

# Bayesian Analysis In Mplus: A Brief Introduction

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## **Abstract**

This paper uses a series of examples to give an introduction to how Bayesian analysis is carried out in Mplus. The examples are a mediation model with estimation of an indirect effect, a structural equation model, a two-level regression model with estimation of a random intercept variance, a multiple-indicator binary growth model with a large number of latent variables, a two-part growth model, and a mixture model. It is shown how the use of Mplus graphics provides information on estimates, convergence, and model fit. Comparisons are made with frequentist estimation using maximum likelihood and weighted least squares. Data and Mplus scripts are available on the Mplus website.

# 1 Introduction

Frequentist (e.g., maximum likelihood) and Bayesian analysis differ by the former viewing parameters as constants and the latter as variables. Maximum likelihood (ML) finds estimates by maximizing a likelihood computed for the data. Bayes combines prior distributions for parameters with the data likelihood to form posterior distributions for the parameter estimates. The priors can be diffuse (non-informative) or informative where the information may come from previous studies. The posterior provides an estimate in the form of a mean, median, or mode of the posterior distribution.

There are many books on Bayesian analysis and most are quite technical. Gelman et al. (2004) provides a good general statistical description, whereas Lynch (2010) gives a somewhat more introductory account. Lee (2007) gives a discussion from a structural equation modeling perspective. Schafer (1997) gives a statistical discussion from a missing data and multiple imputation perspective, whereas Enders (2010) gives an applied discussion of these same topics. Statistical overview articles include Gelfand et al. (1990) and Casella and George (1992). Overview articles of an applied nature and with a latent variable focus include Scheines et al. (1999), Rupp et al. (2004), and Yuan and MacKinnon (2009).

Bayesian analysis is firmly established in mainstream statistics. Its popularity is growing and currently appears to be featured at least half as often as frequentist analysis. Part of the reason for the increased use of Bayesian analysis is the success of new computational algorithms referred to as Markov chain Monte Carlo (MCMC) methods. Outside of statistics, however, application of Bayesian analysis lags behind. One possible reason is that Bayesian analysis is perceived as difficult to do, requiring complex statistical specifications such as those used in the flexible, but technically-oriented general Bayes program WinBUGS. These observations were the background for developing Bayesian analysis in Mplus (Muthén & Muthén, 1998-2010). In Mplus, simple analysis specifications

with convenient defaults allow easy access to a rich set of analysis possibilities. Diffuse priors are used as the default with the possibility of specifying informative priors. A range of graphics options are available to easily provide information on estimates, convergence, and model fit.

Three key points motivate taking an interest in Bayesian analysis:

1. More can be learned about parameter estimates and model fit
2. Analyses can be made less computationally demanding
3. New types of models can be analyzed

Point 1 is illustrated by parameter estimates that do not have a normal distribution. ML gives a parameter estimate and its standard error and assumes that the distribution of the parameter estimate is normal based on asymptotic (large-sample) theory. In contrast, Bayes does not rely on large-sample theory and provides the whole distribution not assuming that it is normal. The ML confidence interval  $Estimate \pm 1.96 \times SE$  assumes a symmetric distribution, whereas the Bayesian credibility interval based on the percentiles of the posterior allows for a strongly skewed distribution. Bayesian exploration of model fit can be done in a flexible way using Posterior predictive checking (PPC; see, e.g., Gelman et al., 1996; Gelman et al., 2004, Chapter 6; Lee, 2007, Chapter 5; Scheines et al., 1999). Any suitable test statistics for the observed data can be compared to statistics based on simulated data obtained via draws of parameter values from the posterior distribution, avoiding statistical assumptions about the distribution of the test statistics. Examples of non-normal posteriors are presented in Section 2 for single-level models as well as in Section 4 for multilevel models. Examples of PPC are given in Section 3.

Point 2 may be of interest for an analyst who is hesitant to move from ML estimation to Bayesian estimation. Many models are computationally cumbersome or impossible using ML, such as with categorical outcomes and many latent variables resulting in many dimensions of numerical integration. Such an analyst may view the Bayesian analysis

simply as a computational tool for getting estimates that are analogous to what would have been obtained by ML had it been feasible. This is obtained with diffuse priors, in which case ML and Bayesian results are expected to be close in large samples (Browne & Draper, 2006; p. 505). Examples of this are presented in Section 5.

Point 3 is exemplified by models with a very large number of parameters or where ML does not provide a natural approach. Examples of the former include image analysis (see, e.g., Green, 1996)) and examples of the latter include random change-point analysis (see, e.g., Dominicus et al., 2008).

This paper gives a brief introduction to Bayesian analysis as implemented in Mplus. For a technical discussion of this implementation, see Asparouhov and Muthén (2010a) with latent variable model investigations in Asparouhov and Muthén (2010b). Section 2 provides two mediation modeling examples which illustrate a non-normal posterior, how to use priors, and how to do a basic Bayes analysis in Mplus. Section 3 uses a CFA example to illustrate both informative priors and the use of PPC. Section 4 uses two-level regression to illustrate how to get correct a correct assessment of the size of a skewed random effect variance estimate and intraclass correlation even with a small number of clusters. Section 5 uses a two-part growth model to illustrate the speed advantage of Bayes over ML with many dimensions. Section 6 uses multiple-indicator growth for binary items to illustrate high-dimensional analysis that is not possible with ML. Section 7 uses a mixture model to illustrate how to handle label switching. Section 8 discusses alternative approaches to missing data modeling. Data and Mplus scripts are available on the Mplus web site under Mplus Examples, Applications using Mplus.

## 2 Two mediation modeling examples

Two mediation modeling examples are considered. The first example uses the ATLAS data of MacKinnon et al. (2004) and illustrates how different conclusions about the intervention effect are arrived at using ML versus Bayes. The second example uses the firefighter data of Yuan and MacKinnon (2009) to illustrate the use of priors based on information from previous studies to shorten the credibility interval (the Bayesian counterpart to confidence intervals) for the intervention effect.

### 2.1 The ATLAS example: Different conclusions using Bayes vs ML

The mediational model in Figure 1 was considered in MacKinnon et al. (2004). The intervention program ATLAS (Adolescent Training and Learning to Avoid Steroids) was administered to high school football players to prevent use of anabolic steroids. MacKinnon et al. (2004) used a sample of  $n = 861$  with complete data from 15 treatment schools and 16 control schools (the multilevel nature of the data was ignored and is ignored here as well; multilevel Bayesian mediational modeling is, however, available in Mplus). One part of the intervention aimed at increasing perceived severity of using steroids. This in turn was hypothesized to increase good nutrition behaviors. In Figure 1 these three variables are denoted  $tx$ ,  $severity$ , and  $nutrition$ , respectively.

[Figure 1 about here.]

A key parameter is the indirect effect of intervention on the nutrition outcome,  $a \times b$ . The ML point estimate (SE) for this is 0.020 (0.011) with an asymptotically-normal  $z$  test value of 1.913. Because this  $z$  value is not greater than 1.96, the indirect effect of the intervention is not deemed significant at the 5% level. Correspondingly, the ML 95%

confidence interval obtained by the CINTERVAL option of the OUTPUT command is  $0 - 0.041$ , that is, not excluding zero.

The Mplus input for the corresponding Bayesian analysis is shown in Table 1. The only change is to replace ESTIMATOR = ML with ESTIMATOR = BAYES. When two processors are used faster computations are obtained with the default of two MCMC chains to be discussed below. Note that the indirect effect is defined as the NEW parameter "indirect" in MODEL CONSTRAINT. Bayesian graphics are obtained with the option TYPE = PLOT2.

[Table 1 about here.]

The analysis results are shown in Table 2. The first column gives the point estimate, which by default is the median of the posterior distribution. The mean or mode can be obtained using the POINT option of the ANALYSIS command. The second column gives the standard deviation of the posterior distribution. A normally distributed z ratio is not used in Bayesian analysis. The third column gives a one-tailed p-value based on the posterior distribution. For a positive estimate, the p-value is the proportion of the posterior distribution that is below zero. For a negative estimate, the p-value is the proportion of the posterior distribution that is above zero. The fourth and fifth columns give the 2.5 and 97.5 percentiles in the posterior distribution, resulting in a 95% Bayesian credibility interval.

Using the default posterior median point estimate, the indirect effect estimate is 0.016, that is, slightly lower than the ML value with a slightly higher posterior distribution standard deviation of 0.013. Unlike the ML confidence interval, the Bayesian 95% credibility interval of  $0.002 - 0.052$  does not include zero, implying a positive intervention effect. The reason for this ML-Bayes discrepancy is found when studying the posterior distribution of the indirect effect.

[Table 2 about here.]

View Graphs is used to open the Bayes graphs. The first menu item is Bayesian posterior parameter distributions. Staying in histogram mode and selecting Parameter 8, indirect shows a skewed distribution for the indirect effect with a median of 0.01644; see Figure 2. A smoother picture of the posterior distribution is obtained by requesting the Kernel density (Botev et al., 2010) option instead of histogram; see Figure 3. The mean, median, and mode are marked as vertical lines in the distribution and are different due to the skewness of the distribution. It is clear that the ML normality assumption is not suitable for the indirect effect parameter (for technical arguments, see also MacKinnon, 2008). Therefore, the symmetric confidence interval that ML uses is not appropriate. Instead, the Bayesian credibility interval uses the 2.5 and 97.5 percentiles of the posterior distribution, allowing for skewness.

