Methodological Considerations in Mediation Analysis and Related Modeling Procedures

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APPROVAL OF THE DISSERTATION

This dissertation, "Methodological Considerations in Mediation Analysis and Related Modeling Procedures," has been approved by the Graduate Faculty of the School of Education and Human Development in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

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OVERVIEW

One of the fundamental endeavors of social science research is to advance explanations of human behavior. Beyond mere description, scientific explanation attempts to open the black box and answer questions about *how* or *why* things are related, or an effect occurs. Quantitative methods play an important role in fostering explanatory understandings of the social world. Such methods involve statistical models that are used as inferential tools to evaluate uncertainty in quantitative data. These models are abstract, mathematical approximations of real-world systems and are designed to reliably make inferences about the events, or constructs, they represent. Just as the kinds of phenomena that concern the social sciences are highly complex and variable, there is an equally complex and variable array of approaches to statistical modeling. Within this methodological pluralism, mediation analysis is a key statistical method used by social scientists to evaluate explanatory theories about relations between independent and dependent variables. For example, when a bivariate association between an independent variable (X) and a dependent variable (Y) is observed, mediation analysis can be used to test hypotheses about the process or mechanism by which the two variables are related. Mediation analysis attempts to model the underlying process in terms of its component parts by specifying the indirect pathways between one or more intervening variables that link X to Y.

In recent years, applications of mediation models have become ubiquitous across the social sciences. The popularity of these models is attributable in part to their utility in facilitating judgements about explanatory theories. For example, in educational research, understanding the process by which an intervention affects student outcomes has significant implications for policy and practice. Of course, there are various design features that researchers must consider when conducting any statistical analysis, including mediation. Features such as multiple groups, small sample sizes, nested data structures, and latent variables are commonly encountered in educational and behavioral studies and can pose additional challenges for applied researchers in terms of model estimation and interpretation. Advanced methodological tools are needed to construct more sophisticated mediation models that are required to accommodate these complex design features.

This dissertation is a compilation of three papers that address such methodological issues in mediation analysis. The three papers, each of which constitute a chapter in this dissertation, examine different concerns related to mediation analysis that arise in applied settings. Each chapter considers a particular methodological issue through the lens of statistical theory. Monte Carlo simulations are used to evaluate the methods under a variety of design conditions. Moreover, given that the ultimate purpose of statistics is its application to real-world data, empirical examples are provided as guidance to substantive researchers. Data for these examples come from educational research on school climate; however, the methods considered here are effectively applicable to many areas of social science research.

Chapter 1 addresses how to include tests of moderation effects in mediation analysis. It begins by reviewing key elements of mediation and moderation and then discusses methods for integrating the two into a single moderated mediation model. The chapter provides a historical perspective on methodological trends in mediation analysis, setting the stage for subsequent chapters that consider more advanced topics.

Chapter 2 extends mediation analysis to the case of nested data structures with small sample sizes and latent variables. It considers multilevel mediation models within the context of the structural equation modeling (SEM) framework and compares the performance of Bayesian and frequentist estimation approaches. Results from a Monte Carlo simulation study are presented which demonstrate the impact of Bayesian priors on indirect effect estimates.

Chapter 3 addresses the issue of model selection. Establishing a well-fitting measurement model is a necessary first step in testing mediation in any structural model that includes latent variables. Methods for evaluating model fit are well established in the frequentist framework; however, less work has focused on developing model fit criteria in Bayesian SEM. Applied researchers who wish to conduct mediation analysis with latent variables in the Bayesian framework may find the process of first selecting a measurement model challenging. Chapter 3 discusses recent advances in Bayesian model selection and presents a simulation study that rigorously investigates the performance of various Bayesian model fit indices under different model and data conditions.

Taken together, the papers presented in this dissertation synthesize developments in mediation analysis and contribute new understandings to methodological issues that researchers often encounter in applied settings. Extensions and applications of mediation models to moderated mediation, multilevel designs, small sample sizes, SEM, and Bayesian approaches are explored. Although the range of topics is broad and covers both established and emerging methods, each chapter investigates a clearly defined research problem that motivates the subsequent inquiry of later chapters. Overall, the aim is to provide an account of advanced methodological issues that are relevant for mediation analysis and broadly applicable to substantive researchers.

CHAPTER 1

Moderated Mediation Analysis: A Review and Application to School Climate Research

Abstract

Moderated mediation analysis is a valuable technique for assessing whether an indirect effect is conditional on values of a moderating variable. We review the basis of moderation and mediation and their integration into a combined model of moderated mediation within a regression framework. Thereafter, an analytic and interpretive illustration of the technique is provided in the context of a substantive school climate research question. The illustration is based on a sample of 318 high schools that examines whether school-wide student engagement mediates the association between the prevalence of teasing and bullying (PTB) and academic achievement on a state-mandated reading exam; and whether this indirect effect was moderated by student perceptions of teacher support.

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Introduction

Contemporary research questions in the social sciences increasingly involve complex relationships among multiple variables that operate in concert. Some of these complexities arise when variable associations are conditional on other variables. For example, *when* the relationship between social support and adolescent mental health changes across levels of academic achievement (Stewart & Suldo, 2011); or when the association between pre-kindergarten school-readiness skills and later academic achievement among low-income Black children differs between immigrant and non-immigrant status (Calzada et al., 2015).

In other instances, variable associations might be best understood in the presence of an intervening, or mediating, variable that illuminates how or w*hy* other variables are related. For example, Fredrick and Demaray (2018) demonstrated that peer victimization led to depressive symptoms, which in turn resulted in suicidal ideation. Inclusion of depression as a mediating variable in this work allowed for a more complete understanding of ‘how’ peer victimization was related to suicidal ideation. Other substantive examples of mediation analysis can be found in Fantuzzo et al. (2012); Mittleman (2018); Purpura et al. (2013); Raver et al. (2011); and Ruzek et al. (2016).

Moderation and mediation analyses are two commonly used techniques to address questions of when and why variables are related, respectively. Moderation occurs when the magnitude and/or direction of a relationship between variables is conditional on a third variable, and tests of moderation can be useful for evaluating the boundary conditions under which associations between two (or more) variables occur (Aguinis, 2004). In other words, whether variable associations hold across different situations or for different groups of people. By contrast, mediation analysis provides a means to test how or why two or more variables might be related. A mediating variable can be conceptualized as a third variable that intervenes in the relationship between two or more other variables, acting as a mechanism, through which one variable's effect is transmitted to another (Baron & Kenny, 1986).

Although moderation and mediation are each useful on their own, integrating both into a single model enables researchers to examine even more nuanced relationships among variables. These combined forms are commonly referred to as *moderated mediation* or *conditional process models* (Hayes & Preacher, 2013), and allow for evaluations of whether an indirect effect is moderated by another variable. Moderated mediation models are particularly useful when there is interest in understanding both why and under what conditions variables are related to one another. This combined model provides an opportunity to simultaneously investigate contingent and indirect effects. For example, one recent study examined the moderating effect of certain genetic markers on the indirect effect of parenting behavior on children's ADHD symptoms through neurocognitive functioning (Morgan et al., 2018). Results indicated that positive parental praise actually impaired children's neurocognitive functioning during a battery of tasks, which then resulted in more pronounced ADHD symptoms. However, this indirect effect was moderated by two genetic polymorphisms, such that the strength of the mediating effect varied across children with different genotypes. As this example illustrates, the use of moderated mediation allowed for an evaluation of how neurocognitive functioning mediated the relationship between parenting behavior and ADHD symptoms, and for whom this occurred (i.e., different genetic marker groups).

While other recent applications of moderated mediation can be found in Dicke et al. (2014); Guo et al. (2018); and O'Neal et al. (2018), the use of these models is far less prevalent in the social sciences than are uses of moderation or mediation by themselves. In the sections below we briefly review methods for conducting moderation and mediation, and describe their integration for testing moderated mediating effects. Thereafter, we illustrate the usefulness and application of the approach in the context of education research. Given continued interest in providing students with healthy learning environments and its importance in national policy (e.g., the 2015 Every Student Succeeds Act, Public Law 114-95), we examine the role of student engagement in mediating the association between the prevalence of bullying in schools and academic achievement, and we test whether these relationships are moderated by levels of supportive school climate. In doing so, we describe the interpretable elements of the model to motivate more widespread use of this analytic approach and provide the PROCESS code used to estimate the model in SPSS.

Moderation Analysis

A linear model that evaluates the relationship between two continuous regressors (*X* and *W*) and a single outcome (*Y*) can be expressed as

$$Y = i_Y + b_1X + b_2W \tag{1}$$

where the unstandardized form of b_1 represents the expected change in *Y* for a unit increase in *X*, b_2 represents the expected change in *Y* for a unit change in *W*, and i_Y is an estimate of the expected value of *Y* when *X* and *W* are equal to zero. Importantly, the relationship (b_j) between a regressor (e.g., *X*) and *Y* holds across all values of the other regressor (e.g., *W*) in this additive form of the equation. The viability of b_j representing the amount of *Y* change for a unit change in its associated regressor, across all points of the other regressor in the model, can be evaluated through inclusion of a product term of the two regressors (*XW*) into Equation 1:

$$Y = i_Y + b_1X + b_2W + b_3XW \tag{2}$$

Equation 2 is graphically represented in Figure 1A. Here, b_3 estimates the amount of change in b_1 for a unit increase in W, or conversely, how b_2 changes across values of X. A non-zero b_3 term indicates that the Y,X or Y,W relationships are not constant across levels of the other regressor. A non-zero b_3 coefficient signals the presence of a *moderating effect* (Saunders, 1956), or *interaction* (Cohen, 1968), where the relationship between two variables is conditional on a third variable. Establishing a significant relationship between two variables is not a necessary pre-condition to testing for moderation, as evidence of an association between two variables may sometimes only be found when considered in the context of a third moderating variable (Aguinis, 2004). Tests of moderation can be particularly useful for evaluating whether relationships hold across situations, settings, and people.

Mediation Analysis

Although the concept of intervening variables pre-dates the seminal works of Kenny and colleagues (Baron & Kenny, 1986; Judd & Kenny, 1981), their contributions helped to establish statistical mediation analysis in the methods literature as well as promote its use by applied researchers. Judd and Kenny (1981) recommended evaluating mediation hypotheses through a series of regression equations, an approach they termed *process analysis*. They outlined three conditions that must hold in order to validate a proposed mediation effect: (1) the treatment affects the outcome, (2) the treatment affects the mediator, and (3) the treatment does not affect the outcome when controlling for the mediator. These conditions were tested by three regression equations: regressing the outcome on the treatment variable, regressing the mediator on the treatment variable, and regressing the outcome on both the mediator and treatment variable.

Baron and Kenny (1986) restated and expanded upon Judd and Kenny's guidelines, further popularizing the so-called *causal steps approach* to mediation. As outlined in Baron and Kenny, the first step was to estimate the *total effect* of X on Y,

$$Y = i_Y + cX \tag{3}$$

where i_Y is the intercept, and the coefficient c is the slope. The upper model in Figure 1B illustrates the total effect of X on Y (path c). After estimating a statistically significant total effect, the second step was to establish that X was related to M, as depicted by path a in the lower model in Figure 1B:

$$M = i_M + aX \tag{4}$$

The third step was to show that M was associated with Y when controlling for X, as represented by path b in Figure 1B:

$$Y = i_Y + c'X + bM \tag{5}$$

The final step required estimation of the *direct effect* of X on Y, holding M constant (path c' in Figure 1B, and coefficient c' in Equation 5).

In school psychology research, for example, Fairchild and McQuillin (2010) found that the majority of mediation studies in three of the field's top journals followed the causal steps approach. However, the methodological field has moved away from this approach as more recent advances in mediation analysis have been developed (e.g., Hayes, 2009; MacKinnon et al., 2002; Rucker et al., 2011; Shrout & Bolger, 2002; Zhao et al., 2010). While Baron and Kenny's (1986) method used a series of hypothesis tests to assess mediation, contemporary approaches focus directly on quantifying the indirect effect of X on Y through the mediator. This indirect effect is estimated as the product of the effect of X on M and the effect of M on Y, represented by paths a

and b in Figure 1B. By substituting Equation 4 into Equation 5, the mediation model can be expressed as a single equation:

$$Y = i_Y + c'X + bi_M + abX \tag{6}$$

The ab product term quantifies the estimated change in the outcome that results from a one-unit change in the independent variable through the mediator.

Through OLS regression, the indirect effect is equal to the total effect minus the direct effect, $ab = c - c'$ (MacKinnon et al., 1995). This equivalence is noteworthy because it highlights an important flaw in the assumptions underlying the causal steps logic. According to the causal steps approach, if there is no significant association between the independent and dependent variables, the analysis stops, and mediation is said to be non-existent. Although intuition may suggest that there must be a total effect of X on Y in order for an indirect effect to exist, mathematically it is not the case. When a significant indirect effect ab and a significant direct effect c' have opposite signs, they can cancel each other out, such that their sum (the total effect c) is not significantly different from zero (MacKinnon et al., 2002). Thus, researchers following the causal steps approach could mistakenly dismiss the presence of mediation. In light of this, methodologists today no longer require evidence of an association between X and Y as a pre-condition for evaluating the presence of a mediating effect.

Another requirement for mediation using the causal steps approach that is no longer considered necessary today is the notion of full mediation. In the methodological literature, a distinction is made between *fully* and *partially* mediated models. When the direct effect c' of X on Y, controlling for M, is zero, and the indirect effect is statistically greater than zero, the combined results could be said to support full mediation (Baron & Kenny, 1986; Judd & Kenny, 1981). Justification for full mediation requires that all mediating pathways between X and Y have been identified and that they completely account for the *X*-*Y* association. By contrast, when both the direct and indirect effects are statistically significant, the results are said to support partial mediation because the mediating variable only accounts for part of the relationship between *X* and *Y*.

Evaluating the statistical significance of a mediating effect has been an active area of research in recent years. Historically, researchers have relied on the Sobel test (i.e., delta method or normal theory approach; Sobel, 1982). This procedure generates a standard error from the *ab* indirect effect sampling distribution that is, in turn, used as the basis for a test statistic or confidence interval. An assumption of the Sobel test is that the sampling distribution of *ab* is normal; however, the sampling distribution of a product of two normally distributed variables is not necessarily normally distributed (Aroian, 1947). Simulation studies have demonstrated that the Sobel test is less powerful than alternative methods when the indirect effect is nonzero and has a skewed distribution, particularly for small sample sizes of less than 100 (Hayes & Scharkow, 2013; MacKinnon et al., 2004; Preacher & Selig, 2012; Shrout & Bolger, 2002).

By contrast, bootstrap confidence intervals (Preacher & Hayes, 2004, 2008; Shrout & Bolger, 2002) and Monte Carlo confidence intervals (MacKinnon et al., 2004; Preacher & Selig, 2012) avoid this problem by not assuming a normal sampling distribution. Introduced by Bollen and Stine (1990), and further discussed in Lockwood and MacKinnon (1998), the bootstrap approach for inferences regarding indirect effects has become one of the more popular techniques in the mediation methods literature. Here, a random sample is repeatedly drawn with replacement from the analytic sample, and estimates of *ab* are obtained for each bootstrap sample with the goal of developing a confidence interval for the indirect effect. Resampling is typically done thousands of times, resulting in *k* estimates of *ab*, which are used as an empirical sampling distribution of the statistic. A ($1 - \alpha$) percentile confidence interval for the indirect effect is calculated using the limits of the $100(1 - \alpha)\%$ of the bootstrap distribution (Bollen & Stine, 1990). Confidence intervals that do not contain zero support the claim that *M* mediates *X*'s effect on *Y*. As discussed in Preacher and Selig (2012), more complex variations of the bootstrap-based technique include bias-corrected, bias-corrected and accelerated, residual based, and parametric based procedures. The advantage of the bootstrap procedure over the Sobel test is that it does not assume normality, it can accommodate small sample sizes, and is adaptable to more complex models (Hayes, 2009).

Monte Carlo methods for creating confidence intervals for indirect effects involve using the sample estimates, $\hat{a}$ and $\hat{b}$, and their asymptotic variances and covariances to simulate a sampling distribution of *ab* based on repeated random draws from a defined multinormal distribution, rather than from resampling (MacKinnon et al., 2004). A confidence interval for *ab* is then calculated, as described previously for the bootstrap method. Like bootstrap procedures, the Monte Carlo method makes no parametric assumptions about the distribution of *ab*. Theoretically, both approaches provide a useful pathway for evaluating indirect effects. Currently, however, only the Monte Carlo approach has been developed for applications in multilevel contexts (Bauer et al., 2006; Preacher & Selig, 2012).

Mediation analysis in a regression-based framework relies upon the same model assumptions that are typical of OLS general linear models. It is assumed that the residuals are normally distributed, independent, and that homoscedasticity holds (Williams et al., 2013). In addition, it is worth noting that when conducting mediation analysis there is an implied assumption of temporal precedence. That is, the assumption that *X* precedes *M*, which precedes *Y*. This strong assumption cannot be met when mediation analysis is conducted with cross-sectional data. As a result, causal inferences about mediation should not be made with cross-sectional data. In fact, some methodologists reserve the term *mediation* for causal interpretations based exclusively on longitudinal designs (Little, 2013; Maxwell & Cole, 2007).

Moderated Mediation Analysis

The term *moderated mediation* is used to convey instances when the mechanism through which X affects Y is moderated by a fourth variable W, such that the indirect effect is different at different values of W. When one or both of the component paths ($X \rightarrow M$, $M \rightarrow Y$) through the mediator is moderated, X's effect on Y is described as a *conditional indirect effect*. The simplest conceptualization of conditional indirect effects involves evaluating whether the moderating variable (W) influences the $X \rightarrow M$ relationship (*first stage* moderated mediation) or the $M \rightarrow Y$ relationships (*second stage moderated mediation*; Edwards & Lambert, 2007), see Figure 1. The first and second stages refer to the particular path (i.e., path a or b, respectively) of the indirect effect that is believed to be moderated by another variable. A first stage model is estimated with two equations:

$$M = i_M + a_1X + a_2W + a_3XW \tag{7}$$

$$Y = i_Y + c'X + bM \tag{8}$$

By including the moderator (W) and the product term (XW) in Equation 7, the effect of the independent variable on the mediator can vary as a function of the moderator. Similar to a general mediation model, the indirect effect of X on Y is calculated as the product of the effects of X on M and M on Y. However, in moderated mediation, the product term must also allow for the indirect effect to be conditional on W. By substituting Equation 7 into Equation 8, the first stage moderated mediation model can be estimated as

$$Y = i_Y + c'X + bi_M + a_1bX + a_2bW + a_3bXW \tag{9}$$

Here, X's effect on M is expressed as $(a_1 + a_3W)$, and M's effect on Y is b. The conditional indirect effect (ω) of X on Y is then expressed as $\omega = (a_1 + a_3W)b$, which when rearranged is $\omega = a_1b + a_3bW$. Thus, the coefficient a_3b is the estimated effect of W on the indirect effect of X on Y through M.

In a second stage model, W moderates the path between the mediator and the dependent variable, see Figure 1D. This model is similarly estimated with two equations:

$$M = i_M + aX \tag{10}$$

$$Y = i_Y + c'X + b_1M + b_2W + b_3MW \tag{11}$$

Here, the moderator (W) and the product term (MW) are included in Equation 11, and Equations 10 and 11 can be rewritten as:

$$Y = i_Y + c'X + b_1i_M + ab_1X + b_2W + b_3i_MW + ab_3XW \tag{12}$$

The conditional indirect effect (ω) of a second stage model is quantified as $\omega = a(b_1 + b_3W)$, where a is the effect of X on M, and $(b_1 + b_3W)$ is the effect of M on Y. The expression $a(b_1 + b_3W)$ can be rewritten as $ab_1 + ab_3W$, where the coefficient ab_3 quantifies the effect of W on the indirect effect of X on Y through M.

Hypothesis testing to determine whether the a_3b (or ab_3) coefficient, known as the *index of moderated mediation*, is statistically different from zero can be carried out through bootstrap confidence interval evaluations (Hayes, 2015). A confidence interval that does not contain zero is evidence that the indirect effect is moderated. The index approach to testing moderated mediation is useful because it relies on only one inferential test and directly assesses the statistical significance of the relationship between the moderator and the indirect effect. An alternative method, referred to as the *piecemeal approach* (Edwards & Lambert, 2007), involves separately testing moderation and mediation and then jointly interpreting the results. While the piecemeal approach should not be used in place of the index test, it can be useful to conduct separate analyses of moderation and mediation prior to or following the integrated method in order to better understand the nature of the conditional indirect effect (Hayes, 2018a). The index approach is well suited for instances in which the indirect effect is a linear function of *W*, as in a simple first *or* second stage model. However, it cannot be used when *X*'s effect on *M and M*'s effect on *Y* are both moderated by the same continuous variable. In this case, the indirect effect takes on a non-linear, quadratic, form as a function of *W* (Edwards & Lambert, 2007; Hayes, 2015).

A statistically significant index of moderated mediation provides evidence that the indirect effect is conditional on values of the moderator; however, this does not imply that the indirect effect is statistically different from zero at all points of *W*. In order to ascertain at which points of *W* the indirect effect is significant, formal testing of the indirect effect at various values of *W* is required. When the moderator is categorical, the indirect effect is simply tested at the coded values of *W*. For continuous variables, the choice of *W* values at which to test the indirect effect is less straightforward. Researchers often rely on commonly used conventions to select points that represent low, medium, and high values on the moderator. One convention is to plot the mean and one standard deviation both above and below the mean. Another common choice is to select values representing various percentiles of the variable's distribution, such as the 25th, 50th, and 75th percentiles. In other situations, the choice of values may be guided by theory, such that specific values are most relevant to the research question or clinical practice. Once values of the moderator are selected, the indirect effect is estimated and tested at each selected value of *W* with the construction of confidence intervals.

After estimating a statistically significant index of moderated mediation, practical significance is assessed with measures of effect size. A common method for obtaining effect sizes is to standardize the direct and indirect effects, thereby expressing the effects in terms of standard deviations. When *X* and *Y* are both continuous, the completely standardized direct and indirect effects quantify the amount of standard deviation change in *Y* that is associated with a one standard deviation increase in *X*. In moderated mediation analysis, standardized effect size measures are obtained by standardizing the conditional indirect effects of *X* on *Y* at various values of the moderator. For example, in a second-stage model where *W* moderates the path between *M* and *Y*, the completely standardized conditional indirect effect is expressed as

$$\omega_{\text{cs}} = [s_X (ab_1 + ab_3W)]/s_Y \tag{13}$$

where s_X and s_Y are the standard deviations of *X* and *Y*. When *X* is dichotomous (e.g., representing group membership) and *Y* is continuous, standardization by the scale of only *Y* provides partially standardized direct and indirect effects. The partially standardized conditional indirect effect in a second-stage model is

$$\omega_{\text{ps}} = (ab_1 + ab_3W)/s_Y \tag{14}$$

For mediation models without moderation, standardized effect sizes have been shown to perform better than other effect size measures in terms of bias, power and Type I error rates (Miočević et al., 2018). In addition, Lachowicz et al. (2018) recently proposed a novel effect size measure for quantifying the explained variance in mediation models. Further research is needed to develop effect size measures for moderated mediation analysis.

The review of moderated mediation analysis presented in this paper is relevant for estimating conditional indirect effects using ordinary least squares (OLS) regression. Moderated mediation can be implemented in many statistical software programs (e.g., Mplus, R, SAS, SPSS, Stata) through specification of a number of regression equations. However, the PROCESS macro (Hayes, 2018a) is specifically tailored for conducting regression-based moderated mediation analyses in SPSS and SAS with minimal programming required. With a single line of syntax, the PROCESS macro estimates all model coefficients, standard errors, test statistics, and bootstrap confidence intervals, including those for the index of moderated mediation. Alternatively, conditional indirect effects can be estimated using a structural equation modelling (SEM) framework. Rather than estimate each equation separately as is done in OLS regression, SEM estimates all model parameters simultaneously, using an iterative process such as maximum likelihood. Moreover, SEM allows for the analysis of latent variable models, whereas OLS regression can accommodate only observed variables.

Illustration

While examples of moderation and mediation are abundant in social science research, fewer studies integrate the two analyses in a single model. We illustrate the usefulness of moderated mediation analysis to education research in the context of evaluating whether school-wide student engagement mediates the association between the prevalence of teasing and bullying (PTB) and school-level performance on a standardized reading exam, and whether this association is moderated by supportive school climate. Prior research at the middle-school level has demonstrated that student engagement partially mediates the association between perceptions of PTB and passing rates on standardized exams (Lacey et al., 2017). We extend this work by investigating whether the indirect effect of PTB through student engagement at the high-school level is contingent upon levels of supportive school climate. We hypothesize that support moderates the proposed indirect effect of PTB, such that when a school has a less supportive climate, PTB has a stronger negative association with standardized exam performance through student engagement. To control for school composition effects, two school demographic variables were included as covariates: the percentage of racial minority students and the percentage of students eligible for free or reduced price meals (FRPM).

Figure 2 provides a graphic representation of our path model. PTB was the focal predictor (X), engagement was the mediator (M), support was the moderator (W), and reading achievement was the dependent variable (Y). The percentage of students eligible for FRPM and the percentage of racial minority students were included as covariates. As illustrated in Figure 2, we hypothesized a first-stage moderated mediation model, in which support was allowed to moderate the first-stage indirect path (a) through engagement. A direct effect of X on Y in mediation analysis can also be moderated, producing a *conditional direct effect*. To illustrate this, support was also allowed to moderate the direct path (c') between PTB and reading achievement.

Although the present study uses school climate survey data from a state-wide sample of students in high schools, we estimate a series of single-level regression models using schools as the unit of analysis. We chose this modelling approach for two reasons. First, school climate is broadly defined as a multidimensional construct that encompasses the "quality and character of school life" and is "based on patterns of people's experiences of school life" (Cohen et al., 2009, p. 182). By this definition, school climate is a characteristic of the school, not individual students. Therefore, in school climate research, student ratings of the school environment are aggregated to the school level, reflecting the collective perspective of students (Lüdtke et al., 2009; Marsh et al., 2012). Accordingly, in the present study, the substantive predictors are conceptualized as school-level constructs that represent students' shared perceptions of the school. Second, in order to present an introductory tutorial of moderated mediation analysis, we restrict our analysis to the school level, using single-level models with manifest variables.

Methods for assessing multilevel moderated mediation with latent variable interactions have only recently been developed (Zyphur et al., 2019) and are beyond the scope of this article.

Methods

Sample

Data came from the 2018 Virginia Secondary School Climate Survey. The sample consisted of 318 public high schools. The total school enrollment for Grades 9 to 12 ranged between 58 and 3,963 students (*M* = 1,214.30, *SD* = 720.76). Across schools, the percentage of students eligible for free or reduced-priced meals varied between 2.0% and 100% (*M* = 42.8%, *SD* = 22.8%). The percentage of racial minority students in each school ranged from 0.0% to 99.2% (*M* = 42.0%, *SD* = 26.6%).

Procedure

The survey was administered to students in grades 9-12 as part of the state's mandatory annual School Safety Audit. The participation rate was 99.4% for schools and 82.0% for students. Parental passive consent and student assent were obtained for all participants. The survey was administered anonymously through a secure online platform. Students completed the survey during normal school hours under the supervision of school staff. Of the 324 schools eligible for participation in the survey, the analytic sample consisted of 318 schools that completed the survey. Alternative schools for special populations, such as students transitioning from juvenile correctional centers, were excluded from the analytic sample.

Measures

The 108-item survey assessed student perceptions of school climate and safety conditions. Three survey scales relevant to this study included the prevalence of teasing and bullying, student engagement, and support. Scale items were measured using a 4-point response format (1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, 4 = *strongly agree*). To assess the reliability of the aggregated student ratings of each scale, we used the intraclass correlations *ICC*(1) and *ICC*(2) (Lüdtke et al., 2009).[1] The *ICC*(1) is an indicator of the amount of variation in a variable that can be attributed to differences between clusters (i.e., schools). The *ICC*(2) estimates the reliability of cluster-mean ratings, where values closer to 1 indicate greater reliability.

Prevalence of teasing and bullying. PTB was measured with five items that assessed student perceptions of the extent of teasing and bullying at school. Previous studies using the PTB scale have found good overall model fit for the factor structure in samples of high school students (Bandyopadhyay et al., 2009; Klein et al., 2012). In contrast to other measures in this study, higher PTB scores are reflective of more adverse conditions (i.e., higher levels of teasing and bullying). Cronbach's alpha was .86 in the current sample. The *ICC*(1) was .08, indicating that 8% of the total variation in student ratings of PTB was attributable to the nesting of students within schools. The *ICC*(2) was .98, indicating a high degree of reliability of the school-mean ratings.

Student engagement. The student engagement scale consisted of six items that assessed both cognitive (e.g., Getting good grades is very important to me) and affective (e.g., I feel like I belong at this school) aspects of engagement that combine into a single measure of student engagement (Konold et al., 2014). The scale was adapted from the Commitment to School scale (Thornberry et al., 1991). In the current study, Cronbach's alpha was .77, *ICC*(1) was .06, and *ICC*(2) was .98.

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[1] The *ICC*(1) = τ^2 / [τ^2 + σ^2], where τ^2 is the variance between clusters and σ^2 is the variance within clusters. The *ICC*(2) = $\frac{k \times ICC(1)}{1+(k-1) \times ICC(1)}$, where *k* is the average number of units within a cluster. In the present study, *k* = 671.

Support. Student perceptions of their teachers as being supportive was measured with an eight-item scale that demonstrated good psychometric properties when evaluated through multilevel confirmatory factor models (Konold et al., 2014). Questions asked students to rate how strongly they agreed or disagreed that teachers at their school care about students (e.g., Most teachers listen to what students have to say; If I tell a teacher about a problem I am having, the teacher will do something to help). Cronbach's alpha was .87 in this sample. The *ICC*(1) was .05, and *ICC*(2) was .97.

Reading achievement. Reading achievement was measured using school-mean scaled scores on the Virginia Standards of Learning (SOL) End of Course (EOC) English Reading exam. SOL exams assess student proficiency in meeting the state's minimum expectations for end-of-year competency in various subjects. School-level SOL data were obtained from the Virginia Department of Education. We chose to measure academic achievement using 11th-grade reading scores because the majority of Virginia public high school students take the English Reading exam at the end of grade 11.

Analytic Plan

To evaluate whether student engagement mediates the association between PTB and reading scores, and whether the indirect effect is further conditional on levels of support, a moderated mediation model was tested using the PROCESS macro (V3.3; Hayes, 2018a) for SPSS. PROCESS is preprogrammed with 92 models and numerous options for model specification. The present study used Model 8 that specifies a first-stage moderated mediation model in which W is allowed to moderate the direct path from X to Y and the first-stage indirect path from X to M. Support and PTB were mean centered prior to creating product terms, and the index of moderated mediation was tested with a 95% bias-corrected bootstrap confidence interval based on 10,000 replications. Moderation was further probed by estimating and plotting the conditional direct and indirect effects of PTB at values of support corresponding to the 16th, 50th, and 84th percentile points. These three points represented low (W = 2.94), moderate (W = 3.07), and high (W = 3.19) values of support in the current sample. Using PROCESS, hypothesis tests were conducted to determine whether the conditional indirect effect of PTB was statistically different from zero at these values of support. SPSS output from the PROCESS macro is provided in the Appendix.

Results

Descriptive statistics for all variables in the current analysis are presented in Table 1. As expected, PTB was negatively associated with student engagement (r = –.60, p < .001), support (r = –.52, p < .001), and reading scores (r = –.36, p < .001). In addition, engagement was positively associated with support (r = .77, p < .001) and reading scores (r = .44, p < .001). Finally, support was positively associated with reading scores (r = .15, p < .01).

Results of the moderated mediation analysis are provided in Table 2. The direct association between PTB and readings scores was found to be moderated by support (c'_3 = 36.69, p = .01). The association between PTB and the mediator (i.e., student engagement) was also conditional on levels of support (a_3 = 0.74, p < .001). In addition to estimating model parameters, it is helpful to visualize the results. Figure 3 presents a visual depiction of the interaction between X and W on Y (plot A) and on M (plot B). Plot A was constructed by estimating the simple effect of PTB on reading scores for low, moderate, and high values of support. Similarly, plot B was constructed by estimating the simple effect of PTB on student engagement for the three levels of support.

As shown in Figure 3 plot A, PTB was negatively associated with reading scores for all levels of support, such that as PTB increased, reading scores decreased. However, as depicted by the steepness of the slopes, the negative relation between PTB and reading scores was largest in magnitude among schools characterized by low levels of support. Likewise, Figure 3 plot B illustrates that support moderated the association between PTB and student engagement, such that the magnitude of the association was strongest for schools with low support.

Most notably, a formal test of moderated mediation based on the index term (Hayes, 2015) revealed that support moderated the indirect effect of PTB on reading scores ($a_3b_1 = 25.66$, 95% CI = 6.69, 43.40). Further hypothesis tests were conducted to determine whether the conditional indirect effect ($\omega = a_1b_1 + a_3b_1W$) was statistically significant at values corresponding to low ($W = 2.94$), moderate ($W = 3.07$), and high ($W = 3.19$) values of support as noted above. This was accomplished through PROCESS as the default, in that PROCESS automatically generates these conditional indirect effects at moderator values corresponding to the 16th, 50th, and 84th percentile points in the sample data. Results revealed that student engagement mediated the association between PTB and reading scores for schools with low support ($\omega_{\text{Low}} = –8.66$, CI = –13.30, –4.09) and moderate support ($\omega_{\text{Moderate}} = –5.37$, CI = –8.74, –2.40), but there was no evidence of an indirect effect for schools with high levels of support ($\omega_{\text{High}} = –3.77$, CI = –9.89, 2.35). The magnitude of the indirect effect was more negative among schools with relatively low levels of perceived support. As support decreased, PTB was associated with less student engagement, which, in turn, was associated with lower reading achievement.

The conditional direct and indirect effects of PTB on reading scores are depicted in Figure 4. The graph was constructed by plotting the estimated direct and indirect effects as functions of support. The horizontal axis shows the support scale centered around the sample mean of 3.07. The conditional direct effect is $c'_1 + c'_3W$, where c'_1 indicates the level of the direct effect at $W = 0$, and c'_3 is the slope. The conditional indirect effect is $a_1b_1 + a_3b_1W$, where a_1b_1 indicates the level of the indirect effect when $W = 0$, and a_3b_1 is the slope. Figure 4 shows that the indirect effect of PTB through engagement is stronger in magnitude (i.e., further away from zero) for schools with lower levels of support. The same trend is depicted for the conditional direct effect of PTB. Moreover, the graph illustrates that as support increases, both the direct effect and indirect effect diminish, meaning the effects approach zero.

Discussion

Both moderation and mediation allow researchers to address questions concerning contingencies and mechanisms that can better reveal the complexities of how a set of variables is interrelated. In recent years, applications of statistical mediation have become more prevalent in social science research for testing assumptions about why or how an independent variable is associated with an outcome of interest. However, mediation may not hold in all conditions or for all groups of people. In this paper, we reviewed and illustrated how moderated mediation analysis can be used to test whether an indirect effect is conditional on values of a proposed moderating variable. Despite its advantages for modeling complex relationships among variables, moderated mediation is under-utilized in the substantive literatures. Instead, researchers typically analyze interactions and mechanisms separately, or rely on other outdated methods for testing moderated mediation.

In our applied example, we found that student engagement mediated associations between PTB and readings scores, and this indirect effect differed among schools with varying degrees of supportive school climate. We used the index of moderated mediation (Hayes, 2015) to formally test our hypothesis. Unfortunately, some applied researchers continue to evaluate the presence of moderated mediation using subgroup analysis, in which mediation analyses are conducted separately for different groups of the sample based on values of the moderator. For instance, using our example, subgroup analysis would involve creating a priori subsamples of schools based on levels of support (e.g., low, moderate, and high), estimating indirect effects separately for each group, and then evaluating moderated mediation based on a descriptive comparison of the indirect effects. This approach is problematic because it (1) requires the categorization of a continuous moderator, which results in loss of information, and (2) does not formally test whether differences between indirect effects across subgroups are statistically significant (Hayes, 2018a).

Alternatively, other researchers more appropriately use the entire sample to estimate the indirect effect, but evaluate moderated mediation based solely on the conditional direct effect of X on M in a first-stage model, or M on Y in a second-stage model. In this case, no formal test of the product term, or index of moderated mediation, is conducted. The problem here is that the presence of a statistically significant interaction between two regressors on a mediator (e.g., path a_3, in Figure 2) is not sufficient evidence of a conditional indirect effect (Hayes, 2015). In our example, although support moderated the association between PTB and engagement, we would have concluded that the indirect effect was not moderated if the index term was not statistically significant.

Substantively, we illustrated the application of moderated mediation analysis within the context of school climate research. Given that school climate is widely considered a key factor in promoting positive student outcomes, it is important to understand both the mechanisms underlying school climate effects as well as the conditions that may constrain these processes.

Prior research has established that the prevalence of teasing and bullying is indirectly linked to academic achievement through student engagement in school (Lacey et al., 2017). The results presented here extend this work by demonstrating that the indirect effect of PTB through engagement is different for schools with different levels of supportive school climate. These findings are consistent with literature positing that supportive teacher-student relationships are important for fostering a school climate characterized by high student engagement (Pianta et al., 2012).

In answering our substantive research questions, a moderation focus alone would have allowed for examination of how the association between PTB and achievement was conditional on levels of supportive school climate. However, it would not have provided a test of the underlying process model linking PTB to achievement. Conversely, a focus on only the extent to which student engagement mediated the association between PTB and achievement would have tested the indirect effect, but a simple mediation analysis would not have revealed that the process model differed between schools with varying degrees of supportive climate. Moderated mediation analysis allowed for a simultaneous test of the mediating effect of engagement and the moderating effect of support.

Our application of moderated mediation within a linear regression framework was based on a relatively simple model with a single mediator and a single continuous moderator. Furthermore, we do not make inferences regarding causality. The methodological approaches discussed here can be extended to more complex models, such as those with multiple mediators (Preacher & Hayes, 2008), multiple moderators (Hayes, 2018b), multicategorical variables (Hayes & Preacher, 2014), latent variables (Lau & Cheung, 2012), longitudinal data (Cole & Maxwell, 2003), multilevel designs (Preacher et al., 2010), and Bayesian methods (Wang &

Preacher, 2015). Readers interested in moderation and mediation within the context of causal inference are encouraged to see VanderWeele (2015). More generally, Hayes (2018a) provides a comprehensive treatment of regression-based methods and is an excellent resource for readers interested in learning more about the models discussed here.

The following limitations of our applied illustration should be kept in mind when conducting moderated mediation. First, the use of cross-sectional data limits interpretations to non-causal inferences. Researchers are encouraged to use longitudinal data, or prior state covariates, to establish temporal precedence and better inform understanding of the causal processes linking predictors (e.g., bullying) and outcomes (e.g., academic achievement). Second, although the measures of PTB, support, and engagement used in this illustration were based on Likert scales with four response categories; rating scales with more than four response categories have been shown to have better psychometric properties (i.e., less skewness and kurtosis) and are more likely to better approximate interval scales (Leung, 2011). Third, our moderated mediation model used schools as the unit of analysis by aggregating student ratings to the school level. Given clustered data structures, researchers are encouraged to consider recently developed methods for multilevel moderated mediation analysis (Zyphur et al., 2019) that account for measurement error and the sampling of students within schools.

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Tables

Table 1

Descriptive Statistics and Correlations Among Variables

	Mean	SD	Min	Max	2	3	4	5	6
1. Reading scores	440.04	12.93	371	497	–.29**	–.72**	–.36**	.44**	.15**
2. % Minority	41.95	26.61	0.00	99.18	—	.34**	–.07	–.20**	–.29**
3. % FRPM	42.75	22.82	2.00	100		—	.35**	–.34**	–.13*
4. PTB	2.43	0.22	1.72	2.96			—	–.61**	–.52**
5. Engagement	3.10	0.14	2.58	3.50				—	.77**
6. Support	3.07	0.13	2.68	3.48					—

Note. *$p < .05$; **$p < .01$

Table 2

Moderated Mediation Results

Predictor	Student Engagement (M) Coeff. (SE)		Reading Scores (Y) Coeff. (SE)	
Control variables				
% FRPM	–0.10 (0.02)**	a_4	–29.44 (2.57)**	b_2
% Minority	0.01 (0.02)	a_5	–7.55 (2.29)**	b_3
Independent variables				
PTB (X)	–0.15 (0.03)**	a_1	–8.15 (3.07)**	c'_1
Support (W)	0.71 (0.04)**	a_2	–31.79 (6.47)**	c'_2
Student engagement (M)	—		34.80 (6.17)**	b_1
Interaction term				
PTB X Support	0.74 (0.13)**	a_3	36.69 (14.56)*	c'_3
R^2	0.72		0.60	
Conditional indirect effects	Coeff. *(SE)*		*95% CI*	
Low support	–8.66 (2.37)*		–13.25, –4.06	
Moderate support	–5.37 (1.63)*		–8.70, –2.38	
High support	–2.30 (1.57)		–5.63, 0.49	
Index of moderated mediation	25.66 (9.30)*		6.87, 43.16	

Note. Regression coefficients are unstandardized; standard errors are in parentheses. Bootstrap sample size = 10,000. CI, confidence interval. Path labels (e.g., a_1) correspond to Figure 2. *$p < .05$; **$p < .01$.

Figures

Figure 1

Statistical diagrams of moderation, mediation (total effect model on top and mediation model on bottom), first-stage moderated mediation, and second-stage moderated mediation

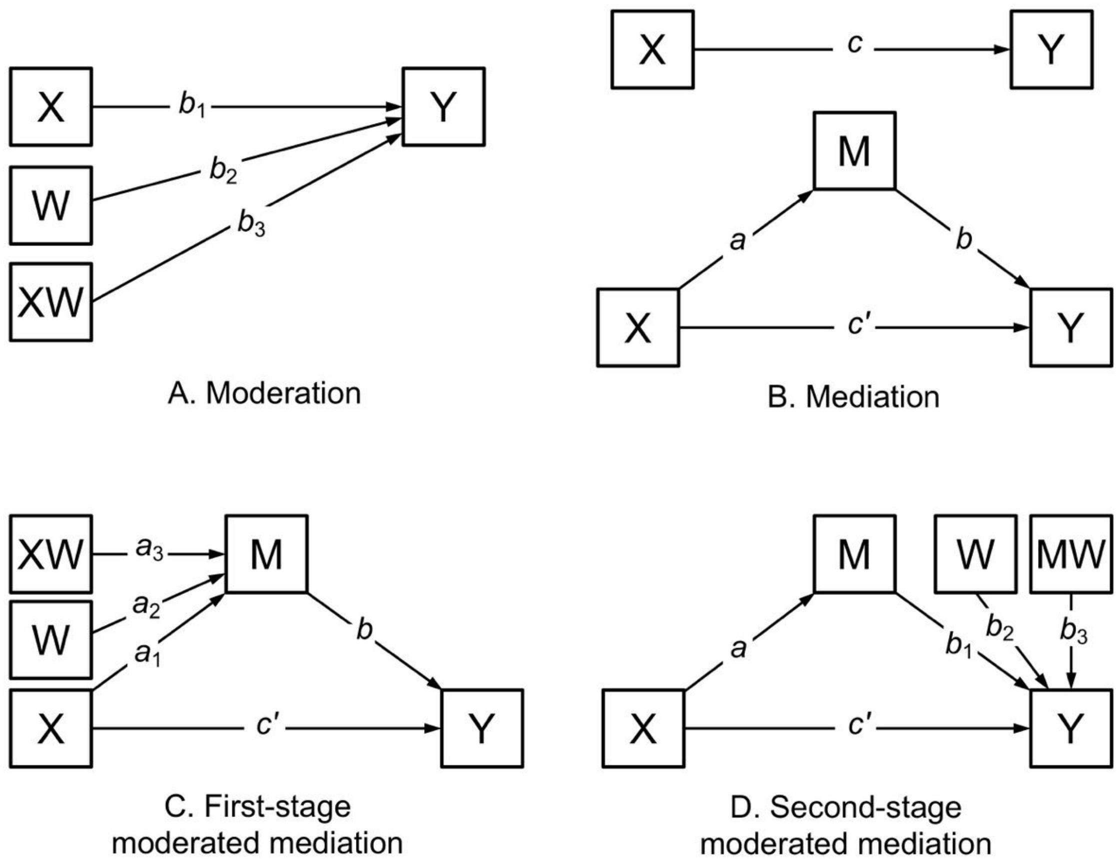


Figure 2

Moderated mediation model of associations between prevalence of teasing and bullying and reading achievement scores, with student engagement as the mediator, and support as the moderator

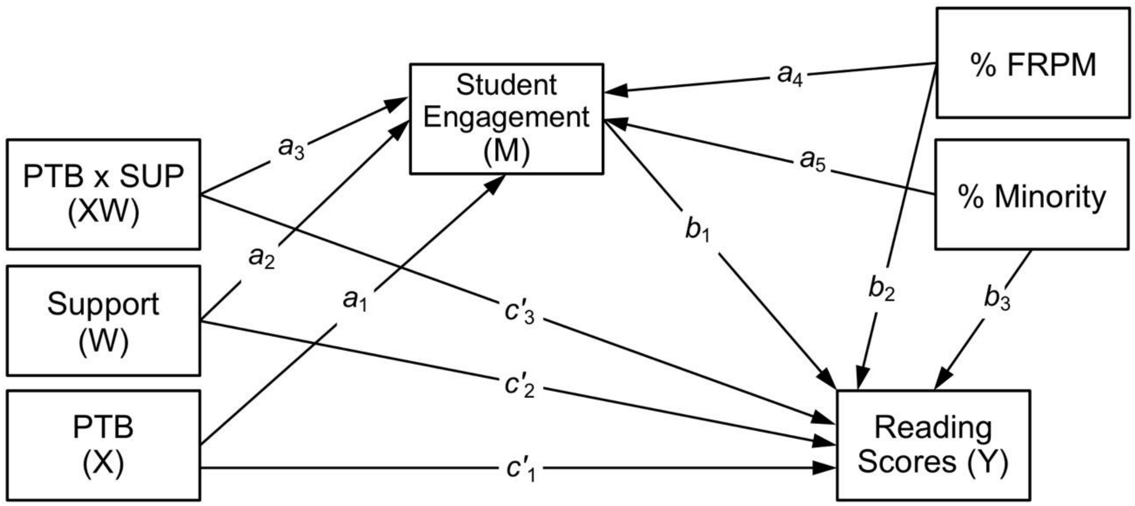


Figure 3

Conditional direct effects of PTB on reading scores (plot A) and student engagement (plot B)

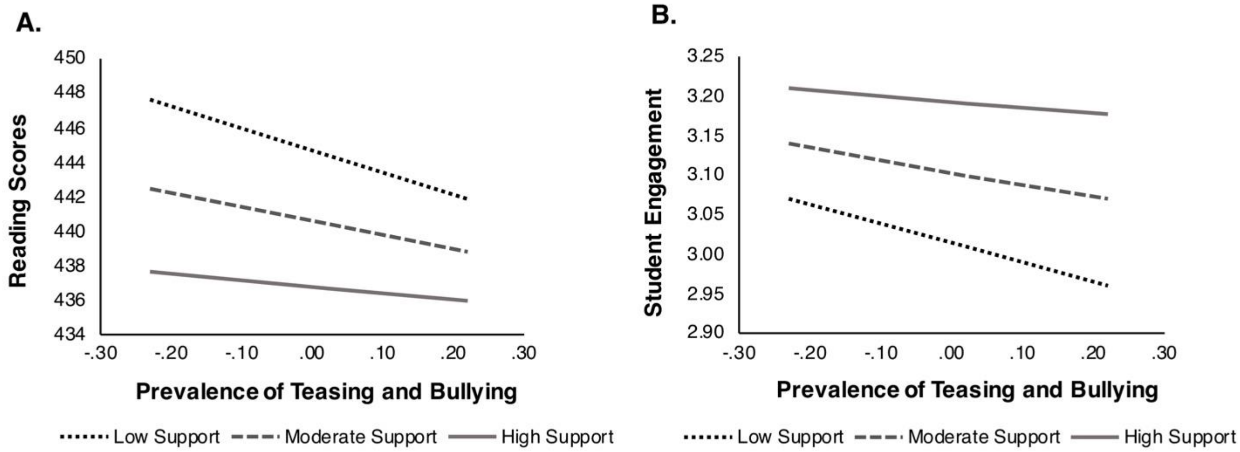
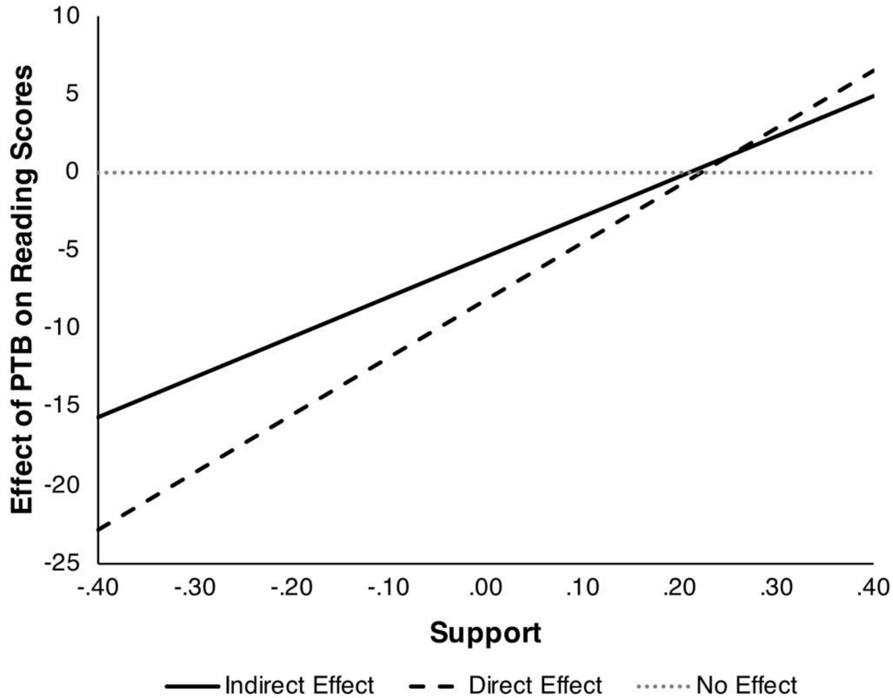


Figure 4

Direct and indirect effects of PTB on reading scores conditional on support



CHAPTER 2

Bayesian Multilevel Mediation: Evaluation of Inaccurate Priors in Latent 1-1-1 Designs

Abstract

When latent constructs are measured by observed indicators from individuals nested within groups, multilevel structural equation modeling (MSEM) for 1-1-1 mediation designs allows researchers to simultaneously test indirect effects at each level of the data structure. However, with small samples (i.e., few clusters and/or small cluster sizes), such complex mediation models often run into estimation problems like nonconvergence, biased estimates, and insufficient power. Although Bayesian estimation with accurate informative priors can help alleviate these problems, it is unrealistic in practice to assume priors are correctly specified at the true population value. This study evaluates the performance of inaccurate (informative) priors in 1-1-1 MSEM mediation under varying sample sizes, ICCs, and effect sizes. Results indicate that while within-level indirect effect estimates are somewhat robust to inaccurate priors, between-level estimates are severely impacted, especially at small sample sizes. Implications and recommendations for conducting 1-1-1 MSEM mediation with Bayesian methods are discussed.

