Bayesian Structural Equation Modeling with Cross-Loadings and Residual Covariances: Comments on Stromeyer et al.

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Abstract

A recent article in the Journal of Management gives a critique of a Bayesian approach to factor analysis proposed in Psychological Methods. This commentary responds to the authors’ critique by clarifying key issues, especially the use of priors for residual covariances. A discussion is also presented of cross-loadings and model selection tools. Simulated data are used to illustrate the ideas. A re-analysis of the example used by the authors reveals a superior model overlooked by the authors.
1 Introduction

Stromeyer et al. (2014) provides a discussion of the BSEM (Bayesian Structural Equation Modeling) technique proposed in Muthén and Asparouhov (2012), stating

"Given the promise we see in the BSEM technique to enable management scholars to push the boundaries of theory testing, we offer the following series of recommendations to guide the future use of the BSEM technique with regards to measurement model development."

Muthén and Asparouhov (2012) discussed two key factor analysis application areas for BSEM: residual covariances and cross-loadings. Stromeyer et al. (2014) is critical of the residual covariance application of BSEM. Recommendation 6 (pp. 24-25) states three reasons for why this technique should be avoided and concludes that this technique should not be used until guidelines become available. In this commentary we present our disagreement with this view, addressing the Stromeyer et al. (2014) concerns by providing a detailed account of the proper use of BSEM with residual covariances. It is shown that this technique in fact provides unique insights not obtained by other factor analysis approaches.

This commentary also presents our disagreement with Recommendation 5 of Stromeyer et al. (2014, pp. 23-24) where it is stated that BIC (Bayesian Information Criterion) should be given preference over DIC (Discrepancy
Information Criterion) for model selection involving BSEM. Our view is that only DIC properly accounts for the BSEM parameters with small-variance priors.

Stromeyer et al. (2014) also have objections about BSEM with cross-loadings, arguing that this can obscure measurement problems and lead to misestimated factor correlations. Based on our experience and our simulation studies we dismiss these objections.

Section 2 presents the approach to BSEM with residual covariances. Illustrations are provided using several simulated data examples. Section 3 discusses DIC versus BIC for BSEM analysis. In Section 4 we discuss the use of cross-loadings in BSEM. Section 5 applies the BSEM techniques in a re-analysis of the Stromeyer et al. (2014). This re-analysis leads to an alternative model that is overlooked by using ordinary factor analysis or BSEM with only cross-loadings. Section 6 concludes.

2 BSEM applications with residual covariance

Stromeyer et al. (2014) point out that BSEM cross-loadings analysis is much easier to estimate and interpret by SEM researchers than BSEM residual covariance analysis. We argue here that this should not be the case and that both approaches use the same basic idea. We add to the model a set of potentially misspecified parameters with small priors around zero. These parameters are neither completely fixed to zero nor are completely free, but
are instead approximately fixed to zero. In the BSEM analysis we preserve the hypothesized SEM model while allowing the data to drive away from zero some of these additional parameters when evidence in the data exists. Despite the fact that the priors for the BSEM residual covariance analysis are somewhat more advanced than the priors for the BSEM cross-loadings analysis due to its multivariate nature, simple guidelines are available and are clarified below.

The BSEM method with residual covariances uses small informative priors for the residual covariance parameters in CFA (confirmatory factor analysis) to estimate a full residual variance covariance matrix as part of the CFA model estimation. With this method the residual covariance matrix is unconstrained by the model but is constrained by the prior. We consider a simple CFA model for a factor $\eta$ and a loading matrix $\Lambda$

\[ Y = \nu + \Lambda \eta + \varepsilon, \tag{1} \]

where

\[ \text{Var}(\varepsilon) = \Theta \tag{2} \]

is a diagonal residual covariance matrix. We consider situations where the CFA model does not fit the data well according to the Posterior Predictive P-value (PPP; Muthén & Asparouhov, 2012) and we illustrate what can be learned from a BSEM analysis with unconstrained residual covariances.

For the BSEM method we set a prior for the $\Theta$ matrix as the Inverse
Wishart prior

\[ \Theta \sim IW(dD, d), \quad \text{(3)} \]

where \( d \) is the degrees of freedom of the distribution and \( D \) is the diagonal matrix equal to the CFA estimate of \( \Theta \). This choice of prior is motivated as follows, drawing on Muthén and Asparouhov (2012, p. 335). The prior mean for \( \Theta \) is

\[ \frac{d}{d - p - 1} D, \quad \text{(4)} \]

where \( p \) is the number of observed variables. The prior mode for \( \Theta \) is

\[ \frac{d}{d + p + 1} D. \quad \text{(5)} \]

