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Fitting Meta-Analytic Structural Equation Models with Complex Datasets

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In many social science disciplines, including education and organizational psychology, meta-analysis of correlation coefficients is an attractive technique for summarizing research on relationships between variables. Correlational meta-analyses, in their simplest form, investigate the relationship between two variables. Many researchers, however, are interested in more complex questions that involve multiple variables and how those variables relate to each other (Kline, 2011). In fact, it is rare to find primary studies that examine a single relationship between only two variables. Much more common are complex theoretical models involving a number of variables that are investigated with multivariate analyses.

Well-developed techniques for synthesizing bivariate correlations are available (e.g., Schmidt & Hunter, 2014) as well as methods for synthesizing the correlation matrices reported in primary studies that examine complex models (Becker, 2009). An increasingly popular technique for synthesizing multivariate correlational research is meta-analytic structural equation modeling (Cheung & Chan, 2005). As methods for synthesizing correlation matrices and fitting meta-analytic structural equation models have matured, meta-analysts have been able to address questions about complex models and associations among multiple variables measured concurrently or longitudinally using the results of many primary studies.

The statistical developments for investigating such complex models and the availability of software packages for performing the analyses (Cheung, 2014b) have supported a number of published examples employing variations on meta-analytic structural equation modeling (MASEM), including path analysis, factor analysis, and structural equation models with latent factors (e.g., Bauer, Bodner, Erdogan, Truxillo, & Tucker, 2007; Hong, Liao, Hu, & Jiang, 2013; Norton, Cosco, Doyle, Done, & Sacker, 2013; Topa, Moriano, Depolo, Alcover, & Morales, 2009). Some research literatures and the associated meta-analytic databases, however, are not easily handled by the current techniques. As a result, a number of MASEM applications utilize work-arounds to fit these models with the rather messy data commonly encountered in, for example, the social and behavioral sciences (e.g., Bauer, et al., 2007; Jak, Oort, Roorda, & Koomen, 2013; Kossek, Pichler, Bodner, Hammer, 2011; Meriac, Hoffman,

Woehr, & Fleisher, 2008; Michel, Clark, & Jaramillo, 2011). These work-arounds are often ad hoc and not well developed.

The purpose of this paper is to describe an application of MASEM that is appropriate for the idiosyncrasies of large-scale complex correlational meta-analysis. Our approach extends current techniques in two ways. First, it accommodates the statistical dependencies that result when multiple effect sizes from the same study are included within the cells of the synthesized correlation matrix. Second, it incorporates a procedure for generating covariate-adjusted correlation coefficients for input to the synthesized correlation matrix capable of reducing the influence of selected sources of heterogeneity expected to obscure the relationships between the underlying constructs of interest or compromise the comparability of the correlations across cells. The presentation here is largely non-technical and intended for applied meta-analysts who wish to investigate complex correlational structures within the meta-analytic framework.

The context for this paper is a large-scale meta-analysis we have underway that is framed around the risk and protective factors that are predictive of later antisocial behavior, substance use, or school failure. While the research questions in this meta-analysis are ideally suited to meta-analytic structural equation models, the primary data present complications that make the currently available techniques difficult to apply. In what follows, we first describe in more detail the characteristics of correlational studies that are not easily handled with the first stage of the standard two-stage MASEM method. We then present the techniques we have developed for accommodating these characteristics in the analysis. Finally, we employ a subset of our larger meta-analytic dataset to illustrate the techniques. The illustration focuses on the strength of three forms of parental support for predicting later student achievement, with socioeconomic status as a covariate.

Two-stage Meta-analytic Structural Equation Modeling

MASEM is typically performed as a two-stage process in which individual studies' correlation matrices are first collected and pooled and then, in the second stage, subjected to structural equation modeling (Cheung & Chan, 2005). Ideally, each primary study will contribute a complete, or nearly complete, matrix of correlations among the variables. There may be variations across studies in how the variables are measured, the characteristics of the samples, and so forth, but each study provides a sufficient set of correlations for addressing the research question.

Once the studies are collected and the effect sizes coded, the correlation matrices from each study are pooled into a synthesized correlation matrix and the heterogeneity of that matrix is examined. Depending on the amount of heterogeneity, the studies may be divided into various subgroups defined by selected moderator variables, for example those using male vs. female participant samples, with pooled correlation matrices created for each subgroup. The resulting synthesized correlation matrix or subgroup matrices can then be subjected to path or factor analysis. These steps can be conducted using the *metaSEM* package in the R statistical environment (Cheung, 2014b).

Difficulties Using the Standard MASEM Analyses and Ad Hoc Solutions

Two inherent complexities make the first stage of this two-stage method problematic for complex research literatures. First, it is common for the primary studies in such literatures to employ more than one measure of some of the constructs of interest (Tanner-Smith & Tipton, 2014). A single instrument might be used with different informants (e.g., parent and teacher reports of children's aggressive behavior), multiple measures may be used to capture different facets of the same construct (e.g., expressive and receptive vocabulary), or the construct may be measured with more than one instrument (e.g., two different social skills inventories). Whether these different operationalizations will be taken as measures of the same construct in a meta-analysis depends on the literature at issue, the nature of the questions the meta-analysis is addressing, and the meta-analyst's assessment of which operationalizations represent the same underlying construct. However the meta-analyst groups the different operationalizations into construct categories, the diversity of measures used in many research literatures makes it quite likely that some studies will contribute data from more than one measure to any given construct category. Nearly every study represented in the meta-analysis that provides the context for this paper exhibits at least one instance of different operationalizations that we have judged to be measures of essentially the same construct. Table 1 shows a pooled correlation matrix from the meta-analysis used as an example later in this paper; note that every cell contains more effect sizes (m) than studies (k).

The typical recommendations for avoiding the statistical dependencies associated with multiple effect sizes from the same study samples are to average them into one estimate or to select one of them based on some *a priori* decision rule (Schmidt & Hunter, 2014). These solutions are undesirable for several reasons. In the former case, averaging limits the ability of meta-analysts to examine the influence of measurement characteristics on the effect sizes produced by the studies involved. Those measurement characteristics (e.g., informants, modes of administration, or facets of the construct) might be important moderators of effect size variability. For example, if a study provides both teacher and parent reports of the same construct and the meta-analyst averages all correlations between that construct (whoever the informant) and the constructs with which it is correlated, informant is no longer available for analysis as a potential moderator. Using a decision rule to select only a single estimate when multiple estimates are available, on the other hand, omits otherwise available information from the contributing studies and leaves no basis for examining the influence of that deletion on the findings of the meta-analysis.

A common approach for meta-analyses of correlational effect sizes that include multiple dependent estimates is to create the synthesized correlation matrix cell-by-cell via a series of sub-meta-analyses. In this approach, a single pooled estimate within each cell is created from the set of bivariate correlations available for that cell, typically without considering the covariance between the correlations from studies that contribute multiple estimates (e.g., Bauer, et al., 2007; Meriac, Hoffman, Woehr, & Fleisher, 2008). As with averaging dependent effect sizes within each study, however, pooling the estimates within each cell prior to the structural equation analysis limits the ability of that analysis to fully investigate moderators related to the way the constructs are measured within and between studies. In

addition, this cell-by-cell approach does not allow a consistent approach to be used for examining the variability between cells and the moderators that might account for those between cell differences.

A second problematic aspect of the initial stage of the MASEM approach relates to the nature of the correlation matrices that are pooled and the individual studies that provide those matrices. Differences in the characteristics of these studies can influence the correlation coefficients they report in ways that obscure or distort the underlying relationships of interest. Education studies, for instance, might report correlations involving mathematics achievement measured with any of a number of widely used standardized tests, researcher developed assessments, math grades, and the like. Although we may believe these different operationalizations measure the same underlying construct, they may be confounded with other variables of interest in ways that influence the magnitude of the correlations with those other variables. The result will be heterogeneity within and between cells in which the operationalizations vary that will tend to mask the underlying relationships between the constructs that are of interest. Moreover, to the extent that operationalizations that tend to produce higher (or lower) correlations are concentrated in some cells, the mean correlations in those cells will show an upward or downward bias relative to those in other cells. Standard MASEM techniques can represent the associated heterogeneity in these instances as random effects, but offer little capability to reduce the influence of sources of variability and bias of this sort.

Even more problematic is the uneven contribution of different studies to different cells in the pooled correlation matrix. When every study provides a full or nearly full correlation matrix for the synthesis, there is a high degree of comparability across the cells for the correlations in each cell. Whatever influence different study characteristics have on those correlations, the results are the same in each cell because the same studies are represented in every cell. Thus the correlations in one cell are not likely to be higher or lower than those in another cell simply because they come from different studies with different characteristics. When all studies contribute to all cells, such differences are more likely to reflect actual differences in the magnitude of the underlying relationships.

