034
.840		500	.022	1.581	3.658	9.464	-.237	.356	-.000	.021	-.000	.021
	.5	100	.078	.813	1.715	7.406	-.047	.177	.000	.048	.001	.048
		200	.021	.228	.383	3.362	-.025	.122	-.000	.034	.001	.034
		500	.008	.103	.012	.107	-.002	.073	.000	.021	.000	.021
	1	100	.003	.102	.009	.113	-.007	.070	-.001	.046	-.001	.050
		200	.000	.064	.001	.063	-.005	.052	-.001	.031	-.000	.034
		500	.000	.040	.000	.039	-.000	.032	.000	.019	.000	.021
λ_{51}	0	100	-.069	.358	.001	.063	-.074	.356	-.001	.061	-.001	.061
		200	-.080	.354	-.000	.044	-.077	.360	-.003	.044	-.003	.044
.650		500	-.062	.351	.001	.029	-.073	.347	-.001	.028	-.001	.028
	.5	100	-.004	.198	-.001	.060	-.010	.212	-.003	.062	-.003	.062
		200	-.008	.154	-.001	.043	-.004	.150	.000	.042	.000	.042
		500	.000	.096	-.000	.028	-.010	.098	-.002	.028	-.002	.028
	1	100	-.003	.120	-.001	.063	-.007	.123	-.003	.065	-.002	.065
		200	-.003	.090	.001	.044	-.001	.086	-.001	.045	-.001	.045
		500	-.000	.055	.001	.027	-.007	.056	-.003	.028	-.003	.028
λ_{56}	0	100	-.196	.276	-.000	.026	-.175	.250	-.000	.028	-.001	.028
		200	-.198	.268	-.000	.019	-.188	.281	-.000	.019	.000	.019
.900		500	-.186	.265	.000	.012	-.186	.253	.000	.011	.000	.011
	.5	100	-.044	.134	-.001	.027	-.043	.121	-.000	.026	-.000	.026
		200	-.026	.090	-.000	.019	-.026	.093	.000	.019	.000	.019
		500	-.010	.060	.000	.011	-.010	.061	.000	.012	.000	.012
	1	100	-.012	.072	-.001	.026	-.009	.070	-.000	.026	-.001	.027
		200	-.007	.054	-.001	.019	-.008	.051	-.001	.019	-.001	.020
		500	-.002	.032	.000	.011	-.003	.032	-.001	.011	-.000	.011

Table 4 Estimation error of reliabilities with normal data for Small Model

Variable	Scale	N	PLS composites						Unit weighted composites					
			CR_U		CR_W		Alpha		CR_U		CR_W		Alpha	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ξ1	0	100	.153	3.037	.207	1.666	.004	.054	39.658	89.198	39.813	89.675	-.002	.020
		200	.067	.524	.149	.517	.005	.065	35.897	76.062	35.960	76.229	-.002	.013
		500	.067	.434	.175	.815	.003	.021	25.644	55.709	25.662	55.762	-.001	.008
	.5	100	.012	.047	.040	.136	-.003	.022	2.765	26.790	2.776	26.924	-.002	.020
		200	.007	.043	.026	.132	-.003	.014	.461	9.120	.461	9.134	-.002	.014
		500	-.000	.009	.006	.015	-.004	.009	.002	.010	.002	.010	-.002	.008
	1	100	-.001	.020	.004	.023	-.004	.021	.001	.021	.001	.021	-.002	.020
		200	-.002	.014	.002	.015	-.004	.014	.000	.014	.000	.014	-.002	.014
		500	-.002	.008	.001	.009	-.004	.009	.000	.008	.000	.008	-.002	.008
ξ2	0	100	-.114	.115	.054	.147	.117	.142	-.000	.047	-.002	.048	-.009	.048
		200	-.114	.105	.051	.142	.112	.135	-.000	.032	-.000	.032	-.007	.033
		500	-.127	.106	.038	.114	.116	.127	-.000	.021	-.000	.021	-.006	.022
	.5	100	-.037	.053	.020	.051	-.016	.050	-.000	.046	-.001	.046	-.009	.048
		200	-.028	.035	.012	.035	-.021	.034	-.000	.032	-.000	.032	-.008	.033
		500	-.023	.022	.005	.022	-.024	.022	-.000	.021	-.000	.021	-.006	.022
	1	100	-.028	.046	.004	.045	-.031	.047	-.001	.045	-.002	.045	-.009	.047
		200	-.023	.032	.002	.031	-.028	.033	-.001	.031	-.000	.031	-.008	.033
		500	-.022	.021	.000	.021	-.027	.021	-.000	.021	-.000	.020	-.006	.022
η3	0	100	-.065	.117	.086	.205	.032	.149	-.000	.030	-.001	.030	-.016	.034
		200	-.060	.122	.089	.236	.028	.133	-.001	.022	-.001	.021	-.016	.024
		500	-.062	.114	.095	.236	.031	.130	.000	.013	-.000	.013	-.015	.015
	.5	100	-.062	.103	.067	.180	.007	.109	-.000	.031	-.001	.030	-.017	.035
		200	-.053	.079	.055	.134	-.012	.076	-.000	.022	-.000	.021	-.016	.025
		500	-.050	.058	.031	.060	-.030	.040	-.000	.013	-.000	.013	-.015	.015
	1	100	-.051	.072	.042	.118	-.026	.065	-.000	.030	-.000	.030	-.017	.035
		200	-.045	.046	.026	.074	-.037	.042	-.000	.022	-.000	.021	-.016	.025
		500	-.043	.028	.015	.034	-.044	.025	-.000	.013	-.000	.012	-.015	.015
η4	0	100	.563	5.925	.979	6.689	.011	.119	107.477	194.713	108.461	197.203	-.020	.060
		200	.673	5.700	1.113	6.048	.019	.115	96.219	169.132	96.640	170.095	-.018	.044
		500	.960	15.428	2.508	47.453	.022	.115	73.438	127.609	73.571	127.925	-.017	.026
	.5	100	.202	2.227	.420	2.785	-.025	.077	31.438	123.968	31.765	125.597	-.020	.058
		200	.072	1.422	.162	1.365	-.031	.056	4.942	43.370	4.965	43.621	-.018	.043
		500	-.008	.075	.044	.213	-.037	.032	.011	.050	.011	.050	-.017	.026
	1	100	-.020	.067	.020	.116	-.043	.064	.250	7.749	.251	7.770	-.020	.059
		200	-.024	.045	.005	.056	-.042	.047	.000	.045	.000	.045	-.018	.043
		500	-.025	.027	.001	.033	-.041	.028	-.001	.027	-.001	.027	-.016	.026
η5	0	100	-.041	.076	.057	.093	.021	.085	-.000	.016	-.000	.015	-.004	.016
		200	-.043	.086	.054	.099	.017	.077	-.000	.011	-.000	.010	-.004	.011
		500	-.043	.104	.054	.116	.019	.093	-.000	.007	-.000	.007	-.003	.007
	.5	100	-.017	.020	.015	.022	-.011	.018	-.000	.015	-.000	.015	-.004	.016
		200	-.014	.012	.009	.014	-.012	.012	-.000	.010	-.000	.010	-.004	.011
		500	-.012	.007	.003	.008	-.013	.007	-.000	.007	-.000	.007	-.003	.007
	1	100	-.012	.015	.001	.015	-.015	.016	-.000	.015	-.000	.015	-.004	.016
		200	-.012	.011	.000	.010	-.015	.011	-.000	.011	-.000	.010	-.004	.011
		500	-.011	.007	-.000	.006	-.014	.007	-.000	.007	-.000	.006	-.003	.007

***Note**: Loadings for PLS composites are estimated with PLSc and loadings for unit weighted composites are estimated with ML-CFA.*

Table 5 Path estimates with normal data for Small Model

Param.	Scale	N	PLSc				EIV$_{ML\text{-}CFA}$				ML SEM	
			Original		Manipulated		Original		Manipulated		Original	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
γ_{23}	0	100	-.025	.521	.002	.259	-.004	.133	-.006	.135	-.004	.126
		200	-.012	.357	-.015	.173	-.005	.097	-.009	.098	-.005	.093
0		500	-.001	.321	-.002	.171	-.000	.061	.001	.060	-.001	.057
	.5	100	-.033	.232	-.007	.165	-.005	.133	-.001	.137	-.005	.126
		200	-.009	.124	-.005	.097	.002	.097	-.006	.096	.001	.092
		500	-.005	.067	-.000	.060	-.002	.065	-.001	.061	-.000	.060
	1	100	-.018	.147	.002	.130	-.000	.135	.006	.133	-.000	.122
		200	-.001	.094	.001	.089	.008	.095	.001	.091	.003	.085
		500	-.001	.061	.002	.060	.002	.063	.001	.062	.002	.056
γ_{14}	0	100	-.087	2.719	.001	.147	.002	.101	.002	.091	.003	.097
		200	-.005	.168	.007	.206	-.003	.069	-.000	.062	-.004	.067
0		500	.012	.438	-.001	.063	-.003	.042	-.001	.037	-.002	.041
	.5	100	.023	.629	.001	.118	-.004	.125	-.007	.120	-.004	.129
		200	.010	.084	.010	.080	.000	.094	.002	.090	.001	.094
		500	.002	.055	.004	.054	-.001	.061	.001	.059	-.002	.060
	1	100	-.022	.202	.010	.178	-.026	.220	-.023	.296	-.020	.212
		200	-.007	.136	.007	.121	-.007	.144	-.003	.133	-.005	.136
		500	-.004	.085	-.000	.080	-.004	.089	-.004	.084	-.002	.083
γ_{24}	0	100	-.073	2.710	.008	.228	.002	.120	.002	.110	.003	.121
		200	-.001	.333	-.003	.226	-.001	.086	.002	.070	-.002	.084
.7		500	.008	.485	.004	.121	-.002	.053	.002	.046	-.001	.053
	.5	100	.007	.594	-.019	.146	-.016	.168	-.021	.160	-.023	.170
		200	.007	.106	-.022	.097	-.009	.115	-.012	.106	-.011	.115
		500	.002	.068	-.011	.061	-.002	.069	-.005	.062	-.002	.069
	1	100	.035	.203	-.017	.174	.028	.219	.023	.293	.020	.215
		200	.013	.135	-.011	.119	.008	.142	.003	.130	.005	.137
		500	.006	.086	-.001	.076	.004	.089	.005	.081	.002	.085
γ_{15}	0	100	-.117	3.363	-.011	.381	-.002	.103	-.003	.096	-.001	.096
		200	-.363	12.085	.007	.451	-.005	.069	-.002	.066	-.006	.065
.22		500	-.016	.833	-.003	.102	-.002	.045	-.002	.044	-.002	.043
	.5	100	.035	1.385	-.016	.149	-.001	.121	.001	.116	-.006	.120
		200	-.008	.145	-.015	.083	.000	.088	.002	.085	-.000	.086
		500	-.004	.050	-.006	.050	.002	.050	.002	.052	.001	.049
	1	100	.008	.194	-.004	.176	.017	.208	.032	.252	.010	.194
		200	.008	.127	-.003	.118	.012	.133	.010	.126	.008	.127
		500	.008	.077	-.001	.073	.010	.078	.005	.076	.007	.075
γ_{25}	0	100	-.194	8.184	.004	.575	-.004	.129	.002	.130	-.001	.128
		200	-.766	22.527	.003	.880	-.001	.089	.001	.087	-.000	.087
-.7		500	-.061	1.231	.009	.163	-.001	.057	.001	.057	-.001	.055
	.5	100	-.179	4.659	.001	.342	-.001	.137	-.005	.131	.002	.132
		200	-.017	.258	.013	.091	-.001	.094	-.002	.092	-.000	.091
		500	-.003	.055	.006	.054	.001	.057	-.001	.055	.001	.054
	1	100	-.023	.192	.003	.176	-.024	.205	-.037	.253	-.015	.192
		200	-.014	.123	.004	.117	-.014	.129	-.010	.125	-.009	.122
		500	-.010	.078	.002	.072	-.010	.080	-.004	.076	-.007	.076
β_{35}	0	100	.268	7.348	.011	.590	-.005	.119	.000	.120	-.002	.115
		200	-.626	18.853	.028	.887	-.002	.086	-.001	.083	-.001	.081
.35		500	-.045	.881	.003	.104	-.002	.052	-.001	.053	-.002	.049
	.5	100	-.106	4.455	-.009	.329	.001	.116	.006	.116	.000	.112
		200	.030	.248	-.001	.090	.003	.081	.004	.077	.002	.076
		500	.008	.049	-.001	.051	.001	.051	.001	.051	.002	.048
	1	100	.013	.112	.004	.102	.003	.108	.011	.106	.001	.092
		200	.008	.072	-.005	.072	.004	.076	-.001	.074	-.001	.067
		500	.002	.047	-.001	.044	.001	.048	-.000	.045	-.001	.041

Table 6 Path estimates with normal data for Large Model

Param.	Scale	N	PLSc				$EIV_{ML\text{-}CFA}$				EIV_{minres}				ML SEM	
			Original		Manipulated		Original		Manipulated		Original		Manipulated		Original	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
γ_{23}	0	100	-.016	.709	-.003	.406	-.009	.136	.001	.132	-.009	.136	.001	.131	-.007	.131
		200	-.047	1.037	-.001	.358	-.005	.097	-.006	.096	-.005	.097	-.006	.096	-.004	.092
0		500	.009	.283	.002	.117	-.001	.057	-.002	.057	-.001	.057	-.002	.057	-.002	.055
	.5	100	-.024	.236	-.003	.166	-.003	.134	-.003	.133	-.003	.134	-.003	.133	-.004	.127
		200	-.008	.135	-.002	.106	-.002	.100	-.004	.095	-.002	.100	-.004	.095	-.000	.094
		500	-.007	.064	-.000	.057	-.003	.062	.000	.060	-.003	.062	.000	.060	-.002	.059
	1	100	-.015	.141	.002	.129	.002	.130	.001	.129	.002	.130	.001	.129	.002	.120
		200	-.005	.097	.002	.087	.002	.097	.002	.091	.002	.097	.002	.091	.002	.087
		500	-.003	.060	.003	.058	.001	.061	.003	.060	.001	.061	.003	.060	-.000	.056
γ_{14}	0	100	-.071	2.449	.008	.344	.000	.119	.004	.118	.000	.119	.004	.118	.001	.115
		200	-.005	.279	-.004	.129	.000	.080	-.003	.081	.000	.080	-.003	.081	-.001	.079
0		500	.002	.164	-.018	1.219	-.001	.050	-.001	.049	-.001	.050	-.001	.049	-.001	.049
	.5	100	-.004	.153	.011	.188	-.006	.122	-.003	.125	-.006	.123	-.002	.125	-.005	.119
		200	.005	.081	.005	.081	-.001	.083	-.000	.085	-.001	.083	.000	.085	-.001	.082
		500	.003	.051	.002	.058	-.001	.053	.000	.053	-.001	.053	.000	.053	-.001	.052
	1	100	-.015	.183	.004	.168	-.019	.193	-.021	.198	-.020	.199	-.018	.191	-.014	.184
		200	-.008	.120	.002	.112	-.008	.122	-.010	.121	-.008	.124	-.009	.120	-.009	.121
		500	-.006	.076	-.001	.071	-.005	.078	-.005	.075	-.006	.079	-.005	.074	-.005	.075
γ_{24}	0	100	-.088	2.856	.006	.389	.004	.139	.001	.130	.004	.139	.001	.130	.005	.137
		200	.011	.389	-.001	.165	-.001	.093	.000	.092	-.001	.093	.000	.092	.001	.090
.7		500	.006	.267	-.012	1.243	.002	.058	-.000	.058	.002	.058	-.000	.058	.002	.056
	.5	100	.051	.157	-.013	.201	.009	.137	.008	.134	.009	.138	.008	.134	.008	.135
		200	.018	.091	-.011	.093	.000	.096	-.000	.094	.000	.096	-.000	.094	-.000	.093
		500	.005	.058	-.008	.060	-.001	.058	-.003	.058	-.001	.058	-.003	.058	-.002	.056
	1	100	.031	.180	-.007	.163	.021	.191	.022	.192	.022	.197	.020	.185	.016	.183
		200	.013	.119	-.004	.110	.007	.123	.011	.119	.006	.125	.010	.117	.008	.121
		500	.009	.076	.000	.069	.006	.079	.005	.073	.006	.080	.005	.072	.006	.076
γ_{15}	0	100	.050	.708	-.003	.322	-.003	.108	-.004	.106	-.003	.108	-.004	.106	-.004	.106
		200	.050	1.670	-.012	.176	-.003	.075	-.003	.074	-.003	.075	-.003	.074	-.003	.073
.22		500	-.001	.150	.004	.210	-.002	.049	-.002	.048	-.002	.049	-.002	.048	-.002	.048
	.5	100	.005	.166	-.018	.260	.006	.118	.002	.116	.006	.118	.002	.116	.004	.114
		200	.001	.095	-.004	.087	.003	.085	.003	.083	.003	.085	.003	.083	.002	.083
		500	-.001	.059	-.001	.054	.001	.052	.003	.051	.001	.052	.003	.051	.001	.050
	1	100	.019	.188	-.011	.163	.026	.198	.020	.201	.027	.203	.017	.193	.016	.189
		200	.008	.120	-.002	.113	.012	.123	.012	.124	.012	.125	.011	.123	.007	.118
		500	.005	.078	-.000	.069	.007	.080	.005	.073	.007	.081	.005	.073	.004	.076
γ_{25}	0	100	-.012	1.223	.026	.472	.002	.132	-.002	.128	.002	.132	-.002	.128	.001	.127
		200	.227	5.259	.023	.779	.004	.088	.001	.085	.004	.089	.001	.085	.003	.087
-.7		500	.025	.485	-.000	.250	.003	.056	.001	.056	.003	.056	.001	.056	.002	.054
	.5	100	-.016	.675	.002	.308	-.002	.137	-.004	.128	-.002	.137	-.004	.128	-.001	.133
		200	-.016	.096	.008	.096	-.002	.096	-.001	.091	-.003	.096	-.001	.091	-.001	.093
		500	-.004	.063	.004	.056	.001	.057	-.001	.054	.001	.057	-.001	.054	.001	.055
	1	100	-.036	.197	.008	.172	-.031	.203	-.024	.206	-.032	.209	-.021	.198	-.022	.190
		200	-.014	.120	.004	.112	-.013	.123	-.012	.122	-.013	.126	-.011	.121	-.008	.117
		500	-.007	.079	.004	.070	-.006	.081	-.002	.074	-.007	.082	-.002	.074	-.004	.077
β_{35}	0	100	-.009	1.122	.001	.309	-.002	.120	-.004	.120	-.002	.120	-.004	.119	-.002	.114
		200	-.245	5.612	-.030	.760	-.004	.085	-.001	.082	-.004	.085	-.001	.082	-.002	.081
.35		500	-.015	.445	.005	.136	-.001	.053	.000	.053	-.001	.053	.000	.053	-.001	.050
	.5	100	.023	.698	.006	.336	.002	.118	.004	.117	.002	.118	.004	.117	.001	.110
		200	.020	.102	-.003	.092	.003	.079	.002	.079	.003	.079	.002	.079	.001	.074
		500	.008	.049	-.002	.051	.001	.051	.001	.051	.001	.051	.001	.051	.000	.048
	1	100	.016	.109	-.001	.106	.007	.110	.004	.107	.006	.110	.004	.106	.002	.091
		200	.007	.073	-.007	.070	.003	.077	-.003	.072	.003	.077	-.003	.072	.002	.064
		500	.002	.046	-.000	.042	.001	.047	.002	.044	.001	.047	.002	.044	-.000	.041

