Meta-analytic structural equation modelling with missing correlations

Jak, S.; Oort, F.J.; Roorda, D.L.; Koomen, H.M.Y.

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Cheung and Chan (2005) proposed a two-stage method to conduct meta-analytic structural equation modelling (MASEM). MASEM refers to the technique of fitting structural equation models to pooled correlation or covariance matrices from several studies. Unfortunately, researchers do not always report all correlations between the variables of interest. In this paper, we propose a method to deal with missing correlations in the two-stage approach. We illustrate the proposed model with a meta-analysis of teacher-child relationships variables from 99 studies. In addition, using simulated data, we show that our method leads to more precise parameter estimates than the existing approach.


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Authors: Suzanne Jak*, Frans J. Oort*, Debora L. Roorda** and Helma M. Y. Koomen*

Meta-analytic structural equation modelling (MASEM) refers to the technique of fitting structural equation models to correlation or covariance matrices from several studies. A well-known approach to conduct MASEM is the two-stage approach of Cheung and Chan (2005). In the first stage, correlation matrices are tested for homogeneity across studies. If the matrices are not significantly different from each other, they are combined to form a pooled correlation matrix. In the second stage, the pooled correlation matrix is taken as the observed matrix in an SEM analysis. User-friendly software to apply the two-stage method is available in the R-Package metaSEM (Cheung, 2011), which utilises the OpenMx package (Boker et al., 2011). MetaSEM gives parameter estimates with standard errors, a chi-square measure of fit, and likelihood based confidence intervals (see Neale & Miller, 1997) for parameters at both stages of the analysis.

Ideally, researchers always report the correlations between all variables in their study. However, often not all correlations between the research variables are given in a paper. Sometimes, the missing correlations can be derived from other statistics that the authors do provide, such as regression coefficients. However, this is not always possible, for example when two variables are both outcome variables in regression analyses. The two-stage approach incorporates studies with missing variables, but a way to handle missing correlations has not yet been proposed. As a consequence, for each missing correlation, one of the two variables associated with the correlation has to be treated as missing. We will refer to this method as the omitted variables approach (OV approach).

In the present paper, we propose a method to deal with missing correlations in the two-stage approach. This method involves adding one parameter to the model for each missing correlation. We will refer to this method as the omitted correlations approach (OC approach). After outlining the method, we illustrate its use with a meta-analysis of teacher-child relationships variables.

**Research Institute of Child Development and Education, University of Amsterdam, the Netherlands, **School Psychology and Child and Adolescent Development, University of Leuven, Belgium

**Correspondence to: Suzanne Jak, Methods and Statistics Department of the Research Institute of Child Development and Education, University of Amsterdam, Amsterdam, the Netherlands, e-mail: S.Jak@uva.nl

Meta-analysis combines the results from several studies. For MASEM, correlation matrices of the
variables of interest will be collected from several studies. The analysis has two stages.

Stage 1: Pooling correlation matrices from several studies

Let \( R_g \) be the population correlation matrix for all present correlations and a free parameter for each missing correlation. We obtain an estimate of \( R_g \) by constraining the elements of the input matrix \( R^* \) to the missing correlation. We substitute an arbitrary value (e.g., zero) in the observed matrix \( R_g \) for a missing correlation. We obtain an estimate of the population correlation matrix \( R^* \) of all \( p \) variables by fitting a multigroup SEM model, in which the model for each group (study) is:

\[
\Sigma_g = D_g (M_g R_{pg} M_g^t) D_g^t + C_g.
\]

In this model, \( R_{pg} \) is the \( p \times p \) population correlation matrix with diag\( (R_{pg}) = 1 \), matrix \( M_g \) is a \( p \times p \) selection matrix that filters out the missing variables in study \( g \). Matrix \( M_g \) is constructed by taking a \( p \times p \) identity matrix and removing the rows corresponding to the missing variables in study \( g \). \( D_g \) is a \( p \times p \) diagonal matrix that accounts for differences in variances across the \( g \) studies. In the OC approach is the addition of Matrix \( C_g \), which is used to account for missing correlations. Matrix \( C_g \) is a symmetric \( p \times p \) correction matrix, with fixed zeros for all present correlations and a free parameter for the missing correlations in study \( g \).