Thus for all off-diagonal elements of \( \Theta \) the prior mean and the prior mode are both zero. For the diagonal elements of \( \Theta \) and sufficiently large \( d \) both the prior mode and the prior mean will be close to \( D \). As \( d \) increases the prior variance for all parameter converges to 0, see formulas (A15) and (A17) in Muthén and Asparouhov (2012). Setting the \( d \) parameter to a large value is equivalent to analyzing the CFA model with residual variance parameters fixed to the CFA estimates \( D \) and residual covariance parameters fixed to zero. Thus the estimated BSEM model for large \( d \) would be equivalent to the CFA model and it would yield PPP=0 when the CFA model has PPP=0. We conclude that the BSEM model would be rejected when \( d \) is sufficiently large.
Stromeyer et al. (2014) state that BSEM models with unconstrained residual covariances will yield outstanding model fit regardless of what model is specified. Clearly this statement is incorrect for three reasons. First, the authors ignore the basic asymptotic results that as \( d \) is sufficiently large the PPP for the BSEM model will become the same as the PPP for the CFA model, i.e., the BSEM model with large \( d \) will reject the model in those cases where the CFA model is rejected. Second, Stromeyer et al. (2014), in their own data analysis fail to investigate prior sensitivity as recommended in Muthén and Asparouhov (2012). If these authors had explored Inverse Wishart priors with different degrees of freedom they would have inevitably obtained BSEM models with large degrees of freedom parameter \( d \) and PPP=0. Just as in the cross-loading BSEM analysis, very small prior variances for the cross-loadings is necessary as part of the model estimation, so is the BSEM residual covariance analysis with large degrees of freedom parameter \( d \). The idea behind the BSEM modeling is very simple. Attach a small variance prior to all possible additions to the CFA model and let the data determine if such additions are necessary. The basic BSEM logic converts a fixed to zero parameter to an approximately fixed to zero parameter by specifying a small-variance prior. In that regard Stromeyer et al. (2014) misrepresent the BSEM logic and the basic BSEM implementation. Third, the authors misrepresent the primary goal of estimating a BSEM model. The goal of the BSEM model is not to confirm or not to confirm the CFA model but to provide the means to evaluate the difference between the hypothe-
sized CFA model and the data. The interpretation of that difference and the actual conclusions of the BSEM analysis is entirely up to the substantive researcher.

Gradually lowering the degrees of freedom parameter \( d \) in the BSEM model would yield a more flexible model where the residual covariances are no longer severely constrained to zero. For sufficiently low degrees of freedom parameter the BSEM model will essentially estimate a completely unconstrained variance covariance matrix. Therefore such a model would yield a high PPP value and the model would not be rejected. This happens because the prior restrictions are minimal and thus the BSEM model is sufficiently close to the unidentified and unrestricted model without the prior restrictions. This does not imply that the BSEM residual covariance approach is flawed. The focus of this approach is not only to test the model, but to generate ideas about possible model modifications that can yield a better fitting model.

In this section we illustrate the proper usage of the BSEM analysis with several examples. For each example a CFA model is estimated and the CFA model is rejected based on \( \text{PPP}=0 \). The CFA analysis is then followed up with a BSEM analysis. Here we assume that any cross-loading BSEM analysis has already been completed and we focus only on the BSEM analysis of the residual covariance. With a sufficiently low degrees of freedom parameter \( d \) the PPP for the BSEM analysis is guaranteed to be greater than 0.05. We conduct BSEM sensitivity analysis by varying the degrees of freedom
parameter $d$ with the following as the primary goal.

- Goal: Determine the largest degrees of freedom parameter $d$ that yields a PPP value greater than 0.05.

This model is what we consider to be the BSEM model of interest. By definition this BSEM model is not rejected by the data and can be considered to be the BSEM model closest to the CFA model that fits well enough. This model resolves all of the CFA model misfits. At the same time the larger the degrees of freedom parameter $d$ is the stricter the prior is and thus the CFA model modifications will be the smallest possible. This model is also better identified than models with lower $d$ parameters and yields faster convergence.

We summarize the BSEM sensitivity analysis in several steps.

1. Step 1. Select a starting value for $d$. One possible starting value is $d = 100$ (for sample size near 500), however for models with large sample size $d = 1000$ (for sample size near 5000) or $d = 10000$ (for sample size near 50000) should be used.

2. Step 2. Estimate the BSEM model with the initial or current $d$ value. There are three possible outcomes.

   (a) Fast convergence (not much slower than the corresponding CFA model) and PPP>0.05. In this case you can use that BSEM model.

   (b) Slow or no convergence. Increase $d$. Repeat Step 2 with new $d$. 


(c) Fast convergence but PPP<0.05. Decrease $d$. Repeat Step 2 with new $d$.

In the above process the rate of increase or decrease of the $d$ values can be selected in an ad-hoc manner. For example if a starting value of $d = 100$ is used, depending on the result the next value of $d$ can be 50 or 150. The above iterative process should not take more than 5 iterations ideally. Note also that following the above process we technically do not arrive at the maximum $d$ values for which PPP>0.05. We arrive at a $d$ value that yields fast convergence, which can be interpreted as the model is sufficiently identified, and for which PPP>0.05, which can be interpreted as the model fits sufficiently well as compared to the CFA model. These two characteristics of the BSEM model should be sufficient to make inference on the needed model modifications. If the inference is not clear, one possibility is to consider higher values of $d$ that still yield PPP>0.05. This will tend to reduce the values of the estimated residual covariance and perhaps make the inference easier.

Also note that in the construction of the Inverse Wishart prior it is important to use the exact $D$ matrix from the Bayes CFA estimation when the degrees of freedom parameter $d$ is large. If $d$ is small one can use an approximate and rounded $D$ matrix because the prior is not strong and unlikely to yield misfit due to mismatch in the residual variances. For large $d$ however, if $D$ is not set as in the CFA model the PPP may reject the BSEM model due to a mismatch in the residual variance rather than the residual covariance.
The BSEM model can help us discover the places where the CFA model fails. Whether or not the CFA model is modified based on the BSEM discoveries is a separate issue. This decision should depend on what the BSEM analysis determines and the possible substantive interpretations. Below we illustrate five principally different possible outcomes from the BSEM analysis. In some situations good model modifications can be discovered. In others, the BSEM analysis would suggest that the CFA misfit is due to small and unimportant residual correlations and the main model should stay unchanged despite the misfit.