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Introduction

Mediation analysis is used to evaluate possible mechanisms by which an intervention/exposure affects an outcome. Here, the total effect of a predictor on an outcome can be decomposed into a direct effect and an indirect effect through a mediating variable(s). When data are nested and research questions exist at multiple levels, multilevel structural equation modeling (MSEM) is a useful approach that can be extended to accommodate indirect effects (Preacher et al., 2010, 2011). MSEM fully separates between- and within-cluster effects, allowing for simultaneous tests of indirect effects at both within- and between-levels of a multilevel mediation model. This analytic technique has many applications in fields like education and psychology when ratings from individual informants are used to measure multilevel constructs that reflect: (1) characteristics of individuals and (2) shared characteristics of the group to which the individuals are nested. For example, in organizational psychology, survey responses from employees nested within departments are used to measure constructs like occupational wellbeing that operate at both the employee and department levels (Mauno et al., 2014). In education, ratings from students nested within classrooms are used to measure constructs such as motivation and engagement, which can be conceptualized as having both student- and classroom-level latent components (Arens et al., 2015).

In these examples, MSEM is leveraged to test mediating relations among a set of latent variables at both levels of the data structure. Such models are referred to as 1-1-1 mediation designs because the predictor, mediator, and outcome variables are all measured at the lowest level (i.e., level one) of a multilevel data structure (Krull & MacKinnon, 2001). Other multilevel mediation designs may include variables that are measured at higher levels. For example, in 2-1-

1 designs, the predictor is measured at level two, and the mediator and outcome variables are measured at level one. However, unlike the 1-1-1 design, the 2-1-1 model cannot include within-level indirect effects because the predictor variable only exists at level two.

Although MSEM provides a flexible modeling strategy for mediation analysis with multilevel data and latent variables, a notable drawback of this technique is the large sample size requirement at both levels. With maximum likelihood (ML) estimation, the optimal minimum number of clusters for MSEM is around 100 (Hox & Maas, 2001). For mediation analysis in the MSEM framework, estimation problems such as nonconvergent cases, biased estimates, and inflated Type I error rates are encountered when dealing with small numbers of clusters, small cluster sizes, and low intraclass correlations (ICCs; Li & Beretvas, 2013; McNeish, 2017; Preacher et al., 2010; Zigler & Ye, 2019). However, in practice, it can be difficult for researchers to obtain large sample sizes, particularly large numbers of clusters (e.g., schools). Indeed, McNeish's (2017) literature review of empirical MSEM mediation studies found that the majority of studies (89%) used samples with less than 100 clusters. This finding reflects the fact that applied researchers are conducting MSEM mediation studies with far fewer numbers of clusters than are recommended to obtain trustworthy results, and underscores the need to provide researchers with guidance and techniques for conducting multilevel mediation analyses with the smaller samples they are likely to encounter in practice.

In an effort to address this need, recent work has examined how a Bayesian approach to MSEM can be used to overcome problems associated with small sample sizes (Depaoli & Clifton, 2015; Helm, 2018; Zitzmann et al., 2016), and this work has been extended to MSEM for mediation models more specifically (Fang et al., 2019; McNeish, 2017). However, these simulation studies show that when sample sizes are small, the choice of priors can have a serious impact on model results. When applied to MSEM models under conditions of few clusters and small cluster sizes, Bayesian methods using default uninformative (i.e., diffuse) prior specifications will result in biased estimates. Instead, informative priors that provide some degree of information to the construction of the posterior are needed to offset the detrimental impact of small sample sizes. Yet, in practice, this presents a formidable challenge to applied researchers who cannot know with certainty whether informative priors are correctly centered on the population value. Further, relatively little research provides insights about the robustness of MSEM mediation with inaccurate priors. Hence, prior specifications remain an area of unresolved concern. In the current study, we provide additional clarity to the conversation on the impact of prior specifications in Bayesian latent variable modeling. Our investigation is situated in 1-1-1 MSEM mediation given the model's usefulness in applied studies when there is interest in testing both within- and between-level components of the indirect effect. Specifically, we seek to identify the design conditions in which results may be robust to prior misspecifications, and to provide guidance on the degree of informativeness that might be needed to mitigate the effects of inaccurate priors.

MSEM for 1-1-1 Designs

MSEM partitions the variance of observed within-level variables into two orthogonal latent components (Muthén, 1989, 1994). Individual observations Y_{ij} are decomposed into cluster means (μ_j) and individuals' deviations from the cluster means (η_{ij}),

$$Y_{ij} = \mu_j + \eta_{ij}. \tag{1}$$

where i indicates individual units, j indicates clusters, and Y_{ij} is a vector of observed indicators. Because μ_j and η_{ij} are independent, the total variance-covariance matrix of Y_{ij} is partitioned into separate within-cluster and between-cluster covariance matrices,

$$\boldsymbol{\Sigma}_T = \boldsymbol{\Sigma}_B + \boldsymbol{\Sigma}_W, \tag{2}$$

where $\boldsymbol{\Sigma}_B$ is the between covariance matrix representing variation across clusters, and $\boldsymbol{\Sigma}_W$ is the within covariance matrix representing variation within clusters. The measurement model at the within level is specified as:

$$Y_{kij} = \mu_{kj} + \lambda_{kW}\,\eta_{ijW} + \varepsilon_{kijW} \tag{3}$$

Here, μ_{kj} is the intercept for item k in cluster j, λ_{kW} is the within-level factor loading for item k, η_{ijW} is the factor score for individual i in cluster j, and ε_{kijW} is the within-level residual on item k for individual i in cluster j. Then the measurement model at the between level is expressed as:

$$\mu_{kj} = \mu_k + \lambda_{kB}\,\eta_{jB} + \varepsilon_{kjB} \tag{4}$$

where μ_k is the intercept for item k, λ_{kB} is the between-level factor loading for item k, η_{jB} is the factor score for cluster j, and ε_{kjB} is the between-level residual on item k for cluster j.

Applying the MSEM framework to the 1-1-1 mediation model (as depicted in Figure 1), in which the predictor X, mediator M, and outcome Y are measured with p observed indicators, indirect effects can be estimated at both levels. Following the notation in Figure 1, the within-level indirect effect is computed as the product of the a_W and b_W paths, and the between-level indirect effect is the product of the a_B and b_B paths. When the within- and between-level latent factors represent the level-specific components of the same construct (Stapleton et al., 2016), cross-level invariance constraints can be imposed on factor loadings, thereby setting the metric of the latent factors to be equal across levels (Mehta & Neale, 2005) and reducing the number of estimated model parameters (Jak, 2019). The covariance matrix $\boldsymbol{\Phi}_B$ for the cluster-level factor scores η_{jB} is then:

$$\boldsymbol{\Phi}_B = (\mathbf{I} - \boldsymbol{\beta}_B)^{-1}\,\boldsymbol{\Psi}_B\,(\mathbf{I} - \boldsymbol{\beta}_B)^{-1\mathrm{T}} \tag{5}$$

where $\boldsymbol{\beta}_B$ is a 3 × 3 matrix of the structural regression coefficients (a_B, b_B, and c'_B) between factors, $\mathbf{I}$ is a 3 × 3 identity matrix, and $\boldsymbol{\Psi}_B$ is a symmetric matrix of the between-level (co)variances. The within-level covariance matrix $\boldsymbol{\Sigma}_W$ is

$$\boldsymbol{\Sigma}_W = \boldsymbol{\Lambda}\,\boldsymbol{\Phi}_W\,\boldsymbol{\Lambda}^{\mathrm{T}} + \boldsymbol{\Theta}_W \tag{6}$$

where $\boldsymbol{\Lambda}$ is a $p \times 3$ matrix of factor loadings that are constrained to be equal across levels, $\boldsymbol{\Phi}_W$ is a 3 × 3 matrix of structural regression coefficients at the within level, and $\boldsymbol{\Theta}_W$ is a $p \times p$ matrix of within-level residual (co)variances.

Estimation of MSEM Mediation Models

MSEM mediation models are traditionally evaluated using a frequentist approach through maximum likelihood (ML) estimation, which assumes asymptotic normality. This assumption poses challenges when evaluating the statistical significance of the indirect effect (*ab*) because the sampling distribution of the product of two normally distributed variables is not necessarily normal (Aroian, 1947). In many statistical software programs (e.g., M*plus,* Stata), the delta method is implemented by default for computing the *ab* confidence interval (CI) when the indirect effect is specified as the product of two regression coefficients. Based on the Sobel test (Sobel, 1982), the delta method computes the asymptotic CI for the indirect effect by approximating the product of *a* and *b* as a normal distribution. However, this approximation is problematic because the indirect effect may not follow a normal distribution (MacKinnon et al., 2004). Within the frequentist framework, several alternative methods for constructing CIs for indirect effects have been developed that do not rely on the assumption of normality. These alternatives include the distribution of the product method (MacKinnon et al., 2004), bootstrapping (Preacher & Hayes, 2008), and the Monte Carlo method (Preacher & Selig, 2012).

Among these approaches, the Monte Carlo procedure is particularly well-suited to clustered data because it does not require resampling from the data, which can be computationally demanding. Instead, the Monte Carlo method constructs confidence intervals for the indirect effect by using the sample estimates of *a* and *b* and their asymptotic variances and covariances.

However, a remaining problem is the large sample sizes required for ML numerical integration. With few clusters and small cluster sizes, ML estimation for MSEM will lead to downwardly biased variance components and standard errors, resulting in inflated Type I error rates (Hox & Maas, 2001). Low values of the intraclass correlation (ICC), which measures the amount of variability explained at the between-cluster level, can also downwardly bias estimates (Goldstein, 1995). These issues are further exacerbated in more complex MSEM mediation models. For example, several simulation studies have evaluated the performance of ML estimation for MSEM mediation models with small samples. Using a 2-1-1 mediation design, Preacher et al. (2011) found that power for the between-level indirect effect decreased as ICC, number of clusters, and cluster size decreased. With a relatively small ICC of .10, a minimum of 100 clusters of size 20 was necessary to reach the minimum optimal threshold for power of .80 (Preacher et al., 2011). Similarly, Fang et al. (2019) and McNeish (2017) showed that CI coverage and power of the between-level indirect effect declined as within- and between-level sample sizes decreased. Li and Beretvas (2013) found comparable results using a 2-2-1 mediation model and reported poor convergence with fewer than 80 clusters. Zigler and Ye (2019) evaluated the performance of ML estimation for MSEM using a 1-1-1 design with random slopes under varying sample size conditions. Simulation results indicated that MSEM with ML estimation had insufficient power to detect the between-level indirect effect in conditions with small sample sizes and low ICC (e.g., 60 clusters of size 20 and ICC = .10;

Zigler & Ye, 2019). Taken together, these studies demonstrate that ML estimation for MSEM mediation is limited with small sample sizes.

Bayesian Estimation Methods

Bayesian methods provide an alternative estimation approach for MSEM mediation that does not rely on large sample theory. In the Bayesian framework, parameters are treated as random variables, and prior information about the parameters is used to construct a prior distribution of the model parameters. Using the Markov chain Monte Carlo (MCMC) method, the observed data are then combined with the prior distribution to approximate the posterior distribution. In mediation analysis, an empirical distribution of the indirect effect is obtained by computing *ab* for each MCMC iteration. Statistical significance of the indirect effect is assessed using a 95% credible interval that is calculated from the empirical distribution, which does not assume asymptotic normality. In the Bayesian framework, a 95% credible interval indicates a 95% probability that the interval contains the parameter value.

A critical step of Bayesian analysis is the specification of priors. Uninformative, or *diffuse*, priors can be used when relevant prior information about the model parameters is unknown. These priors can be implemented using the default prior distributions provided in many statistical software packages without requiring any substantive prior specification on the part of the researcher. For example, the default priors in M*plus* for intercepts, factor loadings, and regression coefficients are specified using a normal distribution with a mean of zero and a large variance of 10^{10}, thereby providing very little prior information about the parameter values. Conversely, informative priors, which are selected by the researcher, provide some degree of certainty in the estimation process. Depending on the magnitude of the variance hyperparameter relative to the scale of the model parameter, informative priors are classified on a continuum of informativeness that ranges from weak to strong.

The choice of priors can have a substantial impact on point estimates and credibility intervals obtained from Bayesian estimation, especially when data are clustered and sample sizes at each level are small. For example, diffuse priors have been found to perform worse than ML estimation methods with small samples. This has been shown in MSEM mediation models with single-level designs (van Erp et al., 2018) and 2-1-1 multilevel designs (McNeish, 2017). Moreover, in the context of 2-1-1 mediation, Fang et al. (2019) showed that Bayesian methods with accurate informative priors outperformed ML methods in the point and interval estimation of indirect effects when sample sizes were small. Of course, upper-bound performance of Bayesian priors may not be all that helpful for applied researchers who cannot know with certainty how accurately their priors reflect the true population values. Although there is a growing number of resources to help researchers construct thoughtful priors for Bayesian latent variable models (e.g., Miočević & Golchi, 2021; Smid et al., 2020; Smid & Winter, 2020, Zondervan-Zwijnenburg et al., 2017), there is still work to be done to fully understand the extent to which priors can be robust to misspecification.

The Current Study

The application of Bayesian methods to latent variable modeling has gained considerable attention in recent years as a solution to problems encountered with small samples in the frequentist framework. However, small samples have also been shown to be problematic with Bayesian methods in that they require accurate informative priors. To date, Bayesian methods have been examined in additive multilevel models without testing for mediation effects (Depaoli & Clifton, 2015; Zitzmann et al., 2016) and in mediation models that result from 2-1-1 designs

(Fang et al., 2019; McNeish, 2017). In the current study, we extend this work through consideration of the common instances in which all clustered data are collected at level 1 (Huang, 2016; McNeish et al., 2017), and substantive questions of mediation are of interest at both level 1 and level 2 of a 1-1-1 design. Currently, there are no clear recommendations for applied researchers looking to estimate 1-1-1 models with Bayesian methods. Because it is unrealistic to expect that priors are centered on the true population value, we examine the extent to which Bayesian 1-1-1 MSEM mediation models yield results that are robust to misspecified priors across a variety of design conditions (i.e., different sample sizes, ICCs, and effect sizes). In doing so, we expand the design framework to include a more comprehensive examination of prior specifications than those from previous studies. On the basis of results from the current simulation study, we provide recommendations for testing multilevel mediation given various methodological considerations and point readers to additional resources for current "best practices" in Bayesian mediation analysis.

Methods

Data were generated in M*plus* version 8.4 (Muthén & Muthén, 1998-2017) using a two-level (1-1-1) mediation model with random intercepts and fixed slopes. The latent predictor (*X*), latent mediator (*M*), and latent outcome (*Y*) were each measured with three observed indicators, each with standardized factor loadings of 0.7 at both the within- and between-cluster levels. Figure 1 shows the population values for one of the simulation conditions.

The conditions manipulated in this study were ICC values (.05, .20), the numbers of clusters (10, 20, 50, 100, 200), cluster sizes (5, 10, 20, 50), and between-level indirect effect sizes (0, .02, .16), leading to 120 design conditions. ICCs were selected to reflect small (.05) and large (.20) values that have been evaluated in previous MSEM simulation studies (Helm, 2018;

Lüdtke et al., 2011; Preacher et al., 2011; Zitzmann et al., 2016). Sample sizes at the within- and between-cluster levels were generated to be representative of the range typically reported in empirical multilevel mediation studies (McNeish, 2017). Between-level indirect effect sizes were chosen to reflect small (.02) and medium (.16) effect sizes similar to those used in previous simulation studies (Fang et al., 2019; McNeish, 2017; Preacher et al., 2011; Zigler & Ye, 2019). In addition, a null between-level indirect effect condition ($ab_B = 0$) was simulated by setting the population regression parameters at the between level to zero (a_B, b_B, $c'_B = 0$). The within-level indirect effect was equal to .09 and did not vary across conditions, following Zigler and Ye (2019). For each simulation condition, 1,000 data sets were generated.

The 1-1-1 mediation model was estimated in M*plus* using the following estimation/prior specification approaches: (1) maximum likelihood (ML) with robust standard errors, and Bayesian MCMC with (2) diffuse, (3) accurate informative, (4) and inaccurate informative priors. Although the primary focus of the study was on Bayesian estimation with informative priors, ML and Bayesian diffuse methods were included for comparison. Diffuse priors were specified using the M*plus* defaults of $N(0, 10^{10})$ for intercepts, factor loadings, and regression coefficients, and $\Gamma^{-1}(-1, 0)$ for variance parameters.[1] For accurate and inaccurate regression priors, three levels of informativeness were evaluated based on variance hyperparameters equal to 1.0, 0.10, and 0.01. Mean hyperparameters for accurate regression priors were equal to the population values, and inaccurate (informative) priors were constructed by specifying mean hyperparameters that deviated from the population values by one and two standard deviations,

[1] Priors for all parameters were specified as univariate priors. Although the multivariate inverse Wishart prior is the default prior for the covariance matrix in M*plus*, the covariance matrix can be decomposed into individual univariate elements, which are then assigned univariate separation strategy priors (Liu et al., 2016).

following methods described in Depaoli (2014) and Miočević et al. (2021). Diffuse priors were used for all other model parameters in the informative prior conditions.

The informative accurate and inaccurate prior specifications for all regression parameters are shown in Table 1. For example, when the population value of the regression coefficient a_B was 0.40 and the variance hyperparameter was 0.01, the accurate prior was specified as $a_B \sim N(0.40, 0.01)$. The corresponding inaccurate prior that deviated from the true value by one standard deviation was specified as $a_B \sim N(0.30, 0.01)$, where the mean hyperparameter was computed as $0.40 - \sqrt{(0.01)} = 0.30$. Figure 2 depicts the informative accurate and inaccurate prior distributions for the between-level regression parameters a_B and b_B at each level of informativeness, as specified with variance hyperparameters values of 1.0, 0.10, and 0.01. The priors presented in Figure 2 correspond to the population values for the simulation cell represented in Figure 1 (i.e., when $ab_{\mathrm{B}} = 0.16$). For example, as shown in the leftmost plot in Figure 2, the distributions for the accurate priors are correctly centered on the true value of 0.40. In each plot, the variance hyperparameter is equal to 1.0 for the prior represented by the solid black line, 0.1 for the dashed black line, and 0.01 for the dotted gray line.

The first indicator of each latent variable was fixed to an unstandardized value of 1.0 across all conditions for purposes of identification. In addition, cross-level equality constraints were imposed on all factor loadings to avoid overparameterized models (Jak, 2019). For the ML models, 95% confidence intervals for the indirect effect were computed in R (R Core Team, 2018) using the Monte Carlo method with 20,000 random draws based on code adapted from Selig and Preacher (2008). Bayesian MCMC models were estimated using the Gibbs sampler algorithm (Geman & Geman, 1984) and featured two chains and a maximum of 50,000 iterations, with the first half of iterations discarded as burn-in.

Evaluation Criteria

Performance of the estimation approaches was evaluated using five outcome measures: convergence rate, relative percentage bias, root mean square error (RMSE), confidence (or credible) interval coverage rate, and non-null detection rate for the indirect effect estimates at both the within- and between-cluster levels. Convergence rates were computed as the percentage of replications with admissible solutions for each design condition. For replications estimated with ML, solutions with negative between-level variance estimates were considered non-admissible and removed from subsequent analyses. For models estimated with MCMC, convergence was evaluated using the potential scale reduction (PSR) factor (Gelman and Rubin, 1992), with PSR < 1.05 as the criterion for convergence. Relative percentage bias was computed as $[(\overline{\widehat{ab}} - ab)/ab] \times 100$, where ab was the population value of the indirect effect, and $\overline{\widehat{ab}}$ was the average indirect effect estimate across replications. Values of relative percentage bias ±10% were considered extreme (Kaplan, 1988). RMSE was used as an index of overall accuracy that combines both bias and variability, and was computed as the square root of the mean square error (MSE):

$$\sum_{r=1}^{R} (\widehat{ab} - \overline{\widehat{ab}})^2 / R + (\overline{\widehat{ab}} - ab)^2 \tag{7}$$

where R denotes the number of replications for each design condition. In MCMC analyses, relative percentage bias and RMSE were computed using the posterior median of the indirect effect. The coverage of the 95% confidence (or credible) interval (CI) was computed as the percentage of replications in which the population value for the indirect effect was within the estimated CI. Approximately 95% of replications should contain the population value, and values below 92.5% or above 97.5% indicate CI coverage is too low or high, respectively (Bradley, 1978). Non-null detection rates were computed as the proportion of replications in which the estimated CI did not contain zero. In the frequentist framework, non-null detection rates are equivalent to power, which is defined as the probability of correctly rejecting the null hypothesis when it is false. Power of at least .80 is typically considered adequate (Casella & Berger, 2002). For the condition in which the population between-level indirect effect was zero (i.e., $ab_B = 0$), Type I Error rates are reported.

Results

This section is organized as follows. First, nonconvergence results are described for all estimation approaches. Then, given our primary interest in evaluating informative priors, we limit the remaining results section to MCMC conditions with informative (accurate and inaccurate) priors. For brevity, within-level results are presented only in text because estimation issues were encountered more often at the between-cluster level. Full tables of results across all simulated conditions are provided in Appendix B (Tables B1-B10).

Nonconvergence

As expected, Bayesian estimation resulted in higher convergence rates compared to ML estimation. Informative priors yielded 100% convergence across replications, and diffuse priors yielded consistently high (≥ 98.5%) rates of convergence. ML estimation resulted in convergence rates ranging from 1.2% to 100%, with lower rates occurring in conditions with smaller sample sizes. With small numbers of clusters (e.g., $J \leq 20$) and small cluster sizes (e.g., $N_j \leq 10$) convergence rates for ML were less than 35%. However, ML convergence rates were generally higher in the ICC = .20 condition compared to the ICC = .05 condition.[2]

[2] Table B1 in Appendix B provides convergence rates for ML and diffuse Bayesian conditions.

Within-Cluster Level

Relative Bias and RMSE

Unbiased estimates of the within-level indirect effect were recovered for nearly all conditions with accurate informative priors. The only exception to this trend was in the smallest sample size combination: 10 clusters ($J = 10$) each of size 5 units ($N_j = 5$). Specifically, when $J = 10$ and $N_j = 5$, accurate informative priors with a variance hyperparameter of 0.10 yielded values of relative percent bias greater than ±10%. Results with inaccurate priors showed that within-level indirect effect estimates became more biased as priors became more inaccurate and more informative, especially as sample sizes decreased. For example, when priors were centered 2 standard deviations below the population value and specified with a tight variance hyperparameter of 0.01, estimates were downwardly biased in conditions with 20 or fewer clusters. However, when priors were centered only 1 standard deviation away from the true value and given a wider variance hyperparameter of 1.0, unbiased estimates were recovered with as few as 10 clusters of size 20 units or more (i.e., $J \geq 10$ and $N_j \geq 20$). Finally, when the number of clusters was as large as 200, unbiased estimates were adequately recovered across all prior specifications.

RMSE of the within-level indirect effect was less than 0.20 across all informative priors and generally decreased as the number of clusters and cluster size increased. In the largest sample size condition of 200 clusters each of size 50 ($J = 200$ and $N_j = 50$), RMSE values were equal to zero across all prior specifications. As priors became more informative (meaning smaller variance hyperparameters), RMSE values became smaller. Comparisons between accurate and inaccurate prior specifications revealed that RMSE decreased as the amount of inaccuracy increased. Larger differences in RMSE across levels of prior inaccuracy were observed as (a) variance hyperparameters decreased and (b) sample sizes decreased.

Coverage Rate

Coverage rates of the within-level indirect effect were generally close to the nominal 0.95 value when priors were specified as weakly informative with a variance hyperparameter equal to 1.0. As priors became more informative, coverage tended to fall outside of Bradley's (1978) robustness criterion. Patterns of coverage were different for accurate and inaccurate priors as sample sizes decreased. Whereas accurate priors yielded coverage rates above 0.95 in small samples, inaccurate priors resulted in coverage well below 0.95 in small samples. For inaccurate priors, coverage rates decreased as priors were centered further below the true value, and this pattern was most pronounced for the strongly informative inaccurate prior $N(2sd, 0.01)$.

Non-Null Detection Rate

Non-null detection rates were ≥ 0.99 in conditions with strongly informative accurate priors $N(\mu, 0.01)$. This indicated the upper-bound performance of Bayesian estimation at the within-level. The other, slightly wider accurate prior specifications of $N(\mu, 0.10)$ and $N(\mu, 1.0)$ yielded similarly high detection rates at large sample sizes. However, as the number of clusters and cluster size decreased, detection rates decreased for these less informative accurate priors. Likewise, for inaccurate priors, non-null detection rates decreased as sample sizes decreased. Interestingly, for weakly informative priors, there were negligible differences in detection rates between accurate and inaccurate prior specifications, and this pattern held across sample sizes. On the other hand, strongly informative priors with different amounts of accuracy resulted in highly divergent detection rates, particularly at small sample sizes.

Between-Cluster Level

Relative Bias and RMSE

As shown in Table 2, results indicated that all MCMC replications failed to recover unbiased parameter estimates when the effect size of the between-level indirect effect was small ($ab_B = .02$). At the medium effect-size level ($ab_B = .16$), results of relative bias improved; however, unbiased estimates were recovered mostly with accurate priors. Inaccurate priors yielded unbiased results only under conditions with wide variance hyperparameters and large sample sizes. For example, the weakly informative inaccurate priors $N(1sd, 1.0)$ and $N(2sd, 1.0)$ adequately recovered parameters with 100 and 200 clusters, respectively. For RMSE, lower values were typically associated with larger sample sizes and accurate priors with tighter variance hyperparameters (Table 3). In addition, although estimates were more biased in the small effect size condition, RMSE values that additionally capture variability, generally were higher in the medium effect size condition.

Coverage Rate

Accurate informative priors resulted in coverage rates that were higher than expected (near 1.0) across most conditions, particularly in the small effect size condition (Figure 3). However, coverage rates for inaccurate priors ranged widely from 0.0 to 1.0. Consistent with previous literature on Bayesian mediation (Miočević et al., 2021), coverage of the small indirect effect was low in small sample size conditions when priors were specified with 2*sd* inaccuracy and a wide variance equal to 1.0 (Figure 3). For the medium effect size, larger deviations in the mean hyperparameter were generally associated with under-coverage, especially as priors became more strongly informative. For example, at $ab_B = .16$, the strongly informative inaccurate prior $N(2sd, 0.01)$ resulted in under-coverage across all levels of ICC and sample sizes (Figure

4). Coverage rates for the null indirect effect ($ab_B = 0$) at ICC = 0.20 are presented in Figure 5. When the population indirect effect was zero, coverage for accurate and 1*sd* inaccurate priors were > 0.98, whereas coverage for 2*sd* inaccurate priors ranged widely from 0.55 to 1.0.

Non-Null Detection Rate

Non-null rates across all MCMC conditions showed that it was not possible to detect a small non-zero indirect-effect size at the between level (Figure 6). Even with 200 clusters each of size 50 at ICC = .20, the strongly informative accurate prior $N(\mu, 0.01)$ only yielded a detection rate of 0.28. However, in the medium effect size condition, the same prior $N(\mu, 0.01)$ consistently detected the indirect effect across all levels of ICC and sample sizes (Figure 7). For the other prior specifications, although detection rates increased from zero as sample size and ICC increased, rates were usually well below the optimal threshold of 0.80 in non-null effect size conditions. Type I Error rates are presented in Figure 8 for the null indirect effect ($ab_B = 0$) condition. As shown in Figure 8, rates were near zero for accurate and 1*sd* inaccurate priors, across all levels of informativeness when the population between-level indirect effect was equal to zero. However, inaccurate priors that were centered two standard deviations (2*sd*) away from the true value yielded higher error rates, particularly when the number of clusters and cluster size were low.

Discussion

As Bayesian methods continue to become increasingly utilized in applied contexts (van de Schoot et al., 2017), there is a growing need to understand how these methods can best be implemented in various statistical models, such as mediation analysis. Previous research has evaluated Bayesian methods in single level mediation (e.g., Chen et al., 2014; Miočević et al., 2017; Yuan & MacKinnon, 2009) as well as 2-1-1 multilevel mediation designs (Fang et al., 2019; McNeish, 2017). The current study extends this work by evaluating the performance of Bayesian methods in 1-1-1 multilevel mediation with latent variables, with particular focus on the degree of prior accuracy and informativeness needed to estimate models with smaller sample sizes. As expected, results indicated that non-convergence was a problem for ML estimation with small samples. With respect to the conditions evaluated in this study, at least 50 clusters of size 50 units at small ICCs were required for ML convergence rates to rise above 80%, and 50 clusters of size 10 units were needed for larger ICC values. By contrast, the current study found that Bayesian estimation achieved more optimal rates of convergence, suggesting that a Bayesian approach to MSEM mediation can be a viable alternative to frequentist methods when ML estimation fails to converge. However, results confirmed that simply relying on diffuse prior specifications is not always advisable. When sample sizes are small relative to the model's complexity (e.g., fewer than 100 clusters for MSEM), the amount of information carried by the priors can have large impacts on the performance of Bayesian estimation (as shown by McNeish, 2016; Miočević et al., 2017; Smid et al., 2020). This was particularly true for between-level indirect effect estimates in instances of few clusters, small cluster sizes, low ICC values, and small effect sizes. Hence, our 1-1-1 model results are consistent with those for 2-1-1 designs (Fang et al., 2019; McNeish, 2017) in that caution must be applied when selecting priors for MSEM mediation analysis.

In line with previous research on single-level mediation with observed (Miočević et al., 2017; Yuan & MacKinnon, 2009) and latent variables (Miočević et al., 2021), the current study found that accurate informative priors increase power and decrease bias when sample sizes are small. However, the results reported here show that inaccuracy in the priors of structural coefficients in 1-1-1 mediation is more problematic for the statistical properties of the between-level indirect effect compared to those of the within-level. At the within-cluster level, the impact of prior misspecification was more pronounced for bias than for power. Although unbiased point estimates of the within-level indirect effect were recovered with accurate priors in nearly all sample size conditions, estimates became increasingly biased with inaccurate priors as sample sizes decreased. However, non-null detection rates at the within level were more invariant to inaccuracies in prior specifications and instead were impacted more by sample size. Moving to the between-cluster level, simulation results showed that when the indirect effect size was small (i.e., $ab_B = .02$), all estimation methods were underpowered and unable to recover unbiased estimates. Even at the largest sample sizes included in this study (i.e., 200 clusters each of size 50 units), MCMC with accurate informative priors had negligible power to detect the small indirect effect. These results are consistent with findings reported in previous simulation studies. For 1-1-1 models with latent variables and maximum likelihood estimation, Zigler and Ye (2019) reported low power (< .2) with 500 clusters and a small between-level indirect effect size ($ab_B = .01$). For 2-1-1 models with observed variables and Bayesian methods, Fang et al. (2019) found that detection rates never exceeded .38 with 100 clusters and a small effect size ($ab_B = .02$), even when informative accurate priors were specified. In the current study, non-null detection rates reached more optimal levels only when the between-level indirect effect size was increased to $ab_B = .16$. However, in the larger effect size condition, strongly informative priors with tight variance hyperparameters were required to adequately detect non-null effects, particularly in small sample conditions. When the value of the variance hyperparameter was increased, thereby making the prior less informative, power was below the optimal threshold of .80 in all but the largest sample size condition of 200 clusters. In addition, 1*sd* inaccuracy in the mean hyperparameter generally resulted in biased between-level estimates in small sample conditions.

Based on these findings, applied researchers are advised against conducting 1-1-1 mediation analysis within an MSEM framework if the number of clusters is less than 100. Our simulation results indicate that when sample sizes are small, the model requires strongly informative accurate priors that are correctly specified at the true population value. Because the assumption of correct prior specification is unlikely to be met in practice, inferences made about indirect effects in the 1-1-1 MSEM model may be misguided when informative priors are used with small samples. When the number of clusters is small, researchers should instead consider testing the 1-1-1 model within the more traditional regression-based multilevel modeling (MLM) framework, which can leverage small sample methods such as restricted maximum likelihood and the Kenward-Roger correction. Similar recommendations were provided by McNeish (2017) for 2-1-1 designs and by Zigler and Ye (2019) for 1-1-1 mediation. Although MLM mediation models cannot accommodate latent variables, the "simplicity" of MLM can afford researchers the ability to test level-specific indirect effects with much smaller sample sizes. On the other hand, when the larger sample size requirements are met, researchers are encouraged to use the MSEM approach to multilevel mediation and to consider Bayesian estimation. The current study found that as the amount of information provided by the data increases (i.e., larger samples sizes, ICCs, and effect sizes), results may be robust to small prior misspecifications, particularly if the priors are weakly informative. For example, with 200 clusters, regression priors specified with a mean hyperparameter centered 1*sd* away from the population value and a relatively large variance hyperparameter can recover unbiased and efficient estimates of the indirect effect at both levels. However, it is worth noting that as sample sizes increase, results obtained with informative priors are comparable to those obtained with diffuse priors. Hence, if researchers lack prior information about the model parameters, completely diffuse (default) priors may be sufficient to obtain trustworthy results with large samples.

For researchers interested in using Bayesian methods for 1-1-1 MSEM mediation with appropriately sized samples, several resources are available to help inform the elicitation of prior information (see e.g., Zondervan-Zwijnenburg et al., 2017). In addition, we refer readers to Smid et al. (2020) for their discussion of how to construct thoughtful priors, as well as Miočević and Golchi (2021) for specifying informative priors for mediation analysis using a historical data set. The selection of appropriate priors is further facilitated through the process of prior predictive checks, which allow researchers to evaluate how well the chosen priors reflect their prior beliefs. Gabry et al. (2019) provide an accessible introduction to prior predictive checks, and van Zundert et al. (2021) present a user-friendly Shiny app for implementing this process in Bayesian mediation analysis. We also emphasize the importance of conducting a prior sensitivity analysis as a follow-up procedure to testing MSEM mediation. Sensitivity analysis allows researchers to evaluate the robustness of results given a particular choice of priors. The analysis involves estimating the model with different prior specifications based on adjustments to the prior hyperparameters. Thereafter, researchers can evaluate subsequent changes in the posterior distributions to determine the extent to which model results are sensitive to different prior settings. Interested readers are encouraged to consult Depaoli et al. (2020) for detailed descriptions of conducting prior sensitivity.

The findings reported here are limited to 1-1-1 mediation models with three latent factors, continuous indicators, and random intercepts. Estimation of more complex models, such as those with additional covariates or random slopes, are likely to require even larger sample sizes to perform well in terms of both convergence and model estimates (Preacher et al., 2010; McNeish, 2017). Although more research is needed to understand how Bayesian methods perform in 1-1-1 mediation designs in situations with random slopes, we would expect such models to result in poorer recovery (McNeish, 2017). In addition, we did not vary the within-level indirect effect because we were more focused on how model performance was affected at the between-cluster level. Previous studies that examined the performance of Bayesian methods for MSEM with latent variables demonstrated that parameter estimates are generally well recovered at the within level (e.g., Depaoli & Clifton, 2015; Zitzmann et al., 2016). It is also important to note that the inaccurate priors used in this study were designed to be inaccurate with respect to the simulated population parameter values. However, the degree of inaccuracy in these priors was also dependent upon the level of informativeness. Therefore, more informative priors (i.e., those with smaller variance hyperparameters) were less inaccurate compared to priors with higher variance hyperparameters. Previous studies have also noted this limitation (Miočević et al., 2021); nevertheless, care must be taken when interpreting the combined effects of prior inaccuracy and informativeness. Finally, in consideration of the current study's findings that reveal the limitations of Bayesian estimation for 1-1-1 MSEM mediation with small sample sizes, an important area for future research is the development of methods for constructing accurate informative priors. These innovations would offer the needed support for researchers applying Bayesian methods to multilevel mediation with small samples.

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Tables

Table 1

Prior Specifications with Informative Accurate and Inaccurate Priors for Structural Regression Parameters

Variance hyperparameter	Regression parameter	Accurate	Inaccurate 1*sd*	Inaccurate 2*sd*
		Small between-level indirect effect (ab_B = .02)		
1.00	a_W, b_W	~ N (0.30, 1.00)	~ N (-0.70, 1.00)	~ N (-1.70, 1.00)
	c'_W, c'_B	~ N (0.20, 1.00)	~ N (-0.80, 1.00)	~ N (-1.80, 1.00)
	a_B, b_B	~ N (0.14, 1.00)	~ N (-0.86, 1.00)	~ N (-1.86, 1.00)
0.10	a_W, b_W	~ N (0.30, 0.10)	~ N (-0.02, 0.10)	~ N (-0.33, 0.10)
	c'_W, c'_B	~ N (0.20, 0.10)	~ N (-0.12, 0.10)	~ N (-0.43, 0.10)
	a_B, b_B	~ N (0.14, 0.10)	~ N (-0.18, 0.10)	~ N (-0.49, 0.10)
0.01	a_W, b_W	~ N (0.30, 0.01)	~ N (0.20, 0.01)	~ N (0.10, 0.01)
	c'_W, c'_B	~ N (0.20, 0.01)	~ N (0.10, 0.01)	~ N (0.00, 0.01)
	a_B, b_B	~ N (0.14, 0.01)	~ N (0.04, 0.01)	~ N (-0.06, 0.01)
		Medium between-level indirect effect (ab_B = .16)		
1.00	a_W, b_W	~ N (0.30, 1.00)	~ N (-0.70, 1.00)	~ N (-1.70, 1.00)
	c'_W, c'_B	~ N (0.20, 1.00)	~ N (-0.80, 1.00)	~ N (-1.80, 1.00)
	a_B, b_B	~ N (0.40, 1.00)	~ N (-0.60, 1.00)	~ N (-1.60, 1.00)
0.10	a_W, b_W	~ N (0.30, 0.10)	~ N (-0.02, 0.10)	~ N (-0.33, 0.10)
	c'_W, c'_B	~ N (0.20, 0.10)	~ N (-0.12, 0.10)	~ N (-0.43, 0.10)
	a_B, b_B	~ N (0.40, 0.10)	~ N (0.08, 0.10)	~ N (-0.23, 0.10)
0.01	a_W, b_W	~ N (0.30, 0.01)	~ N (0.20, 0.01)	~ N (0.10, 0.01)
	c'_W, c'_B	~ N (0.20, 0.01)	~ N (0.10, 0.01)	~ N (0.00, 0.01)
	a_B, b_B	~ N (0.40, 0.01)	~ N (0.30, 0.01)	~ N (0.20, 0.01)
		Null between-level indirect effect (ab_B = 0)		
1.00	a_W, b_W	~ N (0.30, 1.00)	~ N (-0.70, 1.00)	~ N (-1.70, 1.00)
	c'_W	~ N (0.20, 1.00)	~ N (-0.80, 1.00)	~ N (-1.80, 1.00)
	a_B, b_B, c'_B	~ N (0.00, 1.00)	~ N (-1.00, 1.00)	~ N (-2.00, 1.00)
0.10	a_W, b_W	~ N (0.30, 0.10)	~ N (-0.02, 0.10)	~ N (-0.33, 0.10)
	c'_W	~ N (0.20, 0.10)	~ N (-0.12, 0.10)	~ N (-0.43, 0.10)
	a_B, b_B, c'_B	~ N (0.00, 0.10)	~ N (-0.32, 0.10)	~ N (-0.63, 0.10)
0.01	a_W, b_W	~ N (0.30, 0.01)	~ N (0.20, 0.01)	~ N (0.10, 0.01)
	c'_W	~ N (0.20, 0.01)	~ N (0.10, 0.01)	~ N (0.00, 0.01)
	a_B, b_B, c'_B	~ N (0.00, 0.01)	~ N (-0.10, 0.01)	~ N (-0.20, 0.01)

Table 2

Relative Percentage Bias for Between-Level Indirect Effects in Informative Prior Conditions

N_j	J	μ,1.0	1*sd*,1.0	2*sd*,1.0	μ,.10	1*sd*,.10	2*sd*,.10	μ,.01	1*sd*,.01	2*sd*,.01
					ab_B = .02, ICC = .05					
5	10	-46.0	1049.0	9515.5	-66.0	-57.0	790.0	-23.0	-97.5	-94.0
	20	-57.5	975.5	8468.5	-63.5	-58.0	762.5	-23.0	-97.5	-94.5
	50	-37.0	910.5	7619.5	-58.0	-57.0	737.0	-22.5	-97.5	-94.5
	100	-59.5	879.5	7193.5	-59.0	-52.5	725.5	-23.0	-97.0	-95.0
	200	-48.0	832.0	6663.0	-53.0	-54.0	689.0	-24.0	-97.0	-95.0
10	10	-59.0	1048.0	8909.0	-67.0	-56.0	774.0	-23.0	-97.5	-94.0
	20	-50.0	955.0	7708.5	-61.5	-54.0	746.0	-23.5	-97.5	-94.0
	50	-43.5	844.5	6759.5	-52.5	-50.5	706.5	-23.0	-97.0	-94.5
	100	-51.5	613.0	5812.5	-45.5	-57.5	597.0	-22.0	-96.0	-95.0
	200	-47.5	363.5	4256.5	-37.5	-65.5	413.5	-21.5	-93.5	-96.0
20	10	-44.0	962.5	8228.5	-60.5	-55.0	756.5	-22.5	-97.5	-94.5
	20	-11.0	796.0	6959.5	-49.0	-53.5	679.5	-22.5	-97.0	-94.5
	50	-31.5	494.5	5062.5	-39.5	-62.5	496.5	-22.0	-95.5	-95.0
	100	-24.0	157.0	2723.0	-29.0	-76.5	220.5	-20.0	-92.5	-97.0
	200	-30.5	-30.0	343.5	-27.0	-75.0	**-7.5**	-18.5	-86.0	-98.5
50	10	-21.5	810.0	7228.0	-48.0	-55.0	688.5	-22.0	-97.5	-94.5
	20	-60.0	402.0	4787.5	-43.5	-69.0	476.0	-21.5	-96.0	-95.0
	50	-59.5	15.0	1270.0	-34.0	-86.0	103.0	-20.0	-92.5	-97.0
	100	-33.5	-48.5	-14.5	-25.5	-76.5	-70.0	-17.0	-85.5	-99.0
	200	-23.5	-37.0	-49.0	-20.0	-57.0	-80.5	-14.0	-73.5	-97.0
					ab_B = .02, ICC = .20					
5	10	-26.5	1129.5	9710.0	-60.0	-56.0	764.5	-23.0	-97.5	-94.5
	20	-30.5	946.0	8286.5	-53.5	-55.5	696.5	-23.0	-97.0	-95.0
	50	-55.0	512.5	5777.5	-43.0	-65.5	476.5	-22.5	-94.5	-96.5
	100	-61.5	117.5	2824.5	-40.5	-81.0	179.0	-22.5	-91.0	-98.0
	200	-36.5	-38.5	268.5	-31.5	-73.0	-46.0	-19.5	-83.0	-99.0
10	10	-58.5	969.0	8674.5	-59.0	-52.5	729.0	-23.5	-97.5	-94.0
	20	-22.0	685.0	6097.0	-41.0	-58.0	524.5	-23.0	-96.0	-95.0
	50	-45.0	60.5	1846.5	-28.0	-82.5	107.0	-20.0	-91.5	-97.5
	100	-24.0	-46.5	44.5	-23.0	-75.5	-68.0	-17.0	-84.5	-99.0
	200	-15.5	-29.5	-42.0	-16.0	-52.5	-77.0	-12.5	-71.0	-96.5
20	10	-12.0	713.0	7463.0	-42.0	-62.0	620.5	-21.0	-96.5	-94.5
	20	-14.5	235.5	3504.5	-27.0	-74.0	285.5	-19.5	-94.5	-96.0
	50	-37.5	-59.0	154.0	-26.5	-86.0	-47.5	-18.0	-89.0	-98.5
	100	-19.0	-40.0	-56.0	-19.0	-66.5	-88.0	-14.5	-79.5	-99.0
	200	-18.0	-28.5	-38.5	-17.0	-47.0	-69.0	-13.0	-65.5	-93.0
50	10	-16.5	547.5	6234.0	-38.5	-63.5	515.5	-21.0	-96.5	-94.5
	20	-61.5	25.5	1819.5	-39.0	-91.0	143.0	-20.5	-94.5	-96.5
	50	-29.0	-57.0	-53.0	-23.5	-82.5	-81.0	-17.0	-86.5	-99.0
	100	-18.0	-35.0	-49.0	-18.0	-59.5	-84.5	-13.5	-75.0	-98.0
	200	-14.5	-24.0	-32.5	-14.5	-40.5	-60.5	-11.0	-59.5	-88.0

Table 2 (continued)

N_j	J	μ,1.0	1*sd*,1.0	2*sd*,1.0	μ,.10	1*sd*,.10	2*sd*,.10	μ,.01	1*sd*,.01	2*sd*,.01
					ab_B = .16, ICC = .05					
5	10	-63.2	-45.8	757.4	-26.8	-98.1	-87.9	**-3.4**	-46.6	-77.5
	20	-60.9	-51.1	669.5	-26.1	-97.6	-88.3	**-3.3**	-46.2	-76.9
	50	-46.3	-54.2	579.2	-22.4	-95.3	-89.4	**-3.0**	-45.3	-76.1
	100	-37.6	-57.1	507.0	-20.4	-93.3	-89.9	**-2.8**	-44.5	-75.4
	200	-14.4	-55.9	411.4	-14.3	-87.2	-92.1	**-2.5**	-43.2	-73.9
10	10	-61.9	-52.0	691.6	-26.9	-97.8	-88.1	**-3.5**	-46.4	-77.4
	20	-47.6	-51.8	572.9	-23.3	-95.9	-88.7	**-3.1**	-45.7	-76.6
	50	-17.2	-55.9	448.3	-14.7	-89.6	-91.3	**-2.3**	-44.0	-75.0
	100	**4.5**	-49.0	277.1	**-6.6**	-76.8	-93.4	**-1.3**	-41.6	-72.4
	200	21.9	-19.5	84.1	**0.3**	-53.9	-88.4	**-0.5**	-37.8	-67.7
20	10	-39.7	-58.0	602.9	-21.1	-96.1	-89.6	**-2.8**	-45.9	-76.8
	20	-16.2	-57.5	417.3	-13.8	-90.3	-92.2	**-2.0**	-44.4	-75.4
	50	12.3	-40.9	154.9	**-3.8**	-71.6	-95.1	**-1.3**	-41.4	-71.9
	100	23.2	**-7.5**	**8.1**	**2.0**	-47.3	-82.9	**-0.5**	-37.0	-66.4
	200	10.2	**-0.9**	-13.8	**1.8**	-26.4	-52.7	**-0.9**	-31.3	-57.8
50	10	-19.9	-62.9	438.4	-15.1	-91.4	-92.2	**-2.1**	-44.8	-75.9
	20	**-2.5**	-56.8	136.7	**-6.9**	-78.8	-96.6	**-1.1**	-42.7	-73.4
	50	**8.3**	-18.8	-31.1	**-1.8**	-49.5	-83.1	**-1.0**	-37.8	-67.0
	100	**4.4**	**-7.4**	-18.2	**-0.5**	-28.1	-52.9	**-1.0**	-31.9	-58.1
	200	**1.9**	**-3.8**	**-9.0**	**0.2**	-14.5	-28.6	**-0.8**	-24.3	-45.4
					ab_B = .16, ICC = .20					
5	10	-34.3	-50.2	699.4	-18.7	-95.6	-90.3	**-2.5**	-45.5	-76.6
	20	-3.3	-57.9	520.9	-10.9	-89.1	-93.3	**-1.9**	-43.8	-74.6
	50	24.2	-35.0	186.6	**-0.9**	-65.8	-93.1	**-0.9**	-39.6	-69.5
	100	19.3	**-8.8**	**2.1**	**-0.1**	-43.0	-77.3	**-1.4**	-35.8	-63.4
	200	**7.8**	**-2.1**	-11.6	**0.3**	-22.8	-44.4	**-1.6**	-29.3	-53.3
10	10	-12.8	-59.3	564.4	-12.9	-92.4	-91.8	**-2.1**	-44.6	-75.8
	20	14.1	-47.6	241.0	**-6.3**	-77.7	-95.1	**-1.3**	-42.3	-72.9
	50	18.8	-14.8	-30.1	**1.1**	-47.3	-81.3	**-0.8**	-37.3	-65.9
	100	**8.1**	**-2.4**	-16.3	**1.4**	-26.6	-50.8	**-0.6**	-31.3	-56.9
	200	**3.6**	**-1.8**	**-6.5**	**1.7**	-12.6	-26.4	**-0.3**	-23.6	-44.1
20	10	**8.3**	-64.9	349.0	**-7.0**	-86.2	-95.4	**-1.0**	-43.6	-74.7
	20	23.3	-34.7	22.3	**-1.0**	-66.4	-94.6	**-0.6**	-40.9	-71.3
	50	**9.8**	**-8.8**	-26.8	**-0.4**	-37.9	-67.6	**-1.1**	-35.5	-63.2
	100	**2.9**	**-5.1**	-12.6	**0.4**	-20.6	-39.8	**-0.8**	-28.6	-52.6
	200	**0.0**	**-3.8**	**-7.4**	**-0.4**	-11.3	-21.8	**-0.9**	-20.9	-39.2
50	10	**9.9**	-58.6	217.2	**-5.8**	-80.5	-96.3	**-1.0**	-43.1	-74.3
	20	**9.6**	-35.4	-43.0	**-3.6**	-63.1	-94.6	**-1.1**	-40.4	-70.4
	50	**2.9**	-10.4	-24.2	**-1.4**	-33.4	-60.6	**-0.9**	-33.9	-60.9
	100	**0.0**	**-6.2**	-12.5	**-0.8**	-18.1	-34.2	**-0.9**	-26.6	-49.1
	200	**-0.4**	**-3.3**	**-6.4**	**-0.5**	**-9.6**	-18.2	**-0.6**	-18.6	-35.3

Note. μ denotes mean hyperparameter equal to population value (i.e., accurate prior). 1*sd* and 2*sd* denote mean hyperparameters equal to 1 and 2 standard deviations from population value (i.e., inaccurate prior). N_j = cluster size; J = number of clusters; ab_B = *between-level indirect effect.* Values in bold indicate bias < ±10%.