It is for this reason that current MASEM methods work best when all the source studies contribute correlations to every cell; that is, each study contributes a full correlation matrix. As meta-analysts investigate more complex patterns of empirical relationships, however, they must undertake syntheses that involve many variables and require input from many studies. In most such situations it will be necessary to create the pooled correlation matrix from a patchwork of studies, some contributing to many cells, some to only a few, and almost none contributing to all the cells. The result is a large missing data problem in which any given cell lacks contributions from a number of studies that should be represented under the desired scenario in which all studies contribute to all cells.

To the extent that different studies have different characteristics that are related to the magnitude of the correlation coefficients they report, this uneven distribution of studies across the cells of the matrix will almost certainly undermine the comparability of the synthesized correlations across the cells. A larger mean correlation in one cell than another

will not necessarily mean that the underlying relationship is larger in that cell; it may only mean that the studies contributing to that cell were different in ways associated with larger correlations. Perhaps a greater proportion of the studies in that cell used samples with older participants, and perhaps older samples tend to show higher correlations on all the relationships of interest. Or, perhaps studies with higher attrition are concentrated in some cells of the synthesized matrix while other cells are populated more heavily with low attrition studies. To the extent that attrition is associated with larger or smaller effects, the differences in the mean correlations across cells will be at least partly due to attrition rather than to differences in the true magnitude of the relationships between constructs. The difference in mean correlation coefficients that should reflect differences in the strength of the relationships between the respective constructs thus is instead partly or maybe entirely due to this uneven distribution of studies.

The importance of these latter issues cannot be overstated. In meta-analyses of correlation coefficients in the social and behavioral sciences, the heterogeneity of the coefficients is often large enough to easily overwhelm any important substantive relationships between the variables of interest (e.g., Derzon & Lipsey, 1999; Friso-van den Bos, et al., 2013). And, while some of it may essentially be statistical noise that obscures but does not necessarily distort the underlying relationships, there is considerable potential for systematic differences that do distort the magnitude of the correlations for different relationships in ways that bias the results of comparisons between them. In these circumstances, it is important to have techniques that allow us to better investigate sources of heterogeneity and, especially, to deal with it in ways that help us better discern the underlying relationships of interest in our analyses.

Both of the complications we have described are associated with the first stage of the typical two-stage MASEM procedure; that is, they involve issues associated with pooling the correlations, not with the path analyses or structural equation analyses that can be conducted once a pooled correlation matrix is estimated. Like others who have encountered these issues, we have attempted to find techniques for producing a pooled correlation matrix that will support applications of MASEM that yield credible results despite the difficulties. We now turn to a description of the approach we have developed and that we believe improves on the currently available options.

Method for Pooling Complex Meta-Analytic Datasets

Effect Size Estimates

We begin with a set of coded studies, each contributing a matrix of bivariate product moment correlation coefficients indexing the relationships between pairs of constructs and a profile of descriptive information about a variety of study characteristics. As with any meta-analysis, a number of initial adjustments and corrections might be applied to the coded correlational effect sizes. The distribution of those effect sizes, and the distribution of the sample sizes on which the effect size weights will be based, might be examined for outliers and any outlying values Winsorized or otherwise addressed (Lipsey & Wilson, 2001). In addition, the correlations may be adjusted for unreliability or other artifacts per Schmidt and Hunter (2014).

Pooling Correlation Matrices Using Multilevel Modeling

The typical MASEM analysis first creates a variance-covariance matrix that estimates the between effect size variance across the effect sizes individual studies contribute to each cell. That variance-covariance matrix is then used in a procedure that combines the correlation matrices from the different studies into a pooled correlation matrix (Cheung, 2014a). This method permits each study to contribute more than one correlation to the synthesized matrix, but only if each of those correlations is located in a different cell of that synthesized matrix. Each coefficient in a cell is thus assumed to be independent, i.e., based on a different subject sample.

As an alternative approach to this first stage of MASEM that does allow each study to contribute more than one correlation indexing the same bivariate relationship to any cell, we estimate the synthesized correlation matrix using a three-level hierarchical model. A multilevel model of this sort takes account of the statistical dependencies associated with the clustering of units within levels, including therefore those resulting from inclusion of multiple effect sizes from the same studies (Konstantopoulos, 2011; Van den Noortgate, López-López, Marín-Martínez, & Sánchez-Meca, 2013). Table 2 illustrates how a dataset with this structure might be organized. In this hypothetical dataset, there are four studies reporting relationships among four constructs (or variables) of interest and, therefore, six possible pairs of constructs. Each case in the dataset is a unique correlation coefficient effect size (identified in the ESID column). The effect sizes are nested within studies, each of which is indicated by a unique StudyID. The Cell column identifies the pair of constructs represented in each correlation coefficient and, thus, the cell of the synthesized correlation matrix in which each case belongs, numbered from 1 to p . We have included a “Label” column to further illustrate that each case in the dataset is a correlation between a pair of variables representing different constructs (C1, C2, etc. as in Table 1). Note that the four studies all contribute multiple correlations to the analysis and that some of the studies contribute more than one correlation between the same pair of constructs (e.g., ESIDs 5 and 6 within Study 2 are correlations between the same pair of constructs and thus belong in the same cell of the synthesized matrix). The cell of the matrix in which each correlation resides can also be represented by a series of dummy codes; these are shown as columns Cell₁-Cell₆ in Table 2.

To create the synthesized correlation matrix, we use a multilevel multivariate mixed-effects weighted meta-regression to estimate a synthesized correlation for each matrix cell. The input to that meta-regression is a set of individual correlation coefficients structured as shown in Table 2, each of which is accompanied by its sample size (more about sample size weights below). The key to estimating the synthesized correlations in this model is to represent each cell of the pooled correlation matrix with a unique dummy variable. The location of each individual correlation in the matrix is then identified by its profile on that set of dummy variables with a 1 coded for the correct cell and 0 for all other cells (see the Cell₁-Cell₆ columns in Table 2). To estimate the synthesized correlation in each of the cells identified by this set of dummy codes, we use the following no-intercept model:

$$r_{ik} = \beta_1 Cell_{1ik} + \dots + \beta_p Cell_{pik} + \nu_{0k} + \eta_{ik} + \varepsilon_{ik} \quad (1)$$

where r_{ik} is an observed correlation coefficient i from study k . Each $Cell_{pik}$ represents a dummy variable identifying each cell, p , in the correlation matrix that takes a value of 1 if coefficient i from study k is assigned to that cell and a value of 0 otherwise. Each β_p in this model can then be interpreted as the weighted mean or synthesized correlation coefficient for that cell. In addition, ν_{0k} is the Level 3 random effect for the studies, assumed to be normally distributed with a mean of zero and variance $\omega(\omega > 0)$; η_{ik} is the Level 2 random effect, assumed to be normally distributed with a mean of zero and variance $\tau(\tau > 0)$; and ε_{ik} is the error of estimation for correlation coefficient i and is assumed to be normally distributed with a mean of zero and a variance of ν_{ik} .¹ The conditional sampling covariance between observed correlations from the same study is approximated by the unconditional Level 2 random effects (Cheung, 2015). We assume that the errors at different levels are uncorrelated (see also Konstantopoulos, 2011 for a fuller discussion of the assumptions for three-level meta-analysis).

Applying this procedure to the hypothetical dataset in Table 2 would allow us to estimate a synthesized 4×4 lower triangle correlation matrix with 1s inserted on the diagonal and six cells representing the possible correlations between any two of the four variables in the matrix. Using a no-intercept model permits us to interpret the regression coefficients as the weighted means or synthesized correlation coefficients needed for Stage 2 of the MASEM procedure. In addition, the asymptotic covariance matrix of the pooled correlation matrix, which indexes the precision of the correlation estimates, is also available from equation 1 (see Becker, 1992, 2009; Cheung & Chan, 2005 for the derivation). This matrix is employed later in the MASEM procedure (Cheung, 2014a). The R package *metafor* (Viechtbauer, 2010) can be used to fit the three-level model, obtain the weighted mean correlation estimates for each cell, and produce the asymptotic covariance matrix. Annotated R-code for this and each of the steps in this analysis can be found in Appendix A.