The advantage of using BSEM analysis for model modifications is that the model modifications are based on the original CFA model and the BSEM analysis includes the original CFA loadings pattern. For example, evaluating the differences between the model-estimated and observed variance covariance matrix does not provide that kind of embedding of the original model and would simply point out which observed covariances are not matched by the model rather than how the model should be modified.

2.1 Large isolated residual covariances

In this section we show that the BSEM analysis can pinpoint a few large residual correlations that are responsible for the misfit. Such large correlations can be included in a modified CFA model and interpretation for such correlations should be sought. Consider a simulated factor analysis example with 6 indicator variables and a single factor. All means are set to zero, all
loadings and residual variances are set to 1. In the generation of the data we also include a residual correlation of 0.50 between the first two indicators. The sample size for this simulated example is 500. The CFA analysis without any residual correlations is rejected with PPP=0. The BSEM model with \( d = 100 \) is not rejected and satisfies the goal of the BSEM sensitivity analysis. To set up the prior for the residual covariances in BSEM we set \( D \) to be the identity matrix as all CFA residual variance estimates are close to 1. The estimate for the residual correlation between the first two variables is 0.30 and is statistically significant. All of the remaining residual correlations are smaller than 0.11 and are not significant. Thus the BSEM analysis suggests that an isolated residual correlation is the main reason for the CFA model misfit. This correlation can be included in the CFA model to improve the model fit, to improve the accuracy of the factor model parameter estimates and to improve the accuracy of the factor score estimates.

### 2.2 Missing factor

In this section we show that the BSEM analysis can point to a missing factor in the CFA analysis. We generate a data set based on a two-factor model where each factor has three indicators. Parameters are set as in the previous section. Estimating a CFA model with one factor yields model rejection. The BSEM model with \( d = 250 \) is not rejected and satisfies the goal of the BSEM sensitivity analysis. All residual correlations are estimated to be between 0.25 and 0.38 by absolute value and all are statistically significant.
Some correlations are positive and some are negative. Clearly this situation is easy to distinguish from the situation presented in the previous section. The fact that all correlations are misfitted should be interpreted as evidence that the one-factor model is an insufficient representation of the data and the possibility for more factors should be explored.

2.3 Extra factor: two factors instead of one

In this section we show that the BSEM analysis can suggest reducing the number of factors by combining two highly correlated factors into one. We simulate a factor analysis example with 6 indicator variables and a single factor. In the generation of the data we also include a residual correlation of 0.7 between the first two indicators. The data is analyzed with a CFA model with two factors with 3 indicators each. The CFA model is rejected. The correlation between the two factors is estimated to be 0.8, which is high but not sufficiently high to consider combing the two factors. The standard error for the factor correlation parameter is 0.06. The corresponding BSEM analysis with $d = 50$ is not rejected. The correlation between the two factors is 0.98 with a standard error of 0.05. This is clearly enough evidence to consider combing the two factors into one. In addition, the BSEM analysis points to a residual correlation between the first two indicators. That residual correlation parameter is estimated to be 0.41 and is statistically significant. All other residual correlation parameters are smaller than 0.19 and can be considered ignorable. Using this BSEM analysis we can conclude that the
two factors should be combined as one and that there is one isolated residual correlation.

### 2.4 Extra factor: unstable factor that can be replaced by residual correlations

In this section we show that the BSEM analysis can suggest reducing the number of factors by eliminating unstable factors and replacing them with isolated residual correlations. We simulate a factor analysis example with 6 indicators but only the first three have loadings 1 and the remaining 3 have loadings 0. Two residual correlations are included in the data generation $\theta_{34} = 0.4$ and $\theta_{56} = 0.7$. The sample size for this simulation is 200. We analyze the data with a two-factor CFA model. The first factor is measured by the first 3 indicators. The second factor is measured by indicators 3 through 6. Thus the CFA model includes a cross-loading from the second factor to the third indicator. The CFA is rejected with PPP=0, however, all of the main loadings are significant. The cross-loading is not significant. The BSEM model with $d = 50$ is not rejected. In the BSEM model the structure for the first factor appears to be unchanged, but the structure for the second factor is changed completely. Now the loadings for the last two indicators are small and insignificant while the cross-loading is significant. This indicates that the second factor is poorly defined and is constructed simply to account for some isolated residual correlations. The estimate for $\theta_{56}$ is 0.55 and is
statistically significant while all other covariances are not. The remaining structure of the second factor is now based only on one main loading (for indicator 4) and one cross-loading (for indicator 3) which also suggests that the factor is replaceable by the residual correlation $\theta_{34}$. The BSEM analysis identified a poorly defined factor and identified two residual correlations that can be added to the model instead of that factor, arriving again at the true model that generated the data.

2.5 Small residual correlations

In this section we show that the BSEM analysis can suggest that the failure of the CFA model may be due simply to small residual correlations. If these correlations are small one option is to retain the original CFA model and treat it as a good approximation to the data. Here we generate a data set from a one-factor model with 6 indicators. We add the following residual correlations for the data generation $\theta_{12} = \theta_{14} = 0.05$ and $\theta_{13} = \theta_{35} = -0.05$. The sample size is 500. The CFA one-factor model is rejected while the BSEM model with $d = 100$ is not rejected. The BSEM residual correlations are all less than 0.1 and are not statistically significant. Clearly these BSEM results are quite different from those in the previous sections and can lead us to the conclusion that no major model change is needed and the misfit in the CFA analysis is due to minor difference between the model and the data.
2.6 Conclusion

The BSEM model points out which residual correlations are not accounted for by the CFA model, which factors have stable structures and which do not. That information can be used for modifying the CFA model to obtain a better fitting model. One key issue in considering the BSEM results is which covariances/correlations should be freed as candidates to be included in the CFA model. In making this decision we should consider the statistical significance as computed by the BSEM model estimation as well as the substantive significance, meaning, whether or not the estimated value is perceived to be sufficiently large to be of substantive importance.