Table 3

Root Mean Square Error (RMSE) for Between-Level Indirect Effects in Informative Prior Conditions

N_j	*J*	μ,1.0	1*sd*,1.0	2*sd*,1.0	μ,.10	1*sd*,.10	2*sd*,.10	μ,.01	1*sd*,.01	2*sd*,.01
					ab_B = .02, ICC = .05					
5	10	0.04	0.26	1.95	0.01	0.01	0.16	0.00	0.02	0.02
	20	0.05	0.27	1.76	0.01	0.01	0.16	0.00	0.02	0.02
	50	0.08	0.27	1.62	0.02	0.01	0.15	0.00	0.02	0.02
	100	0.08	0.29	1.56	0.02	0.02	0.16	0.00	0.02	0.02
	200	0.09	0.29	1.46	0.02	0.02	0.15	0.00	0.02	0.02
10	10	0.04	0.27	1.84	0.01	0.01	0.16	0.00	0.02	0.02
	20	0.06	0.29	1.63	0.01	0.01	0.16	0.00	0.02	0.02
	50	0.09	0.28	1.48	0.02	0.02	0.16	0.00	0.02	0.02
	100	0.10	0.24	1.33	0.02	0.02	0.14	0.00	0.02	0.02
	200	0.09	0.20	1.08	0.03	0.02	0.12	0.01	0.02	0.02
20	10	0.06	0.28	1.73	0.01	0.01	0.16	0.00	0.02	0.02
	20	0.09	0.28	1.52	0.02	0.02	0.15	0.00	0.02	0.02
	50	0.10	0.23	1.22	0.03	0.02	0.13	0.00	0.02	0.02
	100	0.09	0.15	0.83	0.03	0.02	0.09	0.01	0.02	0.02
	200	0.04	0.06	0.28	0.03	0.02	0.04	0.01	0.02	0.02
50	10	0.10	0.30	1.58	0.02	0.02	0.15	0.00	0.02	0.02
	20	0.11	0.23	1.20	0.02	0.02	0.13	0.00	0.02	0.02
	50	0.09	0.11	0.57	0.03	0.03	0.07	0.01	0.02	0.02
	100	0.05	0.04	0.10	0.03	0.02	0.03	0.01	0.02	0.02
	200	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02
					ab_B = .02, ICC = .20					
5	10	0.07	0.31	2.03	0.01	0.01	0.16	0.00	0.02	0.02
	20	0.09	0.32	1.80	0.02	0.02	0.15	0.00	0.02	0.02
	50	0.11	0.25	1.39	0.03	0.02	0.13	0.01	0.02	0.02
	100	0.07	0.14	0.89	0.03	0.02	0.08	0.01	0.02	0.02
	200	0.04	0.04	0.29	0.03	0.02	0.03	0.01	0.02	0.02
10	10	0.09	0.33	1.87	0.02	0.02	0.16	0.00	0.02	0.02
	20	0.12	0.29	1.47	0.03	0.02	0.14	0.00	0.02	0.02
	50	0.09	0.11	0.72	0.03	0.02	0.07	0.01	0.02	0.02
	100	0.05	0.04	0.15	0.03	0.02	0.02	0.01	0.02	0.02
	200	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02
20	10	0.11	0.29	1.71	0.02	0.02	0.15	0.00	0.02	0.02
	20	0.12	0.19	1.05	0.03	0.03	0.10	0.01	0.02	0.02
	50	0.07	0.06	0.24	0.03	0.02	0.03	0.01	0.02	0.02
	100	0.03	0.03	0.03	0.03	0.02	0.02	0.01	0.02	0.02
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02
50	10	0.11	0.28	1.51	0.02	0.02	0.13	0.00	0.02	0.02
	20	0.11	0.15	0.75	0.03	0.03	0.07	0.01	0.02	0.02
	50	0.05	0.05	0.08	0.03	0.03	0.03	0.01	0.02	0.02
	100	0.03	0.03	0.03	0.02	0.02	0.02	0.01	0.02	0.02
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02

Table 3 (continued)

N_j	J	μ,1.0	1*sd*,1.0	2*sd*,1.0	μ,.10	1*sd*,.10	2*sd*,.10	μ,.01	1*sd*,.01	2*sd*,.01
					ab_B = .16, ICC = .05					
5	10	0.13	0.11	1.26	0.05	0.16	0.14	0.00	0.07	0.12
	20	0.14	0.13	1.15	0.05	0.16	0.14	0.01	0.07	0.12
	50	0.16	0.15	1.04	0.06	0.15	0.14	0.01	0.07	0.12
	100	0.17	0.16	0.96	0.07	0.15	0.14	0.01	0.07	0.12
	200	0.20	0.17	0.86	0.08	0.14	0.15	0.01	0.07	0.12
10	10	0.13	0.12	1.17	0.05	0.16	0.14	0.01	0.07	0.12
	20	0.15	0.15	1.03	0.06	0.15	0.14	0.01	0.07	0.12
	50	0.18	0.16	0.91	0.07	0.15	0.15	0.01	0.07	0.12
	100	0.22	0.17	0.71	0.08	0.13	0.15	0.01	0.07	0.12
	200	0.21	0.18	0.44	0.09	0.11	0.15	0.02	0.06	0.11
20	10	0.16	0.14	1.07	0.06	0.15	0.14	0.01	0.07	0.12
	20	0.20	0.16	0.87	0.07	0.15	0.15	0.01	0.07	0.12
	50	0.22	0.18	0.58	0.09	0.13	0.15	0.02	0.07	0.12
	100	0.21	0.19	0.31	0.09	0.10	0.14	0.02	0.06	0.11
	200	0.14	0.13	0.13	0.08	0.08	0.10	0.03	0.05	0.09
50	10	0.19	0.16	0.92	0.07	0.15	0.15	0.01	0.07	0.12
	20	0.22	0.18	0.58	0.08	0.13	0.16	0.01	0.07	0.12
	50	0.19	0.18	0.22	0.09	0.11	0.14	0.02	0.06	0.11
	100	0.13	0.12	0.12	0.08	0.08	0.10	0.03	0.06	0.09
	200	0.08	0.07	0.07	0.06	0.06	0.07	0.03	0.05	0.08
					ab_B = .16, ICC = .20					
5	10	0.16	0.14	1.23	0.05	0.15	0.14	0.01	0.07	0.12
	20	0.20	0.18	1.06	0.07	0.14	0.15	0.01	0.07	0.12
	50	0.23	0.19	0.68	0.09	0.12	0.15	0.02	0.06	0.11
	100	0.19	0.18	0.33	0.09	0.10	0.13	0.02	0.06	0.10
	200	0.12	0.11	0.12	0.07	0.08	0.09	0.03	0.05	0.09
10	10	0.21	0.17	1.11	0.06	0.15	0.15	0.01	0.07	0.12
	20	0.24	0.20	0.77	0.09	0.13	0.15	0.02	0.07	0.12
	50	0.20	0.18	0.26	0.09	0.10	0.14	0.02	0.06	0.11
	100	0.13	0.12	0.12	0.08	0.08	0.10	0.03	0.05	0.09
	200	0.08	0.08	0.08	0.06	0.06	0.07	0.03	0.05	0.07
20	10	0.24	0.19	0.90	0.08	0.14	0.15	0.01	0.07	0.12
	20	0.24	0.20	0.46	0.09	0.12	0.15	0.02	0.07	0.11
	50	0.16	0.15	0.15	0.09	0.09	0.12	0.02	0.06	0.10
	100	0.10	0.09	0.09	0.07	0.07	0.09	0.03	0.05	0.09
	200	0.06	0.06	0.06	0.05	0.05	0.06	0.03	0.04	0.07
50	10	0.24	0.19	0.77	0.08	0.14	0.16	0.01	0.07	0.12
	20	0.22	0.19	0.32	0.09	0.12	0.15	0.02	0.07	0.11
	50	0.13	0.13	0.13	0.08	0.09	0.11	0.02	0.06	0.10
	100	0.08	0.08	0.08	0.07	0.07	0.08	0.03	0.05	0.08
	200	0.05	0.05	0.05	0.05	0.05	0.05	0.03	0.04	0.06

Note. μ denotes mean hyperparameter equal to population value (i.e., accurate prior). 1*sd* and 2*sd* denote mean hyperparameters equal to 1 and 2 standard deviations from population value (i.e., inaccurate prior). N_j = cluster size; J = number of clusters; ab_B = *between-level indirect effect*.

Figures

Figure 1

Population 1-1-1 mediation model with parameter values from which the data were generated in the ICC = .05 and between-level indirect effect = .16 condition

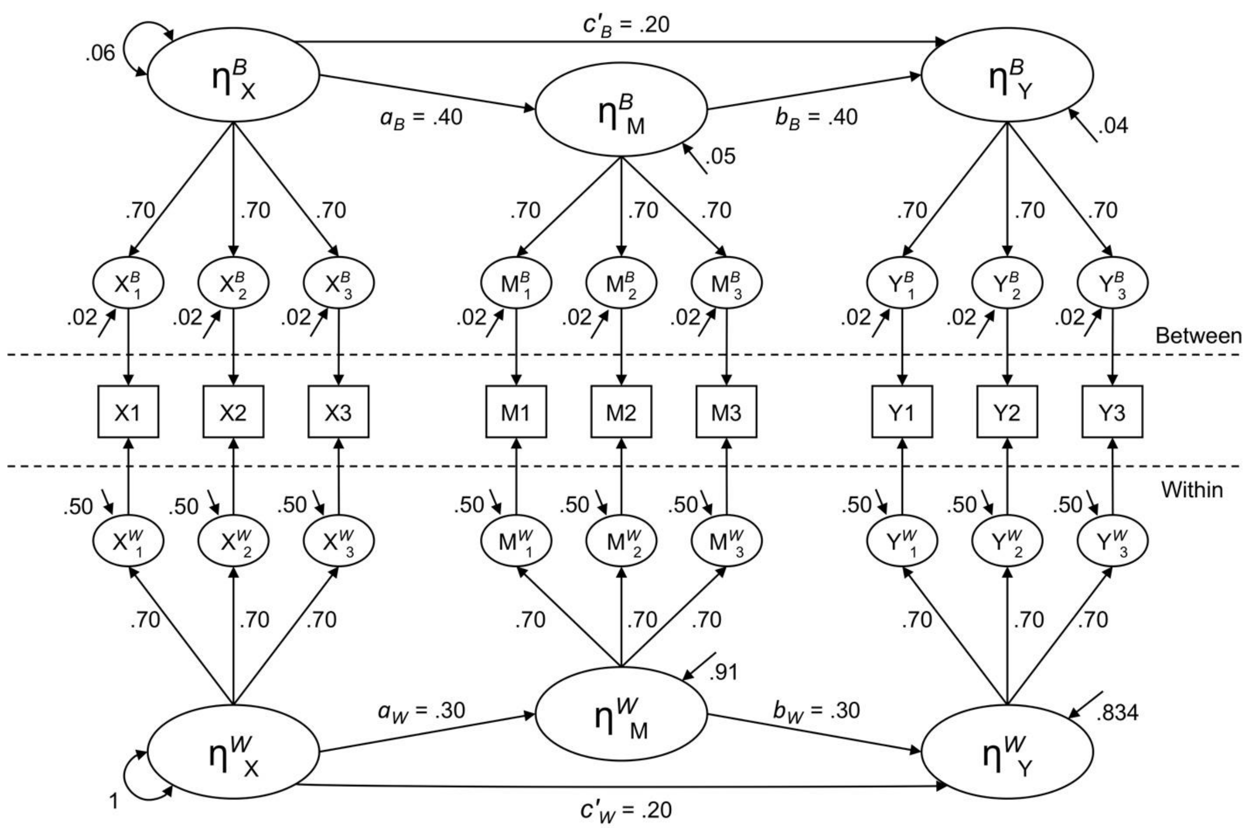


Figure 2

Informative accurate and inaccurate priors for the between-level structural regression parameters (a and b) in the between-level indirect effect size ab_B = .16 condition.

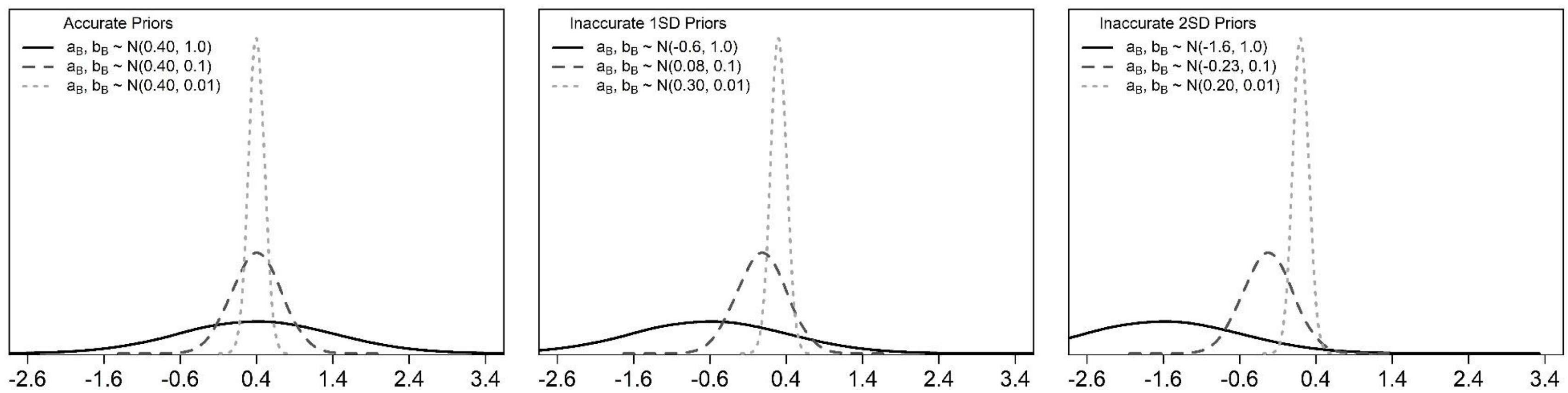
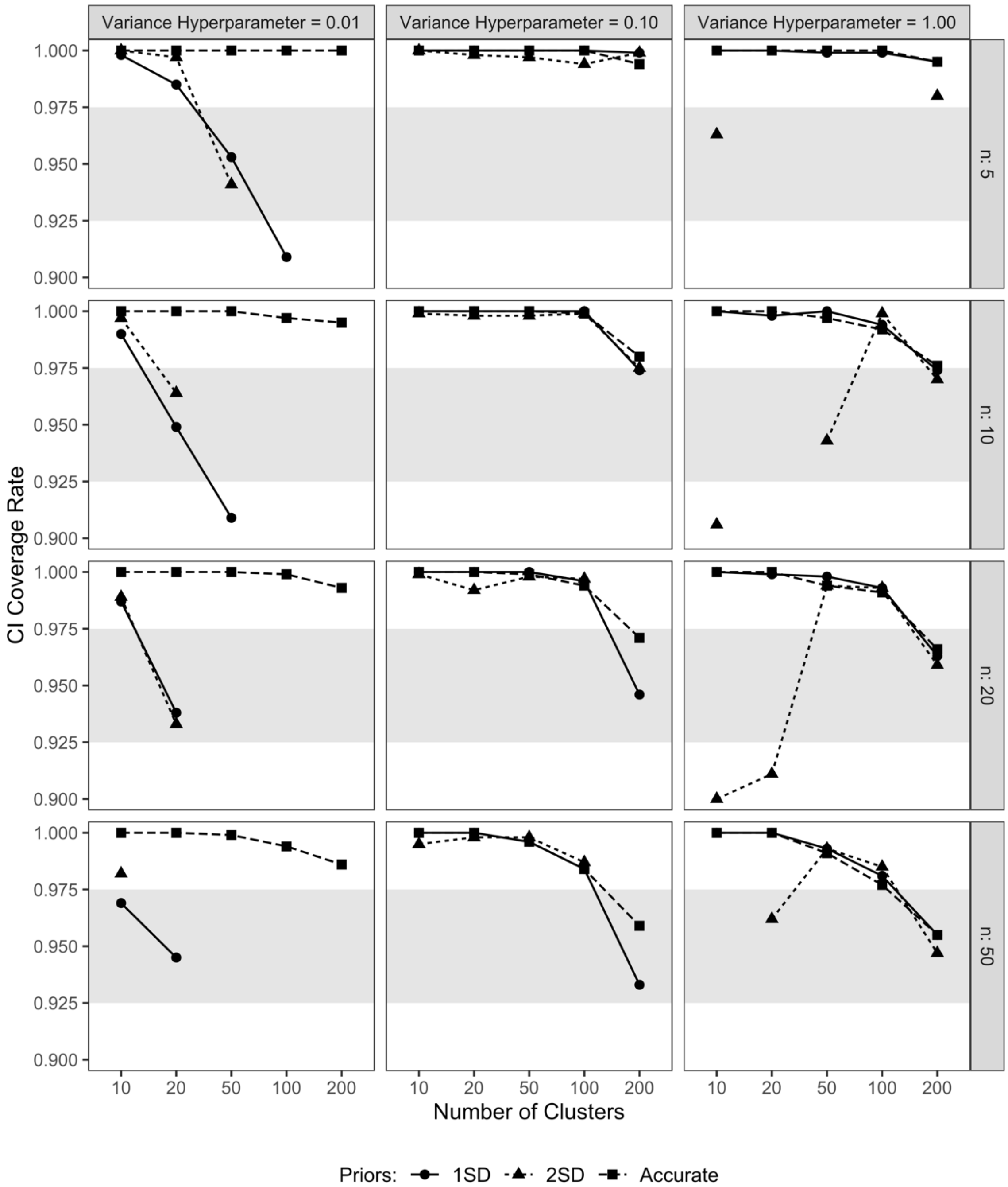


Figure 3

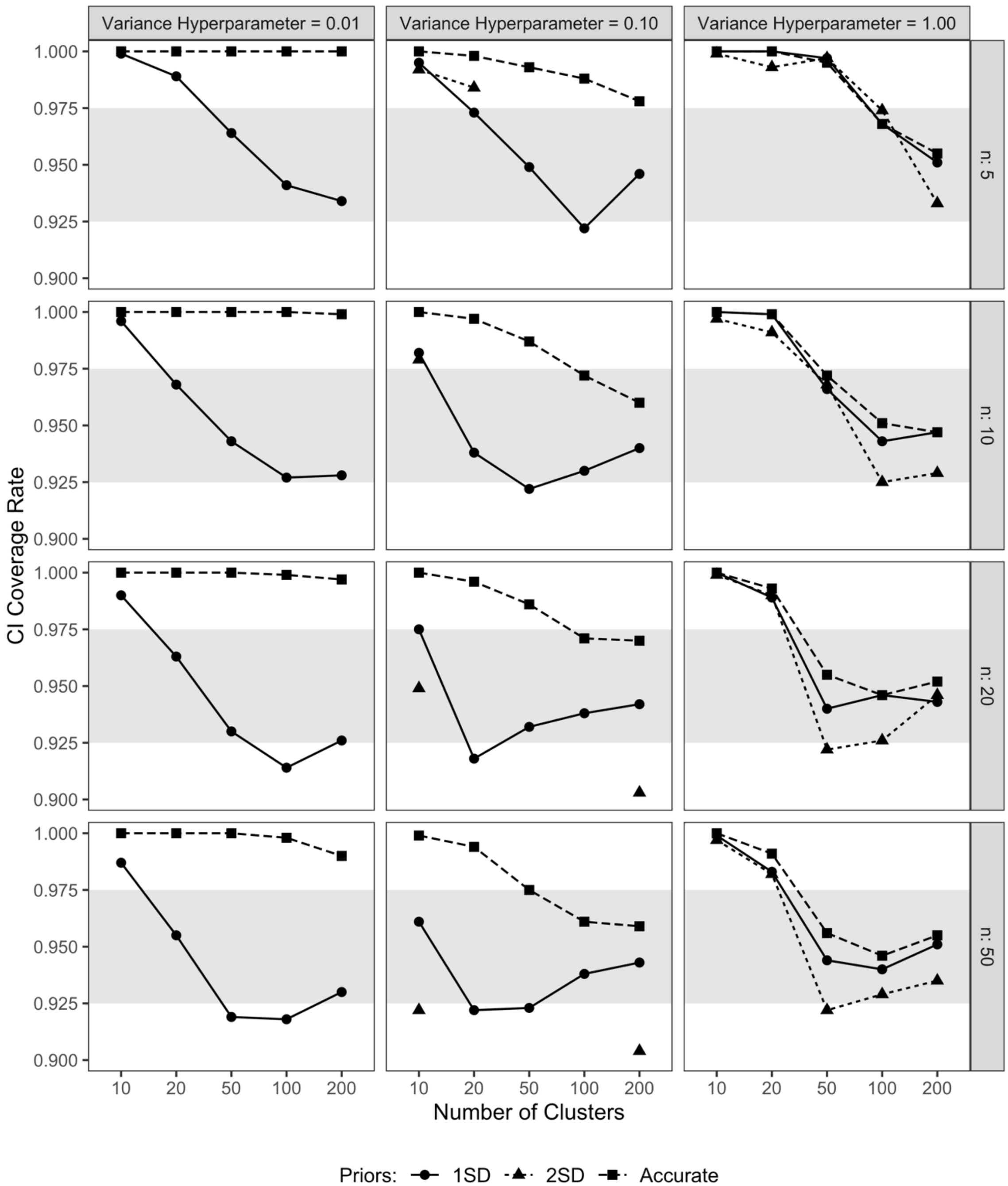
95% CI coverage rates for the 0.02 between-level indirect effect at ICC of 0.20 in informative prior conditions



Note. n = cluster size. Area in grey depicts Bradley's (1978) criteria.

Figure 4

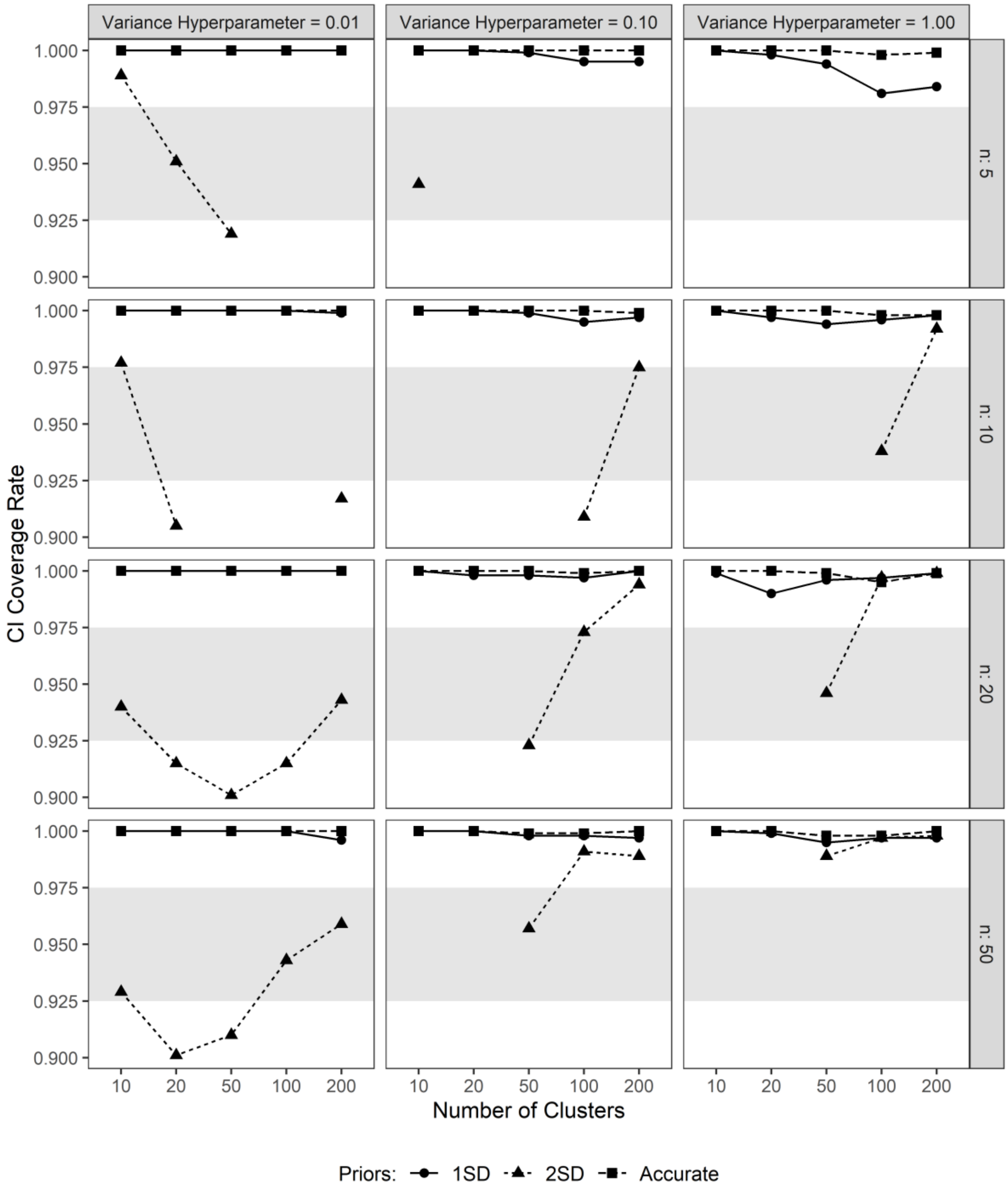
95% CI coverage rates for the 0.16 between-level indirect effect at ICC of 0.20 in informative prior conditions



Note. n = cluster size. Area in grey depicts Bradley's (1978) criteria.

Figure 5

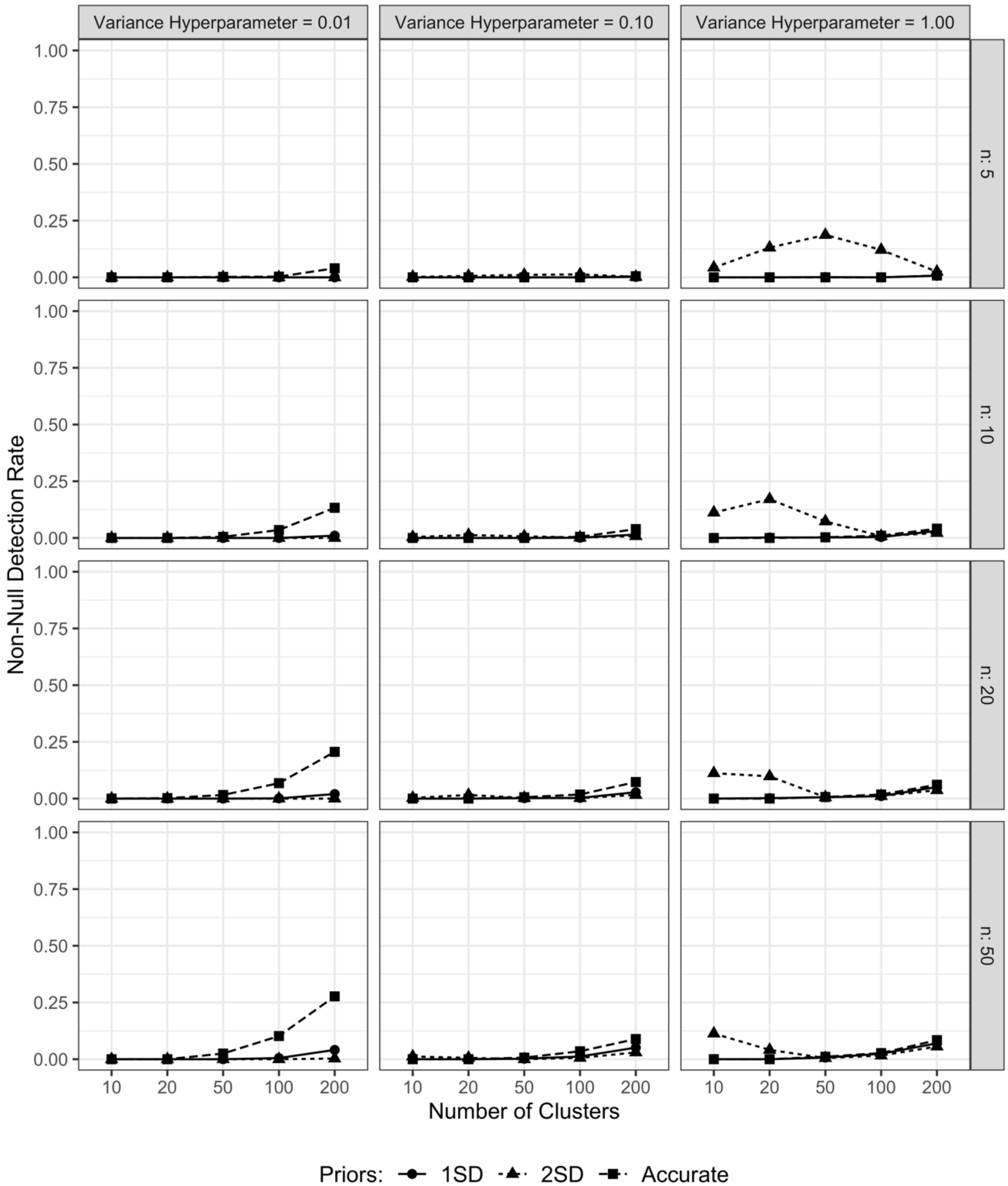
95% CI coverage rates for the null between-level indirect effect at ICC of 0.20 in informative prior conditions



Note. n = cluster size. Area in grey depicts Bradley's (1978) criteria.

Figure 6

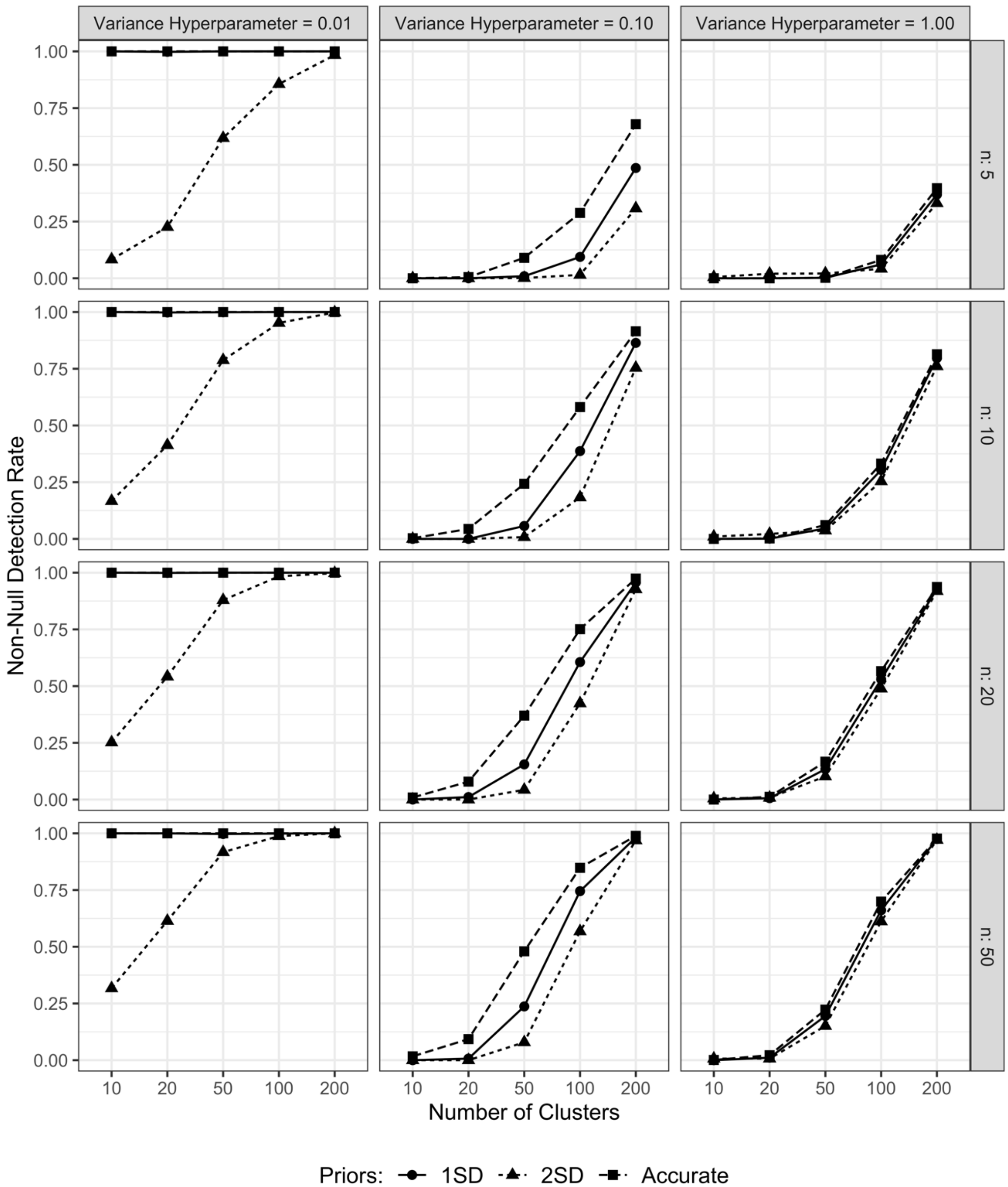
Non-null detection rates for the 0.02 between-level indirect effect at ICC of 0.20 in informative prior conditions



Note. n = cluster size.

Figure 7

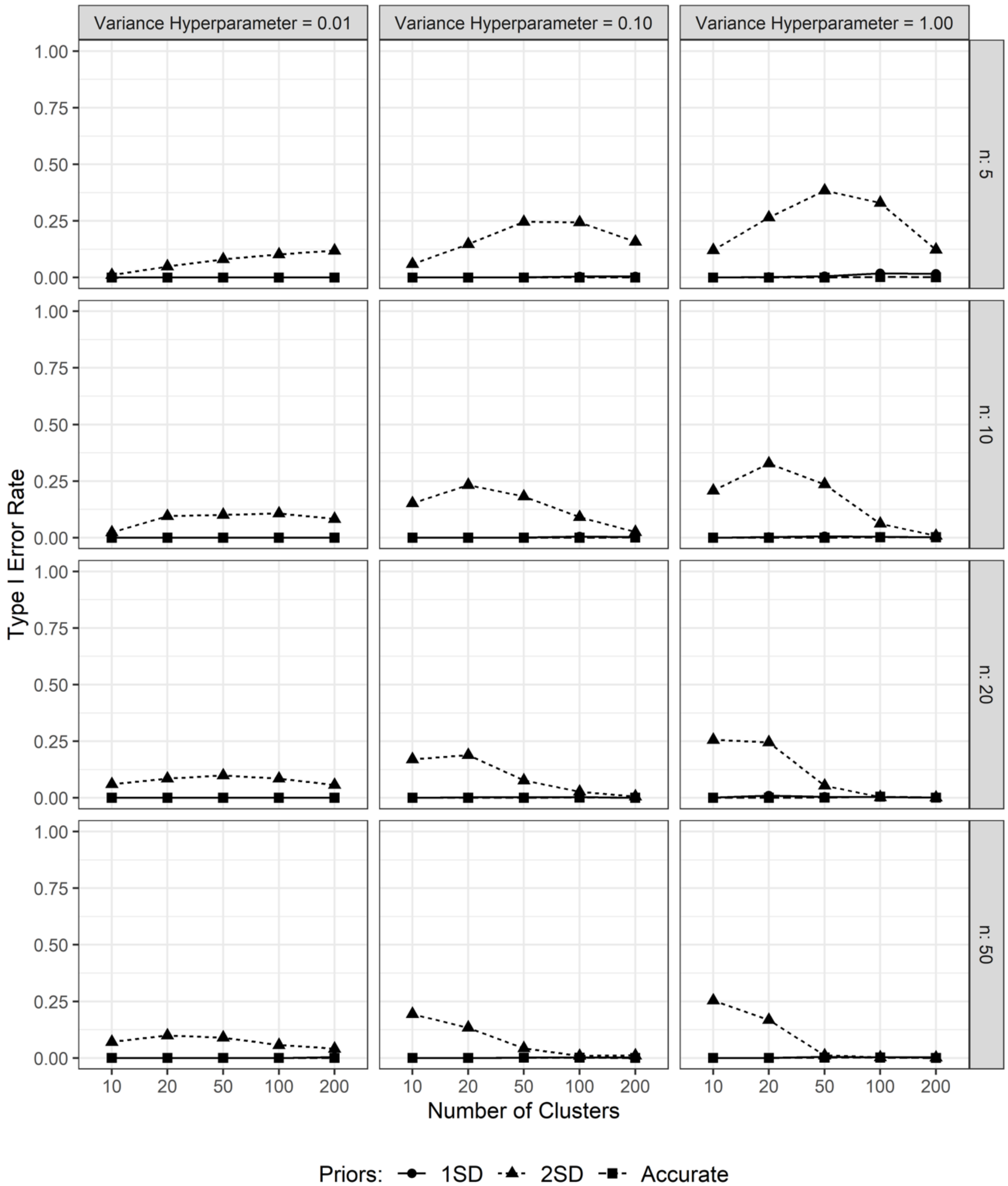
Non-null detection rates for the 0.16 between-level indirect effect at ICC of 0.20 in informative prior conditions



Note. n = cluster size.

Figure 8

Type I error rates for the null between-level indirect effect at ICC of 0.20 in informative prior conditions



Note. n = cluster size.

CHAPTER 3

Performance of Model Fit Indices in Bayesian Confirmatory Factor Analysis

Abstract

Assessing model fit is a key component of structural equation modeling (SEM); however, measures of fit in Bayesian SEM remain limited. Recently, versions of frequentist fit indices have been adapted for use in Bayesian models, but the impact of prior information on these fit indices remains unknown. This simulation study investigates the performance of three fit indices (RMSEA, CFI, and TLI) in Bayesian confirmatory factor analysis (CFA) across a variety of model conditions and prior specifications. Priors with different degrees of informativeness and inaccuracy are evaluated. Results show that Bayesian fit indices are impacted less by prior choice than by other model characteristics. We discuss implications of assessing model fit with Bayesian fit indices and provide recommendations for applied researchers.

Introduction

Confirmatory factor analysis (CFA) is a useful tool for evaluating the quality of measurement models that form the basis for examining relationships among latent variables in a structural equation modeling (SEM) framework. In practice, CFA is commonly conducted using frequentist methods that include maximum likelihood estimation; however, in the last decade, Bayesian estimation for CFA has gained attention as a tractable alternative (e.g., Kaplan & Depaoli, 2012; Muthén & Asparouhov, 2012; van de Schoot et al., 2017). Applications of Bayesian CFA are increasingly found in behavioral and educational research (e.g., de Beer & Bianchi, 2019; Dombrowski et al., 2018; Falkenstrom et al., 2015; Modrowski et al., 2021; Murray et al., 2019; Reis, 2019; Taylor, 2019). Yet, as the Bayesian approach continues to grow in popularity among methodologists and applied researchers alike, more research is needed to fully develop these methods. Much of the extant methodological literature has focused on parameter estimate bias in Bayesian SEM, but there are a number of other considerations that remain understudied. One issue that deserves greater attention is the development of methods for model selection within the Bayesian context.

A key aspect of CFA is assessing model fit to determine how well a proposed measurement model is consistent with the observed data. In the frequentist framework, model fit is traditionally evaluated with multiple measures that address different aspects of (mis)fit, including the chi-square test statistic and a variety of descriptive indices (e.g., RMSEA, CFI, TLI). Descriptive fit indices are useful because they are less sensitive to sample size compared to the chi-square test statistic, which tends to reject approximately well-fitting models with large samples (Bentler & Bonett, 1980). In Bayesian analysis, model evaluation typically involves using the posterior predictive p-value (PPP); however, the PPP method has a number of limitations, most notable of which is its sensitivity to sample size. With large sample sizes, PPP will also reject models with even the slightest amount of misspecification, essentially rendering PPP useless for evaluating approximately well-fitting models in large samples (Asparouhov & Muthén, 2010; Cain & Zhang, 2019). In an effort to develop alternative methods of model evaluation for Bayesian SEM models, versions of RMSEA, CFI, and TLI were recently extended to the Bayesian context (Garnier-Villarreal & Jorgensen, 2020; Hoofs et al., 2018). These Bayesian approximate fit indices have been shown to be less sensitive to large sample sizes compared to PPP (Garnier-Villarreal & Jorgensen, 2020).

Although the extension of these measures to the Bayesian framework represents significant progress for the field, questions remain around their utility in applied settings. Specifically, it is unclear how the proposed fit indices perform under different prior specifications. It is well established that prior choice can severely impact parameter estimation in Bayesian models (e.g., Gelman, 2006). Uninformative and (informative) inaccurate priors result in biased estimates and insufficient power, particularly when sample sizes are small (Depaoli et al., 2021; van Erp et al., 2018). Recent work shows that PPP is also influenced by prior specification in Bayesian CFA models, suggesting that model fit evaluation is prior dependent (Cain & Zhang, 2019). With respect to Bayesian approximate fit indices (e.g., RMSEA, CFI, and TLI), previous simulation research has only evaluated these indices in the context of diffuse (i.e., uninformative) prior specifications, using default prior settings readily available in statistical software packages such as M*plus* (Muthén & Muthén, 2021) and the R package blavaan (Merkle & Rosseel, 2018). With uninformative priors, Bayesian fit indices are shown to behave similarly to frequentist fit indices (Garnier-Villarreal & Jorgensen, 2020); however, their behavior in the context of informative or inaccurate priors remains unknown. Understanding the influence of different prior specifications on Bayesian fit indices is important given that priors play a critical role in Bayesian analysis. Building on previous work (Asparouhov & Muthén, 2021; Garnier-Villarreal & Jorgensen, 2020; Hoofs et al., 2018), this paper presents a simulation study that evaluates the performance of Bayesian fit indices under various design conditions, with particular focus on the impact of different prior specifications not previously examined. In the following sections we describe frequently used methods of model evaluation in frequentist and Bayesian CFA, with attention to their similarities and differences; and discuss factors, such as sample size, that are known to impact model fit in both traditions. We then present our study design and results, and conclude with a discussion of our findings, in which we outline recommendations for using fit indices in applications of Bayesian CFA.

Frequentist Methods

Measurement models within an SEM framework are used to quantify various aspects of relationships among a set of observed variables and their underlying latent construct(s). CFA is often conducted to evaluate the quality of these models. Thereafter, relationships among the resulting latent variables can be examined in a variety of SEM applications (e.g., multilevel, mediation, mixture, etc.). For model evaluation in the frequentist tradition, the likelihood ratio test, which is distributed as chi-square (χ^2), evaluates the discrepancy between the observed covariance matrix and the model implied covariance matrix. The χ^2 statistic provides a test of exact model fit, such that any statistically significant discrepancy (beyond random sampling error) leads to the conclusion that the model is misspecified. Non-statistically significant results are often taken to imply that the model provides a reasonable approximation to the data. However, this test is somewhat controversial given that it is based on a number of assumptions that are unlikely to be met in applied work (Bollen, 1989), it tends to be over-powered in rejecting reasonable models (Kaplan, 1990), and the χ^2 approximation may not hold in a variety of circumstances (Chen et al., 2020). In light of these limitations, several fit indices have been developed as alternative measures of model fit. Among the more popular approaches that have been adapted to the Bayesian framework are the root mean square error of approximation (RMSEA; Steiger & Lind, 1980), comparative fit index (CFI; Bentler, 1990), and Tucker-Lewis Index (TLI; Tucker & Lewis, 1973).

Root Mean Square Error of Approximation (RMSEA)

RMSEA is an absolute fit measure of the average discrepancy between the model-implied covariance matrix and that of the observed data per degrees of freedom. Unlike the χ^2 test of exact model-data fit, RMSEA is used to evaluate how well a model approximates the observed data. Based on the notion that some misspecification is inherent in all models, RMSEA assumes a noncentral χ^2 distribution that is defined by discrepancies attributable to both sampling error and specification error (Browne & Cudeck, 1992). When estimated using maximum likelihood, RMSEA is computed as a function of the hypothesized model's χ^2 statistic (χ^2_H), degrees of freedom (df_H), and sample size (N):

$$RMSEA = \sqrt{\max\left[0, \frac{\chi^2_H - df_H}{df_H \times N}\right]}\ . \tag{1}$$

The degree of model misspecification is measured by the noncentrality parameter, which is equal to $\chi^2_H - df_H$. As shown in Equation 1, the noncentrality parameter is then divided by the product of df_H and N. In effect, RMSEA accounts for model complexity (i.e., the number of model parameters) and sample size. The lower bound of RMSEA is zero, with higher values indicating increasingly poorer fit.

Comparative Fit Index (CFI)

CFI is an incremental fit index that compares the hypothesized model to a more restricted baseline model (i.e., a null, or independence, model) to measure the improvement of model fit (Bentler, 1990). The baseline model is assumed to be nested under a theoretically best-fitting model that imposes no constraints on the covariance structure (i.e., a saturated model). The hypothesized model then lies somewhere on a continuum between the baseline and saturated models. CFI is normed to a scale of 0 to 1, such that values near 0 indicate the hypothesized model more closely resembles the baseline model and therefore provides poor fit. At the other end of the scale, CFI values near 1 indicate that the hypothesized model fits the data nearly as well as the saturated model. CFI is expressed as

$$CFI = 1 - \frac{\max[0, (\chi^2_H - df_H)]}{\max[0, (\chi^2_B - df_B)]}, \tag{2}$$

where $\chi^2_H - df_H$ and $\chi^2_B - df_B$ correspond to the noncentrality parameters of the hypothesized and baseline models, respectively. Thus, CFI can be interpreted as a normed ratio, or comparison, of the degree of misspecification in the nested models.

Tucker-Lewis Index (TLI)

TLI is also an incremental fit index that evaluates a hypothesized model's fit relative to the fit of the baseline model (Bentler & Bonett, 1980; Tucker & Lewis, 1973); however, unlike CFI, values of TLI can exceed the range of 0 to 1, and TLI is not based on the noncentral χ^2 distribution. The formula for TLI is

$$TLI = \frac{(\chi^2_B/df_B) - (\chi^2_H/df_H)}{(\chi^2_B/df_B) - 1}. \tag{3}$$

where the ratio χ^2/df imposes a penalty for model complexity. Like CFI, higher values of TLI indicate better fit.

Findings from previous studies demonstrate that RMSEA, CFI, and TLI are largely robust to the effects of large sample sizes (Bentler, 1990; Fan et al., 1999; Marsh et al., 1988; Tanguma, 2001). When correctly specified models are fit to large-sample data, fit indices tend to appropriately characterize model fit, even when the chi-square test statistic is inflated. However, factors other than sample size have been shown to impact the performance of fit indices. Such factors include non-normality (Jobst et al., 2021), missing data (Zhang & Savalei, 2020), factor loading magnitude (Gagne & Hancock, 2006), and model size (Kenny & McCoach, 2003; Shi et al., 2019). Due to the influence of these factors, it is difficult to establish fixed cutoff values of RMSEA, CFI, and TLI that can be universally applied to different modeling contexts. Although fixed values of CFI and TLI > .95 and RMSEA < .06 are often cited as indicative of good model fit following the seminal work of Hu and Bentler (1999), an alternative method of *dynamic* fit indices was recently introduced by McNeish and Wolf (2021). This method allows researchers to determine appropriate cutoff values of RMSEA, CFI, and TLI that account for specific model characteristics. Notwithstanding the oft-cited ambiguity of fixed cutoffs (e.g., Shi et al., 2019; Ximénez et al., 2022; Yuan et al., 2016), fit indices continue to provide empirical researchers with a practical method of model evaluation that is otherwise not available with large sample sizes. In the next section we review Bayesian methods and describe extensions of frequentist fit indices to Bayesian models.

Bayesian Methods

Although confirmatory factor analysis (and SEM, more generally) has a long tradition in the frequentist framework, applications of Bayesian SEM in the social and behavioral sciences have become more prevalent in recent years (van de Schoot et al., 2017). One advantage of the Bayesian approach is that it does not rely on strict assumptions of multivariate normality and asymptotic theory, which are assumed with frequentist estimators, such as maximum likelihood. As a result, Bayesian estimation has been shown to outperform frequentist estimation with small sample sizes and more complex models (Muthén & Asparouhov, 2012). Whereas frequentist inference treats model parameters as fixed and uses null hypothesis testing, Bayesian inference treats parameters as random and can incorporate prior beliefs about the parameters into the model. Prior information is combined with the observed data to construct the posterior distribution

$$p(\theta|x) \propto p(x|\theta)p(\theta), \tag{4}$$

where θ is a vector of unknown parameters, x is the observed data, $p(x|\theta)$ is the conditional data likelihood function, and $p(\theta)$ is the prior distribution. Markov chain Monte Carlo (MCMC) methods are often used to compute an empirical approximation of the posterior distribution.

One of the main components of Bayesian analysis is the prior distribution, which allows researchers to incorporate their domain knowledge into the statistical model. In Bayesian CFA, priors are specified for factor loadings, indicator residual variances, and latent factor variances and covariances. For example, the prior distribution for factor loadings is typically specified as the normal distribution, $\sim N(\mu, \sigma^2)$, with mean (μ) and variance (σ^2) hyperparameters. The variance hyperparameter determines the amount of information that the prior distribution contributes to the posteriors. When relevant prior information about the model parameters is unknown, uninformative (i.e., diffuse) priors can be specified using large variances, so less information is contributed to the posterior distribution. Alternatively, informative priors can be specified using smaller variances, such that the prior contributes more information to the posterior, thereby reflecting more certainty about the parameters. The mean hyperparameter determines the accuracy of the prior distribution. As the value of the mean hyperparameter approaches the true value of the population parameter, the prior is said to be increasingly accurate.

Extensive research shows that the choice of priors can have a substantial impact on results in Bayesian analysis. Relying on default diffuse priors is not always appropriate and can result in biased estimates, especially when sample sizes are small (e.g., McNeish, 2016; Smid & Winter, 2020; van Erp et al., 2018). Because the prior distribution is combined with the data (Equation 4), sample size plays a non-trivial role in the formation of the posterior. With large samples, the information contributed to the posterior distribution by the likelihood function $p(x|\theta)$ outweighs the amount of information contributed by the prior. However, with small samples, the likelihood function contributes less information from the data, so the prior distribution has a greater impact on the posterior. As a result, in small sample contexts, priors would ideally be specified as strongly informative with small variance hyperparameters, assuming the prior is accurately centered on the population parameter value. Yet, in empirical settings, researchers cannot know with certainty how accurate (or inaccurate) a prior is with respect to the true value, and inaccurate informative priors coupled with small samples will result in biased parameter estimates (Depaoli, 2014; van de Schoot et al., 2018). Hence, careful consideration must be given to the choice of priors.

Posterior Predictive Model Checking

Evaluation of model fit in Bayesian analysis is typically conducted with posterior predictive model checking (PPMC; Gelman et al., 1996). PPMC assesses whether the model adequately summarizes the data by comparing the observed data to replicated data that is predicted by the model. Draws from the posterior distribution are simulated to empirically construct the posterior predictive distribution, which is the conditional distribution of the replicated data given the observed data and the model. Discrepancy measures are then used to assess any significant difference between the replicated and observed data. The realized discrepancy measure (D^{obs}) is obtained from the observed data, and the predictive discrepancy measure (D^{rep}) is obtained from the replicate data. The proportion of iterations in which D^{obs} is greater than D^{rep} is called the posterior predictive p-value (PPP). Values of PPP near 0.5 indicate good data-model fit, and PPP < 0.05 is generally the recommended criterion for model misspecification (Asparouhov & Muthén, 2010).

Although PPMC is a common procedure for model-fit evaluation in Bayesian SEM (Levy, 2011; Zhang et al., 2022), PPP is known to be sensitive to sample size (Asparouhov & Muthén, 2010; Hoijtink & van de Schoot, 2017; Lee & Song, 2004; Rindskopf, 2012; Rupp et al., 2004). In large samples, PPP values tend to reject models with negligible misspecification. In addition, research shows that PPP is sensitive to other factors, including prior specification, model misspecification, and model size (Cain & Zhang, 2019). This work has demonstrated that factor-loading priors with one standard deviation of inaccuracy will result in high PPP false rejection rates (Cain & Zhang, 2019). Thus, conclusions about Bayesian model fit based on PPP values may be misguided depending on characteristics of the model and data.

Bayesian Fit Indices

Recently, versions of RMSEA, CFI, and TLI have been adapted for use in Bayesian SEM as alternatives to PPP (Garnier-Villarreal & Jorgensen, 2020; Hoofs et al., 2018), and are readily available in popular software packages (e.g., M*plus*; Asparouhov & Muthén, 2021). These fit indices are formulated by replacing frequentist measures of model complexity and misspecification in Equations 1-3 with analogous forms from the Bayesian framework. Specifically, $p^* - pD$ is used in place of df as a measure of model complexity, where p^* is the number of model parameters and pD is the estimated number of parameters in the null model. In addition, $D_i^{\text{obs}} - pD$ is used in place of χ^2_H as a measure of model misspecification, where D_i^{obs} is the discrepancy function for the observed data.

The Bayesian form of RMSEA, initially introduced by Hoofs et al. (2018) and later modified by Garnier-Villarreal and Jorgensen (2020), is computed for each MCMC iteration (i) as:

$$RMSEA_i = \sqrt{\max\left[0, \frac{D_i^{\text{obs}} - p^*}{(p^* - pD)N}\right]}. \tag{5}$$

Using the values of $RMSEA_i$, the posterior distribution of RMSEA is constructed. Compared to the frequentist formulation of RMSEA in Equation 1, the Bayesian version in Equation 5 replaces the noncentrality parameter ($\chi^2_H - df_H$) in the numerator with $D_i^{\text{obs}} - p^*$, and replaces df_H in the denominator with $p^* - pD$. CFI is computed for Bayesian models as:

$$CFI_i = 1 - \frac{D_i^{\text{obs}} - p^*}{D_{Bi}^{\text{obs}} - p^*}, \tag{6}$$

where D_{Bi}^{obs} is the discrepancy function for the observed data in the baseline model. Then CFI_i from each MCMC iteration is combined to obtain the posterior distribution of CFI. In Equation 6, D_i^{obs} and D_{Bi}^{obs} are used in place of χ^2_H and χ^2_B, respectively, and p^* is used in place of the frequentist df. The formula for Bayesian TLI is:

$$TLI_i = \frac{\left(D_{Bi}^{obs} - pD_B \big/ p^* - pD_B\right) - \left(D_i^{obs} - pD \big/ p^* - pD\right)}{\left(D_{Bi}^{obs} - pD_B \big/ p^* - pD_B\right) - 1}. \tag{7}$$

Similarly, values of TLI_i for all iterations are used to construct the posterior distribution of TLI. Point estimates and credibility intervals of Bayesian RMSEA, CFI, and TLI can be obtained using summary statistics of the respective posteriors.