[Figure 2 about here.]

It is important to carefully consider convergence in Bayesian analysis. The default convergence criterion is that a Proportional Scale Reduction (PSR) factor is close enough to 1 for each parameter. For a technical definition, see Gelman and Rubin (1992), Gelman et al. (2004), and Asparouhov and Muthén (2010). Briefly stated, Bayesian analysis uses Markov chain Monte Carlo (MCMC) algorithms to iteratively obtain an approximation to the posterior distributions of the parameters from which the estimates are obtained as means, medians, or modes. Such iterations are referred to as a chain. In Mplus several such chains are carried out in parallel when using multiple processors. The PSR approach to determining convergence compares the parameter variation within each chain to that across chains to make sure that the different chains do not converge to different values. The PSR criterion essentially requires the between-chain variation to be small relative to the total of between- and within-chain variation. Mplus uses the default of two chains which usually gives good PSR information that compares well with using more chains. The first half of the iterations are considered as a "burn-in" phase and are not used to represent the



posterior distribution.

[Figure 3 about here.]

Figure 4 shows a trace plot of the two chains for the residual variance of the *severity* variable. It is seen how a starting value is improved in a few iterations. A total of 100 iterations are used at which point the convergence criterion is fulfilled. The TECH8 output shown on the screen and printed at the end of the output shows that for this example the largest PSR value at 100 iterations is 1.037. In the trace plot the burn-in phase is denoted by a vertical line at 50 iterations. The last 50 iterations appear to show a stable process with no upward or downward trend with the two chains overlapping in their variation. The posterior distribution shown in Figure 2 is determined by the remaining 50 values for each of the two chains, resulting in a distribution based on 100 points.

[Figure 4 about here.]

A good approach to gain further evidence of convergence is to run longer chains and check that the parameter values have not changed in important ways and that the PSR still remains close to 1. The Mplus option FBITERATIONS in the ANALYSIS command can be used to request a fixed number of Bayes iterations. Requesting 10,000 iterations gives the progression of PSR values in TECH8 seen in Table 3. Only the first 1000 iterations are shown. For more complex models 50,000 or 100,000 iterations may be used for further convergence checks.

When FBITERATIONS is used the PSR convergence criterion is not applied by Mplus. Although Mplus prints THE MODEL ESTIMATION TERMINATED NORMALLY convergence has to be verified by the user when using FBITERATIONS. The results are shown in Table 4. The estimates are rather close to those shown earlier for 100 iterations in Table 2.

[Table 3 about here.]

[Table 4 about here.]

Figure 5 shows the posterior distribution for the indirect effect. It is now smoother than in Figure 2 due to using longer chains, but still shows the skewness.

[Figure 5 about here.]

A further check of the posterior distributions is obtained by an autocorrelation plot. Figure 6 shows this for the indirect effect in the 10,000 iteration analysis. Autocorrelations show the degree of correlatedness of parameter values across iterations for different lags (intervals in the chain). A small value is desirable to obtain approximately independent draws from the posterior. A value of 0.1 or lower has been suggested. If the autocorrelation is high for small lags but decreases with increasing lags, using only every  $k$ th iteration can be accomplished by thinning using the THIN option of the ANALYSIS command. Thinning is also useful when a large number of iterations is needed for convergence, but a smaller number is desired for displaying the posterior distributions to reduce computer storage (this influences the size of the Mplus .gph file).

[Figure 6 about here.]

## 2.2 The firefighter example: Using informative priors

Yuan and MacKinnon (2009) discusses the benefits of Bayesian analysis for mediational analysis. Here it is shown how their firefighter example is carried out in Mplus. The example uses  $x$  to represent exposure to the randomized experiment,  $m$  to represent change in knowledge of the benefits of eating fruit and vegetables, and  $y$  to represent reported eating of fruits and vegetables. The model diagram is analogous to Figure 1. The sample size is  $n = 354$ . The focus is on the indirect effect  $a \times b$ . This example illustrates the use of priors. As a first step the analysis is done using the default of diffuse priors. The Mplus input is shown in Table 5 and the output in Table 6. Yuan and MacKinnon (2009) give the

corresponding WinBUGS code in their appendix. Table 6 shows a positive indirect effect with 95% credibility interval 0.011 – 0.117.

The firefighter example is used to illustrate the benefit of informative priors. Yuan and MacKinnon (2009, p. 311) put priors on the  $a$  and  $b$  slopes based on previous studies to show how this can reduce the width of the credibility interval for the indirect effect of the intervention. A normal prior is used for both slopes. For  $a$  the prior has mean 0.35 and variance 0.04 and for  $b$  the prior has mean 0.1 and variance 0.01. The prior variances are four times larger than what had been observed in previous studies in order to take into account possible differences in the current study. The Mplus input is shown in Table 7. The MODEL PRIORS command uses the labels  $a$  and  $b$  to apply the normal priors.

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

The output given in Table 8 shows a 95% credibility interval of 0.012–0.102. Compared to the Table 6 analysis with the default diffuse priors, this represents a 16% shortening of the credibility interval. The results agree with those of Yuan and MacKinnon (2009). With a smaller sample, the prior has a stronger effect. Figure 7 shows that the indirect effect has a skewed posterior distribution.

[Table 8 about here.]

[Figure 7 about here.]

## 2.3 Mediation modeling summary

The mediation modeling showed that the indirect effect has a non-normal distribution which is allowed for in the posterior distribution of Bayesian analysis. This can

result in incorrect conclusions when using regular ML due to the ML assumption of symmetric, normal distributions for parameter estimates. Bayesian analysis also allows the incorporation of prior information about parameter values, resulting in shorter intervals for the intervention effect. The use of informative priors clearly needs to be approached with caution. An investigator must not choose a certain prior because it makes it more likely to find an intervention effect. Priors need to draw on information from other similar studies.

An alternative approach to the Bayesian analysis discussed here is to use ML estimates combined with bootstrap-generated confidence intervals that do not assume a symmetric, normal distribution (see, e.g., MacKinnon et al., 1994; Shrout & Bolger, 2002). Such procedures are available in Mplus as described in Muthén & Muthén (1998-2010). An interesting line of research is to study the relative performance of Bayes versus ML with bootstrap.

### **3 Bayes CFA: Using informative priors for small cross-loadings instead of fixing them to zero**

The context of confirmatory factor analysis (CFA) is used to introduce a new Bayesian concept, Posterior Predictive Checking (PPC). With continuous outcomes, PPC in Mplus builds on the standard likelihood-ratio chi-square statistic in mean- and covariance-structure modeling, where a specific  $H_0$  model is tested against the unrestricted  $H_1$  model. This PPC procedure is described in Scheines et al. (1999) and Asparouhov and Muthén (2010), drawing on Gelman et al. (1996). This statistic is evaluated for the data at the Bayes-estimated parameter values. It is compared to a distribution of such values obtained by many replications of the sequence: (1) drawing Bayes parameter estimates from the posterior distribution; (2) drawing a sample of synthetic observations on the

outcomes given the parameter values obtained in (1); and (3) computing the likelihood-ratio chi-square statistic for this synthetic sample. The extremeness of the value of the observed-data statistic is evaluated using the synthetic-data statistics by where it falls in the synthetic-data test statistic distribution. An extreme value shows that the model does not adequately represent the data.

This section also demonstrates the use of the Deviance Information Criterion (DIC; Spiegelhalter et al., 2002; Gelman et al., 2004). Models with small DIC values are preferred. DIC is a Bayesian generalization of the AIC and BIC which draw on ML estimation and balance the largeness of the likelihood with a penalty for the number of parameters expended. For DIC the number of parameters used in the penalty is the effective number of parameters referred to as  $p_D$ .

### 3.1 Holzinger-Swineford mental abilities study

As an example of a confirmatory factor analysis (CFA) using Bayesian estimation, data are considered from the classic 1939 study by Holzinger and Swineford (1939). Twenty-six tests intended to measure a general factor and five specific factors were administered to seventh and eighth grade students in two schools, the Grant-White School ( $n = 145$ ) and the Pasteur School ( $n = 156$ ). Students from the Grant-White School came from homes where the parents were American-born and this sample is considered here.

Factor analyses of these data have been described e.g. by Harman (1976; pp. 123-132). Of the 26 tests, nineteen were intended to measure different specific domains, five were intended to measure general deduction and two were revisions/new test versions. Typically, the last two are not analyzed. Excluding the five general deduction tests, 19 tests measuring four domains are considered here: spatial ability, verbal ability, speed, and recognition/memory. The design of the measurement of the four domains by the 19 tests is shown in the factor loading pattern matrix of Table 9. Here, an X denotes a free loading

to be estimated and 0 a fixed, zero loading. This corresponds to a simple structure CFA model with variable complexity one, that is, each variable loads on only one factor.

[Table 9 about here.]

### 3.2 Simple structure CFA

Table 10 shows the Mplus input for a Bayesian CFA with a simple structure where an item loads on only its hypothesized factor. To obtain convergence, ML starting values and 20,000 iterations in each of the two default chains are requested in the ANALYSIS command. The factor metric is determined by fixing the factor variances at one.

[Table 10 about here.]

