Advancing the Formulation and Testing of Multilevel Mediation and Moderated Mediation Models

A Thesis

Presented in Partial Fulfillment of the Requirements for the Degree
Master of Arts in the Graduate School of The Ohio State University

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2017

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Abstract

Researchers in the social sciences are often interested in explaining causal processes in which the effect of one variable is transmitted to another through one or more intervening (or mediator) variables. Statistical mediation analysis can be used by researchers to gain a better understanding of these causal processes. The methods traditionally used to quantify and test a mediation process, or indirect effect, are not directly applicable when the data are nested hierarchically, which is common in educational, organizational, and behavioral sciences where students may be nested within classrooms, employees may be nested within companies, or repeated measurements may be nested within individuals. Multilevel modeling (MLM) is a method for analyzing hierarchical data that allows for the simultaneous estimation of the effects of variables at multiple levels of the hierarchy. As such, several researchers have proposed methods for testing mediation using MLM. A majority of these methods have focused on models in which the independent variable is a level-2 variable, the mediator is either a level-2 or a level-1 variable, and the dependent variable is a level-1 variable. Although some (Kenny, Korchmaros, & Bolger, 2003; Bauer, Preacher, & Gil, 2006) have focused on models in which all three variables are measured at the lowest level, the methods proposed are not without their shortcomings. The aim of this thesis is to address and mitigate some of these shortcomings, as well as provide advancements in the formulation and testing of a number of interesting effects that can be

modeled using MLM. The major contributions include demonstrating how to simultaneously estimate between-group and within-group indirect effects using traditional MLM software. A test for the difference between within-group and between-group indirect effects is also conceptualized and explained. Further, the model is expanded to include multiple mediators with either fixed or random slopes. In the case where one or more paths for one indirect effect covary with one or more paths from another, the covariance between the random indirect effects is derived. Finally, the index of moderated mediation (Hayes, 2015) is applied to the multilevel context to test the moderating effect of a level-2 variable on the within-group and/or between-group indirect effect. To demonstrate the methods discussed throughout this thesis, two real-world datasets are analyzed using `MLmed`, a free SPSS macro developed in conjunction with this thesis and designed specifically to fit multilevel mediation and moderated mediation models. The parameter estimates obtained using `MLmed` are comparable to those obtained using Mplus (Muthén & Muthén, 2015) and the lme4 package (Bates, Mächler, Bolker, & Walker, 2015) in R (R Core Team, 2016), but with considerably less programming effort required.

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Hayes, A.F., Montoya, A.K., & Rockwood, N.J. (2017). "The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling". *Australasian Marketing Journal.*

Fields of Study

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Chapter 1: Introduction

Over the past several decades, researchers in the social sciences have moved beyond hypothesizing the mere existence of causal effects and have begun to focus on explaining such effects. Often, these hypotheses involve a causal process in which the effect of one variable is transmitted to another through one or more intervening variables.

Statistical mediation analysis can be used by researchers to gain a better understanding of these causal processes. Within the mediation literature, an intervening variable is often labeled a mediator (denoted M here), and is said to mediate the relationship between the two variables on each side of its causal chain. The variable that influences the mediator is the independent variable (denoted X here), and the variable that is influenced by the mediator is the dependent variable (denoted Y here). Hence, X transmits its effect on Y indirectly through M. This effect is labeled the *indirect effect*. X may also influence Y independent of M. This effect is known as the *direct effect*, as it does not operate through M.

The simple three variable mediation model, as well as models that include additional mediators, have been widely applied in various fields including psychology, education, business and organizational behavior, communications, medicine, and economics. For example, Richter, König, Koppermann, and Schilling (2016) found that

participation in a managerial training program reduced negative consequences when acting out the situation of laying off an employee. Specifically, employees who were "laid-of" by a manager that had completed the training were less likely to be angry, to complain, and to seek legal action, and each of these relationships were mediated by the employee's perception of procedural justice. Schleider, Patel, Krumholz, Chorpita, and Weisz (2015) found support for the hypothesis that parents' poor mental health indirectly led to youth problems (such as delinquent and aggressive behavior) through parent-youth stress.

Traditional methods for assessing mediation analysis based on ordinary least squares (OLS) regression are not directly applicable when the data are nested. Nested data occurs when the sampling units belong to, or are nested within, distinct groups or clusters. For example, students may be nested within classrooms, employees may be nested within organizations, or repeated measurements may be nested within individuals. Nested data are often referred to as hierarchical data, to emphasize that there may be data collected at different *levels* of the hierarchy. Referring to the student/classroom example, there may be lower (student) level variables, such as gender and socioeconomic status (SES), as well as upper (classroom) level variables, such as the number of students in the class, or the tenure of the teacher.

Multilevel models (MLMs), sometimes referred to as hierarchical models, random effects models, random coefficient models, or mixed models, account for the dependence of data within groups. Further, the between-group and within-group variance of an outcome variable can be separated and explained by variables at the upper and lower levels, respectively, and relationships between lower level variables can randomly vary across groups or be explained by group-level variables. Due to the

flexibility of MLMs coupled with advances in model estimation and computing techniques, multilevel modeling has proved to be an indispensable method for analyzing nested data.

As the popularity of implementing multilevel models in social science research has increased, many researchers have proposed methods of testing mediation hypotheses involving nested data using such models (Preacher, 2015). Because of the multiple levels of data, the mediation process can take several forms based on the level at which the independent, mediator, and dependent variables are measured. A popular method for differentiating such forms is to label the three variable process based on the levels at which X, M, and Y are measured. For example, a mediation model in which X and M are measured at level-2 and Y is measured at level-1 would be labeled a 2-2-1 model. A 2-1-1 model would contain a level-2 X variable, and level-1 M and Y variables, and a 1-1-1 model would contain X, M, and Y variables measured at the lowest level.

Like single-level mediation models, multilevel mediation models have been applied in a number of fields. For example, Zhu, Gardner, and Chen (2016) found that intrinsic motivation in the workplace (a level-1 variable) mediates the relationship between collaborative team climate (a level-2 variable) and creativity (a level-1 variable). Bakker, Vergel, and Kuntze (2015) found a significant indirect effect of students' personal resources on observed learning activities through study engagement. The study was longitudinal, where repeated measurements (level-1) were nested within individuals (level-2).

An important topic within MLM that has made its way into the multilevel mediation literature is that of centering level-1 predictor variables. Zhang, Zyphur, and

Preacher (2009) argued that most of the advances made within multilevel mediation have failed to acknowledge centering decisions, which may result in biased or conflated estimates of indirect effects composed of within-group and between-group effects. They provided recommendations to decompose such effects to obtain accurate estimates of the underlying processes.

This thesis expands upon the work of Kenny et al. (2003) and Bauer et al. (2006) focused on 1-1-1 multilevel mediation models by following the recommendation of Zhang et al. (2009) and explicitly decomposing within-group and between-group direct and indirect effects and making inferences about such effects. In addition, this thesis provides a number of advancements related to 1-1-1 multilevel mediation models. First, an *indirect contextual effect* is described, and methods of testing are explained. Next, multilevel multiple mediator models, which allow for the comparison of indirect effects at the same level, are formulated within the framework of Bauer et al. (2006). The covariance between random indirect effects in these models is also derived. Finally, the index of moderated mediation (Hayes, 2015) is extended to the multilevel context to allow for testing whether a level-2 variable moderates the within-group or between-group indirect effect.

I begin by providing an overview of single-level mediation analysis and describe the addition of covariates, multiple mediators, and moderators. Next, I describe the general multilevel modeling framework and discuss centering methods and their effects on parameter interpretations. Following, I review the previous literature on multilevel mediation and provide a detailed account of the work presented by Kenny et al. (2003) and Bauer et al. (2006). I outline the decomposition of effects as described by MacKinnon (2008) and Zhang et al. (2009), make the model extensions discussed

previously, and describe the limitations of the model. The use of an SPSS macro that vastly simplifies the fitting of multilevel mediation and moderated mediation models is then demonstrated using two example datasets, and the estimates obtained from the macro are compared to other popular software packages. The thesis concludes with an overview of practical and theoretical issues related to fitting the models discussed throughout this thesis, as well as recommendations for future research.

Chapter 2: Single-Level Mediation

A three variable statistical mediation model with continuous M and Y variables is often estimated using the following equations:

$$M_i = d_1 + aX_i + e_{1i} \tag{2.1}$$

$$Y_i = d_2 + c'X_i + bM_i + e_{2i} \tag{2.2}$$

$$Y_i = d_3 + cX_i + e_{3i}, \tag{2.3}$$

where $e_{1i} \sim N(0, \sigma_1^2)$, $e_{2i} \sim N(0, \sigma_2^2)$, and $e_{3i} \sim N(0, \sigma_3^2)$. The regression coefficient c quantifies the expected change in Y resulting from a one unit change in X and is referred to as the *total effect*. In equation 2.2, c' is the *direct effect* of X on Y and quantifies the expected change in Y resulting from a one unit change in X while holding M constant. The *indirect effect*, which quantifies the expected change in Y through M resulting from a one unit change on X, is the product of a and b, ab. When the model is estimated using OLS or maximum likelihood, the total effect is equal to the sum of the indirect and direct effects. That is, $c = ab + c'$.

2.1 Methods of Inference about the Indirect Effect

Inference about the direct and total effects can be conducted by calculating the ratio of the estimated effect to its standard error and comparing this ratio to the t distribution with the appropriate degrees of freedom. Inference about the indirect effect, however, has become a topic of heavy debate and research within the methodological literature (MacKinnon, Lockwood, & Williams, 2004; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002; Hayes & Scharkow, 2013).

2.1.1 Causal Steps

The causal steps approach (Baron & Kenny, 1986) involves estimating equations 2.1 - 2.3. Mediation can be concluded if the following four conditions are satisfied:

1. The estimated total effect of X on Y, $\hat{c}$, is statistically significant.

2. The estimated effect of X on M, $\hat{a}$, is statistically significant.

3. The estimated effect of M on Y controlling for X, $\hat{b}$, is statistically significant.

4. The estimated direct effect of X on Y controlling for M, $\hat{c}'$, is not statistically significant.

If conditions 1-3 are satisfied, but the direct effect is statistically significant, M is said to partially mediate the relationship between X and Y. Unfortunately, the causal steps approach has some major flaws. First, it relies heavily on tests of statistical significance and has been show to have very low statistical power relative to alternative inferential methods (Hayes & Scharkow, 2013). Second, researchers have argued that condition 1 does not need to be met for a mediation process to operate (Hayes, 2009;

Shrout & Bolger, 2002; Rucker, Preacher, Tormala, & Petty, 2011). It is possible for the indirect and direct effect to be opposite in sign. If this is the case, yet both effects are equal in strength, the addition of the effects (which is equal to the total effect) would equal zero. Therefore, a meaningful indirect effect, or mediation process, can exist even if the total effect is zero. And third, the causal steps approach makes inferences about the indirect effect by testing each of the individual paths, as opposed to the indirect effect itself. Consequently, confidence intervals for the indirect effect cannot be constructed, so the precision of the estimated effect is unknown when the causal steps method is used.

2.1.2 Method of Joint Significance

The test of joint significance directly overcomes the second problem with the causal steps approach by relaxing the necessity of demonstrating a statistically significant total effect. Specifically, mediation can be concluded using the method of joint significance by demonstrating the statistical significance of $\hat{a}$ and $\hat{b}$. The first problem listed for the causal steps approach is also reduced with the method of joint significance because now fewer pathways have to be determined significant. However, the third problem is still present, as inference is made about $\hat{a}$ and $\hat{b}$ separately, as opposed to the indirect effect as a whole, and a confidence interval for ab cannot be constructed.

2.1.3 Sobel Test/Delta Method

The Sobel (1982) test involves calculating the standard error of the estimated indirect effect, $\hat{a}\hat{b}$, using the delta method. The standard error is estimated as

$$\hat{\sigma}_{\hat{a}\hat{b}} = \sqrt{\hat{b}^2\hat{\sigma}_{\hat{a}}^2 + \hat{a}^2\hat{\sigma}_{\hat{b}}^2 + \hat{\sigma}_{\hat{a}}^2\hat{\sigma}_{\hat{b}}^2} \tag{2.4}$$

where $\hat{a}$ and $\hat{b}$ are the estimated regression coefficients and $\hat{\sigma}_{\hat{a}}$ and $\hat{\sigma}_{\hat{b}}$ are their standard errors. A test statistic can then be calculated by dividing the estimated indirect effect by its standard error. Assuming normality of the sampling distribution of $\hat{a}\hat{b}$, this ratio is distributed as a standard normal random variable under the null hypothesis of $ab = 0$, so a p-value can easily be calculated. Further, confidence intervals for the indirect effect can be calculated using

$$\hat{a}\hat{b} \pm Z_{\frac{\alpha}{2}}\sigma_{\hat{a}\hat{b}} \tag{2.5}$$

where $Z_{\frac{\alpha}{2}}$ is the value for which $(\frac{\alpha}{2})100$ percent of the standard normal distribution falls above. Although Equation 2.4 provides a good estimate of the standard error of the indirect effect, many researchers have cautioned against its use for hypothesis testing and confidence interval construction due to the non-normal sampling distribution of the indirect effect (MacKinnon et al., 2004; Hayes & Scharkow, 2013). The sampling distributions of both $\hat{a}$ and $\hat{b}$ are assumed to be normally distributed and, typically, the distribution of the product of two normally distributed random variables is not normally distributed (Aroian, 1947). Therefore, comparing the test statistic to a standard normal distribution or constructing symmetric confidence intervals using the standard error is not appropriate. Several simulation studies have demonstrated that the Sobel test is substantially less powerful than newer methods of inference that

are discussed in the following sections (Hayes & Scharkow, 2013; Preacher & Selig, 2012).

2.1.4 Cases Bootstrap

The cases boostrap (Efron & Tibshirani, 1994) is a resampling procedure that has been shown to be useful for making inferences when the sampling distribution of a test statistic is either unknown or difficult to derive analytically. The cases bootstrap involves repeatedly drawing a random sample with replacement of original sample size n from the dataset and calculating the statistic in the resample. In the context of mediation, $\hat{a}\hat{b}$ is calculated in every resample. This process is repeated k times, with k being an arbitrarily large number (usually 1,000+).

The k values of $\hat{a}\hat{b}$ serve as an empirical sampling distribution of $\hat{a}\hat{b}$, and a $100(1-\alpha)\%$ *percentile-based* confidence interval can be calculated using the $100(\frac{\alpha}{2})$ and $100(1-\frac{\alpha}{2})$ percentiles as the upper and lower limits, respectively. The indirect effect can be considered statistically significant at level α if the confidence interval does not contain zero.

2.1.5 Monte Carlo Method

The Monte Carlo method (Preacher & Selig, 2012) is another procedure that uses data simulation to make inferences about an effect. The method uses information about the sampling distribution of individual model parameters to make inferences about combinations or transformations of parameters. Within the context of mediation, the Monte Carlo method utilizes the assumed sampling distributions of a and b to obtain information about the sampling distribution of ab.

The procedure is implemented by first estimating the regression coefficients and their standard errors from Equations 2.1 and 2.2. Because the joint sampling distribution of a and b is assumed multivariate normal, the sampling distribution of the indirect effect can be estimated by generating k x 2 random numbers from the following multivariate normal distribution:

$$\begin{bmatrix} a^* \\ b^* \end{bmatrix} \sim MVN\left(\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix}, \begin{bmatrix} \hat{\sigma}_{\hat{a}}^2 & \hat{\sigma}_{\hat{a},\hat{b}} \\ \hat{\sigma}_{\hat{a},\hat{b}} & \hat{\sigma}_{\hat{b}}^2 \end{bmatrix} \right)$$

where $\hat{a}$ and $\hat{b}$ are the estimated regression coefficients, $\hat{\sigma}_{\hat{a}}^2$ and $\hat{\sigma}_{\hat{b}}^2$ are their estimated sampling variances, $\hat{\sigma}_{\hat{a},\hat{b}}$ is the estimated sampling covariance for a and b, and k is an arbitrarily large number. Next, the k simulated values of a are multiplied element-wise by the k simulated values of b to generate k values of a^*b^*. A confidence interval for the indirect effect can be calculated using the k simulated values following the procedure described using the cases bootstrap.

In addition to inference about indirect effects, the Monte Carlo method can be used to construct confidence intervals for a number of other parameters with unknown sampling distributions that are a transformation or combination of estimated parameters with known sampling distributions. Further, using data simulation is often much faster than bootstrapping, as the model only has to be fit once. Therefore, the Monte Carlo method is particularly useful for complex models. This method will be relied upon heavily in later chapters of this thesis when the focus is on multilevel modeling.

2.2 Extending the Mediation Model

The simple mediation model can be extended in a number of ways, including the addition of other variables as covariates, mediators, or moderators.

2.2.1 Adding Covariates

An important topic in all scientific fields is that of causal inference. While statistical mediation analysis is conducted to better understand causal processes, no statistical method can prove causality. Rather, claims of causality rely on theory and careful research design. Within such design is an inherent need to control for confounding variables either through randomization or measuring and statistically controlling for such variables. Because the underlying goal of statistical mediation analysis is to provide support for causal processes, it is important to be able to include additional variables, or covariates, in mediation models to control for their effects and obtain an unconfounded indirect effect.

Adding covariates into a mediation model is simple and can be accomplished by merely adding the covariates as additional predictors in each of the mediation equations[1]. This ensures that the linear effects of the covariates on M and Y are partialled out of the estimated a and b regression coefficients, resulting in an unconfounded estimate of ab. The methods of inference described in the previous sections can then be carried out using these new estimates.

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[1]If the researcher has reason to believe that one or more of the covariates is only a potentially confounding variable in one of the equations, the covariate may be excluded from the other equations. If excluded, $c \neq ab + c'$.

2.2.2 Parallel Mediation Model

A parallel mediation model refers to a mediation model in which there is one independent variable X, one dependent variable Y, and k mediators M_1, M_2, ..., M_k without a hypothesized causal pathway between the mediators. That is, the indirect effects act in parallel to each other. The equations to estimate a parallel mediator model that includes k mediators are:

$$M_{1i} = d_1 + a_1 X_i + e_{1i} \tag{2.6}$$

$$M_{2i} = d_2 + a_2 X_i + e_{2i} \tag{2.7}$$

$$\vdots$$

$$M_{ki} = d_k + a_k X_i + e_{ki} \tag{2.8}$$

$$Y_i = d_{(k+1)} + b_1 M_{1i} + b_2 M_{2i} + \cdots + b_k M_{ki} + c' X_i + e_{(k+1)i} \tag{2.9}$$

$$Y_i = d_{(k+2)} + c X_i + e_{(k+2)i} \tag{2.10}$$

Notice that c still quantifies the total effect without taking into account the mediators. Further, c' still represents the direct effect of X on Y, but rather than controlling for the effect of a single mediator, it is controlling for the effects of all of the mediators. Also, now there are m indirect effects, each of which is termed a *specific indirect effect*. A specific indirect effect through a given mediator can be calculated by multiplying the product of the paths from X to the given mediator and from that mediator to Y. For example, the specific indirect effect of X on Y through M_2 is quantified as $a_2 b_2$. And, because there are now additional mediators in the model, the specific indirect effect is interpreted as the effect of X on Y through M_2 holding all other mediators constant. Unless the mediators are orthogonal, a specific indirect effect, as well as the

direct effect, will change with the inclusion of additional mediators. The summation of all of the specific indirect effects, $\sum_{i=1}^{m} a_i b_i$ is labeled the *total indirect effect.* It is the effect of X on Y through all of the mediators. The sum of the total indirect effect and the direct effect is equivalent to the total effect. That is, $c = \sum_{i=1}^{m} a_i b_i + c'$.

Sometimes the focus of a linear regression analysis is to test the hypothesis that two effects are equal in strength and direction. The same hypothesis can be tested about indirect effects with a parallel mediation model (Preacher & Hayes, 2008; Hayes, 2013). To test whether two indirect effects are significantly different from each other, an empirical sampling distribution of the difference between two indirect effects can be estimated using the bootstrap method presented earlier. That is, in each bootstrap sample, the difference between the indirect effects can be calculated and confidence intervals can be constructed using many samples. For example, to test whether the indirect effect through M_1 is significantly different than M_2, $a_2 b_2 - a_1 b_1$ can be calculated in each bootstrap sample. If the percentile-based confidence interval based on many bootstrap samples does not contain zero, the null hypothesis that $a_1 b_1 = a_2 b_2$ can be rejected. It is important to note that this is a test of whether two effects differ, which is not necessarily the same as whether one effect is stronger than another. It can only be concluded that one effect is stronger than the other using this method if they are each of the same sign. However, if the strength of the effects are equal but opposite in sign, the null hypothesis would be rejected given a large enough sample size.

As with the basic mediation model, covariates can be added by including them as predictors in the appropriate equations. Further, the methods of inference about the

indirect effects discussed previously easily generalize to inferences about the specific indirect effects and the direct and total effects in multiple mediator models.

2.2.3 Moderated Mediation Model

Moderated mediation is a term used to describe a situation where an indirect effect changes as a function of a fourth variable, W. In this case, W is referred to as a moderator. Moderated mediation is important because it allows researchers to gain an understanding of the boundary conditions for the causal process. That is, a causal process may be situational, it may exist for only a subset of the population, or its strength or direction may depend on an additional variable. As such, models combining mediation and moderation are commonly referred to as *conditional process models* (Hayes, 2013). There are many different ways in which mediation and moderation can be combined into a single model (Preacher, Rucker, & Hayes, 2007; Edwards & Lambert, 2007; Hayes, 2013). A simple moderated mediation model where the relationship between M and Y is conditional on W can be formulated as:

$$M_i = d_1 + aX_i + e_{1i} \tag{2.11}$$

$$Y_i = d_2 + c'X_i + b_1 M_i + b_2 W_i + b_3 M_i W_i + e_{2i} \tag{2.12}$$

Note that the equation for M remains the same as that for the simple mediation model. The equation for Y, however, now includes W and the product of M and W, MW, as additional predictors. The inclusion of the product term is what allows the relationship between M and Y to be conditional on W as demonstrated by rearranging the equation for Y:

$$Y_i = d_2 + c'X_i + b_2 W_i + (b_1 + b_3 W_i)M_i + e_{2i} \tag{2.13}$$

When $W = 0$, the effect of M on Y, controlling for X, is quantified as b_1. Yet, when $W = 1$, the effect is quantified as $(b_1 + b_3)$. This also demonstrates that b_1 is no longer a "main effect" of M, but rather a conditional effect. Conversely, b_2 is a conditional effect of W on Y, conditioning on $M = 0$.

Because the pathway from M to Y is conditional on W, the effect of X on Y through M is also conditional on W. This effect can be quantified by multiplying the effect of X on M by the effect of M on Y, controlling for X. As such, the indirect effect is equal to $a(b_1 + b_3 W) = ab_1 + ab_3 W$.

In the past, moderated mediation was concluded if the interaction coefficient, b_3, was statistically significant. However, a significant b_3 is not necessarily indicative of moderated mediation (Hayes, 2015). Instead, a hypothesis test should be conducted on ab_3, which has been termed the *index of moderated mediation* (Hayes, 2015). A significant ab_3 demonstrates that the indirect effect of X on Y through M changes as a function of W. To conduct the inferential test, a percentile-based bootstrap confidence interval can be constructed. A confidence interval that does not contain zero would be evidence that the strength of the indirect effect changes systematically as a function of the moderator.

Next, the moderation can be probed by calculating the indirect effect at different values of W. These values are usually the mean and one standard deviation above and below the mean, or different percentiles of W. A simple method to conduct such an analysis is to center W at different values and re-conduct the analysis. That is, using $W_C = W - w$ in place of W allows the calculation of the conditional indirect effect when $W = w$ as $a(b_1 + b_3 W_C) = a[b_1 + b_3(W - w)] = ab_1$.

The method discussed to test and probe conditional indirect effects can be generalized to models that include multiple mediators and/or moderators. And, as with the other mediation models discussed, covariates can easily be included by adding them as predictors to each equation.

Chapter 3: Overview of Multilevel Models

Multilevel models (MLMs) are sometimes referred to as hierarchical models, random effects models, random coefficient models, or mixed models. This is predominantly a result of MLMs being advanced in many different fields simultaneously. As they were being developed, the major complication of implementing MLMs was on parameter estimation, as the estimation process must be iterative because there are no closed form solutions. Advancements in estimation algorithms, computing methods, and software implementation have led to a widespread use of MLMs in a variety of research fields.

3.1   The Unconditional Model

Multilevel models are often expressed either as separate equations for the different levels of the model, or as one combined model. The lower-level equation for a two-level unconditional model with 1 level-1 predictor can be expressed as (Raudenbush & Bryk, 2002):

$$Y_{ij} = d_{0j} + b_{1j}X_{ij} + e_{ij} \qquad (3.1)$$

where Y_{ij} and X_{ij} represent the responses for the ith person in group j, d_{0j} is the intercept, b_{1j} is the slope, and $e_{ij} \sim N(0, \sigma^2)$. Note that this is equivalent to a single-level model except for the j subscript for the intercept and slope indicating that these

values are allowed to randomly vary across groups, and are therefore termed *random effects*. The slope and intercepts themselves can be modeled. An unconditional model means that there are no level-2 predictors. The unconditional level-2 models are:

$$d_{0j} = d_0 + u_{0j} \tag{3.2}$$

$$b_{1j} = b_1 + u_{1j} \tag{3.3}$$

where d_0 and b_1 represent the grand mean intercept and slope values, respectively, and u_{0j} and u_{1j} represents group js deviations from the grand mean. Generally, the variances of the deviations, notated as τ_{00} and τ_{11} respectively, are estimated rather than the specific deviations. The random effects are assumed to be multivariate normal with covariance matrix

$$\mathbf{T} = \begin{bmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{bmatrix} \tag{3.4}$$

Further assumptions include that the $\mathrm{E}(u_{0j}) = \mathrm{E}(u_{1j}) = 0$ and $\mathrm{Cov}(u_{0j},\ e_{ij}) = \mathrm{Cov}(u_{1j},\ e_{ij}) = 0$.

The combined form of the two-level model can be formulated by plugging the intercept and slope equations into their respective spots in the lower-level model:

$$Y_{ij} = (d_0 + u_{0j}) + (b_1 + u_{1j})X_{ij} + e_{ij} \tag{3.5}$$

Expanding and rearranging the terms to separate the fixed and random components yields:

$$Y_{ij} = \underbrace{d_0 + b_1 X_{ij}}_{\text{fixed}} + \underbrace{u_{0j} + u_{1j}X_{ij} + e_{ij}}_{\text{random}} \tag{3.6}$$

which demonstrates that the response for the ith person in group j is a function of the grand mean intercept and slope, the deviations from the grand mean intercept and slope for group j, and an individual-specific residual.

3.2 Adding Level-2 Predictors

The researcher may wish to add level-2 predictors to explain such variability in the intercept or slope. Adding one level-2 predictor, W_j, for the intercept and slope results in the following level-2 equations:

$$d_{0j} = d_0 + g_{01}W_j + u_{0j} \tag{3.7}$$

$$b_{1j} = b_1 + g_{11}W_j + u_{1j} \tag{3.8}$$

Much like the intercept in a single-level regression equation, d_0 and b_1 now represent the expected intercept and slope values for a group whose value for $W_j = 0$. The systematic change in expected group intercept and slope values as a function of W_j is represented by the level-2 regression coefficients g_{01} and g_{11}. Now, the covariance matrix of random effects, $\mathbf{T}$, contains residual variances and covariances of the random effects, after removal of variance explained by W_j. The level-2 residuals are assumed multivariate normal with mean 0.

The combined model for this conditional two-level model with one level-1 predictor and one level-2 predictor becomes:

$$Y_{ij} = (d_0 + g_{01}W_j + u_{0j}) + (b_1 + g_{11}W_j + u_{1j})X_{ij} + e_{ij} \tag{3.9}$$

Expanding and rearranging the terms yields:

$$Y_{ij} = \underbrace{d_0 + g_{01}W_j + b_1 X_{ij} + g_{11}W_j X_{ij}}_{\text{fixed}} + \underbrace{u_{0j} + u_{1j}X_{ij} + e_{ij}}_{\text{random}} \tag{3.10}$$

Note that the addition of W_j as a predictor of b_{1j} acts as a moderator, in that the effect of X_{ij} on Y_{ij} changes as a function of W_j. Because the relationship (or slope) between X_{ij} and Y_{ij} changes as a function of W_j, the interaction between X_{ij} and W_j is termed a cross-level interaction.

3.3 The General Model

The two-level model presented in the previous section can be expanded to include additional level-1 and level-2 predictors. The general model with Q level-1 predictors and S_q level-2 predictors for each random effect can be formulated as (Raudenbush & Bryk, 2002):

$$Y_{ij} = d_{0j} + b_{1j}X_{1ij} + b_{2j}X_{2ij} + \cdots + b_{Qj}X_{Qij} + e_{ij} \tag{3.11}$$

$$d_{0j} = d_0 + g_{01}W_{1j} + g_{02}W_{2j} + \cdots + g_{0s_q}W_{s_q j} + u_{0j} \tag{3.12}$$

$$b_{qj} = b_q + g_{q1}W_{1j} + g_{q2}W_{2j} + \cdots + g_{qs_q}W_{s_q j} + u_{qj} \tag{3.13}$$

where $e_{ij} \sim N(0, \sigma^2)$, and the random effects u_{qj} are multivariate normal with mean 0 and $\text{Var}(u_{qi}) = \tau_{qq}$. The random effects are collected into covariance matrix $\mathbf{T}$ with dimensions $(Q + 1)$ by $(Q + 1)$. It is important to note that any b_{qj} can be specified as fixed by specifying $b_{qj} = b_q$ or nonrandomly varying by specifying $b_{qj} = b_q + g_{q1}W_{1j} + g_{q2}W_{2j} + \cdots + g_{qs_q}W_{s_q j}$. For each of these specifications, there is no longer a random component. Further, each b_{qj} can have a unique set of level-2 predictors.

The inclusion of a level-two predictor for one b_{qj} does not necessitate the inclusion of the predictor for the rest.

3.4 Centering Predictors

Considerable attention has been devoted to parameter interpretations using different centering strategies for level-1 predictors (Kreft, De Leeuw, & Aiken, 1995; Hofmann & Gavin, 1998; Raudenbush & Bryk, 2002; Enders & Tofighi, 2007). There are two methods that are popular, each with their own benefits and limitations. These methods are grand-mean centering and centering within group.

3.4.1 Grand-Mean Centering

Grand-mean centering involves subtracting the overall mean of a level-1 predictor from each individual's score on that predictor. In behavioral research, variables often do not have a meaningful value for zero, which makes the intercept of a regression equation meaningless. By grand-mean centering, the intercept for group j in an unconditional model can now be interpreted as the expected value for a person in group j who has a value equal to the grand-mean on that variable. Further, grand-mean centering is a linear transformation, so the ordering between two individuals' scores remains the same, regardless of what group they are in. Also, the variance of the random intercepts, τ_{00}, is the intercept variance after adjusting for differences on the Level-1 predictor. Enders and Tofighi (2007) recommend grand-mean centering level-1 predictors when the focus of the analysis is on a level-2 predictor, but the researcher wants to control for individual differences on the level-1 predictors.

3.4.2 Centering Within Group

When the focus is on level-1 predictors, grand-mean centering is not recommended (Raudenbush & Bryk, 2002; Enders & Tofighi, 2007). The coefficients for level-1 predictors cannot easily be interpreted when grand-mean centering is used because they are contaminated by between-group effects. That is, the coefficients are a weighted average of within-group and between-group effects. To remove between-group effects, it is recommended that level-1 predictors are centered within group. This involves subtracting the group mean of a level-1 predictor from each individuals' score on that predictor. This centers each group's mean at 0 and the intercept for group j in an unconditional model is now interpreted as the expected response for individuals in group j who have their average group response on the level-1 predictors. The coefficients for the level-1 predictors now represent the within-group relationship between the predictor and the outcome. Centering within group is also recommended when the focus of the analysis is on a cross-level interaction because the interest is on the systematic change of the within-group relationship between the level-1 predictor and the outcome as a function of the level-2 predictor.

3.4.3 Contextual Effects

Sometimes a researcher is interested in the within-group relationship between a level-1 predictor and an outcome as well as the between-group relationship. Scenarios in which the between-group effect differs from the within-group effect are labeled contextual effects (Raudenbush & Bryk, 2002). The between-group relationship can be tested by adding the group mean of the level-1 predictor as a level-2 predictor for the random intercept. Although the model will be algebraically equivalent if the

level-1 predictor is either grand-mean centered or centered within group (Kreft et al., 1995; Enders & Tofighi, 2007), it is recommended that centering within group is used to ease the interpretation of the parameters.

A two-level model with one within-group centered level-1 predictor and the group mean on the predictor added as a level-2 predictor of the intercept is:

$$Y_{ij} = b_{0j} + b_{1j}(X_{ij} - \overline{X}_{.j}) + e_{ij} \tag{3.14}$$

$$d_{0j} = d_0 + g_{01}\overline{X}_{.j} + u_{0j} \tag{3.15}$$

$$b_{1j} = b_1 + u_{1j} \tag{3.16}$$

where $\overline{X}_{.j}$ is the mean of X_{ij} for group j. The combined model is:

$$Y_{ij} = (d_0 + g_{01}\overline{X}_{.j} + u_{0j}) + (b_1 + u_{1j})(X_{ij} - \overline{X}_{.j}) + e_{ij} \tag{3.17}$$

which can be expanded and rearranged as:

$$Y_{ij} = \underbrace{d_0 + g_{01}\overline{X}_{.j} + b_1(X_{ij} - \overline{X}_{.j})}_{\text{fixed}} + \underbrace{u_{0j} + u_{1j}(X_{ij} - \overline{X}_{.j}) + e_{ij}}_{\text{random}} \tag{3.18}$$

The average within-group effect of X_{ij} on Y_{ij} is represented as b_1 with variance $\text{Var}(b_{1j}) = \text{Var}(u_{1j}) = \tau_{11}$, and the between group-effect is represented as g_{01}. Differences between b_1 and g_{01} indicate the presence of a contextual effect.

3.5 Model Building

An important consideration within statistical modeling is the method in which to build the model. This topic is particularly relevant to multilevel modeling due to practical issues with estimation as well as model specifications at different levels.

Although the technical issues associated with estimating multilevel modeling parameters are omitted from this thesis, a brief overview is provided so as to make methods for performing statistical tests on individual parameters clear.

3.5.1   Estimation Methods

From a frequentist perspective, there are two popular estimation methods for multilevel models. The first is Full Maximum Likelihood (ML) and the second is Restricted Maximum Likelihood (REML). Both methods involve obtaining the parameter estimates that maximize the likelihood of the data conditional on the parameter values. The difference between the two methods is in how the fixed effects are treated when estimating the variance and covariance parameters. With ML, these estimates are conditional on the point estimates of the fixed effects, while REML corrects for the uncertainty in the estimation of the fixed effects (Raudenbush & Bryk, 2002). Consequently, the variance parameter estimates are downwardly biased with ML, but the difference between ML and REML estimates is usually small when the number of level-2 units is large.

3.5.2   Testing Fixed and Random Effects

For fixed effects, tests of individual parameters follow similarly as tests of OLS regression parameters, where the coefficient is divided by its standard error and compared to the t-distribution, with the appropriate degrees of freedom. In the MLM framework, however, degree of freedom calculation is more complex and some software programs (e.g., SPSS) make degree of freedom corrections. Usually, substantive differences will not arise from these different methods.

For variance and covariance parameters, tests based on the ratio of the parameter estimate to its standard error are even more problematic because the asymptotic properties that serve as the underlying justification for such tests generally do not hold. Many researchers have cautioned about using this method, and some software programs purposefully omit the standard errors for (co)variance parameter to deter users from using them for calculating test statistics (e.g., the lme4 package for R).

An alternative approach to testing parameter estimates is to use a likelihood-ratio test statistic, which is calculated using the deviances of nested models (Raudenbush & Bryk, 2002). The deviance of a given model is -2 times the maximum log-likelihood of the model. Under the null hypothesis that the additional parameters estimated in the unrestricted model are equal to their constrained value (usually 0) in the constrained model, the difference in deviances between nested models is distributed as χ^2 with degrees of freedom equal to the difference of parameters between the two models. An extreme test statistic is indication that the constraints imposed on the restricted model results in significantly worse model fit than the unrestricted model. For example, if the covariance between two random effects was constrained to zero in a model, and the same model was fit again with the only difference being that the covariance was freely estimated, a large difference between the deviances of these two models would indicate that zero may not be a plausible value for the covariance.

The likelihood-ratio test can be used to simultaneously test fixed effects and variance/covariance parameters if ML is used. If REML is used, only variance/covariance parameters can be tested, and the fixed effect specification must remain the same for both models (Raudenbush & Bryk, 2002). While the likelihood-ratio test is a more reliable method for tests of variance parameters than comparing the estimate to its

standard error, it should be noted that the test can be conservative since the null hypothesis variance value of zero lies on the boundary of the parameter space which results in the true null distribution being a mixture of χ^2 distributions (Pinheiro & Bates, 2000; Raudenbush & Bryk, 2002).