Weighting effect sizes in multilevel modeling—The three-level model described above assumes that the correlational effect sizes are weighted, as is typical in meta-analysis to account for the fact that effect sizes based on larger samples are more precise than those based on smaller samples. In many meta-analyses, the inverse of the within-study sampling variance is used for this purpose. For correlation coefficients, however, there are additional choices to be considered (Becker, 2009; Schmidt & Hunter, 2014). The standard error for a correlation coefficient and, therefore, the inverse variance weight depends on the correlation itself, so most meta-analysts working with correlation coefficients use one of several options. These include conducting the analysis with Fisher z transformed correlations, which simplifies the computation of the standard error estimates. That option was not desirable for our purposes, however, because we wanted to retain the correlation metric and the associated

¹Because the correlation coefficients in all cells of the synthesized matrix are examined in the model in equation 1, the Level-2 random effect captures the random effects of all the cells in the matrix and the Level-3 random effect is the random effect of all the correlation coefficients in the matrix. Readers are reminded that τ and ω cannot, therefore, be interpreted as they would be in more typical three-level models.

variances and covariances among the correlations for use in Stage 2 of MASEM. We, therefore, have elected to use simple sample size weighting as recommended by Schmidt and Hunter (2014). Note that the *metafor* package calls for a variance estimate for each effect size that it then uses for inverse variance weighting. To use sample size weighting with *metafor*, we therefore input the inverse of the sample size in place of those variance estimates.

Examining and Adjusting for Differences among the Correlations

The procedure described above estimates the random effects mean correlation coefficient for each relationship of interest, thus producing the pooled correlation matrix. We could, therefore, use this matrix as the basis for the next step, the MASEM analysis. As mentioned earlier, however, many meta-analyses will exhibit a great deal of within and between cell heterogeneity among the correlation coefficients contributing to that pooled correlation matrix. At least some of that heterogeneity is likely to be associated with characteristics of the methods, samples, and measures used in the studies included in the meta-analysis. If descriptive variables representing such characteristics have been coded in the meta-analysis, they can be used as moderator variables to investigate possible sources of that heterogeneity. An appropriate way to conduct this investigation with multiple moderator variables is to use them as independent variables in a meta-regression model with the correlation coefficients that will contribute to the pooled correlation matrix as the dependent variable. Further, and of particular interest here, the results of that meta-regression may be used to create covariate-adjusted correlation coefficients that can be substituted for the observed correlations as input into the procedure for producing the synthesized correlation matrix described above.

The rationale for making adjustments of this sort to the correlation coefficients before they are used to create a synthesized correlation matrix is twofold. We first note that some moderator variables are sources of what is essentially nuisance variance that tends to obscure and possibly distort the underlying relationships of interest. These often relate to methodological and procedural variation. For example, the moderator analysis may reveal that the relationship between x and y is smaller when x is measured via self-reports than when measured via parent reports. In such circumstances, we may wish to adjust the respective correlations to the values that would be expected if all of the instances of x correlated with any other variable in the matrix were measured in the same way, perhaps the way most common in the body of research represented in the meta-analysis. Similarly, the moderator analysis may show that the attrition that occurs between initial sample selection and the time of measurement attenuates correlations such that studies with greater attrition contribute correlations that are smaller than those from studies with less attrition, all else equal. The meta-analyst might, therefore, want to adjust the correlation coefficients to correct, to the extent possible, for this attenuating influence of attrition.

Adjusting the correlation coefficients to correct for influences from such sources has much the same rationale as for the adjustments recommended by Schmidt and Hunter (2014). Their suggested adjustments to correlation coefficients to correct for unreliable measures, range restrictions, and the like are aimed at reducing the extent to which the observed

correlations are influenced by factors that distort or obscure the underlying relationships. In similar spirit, we believe there are many situations in which it is advantageous to adjust the correlation coefficients in ways that reduce the influence of methodological or procedural differences between studies that are largely irrelevant to the relationships of interest in the meta-analysis but can potentially distort the representations of those relationships provided by the correlation coefficients.

In other cases, however, the rationale for adjusting the correlation coefficients that will be used in the synthesized matrix may have more to do with smoothing out differences associated with the uneven representation of studies across the cells of the synthesized matrix. Ideally, every study would contribute a correlation to every cell in the matrix. Though there would quite likely be heterogeneity around the mean correlation in each cell, those means would average over similar study characteristics in every cell. If there was variation in the mean age of the participant samples, for instance, there would be consistency across the cells in the matrix in the distribution of mean ages for the correlations in those cells because every study contributed to every cell. Such consistency creates an important degree of comparability across the cells. If the mean correlation in one cell is larger than that in another cell, we have some assurance that the difference represents a stronger relationship between the respective variables rather than, for example, a situation in which older samples for which the correlations might tend to be higher or lower are unevenly distributed across the cells.

The ideal of every study contributing to every cell is rarely attained in meta-analyses of correlation matrices. As more variables and more studies are included to allow investigation of more complex patterns of relationships, there will typically be fewer studies that contribute correlations to every cell and many studies that contribute to only a fraction of those cells. Indeed, there may be cells in such a matrix that have no studies in common. This is essentially a missing data problem that is potentially problematic but difficult to overcome in such meta-analyses. Any relationship between study characteristics and the correlation coefficients reported in those studies will compromise the comparability of the mean correlations across cells when the distribution of those characteristics varies across the cells.

One way to reduce such distortions is to identify study characteristics that moderate the magnitude of the correlation coefficients and use the results of that analysis to adjust the correlations that contribute to each cell in ways that make them more comparable. For example, if the average age of participant samples is related to the magnitude of the correlations found across those samples, it might then be advantageous to use that information to estimate the magnitude the correlations would be expected to have if all the samples had the same average age. Those adjusted correlations would then be more comparable across cells representing samples of different ages from different studies than the original unadjusted correlations and, thus, those age differences would have less distorting influence on the synthesized correlation matrix and the analyses that are then based on it.

If all the study characteristics that moderated the magnitude of the correlations could be identified and statistically modeled, a set of adjusted correlation coefficients could be

created that would approximate the ideal situation in which every study contributed equally to every cell of the matrix. How close an approximation to that ideal is possible depends upon whether all the relevant moderator variables are available and how well their collective relationships to the correlations in the different cells can be statistically represented. Even with a less than fully sufficient set of moderators, however, effective use of those available can increase the comparability of the synthesized correlations across cells and reduce the influence of distortions stemming from confounds with unevenly distributed study characteristics.

Covariate-adjusted correlation coefficients—A meta-regression model with an assortment of well selected moderator variables is an especially appropriate technique for investigating the influence of those variables on the correlation coefficients that will contribute to a synthesized correlation matrix. Moreover, to the extent that any of those variables are related to the observed correlation coefficients, that same meta-regression model can be used to statistically adjust the coefficients to reduce those influences if that is deemed desirable. The meta-regression model we estimate for these purposes is a three-level mixed effects meta-regression fit to the entire dataset that includes an intercept and study or effect size characteristics as independent variables. In this form, the procedure assumes that the regression coefficient for a moderator is the same across all cells of the matrix, a reasonable assumption in some cases. For instance, correlations may be consistently larger when the operationalizations for the two constructs involved are provided by the same informant (e.g., a parent) than when provided by different informants (e.g., a parent and a teacher). Other moderator variables may operate differently across the matrix and that possibility can be explored by incorporating interaction terms that cross dummy variables representing particular cells in the matrix with a moderator. For example, a meta-analyst may wish to explore whether the way sample demographics moderate the relationship between home environment and academic achievement is different from the way they moderate the relationships between parent-school involvement and achievement.

The overall objective here is to incorporate a technique for examining multiple sources of heterogeneity simultaneously in the general multilevel modeling approach we have described for handling multiple effect sizes from the same study. The choice of moderators, of course, depends on the research being reviewed and the interests of the meta-analyst. Because studies may contribute more than one correlation to the cells of the matrix, both effect size- and study-level moderators can be employed. At the effect size level, for example, the measurement characteristics of the different operationalizations of the individual constructs might be used as moderators. At the study level, the demographic characteristics of the samples, study timing, and features of study methodology could be entered as moderators. In addition, effect size-level moderators may be aggregated and entered at the study level in the multilevel model to examine their influence on both the variation between effect sizes and the variation between studies. A general meta-regression model of this sort can be represented as follows:

$$r_{ik} = \beta_{00} + \beta_1 X_{ik} + \beta_2 X_{0k} + \nu_{0k} + \eta_{ik} + \varepsilon_{ik} \quad (2)$$

where X_{jk} represents an effect-size level covariate, such as the attrition for the particular effect size and X_{ok} represents a study-level covariate, for example whether the study was published or unpublished. The random-effects (v_{ok} and η_{jk}) represent the additional heterogeneity associated with study-level differences and differences between correlations from the same studies within cells, respectively, and ε_{jk} is the error of estimation for each effect size. The properties of the error terms are as described above for equation 1. As in virtually all meta-regressions, the effect sizes are weighted. As explained earlier, we have elected to use sample size weights (Schmidt & Hunter, 2014) but, as noted there, other options are available.