Bayesian versions of the fit indices appear to perform well under the simulation conditions examined thus far. Point estimates of Bayesian RMSEA, CFI, and TLI based on posterior means are consistent with values of the frequentist fit indices across a variety of model types (CFA and SEM), sample sizes, and misspecification levels (Garnier-Villarreal & Jorgensen, 2020). In addition, the Bayesian framework provides credibility intervals for fit indices, which allow researchers to summarize uncertainty around the point estimates. As noted by Asparouhov and Muthén (2021), credibility intervals of the Bayesian fit indices are particularly useful when determining whether sample sizes are large enough to conclusively evaluate model fit. If the sample is too small, credibility intervals for fit indices will be too wide such that they will contain the cutoff value. In that case, model fit is said to be inconclusive based on fit indices, and PPP values should be used instead (Asparouhov and Muthén, 2021).

Bayesian versions of RMSEA, CFI, and TLI provide researchers with additional methods of model fit evaluation beyond the traditional PPMC. However, the methodological literature on the applicability of these fit indices across a range of modeling conditions is limited. Thus far, research on Bayesian fit indices has considered performance with default diffuse priors. As a result, a systematic understanding of how the choice of priors influences Bayesian fit indices remains incomplete. This simulation study aims to address this gap by examining the performance of fit indices across priors with different degrees of (in)accuracy and informativeness. Based on previous work that documented the effect of prior specifications on PPP (Cain & Zhang, 2019), we expect priors to also impact Bayesian approximate fit indices. In addition, we expect sample size to play a role, such that priors with higher levels of informativeness and inaccuracy will have a larger impact on results obtained with smaller sample sizes. Finally, our investigation considers how these modeling factors may differentially impact fit assessment when using credibility intervals instead of point estimates of the fit indices.

Method

The primary focus of the current study was on the performance of three Bayesian model fit indices (i.e., RMSEA, CFI, and TLI) in models estimated with MCMC under conditions of varying prior distributions. ML estimation was also included as a design facet for purposes of comparison. The behavior of these fit indices was further evaluated by varying the following additional conditions: (a) model complexity (simple structure and cross-loadings); (b) model specification (misspecified and correctly specified); (c) number of observed indicators (6 and 12); (d) magnitude of factor loadings (0.5 and 0.7); (e) degree of correlation between latent factors (0.3 and 0.5); and (f) sample size (50, 100, 250, 500, and 1,000). Two population CFA models were used for data generation (Models A and B; Figure 1), based on the two-factor reference model used in Hoofs et al. (2018) to contrast Bayesian and frequentist versions of RMSEA. Model A was a simple structure (no cross-loadings) two-factor model with a non-zero covariance between factors and was misspecified by constraining the non-zero covariance between factors to zero. The second reference model (Model B) included the addition of a non-zero cross-loading and was misspecified by constraining both the latent factor covariance and non-zero cross-loading to zero. Population parameter values for both models included factor variances set to 1.0 and intercepts and latent means set to zero.

For each design condition (2 reference models × 2 numbers of indicators × 2 factor loading values × 2 latent factor correlations × 5 sample sizes), 1,000 datasets were generated, and all models were estimated in M*plus* version 8.5 (Muthén & Muthén, 1998-2021). The study compared two different estimation methods: maximum likelihood (ML) and Bayesian MCMC.

In addition, different prior specifications were examined for Bayesian models: diffuse, weakly informative, and inaccurate priors. MCMC diffuse (i.e., uninformative) priors were specified using the M*plus* default prior specifications, which include $N(0, 10^{10})$ for factor loadings and $\Gamma^{-1}(-1, 0)$ for variance parameters. For MCMC weak, informative priors were specified for factor loadings using the normal prior distribution with a mean hyperparameter equal to the population value (i.e., 0.5 or 0.7) and a variance hyperparameter equal to 0.05 (SD = 0.22). This specification was considered weakly informative because although the prior was centered on the population value, 95% of loadings would fall within a range of ±0.44 from the true value, reflecting some uncertainty about the parameters. For MCMC inaccurate, two levels of inaccuracy were investigated. In the first condition, inaccurate priors were specified with a mean hyperparameter equal to 1 standard deviation *above* the population value (+1*SD*), and in the second condition, 1 standard deviation *below* the true value (-1*SD*). In both inaccurate prior conditions, the variance hyperparameter was set equal to 0.05, to be the same degree of informativeness as the weakly informative condition. Diffuse priors using the M*plus* defaults were specified for all other model parameters in the MCMC conditions. Bayesian estimation was conducted using the Gibbs sampler, two chains, and 50,000 iterations per chain with the first half discarded as burn-in.

Fit measures (RMSEA, CFI, TLI, and p-value/PPP) for all models were obtained during the estimation process in M*plus.* In addition, 90% credibility intervals for RMSEA, CFI, and TLI were computed for MCMC models. To evaluate the applicability of common cut-off values for the fit indices in Bayesian CFA, model fit for each replication was classified based on recommendations provided in Hu and Bentler (1999): 0.06 for RMSEA, and 0.95 for CFI and TLI. In addition, PPP cutoff values were set at 0.05 for comparison with p-values for ML models

(Asparouhov & Muthén, 2010). Two different methods were used to classify model fit, following the approach described in Asparouhov and Muthén (2021). In the first method, model fit was classified as either "good" or "poor" based on point estimates of fit indices. That is, model fit was determined to be good when the point estimate met the cutoff criterion, and poor otherwise. The second method involved using 90% credibility intervals (CIs) of the Bayesian fit indices instead of point estimates. Model fit was classified as good when the entire CI met the cutoff criterion, and poor when the entire CI was beyond the threshold. When the CI contained the cutoff value, model fit was classified as "inconclusive." Finally, analysis of variance (ANOVA) was conducted to evaluate the strength of association between the simulation design conditions and model fit indices. Effect sizes were evaluated based on partial eta-squared with a cutoff criterion of $\eta^2_p \geq 0.14$, indicating a large effect size (Cohen, 1988).

Results

We first present ANOVA results to show the effect of each design condition on RMSEA, CFI, TLI, and p-value/PPP. Partial eta-squared values are provided in Table 1 for each measure of model fit as a function of simulation conditions. As expected, model (mis)specification generally explained the largest amount of variance in fit measures, and this effect was greater for the model with cross loadings (Model B) relative to the simple-structure model (Model A). Large effects ($\eta^2_p \geq 0.14$) were observed for the number of items in Model B, while only small to moderate effects were observed in Model A ($\eta^2_p \leq 0.08$). For MCMC models, sample size was shown to have large effects on CFI ($\eta^2_p = 0.17$) and TLI ($\eta^2_p = 0.14$) in Model A; however, these effects were smaller in Model B. Finally, small to moderate effects were observed for latent factor correlation ($\eta^2_p \leq 0.06$) and factor loading magnitude ($\eta^2_p \leq 0.11$) across estimation methods and model types. These results are consistent with those reported in previous simulation studies (Gagne & Hancock, 2006; Garnier-Villarreal & Jorgensen, 2020; Kenny & McCoach, 2003; Shi et al., 2019). That is, the fit indices are affected by model conditions, including model (mis)specification, complexity, and size. Notably, ANOVA results for MCMC estimation revealed that the effect of priors on fit measures was negligible ($\eta^2_p = 0.01$), holding constant all other factors included in the analysis. For both Models A and B, different priors accounted for only 1% of the variance in each fit measure, after accounting for the variance explained by the other design facets.

Table 2 shows the mean and standard deviation of point estimates for all fit indices and P-value/PPP across model type, number of items, level of model misspecification, and estimation method. For brevity, these results are aggregated across levels of sample size, latent factor correlation, and factor loading magnitude; full tables of disaggregated results are provided in Appendix C (Tables C1-C32). Overall, ML and MCMC results were consistent across design conditions, demonstrating that the Bayesian fit indices perform similarly to their frequentist analogues. Correctly specified models tended to yield fit indices that met cutoff values for good model fit, while misspecified models produced fit indices that indicated poor fit. However, there were two notable exceptions to this pattern of results. First, RMSEA indicated acceptable fit (RMSEA < 0.06) when Model A with 12 items was misspecified. However, this finding is consistent with other research that shows RMSEA improves as the number of items increases, particularly when the degree of model misspecification is minimal (Kenny & McCoach, 2003; Shi et al., 2019). Second, MCMC -1*SD* estimation of correctly specified models with 6 items resulted in poor model fit for Model A (TLI = 0.93) and Model B (TLI = 0.94), whereas all other MCMC prior specifications resulted in TLI > 0.95 when models were correctly specified. Furthermore, for correctly specified models, +1*SD* priors consistently resulted in better fit compared to -1*SD* priors, suggesting that centering priors 1*SD below* population values was more detrimental to model fit than centering priors 1*SD above* population values. However, this pattern was not observed for misspecified models, indicating that the effect of inaccurate priors depended on the type of model (mis)specification. As expected, weakly informative accurate priors (i.e., MCMC weak) outperformed all other prior specifications.

To provide a more nuanced understanding of how Bayesian fit indices varied across the different design conditions, point estimates and credibility intervals (CIs) of the fit indices were further evaluated across levels of sample size. Figures 2-4 present plots of point estimates and 90% CIs for the Bayesian fit indices across levels of sample size and prior specification for RMSEA, CFI, and TLI, respectively. These results are also presented in full in Tables D1-D8 (Appendix D). As shown in Figures 2-4, point estimates varied between different priors in small sample sizes but tended to converge on the same value as sample size increased, such that negligible differences in point estimates were observed across priors in the largest sample size condition (N = 1,000). In addition, larger differences between priors were observed for CFI and TLI compared to RMSEA, suggesting that CFI and TLI are more sensitive to the choice of priors compared to RMSEA in small samples. In addition, across all fit measures, differences between priors at small sample sizes tended to be larger for correctly specified models compared to misspecified models.

Looking at the 90% CIs in Figures 2-4, we found that when sample sizes were small, CIs consistently contained the fixed cutoff values for all Bayesian fit indices. In other words, CIs were too wide in small samples to provide conclusive model fit evaluation. Even when priors were accurately specified (MCMC weak), CIs for RMSEA, CFI, and TLI generally indicated inconclusive fit at small sample sizes. However, as sample size increased, CIs became narrower and no longer contained cutoff values. Comparing results across point estimates and CIs revealed that evaluation of Bayesian model fit as either good or poor (based on fixed cutoff values) was dependent on whether point estimates or CIs were used. Figures 5-7 present stacked bar charts of model fit for point estimates (left panel) and 90% CIs (right panel) across the different prior specifications and sample sizes, where each bar depicts the proportion of replications that resulted in good, poor, and inconclusive (for CIs) model fit. Results showed that when CIs were used for model evaluation, fit was largely inconclusive for MCMC models at small sample sizes ($N \leq 100$), contradicting conclusions about model fit that would otherwise be drawn from point estimates under the same conditions. For example, as shown in Figure 5, when Model A was correctly specified at $N = 100$, more than 75% of replications resulted in good model fit based on point estimates of RMSEA. However, under the same model/data conditions, when CIs were used to assess model fit, most replications (> 60%) yielded inconclusive fit. Similar results were observed for CFI and TLI (Figures 6-7).

Discussion

The present simulation study was designed to evaluate the effect of different model characteristics and prior specifications on the performance of fit indices in Bayesian CFA. Although there has been increasing interest in Bayesian applications of latent variable modeling to educational and behavioral research (König & van de Schoot, 2018; Levy, 2016; van de Schoot et al., 2017), methodological guidance on model fit evaluation within the Bayesian SEM framework is still limited (Cain & Zhang, 2019; Fife et al., 2022; Levy, 2011; Muthén & Asparouhov, 2012). The recent development of Bayesian approximate fit indices (Garnier-Villarreal & Jorgensen, 2020; Hoofs et al., 2018) has prompted some additional work on this topic (Asparouhov & Muthén, 2021; Winter & Depaoli, 2022); however, the utility of these fit indices for model fit assessment in Bayesian contexts remains understudied. In the methodological literature, questions have long been raised about the use of approximate fit indices in the frequentist framework (Marsh et al., 2004). Specifically, extensive research has shown that fit indices are impacted by various model characteristics (e.g., Gagne & Hancock, 2006; Jobst et al., 2021; Kenny & McCoach, 2003; Shi et al., 2019; Zhang & Savalei, 2020), which undermines the applicability of commonly used fixed cutoff values (McNeish & Wolf, 2021). Hence, if Bayesian fit indices are to hold any adjudicative value, factors that may affect their performance should be well understood. Importantly, the current study focused on how different prior specifications impact model fit. Considerable attention has been paid to the influence of prior choice on parameter estimation in Bayesian latent variable models (e.g., Depaoli, 2014; McNeish, 2016; Smid & Winter, 2020; van Erp et al., 2018). Collectively, these previous studies show that uninformative and inaccurate priors can yield biased estimates, especially in the context of small samples. We add to this corpus of work by documenting the performance of Bayesian fit indices under different prior specifications.

Consistent with previous literature on frequentist fit indices, the results of this study show that Bayesian versions of RMSEA, CFI, and TLI are influenced by several model characteristics, including model (mis)specification type, model complexity, and model size. Our findings extend the work of others who found that, for frequentist CFA, increasing the number of observed indicators improves fit indices (Kenny & McCoach, 2003; Shi et al., 2019). The results for Bayesian CFA reported here show that by increasing the number of items from 6 to 12 in a two-factor misspecified model, RMSEA decreases and CFI/TLI increases, indicating an improvement in model fit. Notably, these results provide further support that fit indices perform similarly across frequentist and Bayesian contexts (Garnier-Villarreal & Jorgensen, 2020).

In addition, this study builds upon the extant literature on Bayesian fit indices by providing additional insight into how the choice of priors impacts model fit. While previous work has evaluated Bayesian fit indices using diffuse priors (Asparouhov & Muthén, 2021; Garnier-Villarreal & Jorgensen, 2020; Hoofs et al., 2018; Winter & Depaoli, 2022), results of the current study show how different prior specifications influence Bayesian versions of RMSEA, CFI, and TLI. Although ANOVA main-effect results revealed negligible effects of prior specification, differences between priors were observed at small sample sizes. In general, these differences diminished as sample size increased, such that at large sample sizes, results were largely the same for all priors. This finding is consistent with Bayes theory, as we would expect to see the priors contribute less information to the posterior distribution when the data contributes more information in the form of larger *N*. Additionally, our results for RMSEA, CFI, and TLI are in line with those reported by Cain and Zhang (2019), who showed that prior specification had a larger impact on PPP at smaller sample sizes. We extend their work by showing that PPP and Bayesian approximate fit indices perform similarly with respect to slight inaccuracies in priors for factor loadings. Finally, in evaluating the impact of different prior specifications on fit indices, we found that for correctly specified models with small samples, -1*SD* inaccurate priors performed consistently worse than +1*SD* inaccurate priors. That is, point estimates of RMSEA, CFI, and TLI indicated worse model fit when priors for factor loadings were inaccurately centered one standard deviation (1*SD*) below the population value, compared to 1*SD* above. These results suggest that the direction of inaccuracy (i.e., above/below) in the mean hyperparameter plays a role in the behavior of the fit indices. However, future research is needed to fully examine the impact that different directions of prior inaccuracy for factor loadings have on model fit.

One issue that emerged from this study was how the different posterior summary statistics of the fit indices can have implications for evaluating model fit. In the Bayesian framework, posterior distributions are computed for RMSEA, CFI, and TLI. As a result of this distributional property, the posterior can be summarized using a point estimate, such as the posterior median, and a 90% credibility interval (CI). Although evaluating model fit with point estimates of Bayesian fit indices is more comparable to the frequentist tradition, the results of the current study demonstrate the advantages of using CIs. At small sample sizes, CIs for the fit indices had large interval widths that spanned the fixed cutoff values, indicating that model fit was inconclusive. As sample size increased, CIs became narrower such that models could be conclusively characterized as having either “good” or “poor” fit. These results were largely consistent across different prior specifications, and in line those reported in previous investigations that focused on diffuse priors (Asparouhov & Muthén, 2021; Hoofs et al., 2018; Winter & Depaoli, 2022). As noted in Asparouhov and Muthén (2021), the use of CIs in this context can thus help researchers identify whether their sample size is more conducive to the use of fit indices or PPP values. When model fit is inconclusive based on the CI, the sample size is likely to be too small, and researchers should instead use PPP values to evaluate model fit. On the other hand, when the CI provides conclusive model fit, the sample size is likely large enough that PPP values will no longer be useful (Cain & Zhang, 2019).

It is important to note that these findings are limited to the model characteristics we evaluated. Our simulation study considered the two-factor CFA model; however, results may not generalize to models with more latent factors. One area for future research, then, is the investigation of Bayesian fit indices with larger factor structures. In addition, we only evaluated four different prior specifications and focused on priors for factor loadings. Although the priors used in the current study represent a range of informative and (in)accurate priors, a logical next step for this work would be to consider additional levels of informativeness and inaccuracy in prior settings. Moreover, additional research is needed to understand how priors for other parameters (i.e., residual variances and latent factor covariance matrix) impact fit indices in Bayesian CFA. Finally, the use of fixed cutoff values in the current study poses additional limitations. As we highlight above, fixed cutoff values are known to be inappropriate beyond the modeling conditions for which they were originally recommended (Hu & Bentler, 1999). Recently, McNeish and Wolf (2021) introduced a method for constructing dynamic fit cutoffs for use in frequentist SEM. An interesting extension of this work would be the development of dynamic fit cutoffs for the Bayesian framework that applied researchers could easily implement in their own work.

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Tables

Table 1

Partial Eta-Squared Values for ANOVA Results

Estimation	Model	Effect	RMSEA	CFI	TLI	P-value/PPP
ML	A	Model (mis)specification	**0.33**	**0.20**	**0.20**	**0.34**
		Number of items	0.08	0.02	0.06	0.01
		Latent factor correlation	0.06	0.05	0.05	0.01
		Factor loading magnitude	0.03	0.07	0.07	0.00
		Sample size	0.07	0.10	0.08	0.01
	B	Model (mis)specification	**0.65**	**0.62**	**0.58**	**0.52**
		Number of items	**0.25**	**0.14**	**0.24**	0.00
		Latent factor correlation	0.03	0.03	0.03	0.00
		Factor loading magnitude	0.09	0.11	0.09	0.00
		Sample size	0.04	0.04	0.03	0.00
MCMC	A	Model (mis)specification	**0.27**	0.12	0.13	**0.35**
		Number of items	0.07	0.02	0.05	0.00
		Latent factor correlation	0.06	0.03	0.04	0.02
		Factor loading magnitude	0.03	0.08	0.08	0.01
		Sample size	0.12	**0.17**	**0.14**	0.08
		Priors	0.01	0.01	0.01	0.00
	B	Model (mis)specification	**0.61**	**0.56**	**0.53**	**0.60**
		Number of items	**0.24**	0.13	**0.20**	0.00
		Latent factor correlation	0.04	0.03	0.02	0.00
		Factor loading magnitude	0.09	0.11	0.09	0.01
		Sample size	0.07	0.11	0.05	0.02
		Priors	0.01	0.01	0.01	0.01

Note. All values were statistically significant at $p < .001$. Values in bold indicate large effect sizes ($\eta^2_p \geq 0.14$). Model A = model with simple structure. Model B = model with cross-loading.

Table 2

Mean and (SD) of Fit Measures Across Conditions of Model Complexity, Number of Items, and Estimation Method for Correctly Specified and Misspecified Models

	Correctly Specified Models								Misspecified Models							
Estimation	RMSEA (*SD*)		CFI (*SD*)		TLI (*SD*)		P-value/ PPP (*SD*)		RMSEA (*SD*)		CFI (*SD*)		TLI (*SD*)		P-value/ PPP (*SD*)	
Model A, 6 Items																
ML	.020	(.033)	.985	(.041)	.972	(.075)	.504	(.291)	**.084**	(.047)	**.899**	(.096)	**.833**	(.152)	.111	(.209)
MCMC Diffuse	.026	(.038)	.973	(.074)	.953	(.118)	.479	(.176)	**.083**	(.046)	**.894**	(.107)	**.831**	(.160)	.163	(.205)
MCMC Weak	.020	(.032)	.979	(.061)	.970	(.084)	.507	(.183)	**.074**	(.044)	**.906**	(.096)	**.865**	(.125)	.184	(.228)
MCMC -1*SD*	.035	(.048)	.951	(.101)	**.933**	(.129)	.437	(.204)	**.079**	(.044)	**.896**	(.102)	**.851**	(.133)	.166	(.212)
MCMC +1*SD*	.025	(.035)	.968	(.095)	.957	(.109)	.477	(.181)	**.079**	(.043)	**.890**	(.121)	**.847**	(.144)	.163	(.207)
Model A, 12 Items																
ML	.020	(.026)	.976	(.053)	.970	(.066)	.432	(.293)	.047	(.025)	**.939**	(.064)	**.925**	(.078)	.113	(.197)
MCMC Diffuse	.023	(.028)	.970	(.064)	.963	(.078)	.476	(.235)	.049	(.025)	**.932**	(.072)	**.918**	(.087)	.173	(.225)
MCMC Weak	.019	(.025)	.976	(.053)	.973	(.060)	.507	(.239)	.045	(.024)	**.940**	(.063)	**.931**	(.070)	.195	(.248)
MCMC -1*SD*	.024	(.031)	.962	(.080)	.956	(.090)	.460	(.244)	.047	(.025)	**.935**	(.068)	**.925**	(.075)	.180	(.234)
MCMC +1*SD*	.023	(.027)	.967	(.068)	.963	(.076)	.461	(.235)	.049	(.024)	**.929**	(.076)	**.919**	(.084)	.167	(.221)
Model B, 6 Items																
ML	.021	(.034)	.989	(.029)	.977	(.062)	.493	(.289)	**.170**	(.052)	**.758**	(.100)	**.599**	(.161)	**.017**	(.075)
MCMC Diffuse	.031	(.046)	.979	(.054)	.955	(.116)	.471	(.164)	**.166**	(.051)	**.753**	(.106)	**.609**	(.167)	**.039**	(.102)
MCMC Weak	.020	(.033)	.986	(.042)	.979	(.058)	.507	(.173)	**.156**	(.052)	**.764**	(.102)	**.658**	(.143)	**.046**	(.117)
MCMC -1*SD*	.041	(.053)	.960	(.078)	**.943**	(.104)	.414	(.204)	**.160**	(.050)	**.752**	(.105)	**.644**	(.143)	**.038**	(.102)
MCMC +1*SD*	.026	(.036)	.977	(.064)	.968	(.081)	.469	(.171)	**.159**	(.050)	**.753**	(.112)	**.645**	(.149)	**.039**	(.103)
Model B, 12 Items																
ML	.020	(.027)	.979	(.046)	.974	(.058)	.430	(.292)	**.082**	(.024)	**.872**	(.064)	**.844**	(.079)	**.025**	(.087)
MCMC Diffuse	.023	(.029)	.974	(.056)	.967	(.070)	.475	(.230)	**.083**	(.024)	**.866**	(.071)	**.838**	(.085)	.058	(.134)
MCMC Weak	.019	(.025)	.980	(.045)	.977	(.051)	.508	(.234)	**.079**	(.024)	**.874**	(.064)	**.853**	(.072)	.070	(.156)
MCMC -1*SD*	.025	(.032)	.965	(.072)	.960	(.081)	.452	(.242)	**.081**	(.024)	**.868**	(.068)	**.846**	(.076)	.061	(.143)
MCMC +1*SD*	.023	(.028)	.972	(.060)	.968	(.067)	.457	(.231)	**.082**	(.023)	**.864**	(.073)	**.843**	(.080)	.056	(.133)

Note. Bolded values indicate results that did not meet the fixed cutoff criteria.

Figures

Figure 1

Reference models from which the population data were generated. Model A is simple structure with no cross-loadings. Model B includes cross-loadings. Dotted lines indicate non-zero paths that were fixed to zero for misspecified model conditions.

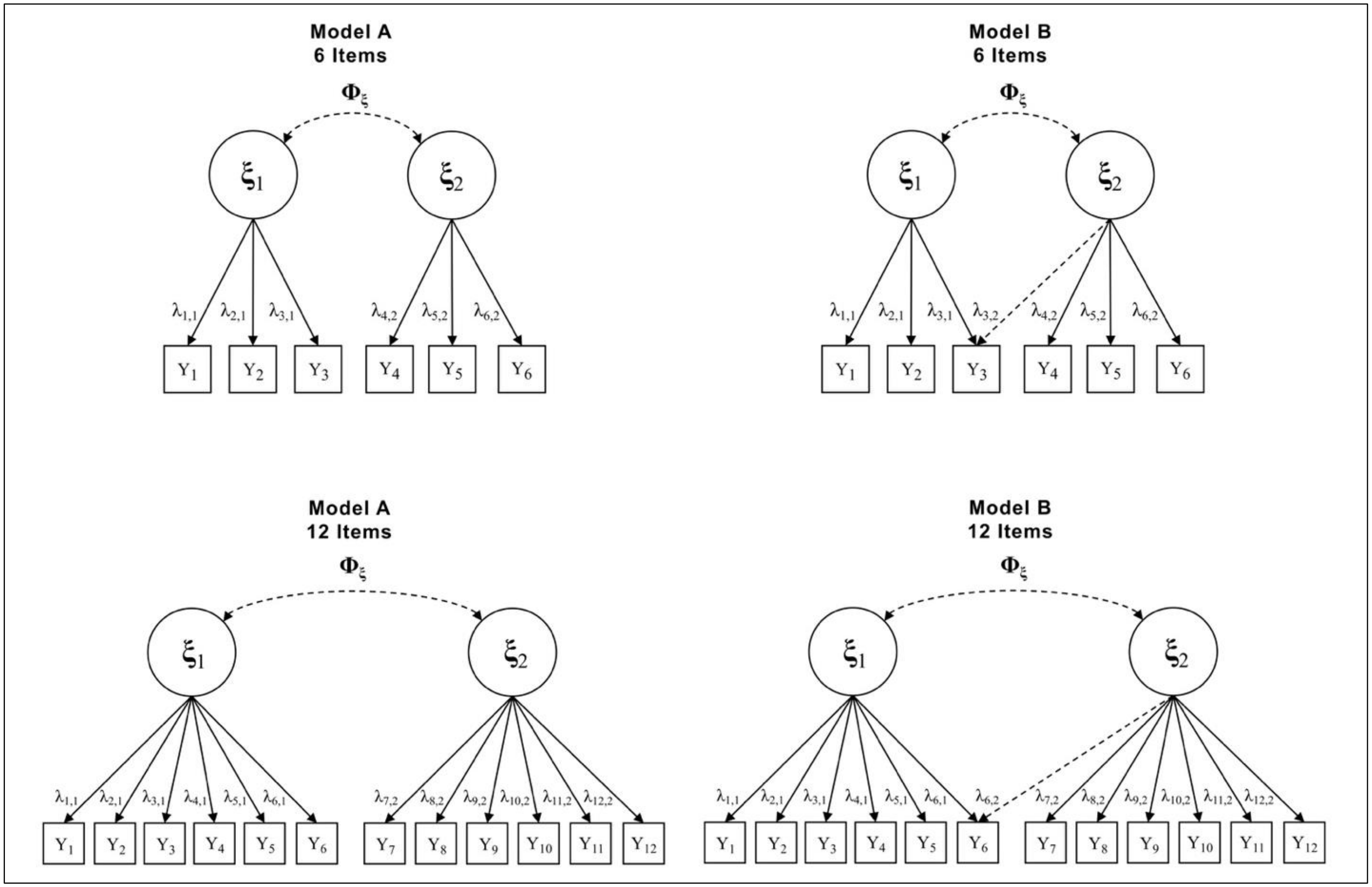


Figure 2

RMSEA point estimates and 90% credible intervals for MCMC prior specifications. Point estimates are depicted with solid black points along the CIs. The dotted horizontal line represents the fixed cutoff value of .06.

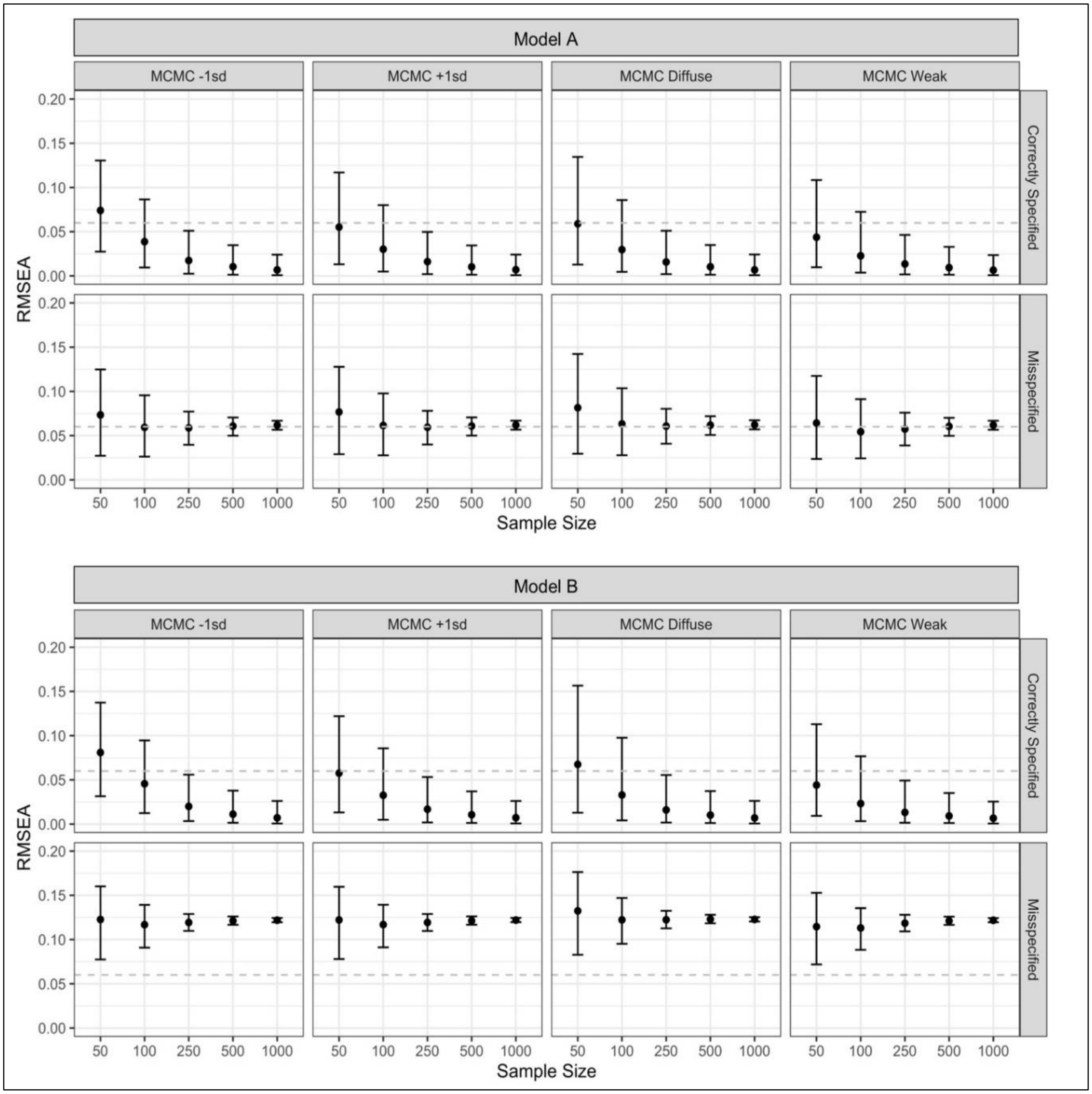


Figure 3

CFI point estimates and 90% credible intervals for MCMC prior specifications. Point estimates are depicted with solid black points along the CIs. The dotted horizontal line represents the fixed cutoff value of .95.

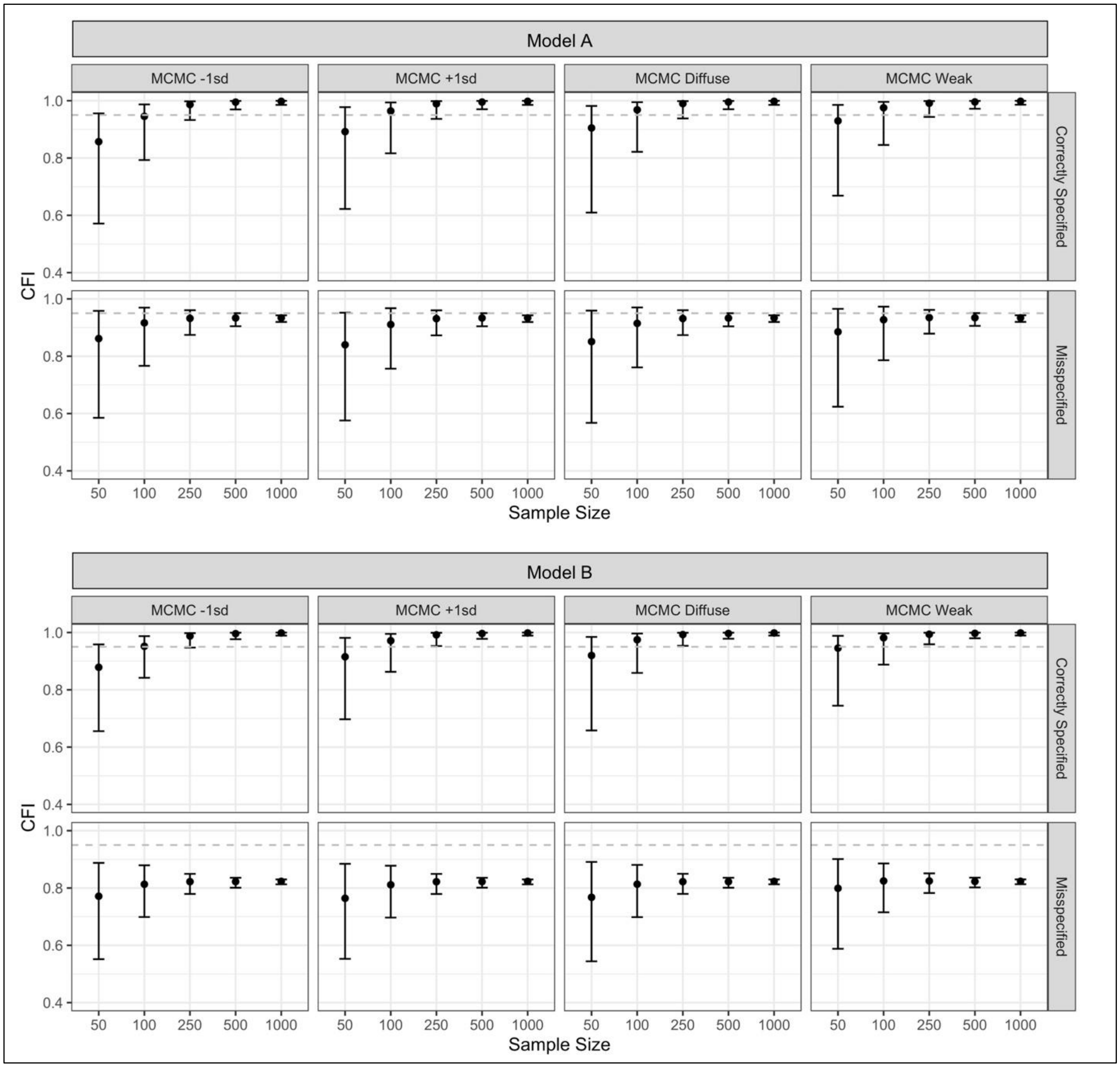


Figure 4

TLI point estimates and 90% credible intervals for MCMC prior specifications. Point estimates are depicted with solid black points along the CIs. The dotted horizontal line represents the fixed cutoff value of .95.

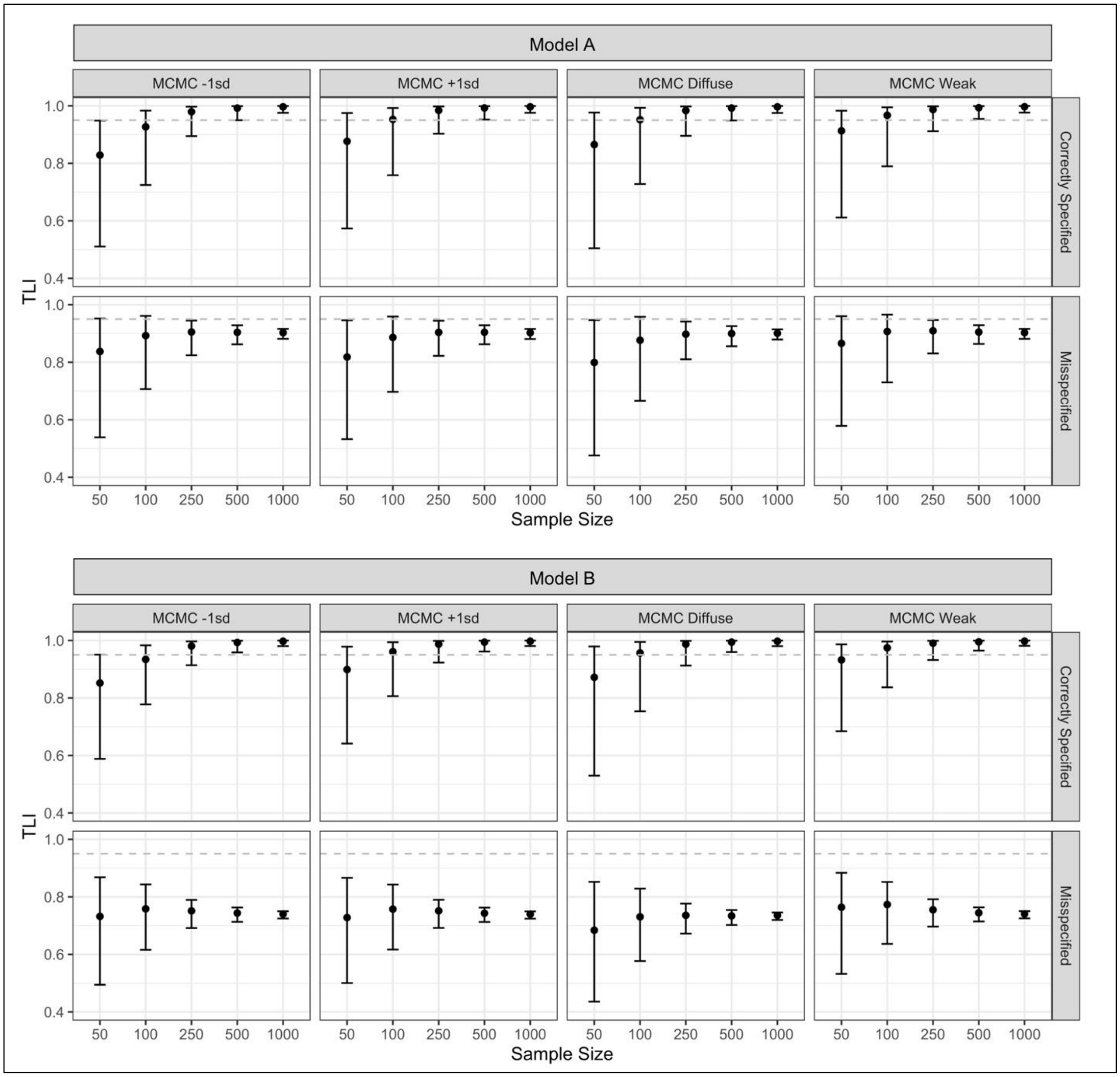


Figure 5

RMSEA fit results based on point estimates (left) and 90% CIs (right) for MCMC models across different prior specifications and sample sizes. Stacked bar charts illustrate the proportion of replications with good/poor (or inconclusive, for CIs) model fit, based on RMSEA < .06.

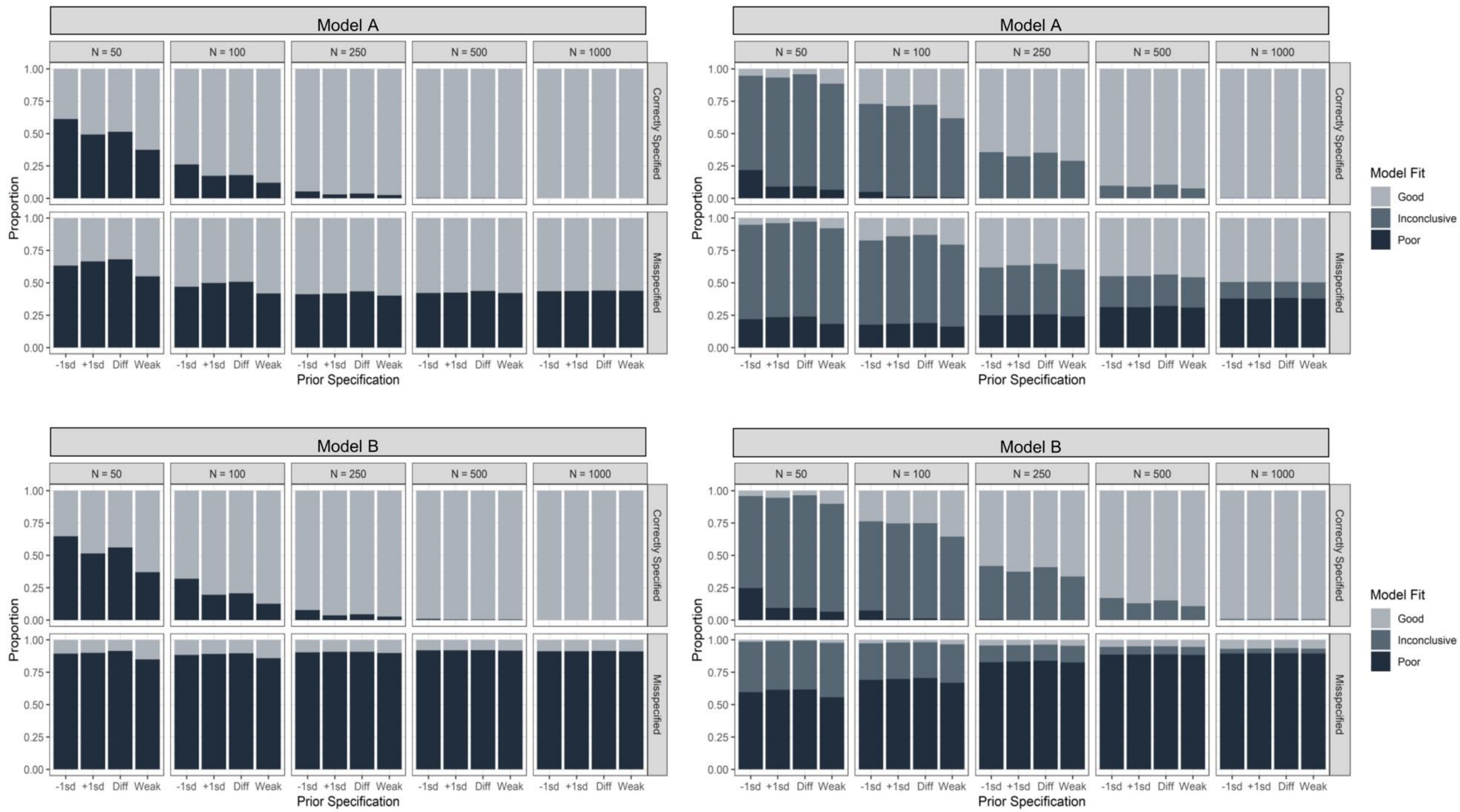


Figure 6

CFI fit results based on point estimates (left) and 90% CIs (right) for MCMC models across different prior specifications and sample sizes. Stacked bar charts illustrate the proportion of replications with good/poor (or inconclusive, for CIs) model fit, based on CFI > .95.

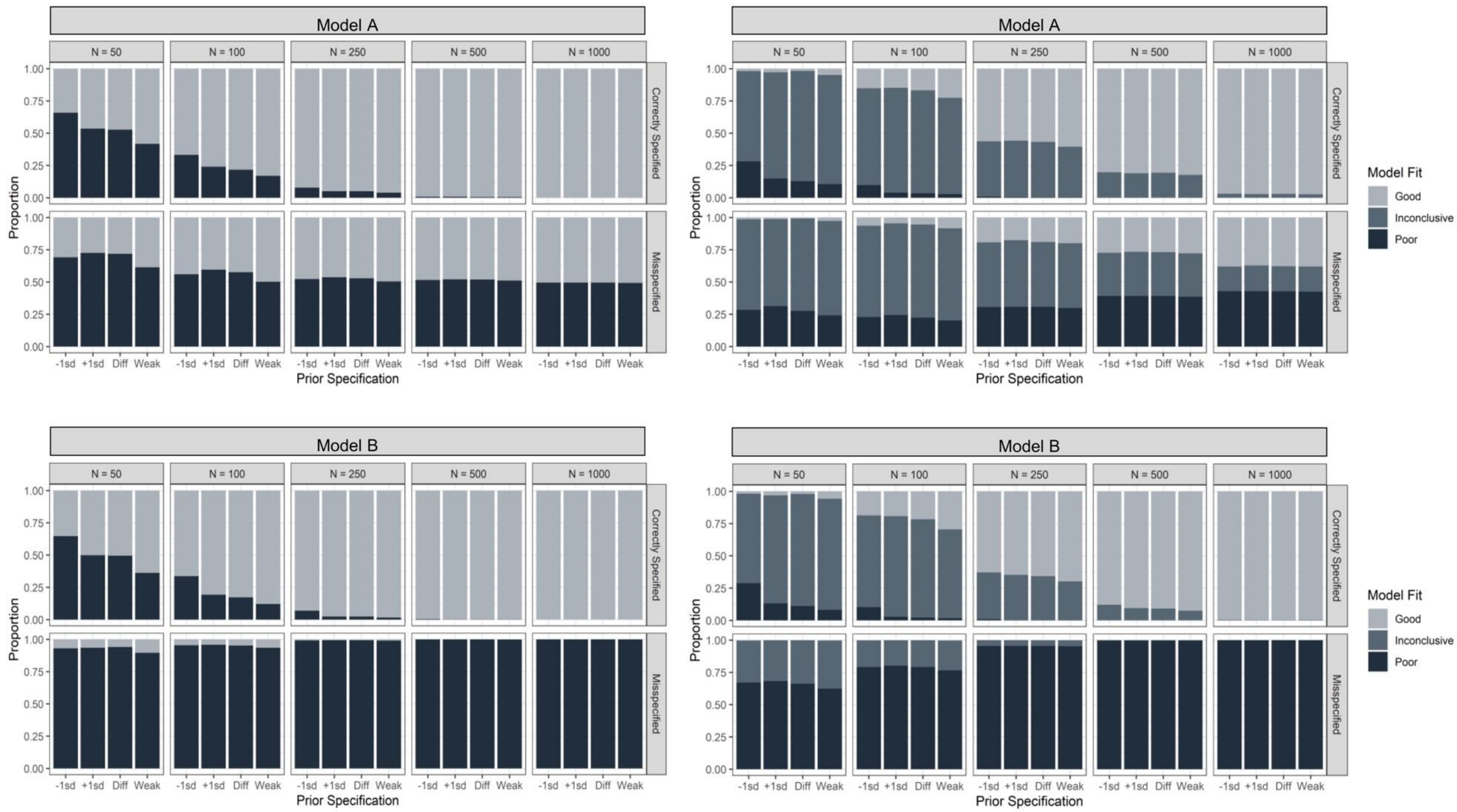
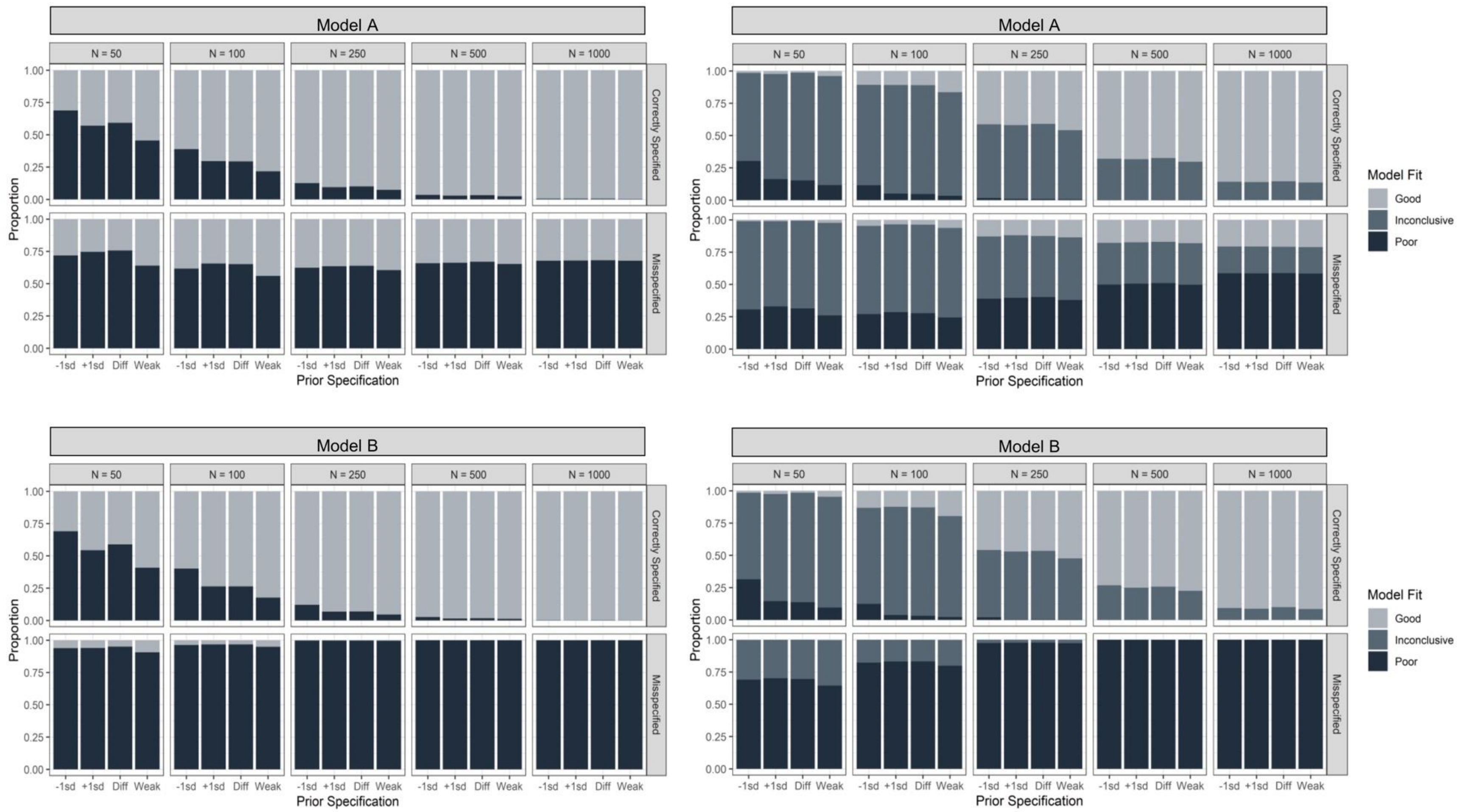


Figure 7

TLI fit results based on point estimates (left) and 90% CIs (right) for MCMC models across different prior specifications and sample sizes. Stacked bar charts illustrate the proportion of replications with good/poor (or inconclusive, for CIs) model fit, based on TLI > .95.