3.5.3 Non-nested Model Comparison

In addition to the likelihood-ratio test for comparing nested models, there are multiple model fit indices that can be used to compare non-nested models. Two popular indices include the AIC (Akaike, 1974) and the BIC (Schwarz, 1978). These indices penalize the inclusion of additional parameters that do not meaningfully contribute to improved model fit, and smaller AIC and BIC values are preferred.

3.5.4 Order of Model Building

Because of the complexities involved with parameter estimation, it is often recommended to start with a small subset of the fully hypothesized model and build it up using the tests and model fit indices described previously. Because the level-2 model relies heavily on the specification of the level-1 model (Raudenbush & Bryk, 2002), it is also recommended that level-1 model building should precede level-2 model building. Therefore, the focus should begin on determining which level-1 predictors should be included, and whether they should be allowed to vary across level-2 units. Then, level-2 predictors of the random intercept should be specified before cross-level interactions.

Chapter 4: Multilevel Mediation

Due to the popularity of statistical mediation analysis and the growing prevalence of nested data structures, the basic mediation model has been adapted to the multilevel context. Multilevel mediation analysis can be classified as any mediation analysis that takes into account the nesting of hierarchical data. In some instances the hierarchy is of direct importance, where it may be hypothesized that a level-2 variable causes a level-1 variable through either a level-2 or level-1 variable, or the causal effects of level-1 variables are thought to differ across level-2 units. In other cases, the hierarchy may be a nuisance, where the researcher is interested in a mediation analysis involving variables all measured at one level, but the researcher needs to account for the dependencies in the data that result from the nested structure.

Multilevel mediation models have been categorized either as upper- or lower-level mediation, or by using a number system to describe the level at which each variable is measured. There have been some inconsistencies in regards to classifying upper-level mediation as some researchers have suggested that the model fits this classification if X is measured at level 2, while others have termed upper level mediation for when M is measured at level 2. Therefore, the number system in which the level at which X, M, and Y are ordered will be used here as it is unambiguous.

There is a relatively large body of work on 2-1-1 and 2-2-1 multilevel media-
tion models. This includes the work of Raudenbush and Sampson (1999), Krull and
MacKinnon (1999, 2001), Pituch, Stapleton, and Kang (2006), and Pituch and Sta-
pleton (2008, 2012). Because the independent variable is a level-2 predictor in each
of these models, it is often stated that only-between group indirect effects may be
of interest (Zhang et al., 2009). A between-group indirect effect is the effect of the
group differences in X on Y through M. Pituch and Stapleton (2012) argue, however,
that within-group effects may still be of interest, depending on the research question.
A within-group indirect effect is the (average) indirect effect of X on Y through M
within each level-2 unit. Nevertheless, in each of these model formulations, slopes
were specified as fixed effects and, therefore, the indirect effects were also fixed.

4.1   1-1-1 Mediation

The existing literature on the 1-1-1 mediation model is a bit more limited, but
the model has recently been gaining in popularity. The 1-1-1 model is different
than the 2-2-1 and 2-1-1 models in that random effects can play a more interesting
role, and the indirect effect may randomly vary across the level-2 units. 1-1-1 models
were discussed in Krull and MacKinnon (2001) and Pituch, Whittaker, and Stapleton
(2005), but the slopes were not specified as random. Kenny et al. (2003) were the first
to formally document such a model with random slopes, but were limited to a piece-
wise approach. Bauer et al. (2006) proposed a method of simultaneously estimating
the M and Y equations to allow for the estimation of all appropriate parameters
necessary to calculate and make inferences about the indirect effect. Both studies

described adding level-2 predictors to moderate the indirect effect, which is a topic that will be discussed further in this thesis.

4.1.1 Kenny et al. (2003)

Following similar notation of Kenny et al. (2003) and Bauer et al. (2006), the lower level equations for the 1-1-1 mediation model with random effects can be formulated as:

$$Y_{ij} = d_{0j} + c_j X_{ij} + e_{ij} \tag{4.1}$$

$$M_{ij} = d_{Mj} + a_j X_{ij} + e_{ij} \tag{4.2}$$

$$Y_{ij} = d_{Yj} + c'_j X_{ij} + b_j M_{ij} + e_{ij} \tag{4.3}$$

Where d represents random intercepts, c represents the total effect of X on Y, a represents the effect of X on M, c' represents the effect of X on Y controlling for M, and b represents the effect of M on Y controlling for X. The e_{ij} are independent and normally distributed random errors. The level-2 equations for the slopes presented by Kenny et al. (2003) are:

$$c_j = c + u_{0j} \tag{4.4}$$

$$a_j = a + u_{1j} \tag{4.5}$$

$$b_j = b + u_{2j} \tag{4.6}$$

$$c'_j = c' + u_{3j} \tag{4.7}$$

That is, unit j's slope is a function of the grand mean slope across all level-2 units as well as group j's deviation from the grand mean. The equations for the random intercepts follow a similar form, where they contain the grand mean intercept and

group deviations from the mean. The random effects are assumed to be multivariate normal with mean 0.

Because the random slopes are allowed to covary, the expected value of the indirect effect $a_j b_j$ is not equal to the product of the expected value of a_j and b_j (Goodman, 1960), but rather

$$E(a_j b_j) = ab + \sigma_{a_j, b_j} \tag{4.8}$$

where σ_{a_j, b_j} is the covariance between a_j and b_j. This suggests that, if there is covariance between a_j and b_j, there may be a non-zero expected indirect effect even if the expected value of a_j and b_j are each zero. Therefore, Kenny et al. (2003) state that the estimation and inclusion of σ_{a_j, b_j} into the calculation of the indirect effect is crucial.

The expected value for the total effect follows as:

$$E(c_j) = c' + ab + \sigma_{a_j, b_j} \tag{4.9}$$

which eliminates the need to estimate the total effect using equation 4.1.

Kenny et al. (2003) derived the variance of the indirect and total effects assuming multivariate normality as:

$$Var(a_j b_j) = b^2 \sigma_{a_j}^2 + a^2 \sigma_{b_j}^2 + \sigma_{a_j}^2 \sigma_{b_j}^2 + 2ab\sigma_{a_j, b_j} + \sigma_{a_j, b_j}^2 \tag{4.10}$$

and

$$Var(a_j b_j + c_j') = b^2 \sigma_{a_j}^2 + a^2 \sigma_{b_j}^2 + \sigma_{a_j}^2 \sigma_{b_j}^2 + 2ab\sigma_{a_j, b_j} + \sigma_{a_j, b_j}^2 + \sigma_{c_j'}^2 + 2b\sigma_{a_j, c_j'} + 2a\sigma_{b_j, c_j'} \tag{4.11}$$

4.1.2 Bauer et al. (2006)

The major limitation of Kenny et al. (2003) is their procedure for estimating σ_{a_j,b_j}. Because a_j and b_j are from separate equations, single-equation MLM methods do not provide an estimate of σ_{a_j,b_j}. Therefore, Kenny et al. (2003) proposed a piece-wise approach to obtaining such an estimate. Bauer et al. (2006) worked around the problem by demonstrating how the mediation equations can be estimated simultaneously in one equation, which allows the estimation of σ_{a_j,b_j}. Further, Bauer et al. (2006) derived the sampling variances of the average indirect and total effects and more thoroughly developed the addition of a level 2 predictor as a moderator of the indirect effect.

Bauer et al. (2006) proposed combining equations 4.2 and 4.3 into a single equation by stacking M and Y and creating indicator variables to toggle between the equations. They stacked M and Y into a variable labeled Z and created indicators S_M and S_Y, where S_M equaled 1 and S_Y equaled 0 when Z referred to M. When Z referred to Y, S_M equaled 0 and S_Y equaled 1. This permits the lower level equation to be equal to:

$$Z_{ij} = S_{M_{ij}}(d_{M_j} + a_j X_{ij}) + S_{Y_{ij}}(d_{Y_j} + b_j M_{ij} + c'_j X_{ij}) + e_{Zij} \qquad (4.12)$$

which can be expanded as:

$$Z_{ij} = d_{M_j} S_{M_{ij}} + a_j(S_{M_{ij}} X_{ij}) + d_{Y_j} S_{Y_{ij}} + b_j(S_{Y_{ij}} M_{ij}) + c'_j(S_{Y_{ij}} X_{ij}) + e_{Zij} \qquad (4.13)$$

Therefore, the model can be estimated by specifying random slopes for $S_{M_{ij}}$, $S_{Y_{ij}}$, $(S_{M_{ij}} X_{ij})$, $(S_{Y_{ij}} M_{ij})$, and $(S_{Y_{ij}} X_{ij})$, and not estimating an intercept. Further, the variance of the errors for the M and Y equations should be allowed to differ depending

on whether Z is a value of M or Y. Specifying the model in this manner allows the estimation of the covariance matrix of all random effects.

Bauer et al. (2006) also derived the sampling variance of the estimate of the average indirect and total effects as:

$$
\begin{aligned}
Var(\hat{a}\hat{b} + \hat{\sigma}_{a_j,b_j}) = {}& b^2 Var(\hat{b}) + a^2 Var(\hat{a}) + Var(\hat{a}) Var(\hat{b}) \\
& + 2abCov(\hat{a}, \hat{b}) + Cov(\hat{a}, \hat{b})^2 + Var(\hat{\sigma}_{a_j,b_j})
\end{aligned}
\tag{4.14}
$$

and

$$
\begin{aligned}
Var(\hat{a}\hat{b} + \hat{\sigma}_{a_j,b_j} + \hat{c}') = {}& b^2 Var(\hat{b}) + a^2 Var(\hat{a}) + Var(\hat{a}) Var(\hat{b}) \\
& + 2abCov(\hat{a}, \hat{b}) + Cov(\hat{a}, \hat{b})^2 + Var(\hat{c}') \\
& + 2bCov(\hat{a}, \hat{c}') + 2aCov(\hat{b}, \hat{c}') + Var(\hat{\sigma}_{a_j,b_j})
\end{aligned}
\tag{4.15}
$$

where Var and Cov represent the asymptotic sampling variance and covariance, respectively, of the estimates. The estimated sampling variances can be used to construct confidence intervals or hypothesis tests on the average indirect and total effects. For example, a 95% confidence interval for the average indirect effect could be calculated as:

$$
(\hat{a}\hat{b} + \hat{\sigma}_{a_j,b_j}) \pm 1.96[\hat{Var}(\hat{a}\hat{b} + \hat{\sigma}_{a_j,b_j})]^{1/2}
\tag{4.16}
$$

Unfortunately, as with single level mediation, the sampling distribution of the indirect effect is not normally distributed, which makes the use of symmetric confidence intervals around the effect inappropriate. To obtain an asymmetric confidence interval for the average indirect effect, the Monte Carlo method described in the single-level mediation section can be applied by simulating k values of a^*, b^*, and $\sigma^*_{a_j,b_j}$ from the

multivariate distribution (Bauer et al., 2006):

$$\begin{bmatrix} a^* \\ b^* \\ \sigma^*_{a_j,b_j} \end{bmatrix} \sim MVN\left(\begin{bmatrix} \hat{a} \\ \hat{b} \\ \hat{\sigma}_{a_j,b_j} \end{bmatrix}, \begin{bmatrix} \hat{\sigma}^2_{\hat{a}} & \hat{\sigma}_{\hat{a},\hat{b}} & 0 \\ \hat{\sigma}_{\hat{a},\hat{b}} & \hat{\sigma}^2_{\hat{b}} & 0 \\ 0 & 0 & \hat{\sigma}^2_{\hat{\sigma}_{a,b}} \end{bmatrix} \right)$$

Then, formula 4.8 can be applied to each set of simulated values to construct an empirical sampling distribution of the average indirect effect, and percentiles can be used as endpoints of a confidence interval. Constructing a Monte Carlo confidence interval for the total effect can be done using the same method, where the mean vector is expanded to included the estimated c' value, and the covariance matrix is expanded to include the sampling variance of c' and its sampling covariance with the other estimates.

Adding predictors of a_j, b_j, and c'_j were further discussed by Bauer et al. (2006). That is, the Level-2 equations, with the addition of level-2 predictor W now become:

$$a_j = a + g_{a1}W_j + u_{aj} \tag{4.17}$$

$$b_j = b + g_{b1}W_j + u_{bj} \tag{4.18}$$

$$c'_j = c' + g_{c'1}W_j + u_{c'j} \tag{4.19}$$

They recommend that W should also be added as a predictor of the random intercepts as well. This is equivalent to lower order terms being added to an interaction equation in OLS regression. Therefore, the intercept equations now become:

$$d_{M_j} = d_M + g_{d_M1}W_j + u_{d_Mj} \tag{4.20}$$

$$d_{Y_j} = d_Y + g_{d_Y1}W_j + u_{d_Yj} \tag{4.21}$$

Bauer et al. (2006) argue that moderated mediation can be concluded if W is a significant predictor of a_j and/or b_j. These can be tested individually, or as a joint test. When W is included as a predictor of the slopes, the average indirect effect is now conditional on the value of W. When $W = 0$, the average conditional indirect effect can be formulated as (Bauer et al., 2006):

$$E(a_j b_j | W_j = 0) = ab + \sigma_{u_{aj}, u_{bj}} \tag{4.22}$$

with sampling variance:

$$Var(\hat{a}\hat{b} + \hat{\sigma}_{u_{aj}, u_{bj}}) = b^2 Var(\hat{a}) + a^2 Var(\hat{b}) + Var(\hat{a}) Var(\hat{b})$$
$$+ 2ab Cov(\hat{a}, \hat{b}) + Cov(\hat{a}, \hat{b})^2 + Var(\hat{\sigma}_{u_{aj}, u_{bj}}) \tag{4.23}$$

This equation is equivalent to 4.14, except the parameters are conditional on $W_j = 0$. The average conditional indirect effect at different values of W can be calculated by centering W around the value of interest and refitting the model. That is, $E(a_j b_j | W_j = w)$ can be calculated by using $W_C = W - w$ in place of W (Bauer et al., 2006). This is analogous to the simple slopes strategy of probing interaction effects in moderated regression.

Chapter 5: Extending Multilevel Mediation Models

Although the methods described by Kenny et al. (2003) and Bauer et al. (2006) have aided many researchers in understanding and implementing 1-1-1 multilevel mediation models, they are not without their shortcomings. The aim of this chapter, and the main contribution of this thesis, is to address and mitigate some of these shortcomings, as well as provide advancements in the formulation and testing of a number of interesting effects that can be modeled using MLM.

First, while recent research on multilevel mediation has focused on disentangling between- and within-group indirect effects, this has yet to be formulated in the stacked equation method explained by Bauer et al. (2006) to allow for the simultaneous testing of these effects using traditional MLM software. Without this model formulation, the parameter estimates necessary to quantify within-group indirect effects cannot be obtained. Therefore, this section begins with an overview of the decomposition of within-group and between-group indirect effects, and an explanation of how to formulate the model using a single equation. Further, comparisons between the within-group and between-group indirect effects are examined, and a method for testing the difference between these effects is described. The inclusion of covariates is also addressed in this formulation.

Next, the single-equation formulation is expanded to include multilevel models with multiple mediators. As in the single-level multiple mediator case, tests of differences between indirect effects can be conducted, but now these comparisons can be made at both levels. An interesting scenario unfolds in a multiple mediator model where one or more of the paths in one indirect effect are permitted to covary with those from another. In this situation, the random specific indirect effects may covary. Derivations are provided, and the substantive interpretation of the covariance is explained.

Finally, more sophisticated tests of multilevel moderated mediation are adapted from the single-level moderated mediation literature (Hayes, 2015) and applied to scenarios where a level-2 variable is a predictor of a_j and/or b_j. That is, this thesis is the first to apply the index of moderated mediation (Hayes, 2015) to the multilevel context. Because the within-group and between-group indirect effects have been separated, each of these can be moderated by a level-2 variable. As an interesting case, the between group effect of X or M can serve as a moderator of the within-group indirect effect of X on Y through M.

5.1   Decomposing Between and Within Effects

As described previously, when level-1 predictor variables are grand mean centered or left uncentered, the estimated coefficients are a mix of between-group and within-group effects. Therefore, if between and within effects differ, the coefficients are not easily interpreted. Consequently, the indirect effect calculated using such methods are ambiguous in meaning. To disentangle the effects in regular multilevel models and multilevel mediation models, some have suggested using within-group centering

and adding the group means as level-2 predictors of the intercept (Zhang et al., 2009). The lower level equations for the 1-1-1 multilevel mediation model using this centering method become:

$$M_{ij} = d_{Mj} + a_j(X_{ij} - \overline{X}_{.j}) + e_{ij} \tag{5.1}$$

$$Y_{ij} = d_{Yj} + c'_j(X_{ij} - \overline{X}_{.j}) + b_j(M_{ij} - \overline{M}_{.j}) + e_{ij} \tag{5.2}$$

where $\overline{X}_{.j}$ and $\overline{M}_{.j}$ represent the observed group means of X and M, respectively. The upper level equations are:

$$d_{Mj} = d_M + a_B\overline{X}_{.j} + u_{Mj} \tag{5.3}$$

$$d_{Yj} = d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + u_{Yj} \tag{5.4}$$

$$a_j = a_W + u_{aj} \tag{5.5}$$

$$b_j = b_W + u_{bj} \tag{5.6}$$

$$c'_j = c'_W + u_{c'j} \tag{5.7}$$

which disentangles the within-group effects from the between-group effects, denoted with the subscripts W and B, respectively. As a result, one can estimate the within-group and between-group indirect effects separately. The expected within-group indirect effect can be calculated following methods similar to those provided by Kenny et al. (2003) and Bauer et al. (2006) using equation 4.8, where now a_j and b_j refer to the random slopes for the centered Level-1 variables. In addition, the variance of within-group indirect effects across groups can be calculated using formula 4.10. Further, an inferential test of the average within-group indirect effect can be conducted using the Monte Carlo method discussed previously.

An estimate of the between-group indirect effect can be calculated as (Tofighi, West, & MacKinnon, 2013):

$$E(a_B b_B) = a_B b_B \tag{5.8}$$

which follows traditional methods of calculating indirect effects because the between-group effects are fixed and, thus, cannot covary. The asymptotic sampling variance of the between-group indirect effect can be computed using the delta method as:

$$Var(\hat{a}_B \hat{b}_B) = b_B^2 Var(\hat{a}_B) + a_B^2 Var(\hat{b}_B) + Var(\hat{a}_B)Var(\hat{b}_B) \tag{5.9}$$

However, the use of $Var(\hat{a}_B \hat{b}_B)$ in the construction of confidence intervals or hypothesis tests is not recommended due to the non-normality of the sampling distribution of $a_B b_B$. Instead, a Monte Carlo confidence interval can be calculated by simulating k values of a_B^* and b_B^* from the multivariate distribution:

$$\begin{bmatrix} a_B^* \\ b_B^* \end{bmatrix} \sim MVN\left(\begin{bmatrix} \hat{a}_B \\ \hat{b}_B \end{bmatrix}, \begin{bmatrix} \hat{\sigma}_{\hat{a}_B}^2 & \hat{\sigma}_{\hat{a}_B \hat{b}_B} \\ \hat{\sigma}_{\hat{a}_B \hat{b}_B} & \hat{\sigma}_{\hat{b}_B}^2 \end{bmatrix} \right)$$

5.1.1 Interpretation of Between- and Within-group Indirect Effects

Between-group and within-group indirect effects are orthogonal and conceptually distinct. The within-group indirect effect is the expected difference in Y through M for two level-1 units in the same level-2 unit who differ by one unit on X. That is, it is the effect of X on Y through M within a particular level-2 unit, so the focus is on the relative standing of level-1 units within level-2 units. Of interest is the average and variability of within-group indirect effects across level-2 units.

The between-group indirect effect, on the other hand, is the expected difference in the group aggregate of Y through the group-aggregate of M for two level-2 units that

differ by one-unit in the group-aggregate of X. Between-group effects can be difficult to understand or easy to misinterpret. For example, Preacher, Zyphur, and Zhang (2010) make use of an example differentiating individual efficacy and the collective efficacy of a group. They argue that, while the aggregated individual efficacy for a given group is in fact a group-level variable (in that it only varies between groups), the focus is still at the individual level and the meaning of such a variable is likely to differ from the meaning of a variable characterizing the dynamics of the self efficacy of the group as a collective. Therefore, caution is recommended when interpreting the meaning of between-group effects.

5.1.2 Indirect Contextual Effect

Recall that a difference between the within-group and between-group effect of a variable is termed a contextual effect. Such a difference may also arise between a within-group and a between-group indirect effect, and this difference may be substantively meaningful. I call this an *indirect contextual effect*, which is defined as the expected difference in Y through M for two level-1 units that have the same value of X but belong to level-2 units that differ by one unit in the group aggregate of X.

To test for the presence of an indirect contextual effect, a Monte Carlo confidence interval can be constructed around the difference between the within-group and between-group indirect effects, $a_B b_B - (a_W b_W + \sigma_{a_j, b_j})$. A confidence interval that does not include zero would suggest the presence of an indirect contextual effect.

5.1.3 Using Stacked Equations

To obtain all of the parameter estimates necessary to calculate the within-group and between-group indirect effects, the model can be combined as a single equation

following the method utilized by Bauer et al. (2006). The lower-level equation under this formulation is:

$$Z_{ij} = S_{M_{ij}}[d_{M_j} + a_j(X_{ij} - \overline{X}_{.j})] + S_{Y_{ij}}[d_{Y_j} + b_j(M_{ij} - \overline{M}_{.j}) + c'_j(X_{ij} - \overline{X}_{.j})] + e_{Zij} \quad (5.10)$$

where again $S_{M_{ij}}$ and $S_{Y_{ij}}$ are indicator variables, and the upper-level equations are 5.3 - 5.7. Therefore, the combined model is:

$$Z_{ij} = S_{M_{ij}}[d_M + a_B\overline{X}_{.j} + u_{Mj} + (a_W + u_{aj})(X_{ij} - \overline{X}_{.j})]$$
$$+ S_{Y_{ij}}[d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + u_{Yj} + (b_W + u_{bj})(M_{ij} - \overline{M}_{.j}) \quad (5.11)$$
$$+ (c'_W + u_{c'j})(X_{ij} - \overline{X}_{.j})] + e_{Zij}$$

Expanding the terms within the brackets yields:

$$Z_{ij} = S_{M_{ij}}[d_M + a_B\overline{X}_{.j} + u_{Mj} + a_W(X_{ij} - \overline{X}_{.j}) + u_{aj}(X_{ij} - \overline{X}_{.j})]$$
$$+ S_{Y_{ij}}[d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + u_{Yj} + b_W(M_{ij} - \overline{M}_{.j}) + u_{bj}(M_{ij} - \overline{M}_{.j}) \quad (5.12)$$
$$+ c'_W(X_{ij} - \overline{X}_{.j}) + u_{c'j}(X_{ij} - \overline{X}_{.j})] + e_{Zij}$$

Finally, distributing $S_{M_{ij}}$ and $S_{Y_{ij}}$ and rearranging the terms yields:

$$Z_{ij} = d_M[S_{M_{ij}}] + d_Y[S_{Y_{ij}}] + a_B[S_{M_{ij}}\overline{X}_{.j}] + c'_B[S_{Y_{ij}}\overline{X}_{.j}] + b_B[S_{Y_{ij}}\overline{M}_{.j}]$$
$$+ a_W[S_{M_{ij}}(X_{ij} - \overline{X}_{.j})] + c'_W[S_{Y_{ij}}(X_{ij} - \overline{X}_{.j})] + b_W[S_{Y_{ij}}(M_{ij} - \overline{M}_{.j})]$$
$$+ u_{aj}[S_{M_{ij}}(X_{ij} - \overline{X}_{.j})] + u_{c'j}[S_{Y_{ij}}(X_{ij} - \overline{X}_{.j})] + u_{bj}[S_{Y_{ij}}(M_{ij} - \overline{M}_{.j})] \quad (5.13)$$
$$+ u_{Mj}[S_{M_{ij}}] + u_{Yj}[S_{Y_{ij}}] + e_{Zij}$$

The terms in the brackets represent variables that must be created in the dataset. These include the two indicator variables $S_{M_{ij}}$ and $S_{Y_{ij}}$, as well as the product of the indicator variables with level-1 within-cluster centered variables and the observed cluster means. Random slopes for the indicator variables and the product between the indicator variables and centered level-1 predictors should be specified, as well as fixed

effects for the product of the indicator variables and group means. Further, there should be no intercept, and the error variance should be allowed to differ depending on which equation Z represents.

5.1.4 Adding Covariates

As with single-level mediation models, the omission of confounding variables, or covariates, can bias the estimated indirect effects and muddle causal interpretations. Recently, there has been attention brought to the omission of level-2 and level-1 covariates in 1-1-1 multilevel mediation models (Tofighi et al., 2013; Tofighi & Kelley, 2016).

Tofighi et al. (2013) indicate that the covariance between the random intercepts for the M and Y equations may signal that a level-2 confounding variable has been omitted from the intercept equations. Further, the covariance between a_j and b_j may indicate that the slopes are both influenced by an omitted variable. Preacher (2015) recommends, however, that the covariance term, σ_{a_j,b_j}, should remain in equation 4.8 and potential confounding effects should be explored.

Adding level-2 covariates to the random intercept equations can easily be accomplished by multiplying the covariate value by the respective indicator variables. For example, level-2 covariate G can be included by adding the terms $G_j S_{M_{ij}}$ and $G_j S_{Y_{ij}}$ as predictors in Equation 5.13. The coefficients that are estimated for each of these variables represent the effect of G on M and Y, respectively, while holding all other variables constant. Consequently, the estimated between-group indirect effect will be the estimated effect when holding G constant.

The model can also easily be expanded to include level-2 predictors of the random slopes, but the details are left to a later section on adding moderators, as a predictor of a random slope acts as a moderator.

Tofighi and Kelley (2016) explored how omitted level-1 variables may impact parameter estimates for 1-1-1 multilevel mediation models. They found that both between-group and within-group indirect effect estimates may be affected. They also propose a sensitivity analysis to assess such a confounding effect, but the technique is beyond the scope of the present thesis.

Nevertheless, inclusion of confounding level-1 variables is undoubtedly important. They can easily be added to the model provided in equation 5.13. It is recommended that the centering strategy of level-1 covariates follows that of other level-1 predictors to gain an accurate estimate of the between- and within-group effects of the covariates. That is, level-1 covariates should be within-group centered, and the observed group means should be added as level-2 predictors of the random intercepts. In equation 5.13, this can be accomplished for an arbitrary level-1 covariate V by multiplying $(V_{ij} - \overline{V}_{.j})$ and $\overline{V}_{.j}$ by the indicators $S_{M_{ij}}$ and $S_{Y_{ij}}$. Then, random slopes are specified for $S_{M_{ij}}(V_{ij} - \overline{V}_{.j})$ and $S_{Y_{ij}}(V_{ij} - \overline{V}_{.j})$ and fixed effects are specified for $S_{M_{ij}}\overline{V}_{.j}$ and $S_{Y_{ij}}\overline{V}_{.j}$. Of course, if the effect of V is not expected to vary across level-2 units, the slopes can be specified as fixed rather than random. Now, the within-group indirect effect is the estimated effect after controlling for V_{ij} and the between-group indirect effect is the estimated effect after controlling for $\overline{V}_{.j}$. Confidence intervals for these indirect effects follow previously described procedures.

5.2 More Than One Mediator

A model containing multiple mediators was hinted at by Bauer et al. (2006), but never developed. However, the method of stacking equations that they used can be adapted to allow for multiple mediators. The lower level equations for a 1-1-1 parallel mediation model with k mediators is:

$$M_{1ij} = d_{M1j} + a_{1j}(X_{ij} - \overline{X}_{.j}) + e_{ij} \tag{5.14}$$

$$M_{2ij} = d_{M2j} + a_{2j}(X_{ij} - \overline{X}_{.j}) + e_{ij} \tag{5.15}$$

$$\vdots$$

$$M_{kij} = d_{Mkj} + a_{kj}(X_{ij} - \overline{X}_{.j}) + e_{ij} \tag{5.16}$$

$$Y_{ij} = d_{Yj} + c'_j(X_{ij} - \overline{X}_{.j}) + b_{1j}(M_{1ij} - \overline{M}_{1.j})$$
$$+ b_{2j}(M_{2ij} - \overline{M}_{2.j}) + \cdots + b_{kj}(M_{kij} - \overline{M}_{k.j}) + e_{ij} \tag{5.17}$$

The upper level equations, with no level-2 predictors except observed group means are:

$$d_{M1j} = d_{M1} + a_{B1}\overline{X}_{.j} + u_{M1j} \tag{5.18}$$

$$d_{M2j} = d_{M2} + a_{B2}\overline{X}_{.j} + u_{M2j} \tag{5.19}$$

$$\vdots$$

$$d_{Mkj} = d_{Mk} + a_{Bk}\overline{X}_{.j} + u_{Mkj} \tag{5.20}$$

$$d_{Yj} = d_Y + c'_B\overline{X}_{.j} + b_{B1}\overline{M}_{1.j} + b_{B2}\overline{M}_{2.j} + \cdots + b_{Bk}\overline{M}_{k.j} + u_{Yj} \tag{5.21}$$

$$a_{1j} = a_{W1} + u_{a1j} \tag{5.22}$$

$$a_{2j} = a_{W2} + u_{a2j} \tag{5.23}$$

$$\vdots$$

$$a_{kj} = a_{Wk} + u_{akj} \tag{5.24}$$

$$b_{1j} = b_{W1} + u_{b1j} \tag{5.25}$$

$$b_{2j} = b_{W2} + u_{b2j} \tag{5.26}$$

$$\vdots$$

$$b_{kj} = b_{Wk} + u_{bkj} \tag{5.27}$$

$$c'_j = c'_W + u_{c'j} \tag{5.28}$$

With k mediators, there are k specific within-group and between-group indirect effects and one within-group and between-group direct effect. The average specific within-group indirect effect that quantifies the within-group indirect effect of X on Y through M_h is calculated as:

$$E(a_{Wh}b_{Wh}) = a_{Wh}b_{Wh} + \sigma_{a_{hj},b_{hj}} \tag{5.29}$$

and the corresponding specific between-group indirect effect is calculated as:

$$E(a_{Bh}b_{Bh}) = a_{Bh}b_{Bh} \tag{5.30}$$

Due to the covariance between the slopes being a necessary component of the calculation of specific indirect effects, the equations must be stacked to estimate all necessary parameters. Because there are now $k+1$ lower-level equations, to combine all equations into one requires $k+1$ indicator variables, $S_{M_{1ij}}$, $S_{M_{2ij}}$, ..., $S_{M_{kij}}$, and $S_{Y_{ij}}$ where $S_{M_{1ij}} = 1$ and all other indicators equal 0 when Z refers to M_1, $S_{M_{2ij}} = 1$ and all other indicators equal 0 when Z refers to M_2, and so forth. Thus, the stacked single lower-level equation to represent the 1-1-1 mediation model with m parallel

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mediators is:

$$Z_{ij} = S_{M_{1ij}}[d_{M1_j} + a_{1j}(X_{ij} - \overline{X}_{.j})] + S_{M_{2ij}}[d_{M2_j} + a_{2j}(X_{ij} - \overline{X}_{.j})]$$

$$+ \cdots + S_{M_{kij}}[d_{Mk_j} + a_{kj}(X_{ij} - \overline{X}_{.j})]$$

$$+ S_{Y_{ij}}[d_{Y_j} + b_{1j}(M_{1ij} - \overline{M}_{1.j}) + b_{2j}(M_{2ij} - \overline{M}_{2.j})$$

$$+ \cdots + b_{kj}(M_{kij} - \overline{M}_{k.j}) + c'_j(X_{ij} - \overline{X}_{.j})] + e_{Zij}$$

(5.31)

The upper-level equations remain as before. It should be noted that, as with co-variates, any within-group effects not expected to vary across level-2 units can be specified as fixed. This is done for parsimony, as well as practicality, as computational burden and nonconvergence issues increase with each additional random effect. Once all parameters are estimated, inference about the specific within and between indirect effects follow the Monte Carlo procedures discussed previously. Of course, a specific indirect effect is interpreted as the indirect effect of X on Y through the given mediator, while holding all other mediators constant. This conforms to the interpretation of a specific indirect effect in a single-level parallel mediation model.

5.2.1 Indirect Effect Contrasts

Tests for differences between specific indirect effects can be conducted similarly to how they are for single-level multiple mediator models. Now, however, there can be indirect effect contrasts at each level. For example, in a two-mediator model the within-group indirect effects may statistically differ from each other, even though the between-group indirect effects may not.

5.2.2 Covariance Between Random Indirect Effects

If at least one of the paths from one indirect effect is permitted to covary with a path from another, then the random indirect effects may covary. A positive covariance

between indirect effects would suggest that lower-level units that have higher than average within-group indirect effects through one mediator tend to have higher than average within-group indirect effects through the other. Following derivations of the covariance between the products of jointly normally distributed random variables (Bohrnstedt & Goldberger, 1969), the covariance between random indirect effects i and j is:

$$Cov(a_i b_i, a_j b_j) = E(a_i)E(a_j)Cov(b_i, b_j) + E(a_i)E(b_j)Cov(b_i, a_j)$$

$$+E(b_i)E(a_j)Cov(a_i, b_j) + E(b_i)E(b_j)Cov(a_i, a_j) \qquad (5.32)$$

$$+Cov(a_i, a_j)Cov(b_i, b_j) + Cov(a_i, b_j)Cov(b_i, a_j)$$

Of course, if some coefficients are not permitted to covary with others, some terms will equal zero and can be removed from the equation. A special case is if all covariances between the coefficients are zero, in which case the covariance between the random indirect effects is also zero. The parameter estimates can be used in place to estimate the covariance. Although a zero covariance between normally distributed random variables implies independence, a zero covariance between indirect effects is not necessarily indicative of independence, as the indirect effects are not typically normally distributed.

5.3   Adding Level-2 Moderators

Level-2 moderators can be included in multilevel mediation models in a variety of ways to help answer interesting research questions and gain a better understanding of the conditional nature of indirect effects. This section characterizes different forms of multilevel moderated mediation that have not previously been formulated.

5.3.1 Within-group Moderated Mediation

When there is variability in the random slopes, the researcher may wish to explain this variability or covariance by adding a level-2 predictor, Q_j, of the random slopes. Here, Q_j acts as a moderator in that the effect of the lower level relationships, a_j and b_j, may change systematically as a function of Q_j. The level-2 equations for a_j and b_j with one predictor Q_j are:

$$a_j = a_W + g_{a1}Q_j + u_{aj} \tag{5.33}$$

$$b_j = b_W + g_{b1}Q_j + u_{bj} \tag{5.34}$$

where a_W and b_W now quantify the expected slopes conditioned on $Q_j = 0$, and g_{a1} and g_{b1} quantify the expected change in a_j and b_j resulting from a one-unit increase in Q_j, respectively. If, g_{a1} and g_{b1} are statistically significant, it can be said that Q_j moderates the relationships between X_{ij} and M_{ij}, and M_{ij} and Y_{ij}, respectively. In the past, if Q_j significantly predicted a_j or b_j, this was deemed moderated mediation, in that the indirect effect $a_j b_j$ was thought to systematically vary as a function of Q_j (Bauer et al., 2006). However, a formal test of moderated mediation should be conducted on the indirect effect, rather than the individual components. The index of moderated mediation (Hayes, 2015), derived for the single-level case, can be extended to multilevel designs.

Consider the case where Q_j is a predictor of b_j, but not a_j. This is analogous to the single level case described in Section 2.2.3. The within-group effect of X_{ij} on Y_{ij} is $a_j = a_W + u_{aj}$, and the within-group effect of M_{ij} on Y_{ij} controlling for X_{ij} is $b_j = b_W + g_{b1}Q_j + u_{bj}$. Therefore, the average within-group indirect effect of X_{ij} on

Y_{ij} is:

$$E(a_j b_j) = a_W b_W + a_W g_{b1} Q_j + \sigma_{a_j, b_j} \tag{5.35}$$

where σ_{a_j, b_j} is the residual covariance between a_j and b_j after removing the variance explained by Q_j. This demonstrates that a formal test of moderated mediation would involve testing whether $a_W g_{b1}$ is significantly different from zero, as this determines how the indirect effect changes systematically as a function of Q_j. In the single-level case, this is often tested using bootstrapping. However, it can be tested using the Monte Carlo method as well, which can be easier to implement in the multilevel case. Here, data can be generated from the multivariate distribution:

$$\begin{bmatrix} a_W^* \\ g_{b1}^* \end{bmatrix} \sim MVN\left(\begin{bmatrix} \hat{a}_W \\ \hat{g}_{b1} \end{bmatrix}, \begin{bmatrix} \hat{\sigma}_{\hat{a}_W}^2 & \hat{\sigma}_{\hat{a}_W, \hat{g}_{b1}} \\ \hat{\sigma}_{\hat{a}_W, \hat{g}_{b1}} & \hat{\sigma}_{\hat{g}_{b1}}^2 \end{bmatrix} \right)$$

and a Monte Carlo confidence interval for $a_W g_{b1}$ can be constructed. After obtaining evidence of moderated mediation, the moderation can be probed at different values of Q_j by centering Q_j around the value of interest and refitting the model, as discussed previously and by Bauer et al. (2006).