Table 11 shows that the model is rejected based on the Bayesian Posterior Predictive Checking (PPC) using the likelihood-ratio chi-square statistic (Asparouhov & Muthén, 2010). The Posterior Predictive P-value (PPP) is 0.006. The 95% confidence interval for the difference between the observed-data test statistic and the replicated-data test statistic is 17 to 112, indicating that the observed-data statistic is much larger than what would have been generated by the model. The corresponding PPC distribution is shown in Figure 8. The location of the observed-data test statistic is marked by a vertical line at zero. The corresponding PPC scatter plot is shown in Figure 9, where the proportion of points above the 45 degree line corresponds to the p-value. These type of displays are further discussed in Gelman et al. (2004, p. 164). The model rejection is in line with ML likelihood-ratio chi-square testing which also rejects the model and obtains a p-value of 0.0002 (CFI = 0.93, RMSEA = 0.057, SRMR = 0.063).

[Table 11 about here.]

[Figure 8 about here.]

[Figure 9 about here.]

Despite the poor fit, it is of interest to display the estimates from the simple structure CFA as a basis for comparison with revised models. Table 12 gives the parameter estimates, except for the intercepts and the residual variances. The factor loadings are presented column-wise in the factor loading matrix, one factor at a time.

[Table 12 about here.]

### **3.3 Adding priors for cross-loadings**

The simple structure CFA hypothesizes that an item loads on only one factor, that is, no items have cross-loadings. This can be argued to be a strongly simplified representation of the real measurement situation and not essential to the notion that each item is designed to measure a specific factor. A more realistic hypothesis might be that each item has a major loading on the hypothesized factor but that small cross-loadings are possible due to a minor influence on the item from some of the other factors. For example a spatial item may involve a speed or memory component due to how the tests were formulated. To reflect this, cross-loadings can be given informative priors where the mean is zero, and where the variance is small but not zero. The specification of this type of Bayesian CFA is shown in Table 13, where a normal prior with a small variance is specified for each cross-loading. These cross-loadings are not all identified in the sense that if an ML analysis freed all of them the model would not be identified. The loadings are in a standardized metric because the items are standardized and the factor variances are fixed at one. This is a scale-free model so the model fit, standardized solution, and confidence/credibility intervals are the same for items that have been standardized or not (the item standardization is seen in Table 10). A variance prior of 0.01 is chosen. It implies that the range of cross-loading values two standard deviations away from the prior mean of zero is  $-0.2$  to  $0.2$ , that is, approximately

95% of the prior is within this rather narrow range. Several other variances for the priors were explored where the 0.01 choice resulted in the smallest Deviance Information Criterion (DIC). The variance (DIC) values were: 0.001 (6986), 0.01 (6967), 0.05 (6971), 0.1 (6975), 0.5 (no convergence).

[Table 13 about here.]

Table 14 shows that the Bayes model with priors for cross-loadings matches the data rather well with a PPP of 0.353. The corresponding distribution of test statistics based on data generated from the parameter posteriors and the position of the real-data test statistic are shown in Figure 10. The vertical line is now more centrally located in the distribution on the left and a substantial portion of the points in the scatter plot on the right are above the 45-degree line. This is in contrast to the poor match between the model and data shown in Figure 8 and Figure 9 for the original CFA. The DIC value has also improved from the original model's 6997 to the current model's 6967.

[Table 14 about here.]

[Figure 10 about here.]

All cross-loadings are small. The spatial factor loadings are shown in Table 15, where cross-loadings are displayed between the red horizontal lines. Only the three spatial factor items addition, straight, and object have one-tailed p-values less than 0.05. The three items are also the ones that have the largest modification indices in the ML analysis of the simple structure CFA. It is interesting to see that Bayesian analysis can in this way provide a counterpart to the use of ML modification indices for modifying a model. Table 16 shows that the factor correlations are smaller in this analysis than in the simple structure CFA of Table 12. This is a useful side effect of letting the correlations between the items be channeled through more factors instead of only their primary factors which might force inflated factor correlations.



[Table 15 about here.]

[Table 16 about here.]

### 3.4 Freeing cross-loadings

As a final step in the Bayesian CFA, the three cross-loadings for the spatial factor, addition, straight and object, are freed. Table 17 shows the input and Table 18 - Table 20 give output excerpts. Only the loadings for the spatial factor are shown. The Posterior Predictive p-value is 0.173. The corresponding p-value for the likelihood-ratio chi-square test in the ML analysis with these three free cross-loadings is 0.0492. The lower p-value for ML may indicate that the LRT is somewhat more powerful than the PPC. The model may have further cross-loadings that should be free, but this is not investigated here. The DIC value has now improved to 6958 from the value 6967 of the earlier model with informative priors.

Table 19 shows that the spatial factor loadings that were freed for the three items addition, straight, and object are larger than in Table 15. This is because default diffuse priors have replaced the informative small-variance priors for these three loadings.

[Table 17 about here.]

[Table 18 about here.]

[Table 19 about here.]

[Table 20 about here.]

An alternative Bayesian analysis adds to the model with three free cross-loadings by using informative priors for the remaining cross-loadings with the small prior variance applied earlier. This may indicate that new cross-loadings should be freed. A summary of DIC and PPC model test results for this model and the previous three is shown in Table 21, also adding the ML results.

[Table 21 about here.]

### 3.5 Bayes CFA summary

The Bayes CFA example showed another use of informative priors. A considerably better fit to the data was obtained by avoiding the ML use of cross-loadings fixed exactly at zero and instead allowing cross-loadings to have priors with a narrow range around zero. The example showed that model fit can be assessed by PPC and models can be compared using DIC. Model modification was possible based on posterior estimates of cross-loadings. The idea of using priors with small variances for cross-loadings can be generalized to other model settings. An example is MIMIC modeling where all direct effects from covariates to factor indicators cannot be identified but can be given such priors and thereby point to model modification in terms of freeing direct effects.

An alternative approach that also avoids fixing cross-loadings to zero is exploratory factor analysis (EFA), which has been generalized to exploratory structural equation modeling (ESEM; Asparouhov & Muthén, 2009). A four-factor EFA gives the ML p-value of 0.248. Compared to model 3 in Table 21 this suggests that more cross-loadings should be freed. EFA, however, may not be optimal in cases with a strong hypothesis and well-known measurements in that it moves further away from the original simple structure CFA hypothesis and only maintains the hypothesis of the number of factors. Bayes stays with the original CFA model while allowing minor cross-loadings.

PPC procedures including the likelihood-ratio chi-square used here need more research to gauge their performance in terms of power to detect different kinds of misspecification at different sample sizes. Alternative PPC test statistics can be explored. It should be noted that PPC p-values were obtained also for the just-identified mediation models of Section 2. In such cases the testing is mostly in terms of normality assumptions being fulfilled or not. Sensitivity of PPC to non-normality needs to be explored.

## 4 Bayes multilevel regression

This section shows how Bayesian analysis can be used in twolevel settings even in examples where there are few cluster units. The important choice of level-2 variance priors is discussed. Examples are given of how to perform simulation studies in Mplus to explore the impact of different choices of variance priors.

Consider a two-level regression model for individuals  $i = 1, 2, \dots, n_j$  in clusters  $j = 1, 2, \dots, J$ ,

$$\begin{aligned}y_{ij} &= \beta_{0j} + \beta_{1j} x_{ij} + r_{ij}, \\ \beta_{0j} &= \gamma_{00} + u_{0j}, \\ \beta_{1j} &= \gamma_{10}.\end{aligned}\tag{1}$$

so that the intercept  $\beta_{0j}$  is random and the slope  $\beta_{1j}$  is fixed. Here,  $r_{ij}$  and  $u_{0j}$  are assumed independently and normally distributed with zero means and variances to be estimated.

### 4.1 An example

In many settings, the number of cluster units  $J$  is small, whereas the number of individuals in a cluster  $n_j$  is not small. An example is a school-based study where it is easier to sample many students within schools than to sample many schools. Another example is individuals observed within countries. Consider a data set with 10 schools each with 50 students. This is a type of situation where Bayesian analysis performs well. Bayes is expected to perform better than ML because the number of independent observations is only 10 so that the large-sample ML theory does not provide a good approximation. It is of interest to study the degree of heterogeneity across schools in terms of the random intercept variance and the intraclass correlation. If substantial heterogeneity is found, school-level predictors of the random effect may be explored.

Table 22 shows the Mplus input for Bayesian analysis of the model in (1). Here,  $y$  on level-2 (BETWEEN) denotes the random intercept. The variance of the random intercept is given the parameter label  $b$ . A common variance prior uses the inverse-gamma distribution  $IG(\alpha, \beta)$ , where  $\alpha$  is a shape parameter and  $\beta$  is a scale parameter. The mean of the inverse-gamma distribution is  $\beta/(\alpha - 1)$  for  $\alpha > 1$  and the mode is  $\beta/(\alpha + 1)$ . For a discussion of this prior, see, e.g., Gelman et al. (2004). With  $\epsilon$  denoting a small value, an  $IG(\epsilon, \epsilon)$  variance prior is commonly used for the random intercept variance  $b$  with  $\epsilon = 0.001$ . The  $IG(0.001, 0.001)$  variance prior is, for example, frequently used in the BUGS literature (Spiegelhalter et al., 1997). The intraclass correlation is defined in MODEL CONSTRAINT using the level-1 (WITHIN) residual variance  $w$  and the level-2 (BETWEEN) variance  $b$ .