Table 7 95% percentile confidence intervals with normal data for Small Model

Param.	Scale	N	PLSc				$EIV_{ML\text{-}CFA}$			
			Coverage			Incl. zero	Coverage			Incl. zero
			Under	Within	Over		Under	Within	Over	
γ_{23}	0	100	.008	.979	.013	.979	.024	.951	.025	.951
		200	.014	.972	.014	.972	.029	.938	.033	.938
0		500	.011	.977	.012	.977	.026	.945	.029	.945
	.5	100	.008	.962	.030	.962	.017	.959	.024	.959
		200	.014	.954	.032	.954	.032	.943	.025	.943
		500	.021	.936	.043	.936	.043	.925	.032	.925
	1	100	.007	.947	.046	.947	.025	.941	.034	.941
		200	.015	.958	.027	.958	.033	.945	.022	.945
		500	.023	.938	.039	.938	.040	.931	.029	.931
γ_{14}	0	100	.004	.995	.001	.995	.028	.942	.030	.942
		200	.007	.988	.005	.988	.029	.943	.028	.943
0		500	.005	.987	.008	.987	.016	.957	.027	.957
	.5	100	.011	.977	.012	.977	.019	.953	.028	.953
		200	.024	.967	.009	.967	.027	.947	.026	.947
		500	.027	.963	.010	.963	.025	.954	.021	.954
	1	100	.013	.955	.032	.955	.015	.955	.030	.955
		200	.021	.947	.032	.947	.026	.940	.034	.940
		500	.031	.941	.028	.941	.026	.952	.022	.952
γ_{24}	0	100	.013	.979	.008	.979	.033	.943	.024	.943
		200	.011	.980	.009	.980	.026	.946	.028	.946
.7		500	.009	.980	.011	.980	.025	.946	.029	.946
	.5	100	.041	.955	.004	.427	.011	.962	.027	.350
		200	.041	.951	.008	.115	.018	.950	.032	.106
		500	.031	.941	.028	.000	.023	.944	.033	.001
	1	100	.046	.944	.010	.033	.033	.955	.012	.086
		200	.043	.942	.015	.002	.030	.952	.018	.002
		500	.034	.946	.020	.000	.031	.945	.024	.000
γ_{15}	0	100	.000	1.000	.000	1.000	.025	.948	.027	.948
		200	.001	.998	.001	.998	.016	.951	.033	.951
.22		500	.005	.985	.010	.985	.025	.942	.033	.942
	.5	100	.002	.989	.009	.951	.014	.958	.028	.849
		200	.009	.961	.030	.828	.031	.939	.030	.722
		500	.010	.968	.022	.486	.023	.964	.013	.430
	1	100	.017	.958	.025	.768	.034	.947	.019	.739
		200	.032	.953	.015	.489	.035	.953	.012	.515
		500	.039	.938	.023	.100	.040	.942	.018	.115
γ_{25}	0	100	.002	.997	.001	.997	.029	.948	.023	.948
		200	.004	.995	.001	.995	.031	.949	.020	.949
-.7		500	.005	.990	.005	.990	.023	.949	.028	.949
	.5	100	.000	.970	.030	.618	.026	.932	.042	.274
		200	.006	.958	.036	.137	.025	.937	.038	.051
		500	.011	.950	.039	.000	.025	.948	.027	.000
	1	100	.011	.957	.032	.081	.015	.943	.042	.060
		200	.011	.960	.029	.000	.008	.957	.035	.000
		500	.015	.948	.037	.000	.013	.949	.038	.000
$\beta 35$	0	100	.000	.999	.001	.999	.030	.938	.032	.938
		200	.001	.997	.002	.997	.028	.936	.036	.936
.35		500	.001	.989	.010	.989	.018	.949	.033	.949
	.5	100	.027	.973	.000	.845	.034	.950	.016	.681
		200	.060	.938	.002	.552	.034	.939	.027	.426
		500	.046	.952	.002	.117	.025	.947	.028	.074
	1	100	.022	.975	.003	.295	.022	.965	.013	.208
		200	.041	.950	.009	.018	.036	.944	.020	.009
		500	.029	.947	.024	.000	.025	.947	.028	.000

Table 8 95% percentile confidence intervals with normal data for Large Model

Param.	Scale	N	PLSc				$EIV_{ML\text{-}CFA}$				EIV_{minres}			
			Coverage			Incl. zero	Coverage			Incl. zero	Coverage			Incl. zero
			Under	Within	Over		Under	Within	Over		Under	Within	Over	
γ_{23}	0	100	.007	.972	.021	.972	.026	.934	.040	.934	.026	.934	.040	.934
		200	.010	.977	.013	.977	.028	.933	.039	.933	.028	.933	.039	.933
0		500	.008	.980	.012	.980	.018	.953	.029	.953	.018	.953	.029	.953
	.5	100	.007	.971	.022	.971	.028	.949	.023	.949	.028	.949	.023	.949
		200	.014	.943	.043	.943	.033	.928	.039	.928	.033	.928	.039	.928
		500	.009	.957	.034	.957	.025	.945	.030	.945	.025	.945	.030	.945
	1	100	.008	.950	.042	.950	.033	.944	.023	.944	.033	.944	.023	.944
		200	.012	.944	.044	.944	.029	.942	.029	.942	.029	.942	.029	.942
		500	.013	.941	.046	.941	.028	.937	.035	.937	.028	.937	.035	.937
γ_{14}	0	100	.004	.993	.003	.993	.030	.940	.030	.940	.030	.940	.030	.940
		200	.007	.990	.003	.990	.029	.949	.022	.949	.029	.949	.022	.949
0		500	.004	.988	.008	.988	.017	.958	.025	.958	.017	.958	.025	.958
	.5	100	.014	.977	.009	.977	.020	.948	.032	.948	.019	.950	.031	.950
		200	.022	.973	.005	.973	.024	.956	.020	.956	.024	.956	.020	.956
		500	.027	.969	.004	.969	.023	.952	.025	.952	.024	.950	.026	.950
	1	100	.013	.947	.040	.947	.013	.949	.038	.949	.015	.949	.036	.949
		200	.021	.942	.037	.942	.018	.944	.038	.944	.019	.943	.038	.943
		500	.017	.950	.033	.950	.016	.950	.034	.950	.016	.955	.029	.955
γ_{24}	0	100	.011	.976	.013	.976	.039	.929	.032	.929	.039	.928	.033	.928
		200	.007	.985	.008	.985	.023	.944	.033	.944	.023	.944	.033	.944
.7		500	.012	.979	.009	.979	.027	.947	.026	.947	.027	.947	.026	.947
	.5	100	.088	.912	.000	.384	.052	.927	.021	.283	.047	.930	.023	.281
		200	.064	.934	.002	.074	.030	.946	.024	.061	.030	.946	.024	.061
		500	.032	.957	.011	.000	.020	.954	.026	.000	.019	.954	.027	.000
	1	100	.054	.941	.005	.016	.047	.942	.011	.052	.048	.938	.014	.045
		200	.048	.937	.015	.000	.035	.949	.016	.000	.034	.951	.015	.000
		500	.039	.943	.018	.000	.033	.945	.022	.000	.028	.949	.023	.000
γ_{15}	0	100	.001	.999	.000	.999	.025	.953	.022	.953	.025	.952	.023	.952
		200	.004	.994	.002	.994	.019	.950	.031	.950	.019	.950	.031	.950
.22		500	.009	.979	.012	.979	.026	.941	.033	.941	.026	.941	.033	.941
	.5	100	.005	.992	.003	.955	.030	.955	.015	.824	.030	.955	.015	.823
		200	.028	.963	.009	.819	.040	.940	.020	.721	.040	.941	.019	.719
		500	.018	.956	.026	.482	.025	.952	.023	.406	.024	.953	.023	.409
	1	100	.031	.959	.010	.713	.041	.949	.010	.699	.049	.939	.012	.696
		200	.034	.945	.021	.469	.034	.949	.017	.494	.038	.944	.018	.503
		500	.028	.945	.027	.112	.028	.943	.029	.121	.031	.941	.028	.125
γ_{25}	0	100	.005	.995	.000	.995	.032	.942	.026	.942	.032	.942	.026	.942
		200	.005	.993	.002	.993	.031	.949	.020	.949	.031	.949	.020	.949
-.7		500	.007	.990	.003	.990	.026	.952	.022	.952	.026	.952	.022	.952
	.5	100	.000	.979	.021	.631	.022	.937	.041	.294	.026	.935	.039	.291
		200	.003	.950	.047	.142	.024	.937	.039	.042	.024	.936	.040	.042
		500	.011	.945	.044	.000	.025	.945	.030	.000	.025	.944	.031	.000
	1	100	.005	.951	.044	.066	.007	.932	.061	.052	.008	.935	.057	.050
		200	.012	.950	.038	.001	.017	.950	.033	.000	.014	.953	.033	.000
		500	.016	.940	.044	.000	.023	.939	.038	.000	.021	.940	.039	.000
β_{35}	0	100	.000	1.000	.000	1.000	.029	.940	.031	.940	.029	.940	.031	.940
		200	.002	.996	.002	.996	.025	.935	.040	.935	.024	.936	.040	.936
.35		500	.000	.993	.007	.993	.029	.948	.023	.948	.029	.948	.023	.948
	.5	100	.033	.967	.000	.841	.033	.945	.022	.685	.034	.943	.023	.683
		200	.045	.953	.002	.541	.022	.944	.034	.417	.021	.947	.032	.417
		500	.047	.952	.001	.106	.031	.944	.025	.072	.031	.944	.025	.071
	1	100	.029	.967	.004	.282	.026	.952	.022	.183	.026	.951	.023	.179
		200	.037	.955	.008	.009	.032	.944	.024	.004	.032	.946	.022	.004
		500	.032	.937	.031	.000	.028	.940	.032	.000	.028	.942	.030	.000

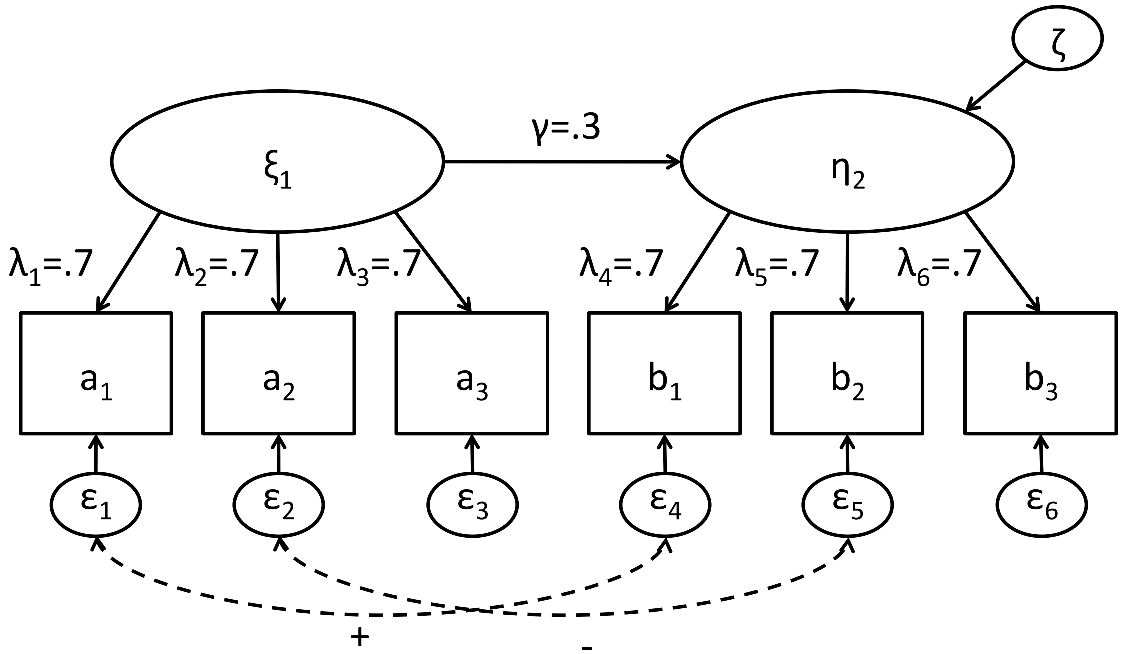

Figure 1 Example of chance correlations

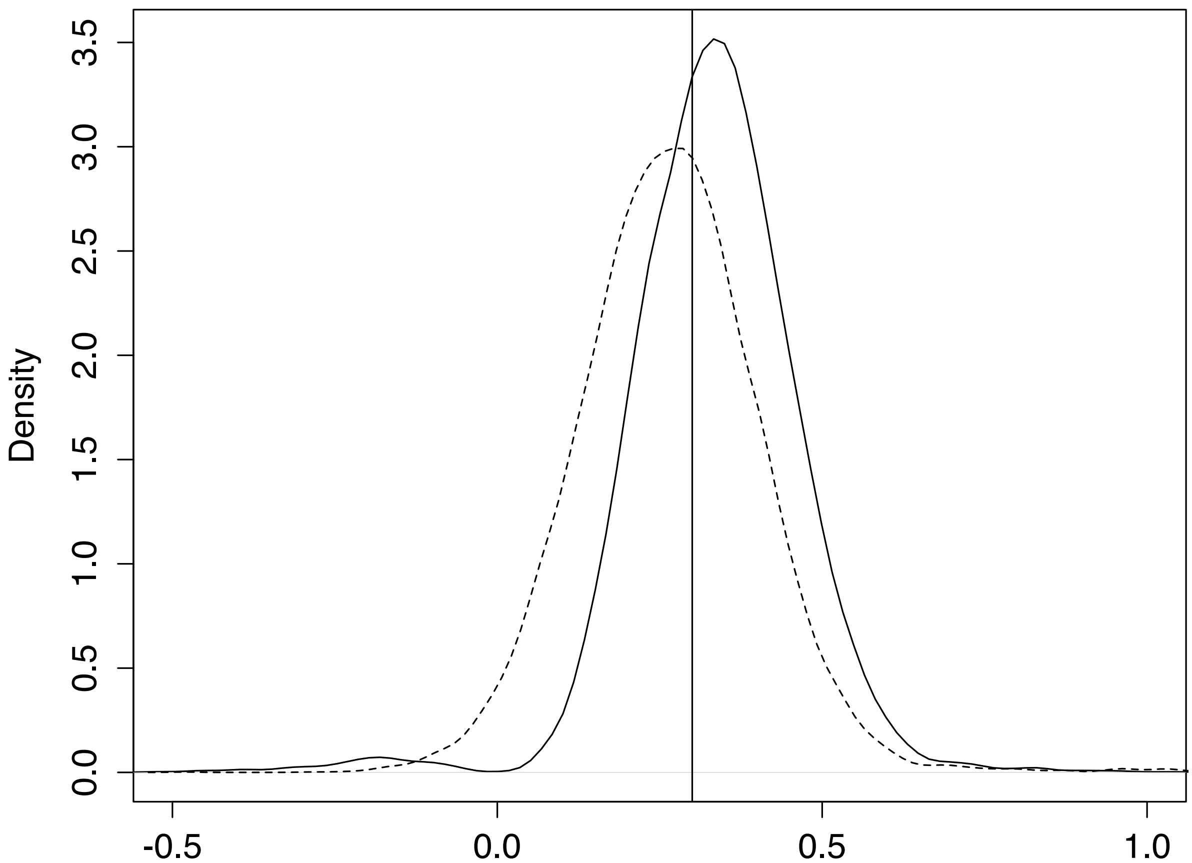

Figure 2 Normal PLSc estimates (solid line) and estimates with weights and reliabilities estimated from hold-out sample (dashed lines)

Appendix A: Full results tables

This appendix contains the full results tables for both normal and non-normal data, excluding the tables that are included in the main document.

Table 1 Inadmissible replications over 1000 replications for non-normal data

Model	Scale	N	Inadmissible loadings				Inadmissible reliabilities			Inadmissible factor correlations			
			PLSc	$EIV_{ML\text{-}CFA}$	EIV_{minres}	ML-SEM	PLSc	$EIV_{ML\text{-}CFA}$	EIV_{minres}	PLSc	$EIV_{ML\text{-}CFA}$	EIV_{minres}	ML-SEM
Small Model	0	100	949	936	N/A	935	749	747	N/A	102	0	N/A	2
		200	938	935	N/A	945	768	748	N/A	37	0	N/A	0
		500	947	937	N/A	930	767	749	N/A	20	0	N/A	0
	.5	100	849	679	N/A	636	517	238	N/A	16	0	N/A	0
		200	780	433	N/A	416	451	79	N/A	6	0	N/A	0
		500	614	186	N/A	183	238	2	N/A	1	0	N/A	0
	1	100	438	170	N/A	162	71	3	N/A	23	18	N/A	14
		200	281	43	N/A	43	10	0	N/A	0	0	N/A	0
		500	62	1	N/A	1	0	0	N/A	0	0	N/A	0
Large Model	0	100	976	43	0	35	603	0	0	131	0	0	0
		200	971	6	0	5	592	0	0	63	0	0	0
		500	973	0	0	0	572	0	0	23	0	0	0
	.5	100	931	38	0	38	386	0	0	14	0	0	4
		200	903	2	0	1	359	0	0	1	0	0	0
		500	811	0	0	0	140	0	0	0	0	0	0
	1	100	559	18	0	18	20	0	0	7	6	9	5
		200	303	1	0	2	3	0	0	0	0	0	0
		500	83	0	0	0	0	0	0	0	0	0	0

Note: Loadings and reliabilities are invalid if any value in a replication has absolute value greater than one. Reliabilities are inadmissible if any index exceeds one in absolute value. Linear effects are inadmissible if the disattenuated composite covariance matrix is invalid. Small Model: Original model, Large Model: Model with duplicated indicators for $\xi 1$ and $\eta 4$. N/A = not estimated.

Table 2 Loadings over 1000 replications for normal data

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{11}	0	100	.117	.776	2.649	7.864	-.068	.366	-.002	.028	-.003	.028
		200	.116	.695	2.717	7.685	-.055	.354	-.001	.020	-.001	.020
.870		500	.112	.731	2.245	6.434	-.062	.353	-.001	.012	-.001	.012
	.5	100	.073	.528	.164	2.259	-.075	.335	-.001	.028	-.002	.028
		200	.081	.706	.036	.968	-.045	.309	-.001	.020	-.001	.020
		500	.009	.227	-.000	.044	-.030	.192	-.001	.012	-.001	.012
	1	100	.001	.070	-.002	.050	-.008	.085	-.002	.027	-.002	.028
		200	-.001	.051	-.001	.035	-.001	.057	-.000	.019	-.001	.019
		500	-.001	.029	-.000	.020	-.003	.037	-.001	.012	-.002	.012
λ_{11b}	0	100	N/A	N/A	N/A	N/A	-.096	.361	-.002	.028	-.002	.028
		200	N/A	N/A	N/A	N/A	-.059	.351	-.000	.020	-.000	.020
.870		500	N/A	N/A	N/A	N/A	-.069	.356	-.000	.012	-.000	.012
	.5	100	N/A	N/A	N/A	N/A	-.066	.323	-.001	.029	-.001	.029
		200	N/A	N/A	N/A	N/A	-.036	.290	-.000	.020	-.001	.020
		500	N/A	N/A	N/A	N/A	-.021	.220	-.000	.013	-.001	.013
	1	100	N/A	N/A	N/A	N/A	-.002	.088	-.001	.029	-.002	.029
		200	N/A	N/A	N/A	N/A	-.002	.060	-.000	.019	-.001	.019
		500	N/A	N/A	N/A	N/A	.000	.037	-.000	.012	-.001	.013
λ_{12}	0	100	.034	.901	2.486	7.718	-.110	.321	-.000	.017	-.000	.017
		200	.021	.759	2.264	7.072	-.115	.297	-.001	.012	-.001	.012
.940		500	-.007	.821	1.896	5.984	-.095	.287	.000	.007	.000	.007
	.5	100	.022	.540	.287	2.689	-.079	.277	.000	.017	.000	.017
		200	.037	.799	.036	.903	-.076	.244	-.001	.012	-.001	.012
		500	.019	.260	.001	.048	-.032	.173	-.000	.007	.000	.008
	1	100	.001	.073	.001	.048	-.005	.068	-.000	.017	.000	.017
		200	.002	.052	.001	.033	-.002	.046	-.001	.012	-.000	.012
		500	.001	.029	-.000	.019	-.001	.029	-.000	.007	.000	.007
λ_{12b}	0	100	N/A	N/A	N/A	N/A	-.114	.305	-.001	.017	-.000	.017
		200	N/A	N/A	N/A	N/A	-.112	.288	-.001	.012	-.000	.012
.940		500	N/A	N/A	N/A	N/A	-.107	.303	-.000	.007	.000	.008
	.5	100	N/A	N/A	N/A	N/A	-.104	.281	.000	.017	.000	.017
		200	N/A	N/A	N/A	N/A	-.068	.235	-.001	.012	-.001	.012
		500	N/A	N/A	N/A	N/A	-.027	.172	-.000	.007	-.000	.007
	1	100	N/A	N/A	N/A	N/A	-.001	.066	-.000	.017	.000	.017
		200	N/A	N/A	N/A	N/A	-.003	.047	-.001	.011	-.001	.012
		500	N/A	N/A	N/A	N/A	-.001	.028	-.000	.007	-.000	.007
λ_{21}	0	100	-.144	.303	-.000	.107	-.142	.292	-.006	.106	-.005	.105
		200	-.150	.293	.001	.076	-.153	.284	-.002	.076	-.002	.075
.410		500	-.153	.290	-.001	.047	-.167	.280	.001	.046	.001	.046
	.5	100	-.033	.195	-.001	.106	-.036	.199	-.005	.107	-.003	.109
		200	-.023	.146	-.004	.072	-.019	.144	-.004	.069	-.003	.070
		500	-.007	.093	-.001	.044	-.006	.090	-.002	.046	-.001	.047
	1	100	-.007	.122	-.000	.097	-.006	.121	-.001	.097	-.002	.104
		200	.001	.087	.001	.066	-.005	.084	-.003	.067	-.003	.073
		500	-.001	.054	-.000	.043	-.005	.053	-.003	.043	-.002	.046