Two of the possible outcomes are clear. If a correlation is substantively and statistically significant they should be included in the CFA. If a correlation is substantively and statistically insignificant it should not be included and it should be fixed to zero. There is some ambivalence in the remaining two situations and the decision is somewhat subjective. We provide some general guidance in that regard. If a correlation is substantively significant but not statistically significant one can increase the degrees of freedom parameter \( d \) in the BSEM estimation. If that parameter is not sufficiently large the estimated standard errors in the BSEM estimation may be artificially too large due to poor model identification. Thus increasing \( d \) may align the substantive and statistical significance. On the other hand, if a parameter is substantively insignificant but statistically significant we may choose to treat that parameter as approximately zero and interpret the CFA model as
a sufficiently good approximation for the data. In addition, consider the fact that the estimation of the residual correlation parameters is tied up with the estimation of the factor model, i.e., the estimates of the residual correlation parameters are not independent. If only one correlation is misfitted by the CFA model the BSEM model may show more than one statistically significant correlations involving the same variables due to the fact that the factor analysis model will attempt to compensate the misfit and thereby affect the remaining correlations related to those indicator variables. In such situations focusing on the biggest correlations in the BSEM model can be used as a good strategy. For example if two correlations are statistically significant within the same set of factor indicators but only one is substantively significant we can choose to free only that one in the CFA model and hope that the resulting factor model adjustment will reduce the value of the remaining one. In this somewhat ad-hoc process the PPP value should be used to evaluate the CFA model fit.

3 The use of DIC versus BIC in BSEM analysis

Stromeyer et al. (2014) discuss the use of DIC and BIC to choose among models in BSEM analysis. Because of the special nature of the BSEM parameters, we think DIC is more appropriate than BIC. The model complexity penalty for DIC is based on the estimated number of parameters while the penalty for
BIC is based on the actual number of parameters. Thus BIC can unnecessarily penalize the BSEM model by counting small-variance prior parameters as actual parameters and thereby overshadowing information provided by the BSEM analysis. For this reason we find that the recommendation given in Stromeyer et al. (2014, p. 24) to place more weight on BIC instead of DIC is misguided and we illustrate this below with a simulation study.

For both BSEM and CFA models DIC is computed as follows. In each MCMC iteration we compute the deviance for the current parameters

\[
D(\theta) = -2 \log(p(Y|\theta)),
\]

where \(p(Y|\theta)\) represents the likelihood of the observed data given the current parameters \(\theta\). We then compute the effective number of parameters \(p_D\)

\[
p_D = \bar{D} - D(\bar{\theta}),
\]

where \(\bar{D}\) represents the average deviance across all MCMC iterations and \(\bar{\theta}\) represents the average of the parameters across the MCMC iterations. Finally DIC is computed as

\[
DIC = \bar{D} + p_D.
\]
The computation of BIC in Mplus is performed as follows

\[ BIC = D(\bar{\theta}) + k \log(N), \]  

where \( k \) is the number of model parameters and \( N \) is the sample size. \(^1\)

For both BIC and DIC a low value is preferred. This is obtained for high log-likelihood / low deviance and low model complexity penalty, where the complexity penalty for DIC is the estimated number of parameters \( p_D \) and for BIC it is \( k \log(N) \). For BIC the model complexity penalty increases with the sample size and uses the actual number of parameters \( k \) rather than the estimated as in DIC.

Consider the following simulated example that illustrates the advantage of DIC over BIC for BSEM residual covariance analysis. We generate data according to a factor analysis model with one factor and ten indicators. All factor loadings and residual variances are set to one and the means are set to zero. For the data generation model we also include a residual correlation of 0.5 for two of the indicators. The sample size for this simulation example is 200. We analyze the data with the one-factor CFA model and the corresponding BSEM model with \( d = 200 \). Table 1 contains the results of this simulation. Using BIC for model selection yields the incorrect conclusion to prefer the CFA model with no residual correlations in the model. Using DIC

\[^1\text{In principle, in the computation of BIC, the deviance should be evaluated at the ML parameter estimates rather than the posterior mean, however, asymptotically the two are the same and we use the above computation as an approximation for the actual BIC value. The exact BIC value can not be estimated naturally within the MCMC estimation.}\]
Table 1: DIC v.s. BIC comparison for BSEM

<table>
<thead>
<tr>
<th>Model</th>
<th>BIC</th>
<th>DIC</th>
</tr>
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<tbody>
<tr>
<td>CFA</td>
<td>6267</td>
<td>6172</td>
</tr>
<tr>
<td>BSEM</td>
<td>6460</td>
<td>6144</td>
</tr>
</tbody>
</table>

for model selection yields the correct conclusion to prefer the BSEM model which has one large residual correlation in the model. In this example PPP also agrees with DIC and the CFA model is rejected by PPP while the BSEM model is not. In this BSEM example it is interesting to note that the complexity penalty for the BIC criterion uses $k = 75$ true parameters, while for the DIC criterion the estimated number of parameters is $p_D = 40$. The DIC criterion recognizes that most of the extra residual covariance parameters are nothing more than parameters nearly fixed to 0 and it is not penalizing for those parameters.