This meta-regression allows the analyst to investigate the extent to which various moderators and their interactions are related to the correlation coefficients used as dependent variables in the analysis. Some of those relationships will be of substantive interest and informative in their own right. Other relationships, however, may reflect the influence of the kind of variables described above that the meta-analyst might want to adjust for consistency. For those variables, the meta-regression functions as a prediction model that the analyst can use to predict the correlation coefficients expected with selected values of the respective moderators. Those adjusted coefficients can then be used to create a pooled correlation matrix that is more homogeneous with respect to the influence of the selected moderators while retaining the variability from other sources.

The adjustment procedure we use for this purpose takes advantage of the additive structure of the meta-regression model whereby each observed correlation coefficient is represented as the sum of a constant intercept value (β_{00} in equation 2 above), a set of predicted values (the βX terms in equation 2), and a residual that is simply the difference between the observed value of the correlation coefficient and the sum of the intercept and the predicted values for that coefficient, i.e., the portion of the correlation that cannot be predicted from the independent variables. An observed correlation coefficient is adjusted for a given predictor variable in this scheme by substituting a selected value of the predictor for the actual X value associated with that coefficient, computing the corresponding βX value and using it in place of the actual βX value, then adding up all the components, including the residual, to estimate what will now be the adjusted correlation coefficient.

To be more specific, the regression equation is solved for each correlation coefficient by adding (a) the constant intercept, (b) another constant that represents the sum of the βX values for which constant values of X have been assigned, (c) a set of values specific to that coefficient for the βX components in which the original value of X for that coefficient is retained (if desired), and (d) the residual for that coefficient determined from the meta-regression model prior to the adjustment procedure. This procedure works to standardize all the coefficients across the selected covariates through the assignment of a constant value (the X) for each respective covariate. The constant values of the respective X s involved in the adjustment might be modal, average, or ideal values for the respective moderators in the model. For example, we might use in the average attrition rate across all of the studies or select an attractive attrition rate within a realistic range for those studies. For measurement characteristics, we might choose the most common measurement characteristics as the standard values.

The heterogeneity of the resulting adjusted correlation coefficients will necessarily be reduced by the amount associated with the moderator variables held statistically constant by this adjustment procedure. It is important to recognize, however, that this procedure cannot be expected to perfectly correct for any relationship between the moderator and the correlation coefficients that are being predicted. The moderator variables can be expected to be correlated with each other and with other unobserved variables that are not represented in the meta-regression model. The regression model by its nature attempts to estimate the independent contribution of each moderator to predicting the dependent variable, but there is also shared variance that must be divided between moderators and shared variance with any unobserved variables correlated with the moderator. Adjusting a given moderator thus also entails adjusting for the portion of other variables that share variance with that variable.

Because of the potential confounds between moderators, care must be taken when selecting the moderators to be adjusted and the set of moderators to be included in the meta-regression on which those adjustments are based. Suppose, for example, that the mean age of the participant samples and the attrition rate are related to the magnitude of the correlation coefficients across studies and, additionally, are correlated with each other. Adjusting the correlation coefficients for attrition based on the results of a meta-regression that includes attrition, but does not also include mean sample age among the predictors will thus not only adjust for attrition differences across studies but also for the influence of the correlated portion of mean sample age. Suppose further that, prior to adjustment, mean sample age was rather evenly distributed across cells and not seen as problematic, but attrition was unevenly distributed. The correlation coefficients adjusted for attrition based on a meta-regression that omitted sample age as a predictor would then also have been adjusted to some extent for sample age in ways that were not apparent or intended. As a result, those coefficients would no longer represent an even sample age distribution across cells and some of the differences in the magnitude of the correlations across cells would stem from the variation in sample age produced by the differential adjustment for the correlated attrition moderator across those cells.

Creating adjusted correlation coefficients must thus be done cautiously with attention to the intercorrelations among the moderators used in those adjustments and plausible confounds between the observed moderators and unobserved ones. With that caveat in mind, this adjustment technique has been applied to effect sizes in other forms of meta-analysis where the adjustment was based on the same profile of constant values on the selected moderators for all the effect sizes (e.g., Lipsey & Wilson, 1998; Wilson & Tanner-Smith, 2013). In application to correlation coefficients used to create a synthesized correlation matrix, such universal adjustments may be appropriate in some cases. A distinctive option in this application, however, is to make adjustments for the measurement characteristics associated with the individual *constructs* in the matrix.

This construct-level differentiation in the adjustments is illustrated in the example we present below, but we describe the logic of these adjustments in some detail here. The independent variables in our ultimate path model for that example (home involvement, school involvement, and parental expectations) are typically reported by either parents or other informants, while the outcome (academic achievement) is generally measured via

either a written or oral test completed by the student. The measurement characteristics of the constructs in our example are shown in the upper triangle of Table 1. The cells in the synthesized correlation matrix for the relationships between home involvement and any other construct in the matrix are populated by correlation coefficients for which home involvement is frequently reported by a parent (shown in the first row of the upper triangle in Table 1). However, other informants are employed in some cases and those informant differences may be related to the magnitude of the corresponding correlation coefficients. Each of the other constructs in the matrix also have variations in their measurement characteristics that may be associated with the magnitude of the correlations representing their relationships with the other constructs in the matrix.

To reduce the variation associated with the different forms of measurement represented in these correlations, a series of dummy variables can be created that identifies the measurement characteristics of each construct that allows us to adjust the constructs for their distinct measurement characteristics. This must be done consistently across all the cells in the matrix that involve an individual construct; that is, the correlations in each of the cells involving a construct must be standardized on the same measurement characteristics for that construct regardless of the other construct represented in the bivariate correlations. An example of how the series of dummy variables that enable this are created for the constructs shown in Table 1 is as follows. For the first dummy code, each correlation coefficient in which parent reports are used to measure home involvement receives a 1; correlation coefficients with home involvement measured otherwise *and* correlations that do not involve home involvement as a construct receive a 0. For the next dummy code, each correlation in which achievement is obtained via oral assessment receives a 1; correlations with achievement measured otherwise *and* correlations that do not involve achievement as a construct receive a 0. Additional dummy codes of this sort are then created for each of the other constructs that define the cells in the matrix. This results in pairs of dummy variables that define each cell of the matrix, e.g., the dummy for how home involvement is measured and that for how achievement is measured define the measurement characteristics of the correlations in the cell that describes the relationship between home involvement and achievement. More importantly, the regression coefficient for an individual dummy variable when it is used as a predictor variable in a meta-regression indexes the relationship of the measurement characteristic for a single construct consistently across all the correlation coefficients that involve that construct. That regression coefficient, in turn, can be used to adjust the respective correlations in a uniform way across all the cells in the synthesized matrix that involve the construct. We provide further details for this procedure when we present the illustrative example below.

With the desired covariate-adjusted correlation coefficients in hand, the final step is to use them to create a pooled correlation matrix. The model used to produce that matrix is exactly the same as in equation 1 presented earlier, but with the covariate-adjusted correlations used in place of the observed correlations when they differ. As described earlier, the asymptotic covariance matrix of the correlation estimates needed for any SEM models in stage 2 can also be obtained as part of this analysis. As above, we use the R package *metafor* (Viechtbauer, 2010) to conduct the meta-regression analysis, produce the adjusted pooled correlation matrix, and obtain its asymptotic covariance matrix (see Appendix A). We note

that the synthesized correlation matrix that results is no longer a synthesis of only observed correlations—it is a synthesis of a mix of observed correlations and adjusted correlations. As such, the mean correlations in each cell will be different, presumably in advantageous ways for any analysis based on the synthesized matrix, and the within and between cells variance will be different.

Fitting a Meta-Analytic Structural Equation Model

The result of the analyses described above is a pooled correlation matrix. The matrix may include unadjusted and/or covariate-adjusted correlations; regardless, the steps for estimating structural models from that matrix follow the standard procedure. Briefly, two matrices and the total sample size are required as input for this second stage of a MASEM analysis. The first matrix is the pooled correlation matrix with a weighted mean correlation coefficient in each cell, created as described above. The second matrix, the asymptotic covariance matrix, is used as the weight matrix for the MASEM model and, in our application, is produced as part of the procedure for fitting the multilevel model in equation 1. Finally, the overall sample size must be estimated for use in the calculation of fit statistics. We choose to use the sum of the sample sizes of each study represented in the meta-analysis, but there are other choices that might be made (Cheung, 2013; 2014).