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{22}	0	100	-.159	.292	-.002	.110	-.160	.295	-.011	.111	-.010	.110
		200	-.160	.289	-.002	.075	-.153	.299	.002	.074	.002	.074
.410		500	-.159	.284	-.002	.046	-.152	.299	-.004	.047	-.004	.047
	.5	100	-.026	.196	-.003	.105	-.038	.193	-.007	.104	-.006	.104
		200	-.021	.151	-.005	.073	-.008	.140	.003	.075	.003	.077
		500	-.007	.092	-.002	.044	-.003	.086	-.001	.045	-.002	.047
	1	100	-.006	.122	-.004	.096	-.008	.119	-.003	.098	-.004	.107
		200	-.005	.085	-.003	.067	-.006	.082	.000	.068	.002	.075
		500	.001	.058	-.001	.043	-.001	.052	-.000	.041	-.001	.047
λ_{23}	0	100	-.190	.298	-.008	.100	-.192	.289	-.002	.104	-.001	.102
		200	-.195	.287	-.004	.074	-.181	.291	-.003	.071	-.003	.071
.470		500	-.200	.284	-.000	.046	-.187	.285	-.002	.043	-.002	.044
	.5	100	-.045	.191	-.008	.101	-.030	.182	.002	.100	.001	.103
		200	-.021	.142	-.002	.071	-.014	.131	-.002	.067	-.001	.068
		500	-.005	.088	.001	.042	-.009	.086	-.002	.042	-.002	.043
	1	100	-.013	.115	-.007	.094	.001	.110	.004	.090	.004	.103
		200	-.008	.081	-.002	.064	-.003	.077	-.002	.062	-.001	.069
		500	-.002	.052	.000	.040	-.000	.048	-.001	.039	-.001	.044
λ_{24}	0	100	-.288	.289	-.001	.093	-.271	.288	-.005	.094	-.004	.093
		200	-.265	.284	.002	.063	-.289	.278	-.003	.062	-.003	.061
.600		500	-.287	.290	-.001	.040	-.294	.285	-.000	.039	.000	.039
	.5	100	-.053	.169	-.002	.089	-.044	.161	.001	.085	.003	.090
		200	-.035	.123	-.002	.059	-.027	.121	-.003	.061	-.003	.063
		500	-.014	.078	-.001	.038	-.013	.078	.001	.037	.002	.039
	1	100	-.013	.098	-.002	.077	-.010	.100	.002	.078	-.000	.090
		200	-.009	.070	-.003	.053	-.006	.068	-.002	.053	-.002	.063
		500	-.004	.047	-.002	.035	-.002	.044	.000	.034	.000	.040
λ_{25}	0	100	-.303	.292	-.002	.093	-.286	.290	-.003	.095	-.004	.092
		200	-.300	.285	-.000	.063	-.291	.279	-.001	.064	-.001	.064
.630		500	-.296	.275	-.001	.039	-.294	.284	-.000	.038	-.000	.038
	.5	100	-.062	.173	.001	.086	-.053	.164	-.006	.086	-.007	.090
		200	-.025	.120	.003	.060	-.031	.111	.000	.057	-.000	.062
		500	-.012	.078	-.001	.038	-.010	.074	-.002	.037	-.002	.040
	1	100	-.010	.093	.003	.074	-.019	.094	-.008	.076	-.006	.092
		200	-.006	.069	.002	.053	-.004	.065	.001	.050	.001	.061
		500	-.005	.045	-.001	.034	-.005	.042	-.003	.032	-.002	.039
λ_{26}	0	100	-.323	.284	-.002	.094	-.294	.283	-.001	.094	-.001	.092
		200	-.305	.287	-.001	.060	-.301	.292	-.000	.060	-.001	.060
.650		500	-.306	.282	-.000	.039	-.319	.279	-.002	.039	-.002	.038
	.5	100	-.056	.162	-.004	.086	-.062	.160	-.004	.088	-.004	.091
		200	-.022	.116	-.001	.058	-.024	.109	-.000	.057	-.000	.060
		500	-.009	.077	.001	.038	-.011	.072	-.001	.037	-.001	.039
	1	100	-.014	.096	-.003	.073	-.013	.094	-.003	.078	-.001	.094
		200	-.008	.065	-.001	.051	-.005	.066	-.000	.051	-.001	.061
		500	-.003	.045	.001	.034	-.004	.040	-.001	.032	-.001	.039
λ_{31}	0	100	-.059	.398	-.003	.087	-.096	.413	-.005	.084	-.003	.083
		200	-.047	.397	-.001	.061	-.041	.410	.000	.059	.001	.059
.490		500	-.064	.387	-.000	.039	-.083	.402	-.000	.037	-.000	.037
	.5	100	-.065	.346	-.003	.089	-.070	.351	-.001	.087	.000	.086
		200	-.028	.302	-.002	.060	-.021	.291	-.001	.058	-.001	.058
		500	-.021	.212	-.000	.037	-.010	.205	.001	.037	.001	.037
	1	100	-.027	.241	-.003	.088	-.014	.242	-.000	.087	.000	.086
		200	-.014	.167	-.002	.060	-.016	.160	-.002	.058	-.001	.058
		500	-.006	.101	-.000	.037	-.009	.107	.001	.037	.001	.037

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{32}	0	100	-.135	.406	-.003	.074	-.123	.411	-.006	.076	-.005	.074
		200	-.122	.407	-.002	.053	-.136	.384	-.002	.052	-.002	.052
.600		500	-.133	.403	-.002	.033	-.132	.398	.000	.033	.000	.033
	.5	100	-.096	.349	-.004	.072	-.093	.339	-.005	.074	-.003	.073
		200	-.076	.279	-.002	.051	-.078	.287	-.001	.053	-.001	.053
		500	-.038	.200	.000	.034	-.019	.181	-.000	.032	-.000	.032
	1	100	-.037	.204	-.004	.072	-.038	.215	-.004	.073	-.003	.073
		200	-.018	.149	-.001	.052	-.016	.150	-.002	.053	-.001	.053
		500	.000	.089	.001	.034	-.004	.090	-.000	.032	-.000	.032
λ_{33}	0	100	-.270	.374	-.001	.059	-.261	.360	-.003	.060	-.000	.056
		200	-.260	.361	.001	.041	-.279	.365	-.000	.040	.001	.040
.800		500	-.257	.381	.001	.026	-.251	.365	.000	.024	.001	.024
	.5	100	-.178	.311	-.001	.058	-.185	.308	-.003	.058	-.001	.055
		200	-.119	.255	-.000	.040	-.109	.246	-.001	.041	-.000	.041
		500	-.036	.161	.001	.025	-.038	.142	.001	.024	.001	.024
	1	100	-.043	.174	-.001	.056	-.054	.173	-.002	.054	-.001	.055
		200	-.022	.116	-.000	.038	-.019	.110	-.001	.040	-.000	.041
		500	-.008	.070	.001	.024	-.006	.069	.001	.023	.001	.024
λ_{34}	0	100	-.354	.361	.000	.056	-.341	.345	.004	.055	.000	.049
		200	-.336	.344	.001	.037	-.328	.342	.001	.035	-.000	.034
.900		500	-.340	.362	-.001	.022	-.327	.346	-.000	.023	-.001	.023
	.5	100	-.217	.314	-.000	.055	-.220	.314	.004	.053	.001	.049
		200	-.122	.238	.001	.036	-.137	.248	-.000	.035	-.001	.035
		500	-.045	.144	-.000	.022	-.043	.135	-.000	.023	-.001	.023
	1	100	-.060	.160	-.000	.052	-.059	.158	.002	.048	.001	.049
		200	-.019	.099	.001	.034	-.018	.100	-.000	.033	-.001	.035
		500	-.008	.063	-.000	.020	-.006	.064	-.000	.022	-.001	.023
λ_{41}	0	100	.218	1.507	4.880	11.634	-.107	.397	-.005	.070	-.005	.070
		200	.188	1.104	4.668	10.970	-.103	.399	-.001	.049	-.001	.049
.630		500	.195	1.258	4.252	9.601	-.100	.402	-.002	.031	-.002	.031
	.5	100	.018	.245	.633	4.785	-.033	.227	-.004	.072	-.004	.072
		200	.008	.132	.075	1.636	-.016	.159	.001	.048	.001	.049
		500	-.001	.075	-.004	.078	-.006	.101	-.002	.032	-.002	.032
	1	100	-.001	.089	-.005	.090	-.010	.109	-.002	.070	-.002	.071
		200	-.001	.064	-.001	.064	-.005	.074	-.002	.049	-.002	.050
		500	-.001	.039	-.001	.038	-.002	.046	-.001	.031	-.002	.032
λ_{41b}	0	100	N/A	N/A	N/A	N/A	-.096	.408	-.002	.075	-.002	.074
		200	N/A	N/A	N/A	N/A	-.122	.402	-.003	.049	-.003	.049
.630		500	N/A	N/A	N/A	N/A	-.120	.395	.001	.031	.000	.031
	.5	100	N/A	N/A	N/A	N/A	-.034	.229	-.001	.071	-.000	.071
		200	N/A	N/A	N/A	N/A	-.009	.164	-.001	.051	-.001	.051
		500	N/A	N/A	N/A	N/A	-.011	.104	-.000	.030	-.000	.030
	1	100	N/A	N/A	N/A	N/A	-.009	.109	-.004	.070	-.003	.071
		200	N/A	N/A	N/A	N/A	-.003	.076	-.000	.049	-.000	.050
		500	N/A	N/A	N/A	N/A	-.003	.049	-.001	.030	-.001	.030
λ_{42}	0	100	-.073	.768	4.594	11.563	-.273	.366	-.002	.050	-.001	.049
		200	.118	4.488	4.314	10.964	-.258	.346	-.000	.034	.000	.034
.840		500	.022	1.581	3.658	9.464	-.237	.356	-.000	.021	-.000	.021
	.5	100	.078	.813	1.715	7.406	-.047	.177	.000	.048	.001	.048
		200	.021	.228	.383	3.362	-.025	.122	-.000	.034	.001	.034
		500	.008	.103	.012	.107	-.002	.073	.000	.021	.000	.021
	1	100	.003	.102	.009	.113	-.007	.070	-.001	.046	-.001	.050
		200	.000	.064	.001	.063	-.005	.052	-.001	.031	-.000	.034
		500	.000	.040	.000	.039	-.000	.032	.000	.019	.000	.021

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{42b}	0	100	N/A	N/A	N/A	N/A	-.247	.359	-.001	.048	-.001	.047
		200	N/A	N/A	N/A	N/A	-.240	.373	-.001	.035	-.001	.035
.840		500	N/A	N/A	N/A	N/A	-.242	.360	-.001	.022	-.000	.022
	.5	100	N/A	N/A	N/A	N/A	-.043	.179	-.000	.048	.000	.047
		200	N/A	N/A	N/A	N/A	-.015	.112	-.000	.033	.000	.034
		500	N/A	N/A	N/A	N/A	-.008	.074	-.001	.022	-.000	.022
	1	100	N/A	N/A	N/A	N/A	-.004	.074	-.001	.045	-.001	.048
		200	N/A	N/A	N/A	N/A	-.001	.049	-.001	.031	-.001	.034
		500	N/A	N/A	N/A	N/A	-.002	.032	-.000	.020	.000	.023
λ_{51}	0	100	-.069	.358	.001	.063	-.074	.356	-.001	.061	-.001	.061
		200	-.080	.354	-.000	.044	-.077	.360	-.003	.044	-.003	.044
.650		500	-.062	.351	.001	.029	-.073	.347	-.001	.028	-.001	.028
	.5	100	-.004	.198	-.001	.060	-.010	.212	-.003	.062	-.003	.062
		200	-.008	.154	-.001	.043	-.004	.150	.000	.042	.000	.042
		500	.000	.096	-.000	.028	-.010	.098	-.002	.028	-.002	.028
	1	100	-.003	.120	-.001	.063	-.007	.123	-.003	.065	-.002	.065
		200	-.003	.090	.001	.044	-.001	.086	-.001	.045	-.001	.045
		500	-.000	.055	.001	.027	-.007	.056	-.003	.028	-.003	.028
λ_{52}	0	100	-.063	.340	-.001	.056	-.065	.351	-.003	.063	-.003	.063
		200	-.069	.344	-.002	.043	-.088	.347	-.001	.041	-.001	.041
.670		500	-.062	.347	-.000	.026	-.075	.338	-.000	.027	-.000	.027
	.5	100	-.030	.194	-.003	.057	-.038	.204	-.005	.059	-.004	.059
		200	-.004	.140	.001	.043	-.005	.143	.000	.044	-.000	.044
		500	-.007	.095	-.000	.027	-.003	.098	.000	.026	.000	.026
	1	100	-.010	.120	-.004	.061	-.015	.123	-.004	.061	-.004	.061
		200	-.002	.085	-.000	.042	-.000	.086	-.001	.045	-.001	.045
		500	-.002	.052	-.001	.026	.000	.056	.000	.026	.000	.026
λ_{53}	0	100	-.118	.326	.001	.049	-.104	.296	.002	.048	.002	.048
		200	-.123	.330	-.001	.033	-.110	.319	-.002	.034	-.002	.034
.750		500	-.116	.310	-.000	.022	-.114	.325	.000	.022	-.000	.022
	.5	100	-.031	.182	-.002	.050	-.022	.171	-.001	.046	-.001	.046
		200	-.003	.122	.001	.034	-.018	.133	-.002	.035	-.002	.035
		500	-.008	.079	-.001	.023	-.002	.083	.001	.022	.001	.022
	1	100	-.011	.100	-.001	.048	-.002	.099	-.000	.047	-.000	.047
		200	-.002	.072	-.000	.035	-.008	.075	-.002	.035	-.002	.035
		500	-.003	.046	-.001	.022	-.000	.047	.000	.021	.000	.021
λ_{54}	0	100	-.112	.326	.000	.050	-.120	.321	.001	.049	.001	.049
		200	-.101	.318	-.000	.035	-.115	.323	-.000	.035	-.001	.035
.750		500	-.115	.323	-.001	.022	-.102	.326	-.000	.021	-.000	.021
	.5	100	-.022	.171	-.002	.050	-.029	.173	-.002	.048	-.002	.048
		200	-.019	.132	-.000	.034	-.018	.135	-.000	.035	-.000	.035
		500	-.005	.084	-.000	.023	-.006	.084	-.001	.021	-.001	.021
	1	100	-.006	.103	-.002	.050	-.010	.103	-.001	.047	-.001	.047
		200	-.006	.073	-.002	.036	-.007	.075	-.001	.037	-.002	.037
		500	-.003	.047	-.001	.022	-.002	.047	-.001	.021	-.001	.021
λ_{55}	0	100	-.185	.262	.000	.028	-.183	.265	-.001	.026	-.001	.026
		200	-.180	.253	-.001	.020	-.192	.278	.000	.019	.000	.019
.900		500	-.187	.271	-.000	.012	-.189	.264	.001	.012	.001	.012
	.5	100	-.044	.130	-.001	.028	-.046	.132	-.002	.027	-.003	.027
		200	-.026	.092	-.001	.019	-.019	.091	.000	.019	.000	.019
		500	-.008	.061	-.000	.011	-.008	.060	.000	.011	.000	.012
	1	100	-.012	.072	.000	.026	-.014	.073	-.002	.027	-.002	.027
		200	-.008	.050	-.001	.019	-.006	.050	-.000	.018	.000	.019
		500	-.002	.033	-.001	.012	-.002	.032	-.000	.011	-.000	.012

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{56}	0	100	-.196	.276	-.000	.026	-.175	.250	-.000	.028	-.001	.028
		200	-.198	.268	-.000	.019	-.188	.281	-.000	.019	.000	.019
.900		500	-.186	.265	.000	.012	-.186	.253	.000	.011	.000	.011
	.5	100	-.044	.134	-.001	.027	-.043	.121	-.000	.026	-.000	.026
		200	-.026	.090	-.000	.019	-.026	.093	.000	.019	.000	.019
		500	-.010	.060	.000	.011	-.010	.061	.000	.012	.000	.012
	1	100	-.012	.072	-.001	.026	-.009	.070	-.000	.026	-.001	.027
		200	-.007	.054	-.001	.019	-.008	.051	-.001	.019	-.001	.020
		500	-.002	.032	.000	.011	-.003	.032	-.001	.011	-.000	.011

Note: N/A = not estimated.

Table 3 Loadings over 1000 replications for non-normal data

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{11}	0	100	.107	.743	2.540	7.480	-.061	.355	-.002	.028	-.003	.028
		200	.123	1.001	2.547	7.346	-.054	.352	-.001	.020	-.001	.020
.870		500	.114	.773	2.269	6.470	-.063	.346	-.001	.012	-.001	.012
	.5	100	.081	.554	.209	2.340	-.065	.327	-.001	.028	-.002	.028
		200	.115	.943	.087	1.529	-.043	.303	-.000	.020	-.001	.020
		500	.012	.200	-.001	.045	-.027	.197	-.001	.012	-.001	.013
	1	100	.002	.070	-.001	.049	-.008	.086	-.002	.027	-.002	.028
		200	-.001	.051	-.002	.035	-.001	.057	-.000	.019	-.001	.019
		500	-.001	.029	-.000	.020	-.003	.037	-.001	.012	-.001	.012
λ_{11b}	0	100	N/A	N/A	N/A	N/A	-.084	.355	-.002	.028	-.002	.028
		200	N/A	N/A	N/A	N/A	-.068	.350	.000	.020	-.000	.020
.870		500	N/A	N/A	N/A	N/A	-.065	.350	-.000	.012	-.000	.012
	.5	100	N/A	N/A	N/A	N/A	-.068	.318	-.001	.029	-.001	.029
		200	N/A	N/A	N/A	N/A	-.038	.294	-.000	.020	-.000	.020
		500	N/A	N/A	N/A	N/A	-.023	.220	-.000	.012	-.001	.013
	1	100	N/A	N/A	N/A	N/A	-.003	.089	-.001	.029	-.002	.029
		200	N/A	N/A	N/A	N/A	-.002	.059	-.000	.019	-.000	.020
		500	N/A	N/A	N/A	N/A	-.000	.038	-.000	.012	-.001	.013
λ_{12}	0	100	.031	.908	2.596	8.092	-.109	.312	-.000	.017	.000	.017
		200	.010	.654	2.163	6.864	-.120	.297	-.001	.012	-.001	.012
.940		500	.029	.966	1.843	5.877	-.098	.297	.000	.007	.000	.007
	.5	100	.052	.878	.209	2.246	-.085	.289	.000	.017	.001	.017
		200	.027	.717	.034	.856	-.077	.244	-.001	.012	-.001	.012
		500	.053	1.062	.002	.048	-.031	.173	-.000	.007	-.000	.007
	1	100	.001	.074	.001	.049	-.005	.069	.000	.017	.000	.017
		200	.002	.052	.001	.033	-.002	.046	-.001	.012	-.001	.012
		500	.000	.030	-.001	.020	-.001	.028	-.000	.007	.000	.007
λ_{12b}	0	100	N/A	N/A	N/A	N/A	-.112	.296	-.001	.017	-.001	.017
		200	N/A	N/A	N/A	N/A	-.109	.297	-.001	.012	-.001	.012
.940		500	N/A	N/A	N/A	N/A	-.105	.297	.000	.007	.000	.008
	.5	100	N/A	N/A	N/A	N/A	-.105	.278	-.000	.017	.000	.017
		200	N/A	N/A	N/A	N/A	-.070	.239	-.001	.012	-.001	.012
		500	N/A	N/A	N/A	N/A	-.027	.171	-.000	.007	-.000	.007
	1	100	N/A	N/A	N/A	N/A	-.001	.067	-.000	.017	-.000	.017
		200	N/A	N/A	N/A	N/A	-.003	.047	-.001	.011	-.001	.012
		500	N/A	N/A	N/A	N/A	-.001	.028	-.000	.007	-.000	.007

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{21}	0	100	-.148	.302	.001	.108	-.141	.294	-.007	.108	-.006	.107
		200	-.151	.291	.001	.075	-.149	.284	-.002	.076	-.002	.076
.410		500	-.150	.290	-.002	.048	-.160	.284	.001	.046	.001	.046
	.5	100	-.032	.193	-.000	.105	-.034	.196	-.005	.106	-.004	.109
		200	-.022	.143	-.003	.072	-.020	.145	-.004	.070	-.003	.071
		500	-.005	.094	.000	.044	-.006	.089	-.001	.046	-.001	.047
	1	100	-.008	.123	.000	.097	-.006	.121	-.001	.098	-.003	.104
		200	.001	.088	.001	.066	-.005	.084	-.003	.068	-.003	.074
		500	-.000	.054	.001	.043	-.005	.053	-.003	.043	-.002	.046
λ_{22}	0	100	-.160	.293	-.002	.109	-.153	.291	-.010	.111	-.009	.111
		200	-.153	.291	-.002	.074	-.157	.291	.002	.075	.003	.075
.410		500	-.153	.282	-.002	.045	-.146	.295	-.004	.047	-.004	.047
	.5	100	-.025	.196	-.003	.105	-.034	.194	-.006	.104	-.006	.104
		200	-.022	.150	-.005	.073	-.007	.140	.003	.075	.003	.077
		500	-.007	.091	-.002	.044	-.003	.086	-.002	.045	-.003	.047
	1	100	-.007	.124	-.003	.096	-.007	.119	-.002	.097	-.003	.107
		200	-.005	.085	-.003	.067	-.005	.082	.001	.068	.003	.075
		500	.000	.057	-.001	.044	-.001	.052	-.000	.041	-.002	.047
λ_{23}	0	100	-.192	.295	-.008	.100	-.190	.288	-.002	.104	-.001	.103
		200	-.194	.286	-.004	.074	-.183	.289	-.003	.072	-.003	.071
.470		500	-.206	.287	-.000	.046	-.186	.288	-.002	.043	-.002	.043
	.5	100	-.044	.189	-.008	.102	-.031	.180	.002	.100	.001	.103
		200	-.019	.141	-.002	.071	-.013	.131	-.001	.067	-.001	.069
		500	-.006	.088	.001	.042	-.009	.085	-.002	.041	-.002	.043
	1	100	-.013	.116	-.006	.095	.000	.110	.004	.090	.004	.103
		200	-.007	.082	-.002	.064	-.003	.076	-.002	.062	-.001	.069
		500	-.002	.053	.000	.040	-.000	.048	-.001	.039	-.001	.043
λ_{24}	0	100	-.290	.288	-.002	.095	-.268	.292	-.005	.095	-.005	.094
		200	-.257	.286	.002	.063	-.291	.284	-.003	.062	-.003	.061
.600		500	-.284	.290	-.001	.040	-.293	.283	-.000	.040	-.000	.039
	.5	100	-.051	.169	-.002	.089	-.043	.159	.001	.085	.003	.091
		200	-.034	.122	-.002	.059	-.026	.120	-.003	.061	-.003	.063
		500	-.014	.078	-.001	.038	-.014	.078	.000	.038	.002	.039
	1	100	-.013	.097	-.003	.077	-.010	.100	.002	.078	-.000	.091
		200	-.008	.070	-.002	.053	-.006	.069	-.002	.053	-.002	.063
		500	-.004	.047	-.002	.035	-.002	.044	.000	.034	.000	.040
λ_{25}	0	100	-.311	.293	-.001	.093	-.283	.293	-.003	.096	-.004	.093
		200	-.299	.283	.000	.063	-.294	.276	-.001	.063	-.001	.063
.630		500	-.288	.267	-.002	.040	-.295	.286	-.000	.037	-.000	.037
	.5	100	-.061	.171	.001	.086	-.051	.164	-.005	.086	-.007	.090
		200	-.024	.120	.003	.061	-.032	.112	-.000	.057	-.000	.062
		500	-.012	.077	-.001	.037	-.010	.074	-.002	.037	-.002	.039
	1	100	-.010	.094	.003	.074	-.018	.095	-.007	.075	-.005	.091
		200	-.005	.070	.003	.053	-.004	.065	.001	.050	.002	.061
		500	-.005	.045	-.002	.034	-.005	.042	-.003	.032	-.002	.039
λ_{26}	0	100	-.320	.288	-.002	.093	-.298	.291	-.000	.092	-.001	.090
		200	-.303	.288	-.002	.060	-.310	.291	-.001	.060	-.001	.059
.650		500	-.299	.281	-.000	.039	-.323	.275	-.003	.038	-.003	.038
	.5	100	-.055	.161	-.003	.086	-.062	.158	-.003	.088	-.003	.090
		200	-.022	.117	-.001	.058	-.026	.110	-.001	.057	-.001	.060
		500	-.009	.077	.002	.037	-.011	.070	-.001	.036	-.002	.038
	1	100	-.014	.096	-.002	.073	-.014	.094	-.003	.078	-.000	.093
		200	-.008	.066	-.002	.051	-.005	.066	-.000	.050	-.001	.061
		500	-.003	.045	.001	.034	-.003	.040	-.001	.032	-.001	.038