The BIC criterion is asymptotically guaranteed to select the correct model (Schwarz, 1978). In the above example it is key that the sample size is small ($n = 200$). In this case, the deviance gains of the BSEM analysis are overpowered by the inflated penalty of BIC and that leads to the incorrect conclusion when using BIC. If the sample size is larger both BIC and DIC would pick the BSEM model because the deviance component of the information criteria becomes dominant. Note, however, that for any sample size we can construct a factor analysis model with a sufficiently large number of indicators where the BIC criterion will fail. This is because the inflation of the penalty in
BIC will be even larger for examples with more indicator variables and thus one can expect such problems to occur even with larger sample sizes. Thus we recommend using DIC for comparing BSEM models with other BSEM or regular CFA models. Comparing CFA models estimated by Bayes, BIC may still be preferable.

4 Cross-loadings in BSEM

First we want to point out that the Stromeyer et al. (2014) criticism of the cross-loadings use with BSEM has nothing to do with the BSEM method per se, but concerns cross-loadings in general. The authors do not have a problem with how cross-loadings are found and estimated with the BSEM technique, rather the authors argue against the general use of cross-loadings, thereby dismissing several other well accepted modeling techniques, such as EFA, ESEM, the use of modification indices in SEM and other model modification techniques. Stromeyer et al. (2014) argue that modeling cross-loadings is akin to “modeling noise”. We disagree. Psychometric indicators are seldom perfectly pure construct indicators. Even completely reliable ratings of insomnia or physiological measures of sleep patterns are likely to present significant levels of true score (i.e., valid) associations with multiple constructs such as burnout, depression, stress, drug abuse, etc. Morin et al. (2015; p. 32) note:

Remember that, according to the reflective logic of factor analy-
ses, the factors are specified as influencing the indicators, rather than the reverse. Thus, small cross-loadings should be seen as reflecting the influence of the factor on the construct-relevant part of the indicators, rather than the indicators having an impact on the nature of the factor itself.

It follows that these small cross-loadings are not “noise” and do not taint the constructs by adding “noise”, but rather allow them to be estimated using all of the relevant information present at the indicator level.

Stromeyer et al. (2014) go on to ask why scholars would want to develop instruments that include cross-loadings. We do not argue that researchers should not aspire to develop indicators that are as close to perfect as possible. Although ”pure” indicators of a single construct may exist, we surmise that such indicators remain at best a convenient fiction and that in practice most indicators will present both some level of random noise and also some level of construct-relevant association with other constructs (Marsh et al., 2013; Sass & Schmitt, 2010; Schmitt & Sass, 2011; Marsh et al. 2014; Morin et al., 2015). Relying on a measurement model that makes these associations explicit through cross-loadings is clearly a better way forward than relying on methods where these cross-loadings are swept under the rug. Thurstone (1947) proposed his ”simple structure” principles to ensure conceptual clarity in the assessed constructs and as a set of rules to guide factor rotation, not as a set of guidelines to determine whether a factor solution was meaningful or not. In a typical BSEM cross-loading model a limited number of mid-
size cross-loadings will be added to the CFA model and all remaining cross-
loadings will be near zero. Thus the BSEM cross-loading model does not
compromise the conceptual clarity of the constructs.

Stromeyer et al. (2014) take issue with the argument that the exclusion of
cross-loadings will result in "inflated" factor correlations. Recent statistical
literature on measurement models including cross-loadings (Marsh et al.,
2009, 2010, 2014; Morin et al., 2015) show that factor correlations tend to be
upwardly biased when true cross-loadings are constrained to be zero. This
argument is not based on an opinion, but on the results from simulation
studies (Asparouhov & Muthén, 2009; Sass & Schmitt, 2010; Schmitt &
Sass, 2011), and studies based on simulated data (Marsh et al., 2013; Morin
et al., 2015). The advantage of such studies is that the true population
model is known and thus could be used as an objective benchmark against
which to compare the results from the estimated models. Thus, such studies
are able to provide guidelines that are based on empirical facts, rather than
opinions such as those expressed in Stromeyer et al. (2014). In addition,
simulation studies can be used to show that adding small variance prior cross-
loadings in a BSEM model does not lead to "artificially reduced common
factor covariance", contrary to what Stromeyer et al. (2014) claim to be a
logical conclusion.

What the above mentioned studies showed was that even when small
and substantively meaningless cross-loadings are present in the population
model but ignored in classical CFA models, the factor correlations will tend
to be substantially biased. Interestingly, these studies also show that when the population model meets the independent cluster assumptions inherent in CFA, relying on models allowing for the estimation of cross-loadings will nevertheless result in unbiased estimates of factor correlations notwithstanding the loss in parsimony associated with these models. Overall, these studies clearly show that the inclusion of cross-loadings is neither logically flawed nor logically incorrect, but rather empirically supported by statistical research. Going back to the flawed argument that cross-loadings "taint" the nature of the constructs, these results rather show that it is the exclusion of these cross-loadings that modifies the meaning of the constructs.

The key to successful use of cross-loadings in a BSEM application is determining the small variance of the cross-loadings prior that will allow the non-zero cross-loadings to be estimated while keeping the rest near zero. This should be done as it was done in Section 2 for the residual covariances, i.e., beginning with a very small variance that makes the BSEM and the CFA model identical, and slowly increasing the variance until improvements in model fit diminish and/or quality of model identification diminish as measured by the rate of convergence in the MCMC sequence. Appendix 1 gives a summary of the steps recommended for BSEM with both cross-loadings and residual covariances.
5 Application to Stromeyer et al. example

This section applies the BSEM method with residual covariances to the 5-factor model for the ESE scale of 19 items analyzed by Stromeyer et al. (2014). The resulting BSEM model is compared to the BSEM model with cross-loadings of Stromeyer et al. The two CFA models suggested by the BSEM models are compared as well. Data from both of the randomly drawn samples 1 and 2 are considered (n = 500 in both samples). Sample 1 data are analyzed first, using sample 2 for comparison and cross-validation.