The MASEM analysis is then conducted with the *metaSEM* package in R using the two matrices and the estimated sample size. We do not describe this process in detail here as it is fully described elsewhere (Cheung & Chan, 2005). Of note, we use the weighted-least squares (*wls*) function in the *metaSEM* package instead of the integrated two-stage procedure using the *tssem1* and *tssem2* functions because the two input matrices in our procedure are not estimated via stage 1 in *metaSEM*. The same functionality and output is available with the *wls* function as with the integrated two-stage procedure in *metaSEM* (see Appendix A) because the *tssem* functions are wrappers for the *wls* function. Interpretation of parameters and fit statistics is therefore the same as well. We now turn to a brief illustration of our method using a subset of studies from our larger meta-analysis that report correlations for the predictive relationships between variables measured at one time and various child and youth outcomes measured at a later time.

Illustrative Example

To provide some context for our example, assume we are interested in adding a family module to a tutoring program for struggling students and wish to know whether our enhancement should focus on encouraging parents to espouse higher expectations for their children, promoting parent support for students in the home (e.g., monitoring homework), or increasing parent participation and involvement at the school. Understanding the relative strength of each of these three parental support factors for predicting later academic achievement could help us design an intervention with the best chance of success.

From our larger meta-analytic database, we selected any longitudinal study that reported a relationship between one of our three parental support predictors and later academic achievement or a cross-sectional relationship between any pair of our three predictors. In addition, we selected studies that reported relationships between socioeconomic status and

any of the three predictors or achievement. This process located 119 longitudinal studies that provided 671 correlation coefficients relevant to our analysis. A variety of study characteristics appropriate for use as moderators were also extracted (see Table 3 and the upper triangle in Table 1, which shows the measurement characteristics for each construct). This dataset is available from the authors upon request.

The set of effect sizes thus consisted of correlations among five variables of interest: the three parental support predictors, the academic achievement outcome, and socioeconomic status. The pooled correlation matrix needed for MASEM, therefore, will include ten cells, each one synthesizing the available correlation coefficients for one of the bivariate relationships between these variables.

Computing the Adjusted Pooled Correlation Matrix

To construct the initial unadjusted correlation matrix, we estimated the random effects weighted mean correlation coefficient for each cell of the matrix using the three-level random effects model shown in equation 1. We used the R package *metafor* (Viechtbauer, 2010) to perform this analysis with the R code provided in Appendix A. Each regression coefficient estimated in this analysis represents the synthesized (weighted mean) correlation coefficient for a cell of the pooled matrix. The lower triangle of Table 1 presents these unadjusted synthesized correlations as the first element in each cell.

To obtain correlations that are adjusted for selected effect size and study characteristics, we fit a three-level meta-regression model to the data as shown in equation 2 and illustrated in Step 2 in Appendix A. The moderators for this analysis include variables at level 2 and level 3, as follows. At level 2 (the effect size level), we used three continuous moderator variables: percent attrition (*attrition*), the mean age of the sample at the time of predictor measurement (*wIage*), and the time interval between predictor and outcome measurement (*time*; zero for the cross-sectional correlations). In our data, these characteristics vary within studies, but this may not be the case in other applications.

Also at the effect size level we included the dummy variables described earlier that are designed to allow us to examine the influence of the different ways the constructs represented in the pairs of variables in each correlation are measured. For each of the five constructs in the analysis, dummy variables were created to identify the different informants or modes of data collection for the variable representing that construct. One dummy variable was created to represent each type of parental involvement variable and socioeconomic status (labeled with construct measurement characteristic (*cmc*) 1, 3, 5, and 7 in both Appendix A and Table 4). For each of these variables, parent-reports were given a 1 and all other informants made up the reference category. Two dummy variables were created for the achievement outcome (*cmc9* and *cmc10*); one for written tests and one for orally administered tests, with all other sources making up the reference category. Each correlation coefficient in the dataset, therefore, was accompanied by a set of dummy variables to identify the measurement characteristics of each of the two constructs in the correlation with the dummy variables associated with each construct being the same across all the cells of the matrix in which that construct was found.

In addition to the specific measurement characteristics of interest for each of these five variables, correlations in which the measurement of both variables shared a characteristic (e.g., two variables based on parent-reports) were identified with another dummy coded variable (*samemc*; 1 for the same informant and 0 for different informants). Correlation coefficients for which one or both variables were dichotomous were corrected for attenuation (Schmidt & Hunter, 2014) and a dummy variable (*scale*) was also added to indicate which correlations were corrected in this way.

At the study level (level 3), selected characteristics of the participant samples were used as moderator variables. These included the gender (*permale*), ethnic (*white*), socioeconomic (*poor*) and risk-level (*risky*) mix of the sample. Furthermore, while we restricted studies to those with participant samples with an age range of no more than 4 years, there was variation within that range. We, therefore, also included a moderator variable describing the age range of the students in the study sample, varying from 1 to 4 years (*w1agerange*).

Table 4 shows the results of the meta-regression model predicting the correlation coefficients from this set of moderator variables that was fit using the *metafor* package in R. We do not interpret the regression coefficients here, but note that the results of such moderator analyses may well be of substantive interest. To create covariate-adjusted correlation coefficients that adjust for the influence of their different values on these moderators, we used these regression coefficients to estimate the magnitude each correlation would have if the values on the moderator variables were each held constant at a specified level. We first selected the average or modal value for each covariate at level 3 (i.e., gender, ethnic, socioeconomic and risk-level mix and age range) and attrition and age at level 2 as the uniform adjustment across all the correlation coefficients. For example, we used the average of 15.6% as the value for attrition and the average age at time 1 (7.61) for age. For the covariates associated with the construct characteristics, we selected the value for each covariate that corresponded to the most common measurement characteristic for that construct across all the cells involving that construct to ensure that all cells with the same construct were adjusted in the same way. In addition, because we have both longitudinal and cross-sectional correlations in the dataset, the time interval between waves (*time*) was set to 0 for the cross-sectional correlations and set to the mean for the longitudinal correlations.

The result of these procedures was a different adjustment for the correlation coefficients in each cell of the synthesized matrix obtained by inserting different values for the moderator variables in the regression equation used to compute the adjusted correlations for each cell. One constant set of values across all cells was for the moderators representing the characteristics like age or gender mix that we wanted to standardize for the entire matrix. The adjustment for *time* depended on whether the cell represented a cross-sectional relationship between the upstream constructs (the three parental support constructs) or a longitudinal relationship between one of those constructs and achievement (0 for all cross-sectional cells and $b \cdot X$ for all longitudinal cells). The selected values for the dummy codes identifying the measurement characteristics for each variable representing a given construct provided another set of constants for each corresponding correlation coefficient. Note that while different constants are computed for each cell, the same adjustments is applied for each construct across the different cells in which it is represented. The respective constants

that resulted from calculating the terms in the regression model with the selected moderator values were then added to the intercept and the residual for each correlation coefficient that were saved from the initial regression analysis. For example, the procedure for adjusting a correlation coefficient in the first cell in Table 1 (indexing the relationship between home involvement and school involvement) is:

$$\begin{aligned}
 r_{cell1} = & residual + intercept + (b_{w1age} * 7.61) \\
 & + (b_{w1agerange} * 1.39) \\
 & + (b_{time} * 0) \\
 & + (b_{permale} * .45) \\
 & + (b_{white} * 3.2) \\
 & + (b_{poor} * 3.36) + (b_{risky} * 0) \\
 & + (b_{attrition} * .156) \\
 & + (b_{scale+1}) + (b_{samemc} * 1) \\
 & + (b_{cmc1} * 1) + (b_{cmc3} * 1)
 \end{aligned}$$

Step 3 in Appendix A illustrates this process for every cell of the matrix.

The pooled correlation matrix was then estimated using the no-intercept model described above in equation 1, but with the adjusted correlation coefficients now used as the dependent variable (see Step 4 in Appendix A). The resulting adjusted synthesized correlation coefficients are shown in parentheses in Table 1 in the lower triangle.

Estimating the metaSEM Model

With the adjusted pooled correlation matrix, its asymptotic covariance matrix, and the estimated sample size across all studies in the analysis as input, we then used the *wls* function from the *metaSEM* package to estimate a simple path model in which each of the three forms of parental support and socioeconomic status predict later academic achievement. In this path model, we allowed the predictors to covary and the outcome to have an estimated variance. We used the sum of the sample sizes from each study ($n = 117,120$) to represent the total sample size (see Step 5 in Appendix A for the R code). Meta-analysts may have reasons to report unadjusted path or SEM models, for example, in cases where little heterogeneity is evident. There may be reasons to report adjusted results, however, as in situations where there are differences in the number or characteristics of studies in different cells of the matrix. To illustrate the influence of the covariate adjustment process and demonstrate that the path or other structural equation models may be estimated on either the adjusted or unadjusted matrices, we estimated both in our illustrative example.