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{31}	0	100	-.058	.393	-.003	.086	-.088	.399	-.005	.084	-.003	.082
		200	-.048	.396	-.000	.060	-.044	.437	.000	.059	.001	.059
.490		500	-.065	.380	-.000	.039	-.081	.400	-.000	.037	-.000	.037
	.5	100	-.068	.352	-.003	.089	-.067	.354	-.000	.086	.001	.085
		200	-.031	.304	-.002	.060	-.019	.286	-.002	.059	-.002	.058
		500	-.020	.211	-.000	.037	-.008	.203	.001	.037	.001	.037
	1	100	-.030	.244	-.003	.088	-.012	.239	.000	.086	.001	.085
		200	-.015	.171	-.002	.060	-.015	.160	-.002	.059	-.002	.058
		500	-.005	.101	-.000	.037	-.008	.105	.001	.037	.001	.037
λ_{32}	0	100	-.128	.387	-.002	.074	-.114	.394	-.005	.075	-.004	.074
		200	-.124	.403	-.002	.053	-.131	.391	-.002	.052	-.001	.052
.600		500	-.127	.404	-.002	.033	-.138	.389	-.000	.032	-.000	.032
	.5	100	-.089	.333	-.003	.073	-.090	.338	-.004	.074	-.003	.073
		200	-.074	.282	-.002	.052	-.076	.292	-.002	.053	-.002	.053
		500	-.039	.200	.001	.033	-.021	.186	-.000	.032	-.000	.032
	1	100	-.034	.206	-.003	.072	-.039	.217	-.004	.073	-.003	.073
		200	-.017	.147	-.002	.052	-.018	.149	-.002	.053	-.002	.053
		500	-.001	.088	.001	.033	-.004	.090	-.000	.032	-.000	.032
λ_{33}	0	100	-.259	.368	-.001	.060	-.267	.373	-.003	.060	-.000	.056
		200	-.264	.374	.001	.041	-.274	.356	-.000	.040	.001	.040
.800		500	-.239	.367	.001	.026	-.247	.366	.000	.024	.001	.024
	.5	100	-.173	.304	-.000	.059	-.181	.305	-.004	.057	-.001	.055
		200	-.120	.250	-.000	.040	-.106	.246	-.001	.040	.000	.040
		500	-.035	.160	.001	.025	-.039	.149	.001	.024	.001	.024
	1	100	-.044	.173	-.000	.056	-.054	.170	-.003	.054	-.001	.055
		200	-.022	.116	-.000	.038	-.020	.110	-.001	.039	.000	.040
		500	-.008	.069	.001	.024	-.005	.069	.001	.023	.001	.024
λ_{34}	0	100	-.342	.362	.000	.057	-.341	.348	.004	.055	.000	.049
		200	-.333	.344	.001	.037	-.327	.337	.000	.036	-.001	.034
.900		500	-.334	.360	-.000	.022	-.329	.348	-.000	.023	-.001	.022
	.5	100	-.219	.312	-.001	.055	-.213	.308	.003	.053	.001	.050
		200	-.123	.244	.001	.036	-.136	.243	-.001	.035	-.001	.035
		500	-.044	.141	.000	.021	-.045	.141	-.000	.023	-.001	.023
	1	100	-.059	.160	-.001	.052	-.057	.155	.002	.048	.001	.050
		200	-.020	.098	.001	.034	-.018	.102	-.000	.034	-.001	.035
		500	-.007	.063	.000	.020	-.007	.064	-.000	.021	-.001	.023
λ_{41}	0	100	.225	1.542	4.875	11.864	-.105	.393	-.005	.070	-.005	.070
		200	.167	1.123	4.849	11.164	-.108	.408	-.001	.049	-.002	.049
.630		500	.218	1.194	4.002	9.325	-.108	.399	-.002	.031	-.002	.031
	.5	100	.016	.229	.934	5.645	-.035	.229	-.004	.072	-.003	.072
		200	.008	.130	.096	1.741	-.017	.161	.001	.049	.001	.049
		500	-.001	.074	-.004	.077	-.006	.102	-.002	.032	-.002	.032
	1	100	-.002	.090	-.005	.090	-.011	.108	-.002	.070	-.002	.071
		200	-.001	.064	-.001	.064	-.005	.075	-.002	.049	-.002	.050
		500	-.001	.039	-.001	.038	-.002	.047	-.001	.031	-.001	.032
λ_{41b}	0	100	N/A	N/A	N/A	N/A	-.107	.416	-.001	.074	-.001	.074
		200	N/A	N/A	N/A	N/A	-.119	.402	-.003	.050	-.003	.050
.630		500	N/A	N/A	N/A	N/A	-.108	.397	.000	.031	-.000	.031
	.5	100	N/A	N/A	N/A	N/A	-.033	.226	-.000	.071	-.000	.071
		200	N/A	N/A	N/A	N/A	-.007	.164	-.000	.052	-.001	.052
		500	N/A	N/A	N/A	N/A	-.011	.104	-.000	.030	-.000	.030
	1	100	N/A	N/A	N/A	N/A	-.008	.108	-.003	.070	-.003	.071
		200	N/A	N/A	N/A	N/A	-.002	.077	.000	.049	-.000	.050
		500	N/A	N/A	N/A	N/A	-.003	.049	-.001	.030	-.001	.030

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{42}	0	100	-.017	.907	4.954	12.049	-.269	.362	-.002	.050	-.001	.049
		200	-.004	1.423	4.339	11.042	-.253	.351	-.000	.034	.000	.034
.840		500	-.046	.890	3.404	9.181	-.247	.367	-.000	.021	-.000	.021
	.5	100	.052	.559	1.521	6.870	-.047	.176	.001	.048	.001	.048
		200	.020	.217	.338	3.191	-.025	.122	-.000	.033	.001	.034
		500	.008	.104	.013	.108	-.003	.073	.000	.021	.000	.021
	1	100	.004	.103	.009	.103	-.006	.070	-.001	.045	-.000	.050
		200	.000	.064	.001	.064	-.005	.052	-.001	.031	-.001	.034
		500	-.000	.041	-.000	.039	.000	.032	.000	.019	.000	.021
λ_{42b}	0	100	N/A	N/A	N/A	N/A	-.253	.364	-.001	.049	-.001	.048
		200	N/A	N/A	N/A	N/A	-.233	.365	-.001	.035	-.001	.035
.840		500	N/A	N/A	N/A	N/A	-.252	.357	-.001	.022	-.000	.022
	.5	100	N/A	N/A	N/A	N/A	-.042	.174	-.000	.048	-.000	.048
		200	N/A	N/A	N/A	N/A	-.016	.111	-.000	.033	-.000	.034
		500	N/A	N/A	N/A	N/A	-.008	.073	-.000	.022	.000	.022
	1	100	N/A	N/A	N/A	N/A	-.003	.073	-.001	.045	-.001	.049
		200	N/A	N/A	N/A	N/A	-.002	.049	-.001	.031	-.001	.034
		500	N/A	N/A	N/A	N/A	-.001	.032	-.000	.020	.000	.022
λ_{51}	0	100	-.070	.364	.001	.063	-.085	.371	-.001	.061	-.001	.061
		200	-.082	.358	-.000	.044	-.069	.355	-.003	.044	-.003	.044
.650		500	-.064	.356	.001	.029	-.065	.355	-.001	.028	-.001	.028
	.5	100	-.003	.195	-.001	.060	-.012	.213	-.003	.062	-.003	.062
		200	-.010	.157	-.001	.043	-.002	.149	.000	.043	-.000	.043
		500	-.001	.096	.000	.028	-.010	.096	-.002	.027	-.002	.027
	1	100	-.003	.119	-.001	.062	-.009	.123	-.003	.065	-.003	.065
		200	-.004	.091	.001	.044	-.001	.086	-.000	.045	-.000	.045
		500	-.001	.055	.001	.027	-.007	.055	-.002	.028	-.002	.028
λ_{52}	0	100	-.069	.335	-.001	.056	-.065	.358	-.003	.063	-.003	.063
		200	-.064	.344	-.002	.043	-.091	.347	-.001	.041	-.002	.041
.670		500	-.067	.338	-.000	.026	-.087	.352	-.000	.027	-.000	.027
	.5	100	-.028	.193	-.003	.057	-.038	.208	-.005	.060	-.004	.059
		200	-.004	.141	.000	.043	-.005	.144	-.000	.044	-.000	.044
		500	-.006	.095	-.000	.027	-.003	.097	.000	.026	.000	.027
	1	100	-.009	.119	-.003	.061	-.015	.121	-.004	.061	-.004	.061
		200	-.002	.085	-.000	.042	.000	.086	-.001	.044	-.002	.044
		500	-.002	.052	-.001	.026	.000	.055	.000	.026	.000	.026
λ_{53}	0	100	-.123	.327	.000	.050	-.109	.301	.002	.048	.001	.048
		200	-.122	.326	-.001	.033	-.112	.327	-.002	.034	-.002	.034
.750		500	-.112	.322	-.000	.022	-.116	.323	-.000	.022	-.000	.022
	.5	100	-.031	.181	-.002	.050	-.024	.177	-.001	.047	-.001	.047
		200	-.003	.122	.001	.034	-.018	.133	-.001	.035	-.002	.035
		500	-.007	.080	-.001	.023	-.001	.082	.000	.022	.000	.022
	1	100	-.011	.101	-.001	.047	-.001	.098	-.000	.047	-.001	.047
		200	-.002	.073	-.000	.035	-.007	.074	-.002	.035	-.002	.035
		500	-.003	.046	-.001	.022	-.000	.047	.000	.021	-.000	.021
λ_{54}	0	100	-.108	.330	.000	.049	-.119	.321	.001	.049	.001	.049
		200	-.109	.337	-.000	.035	-.121	.322	-.001	.034	-.001	.034
.750		500	-.116	.322	-.001	.022	-.098	.321	-.000	.021	-.000	.021
	.5	100	-.020	.170	-.002	.050	-.029	.176	-.002	.048	-.002	.048
		200	-.020	.132	-.000	.035	-.018	.133	-.000	.035	-.000	.035
		500	-.004	.083	-.001	.023	-.006	.084	-.001	.021	-.001	.021
	1	100	-.006	.103	-.002	.049	-.010	.102	-.001	.047	-.001	.047
		200	-.006	.074	-.001	.036	-.007	.074	-.001	.036	-.002	.036
		500	-.002	.047	-.001	.022	-.002	.047	-.001	.022	-.001	.022

Param.	Scale	N	Small Model				Large Model					
			PLSc		ML-CFA		PLSc		ML-CFA		minres	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
λ_{55}	0	100	-.187	.262	.000	.028	-.184	.267	-.001	.026	-.001	.026
		200	-.189	.263	-.001	.019	-.191	.266	.000	.019	.000	.019
.900		500	-.194	.273	-.000	.012	-.185	.262	.001	.012	.001	.012
	.5	100	-.046	.128	-.001	.028	-.048	.133	-.002	.027	-.002	.027
		200	-.025	.091	-.001	.019	-.019	.091	.000	.018	.000	.019
		500	-.008	.060	-.000	.011	-.008	.060	.000	.012	.001	.012
	1	100	-.013	.072	.000	.026	-.015	.074	-.002	.027	-.002	.027
		200	-.008	.050	-.001	.019	-.007	.051	-.000	.018	-.000	.019
		500	-.002	.032	-.001	.012	-.002	.032	-.000	.011	.000	.012
λ_{56}	0	100	-.195	.277	-.000	.026	-.179	.262	-.001	.028	-.001	.028
		200	-.202	.273	-.000	.019	-.190	.274	-.000	.019	-.000	.019
.900		500	-.197	.271	.001	.012	-.188	.253	.000	.011	.000	.011
	.5	100	-.044	.132	-.002	.027	-.046	.134	-.000	.026	-.001	.026
		200	-.026	.090	-.000	.019	-.026	.095	.000	.018	.000	.018
		500	-.010	.060	.000	.012	-.009	.061	.000	.012	.000	.012
	1	100	-.013	.071	-.001	.026	-.009	.070	-.001	.026	-.001	.027
		200	-.007	.054	-.001	.019	-.008	.052	-.001	.019	-.001	.020
		500	-.003	.032	.000	.011	-.003	.032	-.001	.011	-.000	.012

Note: N/A = not estimated.

Table 4 Estimation error of reliabilities with normal data for Large Model

Variable	Scale	N	PLS composites						Unit weighted composites					
			CR_U		CR_W		Alpha		CR_U		CR_W		Alpha	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ξ1	0	100	-.005	.023	.043	.059	.002	.012	-.000	.009	-.000	.009	-.001	.009
		200	-.003	.036	.047	.082	.004	.056	.000	.006	.000	.006	-.000	.006
		500	-.005	.031	.044	.062	.002	.009	.000	.004	.000	.004	-.000	.004
	.5	100	-.002	.009	.015	.019	-.001	.009	-.000	.009	-.000	.009	-.001	.009
		200	-.001	.006	.008	.010	-.001	.006	.000	.006	.000	.006	-.000	.006
		500	-.001	.004	.004	.005	-.002	.004	.000	.004	-.000	.004	-.000	.004
	1	100	-.002	.009	.002	.009	-.002	.009	-.000	.009	-.000	.009	-.001	.009
		200	-.001	.006	.001	.006	-.002	.006	.000	.006	.000	.006	-.000	.006
		500	-.001	.004	.000	.004	-.002	.004	.000	.004	.000	.004	-.000	.004
ξ2	0	100	-.113	.109	.052	.127	.108	.139	-.003	.047	-.005	.048	-.012	.049
		200	-.115	.104	.049	.130	.116	.137	.000	.032	-.000	.032	-.007	.033
		500	-.114	.099	.048	.121	.110	.129	-.000	.020	-.000	.020	-.007	.021
	.5	100	-.039	.054	.016	.051	-.021	.050	-.003	.048	-.004	.048	-.012	.049
		200	-.028	.036	.011	.034	-.021	.034	.000	.032	-.000	.032	-.007	.033
		500	-.023	.022	.004	.021	-.024	.022	-.000	.020	-.000	.020	-.007	.021
	1	100	-.030	.048	.001	.047	-.034	.050	-.004	.047	-.004	.047	-.012	.049
		200	-.024	.033	.002	.031	-.028	.034	-.000	.031	-.001	.031	-.007	.033
		500	-.022	.021	.000	.020	-.027	.022	-.001	.020	-.001	.020	-.007	.021
η3	0	100	-.066	.122	.088	.242	.026	.131	.000	.030	-.001	.030	-.016	.034
		200	-.064	.112	.076	.210	.021	.113	.000	.021	-.000	.021	-.015	.024
		500	-.066	.115	.077	.212	.019	.105	.000	.013	-.000	.013	-.015	.015
	.5	100	-.068	.107	.052	.132	-.003	.084	.001	.029	.000	.029	-.016	.033
		200	-.053	.080	.053	.127	-.014	.064	.000	.021	.000	.021	-.015	.024
		500	-.045	.050	.035	.081	-.030	.048	-.000	.013	-.000	.013	-.015	.015
	1	100	-.054	.077	.035	.087	-.024	.065	.001	.029	.000	.029	-.016	.033
		200	-.046	.048	.026	.060	-.038	.037	.000	.021	-.000	.020	-.015	.024
		500	-.041	.026	.014	.033	-.043	.026	-.000	.013	-.000	.013	-.015	.015
η4	0	100	-.036	.098	.097	.232	.030	.107	-.001	.027	-.001	.026	-.008	.028
		200	-.043	.098	.092	.208	.026	.092	.000	.019	.000	.019	-.006	.020
		500	-.034	.085	.098	.202	.023	.087	.000	.012	.000	.012	-.006	.013
	.5	100	-.026	.052	.041	.070	-.008	.044	-.001	.026	-.001	.026	-.008	.028
		200	-.021	.034	.028	.040	-.013	.025	.000	.018	-.000	.018	-.006	.020
		500	-.018	.016	.014	.023	-.020	.015	.000	.012	.000	.012	-.006	.013
	1	100	-.020	.029	.006	.029	-.024	.030	-.001	.026	-.001	.026	-.008	.028
		200	-.017	.019	.004	.020	-.022	.020	.000	.018	.000	.018	-.006	.020
		500	-.017	.013	.002	.013	-.022	.013	.000	.012	.000	.012	-.006	.013
η5	0	100	-.040	.069	.052	.081	.012	.041	-.000	.016	-.000	.015	-.004	.016
		200	-.045	.079	.051	.088	.015	.050	.000	.011	-.000	.011	-.003	.012
		500	-.042	.071	.056	.087	.013	.046	-.000	.007	-.000	.007	-.003	.007
	.5	100	-.016	.020	.015	.023	-.011	.018	-.000	.016	-.000	.016	-.004	.017
		200	-.013	.012	.008	.013	-.012	.012	.000	.011	.000	.011	-.003	.011
		500	-.012	.007	.003	.008	-.013	.007	-.000	.007	-.000	.007	-.003	.007
	1	100	-.012	.015	.001	.015	-.015	.016	-.000	.016	-.000	.015	-.004	.016
		200	-.011	.011	.001	.011	-.014	.011	.000	.011	.000	.010	-.003	.012
		500	-.011	.007	.000	.007	-.014	.007	-.000	.007	.000	.006	-.003	.007

Note: Loadings for PLS composites are estimated with PLSc and loadings for unit weighted composites are estimated with ML-CFA.