When Q_j is a predictor of both a_j and b_j, the formal test of moderated mediation becomes more complex. In this scenario, the within-group effect of X_{ij} on Y_{ij} is $a_j = a_W + g_{a1} Q_j + u_{aj}$, and the within-group effect of M_{ij} on Y_{ij} controlling for X_{ij} is $b_j = b_W + g_{b1} Q_j + u_{bj}$. Therefore, the average within-group indirect effect of X_{ij} on Y_{ij} is:

$$E(a_j b_j) = a_W b_W + (a_W g_{b1} + b_W g_{a1}) Q_j + g_{a1} g_{b1} Q_j^2 + \sigma_{a_j, b_j} \tag{5.36}$$

Note that now there is both a linear and a quadratic effect of Q_j. Therefore, both $a_W g_{b1} + b_W g_{a1}$ and $g_{a1} g_{b1}$ can be tested to determine if there is evidence of moderated

mediation. Data can be generated from the multivariate distribution:

$$
\begin{bmatrix} a_W^* \\ b_W^* \\ g_{a1}^* \\ g_{b1}^* \end{bmatrix} \sim MVN \left(\begin{bmatrix} \hat{a}_W \\ \hat{b}_W \\ \hat{g}_{a1} \\ \hat{g}_{b1} \end{bmatrix}, \begin{bmatrix} \hat{\sigma}_{\hat{a}}^2 & \hat{\sigma}_{\hat{a},\hat{b}} & \hat{\sigma}_{\hat{a},\hat{g}_{a1}} & \hat{\sigma}_{\hat{a},\hat{g}_{b1}} \\ \hat{\sigma}_{\hat{a},\hat{b}} & \hat{\sigma}_{\hat{b}}^2 & \hat{\sigma}_{\hat{b},\hat{g}_{a1}} & \hat{\sigma}_{\hat{b},\hat{g}_{b1}} \\ \hat{\sigma}_{\hat{g}_{a1},\hat{a}} & \hat{\sigma}_{\hat{g}_{a1},\hat{b}} & \hat{\sigma}_{\hat{g}_{a1}}^2 & \hat{\sigma}_{\hat{g}_{a1},\hat{g}_{b1}} \\ \hat{\sigma}_{\hat{g}_{b1},\hat{a}} & \hat{\sigma}_{\hat{g}_{b1},\hat{b}} & \hat{\sigma}_{\hat{g}_{a1},\hat{g}_{b1}} & \hat{\sigma}_{\hat{g}_{b1}}^2 \end{bmatrix} \right)
$$

A confidence interval for $g_{a1}g_{b1}$ that does not contain zero would suggest that the indirect effect changes systematically as a function of Q in a quadratic way. Note that the only way for there to be a quadratic effect is if both g_{a1} and g_{b1} do not equal zero. If either equal zero, the indirect effect reduces to the linear form.

5.3.2 Between-group Moderated Mediation

Each of the moderated mediation hypotheses discussed thus far occur when the within-group indirect effect changes systematically as a function of a level-2 variable. It is also possible for the between-group indirect effect to be moderated by a level-2 variable. Recall that the between-group effects for level-1 variables take the form of observed group means, which act as predictors for the random intercepts. That is, $\overline{X}_{.j}$ is a predictor of the intercept for M_{ij} and its coefficient represents the between-group effect of X_{ij} on M_{ij}. When a level-2 variable, say Q_j, is added to the model as a predictor of a random slope, it should also be added as a predictor of the random intercept. The inclusion of an additional variable, $Q_j\overline{X}_{.j}$, in the intercept equation for M_{ij} can be used to test whether the between-group effect of X_{ij} on M_{ij} is moderated by Q_j.

Returning to the example where the effect of M_{ij} on Y_{ij} is moderated by Q_j, the intercept equations for M_{ij} and Y_{ij} can be specified as:

$$
d_{Mj} = d_M + a_B \overline{X}_{.j} + u_{Mj} \tag{5.37}
$$

$$d_{Yj} = d_Y + c'_B \overline{X}_{.j} + b_B \overline{M}_{.j} + g_{Y3}Q_j + g_{Y4}\overline{M}_{.j}Q_j + u_{Yj} \tag{5.38}$$

Note that the between-group effect of M_{ij} on Y_{ij} is now conditional on Q_j. This effect is quantified as $b_B + g_{Y4}Q_j$. Therefore, the between-group indirect effect of X_{ij} on Y_{ij} is also conditional on Q_j, and can be quantified as $a_B(b_B + g_{Y4}Q_j) = a_B b_B + a_B g_{Y4}Q_j$. Formal testing of between-group moderated mediation can be conducted by constructing a Monte Carlo confidence interval for $a_B g_{Y4}$ following the logic discussed previously, and the conditional between-group indirect effect can be probed at different values of the moderator.

5.3.3 When the Between Effect of X or M is a Moderator of the Within-group Indirect Effect

A conceptually interesting phenomenon that can be tested within multilevel mediation is whether the between effect of X or M moderates the within-group indirect effect of X on Y through M. To conduct such a test, the group aggregate of X, $\overline{X}_{.j}$, or M, $\overline{M}_{.j}$, is simply added as a predictor of the slope for the relationship in which it is hypothesized to moderate. For example, if the group aggregate of X is hypothesized to moderate the within-group X to M relationship, the level-two model for a_j would be:

$$a_j = a_W + g_{a1}\overline{X}_{.j} + u_{aj} \tag{5.39}$$

and $\overline{X}_{.j}$ should also remain as a predictor of the random intercepts. Now, however, the effect of $\overline{X}_{.j}$ on the intercept of M is a conditional effect. The conditional within-group indirect effect is then the product of a_j and b_j, $a_W b_W + g_{a1} b_W \overline{X}_{.j} + \sigma_{a_j, b_j}$. A test for moderated mediation can be conducted by constructing a confidence interval

around the index of moderated mediation for the model, $g_{a1}b_W$, following the method described in Section 5.3.1.

A statistically significant positive index of moderated mediation would suggest that the within-group indirect effect tends to be higher for level-2 units whose group aggregate of X is above the average group aggregate than for level-2 units whose group aggregate is below the average group aggregate.

5.4   Limitations of MLM

The formulation of multilevel mediation models described here is not without its limitations. First, all of the independent and mediator variables are assumed to be measured without error. When an independent variable in a simple linear regression model is measured with error, the estimated coefficient is attenuated by the degree of unreliability of the measurement. In mediation analysis, if the mediator is measured with error, the problem can be exacerbated. These issues with measurement error generalize to the multilevel context and can result in biased parameter estimates.

Another limitation of using multilevel modeling to assess mediation is that the final outcome variable must be measured at the lowest level, and a given variable may only influence other variables at either it's same level or a lower level. Hence, MLM can only be used to assess 2-2-1, 2-1-1, and 1-1-1 mediation models.[2]

Finally, using the observed group mean as a level-2 predictor only acts as a proxy for the true group mean value. Therefore, between-group effects that are a result of using observed group means on lower-level variables may be biased. Lüdtke et al. (2008) and Preacher et al. (2010) demonstrate that the between-group effect for a

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[2]Other multilevel mediation models can be assessed using MLM if there are more than two levels.

1-1 relationship is biased. This bias is largest when the within-group sample sizes are small, and the intraclass correlation is low.

To circumvent these limitations, several researchers (e.g., Preacher et al., 2010) have recommended analyzing hierarchical data using structural equation modeling, in a general framework that has become known as *multilevel structural equation modeling* (MSEM). Within MSEM, latent variables can be measured using indicator variables, which may reduce or eliminate measurement error. Further, mediation models involving "upward effect" can be hypothesized and tested. That is, a researcher may model a 1-2-1 or 2-1-2 mediation process, or any other hypothesized set of pathways. In addition, observed group means may be replaced with latent group means which take the form of random intercepts in MSEM. This removes the bias in between-group effects.

While MSEM can be incredibly useful in formulating multilevel mediation processes, here I continues to use traditional MLM techniques. This is not to suggest that MSEM may not be helpful in addressing the research questions that the models presented here address. Rather, it serves to highlight that, under some circumstances, formulating the model using MSEM is not necessary. This is particularly true when the independent variables are measured reliably, there are no hypothesized "upward effects" and the group sample sizes are large enough, and the intraclass correlation is high enough, to yield reliable estimates of the true group means. The MLM method would also be appropriate for 1-1-1 models if the last condition isn't satisfied, but the focus of the analysis is on the within-group indirect effect, which remains unbiased.

Chapter 6: Example Analyses

The previous chapter described several advancements in the formulation and testing of multilevel mediation and moderated mediation, including the simultaneous estimation of between-group and within-group indirect effects as well as a comparison between these effects, the inclusion of multiple mediators, and formal tests of within-group and between-group moderated mediation. In this chapter, some of these ideas are explored using two real-world datasets.

The first dataset comes from a large-scale educational assessment. Data from one country is used which includes individual data for students nested within schools. Using this dataset, within-group and between-group indirect effects will be tested and compared. The within-group indirect effect will also be permitted to randomly vary across schools, and some of this variability will be explained using a level-2 moderator. The second example includes repeated measurements from participants who completed multiple research conditions. The focus of this analysis is on the within-person level, in which several mediators will be included in the model simultaneously, and some of the specific indirect effects will be permitted to covary. Further, comparisons between these specific indirect effects will be made, and a test of the index of moderated mediation will be conducted for one of these specific indirect effects in

which the person-level aggregate of the independent variable will be included as the level-2 moderator.

Throughout this chapter, analyses are conducted using `MLmed`, a free SPSS macro developed in conjunction with this thesis. The purpose of `MLmed` is to simplify the work necessary to conduct a multilevel mediation or moderated mediation analysis using the methods described throughout this thesis. Even for a researcher with programming experience, the data manipulations necessary to prepare the data for the analysis (such as the within-group centering of variables, the stacking of equations, the creation of indicator variables, and the unusual specification of the model) are quite tedious and leave much room for error. Further, no multilevel software automatically provides Monte Carlo confidence intervals for indirect effects, indirect contextual effects, indirect effect contrasts, or the index of moderated mediation. Instead, these intervals have to be constructed using the asymptotic covariance matrices of the parameter estimates.

Using only a few lines of syntax, `MLmed` performs all of the data management and equation stacking necessary to conduct multilevel mediation analysis, within-group centers predictor variables, and takes advantaged of the MIXED procedure in SPSS for estimation. Monte Carlo confidence intervals are automatically calculated for indirect effects, indirect contextual effects, indirect effect contrasts, and tests of moderated mediation. The code necessary to conduct these analyses is provided, as well as information about interpreting the output. Users are encouraged to reference Appendix B for the macro documentation which explains the syntax structure and available arguments.

Finally, to ensure that the solutions using `MLmed` are reasonable, all analyses are also conducted using Mplus (Muthén & Muthén, 2015) and the lme4 package (Bates et al., 2015) in R (R Core Team, 2016) to allow for comparisons.

6.1 Example 1 - PISA

6.1.1 Data

The data for this example are taken from the 2015 Programme for International Student Assessment (PISA). The PISA dataset contains test scores of 15-year olds from 72 countries on a variety of school subjects, as well as student, teacher, and school questionnaires. For this example, the Canadian sample will be used. In total, the sample contains 12,722 students from 643 schools. The variables of interest include the student's sense of belonging within his or her school (labeled BELONG in the dataset), the degree to which the student enjoys cooperation (labeled COOPERATE), the student's math achievement score (labeled PV1MATH), the number of hours of out-of-school study time per week (OUTHOURS), and an index of the student's economic, social, and cultural status (ESCS). In addition, the dataset contains a school identifier (SCHID) and school population size in hundreds of students (SCHS_100).

6.1.2 Research Questions

Before proceeding, it should be noted that the results presented in this section are for pedagogical purposes only. The research questions of interest for this example include to what degree the enjoyment of cooperation mediates the within-group relationship between students sense of belonging and math achievement score, after statistically controlling for number of study hours and status. Further, does the

within-group indirect effect vary across schools, and can some of this variability be explained by school size?

6.1.3 Analysis

Because it can sometimes be useful to begin with a less complex model than the one hypothesized, the first analysis will not include the random slopes or the moderator. The syntax for this first model is:

```
 mlmed data = can_data
/x = BELONG
/m1 = COOPERATE
/cov1 = OUTHOURS
/cov2 = ESCS
/y = PV1MATH
/cluster = SCHID
/est = ML
/folder = /Users/rockwood.19/Desktop/.
```

which corresponds to the following equations:

$$COOP_{ij} = d_{Mj} + a_j(BELONG_{ij} - \overline{BELONG}_{.j})$$

$$+ q_{1j}(OUT_{ij} - \overline{OUT}_{.j}) + q_{2j}(ESCS_{ij} - \overline{ESCS}_{.j}) + e_{ij}$$

$$PV1MATH_{ij} = d_{Yj} + c'_j(BELONG_{ij} - \overline{BELONG}_{.j}) + b_j(COOP_{ij} - \overline{COOP}_{.j})$$

$$+ q_{3j}(OUT_{ij} - \overline{OUT}_{.j}) + q_{4j}(ESCS_{ij} - \overline{ESCS}_{.j}) + e_{ij}$$

$$d_{Mj} = d_M + a_B\overline{BELONG}_{.j} + g_1\overline{OUT}_{.j} + g_2\overline{ESCS}_{.j} + u_{Mj}$$

$$d_{Yj} = d_Y + c'_B\overline{BELONG}_{.j} + b_B\overline{COOP}_{.j} + g_3\overline{OUT}_{.j} + g_4\overline{ESCS}_{.j} + u_{Yj}$$

$$a_j = a_W, \;\; b_j = b_W, \;\; c'_j = c'_W, \;\; q_{1j} = q_1, \;\; q_{2j} = q_2, \;\; q_{3j} = q_3, \;\; q_{4j} = q_4$$

Figure 6.1 displays the output which, in this example, is broken down into four main sections. The first section contains an overview of the model specifications and the fit

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indices. The next section contains fixed effect estimates, which are broken up by each equation and by between and within effects. The following section contains the random effects, which include the residual (co)variances and random effect (co)variances. The last section contains indirect effect estimates.

As can be seen in the Model Specification table, the number of estimated parameters includes 16 fixed effects, 2 level-1 variances, and 2 level-2 variances for a total of 20 parameters. The deviance of this model is 181,282.2.

The first part of the Fixed Effects section contains the within- and between-group estimates for the M (COOPERATE) equation. The only nonsignificant effect is the between-group effect of OUTHOURS. The next part of the Fixed Effects section contains the estimates for the Y (PV1MATH) equation. The within-group effect of BELONG and the between-group effect of COOPERATE are nonsignificant.

In the Random Effects section, it can be seen that the level-1 residual variances for COOPERATE and PV1MATH are .94 and 5240.31, respectively and the variances of the random M and Y intercepts are .01 and 647.48, respectively.

The final section contains the expected value and variance of the within-group indirect effect, as well as inferential tests on the average within-group indirect effect, the between-group indirect effect, and the indirect contextual effect. Because this model is a simplification of the hypothesized model, these effects will not be interpreted until the final model is chosen. However, it is useful to understand how these effects are calculated. Note that the estimated average within-group indirect effect is 1.43, which is the product of the within-group effects of BELONG on COOPERATE (.20) and COOPERATE on PV1MATH (7.12). Because there are no random slopes, the variance of the indirect effect is zero. The between-group indirect effect

```
***************************** MLmed  *****************************

*********************************************************************

Model Specification
N          12722
Fixed         16
Rand(L1)       2
Rand(L2)       2
Total         20

Model Fit Statistics
        Value
-2LL 181282.2
AIC  181322.2
AICC 181322.3
CAIC 181505.1
BIC  181485.1



************************* FIXED EFFECTS  *************************

*********************************************************************
 Outcome: COOPERAT

Within- Effects
         Estimate     S.E.        df         t         p        LL        UL
constant    .0561    .0446  675.0432    1.2579    .2089    -.0315     .1437
BELONG      .2014    .0089  12154.80   22.6882    .0000     .1840     .2188
OUTHOURS    .0027    .0007  12154.80    4.1423    .0000     .0014     .0040
ESCS        .0928    .0120  12154.80    7.7487    .0000     .0693     .1163

Between- Effects
         Estimate     S.E.        df         t         p        LL        UL
BELONG      .3000    .0354  759.4266    8.4713    .0000     .2304     .3695
OUTHOURS    .0029    .0024  718.2089    1.2165    .2242    -.0018     .0076
ESCS        .1331    .0268  613.9690    4.9725    .0000     .0805     .1857

*********************************************************************
 Outcome: PV1MATH

Within- Effects
         Estimate     S.E.        df         t         p        LL        UL
constant 507.3043   5.3395  748.2634   95.0096    .0000  496.8221  517.7865
BELONG    -1.0739    .6767  12117.68   -1.5870    .1125   -2.4003     .2525
COOPERAT   7.1197    .6791  12117.68   10.4838    .0000    5.7885    8.4508
OUTHOURS   -.6971    .0492  12117.68  -14.1827    .0000    -.7935    -.6008
ESCS      21.4665    .8960  12117.68   23.9572    .0000   19.7101   23.2229

Between- Effects
         Estimate     S.E.        df         t         p        LL        UL
BELONG    21.4802   4.3063  882.3916    4.9880    .0000   13.0283   29.9321
COOPERAT   4.2247   4.6610  792.7687     .9064    .3650   -4.9246   13.3739
OUTHOURS  -1.1179    .2835  780.7099   -3.9432    .0001   -1.6745    -.5614
ESCS      53.5280   3.3243  694.9366   16.1021    .0000   47.0011   60.0549
```

Continued

Figure 6.1: MLmed output for the first model of Example 1.

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Figure 6.1 continued

```
**********************************************************************

*************************  RANDOM EFFECTS  *************************

Level-1 Residual Estimates
          Estimate    S.E.    Wald Z        p        LL        UL
PV1MATH   5240.313   67.3228  77.8386    .0000  5110.010  5373.938
COOPERAT     .9404     .0121  77.9577    .0000     .9171     .9643


Random Effect Estimates
   Estimate      S.E.    Wald Z        p        LL        UL
1     .0124     .0033    3.7676    .0002     .0074     .0208
2  647.4753   52.5476   12.3217    .0000  552.2576  759.1101


Random Effect Key
1    Int        COOPERAT
2    Int        PV1MATH

**********************************************************************

***********************  INDIRECT EFFECT(S)  ***********************

Within- Indirect Effect(s)
            E(ab)    Var(ab)    SD(ab)
COOPERAT   1.4340     .0000      .0000


Within- Indirect Effect(s)
           Effect       SE        Z        p      MCLL      MCUL
COOPERAT   1.4340     .1508   9.5093    .0000    1.1478    1.7345


Between- Indirect Effect(s)
           Effect       SE        Z        p      MCLL      MCUL
COOPERAT   1.2672    1.4157    .8951    .3707   -1.4419    4.1100


Test of Indirect Contextual Effect(s): Between - Within
             Dif      MCLL      MCUL
COOPERAT   -.1668   -2.8958    2.7018

------ END MATRIX -----
```

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is 1.27, which is calculated as the between-group effects of BELONG on COOPER-ATE (.30) and COOPERATE on PV1MATH(4.22). Finally, the indirect contextual effect is the difference between the between-group and within-group indirect effects, $1.27 - 1.43 = -.17$.

Adding Random Slopes

Since there is interest in the variability of the within-group indirect effect across level-2 units, the a and b paths can be specified as random. Adding the arguments `randx = 01` and `randm = 1` to the `MLmed` syntax estimates these additional parameters. The complete syntax for this new specification is:

```
 mlmed data = can_data
/x = BELONG
/randx = 01
/m1 = COOPERATE
/randm = 1
/cov1 = OUTHOURS
/cov2 = ESCS
/y = PV1MATH
/cluster = SCHID
/est = ML
/folder = /Users/rockwood.19/Desktop/.
```

and the corresponding equations remain as before, with the exception that now $a_j = a_W + u_{aj}$, $b_j = b_W + u_{bj}$, and $\sigma_{a_j,b_j} = 0$. The Random Effects section of the new output, displayed in Figure 6.2, contains the variance of the a and b paths. These are .01 and 34.14, respectively. The ratio of the new variance estimates to their standard errors are both statistically significant. However, these tests are not always reliable for variance parameters. Instead, the likelihood ratio test can be conducted to test whether the model without the additional variance parameters fits significantly worse than the model relaxing these constraints.

```
*********************************************************************

*************************  RANDOM EFFECTS  *************************

Level-1 Residual Estimates
           Estimate     S.E.     Wald Z        p       LL        UL
PV1MATH  5206.502   68.2679   76.2658     .0000 5074.404 5342.039
COOPERAT     .9272     .0122   76.1368     .0000    .9036    .9514

Random Effect Estimates
    Estimate      S.E.     Wald Z         p        LL        UL
1     .0130      .0033     3.9410     .0001     .0079     .0213
2  649.1810   52.5681    12.3493     .0000 553.9096 760.8391
3     .0136      .0036     3.8041     .0001     .0081     .0227
4   34.1419   15.9486     2.1407     .0323  13.6669  85.2918

Random Effect Key
1    Int           COOPERAT
2    Int           PV1MATH
3    Slope         BELONG        ->        COOPERAT
4    Slope         COOPERAT      ->        PV1MATH

*********************************************************************

***********************  INDIRECT EFFECT(S)  ***********************

Within- Indirect Effect(s)
            E(ab)   Var(ab)   SD(ab)
COOPERAT   1.4650    2.5765   1.6052
```

Figure 6.2: MLmed output containing the random effect estimates from the second model of Example 1.

The deviance for the model with the additional parameters is 181,254.7, with 22 total parameters estimated. The difference between the deviance of this model and the previous model is 27.5, and the difference in the number of parameters is 2. The test can be conducted using the MLmed macro with the following syntax:

```
LRT D0 = 181282.2 / P0 = 20 / D1 = 181254.7 / P1 = 22.
```

where D0 and P0 are the deviance and number of parameters of the restricted model, and D1 and P1 are the deviance and number of parameters of the unconstrained model. The p-value for this test is $<.001$, which suggests there is significant variability for the a and b paths. Therefore, the restricted model is rejected. For this new model,

the within-group indirect effect remained relatively the same, but now has a non-zero variance of 2.58 (SD = 1.61). Therefore, although the average within-group indirect effect is estimated to be positive, for some schools this indirect effect is much smaller or larger.

Permitting the Random Slopes to Covary

By default, the random a and b paths are not permitted to covary. The argument `covmat = UN` can be used to override this specification. Refitting the model with this additional argument results in a new model deviance of 181,250.5 with a total of 23 parameters. The estimated covariance between a and b can be found in the Random Effect Estimates table, displayed in Figure 6.3, in the row labeled (4,3), as this corresponds to the covariance between the 4th and 3rd random effects as labeled in the Random Effect Key table. This estimate is .35, with a p-value of .042. Using the likelihood ratio test results in a p-value of .040. Thus, the results of the two tests are nearly the same, and both suggest that freely estimating the covariance improves the fit of the model.

Now, the estimated average within-group indirect effect is 1.81, which is calculated as the product of the average within-group effects of BELONG on COOPERATE (.20) and COOPERATE on PV1MATH (7.20), plus the covariance between these random effects (.35). The Within- Indirect Effect(s) table contains a normal-theory p-value and a 95% Monte Carlo confidence interval. The Monte Carlo confidence interval is a more reliable test for the indirect effect because it does not assume that the indirect effect is normally distributed. In this scenario, both tests result in similar conclusions, as the confidence interval does not include 0 and the p-value is less than .05. This suggests that the average within-group indirect effect significantly differs from zero.

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```
**************************************************************************

************************** RANDOM EFFECTS **************************

Level-1 Residual Estimates
         Estimate    S.E.    Wald Z        p       LL        UL
PV1MATH  5207.439  68.2842  76.2612    .0000 5075.310 5343.009
COOPERAT    .9270    .0122  76.1539    .0000    .9034    .9511

Random Effect Estimates
        Estimate    S.E.    Wald Z        p       LL        UL
(1,1)     .0130    .0033   3.9443    .0001    .0079    .0213
(2,2) 649.1337  52.5677  12.3485    .0000 553.8635 760.7914
(3,3)     .0139    .0036   3.8736    .0001    .0084    .0231
(4,3)     .3510    .1725   2.0350    .0419    .0129    .6890
(4,4)  33.0623  15.8386   2.0875    .0368  12.9289  84.5480

Random Effect Covariance Matrix
           1         2         3         4
1    .0130     .0000     .0000     .0000
2    .0000 649.1337     .0000     .0000
3    .0000     .0000     .0139     .3510
4    .0000     .0000     .3510  33.0623

Random Effect Correlation Matrix
           1         2         3         4
1   1.0000     .0000     .0000     .0000
2    .0000   1.0000     .0000     .0000
3    .0000     .0000   1.0000     .5173
4    .0000     .0000     .5173   1.0000

Random Effect Key
1    Int        COOPERAT
2    Int        PV1MATH
3    Slope      BELONG         ->        COOPERAT
4    Slope      COOPERAT       ->        PV1MATH

**************************************************************************

********************** INDIRECT EFFECT(S) **********************

Within- Indirect Effect(s)
            E(ab)   Var(ab)   SD(ab)
COOPERAT   1.8149    3.7005    1.9237

Within- Indirect Effect(s)
            Effect       SE        Z         p      MCLL      MCUL
COOPERAT   1.8149     .2428   7.4749     .0000    1.3472    2.3072

Between- Indirect Effect(s)
            Effect       SE        Z         p      MCLL      MCUL
COOPERAT   1.2661    1.4144    .8951     .3707   -1.4506    4.0454
```

Figure 6.3: MLmed output containing the random effect estimates from the third model of Example 1.

On average, within a given school, a one-unit increase in sense of belonging results in a 1.81 unit increase in math achievement score by way of enjoyment of cooperation. The variance of this indirect effect across schools is estimated as 3.70 (SD = 1.92).

The between-group indirect effect is estimated as 1.27, which does not significantly differ from zero by using the Monte Carlo confidence interval or normal-theory test. There is not evidence that an increase in school-aggregate student belonging score results in an increase in school-aggregate math achievement by way of school-aggregate enjoyment of cooperation.

If it was thought that the random a and b paths also covary with the random intercept for the Y equation, these covariances could be estimated. In this example, the estimation of the additional parameters does not result is substantially better fit, and so these parameters will remain constrained to zero.

Adding a level-2 Moderator

It may be of interest to try to explain the variability of the within-group indirect effect by adding a level-2 moderator. To try to explain the random variability in this example, school size (SCHS_100) is included as a moderator of the b path using the argument `modYcent`. Recall that when a moderator is included the estimated indirect effect is conditional on a moderator value of zero, which is meaningless in the present example since there are no schools with zero students. Therefore, SCHS_100 can be centered using the `modYcent` argument. The average SCHS_100 value is 7.92 (792 students), so that value will be used initially. The complete syntax is now:

```
 mlmed data = can_data
/x = BELONG
/randx = 01
/m1 = COOPERATE
/randm = 1
/cov1 = OUTHOURS
/cov2 = ESCS
/modY = SCHS_100
/modYcent = 7.92
/y = PV1MATH
/covmat = UN
/cluster = SCHID
/est = ML
/folder = /Users/rockwood.19/Desktop/.
```

and the corresponding changes to the equations for b_j and d_{Yj} are:

$$b_j = b_W + g_5(SCHS_j - 7.92) + u_{bj}$$

$$d_{Yj} = d_Y + c'_B\overline{BELONG}_{.j} + b_B\overline{COOP}_{.j} + g_3\overline{OUT}_{.j} + g_4\overline{ESCS}_{.j}$$

$$+ g_6(SCHS_j - 7.92) + g_7[(SCHS_j - 7.92)(\overline{COOP}_{.j})] + u_{Yj}$$

Of particular interest in this new model is the index of moderated mediation, which is placed between the Random Effects section and the Indirect Effect(s) section. This can be seen in Figure 6.4. By default, MLmed includes the within-group and between-group interaction term to test for moderated mediation at both levels.

The within-group index of moderated mediation is calculated as the product of the within-group effect of BELONG on COOPERATE (.20) and the within-group interaction term for COOPERATE and SCHS_100 (-.35). This value is -.07, and the Monte Carlo confidence interval does not contain zero, which suggests that the within-group indirect effect systematically varies as a function of school size. The within-school indirect effect of sense of belonging on math achievement through enjoyment

```
********************************************************************
******************  INDEX OF MODERATED MEDIATION  ******************

Within- Index of Moderated Mediation
             Est      MCLL      MCUL
SCHS_100   -.0708    -.1335    -.0079

Between- Index of Moderated Mediation
             Est      MCLL      MCUL
SCHS_100   -.0235    -.5901     .5401

********************************************************************
```

Figure 6.4: MLmed output containing the index of moderated mediation from the fourth model of Example 1.

of cooperation is expected to differ by .07 units for schools that differ in size by 100 students, where the indirect effect decreases as school size increases.

The between-group index of moderated mediation, on the other hand, is -.02. The confidence interval contains zero, suggesting that the between-group indirect effect is not moderated by school size. For the purpose of parsimony, the between-group interaction term can be removed from the model.

Probing the Interaction

After the between-group moderator is removed from the model, the within-group index of moderated mediation remains largely the same, suggesting it is an important component of the model. To gain a better understanding of the underlying process, the moderation of the within-group indirect effect can be probed at multiple values of the moderator. Because `ModYcent` was set equal to 7.92 (the mean), the estimated average indirect effect in the output corresponds to the conditional within-group indirect effect of belonging on math achievement through enjoyment of cooperation for a school containing 792 students. This value is 1.84, and the Monte Carlo confidence

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```
************************  INDIRECT EFFECT(S)  ************************

NOTE: First Within- Indirect Effect is Conditional on a Moderator Value of:
            value
SCHS_100    3.3500

Within- Indirect Effect(s)
            E(ab)   Var(ab)   SD(ab)
COOPERAT    2.1644   4.2472    2.0609

Within- Indirect Effect(s)
            Effect      SE        Z        p      MCLL     MCUL
COOPERAT    2.1644    .2865    7.5533    .0000   1.6070   2.7424




************************  INDIRECT EFFECT(S)  ************************

NOTE: First Within- Indirect Effect is Conditional on a Moderator Value of:
            value
SCHS_100    7.9200

Within- Indirect Effect(s)
            E(ab)   Var(ab)   SD(ab)
COOPERAT    1.8410   3.6496    1.9104

Within- Indirect Effect(s)
            Effect      SE        Z        p      MCLL     MCUL
COOPERAT    1.8410    .2423    7.5986    .0000   1.3763   2.3258




************************  INDIRECT EFFECT(S)  ************************

NOTE: First Within- Indirect Effect is Conditional on a Moderator Value of:
            value
SCHS_100    12.4900

Within- Indirect Effect(s)
            E(ab)   Var(ab)   SD(ab)
COOPERAT    1.5177   3.1224    1.7670

Within- Indirect Effect(s)
            Effect      SE        Z        p      MCLL     MCUL
COOPERAT    1.5177    .2754    5.5099    .0000    .9660   2.0422
```

Figure 6.5: MLmed output containing the conditional average within-group indirect effect probed at three values of SCHS_100. The top is conditional on a value of 3.35, the middle is conditional on a value of 7.92, and the bottom is conditional on a value of 12.49.

interval does not contain zero. Further, the variance of the conditional indirect effect is estimated as 3.65 (SD = 1.91).

The analysis is then be repeated after changing the value of `ModYcent`. Note that, while changing this value will change the conditional indirect effect, it will not change the index of moderated mediation. For this example, the analysis was repeated using values of 3.35 (335 students) and 12.49 (1,249 students) which correspond to one standard deviation below and above the mean school size across all schools. As seen in Figure 6.5, conditional on a school size of 335, the average within-group indirect effect is estimated as 2.16 and this value significantly differs from zero. The conditional variance of this effect is estimated as 4.25 (SD = 2.06). The estimated within-group indirect effect conditional on a school size of 1,249 is 1.52, which also significantly differs from zero. The variance is 3.12 (SD = 1.77).

So, after probing the interaction, it seems that although the average within-group indirect effect decreases by .07 units for each additional 100 students, the effect remains positive and significant for low, medium, and high school sizes. This is best summarized in Figure 6.6, which plots the school size on the x-axis, and the average within-group indirect effect on the y-axis. The inner vertical bars are the 95% Monte Carlo confidence intervals constructed around the average within-group indirect effect at each value of school size that the interaction was probed. None of confidence intervals contain zero. The outer bars, on the other hand, demonstrate the variability of the within-group indirect effect across schools. These bars plot one standard deviation above and below the average effect. Clearly, although the average within-group indirect effect is positive and significant at each value probed, it's estimated that many schools may have a much larger or smaller within-group indirect effect.
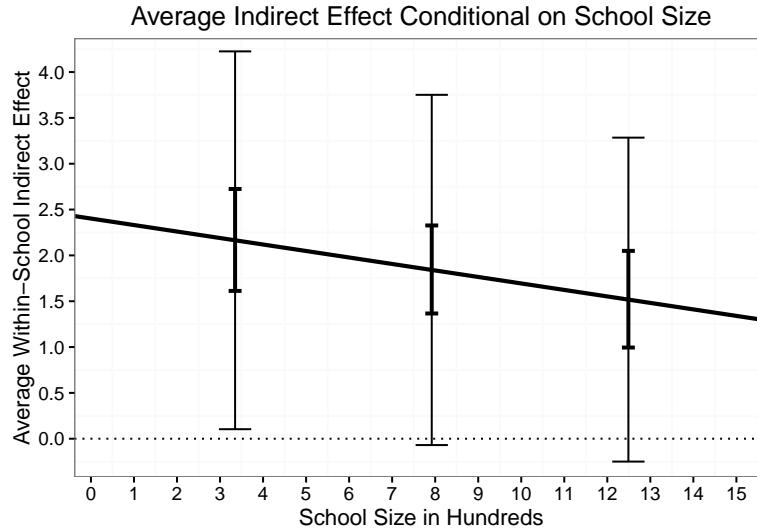
Figure 6.6: Average within-group indirect effect conditional on school size. The inner bars are 95% Monte Carlo confidence intervals for the average indirect effect. The outer bars are one standard deviation above and below the average conditional effect.

Because the between-group interaction effect was removed from the model, the estimated between-group indirect effect is not conditional on the school size. Note that changing the value of `ModYcent` has no effect on the between-group indirect effect, which is estimated as 1.52. There is not enough evidence to conclude that this effect significantly differs from zero.

Finally, because the average within-group indirect effect changes depending on the school size, the difference between the within-group and between-group indirect effects also change. In this example, none of the values of the moderator that were conditioned on resulted in a significant indirect contextual effect.

6.1.4 Comparison with Other Software

The estimates of the final model, with SCHS_100 centered around 7.92 are displayed in Table 6.1. In addition, estimates obtained from fitting the same model using lme4 and Mplus are provided for comparison. The model was fit piece-wise in lme4, so the covariance between the random slopes was not estimated and the within-group indirect effect was also not computed. Overall, the estimates using all programs are very similar to each other. And, while there are small discrepancies in these estimates due to differences in estimation algorithms, the overall substantive conclusions reached from the analysis remain the same no matter which software is used.

It should be noted that each model has one additional parameter that is not listed in Table 6.1 because there is a slight difference in the models fit using each program. Using Mplus, the group means of M are regressed on the group means of X and the covariates to obtain the corresponding between-group effects. For `MLmed` and lme4, however, the between-group effects of X and the covariates on M are estimated by regressing the "complete" M variable (not just group means) on the group means of X and the covariates. This does not cause any issues with estimating the between-group effects because the group means of X and the covariates have no within-group variability, so they cannot explain within-group variability in M. Therefore, the between-group effects of X and the covariates on M obtained from using the group means of M or the "complete" M will be equivalent. The only difference that does arise is the estimated intercept and level-2 residual variance for M. In Mplus, this variance is the residual variance of the group means of M, while in `MLmed` and lme4 this variance is the residual variance of the M intercept.

Table 6.1: Estimates (and standard errors) from the final model of Example 1 obtained using MLmed, Mplus, and lme4.