Appendix A

Process macro documentation

```
process y=READING/x=PTB/m=ENGAGE/w=SUPPORT/cov=MINORITY FRPM/model=8/plot=1/
boot=10000/center=1/seed=1245.
Matrix
Run MATRIX procedure:
*************** PROCESS Procedure for SPSS Version 3.3 ******************
          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3
**************************************************************************
Model  : 8
    Y  : READING
    X  : PTB
    M  : ENGAGE
    W  : SUPPORT
Covariates:
 MINORITY FRPM
Sample
Size:  318
Custom
Seed:     1245
**************************************************************************
OUTCOME VARIABLE:
 ENGAGE
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .8463      .7162      .0057   157.4365     5.0000   312.0000      .0000
Model
             coeff         se          t          p       LLCI       ULCI
constant    3.1472      .0108   291.6162      .0000     3.1260     3.1684
PTB         -.1542      .0267    -5.7655      .0000     -.2069     -.1016
SUPPORT      .7109      .0436    16.2976      .0000      .6251      .7968
Int_1        .7373      .1268     5.8141      .0000      .4878      .9868
MINORITY     .0059      .0210      .2822      .7779     -.0354      .0472
FRPM        -.1016      .0229    -4.4385      .0000     -.1467     -.0566
Product terms key:
 Int_1    :        PTB      x        SUPPORT
Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0308    33.8041     1.0000   312.0000      .0000
----------
    Focal predict: PTB      (X)
          Mod var: SUPPORT  (W)
Conditional effects of the focal predictor at values of the moderator(s):
    SUPPORT     Effect         se          t          p       LLCI       ULCI
     -.1285     -.2489      .0337    -7.3818      .0000     -.3153     -.1826
      .0000     -.1542      .0267    -5.7658      .0000     -.2069     -.1016
      .1195     -.0661      .0283    -2.3370      .0201     -.1217     -.0104
Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.
DATA LIST FREE/
   PTB        SUPPORT    ENGAGE     .
BEGIN DATA.
     -.2304     -.1285     3.0726
      .0213     -.1285     3.0099
```

```
      .2181     -.1285     2.9609
     -.2304      .0000     3.1421
      .0213      .0000     3.1033
      .2181      .0000     3.0729
     -.2304      .1195     3.2068
      .0213      .1195     3.1901
      .2181      .1195     3.1771
END DATA.
GRAPH/SCATTERPLOT=
 PTB      WITH     ENGAGE   BY       SUPPORT  .
**************************************************************************
OUTCOME VARIABLE:
 READING
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7774      .6044    67.4556    79.1775     6.0000   311.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
constant   348.9978    19.4619    17.9324      .0000   310.7042   387.2913
PTB         -8.1538     3.0679    -2.6578      .0083   -14.1902    -2.1173
ENGAGE      34.7987     6.1725     5.6377      .0000    22.6535    46.9440
SUPPORT    -31.7937     6.4712    -4.9131      .0000   -44.5267   -19.0608
Int_1       36.6864    14.5552     2.5205      .0122     8.0472    65.3256
MINORITY    -7.5531     2.2879    -3.3013      .0011   -12.0549    -3.0513
FRPM       -29.4441     2.5735   -11.4412      .0000   -34.5078   -24.3804
Product terms key:
 Int_1    :        PTB      x        SUPPORT
Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0081     6.3529     1.0000   311.0000      .0122
----------
    Focal predict: PTB      (X)
          Mod var: SUPPORT  (W)
Conditional effects of the focal predictor at values of the moderator(s):
    SUPPORT     Effect         se          t          p       LLCI       ULCI
     -.1285   -12.8670     3.9850    -3.2288      .0014   -20.7081    -5.0260
      .0000    -8.1542     3.0679    -2.6579      .0083   -14.1907    -2.1177
      .1195    -3.7684     3.1103    -1.2116      .2266    -9.8883     2.3515
Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.
DATA LIST FREE/
   PTB        SUPPORT    READING    .
BEGIN DATA.
     -.2304     -.1285   447.6300
      .0213     -.1285   444.3918
      .2181     -.1285   441.8595
     -.2304      .0000   442.4599
      .0213      .0000   440.4078
      .2181      .0000   438.8030
     -.2304      .1195   437.6487
      .0213      .1195   436.7003
      .2181      .1195   435.9587
END DATA.
GRAPH/SCATTERPLOT=
 PTB      WITH     READING  BY       SUPPORT  .
***************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************
Conditional direct effect(s) of X on Y:
    SUPPORT     Effect         se          t          p       LLCI       ULCI
```

```
     -.1285   -12.8670     3.9850    -3.2288      .0014   -20.7081    -5.0260
      .0000    -8.1542     3.0679    -2.6579      .0083   -14.1907    -2.1177
      .1195    -3.7684     3.1103    -1.2116      .2266    -9.8883     2.3515
Conditional indirect effects of X on Y:
INDIRECT EFFECT:
 PTB         ->    ENGAGE      ->    READING
    SUPPORT     Effect     BootSE   BootLLCI   BootULCI
     -.1285    -8.6629     2.3673   -13.2484    -4.0573
      .0000    -5.3671     1.6272    -8.7016    -2.3828
      .1195    -2.3000     1.5687    -5.6288      .4869
      Index of moderated mediation:
             Index     BootSE   BootLLCI   BootULCI
SUPPORT    25.6560     9.2996     6.8690    43.1603
---
*********************** ANALYSIS NOTES AND ERRORS ************************
Level of confidence for all confidence intervals in output: 95.0000
Number of bootstrap samples for percentile bootstrap confidence intervals: 10000
W values in conditional tables are the 16th, 50th, and 84th percentiles.
NOTE: The following variables were mean centered prior to analysis: SUPPORT  PTB
------ END MATRIX -----
```

Appendix B

Table B1

Percentage of Converged Replications for Frequentist and Diffuse Bayesian Estimation Methods

			ab_B = .02		ab_B = .16		*Null* ab_B	
ICC	N_j	J	ML	Diffuse	ML	Diffuse	ML	Diffuse
.05	5	10	5.2	99.7	5.0	99.2	6.0	99.7
		20	6.2	99.9	6.1	99.6	6.2	99.6
		50	13.0	100.0	13.5	100.0	13.9	100.0
		100	30.8	99.7	30.6	99.5	32.2	99.7
		200	55.3	98.7	57.0	98.5	57.9	98.5
	10	10	5.0	99.9	4.8	99.6	4.9	99.7
		20	6.0	100.0	5.6	100.0	5.7	100.0
		50	28.0	99.9	28.3	99.8	28.3	100.0
		100	64.3	99.6	61.1	99.4	67.8	99.7
		200	89.3	99.5	87.4	99.3	87.3	99.3
	20	10	1.8	100.0	1.4	100.0	2.1	100.0
		20	11.8	100.0	11.9	100.0	12.2	100.0
		50	65.8	99.9	68.4	100.0	65.5	99.9
		100	95.2	99.7	94.0	99.7	93.9	99.7
		200	100.0	99.9	100.0	100.0	100.0	99.9
	50	10	4.8	100.0	4.7	100.0	4.7	100.0
		20	44.4	100.0	41.9	100.0	44.0	100.0
		50	97.9	100.0	97.0	99.9	97.7	100.0
		100	100.0	100.0	100.0	100.0	100.0	100.0
		200	100.0	100.0	100.0	100.0	100.0	100.0
.20	5	10	1.7	99.4	1.2	99.6	1.6	99.3
		20	11.2	99.8	11.7	99.5	12.1	99.7
		50	60.6	99.9	57.0	100.0	55.4	99.9
		100	93.4	99.9	93.8	99.8	92.4	99.9
		200	99.9	100.0	99.9	100.0	99.8	100.0
	10	10	1.9	99.5	2.4	99.8	2.4	99.5
		20	32.7	100.0	34.6	100.0	31.2	100.0
		50	94.3	99.9	94.4	100.0	93.3	100.0
		100	99.9	100.0	99.9	100.0	99.9	100.0
		200	100.0	100.0	100.0	100.0	100.0	100.0
	20	10	8.8	100.0	8.9	100.0	8.7	100.0
		20	68.1	100.0	67.1	99.9	67.9	100.0
		50	99.5	99.9	99.7	100.0	99.4	100.0
		100	100.0	100.0	100.0	100.0	100.0	100.0
		200	100.0	100.0	100.0	100.0	100.0	100.0
	50	10	27.8	100.0	25.9	100.0	26.7	100.0
		20	89.4	100.0	88.1	99.9	89.6	100.0
		50	99.9	100.0	99.9	100.0	99.9	100.0
		100	100.0	100.0	100.0	100.0	100.0	100.0
		200	100.0	100.0	100.0	100.0	100.0	100.0

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B2

Relative Percentage Bias for Within-Level Indirect Effects

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						ab_B = .02, ICC = .05						
5	10	-1.6	302593.1	-0.2	-30.3	-64.9	-16.8	-63.0	-89.2	-9.1	-52.8	-82.1
	20	5.8	5936.2	-1.8	-11.0	-20.7	-7.8	-35.6	-57.9	-7.3	-43.3	-70.2
	50	-2.3	-2.8	-3.8	-4.1	-6.0	-4.4	-14.3	-24.3	-4.6	-28.2	-48.0
	100	-1.0	-1.9	-2.3	-0.7	-0.4	-2.0	-5.6	-9.9	-2.4	-17.1	-30.4
	200	-0.6	-0.1	-0.3	1.9	3.0	-0.1	-0.3	-1.6	-0.4	-8.3	-16.0
10	10	4.6	7124.8	-3.9	-15.2	-25.3	-9.3	-37.2	-59.7	-7.7	-43.6	-70.4
	20	1.3	-0.8	-2.7	-5.7	-9.4	-4.2	-18.2	-31.1	-4.8	-31.6	-53.6
	50	-0.9	-1.4	-1.9	-1.2	-1.7	-1.8	-6.2	-10.9	-2.4	-17.1	-30.4
	100	-0.7	-0.2	-0.3	0.9	1.8	-0.2	-1.2	-2.6	-0.6	-8.7	-16.3
	200	0.1	-0.2	-0.2	0.9	2.3	-0.1	0.1	0.6	-0.3	-4.1	-7.9
20	10	-11.4	0.4	-1.4	-5.6	-10.1	-3.0	-18.3	-31.6	-4.4	-31.4	-53.6
	20	7.6	-0.7	-1.3	-2.2	-3.6	-2.0	-8.8	-15.2	-2.8	-20.4	-35.8
	50	-0.6	-0.6	-0.7	-0.2	0.2	-0.7	-2.7	-4.3	-1.0	-9.6	-17.2
	100	-0.1	-0.4	-0.4	-0.1	0.7	-0.4	-1.1	-1.2	-0.6	-4.9	-8.9
	200	0.1	0.0	0.0	0.0	0.2	-0.1	-0.2	-0.1	-0.1	-2.2	-3.9
50	10	3.4	0.0	-2.3	-2.0	-3.8	-2.1	-7.1	-12.8	-1.9	-17.1	-30.7
	20	-0.3	0.1	0.0	-0.8	-1.0	-0.4	-3.0	-5.6	-0.7	-9.3	-17.6
	50	-0.3	0.2	0.0	-0.1	-0.1	-0.1	-1.0	-1.7	-0.2	-3.9	-7.4
	100	0.1	-0.2	-0.3	-0.3	-0.4	-0.3	-0.8	-1.1	-0.3	-2.2	-4.0
	200	0.0	-0.2	-0.2	-0.3	-0.3	-0.2	-0.4	-0.7	-0.2	-1.1	-2.0
						ab_B = .02, ICC = .20						
5	10	16.6	175548.2	-1.3	-30.8	-69.4	-18.6	-64.8	-91.0	-9.4	-53.3	-82.7
	20	6.7	18940.7	-2.2	-8.1	-16.1	-9.3	-35.9	-57.6	-7.6	-44.2	-71.3
	50	-2.2	-3.2	-3.6	-2.7	-0.2	-4.8	-13.1	-19.8	-4.9	-29.0	-49.1
	100	0.0	-0.4	-0.3	0.6	3.8	-1.0	-4.1	-5.1	-1.9	-17.0	-30.1
	200	-1.3	1.6	1.6	1.4	2.0	1.4	0.0	-0.2	0.3	-7.8	-14.9
10	10	-8.0	113.8	-2.7	-10.9	-23.1	-9.1	-37.3	-59.8	-7.9	-44.2	-71.1
	20	-0.6	-0.1	-1.4	-3.9	-5.9	-3.8	-17.4	-29.6	-4.6	-32.1	-54.2
	50	1.0	-0.4	-0.7	-1.4	-1.0	-1.3	-6.3	-9.9	-2.0	-17.6	-31.0
	100	-0.6	0.7	0.7	-0.1	-0.6	0.4	-2.2	-4.2	-0.2	-9.0	-16.9
	200	-0.2	0.2	0.4	-0.2	-0.6	0.2	-1.1	-2.2	0.0	-4.7	-8.8
20	10	-1.9	1.0	-0.4	-5.7	-9.9	-3.0	-18.8	-32.0	-4.7	-31.9	-54.3
	20	0.6	-0.3	-1.0	-2.8	-4.0	-1.7	-9.3	-15.8	-3.0	-21.0	-36.8
	50	-0.4	0.0	-0.1	-1.1	-1.7	-0.3	-3.6	-5.9	-1.0	-9.9	-18.2
	100	-0.3	-0.2	-0.3	-0.7	-1.2	-0.3	-1.9	-3.3	-0.6	-5.2	-9.9
	200	0.2	0.1	0.0	-0.1	-0.4	0.0	-0.8	-1.6	0.0	-2.6	-4.9
50	10	-1.1	0.3	-0.3	-2.3	-4.3	-0.9	-7.3	-13.3	-2.0	-17.6	-31.2
	20	-0.3	0.2	0.1	-0.9	-1.9	-0.3	-3.4	-6.2	-0.7	-9.8	-18.1
	50	-0.4	0.1	0.1	-0.3	-0.7	0.0	-1.3	-2.4	-0.2	-4.2	-8.0
	100	0.1	-0.2	-0.2	-0.4	-0.7	-0.2	-1.0	-1.6	-0.3	-2.4	-4.3
	200	0.0	-0.1	-0.1	-0.3	-0.3	-0.2	-0.6	-0.9	-0.2	-1.3	-2.3

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B2 (continued)

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						ab_B = .16, ICC = .05						
5	10	15.1	116091.3	2.0	-26.7	-65.0	-15.2	-61.9	-89.0	-8.7	-52.3	-81.8
	20	17.9	761.9	2.4	-7.1	-16.2	-6.3	-34.0	-56.2	-6.7	-42.9	-70.0
	50	-0.2	1.3	-0.2	0.2	-0.9	-2.4	-12.0	-21.1	-3.7	-27.4	-47.2
	100	1.4	2.3	1.1	3.2	4.7	0.0	-3.0	-6.2	-1.2	-15.9	-28.8
	200	0.9	2.9	2.2	4.9	7.7	1.8	2.0	2.1	0.9	-6.9	-14.1
10	10	4.6	17392.2	-2.0	-12.7	-23.0	-8.2	-36.1	-58.4	-7.2	-43.1	-70.1
	20	2.1	1.7	-0.1	-3.1	-5.8	-2.2	-16.6	-28.9	-4.1	-31.1	-53.0
	50	0.4	0.9	0.0	0.8	1.9	-0.8	-4.8	-8.4	-1.7	-16.4	-29.7
	100	0.1	1.3	0.8	1.8	3.9	0.6	-0.4	-0.8	0.0	-8.1	-15.4
	200	0.3	0.2	-0.2	0.6	2.2	0.2	0.1	1.0	0.1	-3.8	-7.3
20	10	-0.9	1.7	-0.4	-4.6	-8.8	-2.3	-17.7	-30.7	-4.0	-31.1	-53.3
	20	8.7	0.6	-0.3	-1.2	-2.0	-1.3	-8.1	-13.9	-2.4	-20.2	-35.6
	50	0.2	0.1	-0.2	-0.2	0.9	-0.4	-2.3	-4.0	-0.8	-9.2	-17.0
	100	-0.1	-0.3	-0.7	-0.6	-0.2	-0.3	-1.3	-1.6	-0.6	-4.9	-8.9
	200	0.1	-0.1	-0.2	-0.3	-0.4	-0.1	-0.6	-0.8	-0.1	-2.2	-4.1
50	10	1.6	0.6	-0.3	-3.3	-3.2	-0.8	-6.9	-12.6	-1.7	-17.0	-30.7
	20	0.3	0.3	0.1	-0.8	-0.9	-0.3	-3.1	-5.6	-0.7	-9.3	-17.6
	50	-0.4	0.1	-0.1	-0.3	-0.7	0.0	-1.2	-2.1	-0.2	-4.0	-7.6
	100	0.1	-0.2	-0.3	-0.6	-0.7	-0.3	-1.0	-1.4	-0.4	-2.3	-4.1
	200	0.0	-0.2	-0.2	-0.3	-0.3	-0.2	-0.6	-0.8	-0.2	-1.2	-2.1
						ab_B = .16, ICC = .20						
5	10	34.6	167852.7	7.1	-23.0	-60.2	-15.1	-62.2	-89.3	-8.6	-52.6	-82.3
	20	10.8	5422.4	3.8	-2.8	-6.3	-5.9	-33.3	-53.8	-6.4	-43.4	-70.8
	50	-1.2	-0.9	-3.2	-3.3	1.6	-4.0	-13.6	-19.2	-4.6	-29.0	-48.9
	100	-0.1	-0.7	-2.3	-2.7	-1.0	-1.3	-5.9	-8.2	-1.9	-17.3	-30.7
	200	-1.2	1.2	0.3	-0.2	-0.6	0.8	-1.2	-3.1	0.4	-8.1	-15.8
10	10	2.1	2689.4	-0.9	-11.3	-19.6	-8.3	-37.1	-58.6	-7.4	-43.8	-70.9
	20	1.6	1.0	-0.7	-4.1	-4.9	-3.4	-17.8	-29.4	-4.4	-32.1	-54.3
	50	0.9	-0.7	-1.3	-3.0	-3.9	-1.3	-7.2	-12.0	-2.1	-17.9	-31.6
	100	-0.6	0.4	0.2	-0.7	-1.7	0.2	-2.9	-5.4	-0.2	-9.3	-17.6
	200	-0.1	0.1	0.0	-0.4	-1.0	0.0	-1.6	-3.0	0.0	-4.9	-9.4
20	10	-7.0	1.7	-0.7	-5.6	-9.9	-2.9	-18.8	-32.3	-4.6	-32.2	-54.4
	20	1.0	-0.1	-0.8	-3.4	-4.9	-1.9	-9.7	-16.6	-2.8	-21.2	-37.1
	50	-0.4	-0.1	-0.4	-1.6	-2.3	-0.6	-3.9	-6.8	-1.1	-10.2	-18.6
	100	-0.3	-0.2	-0.3	-0.8	-1.3	-0.2	-2.1	-3.8	-0.6	-5.6	-10.2
	200	0.1	0.0	0.0	-0.3	-0.7	0.0	-0.9	-1.8	-0.1	-2.8	-5.3
50	10	0.3	0.3	-0.3	-2.4	-4.4	-1.0	-8.9	-13.6	-2.0	-17.4	-31.4
	20	-0.3	0.1	0.0	-1.0	-2.0	-0.1	-3.8	-6.8	-0.7	-9.8	-18.1
	50	-0.4	0.0	0.1	-0.3	-0.8	-0.1	-1.4	-2.7	-0.2	-4.3	-8.2
	100	0.1	-0.2	-0.3	-0.6	-0.8	-0.3	-1.0	-1.8	-0.3	-2.6	-4.7
	200	0.0	-0.2	-0.2	-0.3	-0.4	-0.2	-0.6	-1.0	-0.2	-1.3	-2.4

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B2 (continued)

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						Null ab_B, ICC = .05						
5	10	-22.9	289271.3	-2.1	-30.2	-65.0	-17.4	-63.0	-89.8	-9.3	-52.8	-82.1
	20	13.6	167.7	-3.4	-12.9	-22.8	-8.9	-36.4	-59.0	-7.3	-43.6	-70.4
	50	-7.4	-4.6	-5.4	-6.1	-8.6	-5.2	-15.8	-25.9	-5.0	-28.8	-48.7
	100	-2.7	-3.4	-3.8	-2.7	-3.0	-3.1	-7.2	-12.1	-3.1	-17.9	-31.4
	200	-1.3	-1.8	-1.7	0.1	0.6	-0.9	-1.9	-3.7	-1.0	-9.3	-17.2
10	10	1.7	-2008.0	-4.7	-15.9	-26.3	-9.1	-37.9	-60.1	-8.0	-43.8	-70.4
	20	-5.3	-1.8	-3.2	-6.9	-11.2	-4.8	-19.2	-32.4	-5.1	-32.0	-54.0
	50	-0.7	-2.7	-2.9	-2.8	-3.7	-2.7	-7.2	-12.4	-2.9	-17.8	-31.1
	100	-1.0	-1.0	-1.0	0.0	0.1	-0.8	-2.1	-4.0	-0.9	-9.1	-17.1
	200	-0.1	-0.6	-0.4	0.7	1.2	-0.3	-0.3	-0.6	-0.4	-4.6	-8.4
20	10	-8.7	0.0	-2.0	-6.3	-11.2	-3.4	-18.7	-32.6	-4.7	-31.6	-53.7
	20	4.2	-1.1	-1.9	-3.1	-5.1	-2.2	-9.3	-16.0	-3.0	-20.7	-36.2
	50	-0.7	-0.8	-0.8	-0.7	-0.7	-0.8	-2.9	-5.0	-1.2	-9.7	-17.4
	100	-0.2	-0.3	-0.3	0.0	0.4	-0.4	-1.0	-1.4	-0.6	-4.9	-9.0
	200	0.1	0.0	0.1	0.3	0.7	-0.1	-0.1	0.1	-0.2	-2.1	-4.1
50	10	4.2	-0.1	-0.6	-2.2	-4.0	-1.1	-7.3	-13.0	-2.0	-17.1	-30.7
	20	-0.6	0.1	-0.2	-0.7	-1.1	-0.4	-3.2	-5.7	-0.7	-9.6	-17.4
	50	-0.4	0.0	0.0	0.0	0.0	0.0	-0.9	-1.7	-0.1	-3.9	-7.4
	100	0.1	-0.2	-0.2	-0.3	-0.2	-0.3	-0.7	-0.9	-0.3	-2.1	-3.9
	200	0.0	-0.2	-0.1	-0.2	-0.3	-0.2	-0.3	-0.6	-0.2	-1.1	-1.9
						Null ab_B, ICC = .20						
5	10	48.6	56418.9	-5.2	-36.0	-75.9	-20.9	-66.0	-91.7	-9.9	-53.7	-82.9
	20	1.6	12580.9	-5.3	-13.1	-22.0	-9.3	-38.6	-60.8	-8.2	-45.0	-71.9
	50	-3.8	-4.6	-4.7	-3.9	-4.2	-5.0	-14.1	-22.6	-5.3	-29.6	-49.6
	100	-0.3	-0.7	-0.1	1.6	3.7	-1.1	-3.7	-5.6	-2.2	-17.1	-30.3
	200	-1.3	1.8	2.2	2.8	4.4	1.4	0.8	1.4	0.2	-7.6	-14.8
10	10	-23.6	123.6	-4.2	-15.0	-24.9	-9.6	-38.3	-60.9	-8.3	-44.4	-71.2
	20	1.1	-1.1	-1.6	-5.0	-8.1	-4.0	-18.1	-30.3	-4.9	-32.1	-54.6
	50	1.1	-0.8	-0.1	-0.6	-0.2	-1.0	-5.8	-9.4	-2.1	-17.3	-30.9
	100	-0.6	0.8	1.0	0.4	0.7	0.3	-1.7	-2.9	-0.2	-8.8	-16.6
	200	-0.2	0.2	0.3	0.1	-0.1	0.3	-0.8	-1.6	0.0	-4.4	-8.3
20	10	-5.7	0.7	-0.9	-5.9	-10.4	-3.0	-18.6	-32.6	-4.6	-31.9	-54.3
	20	0.4	-0.4	-0.7	-2.4	-4.0	-1.7	-9.0	-15.6	-2.8	-20.9	-36.8
	50	-0.4	0.0	-0.1	-0.7	-1.1	-0.3	-3.0	-5.2	-1.0	-9.8	-17.8
	100	-0.3	-0.2	-0.1	-0.6	-0.9	-0.2	-1.7	-2.7	-0.6	-5.1	-9.6
	200	0.2	0.0	0.1	-0.1	-0.3	0.1	-0.6	-1.2	-0.1	-2.4	-4.6
50	10	-0.6	0.1	-0.4	-2.2	-4.3	-0.8	-7.2	-13.4	-2.0	-17.4	-31.2
	20	-0.2	0.1	0.0	-0.8	-1.6	-0.2	-3.3	-6.0	-0.7	-9.6	-18.0
	50	-0.4	0.1	0.2	-0.2	-0.6	0.0	-1.1	-2.2	-0.2	-4.1	-7.8
	100	0.1	-0.2	-0.2	-0.4	-0.7	-0.3	-0.9	-1.4	-0.3	-2.3	-4.2
	200	0.0	-0.2	-0.2	-0.2	-0.3	-0.2	-0.4	-0.8	-0.2	-1.2	-2.1

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B3

Relative Percentage Bias for Between-Level Indirect Effects

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						ab_B = .02, ICC = .05						
5	10	153.5	-11690.0	-46.0	1049.0	9515.5	-66.0	-57.0	790.0	-23.0	-97.5	-94.0
	20	-192.0	-7457.0	-57.5	975.5	8468.5	-63.5	-58.0	762.5	-23.0	-97.5	-94.5
	50	-218.0	-684.0	-37.0	910.5	7619.5	-58.0	-57.0	737.0	-22.5	-97.5	-94.5
	100	11.5	294.5	-59.5	879.5	7193.5	-59.0	-52.5	725.5	-23.0	-97.0	-95.0
	200	-144.5	312.5	-48.0	832.0	6663.0	-53.0	-54.0	689.0	-24.0	-97.0	-95.0
10	10	-107.0	-10587.5	-59.0	1048.0	8909.0	-67.0	-56.0	774.0	-23.0	-97.5	-94.0
	20	25.5	1019.5	-50.0	955.0	7708.5	-61.5	-54.0	746.0	-23.5	-97.5	-94.0
	50	-150.5	-833.0	-43.5	844.5	6759.5	-52.5	-50.5	706.5	-23.0	-97.0	-94.5
	100	-47.0	-284.0	-51.5	613.0	5812.5	-45.5	-57.5	597.0	-22.0	-96.0	-95.0
	200	-56.5	-57.0	-47.5	363.5	4256.5	-37.5	-65.5	413.5	-21.5	-93.5	-96.0
20	10	571.5	5590.5	-44.0	962.5	8228.5	-60.5	-55.0	756.5	-22.5	-97.5	-94.5
	20	174.0	-1027.5	-11.0	796.0	6959.5	-49.0	-53.5	679.5	-22.5	-97.0	-94.5
	50	-61.5	546.5	-31.5	494.5	5062.5	-39.5	-62.5	496.5	-22.0	-95.5	-95.0
	100	-40.5	12.5	-24.0	157.0	2723.0	-29.0	-76.5	220.5	-20.0	-92.5	-97.0
	200	-23.0	-28.0	-30.5	-30.0	343.5	-27.0	-75.0	-7.5	-18.5	-86.0	-98.5
50	10	352.0	141.0	-21.5	810.0	7228.0	-48.0	-55.0	688.5	-22.0	-97.5	-94.5
	20	-74.5	2941.5	-60.0	402.0	4787.5	-43.5	-69.0	476.0	-21.5	-96.0	-95.0
	50	-70.0	-89.5	-59.5	15.0	1270.0	-34.0	-86.0	103.0	-20.0	-92.5	-97.0
	100	-26.0	-33.0	-33.5	-48.5	-14.5	-25.5	-76.5	-70.0	-17.0	-85.5	-99.0
	200	-9.5	-21.5	-23.5	-37.0	-49.0	-20.0	-57.0	-80.5	-14.0	-73.5	-97.0
						ab_B = .02, ICC = .20						
5	10	121.0	13819.5	-26.5	1129.5	9710.0	-60.0	-56.0	764.5	-23.0	-97.5	-94.5
	20	463.5	-3438.0	-30.5	946.0	8286.5	-53.5	-55.5	696.5	-23.0	-97.0	-95.0
	50	-10381.5	184.5	-55.0	512.5	5777.5	-43.0	-65.5	476.5	-22.5	-94.5	-96.5
	100	-37.5	-74.5	-61.5	117.5	2824.5	-40.5	-81.0	179.0	-22.5	-91.0	-98.0
	200	-12.5	-34.0	-36.5	-38.5	268.5	-31.5	-73.0	-46.0	-19.5	-83.0	-99.0
10	10	25.5	-1828.5	-58.5	969.0	8674.5	-59.0	-52.5	729.0	-23.5	-97.5	-94.0
	20	-161.5	1894.0	-22.0	685.0	6097.0	-41.0	-58.0	524.5	-23.0	-96.0	-95.0
	50	-35.0	-2335.5	-45.0	60.5	1846.5	-28.0	-82.5	107.0	-20.0	-91.5	-97.5
	100	-8.0	-25.0	-24.0	-46.5	44.5	-23.0	-75.5	-68.0	-17.0	-84.5	-99.0
	200	-7.0	-14.0	-15.5	-29.5	-42.0	-16.0	-52.5	-77.0	-12.5	-71.0	-96.5
20	10	-778.5	1868.5	-12.0	713.0	7463.0	-42.0	-62.0	620.5	-21.0	-96.5	-94.5
	20	-19.5	-155.5	-14.5	235.5	3504.5	-27.0	-74.0	285.5	-19.5	-94.5	-96.0
	50	-16.0	-38.5	-37.5	-59.0	154.0	-26.5	-86.0	-47.5	-18.0	-89.0	-98.5
	100	-3.0	-21.0	-19.0	-40.0	-56.0	-19.0	-66.5	-88.0	-14.5	-79.5	-99.0
	200	-2.5	-19.0	-18.0	-28.5	-38.5	-17.0	-47.0	-69.0	-13.0	-65.5	-93.0
50	10	1612.5	1308.0	-16.5	547.5	6234.0	-38.5	-63.5	515.5	-21.0	-96.5	-94.5
	20	-67.0	-269.0	-61.5	25.5	1819.5	-39.0	-91.0	143.0	-20.5	-94.5	-96.5
	50	-22.5	-43.5	-29.0	-57.0	-53.0	-23.5	-82.5	-81.0	-17.0	-86.5	-99.0
	100	-12.0	-21.0	-18.0	-35.0	-49.0	-18.0	-59.5	-84.5	-13.5	-75.0	-98.0
	200	-4.5	-16.0	-14.5	-24.0	-32.5	-14.5	-40.5	-60.5	-11.0	-59.5	-88.0

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B3 (continued)

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						ab_B = .16, ICC = .05						
5	10	-16.1	519.2	-63.2	-45.8	757.4	-26.8	-98.1	-87.9	-3.4	-46.6	-77.5
	20	-44.1	109.6	-60.9	-51.1	669.5	-26.1	-97.6	-88.3	-3.3	-46.2	-76.9
	50	-81.7	-176.6	-46.3	-54.2	579.2	-22.4	-95.3	-89.4	-3.0	-45.3	-76.1
	100	-5.9	-205.6	-37.6	-57.1	507.0	-20.4	-93.3	-89.9	-2.8	-44.5	-75.4
	200	-23.1	-10.6	-14.4	-55.9	411.4	-14.3	-87.2	-92.1	-2.5	-43.2	-73.9
10	10	-107.7	403.7	-61.9	-52.0	691.6	-26.9	-97.8	-88.1	-3.5	-46.4	-77.4
	20	-97.3	-922.7	-47.6	-51.8	572.9	-23.3	-95.9	-88.7	-3.1	-45.7	-76.6
	50	16.3	-109.0	-17.2	-55.9	448.3	-14.7	-89.6	-91.3	-2.3	-44.0	-75.0
	100	5.3	-33.3	4.5	-49.0	277.1	-6.6	-76.8	-93.4	-1.3	-41.6	-72.4
	200	36.1	73.3	21.9	-19.5	84.1	0.3	-53.9	-88.4	-0.5	-37.8	-67.7
20	10	-19.0	527.9	-39.7	-58.0	602.9	-21.1	-96.1	-89.6	-2.8	-45.9	-76.8
	20	-72.1	7.9	-16.2	-57.5	417.3	-13.8	-90.3	-92.2	-2.0	-44.4	-75.4
	50	-7.4	-155.2	12.3	-40.9	154.9	-3.8	-71.6	-95.1	-1.3	-41.4	-71.9
	100	-1.6	11.9	23.2	-7.5	8.1	2.0	-47.3	-82.9	-0.5	-37.0	-66.4
	200	2.2	2.4	10.2	-0.9	-13.8	1.8	-26.4	-52.7	-0.9	-31.3	-57.8
50	10	-62.3	-3.9	-19.9	-62.9	438.4	-15.1	-91.4	-92.2	-2.1	-44.8	-75.9
	20	-14.4	108.1	-2.5	-56.8	136.7	-6.9	-78.8	-96.6	-1.1	-42.7	-73.4
	50	-2.6	-5.9	8.3	-18.8	-31.1	-1.8	-49.5	-83.1	-1.0	-37.8	-67.0
	100	0.4	-3.3	4.4	-7.4	-18.2	-0.5	-28.1	-52.9	-1.0	-31.9	-58.1
	200	1.5	-2.5	1.9	-3.8	-9.0	0.2	-14.5	-28.6	-0.8	-24.3	-45.4
						ab_B = .16, ICC = .20						
5	10	112.9	812.0	-34.3	-50.2	699.4	-18.7	-95.6	-90.3	-2.5	-45.5	-76.6
	20	116.7	-400.0	-3.3	-57.9	520.9	-10.9	-89.1	-93.3	-1.9	-43.8	-74.6
	50	18.9	109.5	24.2	-35.0	186.6	-0.9	-65.8	-93.1	-0.9	-39.6	-69.5
	100	6.0	-14.9	19.3	-8.8	2.1	-0.1	-43.0	-77.3	-1.4	-35.8	-63.4
	200	2.0	-0.7	7.8	-2.1	-11.6	0.3	-22.8	-44.4	-1.6	-29.3	-53.3
10	10	-95.5	103.3	-12.8	-59.3	564.4	-12.9	-92.4	-91.8	-2.1	-44.6	-75.8
	20	87.4	-695.3	14.1	-47.6	241.0	-6.3	-77.7	-95.1	-1.3	-42.3	-72.9
	50	3.6	15.8	18.8	-14.8	-30.1	1.1	-47.3	-81.3	-0.8	-37.3	-65.9
	100	4.0	0.6	8.1	-2.4	-16.3	1.4	-26.6	-50.8	-0.6	-31.3	-56.9
	200	1.1	1.1	3.6	-1.8	-6.5	1.7	-12.6	-26.4	-0.3	-23.6	-44.1
20	10	-6.3	161.3	8.3	-64.9	349.0	-7.0	-86.2	-95.4	-1.0	-43.6	-74.7
	20	-7.0	-112.3	23.3	-34.7	22.3	-1.0	-66.4	-94.6	-0.6	-40.9	-71.3
	50	4.3	-1.0	9.8	-8.8	-26.8	-0.4	-37.9	-67.6	-1.1	-35.5	-63.2
	100	2.4	-1.5	2.9	-5.1	-12.6	0.4	-20.6	-39.8	-0.8	-28.6	-52.6
	200	1.6	-1.9	0.0	-3.8	-7.4	-0.4	-11.3	-21.8	-0.9	-20.9	-39.2
50	10	-19.6	-2123.1	9.9	-58.6	217.2	-5.8	-80.5	-96.3	-1.0	-43.1	-74.3
	20	-3.5	2.4	9.6	-35.4	-43.0	-3.6	-63.1	-94.6	-1.1	-40.4	-70.4
	50	-0.1	-6.0	2.9	-10.4	-24.2	-1.4	-33.4	-60.6	-0.9	-33.9	-60.9
	100	-0.3	-3.3	0.0	-6.2	-12.5	-0.8	-18.1	-34.2	-0.9	-26.6	-49.1
	200	0.9	-1.7	-0.4	-3.3	-6.4	-0.5	-9.6	-18.2	-0.6	-18.6	-35.3

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B4

Root Mean Square Error (RMSE) for Within-Level Indirect Effects

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						ab_B = .02, ICC = .05						
5	10	0.16	***	0.11	0.09	0.12	0.06	0.07	0.08	0.02	0.05	0.07
	20	0.09	155.41	0.07	0.07	0.06	0.05	0.05	0.06	0.02	0.04	0.06
	50	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	100	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
10	10	0.08	132.00	0.07	0.07	0.06	0.05	0.05	0.06	0.02	0.04	0.06
	20	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.02	0.03	0.05
	50	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	100	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
20	10	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	20	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.04
	50	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
50	10	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	20	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
	50	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
						ab_B = .02, ICC = .20						
5	10	0.13	***	0.11	0.09	0.13	0.06	0.07	0.08	0.02	0.05	0.07
	20	0.08	***	0.08	0.07	0.07	0.05	0.05	0.06	0.02	0.04	0.06
	50	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	100	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
10	10	0.06	2.20	0.07	0.07	0.07	0.05	0.05	0.06	0.02	0.04	0.06
	20	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.02	0.03	0.05
	50	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	100	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
20	10	0.04	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	20	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.04
	50	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
50	10	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	20	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	50	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect. Cells with asterisks indicate standard errors were too large to compute RMSE.

Table B4 (continued)

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						ab_B = .16, ICC = .05						
5	10	0.14	***	0.11	0.09	0.13	0.06	0.07	0.08	0.02	0.05	0.07
	20	0.08	17.85	0.07	0.07	0.07	0.05	0.05	0.06	0.02	0.04	0.06
	50	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	100	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
10	10	0.07	***	0.07	0.07	0.06	0.05	0.05	0.06	0.02	0.04	0.06
	20	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.02	0.03	0.05
	50	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	100	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
20	10	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	20	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.04
	50	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
50	10	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	20	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
	50	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
						ab_B = .16, ICC = .20						
5	10	0.15	***	0.11	0.10	0.15	0.06	0.07	0.08	0.02	0.05	0.07
	20	0.08	102.00	0.08	0.07	0.07	0.05	0.05	0.06	0.02	0.04	0.06
	50	0.05	0.05	0.04	0.04	0.05	0.04	0.04	0.04	0.02	0.03	0.05
	100	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
10	10	0.07	57.72	0.07	0.07	0.07	0.05	0.05	0.06	0.02	0.04	0.06
	20	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.02	0.03	0.05
	50	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	100	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
20	10	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	20	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.04
	50	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
50	10	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	20	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	50	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect. Cells with asterisks indicate standard errors were too large to compute RMSE.

Table B4 (continued)

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						Null ab_B, ICC = .05						
5	10	0.16	***	0.10	0.09	0.13	0.06	0.07	0.08	0.02	0.05	0.07
	20	0.08	3.18	0.07	0.07	0.06	0.05	0.05	0.06	0.02	0.04	0.06
	50	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	100	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
10	10	0.08	206.03	0.07	0.07	0.06	0.05	0.05	0.06	0.02	0.04	0.06
	20	0.04	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.02	0.03	0.05
	50	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	100	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
20	10	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	20	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.04
	50	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
50	10	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	20	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
	50	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
						Null ab_B, ICC = .20						
5	10	0.16	***	0.11	0.09	0.14	0.06	0.07	0.09	0.02	0.05	0.07
	20	0.07	***	0.07	0.07	0.07	0.05	0.05	0.06	0.02	0.04	0.07
	50	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	100	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
10	10	0.05	2.64	0.07	0.07	0.07	0.05	0.05	0.07	0.02	0.04	0.06
	20	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.02	0.03	0.05
	50	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	100	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
20	10	0.04	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.02	0.03	0.05
	20	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.04
	50	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
50	10	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03
	20	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	50	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	100	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	200	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect. Cells with asterisks indicate standard errors were too large to compute RMSE.

Table B5

Root Mean Square Error (RMSE) for Between-Level Indirect Effects

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						ab_B = .02, ICC = .05						
5	10	1.07	44.85	0.04	0.26	1.95	0.01	0.01	0.16	0.00	0.02	0.02
	20	0.80	42.80	0.05	0.27	1.76	0.01	0.01	0.16	0.00	0.02	0.02
	50	0.52	6.38	0.08	0.27	1.62	0.02	0.01	0.15	0.00	0.02	0.02
	100	0.54	1.93	0.08	0.29	1.56	0.02	0.02	0.16	0.00	0.02	0.02
	200	0.48	2.46	0.09	0.29	1.46	0.02	0.02	0.15	0.00	0.02	0.02
10	10	0.83	47.84	0.04	0.27	1.84	0.01	0.01	0.16	0.00	0.02	0.02
	20	0.88	32.28	0.06	0.29	1.63	0.01	0.01	0.16	0.00	0.02	0.02
	50	0.35	4.47	0.09	0.28	1.48	0.02	0.02	0.16	0.00	0.02	0.02
	100	0.31	1.33	0.10	0.24	1.33	0.02	0.02	0.14	0.00	0.02	0.02
	200	0.13	0.38	0.09	0.20	1.08	0.03	0.02	0.12	0.01	0.02	0.02
20	10	1.00	29.01	0.06	0.28	1.73	0.01	0.01	0.16	0.00	0.02	0.02
	20	0.66	8.91	0.09	0.28	1.52	0.02	0.02	0.15	0.00	0.02	0.02
	50	0.30	2.42	0.10	0.23	1.22	0.03	0.02	0.13	0.00	0.02	0.02
	100	0.14	0.41	0.09	0.15	0.83	0.03	0.02	0.09	0.01	0.02	0.02
	200	0.05	0.05	0.04	0.06	0.28	0.03	0.02	0.04	0.01	0.02	0.02
50	10	1.06	15.08	0.10	0.30	1.58	0.02	0.02	0.15	0.00	0.02	0.02
	20	0.32	37.54	0.11	0.23	1.20	0.02	0.02	0.13	0.00	0.02	0.02
	50	0.20	0.17	0.09	0.11	0.57	0.03	0.03	0.07	0.01	0.02	0.02
	100	0.05	0.05	0.05	0.04	0.10	0.03	0.02	0.03	0.01	0.02	0.02
	200	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02
						ab_B = .02, ICC = .20						
5	10	0.63	87.91	0.07	0.31	2.03	0.01	0.01	0.16	0.00	0.02	0.02
	20	1.89	18.94	0.09	0.32	1.80	0.02	0.02	0.15	0.00	0.02	0.02
	50	50.12	1.61	0.11	0.25	1.39	0.03	0.02	0.13	0.01	0.02	0.02
	100	0.10	0.14	0.07	0.14	0.89	0.03	0.02	0.08	0.01	0.02	0.02
	200	0.04	0.04	0.04	0.04	0.29	0.03	0.02	0.03	0.01	0.02	0.02
10	10	0.28	18.37	0.09	0.33	1.87	0.02	0.02	0.16	0.00	0.02	0.02
	20	0.54	9.20	0.12	0.29	1.47	0.03	0.02	0.14	0.00	0.02	0.02
	50	0.12	11.55	0.09	0.11	0.72	0.03	0.02	0.07	0.01	0.02	0.02
	100	0.05	0.04	0.05	0.04	0.15	0.03	0.02	0.02	0.01	0.02	0.02
	200	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02
20	10	0.95	18.53	0.11	0.29	1.71	0.02	0.02	0.15	0.00	0.02	0.02
	20	0.28	1.34	0.12	0.19	1.05	0.03	0.03	0.10	0.01	0.02	0.02
	50	0.07	0.07	0.07	0.06	0.24	0.03	0.02	0.03	0.01	0.02	0.02
	100	0.04	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.01	0.02	0.02
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02
50	10	5.11	4.42	0.11	0.28	1.51	0.02	0.02	0.13	0.00	0.02	0.02
	20	0.18	1.01	0.11	0.15	0.75	0.03	0.03	0.07	0.01	0.02	0.02
	50	0.06	0.08	0.05	0.05	0.08	0.03	0.03	0.03	0.01	0.02	0.02
	100	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.01	0.02	0.02
	200	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B5 (continued)

N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						ab_B = .16, ICC = .05						
5	10	1.40	24.94	0.13	0.11	1.26	0.05	0.16	0.14	0.00	0.07	0.12
	20	0.86	10.35	0.14	0.13	1.15	0.05	0.16	0.14	0.01	0.07	0.12
	50	0.69	5.97	0.16	0.15	1.04	0.06	0.15	0.14	0.01	0.07	0.12
	100	0.65	4.79	0.17	0.16	0.96	0.07	0.15	0.14	0.01	0.07	0.12
	200	0.57	2.05	0.20	0.17	0.86	0.08	0.14	0.15	0.01	0.07	0.12
10	10	0.82	17.72	0.13	0.12	1.17	0.05	0.16	0.14	0.01	0.07	0.12
	20	1.30	30.16	0.15	0.15	1.03	0.06	0.15	0.14	0.01	0.07	0.12
	50	0.60	8.90	0.18	0.16	0.91	0.07	0.15	0.15	0.01	0.07	0.12
	100	0.50	2.32	0.22	0.17	0.71	0.08	0.13	0.15	0.01	0.07	0.12
	200	1.17	2.45	0.21	0.18	0.44	0.09	0.11	0.15	0.02	0.06	0.11
20	10	0.69	16.84	0.16	0.14	1.07	0.06	0.15	0.14	0.01	0.07	0.12
	20	0.79	4.26	0.20	0.16	0.87	0.07	0.15	0.15	0.01	0.07	0.12
	50	0.39	6.04	0.22	0.18	0.58	0.09	0.13	0.15	0.02	0.07	0.12
	100	0.28	0.41	0.21	0.19	0.31	0.09	0.10	0.14	0.02	0.06	0.11
	200	0.11	0.17	0.14	0.13	0.13	0.08	0.08	0.10	0.03	0.05	0.09
50	10	0.93	8.34	0.19	0.16	0.92	0.07	0.15	0.15	0.01	0.07	0.12
	20	0.50	4.88	0.22	0.18	0.58	0.08	0.13	0.16	0.01	0.07	0.12
	50	0.23	0.28	0.19	0.18	0.22	0.09	0.11	0.14	0.02	0.06	0.11
	100	0.12	0.13	0.13	0.12	0.12	0.08	0.08	0.10	0.03	0.06	0.09
	200	0.07	0.07	0.08	0.07	0.07	0.06	0.06	0.07	0.03	0.05	0.08
						ab_B = .16, ICC = .20						
5	10	1.05	22.39	0.16	0.14	1.23	0.05	0.15	0.14	0.01	0.07	0.12
	20	2.78	15.69	0.20	0.18	1.06	0.07	0.14	0.15	0.01	0.07	0.12
	50	0.47	3.81	0.23	0.19	0.68	0.09	0.12	0.15	0.02	0.06	0.11
	100	0.20	1.30	0.19	0.18	0.33	0.09	0.10	0.13	0.02	0.06	0.10
	200	0.11	0.11	0.12	0.11	0.12	0.07	0.08	0.09	0.03	0.05	0.09
10	10	0.28	15.74	0.21	0.17	1.11	0.06	0.15	0.15	0.01	0.07	0.12
	20	3.01	33.21	0.24	0.20	0.77	0.09	0.13	0.15	0.02	0.07	0.12
	50	0.21	0.42	0.20	0.18	0.26	0.09	0.10	0.14	0.02	0.06	0.11
	100	0.11	0.13	0.13	0.12	0.12	0.08	0.08	0.10	0.03	0.05	0.09
	200	0.07	0.08	0.08	0.08	0.08	0.06	0.06	0.07	0.03	0.05	0.07
20	10	0.91	5.53	0.24	0.19	0.90	0.08	0.14	0.15	0.01	0.07	0.12
	20	0.47	3.49	0.24	0.20	0.46	0.09	0.12	0.15	0.02	0.07	0.11
	50	0.15	0.17	0.16	0.15	0.15	0.09	0.09	0.12	0.02	0.06	0.10
	100	0.09	0.09	0.10	0.09	0.09	0.07	0.07	0.09	0.03	0.05	0.09
	200	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.06	0.03	0.04	0.07
50	10	0.64	115.60	0.24	0.19	0.77	0.08	0.14	0.16	0.01	0.07	0.12
	20	0.36	0.60	0.22	0.19	0.32	0.09	0.12	0.15	0.02	0.07	0.11
	50	0.13	0.14	0.13	0.13	0.13	0.08	0.09	0.11	0.02	0.06	0.10
	100	0.08	0.08	0.08	0.08	0.08	0.07	0.07	0.08	0.03	0.05	0.08
	200	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.03	0.04	0.06

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B6

95% CI Coverage Rates for Within-Level Indirect Effects

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
Small between-level indirect effect size (ab_B = .02)													
.05	5	10	0.96	0.99	0.99	0.97	0.96	0.98	0.90	0.77	1.00	0.87	0.06
		20	0.94	0.96	0.96	0.95	0.93	0.97	0.91	0.81	1.00	0.87	0.25
		50	0.91	0.95	0.95	0.95	0.94	0.95	0.94	0.90	0.99	0.89	0.57
		100	0.94	0.95	0.95	0.95	0.95	0.96	0.95	0.93	0.98	0.92	0.76
		200	0.94	0.95	0.96	0.96	0.95	0.96	0.96	0.96	0.97	0.95	0.89
	10	10	0.90	0.95	0.96	0.94	0.92	0.97	0.91	0.79	1.00	0.87	0.24
		20	0.90	0.96	0.95	0.95	0.95	0.96	0.94	0.87	0.99	0.89	0.50
		50	0.96	0.96	0.96	0.95	0.95	0.95	0.95	0.92	0.98	0.91	0.76
		100	0.94	0.96	0.96	0.96	0.96	0.96	0.95	0.95	0.97	0.94	0.87
		200	0.95	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.97	0.95	0.93
	20	10	0.83	0.95	0.96	0.95	0.95	0.96	0.93	0.88	0.99	0.89	0.51
		20	0.92	0.95	0.95	0.96	0.95	0.96	0.95	0.92	0.98	0.91	0.69
		50	0.95	0.95	0.95	0.95	0.95	0.95	0.96	0.95	0.97	0.94	0.84
		100	0.95	0.95	0.95	0.96	0.96	0.95	0.95	0.95	0.96	0.95	0.90
		200	0.94	0.94	0.94	0.95	0.95	0.95	0.95	0.95	0.95	0.94	0.92
	50	10	0.92	0.93	0.96	0.93	0.94	0.94	0.92	0.91	0.97	0.90	0.74
		20	0.94	0.95	0.95	0.94	0.95	0.95	0.94	0.93	0.97	0.92	0.84
		50	0.93	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.95	0.94	0.90
		100	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.92
		200	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.93	0.93
.20	5	10	0.94	0.99	0.98	0.98	0.97	0.98	0.91	0.80	1.00	0.88	0.06
		20	0.92	0.95	0.95	0.95	0.94	0.97	0.92	0.83	1.00	0.88	0.26
		50	0.93	0.95	0.95	0.95	0.96	0.95	0.95	0.92	0.99	0.91	0.57
		100	0.94	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.93	0.78
		200	0.93	0.95	0.95	0.95	0.94	0.95	0.95	0.95	0.97	0.95	0.90
	10	10	0.95	0.96	0.95	0.94	0.94	0.97	0.92	0.81	1.00	0.87	0.23
		20	0.93	0.95	0.96	0.95	0.95	0.97	0.93	0.88	0.99	0.89	0.49
		50	0.94	0.95	0.96	0.96	0.96	0.97	0.95	0.93	0.99	0.91	0.76
		100	0.94	0.96	0.96	0.95	0.96	0.96	0.96	0.95	0.97	0.94	0.87
		200	0.95	0.96	0.96	0.96	0.96	0.96	0.95	0.95	0.97	0.96	0.93
	20	10	0.94	0.96	0.95	0.95	0.95	0.97	0.95	0.88	0.99	0.90	0.49
		20	0.93	0.95	0.96	0.95	0.95	0.96	0.95	0.92	0.98	0.91	0.67
		50	0.95	0.95	0.95	0.95	0.95	0.95	0.94	0.94	0.97	0.94	0.84
		100	0.95	0.95	0.95	0.95	0.95	0.95	0.94	0.94	0.96	0.94	0.89
		200	0.94	0.94	0.94	0.94	0.93	0.94	0.94	0.94	0.95	0.93	0.91
	50	10	0.92	0.93	0.94	0.93	0.93	0.94	0.93	0.90	0.97	0.90	0.74
		20	0.93	0.95	0.94	0.94	0.94	0.95	0.94	0.93	0.97	0.93	0.83
		50	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.90
		100	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.92
		200	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.92