Table 5 Estimation error of reliabilities with non-normal data for Small Model

Variable	Scale	N	PLS composites						Unit weighted composites					
			CR_U		CR_W		Alpha		CR_U		CR_W		Alpha	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ξ1	0	100	.125	1.482	.210	1.031	.007	.086	39.676	89.480	39.839	89.993	-.002	.020
		200	.093	1.300	.165	.805	.003	.021	33.200	71.734	33.256	71.886	-.002	.013
		500	.061	.311	.188	1.066	.002	.018	25.384	54.363	25.399	54.403	-.002	.009
	.5	100	.011	.041	.039	.114	-.003	.022	2.429	23.863	2.439	23.986	-.002	.020
		200	.007	.060	.026	.197	-.003	.014	.433	8.180	.434	8.189	-.002	.013
		500	-.000	.010	.007	.016	-.004	.009	.002	.010	.002	.010	-.002	.009
	1	100	-.001	.020	.004	.022	-.004	.021	.001	.020	.001	.020	-.002	.020
		200	-.002	.013	.002	.014	-.004	.014	.000	.013	.000	.013	-.002	.013
		500	-.003	.009	.001	.009	-.004	.009	-.000	.009	-.000	.009	-.002	.009
ξ2	0	100	-.116	.111	.054	.139	.119	.141	.000	.048	-.001	.049	-.008	.049
		200	-.116	.106	.048	.125	.109	.130	.000	.032	-.000	.033	-.007	.033
		500	-.122	.106	.042	.115	.116	.136	-.000	.021	-.000	.021	-.007	.022
	.5	100	-.037	.055	.021	.053	-.015	.051	.000	.047	-.001	.047	-.008	.049
		200	-.027	.035	.012	.035	-.020	.034	.000	.032	-.000	.032	-.007	.033
		500	-.023	.022	.005	.022	-.024	.022	-.000	.021	-.000	.021	-.006	.022
	1	100	-.028	.047	.004	.045	-.031	.049	-.001	.046	-.001	.046	-.009	.048
		200	-.023	.032	.002	.031	-.028	.033	-.000	.031	-.000	.031	-.007	.033
		500	-.022	.021	.000	.021	-.027	.022	-.000	.021	-.000	.020	-.006	.022
η3	0	100	-.061	.123	.090	.231	.029	.150	.000	.030	-.001	.030	-.016	.033
		200	-.058	.118	.096	.263	.030	.134	-.000	.022	-.000	.022	-.016	.025
		500	-.060	.119	.100	.286	.030	.126	.000	.013	.000	.013	-.015	.015
	.5	100	-.059	.104	.076	.274	.006	.104	.000	.030	-.001	.030	-.016	.034
		200	-.055	.082	.051	.129	-.012	.071	-.000	.022	-.000	.022	-.016	.025
		500	-.049	.054	.032	.059	-.030	.044	.000	.013	-.000	.013	-.015	.015
	1	100	-.052	.074	.044	.134	-.025	.065	.000	.030	-.000	.030	-.016	.034
		200	-.045	.045	.028	.077	-.036	.043	-.000	.022	-.000	.022	-.016	.025
		500	-.042	.030	.016	.041	-.044	.026	-.000	.013	-.000	.012	-.015	.015
η4	0	100	.377	2.095	.809	4.139	.009	.114	114.486	204.100	115.591	206.757	-.020	.060
		200	.670	4.721	1.247	7.536	.020	.111	98.905	171.021	99.345	171.991	-.018	.043
		500	.901	10.264	1.357	9.972	.016	.107	68.564	124.292	68.688	124.588	-.017	.026
	.5	100	.151	1.136	.399	2.550	-.024	.078	32.788	125.404	33.118	127.022	-.020	.057
		200	.081	1.429	.194	1.658	-.031	.054	5.460	50.155	5.489	50.474	-.018	.042
		500	-.008	.072	.043	.201	-.037	.032	.011	.050	.011	.050	-.017	.026
	1	100	-.020	.065	.020	.106	-.044	.063	.271	8.414	.272	8.436	-.020	.058
		200	-.024	.044	.006	.055	-.042	.047	.000	.044	.000	.044	-.018	.043
		500	-.025	.027	.001	.033	-.041	.028	-.001	.027	-.001	.027	-.017	.026
η5	0	100	-.044	.081	.056	.109	.021	.078	-.000	.016	-.000	.015	-.004	.016
		200	-.040	.087	.054	.102	.017	.086	-.000	.011	-.000	.010	-.004	.011
		500	-.042	.084	.055	.135	.017	.079	-.000	.007	-.000	.007	-.003	.007
	.5	100	-.017	.021	.015	.022	-.011	.018	-.000	.015	-.001	.015	-.004	.016
		200	-.014	.012	.009	.014	-.012	.012	-.000	.010	-.000	.010	-.004	.011
		500	-.012	.007	.003	.008	-.013	.007	-.000	.007	-.000	.007	-.003	.007
	1	100	-.012	.015	.001	.015	-.015	.016	-.000	.015	-.001	.015	-.004	.016
		200	-.012	.010	.000	.010	-.015	.011	-.000	.010	-.000	.010	-.004	.011
		500	-.011	.007	-.000	.006	-.014	.007	-.000	.007	-.000	.006	-.003	.007

***Note**: Loadings for PLS composites are estimated with PLSc and loadings for unit weighted composites are estimated with ML-CFA.*

Table 6 Estimation error of reliabilities with non-normal data for Large Model

Variable	Scale	N	PLS composites						Unit weighted composites					
			CR_U		CR_W		Alpha		CR_U		CR_W		Alpha	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ξ1	0	100	-.005	.032	.045	.079	.002	.012	-.000	.009	-.000	.009	-.001	.009
		200	-.005	.033	.044	.067	.002	.010	.000	.006	.000	.006	-.000	.006
		500	-.004	.027	.042	.050	.002	.008	.000	.004	.000	.004	-.000	.004
	.5	100	-.002	.009	.015	.019	-.001	.009	-.000	.009	-.000	.009	-.001	.009
		200	-.001	.006	.009	.011	-.001	.006	.000	.006	.000	.006	-.000	.006
		500	-.001	.004	.004	.005	-.002	.004	.000	.004	.000	.004	-.000	.004
	1	100	-.002	.009	.002	.009	-.002	.009	-.000	.009	-.000	.009	-.001	.009
		200	-.001	.006	.001	.006	-.002	.006	.000	.006	.000	.006	-.000	.006
		500	-.001	.004	.000	.004	-.002	.004	.000	.004	.000	.004	-.000	.004
ξ2	0	100	-.112	.110	.052	.135	.111	.144	-.003	.048	-.004	.049	-.012	.049
		200	-.118	.106	.046	.130	.120	.142	.000	.032	-.000	.032	-.007	.033
		500	-.116	.100	.048	.121	.111	.129	-.000	.020	-.000	.020	-.007	.021
	.5	100	-.038	.055	.017	.052	-.020	.050	-.002	.048	-.003	.049	-.011	.050
		200	-.027	.036	.011	.033	-.021	.034	.000	.032	-.000	.032	-.007	.033
		500	-.023	.021	.004	.021	-.024	.021	-.001	.020	-.000	.020	-.007	.021
	1	100	-.030	.048	.001	.047	-.033	.050	-.003	.047	-.004	.047	-.011	.050
		200	-.024	.032	.001	.031	-.028	.034	-.000	.031	-.000	.031	-.007	.033
		500	-.022	.021	.000	.020	-.027	.021	-.001	.020	-.001	.020	-.007	.021
η3	0	100	-.065	.113	.090	.217	.027	.131	.000	.030	-.001	.030	-.016	.034
		200	-.063	.156	.087	.521	.023	.112	.000	.021	-.000	.021	-.015	.024
		500	-.067	.112	.071	.173	.018	.107	-.000	.013	-.000	.013	-.015	.015
	.5	100	-.065	.101	.054	.127	-.001	.087	.001	.030	-.000	.030	-.016	.034
		200	-.050	.075	.056	.140	-.015	.062	.001	.021	.000	.021	-.015	.025
		500	-.045	.051	.035	.080	-.029	.048	-.000	.013	-.000	.013	-.015	.015
	1	100	-.055	.081	.037	.095	-.022	.071	.000	.030	.000	.030	-.016	.034
		200	-.046	.047	.026	.057	-.038	.037	.001	.021	.000	.020	-.015	.025
		500	-.041	.027	.014	.033	-.044	.026	-.000	.013	-.000	.013	-.015	.015
η4	0	100	-.038	.093	.088	.183	.028	.098	-.000	.027	-.000	.027	-.007	.029
		200	-.044	.107	.084	.202	.025	.089	.000	.018	.000	.018	-.006	.019
		500	-.036	.091	.098	.202	.024	.088	.000	.012	.000	.012	-.006	.013
	.5	100	-.025	.052	.042	.078	-.009	.044	-.001	.027	-.001	.027	-.008	.029
		200	-.021	.036	.029	.040	-.013	.025	.000	.018	.000	.018	-.006	.019
		500	-.018	.015	.014	.022	-.019	.015	.000	.012	.000	.012	-.006	.013
	1	100	-.020	.029	.006	.029	-.024	.030	-.001	.027	-.001	.027	-.008	.029
		200	-.017	.019	.004	.020	-.022	.020	.000	.018	.000	.018	-.006	.019
		500	-.017	.013	.002	.013	-.022	.013	.000	.012	.000	.012	-.006	.013
η5	0	100	-.040	.076	.052	.082	.014	.067	-.000	.016	-.001	.015	-.004	.016
		200	-.046	.087	.051	.095	.017	.071	.000	.011	-.000	.011	-.003	.012
		500	-.040	.083	.058	.131	.016	.070	-.000	.007	-.000	.007	-.003	.007
	.5	100	-.017	.020	.015	.022	-.011	.018	-.000	.016	-.001	.015	-.004	.016
		200	-.013	.012	.008	.014	-.012	.012	.000	.011	-.000	.011	-.003	.011
		500	-.012	.007	.003	.008	-.013	.007	-.000	.007	-.000	.007	-.003	.007
	1	100	-.012	.015	.000	.015	-.015	.016	-.000	.015	-.000	.015	-.004	.016
		200	-.011	.011	.001	.011	-.014	.011	.000	.011	-.000	.010	-.003	.012
		500	-.011	.007	.000	.006	-.014	.007	-.000	.007	.000	.006	-.003	.007

Note*: Loadings for PLS composites are estimated with PLSc and loadings for unit weighted composites are estimated with ML-CFA.*

Table 7 Path estimates with non-normal data for Small Model

Param.	Scale	N	PLSc				$EIV_{ML\text{-}CFA}$				ML SEM	
			Original		Manipulated		Original		Manipulated		Original	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
γ_{23}	0	100	-.015	.769	-.016	.381	-.005	.133	-.007	.135	-.005	.127
		200	-.015	.359	-.008	.176	-.006	.097	-.007	.098	-.006	.093
0		500	-.008	.231	-.001	.099	-.000	.061	.001	.059	-.001	.058
	.5	100	-.021	.308	-.010	.186	-.005	.132	-.002	.138	-.006	.126
		200	-.013	.149	-.006	.105	.001	.098	-.007	.096	-.000	.092
		500	-.005	.067	-.000	.060	-.001	.065	-.001	.061	-.000	.060
	1	100	-.020	.146	.001	.132	-.001	.134	.004	.134	-.000	.122
		200	-.002	.094	-.000	.088	.008	.094	-.001	.090	.003	.085
		500	-.001	.061	.001	.060	.002	.063	.000	.061	.002	.056
γ_{14}	0	100	-.017	.522	.008	.241	.002	.101	.002	.090	.003	.098
		200	.003	.221	.002	.089	-.003	.069	-.000	.062	-.004	.068
0		500	-.006	.087	-.001	.098	-.003	.043	-.002	.038	-.002	.041
	.5	100	.005	.118	.002	.111	-.004	.124	-.009	.119	-.002	.129
		200	.009	.084	.011	.079	-.001	.094	.003	.090	-.000	.095
		500	.002	.056	.003	.054	-.002	.061	-.000	.059	-.002	.060
	1	100	-.025	.203	.012	.179	-.028	.222	-.024	.376	-.023	.215
		200	-.009	.137	.006	.120	-.008	.144	-.005	.132	-.007	.137
		500	-.004	.086	.001	.078	-.004	.089	-.003	.082	-.003	.084
γ_{24}	0	100	.007	.639	.005	.276	.002	.119	.004	.109	-.000	.118
		200	.001	.350	.008	.143	.001	.086	.003	.071	-.000	.085
.7		500	-.012	.205	.011	.142	-.001	.054	.002	.047	-.001	.053
	.5	100	.026	.151	-.023	.143	-.018	.170	-.025	.161	-.024	.171
		200	.007	.106	-.023	.097	-.008	.115	-.014	.106	-.010	.115
		500	.002	.068	-.011	.061	-.002	.069	-.004	.061	-.003	.069
	1	100	.037	.203	-.021	.174	.029	.220	.022	.376	.023	.217
		200	.014	.137	-.012	.119	.009	.143	.002	.130	.006	.138
		500	.006	.086	-.002	.075	.004	.089	.004	.079	.003	.086
γ_{15}	0	100	-.017	.370	-.006	.214	-.003	.104	-.003	.097	-.001	.097
		200	-.000	1.094	-.006	.145	-.006	.068	-.003	.066	-.005	.065
.22		500	-.003	.109	.002	.191	-.002	.045	-.002	.043	-.002	.043
	.5	100	.032	1.018	.011	1.009	-.001	.121	.001	.117	-.006	.119
		200	-.004	.163	-.028	.505	.001	.088	.003	.085	-.000	.087
		500	-.003	.052	-.005	.051	.002	.051	.003	.052	.001	.049
	1	100	.007	.193	-.005	.170	.017	.212	.033	.287	.009	.195
		200	.007	.126	-.003	.118	.011	.130	.010	.125	.008	.126
		500	.008	.077	-.001	.074	.010	.078	.005	.077	.007	.076
γ_{25}	0	100	-.044	1.003	.019	.468	-.003	.130	.003	.129	-.001	.128
		200	-.019	3.279	.019	.586	-.000	.090	-.001	.088	.000	.088
-.7		500	-.005	.320	.015	.296	-.001	.057	.001	.057	-.001	.055
	.5	100	.024	1.058	.008	.313	-.001	.136	-.005	.131	.002	.131
		200	-.016	.162	.017	.149	-.001	.094	-.001	.091	.000	.091
		500	-.003	.055	.005	.055	.001	.057	-.001	.056	.001	.055
	1	100	-.023	.197	.006	.174	-.023	.211	-.037	.289	-.015	.194
		200	-.013	.122	.006	.116	-.012	.127	-.009	.123	-.008	.121
		500	-.010	.077	.002	.073	-.010	.079	-.004	.077	-.007	.076
β_{35}	0	100	-.052	.915	-.009	.433	-.004	.119	.001	.120	-.002	.115
		200	.053	3.051	.021	.566	-.002	.086	.001	.083	-.001	.081
.35		500	-.014	.327	.007	.249	-.002	.052	-.001	.053	-.002	.049
	.5	100	.020	1.636	.038	.990	.002	.116	.005	.115	.001	.112
		200	.016	.177	-.019	.475	.003	.081	.003	.078	.002	.076
		500	.010	.056	-.001	.050	.001	.051	.001	.051	.002	.048
	1	100	.013	.106	.004	.107	.004	.107	.011	.106	.002	.092
		200	.007	.072	-.004	.072	.004	.076	-.000	.074	-.001	.067
		500	.002	.047	-.002	.043	.001	.049	-.000	.044	-.000	.041

Table 8 Path estimates with non-normal data for Large Model

Param.	Scale	N	PLSc				$EIV_{ML\text{-}CFA}$				EIV_{minres}				ML SEM	
			Original		Manipulated		Original		Manipulated		Original		Manipulated		Original	
			Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD	Bias	SD
γ_{23}	0	100	.092	4.365	-.008	.429	-.009	.136	-.001	.133	-.009	.136	-.001	.133	-.007	.132
		200	-.023	.395	-.000	.263	-.005	.096	-.005	.095	-.005	.096	-.005	.095	-.004	.092
0		500	-.010	.700	-.001	.185	-.002	.057	-.002	.058	-.002	.057	-.002	.058	-.002	.055
	.5	100	-.025	.206	-.002	.148	-.003	.134	-.003	.133	-.003	.134	-.003	.132	-.003	.128
		200	-.011	.122	-.002	.096	-.002	.100	-.005	.094	-.002	.100	-.005	.094	-.000	.094
		500	-.007	.064	.000	.058	-.003	.062	-.000	.060	-.003	.062	-.000	.060	-.002	.059
	1	100	-.015	.140	.001	.126	.002	.130	-.000	.129	.002	.130	-.000	.128	.002	.121
		200	-.005	.097	.002	.086	.002	.097	.002	.090	.002	.097	.002	.090	.002	.086
		500	-.002	.060	.003	.058	.002	.061	.003	.059	.002	.061	.003	.059	.000	.056
γ_{14}	0	100	-.051	1.393	.022	.494	.001	.118	.004	.118	.001	.118	.004	.118	.002	.115
		200	.004	.260	-.006	.142	-.000	.081	-.004	.081	-.000	.081	-.004	.081	-.001	.079
0		500	.004	.119	.001	.093	-.001	.050	-.001	.049	-.001	.050	-.001	.049	-.001	.049
	.5	100	-.001	.176	.008	.134	-.005	.123	-.002	.124	-.005	.123	-.002	.124	-.003	.120
		200	.005	.080	.003	.081	-.002	.083	-.002	.085	-.002	.083	-.002	.085	-.001	.082
		500	.003	.050	.003	.051	-.001	.053	.000	.053	-.001	.053	.000	.053	-.001	.052
	1	100	-.014	.179	.004	.168	-.017	.189	-.020	.193	-.018	.195	-.019	.190	.257	8.509
		200	-.008	.119	.003	.110	-.008	.123	-.010	.119	-.008	.124	-.008	.117	-.009	.121
		500	-.005	.076	-.002	.071	-.005	.078	-.006	.075	-.005	.079	-.006	.074	-.005	.075
γ_{24}	0	100	.049	1.492	.025	.560	.004	.140	.001	.130	.004	.140	.001	.130	.004	.138
		200	.002	.465	-.003	.206	-.001	.093	.001	.092	-.001	.093	.001	.092	.001	.090
.7		500	.017	.217	.001	.136	.002	.058	-.000	.058	.002	.058	-.000	.058	.002	.056
	.5	100	.046	.190	-.012	.143	.007	.137	.005	.133	.007	.138	.005	.133	.007	.132
		200	.017	.091	-.008	.093	-.000	.096	.002	.095	-.000	.096	.002	.095	-.001	.093
		500	.005	.057	-.009	.057	-.001	.059	-.004	.057	-.001	.059	-.004	.058	-.002	.057
	1	100	.029	.176	-.007	.161	.019	.187	.021	.185	.020	.194	.020	.182	-.255	8.516
		200	.013	.119	-.004	.108	.007	.124	.010	.117	.007	.126	.009	.115	.008	.121
		500	.008	.077	-.000	.069	.005	.079	.005	.073	.005	.080	.005	.072	.005	.076
γ_{15}	0	100	-.003	.759	.019	.316	-.003	.108	-.004	.108	-.003	.108	-.004	.108	-.003	.106
		200	.008	.523	-.010	.133	-.003	.075	-.004	.074	-.003	.075	-.004	.074	-.003	.073
.22		500	-.005	.100	-.002	.080	-.002	.049	-.002	.048	-.002	.049	-.002	.048	-.002	.048
	.5	100	-.010	.369	.009	1.033	.005	.118	.002	.116	.005	.118	.002	.116	.004	.114
		200	.001	.090	-.004	.083	.003	.085	.004	.084	.003	.085	.004	.084	.002	.083
		500	-.001	.053	-.002	.052	.001	.052	.002	.051	.001	.052	.002	.051	.001	.050
	1	100	.016	.183	-.011	.175	.023	.193	.016	.197	.024	.199	.015	.194	-.263	8.710
		200	.008	.118	.000	.116	.011	.121	.015	.126	.011	.124	.014	.125	.006	.116
		500	.006	.078	-.000	.068	.007	.081	.005	.073	.007	.082	.005	.073	.005	.077
γ_{25}	0	100	.061	1.317	-.018	.543	.002	.131	-.001	.128	.001	.131	-.001	.128	.001	.127
		200	-.018	1.554	.009	.228	.003	.089	.001	.085	.003	.089	.001	.085	.002	.087
-.7		500	.003	.222	-.002	.127	.003	.056	.001	.056	.003	.056	.001	.056	.002	.054
	.5	100	-.026	.535	-.089	3.280	-.001	.137	-.004	.127	-.001	.137	-.004	.127	-.000	.133
		200	-.015	.099	.008	.091	-.002	.096	-.001	.092	-.002	.096	-.001	.092	-.002	.093
		500	-.005	.057	.004	.056	.001	.057	-.000	.055	.001	.057	-.000	.055	.001	.055
	1	100	-.032	.188	.010	.173	-.028	.198	-.020	.200	-.029	.204	-.019	.198	.257	8.708
		200	-.013	.118	.001	.113	-.012	.122	-.014	.123	-.012	.125	-.014	.122	-.006	.116
		500	-.007	.080	.004	.070	-.007	.082	-.002	.074	-.007	.083	-.002	.073	-.005	.079
β_{35}	0	100	-.041	1.067	.012	.470	-.002	.121	-.001	.119	-.002	.120	-.001	.118	-.002	.114
		200	-.031	1.514	-.001	.168	-.004	.086	-.001	.083	-.004	.086	-.001	.083	-.003	.082
.35		500	-.001	.199	-.002	.087	-.001	.053	.000	.053	-.001	.053	.000	.053	-.001	.049
	.5	100	.025	.654	.094	3.086	.002	.118	.004	.116	.002	.118	.004	.115	.001	.110
		200	.023	.096	-.002	.082	.003	.079	.002	.078	.003	.079	.002	.078	.001	.074
		500	.008	.050	-.002	.052	.001	.051	.001	.051	.001	.051	.001	.051	.000	.048
	1	100	.015	.105	-.003	.114	.007	.108	.002	.108	.007	.109	.002	.107	.002	.091
		200	.007	.073	-.007	.070	.003	.076	-.003	.073	.003	.077	-.003	.073	.002	.064
		500	.002	.046	-.000	.043	.001	.047	.001	.044	.001	.047	.001	.044	-.000	.041