Outcome	Level	Effect	MLmed	Mplus (MLM)	lme4
COOPERATE	Within	Intercept	.056 (.045)	.065 (.046)	.056 (.045)
		BELONG	.203 (.010)	.204 (.010)	.203 (.010)
		OUTHOURS	.003 (.001)	.003 (.001)	.003 (.001)
		ESCS	.093 (.012)	.093 (.012)	.093 (.012)
	Between	BELONG	.300 (.035)	.308 (.032)	.300 (.035)
		OUTHOURS	.003 (.002)	.003 (.002)	.003 (.002)
		ESCS	.133 (.027)	.127 (.030)	.133 (.027)
PV1MATH	Within	Intercept	511.134 (5.236)	511.135 (5.239)	511.134 (5.236)
		Interaction	-.348 (.152)	-.348 (.152)	-.326 (.153)
		BELONG	-1.411 (.677)	-1.416 (.692)	-1.096 (.677)
		COOPERATE	7.200 (.721)	7.200 (.722)	7.23 (.723)
		OUTHOURS	-.693 (.049)	-.693 (.049)	-.693 (.049)
		ESCS	21.457 (.896)	21.458 (.896)	21.433 (.896)
	Between	SCHS_100	1.658 (.267)	1.658 (.267)	1.658 (.267)
		BELONG	21.129 (4.204)	21.129 (4.206)	21.128 (4.204)
		COOPERATE	2.128 (4.557)	2.125 (4.557)	2.128 (4.557)
		OUTHOURS	-1.153 (.276)	-1.154 (.277)	-1.153 (.276)
		ESCS	48.899 (3.323)	48.900 (3.323)	48.899 (3.223)
(Co)Variance	Within	COOPERATE	.927 (.012)	.878 (.011)	.927
		PV1MATH	5206.422 (68.260)	5206.511 (68.261)	5205.32
	Between	Var(Y Intercept)	598.597 (49.469)	598.549 (49.463)	598.65
		Var(a)	.014 (.004)	.016 (.004)	.014
		Var(b)	30.442 (15.687)	30.357 (15.677)	31.69
		Cov(a,b)	.377 (.172)	.385 (.173)	
Indirect Effects	Within	Index	-.071	-.071	-.066
		Indirect Effect	1.841 (.243)	1.851 (.243)	
	Between	Indirect Effect	.638 (1.378)	.654 (1.403)	.638

6.2 Example 2 - Competition

6.2.1 Data

The data for this example come from a study conducted by Cooke, Kavussanu, McIntyre, and Ring (2013) on the effect of individual and team competitions. Sixty-four participants completed a handgrip endurance task under four conditions. One of the conditions was a time-trial, while the other three conditions were one-on-one, two-on-two, and four-on-four competitions. The dataset also contains a variable dichotomizing the conditions to compare the time-trial condition (coded 0) to the head-to-head conditions (coded 1). This variable is labeled COMP in the dataset. For each condition, the participants' effort (labeled EFF), enjoyment (labeled ENJ), and anxiety (labeled ANX) were recorded, as well as the duration (labeled DUR) in which they were able to perform the handgrip task. There is also a subject identifier, which is labeled SUBJECT. The analyses conducted here are loosely based on those from Cooke et al. (2013), but deviate some for pedagogical purposes. Researchers interested in the theory behind the study and the full study results should reference Cooke et al. (2013).

6.2.2 Research Questions

The research questions that are addressed in this example include to what degree effort, enjoyment, and anxiety mediate the within-participant relationship between competition formats (Time Trial vs. head-to-head competitions) and performance. Further, do these indirect effects vary across participants? Do they covary? And lastly, does the strength of the within-person indirect effect systematically differ across participants as a function of average effort level across all conditions?

6.2.3 Analysis

As with the previous example, the first model fit will contain only a subset of the parameters of interest. While all three mediators are included, the only level-2 random components are the intercepts, and their covariance is not estimated. The syntax for this first model is:

```
 mlmed data = DataSet1
/x = COMP
/xB = 0
/m1 = EFF
/m2 = ENJ
/m3 = ANX
/y = DUR
/cluster = SUBJECT
/est = ML
/folder = /Users/rockwood.19/Desktop/.
```

which corresponds to the following equations:

$$EFF_{ij} = d_{M1j} + a_{1j}(COMP_{ij} - \overline{COMP}_{.j}) + e_{1ij}$$

$$ENJ_{ij} = d_{M2j} + a_{2j}(COMP_{ij} - \overline{COMP}_{.j}) + e_{1ij}$$

$$ANX_{ij} = d_{M3j} + a_{3j}(COMP_{ij} - \overline{COMP}_{.j}) + e_{1ij}$$

$$DUR_{ij} = d_{Yj} + c'_j(COMP_{ij} - \overline{COMP}_{.j}) + b_{1j}(EFF_{ij} - \overline{EFF}_{.j})$$

$$+ b_{2j}(ENJ_{ij} - \overline{ENJ}_{.j}) + b_{3j}(ANX_{ij} - \overline{ANX}_{.j}) + e_{ij}$$

$$d_{M1j} = d_{M1} + u_{M1j}, \qquad d_{M2j} = d_{M2} + u_{M2j}, \qquad d_{M3j} = d_{M3} + u_{M3j}$$

$$d_{Yj} = d_Y + b_{1B}\overline{EFF}_{.j} + b_{2B}\overline{ENJ}_{.j} + b_{3B}\overline{ANX}_{.j} + u_{Yj}$$

$$a_{1j} = a_{1W}, \ a_{2j} = a_{2W}, \ a_{3j} = a_{3W}, \ b_{1j} = b_{1W}, \ b_{2j} = b_{2W}, \ b_{3j} = b_{3W}, \ c'_j = c'_W$$

Most of these syntax arguments have already been explained. Now, however, there are three M variables. Another new argument is xB which omits the between-group

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effect of X from the model if set equal to zero, as it is in this example. The reasoning for removing this effect is that all participants completed all experimental conditions. Therefore, there is no between-person variability in X and including the person means on X would be equivalent to including an additional intercept, which is redundant. Also, because there is no between-person variability in X there cannot be a between-person indirect effect.

The output for this model is displayed in Figure 6.7. There are a few differences in the layout of the output compared to that from the previous example. First, there are now Fixed Effects sections for each mediator. And, because $xB = 0$ and there are no level-2 covariates, there are no between-person effects for the equations with the mediators as the outcomes. Also, there are no Between- Indirect Effect(s) in the Indirect Effect(s) section. Because there are multiple mediators, however, there is new output that contains indirect effect contrasts comparing the three within-person indirect effects. If there were between-person indirect effects, their contrasts would also be in this section. Since this model is only a subset of the fully hypothesized model, it will not be fully interpreted now.

Including Random Slopes

The inclusion of random slopes was described in detail in Section 6.1.3. To determine which slopes should be specified as random in this model, the same model tests and comparisons were conducted, but the details are omitted. In the end, it was decided that the slopes from COMP to EFF and from COMP to ENJ should vary randomly, as well as covary. All other slopes remain fixed. The corresponding syntax for the model is:

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```
***************************** MLmed  *****************************

*********************************************************************

Model Specification
N              256
Fixed           14
Rand(L1)         4
Rand(L2)         4
Total           22

Model Fit Statistics
        Value
-2LL 6422.642
AIC  6466.642
AICC 6467.653
CAIC 6597.134
BIC  6575.134




*************************** FIXED EFFECTS  ***************************

*********************************************************************
 Outcome: EFF

Within- Effects
         Estimate      S.E.        df         t         p        LL        UL
constant  87.4297    1.9491  64.0000   44.8568    .0000   83.5359   91.3234
COMP      16.8021    2.4416 192.0000    6.8816    .0000   11.9863   21.6179

Note: No Between- Effect(s) Specified.

*********************************************************************
 Outcome: ENJ

Within- Effects
         Estimate      S.E.        df         t         p        LL        UL
constant   3.8745     .1076  64.0000   35.9916    .0000    3.6594    4.0895
COMP        .8172     .1080 192.0000    7.5680    .0000     .6042    1.0302

Note: No Between- Effects Specified.

*********************************************************************
 Outcome: ANX

Within- Effects
       Estimate      S.E.        df         t         p        LL        UL
Int      5.2383     .2031  64.0000   25.7939    .0000    4.8326    5.6440
COMP     1.1927     .1911 192.0000    6.2421    .0000     .8158    1.5696

Note: No Between- Effects Specified.

*********************************************************************
 Outcome: DUR

Within- Effects
         Estimate      S.E.        df         t         p        LL        UL
constant  24.4710   18.4308  64.0000    1.3277    .1890  -12.3487   61.2908
COMP       1.6181    5.1255 192.0000     .3157    .7526   -8.4914   11.7277
```

Continued

Figure 6.7: The MLmed output for the first model of Example 2.

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Figure 6.7 continued

```
EFF          .5796     .1347 192.0000    4.3029     .0000     .3139     .8453
ENJ        22.4873    2.9858 192.0000    7.5314     .0000   16.5981   28.3765
ANX        -3.3662    1.6916 192.0000   -1.9899     .0480   -6.7027    -.0296


Between- Effects
      Estimate      S.E.        df         t         p        LL        UL
EFF     .1911      .1734   64.0000    1.1021     .2746    -.1553     .5376
ENJ   12.6625     3.1885   64.0000    3.9713     .0002    6.2928   19.0322
ANX    -.4108     1.6414   64.0000    -.2503     .8032   -3.6899    2.8683


**************************************************************************

************************* RANDOM EFFECTS  *************************

Level-1 Residual Estimates
      Estimate      S.E.     Wald Z         p        LL        UL
DUR 850.2833    86.7817     9.7980     .0000 696.1266 1038.578
EFF 286.1465    29.2047     9.7980     .0000 234.2680 349.5133
ENJ    .5597      .0571     9.7980     .0000     .4583     .6837
ANX   1.7524      .1789     9.7980     .0000    1.4347    2.1405


Random Effect Estimates
    Estimate      S.E.     Wald Z         p        LL        UL
1 171.5952    43.5958     3.9361     .0001 104.2911 282.3337
2    .6017      .1319     4.5626     .0000     .3916     .9246
3   2.2014      .4687     4.6964     .0000    1.4503    3.3415
4 228.3637    80.9099     2.8224     .0048 114.0365 457.3095


Random Effect Key
1    Int        EFF
2    Int        ENJ
3    Int        ANX
4    Int        DUR


**************************************************************************

*********************  INDIRECT EFFECT(S)  *************************

Within- Indirect Effect(s)
       E(ab)    Var(ab)    SD(ab)
EFF   9.7384     .0000     .0000
ENJ  18.3775     .0000     .0000
ANX  -4.0148     .0000     .0000


Within- Indirect Effect(s)
       Effect        SE         Z         p      MCLL      MCUL
EFF   9.7384    2.6894    3.6210     .0003    4.8134   15.5188
ENJ  18.3775    3.4576    5.3151     .0000   12.0202   25.6407
ANX  -4.0148    2.1422   -1.8742     .0609   -8.5761    -.0253


Note: No Between- Indirect Effect(s) Specified.

**************************************************************************


Within- Indirect Effect Contrasts
              Dif      MCLL      MCUL
ab2-ab1   8.6391    -.4893   18.2216
ab3-ab1 -13.7532  -21.5620   -6.5054
ab3-ab2 -22.3923  -31.1922  -14.3323
```

```
 mlmed data = DataSet1
/x = COMP
/randx = 0110
/xB = 0
/m1 = EFF
/m2 = ENJ
/m3 = ANX
/y = DUR
/covmat = UN
/cluster = SUBJECT
/est = ML
/folder = /Users/rockwood.19/Desktop/.
```

where now $a_{1j} = a_{1W} + u_{a1j}$, $a_{2j} = a_{2W} + u_{a2j}$, and $\sigma_{a1j,a2j}$ is freely estimated. If it was expected that the M intercepts covary with each other, the covariances could be estimated using the command mcovmat = UN. In this example, estimating the covariances does not improve the fit of the model, so they are not included in the analyses.

The covariance between the random slopes is estimated as 9.31, which translates to a correlation of .83, indicating that participants that have a higher than average COMP to EFF slope tend to have a higher than average COMP to ENJ slope as well.

All of the fixed effects remained relatively the same when the new parameters were included in the model. But, within the new output for the Indirect Effect(s) section, displayed in Figure 6.8, are two new matrices for the random indirect effects, which include the estimated covariances and correlations. The covariance between the random indirect effects through EFF and ENJ is estimated as 121.28, which corresponds to a correlation of .83. Participants with a higher than average indirect effect of COMP on DUR through EFF tend to also have a higher than average indirect effect through ENJ.

```
************************  INDIRECT EFFECT(S)  *************************

Within- Indirect Effect(s)
        E(ab)   Var(ab)   SD(ab)
EFF    9.7384   95.5233   9.7736
ENJ   18.3775  222.1097  14.9033
ANX   -4.0148     .0000     .0000

Within- Indirect Effect Covariance Matrix
         EFF       ENJ       ANX
EFF   95.5233  121.2829     .0000
ENJ  121.2829  222.1097     .0000
ANX     .0000     .0000     .0000

Within- Indirect Effect Correlation Matrix
         EFF       ENJ       ANX
EFF   1.0000     .8326     .0000
ENJ    .8326    1.0000     .0000
ANX    .0000     .0000    1.0000

Within- Indirect Effect(s)
       Effect       SE        Z        p      MCLL      MCUL
EFF    9.7384    2.8778   3.3840    .0007   4.6964   16.0540
ENJ   18.3775    3.7828   4.8582    .0000  11.5403   26.3012
ANX   -4.0148    2.1422  -1.8742    .0609  -8.5645    -.1139
```

Figure 6.8: MLmed output containing the random indirect effect estimates from Example 2.

Adding a Person-level Moderator

From the fixed effect estimates of the first model (which are close to those of the second model), it can be seen that, within individuals, higher than within-person average effort leads to longer than within-person average duration. It may be hypothesized, however, that this effect is weaker for those who, on average across all conditions, give more effort than others. That is, while giving more effort results in a longer duration, the participants may reach a point where they cannot increase the duration no matter how hard they try. To test the plausibility of this hypothesis, the mean of each participants' effort across the four conditions (labeled EFF_M) can be

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included as a moderator of the within-person slope of effort to duration. This model can be fit in `MLmed` using the following syntax:

```
 mlmed data = DataSet1
/x = COMP
/randx = 0110
/xB = 0
/m1 = EFF
/m2 = ENJ
/m3 = ANX
/mB = 011
/modY = EFF_M
/modYB = 0
/modYcent = 87.4297
/y = DUR
/covmat = UN
/cluster = SUBJECT
/est = ML
/folder = /Users/rockwood.19/Desktop/.
```

The equation for b_j and d_{Yj} are now:

$$b_{1j} = b_{1W} + g_1(\overline{EFF}_{.j} - 87.4297)$$

$$d_{Yj} = d_Y + b_{1B}(\overline{EFF}_{.j} - 87.4297) + b_{2B}\overline{ENJ}_{.j} + b_{3B}\overline{ANX}_{.j} + u_{Yj}$$

The `mB` argument is used to specify which between effects of M on Y are included in the model. The `011` indicates that the between effect of M_1 is not included (specified with a 0), while the between effects of M_2 and M_3 are included (specified with a 1). The reason for specifying that the between effect of EFF is not included, is that the between effect (labeled EFF_M) is specified as a moderator, and any specified moderator is automatically included as a predictor of the intercept for that equation. Therefore, not removing the effect using `mB` would result in a redundant predictor. As with the previous example, the moderator is centered around its mean (87.43) to

ensure that the corresponding conditional indirect effect is meaningful. It should be noted that any moderator included moderates the indirect effect through M_1 only, not any other mediators included in the model.

As seen in Figure 6.9, the index of moderated mediation for this model is estimated as -.32, with a Monte Carlo confidence interval that does not include zero. That is, the within-person indirect effect of head-to-head competition on duration through effort decreases by an estimated .32 units for each additional unit of a participants average effort over all conditions.

The (average) within-person indirect effects through enjoyment and anxiety are not conditional on overall effort level. These are estimated to be 18.24 and -3.99, respectively. For enjoyment, both the Monte Carlo confidence interval and the p-value for the normal theory test agree that the effect is significantly different from zero. Based on the estimated fixed effects, on average the effect of head-to-head competition leads to an increase in enjoyment, which leads to an increase in duration. In addition, the variance of the indirect effect across participants is estimated as 226.94 (SD = 15.06).

For anxiety, on the other hand, the Monte Carlo confidence interval (-8.32, -.09) does not contain zero, but the normal theory p-value is .058. Recall that this test is conservative, and the Monte Carlo test is a more accurate test as it does not inappropriately assume that the sampling distribution of the indirect effect is normally distributed. The estimated fixed effects demonstrate that head-to-head competition leads to an increase in anxiety, which leads to a decrease in duration. Because none of the paths in this indirect effect were random, the indirect effect does not vary across participants.

```
**************************************************************************

*******************  INDEX OF MODERATED MEDIATION  ********************

Within- Index of Moderated Mediation
           Est     MCLL     MCUL
EFF_M   -.3151   -.6004   -.0804


**************************************************************************

***********************  INDIRECT EFFECT(S)  ************************

NOTE: First Within- Indirect Effect is Conditional on a Moderator Value of:
          value
EFF_M  87.4297

Within- Indirect Effect(s)
        E(ab)   Var(ab)   SD(ab)
EFF    7.9692   66.0074    8.1245
ENJ   18.2372  226.9443   15.0647
ANX   -3.9947     .0000     .0000

Within- Indirect Effect Covariance Matrix
           EFF       ENJ       ANX
EFF    66.0074  100.0546     .0000
ENJ   100.0546  226.9443     .0000
ANX      .0000     .0000     .0000

Within- Indirect Effect Correlation Matrix
           EFF       ENJ       ANX
EFF    1.0000     .8175     .0000
ENJ     .8175    1.0000     .0000
ANX     .0000     .0000    1.0000

Within- Indirect Effect(s)
        Effect       SE        Z        p       MCLL      MCUL
EFF    7.9692    2.7778   2.8688    .0041    3.0908   14.0488
ENJ   18.2372    3.7748   4.8313    .0000   11.3916   25.9681
ANX   -3.9947    2.1309  -1.8746    .0608   -8.4461    -.0101

Note: No Between- Indirect Effect(s) Specified.

**************************************************************************

Within- Indirect Effect Contrasts
               Dif      MCLL      MCUL
ab2-ab1    10.2680    1.3678   19.5800
ab3-ab1   -11.9638  -20.0283   -4.8057
ab3-ab2   -22.2318  -31.2377  -13.9697

------ END MATRIX -----
```

Figure 6.9: MLmed output containing the index of moderated mediation and indirect effect estimates from Example 2.

In the indirect effect contrasts table, it can be see that the difference between the indirect effects through anxiety and enjoyment is -22.23 (95% CI = [-31.24, -13.97]). Note that this suggests the indirect effect through enjoyment is larger than the indirect effect through anxiety, but not necessarily stronger, as the effects are in different directions.

Probing the Interaction

The conditional within-person indirect effect of head-to-head competition on duration through effort can be probed at multiple values of person-level effort. The previous syntax probes the effect when average effort equals the mean value (87.43). Conditional on this value, the average indirect effect is estimated as 7.97, with a variance of 63.97 (SD = 8.00). The Monte Carlo confidence interval suggests that the effect significantly differs from zero. The indirect effect contrasts, displayed in Figure 6.10, also suggest that the indirect effect through enjoyment is significantly larger than the conditional indirect effect through effort (difference = 10.27, 95% CI = [1.46, 19.70]), which is significantly larger than the indirect effect through anxiety (difference = 11.96, 95% CI = 5.05, 19.84]).

For a participant with an average effort of one standard deviation above the mean (103.05), the average conditional indirect effect through effort is estimated to be 3.05, which is not statistically significant. The variance of this effect across participants is estimated as 9.35 (SD = 3.06). At this value of the moderator, the average indirect effect through enjoyment is statistically larger than the average conditional indirect effect through effort (difference = 15.19, 95% CI = [5.61, 25.72]), but the effect through effort is not statistically different than the indirect effect through anxiety (difference = 7.04, 95% CI = [-1.12, 15.78]).

```
***********************************************************************

Within- Indirect Effect Contrasts
              Dif       MCLL       MCUL
ab2-ab1    5.3450    -4.3725    14.6632
ab3-ab1  -16.8869   -25.8846    -9.0311
ab3-ab2  -22.2318   -31.3174   -14.0152




    ************************************************************************

Within- Indirect Effect Contrasts
              Dif       MCLL       MCUL
ab2-ab1   10.2680     1.4588    19.6951
ab3-ab1  -11.9638   -19.8371    -5.0543
ab3-ab2  -22.2318   -31.4462   -13.9453




    ***********************************************************************

Within- Indirect Effect Contrasts
              Dif       MCLL       MCUL
ab2-ab1   15.1910     5.6073    25.7211
ab3-ab1   -7.0408   -15.7750     1.1165
ab3-ab2  -22.2318   -31.6038   -14.0795
```

Figure 6.10: The MLmed output for the indirect effect contrasts at different values of the moderator. The top is at one standard deviation below the mean, the middle is at the mean, and the bottom is at one standard deviation above the mean.

Finally, for a participants with an average effort one standard deviation below the mean (71.81), the average conditional indirect effect through effort is estimated as 12.89, with a Monte Carlo confidence interval that does not include zero. The estimated conditional variance of this effect is 167.41 (SD = 12.94). With indirect effect contrasts suggesting that the effect through enjoyment is not significantly different from the effect through effort (difference = 5.35, 95% CI = [-4.37, 14.66]), but the effect through effort is significantly larger than the effect through anxiety (difference = 16.89, 95% CI = [9.03, 25.88]).

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6.2.4 Comparison with Other Software

The parameter estimates obtained using MLmed for the final model conditional on a moderator value of 87.43 are displayed in Table 6.2. For comparison, the results obtained using Mplus and lme4 are also displayed. As before, the estimates from MLmed and lme4 are essentially the same. And because the piecewise approach was used for lme4, the covariance between the random slopes was not estimated. The results obtaining using Mplus are also very similar, though some differences arise in the estimation of the variance parameters. Overall, the conclusions reached using each software package remain the same.

Table 6.2: Estimates (and standard errors) from the final model of Example 2 obtained using MLmed, Mplus, and lme4.

Outcome	Level	Effect	MLmed	Mplus (MLM)	lme4
EFF	Within	Intercept	87.430 (1.949)	87.430 (1.949)	87.430 (1.949)
		COMP	16.802 (2.987)	16.802 (2.987)	16.802 (2.987)
ENJ		Intercept	3.875 (.108)	3.874 (.108)	3.875 (.108)
		COMP	.817 (.127)	.817 (.127)	.817 (.127)
ANX		Intercept	5.238 (.203)	5.238 (.203)	5.238 (.203)
		COMP	1.193 (.191)	1.193 (.165)	1.193 (.191)
DUR		Intercept	41.182 (14.020)	24.471 (18.431)	41.182 (14.019)
		Interaction	-.019 (.007)	-.019 (.007)	-.019 (.007)
		COMP	1.732 (5.030)	1.732 (5.030)	1.732 (5.030)
		EFF	.474 (.138)	.474 (.138)	.474 (.138)
		ENJ	22.316 (2.931)	22.316 (2.931)	22.316 (2.931)
		ANX	-3.349 (1.660)	-3.349 (1.660)	-3.349 (1.660)
	Between	EFF_M	.191 (.173)	.191 (.173)	.191 (.173)
		ENJ	12.663 (3.189)	12.662 (3.188)	12.662 (3.188)
		ANX	-.411 (1.641)	-.411 (1.641)	-.411 (1.641)
Variance	Within	DUR	818.837 (83.572)	818.839 (83.573)	818.8
		EFF	215.057 (26.882)	143.372 (14.633)	215.1
		ENJ	.450 (.056)	.300 (.031)	.450
		ANX	1.752 (.179)	1.314 (.116)	1.752
	Between	Var (Y Intercept)	236.225 (80.699)	236.224 (80.698)	236.2
		Var(a1)	284.357 (107.131)	379.939 (102.826)	284.4
		Var(a2)	.439 (.198)	.693 (.188)	.439
		Cov(a1, a2)	9.306 (3.260)	9.306 (3.260)	
Indirect Effect	Within	Index	-.315	-.315	-.315
		EFF	7.969 (2.745)	7.969 (2.714)	7.969
		ENJ	18.237 (3.737)	18.237 (3.718)	18.237
		ANX	-3.995 (2.105)	-3.995 (2.056)	-3.995

Chapter 7: Discussion

Multilevel mediation and moderated mediation allow researchers to formulate and test a number of interesting hypotheses regarding causal processes and the boundary conditions of these processes when faced with nested data structures. These include research designs in which participants are nested within groups, which allow for the testing of between-group and within-group indirect effects, as well as the variability of the indirect effect across level-2 units. Further, the models can be used to test within-person processes and individual differences in these processes by using data containing repeated measurements. This thesis serves to highlight these methods as well as provide advancements in their formulation, conceptualization, and inference.

I began by providing an overview of single-level mediation and multilevel modeling. I then reviewed previous research on multilevel mediation for 1-1-1 designs before providing extensions to the model and introducing new inferential tests to address important and interesting substantive research questions. These extensions include simultaneously estimating between-group and within-group indirect effects using traditional multilevel software, making comparisons between these indirect effects, including multiple mediators that act in parallel, estimating the covariance between specific random indirect effects, and testing moderated mediation of between-group and within-group indirect effects. An SPSS macro to conduct such analyses was also

introduced, and two examples were worked through to demonstrate how to go about fitting the models discussed throughout this thesis.

7.1 Limitations

The most notable practical limitation when conducting multilevel mediation analyses is the estimation of the model parameters. Nonconvergence issues are not uncommon, especially when a large number of random effect parameters are estimated. Often, a nonconvergence issue arises when one or more of the parameters specified as random has little or no true variability. In this circumstance, the parameter should be re-specified as fixed and the model can be refit. A related limitation within `MLmed` is the inability to fully customize the model to suit the data at hand. While many features have been programmed to allow for changes in the model specification, there are some models that may be better suited for other software programs, such as Mplus. This is particularly true when the desired random effect covariance matrix is not available using `MLmed`. Nevertheless, the model formulations described throughout this thesis, as well as the tests of indirect contextual effects, indirect effect contrasts, and moderated mediation can be conducted using any multilevel modeling program. It is recommended that those not conducting their analyses using `MLmed` should still construct Monte Carlo confidence intervals using the asymptotic covariance matrices provided in the software output rather than rely on the standard errors provided by whichever software program is utilized.

As in the single-level case, causal inference using multilevel mediation models relies on more than just large or significant indirect effects. To support causal claims, the methods provided throughout this thesis must be accompanied by sound theory

and research design. There are limitations in every study and it's important for researchers to understand and express these limitations when interpreting the results obtained. This is especially true in multilevel mediation where there may be indirect effects at multiple levels, each with their own substantive meaning.

A potential critique of the present thesis is the specific focus on 1-1-1 multilevel mediation models. However, other multilevel mediation models can actually be seen as special cases of the 1-1-1 model. For example, the 2-1-1 model is a 1-1-1 model without any within-group variance in X. Thus, a 2-1-1 model can be estimated using the formulation provided throughout this thesis by omitting the (non-existent) level-1 predictor of X. In fact, `MLmed` can easily accommodate such a model. Consequently, there is no longer a within-group indirect effect, as there is no within-group effect of X. The 2-2-1 model is a further simplification, in that there is also no within-group effect of M. While the conceptualization remains the same as before, the M model is no longer a multilevel model, as it consists only of the effects on a level-2 variable. Thus, fitting the model in a univariate program would involve a piece-wise approach with a simple regression analysis to estimate a and a multilevel analysis to estimate b and c'.

As described previously, a limitation of traditional multilevel modeling as presented here is the inability to estimate "bottom-up" effects, as the dependent variable in a multilevel model must have variability at the lowest level. Readers interested in testing such effects using MSEM should reference Preacher et al. (2010). Further information about the benefits of an MSEM approach can be found in Section 5.4.

7.2 Future Directions

An avenue for future research is the formulation of mediation models in which lower-level units are cross-classified within multiple overlapping upper-level units, the classic example being students cross-classified within schools and neighborhoods (Raudenbush & Bryk, 2002). These data structures are prevalent in education and organizational behavior, and formulating these models may provide valuable insight into the causal processes in such contexts. In theory, within-group indirect effects could randomly vary across both level-2 grouping units and between-group indirect effects could be estimated for each of the higher levels. However, the research on this topic is limited.

Research on the performance of multilevel moderated mediation is also limited, and simulation studies could be useful in determining the performance of these models formulated using MLM and MSEM, as well as the sample sizes needed at each level to ensure adequate power to detect the effects of interest. The Monte Carlo method of inference should also be thoroughly evaluated in the multilevel mediation context. While the method has been shown to work well for single-level models (Preacher & Selig, 2012), there has not been a comprehensive comparison of methods for multilevel models. Because the standard errors of the individual parameters are used in the construction of the confidence intervals, the intervals may be unreliable in scenarios where the large-sample properties of the standard errors do not hold.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723.

Aroian, L. A. (1947). The probability function of the product of two normally distributed variables. *The Annals of Mathematical Statistics*, 265–271.

Bakker, A. B., Vergel, A. I. S., & Kuntze, J. (2015). Student engagement and performance: A weekly diary study on the role of openness. *Motivation and Emotion*, *39*(1), 49–62.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. doi: 10.18637/jss.v067.i01

Bauer, D. J., Preacher, K. J., & Gil, K. M. (2006). Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: new procedures and recommendations. *Psychological Methods*, *11*(2), 142–163.

Bohrnstedt, G. W., & Goldberger, A. S. (1969). On the exact covariance of products of random variables. *Journal of the American Statistical Association*, *64*(328), 1439–1442.

Cooke, A., Kavussanu, M., McIntyre, D., & Ring, C. (2013). The effects of individual and team competitions on performance, emotions, and effort. *Journal of Sport and Exercise Psychology*, *35*(2), 132–143.

Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: a general analytical framework using moderated path analysis. *Psychological Methods*, *12*(1), 1–22.

Efron, B., & Tibshirani, R. J. (1994). *An introduction to the bootstrap*. CRC press.

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: a new look at an old issue. *Psychological Methods*, *12*(2), 121–138.

Goodman, L. A. (1960). On the exact variance of products. *Journal of the American Statistical Association*, *55*(292), 708–713.

Hayes, A. F. (2009). Beyond baron and kenny: Statistical mediation analysis in the new millennium. *Communication Monographs*, *76*(4), 408–420.

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Press.

Hayes, A. F. (2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research*, *50*(1), 1–22.

Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis does method really matter? *Psychological Science*, 1–10.

Hofmann, D. A., & Gavin, M. B. (1998). Centering decisions in hierarchical linear models: Implications for research in organizations. *Journal of Management*, *24*(5), 623–641.

Kenny, D. A., Korchmaros, J. D., & Bolger, N. (2003). Lower level mediation in multilevel models. *Psychological Methods*, *8*(2), 115–128.

Kreft, I. G., De Leeuw, J., & Aiken, L. S. (1995). The effect of different forms of centering in hierarchical linear models. *Multivariate Behavioral Research*, *30*(1), 1–21.

Krull, J. L., & MacKinnon, D. P. (1999). Multilevel mediation modeling in group-based intervention studies. *Evaluation Review*, *23*(4), 418–444.

Krull, J. L., & MacKinnon, D. P. (2001). Multilevel modeling of individual and group level mediated effects. *Multivariate Behavioral Research*, *36*(2), 249–277.

Lüdtke, O., Marsh, H. W., Robitzsch, A., Trautwein, U., Asparouhov, T., & Muthén, B. (2008). The multilevel latent covariate model: a new, more reliable approach to group-level effects in contextual studies. *Psychological Methods*, *13*(3), 203–229.

MacKinnon, D. P. (2008). *Introduction to statistical mediation analysis*. Routledge.

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., & Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. *Psychological Methods*, *7*(1), 83–118.

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate Behavioral Research*, *39*(1), 99–128.

Muthén, L. K., & Muthén, B. (2015). Mplus version 7.4 [Computer software manual]. Muthén & Muthén.

Pinheiro, J. C., & Bates, D. M. (2000). Linear mixed-effects models: basic concepts and examples. *Mixed-effects models in S and S-Plus*, 3–56.

Pituch, K. A., & Stapleton, L. M. (2008). The performance of methods to test upper-level mediation in the presence of nonnormal data. *Multivariate Behavioral Research*, *43*(2), 237–267.

Pituch, K. A., & Stapleton, L. M. (2012). Distinguishing between cross-and cluster-level mediation processes in the cluster randomized trial. *Sociological Methods & Research*, *41*(4), 630–670.

Pituch, K. A., Stapleton, L. M., & Kang, J. Y. (2006). A comparison of single sample and bootstrap methods to assess mediation in cluster randomized trials. *Multivariate Behavioral Research*, *41*(3), 367–400.

Pituch, K. A., Whittaker, T. A., & Stapleton, L. M. (2005). A comparison of methods to test for mediation in multisite experiments. *Multivariate Behavioral Research*, *40*(1), 1–23.

Preacher, K. J. (2015). Advances in mediation analysis: A survey and synthesis of new developments. *Annual Review of Psychology*, *66*, 825–852.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891.

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research*, *42*(1), 185–227.

Preacher, K. J., & Selig, J. P. (2012). Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures*, *6*(2), 77–98.

Preacher, K. J., Zyphur, M. J., & Zhang, Z. (2010). A general multilevel SEM framework for assessing multilevel mediation. *Psychological Methods*, *15*(3), 209–233.

R Core Team. (2016). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from `https://www.R-project.org/`

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). Sage.

Raudenbush, S. W., & Sampson, R. (1999). Assessing direct and indirect effects in multilevel designs with latent variables. *Sociological Methods & Research*, *28*(2), 123–153.

Richter, M., König, C. J., Koppermann, C., & Schilling, M. (2016). Displaying fairness while delivering bad news: Testing the effectiveness of organizational bad news training in the layoff context. *Journal of Applied Psychology*, *101*(6), 779–792.

Rucker, D. D., Preacher, K. J., Tormala, Z. L., & Petty, R. E. (2011). Mediation analysis in social psychology: Current practices and new recommendations. *Social and Personality Psychology Compass*, *5*(6), 359–371.

Schleider, J. L., Patel, A., Krumholz, L., Chorpita, B. F., & Weisz, J. R. (2015). Relation between parent symptomatology and youth problems: Multiple mediation through family income and parent–youth stress. *Child Psychiatry & Human Development*, *46*(1), 1–9.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461–464.

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: new procedures and recommendations. *Psychological Methods*, *7*(4), 422–445.

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology*, *13*(1982), 290–312.

Tofighi, D., & Kelley, K. (2016). Assessing omitted confounder bias in multilevel mediation models. *Multivariate Behavioral Research*, *51*(1), 86–105.

Tofighi, D., West, S. G., & MacKinnon, D. P. (2013). Multilevel mediation analysis: The effects of omitted variables in the 1–1–1 model. *British Journal of Mathematical and Statistical Psychology*, *66*(2), 290–307.

Zhang, Z., Zyphur, M. J., & Preacher, K. J. (2009). Testing multilevel mediation using hierarchical linear models problems and solutions. *Organizational Research Methods*, *12*(4), 695–719.

Zhu, Y.-Q., Gardner, D. G., & Chen, H.-G. (2016). Relationships between work team climate, individual motivation, and creativity. *Journal of Management*, 1–22.

Appendix A: MLmed Macro for SPSS

The following code can be typed into an SPSS sytnax window and executed to load the `MLmed` macro into SPSS. Then, any syntax previously described can be run to fit the corresponding models.

```
DEFINE LRT (D1 = !charend('/')/ D0 = !charend('/')/ P1 = !charend('/')/
   P0 = !charend('/')).
MATRIX.
compute chi = !D0 - !D1.
compute df = !P1 - !P0.
compute p = 1 - CHICDF(chi,df).
compute table = {chi, df, p}.
print table /title = "Likelihood Ratio Test" /clabels = "Dif" "df" "p" /
   format = F8.4.
END MATRIX.
OUTPUT MODIFY
  /REPORT PRINTREPORT=NO
  /SELECT HEADINGS
  /IF COMMANDS=["Matrix(LAST)"] LABELS=[EXACT("Title")] INSTANCES=[1]
  /DELETEOBJECT DELETE=YES.
!ENDDEFINE.