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B6 (continued)

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
Medium between-level indirect effect size (ab_B = .16)													
.05	5	10	0.96	0.98	0.98	0.97	0.95	0.98	0.90	0.78	1.00	0.87	0.06
		20	0.95	0.95	0.96	0.95	0.94	0.97	0.92	0.81	1.00	0.88	0.26
		50	0.93	0.95	0.95	0.95	0.95	0.97	0.94	0.91	0.99	0.90	0.61
		100	0.95	0.95	0.95	0.95	0.95	0.96	0.95	0.95	0.98	0.93	0.79
		200	0.95	0.95	0.96	0.96	0.96	0.96	0.95	0.95	0.97	0.96	0.91
	10	10	0.92	0.95	0.95	0.94	0.93	0.97	0.91	0.80	1.00	0.87	0.25
		20	0.91	0.96	0.95	0.95	0.95	0.96	0.94	0.89	0.99	0.89	0.51
		50	0.96	0.96	0.95	0.96	0.96	0.95	0.95	0.93	0.99	0.93	0.76
		100	0.94	0.97	0.96	0.96	0.96	0.96	0.96	0.96	0.97	0.94	0.87
		200	0.95	0.96	0.96	0.96	0.95	0.96	0.96	0.96	0.97	0.96	0.93
	20	10	0.86	0.96	0.96	0.95	0.95	0.96	0.94	0.88	0.99	0.89	0.52
		20	0.94	0.96	0.95	0.95	0.95	0.96	0.94	0.93	0.98	0.92	0.69
		50	0.95	0.96	0.96	0.95	0.96	0.95	0.95	0.94	0.96	0.94	0.85
		100	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.96	0.95	0.90
		200	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.95	0.94	0.92
	50	10	0.89	0.94	0.94	0.93	0.93	0.94	0.92	0.90	0.97	0.90	0.73
		20	0.94	0.95	0.95	0.95	0.95	0.95	0.94	0.93	0.96	0.92	0.84
		50	0.94	0.94	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.93	0.90
		100	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.93	0.94	0.94	0.92
		200	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.93
.20	5	10	0.92	0.99	0.98	0.97	0.97	0.99	0.91	0.82	1.00	0.88	0.05
		20	0.94	0.95	0.96	0.95	0.95	0.97	0.93	0.85	1.00	0.89	0.27
		50	0.93	0.95	0.94	0.94	0.94	0.95	0.94	0.93	0.99	0.90	0.59
		100	0.94	0.95	0.95	0.95	0.94	0.95	0.95	0.94	0.98	0.93	0.78
		200	0.93	0.95	0.95	0.94	0.94	0.95	0.94	0.94	0.97	0.95	0.89
	10	10	0.96	0.96	0.95	0.95	0.94	0.97	0.92	0.81	1.00	0.87	0.23
		20	0.93	0.96	0.96	0.96	0.95	0.97	0.94	0.89	0.99	0.89	0.49
		50	0.94	0.95	0.96	0.96	0.95	0.96	0.94	0.92	0.99	0.91	0.75
		100	0.94	0.96	0.95	0.96	0.96	0.96	0.96	0.94	0.97	0.94	0.85
		200	0.95	0.96	0.96	0.96	0.95	0.96	0.96	0.95	0.97	0.95	0.91
	20	10	0.94	0.96	0.96	0.96	0.95	0.96	0.93	0.88	0.99	0.90	0.50
		20	0.93	0.95	0.96	0.95	0.95	0.96	0.94	0.92	0.98	0.91	0.67
		50	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.94	0.97	0.93	0.84
		100	0.95	0.95	0.95	0.95	0.94	0.95	0.95	0.94	0.96	0.94	0.88
		200	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.93	0.95	0.94	0.90
	50	10	0.90	0.94	0.93	0.93	0.93	0.94	0.93	0.90	0.97	0.90	0.73
		20	0.93	0.94	0.95	0.94	0.94	0.95	0.93	0.93	0.96	0.91	0.82
		50	0.93	0.93	0.93	0.94	0.94	0.93	0.94	0.93	0.95	0.93	0.90
		100	0.95	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.91
		200	0.95	0.94	0.94	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.92

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B6 (continued)

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						Null between-level indirect effect (ab_B = 0)							
.05	5	10	0.92	0.99	0.98	0.97	0.96	0.98	0.90	0.77	1.00	0.87	0.07
		20	0.95	0.95	0.96	0.95	0.93	0.97	0.91	0.80	1.00	0.86	0.24
		50	0.89	0.95	0.95	0.95	0.94	0.96	0.94	0.90	0.98	0.90	0.57
		100	0.94	0.94	0.95	0.95	0.94	0.95	0.95	0.93	0.98	0.92	0.74
		200	0.95	0.95	0.96	0.96	0.96	0.96	0.95	0.95	0.97	0.95	0.87
	10	10	0.90	0.95	0.95	0.94	0.92	0.97	0.91	0.79	1.00	0.86	0.23
		20	0.91	0.96	0.96	0.94	0.94	0.96	0.93	0.86	0.99	0.90	0.49
		50	0.95	0.95	0.95	0.95	0.95	0.96	0.94	0.92	0.98	0.91	0.74
		100	0.94	0.96	0.96	0.95	0.95	0.96	0.96	0.95	0.97	0.93	0.85
		200	0.95	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.97	0.95	0.92
	20	10	0.90	0.96	0.95	0.95	0.94	0.96	0.93	0.88	0.99	0.89	0.50
		20	0.88	0.95	0.95	0.95	0.94	0.95	0.94	0.92	0.98	0.92	0.69
		50	0.95	0.95	0.95	0.96	0.95	0.96	0.95	0.94	0.97	0.94	0.84
		100	0.95	0.95	0.95	0.96	0.96	0.95	0.96	0.95	0.96	0.95	0.89
		200	0.94	0.95	0.95	0.94	0.95	0.95	0.94	0.94	0.95	0.94	0.93
	50	10	0.91	0.94	0.94	0.94	0.93	0.93	0.92	0.90	0.97	0.90	0.73
		20	0.94	0.95	0.95	0.95	0.95	0.95	0.95	0.93	0.96	0.93	0.84
		50	0.93	0.94	0.94	0.94	0.94	0.95	0.94	0.93	0.94	0.94	0.90
		100	0.95	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.93
		200	0.94	0.94	0.94	0.94	0.93	0.94	0.94	0.94	0.94	0.94	0.92
.20	5	10	1.00	0.99	0.98	0.98	0.96	0.98	0.91	0.79	1.00	0.87	0.05
		20	0.93	0.94	0.94	0.94	0.93	0.97	0.92	0.81	1.00	0.86	0.22
		50	0.93	0.94	0.95	0.95	0.95	0.95	0.95	0.91	0.99	0.89	0.57
		100	0.94	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.98	0.93	0.78
		200	0.93	0.94	0.94	0.95	0.95	0.95	0.95	0.95	0.97	0.95	0.90
	10	10	0.92	0.96	0.95	0.95	0.93	0.97	0.92	0.80	1.00	0.86	0.22
		20	0.93	0.96	0.96	0.95	0.95	0.96	0.94	0.87	0.99	0.89	0.48
		50	0.94	0.96	0.96	0.96	0.96	0.96	0.95	0.94	0.99	0.91	0.76
		100	0.94	0.96	0.96	0.96	0.96	0.96	0.96	0.95	0.97	0.93	0.87
		200	0.94	0.96	0.96	0.96	0.95	0.95	0.96	0.96	0.97	0.95	0.91
	20	10	0.93	0.96	0.96	0.95	0.95	0.96	0.93	0.87	0.99	0.89	0.50
		20	0.93	0.95	0.96	0.95	0.95	0.96	0.95	0.92	0.98	0.91	0.68
		50	0.95	0.95	0.95	0.96	0.95	0.96	0.95	0.94	0.97	0.94	0.84
		100	0.95	0.96	0.95	0.95	0.95	0.95	0.95	0.94	0.96	0.94	0.89
		200	0.93	0.95	0.94	0.95	0.93	0.94	0.95	0.94	0.95	0.94	0.92
	50	10	0.91	0.94	0.93	0.93	0.93	0.94	0.93	0.90	0.97	0.90	0.73
		20	0.94	0.95	0.94	0.94	0.95	0.95	0.94	0.94	0.96	0.92	0.83
		50	0.93	0.94	0.93	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.90
		100	0.95	0.94	0.94	0.94	0.93	0.94	0.94	0.93	0.94	0.94	0.92
		200	0.94	0.94	0.94	0.93	0.94	0.94	0.94	0.93	0.94	0.94	0.93

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect

Table B7

95% CI Coverage Rates for Between-Level Indirect Effects

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
Small between-level indirect effect size (ab_B = .02)													
.05	5	10	0.98	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
		20	0.98	1.00	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00	1.00
		50	0.98	1.00	1.00	1.00	0.92	1.00	1.00	1.00	1.00	1.00	1.00
		100	0.99	1.00	1.00	1.00	0.86	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	0.83	1.00	1.00	1.00	1.00	0.99	1.00
	10	10	0.98	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	0.93	1.00	1.00	1.00	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	0.86	1.00	1.00	1.00	1.00	0.99	1.00
		100	1.00	1.00	1.00	1.00	0.83	1.00	1.00	0.99	1.00	0.98	0.98
		200	1.00	1.00	1.00	1.00	0.82	1.00	1.00	0.99	1.00	0.93	0.91
	20	10	0.94	1.00	1.00	1.00	0.94	1.00	1.00	1.00	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	0.99	1.00
		50	1.00	1.00	1.00	1.00	0.87	1.00	1.00	1.00	1.00	0.97	0.97
		100	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	0.91	0.84
		200	1.00	1.00	0.99	1.00	0.99	0.99	1.00	1.00	1.00	0.84	0.56
	50	10	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00	0.98	1.00
		20	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	0.97	0.98
		50	1.00	1.00	0.99	1.00	0.96	1.00	1.00	1.00	1.00	0.90	0.80
		100	1.00	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00	0.85	0.46
		200	0.99	0.99	0.98	0.98	0.97	0.99	0.97	0.97	0.99	0.84	0.35
.20	5	10	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	0.88	1.00	1.00	1.00	1.00	0.99	1.00
		50	1.00	1.00	1.00	1.00	0.83	1.00	1.00	1.00	1.00	0.95	0.94
		100	1.00	1.00	1.00	1.00	0.89	1.00	1.00	0.99	1.00	0.91	0.77
		200	1.00	0.99	1.00	1.00	0.98	0.99	1.00	1.00	1.00	0.85	0.45
	10	10	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00	0.99	1.00
		20	1.00	1.00	1.00	1.00	0.84	1.00	1.00	1.00	1.00	0.95	0.96
		50	1.00	1.00	1.00	1.00	0.94	1.00	1.00	1.00	1.00	0.91	0.77
		100	0.99	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	0.86	0.46
		200	0.98	0.98	0.98	0.97	0.97	0.98	0.97	0.98	1.00	0.86	0.38
	20	10	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	0.99	0.99
		20	0.99	1.00	1.00	1.00	0.91	1.00	1.00	0.99	1.00	0.94	0.93
		50	0.99	1.00	0.99	1.00	0.99	1.00	1.00	1.00	1.00	0.90	0.61
		100	0.99	1.00	0.99	0.99	0.99	0.99	1.00	1.00	1.00	0.85	0.35
		200	0.97	0.97	0.97	0.96	0.96	0.97	0.95	0.89	0.99	0.86	0.41
	50	10	0.99	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	0.97	0.98
		20	0.99	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	0.95	0.87
		50	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.87	0.48
		100	0.98	0.98	0.98	0.98	0.99	0.98	0.98	0.99	0.99	0.88	0.32
		200	0.95	0.95	0.96	0.96	0.95	0.96	0.93	0.88	0.99	0.87	0.48

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B7 (continued)

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
Medium between-level indirect effect size (ab_B = .16)													
.05	5	10	0.90	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00
		20	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00
		50	0.99	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	0.00
		100	0.99	1.00	1.00	1.00	0.99	1.00	0.98	0.99	1.00	1.00	0.00
		200	0.98	1.00	1.00	1.00	0.99	1.00	0.97	0.97	1.00	0.99	0.01
	10	10	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00
		20	0.96	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.00
		50	0.99	1.00	1.00	1.00	0.99	1.00	0.97	0.97	1.00	0.99	0.00
		100	0.98	1.00	1.00	1.00	0.99	1.00	0.96	0.94	1.00	0.98	0.02
		200	0.97	0.98	0.99	0.99	0.99	1.00	0.94	0.83	1.00	0.97	0.09
	20	10	0.93	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.00
		20	0.99	1.00	1.00	1.00	1.00	1.00	0.96	0.98	1.00	0.99	0.00
		50	0.97	0.99	1.00	1.00	0.99	1.00	0.94	0.90	1.00	0.97	0.02
		100	0.95	0.97	0.98	0.98	0.98	0.99	0.92	0.79	1.00	0.95	0.11
		200	0.96	0.96	0.96	0.95	0.93	0.99	0.94	0.78	1.00	0.94	0.30
	50	10	0.94	1.00	1.00	1.00	1.00	1.00	0.98	0.99	1.00	1.00	0.00
		20	0.96	1.00	1.00	1.00	0.99	1.00	0.95	0.88	1.00	0.99	0.01
		50	0.95	0.97	0.98	0.97	0.97	0.98	0.92	0.71	1.00	0.94	0.09
		100	0.95	0.94	0.94	0.93	0.92	0.97	0.93	0.80	1.00	0.91	0.27
		200	0.96	0.94	0.94	0.94	0.95	0.96	0.94	0.87	0.99	0.93	0.49
.20	5	10	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.00
		20	0.98	1.00	1.00	1.00	0.99	1.00	0.97	0.98	1.00	0.99	0.00
		50	0.97	0.99	1.00	1.00	1.00	0.99	0.95	0.90	1.00	0.96	0.05
		100	0.96	0.97	0.97	0.97	0.97	0.99	0.92	0.80	1.00	0.94	0.17
		200	0.95	0.95	0.96	0.95	0.93	0.98	0.95	0.83	1.00	0.93	0.40
	10	10	0.96	1.00	1.00	1.00	1.00	1.00	0.98	0.98	1.00	1.00	0.00
		20	0.97	1.00	1.00	1.00	0.99	1.00	0.94	0.90	1.00	0.97	0.01
		50	0.94	0.96	0.97	0.97	0.97	0.99	0.92	0.73	1.00	0.94	0.11
		100	0.95	0.95	0.95	0.94	0.93	0.97	0.93	0.82	1.00	0.93	0.31
		200	0.95	0.95	0.95	0.95	0.93	0.96	0.94	0.88	1.00	0.93	0.52
	20	10	0.97	1.00	1.00	1.00	1.00	1.00	0.98	0.95	1.00	0.99	0.00
		20	0.94	1.00	0.99	0.99	0.99	1.00	0.92	0.77	1.00	0.96	0.04
		50	0.93	0.96	0.96	0.94	0.92	0.99	0.93	0.73	1.00	0.93	0.17
		100	0.94	0.96	0.95	0.95	0.93	0.97	0.94	0.84	1.00	0.91	0.38
		200	0.95	0.95	0.95	0.94	0.95	0.97	0.94	0.90	1.00	0.93	0.59
	50	10	0.95	1.00	1.00	1.00	1.00	1.00	0.96	0.92	1.00	0.99	0.01
		20	0.92	0.99	0.99	0.98	0.98	0.99	0.92	0.69	1.00	0.96	0.03
		50	0.93	0.95	0.96	0.94	0.92	0.98	0.92	0.76	1.00	0.92	0.20
		100	0.94	0.94	0.95	0.94	0.93	0.96	0.94	0.86	1.00	0.92	0.42
		200	0.95	0.95	0.96	0.95	0.94	0.96	0.94	0.90	0.99	0.93	0.65

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B7 (continued)

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
					Null between-level indirect effect ($ab_B = 0$)								
.05	5	10	0.95	1.00	1.00	1.00	0.93	1.00	1.00	0.97	1.00	1.00	0.99
		20	1.00	1.00	1.00	1.00	0.86	1.00	1.00	0.94	1.00	1.00	0.99
		50	0.99	1.00	1.00	1.00	0.81	1.00	1.00	0.89	1.00	1.00	0.99
		100	1.00	1.00	1.00	1.00	0.73	1.00	1.00	0.83	1.00	1.00	0.98
		200	1.00	1.00	1.00	1.00	0.65	1.00	1.00	0.76	1.00	1.00	0.96
	10	10	0.96	1.00	1.00	1.00	0.89	1.00	1.00	0.94	1.00	1.00	0.99
		20	1.00	1.00	1.00	1.00	0.81	1.00	1.00	0.87	1.00	1.00	0.98
		50	1.00	1.00	1.00	1.00	0.72	1.00	1.00	0.79	1.00	1.00	0.97
		100	1.00	1.00	1.00	1.00	0.60	1.00	1.00	0.73	1.00	1.00	0.93
		200	1.00	1.00	1.00	0.98	0.55	1.00	1.00	0.65	1.00	1.00	0.87
	20	10	0.95	1.00	1.00	1.00	0.84	1.00	1.00	0.91	1.00	1.00	0.98
		20	1.00	1.00	1.00	1.00	0.76	1.00	1.00	0.82	1.00	1.00	0.96
		50	1.00	1.00	1.00	1.00	0.66	1.00	1.00	0.76	1.00	1.00	0.90
		100	1.00	1.00	1.00	0.99	0.67	1.00	1.00	0.74	1.00	1.00	0.87
		200	1.00	1.00	1.00	0.99	0.84	1.00	0.99	0.78	1.00	1.00	0.84
	50	10	1.00	1.00	1.00	1.00	0.79	1.00	1.00	0.84	1.00	1.00	0.95
		20	1.00	1.00	1.00	1.00	0.71	1.00	1.00	0.79	1.00	1.00	0.92
		50	1.00	1.00	1.00	0.99	0.80	1.00	1.00	0.83	1.00	1.00	0.89
		100	1.00	1.00	1.00	0.99	0.96	1.00	0.99	0.91	1.00	1.00	0.90
		200	1.00	1.00	1.00	0.99	0.99	1.00	1.00	0.96	1.00	1.00	0.90
.20	5	10	1.00	1.00	1.00	1.00	0.88	1.00	1.00	0.94	1.00	1.00	0.99
		20	1.00	1.00	1.00	1.00	0.74	1.00	1.00	0.85	1.00	1.00	0.95
		50	1.00	1.00	1.00	0.99	0.62	1.00	1.00	0.75	1.00	1.00	0.92
		100	1.00	1.00	1.00	0.98	0.67	1.00	1.00	0.76	1.00	1.00	0.90
		200	1.00	1.00	1.00	0.98	0.88	1.00	1.00	0.84	1.00	1.00	0.88
	10	10	1.00	1.00	1.00	1.00	0.79	1.00	1.00	0.85	1.00	1.00	0.98
		20	1.00	1.00	1.00	1.00	0.67	1.00	1.00	0.77	1.00	1.00	0.91
		50	1.00	1.00	1.00	0.99	0.76	1.00	1.00	0.82	1.00	1.00	0.90
		100	1.00	1.00	1.00	1.00	0.94	1.00	1.00	0.91	1.00	1.00	0.89
		200	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.98	1.00	1.00	0.92
	20	10	1.00	1.00	1.00	1.00	0.74	1.00	1.00	0.83	1.00	1.00	0.94
		20	1.00	1.00	1.00	0.99	0.76	1.00	1.00	0.81	1.00	1.00	0.92
		50	1.00	1.00	1.00	1.00	0.95	1.00	1.00	0.92	1.00	1.00	0.90
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	0.92
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.94
	50	10	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.81	1.00	1.00	0.93
		20	0.99	1.00	1.00	1.00	0.83	1.00	1.00	0.87	1.00	1.00	0.90
		50	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.96	1.00	1.00	0.91
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.94
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.96

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B8

Non-Null Detection Rates for Within-Level Indirect Effects

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
					Small between-level indirect effect size (ab_B = .02)								
.05	5	10	0.00	0.03	0.05	0.03	0.01	0.09	0.01	0.00	1.00	0.63	0.02
		20	0.24	0.21	0.23	0.21	0.18	0.33	0.18	0.09	1.00	0.88	0.29
		50	0.65	0.78	0.79	0.81	0.80	0.86	0.81	0.75	1.00	0.99	0.93
		100	0.97	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	10	10	0.16	0.24	0.24	0.20	0.17	0.35	0.19	0.08	1.00	0.88	0.30
		20	0.57	0.68	0.68	0.67	0.64	0.78	0.68	0.56	1.00	0.99	0.85
		50	0.99	0.99	0.99	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	20	10	0.61	0.72	0.74	0.71	0.68	0.80	0.71	0.59	1.00	0.99	0.85
		20	0.97	0.98	0.98	0.98	0.98	0.99	0.98	0.97	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	50	10	1.00	0.99	1.00	0.99	1.00	1.00	0.99	0.99	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
.20	5	10	0.06	0.03	0.04	0.03	0.01	0.07	0.01	0.00	0.99	0.62	0.01
		20	0.21	0.19	0.20	0.18	0.18	0.29	0.18	0.08	1.00	0.87	0.24
		50	0.67	0.71	0.72	0.73	0.76	0.80	0.77	0.72	1.00	0.99	0.90
		100	0.98	0.99	0.98	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	10	10	0.26	0.21	0.23	0.21	0.15	0.34	0.18	0.08	1.00	0.87	0.26
		20	0.62	0.63	0.64	0.62	0.63	0.75	0.65	0.53	1.00	0.99	0.81
		50	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	20	10	0.69	0.69	0.70	0.67	0.65	0.79	0.68	0.57	1.00	0.98	0.85
		20	0.96	0.97	0.98	0.97	0.97	0.98	0.97	0.96	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	50	10	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B8 (continued)

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
					Medium between-level indirect effect size (ab_B = .16)								
.05	5	10	0.04	0.03	0.05	0.04	0.02	0.08	0.02	0.00	1.00	0.66	0.02
		20	0.26	0.22	0.25	0.22	0.20	0.35	0.21	0.09	1.00	0.89	0.29
		50	0.69	0.80	0.82	0.82	0.82	0.86	0.83	0.79	1.00	1.00	0.93
		100	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	10	10	0.17	0.25	0.24	0.22	0.18	0.35	0.18	0.09	1.00	0.87	0.29
		20	0.63	0.69	0.71	0.68	0.68	0.78	0.69	0.58	1.00	0.98	0.85
		50	0.99	1.00	0.99	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	20	10	0.64	0.74	0.73	0.72	0.70	0.82	0.72	0.60	1.00	0.98	0.86
		20	0.97	0.98	0.98	0.98	0.98	0.99	0.98	0.97	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	50	10	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
.20	5	10	0.08	0.03	0.04	0.04	0.02	0.07	0.01	0.01	1.00	0.65	0.02
		20	0.22	0.20	0.22	0.20	0.20	0.31	0.18	0.10	1.00	0.87	0.25
		50	0.68	0.73	0.71	0.73	0.77	0.80	0.75	0.73	1.00	0.99	0.90
		100	0.98	0.99	0.98	0.98	0.99	0.99	0.99	0.99	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	10	10	0.21	0.21	0.24	0.20	0.17	0.33	0.18	0.08	1.00	0.87	0.26
		20	0.64	0.65	0.64	0.63	0.63	0.74	0.64	0.53	1.00	0.98	0.82
		50	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	20	10	0.65	0.69	0.70	0.69	0.67	0.79	0.68	0.56	1.00	0.98	0.84
		20	0.96	0.97	0.97	0.98	0.97	0.98	0.97	0.96	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	50	10	0.99	0.99	0.99	0.99	1.00	1.00	1.00	0.99	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B8 (continued)

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
						Null between-level indirect effect ($ab_B = 0$)							
.05	5	10	0.02	0.03	0.04	0.03	0.02	0.08	0.01	0.00	0.99	0.65	0.02
		20	0.24	0.21	0.22	0.21	0.17	0.32	0.20	0.09	1.00	0.88	0.28
		50	0.63	0.78	0.79	0.79	0.79	0.86	0.81	0.75	1.00	1.00	0.93
		100	0.98	0.99	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	10	10	0.12	0.23	0.24	0.19	0.17	0.33	0.18	0.08	0.99	0.87	0.28
		20	0.61	0.67	0.67	0.67	0.62	0.76	0.66	0.55	1.00	0.99	0.83
		50	0.99	0.99	0.99	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	20	10	0.62	0.71	0.72	0.70	0.68	0.81	0.71	0.59	1.00	0.98	0.87
		20	0.96	0.98	0.98	0.98	0.97	0.99	0.98	0.97	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	50	10	1.00	0.99	0.99	0.99	0.99	1.00	0.99	0.99	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
.20	5	10	0.00	0.03	0.04	0.02	0.01	0.07	0.01	0.00	0.99	0.61	0.01
		20	0.19	0.17	0.19	0.17	0.15	0.27	0.15	0.07	1.00	0.86	0.23
		50	0.65	0.70	0.71	0.72	0.73	0.80	0.75	0.70	1.00	0.99	0.91
		100	0.98	0.98	0.99	0.98	0.99	0.99	0.99	0.99	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	10	10	0.21	0.21	0.21	0.18	0.15	0.31	0.17	0.07	0.99	0.85	0.25
		20	0.62	0.63	0.64	0.62	0.61	0.74	0.64	0.53	1.00	0.98	0.80
		50	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	20	10	0.67	0.68	0.70	0.67	0.65	0.79	0.68	0.57	1.00	0.98	0.85
		20	0.96	0.97	0.97	0.97	0.96	0.98	0.97	0.96	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	50	10	0.99	0.99	1.00	0.99	0.99	1.00	0.99	0.99	1.00	1.00	1.00
		20	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		100	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		200	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B9

Non-Null Detection Rates for Between-Level Indirect Effects

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
Small between-level indirect effect size (ab_B = .02)													
.05	5	10	0.02	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
		20	0.02	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00
		50	0.02	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00
		100	0.01	0.00	0.00	0.00	0.16	0.00	0.00	0.01	0.00	0.00	0.00
		200	0.00	0.00	0.00	0.00	0.18	0.00	0.00	0.01	0.00	0.00	0.00
	10	10	0.02	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00
		20	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00
		50	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.02	0.00	0.00	0.00
		100	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.02	0.00	0.00	0.00
		200	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.02	0.00	0.00	0.00
	20	10	0.06	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00
		20	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.01	0.00	0.00	0.00
		50	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.01	0.00	0.00	0.00
		100	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.01	0.00	0.00	0.00
		200	0.01	0.01	0.01	0.00	0.02	0.01	0.00	0.01	0.02	0.00	0.00
	50	10	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.01	0.00	0.00	0.00
		20	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.01	0.00	0.00	0.00
		50	0.01	0.00	0.00	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.00
		100	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.04	0.00	0.00
		200	0.03	0.03	0.03	0.02	0.02	0.04	0.02	0.01	0.13	0.00	0.00
.20	5	10	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00
		20	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.01	0.00	0.00	0.00
		50	0.00	0.00	0.00	0.00	0.19	0.00	0.00	0.01	0.00	0.00	0.00
		100	0.01	0.00	0.00	0.00	0.12	0.00	0.00	0.01	0.00	0.00	0.00
		200	0.02	0.01	0.01	0.01	0.03	0.01	0.00	0.00	0.04	0.00	0.00
	10	10	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00
		20	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.01	0.00	0.00	0.00
		50	0.00	0.01	0.00	0.00	0.07	0.00	0.00	0.01	0.01	0.00	0.00
		100	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.04	0.00	0.00
		200	0.04	0.04	0.04	0.03	0.02	0.04	0.02	0.01	0.13	0.01	0.00
	20	10	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00
		20	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.02	0.00	0.00	0.00
		50	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.02	0.00	0.00
		100	0.03	0.02	0.02	0.01	0.01	0.02	0.00	0.00	0.07	0.00	0.00
		200	0.07	0.06	0.06	0.05	0.04	0.07	0.03	0.02	0.21	0.02	0.00
	50	10	0.01	0.00	0.00	0.00	0.11	0.00	0.00	0.01	0.00	0.00	0.00
		20	0.01	0.00	0.00	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.00
		50	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.03	0.00	0.00
		100	0.03	0.02	0.03	0.02	0.02	0.04	0.01	0.01	0.10	0.01	0.00
		200	0.08	0.08	0.08	0.07	0.06	0.09	0.05	0.03	0.28	0.04	0.00

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B9 (continued)

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
Medium between-level indirect effect size (ab_B = .16)													
.05	5	10	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.02
		20	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	1.00	0.04
		50	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	1.00	1.00	0.09
		100	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	1.00	1.00	0.13
		200	0.01	0.00	0.00	0.00	0.04	0.02	0.00	0.00	1.00	1.00	0.28
	10	10	0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	1.00	0.04
		20	0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	1.00	0.08
		50	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	1.00	1.00	0.21
		100	0.01	0.01	0.00	0.00	0.03	0.04	0.00	0.00	1.00	1.00	0.43
		200	0.04	0.05	0.05	0.03	0.04	0.19	0.04	0.01	1.00	1.00	0.71
	20	10	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	1.00	0.09
		20	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	1.00	1.00	0.19
		50	0.01	0.01	0.01	0.00	0.01	0.07	0.00	0.00	1.00	1.00	0.51
		100	0.05	0.07	0.06	0.04	0.04	0.26	0.07	0.01	1.00	1.00	0.78
		200	0.34	0.30	0.30	0.28	0.24	0.58	0.40	0.19	1.00	1.00	0.95
	50	10	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	1.00	0.16
		20	0.01	0.00	0.00	0.00	0.01	0.03	0.00	0.00	1.00	1.00	0.39
		50	0.08	0.05	0.05	0.04	0.03	0.22	0.05	0.01	1.00	1.00	0.76
		100	0.34	0.31	0.33	0.29	0.25	0.56	0.35	0.18	1.00	1.00	0.94
		200	0.82	0.77	0.78	0.77	0.74	0.90	0.83	0.73	1.00	1.00	1.00
.20	5	10	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	1.00	0.08
		20	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	1.00	1.00	0.23
		50	0.02	0.00	0.00	0.00	0.02	0.09	0.01	0.00	1.00	1.00	0.62
		100	0.12	0.09	0.08	0.06	0.04	0.29	0.09	0.02	1.00	1.00	0.86
		200	0.47	0.41	0.40	0.37	0.33	0.68	0.49	0.31	1.00	1.00	0.98
	10	10	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	1.00	0.17
		20	0.01	0.00	0.00	0.00	0.02	0.04	0.00	0.00	1.00	1.00	0.41
		50	0.08	0.06	0.06	0.05	0.04	0.24	0.06	0.01	1.00	1.00	0.79
		100	0.38	0.32	0.33	0.30	0.25	0.58	0.39	0.18	1.00	1.00	0.95
		200	0.84	0.82	0.81	0.80	0.76	0.92	0.86	0.75	1.00	1.00	1.00
	20	10	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	1.00	1.00	0.25
		20	0.02	0.01	0.01	0.01	0.01	0.08	0.01	0.00	1.00	1.00	0.54
		50	0.20	0.15	0.17	0.13	0.10	0.37	0.16	0.04	1.00	1.00	0.88
		100	0.57	0.55	0.57	0.53	0.49	0.75	0.61	0.42	1.00	1.00	0.98
		200	0.95	0.94	0.94	0.93	0.92	0.97	0.96	0.93	1.00	1.00	1.00
	50	10	0.01	0.00	0.00	0.00	0.01	0.02	0.00	0.00	1.00	1.00	0.32
		20	0.06	0.01	0.02	0.01	0.01	0.09	0.01	0.00	1.00	1.00	0.61
		50	0.28	0.19	0.22	0.20	0.15	0.48	0.24	0.08	1.00	1.00	0.92
		100	0.70	0.67	0.70	0.66	0.61	0.85	0.75	0.57	1.00	1.00	0.99
		200	0.98	0.98	0.98	0.98	0.97	0.99	0.98	0.97	1.00	1.00	1.00

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Table B10

Type I Error Rates for the Null Between-Level Indirect Effect (ab_B = 0)

ICC	N_j	J	ML	Diffuse	μ,1.0	1σ,1.0	2σ,1.0	μ,.10	1σ,.10	2σ,.10	μ,.01	1σ,.01	2σ,.01
.05	5	10	0.05	0.00	0.00	0.00	0.07	0.00	0.00	0.03	0.00	0.00	0.01
		20	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.06	0.00	0.00	0.01
		50	0.01	0.00	0.00	0.00	0.20	0.00	0.00	0.11	0.00	0.00	0.01
		100	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.17	0.00	0.00	0.02
		200	0.00	0.00	0.00	0.00	0.35	0.00	0.00	0.24	0.00	0.00	0.04
	10	10	0.04	0.00	0.00	0.00	0.11	0.00	0.00	0.06	0.00	0.00	0.01
		20	0.00	0.00	0.00	0.00	0.19	0.00	0.00	0.13	0.00	0.00	0.02
		50	0.00	0.00	0.00	0.00	0.28	0.00	0.00	0.21	0.00	0.00	0.03
		100	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.27	0.00	0.00	0.07
		200	0.00	0.00	0.00	0.02	0.45	0.00	0.00	0.35	0.00	0.00	0.13
	20	10	0.05	0.00	0.00	0.00	0.16	0.00	0.00	0.09	0.00	0.00	0.02
		20	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.18	0.00	0.00	0.04
		50	0.00	0.00	0.00	0.00	0.34	0.00	0.00	0.24	0.00	0.00	0.10
		100	0.00	0.00	0.00	0.01	0.33	0.00	0.00	0.26	0.00	0.00	0.13
		200	0.00	0.00	0.01	0.01	0.16	0.00	0.01	0.22	0.00	0.00	0.16
	50	10	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.16	0.00	0.00	0.05
		20	0.00	0.00	0.00	0.00	0.30	0.00	0.00	0.21	0.00	0.00	0.08
		50	0.00	0.00	0.00	0.01	0.20	0.00	0.00	0.17	0.00	0.00	0.11
		100	0.00	0.00	0.00	0.01	0.04	0.00	0.01	0.09	0.00	0.00	0.10
		200	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.04	0.00	0.00	0.10
.20	5	10	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.06	0.00	0.00	0.01
		20	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.15	0.00	0.00	0.05
		50	0.00	0.00	0.00	0.01	0.38	0.00	0.00	0.25	0.00	0.00	0.08
		100	0.00	0.00	0.00	0.02	0.33	0.00	0.01	0.24	0.00	0.00	0.10
		200	0.00	0.00	0.00	0.02	0.12	0.00	0.01	0.16	0.00	0.00	0.12
	10	10	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.15	0.00	0.00	0.02
		20	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.23	0.00	0.00	0.10
		50	0.00	0.00	0.00	0.01	0.24	0.00	0.00	0.18	0.00	0.00	0.10
		100	0.00	0.00	0.00	0.00	0.06	0.00	0.01	0.09	0.00	0.00	0.11
		200	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.08
	20	10	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.17	0.00	0.00	0.06
		20	0.00	0.00	0.00	0.01	0.25	0.00	0.00	0.19	0.00	0.00	0.09
		50	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.08	0.00	0.00	0.10
		100	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.09
		200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.06
	50	10	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.19	0.00	0.00	0.07
		20	0.01	0.00	0.00	0.00	0.17	0.00	0.00	0.13	0.00	0.00	0.10
		50	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.04	0.00	0.00	0.09
		100	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.06
		200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.04

Note. N_j = cluster size; J = number of clusters; ab_B = between-level indirect effect.

Appendix C

Table C1

Model A, 6 Items, Correctly Specified, Covariance = 0.3, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.032	(0.048)	0.948	(0.098)	0.905	(0.172)	0.531	(0.288)
	MCMC Diffuse	0.057	(0.055)	0.863	(0.179)	0.778	(0.261)	0.454	(0.169)
	MCMC Weak	0.040	(0.048)	0.896	(0.158)	0.860	(0.205)	0.501	(0.190)
	MCMC -1SD	0.074	(0.055)	0.775	(0.199)	0.722	(0.237)	0.371	(0.203)
	MCMC +1SD	0.052	(0.049)	0.828	(0.238)	0.798	(0.257)	0.463	(0.190)
100	ML	0.025	(0.035)	0.964	(0.065)	0.933	(0.122)	0.515	(0.291)
	MCMC Diffuse	0.029	(0.036)	0.954	(0.075)	0.916	(0.136)	0.486	(0.166)
	MCMC Weak	0.021	(0.031)	0.965	(0.065)	0.947	(0.100)	0.532	(0.181)
	MCMC -1SD	0.051	(0.042)	0.888	(0.117)	0.844	(0.161)	0.374	(0.206)
	MCMC +1SD	0.026	(0.033)	0.947	(0.096)	0.925	(0.130)	0.491	(0.176)
250	ML	0.016	(0.022)	0.984	(0.029)	0.970	(0.054)	0.501	(0.286)
	MCMC Diffuse	0.017	(0.023)	0.982	(0.030)	0.967	(0.059)	0.486	(0.175)
	MCMC Weak	0.014	(0.021)	0.985	(0.028)	0.975	(0.050)	0.519	(0.182)
	MCMC -1SD	0.021	(0.025)	0.976	(0.039)	0.959	(0.065)	0.463	(0.187)
	MCMC +1SD	0.016	(0.021)	0.983	(0.029)	0.972	(0.050)	0.496	(0.178)
500	ML	0.011	(0.016)	0.992	(0.015)	0.985	(0.029)	0.528	(0.296)
	MCMC Diffuse	0.012	(0.016)	0.992	(0.015)	0.983	(0.030)	0.498	(0.179)
	MCMC Weak	0.009	(0.015)	0.993	(0.014)	0.987	(0.025)	0.518	(0.175)
	MCMC -1SD	0.012	(0.016)	0.991	(0.015)	0.984	(0.029)	0.495	(0.177)
	MCMC +1SD	0.010	(0.015)	0.992	(0.015)	0.986	(0.027)	0.507	(0.180)
1000	ML	0.008	(0.011)	0.996	(0.007)	0.992	(0.014)	0.503	(0.286)
	MCMC Diffuse	0.008	(0.011)	0.996	(0.007)	0.992	(0.014)	0.491	(0.172)
	MCMC Weak	0.007	(0.011)	0.996	(0.007)	0.993	(0.013)	0.504	(0.176)
	MCMC -1SD	0.008	(0.011)	0.996	(0.007)	0.992	(0.014)	0.500	(0.181)
	MCMC +1SD	0.008	(0.011)	0.996	(0.007)	0.992	(0.015)	0.498	(0.177)

Table C2

Model A, 6 Items, Correctly Specified, Covariance = 0.3, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.044	(0.054)	0.974	(0.042)	0.950	(0.079)	0.461	(0.293)
	MCMC Diffuse	0.061	(0.056)	0.957	(0.053)	0.928	(0.094)	0.445	(0.174)
	MCMC Weak	0.042	(0.050)	0.969	(0.049)	0.956	(0.069)	0.503	(0.188)
	MCMC -1SD	0.087	(0.072)	0.907	(0.102)	0.876	(0.130)	0.353	(0.225)
	MCMC +1SD	0.058	(0.051)	0.949	(0.065)	0.933	(0.087)	0.437	(0.179)
100	ML	0.029	(0.038)	0.987	(0.022)	0.976	(0.041)	0.486	(0.295)
	MCMC Diffuse	0.032	(0.038)	0.985	(0.023)	0.973	(0.043)	0.476	(0.174)
	MCMC Weak	0.023	(0.034)	0.989	(0.020)	0.982	(0.034)	0.514	(0.178)
	MCMC -1SD	0.033	(0.039)	0.984	(0.026)	0.973	(0.044)	0.472	(0.180)
	MCMC +1SD	0.033	(0.036)	0.983	(0.024)	0.973	(0.039)	0.465	(0.173)
250	ML	0.017	(0.022)	0.996	(0.008)	0.992	(0.015)	0.495	(0.287)
	MCMC Diffuse	0.019	(0.024)	0.995	(0.009)	0.990	(0.018)	0.484	(0.179)
	MCMC Weak	0.015	(0.022)	0.996	(0.008)	0.992	(0.015)	0.502	(0.185)
	MCMC -1SD	0.018	(0.023)	0.995	(0.008)	0.991	(0.016)	0.480	(0.180)
	MCMC +1SD	0.018	(0.023)	0.995	(0.009)	0.990	(0.016)	0.473	(0.179)
500	ML	0.011	(0.016)	0.998	(0.004)	0.996	(0.008)	0.526	(0.297)
	MCMC Diffuse	0.012	(0.017)	0.998	(0.004)	0.995	(0.008)	0.494	(0.185)
	MCMC Weak	0.011	(0.016)	0.998	(0.004)	0.996	(0.008)	0.502	(0.184)
	MCMC -1SD	0.012	(0.016)	0.998	(0.004)	0.996	(0.008)	0.494	(0.184)
	MCMC +1SD	0.012	(0.016)	0.998	(0.004)	0.996	(0.008)	0.493	(0.180)
1000	ML	0.008	(0.011)	0.999	(0.002)	0.998	(0.004)	0.504	(0.285)
	MCMC Diffuse	0.008	(0.011)	0.999	(0.002)	0.998	(0.004)	0.491	(0.181)
	MCMC Weak	0.008	(0.011)	0.999	(0.002)	0.998	(0.004)	0.498	(0.175)
	MCMC -1SD	0.008	(0.011)	0.999	(0.002)	0.998	(0.004)	0.497	(0.180)
	MCMC +1SD	0.008	(0.011)	0.999	(0.002)	0.998	(0.004)	0.492	(0.179)

Table C3

Model A, 6 Items, Correctly Specified, Covariance = 0.5, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.034	(0.049)	0.951	(0.086)	0.907	(0.162)	0.517	(0.288)
	MCMC Diffuse	0.059	(0.056)	0.871	(0.165)	0.785	(0.255)	0.450	(0.162)
	MCMC Weak	0.040	(0.047)	0.909	(0.139)	0.877	(0.183)	0.505	(0.196)
	MCMC -1SD	0.066	(0.054)	0.824	(0.172)	0.779	(0.212)	0.402	(0.205)
	MCMC +1SD	0.051	(0.049)	0.838	(0.227)	0.817	(0.239)	0.457	(0.186)
100	ML	0.026	(0.036)	0.966	(0.060)	0.935	(0.113)	0.505	(0.293)
	MCMC Diffuse	0.030	(0.038)	0.956	(0.071)	0.919	(0.131)	0.486	(0.172)
	MCMC Weak	0.021	(0.031)	0.968	(0.062)	0.951	(0.098)	0.534	(0.183)
	MCMC -1SD	0.053	(0.041)	0.894	(0.104)	0.853	(0.147)	0.365	(0.202)
	MCMC +1SD	0.028	(0.034)	0.951	(0.081)	0.928	(0.118)	0.483	(0.177)
250	ML	0.017	(0.022)	0.985	(0.026)	0.973	(0.048)	0.502	(0.289)
	MCMC Diffuse	0.018	(0.024)	0.983	(0.029)	0.967	(0.057)	0.485	(0.179)
	MCMC Weak	0.014	(0.021)	0.987	(0.025)	0.977	(0.043)	0.518	(0.184)
	MCMC -1SD	0.029	(0.029)	0.965	(0.046)	0.942	(0.075)	0.399	(0.202)
	MCMC +1SD	0.017	(0.022)	0.982	(0.029)	0.971	(0.050)	0.483	(0.188)
500	ML	0.011	(0.016)	0.993	(0.014)	0.987	(0.025)	0.527	(0.294)
	MCMC Diffuse	0.012	(0.016)	0.992	(0.014)	0.985	(0.028)	0.498	(0.177)
	MCMC Weak	0.010	(0.015)	0.993	(0.013)	0.987	(0.025)	0.512	(0.184)
	MCMC -1SD	0.013	(0.017)	0.991	(0.016)	0.983	(0.029)	0.471	(0.181)
	MCMC +1SD	0.011	(0.016)	0.992	(0.014)	0.986	(0.027)	0.493	(0.180)
1000	ML	0.008	(0.011)	0.996	(0.007)	0.993	(0.012)	0.505	(0.286)
	MCMC Diffuse	0.008	(0.011)	0.996	(0.007)	0.993	(0.013)	0.493	(0.178)
	MCMC Weak	0.008	(0.011)	0.997	(0.006)	0.993	(0.013)	0.498	(0.179)
	MCMC -1SD	0.008	(0.011)	0.996	(0.007)	0.993	(0.013)	0.492	(0.182)
	MCMC +1SD	0.008	(0.012)	0.996	(0.007)	0.993	(0.013)	0.490	(0.179)

Table C4

Model A, 6 Items, Correctly Specified, Covariance = 0.5, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.044	(0.054)	0.976	(0.039)	0.954	(0.073)	0.463	(0.292)
	MCMC Diffuse	0.064	(0.058)	0.958	(0.052)	0.926	(0.092)	0.441	(0.169)
	MCMC Weak	0.045	(0.051)	0.969	(0.045)	0.956	(0.063)	0.494	(0.188)
	MCMC -1SD	0.112	(0.069)	0.879	(0.096)	0.843	(0.123)	0.273	(0.228)
	MCMC +1SD	0.059	(0.051)	0.951	(0.061)	0.935	(0.081)	0.431	(0.182)
100	ML	0.029	(0.038)	0.988	(0.020)	0.978	(0.038)	0.487	(0.296)
	MCMC Diffuse	0.034	(0.039)	0.986	(0.022)	0.973	(0.043)	0.471	(0.172)
	MCMC Weak	0.025	(0.035)	0.989	(0.019)	0.982	(0.033)	0.508	(0.177)
	MCMC -1SD	0.051	(0.054)	0.967	(0.049)	0.947	(0.076)	0.401	(0.222)
	MCMC +1SD	0.035	(0.036)	0.983	(0.023)	0.974	(0.037)	0.453	(0.175)
250	ML	0.017	(0.022)	0.996	(0.007)	0.992	(0.014)	0.495	(0.288)
	MCMC Diffuse	0.019	(0.024)	0.995	(0.008)	0.990	(0.016)	0.476	(0.181)
	MCMC Weak	0.017	(0.023)	0.995	(0.008)	0.991	(0.015)	0.495	(0.184)
	MCMC -1SD	0.020	(0.025)	0.995	(0.008)	0.990	(0.017)	0.466	(0.185)
	MCMC +1SD	0.020	(0.024)	0.994	(0.008)	0.990	(0.016)	0.463	(0.181)
500	ML	0.011	(0.016)	0.998	(0.004)	0.996	(0.007)	0.526	(0.295)
	MCMC Diffuse	0.013	(0.017)	0.998	(0.004)	0.995	(0.008)	0.486	(0.184)
	MCMC Weak	0.011	(0.016)	0.998	(0.004)	0.996	(0.007)	0.494	(0.186)
	MCMC -1SD	0.012	(0.017)	0.998	(0.004)	0.996	(0.008)	0.491	(0.182)
	MCMC +1SD	0.013	(0.017)	0.998	(0.004)	0.996	(0.008)	0.482	(0.179)
1000	ML	0.008	(0.011)	0.999	(0.002)	0.998	(0.003)	0.507	(0.286)
	MCMC Diffuse	0.008	(0.011)	0.999	(0.002)	0.998	(0.003)	0.491	(0.179)
	MCMC Weak	0.008	(0.012)	0.999	(0.002)	0.998	(0.004)	0.496	(0.181)
	MCMC -1SD	0.008	(0.011)	0.999	(0.002)	0.998	(0.004)	0.486	(0.181)
	MCMC +1SD	0.009	(0.012)	0.999	(0.002)	0.998	(0.004)	0.490	(0.182)

Table C5

Model A, 6 Items, Misspecified, Covariance = 0.3, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.061	(0.060)	0.853	(0.192)	0.767	(0.284)	0.371	(0.287)
	MCMC Diffuse	0.069	(0.058)	0.810	(0.207)	0.719	(0.288)	0.414	(0.188)
	MCMC Weak	0.048	(0.052)	0.862	(0.190)	0.829	(0.223)	0.470	(0.211)
	MCMC -1SD	0.063	(0.053)	0.812	(0.192)	0.768	(0.231)	0.412	(0.207)
	MCMC +1SD	0.062	(0.052)	0.779	(0.260)	0.753	(0.274)	0.411	(0.205)
100	ML	0.049	(0.043)	0.904	(0.113)	0.840	(0.187)	0.335	(0.282)
	MCMC Diffuse	0.047	(0.043)	0.905	(0.111)	0.845	(0.185)	0.396	(0.195)
	MCMC Weak	0.034	(0.039)	0.928	(0.100)	0.903	(0.138)	0.444	(0.211)
	MCMC -1SD	0.044	(0.040)	0.904	(0.112)	0.871	(0.153)	0.399	(0.207)
	MCMC +1SD	0.043	(0.040)	0.900	(0.123)	0.865	(0.166)	0.401	(0.203)
250	ML	0.046	(0.029)	0.931	(0.060)	0.885	(0.100)	0.209	(0.238)
	MCMC Diffuse	0.044	(0.030)	0.933	(0.062)	0.889	(0.103)	0.296	(0.199)
	MCMC Weak	0.038	(0.028)	0.941	(0.060)	0.912	(0.090)	0.324	(0.213)
	MCMC -1SD	0.041	(0.029)	0.935	(0.061)	0.903	(0.093)	0.302	(0.209)
	MCMC +1SD	0.041	(0.028)	0.934	(0.062)	0.902	(0.095)	0.305	(0.208)
500	ML	0.047	(0.020)	0.936	(0.041)	0.894	(0.069)	0.090	(0.158)
	MCMC Diffuse	0.046	(0.020)	0.939	(0.040)	0.900	(0.067)	0.168	(0.160)
	MCMC Weak	0.043	(0.019)	0.942	(0.040)	0.909	(0.064)	0.177	(0.169)
	MCMC -1SD	0.044	(0.019)	0.940	(0.039)	0.906	(0.064)	0.173	(0.163)
	MCMC +1SD	0.044	(0.019)	0.941	(0.040)	0.908	(0.064)	0.176	(0.167)
1000	ML	0.049	(0.012)	0.937	(0.027)	0.895	(0.046)	0.011	(0.044)
	MCMC Diffuse	0.048	(0.013)	0.940	(0.026)	0.900	(0.048)	0.045	(0.085)
	MCMC Weak	0.046	(0.013)	0.940	(0.026)	0.905	(0.045)	0.047	(0.088)
	MCMC -1SD	0.047	(0.013)	0.940	(0.026)	0.904	(0.045)	0.044	(0.083)
	MCMC +1SD	0.047	(0.013)	0.940	(0.026)	0.904	(0.045)	0.047	(0.090)