Table 9 95% percentile confidence intervals with non-normal data for Small Model

Param.	Scale	N	PLSc Coverage Under	PLSc Coverage Within	PLSc Coverage Over	PLSc Incl. zero	EIV_{ML-CFA} Coverage Under	EIV_{ML-CFA} Coverage Within	EIV_{ML-CFA} Coverage Over	EIV_{ML-CFA} Incl. zero
γ_{23} 0	0	100	.006	.980	.014	.980	.022	.952	.026	.952
		200	.010	.972	.018	.972	.028	.937	.035	.937
		500	.011	.975	.014	.975	.023	.950	.027	.950
	.5	100	.006	.964	.030	.964	.019	.961	.020	.961
		200	.015	.955	.030	.955	.031	.937	.032	.937
		500	.023	.932	.045	.932	.038	.927	.035	.927
	1	100	.007	.947	.046	.947	.023	.945	.032	.945
		200	.013	.954	.033	.954	.026	.954	.020	.954
		500	.023	.941	.036	.941	.047	.923	.030	.923
γ_{14} 0	0	100	.003	.995	.002	.995	.030	.940	.030	.940
		200	.009	.987	.004	.987	.025	.942	.033	.942
		500	.005	.985	.010	.985	.018	.950	.032	.950
	.5	100	.012	.976	.012	.976	.022	.953	.025	.953
		200	.024	.965	.011	.965	.026	.946	.028	.946
		500	.024	.966	.010	.966	.022	.954	.024	.954
	1	100	.013	.954	.033	.954	.016	.952	.032	.952
		200	.020	.944	.036	.944	.022	.946	.032	.946
		500	.028	.943	.029	.943	.028	.943	.029	.943
γ_{24} .7	0	100	.010	.983	.007	.983	.032	.945	.023	.945
		200	.012	.979	.009	.979	.026	.946	.028	.946
		500	.009	.978	.013	.978	.023	.953	.024	.953
	.5	100	.043	.953	.004	.421	.014	.958	.028	.351
		200	.039	.952	.009	.113	.017	.961	.022	.104
		500	.033	.945	.022	.001	.027	.946	.027	.001
	1	100	.041	.952	.007	.031	.029	.960	.011	.074
		200	.043	.941	.016	.002	.036	.945	.019	.002
		500	.035	.943	.022	.000	.031	.944	.025	.000
γ_{15} .22	0	100	.000	1.000	.000	1.000	.028	.946	.026	.946
		200	.001	.998	.001	.998	.017	.949	.034	.949
		500	.006	.984	.010	.984	.024	.945	.031	.945
	.5	100	.002	.989	.009	.950	.013	.954	.033	.851
		200	.010	.954	.036	.827	.031	.941	.028	.725
		500	.006	.967	.027	.492	.021	.964	.015	.446
	1	100	.018	.957	.025	.763	.030	.949	.021	.740
		200	.036	.949	.015	.492	.041	.944	.015	.505
		500	.037	.940	.023	.096	.035	.946	.019	.114
γ_{25} -.7	0	100	.001	.999	.000	.999	.030	.947	.023	.947
		200	.006	.994	.000	.994	.029	.946	.025	.946
		500	.004	.989	.007	.989	.022	.948	.030	.948
	.5	100	.000	.976	.024	.605	.020	.944	.036	.280
		200	.006	.954	.040	.136	.030	.930	.040	.048
		500	.013	.947	.040	.000	.021	.948	.031	.000
	1	100	.012	.959	.029	.075	.018	.936	.046	.066
		200	.009	.957	.034	.001	.011	.952	.037	.000
		500	.015	.949	.036	.000	.016	.951	.033	.000
β_{35} xs .35	0	100	.000	1.000	.000	1.000	.030	.940	.030	.940
		200	.002	.997	.001	.997	.027	.935	.038	.935
		500	.002	.992	.006	.992	.015	.953	.032	.953
	.5	100	.028	.972	.000	.844	.030	.952	.018	.674
		200	.061	.937	.002	.547	.037	.937	.026	.425
		500	.048	.949	.003	.122	.028	.944	.028	.075
	1	100	.020	.977	.003	.289	.020	.964	.016	.191
		200	.042	.950	.008	.019	.036	.944	.020	.010
		500	.034	.946	.020	.000	.026	.944	.030	.000

Table 10 95% percentile confidence intervals with non-normal data for Large Model

Param.	Scale	N	PLSc Coverage Under	PLSc Coverage Within	PLSc Coverage Over	PLSc Incl. zero	$EIV_{ML\text{-}CFA}$ Coverage Under	$EIV_{ML\text{-}CFA}$ Coverage Within	$EIV_{ML\text{-}CFA}$ Coverage Over	$EIV_{ML\text{-}CFA}$ Incl. zero	EIV_{minres} Coverage Under	EIV_{minres} Coverage Within	EIV_{minres} Coverage Over	EIV_{minres} Incl. zero
γ_{23}	0	100	.013	.962	.025	.962	.030	.933	.037	.933	.030	.933	.037	.933
		200	.012	.972	.016	.972	.029	.931	.040	.931	.029	.931	.040	.931
0		500	.009	.979	.012	.979	.018	.958	.024	.958	.018	.958	.024	.958
	.5	100	.006	.973	.021	.973	.031	.946	.023	.946	.031	.946	.023	.946
		200	.013	.944	.043	.944	.034	.928	.038	.928	.034	.928	.038	.928
		500	.013	.946	.041	.946	.029	.941	.030	.941	.029	.941	.030	.941
	1	100	.011	.951	.038	.951	.034	.943	.023	.943	.034	.943	.023	.943
		200	.013	.941	.046	.941	.029	.946	.025	.946	.029	.946	.025	.946
		500	.017	.942	.041	.942	.023	.944	.033	.944	.023	.944	.033	.944
γ_{14}	0	100	.004	.991	.005	.991	.030	.937	.033	.937	.030	.937	.033	.937
		200	.004	.989	.007	.989	.026	.950	.024	.950	.026	.949	.025	.949
0		500	.005	.990	.005	.990	.020	.949	.031	.949	.020	.949	.031	.949
	.5	100	.016	.977	.007	.977	.022	.941	.037	.941	.022	.940	.038	.940
		200	.024	.971	.005	.971	.023	.957	.020	.957	.023	.958	.019	.958
		500	.028	.966	.006	.966	.022	.955	.023	.955	.022	.955	.023	.955
	1	100	.017	.945	.038	.945	.015	.948	.037	.948	.017	.949	.034	.949
		200	.023	.939	.038	.939	.022	.940	.038	.940	.022	.946	.032	.946
		500	.018	.947	.035	.947	.017	.949	.034	.949	.018	.948	.034	.948
γ_{24}	0	100	.012	.976	.012	.976	.040	.923	.037	.923	.040	.923	.037	.923
		200	.007	.986	.007	.986	.025	.946	.029	.946	.025	.946	.029	.946
.7		500	.008	.982	.010	.982	.029	.944	.027	.944	.029	.944	.027	.944
	.5	100	.082	.917	.001	.379	.043	.936	.021	.280	.045	.935	.020	.277
		200	.063	.934	.003	.070	.032	.941	.027	.057	.031	.942	.027	.057
		500	.033	.956	.011	.000	.023	.949	.028	.000	.023	.950	.027	.000
	1	100	.052	.943	.005	.013	.043	.941	.016	.046	.044	.941	.015	.043
		200	.045	.939	.016	.000	.037	.947	.016	.000	.034	.948	.018	.000
		500	.041	.942	.017	.000	.033	.944	.023	.000	.035	.938	.027	.000
γ_{15}	0	100	.002	.998	.000	.998	.027	.951	.022	.951	.027	.950	.023	.950
		200	.005	.993	.002	.993	.021	.949	.030	.949	.021	.949	.030	.949
.22		500	.010	.979	.011	.979	.024	.939	.037	.939	.024	.939	.037	.939
	.5	100	.004	.994	.002	.961	.028	.961	.011	.822	.028	.961	.011	.818
		200	.025	.965	.010	.816	.039	.944	.017	.709	.039	.946	.015	.710
		500	.017	.960	.023	.475	.025	.951	.024	.407	.026	.951	.023	.401
	1	100	.027	.961	.012	.711	.046	.943	.011	.688	.043	.943	.014	.693
		200	.030	.949	.021	.472	.036	.949	.015	.482	.036	.946	.018	.488
		500	.026	.943	.031	.106	.031	.939	.030	.119	.036	.935	.029	.126
γ_{25}	0	100	.005	.995	.000	.995	.032	.938	.030	.938	.032	.938	.030	.938
		200	.007	.991	.002	.991	.028	.951	.021	.951	.028	.951	.021	.951
-.7		500	.009	.986	.005	.986	.030	.946	.024	.946	.030	.946	.024	.946
	.5	100	.000	.975	.025	.626	.023	.937	.040	.276	.024	.938	.038	.274
		200	.003	.959	.038	.133	.027	.933	.040	.042	.027	.931	.042	.042
		500	.011	.947	.042	.002	.023	.948	.029	.000	.022	.950	.028	.000
	1	100	.006	.957	.037	.062	.007	.938	.055	.053	.007	.941	.052	.049
		200	.014	.952	.034	.001	.015	.953	.032	.000	.014	.954	.032	.000
		500	.021	.939	.040	.000	.021	.941	.038	.000	.020	.940	.040	.000
β_{35}	0	100	.000	.998	.002	.998	.030	.937	.033	.937	.030	.936	.034	.936
		200	.002	.997	.001	.997	.025	.931	.044	.931	.025	.932	.043	.932
.35		500	.002	.992	.006	.992	.030	.945	.025	.945	.030	.945	.025	.945
	.5	100	.031	.969	.000	.834	.033	.945	.022	.678	.033	.944	.023	.671
		200	.045	.955	.000	.536	.017	.950	.033	.409	.017	.949	.034	.409
		500	.047	.950	.003	.108	.032	.946	.022	.067	.032	.946	.022	.067
	1	100	.030	.968	.002	.258	.027	.953	.020	.172	.027	.953	.020	.168
		200	.034	.961	.005	.009	.035	.946	.019	.004	.036	.947	.017	.005
		500	.036	.943	.021	.000	.033	.941	.026	.000	.031	.942	.027	.000

Appendix B – Deriving the Refined Factor Loading Corrections

In this appendix we explain how applying the refined per-indicator correction leads to well-established factor analysis techniques. The PLSc correction for factor loadings was derived from the asymptotic case, leading to a consistent estimator. In PLSc, the loadings are estimated (rescaled) as follows (Dijkstra, 2010):

$$\hat{\boldsymbol{\lambda}}_i = c_i \cdot \mathbf{w}_i, \qquad \text{[B1]}$$

where $\mathbf{w}_i$ is the weight vector for the *i*th block of indicators, $\hat{\boldsymbol{\lambda}}_i$ is a parallel vector of factor loading estimates, and c_i is the scaling factor. Because the indicator covariances are implied by the products of factor loadings, c_i is chosen to minimize the Euclidean distance (i.e., sum of squared discrepancies) between (Dijkstra & Henseler, 2015b, p. 12):

$$[\mathbf{S}_{ii} - diag(\mathbf{S}_{ii})] \text{ and } [(c_i \cdot \mathbf{w}_i)(c_i \cdot \mathbf{w}_i)^t - diag((c_i \cdot \mathbf{w}_i)(c_i \cdot \mathbf{w}_i)^t)], \qquad \text{[B2]}$$

where $\mathbf{S}_{ii}$ is the within-block sample covariance matrix of the observed indicators, the superscript *t* is the transposition operator, and *diag* is an operator that zeroes the off-diagonal elements of a matrix. The current estimator of choice for $\hat{c}_i$ is (Dijkstra, 2014. Equation 11):

$$\hat{c}_i = \sqrt{\left(\frac{\mathbf{w}_i^t(\mathbf{S}_{ii} - diag(\mathbf{S}_{ii}))\mathbf{w}_i}{\mathbf{w}_i^t(\mathbf{w}_i\mathbf{w}_i^t - diag(\mathbf{w}_i\mathbf{w}_i^t))\mathbf{w}_i}\right)}\ . \qquad \text{[B3]}$$

A more refined correction can be developed by replacing the single scalars c_i with a vector $\mathbf{c}$, such that each loading is corrected separately. Unfortunately, there is no closed form solution for minimizing the Euclidean distance after this modification, and thus numerical optimization must be used. Another complication arises from the fact that two of the LVs in the model specified by Dijkstra and Henseler (2015b) have only two indicators, and correcting the loadings on these latent variables using information from only one indicator block is not possible because the minimization problem is not identified; it is well known that at least three indicators are required for identification of a single factor model, that is, to obtain a unique solution for the parameter estimates (Bollen, 1989, pp. 238–246)[1]. Given these two considerations, we can estimate all of the correction factors simultaneously by using the full covariance matrix **S** for all *p* observed indicators of the *q* latent variables ($q < p$), and therefore the distance to be minimized becomes:

$$[\mathbf{S} - diag(\mathbf{S})] \text{ and } \left[bd(\mathbf{c} \circ \mathbf{w})\widehat{\mathbf{\Phi}}bd(\mathbf{c} \circ \mathbf{w})^t - diag(bd(\mathbf{c} \circ \mathbf{w})\widehat{\mathbf{\Phi}}bd(\mathbf{c} \circ \mathbf{w})^t)\right], \qquad \text{[B4]}$$

where $\mathbf{c}$ is a p x 1 vector of estimated scaling factors, $\mathbf{w}$ is a parallel vector of indicator weights, the symbol $\circ$ denotes the Hadamard product of vectors (i.e., element-wise multiplication of $\mathbf{c}$ and $\mathbf{w}$), $\widehat{\mathbf{\Phi}}$ is a q x q correlation matrix with freely estimated elements, and *bd* is an operator that transforms a *p*-dimensional vector into a block-diagonal p x q matrix, where a given value on the *i*th column and *j*th row is the *i*th element of the input vector if the *i*th indicator is linked to the *j*th latent variable, and zero otherwise. In other words, *bd* converts the product vector $\mathbf{c} \circ \mathbf{w}$ into a factor loading matrix (or its transpose) with zero cross-loadings. Because minimizing the Euclidean distance is equivalent to minimizing the sum of squares, the minimization problem can be expressed conveniently as:

$$tr\left(\left([bd(\mathbf{c} \circ \mathbf{w})\widehat{\mathbf{\Phi}}bd(\mathbf{c} \circ \mathbf{w})^t - diag(bd(\mathbf{c} \circ \mathbf{w})\widehat{\mathbf{\Phi}}bd(\mathbf{c} \circ \mathbf{w})^t)] - \left(\mathbf{S} - diag(\mathbf{S})\right)\right)^2\right), \qquad \text{[B5]}$$

Raising a symmetric matrix to the second power collects the sums of squares of rows on the diagonals and *tr* is the *trace* operator that sums the elements on the main diagonal of the resulting matrix, thus giving the distance to be minimized.

Numerical minimization requires starting values. A reasonable assumption is to set all elements of $\mathbf{c}$ to 1. We can further simplify the equations to be minimized by considering that the

[1] Identification can be achieved for smaller models by constraining some of the free parameters. A typical example would be constraining the loadings of a two-indicator factor to be equal. However, such models are rare and are not encouraged, as they are unlikely to be capable of providing useful substantive information about the phenomenon under study.

products of weights and correction factors equal factor loadings, as per Equation [B1] above. The $bd(\mathbf{c} \circ \mathbf{w})$ terms in the equation can therefore be replaced with the factor loading matrix $\mathbf{\Lambda}$, which we initially populate with PLS weights. This alternative representation would be equivalent to using the PLS weights as starting values for numerical optimization, which was originally suggested by Dijkstra (1981) and later developed by Huang (2013; see also Bentler & Huang, 2014). Equation [B5] can therefore be equivalently and more compactly written in terms of loadings that would be estimated. Dijkstra (Dijkstra & Schermelleh-Engel, 2013) further suggests that the distance minimization problem can be refined by differentially weighting each element of the indicator covariance matrix. Given these considerations, the distance to be minimized can be written as:

$$tr\left(\left(\left([(\hat{\mathbf{\Lambda}}\hat{\mathbf{\Phi}}\hat{\mathbf{\Lambda}}^t) - diag(\hat{\mathbf{\Lambda}}\hat{\mathbf{\Phi}}\hat{\mathbf{\Lambda}}^t)] - (\mathbf{S} - diag(\mathbf{S}))\right)\mathbf{V}\right)^2\right), \qquad \text{[B6]}$$

where **V** is a weight matrix that can be chosen in multiple ways. Using the inverse of **S** leads to Generalized Least Squares (GLS) estimation. Another alternative would be to use estimation weights **V** calculated based on the inverse of the model-implied correlations, updating the estimation weights **V** after each estimation round. This iteratively reweighted least squares (IRLS) approach is equivalent to maximum likelihood estimation (ML) for correctly specified models (Yuan & Chan, 2005) and is used to obtain ML estimates in, for example, the EQS software package for covariance-based SEM (Bentler, 1995, pp. 134–135).

Finally, consistent estimates of the factor correlations, which are required for consistent estimation of the paths between latent variables, can also be estimated more directly without requiring calculation of the composites. In the *Handbook of Partial Least Squares*, Dijkstra (Dijkstra, 2010, p. 38, eq. 1.33) suggests that although disattenuation could be used to produce consistent estimators of the factor correlations, a more direct way to estimate the correlations between factors would be to minimizing the difference between the model-implied and observed between-block correlation matrix. This approach can be further extended from estimating all between-factor correlations separately to estimating the full factor correlation matrix, which is equivalent to using $\widehat{\mathbf{\Phi}}$ from our Equation [B6]. We tested also an estimator where we calculated regressions directly from this correlation matrix without calculating any composites variables. The results were in all respect nearly identical with maximum likelihood SEM estimates. The similarity is explained by the fact that the SEM model studied by Dijkstra and Henseler (2015b, fig. 4) only imposes two additional constraints over the CFA model: the correlation between ξ_1 and η_3 equals the product of correlations between ξ_1, ξ_2 , ξ_2 and η_3. Similarly, the correlation between η_3 and η_4 equals the product of correlations between η_4, ξ_2, ξ_2, and η_3[2]. Therefore the constraints on the model implied correlation matrix by these two estimators are very similar.

1. References

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[2] The correlation between η_4 and η_5 could be similarly derived, however, the error terms of these two latent variables are typically allowed to be correlated.

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Appendix C – Examples of Applying the EIV Estimators

In this appendix, we provide several examples of how the errors-in-variables (EIV) estimators can be implemented with commonly used statistical software. The general workflow of the analysis is to first estimate either a series of single-–block factor analyses or one multi-block confirmatory factor analysis and either print out or programmatically store the standardized factor loadings. Next, the indicators are standardized and summed by block as composites, followed by standardization of those composites. A simple way to calculate the weights that can be used to calculate a standardized composite from standardized indicators is to regress each standardized composite on its standardized indicators. Equation [2] from the main document is then used to calculate estimated reliabilities for the composites.

The procedures for performing EIV regression vary between statistical packages. A popular approach that can be used with nearly any commonly used statistical package is to estimate the EIV model with a SEM function or software package. In this procedure, each variable in the regression analysis is replaced with a latent variable, which has the corresponding composite as a single indicator. The loadings are fixed at the square roots of the reliability estimates and error variances are fixed at 1-reliability estimates. Because the resulting model is just-identified, all estimators converge to the same solution and the model fits perfectly. This is a well-known model configuration and is documented in the user manuals of many commonly-used SEM software packages (e.g., SAS Institute Inc., 2010, pp. 1317–1342; SPSS Inc, 2009; StataCorp, 2013, pp. 275–278).

We will next provide self-contained example analysis files written for R, SAS, and Stata using data generated based on the indicator covariance matrix reported by Chin, Johnson, and Schwarz (2008, Appendix C).

References

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StataCorp. (2013). *Stata Statistical Software: Release 13.* College Station, TX: StataCorp LP.