DEFINE mlmed (data = !charend('/') !default(DataSet1)
        /x = !charend('/')
        /randx = !charend('/') !default(0000)
        /xB =  !charend('/') !default(1)
        /xW = !charend('/') !default(1)
        /m1 = !charend('/')
        /m2 = !charend('/')
        /m3 = !charend('/')
        /randm = !charend('/') !default(000)
        /randMint = !charend('/') !default(111)
        /mB = !charend('/') !default(111)
        /y = !charend('/')
        /randYint = !charend('/') !default(1)
```

```
        /cluster = !charend('/')
        /cov1 = !charend('/')
        /randc1 = !charend('/') !default(0000)
        /cov1B = !charend('/') !default(1)
        /cov1c = !charend('/')
        /cov2 = !charend('/')
        /randc2 = !charend('/') !default(0000)
        /cov2B = !charend('/') !default(1)
        /cov2c = !charend('/')
        /cov3 = !charend('/')
        /randc3 = !charend('/') !default(0000)
        /cov3B = !charend('/') !default(1)
        /cov3c = !charend('/')
        /l2cov1 = !charend('/')
        /l2cov2 = !charend('/')
        /l2cov3 = !charend('/')
        /modM = !charend('/')
        /modMcent = !charend('/') !default(0)
        /modMB = !charend('/') !default(1)
        /modY = !charend('/')
        /modYcent = !charend('/') !default(0)
        /modYB = !charend('/') !default(1)
        /indint = !charend('/') !default(1)
        /covmat = !charend('/') !default(DIAG)
        /mcovmat = !charend('/') !default(DIAG)
        /ycov = !charend('/') !default(0)
        /rescovmat = !charend('/') !default(DIAG)
        /est=!charend('/') !default(REML)
        /iters = !charend('/') !default(100)
        /mxstep = !charend('/') !default(10)
        /scoring = !charend('/') !default(1)
        /asym = !charend('/') !default(NO)
        /samples = !charend('/') !default(10000)
        /conf = !charend('/') !default(95)
        /eor = !charend('/') !default(0)
        /folder = !charend('!')).

DATASET ACTIVATE !data.
DATASET COPY mlmdata.
DATASET ACTIVATE mlmdata.
AGGREGATE
  /OUTFILE=* MODE=ADDVARIABLES
  /BREAK= !cluster
  /meanx=MEAN(!x)
  /meanm1=MEAN(!m1).
COMPUTE x_c = !x - meanx.
COMPUTE m1_c = !m1 - meanm1.
EXECUTE.
!LET !x_name = !QUOTE(!x).
!LET !y_name = !QUOTE(!y).
!LET !m1_name = !QUOTE(!m1).
```

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```
!LET !eor_1 = (!eor = 1).
!IF (!m2 ~= !NULL) !THEN
   !LET !m2_1 = 1.
   !LET !m2_name = !QUOTE(!m2).
   AGGREGATE
     /OUTFILE=* MODE=ADDVARIABLES
     /BREAK= !cluster
     /meanm2=MEAN(!m2).
   COMPUTE m2_c = !m2 - meanm2.
   EXECUTE.
!ELSE
   !LET !m2_1 = 0.
   !LET !m2_name = !QUOTE(none).
!IFEND
!IF (!m3 ~= !NULL) !THEN
   !LET !m3_1 = 1.
   !LET !m3_name = !QUOTE(!m3).
   AGGREGATE
     /OUTFILE=* MODE=ADDVARIABLES
     /BREAK= !cluster
     /meanm3=MEAN(!m3).
   COMPUTE m3_c = !m3 - meanm3.
   EXECUTE.
!ELSE
   !LET !m3_1 = 0.
   !LET !m3_name = !QUOTE(none).
!IFEND
!IF (!cov1 ~= !NULL) !THEN
   !LET !cov1_1 = 1.
   AGGREGATE
     /OUTFILE=* MODE=ADDVARIABLES
     /BREAK= !cluster
     /meanc1=MEAN(!cov1).
   !IF (!cov1c = !NULL) !THEN
      COMPUTE c1_c = !cov1 - meanc1.
      EXECUTE.
   !ELSE
      COMPUTE c1_c = !cov1 - !cov1c.
      EXECUTE.
   !IFEND
!ELSE
   !LET !cov1_1 = 0.
!IFEND
!IF (!cov2 ~= !NULL) !THEN
   !LET !cov2_1 = 1.
   AGGREGATE
     /OUTFILE=* MODE=ADDVARIABLES
     /BREAK= !cluster
     /meanc2=MEAN(!cov2).
   !IF (!cov2c = !NULL) !THEN
      COMPUTE c2_c = !cov2 - meanc2.
```

```
      EXECUTE.
   !ELSE
      COMPUTE c2_c = !cov2 - !cov2c.
      EXECUTE.
   !IFEND
!ELSE !LET !cov2_1 = 0.
!IFEND
!IF (!cov3 ~= !NULL) !THEN
   !LET !cov3_1 = 1.
   AGGREGATE
     /OUTFILE=* MODE=ADDVARIABLES
     /BREAK= !cluster
     /meanc3=MEAN(!cov3).
   !IF (!cov3c = !NULL) !THEN
      COMPUTE c3_c = !cov3 - meanc3.
      EXECUTE.
   !ELSE
      COMPUTE c3_c = !cov3 - !cov3c.
      EXECUTE.
   !IFEND
!ELSE
   !LET !cov3_1 = 0.
!IFEND
!IF (!l2cov1 ~= !NULL) !THEN
   !LET !l2cov1_1 = 1.
!ELSE
   !LET !l2cov1_1 = 0.
!IFEND
!IF (!l2cov2 ~= !NULL) !THEN
   !LET !l2cov2_1 = 1.
!ELSE
   !LET !l2cov2_1 = 0.
!IFEND
!IF (!l2cov3 ~= !NULL) !THEN
   !LET !l2cov3_1 = 1.
!ELSE
   !LET !l2cov3_1 = 0.
!IFEND
!LET !samemod = 0.
!IF (!modM = !modY) !THEN
   !LET !modYc = !modMcent.
!ELSE
   !LET !modYc = !ModYcent.
!IFEND
!IF (!modM ~= !NULL) !THEN
   !LET !modM_1 = 1.
   !LET !modM_n = !QUOTE(!modM).
   COMPUTE modM_c = !modM - !modMcent.
   EXECUTE.
!ELSE
   !LET !modM_1 = 0.
```

```
   !LET !modM_n = !QUOTE(none).
!IFEND
!IF (!modY ~= !NULL) !THEN
   !LET !modY_1 = 1.
   !LET !modY_n = !QUOTE(!modY).
   !LET !samemod = (!modY = !modM).
   COMPUTE modY_c = !modY - !modYc.
   EXECUTE.
!ELSE
   !LET !modY_1 = 0.
   !LET !modY_n = !QUOTE(none).
!IFEND
!LET !covmat_1 = (!covmat = UN).
!LET !rescov_1 = (!rescovmat = UN).
!LET !bet_x_1 = (!xB = 1).
!LET !wit_x_1 = (!xW = 1).
!LET !modMB_1 = (!modMB = 1).
!LET !modYB_1 = (!modYB = 1).
!LET !bet_c1_1 = (!cov1B = 1).
!LET !bet_c2_1 = (!cov2B = 1).
!LET !bet_c3_1 = (!cov3B = 1).
!LET !bet_m1_1 = 0.
!LET !bet_m2_1 = 0.
!LET !bet_m3_1 = 0.
VARSTOCASES /ID = case_num
 /MAKE Z FROM !m1 !m2 !m3 !y
 /INDEX =DV(Z).
OUTPUT MODIFY
  /REPORT PRINTREPORT=NO
  /SELECT TABLES
  /IF COMMANDS=["Variables to Cases(LAST)"] LABELS=[EXACT("Processing
     Statistics")] INSTANCES=[1]
  /DELETEOBJECT DELETE=YES
  /SELECT TABLES
  /IF COMMANDS=["Variables to Cases(LAST)"] LABELS=[EXACT("Generated
     Variables")] INSTANCES=[1]
  /DELETEOBJECT DELETE=YES
  /SELECT TEXTS
  /IF COMMANDS=["Variables to Cases(LAST)"] LABELS=[EXACT("Active
     Dataset")] INSTANCES=[1]
  /DELETEOBJECT DELETE=YES
  /SELECT HEADINGS
  /IF COMMANDS=["Variables to Cases(LAST)"] LABELS=[EXACT("Title")]
     INSTANCES=[1]
  /DELETEOBJECT DELETE=YES.
RECODE
DV
(!QUOTE(!y)=1) (ELSE=0) INTO y_ind.
EXECUTE.
RECODE
DV
```

```
(!QUOTE(!y)=1) (ELSE=0) INTO y_int.
EXECUTE.
RECODE
DV
(!QUOTE(!m1)=1) (ELSE=0) INTO m1_int.
EXECUTE.
!IF (!m2 ˜= !NULL) !THEN
    RECODE
    DV
    (!QUOTE(!m2)=1) (ELSE=0) INTO m2_int.
    EXECUTE.
!IFEND
!IF (!m3 ˜= !NULL) !THEN
    RECODE
    DV
    (!QUOTE(!m3)=1) (ELSE=0) INTO m3_int.
    EXECUTE.
!IFEND
RECODE DV (!QUOTE(!y)='1').
EXECUTE.
RECODE DV (!QUOTE(!m1)='2').
EXECUTE.
!IF (!m2 ˜= !NULL) !THEN
    RECODE DV (!QUOTE(!m2)='3').
    EXECUTE.
!IFEND
!IF (!m3 ˜= !NULL) !THEN
    RECODE DV (!QUOTE(!m3)='4').
    EXECUTE.
!IFEND
COMPUTE a1_w = m1_int*x_c.
EXECUTE.
COMPUTE cp_w = y_int*x_c.
EXECUTE.
COMPUTE b1_w = y_int*m1_c.
EXECUTE.
COMPUTE a1_b = meanx*m1_int.
EXECUTE.
COMPUTE cp_b = meanx*y_int.
EXECUTE.
COMPUTE b1_b = meanm1*y_int.
EXECUTE.
!IF (!modM ˜= !NULL) !THEN
    COMPUTE qM = modM_c*m1_int.
    EXECUTE.
    COMPUTE qM_x_a_w = qM*a1_w.
    COMPUTE qM_x_a_b = qM*a1_b.
    EXECUTE.
!IFEND
!IF (!modY ˜= !NULL) !THEN
    COMPUTE qY = ModY_c*y_int.
```

```
   EXECUTE.
   COMPUTE qY_x_b_w = qY*b1_w.
   COMPUTE qY_x_b_b = qY*b1_b.
   EXECUTE.
!IFEND
!IF (!cov1 ~= !NULL) !THEN
   COMPUTE g1m1_w = c1_c*m1_int.
   COMPUTE g1y_w = c1_c*y_int.
   COMPUTE g1m1_b = meanc1*m1_int.
   COMPUTE g1y_b = meanc1*y_int.
   EXECUTE.
!IFEND
!IF (!cov2 ~= !NULL) !THEN
   COMPUTE g2m1_w = c2_c*m1_int.
   COMPUTE g2y_w = c2_c*y_int.
   COMPUTE g2m1_b = meanc2*m1_int.
   COMPUTE g2y_b = meanc2*y_int.
   EXECUTE.
!IFEND
!IF (!cov3 ~= !NULL) !THEN
   COMPUTE g3m1_w = c3_c*m1_int.
   COMPUTE g3y_w = c3_c*y_int.
   COMPUTE g3m1_b = meanc3*m1_int.
   COMPUTE g3y_b = meanc3*y_int.
   EXECUTE.
!IFEND
!IF (!l2cov1 ~= !NULL) !THEN
   COMPUTE g1m1_2 = !l2cov1*m1_int.
   COMPUTE g1y_2 = !l2cov1*y_int.
   EXECUTE.
!IFEND
!IF (!l2cov2 ~= !NULL) !THEN
   COMPUTE g2m1_2 = !l2cov2*m1_int.
   COMPUTE g2y_2 = !l2cov2*y_int.
   EXECUTE.
!IFEND
!IF (!l2cov3 ~= !NULL) !THEN
   COMPUTE g3m1_2 = !l2cov3*m1_int.
   COMPUTE g3y_2 = !l2cov3*y_int.
   EXECUTE.
!IFEND
!IF (!m2 ~= !NULL) !THEN
   COMPUTE a2_w = m2_int*x_c.
   COMPUTE b2_w = y_int*m2_c.
   COMPUTE a2_b = m2_int*meanx.
   COMPUTE b2_b = y_int*meanm2.
   EXECUTE.
   !IF (!cov1 ~= !NULL) !THEN
      COMPUTE g1m2_w = c1_c*m2_int.
      COMPUTE g1m2_b = meanc1*m2_int.
      EXECUTE.
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```
   !IFEND
   !IF (!cov2 ~= !NULL) !THEN
      COMPUTE g2m2_w = c2_c*m2_int.
      COMPUTE g2m2_b = meanc2*m2_int.
      EXECUTE.
   !IFEND
   !IF (!cov3 ~= !NULL) !THEN
      COMPUTE g3m2_w = c3_c*m2_int.
      COMPUTE g3m2_b = meanc3*m2_int.
      EXECUTE.
   !IFEND
   !IF (!l2cov1 ~= !NULL) !THEN
      COMPUTE g1m2_2 = !l2cov1*m2_int.
      EXECUTE.
   !IFEND
   !IF (!l2cov2 ~= !NULL) !THEN
      COMPUTE g2m2_2 = !l2cov2*m2_int.
      EXECUTE.
   !IFEND
   !IF (!l2cov3 ~= !NULL) !THEN
      COMPUTE g3m2_2 = !l2cov3*m2_int.
      EXECUTE.
   !IFEND
!IFEND
!IF (!m3 ~= !NULL) !THEN
   COMPUTE a3_w = m3_int*x_c.
   COMPUTE b3_w = y_int*m3_c.
   COMPUTE a3_b = m3_int*meanx.
   COMPUTE b3_b = y_int*meanm3.
   EXECUTE.
   !IF (!cov1 ~= !NULL) !THEN
      COMPUTE g1m3_w = c1_c*m3_int.
      COMPUTE g1m3_b = meanc1*m3_int.
      EXECUTE.
   !IFEND
   !IF (!cov2 ~= !NULL) !THEN
      COMPUTE g2m3_w = c2_c*m3_int.
      COMPUTE g2m3_b = meanc2*m3_int.
      EXECUTE.
   !IFEND
   !IF (!cov3 ~= !NULL) !THEN
      COMPUTE g3m3_w = c3_c*m3_int.
      COMPUTE g3m3_B = meanc3*m3_int.
      EXECUTE.
   !IFEND
   !IF (!l2cov1 ~= !NULL) !THEN
      COMPUTE g1m3_2 = !l2cov1*m3_int.
      EXECUTE.
   !IFEND
   !IF (!l2cov2 ~= !NULL) !THEN
      COMPUTE g2m3_2 = !l2cov2*m3_int.
```

```
            EXECUTE.
     !IFEND
     !IF (!l2cov3 ~= !NULL) !THEN
           COMPUTE g3m3_2 = !l2cov3*m3_int.
           EXECUTE.
     !IFEND
!IFEND
!LET !rm2_1 = 0.
!LET !rm3_1 = 0.
!LET !rm1int_1 = 0.
!LET !rm2int_1 = 0.
!LET !rm3int_1 = 0.
!LET !ryint_1 = 0.
!LET !ylist_w = !CONCAT(constant, !BLANKS(1))
!LET !ylist_b = !CONCAT(!BLANKS(0))
!LET !m1list_w = !CONCAT(constant, !BLANKS(1))
!LET !m1list_b = !CONCAT(!BLANKS(0))
!LET !ranvar = !CONCAT(!BLANKS(0))
!LET !ranint = !CONCAT(!BLANKS(0))
!LET !ranslope = !CONCAT(!BLANKS(0))
!LET !ranslop2 = !CONCAT(!BLANKS(0))
!LET !varlist = !CONCAT(y_int, !BLANKS(1), m1_int)
!IF (!randYint = 1) !THEN
     !LET !ranvar = !CONCAT(!ranvar, y_int)
     !IF (!ycov = 1) !THEN
        !LET !ranslope = !CONCAT(!ranslope, y_int)
     !IFEND
     !LET !ryint_1 = 1.
!IFEND
!IF (!SUBSTR(!randMint,1,1) = 1) !THEN
     !LET !ranvar = !CONCAT(!ranvar,!BLANKS(1), m1_int)
     !LET !ranint = !CONCAT(!ranint, m1_int)
     !LET !rm1int_1 = 1.
!IFEND
!IF (!m2 ~= !NULL) !THEN
     !LET !rm2_1 = 1.
     !LET !varlist = !CONCAT(!varlist, !BLANKS(1), m2_int)
     !IF (!SUBSTR(!randMint,2,1) = 1) !THEN
        !LET !ranvar =  !CONCAT(!ranvar, !BLANKS(1), m2_int)
        !LET !ranint =  !CONCAT(!ranint, !BLANKS(1), m2_int)
        !LET !rm2int_1 = 1.
     !IFEND
     !LET !m2list_w = !CONCAT(constant, !BLANKS(1))
     !LET !m2list_b = !CONCAT(!BLANKS(0))
!IFEND
!IF (!m3 ~= !NULL) !THEN
     !LET !rm3_1 = 1.
     !LET !varlist = !CONCAT(!varlist, !BLANKS(1), m3_int)
     !IF (!SUBSTR(!randMint,3,1) = 1) !THEN
        !LET !ranvar =  !CONCAT(!ranvar, !BLANKS(1), m3_int)
        !LET !ranint =  !CONCAT(!ranint, !BLANKS(1), m3_int)
```

```
      !LET !rm3int_1 = 1.
   !IFEND
   !LET !m3list_w = !CONCAT(Int, !BLANKS(1))
   !LET !m3list_b = !CONCAT(!BLANKS(0))
!IFEND
!IF (!modM ~= !NULL) !THEN
   !LET !varlist =  !CONCAT(!varlist, !BLANKS(1), qM)
      !IF (!xW = 1) !THEN
            !LET !varlist =  !CONCAT(!varlist, !BLANKS(1), qM_x_a_w)
         !IFEND
   !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), !modM)
      !IF (!xW = 1) !THEN
            !LET !m1list_w = !CONCAT(!m1list_w, !BLANKS(1), int_1)
         !IFEND
   !IF (!Xb = 1) !THEN
      !IF (!modMB = 1) !THEN
         !LET !varlist =  !CONCAT(!varlist, !BLANKS(1), qM_x_a_b)
         !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), int_2)
      !IFEND
   !IFEND
!IFEND
!IF (!modY ~= !NULL) !THEN
   !LET !varlist =  !CONCAT(!varlist, !BLANKS(1), qY)
   !LET !varlist =  !CONCAT(!varlist, !BLANKS(1), qY_x_b_w)
   !IF (!modYB = 1) !THEN
      !LET !varlist =  !CONCAT(!varlist, !BLANKS(1), qY_x_b_b)
   !IFEND
   !LET !ylist_w = !CONCAT(!ylist_w, !BLANKS(1), int_1)
   !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !modY)
   !IF (!modYB = 1) !THEN
      !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), int_2)
   !IFEND
!IFEND
!IF (!xW = 1) !THEN
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), cp_w)
   !LET !ylist_w = !CONCAT(!ylist_w, !BLANKS(1), !x)
!IFEND
!IF (!xB = 1) !THEN
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), cp_b)
   !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !x)
!IFEND
!IF (!xW = 1) !THEN
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), a1_w)
   !LET !m1list_w = !CONCAT(!m1list_w, !BLANKS(1), !x)
!IFEND
!IF (!xB = 1) !THEN
   !LET !varlist = !CONCAT(!varlist,  !BLANKS(1), a1_b)
   !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), !x)
!IFEND
!LET !ylist_w = !CONCAT(!ylist_w, !BLANKS(1), !m1)
!LET !varlist = !CONCAT(!varlist, !BLANKS(1), b1_w)
```

```
!IF (!SUBSTR(!mB,1,1) = 1) !THEN
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), b1_b)
   !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !m1)
   !LET !bet_m1_1 = 1.
!IFEND
!IF (!m2 ~= !NULL) !THEN
   !IF (!xW = 1) !THEN
      !LET !varlist = !CONCAT(!varlist, !BLANKS(1), a2_w)
      !LET !m2list_w = !CONCAT(!m2list_w, !BLANKS(1), !x)
   !IFEND
      !IF (!xB = 1) !THEN
         !LET !varlist = !CONCAT(!varlist,  !BLANKS(1), a2_b)
         !LET !m2list_b = !CONCAT(!m2list_b, !BLANKS(1), !x)
      !IFEND
   !LET !ylist_w = !CONCAT(!ylist_w, !BLANKS(1), !m2)
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), b2_w)
   !IF (!SUBSTR(!mB,2,1) = 1) !THEN
      !LET !varlist = !CONCAT(!varlist, !BLANKS(1), b2_b)
      !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !m2)
      !LET !bet_m2_1 = 1.
   !IFEND
!IFEND
!IF (!m3 ~= !NULL) !THEN
   !IF (!xW = 1) !THEN
      !LET !varlist = !CONCAT(!varlist, !BLANKS(1), a3_w)
      !LET !m3list_w = !CONCAT(!m3list_w, !BLANKS(1), !x)
   !IFEND
      !IF (!xB = 1) !THEN
         !LET !varlist = !CONCAT(!varlist,  !BLANKS(1), a3_b)
         !LET !m3list_b = !CONCAT(!m3list_b, !BLANKS(1), !x)
      !IFEND
   !LET !ylist_w = !CONCAT(!ylist_w, !BLANKS(1), !m3)
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), b3_w)
   !IF (!SUBSTR(!mB,3,1) = 1) !THEN
      !LET !varlist = !CONCAT(!varlist, !BLANKS(1), b3_b)
      !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !m3)
      !LET !bet_m3_1 = 1.
   !IFEND
!IFEND
!IF (!cov1 ~= !NULL) !THEN
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1y_w)
   !IF (!bet_c1_1 = 1) !THEN
      !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1y_b)
   !IFEND
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1m1_w)
   !IF (!bet_c1_1 = 1) !THEN
      !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1m1_b)
   !IFEND
   !LET !ylist_w = !CONCAT(!ylist_w, !BLANKS(1), !cov1)
   !IF (!bet_c1_1 = 1) !THEN
      !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !cov1)
```

```
    !IFEND
    !LET !m1list_w = !CONCAT(!m1list_w, !BLANKS(1), !cov1)
    !IF (!bet_c1_1 = 1) !THEN
       !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), !cov1)
    !IFEND
    !IF (!m2 ~= !NULL) !THEN
        !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1m2_w)
        !IF (!bet_c1_1 = 1) !THEN
           !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1m2_b)
        !IFEND
        !LET !m2list_w = !CONCAT(!m2list_w, !BLANKS(1), !cov1)
        !IF (!bet_c1_1 = 1) !THEN
           !LET !m2list_b = !CONCAT(!m2list_b, !BLANKS(1), !cov1)
        !IFEND
    !IFEND
    !IF (!m3 ~= !NULL) !THEN
        !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1m3_w)
            !IF (!bet_c1_1 = 1) !THEN
                !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1m3_b)
            !IFEND
        !LET !m3list_w = !CONCAT(!m3list_w, !BLANKS(1), !cov1)
        !IF (!bet_c1_1 = 1) !THEN
           !LET !m3list_b = !CONCAT(!m3list_b, !BLANKS(1), !cov1)
        !IFEND
    !IFEND
!IFEND
!IF (!cov2 ~= !NULL) !THEN
    !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2y_w)
    !IF (!bet_c2_1 = 1) !THEN
       !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2y_b)
    !IFEND
     !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2m1_w)
    !IF (!bet_c2_1 = 1) !THEN
       !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2m1_b)
    !IFEND
    !LET !ylist_w = !CONCAT(!ylist_w, !BLANKS(1), !cov2)
    !IF (!bet_c2_1 = 1) !THEN
        !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !cov2)
        !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), !cov2)
    !IFEND
    !LET !m1list_w = !CONCAT(!m1list_w, !BLANKS(1), !cov2)
    !IF (!m2 ~= !NULL) !THEN
        !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2m2_w)
        !IF (!bet_c2_1 = 1) !THEN
           !LET !varlist = !CONCAT(!varlist,  !BLANKS(1), g2m2_b)
        !IFEND
        !LET !m2list_w = !CONCAT(!m2list_w, !BLANKS(1), !cov2)
        !IF (!bet_c2_1 = 1) !THEN
           !LET !m2list_b = !CONCAT(!m2list_b, !BLANKS(1), !cov2)
        !IFEND
    !IFEND
```

```
    !IF (!m3 ~= !NULL) !THEN
        !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2m3_w)
        !IF (!bet_c2_1 = 1) !THEN
            !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2m3_b)
        !IFEND
        !LET !m3list_w = !CONCAT(!m3list_w, !BLANKS(1), !cov2)
        !IF (!bet_c2_1 = 1) !THEN
            !LET !m3list_b = !CONCAT(!m3list_b, !BLANKS(1), !cov2)
        !IFEND
    !IFEND
!IFEND
!IF (!cov3 ~= !NULL) !THEN
    !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g3y_w)
    !IF (!bet_c3_1 = 1) !THEN
        !LET !varlist = !CONCAT(!varlist,!BLANKS(1), g3y_b)
    !IFEND
    !LET !varlist = !CONCAT(!varlist,!BLANKS(1), g3m1_w)
    !IF (!bet_c3_1 = 1) !THEN
        !LET !varlist = !CONCAT(!varlist,!BLANKS(1), g3m1_b)
    !IFEND
    !LET !ylist_w = !CONCAT(!ylist_w, !BLANKS(1), !cov3)
    !LET !m1list_w = !CONCAT(!m1list_w, !BLANKS(1), !cov3)
    !IF (!bet_c3_1 = 1) !THEN
        !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !cov3)
        !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), !cov3)
    !IFEND
    !IF (!m2 ~= !NULL) !THEN
        !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g3m2_w)
        !IF (!bet_c3_1 = 1) !THEN
            !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g3m2_b)
            !LET !m2list_b = !CONCAT(!m2list_b, !BLANKS(1), !cov3)
        !IFEND
        !LET !m2list_w = !CONCAT(!m2list_w, !BLANKS(1), !cov3)
    !IFEND
    !IF (!m3 ~= !NULL) !THEN
        !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g3m3_w)
        !IF (!bet_c3_1 = 1) !THEN
            !LET !varlist = !CONCAT(!varlist,  !BLANKS(1), g3m3_b)
            !LET !m3list_b = !CONCAT(!m3list_b, !BLANKS(1), !cov3)
        !IFEND
        !LET !m3list_w = !CONCAT(!m3list_w, !BLANKS(1), !cov3)
    !IFEND
!IFEND
!IF (!l2cov1 ~= !NULL) !THEN
    !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1y_2, !BLANKS(1),
        g1m1_2)
    !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !l2cov1)
    !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov1)
    !IF (!m2 ~= !NULL) !THEN
        !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1m2_2)
        !LET !m2list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov1)
```

```
      !IFEND
      !IF (!m3 ~= !NULL) !THEN
          !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g1m3_2)
          !LET !m3list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov1)
      !IFEND
!IFEND
!IF (!l2cov2 ~= !NULL) !THEN
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2y_2, !BLANKS(1),
      g2m1_2)
   !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !l2cov2)
   !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov2)
   !IF (!m2 ~= !NULL) !THEN
       !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2m2_2)
       !LET !m2list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov2)
   !IFEND
   !IF (!m3 ~= !NULL) !THEN
       !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g2m3_2)
       !LET !m3list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov2)
   !IFEND
!IFEND
!IF (!l2cov3 ~= !NULL) !THEN
   !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g3y_2, !BLANKS(1),
      g3m1_2)
   !LET !ylist_b = !CONCAT(!ylist_b, !BLANKS(1), !l2cov3)
   !LET !m1list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov3)
   !IF (!m2 ~= !NULL) !THEN
       !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g3m2_2)
       !LET !m2list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov3)
   !IFEND
   !IF (!m3 ~= !NULL) !THEN
       !LET !varlist = !CONCAT(!varlist, !BLANKS(1), g3m3_2)
       !LET !m3list_b = !CONCAT(!m1list_b, !BLANKS(1), !l2cov3)
   !IFEND
!IFEND
!LET !rcp_1 = 0.
!LET !ra1_1 = 0.
!LET !ra2_1 = 0.
!LET !ra3_1 = 0.
!LET !rb1_1 = 0.
!LET !rb2_1 = 0.
!LET !rb3_1 = 0.
!IF (!SUBSTR(!randx,1,1) = 1) !THEN
   !LET !rcp_1 = 1.
   !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1),cp_w).
   !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1),cp_w).
   !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1),cp_w).
!IFEND
!IF (!SUBSTR(!randx,2,1) = 1) !THEN
   !LET !ra1_1 = 1.
   !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), a1_w).
   !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), a1_w).
```

```
      !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), a1_w).
!IFEND
!IF (!m2 ~= !NULL) !THEN
   !IF (!SUBSTR(!randx,3,1) = 1) !THEN
      !LET !ra2_1 = 1.
      !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), a2_w).
      !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), a2_w).
      !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), a2_w).
   !IFEND
!IFEND
!IF (!m3 ~= !NULL) !THEN
   !IF (!SUBSTR(!randx,4,1) = 1) !THEN
      !LET !ra3_1 = 1.
      !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), a3_w).
      !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), a3_w).
      !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), a3_w).
   !IFEND
!IFEND
!IF (!SUBSTR(!randm,1,1) = 1) !THEN
   !LET !rb1_1 = 1.
   !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1),b1_w).
   !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1),b1_w).
   !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1),b1_w).
!IFEND
!IF (!m2 ~= !NULL) !THEN
   !IF (!SUBSTR(!randm,2,1) = 1) !THEN
      !LET !rb2_1 = 1.
      !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), b2_w).
      !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), b2_w).
      !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), b2_w).
   !IFEND
!IFEND
!IF (!m3 ~= !NULL) !THEN
   !IF (!SUBSTR(!randm,3,1) = 1) !THEN
      !LET !rb3_1 = 1.
      !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), b3_w).
      !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), b3_w).
      !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), b3_w).
   !IFEND
!IFEND
!IF (!cov1 ~= !NULL) !THEN
   !IF (!SUBSTR(!randc1,1,1) = 1) !THEN
      !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g1y_w).
      !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g1y_w).
      !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g1y_w).
   !IFEND
      !IF (!SUBSTR(!randc1,2,1) = 1) !THEN
         !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g1m1_w).
         !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g1m1_w).
         !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g1m1_w).
      !IFEND
```

```
!IF (!m2 ~= !NULL) !THEN
    !IF (!SUBSTR(!randc1,3,1) = 1) !THEN
        !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g1m2_w).
        !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g1m2_w).
        !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g1m2_w).
    !IFEND
!IFEND
!IF (!m3 ~= !NULL) !THEN
    !IF (!SUBSTR(!randc1,4,1) = 1) !THEN
        !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g1m3_w).
        !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g1m3_w).
        !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g1m3_w).
    !IFEND
!IFEND
!IFEND
!IF (!cov2 ~= !NULL) !THEN
    !IF (!SUBSTR(!randc2,1,1) = 1) !THEN
        !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g2y_w).
        !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g2y_w).
        !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g2y_w).
    !IFEND
        !IF (!SUBSTR(!randc2,2,1) = 1) !THEN
            !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g2m1_w).
            !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g2m1_w).
            !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g2m1_w).
        !IFEND
    !IF (!m2 ~= !NULL) !THEN
        !IF (!SUBSTR(!randc2,3,1) = 1) !THEN
            !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g2m2_w).
            !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g2m2_w).
            !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g2m2_w).
        !IFEND
    !IFEND
    !IF (!m3 ~= !NULL) !THEN
        !IF (!SUBSTR(!randc2,4,1) = 1) !THEN
            !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g2m3_w).
            !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g2m3_w).
            !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g2m3_w).
        !IFEND
    !IFEND
!IFEND
!IF (!cov3 ~= !NULL) !THEN
    !IF (!SUBSTR(!randc3,1,1) = 1) !THEN
        !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g3y_w).
        !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g3y_w).
        !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g3y_w).
    !IFEND
        !IF (!SUBSTR(!randc3,2,1) = 1) !THEN
            !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g3m1_w).
            !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g3m1_w).
            !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g3m1_w).
```

```
      !IFEND
    !IF (!m2 ~= !NULL) !THEN
       !IF (!SUBSTR(!randc3,3,1) = 1) !THEN
          !LET !ranvar = !CONCAT(!ranvar, !BLANKS(1), g3m2_w).
          !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g3m2_w).
          !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g3m2_w).
       !IFEND
    !IFEND
    !IF (!m3 ~= !NULL) !THEN
       !IF (!SUBSTR(!randc3,4,1) = 1) !THEN
          !LET !ranvar = !CONCAT(!ranslope, !BLANKS(1), g3m3_w).
          !LET !ranslope = !CONCAT(!ranslope, !BLANKS(1), g3m3_w).
          !LET !ranslop2 = !CONCAT(!ranslop2, !BLANKS(1), g3m3_w).
       !IFEND
    !IFEND
!IFEND
!LET !rmint = 0.
!IF (!rm1int_1 = 1) !THEN
   !LET !rmint = 1.
!IFEND
!IF (!rm2int_1 = 1) !THEN
   !LET !rmint = 1.
!IFEND
!IF (!rm3int_1 = 1) !THEN
   !LET !rmint = 1.
!IFEND
!LET !intcovmat = ID.
!IF (!rm1int_1 = 1 !AND !rm2int_1 = 1) !THEN
   !LET !intcovmat = !mcovmat.
!IFEND
!IF (!rm1int_1 = 1 !AND !rm3int_1 = 1) !THEN
   !LET !intcovmat = !mcovmat.
!IFEND
!IF (!rm2int_1 = 1 !AND !rm3int_1 = 1) !THEN
   !LET !intcovmat = !mcovmat.
!IFEND
!LET !int_1 = (!intcovmat = UN).
!LET !ycov_1 = (!ycov = 1).
!LET !indint_1 = (!indint = 1).
!LET !covs = 1.
OMS
  /SELECT TABLES
  /IF COMMANDS=['Mixed'] SUBTYPES=['G Matrix']
  /DESTINATION FORMAT=SAV
   OUTFILE=!QUOTE(!CONCAT(!folder,g_mat.sav)) VIEWER=NO.
OMS
  /SELECT TABLES
  /IF COMMANDS=['Mixed'] SUBTYPES=['Parameter Estimates']
  /DESTINATION FORMAT=SAV NUMBERED=TableNumber_
   OUTFILE=!QUOTE(!CONCAT(!folder,p_est.sav)) VIEWER=NO.
* OMS.
```