[Table 22 about here.]

Table 23 shows output excerpts. It is seen that the default median point estimate for the random intercept variance is 0.223 and the 95% credibility interval ranges from 0.073 to 0.805 so that it does not include zero. The credibility interval for the intraclass correlation is also bounded away from zero. The conclusion is that there is an important degree of heterogeneity among schools for the intercept in the regression of  $y$  on  $x$ . Given this finding, the next step is to include level-2 covariates to explain the heterogeneity.

[Table 23 about here.]

The posterior distributions of the random intercept variance and the intraclass correlations are given in Figure 11 and in Figure 12, respectively. Because the distributions are strongly non-normal, it should not be expected that the usual ML-based, symmetric confidence intervals for these parameters behave well.

[Figure 11 about here.]

[Figure 12 about here.]

Table 24 shows the ML results. The random intercept variance estimate is small relative to its estimated standard error. It is, however, well-known that in this case the estimate/SE ratio is not approximately normally distributed and that a regular likelihood-ratio chi-square test of the random intercept variance being zero is not correct. The symmetric ML 95% confidence interval for the random effect variance (not shown in the table) includes zero and even goes into the negative range,  $-0.014$  to  $0.393$ . The symmetric ML 95% confidence interval for the intraclass correlation is  $0.001$  to  $0.166$ , barely not covering zero. The Bayesian results are more trustworthy than the ML results and this is demonstrated in the following simulation study.

[Table 24 about here.]

## 4.2 A simulation study

The data analyzed above come from the first replication of a Monte Carlo simulation study. The data are generated using the model of (1) with a random intercept variance of  $0.222$  and an intraclass correlation of  $0.1$ . Five-hundred replications are used to study the performance of the ML and Bayes estimators. The ML results summary is shown in Table 25. In line with the results of the previous section, the random intercept variance and the intraclass correlation both show poor 95% coverage using the regular symmetric confidence interval. There is also a negative bias in the point estimates for both parameters.

[Table 25 about here.]

Bayesian analysis of the same model produces much better results than ML. For twolevel models the choice of prior for the random intercept variance is important. A good discussion is given in Browne and Draper (2006). Their simulation studies suggest

using either the inverse-Gamma prior  $IG(\epsilon, \epsilon)$  with a median point estimate or the uniform prior  $U(0, 1/\epsilon)$  with a mode point estimate (see p. 483 and p. 502). The Mplus default variance prior is  $IG(-1,0)$  which implies a uniform prior ranging from minus infinity to plus infinity.

Table 26 shows the Monte Carlo input with  $IG(0.001, 0.001)$  and Table 28 - Table 29 show the Monte Carlo results when using  $IG(0.001, 0.001)$ ,  $U(0, 1000)$ , and  $IG(-1,0)$ , respectively. The first two priors give good point estimates and more importantly good 95% coverage for the random intercept variance and intraclass correlation. Here, 95% coverage refers to the proportion of the replications where the 95% Bayesian credibility interval covers the true value. The last column labeled *%Sig* refers to the proportion of the replications where the 95% Bayesian credibility interval does not cover zero. This estimates the power to reject that a non-zero parameter is zero.

The posterior standard deviation is not well estimated, perhaps due to a high autocorrelation in the MCMC chains, but this does not affect the 95% coverage. The default prior  $IG(-1,0)$  does not give a good point estimate in this case. It gets a somewhat better point estimate using the mode instead of the default median point estimate. However, the critical feature in the Bayesian analysis is the coverage which is good for all three priors and much better than the ML coverage. Similar results are obtained with 15 and 25 clusters and intraclass correlation 0.2 instead of 0.1.

[Table 26 about here.]

[Table 27 about here.]

[Table 28 about here.]

[Table 29 about here.]

## 5 Examples where Bayes is faster than ML

### 5.1 Two-part growth modeling

Growth modeling is frequently carried out with an outcome for which at a given point in time a large portion of its subject does not engage in the activity, giving rise to a large number of subjects at the lowest point of the outcome scale. As an example consider the outcome of heavy drinking, measured by the question: How often have you had 6 or more drinks on one occasion during the last 30 days? This question was asked in the National Longitudinal Study of Youth (NLSY), a nationally representative household study of 12,686 men and women born between 1957 and 1964. The responses are coded as: never (0); once (1); 2 or 3 times (2); 4 or 5 times (3); 6 or 7 times (4); 8 or 9 times (5); and 10 or more times (6). There are eight birth cohorts, but the current analysis considers only cohort 64 measured in 1982, 1983, 1984, 1988, 1989, and 1994 at ages 18, 19, 20, 24, and 25. Time-invariant covariates used in the analysis are gender, ethnicity, early onset of regular drinking (es), family history of problem drinking, high school dropout and college education.

Figure 13 shows the idea behind two-part growth modeling, where a variable is split into two parts, a binary part representing engaging in the activity or not and a continuous part representing the amount of the activity when engaged in it. When the binary variable indicates non-engagement, the continuous part is scored as missing. The statistical theory of two-part growth modeling is given in Olsen and Schafer (2002). A strength of the two-part model is that the covariates are allowed to have different effects on the two growth curves.

[Figure 13 about here.]

Table 30 shows the Mplus input using Bayes estimation. The DATA TWOPART command splits the variable into two parts. A quadratic growth model is used for both

the binary and continuous parts. Further information on the Mplus input for two-part growth modeling is given in ex6.16 of the Mplus User's Guide (Muthén & Muthén, 1998-2010). The output is shown in Table 31, Table 32, and Table 33. Not all parameter estimates are shown. Table 31 shows a high p-value for the PPC. The power of this test is, however, only acceptable for misspecifications in the continuous part (Asparouhov & Muthén, 2010).

[Table 30 about here.]

[Table 31 about here.]

[Table 32 about here.]

[Table 33 about here.]

As an example of differences in results between regular growth modeling and two-part growth modeling, consider the covariate *es* (early start, that is, early onset of regular drinking scored as 1 if the respondent had 2 or more drinks per week at age 14 or earlier). Regular growth modeling (not shown) says that *es* has a significant, positive influence on heavy drinking at age 25, increasing the frequency of heavy drinking. Two-part growth modeling says that *es* has a significant, positive influence on the probability of heavy drinking at age 25, but among those who engage in heavy drinking at age 25 there is no significant difference in heavy drinking frequency with respect to *es*, other covariates held constant.

The corresponding ML results are shown in Table 34 and Table 35. A probit link is used for the binary part to match the Bayesian model. The Bayes and ML results are similar. The ML analysis, however, uses three dimensions of numerical integration due to the binary part of the model and is more than two times slower than the Bayesian analysis. A 2-5 times Bayes speedup has also been seen in other two-part growth modeling applications.



Simulations studies of Bayesian analysis of two-part growth models are given in Asparouhov and Muthén (2010b), studying the performance of both parameter credibility intervals and PPC.

[Table 34 about here.]

[Table 35 about here.]

Other examples where Bayes computations are faster than ML include two-level regression with a binary outcome and random slopes. This is particularly the case if a random slope has a very small variance, which tends to strongly slow down the ML convergence.

## **6 Examples using Bayes where ML computations are too heavy**

ML computations are heavy when numerical integration is required and there are many dimensions of integration. Numerical integration is needed when categorical outcomes are modeled with continuous latent variables. This is the case in factor analysis of categorical outcomes, also referred to as Item Response Theory (IRT). This example combines IRT and growth modeling using nine binary indicator of a factor measured at eight time points. With ML, this would give rise to eight dimensions of numerical integration which is not feasible.

The outcome variable of interest in this example is teacher ratings (TOCA-R) of children's aggressive behavior in the classroom (breaks rules, harms property, fights, etc.) in cohort 1 of the Baltimore Public school study, following children through grades 1 to 6. Eight teacher ratings were made from fall and spring for the first two grades and every spring in grades 3 to 6. The ratings are made on a six-point scale but have very skewed

distributions and are dichotomized for the purpose of the present analysis. Figure 14 shows a model diagram for a quadratic growth model for the factors at the eight time points.

[Figure 14 about here.]

The Mplus input is shown in Table 36 and Table 37. Measurement invariance for factor loading and item thresholds is specified and the change in factor means across time is determined by the growth factors,  $i$ ,  $s$ , and  $q$ . A time-invariant covariate gender has been added to the model. A discussion of the input is given for a similar setting in Example 6.15 of the Mplus User's Guide (Muthén & Muthén, 1998-2010). A total of 20,000 iterations are used to ensure convergence in the Bayesian analysis.

[Table 36 about here.]

[Table 37 about here.]

Table 38 - Table 42 show output excerpts from the multiple-indicator growth model. Table 40 shows that males start higher, growth faster initially, and decline faster than females. The PPC model testing of Table 38, however, gives a low p-value of 0.002. This is even more noteworthy given that power for the chi-square PPC with binary outcomes is shown to be rather low in Asparouhov and Muthén (2010b). The low p-value may indicate a lack of unidimensionality among the nine indicators.

[Table 38 about here.]

[Table 39 about here.]

[Table 40 about here.]

[Table 41 about here.]

[Table 42 about here.]