As a first step, the IW(d D, d) residual covariance prior was chosen with D as the residual variances of the Bayes 5-factor CFA model shown in Table 2 of Stromeyer et al. (2014) and d set to 100. This BSEM model maintains the cross-loadings used in Stromeyer et al.’s Table 3, choosing prior variances of 0.01 in line with Muthén and Asparouhov (2012) (Stromeyer et al. used prior variances of 0.02). Because this BSEM analysis gives a posterior predictive p-value (PPP) much greater than 0.05, the next step increases the d value to 200, resulting in PPP=0.129. Given that this PPP value is reasonable close to the stipulated threshold of 0.05, no further increase of d is made. An interesting finding from this BSEM analysis is that the two factors Plan and Marshal are as highly correlated as 0.95 (the sample 2 correlation is 0.93). This suggests combining the Plan and Marshal factors, resulting in a 4-factor model for which the same BSEM priors are applied.²

²An interesting aside is the relationship between prior choices and size of factor correlations in the 5-factor BSEM analysis. Holding the IW prior constant and varying the
Table 2 shows the factor loading and factor correlation estimates from the 4-factor BSEM model using Sample 1 data. It is seen that two cross-loadings are significant and larger than 0.2, S3 loading on Plan-Marshall and P3 loading on Implement Finance. Only two residual correlations (not shown) are significant and greater than 0.2, S3 with P1 and P2 with P3. The Mplus input for this BSEM analysis is shown in Appendix 2, Table 4.

The top of Table 3 shows fit statistics for the Stromeyer et al. (2014) BSEM model (labeled SMSD 5-factor, using the last name initials of the four authors) and our 5-factor and 4-factor models (labeled AM 5-factor/4-factor). These three models are compared using DIC as proposed in Section 3. Table 3 shows that the AM 5-factor model has a better DIC value than the SMSD 5-factor model, 20157 versus 20371. This advantage also holds for sample 2. The AM 4-factor model has a slightly higher (worse) DIC value than the AM 5-factor model, but is preferable due to avoiding the high factor correlation. The AM 4-factor model maintains a PPP value greater than 0.05.

The bottom part of Table 3 shows fit results for the CFA models suggested by the BSEM analyses, referred to as BSEM-based CFA. The SMSD 5-factor CFA model is that of Table 4 in Stromeyer et al. (2014), where three cross-loadings have been added. The AM 4-factor CFA model adds prior variances for the cross-loadings as 0.005, 0.01, and 0.02, the Plan-Marshall factor correlation is 0.99, 0.95, and 0.78 (sample 2 values are 0.99, 0.93, and 0.81). A similar degree of variation in factor correlations does not appear when using only cross-loadings and not residual covariances. A conjecture is that with a more strict cross-loading prior the use of residual covariances gives decreased cross-loadings and that increases the factor correlation because more indicator correlation has to go through the factors.
Table 2: Estimates from 4-factor BSEM with cross-loading prior variance 0.01 and residual covariance priors with d=200 (Sample 1)

<table>
<thead>
<tr>
<th></th>
<th>Search</th>
<th>Plan-Marshall</th>
<th>Implement People</th>
<th>Implement Finance</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>0.93†</td>
<td>-0.04</td>
<td>-0.04</td>
<td>-0.02</td>
</tr>
<tr>
<td>S2</td>
<td>0.98†</td>
<td>-0.07</td>
<td>0.02</td>
<td>-0.00</td>
</tr>
<tr>
<td>S3</td>
<td>0.42†</td>
<td>0.30†</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>P1</td>
<td>0.37†</td>
<td>0.45†</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>P2</td>
<td>0.02</td>
<td>0.64†</td>
<td>-0.05</td>
<td>0.15†</td>
</tr>
<tr>
<td>P3</td>
<td>-0.05</td>
<td>0.65†</td>
<td>-0.09</td>
<td>0.24†</td>
</tr>
<tr>
<td>P4</td>
<td>-0.06</td>
<td>0.83†</td>
<td>-0.09</td>
<td>-0.02</td>
</tr>
<tr>
<td>M1</td>
<td>-0.02</td>
<td>0.89†</td>
<td>0.02</td>
<td>-0.12†</td>
</tr>
<tr>
<td>M2</td>
<td>-0.08</td>
<td>0.75†</td>
<td>0.09</td>
<td>-0.09</td>
</tr>
<tr>
<td>M3</td>
<td>-0.02</td>
<td>0.70†</td>
<td>0.11</td>
<td>-0.05</td>
</tr>
<tr>
<td>IP1</td>
<td>-0.04</td>
<td>-0.07</td>
<td>0.95†</td>
<td>0.01</td>
</tr>
<tr>
<td>IP2</td>
<td>-0.09</td>
<td>0.06</td>
<td>0.85†</td>
<td>0.02</td>
</tr>
<tr>
<td>IP3</td>
<td>-0.06</td>
<td>-0.06</td>
<td>0.93†</td>
<td>0.00</td>
</tr>
<tr>
<td>IP4</td>
<td>0.11†</td>
<td>0.01</td>
<td>0.70†</td>
<td>0.05</td>
</tr>
<tr>
<td>IP5</td>
<td>0.05</td>
<td>0.06</td>
<td>0.76†</td>
<td>-0.06</td>
</tr>
<tr>
<td>IP6</td>
<td>0.03</td>
<td>-0.05</td>
<td>0.76†</td>
<td>-0.01</td>
</tr>
<tr>
<td>IP1</td>
<td>0.01</td>
<td>-0.03</td>
<td>0.05</td>
<td>0.91†</td>
</tr>
<tr>
<td>IF2</td>
<td>0.02</td>
<td>-0.02</td>
<td>-0.02</td>
<td>0.99†</td>
</tr>
<tr>
<td>IF3</td>
<td>-0.04</td>
<td>0.04</td>
<td>0.03</td>
<td>0.79†</td>
</tr>
</tbody>
</table>