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```
OMS
  /SELECT TABLES
  /IF COMMANDS=['Mixed'] SUBTYPES=['Covariance Matrix']
  /DESTINATION FORMAT=SAV NUMBERED=TableNumber_
   OUTFILE=!QUOTE(!CONCAT(!folder,cov_mat.sav)) VIEWER=!asym
  /COLUMNS SEQUENCE=[RALL CALL LALL].
* OMS.
OMS
  /SELECT TABLES
  /IF COMMANDS=['Mixed'] SUBTYPES=['Tests of Fixed Effects']
  /DESTINATION VIEWER=NO.
* OMS.
OMS
  /SELECT TABLES
  /IF COMMANDS=['Mixed'] SUBTYPES=['Model Dimension']
  /DESTINATION FORMAT=SAV NUMBERED=TableNumber_
   OUTFILE=!QUOTE(!CONCAT(!folder,mod_dim.sav)) VIEWER=NO.
OMS
  /SELECT TABLES
  /IF COMMANDS=['Mixed'] SUBTYPES=['Covariance Parameter Estimates']
  /DESTINATION FORMAT=SAV NUMBERED=TableNumber_
   OUTFILE=!QUOTE(!CONCAT(!folder,cov_p_est.sav)) VIEWER=!asym.
OMS
  /SELECT TABLES
  /IF COMMANDS=['Mixed'] SUBTYPES=['Information Criteria']
  /DESTINATION FORMAT=SAV NUMBERED=TableNumber_
   OUTFILE=!QUOTE(!CONCAT(!folder,fit_stat.sav)) VIEWER=NO.
!IF (!indint = 0 !OR !rmint = 0) !THEN
   !IF (!ycov = 1 !OR !indint = 0) !THEN
      MIXED
       Z WITH !varlist
       /CRITERIA = CIN(!conf) MXITER(!iters) MXSTEP(!mxstep) SCORING(!
          scoring)
       /FIXED =  !varlist | NOINT SSTYPE(3)
       /METHOD = !est
       /PRINT = COVB G SOLUTION TESTCOV
       /RANDOM !ranvar | SUBJECT(!cluster) COVTYPE(!covmat)
       /REPEATED DV | SUBJECT(case_num*!cluster) COVTYPE(!rescovmat).
      EXECUTE.
   !ELSE
      !IF (!ranslope ~= !BLANKS(0)) !THEN
        MIXED
          Z WITH !varlist
          /CRITERIA = CIN(!conf) MXITER(!iters) MXSTEP(!mxstep) SCORING
             (!scoring)
          /FIXED =  !varlist | NOINT SSTYPE(3)
          /METHOD = !est
          /PRINT = COVB G SOLUTION TESTCOV
          /RANDOM y_int | SUBJECT(!cluster) COVTYPE(ID)
          /RANDOM !ranslope | SUBJECT(!cluster) COVTYPE(!covmat)
          /REPEATED DV | SUBJECT(case_num*!cluster) COVTYPE(!rescovmat).
```

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```
            EXECUTE.
         !ELSE
            MIXED
             Z WITH !varlist
             /CRITERIA = CIN(!conf) MXITER(!iters) MXSTEP(!mxstep) SCORING
                 (!scoring)
             /FIXED =  !varlist | NOINT SSTYPE(3)
             /METHOD = !est
             /PRINT = COVB G SOLUTION TESTCOV
             /RANDOM y_int | SUBJECT(!cluster) COVTYPE(ID)
             /REPEATED DV | SUBJECT(case_num*!cluster) COVTYPE(!rescovmat).
            EXECUTE.
            !LET !covs = 0.
         !IFEND
      !IFEND
!ELSE
   !IF (!ycov = 1) !THEN
      !IF (!ranslop2 ~= !BLANKS(0)) !THEN
         MIXED
          Z WITH !varlist
          /CRITERIA = CIN(!conf) MXITER(!iters) MXSTEP(!mxstep) SCORING
              (!scoring)
          /FIXED =  !varlist | NOINT SSTYPE(3)
          /METHOD = !est
          /PRINT = COVB G SOLUTION TESTCOV
          /RANDOM !ranint | SUBJECT(!cluster) COVTYPE(!intcovmat)
          /RANDOM !ranslope | SUBJECT(!cluster) COVTYPE(!covmat)
          /REPEATED DV | SUBJECT(case_num*!cluster) COVTYPE(!rescovmat).
         EXECUTE.
      !ELSE
         MIXED
          Z WITH !varlist
          /CRITERIA = CIN(!conf) MXITER(!iters) MXSTEP(!mxstep) SCORING
              (!scoring)
          /FIXED =  !varlist | NOINT SSTYPE(3)
          /METHOD = !est
          /PRINT = COVB G SOLUTION TESTCOV
          /RANDOM !ranint | SUBJECT(!cluster) COVTYPE(!intcovmat)
          /RANDOM !ranslope | SUBJECT(!cluster) COVTYPE(ID)
          /REPEATED DV | SUBJECT(case_num*!cluster) COVTYPE(!rescovmat).
         EXECUTE.
         !LET !covs = 0.
      !IFEND
   !ELSE
      !IF (!ranslope ~= !BLANKS(0)) !THEN
         MIXED
          Z WITH !varlist
          /CRITERIA = CIN(!conf) MXITER(!iters) MXSTEP(!mxstep) SCORING
              (!scoring)
          /FIXED =  !varlist | NOINT SSTYPE(3)
          /METHOD = !est
```

```
                /PRINT = COVB G SOLUTION TESTCOV
                /RANDOM !ranint | SUBJECT(!cluster) COVTYPE(!intcovmat)
                /RANDOM y_int | SUBJECT(!cluster) COVTYPE(ID)
                /RANDOM !ranslope | SUBJECT(!cluster) COVTYPE(!covmat)
                /REPEATED DV | SUBJECT(case_num*!cluster) COVTYPE(!rescovmat).
              EXECUTE.
          !ELSE
             MIXED
               Z WITH !varlist
               /CRITERIA = CIN(!conf) MXITER(!iters) MXSTEP(!mxstep) SCORING
                   (!scoring)
               /FIXED =  !varlist | NOINT SSTYPE(3)
               /METHOD = !est
               /PRINT = COVB G SOLUTION TESTCOV
               /RANDOM !ranint | SUBJECT(!cluster) COVTYPE(!intcovmat)
               /RANDOM y_int | SUBJECT(!cluster) COVTYPE(ID)
               /REPEATED DV | SUBJECT(case_num*!cluster) COVTYPE(!rescovmat).
             EXECUTE.
             !LET !covs = 0.
         !IFEND
      !IFEND
   !IFEND
   OMSEND.
   OUTPUT MODIFY
     /REPORT PRINTREPORT=NO
     /SELECT HEADINGS
     /IF COMMANDS=["Mixed(LAST)"] LABELS=[EXACT("Title")] INSTANCES=[3]
     /DELETEOBJECT DELETE=YES
     /SELECT HEADINGS
     /IF COMMANDS=["Mixed(LAST)"] LABELS=[EXACT("Title")] INSTANCES=[2]
     /DELETEOBJECT DELETE=YES
     /SELECT HEADINGS
     /IF COMMANDS=["Mixed(LAST)"] LABELS=[EXACT("Title")] INSTANCES=[1]
     /DELETEOBJECT DELETE=YES.
   !IF (!indint = 0 !OR !rmint = 0) !THEN
      !IF (!ycov = 0) !THEN
         OUTPUT MODIFY
           /REPORT PRINTREPORT=NO
           /SELECT HEADINGS
           /IF COMMANDS=["Mixed(LAST)"] LABELS=[EXACT("Title")] INSTANCES
               =[1]
           /DELETEOBJECT DELETE=YES.
      !IFEND
   !ELSE
      !IF (!ycov = 1) !THEN
         OUTPUT MODIFY
           /REPORT PRINTREPORT=NO
           /SELECT HEADINGS
           /IF COMMANDS=["Mixed(LAST)"] LABELS=[EXACT("Title")] INSTANCES
               =[1]
           /DELETEOBJECT DELETE=YES.
```

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```
    !ELSE
        OUTPUT MODIFY
          /REPORT PRINTREPORT=NO
          /SELECT HEADINGS
          /IF COMMANDS=["Mixed(LAST)"] LABELS=[EXACT("Title")] INSTANCES
              =[1]
          /DELETEOBJECT DELETE=YES.
        OUTPUT MODIFY
          /REPORT PRINTREPORT=NO
          /SELECT HEADINGS
          /IF COMMANDS=["Mixed(LAST)"] LABELS=[EXACT("Title")] INSTANCES
              =[1]
          /DELETEOBJECT DELETE=YES.
    !IFEND
!IFEND
DATASET CLOSE mlmdata.
DATASET ACTIVATE !data.
MATRIX.
GET fit_stat/file=!QUOTE(!CONCAT(!folder,fit_stat.sav))/variables = Var2
    /MISSING = ACCEPT/SYSMIS=-999.
GET estim/file=!QUOTE(!CONCAT(!folder,p_est.sav))/variables = Estimate
    To UpperBound/MISSING = ACCEPT/SYSMIS=-999.
GET g/file=!QUOTE(!CONCAT(!folder,g_mat.sav))/MISSING = ACCEPT/SYSMIS=0.
GET cov_mat/file=!QUOTE(!CONCAT(!folder,cov_mat.sav))/MISSING = ACCEPT/
    SYSMIS=-999.
GET cov_p/file=!QUOTE(!CONCAT(!folder,cov_p_est.sav))/variables =
    Estimate TO UpperBound/MISSING = ACCEPT/SYSMIS=-999.
GET mod_dim/file=!QUOTE(!CONCAT(!folder,mod_dim.sav))/variables =
    NumberofParameters NumberofSubjects/MISSING = ACCEPT/SYSMIS=-999.
print /title = "*****************************  MLmed
    *****************************".
print /title = "*******************************************
****************************".
compute est = estim(:,1).
compute yeq = estim(1,:).
compute m1eq = estim(2,:).
compute num_int = 2.
compute num_rint = 0.
do if (!ryint_1 = 1).
   compute num_rint = num_rint + 1.
end if.
do if (!rm1int_1 = 1).
   compute num_rint = num_rint + 1.
end if.
do if (!m2_1 = 1).
   compute num_int = num_int + 1.
   compute m2eq = estim(num_int,:).
   do if (!rm2int_1 = 1).
      compute num_rint = num_rint + 1.
   end if.
end if.
```

```
do if (!m3_1 = 1).
   compute num_int = num_int + 1.
   compute m3eq = estim(num_int,:).
   do if (!rm3int_1 = 1).
      compute num_rint = num_rint + 1.
   end if.
end if.
compute sca1b1b = 0.
compute sca2b2b = 0.
compute sca3b3b = 0.
compute num_fix = nrow(est).
compute num_ran = nrow(g).
compute g = g(1:num_ran, 5:(4 + num_ran)).
compute cov_fix = reshape(cov_mat(1, 5:(4 + num_fix**2)), num_fix,
   num_fix).
do if (!rescov_1 = 1).
   compute rfx = cov_p(((num_int&*(num_int + 1)/2) + 1):nrow(cov_p),:).
   compute resfx = cov_p(1:(num_int&*(num_int + 1)/2),:).
else.
   compute rfx = cov_p((num_int + 1):nrow(cov_p),:).
   compute resfx = cov_p(1:num_int,:).
end if.
compute sampsize = mod_dim((nrow(mod_dim)-1),2).
compute tot_par = mod_dim(nrow(mod_dim),1).
compute fix_par = num_fix.
compute ran_l1_p = nrow(resfx).
compute ran_l2_p = tot_par-fix_par-ran_l1_p.
compute mod_spec = {sampsize; fix_par; ran_l1_p; ran_l2_p; tot_par}.
compute ran_mat =(cov_mat(2,((5 + num_fix**2):ncol(cov_mat)))).
compute ranmatn = sqrt(ncol(ran_mat)).
compute cov_ran = reshape(ran_mat, ranmatn, ranmatn).
do if (!rescov_1 = 1).
   compute cov_ran = cov_ran(((num_rint&**2 + 1):ncol(cov_ran)), ((
      num_rint&**2 + 1):ncol(cov_ran))).
else.
   compute cov_ran = cov_ran(((num_rint + 1):ncol(cov_ran)), ((num_rint
      + 1):ncol(cov_ran))).
end if.
compute m1tab_b = {0,0,0,0,0,0,0}.
compute m2tab_b = {0,0,0,0,0,0,0}.
compute m3tab_b = {0,0,0,0,0,0,0}.
compute ytab_b = {0,0,0,0,0,0,0}.
compute fcount = 1.
compute y_int = est(fcount, :).
compute ytab_w = estim(fcount,:).
compute svy_int = cov_fix(fcount, fcount).
compute fcount = fcount + 1.
compute m1_int = est(fcount,:).
compute m1tab_w = estim(fcount,:).
compute svm1_int = cov_fix(fcount, fcount).
compute fcount = fcount + 1.
```

```
do if (!m2_1 = 1).
   compute m2_int = est(fcount,:).
   compute m2tab_w = estim(fcount,:).
   compute svm2_int = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
end if.
do if (!m3_1 = 1).
   compute m3_int = est(fcount,:).
   compute m3tab_w = estim(fcount,:).
   compute svm3_int = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
end if.
do if (!ModM_1 = 1).
   compute qM = est(fcount,:).
   compute m1tab_b = {m1tab_b; estim(fcount,:)}.
   compute svqM = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
   do if (!wit_x_1 = 1).
      compute qMxaw = est(fcount,:).
      compute m1tab_w = {m1tab_w; estim(fcount,:)}.
      compute qMxaw_l = fcount.
      compute svqMxaw = cov_fix(fcount, fcount).
      compute fcount = fcount + 1.
   end if.
   do if (!bet_x_1 = 1 AND !modMB_1 = 1).
      compute qMxab = est(fcount,:).
      compute m1tab_b = {m1tab_b; estim(fcount,:)}.
      compute qMxab_l = fcount.
      compute svqMxab = cov_fix(fcount, fcount).
      compute fcount = fcount + 1.
   end if.
end if.
do if (!ModY_1 = 1).
   compute qY = est(fcount,:).
   compute Ytab_b = {Ytab_b; estim(fcount,:)}.
   compute qY_l = fcount.
   compute svqY = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
   compute qYxbw = est(fcount,:).
   compute Ytab_w = {Ytab_w; estim(fcount,:)}.
   compute qYxbw_l = fcount.
   compute svqYxbw = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
   do if (!modYB_1 = 1).
      compute qYxbb = est(fcount,:).
      compute Ytab_b = {Ytab_b; estim(fcount,:)}.
      compute qYxbb_l = fcount.
      compute svqYxbb = cov_fix(fcount, fcount).
      compute fcount = fcount + 1.
   end if.
end if.
```

```
do if (!wit_x_1 = 1).
   compute cp_w = est(fcount,:).
   compute Ytab_w = {Ytab_w; estim(fcount,:)}.
   compute cp_w_l = fcount.
   compute svcp_w = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
end if.
do if (!bet_x_1 = 1).
   compute cp_b = est(fcount,:).
   compute Ytab_b = {Ytab_b; estim(fcount,:)}.
   compute cp_b_l = fcount.
   compute svcp_b = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
end if.
do if (!wit_x_1 = 1).
   compute a1_w = est(fcount,:).
   compute m1tab_w = {m1tab_w; estim(fcount,:)}.
   compute a1_w_l = fcount.
   compute sva1_w = cov_fix(fcount, fcount).
   do if (!bet_x_1 = 1).
      compute sca1b1w = cov_fix(fcount, fcount + 2).
   else.
      compute sca1b1w = cov_fix(fcount, fcount + 1).
   end if.
   compute fcount = fcount + 1.
end if.
do if (!bet_x_1 = 1).
   compute a1_b = est(fcount,:).
   compute m1tab_b = {m1tab_b; estim(fcount,:)}.
   compute a1_b_l = fcount.
   compute sva1_b = cov_fix(fcount, fcount).
   do if (!bet_m1_1 = 1).
      compute sca1b1b = cov_fix(fcount, fcount + 2).
   end if.
   compute fcount = fcount + 1.
end if.
compute b1_w = est(fcount,:).
compute Ytab_w = {Ytab_w; estim(fcount,:)}.
compute b1_w_l = fcount.
compute svb1_w = cov_fix(fcount, fcount).
compute fcount = fcount + 1.
do if (!bet_m1_1 = 1).
   compute b1_b = est(fcount,:).
   compute Ytab_b = {Ytab_b; estim(fcount,:)}.
   compute b1_b_l = fcount.
   compute svb1_b = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
end if.
do if (!wit_x_1 = 1).
   compute sca1b1w = cov_fix(a1_w_l, b1_w_l).
end if.
```

```
do if (!bet_x_1 = 1 AND !bet_m1_1 = 1).
   compute sca1b1b = cov_fix(a1_b_l, b1_b_l).
end if.
do if (!m2_1 = 1).
   do if (!wit_x_1 = 1).
      compute a2_w = est(fcount,:).
      compute m2tab_w = {m2tab_w; estim(fcount,:)}.
      compute a2_w_l = fcount.
      compute sva2_w = cov_fix(fcount, fcount).
      do if (!bet_x_1 = 1).
         compute sca2b2w = cov_fix(fcount, fcount + 2).
      else.
         compute sca2b2w = cov_fix(fcount, fcount + 1).
      end if.
      compute fcount = fcount + 1.
   end if.
   do if (!bet_x_1 = 1).
      compute a2_b = est(fcount,:).
      compute m2tab_b = {m2tab_b; estim(fcount,:)}.
      compute a2_b_l = fcount.
      compute sva2_b = cov_fix(fcount, fcount).
      do if (!bet_m2_1 = 1).
         compute sca2b2b = cov_fix(fcount, fcount + 2).
      end if.
      compute fcount = fcount + 1.
   end if.
   compute b2_w = est(fcount,:).
   compute Ytab_w = {Ytab_w; estim(fcount,:)}.
   compute b2_w_l = fcount.
   compute svb2_w = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
   do if (!bet_m2_1 = 1).
      compute b2_b = est(fcount,:).
      compute Ytab_b = {Ytab_b; estim(fcount,:)}.
      compute b2_b_l = fcount.
      compute svb2_b = cov_fix(fcount, fcount).
      compute fcount = fcount + 1.
   end if.
   do if (!wit_x_1 = 1).
      compute sca2b2w = cov_fix(a2_w_l, b2_w_l).
   end if.
   do if (!bet_x_1 = 1 AND !bet_m2_1 = 1).
      compute sca2b2b = cov_fix(a2_b_l, b2_b_l).
   end if.
end if.
do if (!m3_1 = 1).
   do if (!wit_x_1 = 1).
      compute a3_w = est(fcount,:).
      compute m3tab_w = {m3tab_w; estim(fcount,:)}.
      compute a3_w_l = fcount.
      compute sva3_w = cov_fix(fcount, fcount).
```

```
      do if (!bet_x_1 = 1).
         compute sca3b3w = cov_fix(fcount, fcount + 2).
      else.
         compute sca3b3w = cov_fix(fcount, fcount + 1).
      end if.
      compute fcount = fcount + 1.
   end if.
   do if (!bet_x_1 = 1).
      compute a3_b = est(fcount,:).
      compute m3tab_b = {m3tab_b; estim(fcount,:)}.
      compute a3_b_l = fcount.
      compute sva3_b = cov_fix(fcount, fcount).
      do if (!bet_m3_1 = 1).
         compute sca3b3b = cov_fix(fcount, fcount + 2).
      end if.
      compute fcount = fcount + 1.
   end if.
   compute b3_w = est(fcount,:).
   compute Ytab_w = {Ytab_w; estim(fcount,:)}.
   compute b3_w_l = fcount.
   compute svb3_w = cov_fix(fcount, fcount).
   compute fcount = fcount + 1.
   do if (!bet_m2_1 = 1).
      compute b3_b = est(fcount,:).
      compute Ytab_b = {Ytab_b; estim(fcount,:)}.
      compute b3_b_l = fcount.
      compute svb3_b = cov_fix(fcount, fcount).
      compute fcount = fcount + 1.
   end if.
   do if (!wit_x_1 = 1).
      compute sca3b3w = cov_fix(a3_w_l, b3_w_l).
   end if.
   do if (!bet_x_1 = 1).
      compute sca3b3b = cov_fix(a3_b_l, b3_b_l).
   end if.
end if.
do if (!cov1_1 = 1).
   compute Ytab_w = {Ytab_w; estim(fcount,:)}.
   compute fcount = fcount + 1.
   do if (!bet_c1_1 = 1).
      compute Ytab_b = {Ytab_b; estim(fcount,:)}.
      compute fcount = fcount + 1.
   end if.
   compute m1tab_w = {m1tab_w; estim(fcount,:)}.
   compute fcount = fcount + 1.
   do if (!bet_c1_1 = 1).
      compute m1tab_b = {m1tab_b; estim(fcount,:)}.
      compute fcount = fcount + 1.
   end if.
   do if (!m2_1 = 1).
      compute m2tab_w = {m2tab_w; estim(fcount,:)}.
```

```
         compute fcount = fcount + 1.
         do if (!bet_c1_1 = 1).
            compute m2tab_b = {m2tab_b; estim(fcount,:)}.
            compute fcount = fcount + 1.
         end if.
      end if.
      do if (!m3_1 = 1).
         compute m3tab_w = {m3tab_w; estim(fcount,:)}.
         compute fcount = fcount + 1.
         do if (!bet_c1_1 = 1).
            compute m3tab_b = {m3tab_b; estim(fcount,:)}.
            compute fcount = fcount + 1.
         end if.
      end if.
   end if.
   do if (!cov2_1 = 1).
      compute Ytab_w = {Ytab_w; estim(fcount,:)}.
      compute fcount = fcount + 1.
      do if (!bet_c2_1 = 1).
         compute Ytab_b = {Ytab_b; estim(fcount,:)}.
         compute fcount = fcount + 1.
      end if.
      compute m1tab_w = {m1tab_w; estim(fcount,:)}.
      compute fcount = fcount + 1.
      do if (!bet_c2_1 = 1).
         compute m1tab_b = {m1tab_b; estim(fcount,:)}.
         compute fcount = fcount + 1.
      end if.
      do if (!m2_1 = 1).
         compute m2tab_w = {m2tab_w; estim(fcount,:)}.
         compute fcount = fcount + 1.
         do if (!bet_c2_1 = 1).
            compute m2tab_b = {m2tab_b; estim(fcount,:)}.
            compute fcount = fcount + 1.
         end if.
      end if.
      do if (!m3_1 = 1).
         compute m3tab_w = {m3tab_w; estim(fcount,:)}.
         compute fcount = fcount + 1.
         do if (!bet_c2_1 = 1).
            compute m3tab_b = {m3tab_b; estim(fcount,:)}.
            compute fcount = fcount + 1.
         end if.
      end if.
   end if.
   do if (!cov3_1 = 1).
      compute Ytab_w = {Ytab_w; estim(fcount,:)}.
      compute fcount = fcount + 1.
      do if (!bet_c3_1 = 1).
         compute Ytab_b = {Ytab_b; estim(fcount,:)}.
         compute fcount = fcount + 1.
```

```
      end if.
      compute m1tab_w = {m1tab_w; estim(fcount,:)}.
      compute fcount = fcount + 1.
      do if (!bet_c3_1 = 1).
         compute m1tab_b = {m1tab_b; estim(fcount,:)}.
         compute fcount = fcount + 1.
      end if.
      do if (!m2_1 = 1).
         compute m2tab_w = {m2tab_w; estim(fcount,:)}.
         compute fcount = fcount + 1.
         do if (!bet_c3_1 = 1).
            compute m2tab_b = {m2tab_b; estim(fcount,:)}.
            compute fcount = fcount + 1.
         end if.
      end if.
      do if (!m3_1 = 1).
         compute m3tab_w = {m3tab_w; estim(fcount,:)}.
         compute fcount = fcount + 1.
         do if (!bet_c3_1 = 1).
            compute m3tab_b = {m3tab_b; estim(fcount,:)}.
            compute fcount = fcount + 1.
         end if.
      end if.
end if.
do if (!l2cov1_1 = 1).
   compute Ytab_b = {Ytab_b; estim(fcount,:)}.
   compute fcount = fcount + 1.
   compute m1tab_b = {m1tab_b; estim(fcount,:)}.
   compute fcount = fcount + 1.
   do if (!m2_1 = 1).
      compute m2tab_b = {m2tab_b; estim(fcount,:)}.
      compute fcount = fcount + 1.
   end if.
   do if (!m3_1 = 1).
      compute m3tab_b = {m3tab_b; estim(fcount,:)}.
      compute fcount = fcount + 1.
   end if.
end if.
do if (!l2cov2_1 = 1).
   compute Ytab_b = {Ytab_b; estim(fcount,:)}.
   compute fcount = fcount + 1.
   compute m1tab_b = {m1tab_b; estim(fcount,:)}.
   compute fcount = fcount + 1.
   do if (!m2_1 = 1).
      compute m2tab_b = {m2tab_b; estim(fcount,:)}.
      compute fcount = fcount + 1.
   end if.
   do if (!m3_1 = 1).
      compute m3tab_b = {m3tab_b; estim(fcount,:)}.
      compute fcount = fcount + 1.
   end if.
```

```
end if.
do if (!l2cov3_1 = 1).
   compute Ytab_b = {Ytab_b; estim(fcount,:)}.
   compute fcount = fcount + 1.
   compute m1tab_b = {m1tab_b; estim(fcount,:)}.
   compute fcount = fcount + 1.
   do if (!m2_1 = 1).
      compute m2tab_b = {m2tab_b; estim(fcount,:)}.
      compute fcount = fcount + 1.
   end if.
   do if (!m3_1 = 1).
      compute m3tab_b = {m3tab_b; estim(fcount,:)}.
      compute fcount = fcount + 1.
   end if.
end if.
compute m1b = 0.
compute m2b = 0.
compute m3b = 0.
compute yb = 0.
do if (nrow(ytab_b) > 1).
   compute ytab_b = ytab_b(2:nrow(ytab_b),:).
   compute yb = 1.
end if.
do if (nrow(m1tab_b) > 1).
   compute m1tab_b = m1tab_b(2:nrow(m1tab_b),:).
   compute m1b = 1.
end if.
do if (!m2_1 = 1).
   do if (nrow(m2tab_b) > 1).
      compute m2tab_b = m2tab_b(2:nrow(m2tab_b),:).
      compute m2b = 1.
   end if.
end if.
do if (!m3_1 = 1).
   do if (nrow(m3tab_b) > 1).
      compute m3tab_b = m3tab_b(2:nrow(m3tab_b),:).
      compute m3b = 1.
   end if.
end if.
compute f_nc = csum(estim(:,4) = -999).
compute r_nc = csum(cov_p(:,3) = -999).
compute e1 = (estim(:,4) = -999)
do if (f_nc > 0).
   print /title = "***Warning: One or more fixed effect parameters could
        not be estimated.".
   print f_nc /title = "Number of fixed effect parameters that could not
        be estimated:".
   print /title =
      "********************************************************
   ***************"/ format = A8.
end if.
```

```
do if (r_nc > 0).
   print /title = "***Warning: One or more random effect parameters
      could not be estimated.".
   print r_nc /title = "Number of random effect parameters that could
      not be estimated:".
   print /title =
      "************************************************************
   **************"/ format = A8.
end if.
do if (r_nc = 0 AND f_nc = 0).
   print mod_spec /title "Model Specification"/format = F8.0 / rlabels =
      "N" "Fixed" "Rand(L1)" "Rand(L2)" "Total".
   print fit_stat /title = "Model Fit Statistics"/format = F8.4/ rlabels
      = "-2LL" "AIC" "AICC" "CAIC" "BIC"/ clabels = "Value".
   print /title = " ".
end if.
do if ((r_nc = 0 AND f_nc = 0) OR !eor_1 = 1).
   print /title = "***************************  FIXED EFFECTS
      **************************".
   compute m1ntab = {"Outcome:", !m1_name}.
   print m1ntab/title =
      "****************************************************
   ********************"/ format = A8.
   print m1tab_w/ title = "Within- Effects" /rlabels = !m1list_w "-"/
      format = F8.4/clabels = "Estimate" "S.E." "df" "t" "p" "LL" "UL".
      do if (m1b = 1).
         print m1tab_b/ title = "Between- Effects" /rlabels = !m1list_b
            "-"/format = F8.4/clabels = "Estimate" "S.E." "df" "t" "p"
            "LL" "UL".
      else.
         print /title = "Note: No Between- Effect(s) Specified.".
      end if.
   do if (!ModM_1 = 1).
      compute indtab1 = {"0", "0", "0", "0", "0", "0"}.
      do if (!xW = 1).
         compute indtab1 = {indtab1; "Within-", !modM_n, "   x   ", !
            x_name, "   ->   ", !m1_name}.
      end if.
      do if (!bet_x_1 = 1 AND !modMB_1 = 1).
         compute indtab1 = {indtab1; "Between-", !modM_n, "   x   ", !
            x_name, "   ->   ", !m1_name}.
      end if.
      compute indtab1 = indtab1(2:nrow(indtab1),:).
      print indtab1 /title = "Interaction Codes" /rlabels = "int_1   " "
         int_2   " /format = A8.
   end if.
   do if (!m2_1 = 1).
      compute m2ntab = {"Outcome:", !m2_name}.
      print m2ntab/title =
         "****************************************************
      ********************"/ format = A8.
```

```
   print m2tab_w/ title = "Within- Effects" /rlabels = !m2list_w "-"/
      format = F8.4/clabels = "Estimate" "S.E." "df" "t" "p" "LL" "
      UL".
   do if (m2b = 1).
      print m2tab_b/ title = "Between- Effects" /rlabels = !m2list_b
         "-"/format = F8.4/clabels = "Estimate" "S.E." "df" "t" "p"
         "LL" "UL".
   else.
      print /title = "Note: No Between- Effects Specified.".
   end if.
end if.
do if (!m3_1 = 1).
   compute m3ntab = {"Outcome:", !m3_name}.
   print m3ntab/title =
      "*****************************************************
*****************"/ format = A8.
   print m3tab_w/ title = "Within- Effects" /rlabels = !m3list_w "-"/
      format = F8.4/clabels = "Estimate" "S.E." "df" "t" "p" "LL" "
      UL".
   do if (m3b = 1).
      print m3tab_b/ title = "Between- Effects" /rlabels = !m3list_b
         "-"/format = F8.4/clabels = "Estimate" "S.E." "df" "t" "p"
         "LL" "UL".
   else.
      print /title = "Note: No Between- Effects Specified.".
   end if.
end if.
compute yntab = {"Outcome:", !y_name}.
print yntab/title =
   "******************************************************
**************"/format = A8.
print ytab_w/ title = "Within- Effects" /rlabels = !ylist_w "-"/
   format = F8.4/clabels = "Estimate" "S.E." "df" "t" "p" "LL" "UL".
do if (yb = 1).
   print ytab_b/ title = "Between- Effects" /rlabels = !ylist_b "-"/
      format = F8.4/clabels = "Estimate" "S.E." "df" "t" "p" "LL" "
      UL".
else.
   print /title = "Note: No Between- Effects Specified.".
end if.
do if (!ModY_1 = 1).
   compute indtab2 = {"Within-", !modY_n, "   x   ", !m1_name, "   ->
         ", !y_name}.
   do if (!modYB_1 = 1).
      compute indtab2 = {indtab2; "Between-", !modY_n, "   x   ", !
         m1_name, "   ->   ", !y_name}.
   end if.
   print indtab2 /title = "Interaction Codes" /rlabels = "int_1   " "
      int_2   " /format = A8.
end if.
print /title = "*************************************************
```

```
                 *******************"/format = A8.
else if (f_nc > 0).
   print /title = "**************************  FIXED EFFECTS
       **************************".
   compute m1ntab = {"Outcome:", !m1_name}.
   print m1ntab/title = "***********************************************
   ************************"/ format = A8.
   print (m1tab_w(:,3) = -999)/ title = "Within- Effects" /rlabels = !
      m1list_w "-"/format = F8.0/clabels = "Error".
      do if (m1b = 1).
         print (m1tab_b(:,3) = -999)/ title = "Between- Effects" /
             rlabels = !m1list_b "-"/format = F8.0/clabels = "Error".
      else.
         print /title = "Note: No Between- Effect(s) Specified.".
      end if.
   do if (!ModM_1 = 1).
      compute indtab1 = {"0", "0", "0", "0", "0", "0"}.
      do if (!xW = 1).
         compute indtab1 = {indtab1; "Within-", !modM_n, "   x   ", !
             x_name, "   ->   ", !m1_name}.
      end if.
      do if (!bet_x_1 = 1 AND !modMB_1 = 1).
         compute indtab1 = {indtab1; "Between-", !modM_n, "   x   ", !
             x_name, "   ->   ", !m1_name}.
      end if.
      compute indtab1 = indtab1(2:nrow(indtab1),:).
      print indtab1 /title = "Interaction Codes" /rlabels = "int_1   " "
          int_2   " /format = A8.
   end if.
   do if (!m2_1 = 1).
      compute m2ntab = {"Outcome:", !m2_name}.
      print m2ntab/title =
          "*************************************************
      ***********************"/ format = A8.
      print (m2tab_w(:,3) = -999)/ title = "Within- Effects" /rlabels =
          !m2list_w "-"/format = F8.0/clabels = "Error".
      do if (m2b = 1).
         print (m2tab_b(:,3) = -999)/ title = "Between- Effects" /
             rlabels = !m2list_b "-"/format = F8.0/clabels = "Error".
      else.
         print /title = "Note: No Between- Effects Specified.".
      end if.
   end if.
   do if (!m3_1 = 1).
      compute m3ntab = {"Outcome:", !m3_name}.
      print m3ntab/title =
          "*************************************************
      ***********************"/ format = A8.
      print (m3tab_w(:,3) = -999)/ title = "Within- Effects" /rlabels =
          !m3list_w "-"/format = F8.0/clabels = "Error".
      do if (m3b = 1).
```

```
          print (m3tab_b(:,3) = -999)/ title = "Between- Effects" /
              rlabels = !m3list_b "-"/format = F8.0/clabels = "Error".
        else.
          print /title = "Note: No Between- Effects Specified.".
        end if.
     end if.
     compute yntab = {"Outcome:", !y_name}.
     print yntab/title = "*******************************
     ****************************************"/format = A8.
     print (ytab_w(:,3) = -999)/ title = "Within- Effects" /rlabels = !
         ylist_w "-"/format = F8.0/clabels = "Error".
     do if (yb = 1).
        print (ytab_b(:,3) = -999)/ title = "Between- Effects" /rlabels =
            !ylist_b "-"/format = F8.0/clabels = "Error".
     else.
        print /title = "Note: No Between- Effects Specified.".
     end if.
     do if (!ModY_1 = 1).
        compute indtab2 = {"Within-", !modY_n, "   x   ", !m1_name, "   ->
              ", !y_name}.
        do if (!modYB_1 = 1).
           compute indtab2 = {indtab2; "Between-", !modY_n, "   x   ", !
               m1_name, "   ->   ", !y_name}.
        end if.
        print indtab2 /title = "Interaction Codes" /rlabels = "int_1    " "
            int_2    " /format = A8.
     end if.
     print /title = "*******************************
     ****************************************"/format = A8.
end if.
do if (!rescov_1 = 1).
   compute rfx = cov_p(((num_int&*(num_int + 1)/2) + 1):nrow(cov_p),:).
   compute resfx = cov_p(1:(num_int&*(num_int + 1)/2),:).
else.
   compute rfx = cov_p((num_int + 1):nrow(cov_p),:).
   compute resfx = cov_p(1:num_int,:).
end if.
compute reskey = {!y_name; !m1_name}.
do if (!m2_1 = 1).
   compute reskey = {reskey; !m2_name}.
end if.
do if (!m3_1 = 1).
   compute reskey = {reskey; !m3_name}.
end if.
compute numrint = num_rint - (!ryint_1 = 1).
do if ((r_nc = 0 AND f_nc = 0) OR !eor_1 = 1).
   print /title = "************************  RANDOM EFFECTS
      *************************".
   do if (!rescov_1 = 1).
      print resfx /title = "Level-1 Residual Estimates" /clabels = "
          Estimate" "S.E." "Wald Z" "p" "LL" "UL"
```

```
          /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)"
             "(4,1)" "(4,2)" "(4,3)" "(4,4)" "(5,1)" "(5,2)" "(5,3)"
             "(5,4)" "(5,5)"  /format = F8.4.
     print reskey/ title = "Level-1 Residual Names"/ rlabels = "1" "2"
        "3" "4" /format = A8.
 else.
    compute list = t(reskey).
    print resfx /title = "Level-1 Residual Estimates" /clabels = "
       Estimate" "S.E." "Wald Z" "p" "LL" "UL" /rlabels = !y !m1 !m2
       !m3 "-"/format = F8.4.
 end if.
 do if ((!covmat_1 = 0 OR !covs = 0) AND !int_1 = 0).
    print rfx/ title = "Random Effect Estimates" /clabels = "Estimate"
        "S.E." "Wald Z" "p" "LL" "UL" /rlabels = "1" "2" "3" "4" "5"
       "6" "7" "8" "9" "10"/ format = F8.4.
 else.
    do if (!indint = 0).
      print rfx/ title = "Random Effect Estimates" /clabels = "
         Estimate" "S.E." "Wald Z" "p" "LL" "UL"
            /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)"
               "(4,1)" "(4,2)" "(4,3)" "(4,4)" "(5,1)" "(5,2)"
               "(5,3)" "(5,4)" "(5,5)" "(6,1)" "(6,2)" "(6,3)" "(6,4)
               " "(6,5)" "(6,6)"
             "(7,1)" "(7,2)" "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)"
               "(8,1)" "(8,2)" "(8,3)" "(8,4)" "(8,5)" "(8,6)" "(8,7)
               " "(8,8)"/ format = F8.4.
    else if (!int_1 = 0 AND !covmat_1 = 1).
       do if ((numrint = -1 AND !ycov = 0) OR (numrint = 1 AND !ycov =
          1)).
         print rfx/ title = "Random Effect Estimates" /clabels = "
            Estimate" "S.E." "Wald Z" "p" "LL" "UL"
            /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)
               " "(4,1)" "(4,2)" "(4,3)" "(4,4)" "(5,1)" "(5,2)"
               "(5,3)" "(5,4)" "(5,5)" "(6,1)" "(6,2)" "(6,3)"
               "(6,4)" "(6,5)" "(6,6)"
             "(7,1)" "(7,2)" "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)"
               "(8,1)" "(8,2)" "(8,3)" "(8,4)" "(8,5)" "(8,6)"
               "(8,7)" "(8,8)"/ format = F8.4.
      else if ((numrint = 0 AND !ycov = 0) OR (numrint = 1 AND !ycov
         = 1)).
         print rfx/ title = "Random Effect Estimates" /clabels = "
            Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                 /rlabels = "(1,1)" "(2,2)" "(3,2)" "(3,3)" "(4,2)"
                    "(4,3)" "(4,4)" "(5,2)" "(5,3)" "(5,4)" "(5,5)"
                    "(6,2)" "(6,3)" "(6,4)" "(6,5)" "(6,6)"
                 "(7,2)" "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)"
                    "(8,2)" "(8,3)" "(8,4)" "(8,5)" "(8,6)" "(8,7)"
                    "(8,8)"/ format = F8.4.
      else if ((numrint = 1 AND !ycov = 0) OR (numrint = 2 AND !ycov
         = 1)).
```