The results of these path models are presented in Figure 1. Two coefficients for each path are shown, the first was estimated from the unadjusted correlation matrix and the second was estimated using the adjusted correlation matrix. The models differ little in terms of estimated coefficients and standard errors, though that will not always be the case. Focusing on the adjusted model, Figure 1 shows that the strongest predictor of academic achievement was socioeconomic status ($b = .22$, $SE = .01$, $p < .01$). Of the three focal predictors, parental expectations ($b = .17$, $SE = .01$, $p < .01$) and home-involvement ($b = .12$, $SE = .01$, $p < .01$)

had the largest relationships with academic achievement. Parental involvement at school, on the other hand, was not associated with later academic achievement ($b = -.01$, $SE = .02$, $p > .10$). We also note that a significant amount of unexplained variability in the achievement outcome remained, as shown by the psi ($\psi = .85$, $SE = .01$, $p < .01$), and that the relationships between the predictors (i.e., the cross-sectional coefficients) were all statistically significant. We might conclude from such an analysis that, although there may be other variables not included in this model that are more strongly associated with achievement than any of these parental support variables, an enhancement to our tutoring program focused on increasing parental support for achievement at home and encouraging parents to raise their expectations might be a promising option.

Discussion

The purpose of this paper is to describe and illustrate a modified method for creating synthesized correlation matrices for meta-analytic SEM that can be applied to a broad range of social and behavioral research results. This method grew out of our need to find a way to pool correlation matrices that accommodates multiple effect sizes from the same studies within cells and uneven contributions to those cells by different studies, allows for a multivariate exploration of moderator variables capable of accounting for heterogeneity within and between studies, and permits creation of adjusted correlations that reduce the influence of selected nuisance variables and/or make the correlations more comparable across the cells of the matrix. The method we have described is not meant to supplant the standard techniques, but rather to provide an option for meta-analytic situations that are not easily handled by those techniques.

Many meta-analysts investigating complex models have discovered that the standard MASEM techniques are difficult to apply to some social and behavioral research literatures (Graham, 2011; Topa, et al., 2009). This has resulted in a variety of ad hoc solutions that are not well-documented or always well-justified. By offering a detailed description of one option that is applicable to a broad range of correlational research appropriate for meta-analytic SEM, we hope to give applied meta-analysts a method that can be applied consistently and with sufficient statistical justification, given the current state of knowledge, for such complex models to produce credible results.

In addition, the meta-regression-based procedure for investigating moderator variables that we have described offers a formal way to assess the conjoint influence of multiple sources of heterogeneity on the pooled correlation matrix. Further, it provides a basis for adjusting the observed correlations in a way that can reduce the undesirable influence any of those moderators has on the synthesized correlation matrix and the analyses based on that matrix. However, we recognize that this adjustment procedure produces artificial values that are only statistical predictions of what the respective correlation coefficients would be under circumstances different from those from which they were actually derived. Meta-analysts using this technique should be careful to select values for the moderator variables involved in any adjustment that are plausible and not too discrepant from those that appear, or could easily appear, in the original data. For example, choosing to plug a value of zero attrition

into the regression equation when no studies in the meta-analysis actually had zero attrition would not be predicting to a situation that existed in any study represented in the data.

More technical work on these techniques and the results of their application is needed. For example, simulation studies that illuminate the conditions under which the results are most robust would be informative, especially with regard to the extent to which large variations in the number of effect sizes or studies per cell contributing to the pooled matrix matter, and the performance of the models with complex, heterogeneous datasets. Another relevant topic that awaits further exploration is the implications of the prior regression-based covariate adjustment step on the standard errors of the MASEM model based on the adjusted correlation coefficients. Such work is beyond the scope of this paper, but we do not believe that meta-analysts need wait for such work to use these techniques. They involve variations on established meta-analytic multilevel modeling, meta-regression, and meta-analytic structural equation modeling that are neither radical nor especially novel. What is most distinctive about this approach is the integration of these techniques into an organized procedure for addressing some of the more problematic aspects of meta-analysis with complex correlational data.

Conclusion

We are encouraged by the development and increasing use of MASEM because it represents a significant step forward in the ability of meta-analysts to use complex models to explore findings synthesized from primary studies. The research questions that can be investigated with meta-analytic path analysis, structural equation models, and factor analysis have the potential to provide useful information in a variety policy and practice arenas. We believe that the methods described in this paper provide a way of extending the reach of MASEM to situations that have been difficult to handle in the past and thus promote greater use of this powerful modeling tool.

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Appendix A

We begin by loading the metafor library and the dataset. We name the dataset "dataset." It includes the correlation coefficient effect sizes (ES), the inverse of the sample size (inv_n) for each case, the effect size id (ES_ID), the study id (Study_ID), a variable indicating the pair of constructs in each correlation (Cell), and all potential covariates. Because the metafor package uses the inverse of the effect size variance to weight each case, we enter the inverse of the sample size and the algorithm uses the inverse for the weights. In this manner, sample size weighting is executed.

```
library(foreign)
library(metafor)
library(corpcor)

dataset=read.spss("parent_data_RSM.sav", use.value.labels=FALSE, to.data.frame=T)

Step 1: We first estimate the unadjusted pooled correlation matrix using the rma.mv function in metafor. We do not estimate an intercept and instead use dummy variables to represent each of the ten cells of the synthesized matrix. We also extract and save the variance-covariance matrix for use in a later metaSEM model.

#Run the meta-regression model with rma.mv
#The correlation coefficients (ES) are entered as yi
#The inverted sample size (inv_n) is used for V
#Study and ES_ID in the random command describe the structure of the data
#The "mods" argument specifies the cell variable as the only covariate
#Including the "-1" in the "mods" argument omits the intercept in the model

Step1 <- rma.mv(yi=ES, V=inv_n,
               data=dataset,
               random=list(~1|Study,~1|ES_ID),
               method="ML", mods=~factor(Cell)-1)

summary (Step1)

##
## Multivariate Meta-Analysis Model (k = 671; method: ML)
##
##      loglik    Deviance      AIC      BIC      AICc
## 429.8187  1444.1551  -835.6375  -781.5323  -835.1633
##
## Variance Components:
##
##      estim    sqrt  nlvs  fixed  factor
## sigma^2.1  0.0093  0.0966  119    no    Study
## sigma^2.2  0.0069  0.0831   671    no    ES_ID
##
## Test for Residual Heterogeneity:
## QE(df = 661) = 4303.1619, p-val < .0001
##
## Test of Moderators (coefficient(s) 1,2,3,4,5,6,7,8,9,10):
## QM(df = 10) = 646.5618, p-val < .0001
##
## Model Results:
##
##      estimate      se      zval      pval      ci.lb      ci.ub
```