Table C6

Model A, 6 Items, Misspecified, Covariance = 0.3, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.077	(0.063)	0.940	(0.066)	0.900	(0.110)	0.303	(0.275)
	MCMC Diffuse	0.083	(0.060)	0.927	(0.070)	0.891	(0.107)	0.364	(0.188)
	MCMC Weak	0.062	(0.056)	0.944	(0.066)	0.929	(0.085)	0.420	(0.210)
	MCMC -1SD	0.072	(0.056)	0.935	(0.067)	0.918	(0.087)	0.385	(0.201)
	MCMC +1SD	0.080	(0.054)	0.919	(0.081)	0.899	(0.102)	0.354	(0.192)
100	ML	0.070	(0.045)	0.956	(0.040)	0.927	(0.066)	0.218	(0.247)
	MCMC Diffuse	0.069	(0.045)	0.956	(0.040)	0.929	(0.066)	0.311	(0.202)
	MCMC Weak	0.057	(0.044)	0.962	(0.039)	0.946	(0.056)	0.343	(0.212)
	MCMC -1SD	0.063	(0.044)	0.958	(0.039)	0.940	(0.058)	0.323	(0.210)
	MCMC +1SD	0.067	(0.042)	0.953	(0.041)	0.934	(0.061)	0.300	(0.197)
250	ML	0.072	(0.027)	0.962	(0.023)	0.936	(0.038)	0.065	(0.131)
	MCMC Diffuse	0.070	(0.029)	0.963	(0.023)	0.939	(0.040)	0.145	(0.159)
	MCMC Weak	0.066	(0.028)	0.964	(0.023)	0.945	(0.037)	0.159	(0.168)
	MCMC -1SD	0.068	(0.028)	0.963	(0.023)	0.942	(0.038)	0.148	(0.167)
	MCMC +1SD	0.069	(0.028)	0.962	(0.023)	0.942	(0.038)	0.144	(0.158)
500	ML	0.074	(0.017)	0.963	(0.015)	0.938	(0.026)	0.008	(0.038)
	MCMC Diffuse	0.073	(0.017)	0.963	(0.015)	0.940	(0.026)	0.029	(0.066)
	MCMC Weak	0.071	(0.017)	0.964	(0.015)	0.943	(0.026)	0.030	(0.069)
	MCMC -1SD	0.071	(0.017)	0.964	(0.015)	0.942	(0.026)	0.029	(0.065)
	MCMC +1SD	0.072	(0.017)	0.963	(0.015)	0.942	(0.025)	0.029	(0.067)
1000	ML	0.075	(0.011)	0.963	(0.010)	0.938	(0.017)	0.000	(0.000)
	MCMC Diffuse	0.073	(0.012)	0.964	(0.010)	0.941	(0.018)	0.001	(0.012)
	MCMC Weak	0.073	(0.012)	0.964	(0.010)	0.941	(0.018)	0.001	(0.011)
	MCMC -1SD	0.073	(0.012)	0.964	(0.010)	0.941	(0.018)	0.001	(0.014)
	MCMC +1SD	0.073	(0.012)	0.964	(0.010)	0.941	(0.018)	0.001	(0.010)

Table C7

Model A, 6 Items, Misspecified, Covariance = 0.5, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.086	(0.065)	0.792	(0.206)	0.667	(0.308)	0.270	(0.267)
	MCMC Diffuse	0.092	(0.061)	0.737	(0.231)	0.615	(0.312)	0.342	(0.194)
	MCMC Weak	0.067	(0.055)	0.808	(0.207)	0.772	(0.236)	0.399	(0.214)
	MCMC -1SD	0.082	(0.056)	0.753	(0.205)	0.705	(0.242)	0.341	(0.209)
	MCMC +1SD	0.080	(0.055)	0.722	(0.262)	0.679	(0.284)	0.345	(0.201)
100	ML	0.081	(0.045)	0.826	(0.133)	0.710	(0.221)	0.174	(0.224)
	MCMC Diffuse	0.076	(0.045)	0.833	(0.134)	0.733	(0.216)	0.282	(0.193)
	MCMC Weak	0.062	(0.043)	0.858	(0.132)	0.811	(0.178)	0.317	(0.214)
	MCMC -1SD	0.070	(0.043)	0.830	(0.135)	0.774	(0.183)	0.278	(0.202)
	MCMC +1SD	0.069	(0.042)	0.827	(0.148)	0.771	(0.193)	0.284	(0.200)
250	ML	0.083	(0.026)	0.838	(0.077)	0.729	(0.128)	0.036	(0.093)
	MCMC Diffuse	0.080	(0.028)	0.844	(0.080)	0.745	(0.136)	0.099	(0.130)
	MCMC Weak	0.073	(0.027)	0.852	(0.080)	0.784	(0.121)	0.111	(0.144)
	MCMC -1SD	0.076	(0.027)	0.844	(0.080)	0.770	(0.122)	0.103	(0.136)
	MCMC +1SD	0.075	(0.026)	0.846	(0.080)	0.773	(0.122)	0.104	(0.134)
500	ML	0.084	(0.016)	0.839	(0.051)	0.732	(0.085)	0.002	(0.012)
	MCMC Diffuse	0.082	(0.017)	0.843	(0.051)	0.741	(0.094)	0.011	(0.037)
	MCMC Weak	0.079	(0.017)	0.845	(0.051)	0.759	(0.090)	0.013	(0.040)
	MCMC -1SD	0.079	(0.016)	0.844	(0.051)	0.759	(0.086)	0.012	(0.040)
	MCMC +1SD	0.079	(0.016)	0.844	(0.051)	0.761	(0.085)	0.013	(0.039)
1000	ML	0.084	(0.011)	0.841	(0.036)	0.734	(0.059)	0.000	(0.000)
	MCMC Diffuse	0.083	(0.012)	0.843	(0.034)	0.742	(0.066)	0.000	(0.003)
	MCMC Weak	0.081	(0.012)	0.844	(0.034)	0.750	(0.065)	0.000	(0.003)
	MCMC -1SD	0.081	(0.012)	0.843	(0.034)	0.751	(0.064)	0.000	(0.001)
	MCMC +1SD	0.082	(0.012)	0.844	(0.034)	0.749	(0.064)	0.000	(0.003)

Table C8

Model A, 6 Items, Misspecified, Covariance = 0.5, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.125	(0.065)	0.887	(0.082)	0.812	(0.137)	0.141	(0.200)
	MCMC Diffuse	0.127	(0.061)	0.874	(0.084)	0.811	(0.133)	0.235	(0.184)
	MCMC Weak	0.103	(0.058)	0.895	(0.081)	0.868	(0.103)	0.277	(0.205)
	MCMC -1SD	0.112	(0.059)	0.882	(0.082)	0.850	(0.108)	0.245	(0.196)
	MCMC +1SD	0.118	(0.053)	0.865	(0.092)	0.834	(0.117)	0.223	(0.175)
100	ML	0.127	(0.041)	0.895	(0.052)	0.825	(0.087)	0.043	(0.104)
	MCMC Diffuse	0.122	(0.043)	0.898	(0.053)	0.837	(0.088)	0.119	(0.141)
	MCMC Weak	0.110	(0.041)	0.905	(0.053)	0.865	(0.079)	0.132	(0.154)
	MCMC -1SD	0.114	(0.041)	0.899	(0.053)	0.857	(0.077)	0.120	(0.146)
	MCMC +1SD	0.116	(0.038)	0.895	(0.053)	0.853	(0.078)	0.107	(0.132)
250	ML	0.128	(0.022)	0.898	(0.030)	0.830	(0.050)	0.001	(0.005)
	MCMC Diffuse	0.126	(0.025)	0.900	(0.030)	0.835	(0.057)	0.005	(0.020)
	MCMC Weak	0.121	(0.023)	0.901	(0.030)	0.847	(0.052)	0.006	(0.023)
	MCMC -1SD	0.122	(0.024)	0.900	(0.030)	0.845	(0.054)	0.006	(0.022)
	MCMC +1SD	0.122	(0.023)	0.899	(0.030)	0.845	(0.051)	0.006	(0.022)
500	ML	0.128	(0.015)	0.899	(0.020)	0.831	(0.034)	0.000	(0.000)
	MCMC Diffuse	0.126	(0.017)	0.900	(0.020)	0.837	(0.040)	0.000	(0.000)
	MCMC Weak	0.124	(0.017)	0.901	(0.020)	0.843	(0.040)	0.000	(0.003)
	MCMC -1SD	0.124	(0.017)	0.900	(0.020)	0.842	(0.040)	0.000	(0.000)
	MCMC +1SD	0.124	(0.017)	0.900	(0.020)	0.842	(0.040)	0.000	(0.000)
1000	ML	0.128	(0.010)	0.899	(0.014)	0.832	(0.024)	0.000	(0.000)
	MCMC Diffuse	0.126	(0.014)	0.900	(0.013)	0.836	(0.034)	0.000	(0.000)
	MCMC Weak	0.125	(0.013)	0.900	(0.014)	0.839	(0.032)	0.000	(0.000)
	MCMC -1SD	0.125	(0.013)	0.900	(0.014)	0.839	(0.032)	0.000	(0.000)
	MCMC +1SD	0.125	(0.014)	0.900	(0.014)	0.839	(0.033)	0.000	(0.000)

Table C9

Model A, 12 Items, Correctly Specified, Covariance = 0.3, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.048	(0.036)	0.886	(0.110)	0.858	(0.137)	0.308	(0.265)
	MCMC Diffuse	0.057	(0.035)	0.849	(0.122)	0.816	(0.149)	0.458	(0.231)
	MCMC Weak	0.044	(0.034)	0.887	(0.111)	0.873	(0.127)	0.527	(0.245)
	MCMC -1SD	0.067	(0.036)	0.793	(0.142)	0.770	(0.157)	0.375	(0.254)
	MCMC +1SD	0.053	(0.034)	0.841	(0.137)	0.825	(0.151)	0.456	(0.244)
100	ML	0.025	(0.024)	0.957	(0.052)	0.946	(0.065)	0.405	(0.284)
	MCMC Diffuse	0.028	(0.024)	0.948	(0.059)	0.935	(0.073)	0.470	(0.236)
	MCMC Weak	0.022	(0.023)	0.959	(0.054)	0.952	(0.063)	0.523	(0.239)
	MCMC -1SD	0.030	(0.025)	0.942	(0.063)	0.931	(0.075)	0.449	(0.241)
	MCMC +1SD	0.028	(0.024)	0.943	(0.063)	0.934	(0.074)	0.458	(0.237)
250	ML	0.013	(0.014)	0.985	(0.021)	0.982	(0.026)	0.467	(0.290)
	MCMC Diffuse	0.013	(0.014)	0.985	(0.020)	0.982	(0.025)	0.485	(0.238)
	MCMC Weak	0.011	(0.014)	0.987	(0.019)	0.985	(0.023)	0.511	(0.236)
	MCMC -1SD	0.013	(0.014)	0.985	(0.020)	0.982	(0.025)	0.489	(0.233)
	MCMC +1SD	0.013	(0.014)	0.984	(0.021)	0.981	(0.026)	0.481	(0.233)
500	ML	0.008	(0.010)	0.994	(0.010)	0.992	(0.012)	0.489	(0.287)
	MCMC Diffuse	0.009	(0.010)	0.993	(0.011)	0.991	(0.013)	0.488	(0.240)
	MCMC Weak	0.008	(0.010)	0.993	(0.010)	0.992	(0.013)	0.496	(0.243)
	MCMC -1SD	0.008	(0.010)	0.993	(0.011)	0.991	(0.013)	0.488	(0.240)
	MCMC +1SD	0.009	(0.010)	0.993	(0.011)	0.991	(0.013)	0.482	(0.236)
1000	ML	0.006	(0.007)	0.997	(0.005)	0.996	(0.006)	0.504	(0.293)
	MCMC Diffuse	0.005	(0.007)	0.997	(0.005)	0.996	(0.006)	0.488	(0.237)
	MCMC Weak	0.005	(0.007)	0.997	(0.005)	0.996	(0.006)	0.502	(0.238)
	MCMC -1SD	0.006	(0.007)	0.997	(0.005)	0.996	(0.006)	0.495	(0.236)
	MCMC +1SD	0.006	(0.007)	0.997	(0.005)	0.996	(0.006)	0.486	(0.236)

Table C10

Model A, 12 Items, Correctly Specified, Covariance = 0.3, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.050	(0.036)	0.957	(0.042)	0.947	(0.052)	0.291	(0.258)
	MCMC Diffuse	0.058	(0.035)	0.945	(0.045)	0.934	(0.055)	0.445	(0.233)
	MCMC Weak	0.046	(0.035)	0.958	(0.042)	0.952	(0.048)	0.519	(0.242)
	MCMC -1SD	0.054	(0.035)	0.949	(0.045)	0.941	(0.053)	0.458	(0.243)
	MCMC +1SD	0.057	(0.034)	0.942	(0.049)	0.935	(0.054)	0.438	(0.238)
100	ML	0.025	(0.024)	0.986	(0.017)	0.982	(0.021)	0.400	(0.284)
	MCMC Diffuse	0.028	(0.024)	0.983	(0.019)	0.979	(0.024)	0.468	(0.234)
	MCMC Weak	0.024	(0.023)	0.986	(0.018)	0.983	(0.021)	0.510	(0.238)
	MCMC -1SD	0.027	(0.024)	0.984	(0.019)	0.981	(0.023)	0.478	(0.239)
	MCMC +1SD	0.031	(0.024)	0.980	(0.021)	0.976	(0.025)	0.433	(0.230)
250	ML	0.013	(0.015)	0.996	(0.007)	0.994	(0.008)	0.466	(0.289)
	MCMC Diffuse	0.013	(0.014)	0.996	(0.006)	0.995	(0.008)	0.486	(0.228)
	MCMC Weak	0.012	(0.014)	0.996	(0.006)	0.995	(0.007)	0.501	(0.230)
	MCMC -1SD	0.013	(0.014)	0.995	(0.006)	0.994	(0.008)	0.488	(0.230)
	MCMC +1SD	0.015	(0.014)	0.995	(0.007)	0.994	(0.008)	0.456	(0.227)
500	ML	0.008	(0.010)	0.998	(0.003)	0.998	(0.004)	0.489	(0.288)
	MCMC Diffuse	0.009	(0.010)	0.998	(0.003)	0.997	(0.004)	0.491	(0.242)
	MCMC Weak	0.008	(0.010)	0.998	(0.003)	0.998	(0.004)	0.500	(0.242)
	MCMC -1SD	0.008	(0.010)	0.998	(0.003)	0.997	(0.004)	0.488	(0.239)
	MCMC +1SD	0.009	(0.010)	0.998	(0.003)	0.997	(0.004)	0.469	(0.234)
1000	ML	0.005	(0.007)	0.999	(0.001)	0.999	(0.002)	0.505	(0.292)
	MCMC Diffuse	0.006	(0.007)	0.999	(0.002)	0.999	(0.002)	0.487	(0.228)
	MCMC Weak	0.005	(0.007)	0.999	(0.002)	0.999	(0.002)	0.495	(0.235)
	MCMC -1SD	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.491	(0.238)
	MCMC +1SD	0.006	(0.007)	0.999	(0.002)	0.999	(0.002)	0.483	(0.236)

Table C11

Model A, 12 Items, Correctly Specified, Covariance = 0.5, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.048	(0.036)	0.888	(0.109)	0.861	(0.135)	0.304	(0.264)
	MCMC Diffuse	0.058	(0.035)	0.850	(0.122)	0.818	(0.149)	0.455	(0.234)
	MCMC Weak	0.044	(0.034)	0.890	(0.109)	0.877	(0.122)	0.525	(0.244)
	MCMC -1SD	0.068	(0.035)	0.796	(0.132)	0.773	(0.147)	0.362	(0.246)
	MCMC +1SD	0.054	(0.034)	0.846	(0.134)	0.831	(0.146)	0.451	(0.245)
100	ML	0.025	(0.024)	0.958	(0.051)	0.948	(0.063)	0.402	(0.284)
	MCMC Diffuse	0.028	(0.024)	0.949	(0.057)	0.937	(0.070)	0.472	(0.235)
	MCMC Weak	0.022	(0.023)	0.961	(0.051)	0.955	(0.060)	0.522	(0.240)
	MCMC -1SD	0.038	(0.027)	0.920	(0.073)	0.907	(0.086)	0.379	(0.249)
	MCMC +1SD	0.029	(0.024)	0.944	(0.061)	0.936	(0.070)	0.451	(0.237)
250	ML	0.013	(0.015)	0.986	(0.020)	0.983	(0.025)	0.466	(0.292)
	MCMC Diffuse	0.013	(0.014)	0.986	(0.020)	0.982	(0.025)	0.482	(0.232)
	MCMC Weak	0.011	(0.014)	0.988	(0.019)	0.985	(0.023)	0.509	(0.239)
	MCMC -1SD	0.013	(0.014)	0.986	(0.020)	0.982	(0.024)	0.477	(0.231)
	MCMC +1SD	0.014	(0.014)	0.984	(0.020)	0.981	(0.025)	0.469	(0.234)
500	ML	0.008	(0.010)	0.994	(0.009)	0.992	(0.012)	0.488	(0.288)
	MCMC Diffuse	0.008	(0.010)	0.993	(0.010)	0.992	(0.012)	0.485	(0.239)
	MCMC Weak	0.008	(0.010)	0.994	(0.010)	0.992	(0.012)	0.497	(0.242)
	MCMC -1SD	0.009	(0.010)	0.993	(0.010)	0.991	(0.013)	0.475	(0.237)
	MCMC +1SD	0.009	(0.010)	0.993	(0.011)	0.991	(0.013)	0.471	(0.237)
1000	ML	0.006	(0.007)	0.997	(0.005)	0.996	(0.006)	0.503	(0.293)
	MCMC Diffuse	0.006	(0.007)	0.997	(0.005)	0.996	(0.006)	0.493	(0.238)
	MCMC Weak	0.005	(0.007)	0.997	(0.005)	0.996	(0.006)	0.498	(0.236)
	MCMC -1SD	0.006	(0.007)	0.997	(0.005)	0.996	(0.006)	0.491	(0.238)
	MCMC +1SD	0.006	(0.007)	0.997	(0.005)	0.996	(0.006)	0.483	(0.238)

Table C12

Model A, 12 Items, Correctly Specified, Covariance = 0.5, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.050	(0.036)	0.958	(0.041)	0.948	(0.051)	0.290	(0.258)
	MCMC Diffuse	0.059	(0.035)	0.946	(0.045)	0.935	(0.054)	0.439	(0.239)
	MCMC Weak	0.047	(0.035)	0.958	(0.041)	0.953	(0.047)	0.507	(0.246)
	MCMC -1SD	0.064	(0.041)	0.932	(0.059)	0.922	(0.068)	0.404	(0.263)
	MCMC +1SD	0.058	(0.034)	0.942	(0.049)	0.936	(0.054)	0.435	(0.241)
100	ML	0.025	(0.024)	0.986	(0.017)	0.983	(0.021)	0.399	(0.284)
	MCMC Diffuse	0.028	(0.024)	0.984	(0.019)	0.980	(0.023)	0.465	(0.233)
	MCMC Weak	0.024	(0.023)	0.986	(0.017)	0.984	(0.021)	0.509	(0.241)
	MCMC -1SD	0.028	(0.024)	0.984	(0.019)	0.980	(0.022)	0.470	(0.235)
	MCMC +1SD	0.032	(0.024)	0.980	(0.021)	0.977	(0.024)	0.427	(0.230)
250	ML	0.013	(0.015)	0.996	(0.006)	0.995	(0.008)	0.465	(0.291)
	MCMC Diffuse	0.013	(0.014)	0.996	(0.006)	0.995	(0.008)	0.487	(0.225)
	MCMC Weak	0.012	(0.014)	0.996	(0.006)	0.995	(0.007)	0.497	(0.232)
	MCMC -1SD	0.013	(0.014)	0.996	(0.006)	0.995	(0.008)	0.484	(0.229)
	MCMC +1SD	0.015	(0.015)	0.995	(0.007)	0.993	(0.008)	0.447	(0.224)
500	ML	0.008	(0.010)	0.998	(0.003)	0.998	(0.004)	0.488	(0.288)
	MCMC Diffuse	0.009	(0.010)	0.998	(0.003)	0.997	(0.004)	0.485	(0.237)
	MCMC Weak	0.008	(0.010)	0.998	(0.003)	0.998	(0.004)	0.500	(0.242)
	MCMC -1SD	0.009	(0.010)	0.998	(0.003)	0.997	(0.004)	0.483	(0.240)
	MCMC +1SD	0.009	(0.010)	0.998	(0.003)	0.997	(0.004)	0.467	(0.231)
1000	ML	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.503	(0.292)
	MCMC Diffuse	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.488	(0.236)
	MCMC Weak	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.495	(0.235)
	MCMC -1SD	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.486	(0.235)
	MCMC +1SD	0.006	(0.007)	0.999	(0.002)	0.999	(0.002)	0.477	(0.231)

Table C13

Model A, 12 Items, Misspecified, Covariance = 0.3, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.053	(0.036)	0.864	(0.119)	0.834	(0.146)	0.266	(0.252)
	MCMC Diffuse	0.062	(0.034)	0.826	(0.129)	0.792	(0.156)	0.422	(0.235)
	MCMC Weak	0.049	(0.034)	0.869	(0.118)	0.856	(0.130)	0.489	(0.248)
	MCMC -1SD	0.056	(0.034)	0.844	(0.121)	0.828	(0.133)	0.442	(0.250)
	MCMC +1SD	0.059	(0.033)	0.818	(0.141)	0.802	(0.154)	0.419	(0.241)
100	ML	0.033	(0.025)	0.936	(0.063)	0.921	(0.077)	0.312	(0.268)
	MCMC Diffuse	0.036	(0.025)	0.926	(0.068)	0.910	(0.083)	0.401	(0.234)
	MCMC Weak	0.030	(0.024)	0.941	(0.063)	0.932	(0.072)	0.439	(0.244)
	MCMC -1SD	0.034	(0.024)	0.930	(0.065)	0.920	(0.074)	0.408	(0.241)
	MCMC +1SD	0.036	(0.024)	0.922	(0.071)	0.911	(0.081)	0.383	(0.235)
250	ML	0.026	(0.016)	0.963	(0.032)	0.955	(0.039)	0.241	(0.246)
	MCMC Diffuse	0.026	(0.016)	0.963	(0.031)	0.955	(0.038)	0.299	(0.216)
	MCMC Weak	0.024	(0.016)	0.966	(0.030)	0.959	(0.036)	0.318	(0.231)
	MCMC -1SD	0.025	(0.016)	0.964	(0.031)	0.957	(0.037)	0.304	(0.226)
	MCMC +1SD	0.026	(0.016)	0.961	(0.031)	0.954	(0.038)	0.292	(0.220)
500	ML	0.026	(0.010)	0.968	(0.019)	0.961	(0.024)	0.111	(0.176)
	MCMC Diffuse	0.026	(0.010)	0.967	(0.019)	0.960	(0.024)	0.158	(0.180)
	MCMC Weak	0.026	(0.010)	0.968	(0.019)	0.962	(0.023)	0.161	(0.177)
	MCMC -1SD	0.026	(0.010)	0.967	(0.019)	0.961	(0.024)	0.156	(0.176)
	MCMC +1SD	0.026	(0.010)	0.967	(0.020)	0.960	(0.024)	0.154	(0.177)
1000	ML	0.027	(0.006)	0.969	(0.012)	0.962	(0.015)	0.017	(0.057)
	MCMC Diffuse	0.027	(0.006)	0.969	(0.012)	0.962	(0.015)	0.031	(0.069)
	MCMC Weak	0.027	(0.006)	0.969	(0.012)	0.962	(0.015)	0.034	(0.080)
	MCMC -1SD	0.027	(0.006)	0.969	(0.012)	0.962	(0.015)	0.030	(0.068)
	MCMC +1SD	0.027	(0.006)	0.969	(0.012)	0.962	(0.015)	0.030	(0.068)

Table C14

Model A, 12 Items, Misspecified, Covariance = 0.3, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.059	(0.035)	0.945	(0.046)	0.933	(0.056)	0.228	(0.235)
	MCMC Diffuse	0.066	(0.035)	0.933	(0.049)	0.921	(0.059)	0.390	(0.239)
	MCMC Weak	0.055	(0.035)	0.947	(0.046)	0.940	(0.052)	0.457	(0.247)
	MCMC -1SD	0.060	(0.034)	0.940	(0.047)	0.932	(0.053)	0.415	(0.246)
	MCMC +1SD	0.065	(0.033)	0.929	(0.052)	0.922	(0.058)	0.378	(0.239)
100	ML	0.039	(0.026)	0.974	(0.023)	0.969	(0.028)	0.256	(0.252)
	MCMC Diffuse	0.041	(0.024)	0.972	(0.023)	0.966	(0.028)	0.345	(0.231)
	MCMC Weak	0.037	(0.024)	0.975	(0.023)	0.971	(0.026)	0.383	(0.239)
	MCMC -1SD	0.039	(0.024)	0.973	(0.023)	0.968	(0.027)	0.352	(0.233)
	MCMC +1SD	0.044	(0.023)	0.968	(0.025)	0.963	(0.028)	0.317	(0.219)
250	ML	0.034	(0.016)	0.983	(0.012)	0.979	(0.014)	0.143	(0.196)
	MCMC Diffuse	0.034	(0.015)	0.983	(0.011)	0.979	(0.014)	0.202	(0.188)
	MCMC Weak	0.033	(0.015)	0.984	(0.011)	0.980	(0.013)	0.209	(0.193)
	MCMC -1SD	0.034	(0.015)	0.983	(0.011)	0.980	(0.014)	0.203	(0.192)
	MCMC +1SD	0.035	(0.014)	0.982	(0.011)	0.978	(0.014)	0.182	(0.172)
500	ML	0.035	(0.009)	0.984	(0.007)	0.981	(0.008)	0.032	(0.091)
	MCMC Diffuse	0.035	(0.009)	0.984	(0.007)	0.981	(0.008)	0.056	(0.100)
	MCMC Weak	0.034	(0.009)	0.984	(0.007)	0.981	(0.008)	0.061	(0.107)
	MCMC -1SD	0.034	(0.009)	0.984	(0.007)	0.981	(0.008)	0.058	(0.104)
	MCMC +1SD	0.035	(0.008)	0.984	(0.007)	0.980	(0.008)	0.054	(0.098)
1000	ML	0.035	(0.005)	0.984	(0.004)	0.981	(0.005)	0.001	(0.012)
	MCMC Diffuse	0.035	(0.005)	0.984	(0.004)	0.981	(0.005)	0.002	(0.020)
	MCMC Weak	0.035	(0.005)	0.984	(0.004)	0.981	(0.005)	0.003	(0.017)
	MCMC -1SD	0.035	(0.005)	0.984	(0.004)	0.981	(0.005)	0.002	(0.016)
	MCMC +1SD	0.035	(0.005)	0.984	(0.004)	0.981	(0.005)	0.003	(0.019)

Table C15

Model A, 12 Items, Misspecified, Covariance = 0.5, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.064	(0.036)	0.830	(0.124)	0.792	(0.152)	0.199	(0.223)
	MCMC Diffuse	0.071	(0.033)	0.791	(0.131)	0.750	(0.158)	0.348	(0.230)
	MCMC Weak	0.059	(0.034)	0.834	(0.125)	0.818	(0.138)	0.423	(0.252)
	MCMC -1SD	0.065	(0.034)	0.809	(0.127)	0.791	(0.140)	0.378	(0.243)
	MCMC +1SD	0.069	(0.032)	0.782	(0.143)	0.763	(0.157)	0.356	(0.239)
100	ML	0.048	(0.025)	0.895	(0.073)	0.871	(0.089)	0.176	(0.212)
	MCMC Diffuse	0.051	(0.023)	0.883	(0.076)	0.858	(0.092)	0.265	(0.212)
	MCMC Weak	0.045	(0.024)	0.900	(0.073)	0.885	(0.085)	0.303	(0.236)
	MCMC -1SD	0.048	(0.024)	0.889	(0.074)	0.872	(0.086)	0.272	(0.220)
	MCMC +1SD	0.051	(0.022)	0.878	(0.077)	0.860	(0.089)	0.258	(0.214)
250	ML	0.046	(0.013)	0.913	(0.039)	0.894	(0.048)	0.046	(0.107)
	MCMC Diffuse	0.046	(0.012)	0.912	(0.037)	0.894	(0.046)	0.081	(0.115)
	MCMC Weak	0.045	(0.012)	0.916	(0.037)	0.900	(0.044)	0.089	(0.123)
	MCMC -1SD	0.045	(0.012)	0.913	(0.037)	0.897	(0.044)	0.084	(0.120)
	MCMC +1SD	0.046	(0.012)	0.911	(0.037)	0.895	(0.044)	0.080	(0.114)
500	ML	0.046	(0.007)	0.914	(0.023)	0.895	(0.029)	0.002	(0.015)
	MCMC Diffuse	0.046	(0.007)	0.913	(0.023)	0.895	(0.029)	0.005	(0.027)
	MCMC Weak	0.046	(0.007)	0.914	(0.023)	0.897	(0.029)	0.006	(0.032)
	MCMC -1SD	0.046	(0.007)	0.914	(0.023)	0.897	(0.029)	0.005	(0.023)
	MCMC +1SD	0.046	(0.007)	0.913	(0.023)	0.896	(0.028)	0.005	(0.023)
1000	ML	0.047	(0.005)	0.915	(0.015)	0.896	(0.019)	0.000	(0.000)
	MCMC Diffuse	0.046	(0.005)	0.915	(0.015)	0.896	(0.019)	0.000	(0.001)
	MCMC Weak	0.046	(0.005)	0.915	(0.015)	0.897	(0.019)	0.000	(0.000)
	MCMC -1SD	0.046	(0.005)	0.915	(0.015)	0.897	(0.018)	0.000	(0.000)
	MCMC +1SD	0.046	(0.005)	0.914	(0.015)	0.897	(0.019)	0.000	(0.000)

Table C16

Model A, 12 Items, Misspecified, Covariance = 0.5, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.076	(0.034)	0.922	(0.050)	0.904	(0.061)	0.132	(0.180)
	MCMC Diffuse	0.082	(0.032)	0.909	(0.052)	0.892	(0.062)	0.283	(0.217)
	MCMC Weak	0.072	(0.034)	0.923	(0.051)	0.913	(0.058)	0.337	(0.241)
	MCMC -1SD	0.076	(0.033)	0.916	(0.050)	0.906	(0.056)	0.308	(0.234)
	MCMC +1SD	0.081	(0.030)	0.905	(0.055)	0.895	(0.060)	0.274	(0.219)
100	ML	0.063	(0.022)	0.949	(0.028)	0.937	(0.034)	0.084	(0.142)
	MCMC Diffuse	0.064	(0.021)	0.945	(0.028)	0.934	(0.034)	0.157	(0.168)
	MCMC Weak	0.060	(0.021)	0.949	(0.027)	0.941	(0.032)	0.182	(0.186)
	MCMC -1SD	0.062	(0.021)	0.947	(0.027)	0.938	(0.032)	0.168	(0.177)
	MCMC +1SD	0.066	(0.019)	0.941	(0.028)	0.932	(0.032)	0.140	(0.155)
250	ML	0.061	(0.011)	0.954	(0.014)	0.944	(0.018)	0.005	(0.028)
	MCMC Diffuse	0.061	(0.010)	0.954	(0.014)	0.944	(0.017)	0.014	(0.039)
	MCMC Weak	0.060	(0.010)	0.955	(0.014)	0.946	(0.017)	0.014	(0.037)
	MCMC -1SD	0.060	(0.010)	0.954	(0.014)	0.945	(0.017)	0.013	(0.036)
	MCMC +1SD	0.061	(0.010)	0.953	(0.014)	0.944	(0.016)	0.010	(0.028)
500	ML	0.061	(0.007)	0.955	(0.009)	0.945	(0.011)	0.000	(0.001)
	MCMC Diffuse	0.061	(0.007)	0.955	(0.009)	0.945	(0.011)	0.000	(0.001)
	MCMC Weak	0.060	(0.007)	0.955	(0.009)	0.946	(0.011)	0.000	(0.002)
	MCMC -1SD	0.060	(0.007)	0.955	(0.009)	0.946	(0.011)	0.000	(0.002)
	MCMC +1SD	0.061	(0.007)	0.954	(0.009)	0.945	(0.011)	0.000	(0.001)
1000	ML	0.061	(0.005)	0.955	(0.006)	0.945	(0.007)	0.000	(0.000)
	MCMC Diffuse	0.060	(0.005)	0.955	(0.006)	0.946	(0.007)	0.000	(0.000)
	MCMC Weak	0.060	(0.005)	0.955	(0.006)	0.946	(0.007)	0.000	(0.000)
	MCMC -1SD	0.060	(0.005)	0.955	(0.006)	0.946	(0.007)	0.000	(0.000)
	MCMC +1SD	0.060	(0.005)	0.955	(0.006)	0.946	(0.007)	0.000	(0.000)

Table C17

Model B, 6 Items, Correctly Specified, Covariance = 0.3, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.036	(0.049)	0.960	(0.068)	0.915	(0.145)	0.500	(0.280)
	MCMC Diffuse	0.071	(0.065)	0.890	(0.132)	0.781	(0.259)	0.434	(0.157)
	MCMC Weak	0.039	(0.047)	0.933	(0.106)	0.908	(0.140)	0.509	(0.182)
	MCMC -1SD	0.076	(0.057)	0.829	(0.160)	0.783	(0.204)	0.370	(0.203)
	MCMC +1SD	0.052	(0.049)	0.885	(0.162)	0.855	(0.192)	0.452	(0.186)
100	ML	0.028	(0.037)	0.973	(0.045)	0.942	(0.096)	0.486	(0.288)
	MCMC Diffuse	0.035	(0.041)	0.964	(0.055)	0.922	(0.124)	0.474	(0.157)
	MCMC Weak	0.020	(0.031)	0.977	(0.044)	0.963	(0.072)	0.531	(0.171)
	MCMC -1SD	0.059	(0.042)	0.906	(0.087)	0.865	(0.127)	0.344	(0.196)
	MCMC +1SD	0.029	(0.034)	0.962	(0.058)	0.942	(0.089)	0.480	(0.164)
250	ML	0.017	(0.023)	0.989	(0.020)	0.977	(0.042)	0.498	(0.288)
	MCMC Diffuse	0.018	(0.025)	0.988	(0.021)	0.974	(0.048)	0.486	(0.166)
	MCMC Weak	0.013	(0.021)	0.991	(0.018)	0.983	(0.035)	0.524	(0.171)
	MCMC -1SD	0.027	(0.029)	0.976	(0.034)	0.957	(0.058)	0.423	(0.193)
	MCMC +1SD	0.016	(0.022)	0.988	(0.020)	0.979	(0.037)	0.494	(0.169)
500	ML	0.011	(0.016)	0.995	(0.010)	0.989	(0.020)	0.518	(0.295)
	MCMC Diffuse	0.012	(0.017)	0.995	(0.010)	0.988	(0.022)	0.492	(0.165)
	MCMC Weak	0.010	(0.015)	0.996	(0.009)	0.991	(0.020)	0.517	(0.170)
	MCMC -1SD	0.013	(0.017)	0.994	(0.010)	0.987	(0.022)	0.486	(0.167)
	MCMC +1SD	0.011	(0.016)	0.995	(0.010)	0.989	(0.021)	0.500	(0.169)
1000	ML	0.008	(0.011)	0.997	(0.005)	0.994	(0.010)	0.501	(0.282)
	MCMC Diffuse	0.009	(0.012)	0.997	(0.005)	0.994	(0.011)	0.488	(0.166)
	MCMC Weak	0.008	(0.011)	0.997	(0.005)	0.995	(0.011)	0.505	(0.169)
	MCMC -1SD	0.008	(0.012)	0.997	(0.005)	0.994	(0.011)	0.490	(0.171)
	MCMC +1SD	0.008	(0.012)	0.997	(0.005)	0.994	(0.011)	0.493	(0.173)

Table C18

Model B, 6 Items, Correctly Specified, Covariance = 0.3, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.046	(0.055)	0.981	(0.031)	0.958	(0.067)	0.457	(0.290)
	MCMC Diffuse	0.072	(0.064)	0.964	(0.042)	0.927	(0.101)	0.428	(0.162)
	MCMC Weak	0.042	(0.051)	0.977	(0.037)	0.965	(0.054)	0.501	(0.179)
	MCMC -1SD	0.110	(0.075)	0.902	(0.090)	0.867	(0.118)	0.293	(0.223)
	MCMC +1SD	0.062	(0.052)	0.960	(0.049)	0.944	(0.067)	0.432	(0.172)
100	ML	0.030	(0.038)	0.991	(0.015)	0.981	(0.031)	0.473	(0.289)
	MCMC Diffuse	0.037	(0.041)	0.988	(0.017)	0.975	(0.038)	0.458	(0.161)
	MCMC Weak	0.025	(0.034)	0.991	(0.015)	0.985	(0.026)	0.510	(0.171)
	MCMC -1SD	0.042	(0.045)	0.983	(0.029)	0.969	(0.049)	0.441	(0.180)
	MCMC +1SD	0.038	(0.037)	0.986	(0.019)	0.976	(0.032)	0.442	(0.164)
250	ML	0.017	(0.024)	0.997	(0.006)	0.993	(0.013)	0.494	(0.290)
	MCMC Diffuse	0.019	(0.026)	0.996	(0.007)	0.992	(0.015)	0.487	(0.167)
	MCMC Weak	0.015	(0.023)	0.997	(0.006)	0.994	(0.012)	0.502	(0.170)
	MCMC -1SD	0.018	(0.024)	0.996	(0.006)	0.992	(0.014)	0.483	(0.169)
	MCMC +1SD	0.020	(0.024)	0.996	(0.007)	0.992	(0.013)	0.470	(0.170)
500	ML	0.012	(0.016)	0.998	(0.003)	0.997	(0.006)	0.517	(0.296)
	MCMC Diffuse	0.011	(0.016)	0.998	(0.003)	0.997	(0.006)	0.499	(0.167)
	MCMC Weak	0.011	(0.016)	0.998	(0.003)	0.997	(0.006)	0.510	(0.172)
	MCMC -1SD	0.011	(0.017)	0.998	(0.003)	0.996	(0.007)	0.493	(0.170)
	MCMC +1SD	0.012	(0.017)	0.998	(0.003)	0.996	(0.008)	0.485	(0.167)
1000	ML	0.008	(0.011)	0.999	(0.001)	0.998	(0.003)	0.501	(0.283)
	MCMC Diffuse	0.008	(0.012)	0.999	(0.001)	0.998	(0.003)	0.493	(0.167)
	MCMC Weak	0.008	(0.012)	0.999	(0.001)	0.998	(0.003)	0.497	(0.170)
	MCMC -1SD	0.009	(0.012)	0.999	(0.001)	0.998	(0.004)	0.494	(0.174)
	MCMC +1SD	0.009	(0.012)	0.999	(0.002)	0.998	(0.004)	0.488	(0.171)

Table C19

Model B, 6 Items, Correctly Specified, Covariance = 0.5, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.040	(0.051)	0.960	(0.066)	0.914	(0.141)	0.481	(0.283)
	MCMC Diffuse	0.079	(0.072)	0.901	(0.115)	0.789	(0.250)	0.423	(0.158)
	MCMC Weak	0.039	(0.048)	0.940	(0.097)	0.918	(0.132)	0.503	(0.191)
	MCMC -1SD	0.066	(0.055)	0.882	(0.125)	0.848	(0.160)	0.406	(0.207)
	MCMC +1SD	0.055	(0.050)	0.893	(0.152)	0.864	(0.179)	0.444	(0.179)
100	ML	0.029	(0.038)	0.977	(0.038)	0.950	(0.082)	0.481	(0.290)
	MCMC Diffuse	0.040	(0.046)	0.967	(0.047)	0.919	(0.130)	0.460	(0.156)
	MCMC Weak	0.022	(0.031)	0.979	(0.038)	0.967	(0.060)	0.520	(0.172)
	MCMC -1SD	0.054	(0.042)	0.930	(0.072)	0.899	(0.104)	0.362	(0.199)
	MCMC +1SD	0.033	(0.036)	0.964	(0.053)	0.944	(0.084)	0.463	(0.167)
250	ML	0.017	(0.023)	0.991	(0.016)	0.981	(0.035)	0.496	(0.288)
	MCMC Diffuse	0.020	(0.026)	0.990	(0.017)	0.976	(0.043)	0.481	(0.167)
	MCMC Weak	0.014	(0.021)	0.992	(0.015)	0.985	(0.029)	0.523	(0.173)
	MCMC -1SD	0.040	(0.030)	0.966	(0.036)	0.944	(0.058)	0.329	(0.199)
	MCMC +1SD	0.019	(0.024)	0.989	(0.019)	0.978	(0.037)	0.480	(0.174)
500	ML	0.011	(0.016)	0.996	(0.008)	0.991	(0.017)	0.515	(0.293)
	MCMC Diffuse	0.012	(0.017)	0.995	(0.008)	0.990	(0.019)	0.496	(0.164)
	MCMC Weak	0.010	(0.016)	0.996	(0.008)	0.992	(0.017)	0.512	(0.170)
	MCMC -1SD	0.019	(0.021)	0.990	(0.015)	0.981	(0.028)	0.428	(0.188)
	MCMC +1SD	0.012	(0.017)	0.995	(0.009)	0.990	(0.018)	0.493	(0.172)
1000	ML	0.008	(0.011)	0.998	(0.004)	0.996	(0.008)	0.501	(0.281)
	MCMC Diffuse	0.009	(0.012)	0.998	(0.004)	0.995	(0.010)	0.489	(0.164)
	MCMC Weak	0.008	(0.011)	0.998	(0.004)	0.995	(0.008)	0.505	(0.170)
	MCMC -1SD	0.009	(0.012)	0.997	(0.004)	0.995	(0.010)	0.476	(0.167)
	MCMC +1SD	0.008	(0.012)	0.998	(0.004)	0.995	(0.009)	0.486	(0.167)

Table C20

Model B, 6 Items, Correctly Specified, Covariance = 0.5, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.046	(0.055)	0.983	(0.027)	0.964	(0.058)	0.454	(0.289)
	MCMC Diffuse	0.082	(0.070)	0.966	(0.037)	0.925	(0.105)	0.413	(0.156)
	MCMC Weak	0.050	(0.054)	0.976	(0.034)	0.965	(0.050)	0.474	(0.179)
	MCMC -1SD	0.130	(0.065)	0.896	(0.073)	0.862	(0.097)	0.220	(0.200)
	MCMC +1SD	0.065	(0.052)	0.963	(0.043)	0.949	(0.059)	0.416	(0.174)
100	ML	0.030	(0.038)	0.992	(0.013)	0.984	(0.027)	0.473	(0.290)
	MCMC Diffuse	0.040	(0.045)	0.989	(0.015)	0.976	(0.039)	0.454	(0.158)
	MCMC Weak	0.026	(0.035)	0.992	(0.013)	0.986	(0.024)	0.502	(0.166)
	MCMC -1SD	0.080	(0.063)	0.957	(0.047)	0.932	(0.072)	0.301	(0.225)
	MCMC +1SD	0.039	(0.036)	0.988	(0.016)	0.980	(0.026)	0.435	(0.158)
250	ML	0.017	(0.024)	0.997	(0.005)	0.994	(0.011)	0.493	(0.290)
	MCMC Diffuse	0.019	(0.025)	0.997	(0.005)	0.993	(0.011)	0.478	(0.162)
	MCMC Weak	0.016	(0.023)	0.997	(0.005)	0.994	(0.010)	0.501	(0.166)
	MCMC -1SD	0.020	(0.026)	0.996	(0.007)	0.992	(0.015)	0.466	(0.171)
	MCMC +1SD	0.020	(0.025)	0.996	(0.006)	0.993	(0.012)	0.459	(0.162)
500	ML	0.012	(0.016)	0.999	(0.002)	0.997	(0.005)	0.516	(0.294)
	MCMC Diffuse	0.012	(0.017)	0.999	(0.003)	0.997	(0.006)	0.492	(0.166)
	MCMC Weak	0.011	(0.017)	0.999	(0.002)	0.997	(0.005)	0.502	(0.161)
	MCMC -1SD	0.012	(0.017)	0.999	(0.003)	0.997	(0.006)	0.486	(0.160)
	MCMC +1SD	0.012	(0.017)	0.999	(0.003)	0.997	(0.006)	0.482	(0.163)
1000	ML	0.008	(0.011)	0.999	(0.001)	0.999	(0.002)	0.502	(0.282)
	MCMC Diffuse	0.009	(0.012)	0.999	(0.001)	0.998	(0.003)	0.485	(0.163)
	MCMC Weak	0.008	(0.012)	0.999	(0.001)	0.998	(0.003)	0.491	(0.172)
	MCMC -1SD	0.009	(0.012)	0.999	(0.001)	0.998	(0.003)	0.483	(0.168)
	MCMC +1SD	0.009	(0.012)	0.999	(0.001)	0.998	(0.003)	0.477	(0.162)

Table C21

Model B, 6 Items, Misspecified, Covariance = 0.3, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.119	(0.065)	0.728	(0.200)	0.561	(0.301)	0.158	(0.207)
	MCMC Diffuse	0.124	(0.059)	0.680	(0.210)	0.535	(0.287)	0.246	(0.181)
	MCMC Weak	0.097	(0.057)	0.741	(0.200)	0.692	(0.234)	0.289	(0.208)
	MCMC -1SD	0.113	(0.054)	0.676	(0.198)	0.618	(0.234)	0.233	(0.191)
	MCMC +1SD	0.108	(0.054)	0.675	(0.235)	0.623	(0.267)	0.252	(0.192)
100	ML	0.119	(0.042)	0.741	(0.134)	0.570	(0.220)	0.054	(0.110)
	MCMC Diffuse	0.115	(0.041)	0.744	(0.132)	0.595	(0.213)	0.134	(0.142)
	MCMC Weak	0.099	(0.040)	0.768	(0.133)	0.691	(0.181)	0.151	(0.162)
	MCMC -1SD	0.106	(0.037)	0.739	(0.130)	0.657	(0.176)	0.130	(0.144)
	MCMC +1SD	0.105	(0.037)	0.743	(0.138)	0.658	(0.186)	0.136	(0.144)
250	ML	0.121	(0.023)	0.745	(0.076)	0.575	(0.127)	0.002	(0.018)
	MCMC Diffuse	0.118	(0.024)	0.749	(0.077)	0.592	(0.139)	0.011	(0.033)
	MCMC Weak	0.111	(0.023)	0.755	(0.076)	0.638	(0.121)	0.011	(0.034)
	MCMC -1SD	0.113	(0.024)	0.749	(0.077)	0.628	(0.126)	0.011	(0.035)
	MCMC +1SD	0.112	(0.023)	0.750	(0.077)	0.631	(0.123)	0.011	(0.033)
500	ML	0.122	(0.015)	0.745	(0.049)	0.575	(0.082)	0.000	(0.000)
	MCMC Diffuse	0.120	(0.017)	0.747	(0.052)	0.582	(0.101)	0.000	(0.000)
	MCMC Weak	0.116	(0.016)	0.750	(0.052)	0.612	(0.094)	0.000	(0.001)
	MCMC -1SD	0.116	(0.016)	0.748	(0.052)	0.614	(0.095)	0.000	(0.000)
	MCMC +1SD	0.116	(0.017)	0.749	(0.052)	0.610	(0.099)	0.000	(0.001)
1000	ML	0.122	(0.010)	0.747	(0.036)	0.578	(0.060)	0.000	(0.000)
	MCMC Diffuse	0.120	(0.013)	0.749	(0.035)	0.588	(0.078)	0.000	(0.000)
	MCMC Weak	0.118	(0.013)	0.750	(0.035)	0.600	(0.076)	0.000	(0.000)
	MCMC -1SD	0.118	(0.013)	0.749	(0.035)	0.599	(0.076)	0.000	(0.000)
	MCMC +1SD	0.118	(0.013)	0.750	(0.035)	0.598	(0.077)	0.000	(0.000)

Table C22

Model B, 6 Items, Misspecified, Covariance = 0.3, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.179	(0.057)	0.830	(0.083)	0.717	(0.138)	0.041	(0.097)
	MCMC Diffuse	0.177	(0.054)	0.814	(0.084)	0.724	(0.135)	0.108	(0.129)
	MCMC Weak	0.154	(0.051)	0.832	(0.084)	0.789	(0.108)	0.125	(0.146)
	MCMC -1SD	0.162	(0.051)	0.819	(0.083)	0.771	(0.111)	0.111	(0.135)
	MCMC +1SD	0.163	(0.047)	0.810	(0.090)	0.765	(0.116)	0.099	(0.120)
100	ML	0.180	(0.034)	0.834	(0.053)	0.723	(0.089)	0.002	(0.008)
	MCMC Diffuse	0.174	(0.035)	0.835	(0.052)	0.740	(0.090)	0.018	(0.048)
	MCMC Weak	0.162	(0.034)	0.840	(0.052)	0.774	(0.079)	0.020	(0.051)
	MCMC -1SD	0.164	(0.034)	0.836	(0.052)	0.768	(0.083)	0.019	(0.051)
	MCMC +1SD	0.165	(0.033)	0.833	(0.053)	0.765	(0.082)	0.017	(0.047)
250	ML	0.180	(0.021)	0.836	(0.033)	0.727	(0.054)	0.000	(0.000)
	MCMC Diffuse	0.176	(0.024)	0.837	(0.032)	0.736	(0.063)	0.000	(0.000)
	MCMC Weak	0.171	(0.023)	0.838	(0.032)	0.751	(0.059)	0.000	(0.001)
	MCMC -1SD	0.172	(0.024)	0.837	(0.032)	0.749	(0.062)	0.000	(0.000)
	MCMC +1SD	0.172	(0.023)	0.837	(0.032)	0.750	(0.059)	0.000	(0.001)
500	ML	0.180	(0.014)	0.837	(0.021)	0.728	(0.035)	0.000	(0.000)
	MCMC Diffuse	0.177	(0.019)	0.838	(0.022)	0.736	(0.052)	0.000	(0.000)
	MCMC Weak	0.175	(0.019)	0.838	(0.022)	0.741	(0.053)	0.000	(0.000)
	MCMC -1SD	0.175	(0.018)	0.838	(0.022)	0.742	(0.049)	0.000	(0.000)
	MCMC +1SD	0.175	(0.019)	0.837	(0.022)	0.741	(0.054)	0.000	(0.000)
1000	ML	0.180	(0.010)	0.837	(0.015)	0.729	(0.026)	0.000	(0.000)
	MCMC Diffuse	0.176	(0.015)	0.838	(0.015)	0.738	(0.043)	0.000	(0.000)
	MCMC Weak	0.175	(0.015)	0.838	(0.015)	0.740	(0.043)	0.000	(0.000)
	MCMC -1SD	0.175	(0.015)	0.838	(0.015)	0.740	(0.042)	0.000	(0.000)
	MCMC +1SD	0.176	(0.015)	0.838	(0.015)	0.739	(0.042)	0.000	(0.000)

Table C23

Model B, 6 Items, Misspecified, Covariance = 0.5, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.149	(0.062)	0.672	(0.184)	0.467	(0.278)	0.086	(0.150)
	MCMC Diffuse	0.151	(0.059)	0.635	(0.191)	0.457	(0.275)	0.176	(0.160)
	MCMC Weak	0.123	(0.056)	0.683	(0.193)	0.621	(0.229)	0.205	(0.186)
	MCMC -1SD	0.136	(0.053)	0.623	(0.185)	0.558	(0.219)	0.161	(0.163)
	MCMC +1SD	0.131	(0.051)	0.630	(0.213)	0.565	(0.245)	0.175	(0.168)
100	ML	0.149	(0.038)	0.678	(0.121)	0.465	(0.198)	0.015	(0.048)
	MCMC Diffuse	0.144	(0.037)	0.680	(0.120)	0.495	(0.196)	0.061	(0.093)
	MCMC Weak	0.128	(0.037)	0.700	(0.123)	0.598	(0.173)	0.067	(0.108)
	MCMC -1SD	0.133	(0.036)	0.674	(0.119)	0.567	(0.165)	0.057	(0.098)
	MCMC +1SD	0.131	(0.035)	0.682	(0.127)	0.575	(0.178)	0.061	(0.099)
250	ML	0.149	(0.022)	0.682	(0.070)	0.470	(0.116)	0.000	(0.002)
	MCMC Diffuse	0.146	(0.023)	0.686	(0.070)	0.489	(0.129)	0.001	(0.006)
	MCMC Weak	0.138	(0.022)	0.690	(0.070)	0.543	(0.116)	0.001	(0.005)
	MCMC -1SD	0.140	(0.022)	0.685	(0.070)	0.533	(0.117)	0.001	(0.007)
	MCMC +1SD	0.139	(0.022)	0.687	(0.070)	0.536	(0.122)	0.001	(0.005)
500	ML	0.150	(0.014)	0.683	(0.045)	0.472	(0.076)	0.000	(0.000)
	MCMC Diffuse	0.147	(0.018)	0.685	(0.048)	0.484	(0.108)	0.000	(0.000)
	MCMC Weak	0.142	(0.017)	0.687	(0.048)	0.519	(0.096)	0.000	(0.000)
	MCMC -1SD	0.144	(0.017)	0.685	(0.047)	0.512	(0.099)	0.000	(0.000)
	MCMC +1SD	0.144	(0.017)	0.686	(0.048)	0.511	(0.099)	0.000	(0.000)
1000	ML	0.149	(0.010)	0.685	(0.033)	0.475	(0.055)	0.000	(0.000)
	MCMC Diffuse	0.147	(0.014)	0.687	(0.032)	0.488	(0.084)	0.000	(0.000)
	MCMC Weak	0.144	(0.013)	0.687	(0.032)	0.505	(0.081)	0.000	(0.000)
	MCMC -1SD	0.145	(0.013)	0.687	(0.032)	0.501	(0.079)	0.000	(0.000)
	MCMC +1SD	0.145	(0.014)	0.687	(0.032)	0.500	(0.084)	0.000	(0.000)