1 Example in R.R

```r
# This file contains example analyses using the EIV estimator in various
# configurations using the data from Appendix C of
#
# Chin, W. W., Johnson, N., & Schwarz, A. (2008). A Fast Form Approach to
# Measuring Technology Acceptance and Other Constructs. MIS Quarterly, 32(4),
# 687  703.
#

# Load libraries
library(psych)
library(matrixpls)
library(lavaan)
library(MASS)
library(boot)

# Set up the data

covariances <- matrix(NA, 16, 16)

covariances[upper.tri(covariances, diag = TRUE)] <- c(
  2.111,
  1.694, 1.903,
  1.662, 1.551, 1.875,
  1.675, 1.570, 1.581, 1.985,
  0.880, 0.798, 0.851, 0.757, 2.137,
  0.929, 0.877, 0.800, 0.765, 1.619, 1.846,
  0.938, 0.895, 0.853, 0.815, 1.541, 1.437, 1.760,
  0.920, 0.864, 0.850, 0.794, 1.199, 1.248, 1.251, 1.648,
  0.922, 0.864, 0.889, 0.850, 1.535, 1.428, 1.443, 1.258, 1.964,
  0.912, 0.873, 0.806, 0.838, 1.620, 1.543, 1.579, 1.346, 1.640, 2.032,
  1.007, 0.939, 0.925, 0.985, 0.644, 0.743, 0.679, 0.676, 0.703, 0.708, 1.436,
  1.026, 0.896, 0.893, 0.883, 0.669, 0.661, 0.666, 0.694, 0.739, 0.693, 1.086, 1.503,
  0.895, 0.864, 0.836, 0.842, 0.564, 0.587, 0.583, 0.641, 0.554, 0.538, 0.956, 0.897, 1.212,
  0.934, 0.945, 0.804, 0.902, 0.526, 0.615, 0.568, 0.602, 0.554, 0.574, 0.978, 0.844, 0.874, 1.311,
  0.831, 0.815, 0.811, 0.856, 0.497, 0.537, 0.576, 0.559, 0.551, 0.528, 0.857, 0.781, 0.778, 0.800,
      1.106,
  0.734, 0.740, 0.677, 0.771, 0.505, 0.535, 0.555, 0.528, 0.531, 0.498, 0.748, 0.705, 0.731, 0.773,
      0.714, 1.015)

covariances[lower.tri(covariances)] <- t(covariances)[lower.tri(covariances)]
colnames(covariances) <- rownames(covariances) <- c("LU4", "LU3", "LU2", "LU1", "EOU1", "EOU2", "EOU3", "
    EOU4", "EOU5", "EOU6", "Use6", "Use5", "Use4", "Use3", "Use2", "Use1")

# Create multivariate normal dataset with the exact covariance structure

rawData <- mvrnorm(283, mu = rep(0,16), Sigma = covariances, empirical = TRUE)

################################################################################
#
# Examples using matrixpls package
#
################################################################################

# Specify the model using Lavaan syntax. (http://lavaan.ugent.be/tutorial/syntax1.html)

modelSpecification <- "

# Define the factors
PredictedUsage =~ LU1 + LU2 + LU3 + LU4
Usefulness =~ Use1 + Use2 + Use3 + Use4 + Use5 + Use6
EaseOfUse =~ EOU1 + EOU2 + EOU3 + EOU4 + EOU5 + EOU6

# Regression between factors
PredictedUsage ~ Usefulness + EaseOfUse
"

# EIV_minres with matrixpls

est1 <- matrixpls(covariances, modelSpecification,
                  # Use unit weights
                  weightFunction = weight.fixed,

                  # Use disattenuation
                  disattenuate = TRUE,

                  # Use blockwise EFA with minres to estimate the reflective part of
                  # the model
                  parametersReflective = estimator.EFALoadings)
```

```
summary(est1)

# EIV_ML-CFA with matrixpls

est2 <- matrixpls(covariances, modelSpecification,
                  # Use unit weights
                  weightFunction = weight.fixed,

                  # Use disattenuation
                  disattenuate = TRUE,

                  # Full model CFA with ML to estimate the reflective part of
                  # the model
                  parametersReflective = estimator.CFALoadings)

summary(est2)

# Bootstrap EIVminres

est1.boot <- matrixpls.boot(rawData, modelSpecification,
                            # Use unit weights
                            weightFunction = weight.fixed,

                            # Use disattenuation
                            disattenuate = TRUE,

                            # Use blockwise EFA with minres to estimate the reflective part
                            # of the model
                            parametersReflective = estimator.EFALoadings,

                            # 500 bootstrap replications
                            R = 500)

# Calculate percentile confidence intervals from bootstrap results

CIs <- lapply(1:length(est1), function(i){
  CI <- boot.ci(est1.boot, type = "perc", index = i)$percent[,4:5]
  names(CI) <- c("lower","upper")
  CI
})

cbind(est1,do.call(rbind,CIs))

# Calculate two-tailed t-tests based on bootstrap SEs

se <- apply(est1.boot$t,2,sd)
t <- est1 / se
p <- (1-pt(abs(t), 283-1))*2
cbind(est1, se, t, p)


################################################################################
#
# Examples using psych and lavaan packages
#
################################################################################

# Calculate three different reliability estiamtes

reliabilities.alpha <- list(LU = alpha(covariances[1:4,1:4])$total$std.alpha,
                            EOU =  alpha(covariances[5:10,5:10])$total$std.alpha,
                            Use =  alpha(covariances[11:16,11:16])$total$std.alpha)


loadings.minres <- list(LU = fa(covariances[1:4,1:4])$loadings,
                        EOU =  fa(covariances[5:10,5:10])$loadings,
                        Use =  fa(covariances[11:16,11:16])$loadings)

# Calculate unit weights

correlations <- cov2cor(covariances)

weights <- list(LU = 1/sqrt(sum(correlations[1:4,1:4])),
                EOU =  1/sqrt(sum(correlations[5:10,5:10])),
                Use =  1/sqrt(sum(correlations[11:16,11:16])))

# Use the equation from the article to calculate reliabilities

reliabilities.minres <- mapply(function(loadings, weight){
  sum(weight * loadings)^2
```

```
}, loadings.minres, weights)


# Specify the CFA model using Lavaan syntax.

modelSpecification <- "

# Define the factors
PredictedUsage =~ LU1 + LU2 + LU3 + LU4
Usefulness =~ Use1 + Use2 + Use3 + Use4 + Use5 + Use6
EaseOfUse =~ EOU1 + EOU2 + EOU3 + EOU4 + EOU5 + EOU6"

cfa1 <- cfa(modelSpecification, sample.cov = correlations,
            sample.cov.rescale = FALSE, sample.nobs = 283, std.lv = TRUE)

loadings.CFA <- list(LU = inspect(cfa1,"est")$lambda[1:4,1],
                     EOU =  inspect(cfa1,"est")$lambda[11:16,3],
                     Use =  inspect(cfa1,"est")$lambda[5:10,2])

reliabilities.CFA <- mapply(function(loadings, weight){
  sum(weight * loadings)^2
}, loadings.CFA, weights)


#
# Calculate unit weighted composites
#

composites <- scale(cbind(PredictedUsage = rowSums(scale(rawData)[,1:4]),
                          Usefulness = rowSums(scale(rawData)[,11:16]),
                          EaseOfUse = rowSums(scale(rawData)[,5:10])))


# Estimate errors in variables model using lavaan and the minres reliability
# estimates

modelSpecification <- paste("
PredictedUsage_star =~ ",sqrt(reliabilities.minres["LU"]),"*PredictedUsage
Usefulness_star =~ ",sqrt(reliabilities.minres["Use"]),"*Usefulness
EaseOfUse_star =~ ",sqrt(reliabilities.minres["EOU"]),"*EaseOfUse

PredictedUsage ~~ ",1-reliabilities.minres["LU"],"*PredictedUsage
Usefulness ~~ ",1-reliabilities.minres["Use"],"*Usefulness
EaseOfUse ~~ ",1-reliabilities.minres["EOU"],"*EaseOfUse

PredictedUsage_star ~ Usefulness_star + EaseOfUse_star
",sep="")

eiv <- sem(modelSpecification,composites)
summary(eiv)
```

2 Example in SAS.sas

```
/*

This file contains example analyses using the EIV estimator in various
configurations using the data from Appendix C of

Chin, W. W., Johnson, N., & Schwarz, A. (2008). A Fast Form Approach to
Measuring Technology Acceptance and Other Constructs. MIS Quarterly, 32(4),
687  703.

*/


/* Set up the data */

FILENAME foo URL 'http://www.ats.ucla.edu/stat/sas/macros/corr2data.sas';
%INCLUDE foo;

DATA C;
INPUT LU4 LU3 LU2 LU1 EOU1 EOU2 EOU3 EOU4 EOU5 EOU6 Use6 Use5 Use4 Use3 Use2 Use1;
DATALINES;
2.111 . . . . . . . . . . . . . . .
1.694 1.903 . . . . . . . . . . . . . .
1.662 1.551 1.875 . . . . . . . . . . . . .
1.675 1.570 1.581 1.985 . . . . . . . . . . . .
0.880 0.798 0.851 0.757 2.137 . . . . . . . . . . .
0.929 0.877 0.800 0.765 1.619 1.846 . . . . . . . . . .
```

```
0.938 0.895 0.853 0.815 1.541 1.437 1.760 . . . . . . . . .
0.920 0.864 0.850 0.794 1.199 1.248 1.251 1.648 . . . . . . . .
0.922 0.864 0.889 0.850 1.535 1.428 1.443 1.258 1.964 . . . . . . .
0.912 0.873 0.806 0.838 1.620 1.543 1.579 1.346 1.640 2.032 . . . . . .
1.007 0.939 0.925 0.985 0.644 0.743 0.679 0.676 0.703 0.708 1.436 . . . . .
1.026 0.896 0.893 0.883 0.669 0.661 0.666 0.694 0.739 0.693 1.086 1.503 . . . .
0.895 0.864 0.836 0.842 0.564 0.587 0.583 0.641 0.554 0.538 0.956 0.897 1.212 . . .
0.934 0.945 0.804 0.902 0.526 0.615 0.568 0.602 0.554 0.574 0.978 0.844 0.874 1.311 . .
0.831 0.815 0.811 0.856 0.497 0.537 0.576 0.559 0.551 0.528 0.857 0.781 0.778 0.800 1.106 .
0.734 0.740 0.677 0.771 0.505 0.535 0.555 0.528 0.531 0.498 0.748 0.705 0.731 0.773 0.714 1.015
;
RUN;

/* Create multivariate normal dataset with the exact covariance structure. */

%corr2data(rawData, C, 283, FULL='F', corr='F');

DATA rawData;
        SET rawData;
        RENAME COL1=LU4 COL2=LU3 COL3=LU2 COL4=LU1 COL5=EOU1 COL6=EOU2 COL7=EOU3 COL8=EOU4 COL9=EOU5
            COL10=EOU6 COL11=Use6 COL12=Use5 COL13=Use4 COL14=Use3 COL15=Use2 COL16=Use1;
RUN;


/********************************************************************************

Example using FACTOR and CALIS

********************************************************************************/

/* Create unit weighted composites and standardize */

PROC STANDARD DATA=rawData MEAN=0 STD=1 OUT=zrawData;
RUN;

DATA zrawData;
        SET zrawData;
        PredictedUsage = LU4 + LU3 + LU2 + LU1;
        Usefulness = Use6 + Use5 + Use4 + Use3 + Use2 + Use1;
        EaseOfUse = EOU1 + EOU2 + EOU3 + EOU4 + EOU5 + EOU6;
RUN;

PROC STANDARD DATA=zrawData MEAN=0 STD=1 OUT=zrawData;
RUN;

/* minres based reliability estimate for PredictedUsage */


PROC FACTOR data=zrawData NFACTORS=1 METHOD=ULS OUTSTAT=factorResults;
        VAR LU4 LU3 LU2 LU1;
RUN;

PROC REG DATA=zrawData OUTEST=regressionResults PLOTS=none;
  MODEL PredictedUsage = LU4 LU3 LU2 LU1;
RUN;

DATA _null_;
        SET regressionResults;
        CALL symput("PredictedUsageWeight",LU4);
RUN;

DATA _null_;
        SET factorResults;
        IF _NAME_ NE "Factor1" THEN DELETE;
        Reliability = ((LU4 + LU3 + LU2 + LU1) * &PredictedUsageWeight)**2;
        CALL symput("PredictedUsageReliability",Reliability);
RUN;

/* minres based reliability estimate for Usefulness */


PROC FACTOR data=zrawData NFACTORS=1 METHOD=ULS OUTSTAT=factorResults;
        VAR Use6 Use5 Use4 Use3 Use2 Use1;
RUN;

PROC REG DATA=zrawData OUTEST=regressionResults PLOTS=none;
  MODEL Usefulness = Use6 Use5 Use4 Use3 Use2 Use1;
RUN;

DATA _null_;
        SET regressionResults;
```

```
        CALL symput("UsefulnessWeight",Use6);
RUN;

DATA _null_;
        SET factorResults;
        IF _NAME_ NE "Factor1" THEN DELETE;
        Reliability = ((Use6 + Use5 + Use4 + Use3 + Use2 + Use1) * &UsefulnessWeight)**2;
        CALL symput("UsefulnessReliability",Reliability);
RUN;


/* minres based reliability estimate for EaseOfUse */

PROC FACTOR data=zrawData NFACTORS=1 METHOD=ULS OUTSTAT=factorResults;
        VAR EOU1 EOU2 EOU3 EOU4 EOU5 EOU6;
RUN;

PROC REG DATA=zrawData OUTEST=regressionResults PLOTS=none;
  MODEL EaseOfUse = EOU1 EOU2 EOU3 EOU4 EOU5 EOU6;
RUN;

DATA _null_;
        SET regressionResults;
        CALL symput("EaseOfUseWeight",EOU1);
RUN;

DATA _null_;
        SET factorResults;
        IF _NAME_ NE "Factor1" THEN DELETE;
        Reliability = ((EOU1 + EOU2 + EOU3 + EOU4 + EOU5 + EOU6) * &EaseOfUseWeight)**2;
        CALL symput("EaseOfUseReliability",Reliability);
RUN;

/* ML-CFA based reliability estimates for all variables */

PROC CALIS DATA=zrawData OUTMODEL=cfaResults;
        FACTOR
                FPredictedUsage ---> LU4-LU1,
                FUsefulness ---> Use6-Use1,
                FEaseOfUse ---> EOU1-EOU6;
        PVAR
                FPredictedUsage FUsefulness FEaseOfUse = 3 * 1;
RUN;

DATA cfaLoadings;
   SET cfaResults;
   IF _TYPE_ NE "LOADING" THEN DELETE;
RUN;

PROC MEANS DATA=cfaLoadings NWAY;
        CLASS _VAR2_;
        VAR _ESTIM_;
        OUTPUT OUT=loadingSums SUM=sum;
RUN;

DATA _null_;
        SET loadingSums;
        IF _VAR2_ NE "FPredictedUsage" THEN DELETE;
        Reliability = (sum * &PredictedUsageWeight)**2;
        CALL symput("PredictedUsageReliabilityCFA",Reliability);
RUN;

DATA _null_;
        SET loadingSums;
        IF _VAR2_ NE "FEaseOfUse" THEN DELETE;
        Reliability = (sum * &EaseOfUseWeight)**2;
        CALL symput("EaseOfUseReliabilityCFA",Reliability);
RUN;

DATA _null_;
        SET loadingSums;
        IF _VAR2_ NE "FUsefulness" THEN DELETE;
        Reliability = (sum * &UsefulnessWeight)**2;
        CALL symput("UsefulnessReliabilityCFA",Reliability);
RUN;


/* Errors in variables regression */

PROC CALIS DATA=zrawData;
        LINEQS
```

```
                FPredictedUsage = b1 * FUsefulness+ b2 * FEaseOfUse + DFPredictedUsage,
                PredictedUsage  = %SYSEVALF(&PredictedUsageReliability**2) * FPredictedUsage + EPredictedUsage,
                Usefulness  = %SYSEVALF(&UsefulnessReliability**2) * FUsefulness + EUsefulness,
                EaseOfUse  = %SYSEVALF(&EaseOfUseReliability**2) * FEaseOfUse + EEaseOfUse;
        VARIANCE
                EPredictedUsage  = %SYSEVALF(1-&PredictedUsageReliability),
                EUsefulness = %SYSEVALF(1-&UsefulnessReliability),
                EEaseOfUse = %SYSEVALF(1-&EaseOfUseReliability);
RUN;

/* List the user macros to see the reliability estimates */
%PUT _USER_;
```

3 Example in Stata.do

```
// This file contains example analyses using the EIV estimator in various
// configurations using the data from Appendix C of
//
// Chin, W. W., Johnson, N., & Schwarz, A. (2008). A Fast Form Approach to
// Measuring Technology Acceptance and Other Constructs. MIS Quarterly, 32(4),
// 687  703.
//


// Estout is used to extract unit weights from regression. Install if not already installed.
capture which estout
if _rc==111 ssc install estout

// Set up the data

clear

matrix input C = (2.111, ///
1.694, 1.903, ///
1.662, 1.551, 1.875, ///
1.675, 1.570, 1.581, 1.985, ///
0.880, 0.798, 0.851, 0.757, 2.137, ///
0.929, 0.877, 0.800, 0.765, 1.619, 1.846, ///
0.938, 0.895, 0.853, 0.815, 1.541, 1.437, 1.760, ///
0.920, 0.864, 0.850, 0.794, 1.199, 1.248, 1.251, 1.648, ///
0.922, 0.864, 0.889, 0.850, 1.535, 1.428, 1.443, 1.258, 1.964, ///
0.912, 0.873, 0.806, 0.838, 1.620, 1.543, 1.579, 1.346, 1.640, 2.032, ///
1.007, 0.939, 0.925, 0.985, 0.644, 0.743, 0.679, 0.676, 0.703, 0.708, 1.436, ///
1.026, 0.896, 0.893, 0.883, 0.669, 0.661, 0.666, 0.694, 0.739, 0.693, 1.086, 1.503, ///
0.895, 0.864, 0.836, 0.842, 0.564, 0.587, 0.583, 0.641, 0.554, 0.538, 0.956, 0.897, 1.212, ///
0.934, 0.945, 0.804, 0.902, 0.526, 0.615, 0.568, 0.602, 0.554, 0.574, 0.978, 0.844, 0.874, 1.311, ///
0.831, 0.815, 0.811, 0.856, 0.497, 0.537, 0.576, 0.559, 0.551, 0.528, 0.857, 0.781, 0.778, 0.800, 1.106, ///
0.734, 0.740, 0.677, 0.771, 0.505, 0.535, 0.555, 0.528, 0.531, 0.498, 0.748, 0.705, 0.731, 0.773, 0.714, 1.015)

// Create multivariate normal dataset with the exact covariance structure

corr2data LU4 LU3 LU2 LU1 EOU1 EOU2 EOU3 EOU4 EOU5 EOU6 Use6 Use5 Use4 Use3 Use2 Use1, n(283) cov(C) cstorage(lower)

////////////////////////////////////////////////////////////////////////////////
//
// Examples using sem, factor, alpha and eivreg
//
////////////////////////////////////////////////////////////////////////////////


// Calculate three different reliability estimates


// Alphas

alpha LU4-LU1, std gen(PredictedUsage)
scalar alpha_PredictedUsage = r(alpha)

alpha Use6-Use1, std gen(Usefulness)
scalar alpha_Usefulness = r(alpha)

alpha EOU1-EOU6, std gen(EaseOfUse)
scalar alpha_EaseOfUse = r(alpha)

// Create standardized the composites
```

```
egen zPredictedUsage = std(PredictedUsage)
egen zUsefulness = std(Usefulness)
egen zEaseOfUse = std(EaseOfUse)

// Exploratory factor analysis based reliability estimates

// Stata's factor command does not do minres factor analysis, but we can use maximum likelihood instead
// (minres is possible with the sem command because minres is equivalent to ULS)

factor LU4-LU1, factors(1) ml
matrix define loadings = e(L)

qui regress PredictedUsage LU4-LU1
estadd beta
matrix define weights_PredictedUsage = e(beta)
matrix define r =  weights_PredictedUsage[1,1..4] * loadings
scalar CRefa_PredictedUsage = r[1,1]^2


factor Use6-Use1, factors(1) ml
matrix define loadings = e(L)

qui regress Usefulness Use6-Use1
estadd beta
matrix define weights_Usefulness = e(beta)
matrix define r =  weights_Usefulness[1,1..6] * loadings
scalar CRefa_Usefulness = r[1,1]^2


factor EOU1-EOU6, factors(1) ml
matrix define loadings = e(L)

qui regress EaseOfUse EOU1-EOU6
estadd beta
matrix define weights_EaseOfUse = e(beta)
matrix define r = weights_EaseOfUse[1,1..6] * loadings
scalar CRefa_EaseOfUse = r[1,1]^2

// Errors in variables regression using reliabilities based on EFA
// Note that eivreg does not adjust for error in the dependent variable.
// To get results that are fully standardized with respect to the error
// free variables, the dependent variable needs to be adjusted before
// estimation so that the reliable part has unit variances

gen sPredictedUsage = zPredictedUsage / sqrt(CRefa_PredictedUsage)

eivreg sPredictedUsage zUsefulness zEaseOfUse, reliab(zUsefulness `=CRefa_Usefulness' zEaseOfUse `=
    CRefa_EaseOfUse')


//
//The following example requires Stata 12 or later
//


// Confirmatory factor analysis based reliability estimates

sem (PredictedUsage -> LU4-LU1) (Usefulness -> Use6-Use1) (EaseOfUse -> EOU1-EOU6), nocapslatent latent(
    PredictedUsage Usefulness EaseOfUse)

// Get the reliabilities from the factor loading matrix
estat framework, standardized
matrix define loadings = r(Gamma)

// Calculate reliabilities

matrix define r =  weights_PredictedUsage[1,1..4] * loadings[1..4,1]
scalar CRcfa_PredictedUsage = r[1,1]^2

matrix define r =  weights_Usefulness[1,1..6] * loadings[5..10,2]
scalar CRcfa_Usefulness = r[1,1]^2

matrix define r = weights_EaseOfUse[1,1..6] * loadings[11..16,3]
scalar CRcfa_EaseOfUse = r[1,1]^2

// Errors in variables model in the SEM framework

sem (PredictedUsage_star <- Usefulness_star EaseOfUse_star) ///
        (PredictedUsage_star -> zPredictedUsage) ///
        (Usefulness_star -> zUsefulness) ///
```

```
        (EaseOfUse_star -> zEaseOfUse), ///
                reliability(zPredictedUsage `=CRcfa_PredictedUsage' ///
                        zUsefulness `=CRcfa_Usefulness' zEaseOfUse `=CRcfa_EaseOfUse') ///
                standardized

// List all reliability estimates
scalar list
```

Appendix D - Full R code for the simulations

This appendix contais the full R code for the simulations used in the paper. The simulation consists of two files. Parameters.R defines the simulation paremeterization and simulations.R implements the simulation.

The files to implement bootstrapping were very similar to these files and are available from the first author by request.

The source code for the two small examples presented in the theory section of the paper is availble in the file example.R after the main analysis files.