Figure 0001


```
## factor(Cell)1      0.2946  0.0235 12.5139 <.0001  0.2485  0.3408 ***
## factor(Cell)2      0.3383  0.0303 11.1618 <.0001  0.2789  0.3977 ***
## factor(Cell)3      0.2188  0.0200 10.9239 <.0001  0.1796  0.2581 ***
## factor(Cell)4      0.2335  0.0253  9.2134 <.0001  0.1838  0.2831 ***
## factor(Cell)5      0.2412  0.0273  8.8469 <.0001  0.1877  0.2946 ***
## factor(Cell)6      0.3715  0.0248 14.9490 <.0001  0.3228  0.4202 ***
## factor(Cell)7      0.1959  0.0157 12.4768 <.0001  0.1651  0.2266 ***
## factor(Cell)8      0.1084  0.0203  5.3348 <.0001  0.0686  0.1482 ***
## factor(Cell)9      0.2668  0.0229 11.6322 <.0001  0.2219  0.3118 ***
## factor(Cell)10     0.2887  0.0145 19.9418 <.0001  0.2603  0.3171 ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#Save the asymptotic variance-covariance matrix
Acov_UnadjES <- Step1$vb

#Create the correlation matrix
#The "vec2sm" function converts the upper half of the correlation matrix to a
symmetrical matrix

Matrix_UnadjES <- vec2sm(vec = c(1, Step1$b[1], Step1$b[2], Step1$b[3], Step1$b[7],
1, Step1$b[4], Step1$b[5], Step1$b[8],
1, Step1$b[6], Step1$b[9],
1, Step1$b[10],
1),
diag = TRUE)

#Add column and row names to the matrix to make it easier to interpret below
colnames(Matrix_UnadjES) <- rownames(Matrix_UnadjES) <- c("Home", "School",
"Expectations", "SES", "Achievement")

Step 2: The next step is to run the meta-regression model for the covariate adjustments. The result
of this model will produce meta-regression coefficients and residuals, both of which will be used to
produce covariate-adjusted correlations. The "mods" statement specifies the moderator variables
in the meta-regression. The residuals from the meta-regression model are then written to the
original data frame using the "residuals.rma" function.

#Run the meta-regression model including covariates to be used for adjustments
#Note that for this model the intercept is included

Step2 <- rma.mv(yi=ES, V=inv_n,
data=dataset,
random=list(~1|Study, ~1|ES_ID),
method="ML",
mods=~ wlage + wlagrange +
time + permale + white + poor + risky +
attrition + scale + samemc + cmc1 + cmc3 +
cmc5 + cmc7 + cmc9 + cmc10)

#Extract the residuals
Resid_Step2 <- residuals.rma(Step2)

#Create a new residuals column in the dataset
dataset$residuals <- Resid_Step2

Step 3: Next, we create the covariate-adjusted correlations. Use the parameter estimates from the
meta-regression model and associated residual values to calculate the new correlations. As shown
below, we calculate covariate-adjusted correlations separately for cross-sectional and longitudinal
effect sizes to reflect the different time intervals. In addition, we adjust each construct for its
measurement characteristics. This is accomplished through a series of "if-else" statements.

#Start by creating a "constant" for the cross-sectional correlations
#Each coefficient in the regression model is multiplied by the value of the moderator
variable specified by the researcher
#The first value, "Step2$b[1]*1", is the intercept multiplied by 1
#The second value, "Step2$b[2]*11.01" is the coefficient for age multiplied by the
mean age of 11.01, and so on

Cross_Constant <- Step2$b[1]*1 + Step2$b[2]*7.61 + Step2$b[3]*1.39 + Step2$b[4]*0 +
Step2$b[5]*.45 + Step2$b[6]*3.20 + Step2$b[7]*3.36 + Step2$b[8]*0 +
Step2$b[9]*.156 + Step2$b[10]*1 + Step2$b[11]*1

#Create the "constant" for the longitudinal correlations
#A different constant is created to adjust for variations in time intervals

Long_Constant <- Step2$b[1]*1 + Step2$b[2]*7.61 + Step2$b[3]*1.39 +
Step2$b[4]*28.72 + Step2$b[5]*.45 + Step2$b[6]*3.20 +
Step2$b[7]*3.36 + Step2$b[8]*0 +
Step2$b[9]*.156 + Step2$b[10]*1 + Step2$b[11]*1

#Next add the cross-sectional or longitudinal constant, the residuals saved in Step
2, and the construct-specific adjustments
#For example, for Cell 1, we are adding in the measurement adjustments specific to
the two constructs in that correlation coefficient
#All cells with a construct are adjusted the same way
dataset$Covadj_ES <- ifelse(dataset$Cell == "1", Cross_Constant + Resid_Step2 +
Step2$b[12]*1 + Step2$b[13]*1,
ifelse(dataset$Cell == "2", Cross_Constant + Resid_Step2 +
Step2$b[12]*1 + Step2$b[14]*1,
ifelse(dataset$Cell == "3", Cross_Constant + Resid_Step2 +
Step2$b[12]*1 + Step2$b[15]*1,
ifelse(dataset$Cell == "4", Cross_Constant + Resid_Step2 +
Step2$b[13]*1 + Step2$b[14]*1,
ifelse(dataset$Cell == "5", Cross_Constant + Resid_Step2 +
Step2$b[13]*1 + Step2$b[15]*1,
ifelse(dataset$Cell == "6", Cross_Constant + Resid_Step2 +
Step2$b[14]*1 + Step2$b[15]*1,
ifelse(dataset$Cell == "7", Long_Constant + Resid_Step2 +
Step2$b[12]*1 + Step2$b[17]*1,
ifelse(dataset$Cell == "8", Long_Constant + Resid_Step2 +
Step2$b[13]*1 + Step2$b[17]*1,
ifelse(dataset$Cell == "9", Long_Constant + Resid_Step2 +
Step2$b[14]*1 + Step2$b[17]*1,
ifelse(dataset$Cell == "10", Long_Constant + Resid_Step2 +
Step2$b[15]*1 + Step2$b[17]*1,0)))))))))
```

Step 4: We then estimate the adjusted pooled correlation matrix using metafor in the same way as in Step 1, but replacing the original correlation coefficients with the adjusted ones. The model again outputs the coefficients and asymptotic covariance matrix (e.g., "Step3\$vb" and "vec2sm" functions, respectively).

```
Step4 <- rma.mv(yi=Covadj_ES, V=inv_n,
               data=dataset,
               random=list(~1|Study, ~1|ES_ID),
               method="ML",
               mods=~ factor(Cell)-1)

summary (Step4)

##
## Multivariate Meta-Analysis Model (k = 671; method: ML)
##
## logLik Deviance AIC BIC AICc
## 438.2892 1427.2141 -852.5784 -798.4732 -852.1043
##
## Variance Components:
##
##      estim  sqrt nlvs fixed factor
## sigma^2.1 0.0081 0.0899 119 no Study
## sigma^2.2 0.0067 0.0817 671 no ES_ID
##
## Test for Residual Heterogeneity:
## QE(df = 661) = 4222.6177, p-val < .0001
##
## Test of Moderators (coefficient(s) 1,2,3,4,5,6,7,8,9,10):
## QM(df = 10) = 842.6613, p-val < .0001
##
## Model Results:
##
##      estimate      se      zval      pval      ci.lb      ci.ub      ***
## factor(Cell)1 0.2676 0.0230 11.6516 <.0001 0.2226 0.3126 ***
## factor(Cell)2 0.3636 0.0293 12.4225 <.0001 0.3062 0.4210 ***
## factor(Cell)3 0.2673 0.0194 13.7690 <.0001 0.2292 0.3053 ***
## factor(Cell)4 0.1949 0.0247 7.8774 <.0001 0.1464 0.2434 ***
## factor(Cell)5 0.2044 0.0266 7.6934 <.0001 0.1523 0.2564 ***
## factor(Cell)6 0.3990 0.0242 16.5208 <.0001 0.3517 0.4464 ***
## factor(Cell)7 0.2361 0.0152 15.5605 <.0001 0.2063 0.2658 ***
## factor(Cell)8 0.0989 0.0197 5.0237 <.0001 0.0603 0.1375 ***
## factor(Cell)9 0.2959 0.0224 13.2277 <.0001 0.2521 0.3398 ***
## factor(Cell)10 0.3179 0.0139 22.8416 <.0001 0.2906 0.3452 ***
##
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#Save the asymptotic variance-covariance matrix
Acov_AdjES <- Step4$vb

#Create the correlation matrix
Matrix_AdjES <- vec2sm(vec = c(1,Step4$b[1],Step4$b[2],Step4$b[3],Step4$b[7],
                             1,Step4$b[4],Step4$b[5],Step4$b[8],
                             1,Step4$b[6],Step4$b[9],
                             1,Step4$b[10],
                             1),
                      diag = TRUE)

colNames(Matrix_AdjES) <- rownames(Matrix_AdjES) <- c("Home", "School",
"Expectations", "SES", "Achievement")
```

Figure 0002

```
1,Step4$b[10],
1),
diag = TRUE)

colNames(Matrix_AdjES) <- rownames(Matrix_AdjES) <- c("Home", "School",
"Expectations", "SES", "Achievement")

Step 5: We continue by loading the metaSEM library and its dependencies.

library(metaSEM)
library(OpenMX)
library(MASS)

Next, load the unadjusted and the adjusted correlation matrices returned from the multilevel meta-analysis models. Note that these are symmetrical matrices. The "n" is the total sample size across all studies.

Matrix_UnadjES      #Unadjusted correlation matrix#
##
##      Home      School Expectations      SES Achievement
## Home      1.0000000 0.2946420      0.3382870 0.2188231 0.1958504
## School      0.2946420 1.0000000      0.2334628 0.2411593 0.1083999
## Expectations 0.3382870 0.2334628      1.0000000 0.3714608 0.2668271
## SES          0.2188231 0.2411593      0.3714608 1.0000000 0.2886796
## Achievement 0.1958504 0.1083999      0.2668271 0.2886796 1.0000000

Matrix_AdjES      #Adjusted correlation matrix#
##
##      Home      School Expectations      SES Achievement
## Home      1.0000000 0.2675633      0.3636007 0.2672944 0.23608375
## School      0.2675633 1.0000000      0.1949434 0.2043584 0.09891301
## Expectations 0.3636007 0.1949434      1.0000000 0.3990425 0.29592867
## SES          0.2672944 0.2043584      0.3990425 1.0000000 0.31789255
## Achievement 0.2360837 0.09891301      0.2959287 0.3178926 1.00000000

n<-117120      #Total sample size#

Using the OpenMX language, we create the S and A matrices.

S1<-create.mxMatrix(c(1,".2*corhomeschool",".2*corhomePE", ".2*corhomeSES",0,1,
".2*corpschoolPE", ".2*corpschoolSES",0,1, ".2*corPESES",0,1,0, ".2*errAA"),
type="Symm",name="S1")

A1<-create.mxMatrix(c(0,0,0,0, ".2*home2ach",0,0,0,0, ".2*school2ach",0,0,0,0,
".2*PE2ach",0,0,0,0, ".2*SES2ach",0,0,0,0,0),
type="Full",ncol=5,nrow=5,name="A1")

Finally, we use the 'wls' function to run the metaSEM models. The "asyCov" matrix is from the meta-regression model above. We run both models to illustrate differences in the unadjusted and adjusted effect size matrices.

unadjusted.metaSEM<-wls(Cov=Matrix_UnadjES,asyCov=Acov_UnadjES,n=n,
Amatrix=A1,Smatrix=S1,cor.analysis=TRUE,diag.constraints=TRUE)
adjusted.metaSEM<-wls(Cov=Matrix_AdjES,asyCov=Acov_AdjES,n=n,
Amatrix=A1,Smatrix=S1,cor.analysis=TRUE,diag.constraints=TRUE)
summary(unadjusted.metaSEM)
summary(adjusted.metaSEM)
```

Figure 0005

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Notes: $N = 117,120$; Upper numbers represent unadjusted model, lower numbers represent adjusted model; ** $p < .01$

Figure 1.
Results of path analysis for unadjusted and adjusted correlation matrices.