With the identification constraint diag\( (R_{pg}) = 1 \) and a free \( D_g \) matrix, the hypothesis that is being tested is equality of covariances (not of correlations) as the variances in each study do not necessarily equal unity. The homogeneity of covariance matrices (covariances and variances) can be tested by constraining the elements of the diagonal matrix \( D_g \) to be equal across studies, so that \( D_g = D \) for all \( g \) (Cheung & Chan, 2005). The unity of variances can be tested by constraining the elements of the diagonal matrix \( D_g \) to unity, \( D_g = I \) for all \( g \).

The model in Equation 1 is identical to the model in Stage 1 of Cheung and Chan’s two-stage approach, except for the correction matrices \( C_g \). In matrix \( C_g \), the free parameter for each missing correlation will take on a value that minimises the difference between the arbitrary chosen value for the missing correlation in the observed matrix \( R_g \) (e.g., zero), and the estimate in \( R^* \) for the corresponding correlation. A chi-square measure of fit for the model in Equation 1 is obtained by comparing its -2 log likelihood with the -2 log likelihood of the saturated model. The saturated model is given by:

\[
\sum_g = D_g R^*_g D_g^t.
\]

The difference between the -2 log likelihoods follows a chi-square distribution with degrees of freedom equal to the difference in numbers of parameters between the two models. When the chi-square test turns out significant, then the hypothesis of homogeneity of covariances is rejected. The chi-square statistic can also be used to calculate approximate fit indices such as the Root Mean Square Error of Approximation (RMSEA, Steiger & Lind, 1980).

When the model fit is not acceptable, then the hypothesis of homogeneity of covariances is not tenable, so that the estimation of \( R_{pg} \) is not valid. Researchers may then create clusters of more similar studies, and construct separate pooled correlation matrices for all clusters of studies. Alternatively, a random effects model could be used, which estimates variances (and covariances) between the pooled correlation coefficients across studies. In this paper we do not consider random effects models.

The model from Equation 1 can be fitted using maximum likelihood estimation with any structural equation modelling program. However, writing the syntax can be very laborious in some programs. OpenMx (Boker et al., 2011) is a very flexible R-package, allowing the use of all R functions (R Development Core Team, 2011).

Stage 2: Fitting structural equation models

At Stage 2, the pooled correlation matrix from Stage 1 is used as the input matrix in an SEM analysis. Cheung and Chan (2005) propose using weighted least squares estimation at this stage. Weighted least squares estimation takes the asymptotic covariance matrix of the correlation coefficients from Stage 1 as the weight matrix in the fit function. Some correlation coefficients at Stage 1 are estimated using information from more studies than other correlation coefficients. As a result, coefficients that are based on more studies will have smaller variance in the asymptotic covariance matrix, and thus get more weight in the estimation process than coefficients that are based on less studies.

SEM generally requires the use of covariance matrices, however, the input matrix at Stage 2 is a
correlation matrix. Treating the correlation matrix as a covariance matrix leads to incorrect results when estimating confidence intervals or when testing specific hypotheses (Cudeck, 1989). To obtain correct results at Stage 2, we add a so-called estimation constraint. This constraint enforces the diagonal of the model implied correlation matrix to identity.

Illustrative example

Data
Roorda, Koomen, Spilt and Oort (2011) collected 99 studies that reported correlations between positive teacher-student relations and negative teacher-student relations on the one hand and student engagement and student achievement on the other hand. Correlations between positive teacher-student relations and negative teacher-student relations were collected afterwards for the present paper. Of these studies, 63 were conducted at primary schools and 36 at secondary schools. In total, there were 129,184 respondents (sample sizes ranging from 42 to 39,553). Based on leading theories about teacher-student relations (Connell & Wellborn, 1991; Pianta, 1999), teacher-student relations were considered as exogenous variables and engagement and achievement as endogenous variables. Out of the 99 studies, 20 studies missed a correlation between two variables, and 90 studies did not include one or more of the four variables.

Results
Table 1a gives the fit results of the several models we fitted to the 99 correlation matrices, using OpenMx (Boker et al., 2011). Model 1 is a saturated model, meaning that a correlation matrix is estimated for each study, without equality restrictions across studies. This model is used as a baseline model, to obtain fit indices for Models 2 to 4. Model 2 is a model in which we restricted all covariances to be equal, without restrictions on the variances across studies (equal covariances). Model 3 is a model in which we restricted all covariances and variances to be equal across studies (equal variances and covariances). Model 4 is a model in which we additionally restricted all variances to be unity (equal variances across studies).