1 parameters.R

```
#
# Model 1 and Model 2 in Lavaan syntax
#

MODELS <- c("
f1 =~ .87*i11 + .94*i12
f2 =~ .40*i21 + .41*i22 + .47*i23 + .60*i24 + .63*i25 + .65*i26
f3 =~ .49*i31 + .60*i32 + .80*i33 + .90*i34
f4 =~ .63*i41 + .84*i42
f5 =~ .65*i51 + .67*i52 + .75*i53 + .75*i54 + .90*i55 + .90*i56

f3 ~ 0*f2
f3 ~~ 1*f3

f4 ~ 0*f1 + .7*f2
f4 ~~ .51*f4

f5 ~ .22*f1 + -.7*f2 + .35*f3
f5 ~~ 0.5547*f5

f1 ~~ .7*f2
f1 ~~ 1*f1
f2 ~~ 1*f2

i11~~(1-.87^2)*i11
i12~~(1-.94^2)*i12
i21~~(1-.40^2)*i21
i22~~(1-.41^2)*i22
i23~~(1-.47^2)*i23
i24~~(1-.60^2)*i24
i25~~(1-.63^2)*i25
i26~~(1-.65^2)*i26
i31~~(1-.49^2)*i31
i32~~(1-.60^2)*i32
i33~~(1-.80^2)*i33
i34~~(1-.90^2)*i34
i41~~(1-.63^2)*i41
```

```
i42~~(1-.84^2)*i42
i51~~(1-.65^2)*i51
i52~~(1-.67^2)*i52
i53~~(1-.75^2)*i53
i54~~(1-.75^2)*i54
i55~~(1-.90^2)*i55
i56~~(1-.90^2)*i56",

"f1 =~ .87*i11a + .94*i12a +.87*i11b + .94*i12b
f2 =~ .40*i21 + .41*i22 + .47*i23 + .60*i24 + .63*i25 + .65*i26
f3 =~ .49*i31 + .60*i32 + .80*i33 + .90*i34
f4 =~ .63*i41a + .84*i42a + .63*i41b + .84*i42b
f5 =~ .65*i51 + .67*i52 + .75*i53 + .75*i54 + .90*i55 + .90*i56

f3 ~ 0*f2
f3 ~~ 1*f3

f4 ~ 0*f1 + .7*f2
f4 ~~ .51*f4

f5 ~ .22*f1 + -.7*f2 + .35*f3
f5 ~~ .1235*f5

f1 ~~ .7*f2
f1 ~~ 1*f1
f2 ~~ 1*f2

i11a~~(1-.87^2)*i11a
i12a~~(1-.94^2)*i12a
i11b~~(1-.87^2)*i11b
i12b~~(1-.94^2)*i12b
i21~~(1-.40^2)*i21
i22~~(1-.41^2)*i22
i23~~(1-.47^2)*i23
i24~~(1-.60^2)*i24
i25~~(1-.63^2)*i25
i26~~(1-.65^2)*i26
i31~~(1-.49^2)*i31
i32~~(1-.60^2)*i32
i33~~(1-.80^2)*i33
i34~~(1-.90^2)*i34
i41a~~(1-.63^2)*i41a
i42a~~(1-.84^2)*i42a
i41b~~(1-.63^2)*i41b
i42b~~(1-.84^2)*i42b
i51~~(1-.65^2)*i51
i52~~(1-.67^2)*i52
i53~~(1-.75^2)*i53
i54~~(1-.75^2)*i54
i55~~(1-.90^2)*i55
i56~~(1-.90^2)*i56")


designMatrix <- expand.grid(sample = c(100, 200, 500),
                            scalingFactor =  c(1, 0.5, 0),
                            excessKurtosis  = c(5,0),
                            estimator = c("PLSc","DRminres","DRml","SEMml",
```

```
                                           "CFAml"),
                              model = 1:2)
```

2 simulations.R

```
library(matrixpls)
library(psych)
library(simsem)
library(lavaan)
library(parallel)
library(MASS)
library(Matrix)
library(heplots)

MULTICORE <- FALSE
DEBUG <- FALSE
SAVERESULTS <- TRUE

REPLICATIONS <- 1000
# 1 = normal, 2 = orthogonalized errors
ESTIMATESETS <- 1:2

source("parameters.R")

# Read the condition number from the command line if given. Otherwise run all
# conditions.

args <- commandArgs(trailingOnly = TRUE)

if(length(args) == 0){
  designNumbers <- 1:nrow(designMatrix)
} else {
  designNumbers <- (as.numeric(args[1]))
}


###############################################################################
#
# Loop over designs
#
###############################################################################



for(designNumber in designNumbers){

  set.seed(12345)

  design <- designMatrix[designNumber, ]

  print(paste("Starting design number", designNumber))
  print(design)

  # Prepare data generation template
```

```r
MODEL <- MODELS[design$model]

parTable <- lavaanify(MODEL)
loadingsParTable <- parTable[parTable$op == "=~",]
observedVariableNames <- unique(loadingsParTable$rhs)

# Derive a SimSem model from lavaan parameter table by fitting a model to
# a diagonal matrix

cvMat <- diag(length(observedVariableNames))
colnames(cvMat) <- rownames(cvMat) <- observedVariableNames
fit <- lavaan::lavaan(MODEL, sample.cov = cvMat, sample.nobs = 100)
dataTemplate <- simsem::model.lavaan(fit)

# Rescale the data template

BE <- rawDraw(dataTemplate@dgen[[1]]$BE)$param * design$scalingFactor
PS <- rawDraw(dataTemplate@dgen[[1]]$PS)$param
i <-  diag(nrow(PS)) == 0
PS[i] <- PS[i] * design$scalingFactor
diag(PS) <- 1 - diag(BE %*% PS %*% t(BE))

dataTemplate@dgen[[1]]$PS@free <- apply(PS, 2, as.character)
dataTemplate@dgen[[1]]$BE@free <- apply(BE, 2, as.character)

Lambda <- rawDraw(dataTemplate@dgen[[1]]$LY)$param
dist <- bindDist("norm", kurtosis = design$excessKurtosis)

# Generate the datasets

print("Generating datasets")

dataSets <- sim(REPLICATIONS, dataTemplate, design$sample, dataOnly = TRUE,
                factDist = dist, errorDist = dist,
                sequential = TRUE, saveLatentVar = TRUE,
                multicore = MULTICORE)


###########################################################################
#
# Estimation
#
###########################################################################

estimator <- design$estimator

#  SEM and regressions with factor correlation matrix after CFA

if(substr(estimator,1,3)=="CFA" || substr(estimator,1,3)=="SEM"){

  if(substr(estimator,1,3)=="SEM"){
    estimatedModel <- (gsub("f[0-9] ~~ f[0-9]","",gsub("[.0-9]+\\*","",gsub("\ni.*","",MODEL))))
    lavaanfun <- "sem"
  }
  else{
    estimatedModel <- gsub("f[0-9] ~ .*$","",gsub("[.0-9]+\\*","",gsub("\ni.*","",MODEL)))
    lavaanfun <- "cfa"
```

```
}

inner <- matrixpls:::parseModelToNativeFormat(MODEL)$inner
exog <- which(rowSums(inner) == 0)

#
# Do the actual simulations
#

sim.res <- sim(model = estimatedModel, rawData = dataSets, lavaanfun = lavaanfun,
               outfundata = function(fit,data){

                 var.lv <- diag(inspect(fit,"cov.lv"))
                 var.ov <- unlist(lapply(data,function(x){
                   sum((x-mean(x))^2)/length(x)
                 }))

                 sd.lv <- sqrt(var.lv)
                 sd.ov <- sqrt(var.ov)

                 C <- cov2cor(inspect(fit,"cov.lv"))
                 S <- matrix(0,0,0,dimnames = list(c(),c()))

                 #
                 # Regressions from LV correlation matrix. We do this for ML
                 # estimation as well because it simplifies the code when
                 # we do not need to treat regression from CFA and ML
                 # as separate special cases
                 #

                 regressions <- matrixpls:::estimatesMatrixToVector(
                   estimator.regression(S, inner, W = NULL, C = C),inner, "~")

                 # Standardize loadings

                 lambda <- inspect(fit,"coef")$lambda * ((1/sd.ov) %o% sd.lv)
                 loadings <- lambda[lambda != 0]
                 names(loadings) <-
                   paste(colnames(lambda)[col(lambda)[lambda != 0]],
                         "=~",
                         rownames(lambda)[row(lambda)[lambda != 0]],sep="")
                 exogC <- C[exog,exog]
                 correlations <- exogC[lower.tri(exogC)]

                 names(correlations) <-
                   paste(colnames(exogC)[col(exogC)[lower.tri(exogC)]],
                         "~~",
                         rownames(exogC)[row(exogC)[lower.tri(exogC)]],sep="")

                 # Check the admissibility of the correlation matrix
                 inadmissible <- ifelse(any(eigen(C)$values < 0),1,0)

                 # Return the standardized estimates from this replication
                 c(inadmissible,regressions,loadings,correlations)
               },
               multicore = MULTICORE)
```

```
  # Add the estimated regressions

  sim.res@coef <- as.data.frame(do.call(rbind,lapply(sim.res@extraOut, function(x){
    if(is.null(x)) return(NA)
    x[-1]
  })))

  # Save paths. (Loadings are saved later)

  estimates <- sim.res@coef[grep("~f",names(sim.res@coef))]

  results <- cbind(inaadmissible = unlist(lapply(sim.res@extraOut, function(x){
    if(is.null(x)) return(1)
    x[1]
  })), estimates)

  print(paste("Saving file: Paths",designNumber,estimator,1,".Rdata", sep="_"))
  print(results)
  print(apply(results,2,mean))
  if(SAVERESULTS) save(results, file = paste("Paths",designNumber,estimator,1,".Rdata", sep="_"))

}

# Composite based estimators, PLSc and EIVxx

else{
  print(paste("Estimating. Estimator:", estimator))

  # Loadings - 1: PLSc loadings, 2: CFA loadings, 3: minres loadings
  estimatorIndex <- (estimator == "PLSc") + 1 * grepl("EIV",estimator) + 1
  if(estimator == "EIVminres") estimatorIndex <- 3

  # Weights - 1: PLS weights, 2: unit weights

  modeIndex <- (estimator == "PLSc") + 1

  sim.res <- matrixpls.sim(model = MODEL, rawData = dataSets,

                           # PLSc estimation with 2 stage least squares where applicable
                           disattenuate = (estimator == "PLSc" ||
                                             grepl("EIV",estimator)),

                           # Use the factor method
                           innerEstimator = inner.factor,

                           # How to calculate loadings
                           parametersReflective = switch(estimatorIndex,
                                                         estimator.PLScLoadings,
                                                         estimator.CFALoadings,
                                                         estimator.EFALoadings),


                           # PLS Mode A or unit weights
                           weightFunction = switch(modeIndex,
                                                   weight.fixed,
                                                   weight.pls),
```

```
                              # We are not interested in bootstrap SEs or fit indices
                              boot.R = FALSE, fitIndices = NULL,

                              # Use parallel processing
                              multicore = MULTICORE,
                              stopOnError = DEBUG
)


print(paste(sum(sim.res@converged != 0), "non-convergent results"))

#
# True reliabities and a few reliability indices for all composites
#

results <- do.call(ifelse(MULTICORE,"mclapply","lapply"),list(sim.res@extraOut, function(pls.res){

  if(is.null(pls.res)) return(NA)

  R <- attr(pls.res,"R")
  names(R) <- paste("R",names(R))

  W <- attr(pls.res,"W")
  l <- loadings(pls.res)
  Q <- colSums(l * t(W))^2
  names(Q) <- paste("Q",names(Q))

  CR <- CR(pls.res)
  names(CR) <- paste("CR",names(CR))

  S <- attr(pls.res,"S")


  a <- apply(W,1,function(x){alpha(S[x!=0,x!=0])$total[1]})
  temp <- paste("Alpha",names(a))
  a <- unlist(a)
  names(a) <- temp

  c(trueR = R,Q,CR,a)
}))

results <- do.call(rbind, results)

results <- cbind(inadmissible = apply(results[,c(6:10)],1,function(x){any(abs(x)>1)}), results)

print(paste("Saving file: QR",designNumber,estimator,".Rdata", sep="_"))

print(results)
if(SAVERESULTS) save(results, file = paste("QR",designNumber,estimator,".Rdata", sep="_"))


#
# Two sets of manipulated estimates (1: normal, 2:orthogonalized errors)
#

for(estimateSet in ESTIMATESETS){
```

```r
results <- do.call(ifelse(MULTICORE,"mcmapply","mapply"), list(function(pls.res, data){

  if(is.null(pls.res)) return(NA)

  # Possibly disattenuated composite correlations
  C <- attr(pls.res,"C")

  # Choose exogenous correlations from C
  exog = apply(attr(pls.res, "model")$inner == 0,1,all)


  # Return two sets of regression estimates and R2s
  # 1) The original estimates
  # 2) Estimates with orthogonalized errors

  # The first estimate set is with the original C.

  if(estimateSet != 1){

    d <- attr(data,"latentVar")
    Eta <- as.matrix(attr(data,"latentVar")[,grepl("^f[0-9]+",names(d))])
    Epsilon <- attr(data,"latentVar")[,grepl("^res_i[0-9]+",names(d))]

    # Orthogonalize the errors
    EpsilonOrth <- gsorth(Epsilon)

    colnames(EpsilonOrth) <- rownames(EpsilonOrth) <- NULL

    data <- Eta %*%  t(Lambda) + EpsilonOrth

    S <- cor(data)

    # Weight matrix
    W <- attr(pls.res,"W")

    # Composite correlation matrix with orthogonalized error data
    C <- cov2cor(W %*% S %*% t(W))

    # Estimated composite reliabilities
    Q <- attr(pls.res,"Q")

    if(! is.null(Q)){
      # Determination of consistent estimates for the correlation between the
      # latent variables, see (15) and (16) of Dijkstra, April 7, 2011.

      C <- C / sqrt(Q) %*% t(sqrt(Q))
      diag(C) <- 1
    }
  }

  # Check the admissibility of the correlation matrix
  inadmissible <- ifelse(any(eigen(C)$values < 0),1,0)

  if(estimateSet != 1){

    model <- attr(pls.res,"model")
```

```r
        a <- tryCatch(
          matrixpls:::regressionsWithCovarianceMatrixAndModelPattern(
            C,model$inner)[model$inner == 1],
                      error=function(cond) {
                        print(cond)
                        print(pls.res)
                        # Choose a return value in case of error
                        return(NA)
                      })

        # Substitute the new estimates and new C
        pls.res[1:sum(model$inner == 1)] <- a

        beta <- model$inner
        beta[beta == 1] <- a
        attr(pls.res,"beta") <- beta

        attr(pls.res,"C") <- C
      }
      estimates <- pls.res[grep("~f",names(pls.res))]

      R2 <- R2(pls.res)
      R2 <- R2[R2 != 0]
      names(R2) <- paste("R2",names(R2))

      # Exogenous correlations

      exogC = C[exog,exog, drop=FALSE]
      indices <- which(lower.tri(exogC))
      n <- paste(colnames(exogC)[col(exogC)[indices]],"~~",
                 rownames(exogC)[row(exogC)[indices]],sep="")

      exogC <- exogC[indices]
      names(exogC) <- n

      c(inadmissible,estimates,exogC,R2)
    }, sim.res@extraOut, dataSets, SIMPLIFY = FALSE))

    results <- do.call("rbind", results)


    print(paste("Saving file: Paths",designNumber,estimator,estimateSet,
                ".Rdata", sep="_"))
    # print(results)
    print(apply(results,2,mean))
    print(apply(results,2,sd))

    if(SAVERESULTS) save(results, file =
                           paste("Paths",designNumber,estimator,estimateSet,
                                 ".Rdata", sep="_"))

  } # End of looping manipulations

} # End of saving composite specific results

#############################################################################
#
```

```
  # Start processing results that are common to composite and latent variable
  # based techniques
  #
  # This is just the loadings
  #
  ##############################################################################

  results <- sim.res@coef[,grep("=~",colnames(sim.res@coef))]
  results <- cbind(inadmissible = apply(results,1,function(x){any(abs(x)>1)}),
                   results)

  print(paste("Saving file: Loadings",designNumber,estimator,".Rdata", sep="_"))
  print(results)
  if(SAVERESULTS) save(results, file = paste("Loadings",designNumber,estimator,
                                             ".Rdata", sep="_"))

  # Clean up
  rm(results)
  rm(sim.res)

}  # End of looping conditions
```

3 examples.R

```
library(matrixpls)
library(parallel)
library(MASS)
library(simsem)

SAMPLE <- 100

MODEL <- "\nA =~ x1 + x2 + x3\nB =~ x4 + x5 + x6\nB ~ A\n"

Lambda <- (diag(2) * 0.7)[rep(1:2, each = 3), ]
Psi <- matrix(c(1, 0.3, 0.3, 1), 2, 2)

Sigma <- Lambda %*% Psi %*% t(Lambda)
diag(Sigma) <- 1
rownames(Sigma) <- colnames(Sigma) <- paste("x", 1:6, sep = "")

se <- sqrt((1 - Sigma[6, 1]^2)/(SAMPLE - 2))

# Adjust one correlation by +1 SD and other by -1 SD
SigmaAdj <- Sigma
SigmaAdj[4, 1] <- SigmaAdj[1, 4] <- SigmaAdj[4, 1] - se
SigmaAdj[5, 2] <- SigmaAdj[2, 5] <- SigmaAdj[5, 2] + se

converged = FALSE
iter <- 0

res <- NULL

while (!converged) {
    plsc <- matrixpls(SigmaAdj, MODEL, iter = iter, parametersReflective = estimator.PLScLoadings,
```

```
        disattenuate = TRUE)

    res <- rbind(res, c(plsc, attr(plsc, "c"), attr(plsc, "Q"), diag(attr(plsc,
        "W") %*% Lambda)^2))
    iter <- iter + 1
    converged <- attr(plsc, "converged")
}

print(res)

dataSets <- mclapply(1:10000, function(x) {
    mvrnorm(100, rep(0, 6), Sigma)
})

sim.res <- matrixpls.sim(model = MODEL, rawData = dataSets, multicore = TRUE,
    parametersReflective = estimator.PLScLoadings, disattenuate = TRUE, boot.R = FALSE,
    fitIndices = NULL)

# Estimate taking weights from a different sample

estimates <- mcmapply(function(matrixpls.res, data) {
    if (is.null(matrixpls.res))
        return(NA)
    W <- attr(matrixpls.res, "W")
    Q <- attr(matrixpls.res, "Q")
    S <- cor(data)
    C <- cov2cor(W %*% S %*% t(W))
    C[1, 2]/(sqrt(Q[1]) * sqrt(Q[2]))
}, sim.res@extraOut, dataSets[c(10000, 1:9999)])

plot(density(sim.res@coef[, 1], na.rm = TRUE), xlim = c(-0.5, 1))
lines(density(unlist(estimates), na.rm = TRUE), lty = 2)
```

1. Appendix E – Partial Replication of Goodhue et al 2012

In this appendix we provide a partial replication of the study by Goodhue, Lewis, and Thompson (2012) to assess the performance of Cronbach's alpha in the conditions that they used. Goodhue et al. implemented disattenuation by correcting the regression estimates with Cronbach's alphas calculated using the population values of indicator reliabilities. Because the exogenous latent variables are uncorrelated in their model, the regression coefficients converge to bivariate correlations, and so applying the disattenuation formula directly to regression estimates produces a consistent estimator. However, as also noted by Dijkstra and Henseler (2015), Cronbach's alpha is an inconsistent estimator for PLS Mode A composites. The population reliabilities for the PLS Mode A composites for the Goodhue et al. model are all .856, whereas Cronbach's alpha from the population correlation matrix is .84, leading to bias of -.016. However, this provides an incomplete picture of how Cronbach's alpha performs as a reliability estimate for PLS composites in the small sample scenarios studied by Goodhue and colleagues. To examine this issue further, we replicated their Study 1 using 1000 Monte Carlo replications for each of the sample sizes used in their Figure 8. The R code for our replication is available in the end of this appendix. Comparing the true reliabilities of the PLS composites and Cronbach's alphas calculated for each sample produced a rather different set of results than what asymptotic comparison would suggest: Instead of being negatively biased, Cronbach's alpha showed a small positive bias of .012, .007, and .004 averaged over all composites for the three sample sizes of 90, 150, and 200 respectively. The direction of bias is positive because the PLS weights can vary widely in small samples and therefore it is possible that a single set of weights may not be close to the optimal weights, leading to decreased composite reliability (Rönkkö & Evermann, 2013).

2. References

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly*, *39*(2), 297–316.

Goodhue, D. L., Lewis, W., & Thompson, R. (2012). Does PLS have advantages for small sample size or non-normal data. *MIS Quarterly*, *36*(3), 981–1001.

Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods*, *16*(3), 425–448. http://doi.org/10.1177/1094428112474693

```r
library(matrixpls)
library(simsem)
library(psych)

MODEL <- "
Ksi1 =~ .7*x1 + .8*x2 + .9*x3
x1 ~~ .51*x1
x2 ~~ .36*x2
x3 ~~ .19*x3
Ksi1 ~~ 1*Ksi1

Ksi2 =~ .7*x4 + .8*x5 + .9*x6
x4 ~~ .51*x4
x5 ~~ .36*x5
x6 ~~ .19*x6
Ksi2 ~~ 1*Ksi2


Ksi3 =~ .7*x7 + .8*x8 + .9*x9
x7 ~~ .51*x7
x8 ~~ .36*x8
x9 ~~ .19*x9
Ksi3 ~~ 1*Ksi3

Ksi4 =~ .7*x10 + .8*x11 + .9*x12
x10 ~~ .51*x10
x11 ~~ .36*x11
x12 ~~ .19*x12
Ksi4 ~~ 1*Ksi4

Eta1 =~ .7*y1 + .8*y2 + .9*y3
y1 ~~ .51*y1
y2 ~~ .36*y2
y3 ~~ .19*y3

Eta1 ~ .48*Ksi1 + .314*Ksi2 + .114*Ksi3
Eta1 ~~ .658008*Eta1
"
for(N in c(90, 150, 200)){
  simres <- matrixpls.sim(1000, MODEL, N, boot.R = FALSE, multicore = TRUE,
                          sequential = TRUE,
                          fitIndices = function(matrixpls.res){
                            R <- attr(matrixpls.res, "R")
                            S <- attr(matrixpls.res, "S")
                            for(i in 1:5){
                              a <- alpha(S[i*3-0:2,i*3-0:2])
                              R[i] <- R[i] - a$total[[1]]
                            }
                            R
                          })

  f <- inspect(simres,"fit")
  print(paste("N:",N,"mean bias:",print(mean(as.matrix(f)))))

}
```