Latent Variable Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>Search</th>
<th>Plan-Marshall</th>
<th>Implement People</th>
<th>Implement Finance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Search</td>
<td>—</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plan-Marshall</td>
<td>.65†</td>
<td>—</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implement People</td>
<td>.46†</td>
<td>.64†</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>Implement Finance</td>
<td>.29†</td>
<td>.55†</td>
<td>.44†</td>
<td>—</td>
</tr>
</tbody>
</table>

*Note:* Factor loadings in bold were freely estimated using diffuse priors. Daggers indicate 95% credibility interval does not contain zero.
### Table 3: BSEM and BSEM-based CFA fit statistics

<table>
<thead>
<tr>
<th>Model</th>
<th>Sample</th>
<th>PPP</th>
<th># Par’s</th>
<th># Est’d Par’s</th>
<th>DIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BSEM</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMSD 5-factor cross-loading BSEM (Table 3)</td>
<td>1</td>
<td>0.000</td>
<td>143</td>
<td>113</td>
<td>20371</td>
<td>21032</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.000</td>
<td>143</td>
<td>113</td>
<td>20346</td>
<td>21006</td>
</tr>
<tr>
<td>AM 5-factor cross-loading, residual</td>
<td>1</td>
<td>0.129</td>
<td>314</td>
<td>156</td>
<td>20157</td>
<td>21792</td>
</tr>
<tr>
<td>covariance BSEM</td>
<td>2</td>
<td>0.149</td>
<td>314</td>
<td>160</td>
<td>20179</td>
<td>21806</td>
</tr>
<tr>
<td>AM 4-factor cross-loading, residual</td>
<td>1</td>
<td>0.115</td>
<td>291</td>
<td>161</td>
<td>20163</td>
<td>21648</td>
</tr>
<tr>
<td>covariance BSEM</td>
<td>2</td>
<td>0.089</td>
<td>291</td>
<td>161</td>
<td>20185</td>
<td>21671</td>
</tr>
<tr>
<td><strong>BSEM-based CFA</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMSD 5-factor (Table 4)</td>
<td>1</td>
<td>0.000</td>
<td>70</td>
<td>71</td>
<td>20449</td>
<td>20742</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.000</td>
<td>70</td>
<td>71</td>
<td>20536</td>
<td>20828</td>
</tr>
<tr>
<td>AM 4-factor</td>
<td>1</td>
<td>0.000</td>
<td>68</td>
<td>67</td>
<td>20424</td>
<td>20712</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.000</td>
<td>68</td>
<td>67</td>
<td>20492</td>
<td>20779</td>
</tr>
</tbody>
</table>
the two cross-loadings and two residual covariances discussed in connection with Table 2. Note that for these models only diffuse priors are used, that is, BSEM-type informative priors are not used. Because of this, the comparison between models is carried out using BIC as this is the more common information criterion with CFA models. BIC favors the AM 4-factor model for both sample 1 and sample 2. The same conclusion is reached when using maximum-likelihood estimation.

Table 7 of Stromeyer et al. (2014) shows the results of cross-validation comparing model estimates for sample 1 and sample 2. The strictest invariance across the samples is the "Strong" case (scalar invariance) where factor indicator intercepts and loadings are held equal across samples while the factor means, factor variances, factor covariances, and indicator residual variances are allowed to vary. Here we also add the more relevant full invariance case where all parameters are held equal across samples. BIC is again considered given that BSEM analysis is not used. The BIC values for the SMSD 5-factor model are for the Strong case and the Full invariance case 41453 and 41275, respectively. These BIC values are higher (worse) than those of the corresponding AM 4-factor values, 41355 and 41189, respectively.

In conclusion, our 4-factor model performs better than the proposed 5-factor model of Stromeyer et al. (2014) in both its BSEM version and its CFA version, and it also cross-validates better. Our 4-factor model would not be entertained unless a residual covariance BSEM model is analyzed. The high correlation between the Plan and Marshal factors is not seen in the cross-
loading BSEM analysis of Stromeyer et al. An interesting aside is that the high factor correlation is also not seen in exploratory factor analysis (EFA). EFA with 5 factors shows the CFA loading pattern that is hypothesized and no high factor correlations are obtained. EFA is, however, limited in that it does not allow residual covariances. Both the 5- and 4-factor EFA BIC values are worse than those of our 4-factor model. All in all, this implies that BSEM analysis with residual covariances is uniquely positioned to uncover a model alternative that would otherwise be overlooked. It enables "thinking outside the box" of regular EFA, CFA, as well as cross-loading BSEM. Our 4-factor model alternative performs better in statistical terms than the 5-factor model preferred by Stromeyer et al.. Whether or not this 4-factor alternative is palatable from a subject-matter point of view is a different matter, but it is a useful discovery nevertheless. If the researcher’s theories strongly suggest a 5-factor model, efforts should be made to investigate other item formulations in the instrument development so that the 4-factor alternative is not competitive.