All three models at Stage 1 had significant chi-square values, indicating that the models do not fit

### Table 1

**Fit results of models at Stage 1 and Stage 2 using two approaches (N = 129,184)**

#### a) Fit results using the OC approach

<table>
<thead>
<tr>
<th>Model</th>
<th>-2 log likelihood</th>
<th>df</th>
<th>$\chi^2$</th>
<th>RMSEA + 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>STAGE 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Saturated</td>
<td>271981.9</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>2. Equal covariances ($D_g = \text{free}$)</td>
<td>277400.2</td>
<td>214</td>
<td>5418.34</td>
<td>.0137 [.0133 ; .0141]</td>
</tr>
<tr>
<td>3. Equal variances and covariances ($D_g = D$)</td>
<td>277957.2</td>
<td>474</td>
<td>5975.35</td>
<td>.0095 [.0092 ; .0097]</td>
</tr>
<tr>
<td>4. Variances equal to unity ($D_g = I$)</td>
<td>277957.4</td>
<td>478</td>
<td>5975.53</td>
<td>.0094 [.0092 ; .0097]</td>
</tr>
<tr>
<td>STAGE 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Mediation model (based on Model 2)</td>
<td>144.73</td>
<td>2</td>
<td>144.73</td>
<td>.0235 [.0197 ; .0274]</td>
</tr>
</tbody>
</table>

#### b) Fit results using the OV approach

<table>
<thead>
<tr>
<th>Model</th>
<th>-2 log likelihood</th>
<th>df</th>
<th>$\chi^2$</th>
<th>RMSEA + 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>STAGE 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Saturated</td>
<td>249821.0</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>2. Equal covariances ($D_g = \text{free}$)</td>
<td>254872.7</td>
<td>193</td>
<td>5051.64</td>
<td>.0140 [.0136 ; .0144]</td>
</tr>
<tr>
<td>3. Equal variances and covariances ($D_g = D$)</td>
<td>255420.2</td>
<td>434</td>
<td>5599.22</td>
<td>.0096 [.0093 ; .0099]</td>
</tr>
<tr>
<td>4. Variances equal to unity ($D_g = I$)</td>
<td>255420.3</td>
<td>438</td>
<td>5599.28</td>
<td>.0096 [.0093 ; .0098]</td>
</tr>
<tr>
<td>STAGE 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Mediation model (based on Model 2)</td>
<td>178.48</td>
<td>2</td>
<td>78.48</td>
<td>.0261 [.0223 ; .0301]</td>
</tr>
</tbody>
</table>
the data exactly. The RMSEAs were all below .05, indicating close approximate fit (Browne & Cudeck, 1992). As we do not have any hypothesis on the variances being equal across studies, we take the result of Model 2 as the estimate of the population correlation matrix. This correlation matrix is given in Table 2, and is used as the input for the Stage 2 analysis.

The Stage 2 model is based on social-motivational theory (Connell & Wellborn, 1991), in which it has been hypothesised that student engagement acts as a mediator in the association between teacher-student relations and student achievement. Empirical studies have provided some support for the mediating role of engagement (e.g., Hughes, Luo, Kwok, & Loyd, 2008). Therefore, the path model we fitted was a mediation model, in which the influence of positive and negative teacher-child relationships on student achievement was mediated by student engagement. This model fitted the population correlation matrix from Stage 1 closely according to the RMSEA.

Results when deleting variables with missing correlations
We compared our results with the results obtained with the OV approach. This involved the deletion of a variable in 20 of the 99 studies. As can be seen in Table 1b, this approach leads to a loss of degrees of freedom and slightly worse model fit. However, the models still fit closely according to the RMSEA. Some parameter estimates are different from the previous analysis, and the likelihood based confidence intervals are somewhat wider. Figure 2 shows a graphical comparison of the parameter estimates and confidence intervals from the two analyses. Each graph pictures the parameter estimate (the dot) with its 95% confidence interval (the line) for the analysis with the OC approach (upper part) and for the analysis with the OV approach (lower part).

Simulation study
In order to investigate the effect of accounting for the missing correlations (OC approach), compared with deleting variables associated with missing correlations (OV approach), we performed an analysis of simulated data. We generated complete data for 100 studies. The pooled correlation matrix was estimated based on the full data, and based on data with missing correlations using the two approaches. The data were simulated under extreme conditions, so that differences between the two analysis methods became more apparent than in the illustration. Our expectation is that the OC approach leads to models with more power, better parameter estimates and smaller confidence intervals than the OV approach.