```
        print rfx/ title = "Random Effect Estimates" /clabels = "
           Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                /rlabels = "(1,1)" "(2,2)" "(3,3)" "(4,3)" "(4,4)"
                    "(5,3)" "(5,4)" "(5,5)" "(6,3)" "(6,4)" "(6,5)"
                    "(6,6)"
                 "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,3)"
                    "(8,4)" "(8,5)" "(8,6)" "(8,7)" "(8,8)"/ format
                    = F8.4.
     else if ((numrint = 2 AND !ycov = 0) OR (numrint = 3 AND !ycov
        = 1)).
        print rfx/ title = "Random Effect Estimates" /clabels = "
           Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                /rlabels = "(1,1)" "(2,2)" "(3,3)" "(4,4)" "(5,4)"
                    "(5,5)" "(6,4)" "(6,5)" "(6,6)"
                 "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,4)" "(8,5)"
                    "(8,6)" "(8,7)" "(8,8)"/ format = F8.4.
     else if (numrint = 3 AND !ycov = 0).
        print rfx/ title = "Random Effect Estimates" /clabels = "
           Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                /rlabels = "(1,1)" "(2,2)" "(3,3)" "(4,4)" "(5,5)"
                    "(6,5)" "(6,6)"
                 "(7,5)" "(7,6)" "(7,7)" "(8,5)" "(8,6)" "(8,7)"
                    "(8,8)"/ format = F8.4.
  end if.
else if (!int_1 = 1 AND !covmat_1 = 1).
  do if (numrint = 2 AND !ycov = 1).
     print rfx/ title = "Random Effect Estimates" /clabels = "
        Estimate" "S.E." "Wald Z" "p" "LL" "UL"
        /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,3)" "(4,3)" "(4,4)
           " "(5,3)" "(5,4)" "(5,5)" "(6,3)" "(6,4)" "(6,5)"
           "(6,6)"
         "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,3)" "(8,4)"
            "(8,5)" "(8,6)" "(8,7)" "(8,8)"/ format = F8.4.
  else if (numrint = 2 AND !ycov = 0).
     print rfx/ title = "Random Effect Estimates" /clabels = "
        Estimate" "S.E." "Wald Z" "p" "LL" "UL"
        /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,3)" "(4,4)" "(5,4)
           " "(5,5)" "(6,4)" "(6,5)" "(6,6)"
         "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,4)" "(8,5)" "(8,6)"
            "(8,7)" "(8,8)"/ format = F8.4.
  else if (numrint = 3 AND !ycov = 1).
     print rfx/ title = "Random Effect Estimates" /clabels = "
        Estimate" "S.E." "Wald Z" "p" "LL" "UL"
        /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)
           " "(4,4)" "(5,4)" "(5,5)" "(6,4)" "(6,5)" "(6,6)"
         "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,4)" "(8,5)" "(8,6)"
            "(8,7)" "(8,8)"/ format = F8.4.
  else if (numrint = 3 AND !ycov = 0).
     print rfx/ title = "Random Effect Estimates" /clabels = "
        Estimate" "S.E." "Wald Z" "p" "LL" "UL"
```

```
                  /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)
                      " "(4,4)" "(5,5)" "(6,5)" "(6,6)"
                    "(7,5)" "(7,6)" "(7,7)" "(8,5)" "(8,6)" "(8,7)" "(8,8)"/
                        format = F8.4.
             end if.
           else if (!int_1 = 1 AND !covmat_1 = 0).
               do if (numrint = 2).
                  print rfx/ title = "Random Effect Estimates" /clabels = "
                      Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                      /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,3)"  "(4,4)"
                          "(5,5)" "(6,6)"
                      "(7,7)" "(8,8)"/ format = F8.4.
                else if (numrint = 3).
                  print rfx/ title = "Random Effect Estimates" /clabels = "
                      Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                      /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)"
                          "(3,3)" "(4,4)" "(5,5)" "(6,6)"
                      "(7,7)" "(8,8)"/ format = F8.4.
                end if.
             end if.
compute rfxtab = {1:20}.
      compute rfxtab = t(rfxtab).
      compute rfxtab = rfxtab(1:nrow(g)).
      print g/title = "Random Effect Covariance Matrix" /clabels = "1"
          "2" "3" "4" "5" "6" "7" "8" / rlabels = "1" "2" "3" "4" "5"
          "6" "7" "8" /format = F8.4.
      compute sds = sqrt(mdiag(diag(g))).
      compute sds_inv = inv(sds).
      compute cor_mat = sds_inv*g*sds_inv.
      print cor_mat/title = "Random Effect Correlation Matrix" /clabels
          = "1" "2" "3" "4" "5" "6" "7" "8" / rlabels = "1" "2" "3" "4"
          "5" "6" "7" "8" /format = F8.4.
   end if.
else if (r_nc > 0).
   print /title = "************************  RANDOM EFFECTS
      ************************".
   do if (!rescov_1 = 1).
      print (resfx(:,3) = -999)/title = "Level-1 Residual Estimates" /
          clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
          /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)"
              "(4,1)" "(4,2)" "(4,3)" "(4,4)" "(5,1)" "(5,2)" "(5,3)"
              "(5,4)" "(5,5)"  /format = F8.4.
      print reskey/ title = "Level-1 Residual Names"/ rlabels = "1" "2"
          "3" "4" /format = A8.
   else.
      compute list = t(reskey).
      print (resfx(:,3) = -999) /title = "Level-1 Residual Estimates" /
          clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL" /rlabels =
          !y !m1 !m2 !m3 "-"/format = F8.4.
   end if.
   do if ((!covmat_1 = 0 OR !covs = 0) AND !int_1 = 0).
```

```
     print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
        clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL" /rlabels =
        "1" "2" "3" "4" "5" "6" "7" "8" "9" "10"/ format = F8.4.
else.
   do if (!indint = 0).
     print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
        clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
           /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)"
              "(4,1)" "(4,2)" "(4,3)" "(4,4)" "(5,1)" "(5,2)"
              "(5,3)" "(5,4)" "(5,5)" "(6,1)" "(6,2)" "(6,3)" "(6,4)
              " "(6,5)" "(6,6)"
            "(7,1)" "(7,2)" "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)"
              "(8,1)" "(8,2)" "(8,3)" "(8,4)" "(8,5)" "(8,6)" "(8,7)
              " "(8,8)"/ format = F8.4.
   else if (!int_1 = 0 AND !covmat_1 = 1).
     do if ((numrint = -1 AND !ycov = 0) OR (numrint = 1 AND !ycov =
        1)).
        print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
           clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
           /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)
              " "(4,1)" "(4,2)" "(4,3)" "(4,4)" "(5,1)" "(5,2)"
              "(5,3)" "(5,4)" "(5,5)" "(6,1)" "(6,2)" "(6,3)"
              "(6,4)" "(6,5)" "(6,6)"
            "(7,1)" "(7,2)" "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)"
              "(8,1)" "(8,2)" "(8,3)" "(8,4)" "(8,5)" "(8,6)"
              "(8,7)" "(8,8)"/ format = F8.4.
     else if ((numrint = 0 AND !ycov = 0) OR (numrint = 1 AND !ycov
        = 1)).
        print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
           clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                 /rlabels = "(1,1)" "(2,2)" "(3,2)" "(3,3)" "(4,2)"
                    "(4,3)" "(4,4)" "(5,2)" "(5,3)" "(5,4)" "(5,5)"
                    "(6,2)" "(6,3)" "(6,4)" "(6,5)" "(6,6)"
                  "(7,2)" "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)"
                    "(8,2)" "(8,3)" "(8,4)" "(8,5)" "(8,6)" "(8,7)"
                    "(8,8)"/ format = F8.4.
     else if ((numrint = 1 AND !ycov = 0) OR (numrint = 2 AND !ycov
        = 1)).
        print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
           clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                 /rlabels = "(1,1)" "(2,2)" "(3,3)" "(4,3)" "(4,4)"
                    "(5,3)" "(5,4)" "(5,5)" "(6,3)" "(6,4)" "(6,5)"
                    "(6,6)"
                  "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,3)"
                    "(8,4)" "(8,5)" "(8,6)" "(8,7)" "(8,8)"/ format
                    = F8.4.
     else if ((numrint = 2 AND !ycov = 0) OR (numrint = 3 AND !ycov
        = 1)).
        print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
           clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
```

```
                /rlabels = "(1,1)" "(2,2)" "(3,3)" "(4,4)" "(5,4)"
                    "(5,5)" "(6,4)" "(6,5)" "(6,6)"
                  "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,4)" "(8,5)"
                    "(8,6)" "(8,7)" "(8,8)"/ format = F8.4.
       else if (numrint = 3 AND !ycov = 0).
          print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
             clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                  /rlabels = "(1,1)" "(2,2)" "(3,3)" "(4,4)" "(5,5)"
                    "(6,5)" "(6,6)"
                  "(7,5)" "(7,6)" "(7,7)" "(8,5)" "(8,6)" "(8,7)"
                    "(8,8)"/ format = F8.4.
     end if.
   else if (!int_1 = 1 AND !covmat_1 = 1).
     do if (numrint = 2 AND !ycov = 1).
        print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
             clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
             /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,3)" "(4,3)" "(4,4)
               " "(5,3)" "(5,4)" "(5,5)" "(6,3)" "(6,4)" "(6,5)"
               "(6,6)"
             "(7,3)" "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,3)" "(8,4)"
                "(8,5)" "(8,6)" "(8,7)" "(8,8)"/ format = F8.4.
       else if (numrint = 2 AND !ycov = 0).
          print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
             clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
             /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,3)" "(4,4)" "(5,4)
               " "(5,5)" "(6,4)" "(6,5)" "(6,6)"
             "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,4)" "(8,5)" "(8,6)"
                "(8,7)" "(8,8)"/ format = F8.4.
       else if (numrint = 3 AND !ycov = 1).
          print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
             clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
             /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)
               " "(4,4)" "(5,4)" "(5,5)" "(6,4)" "(6,5)" "(6,6)"
             "(7,4)" "(7,5)" "(7,6)" "(7,7)" "(8,4)" "(8,5)" "(8,6)"
                "(8,7)" "(8,8)"/ format = F8.4.
       else if (numrint = 3 AND !ycov = 0).
         print (rfx(:,3) = -999)/ title = "Random Effect Estimates" /
             clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
             /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)" "(3,3)
               " "(4,4)" "(5,5)" "(6,5)" "(6,6)"
            "(7,5)" "(7,6)" "(7,7)" "(8,5)" "(8,6)" "(8,7)" "(8,8)"/
               format = F8.4.
     end if.
   else if (!int_1 = 1 AND !covmat_1 = 0).
       do if (numrint = 2).
          print (rfx(:,3) = -999)/ title = "Random Effect Estimates
             " /clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
            /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,3)"  "(4,4)"
                "(5,5)" "(6,6)"
             "(7,7)" "(8,8)"/ format = F8.4.
       else if (numrint = 3).
```

```
                       print (rfx(:,3) = -999)/ title = "Random Effect Estimates
                          " /clabels = "Estimate" "S.E." "Wald Z" "p" "LL" "UL"
                          /rlabels = "(1,1)" "(2,1)" "(2,2)" "(3,1)" "(3,2)"
                             "(3,3)" "(4,4)" "(5,5)" "(6,6)"
                          "(7,7)" "(8,8)"/ format = F8.4.
                 end if.
             end if.
      end if.
      compute va1 = 0.
      compute va2 = 0.
      compute va3 = 0.
      compute vb1 = 0.
      compute vb2 = 0.
      compute vb3 = 0.
      compute rtable = {"0", "0", "0", "0"}.
      compute rcount = 1.
      compute covcount = 1.
      do if (!rm1int_1 = 1).
         compute rtable = {rtable; "Int", !m1_name, " ", " "}.
         compute vm1_int = g(rcount, rcount).
         compute rcount = rcount + 1.
      end if.
      do if (!rm2_1 = 1 AND !rm2int_1 = 1).
         compute rtable = {rtable; "Int", !m2_name, " ", " "}.
         compute vm2_int = g(rcount, rcount).
         compute rcount = rcount + 1.
      end if.
      do if (!rm3_1 = 1 AND !rm3int_1 = 1).
         compute rtable = {rtable; "Int", !m3_name, " ", " "}.
         compute vm3_int = g(rcount, rcount).
         compute rcount = rcount + 1.
      end if.
      compute counter = rcount - 1.
      do if (!int_1 = 1 AND counter > 0).
         compute counter = (counter*(counter + 1))/2.
      end if.
      compute counter = counter + 1.
      compute counter2 = 1.
      do if (!ryint_1 = 1).
         compute rtable = {rtable; "Int", !y_name, " ", " "}.
         compute vy_int = g(rcount, rcount).
         compute rcount = rcount + 1.
         compute covcount = covcount + 1.
         do if (!ycov_1 = 1).
            compute counter2 = counter2 + 1.
         else.
            compute counter = counter + 1.
         end if.
      end if.
      do if (!rcp_1 = 1).
         compute rtable = {rtable; "Slope", !x_name, "   ->", !y_name}.
```

```
      compute vcp = g(rcount, rcount).
      compute rcount = rcount + 1.
      compute counter2 = counter2 + 1.
   end if.
   do if (!ra1_1 = 1).
      compute rtable = {rtable; "Slope", !x_name, "   ->", !m1_name}.
      compute va1 = g(rcount, rcount).
      compute a1loc = rcount.
      compute rcount = rcount + 1.
      compute a1loc2 = counter2.
      compute counter2 = counter2 + 1.
   end if.
   do if (!ra2_1 = 1).
      compute rtable = {rtable; "Slope", !x_name, "   ->", !m2_name}.
      compute va2 = g(rcount, rcount).
      compute a2loc = rcount.
      compute rcount = rcount + 1.
      compute a2loc2 = counter2.
      compute counter2 = counter2 + 1.
   end if.
   do if (!ra3_1 = 1).
      compute rtable = {rtable; "Slope", !x_name, "   ->", !m3_name}.
      compute va3 = g(rcount, rcount).
      compute a3loc = rcount.
      compute rcount = rcount + 1.
      compute a3loc2 = counter2.
      compute counter2 = counter2 + 1.
   end if.
   do if (!rb1_1 = 1).
      compute rtable = {rtable; "Slope", !m1_name, "   ->", !y_name}.
      compute vb1 = g(rcount, rcount).
      compute b1loc = rcount.
      compute rcount = rcount + 1.
      compute b1loc2 = counter2.
      compute counter2 = counter2 + 1.
   end if.
   do if (!rb2_1 = 1).
      compute rtable = {rtable; "Slope", !m2_name, "   ->", !y_name}.
      compute vb2 = g(rcount, rcount).
      compute b2loc = rcount.
      compute rcount = rcount + 1.
      compute b2loc2 = counter2.
      compute counter2 = counter2 + 1.
   end if.
   do if (!rb3_1 = 1).
      compute rtable = {rtable; "Slope", !m3_name, "   ->", !y_name}.
      compute vb3 = g(rcount, rcount).
      compute b3loc = rcount.
      compute rcount = rcount + 1.
      compute b3loc2 = counter2.
      compute counter2 = counter2 + 1.
```

```
end if.
compute rtable = rtable(2:nrow(rtable),:).
print rtable /title = "Random Effect Key" /rlabels = "1" "2" "3" "4" "5"
    "6" "7" "8" "9" "10" "11"/ format = A10.
print /title = "*********************************
**************************************"/format = A8.
compute ca1a2 = 0.
compute ca1a3 = 0.
compute ca1b1 = 0.
compute ca1b2 = 0.
compute ca1b3 = 0.
compute ca2a3 = 0.
compute ca2b1 = 0.
compute ca2b2 = 0.
compute ca2b3 = 0.
compute ca3b1 = 0.
compute ca3b2 = 0.
compute ca3b3 = 0.
compute cb1b2 = 0.
compute cb1b3 = 0.
compute cb2b3 = 0.
compute sv_ca1b1 = 0.
compute sv_ca2b2 = 0.
compute sv_ca3b3 = 0.
compute sc_12 = 0.
compute sc_13 = 0.
compute sc_23 = 0.
compute v_a1b1_w = 0.
compute v_a2b2_w = 0.
compute v_a3b3_w = 0.
do if (!ra1_1 = 1).
   do if (!ra2_1 = 1).
     compute ca1a2 = g(a1loc, a2loc).
   end if.
   do if (!ra3_1 = 1).
     compute ca1a3 = g(a1loc, a3loc).
   end if.
   do if (!rb1_1 = 1).
     compute ca1b1 = g(a1loc, b1loc).
   end if.
   do if (!rb2_1 = 1).
     compute ca1b2 = g(a1loc, b2loc).
   end if.
   do if (!rb3_1 = 1).
     compute ca1b3 = g(a1loc, b3loc).
   end if.
end if.
do if (!ra2_1 = 1).
   do if (!ra3_1 = 1).
     compute ca2a3 = g(a2loc, a3loc).
   end if.
```

```
   do if (!rb1_1 = 1).
      compute ca2b1 = g(a2loc, b1loc).
   end if.
   do if (!rb2_1 = 1).
      compute ca2b2 = g(a2loc, b2loc).
   end if.
   do if (!rb3_1 = 1).
      compute ca2b3 = g(a2loc, b3loc).
   end if.
end if.
do if (!ra3_1 = 1).
   do if (!rb1_1 = 1).
      compute ca3b1 = g(a3loc, b1loc).
   end if.
   do if (!rb2_1 = 1).
      compute ca3b2 = g(a3loc, b2loc).
   end if.
   do if (!rb3_1 = 1).
      compute ca3b3 = g(a3loc, b3loc).
   end if.
end if.
do if (!rb1_1 = 1).
   do if (!rb2_1 = 1).
      compute cb1b2 = g(b1loc, b2loc).
   end if.
   do if (!rb3_1 = 1).
      compute cb1b3 = g(b1loc, b3loc).
   end if.
end if.
do if (!rb2_1 = 1).
   do if (!rb3_1 = 1).
      compute cb2b3 = g(b2loc, b3loc).
   end if.
end if.
compute mc_ca1b1 = make(!samples, 1, 0).
compute mc_ca2b2 = make(!samples, 1, 0).
compute mc_ca3b3 = make(!samples, 1, 0).
do if (!indint = 1 AND counter < nrow(cov_ran)).
   compute cov_ran = cov_ran(counter:nrow(cov_ran), counter:nrow(cov_ran
      )).
end if.
do if (!covmat_1 = 1).
   do if (!ra1_1 = 1 AND !rb1_1 = 1).
      do if (!indint = 1).
         compute a1b1loc = {b1loc2, a1loc2}.
      else.
         compute a1b1loc = {b1loc, a1loc}.
      end if.
      compute rowa1b1 = (((a1b1loc(1,1) - 1)*a1b1loc(1,1))/2) + a1b1loc
         (1,2).
      compute sv_ca1b1 = cov_ran(rowa1b1, rowa1b1).
```

```
end if.
do if (!ra2_1 = 1 AND !rb2_1 = 1).
   do if (!indint = 1).
      compute a2b2loc = {b2loc2, a2loc2}.
   else.
      compute a2b2loc = {b2loc, a2loc}.
   end if.
   compute rowa2b2 = (((a2b2loc(1,1) - 1)*a2b2loc(1,1))/2) + a2b2loc
      (1,2).
   compute sv_ca2b2 = cov_ran(rowa2b2, rowa2b2).
end if.
do if (!ra3_1 = 1 AND !rb3_1 = 1).
   do if (!indint = 1).
      compute a3b3loc = {b3loc2, a3loc2}.
   else.
      compute a3b3loc = {b3loc, a3loc}.
   end if.
   compute rowa3b3 = (((a3b3loc(1,1) - 1)*a3b3loc(1,1))/2) + a3b3loc
      (1,2).
    compute sv_ca3b3 = cov_ran(rowa3b3, rowa3b3).
end if.
 do if (!ra1_1 = 1 AND !rb1_1 = 1 AND !ra2_1 = 1 AND !rb2_1 = 1).
   compute sc_12 = cov_ran(rowa1b1, rowa2b2).
end if.
 do if (!ra1_1 = 1 AND !rb1_1 = 1 AND !ra3_1 = 1 AND !rb3_1 = 1).
   compute sc_13 = cov_ran(rowa1b1, rowa3b3).
end if.
 do if (!ra2_1 = 1 AND !rb2_1 = 1 AND !ra3_1 = 1 AND !rb3_1 = 1).
   compute sc_23 = cov_ran(rowa2b2, rowa3b3).
end if.
compute rcovs = {ca1b1; ca2b2; ca3b3}.
compute rcovmat = {sv_ca1b1, sc_12, sc_13; sc_12, sv_ca2b2, sc_23;
   sc_13, sc_23, sv_ca3b3}.
do if (rcovmat(1,1) = 0).
   compute rcovmat(1,1) = .0000000000001.
   compute rcovmat(1,2) = 0.
   compute rcovmat(1,3) = 0.
   compute rcovmat(2,1) = 0.
   compute rcovmat(3,1) = 0.
end if.
do if (rcovmat(2,2) = 0).
   compute rcovmat(2,2) = .0000000000001.
   compute rcovmat(1,2) = 0.
   compute rcovmat(2,1) = 0.
   compute rcovmat(2,3) = 0.
   compute rcovmat(3,2) = 0.
end if.
do if (rcovmat(3,3) = 0).
   compute rcovmat(3,3) = .0000000000001.
   compute rcovmat(1,3) = 0.
   compute rcovmat(3,1) = 0.
```

```
      compute rcovmat(2,3) = 0.
      compute rcovmat(3,2) = 0.
   end if.
   compute rvec = make(!samples, 1, rcovs(1)).
   loop i=2 TO nrow(rcovs).
      compute rvec_2 = make(!samples, 1, rcovs(i)).
      compute rvec = {rvec,rvec_2}.
   end loop.
   compute rx2 = sqrt(-2*ln(uniform(!samples,ncol(rcovmat))))&*cos
      ((2*3.14159265358979)*uniform(!samples,ncol(rcovmat))).
   compute rx2 = (rx2*chol(rcovmat)) + rvec.
   do if (!ra1_1 = 1 AND !rb1_1 = 1).
      compute mc_ca1b1 = rx2(:,1).
   end if.
   do if (!ra2_1 = 1 AND !rb2_1 = 1).
      compute mc_ca2b2 = rx2(:,2).
   end if.
    do if (!ra3_1 = 1 AND !rb3_1 = 1).
      compute mc_ca3b3 = rx2(:,3).
   end if.
end if.
compute cov_12 = 0.
compute cov_13 = 0.
compute cov_23 = 0.
do if (f_nc = 0 AND r_nc = 0).
do if (!wit_x_1 = 1 AND f_nc = 0).
   compute a1b1_w = a1_w*b1_w + ca1b1.
   compute v_a1b1_w = (b1_w**2)*va1 + (a1_w**2)*vb1 + va1*vb1 + 2*a1_w*
      b1_w*ca1b1 + (ca1b1**2).
   compute sva1b1_w = (b1_w**2)*sva1_w + (a1_w**2)*svb1_w + sva1_w*
      svb1_w + 2*a1_w*b1_w*sca1b1w + (sca1b1w**2) + sv_ca1b1.
   compute se_a1b1w = sqrt(sva1b1_w).
   compute a1b1_w_z = a1b1_w/se_a1b1w.
   compute a1b1_w_p = (1 - cdfnorm(abs(a1b1_w_z)))*2.
end if.
do if (!bet_x_1 = 1 AND !bet_m1_1 = 1 AND f_nc = 0).
   compute a1b1_b = a1_b*b1_b.
   compute sva1b1b = (b1_b**2)*sva1_b + (a1_b**2)*svb1_b + sva1_b*svb1_b
      + 2*a1_b*b1_b*sca1b1b + (sca1b1b**2).
   compute se_a1b1b = sqrt(sva1b1b).
   compute a1b1_b_z = a1b1_b/se_a1b1b.
   compute a1b1_b_p = (1 - cdfnorm(abs(a1b1_b_z)))*2.
end if.
do if (!m2_1 = 1).
   do if (!wit_x_1 = 1 AND f_nc = 0).
      compute a2b2_w = a2_w*b2_w + ca2b2.
      compute v_a2b2_w = (b2_w**2)*va2 + (a2_w**2)*vb2 + va2*vb2 + 2*
         a2_w*b2_w*ca2b2 + (ca2b2**2).
      compute cov_12 = a1_w*a2_w*cb1b2 + a1_w*b2_w*ca2b1 + b1_w*a2_w*
         ca1b2 + b1_w*b2_w*ca1a2 + ca1a2*cb1b2 + ca1b2*ca2b1.
```

```
      compute sva2b2_w = (b2_w**2)*sva2_w + (a2_w**2)*svb2_w + sva2_w*
          svb2_w + 2*a2_w*b2_w*sca2b2w + (sca2b2w**2) + sv_ca2b2.
      compute se_a2b2w = sqrt(sva2b2_w).
      compute a2b2_w_z = a2b2_w/se_a2b2w.
      compute a2b2_w_p = (1 - cdfnorm(abs(a2b2_w_z)))*2.
   end if.
   do if (!bet_x_1 = 1 AND !bet_m2_1 = 1 AND f_nc = 0).
      compute a2b2_b = a2_b*b2_b.
      compute sva2b2b = (b2_b**2)*sva2_b + (a2_b**2)*svb2_b + sva2_b*
          svb2_b + 2*a2_b*b2_b*sca2b2b + (sca2b2b**2).
      compute se_a2b2b = sqrt(sva2b2b).
      compute a2b2_b_z = a2b2_b/se_a2b2b.
      compute a2b2_b_p = (1 - cdfnorm(abs(a2b2_b_z)))*2.
   end if.
end if.
do if (!m3_1 = 1).
   do if (!wit_x_1 = 1 AND f_nc = 0).
      compute a3b3_w = a3_w*b3_w + ca3b3.
      compute v_a3b3_w = (b3_w**2)*va3 + (a3_w**2)*vb3 + va3*vb3 + 2*
          a3_w*b3_w*ca3b3 + (ca3b3**2).
      compute cov_13 = a1_w*a3_w*cb1b3 + a1_w*b3_w*ca3b1 + b1_w*a3_w*
          ca1b3 + b1_w*b3_w*ca1a3 + ca1a3*cb1b3 + ca1b3*ca3b1.
      compute cov_23 = a2_w*a3_w*cb2b3 + a2_w*b3_w*ca3b2 + b2_w*a3_w*
          ca2b3 + b2_w*b3_w*ca2a3 + ca2a3*cb2b3 + ca2b3*ca3b2.
      compute sva3b3_w = (b3_w**2)*sva3_w + (a3_w**2)*svb3_w + sva3_w*
          svb3_w + 2*a3_w*b3_w*sca3b3w + (sca3b3w**2) + sv_ca3b3.
      compute se_a3b3w = sqrt(sva3b3_w).
      compute a3b3_w_z = a3b3_w/se_a3b3w.
      compute a3b3_w_p = (1 - cdfnorm(abs(a3b3_w_z)))*2.
   end if.
   do if (!bet_x_1 = 1 AND !bet_m3_1 = 1 AND f_nc = 0).
      compute a3b3_b = a3_b*b3_b.
      compute sva3b3b = (b3_b**2)*sva3_b + (a3_b**2)*svb3_b + sva3_b*
          svb3_b + 2*a3_b*b3_b*sca3b3b + (sca3b3b**2).
      compute se_a3b3b = sqrt(sva3b3b).
      compute a3b3_b_z = a3b3_b/se_a3b3b.
      compute a3b3_b_p = (1 - cdfnorm(abs(a3b3_b_z)))*2.
   end if.
end if.
compute conf = !conf.
compute cilow=((100-conf)/200).
compute cihigh=1-cilow.
compute cilow=trunc(!samples*cilow).
compute cihigh=trunc((!samples*cihigh)+.999)+1.
do if (!modM_1 = 1 OR !modY_1 = 1).
   print /title = "******************  INDEX OF MODERATED MEDIATION
      ******************".
end if.
compute cov2  = cov_fix.
compute mvec2 = make(!samples, 1, est(1)).
loop i=2 TO nrow(est).
```

```
   compute mvec2_2 = make(!samples, 1, est(i)).
   compute mvec2 = {mvec2,mvec2_2}.
end loop.
compute x2 = sqrt(-2*ln(uniform(!samples,ncol(cov_fix))))&*cos
   ((2*3.14159265358979)*uniform(!samples,ncol(cov_fix))).
compute x2 = (x2*chol(cov2)) + mvec2.
do if (!wit_x_1 = 1).
   compute mc_ab1_w = x2(:,a1_w_l)&*x2(:,b1_w_l) + mc_ca1b1.
end if.
do if (!bet_x_1 = 1 AND !bet_m1_1 = 1).
   compute mc_ab1_b = x2(:,a1_b_l)&*x2(:,b1_b_l).
end if.
do if (!bet_x_1 = 1 AND !wit_x_1 = 1 AND !bet_m1_1 = 1).
   compute mc_ab1_c = mc_ab1_b - mc_ab1_w.
end if.
do if (!m2_1 = 1).
   do if (!wit_x_1 = 1).
      compute mc_ab2_w = x2(:,a2_w_l)&*x2(:,b2_w_l) + mc_ca2b2.
      compute ab_12_w = mc_ab2_w - mc_ab1_w.
   end if.
   do if (!bet_x_1 = 1 AND !bet_m2_1 = 1).
      compute mc_ab2_b = x2(:,a2_b_l)&*x2(:,b2_b_l).
      compute ab_12_b = mc_ab2_b  - mc_ab1_b.
   end if.
   do if (!bet_x_1 = 1 AND !wit_x_1 = 1AND !bet_m2_1 = 1).
      compute mc_ab2_c = mc_ab2_b - mc_ab2_w.
   end if.
end if.
do if (!m3_1 = 1).
   do if (!wit_x_1 = 1).
      compute mc_ab3_w = x2(:,a3_w_l)&*x2(:,b3_w_l) + mc_ca3b3.
      compute ab_13_w = mc_ab3_w - mc_ab1_w.
      compute ab_23_w = mc_ab3_w - mc_ab2_w.
   end if.
   do if (!bet_x_1 = 1 AND !bet_m3_1 = 1).
      compute mc_ab3_b = x2(:,a3_b_l)&*x2(:,b3_b_l).
      compute ab_13_b = mc_ab3_b  - mc_ab1_b.
      compute ab_23_b = mc_ab3_b  - mc_ab2_b.
   end if.
   do if (!bet_x_1 = 1 AND !wit_x_1 = 1 AND !bet_m3_1 = 1).
      compute mc_ab3_c = mc_ab3_b - mc_ab3_w.
   end if.
end if.
do if (!modM_1 = 1).
   do if (!wit_x_1 = 1).
      compute QM_w = qMxaw&*b1_w.
      compute mc_QM_w = x2(:,qMxaw_l)&*x2(:,b1_w_l).
      compute i_sav_w = mc_QM_w.
      compute QMwtmp = mc_QM_w.
      compute QMwtmp(GRADE(mc_QM_w)) = mc_QM_w.
      compute mc_QM_w = QMwtmp.
```

```
         compute QM_wci = {mc_QM_w(cilow,1), mc_QM_w(cihigh,1)}.
         compute tab6 = {QM_w, QM_wci}.
      end if.
      do if (!bet_x_1 = 1 AND !modMB_1 = 1 AND !bet_m1_1 = 1).
         compute QM_b = qMxab&*b1_b.
         compute mc_QM_b = x2(:,qMxab_l)&*x2(:,b1_b_l).
         compute i_sav_b = mc_QM_b.
         compute QMbtmp = mc_QM_b.
         compute QMbtmp(GRADE(mc_QM_b)) = mc_QM_b.
         compute mc_QM_b = QMbtmp.
         compute QM_bci = {mc_QM_b(cilow,1), mc_QM_b(cihigh,1)}.
         compute tab7 = {QM_b,QM_bci}.
      end if.
   end if.
   do if (!modY_1 = 1).
      do if (!wit_x_1 = 1).
         compute QY_w = qYxbw&*a1_w.
         compute mc_QY_w = x2(:,qYxbw_l)&*x2(:,a1_w_l).
         compute QYwtmp = mc_QY_w.
         compute QYwtmp(GRADE(mc_QY_w)) = mc_QY_w.
         compute mc_QY_w = QYwtmp.
         compute QY_wci = {mc_QY_w(cilow,1), mc_QY_w(cihigh,1)}.
         compute tab8 = {QY_w, QY_wci}.
      end if.
      do if (!bet_x_1 = 1 AND !modYB_1 = 1 AND !bet_m1_1 = 1).
         compute QY_b = qYxbb&*a1_b.
         compute mc_QY_b = x2(:,qYxbb_l)&*x2(:,a1_b_l).
         compute QYbtmp = mc_QY_b.
         compute QYbtmp(GRADE(mc_QY_b)) = mc_QY_b.
         compute mc_QY_b = QYbtmp.
         compute QY_bci = {mc_QY_b(cilow,1), mc_QY_b(cihigh,1)}.
         compute tab9 = {QY_b, QY_bci}.
      end if.
   end if.
   compute modmedW = 0.
   compute modmedB = 0.
   do if ((!modY_1 = 1) AND (!samemod = 1)).
         do if (!wit_x_1 = 1).
            compute QMY2_w = qYxbw&*qMxaw.
            compute QMY1_w = qMxaw&*b1_w + qYxbw&*a1_w.
            compute mcQMY2_w = x2(:,qYxbw_l)&*x2(:,qMxaw_l).
            compute mcQMY1_w = i_sav_w + mc_QY_w.
            compute QMYwt2 = mcQMY2_w.
            compute QMYwt2(GRADE(mcQMY2_w)) = mcQMY2_w.
            compute mcQMY2_w = QMYwt2.
            compute QMY2_wci = {mcQMY2_w(cilow,1), mcQMY2_w(cihigh,1)}.
            compute QMYwt1 = mcQMY1_w.
            compute QMYwt1(GRADE(mcQMY1_w)) = mcQMY1_w.
            compute mcQMY1_w = QMYwt1.
            compute QMY1_wci = {mcQMY1_w(cilow,1), mcQMY1_w(cihigh,1)}.
            compute tab10 = {QMY1_w, QMY1_wci; QMY2_w, QMY2_wci}.
```

```
      print tab10/ title = "Within- Index of Moderated Mediation"
         /clabels = "Est" "MCLL" "MCUL" /rlabels = "linear" "quad" /
             format = F8.4.
      compute modmedW = 1.
   end if.
   do if (!bet_x_1 = 1 AND !modMB_1 = 1 AND !modYB_1 = 1 AND !
      bet_m1_1 = 1).
      compute QMY2_b = qYxbb&*qMxab.
      compute QMY1_b = qMxab&*b1_b + qYxbb&*a1_b.
      compute mcQMY2_b = x2(:,qYxbb_l)&*x2(:,qMxab_l).
      compute mcQMY1_b = i_sav_b + mc_QY_b.
       compute QMYbt2 = mcQMY2_b.
      compute QMYbt2(GRADE(mcQMY2_b)) = mcQMY2_b.
      compute mcQMY2_b = QMYbt2.
      compute QMY2_bci = {mcQMY2_b(cilow,1), mcQMY2_b(cihigh,1)}.
       compute QMYbt1 = mcQMY1_b.
      compute QMYbt1(GRADE(mcQMY1_b)) = mcQMY1_b.
      compute mcQMY1_b = QMYbt1.
      compute QMY1_bci = {mcQMY1_b(cilow,1), mcQMY1_b(cihigh,1)}.
      compute tab11 = {QMY1_b, QMY1_bci; QMY2_b, QMY2_bci}.
      print tab11/ title = "Between- Index of Moderated Mediation"
         /clabels = "Est" "MCLL" "MCUL" /rlabels = "linear" "quad" /
             format = F8.4.
      compute modmedB = 1.
   else if (!bet_x_1 = 1 AND !modMB_1 = 1 AND !modYB_1 = 0).
       print tab7/ title = "Between- Index of Moderated Mediation"
            /clabels = "Est" "MCLL" "MCUL" /rlabels = !modM "modM"/
                format = F8.4.
      compute modmedB = 1.
   else if (!bet_x_1 = 1 AND !modMB_1 = 0 AND !modYB_1 = 1).
       print tab9/ title = "Between- Index of Moderated Mediation"
            /clabels = "Est" "MCLL" "MCUL" /rlabels = !modY "modY"/
                format = F8.4.
      compute modmedB = 1.
   end if.
   compute val = {!modMcent}.
   print /title = "******************************
   *********************************************".
   print /title = "***********************  INDIRECT EFFECT(S)
       **********************".
   do if (modmedW = 1 AND modmedB = 1).
      print val/title = "NOTE: First Indirect Effects are Conditional
          on a Moderator Value of:"
        /clabels = "value" /rlabels = !modM "modM" /format = F8.4.
   else if (modmedW = 1 AND modmedB = 0).
      print val/title = "NOTE: First Within- Indirect Effect is
          Conditional on a Moderator Value of:"
        /clabels = "value" /rlabels = !modM "modM" /format = F8.4.
   else if (modmedW = 0 AND modmedB = 1).
      print val/title = "NOTE: First Between- Indirect Effect is
          Conditional on a Moderator Value of:"
```