Other applications using Bayes where ML is not feasible include multiple-indicator growth modeling in cluster samples. This is the situation for the aggression study where data are collected on students within 41 classrooms. Growth modeling in cluster samples is referred to as three-level analysis in the multilevel literature. In the multilevel literature having multiple indicators is often viewed as an additional level, typically holding the loadings equal across the multiple indicators, resulting in a four-level analysis. In Mplus, however, such an analysis is handled by a two-level model for students within classrooms, where both the repeated measures and the multiple indicators within time are arranged in a wide format. This provides a more flexible analysis where loadings can be different across items and where thresholds and loadings for the same item can be different across time using partial measurement invariance modeling.

Figure 15 shows the model diagram for such a model, generalizing the model of Figure 14 to two levels. To avoid multidimensionality misspecification, three items corresponding to property-related aggression are used at each of the eight time points. The analysis is carried out using the outcome in polytomous form modeled as an ordered probit model. The original response format has six categories, but the two highest categories have low frequencies and are combined with the fourth category. Using all six categories gives non-convergence as judged by PSR values for the higher thresholds. A binary version makes convergence difficult, perhaps due to too little information. The four-category version gives convergence after 50,000 iterations using the default of two chains. The Mplus model specification is discussed for a similar case in the User's Guide Example 9.15. A novel feature of the model is shown by the time-specific residuals for the between-level random intercepts for each outcome. The variances of these residuals are not typically included in a model using ML analysis. With eight time points and three items per time point, the between-level part of the model leads to 24 dimensions for the numerical integration used in ML. To this number needs to be added the 8 dimensions on the within level, adding

to 32 dimensions. Without the between-level residuals, the model implies a total of 16 dimensions. Such ML analyses are intractable. The Bayesian analysis results (not shown) give 95% credibility intervals bounded away from zero for all the 24 between-level residual variances.

[Figure 15 about here.]

## 7 Conclusions

Further sections will follow in the next version of this paper. Comments are invited on the discussion so far, including aspects that could be further clarified or added. Please send your email to [bmuthen@ucla.edu](mailto:bmuthen@ucla.edu).

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Figure 1: Mediation model for the ATLAS example

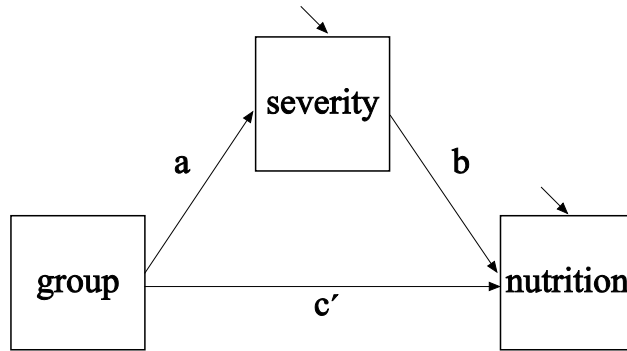


Figure 2: Indirect effect posterior distribution for the ATLAS example

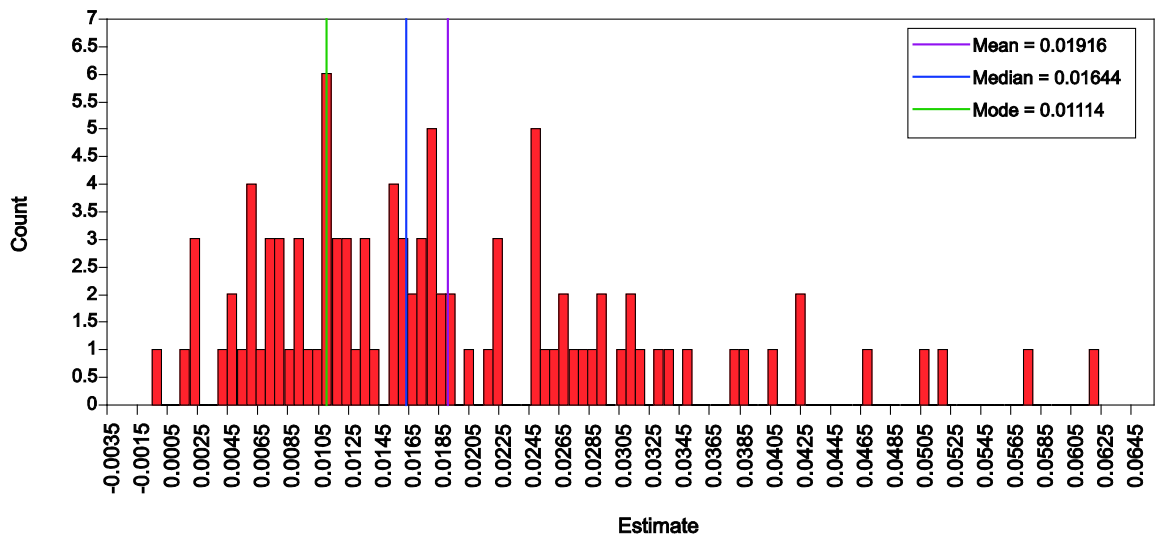


Figure 3: Kernel density estimate of indirect effect posterior distribution for the ATLAS example

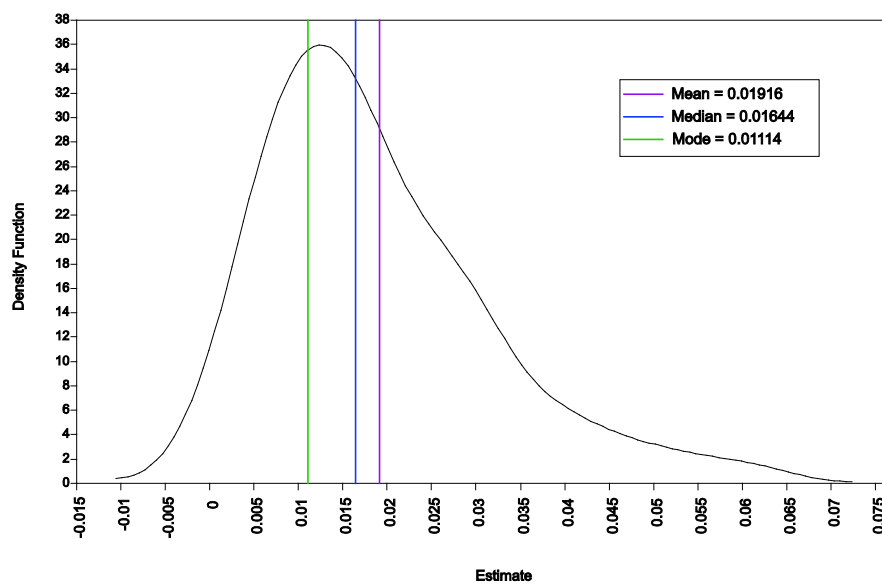


Figure 4: Trace plot of severity residual variance for the ATLAS example

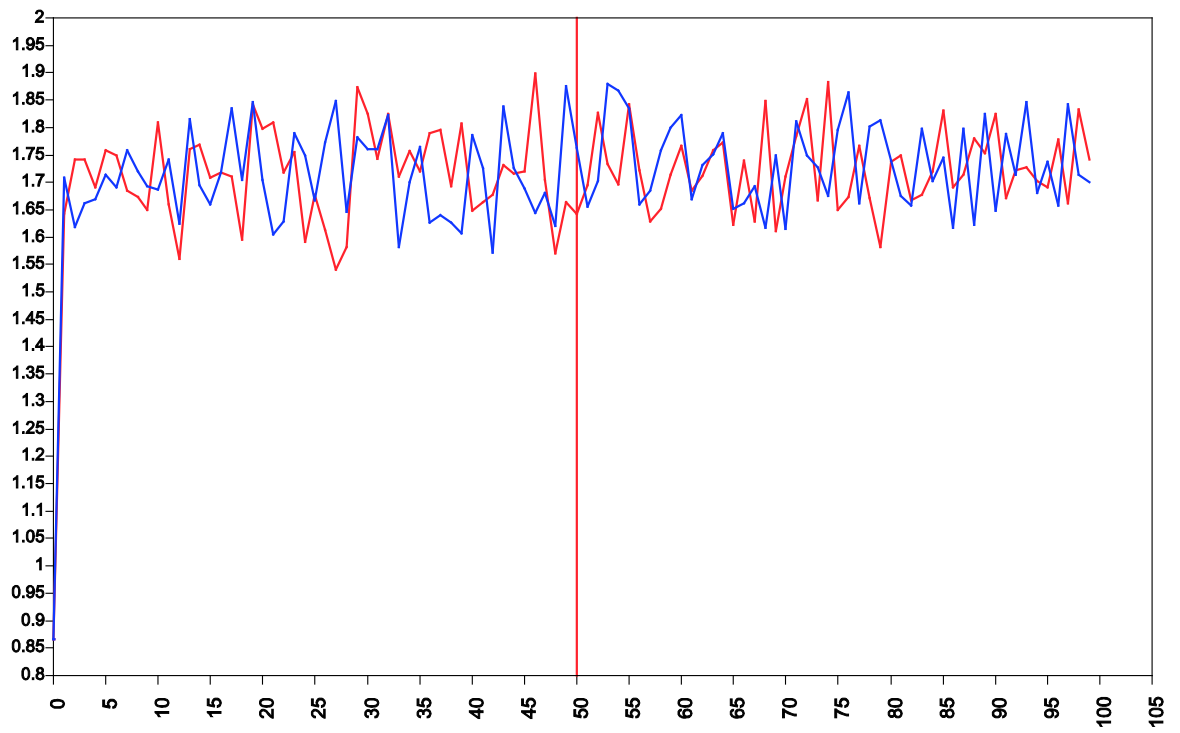


Figure 5: Indirect effect posterior distribution from 10,000 iterations for the ATLAS example