Data generation
We chose values of the population correlations based on the data from Roorda et al. (see Table 2). For each of the 500 replications, complete raw data were generated and the analysis was performed for both the OC approach and the OV approach.
Figure 2 Parameter estimates (dots) with 95% confidence intervals (lines) of all parameters for the analysis with the OC approach (upper dot + line) and the OV approach (lower dot + line).

Note: v1 = Positive teacher-student relations, v2 = Negative teacher-student relations, v3 = Student engagement, v4 = Student achievement
drawn from the multivariate normal distribution, with means equal to zero, and variance covariance matrix equal to the population correlations. We chose 100 as the number of studies, with each study having a sample size of 100. So, each dataset contained $100 \times 100 = 10000$ scores on 4 variables. For each study, the correlation matrix was calculated and included in the meta-analysis.

Results with complete data

Fitting the model from Equation 1 (with $D_g = I$) to the complete data in 500 samples led to the average correlations in Table 3a. Percentages of estimation bias in all parameters are calculated as $100 \times (\text{mean estimated value} - \text{population value}) / \text{population value}$. According to Muthén, Kaplan and Hollis (1987), estimation bias less than 10% can be considered negligible. With complete data, estimation bias was below 1% for all parameters. The model had 994 degrees of freedom, the average chi-square value was 294.48 ($SD = 41.28$).

Results with missing correlations

The correlation between variables 1 and 3 was deleted randomly for 80% of the studies. Also for 80% of the studies we randomly deleted the correlation between variables 2 and 3. In this way, about 64% of the studies missed both correlations, and about 32% studies missed one of them, while only about 4% of the studies had complete data.

Using the OC approach, we obtained the pooled correlation matrix shown in Table 3b. The model had 834 degrees of freedom, the average chi-square value was 119.29 ($SD = 39.60$). The estimated correlations based on the data with missing correlations were close to the population correlations. The largest difference was found for the correlation between variables 1 and 4, which deviated 1.27% from the population correlation. The results in Table 3c were obtained by removing one variable for each missing correlation (the OV approach). This model had 618 degrees of freedom, the average chi-square value was 62.85 ($SD = 29.98$). The results do not differ very much from the results in Table 3b. The largest difference was found for the correlation between variables 1 and 3, which deviated -0.84% from the population value.

The bias in parameter estimates is not very different across the three models (complete data vs. OC approach vs. OV approach). However, a structural

| Table 3 Estimated average pooled correlations and bias percentages with a) complete data, b) the OC approach and c) the OV approach |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a) Complete data | Estimated correlations | Estimation bias (%) | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 1 | Variable 2 | Variable 3 | Variable 4 |
| Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% |
| Variable 2 | -0.371 | 1 | Variable 2 | -0.343 | 1 | Variable 2 | -0.343 | 1 | Variable 2 | -0.343 | 1 |
| Variable 3 | 0.356 | -0.151 | Variable 3 | 0.283 | 1 | Variable 3 | 0.283 | 1 | Variable 3 | 0.283 | 1 |
| Variable 4 | 0.156 | -0.371 | Variable 4 | 0.356 | -0.151 | Variable 4 | 0.356 | -0.151 | Variable 4 | 0.356 | -0.151 |

b) OC approach

| Estimated correlations | Estimation bias (%) | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 1 | Variable 2 | Variable 3 | Variable 4 |
| Variable 1 | 1 | 0.00% | Variable 1 | 1 | 0.00% | Variable 1 | 1 | 0.00% | Variable 1 | 1 | 0.00% |
| Variable 2 | -0.373 | 1 | Variable 2 | -0.349 | 1 | Variable 2 | -0.349 | 1 | Variable 2 | -0.349 | 1 |
| Variable 3 | 0.359 | -0.153 | Variable 3 | 0.287 | 1 | Variable 3 | 0.287 | 1 | Variable 3 | 0.287 | 1 |
| Variable 4 | 0.159 | -0.373 | Variable 4 | 0.359 | -0.153 | Variable 4 | 0.359 | -0.153 | Variable 4 | 0.359 | -0.153 |

| Estimated correlations | Estimation bias (%) | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 1 | Variable 2 | Variable 3 | Variable 4 |
| Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% |
| Variable 2 | -0.371 | 1 | Variable 2 | -0.345 | 1 | Variable 2 | -0.345 | 1 | Variable 2 | -0.345 | 1 |
| Variable 3 | 0.355 | -0.151 | Variable 3 | 0.283 | 1 | Variable 3 | 0.283 | 1 | Variable 3 | 0.283 | 1 |
| Variable 4 | 0.156 | -0.371 | Variable 4 | 0.355 | -0.151 | Variable 4 | 0.355 | -0.151 | Variable 4 | 0.355 | -0.151 |