6 Conclusions

This rejoinder has shown that the BSEM technique is a valuable tool for a thorough analysis of a measurement instrument. The technique provides unique insights not obtained by other types of factor analysis. We hope that our discussion has convinced readers that the guidelines we have presented
negate the Stromeyer et al. (2014) recommendation to avoid this technique.
7 Appendix 1: BSEM analysis steps

This appendix gives a summary of BSEM analysis steps. For more information, see Muthén and Asparouhov (2002).

1. Choose a uniform metric for the variables, e.g. by standardizing the variables when the model is scale-free (no parameter equalities across variables), so that scale issues don’t interfere with prior settings (see Muthén & Asparouhov, 2012).

2. Specify cross-loadings with a prior variance that is small enough that the Mplus output

\[ 95\% \text{ Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values} \]

is the same as for the original CFA model without cross-loadings (with variable on a scale with variance one, a prior variance of 0.001 may be suitable).

3. Increase the cross-loadings prior variance by a factor of 10 and then in smaller steps such as 5 and monitor

- a. Speed of convergence (number of iterations); a too large prior variance leads to non-convergence due to non-identification
- b. 95\% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values
Multiple runs should be done; at least five.

4. From the runs in Step 3 make a subjective selection based on criteria a. and b., where for

   • criterion a. the number of iterations to convergence will increase as prior variance increases
   • criterion b. the confidence interval limits will decrease as prior variance increases, with diminishing returns when stabilizing

Subjectively select a prior variance for the cross-loadings that gets the majority of the decrease in criterion b. without sacrificing much on criterion a.

5. Compute D of the residual covariance IW prior using the residual variance estimates from the CFA model or the cross-loading model

6. Step 1 from page 9

7. Step 2 from page 9

8. Conclude on the model: Possible model modifications and decision on a BSEM-based CFA model v.s. the BSEM model as the final model

8 Appendix 2: Mplus BSEM input

This appendix gives the Mplus input for the BSEM model with cross-loadings and residual covariances presented in Table 2.
Table 4: Mplus input for the 4-factor BSEM model with cross-loadings and residual covariances

```
TITLE: BSEM with crossloadings and residual covariances;
DATA: FILE = ESE_Ordered_Text.txt;
VARIABLE: NAMES = rank group rand id s1 s2 s3
     p1 p2 p3 p4 m1 m2 m3 ip1 ip2 ip3 ip4 ip5
     ip6 if1 if2 if3;
USEVARIABLES = s1 s2 s3 p1 p2 p3 p4
     m1 m2 m3 ip1 ip2 ip3 ip4 ip5 ip6
     if1 if2 if3;
USEOBSERVATION = (group EQ 1);
DEFINE: STANDARDIZE s1 s2 s3 p1 p2 p3 p4
     m1 m2 m3 ip1 ip2 ip3 ip4 ip5 ip6
     if1 if2 if3;
ANALYSIS: ESTIMATOR = BAYES;
  !Activates the Bayesian estimator
  CHAINS = 2;
  !Specifies using two Markov Chains for conducting the analysis
  PROCESSORS = 2;
  !For use in multi-core systems, assigns two processors with one
  !per chain
  FBITERATIONS = 15000;
  !Specifying that the minimum number of Markov Chain
  !iterations is 15000
MODEL: search BY s1* s2 s3
     p1 p2 p3 p4 m1 m2 m3 ip1 ip2 ip3 ip4 ip5 ip6 if1 if2 if3 (xload1-xload16);
     plan BY p1* p2 p3 p4 m1 m2 m3
     s1 s2 s3 ip1 ip2 ip3 ip4 ip5 ip6 if1 if2 if3 (xload17-xload28);
     imp_ppl BY ip1* ip2 ip3 ip4 ip5 ip6
     s1 s2 p1 p2 p3 p4 m1 m2 m3 if1 if2 if3 (xload48-xload60);
     imp_fu BY if1* if2 if3
     s1 s2 s1 p1 p2 p3 p4 m1 m2 m3 ip1 ip2 ip3 ip4 ip5 ip6 (xload61-xload76);
     search WITH plan imp_ppl imp_fu;
     plan WITH imp_ppl imp_fu;
     imp_ppl WITH imp_fu;
     serch@1;
     plan@1;
     imp_ppl@1;
     imp_fu@1;
     s1-if3 (pload1-pload19);
     s1-if3 WITH s1-if3 (cload1-cload171);
```
Table 5: Mplus input continued

MODEL PRIORS:
  xload1-xload76~N(0,0.01);
  pload1~ IW(43.2,200);
  pload2~IW(22.8,200);
  pload3~IW(114.8,200);
  pload4~IW(98.4,200);
  pload5~IW(78.6,200);
  pload6~IW(85.0,200);
  pload7~IW(101.2,200);
  pload8~IW(56.0,200);
  pload9~IW(92.2,200);
  pload10~IW(79.2,200);
  pload11~IW(45.6,200);
  pload12~IW(57.2,200);
  pload13~IW(56.2,200);
  pload14~IW(80.2,200);
  pload15~IW(76.2,200);
  pload16~IW(92.6,200);
  pload17~IW(33.6,200);
  pload18~IW(14.8,200);
  pload19~IW(67.4,200);
  cload1-cload171~IW(0,200);

OUTPUT:  STAND(STDYX);
          RESIDUAL TECH1 TECH8 STDY;
PLOT:  TYPE = PLOT2;
References


tion of Distinct Sources of Construct-Relevant Psychometric Multidi-
mensionality. Structural Equation Modeling.