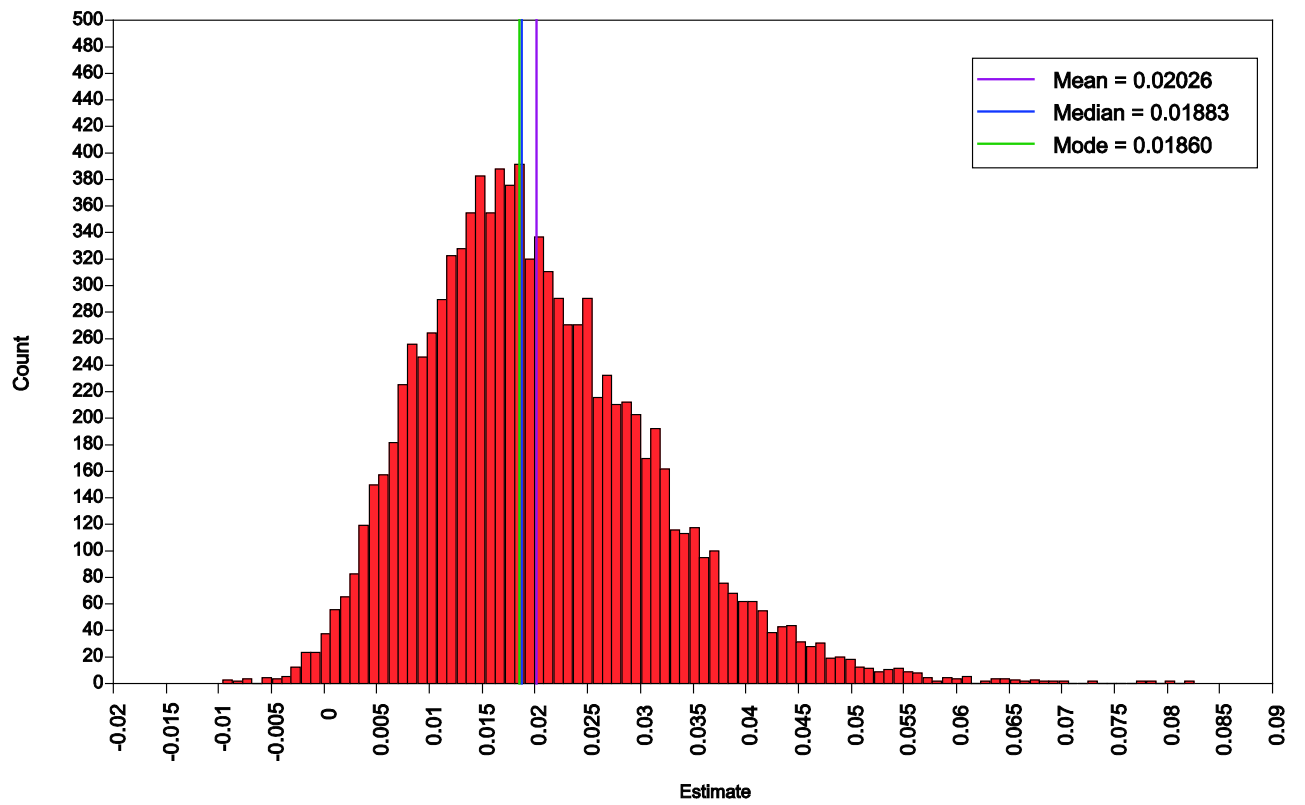


Figure 6: Autocorrelation plot for indirect effect from 10,000 iterations for the ATLAS example

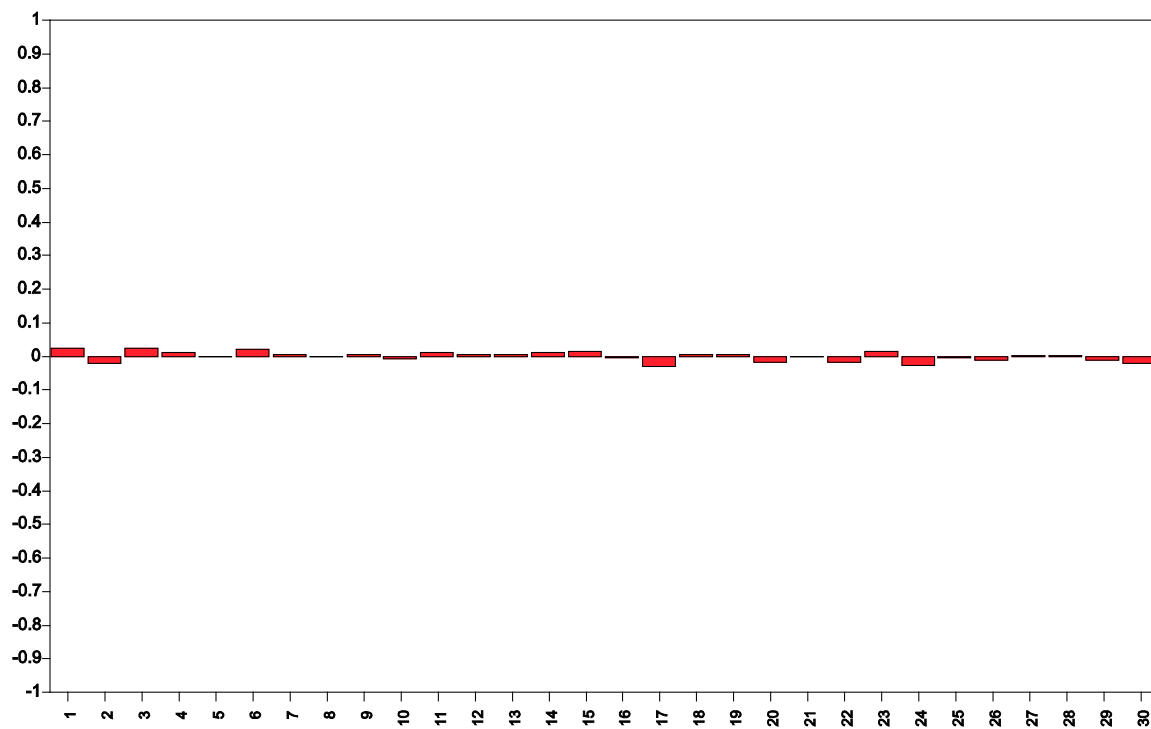


Figure 7: Indirect effect posterior from 10,000 iterations for the Firefighter example using priors

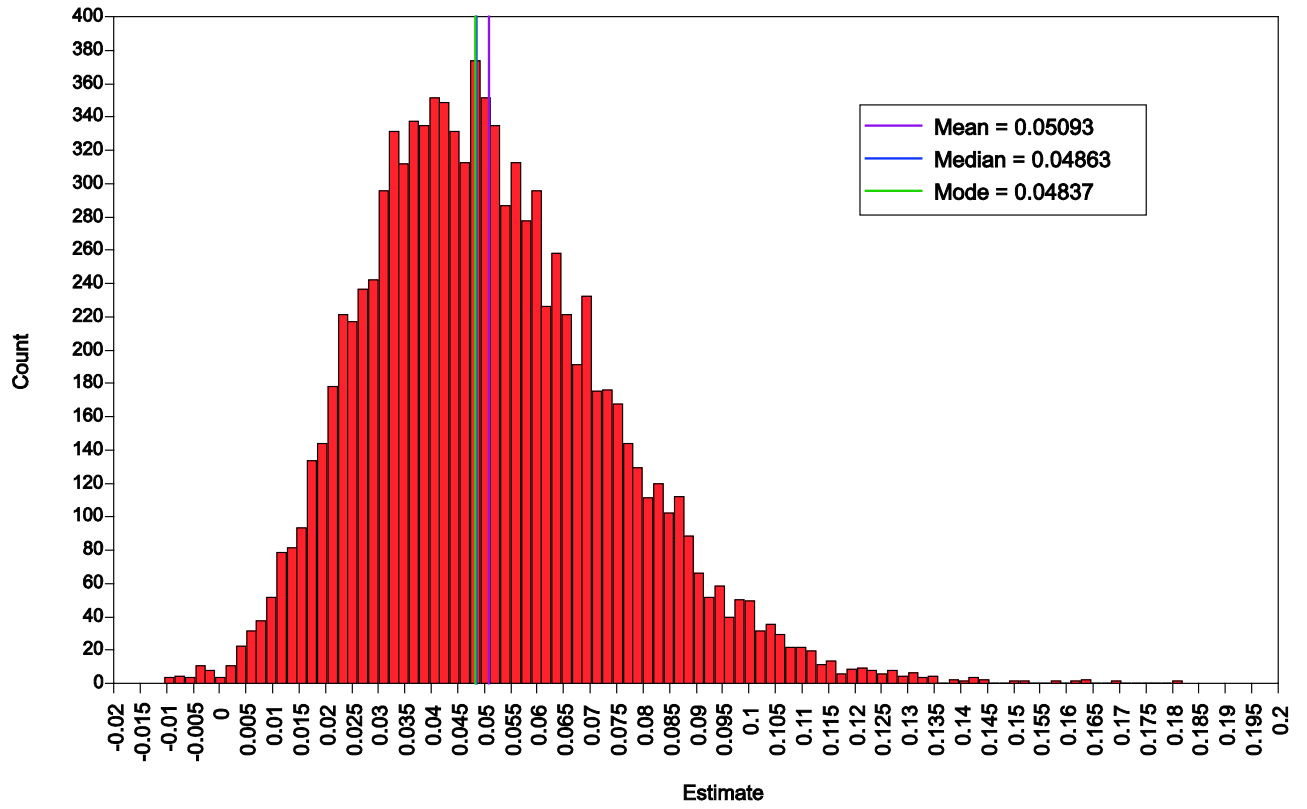




Figure 8: Posterior Predictive Checking (PPC) for Holzinger-Swineford data with simple structure CFA: PPC distribution