```
                /clabels = "value" /rlabels = !modM "modM" /format = F8.4.
         end if.
  end if.
do if (!samemod = 0 AND !modM_1 = 1 AND !modY_1 = 1).
          do if (!wit_x_1 = 1).
          compute comtab = {tab6;tab8}.
          print comtab/ title = "Within- Index of Moderated Mediation"
               /clabels = "Est" "MCLL" "MCUL" /rlabels = !modM !modY "ModM"
                   "modY" /format = F8.4.
          compute modmedW = 1.
          end if.
          do if (!bet_x_1 = 1 AND !modMB_1 = 1 AND !modYB_1 = 1 AND !
             bet_m1_1 = 1).
             compute comtab2 = {tab7; tab9}.
             print comtab2/ title = "Between- Index of Moderated
                Mediation"
                 /clabels = "Est" "MCLL" "MCUL" /rlabels = !modM !modY "
                    modM" "ModY" /format = F8.4.
             compute modmedB = 1.
          else if (!bet_x_1 = 1 AND !modMB_1 = 1 AND !modYB_1 = 0).
             print tab7/ title = "Between- Index of Moderated Mediation"
                 /clabels = "Est" "MCLL" "MCUL" /rlabels = !modM "modM" /
                    format = F8.4.
             compute modmedB = 1.
          else if (!bet_x_1 = 1 AND !modMB_1 = 0 AND !modYB_1 = 1).
             print tab9/ title = "Between- Index of Moderated Mediation"
                 /clabels = "Est" "MCLL" "MCUL" /rlabels = !modY "modY" /
                    format = F8.4.
             compute modmedB = 1.
          end if.
          print /title = "*****************************
          *********************************************".
          print /title = "***********************  INDIRECT EFFECT(S)
             **********************".
          do if (modmedW = 1 AND modmedB = 1).
             print {!modMcent;!modYcent} /title = "NOTE: First Indirect
                Effects are Conditional on a Moderator Value of:"
                 /clabels = "value" /rlabels = !modM !modY "ModM" "ModY" /
                    format = F8.4.
          else if (modmedW = 1 AND modmedB = 0).
             print {!modMcent;!modYcent} /title = "NOTE: First Within-
                Indirect Effect is Conditional on a Moderator Value of:"
                 /clabels = "value" /rlabels = !modM !modY "ModM" "ModY" /
                    format = F8.4.
          else if (modmedW = 0 AND modmedB = 1).
             print {!modMcent;!modYcent} /title = "NOTE: First Between-
                Indirect Effect is Conditional on a Moderator Value of:"
                 /clabels = "value" /rlabels = !modM !modY "ModM" "ModY" /
                    format = F8.4.
          end if.
   end if.
```

```
do if (!samemod = 0 AND !modY_1 = 0 AND !modM_1 = 1).
      do if (!wit_x_1 = 1).
      print tab6/ title = "Within- Index of Moderated Mediation"
         /clabels = "Est" "MCLL" "MCUL" /rlabels = !modM "modM"/
            format = F8.4.
      compute modmedW = 1.
      end if.
      do if (!bet_x_1 = 1 AND !modMB_1 = 1 AND !bet_m1_1 = 1).
         print tab7/ title = "Between- Index of Moderated Mediation"
            /clabels = "Est" "MCLL" "MCUL" /rlabels = !modM "modM"/
               format = F8.4.
      compute modmedB = 1.
      end if.
      print /title = "*************************
*********************************************".
      print /title = "***********************  INDIRECT EFFECT(S)
         *************************".
      do if (modmedW = 1 AND modmedB = 1).
         print !modMcent /title = "NOTE: First Indirect Effects are
            Conditional on a Moderator Value of:"
            /clabels = "value" /rlabels = !modM "modM" /format = F8
               .4.
      else if (modmedW = 1 AND modmedB = 0).
         print !modMcent /title = "NOTE: First Within- Indirect
            Effect is Conditional on a Moderator Value of:"
            /clabels = "value" /rlabels = !modM "modM" /format = F8
               .4.
      else if (modmedW = 0 AND modmedB = 1).
         print !modMcent /title = "NOTE: First Between- Indirect
            Effect is Conditional on a Moderator Value of:"
            /clabels = "value" /rlabels = !modM "modM" /format = F8
               .4.
      end if.
end if.
do if (!samemod = 0 AND !modY_1 = 1 AND !modM_1 = 0).
     do if (!wit_x_1 = 1).
        print tab8/ title = "Within- Index of Moderated Mediation"
             /clabels = "Est" "MCLL" "MCUL" /rlabels = !modY "modY" /
                format = F8.4.
     compute modmedW = 1.
     end if.
     do if (!bet_x_1 = 1 AND !modYB_1 = 1 AND !bet_m1_1 = 1).
        print tab9/ title = "Between- Index of Moderated Mediation"
             /clabels = "Est" "MCLL" "MCUL" /rlabels = !modY "modY"  /
                format = F8.4.
        compute modmedB = 1.
     end if.
     print /title = "***********************
***************************************************".
     print /title = "***********************  INDIRECT EFFECT(S)
        ***********************".
```

```
      do if (modmedW = 1 AND modmedB = 1).
         print !modYcent /title = "NOTE: First Indirect Effects are
            Conditional on a Moderator Value of:"
               /clabels = "value" /rlabels = !modY "modY" /format = F8
                  .4.
      else if (modmedW = 1 AND modmedB = 0).
         print !modYcent /title = "NOTE: First Within- Indirect Effect
            is Conditional on a Moderator Value of:"
               /clabels = "value" /rlabels = !modY "modY" /format = F8
                  .4.
      else if (modmedW = 0 AND modmedB = 1).
         print !modYcent /title = "NOTE: First Within- Indirect Effect
            is Conditional on a Moderator Value of:"
               /clabels = "value" /rlabels = !modY "modY" /format = F8
                  .4.
      end if.
end if.
do if (!modM_1 = 0 AND !modY_1 = 0).
   print /title = "*************************  INDIRECT EFFECT(S)
      *************************".
end if.
do if (!wit_x_1 = 1).
   compute ab1wtmp = mc_ab1_w.
   compute ab1wtmp(GRADE(mc_ab1_w)) = mc_ab1_w.
   compute mc_ab1_w = ab1wtmp.
   compute ab1_wci = {mc_ab1_w(cilow,1), mc_ab1_w(cihigh,1)}.
end if.
do if (!bet_x_1 = 1 AND !bet_m1_1 = 1).
   compute ab1btmp = mc_ab1_b.
   compute ab1btmp(GRADE(mc_ab1_b)) = mc_ab1_b.
   compute mc_ab1_b = ab1btmp.
   compute ab1_bci = {mc_ab1_b(cilow,1), mc_ab1_b(cihigh,1)}.
end if.
do if (!bet_x_1 = 1 AND !wit_x_1 = 1 AND !bet_m1_1 = 1).
   compute ab1ctmp = mc_ab1_c.
   compute ab1ctmp(GRADE(mc_ab1_c)) = mc_ab1_c.
   compute mc_ab1_c = ab1ctmp.
   compute ab1_cci = {mc_ab1_c(cilow,1), mc_ab1_c(cihigh,1)}.
   compute ab1_c = a1b1_b - a1b1_w.
   compute cont_tab = {ab1_c, ab1_cci}.
end if.
do if (!m2_1 = 1).
   do if (!wit_x_1 = 1).
      compute ab12_w = a2b2_w - a1b1_w.
      compute ab2wtmp = mc_ab2_w.
      compute ab2wtmp(GRADE(mc_ab2_w)) = mc_ab2_w.
      compute mc_ab2_w = ab2wtmp.
      compute ab2_wci = {mc_ab2_w(cilow,1), mc_ab2_w(cihigh,1)}.
      compute ab12wtmp = ab_12_w.
      compute ab12wtmp(GRADE(ab_12_w)) = ab_12_w.
      compute ab_12_w = ab12wtmp.
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         compute ab12_wci = {ab_12_w(cilow,1), ab_12_w(cihigh,1)}.
      end if.
      do if (!bet_x_1 = 1 AND !bet_m2_1 = 1).
         compute ab12_b = a2b2_b - a1b1_b.
         compute ab2btmp = mc_ab2_b.
         compute ab2btmp(GRADE(mc_ab2_b)) = mc_ab2_b.
         compute mc_ab2_b = ab2btmp.
         compute ab2_bci = {mc_ab2_b(cilow,1), mc_ab2_b(cihigh,1)}.
         compute ab12btmp = ab_12_b.
         compute ab12btmp(GRADE(ab_12_b)) = ab_12_b.
         compute ab_12_b = ab12btmp.
         compute ab12_bci = {ab_12_b(cilow,1), ab_12_b(cihigh,1)}.
      end if.
      do if (!bet_x_1 = 1 AND !wit_x_1 = 1 AND !bet_m2_1 = 1).
         compute ab2ctmp = mc_ab2_c.
         compute ab2ctmp(GRADE(mc_ab2_c)) = mc_ab2_c.
         compute mc_ab2_c = ab2ctmp.
         compute ab2_cci = {mc_ab2_c(cilow,1), mc_ab2_c(cihigh,1)}.
         compute ab2_c = a2b2_b - a2b2_w.
         compute cont_tab = {cont_tab; ab2_c, ab2_cci}.
      end if.
   end if.
   do if (!m3_1 = 1).
      do if (!wit_x_1 = 1).
         compute ab13_w = a3b3_w - a1b1_w.
         compute ab23_w = a3b3_w - a2b2_w.
         compute ab3wtmp = mc_ab3_w.
         compute ab3wtmp(GRADE(mc_ab3_w)) = mc_ab3_w.
         compute mc_ab3_w = ab3wtmp.
         compute ab3_wci = {mc_ab3_w(cilow,1), mc_ab3_w(cihigh,1)}.
         compute ab13wtmp = ab_13_w.
         compute ab13wtmp(GRADE(ab_13_w)) = ab_13_w.
         compute ab_13_w = ab13wtmp.
         compute ab13_wci = {ab_13_w(cilow,1), ab_13_w(cihigh,1)}.
         compute ab23wtmp = ab_23_w.
         compute ab23wtmp(GRADE(ab_23_w)) = ab_23_w.
         compute ab_23_w = ab23wtmp.
         compute ab23_wci = {ab_23_w(cilow,1), ab_23_w(cihigh,1)}.
      end if.
      do if (!bet_x_1 = 1 AND !bet_m3_1 = 1).
         compute ab13_b = a3b3_b - a1b1_b.
         compute ab23_b = a3b3_b - a2b2_b.
         compute ab3btmp = mc_ab3_b.
         compute ab3btmp(GRADE(mc_ab3_b)) = mc_ab3_b.
         compute mc_ab3_b = ab3btmp.
         compute ab3_bci = {mc_ab3_b(cilow,1), mc_ab3_b(cihigh,1)}.
         compute ab13btmp = ab_13_b.
         compute ab13btmp(GRADE(ab_13_b)) = ab_13_b.
         compute ab_13_b = ab13btmp.
         compute ab13_bci = {ab_13_b(cilow,1), ab_13_b(cihigh,1)}.
         compute ab23btmp = ab_23_b.
```

```
      compute ab23btmp(GRADE(ab_23_b)) = ab_23_b.
      compute ab_23_b = ab23btmp.
      compute ab23_bci = {ab_23_b(cilow,1), ab_23_b(cihigh,1)}.
   end if.
   do if (!bet_x_1 = 1 AND !wit_x_1 = 1 AND !bet_m3_1 = 1).
      compute ab3ctmp = mc_ab3_c.
      compute ab3ctmp(GRADE(mc_ab3_c)) = mc_ab3_c.
      compute mc_ab3_c = ab3ctmp.
      compute ab3_cci = {mc_ab3_c(cilow,1), mc_ab3_c(cihigh,1)}.
      compute ab3_c = a3b3_b - a3b3_w.
      compute cont_tab = {cont_tab; ab3_c, ab3_cci}.
   end if.
end if.
do if (!wit_x_1 = 1).
   compute tab1 = {a1b1_w, v_a1b1_w}.
   compute tab2 = {a1b1_w, se_a1b1w, a1b1_w_z, a1b1_w_p, ab1_wci}.
end if.
do if (!bet_x_1 = 1 AND !bet_m1_1 = 1).
   compute tab3 = {a1b1_b, se_a1b1b, a1b1_b_z, a1b1_b_p, ab1_bci}.
end if.
do if (!m2_1 = 1).
   do if (!wit_x_1 = 1).
      compute tab1_2 =  {a2b2_w, v_a2b2_w}.
      compute tab2_2 = {a2b2_w, se_a2b2w, a2b2_w_z, a2b2_w_p, ab2_wci}.
      compute tab1 = {tab1; tab1_2}.
      compute tab2 = {tab2; tab2_2}.
      compute tab4 = {ab12_w, ab12_wci}.
   end if.
   do if (!bet_x_1 = 1 AND !bet_m2_1 = 1).
      compute tab3_2 = {a2b2_b, se_a2b2b, a2b2_b_z, a2b2_b_p, ab2_bci}.
      compute tab3 = {tab3; tab3_2}.
      compute tab5 = {ab12_b, ab12_bci}.
   end if.
end if.
do if (!m3_1 = 1).
   do if (!wit_x_1 = 1).
      compute tab1_2 =  {a3b3_w, v_a3b3_w}.
      compute tab2_2 = {a3b3_w, se_a3b3w, a3b3_w_z, a3b3_w_p, ab3_wci}.
      compute tab4_2 = {ab13_w, ab13_wci; ab23_w, ab23_wci}.
      compute tab1 = {tab1; tab1_2}.
      compute tab2 = {tab2; tab2_2}.
      compute tab4 = {tab4; tab4_2}.
   end if.
   do if (!bet_x_1 = 1 AND !bet_m3_1 = 1).
      compute tab3_2 = {a3b3_b, se_a3b3b, a3b3_b_z, a3b3_b_p, ab3_bci}.
      compute tab5_2 = {ab13_b, ab13_bci; ab23_b, ab23_bci}.
      compute tab3 = {tab3; tab3_2}.
      compute tab5 = {tab5; tab5_2}.
   end if.
end if.
compute tab1 = {tab1, sqrt(tab1(:,2))}.
```

```
compute numvary = (csum(tab1(:,1) NE 0)).
compute co1_0 = 0.
compute co2_0 = 0.
compute co3_0 = 0.
do if (!wit_x_1 = 1).
   print tab1/ title = "Within- Indirect Effect(s)" /clabels = "E(ab)" "
      Var(ab)" "SD(ab)"/rlabels = !m1 !m2 !m3 /format =F8.4.
   do if (cov_12 NE 0 OR cov_13 NE 0 OR cov_23 NE 0).
      compute ind_cov = {v_a1b1_w, cov_12; cov_12, v_a2b2_w}.
      do if (!m3_1 = 1).
         compute newcol = {cov_13; cov_23}.
         compute newrow = {cov_13, cov_23, v_a3b3_w}.
         compute ind_cov = {ind_cov, newcol}.
         compute ind_cov = {ind_cov; newrow}.
      end if.
      print ind_cov /title = "Within- Indirect Effect Covariance Matrix"
          /clabels = !m1 !m2 !m3 "-" /rlables = !m1 !m2 !m3 "-" /format
          = F8.4.
      do if (ind_cov(1,1) = 0).
         compute co1_0 = 1.
         compute ind_cov(1,1) = .001.
      end if.
      do if (ind_cov(2,2) = 0).
         compute co2_0 = 1.
         compute ind_cov(2,2) = .001.
      end if.
      do if (nrow(ind_cov) > 2 AND ind_cov(3,3) = 0).
         compute co3_0 = 1.
         compute ind_cov(3,3) = .001.
      end if.
      compute sds = sqrt(mdiag(diag(ind_cov))).
      compute sds_inv = inv(sds).
      compute cor_mat = sds_inv*ind_cov*sds_inv.
      print cor_mat /title = "Within- Indirect Effect Correlation Matrix
          " /clabels = !m1 !m2 !m3 "-" /rlables = !m1 !m2 !m3 "-" /
          format = F8.4.
   end if.
   print tab2/ title = "Within- Indirect Effect(s)" /clabels "Effect" "
      SE" "Z" "p" "MCLL" "MCUL" /rlabels = !m1 !m2 !m3 /format = F8.4.
else.
   print /title = "Note: No Within- Indirect Effect(s) Specified.".
end if.
do if (!bet_x_1 = 1).
   print tab3/ title = "Between- Indirect Effect(s)" /clabels "Effect" "
      SE" "Z" "p" "MCLL" "MCUL" /rlabels = !m1 !m2 !m3 /format = F8.4.
else.
   print /title = "Note: No Between- Indirect Effect(s) Specified.".
end if.
do if (!m2_1 = 1).
   print /title = "*******************************
   **************************************".
```

```
print tab4/ title = "Within- Indirect Effect Contrasts" /clabels "Dif
    " "MCLL" "MCUL" /rlabels = "ab2-ab1" "ab3-ab1" "ab3-ab2" /format
    = F8.4.
do if (!bet_x_1 = 1).
    print tab5/ title = "Between- Indirect Effect Contrasts" /clabels
        "Dif" "MCLL" "MCUL" /rlabels = "ab2-ab1" "ab3-ab1" "ab3-ab2" /
        format = F8.4.
end if.
end if.
do if (!bet_x_1 = 1 AND !wit_x_1 = 1).
    print cont_tab/ title = "Test of Indirect Contextual Effect(s):
        Between - Within" /clabels "Dif" "MCLL" "MCUL" /rlabels = !m1 !m2
        !m3 /format = F8.4.
end if.
else.
    print /title = "Note: Indirect Effects Not Calculated Due to Error(s)
        in Estimated Fixed or Random Effects.".
end if.
END MATRIX.
OUTPUT MODIFY
  /REPORT PRINTREPORT=NO
  /SELECT TEXTS
  /IF COMMANDS=["Matrix(LAST)"] LABELS=[EXACT("Active Dataset")]
      INSTANCES=[1]
  /DELETEOBJECT DELETE=YES
  /SELECT HEADINGS
  /IF COMMANDS=["Matrix(LAST)"] LABELS=[EXACT("Title")] INSTANCES=[1]
  /DELETEOBJECT DELETE=YES.
!ENDDEFINE.
```

Appendix B: MLmed Macro for SPSS Documentation

`MLmed` is a computational macro for SPSS that simplifies the fitting of multilevel mediation and moderated mediation models, including models containing more than one mediator. After the model specification, the macro automatically performs all of the tedious data management necessary prior to fitting the model. This includes within-group centering of lower-level predictor variables, creating new variables containing the group means of lower-level predictor variables, and stacking the data as outlined in Bauer et al. (2006) and their supplementary material to allow for the simultaneous estimation of all parameters in the model. The output is conveniently separated by equation, which includes a further separation of between-group and within-group effects. Further, indirect effects, including Monte Carlo confidence intervals around these effects, are automatically provided. The index of moderated mediation is also provided for models involving level-2 moderators of the indirect effect.

B.1   Preparation for Use

Before using `MLmed`, the syntax file containing the code necessary to define the macro (MLmed.sps), must be opened and executed without modification. The file can then be closed, and `MLmed` can be operated using a new syntax file. Note that

the macro will remain active only for the duration of the SPSS session (i.e., until SPSS is closed). The macro will need to be re-executed at the start of a new session.

B.2 Minimum Model Specification

Once the macro is activated, it can be called by typing `MLmed` followed by the appropriate macro arguments. Each argument, except the first, should begin with a forward slash, and the final argument should be followed by a period. The minimum syntax necessary to run the most basic model is:

```
 MLmed data = DataSet1
/x = Xvar
/m1 = Mvar
/y = Yvar
/cluster = group
/folder = FilePath.
```

where the italicized words are replaced with the correct dataset name, variable names, and file location. The dataset name should be the name that appears in brackets on the opened dataset window, rather then the saved `.sav` file name. By default, the first dataset opened in a new SPSS session is named *DataSet1* and `MLmed` defaults to this name. To be safe, specify the correct dataset name, even if it is the default. The `x`, `m1`, and `y` arguments should be the names of the variables in the dataset corresponding to X, M, and Y. The `cluster` argument should be a variable that labels which level-2 unit each row in the dataset belongs to. Finally, the `folder` argument should be a file path on the user's computer. This does not have to be the location of the dataset, syntax file, or any other specific file, but must be a correct folder location on the computer. Note that file paths on a Windows OS will use a backslash between folders, while a Mac OS will use a forward slash. The macro

arguments do not have to be in any specific order, other than the `folder` specification being last.

This minimum syntax will fit a model where `Xvar` is the independent variable, `Mvar` is the mediator, and `Yvar` is the dependent variable. The macro automatically group-mean centers X and uses the group means as a level-2 predictor of M. Further, mean-centered X and M are used as level-1 predictors of Y and the group-means of X and M are used as level-2 predictors. All intercept terms are random. By default, all slope terms (described in this section and later sections) are fixed and the random effect covariance matrix is diagonal, where variances are freely estimated and covariances are constrained to zero. These defaults are useful for increasing the likelihood of convergence. Macro arguments that can change these specifications are described in a later section.

B.3   Adding Fixed Effects

The basic syntax can be expanded to fit models that include additional fixed effects that result from adding mediators, covariates, and moderators.

B.3.1   Mediators

Up to two additional mediators can be specified by including the arguments `m2` and `m3` with the variable name following. Each mediator included will be group-mean centered prior to the analysis. The group means will also be included to estimate between-group effects.

B.3.2 Level-1 Covariates

Up to three level-1 covariates can be included by using the `cov1`, `cov2`, and `cov3` arguments, with the appropriate variable names following. As with other level-1 variables, the covariates are automatically group mean centered to disentangle between-group and within-group effects.

B.3.3 Level-2 Covariates

Up to three level-2 covariates can be included by using the `l2cov1`, `l2cov2`, and `l2cov3` arguments, with the name of the covariates following. Note that the first character of each of these arguments is the letter "l", not the number "1". The user should manually center level-2 covariates prior to using `MLmed` if desired.

B.3.4 Level-2 Moderators

One level-2 moderator can be specified for the a path, and one level-2 moderator can be specified for the b path. These are specified using the `modM` and `modY` arguments, respectively, where the letters `M` and `Y` correspond to the dependent variable for the equation in which the moderator is included in. The user should NOT include the level-2 moderator as a level-2 covariate, as `MLmed` will do this automatically. It should also be noted that the variable is included as a moderator only for the first mediator listed (the one specified by `m1`).

By default, the moderation of both the between-group and within-group effects the will be tested for each moderator included. The same moderator can be specified for both paths to allow for the testing of a quadratic moderation effect. The user can also specify a specific value to center each moderator around using the `modMcent` and

`modYcent` arguments, respectively. Any effect that is moderated will be conditional on the value in which the moderator is centered around (by default, the value is 0).

B.4   Removing Fixed Effects

Some of the effects automatically included by `MLmed` may be omitted from the model. These include a number of between-group effects, and also the within-group effect of X.

B.4.1   Between-group Effects

The general format for removing a between group effect is by listing the argument to specify the original variable followed by a `B` and setting this new argument equal to zero. That is, it can be though of as specifying that between-group effect to be omitted. For example, removing the between-group effect of `x` can be specified using the argument `xB = 0`. The between-group effect of `cov1` can be omitted using `cov1B = 0`. Further, the between-effects of the M and/or Y moderators can be specified using `modMB = 0` and `ModYB = 0`, respectively.

There is, however, a slight deviation from this format for removing the between-group effect(s) of the mediator(s). Rather than the between-group effect of each mediator being specified with its own argument, the between-group effect of all mediators can be specified using `mB`, which should be a list of zeros and ones equal in length to the number of mediators where a 1 denotes that the between-group effect of that particular mediator should be estimated and a 0 denotes it should be omitted. For example, a model including three mediators where the between-group effect of mediators 1 and 3 on Y is estimated, but the effect of mediator 2 on Y is omitted can be specified using `mB = 101`.

There are two main reasons one may wish to omit a between-group effect. The first occurs if there is no actual between-group variability on a given variable. In this scenario, the group-mean for the variable will be the same for each group, making the vector of group means redundant. Consequently, the model cannot be estimated without this effect omitted. The second reason is simply for parsimony, as the removal of the effect can simplify the model. This is particularly true with the removal of the between-group moderator, given that including the moderator makes the indirect effect conditional. It should be noted that if the between-group effect of X or one of the mediators is not estimated, the between-group indirect effect involving that parameter is also not calculated.

B.4.2 Within-group Effect of X

The within-group effect of X can also be omitted using the argument `xW = 0`. Of course, no within-group indirect effects will then be estimated.

The ability to omit the within-group effect of X expands `MLmed` to be able to estimate 2-1-1 multilevel mediation models, as the 2-1-1 model can be seen as a special case of the 1-1-1 model with no within-group variability on X.

B.5 Specifying Random Effects

Any intercept and/or within-group slope included in the model can be specified as randomly varying across groups.

B.5.1 Random Intercepts

By default, all intercepts included in the model are specified as random. Because nonconvergence may be an issue if the variance of a random effect nears zero, the

user can specify any intercept as fixed. For the Y intercept, this is accomplished using `randYint = 0`, indicating that a random term for the Y intercept should be omitted. For M, the argument to omit a random intercept is `randMint`, though the exact specification depends on the number of mediators in the model. A list of zeros and ones that is the length of the number of mediators should be included, where a zero omits the random effect and a one estimates it. For example, `randMint = 011` should be specified to omit the random intercept for the first mediator in a three mediator model.

B.5.2 Random Slopes

Random slopes can be specified using similar syntax as random intercepts. To specify the effect of X to be random, the argument `randx` is used, which should be a list of binaries of length $k + 1$ where k is the number of mediators in the model. The first binary refers to the effect of X on Y (the c' path), the second refers to the effect of X on M_1, the third refers to the effect of X on M_2, and so forth. A 1 corresponds to a random effect, while a 0 corresponds to a fixed effect. Random effects of the mediator(s) on Y are specified using `randm` which should be a list of binaries of length k, where the first refers to the effect of the first mediator on Y, the second refers to the effect of the second mediator on Y and so forth. Random effects of level-1 covariates are specified using `randc1`, `randc2`, and `randc3`. The format of these arguments follow that of `randx`.

B.6 Covariance Matrices

The residual covariance matrix and the covariance matrix of the random effects can be modified.

B.6.1 Residual Covariance Matrix

The residual covaraince matrix is specified as diagonal (`DIAG`) by default, where the residual variance of each equation is freely estimated and the covariance between the residuals of each equation are constrained to zero. The residual covariance matrix can be specified as unconstrained (where all variances and covariances are freely estimated) using the argument `rescovmat = UN`.

B.6.2 Random Effect Covariance Matrix

By default, the random effect covariance matrix is specified as diagonal, where all variances are freely estimated and the covariances are constrained to zero. However, some or all of the random effects can be permitted to covary. If there is more than one random slope, their covaraince(s) can be freely estimated by including the command `covmat = UN`. To estimated the covariance between random slopes and the Y intercept, the command `ycov = 1` can be included (if `covmat = UN`). If more than one mediator is in the model, the covariance between the random intercepts for the mediators can be estimated using `mcovmat = UN`. The covariance between the M and Y intercepts can be included in the model using `indint = 0`. If there are random slopes in the model, `covmat = UN`, `ycov = 1`, and `indint = 0`, then the whole random effect covariance matrix is unstructured, where all variances and covariances are freely estimated.

B.7 Estimation

The default estimator for `MLmed` is Restricted Maximum Likelihood (`REML`). Users may instead estimate the model using Full Maximum Likelihood by including the

argument `est = ML`. The user may also provide a number of specifications that influence the estimation. These specifications include `iters` (maximum number of iterations), `mxstep` (maximum step-halving), and `scoring` (number of iterations in which the Fisher scoring algorithm is used). Further details of these can be found in the SPSS users manual under the section for MIXED.

B.8   Other Specifications

The user may specify the confidence level used for inferences provided in the output using the `conf` argument, which should include a number between 0 and 100 which corresponds to the percentage of confidence. By default, this value is 95. The number of Monte Carlo samples used can be changed using `samples`, which defaults to 10,000. Lastly, when the model fails to converge the estimates of the parameters is omitted from the output. The user may override this by specifying `eor = 1`, which is short for Error Override. This command can be useful for assessing issues in convergence by identifying which parameters may be causing the difficulties.

B.9   Output

The `MLmed` macro provides a very detailed output including individual parameter estimates, and the estimated indirect effects. In addition, the index of moderated mediation is included if a moderator is specified. This section provides an overview on each of the output tables provided.

B.9.1   Errors

If there are any errors when estimating the model, the estimated parameters are disabled from the output (unless this is overridden). Instead, the user is provided with

the number of fixed effect and random effect parameters that could not be estimated, as well as a code labelling the specific parameters, where a 1 indicates the parameter could not be estimated. The user can use this information to respecify the model.

B.9.2 Model Fit Statistics

If the model converges, various statistics are provided, such as the sample size and number of model parameters, as well as several model fit statistics, including -2 times the Log Likelihood (-2LL), Akaike's Information Criterion (AIC), Hurvich and Tsai's Criterion (AICC), Bozdogan's Criterion (CAIC), and Schwarz's Bayesian Criterion (BIC). The fit statistics can be useful when comparing models.

B.9.3 Fixed Effects

After the model fit statistics, the fixed effect estimates are provided. These estimates are grouped by each outcome variable, starting with the mediator(s) and ending with Y. Within each section containing each outcome variable, the effects are broken up by within-group and between-group effects. If no covariates are included in the model and the between-group effect of X is disabled, there will not be any between-group effects in each of the mediators' sections. If any moderators are included, the interaction terms are labeled using `int`, and the *Interaction Codes* section contains information on what each interaction term represents.

B.9.4 Random Effects

If the level-1 residual covariance matrix is specified as diagonal, the estimates are displayed in the *Level-1 Residual Estimates* section. If the matrix is specified as unstructured, the effects are labeled with a number system where the effect is a

variance parameter if the two numbers in parentheses are the same, and a covariance parameter if the two numbers differ. The numbers correspond to the key provided below the table.

If the random effect covariance matrix is specified as diagonal (the default), the *Random Effects* section of the output will contain the estimated variance of each random effect, as well as the relevant test statistics for that effect. If the covariance matrix is specified as unstructured, the *Random Effect Estimates* table will contained each estimated variance and covariance parameter, as well as the relevant test statistics for each of these parameters. These effects use the same number system as the *Level-1 Residual Estimates* section. A table containing the number key for each effect is also included. Finally, the estimated covariance and correlation matrices are provided.

B.9.5 Index of Moderated Mediation

If any moderators are included in the model, an *Index of Moderated Mediation* section follows the *Random Effects* section. This section includes the index of moderated mediation for each interaction term as well as a Monte Carlo confidence interval. If the same variable is specified as a moderator for both a and b, the linear and quadratic terms are included. Further, this section is broken up by within-group and between-group effects.

B.9.6 Indirect Effect(s)

The final section included in the output contains the indirect effect(s). If there are any moderators in the model, a code is provided which states what value of the moderator(s) the indirect effect(s) are conditional on. These are the values specified

using `modMcent` and `modYcent`, which default to `0`. If no moderators are specified, the indirect effects are unconditional. The first *Within- Indirect Effect(s)* section displays the estimated average within-group indirect effect(s), as well as the estimated variability of indirect effects across level-2 units. If neither a nor b are random, the variance of the indirect effect is 0. The next *Within- Indirect Effect(s)* section contains a normal-theory test on the average within-group indirect effect(s). A Monte Carlo confidence interval is also provided. Finally, the *Between- Indirect Effect(s)* section contains the normal-theory test and Monte Carlo confidence interval for the between-group indirect effect(s). If `xB = 0`, this section is omitted.

If multiple mediators are specified, a section containing indirect effect contrasts follows. Every pairwise combination of indirect effects is tested using a Monte Carlo confidence interval. This section is broken up by within-group and between-group effects.

Appendix C: Code Used for Final Models of Example Analyses

The following code was used to obtain the parameter estimates of the final model of each Example in Chapter 6.

C.1 Example 1

MLmed:

```
mlmed data = DataSet1
   /x = BELONG
   /randx = 01
   /m1 = COOPERATE
   /cov1 = OUTHOURS
   /cov2 = ESCS
   /randm = 1
   /modY = SCHS_100
   /modYcent = 7.92
   /modYB = 0
   /y = PV1MATH
   /covmat = UN
   /cluster = SCHID
   /est = ML
   /folder = /Users/nickrockwood/Desktop/.
```

Mplus:

```
TITLE: Example 1 Model;
DATA: FILE IS can_data.dat;
VARIABLE: NAMES ARE schid out belong coop escs math schs
schs100 schsc outm belongm coopm escsm;
USEVAR = schid out belong coop escs math
        schsc outm coopm escsm belongm;
CLUSTER = schid;
WITHIN ARE belong coop escs out;
```

```
BETWEEN ARE outm coopm escsm schsc belongm;
MISSING = .;
DEFINE:
CENTER belong coop escs out(GROUPMEAN);
ANALYSIS: TYPE = twolevel random; ESTIMATOR = ML;
MODEL: \%WITHIN\%
sa | coop ON belong;
sb | math ON coop;
coop ON escs out;
math ON escs out belong;
[coop@0];
\%BETWEEN\%
sb ON schsc (int);
coopm ON belongm(ab);
math ON coopm(bb);
coopm ON escsm outm;
math on escsm outm belongm schsc;
[sa](aw);
[sb](bw);
sa WITH sb(covab);
MODEL CONSTRAINT:
NEW(indw indb modmedw context);
indw=aw*bw+covab;
indb = ab*bb;
modmedw = aw*int;
context = indb-indw;
OUTPUT: tech1 tech8 cinterval;
```

lme4:

```
library(lme4)
mod1 <- lmer(COOPERATE~ BELONG_c + OUT_c + ESCS_c + BELONG_m + OUT_m
        + ESCS_m + (1|SCHID) + (0 + BELONG_c|SCHID), data = data, REML =
            FALSE)
mod2 <- lmer(PV1MATH~ BELONG_c + OUT_c + ESCS_c + BELONG_m + OUT_m
        + ESCS_m + COOP_c + COOP_m + int + SCHS_100c + (1|SCHID)
        + (0 + COOP_c|SCHID), data = data, REML = FALSE)
summary(mod1)
summary(mod2)
```

C.2   Example 2

MLmed:

```
mlmed data = DataSet3
    /x = COMP
    /randx = 0110
    /xB = 0
    /m2 = ENJ
```

```
   /m1 = EFF
   /m3 = ANX
   /mB = 011
   /modY =EFF_M
   /modYB = 0
   /modYcent = 71.8065
   /covmat = UN
   /y = DUR
   /est = ML
   /cluster = SUBJECT
   /folder = /Users/nickrockwood/Desktop/ .
```

Mplus:

```
TITLE: Example 2 Model;
DATA: FILE IS competition_data.dat;
VARIABLE: NAMES ARE subject type eff anx enj dur comp eff_m
 eff_cent int eff_mean anx_m enj_m;
USEVAR = subject comp eff anx enj dur eff_mean int anx_m enj_m;
CLUSTER = subject;
WITHIN ARE comp eff anx enj int;
BETWEEN ARE eff_mean enj_m anx_m;
MISSING = .;
DEFINE:
CENTER comp eff anx enj(GROUPMEAN);
ANALYSIS: TYPE = twolevel random; ESTIMATOR = ML;
MODEL: \%WITHIN\%
sa1 | eff ON comp;
sa2 | enj ON comp;
anx ON comp (a3);
dur ON eff (b1);
dur ON enj (b2);
dur ON anx (b3);
dur ON comp (cp);
dur ON int (inter);
[eff@0];
[enj@0];
[anx@0];
\%BETWEEN\%
dur ON eff_mean enj_m anx_m;
[sa1](a1);
[sa2](a2);
sa1 WITH sa2;
eff_mean enj_m anx_m;
dur;
MODEL CONSTRAINT:
NEW(ind1 ind2 ind3 index ab3_ab1 ab2_ab1 ab3_ab2);
ind1=a1*b1;
ind2=a2*b2;
ind3=a3*b3;
index=a1*inter;
ab3_ab1 = ind3-ind1;
```

```
ab2_ab1 = ind2-ind1;
ab3_ab2 = ind3-ind2;
OUTPUT: tech1 tech8 cinterval;
```

lme4:

```
mod1 <- lmer(Eff~  Comp_c + (1| Subject) + (0 + Comp_c | Subject), data
   = data, REML = FALSE)
mod2 <- lmer(Enj~  Comp_c + (1| Subject) + (0 + Comp_c | Subject), data
   = data, REML = FALSE)
mod3 <- lmer(Anx~ Comp_c + (1 | Subject), data = data, REML = FALSE)
mod4 <- lmer(Dur~ Comp_c + Eff_c + Enj_c + Anx_c + Eff_meanc + Enj_m +
              Anx_m + inter + (1|Subject), data = data, REML = FALSE)
summary(mod1)
summary(mod2)
summary(mod3)
summary(mod4)
```