Table C24

Model B, 6 Items, Misspecified, Covariance = 0.5, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.231	(0.051)	0.770	(0.077)	0.617	(0.128)	0.007	(0.032)
	MCMC Diffuse	0.222	(0.049)	0.758	(0.078)	0.646	(0.125)	0.033	(0.070)
	MCMC Weak	0.200	(0.046)	0.771	(0.079)	0.712	(0.105)	0.040	(0.079)
	MCMC -1SD	0.206	(0.047)	0.760	(0.078)	0.695	(0.108)	0.035	(0.074)
	MCMC +1SD	0.204	(0.042)	0.754	(0.083)	0.698	(0.107)	0.030	(0.061)
100	ML	0.230	(0.032)	0.773	(0.050)	0.622	(0.083)	0.000	(0.000)
	MCMC Diffuse	0.221	(0.033)	0.774	(0.050)	0.650	(0.092)	0.001	(0.009)
	MCMC Weak	0.208	(0.033)	0.779	(0.050)	0.689	(0.080)	0.001	(0.010)
	MCMC -1SD	0.212	(0.033)	0.774	(0.050)	0.677	(0.083)	0.001	(0.011)
	MCMC +1SD	0.210	(0.032)	0.773	(0.050)	0.683	(0.079)	0.001	(0.010)
250	ML	0.230	(0.020)	0.775	(0.031)	0.626	(0.051)	0.000	(0.000)
	MCMC Diffuse	0.225	(0.024)	0.776	(0.030)	0.638	(0.066)	0.000	(0.000)
	MCMC Weak	0.218	(0.023)	0.777	(0.030)	0.661	(0.063)	0.000	(0.000)
	MCMC -1SD	0.219	(0.023)	0.776	(0.030)	0.659	(0.062)	0.000	(0.000)
	MCMC +1SD	0.219	(0.023)	0.776	(0.030)	0.658	(0.063)	0.000	(0.000)
500	ML	0.229	(0.013)	0.776	(0.020)	0.626	(0.033)	0.000	(0.000)
	MCMC Diffuse	0.225	(0.019)	0.777	(0.021)	0.639	(0.055)	0.000	(0.000)
	MCMC Weak	0.222	(0.019)	0.777	(0.021)	0.648	(0.053)	0.000	(0.000)
	MCMC -1SD	0.222	(0.020)	0.777	(0.021)	0.647	(0.057)	0.000	(0.000)
	MCMC +1SD	0.222	(0.018)	0.777	(0.021)	0.649	(0.052)	0.000	(0.000)
1000	ML	0.229	(0.009)	0.777	(0.015)	0.628	(0.024)	0.000	(0.000)
	MCMC Diffuse	0.225	(0.017)	0.777	(0.014)	0.637	(0.054)	0.000	(0.000)
	MCMC Weak	0.224	(0.017)	0.778	(0.014)	0.642	(0.050)	0.000	(0.000)
	MCMC -1SD	0.224	(0.017)	0.778	(0.014)	0.643	(0.050)	0.000	(0.000)
	MCMC +1SD	0.224	(0.016)	0.778	(0.014)	0.643	(0.049)	0.000	(0.000)

Table C25

Model B, 12 Items, Correctly Specified, Covariance = 0.3, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.048	(0.037)	0.899	(0.099)	0.872	(0.126)	0.308	(0.266)
	MCMC Diffuse	0.058	(0.035)	0.862	(0.111)	0.829	(0.139)	0.447	(0.228)
	MCMC Weak	0.044	(0.034)	0.902	(0.098)	0.890	(0.110)	0.533	(0.242)
	MCMC -1SD	0.070	(0.035)	0.807	(0.125)	0.784	(0.139)	0.357	(0.246)
	MCMC +1SD	0.054	(0.034)	0.859	(0.123)	0.844	(0.136)	0.455	(0.244)
100	ML	0.025	(0.024)	0.963	(0.046)	0.952	(0.058)	0.402	(0.282)
	MCMC Diffuse	0.028	(0.024)	0.957	(0.050)	0.946	(0.063)	0.473	(0.232)
	MCMC Weak	0.022	(0.023)	0.966	(0.046)	0.960	(0.055)	0.525	(0.245)
	MCMC -1SD	0.032	(0.026)	0.944	(0.061)	0.933	(0.072)	0.433	(0.247)
	MCMC +1SD	0.029	(0.024)	0.951	(0.054)	0.942	(0.064)	0.450	(0.234)
250	ML	0.013	(0.014)	0.988	(0.018)	0.984	(0.023)	0.465	(0.289)
	MCMC Diffuse	0.013	(0.014)	0.988	(0.017)	0.984	(0.022)	0.488	(0.227)
	MCMC Weak	0.012	(0.013)	0.989	(0.016)	0.987	(0.020)	0.509	(0.228)
	MCMC -1SD	0.013	(0.014)	0.987	(0.017)	0.985	(0.021)	0.481	(0.231)
	MCMC +1SD	0.014	(0.014)	0.986	(0.018)	0.983	(0.022)	0.470	(0.230)
500	ML	0.008	(0.010)	0.995	(0.008)	0.993	(0.011)	0.485	(0.287)
	MCMC Diffuse	0.009	(0.010)	0.994	(0.009)	0.992	(0.011)	0.484	(0.238)
	MCMC Weak	0.008	(0.010)	0.995	(0.009)	0.993	(0.011)	0.501	(0.237)
	MCMC -1SD	0.008	(0.010)	0.994	(0.009)	0.993	(0.011)	0.481	(0.235)
	MCMC +1SD	0.009	(0.010)	0.994	(0.009)	0.992	(0.011)	0.476	(0.237)
1000	ML	0.006	(0.007)	0.997	(0.004)	0.997	(0.005)	0.503	(0.293)
	MCMC Diffuse	0.005	(0.007)	0.997	(0.004)	0.997	(0.005)	0.495	(0.229)
	MCMC Weak	0.005	(0.007)	0.998	(0.004)	0.997	(0.005)	0.500	(0.228)
	MCMC -1SD	0.006	(0.007)	0.997	(0.004)	0.997	(0.005)	0.493	(0.231)
	MCMC +1SD	0.006	(0.007)	0.997	(0.004)	0.997	(0.005)	0.487	(0.227)

Table C26

Model B, 12 Items, Correctly Specified, Covariance = 0.3, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.050	(0.036)	0.962	(0.038)	0.951	(0.048)	0.291	(0.259)
	MCMC Diffuse	0.059	(0.035)	0.950	(0.041)	0.939	(0.051)	0.443	(0.231)
	MCMC Weak	0.046	(0.035)	0.962	(0.037)	0.957	(0.043)	0.513	(0.241)
	MCMC -1SD	0.056	(0.036)	0.953	(0.042)	0.944	(0.049)	0.454	(0.240)
	MCMC +1SD	0.058	(0.034)	0.947	(0.045)	0.940	(0.050)	0.430	(0.235)
100	ML	0.025	(0.024)	0.987	(0.016)	0.984	(0.020)	0.397	(0.282)
	MCMC Diffuse	0.028	(0.024)	0.985	(0.017)	0.981	(0.021)	0.473	(0.234)
	MCMC Weak	0.024	(0.023)	0.988	(0.016)	0.985	(0.019)	0.510	(0.236)
	MCMC -1SD	0.027	(0.024)	0.986	(0.017)	0.983	(0.021)	0.478	(0.237)
	MCMC +1SD	0.032	(0.024)	0.982	(0.019)	0.978	(0.022)	0.428	(0.229)
250	ML	0.013	(0.014)	0.996	(0.006)	0.995	(0.007)	0.463	(0.287)
	MCMC Diffuse	0.013	(0.014)	0.996	(0.006)	0.995	(0.007)	0.483	(0.229)
	MCMC Weak	0.012	(0.014)	0.996	(0.005)	0.995	(0.007)	0.502	(0.227)
	MCMC -1SD	0.013	(0.014)	0.996	(0.006)	0.995	(0.007)	0.483	(0.224)
	MCMC +1SD	0.015	(0.014)	0.995	(0.006)	0.994	(0.007)	0.452	(0.220)
500	ML	0.008	(0.010)	0.998	(0.003)	0.998	(0.003)	0.484	(0.288)
	MCMC Diffuse	0.009	(0.010)	0.998	(0.003)	0.998	(0.004)	0.491	(0.232)
	MCMC Weak	0.008	(0.010)	0.998	(0.003)	0.998	(0.003)	0.496	(0.235)
	MCMC -1SD	0.009	(0.010)	0.998	(0.003)	0.998	(0.004)	0.488	(0.236)
	MCMC +1SD	0.009	(0.010)	0.998	(0.003)	0.997	(0.004)	0.464	(0.233)
1000	ML	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.503	(0.293)
	MCMC Diffuse	0.005	(0.007)	0.999	(0.001)	0.999	(0.002)	0.496	(0.228)
	MCMC Weak	0.005	(0.007)	0.999	(0.001)	0.999	(0.002)	0.498	(0.227)
	MCMC -1SD	0.005	(0.007)	0.999	(0.001)	0.999	(0.002)	0.496	(0.225)
	MCMC +1SD	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.480	(0.226)

Table C27

Model B, 12 Items, Correctly Specified, Covariance = 0.5, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.048	(0.037)	0.905	(0.093)	0.880	(0.118)	0.303	(0.265)
	MCMC Diffuse	0.059	(0.035)	0.872	(0.104)	0.841	(0.130)	0.444	(0.229)
	MCMC Weak	0.044	(0.034)	0.908	(0.092)	0.897	(0.103)	0.527	(0.243)
	MCMC -1SD	0.069	(0.034)	0.825	(0.113)	0.804	(0.127)	0.350	(0.245)
	MCMC +1SD	0.055	(0.034)	0.865	(0.118)	0.851	(0.132)	0.448	(0.243)
100	ML	0.025	(0.024)	0.966	(0.042)	0.956	(0.053)	0.400	(0.282)
	MCMC Diffuse	0.028	(0.025)	0.960	(0.047)	0.950	(0.059)	0.478	(0.233)
	MCMC Weak	0.022	(0.023)	0.969	(0.041)	0.964	(0.048)	0.529	(0.234)
	MCMC -1SD	0.043	(0.027)	0.923	(0.063)	0.909	(0.074)	0.335	(0.242)
	MCMC +1SD	0.030	(0.024)	0.954	(0.050)	0.945	(0.060)	0.446	(0.228)
250	ML	0.013	(0.014)	0.989	(0.016)	0.986	(0.021)	0.464	(0.290)
	MCMC Diffuse	0.013	(0.014)	0.989	(0.015)	0.986	(0.019)	0.484	(0.227)
	MCMC Weak	0.012	(0.013)	0.990	(0.014)	0.988	(0.018)	0.509	(0.231)
	MCMC -1SD	0.014	(0.015)	0.987	(0.017)	0.984	(0.021)	0.464	(0.235)
	MCMC +1SD	0.015	(0.014)	0.987	(0.017)	0.984	(0.021)	0.459	(0.225)
500	ML	0.008	(0.010)	0.995	(0.008)	0.994	(0.010)	0.485	(0.288)
	MCMC Diffuse	0.009	(0.010)	0.995	(0.008)	0.993	(0.010)	0.483	(0.236)
	MCMC Weak	0.008	(0.010)	0.995	(0.008)	0.994	(0.010)	0.503	(0.237)
	MCMC -1SD	0.009	(0.010)	0.995	(0.008)	0.993	(0.010)	0.481	(0.240)
	MCMC +1SD	0.009	(0.010)	0.994	(0.008)	0.993	(0.011)	0.468	(0.236)
1000	ML	0.006	(0.007)	0.998	(0.004)	0.997	(0.005)	0.503	(0.293)
	MCMC Diffuse	0.006	(0.007)	0.998	(0.004)	0.997	(0.005)	0.488	(0.229)
	MCMC Weak	0.005	(0.007)	0.998	(0.004)	0.997	(0.005)	0.497	(0.230)
	MCMC -1SD	0.006	(0.007)	0.998	(0.004)	0.997	(0.005)	0.484	(0.231)
	MCMC +1SD	0.006	(0.007)	0.997	(0.004)	0.997	(0.005)	0.482	(0.227)

Table C28

Model B, 12 Items, Correctly Specified, Covariance = 0.5, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.050	(0.036)	0.965	(0.035)	0.955	(0.044)	0.291	(0.260)
	MCMC Diffuse	0.060	(0.034)	0.953	(0.038)	0.943	(0.047)	0.436	(0.228)
	MCMC Weak	0.047	(0.035)	0.964	(0.035)	0.959	(0.040)	0.504	(0.239)
	MCMC -1SD	0.071	(0.043)	0.933	(0.058)	0.922	(0.067)	0.369	(0.262)
	MCMC +1SD	0.059	(0.034)	0.950	(0.042)	0.943	(0.048)	0.427	(0.236)
100	ML	0.025	(0.024)	0.988	(0.014)	0.985	(0.018)	0.396	(0.282)
	MCMC Diffuse	0.028	(0.024)	0.987	(0.015)	0.983	(0.019)	0.464	(0.228)
	MCMC Weak	0.024	(0.023)	0.989	(0.015)	0.986	(0.018)	0.514	(0.235)
	MCMC -1SD	0.029	(0.024)	0.986	(0.016)	0.983	(0.020)	0.466	(0.229)
	MCMC +1SD	0.032	(0.024)	0.983	(0.017)	0.980	(0.020)	0.424	(0.223)
250	ML	0.013	(0.014)	0.996	(0.005)	0.995	(0.007)	0.463	(0.288)
	MCMC Diffuse	0.013	(0.014)	0.996	(0.005)	0.995	(0.007)	0.483	(0.223)
	MCMC Weak	0.012	(0.014)	0.997	(0.005)	0.996	(0.006)	0.497	(0.223)
	MCMC -1SD	0.013	(0.014)	0.996	(0.005)	0.995	(0.006)	0.479	(0.221)
	MCMC +1SD	0.016	(0.015)	0.995	(0.006)	0.994	(0.007)	0.448	(0.220)
500	ML	0.008	(0.010)	0.998	(0.002)	0.998	(0.003)	0.484	(0.289)
	MCMC Diffuse	0.009	(0.010)	0.998	(0.003)	0.998	(0.003)	0.485	(0.229)
	MCMC Weak	0.008	(0.010)	0.998	(0.003)	0.998	(0.003)	0.500	(0.227)
	MCMC -1SD	0.009	(0.010)	0.998	(0.003)	0.998	(0.003)	0.483	(0.233)
	MCMC +1SD	0.009	(0.010)	0.998	(0.003)	0.998	(0.003)	0.461	(0.227)
1000	ML	0.005	(0.007)	0.999	(0.001)	0.999	(0.001)	0.503	(0.293)
	MCMC Diffuse	0.005	(0.007)	0.999	(0.001)	0.999	(0.001)	0.490	(0.224)
	MCMC Weak	0.006	(0.007)	0.999	(0.001)	0.999	(0.001)	0.493	(0.224)
	MCMC -1SD	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.492	(0.225)
	MCMC +1SD	0.006	(0.007)	0.999	(0.001)	0.999	(0.002)	0.479	(0.221)

Table C29

Model B, 12 Items, Misspecified, Covariance = 0.3, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.072	(0.035)	0.811	(0.122)	0.769	(0.149)	0.155	(0.199)
	MCMC Diffuse	0.080	(0.032)	0.771	(0.125)	0.726	(0.151)	0.299	(0.221)
	MCMC Weak	0.067	(0.033)	0.816	(0.120)	0.798	(0.132)	0.364	(0.242)
	MCMC -1SD	0.074	(0.032)	0.787	(0.120)	0.765	(0.133)	0.318	(0.234)
	MCMC +1SD	0.075	(0.031)	0.768	(0.136)	0.748	(0.148)	0.302	(0.229)
100	ML	0.060	(0.023)	0.866	(0.073)	0.836	(0.090)	0.100	(0.155)
	MCMC Diffuse	0.061	(0.022)	0.856	(0.076)	0.827	(0.093)	0.185	(0.183)
	MCMC Weak	0.056	(0.023)	0.872	(0.076)	0.853	(0.087)	0.219	(0.204)
	MCMC -1SD	0.059	(0.023)	0.859	(0.076)	0.838	(0.088)	0.191	(0.193)
	MCMC +1SD	0.060	(0.021)	0.852	(0.079)	0.831	(0.092)	0.177	(0.180)
250	ML	0.058	(0.011)	0.880	(0.039)	0.853	(0.047)	0.007	(0.029)
	MCMC Diffuse	0.058	(0.011)	0.879	(0.038)	0.853	(0.047)	0.021	(0.052)
	MCMC Weak	0.056	(0.011)	0.882	(0.038)	0.860	(0.046)	0.024	(0.055)
	MCMC -1SD	0.057	(0.011)	0.880	(0.038)	0.858	(0.045)	0.021	(0.053)
	MCMC +1SD	0.057	(0.011)	0.878	(0.038)	0.856	(0.046)	0.020	(0.053)
500	ML	0.058	(0.007)	0.880	(0.024)	0.854	(0.029)	0.000	(0.000)
	MCMC Diffuse	0.058	(0.007)	0.880	(0.025)	0.854	(0.031)	0.000	(0.002)
	MCMC Weak	0.057	(0.007)	0.880	(0.025)	0.857	(0.030)	0.000	(0.003)
	MCMC -1SD	0.058	(0.007)	0.880	(0.025)	0.856	(0.031)	0.000	(0.003)
	MCMC +1SD	0.058	(0.007)	0.879	(0.025)	0.855	(0.030)	0.000	(0.001)
1000	ML	0.058	(0.004)	0.881	(0.016)	0.854	(0.019)	0.000	(0.000)
	MCMC Diffuse	0.058	(0.005)	0.881	(0.016)	0.856	(0.021)	0.000	(0.000)
	MCMC Weak	0.057	(0.005)	0.881	(0.016)	0.857	(0.020)	0.000	(0.000)
	MCMC -1SD	0.058	(0.005)	0.881	(0.016)	0.857	(0.020)	0.000	(0.000)
	MCMC +1SD	0.058	(0.005)	0.881	(0.016)	0.856	(0.020)	0.000	(0.000)

Table C30

Model B, 12 Items, Misspecified, Covariance = 0.3, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.094	(0.030)	0.898	(0.051)	0.875	(0.062)	0.065	(0.118)
	MCMC Diffuse	0.099	(0.028)	0.885	(0.051)	0.865	(0.061)	0.177	(0.174)
	MCMC Weak	0.089	(0.029)	0.899	(0.050)	0.887	(0.057)	0.224	(0.202)
	MCMC -1SD	0.093	(0.029)	0.892	(0.050)	0.879	(0.057)	0.201	(0.194)
	MCMC +1SD	0.096	(0.026)	0.883	(0.054)	0.871	(0.059)	0.173	(0.174)
100	ML	0.084	(0.018)	0.921	(0.028)	0.903	(0.035)	0.016	(0.051)
	MCMC Diffuse	0.084	(0.017)	0.918	(0.029)	0.902	(0.035)	0.052	(0.090)
	MCMC Weak	0.080	(0.018)	0.922	(0.029)	0.910	(0.034)	0.061	(0.101)
	MCMC -1SD	0.083	(0.018)	0.919	(0.029)	0.905	(0.034)	0.053	(0.097)
	MCMC +1SD	0.084	(0.016)	0.914	(0.029)	0.901	(0.034)	0.042	(0.078)
250	ML	0.082	(0.009)	0.926	(0.015)	0.909	(0.018)	0.000	(0.000)
	MCMC Diffuse	0.081	(0.009)	0.926	(0.015)	0.910	(0.018)	0.000	(0.002)
	MCMC Weak	0.080	(0.009)	0.926	(0.015)	0.912	(0.018)	0.000	(0.004)
	MCMC -1SD	0.080	(0.009)	0.926	(0.015)	0.912	(0.018)	0.000	(0.002)
	MCMC +1SD	0.081	(0.009)	0.925	(0.015)	0.910	(0.018)	0.000	(0.001)
500	ML	0.082	(0.006)	0.926	(0.010)	0.910	(0.012)	0.000	(0.000)
	MCMC Diffuse	0.081	(0.006)	0.926	(0.010)	0.910	(0.013)	0.000	(0.000)
	MCMC Weak	0.081	(0.006)	0.926	(0.010)	0.911	(0.013)	0.000	(0.000)
	MCMC -1SD	0.081	(0.006)	0.926	(0.010)	0.911	(0.013)	0.000	(0.000)
	MCMC +1SD	0.081	(0.006)	0.925	(0.010)	0.910	(0.013)	0.000	(0.000)
1000	ML	0.081	(0.004)	0.926	(0.006)	0.910	(0.008)	0.000	(0.000)
	MCMC Diffuse	0.081	(0.004)	0.926	(0.007)	0.911	(0.009)	0.000	(0.000)
	MCMC Weak	0.081	(0.004)	0.926	(0.007)	0.911	(0.009)	0.000	(0.000)
	MCMC -1SD	0.081	(0.004)	0.926	(0.007)	0.911	(0.009)	0.000	(0.000)
	MCMC +1SD	0.081	(0.004)	0.926	(0.007)	0.911	(0.009)	0.000	(0.000)

Table C31

Model B, 12 Items, Misspecified, Covariance = 0.5, Lambda = 0.5

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.085	(0.032)	0.777	(0.117)	0.728	(0.143)	0.098	(0.154)
	MCMC Diffuse	0.090	(0.030)	0.741	(0.121)	0.691	(0.147)	0.233	(0.203)
	MCMC Weak	0.079	(0.031)	0.781	(0.117)	0.760	(0.130)	0.281	(0.228)
	MCMC -1SD	0.085	(0.030)	0.754	(0.116)	0.729	(0.129)	0.245	(0.215)
	MCMC +1SD	0.085	(0.029)	0.740	(0.130)	0.718	(0.142)	0.229	(0.202)
100	ML	0.074	(0.020)	0.823	(0.069)	0.784	(0.085)	0.037	(0.083)
	MCMC Diffuse	0.075	(0.019)	0.814	(0.073)	0.775	(0.091)	0.093	(0.132)
	MCMC Weak	0.070	(0.020)	0.829	(0.072)	0.804	(0.084)	0.109	(0.145)
	MCMC -1SD	0.073	(0.019)	0.818	(0.072)	0.790	(0.085)	0.098	(0.138)
	MCMC +1SD	0.074	(0.018)	0.812	(0.073)	0.785	(0.085)	0.085	(0.126)
250	ML	0.072	(0.010)	0.834	(0.037)	0.797	(0.045)	0.000	(0.003)
	MCMC Diffuse	0.072	(0.010)	0.834	(0.036)	0.799	(0.045)	0.002	(0.011)
	MCMC Weak	0.070	(0.010)	0.837	(0.036)	0.806	(0.044)	0.001	(0.009)
	MCMC -1SD	0.071	(0.010)	0.834	(0.036)	0.803	(0.044)	0.001	(0.010)
	MCMC +1SD	0.071	(0.010)	0.833	(0.036)	0.802	(0.044)	0.001	(0.008)
500	ML	0.072	(0.006)	0.835	(0.023)	0.798	(0.028)	0.000	(0.000)
	MCMC Diffuse	0.072	(0.006)	0.834	(0.024)	0.799	(0.030)	0.000	(0.000)
	MCMC Weak	0.071	(0.006)	0.834	(0.024)	0.801	(0.030)	0.000	(0.000)
	MCMC -1SD	0.072	(0.006)	0.834	(0.024)	0.800	(0.030)	0.000	(0.000)
	MCMC +1SD	0.072	(0.006)	0.833	(0.024)	0.800	(0.029)	0.000	(0.000)
1000	ML	0.072	(0.004)	0.835	(0.016)	0.798	(0.019)	0.000	(0.000)
	MCMC Diffuse	0.072	(0.005)	0.835	(0.016)	0.800	(0.021)	0.000	(0.000)
	MCMC Weak	0.072	(0.004)	0.835	(0.016)	0.801	(0.021)	0.000	(0.000)
	MCMC -1SD	0.072	(0.004)	0.835	(0.016)	0.801	(0.021)	0.000	(0.000)
	MCMC +1SD	0.072	(0.004)	0.835	(0.016)	0.801	(0.021)	0.000	(0.000)

Table C32

Model B, 12 Items, Misspecified, Covariance = 0.5, Lambda = 0.7

N	Estimation	RMSEA	(*SD*)	CFI	(*SD*)	TLI	(*SD*)	P-value/ PPP	(*SD*)
50	ML	0.115	(0.025)	0.866	(0.048)	0.836	(0.059)	0.018	(0.050)
	MCMC Diffuse	0.117	(0.023)	0.855	(0.048)	0.829	(0.057)	0.086	(0.119)
	MCMC Weak	0.109	(0.025)	0.867	(0.048)	0.851	(0.055)	0.107	(0.142)
	MCMC -1SD	0.113	(0.025)	0.860	(0.048)	0.843	(0.055)	0.094	(0.135)
	MCMC +1SD	0.115	(0.022)	0.852	(0.051)	0.836	(0.057)	0.078	(0.113)
100	ML	0.106	(0.015)	0.886	(0.027)	0.860	(0.033)	0.001	(0.005)
	MCMC Diffuse	0.106	(0.015)	0.883	(0.028)	0.860	(0.034)	0.006	(0.023)
	MCMC Weak	0.102	(0.015)	0.887	(0.028)	0.869	(0.032)	0.007	(0.024)
	MCMC -1SD	0.104	(0.015)	0.884	(0.027)	0.865	(0.033)	0.006	(0.025)
	MCMC +1SD	0.105	(0.014)	0.880	(0.028)	0.862	(0.033)	0.004	(0.017)
250	ML	0.104	(0.008)	0.890	(0.015)	0.866	(0.018)	0.000	(0.000)
	MCMC Diffuse	0.103	(0.008)	0.890	(0.015)	0.867	(0.018)	0.000	(0.000)
	MCMC Weak	0.102	(0.009)	0.891	(0.015)	0.870	(0.018)	0.000	(0.000)
	MCMC -1SD	0.103	(0.009)	0.890	(0.015)	0.869	(0.018)	0.000	(0.000)
	MCMC +1SD	0.103	(0.008)	0.889	(0.015)	0.868	(0.018)	0.000	(0.000)
500	ML	0.104	(0.005)	0.891	(0.010)	0.866	(0.012)	0.000	(0.000)
	MCMC Diffuse	0.104	(0.006)	0.890	(0.010)	0.867	(0.013)	0.000	(0.000)
	MCMC Weak	0.103	(0.006)	0.890	(0.010)	0.868	(0.013)	0.000	(0.000)
	MCMC -1SD	0.103	(0.006)	0.890	(0.010)	0.868	(0.013)	0.000	(0.000)
	MCMC +1SD	0.103	(0.006)	0.890	(0.010)	0.867	(0.013)	0.000	(0.000)
1000	ML	0.104	(0.004)	0.891	(0.007)	0.866	(0.008)	0.000	(0.000)
	MCMC Diffuse	0.103	(0.004)	0.891	(0.007)	0.868	(0.009)	0.000	(0.000)
	MCMC Weak	0.103	(0.004)	0.891	(0.007)	0.868	(0.009)	0.000	(0.000)
	MCMC -1SD	0.103	(0.004)	0.891	(0.007)	0.868	(0.009)	0.000	(0.000)
	MCMC +1SD	0.103	(0.004)	0.891	(0.007)	0.868	(0.009)	0.000	(0.000)

Appendix D

Table D1

Model A, 6 Items, Correctly Specified

		RMSEA				CFI				TLI				PPP
N	Prior	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE
50	Diffuse	**.060**	**.005**	**.173**	.168	**.912**	**.497**	**.994**	.497	**.854**	**.344**	**.991**	.647	.447
	Weak	.042	**.005**	**.136**	.131	**.936**	**.565**	**.994**	.429	**.912**	**.478**	**.993**	.515	.501
	-1SD	**.085**	**.027**	**.164**	.137	**.846**	**.444**	**.965**	.521	**.805**	**.360**	**.957**	.597	.350
	+1SD	.055	**.005**	**.145**	.140	**.891**	**.518**	**.991**	.473	**.871**	**.447**	**.989**	.542	.447
100	Diffuse	.031	**.002**	**.115**	.113	.970	**.756**	**.998**	.242	**.945**	**.595**	**.997**	.402	.480
	Weak	.022	**.002**	**.095**	.093	.978	**.788**	**.999**	.211	.965	**.694**	**.998**	.304	.522
	-1SD	.047	**.010**	**.115**	.105	**.933**	**.710**	**.987**	.277	**.904**	**.596**	**.982**	.386	.403
	+1SD	.030	**.002**	**.103**	.101	.966	**.751**	**.998**	.247	.950	**.654**	**.996**	.342	.473
250	Diffuse	.018	**.001**	**.070**	.069	.989	**.914**	**.999**	.085	.978	**.838**	**.998**	.160	.483
	Weak	.015	**.001**	**.063**	.062	.991	**.921**	**.999**	.078	.984	**.866**	**.999**	.133	.508
	-1SD	.022	**.002**	**.071**	.069	.982	**.903**	**.998**	.095	.970	**.836**	**.996**	.160	.452
	+1SD	.018	**.001**	**.067**	.066	.989	**.913**	**.999**	.086	.981	**.855**	**.998**	.143	.479
500	Diffuse	.012	.001	.048	.047	.995	.958	1.00	.042	.990	**.920**	**.999**	.079	.494
	Weak	.011	.001	.045	.044	.995	.961	1.00	.039	.992	**.930**	**.999**	.069	.506
	-1SD	.012	.001	.048	.047	.994	.957	1.00	.043	.990	**.922**	**.999**	.077	.488
	+1SD	.011	.001	.047	.046	.995	.959	1.00	.041	.991	**.927**	**.999**	.072	.494
1000	Diffuse	.008	.000	.034	.034	.998	.980	1.00	.020	.995	.961	1.00	.039	.491
	Weak	.008	.000	.033	.033	.998	.980	1.00	.020	.996	.963	1.00	.037	.499
	-1SD	.008	.001	.034	.033	.997	.979	1.00	.021	.995	.962	1.00	.038	.494
	+1SD	.008	.000	.033	.033	.997	.980	1.00	.020	.995	.962	1.00	.038	.492

PE = point estimate; CI = credibility interval; LL = lower limit of CI; UL = upper limit of CI. Bolded PE values are indicative of poor fit based on fixed cutoffs. Bolded CIs contain fixed cutoff value.

Table D2

Model A, 6 Items, Misspecified

		RMSEA				CFI				TLI				PPP
N	Prior	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE
50	Diffuse	**.093**	**.026**	**.181**	.155	**.837**	**.446**	**.970**	.524	**.759**	**.319**	**.955**	.636	.339
	Weak	**.070**	**.021**	**.145**	.124	**.877**	**.507**	**.973**	.466	**.849**	**.444**	**.967**	.523	.392
	-1SD	**.082**	**.024**	**.155**	.131	**.846**	**.455**	**.966**	.511	**.810**	**.393**	**.959**	.566	.345
	+1SD	**.085**	**.025**	**.158**	.133	**.821**	**.459**	**.963**	.504	**.791**	**.400**	**.956**	.556	.333
100	Diffuse	**.078**	**.033**	**.136**	.103	**.898**	**.675**	**.969**	.294	**.836**	**.516**	**.950**	.434	.277
	Weak	**.066**	**.028**	**.118**	.090	**.913**	**.708**	**.971**	.263	**.881**	**.617**	**.960**	.343	.309
	-1SD	**.073**	**.031**	**.124**	.093	**.898**	**.680**	**.967**	.287	**.861**	**.582**	**.954**	.372	.280
	+1SD	**.074**	**.031**	**.125**	.094	**.894**	**.670**	**.966**	.296	**.856**	**.574**	**.954**	.380	.273
250	Diffuse	**.080**	**.053**	**.107**	.054	**.910**	**.828**	**.950**	.122	**.852**	.718	.918	.200	.136
	Weak	**.074**	**.050**	**.100**	.050	**.915**	**.835**	**.951**	.116	**.872**	.753	.926	.173	.150
	-1SD	**.076**	**.051**	**.102**	.051	**.911**	.828	.949	.121	**.865**	.743	.924	.181	.140
	+1SD	**.077**	**.051**	**.102**	.051	**.910**	.828	.949	.121	**.865**	.742	.924	.182	.140
500	Diffuse	**.082**	.067	.096	.029	**.911**	.870	.935	.065	**.854**	.786	.893	.107	.052
	Weak	**.079**	.065	.093	.028	**.913**	.873	.935	.062	**.863**	.801	.899	.098	.055
	-1SD	**.080**	.065	.093	.028	**.912**	.871	.935	.064	**.862**	.798	.898	.100	.054
	+1SD	**.080**	.065	.093	.028	**.912**	.871	.935	.064	**.863**	.800	.899	.099	.054
1000	Diffuse	**.082**	.075	.089	.014	**.912**	.891	.924	.033	**.855**	.822	.876	.054	**.012**
	Weak	**.081**	.075	.089	.014	**.912**	.892	.924	.032	**.859**	.826	.879	.053	**.012**
	-1SD	**.082**	.075	.088	.013	**.912**	.892	.924	.032	**.859**	.826	.879	.053	**.011**
	+1SD	**.082**	.075	.089	.014	**.912**	.891	.924	.033	**.858**	.825	.878	.053	**.012**

PE = point estimate; CI = credibility interval; LL = lower limit of CI; UL = upper limit of CI. Bolded PE values are indicative of poor fit based on fixed cutoffs. Bolded CIs contain fixed cutoff value.

Table D3

Model A, 12 Items, Correctly Specified

		RMSEA				CFI				TLI				PPP
N	Prior	PE	CI (LL,	UL)	CI Width	PE	CI (LL,	UL)	CI Width	PE	CI (LL,	UL)	CI Width	PE
50	Diffuse	.058	**.020**	**.096**	.076	**.898**	**.722**	**.969**	.247	**.876**	**.665**	**.962**	.297	.449
	Weak	.046	**.015**	**.081**	.066	**.923**	**.773**	**.976**	.203	**.914**	**.745**	**.973**	.228	.520
	-1SD	**.063**	**.028**	**.097**	.069	**.868**	**.698**	**.946**	.248	**.851**	**.661**	**.939**	.278	.400
	+1SD	.055	**.021**	**.089**	.068	**.893**	**.727**	**.964**	.237	**.882**	**.700**	**.960**	.260	.445
100	Diffuse	.028	.007	.057	.050	.966	**.887**	**.991**	.104	.958	**.861**	**.989**	.128	.469
	Weak	.023	.006	.050	.044	.973	**.903**	**.993**	.090	.969	**.886**	**.992**	.106	.516
	-1SD	.031	.009	.058	.049	.957	**.876**	**.987**	.111	.950	**.853**	**.984**	.131	.444
	+1SD	.030	.008	.057	.049	.962	**.882**	**.990**	.108	.956	**.863**	**.988**	.125	.442
250	Diffuse	.013	.003	.031	.028	.991	.962	.998	.036	.988	.953	.997	.044	.485
	Weak	.012	.002	.029	.027	.992	.965	.998	.033	.990	.958	.998	.040	.504
	-1SD	.013	.003	.031	.028	.990	.962	.998	.036	.988	.953	.997	.044	.484
	+1SD	.014	.003	.033	.030	.989	.960	.998	.038	.987	.951	.997	.046	.463
500	Diffuse	.009	.002	.021	.019	.996	.982	.999	.017	.994	.978	.999	.021	.488
	Weak	.008	.002	.020	.018	.996	.983	.999	.016	.995	.979	.999	.020	.498
	-1SD	.009	.002	.021	.019	.995	.982	.999	.017	.994	.977	.999	.022	.484
	+1SD	.009	.002	.022	.020	.995	.981	.999	.018	.994	.977	.999	.022	.473
1000	Diffuse	.006	.001	.014	.013	.998	.991	1.000	.009	.997	.989	.999	.010	.489
	Weak	.005	.001	.014	.013	.998	.992	1.000	.008	.998	.990	.999	.009	.498
	-1SD	.006	.001	.015	.014	.998	.991	1.000	.009	.997	.989	.999	.010	.491
	+1SD	.006	.001	.015	.014	.998	.991	1.000	.009	.997	.989	.999	.010	.482

PE = point estimate; CI = credibility interval; LL = lower limit of CI; UL = upper limit of CI. Bolded PE values are indicative of poor fit based on fixed cutoffs. Bolded CIs contain fixed cutoff value.

Table D4

Model A, 12 Items, Misspecified

		RMSEA				CFI				TLI				PPP
N	Prior	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE
50	Diffuse	**.070**	**.033**	**.104**	.071	**.865**	.689	.948	.259	**.839**	.632	.938	.306	.361
	Weak	.058	**.027**	**.089**	.062	**.893**	**.740**	**.958**	.218	**.882**	**.713**	**.953**	.240	.426
	-1SD	**.064**	**.030**	**.095**	.065	**.877**	**.714**	**.950**	.236	**.864**	.685	.945	.260	.386
	+1SD	**.068**	**.033**	**.098**	.065	**.858**	.692	.941	.249	**.845**	.665	.935	.270	.357
100	Diffuse	.048	**.023**	**.071**	.048	**.931**	**.847**	**.971**	.124	**.917**	**.815**	**.965**	.150	.292
	Weak	.043	**.020**	**.065**	.045	**.941**	**.864**	**.975**	.111	**.932**	**.843**	**.971**	.128	.327
	-1SD	.046	**.022**	**.068**	.046	**.935**	**.853**	**.972**	.119	**.925**	**.831**	**.968**	.137	.300
	+1SD	.049	**.024**	**.070**	.046	**.927**	**.843**	**.968**	.125	**.917**	**.820**	**.964**	.144	.274
250	Diffuse	.042	.028	.053	.025	.953	**.920**	**.971**	.051	**.943**	**.903**	**.965**	.062	.149
	Weak	.040	.027	.052	.025	.955	**.923**	**.972**	.049	**.946**	**.908**	**.967**	.059	.158
	-1SD	.041	.028	.053	.025	.953	**.920**	**.972**	.052	**.945**	**.905**	**.966**	.061	.151
	+1SD	.042	.029	.054	.025	.952	**.918**	**.970**	.052	**.943**	**.902**	**.965**	.063	.141
500	Diffuse	.042	.035	.048	.013	.955	**.938**	**.965**	.027	**.945**	**.925**	**.958**	.033	.055
	Weak	.041	.034	.047	.013	.955	**.939**	**.965**	.026	**.946**	**.927**	**.958**	.031	.057
	-1SD	.042	.034	.048	.014	.955	**.938**	**.965**	.027	**.946**	**.926**	**.958**	.032	.055
	+1SD	.042	.035	.048	.013	.954	**.938**	**.965**	.027	**.945**	**.925**	**.958**	.033	.053
1000	Diffuse	.042	.039	.045	.006	.956	**.947**	**.961**	.014	**.946**	**.936**	**.953**	.017	**.008**
	Weak	.042	.039	.045	.006	.956	**.948**	**.961**	.013	**.947**	**.937**	**.953**	.016	**.009**
	-1SD	.042	.039	.045	.006	.956	**.947**	**.961**	.014	**.947**	**.937**	**.953**	.016	**.008**
	+1SD	.042	.039	.045	.006	.956	**.947**	**.961**	.014	**.946**	**.936**	**.953**	.017	**.008**

PE = point estimate; CI = credibility interval; LL = lower limit of CI; UL = upper limit of CI. Bolded PE values are indicative of poor fit based on fixed cutoffs. Bolded CIs contain fixed cutoff value.

Table D5

Model B, 6 Items, Correctly Specified

		RMSEA				CFI				TLI				PPP
N	Prior	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE
50	Diffuse	**.076**	**.006**	**.215**	.209	**.930**	**.559**	**.996**	.437	**.855**	**.357**	**.991**	.634	.425
	Weak	.043	**.004**	**.144**	.140	.956	**.680**	**.996**	.316	**.939**	**.585**	**.995**	.410	.497
	-1SD	**.095**	**.033**	**.174**	.141	**.877**	**.576**	**.967**	.391	**.840**	**.477**	**.959**	.482	.322
	+1SD	.059	**.005**	**.153**	.148	**.925**	**.631**	**.994**	.363	**.903**	**.546**	**.992**	.446	.436
100	Diffuse	.038	**.002**	**.137**	.135	.977	**.813**	**.999**	.186	**.948**	**.626**	**.998**	.372	.462
	Weak	.024	**.001**	**.103**	.102	.985	**.857**	**.999**	.142	.975	**.771**	**.999**	.228	.516
	-1SD	.059	**.015**	**.129**	.114	**.944**	**.793**	**.987**	.194	**.916**	**.685**	**.982**	.297	.362
	+1SD	.035	**.002**	**.112**	.110	.975	**.827**	**.998**	.171	.960	**.732**	**.998**	.266	.455
250	Diffuse	.019	**.001**	**.079**	.078	.993	**.938**	**1.00**	.062	.984	**.865**	**.999**	.134	.483
	Weak	.014	**.001**	**.068**	.067	.994	**.947**	**1.00**	.053	.989	**.900**	**.999**	.099	.513
	-1SD	.026	**.004**	**.079**	.075	.983	**.928**	**.997**	.069	.971	**.869**	**.995**	.126	.425
	+1SD	.019	**.001**	**.072**	.071	.992	**.940**	**1.00**	.060	.985	**.889**	**.999**	.110	.476
500	Diffuse	.012	.001	.053	.052	.997	.972	1.00	.028	.993	**.939**	**.999**	.060	.495
	Weak	.010	.001	.049	.048	.997	.974	1.00	.026	.994	**.947**	**1.00**	.053	.510
	-1SD	.014	.001	.054	.053	.995	.968	1.00	.032	.991	**.936**	**.999**	.063	.473
	+1SD	.012	.001	.051	.050	.997	.971	1.00	.029	.993	**.943**	**.999**	.056	.490
1000	Diffuse	.008	.001	.037	.036	.998	.986	1.00	.014	.996	.969	1.00	.031	.489
	Weak	.008	.000	.036	.036	.998	.986	1.00	.014	.997	.971	1.00	.029	.499
	-1SD	.009	.001	.037	.036	.998	.985	1.00	.015	.996	.969	1.00	.031	.486
	+1SD	.009	.001	.037	.036	.998	.986	1.00	.014	.996	.970	1.00	.030	.486

PE = point estimate; CI = credibility interval; LL = lower limit of CI; UL = upper limit of CI. Bolded PE values are indicative of poor fit based on fixed cutoffs. Bolded CIs contain fixed cutoff value.

Table D6

Model B, 6 Items, Misspecified

		RMSEA				CFI				TLI				PPP
N	Prior	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE
50	Diffuse	**.168**	.102	.230	.128	**.722**	.428	.880	.452	**.590**	.274	.821	.547	.141
	Weak	**.143**	.088	.195	.107	**.757**	.473	.888	.415	**.703**	.392	.862	.470	.165
	-1SD	**.154**	.095	.205	.110	**.719**	.425	.871	.446	**.660**	.345	.843	.498	.135
	+1SD	**.152**	.094	.203	.109	**.717**	.441	.873	.432	**.663**	.366	.847	.481	.139
100	Diffuse	**.163**	.128	.197	.069	**.758**	.603	.848	.245	**.620**	.403	.761	.358	.054
	Weak	**.149**	.118	.179	.061	**.772**	.623	.852	.229	**.688**	.495	.797	.302	.060
	-1SD	**.154**	.121	.184	.063	**.756**	.600	.844	.244	**.667**	.466	.786	.320	.052
	+1SD	**.153**	.120	.183	.063	**.758**	.602	.845	.243	**.670**	.474	.788	.314	.054
250	Diffuse	**.166**	.154	.180	.026	**.762**	.705	.798	.093	**.614**	.522	.673	.151	**.003**
	Weak	**.160**	.148	.172	.024	**.765**	.709	.800	.091	**.648**	.564	.700	.136	**.003**
	-1SD	**.161**	.149	.174	.025	**.762**	.704	.798	.094	**.642**	.556	.696	.140	**.003**
	+1SD	**.160**	.148	.173	.025	**.762**	.705	.798	.093	**.644**	.559	.698	.139	**.003**
500	Diffuse	**.167**	.161	.174	.013	**.762**	.734	.780	.046	**.610**	.564	.640	.076	**.000**
	Weak	**.164**	.158	.171	.013	**.763**	.735	.780	.045	**.630**	.586	.657	.071	**.000**
	-1SD	**.164**	.158	.171	.013	**.762**	.734	.780	.046	**.629**	.584	.656	.072	**.000**
	+1SD	**.164**	.158	.171	.013	**.762**	.734	.780	.046	**.628**	.584	.656	.072	**.000**
1000	Diffuse	**.167**	.164	.170	.006	**.763**	.749	.772	.023	**.613**	.590	.627	.037	**.000**
	Weak	**.165**	.163	.169	.006	**.763**	.749	.772	.023	**.622**	.600	.636	.036	**.000**
	-1SD	**.165**	.163	.169	.006	**.763**	.749	.772	.023	**.621**	.598	.635	.037	**.000**
	+1SD	**.166**	.163	.169	.006	**.763**	.749	.772	.023	**.620**	.598	.634	.036	**.000**

PE = point estimate; CI = credibility interval; LL = lower limit of CI; UL = upper limit of CI. Bolded PE values are indicative of poor fit based on fixed cutoffs. Bolded CIs contain fixed cutoff value.

Table D7

Model B, 12 Items, Correctly Specified

		RMSEA				CFI				TLI				PPP
N	Prior	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE
50	Diffuse	.059	**.020**	**.098**	.078	**.909**	**.757**	**.973**	.216	**.888**	**.703**	**.967**	.264	.443
	Weak	.045	**.015**	**.082**	.067	**.934**	**.809**	**.980**	.171	**.926**	**.784**	**.978**	.194	.519
	-1SD	**.067**	**.030**	**.101**	.071	**.879**	.735	.949	.214	**.863**	.700	.943	.243	.382
	+1SD	.057	**.021**	**.091**	.070	**.905**	**.763**	**.968**	.205	**.895**	**.737**	**.964**	.227	.440
100	Diffuse	.028	.006	.058	.052	.972	**.905**	**.993**	.088	.965	**.881**	**.992**	.111	.472
	Weak	.023	.005	.051	.046	.978	**.919**	**.995**	.076	.974	**.903**	**.994**	.091	.520
	-1SD	.033	**.010**	**.061**	.051	.960	**.891**	**.987**	.096	.952	**.870**	**.984**	.114	.428
	+1SD	.031	.008	.059	.051	.967	**.899**	**.992**	.093	.961	**.881**	**.990**	.109	.437
250	Diffuse	.013	.002	.032	.030	.992	.968	.998	.030	.990	.960	.998	.038	.485
	Weak	.012	.002	.030	.028	.993	.971	.999	.028	.992	.964	.998	.034	.504
	-1SD	.014	.002	.033	.031	.992	.967	.998	.031	.990	.959	.998	.039	.477
	+1SD	.015	.003	.034	.031	.991	.965	.998	.033	.989	.958	.998	.040	.457
500	Diffuse	.009	.002	.022	.020	.996	.985	.999	.014	.995	.981	.999	.018	.486
	Weak	.008	.002	.021	.019	.997	.986	.999	.013	.996	.982	.999	.017	.500
	-1SD	.009	.002	.022	.020	.996	.985	.999	.014	.995	.981	.999	.018	.484
	+1SD	.009	.002	.023	.021	.996	.984	.999	.015	.995	.980	.999	.019	.467
1000	Diffuse	.005	.001	.015	.014	.998	.993	1.000	.007	.998	.991	1.000	.009	.492
	Weak	.005	.001	.015	.014	.998	.993	1.000	.007	.998	.991	1.000	.009	.497
	-1SD	.006	.001	.015	.014	.998	.993	1.000	.007	.998	.991	1.000	.009	.491
	+1SD	.006	.001	.015	.014	.998	.992	1.000	.008	.998	.990	1.000	.010	.482

PE = point estimate; CI = credibility interval; LL = lower limit of CI; UL = upper limit of CI. Bolded PE values are indicative of poor fit based on fixed cutoffs. Bolded CIs contain fixed cutoff value.

Table D8

Model B, 12 Items, Misspecified

		RMSEA				CFI				TLI				PPP
N	Prior	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE	CI (LL, UL)		CI Width	PE
50	Diffuse	**.096**	.063	.123	.060	**.813**	.660	.902	.242	**.778**	.597	.883	.286	.199
	Weak	**.086**	**.055**	**.110**	.055	**.841**	.703	.914	.211	**.824**	.672	.905	.233	.244
	-1SD	**.091**	**.060**	**.115**	.055	**.823**	.678	.904	.226	**.804**	.643	.893	.250	.215
	+1SD	**.093**	.062	.116	.054	**.811**	.664	.896	.232	**.793**	.634	.886	.252	.196
100	Diffuse	**.081**	.062	.097	.035	**.868**	.793	.914	.121	**.841**	.751	.896	.145	.084
	Weak	**.077**	**.059**	**.092**	.033	**.878**	.807	.919	.112	**.859**	.778	.907	.129	.099
	-1SD	**.080**	.061	.094	.033	**.870**	.798	.914	.116	**.849**	.766	.900	.134	.087
	+1SD	**.081**	.062	.095	.033	**.865**	.791	.910	.119	**.845**	.760	.897	.137	.077
250	Diffuse	**.078**	.071	.085	.014	**.882**	.853	.901	.048	**.858**	.823	.880	.057	**.006**
	Weak	**.077**	.070	.083	.013	**.884**	.856	.902	.046	**.862**	.829	.884	.055	**.006**
	-1SD	**.078**	.071	.084	.013	**.882**	.854	.901	.047	**.860**	.827	.882	.055	**.006**
	+1SD	**.078**	.071	.084	.013	**.881**	.852	.900	.048	**.859**	.825	.882	.057	**.005**
500	Diffuse	**.079**	.075	.082	.007	**.882**	.868	.891	.023	**.857**	.840	.869	.029	**.000**
	Weak	**.078**	.075	.081	.006	**.883**	.869	.892	.023	**.859**	.843	.870	.027	**.000**
	-1SD	**.078**	.075	.081	.006	**.882**	.868	.891	.023	**.859**	.842	.870	.028	**.000**
	+1SD	**.078**	.075	.082	.007	**.882**	.868	.891	.023	**.858**	.841	.869	.028	**.000**
1000	Diffuse	**.078**	.077	.080	.003	**.883**	.876	.888	.012	**.858**	.850	.864	.014	**.000**
	Weak	**.078**	.077	.080	.003	**.883**	.877	.888	.011	**.859**	.851	.865	.014	**.000**
	-1SD	**.078**	.077	.080	.003	**.883**	.876	.888	.012	**.859**	.851	.865	.014	**.000**
	+1SD	**.078**	.077	.080	.003	**.883**	.876	.888	.012	**.859**	.851	.865	.014	**.000**

PE = point estimate; CI = credibility interval; LL = lower limit of CI; UL = upper limit of CI. Bolded PE values are indicative of poor fit based on fixed cutoffs. Bolded CIs contain fixed cutoff value.