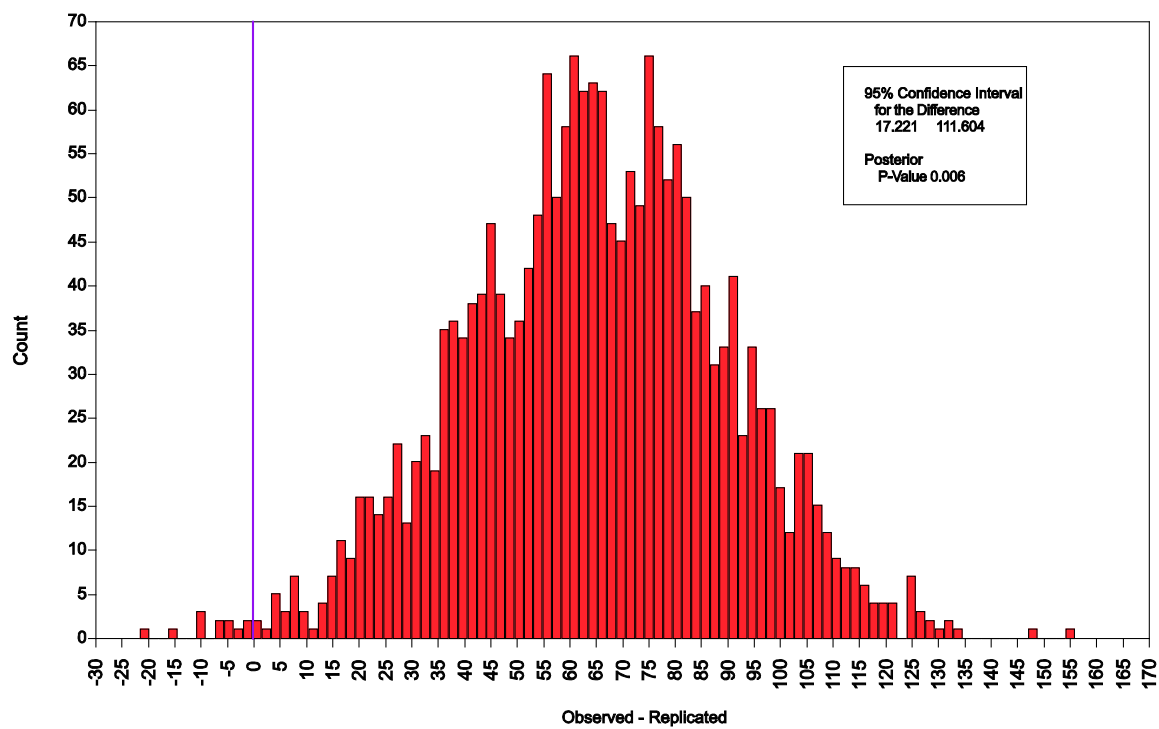
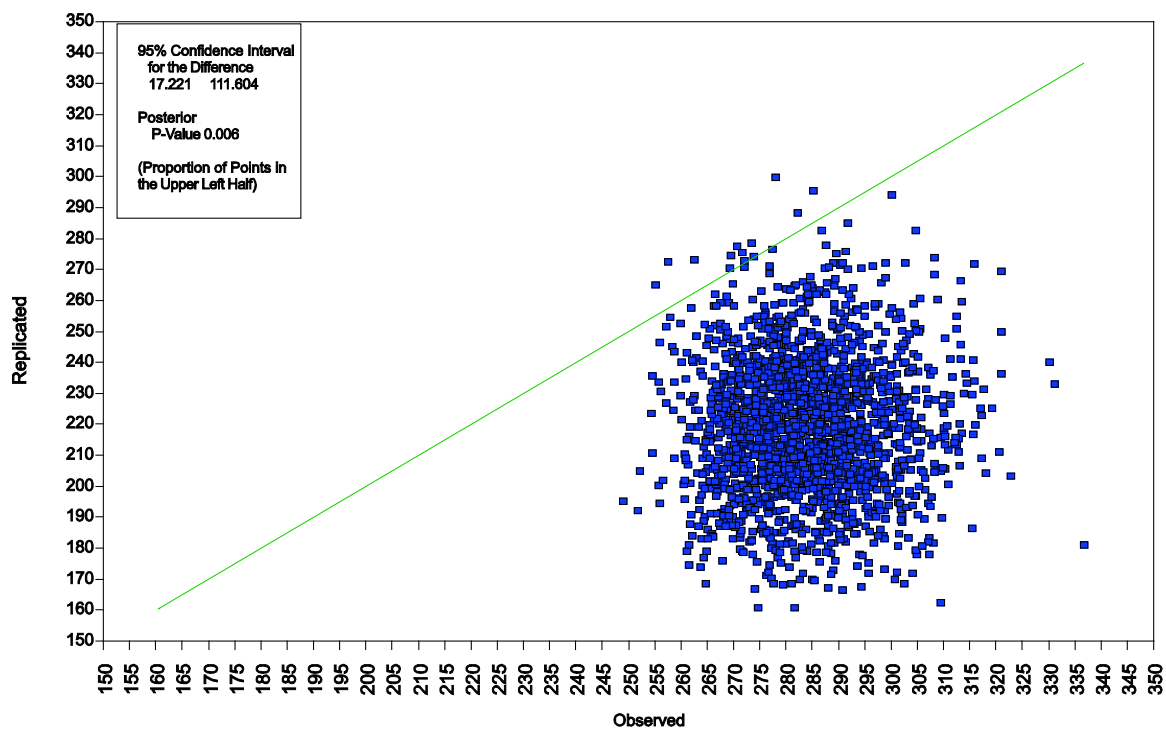
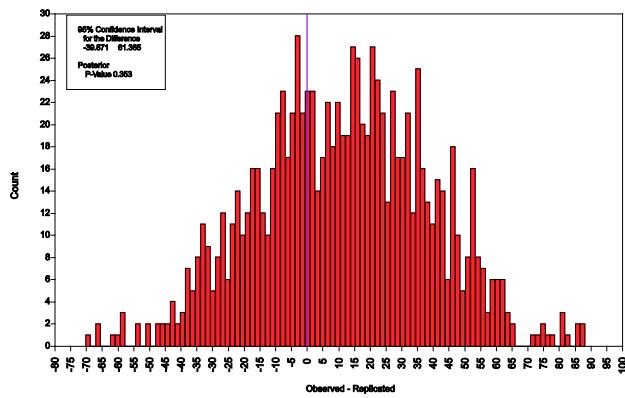
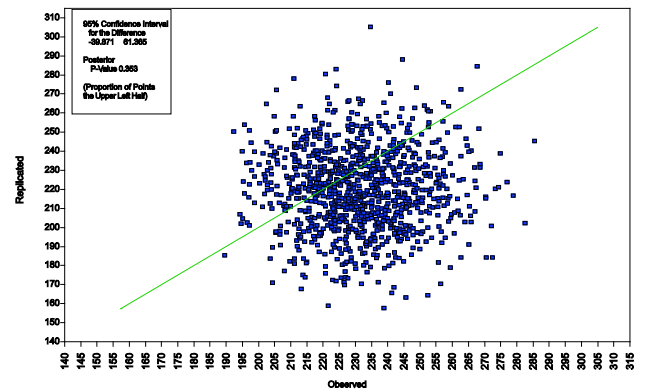


Figure 9: Posterior Predictive Checking (PPC) for Holzinger-Swineford data with simple structure CFA: PPC scatter plot





(a) PPC distribution for Bayes CFA



(b) PPC scatterplot for Bayes CFA

Figure 10: Posterior Predictive Checking (PPC) for Holzinger-Swineford data with priors on cross-loadings