Table 1
Measurement Characteristics and Synthesized Effect Size Estimates of the Case Study Variables

	C1.	C2.	C3.	C4.	C5.
C1. Home-involvement	-	C1: <i>P</i> : 16, <i>O</i> : 23	C1: <i>P</i> : 45, <i>O</i> : 43	C1: <i>P</i> : 52, <i>O</i> : 7	C1: <i>P</i> : 60, <i>O</i> : 71
		C2: <i>P</i> : 18, <i>O</i> : 21	C3: <i>P</i> : 13, <i>O</i> : 75	C4: <i>P</i> : 22, <i>O</i> : 37	C5: <i>W</i> : 45, <i>Or</i> : 80, <i>O</i> : 6
C2. School- Involvement	ES: .29 (.27) <i>m</i> =39 (<i>k</i> =13)	-	C2: <i>P</i> : 11, <i>O</i> : 11	C2: <i>P</i> : 18, <i>O</i> : 2	C2: <i>P</i> : 17, <i>O</i> : 47
			C3: <i>P</i> : 6, <i>O</i> : 16	C4: <i>P</i> : 14, <i>O</i> : 9	C5: <i>W</i> : 50, <i>Or</i> : 12, <i>O</i> : 2
C3. Parental Expectations	ES: .34 (.36) <i>m</i> =88 (<i>k</i> =8)	ES: .23 (.19) <i>m</i> =22 (<i>k</i> =8)	-	C3: <i>P</i> : 21, <i>O</i> : 2	C3: <i>P</i> : 39, <i>O</i> : 5
				C4: <i>P</i> : 14, <i>O</i> : 9	C5: <i>W</i> : 13, <i>Or</i> : 30, <i>O</i> : 1
C4. Socio- economic status	ES: .22 (.27) <i>m</i> =59 (<i>k</i> =24)	ES: .24 (.20) <i>m</i> =20 (<i>k</i> =9)	ES: .37 (.40) <i>m</i> =23 (<i>k</i> =16)	-	C4: <i>P</i> : 171, <i>O</i> : 10
					C5: <i>W</i> : 81, <i>Or</i> : 78, <i>O</i> : 22
C5. Academic Achievement	ES: .20 (.24) <i>m</i> =131 (<i>k</i> =38)	ES: .10 (.10) <i>m</i> =64 (<i>k</i> =20)	ES: .27 (.30) <i>m</i> =44 (<i>k</i> =16)	ES: .29 (.32) <i>m</i> =181 (<i>k</i> =44)	-

Notes: The upper diagonal presents the measurement characteristics for each of the constructs paired in a cell. The lower diagonal shows the unadjusted and adjusted mean correlation coefficients, the number of effect sizes and the number of studies. C1 = Construct 1, C2 = Construct 2, etc.; *P* = Parent report, *O* = Other informant, *W* = Written measure, *Or* = Oral measure; ES = Effect size, Unadjusted (Adjusted); *m* = Number of effect sizes, *k* = Number of studies.

Table 2

Structure of a Hypothetical 3-Level Correlational Dataset

StudyID	ESID	Cell	Label ^d	Cell ₁	Cell ₂	Cell ₃	Cell ₄	Cell ₅	Cell ₆	r
1	1	1	r _{c1c2}	1	0	0	0	0	0	.10
1	2	3	r _{c1c4}	0	0	1	0	0	0	.20
1	3	4	r _{c2c3}	0	0	0	1	0	0	.08
1	4	6	r _{c3c4}	0	0	0	0	0	1	.22
2	5	1	r _{c1c2}	1	0	0	0	0	0	-.18
2	6	1	r _{c1c2}	1	0	0	0	0	0	.27
2	7	2	r _{c1c3}	0	1	0	0	0	0	.14
2	8	5	r _{c2c4}	0	0	0	0	1	0	.31
2	9	6	r _{c3c4}	0	0	0	0	0	1	.04
3	10	3	r _{c1c4}	0	0	1	0	0	0	.06
3	11	4	r _{c2c3}	0	0	0	1	0	0	-.13
3	12	5	r _{c2c4}	0	0	0	0	0	0	.25
3	13	6	r _{c3c4}	0	0	0	0	1	1	.17
4	14	1	r _{c1c2}	1	0	0	0	0	0	-.04
4	15	2	r _{c1c3}	0	1	0	0	0	0	.03
4	16	2	r _{c1c3}	0	1	0	0	0	0	.11
4	17	3	r _{c1c4}	0	0	1	0	0	0	.34
4	18	3	r _{c1c4}	0	0	1	0	0	0	-.27
4	19	6	r _{c3c4}	0	0	0	0	0	1	.02

Notes: Table represents a dataset for estimating a synthesized 4 × 4 correlation matrix (6 correlation pairs); there are multiple correlations within one study between the same pair of constructs.

^dThe C1C2, C1C4, etc. notation for the labels refers to Constructs 1–4, as in Table 1, and indicates which is paired with which.

Table 3

Study Characteristics

	Cross-sectional	Longitudinal
Number of correlational effect sizes	251	420
Number of primary studies	62	79
Mean time interval in months (sd)	0	45.9 (38.9)
	Mean	sd
Average age at Time 1	7.6	4.6
Average age range at Time 1	1.4	.80
Percentage male	.45	.24
Majority white	3.2	1.2
Majority low SES	3.4	1.7
High risk (1=yes; 0=general population)	.14	.35
Percentage attrition	.16	.14
Both constructs on continuous scale (%)	.95	.23
Percentage similar measurement type	.26	.44

Notes: Attrition calculated using number of participants lost at follow-up; the majority white and majority low SES variables are scaled from 1–5 and indicate the approximate percentages of white and low SES students in the samples (1 = none, 3 = half, 5 = all).

Table 4

Results of the Meta-regression Analysis

	Coefficient (SE)	95% C.I.	Values	
Intercept	.28 (.07) **	.14, .42	Cross	Long
Age [years] at time 1 (w1age)	.002 (.003)	-.003, .01	AV	AV
Age [years] range at time 1 (w1agerange)	-.02 (.01)	-.04, .01	AV	AV
Time [years] between wave 1 and 2 (time)	.01 (.01)	-.01, .01	-	4
Percentage male (permale)	-.06 (.04)	-.15, .02	AV	AV
Percentage white (white)	.02 (.01)	-.01, .04	AV	AV
Percentage low SES (poor)	-.01 (.01)	-.03, .01	AV	AV
Percentage of at-risk students (risky)	-.02 (.03)	-.09, .04	AV	AV
Percentage attrition (attrition)	-.01 (.07)	-.14, .13	AV	AV
ES corrected for attenuation (scale)	-.01 (.03)	-.06, .04	1	1
Same measurement characteristics (samemc)	.02 (.02)	-.02, .06	1	1
Home-based inv., parent report (cmc1)	.02 (.02)	-.02, .06	1	-
School-based inv., parent report (cmc3)	-.08 (.02) **	-.13, -.04	1	-
Expectations, parent report (cmc5)	.04 (.02) *	.01, .07	1	-
Socioeconomic status, parent report (cmc7)	.06 (.01) **	.04, .09	1	-
Achievement, written test (cmc9)	-.02 (.02)	-.07, .03	-	-
Achievement, orally admin. test (cmc10)	-.04 (.02) *	-.08, -.01	-	1

Notes: Variable names in the meta-regression models are shown in parentheses; reference group for all measurement characteristics is the “all other” category; AV indicates that the average value was used.

**
 $p < .05$,

*
 $p < .01$.