c) OV approach

| Estimated correlations | Estimation bias (%) | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 1 | Variable 2 | Variable 3 | Variable 4 |
| Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% | Variable 1 | 1 | -0.54% |
| Variable 2 | -0.371 | 1 | Variable 2 | -0.345 | 1 | Variable 2 | -0.345 | 1 | Variable 2 | -0.345 | 1 |
| Variable 3 | 0.355 | -0.151 | Variable 3 | 0.283 | 1 | Variable 3 | 0.283 | 1 | Variable 3 | 0.283 | 1 |
| Variable 4 | 0.156 | -0.371 | Variable 4 | 0.355 | -0.151 | Variable 4 | 0.355 | -0.151 | Variable 4 | 0.355 | -0.151 |
difference can be seen in width of the likelihood based confidence intervals. These are smaller with the use of the OC approach, compared with the OV approach. Figure 3 gives a graphical representation of the parameter estimates and the associated 95% likelihood based confidence intervals. The upper dot and line denote the average parameter estimate and confidence interval of the analysis with the OC approach, while the lower dot and line denote the average parameter estimate and confidence interval of the analysis with the OV approach. The dotted vertical line shows the population value of the parameter. As expected, omitting information leads to larger confidence intervals. The difference is most clearly seen in the correlations between variables 3 and 4 in the lower right corner of the figure. It is not surprising that the difference is so apparent for the correlation between variables 3 and 4. As we deleted the correlation between variables 1 and 3 and between variables 2 and 3, both methods use equal amounts of information about these correlations. However, where our method still uses information about the correlation between variables 3 and 4, this information is often deleted in the other approach, leading to less precise parameter estimates.

**Discussion**

In this paper we have proposed a method to incorporate missing correlations in MASEM. The method was demonstrated with an example from teacher-child interactions. Using simulated data, the method was compared with the current practice, which is to delete one of the variables that is associated with the missing correlation. As the OC approach uses more information than the OV approach we expected that our method would lead to better parameter estimates and smaller confidence intervals. Results from the very small simulation study indicated that the OC approach leads to models with larger degrees of freedom and smaller confidence intervals. The parameter estimates were close to the population values for all methods, indicating that
deleting one or two variables in 80% of the studies did not really influence parameter recovery.

A possible explanation of the similar results with respect to parameter bias between the methods is that in our study the missingness of the correlation coefficients were introduced randomly. Maximum likelihood estimation with data missing at random is known to lead to unbiased parameter estimates (e.g., Enders & Bandalos, 2001; Newman, 2003). In true meta-analysis, the missing correlations may not be missing at random, and it would be interesting to investigate the effect of not-random missingness. For example, if the correlations between variables 3 and 1 and variables 3 and 2 are mainly missing in studies where the correlation between variable 4 and 3 is high, then if we delete variable 3 in the OV approach, the information about the correlation between variable 4 and 3 is lost, and the parameter will be underestimated. Using the OC approach, all remaining information would be used and the parameter estimate is expected to be closer to the true value.

References


R Development Core Team (2011). R: A Language and Environment for Statistical Computing. [Computer software]. Vienna, Austria.


Suzanne Jak

PhD candidate in Methods and Statistics, Research Institute of Child Development and Education, University of Amsterdam. Her research interests include structural equation modelling, measurement bias, multilevel structural equation modelling and meta-analytical structural equation modelling.

Frans J. Oort

Full professor of Methods and Statistics and Director of the Research Institute of Child Development and Education, University of Amsterdam. His research interests include measurement and measurement bias, and statistical modelling, especially non-standard applications of structural equation modelling.

Debora L. Roorda

Postdoc research fellow at the School Psychology and Child and Adolescent Development Department at the University of Leuven, Belgium. Her research interests focus on teacher-student interactions and their influence on children’s emotional well-being, school engagement, and achievement.

Helma M. Y. Koomen

An assistant professor in special education at the Research Institute of Child Development and Education at the University of Amsterdam. Her research interests address student-teacher interaction and teachers’ pedagogical practices in relation to emotional well-being, social adjustment, task behaviours, and achievement of children with and without special need.