Figure 11: Posterior distribution for random intercept variance

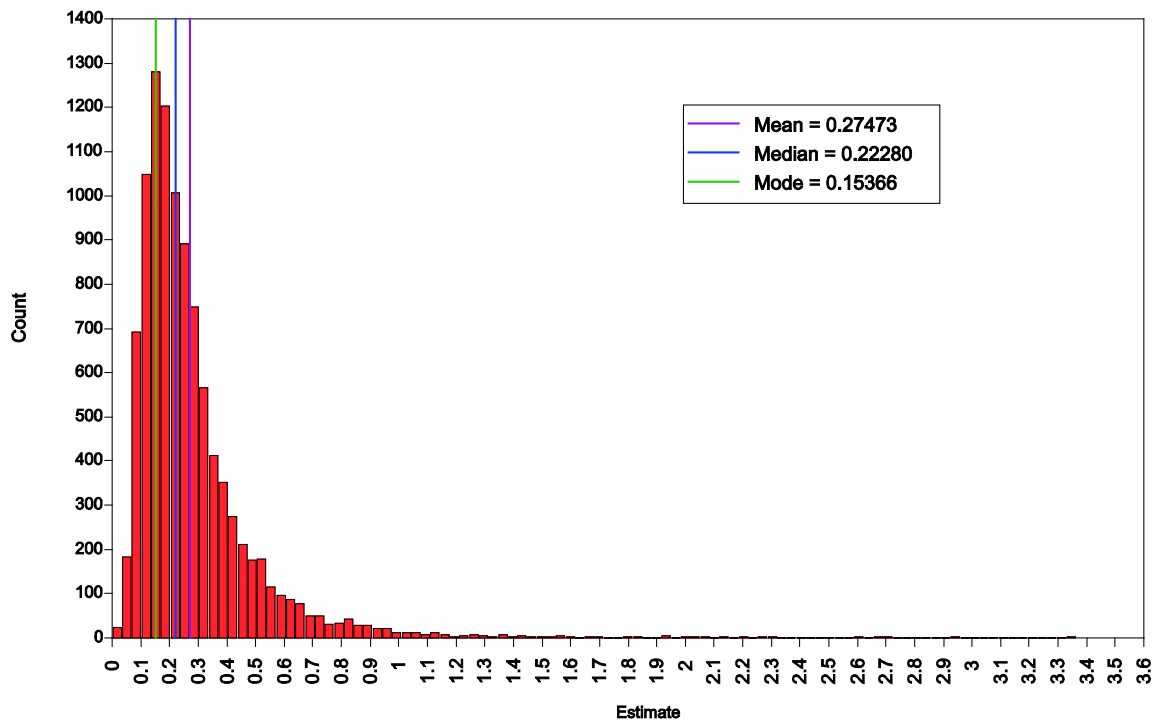


Figure 12: Posterior distribution for intraclass correlation

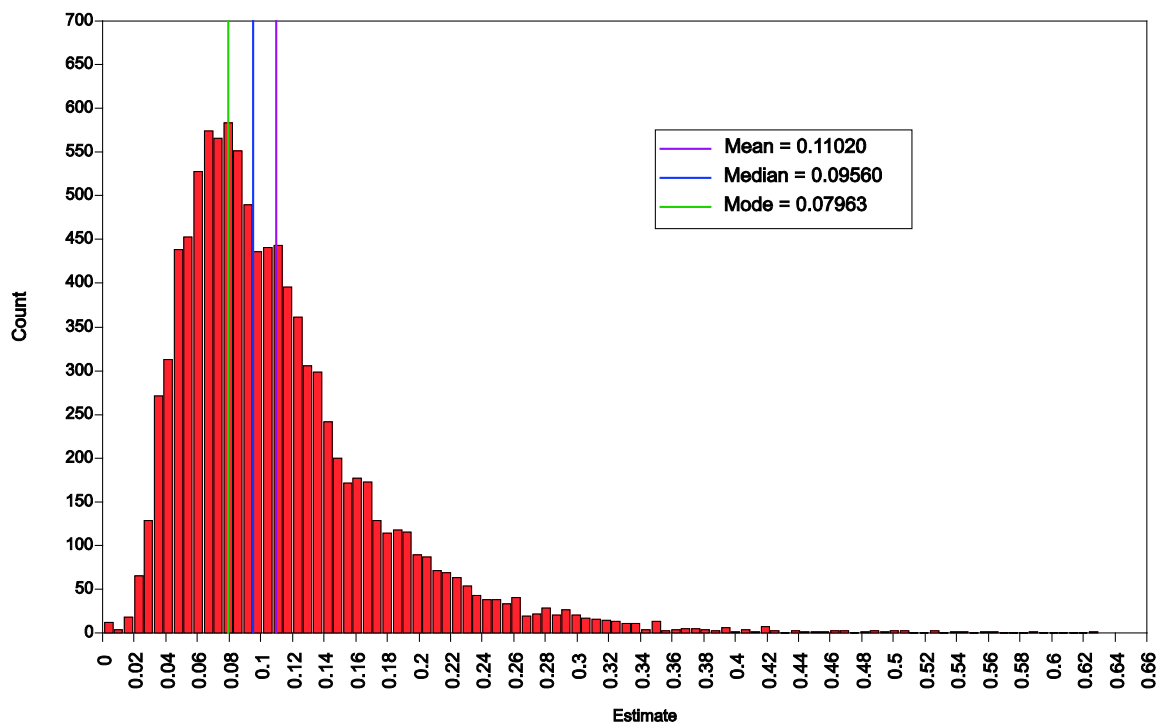


Figure 13: Two-part growth modeling of heavy drinking ages 18 - 25

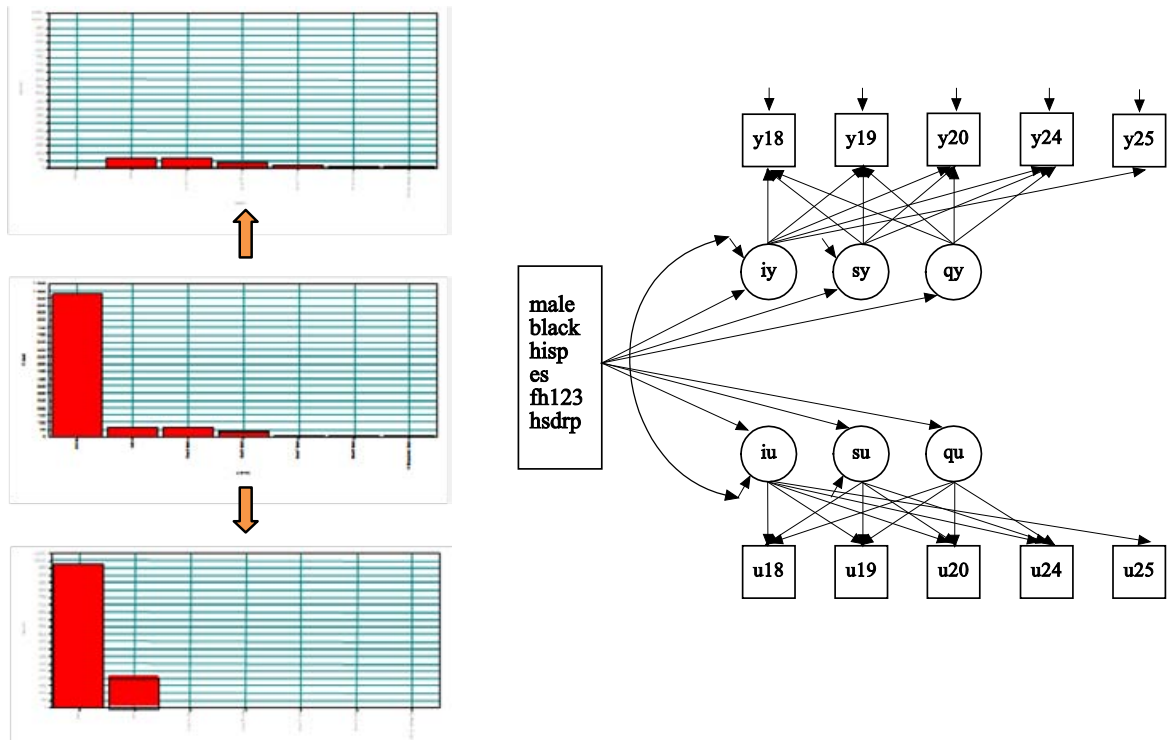


Figure 14: Binary multiple-indicator growth modeling of aggressive behavior over eight time points

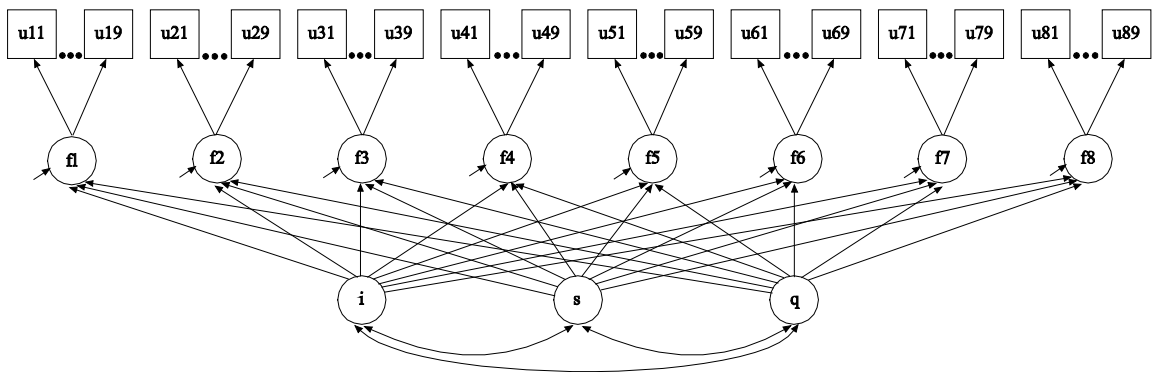
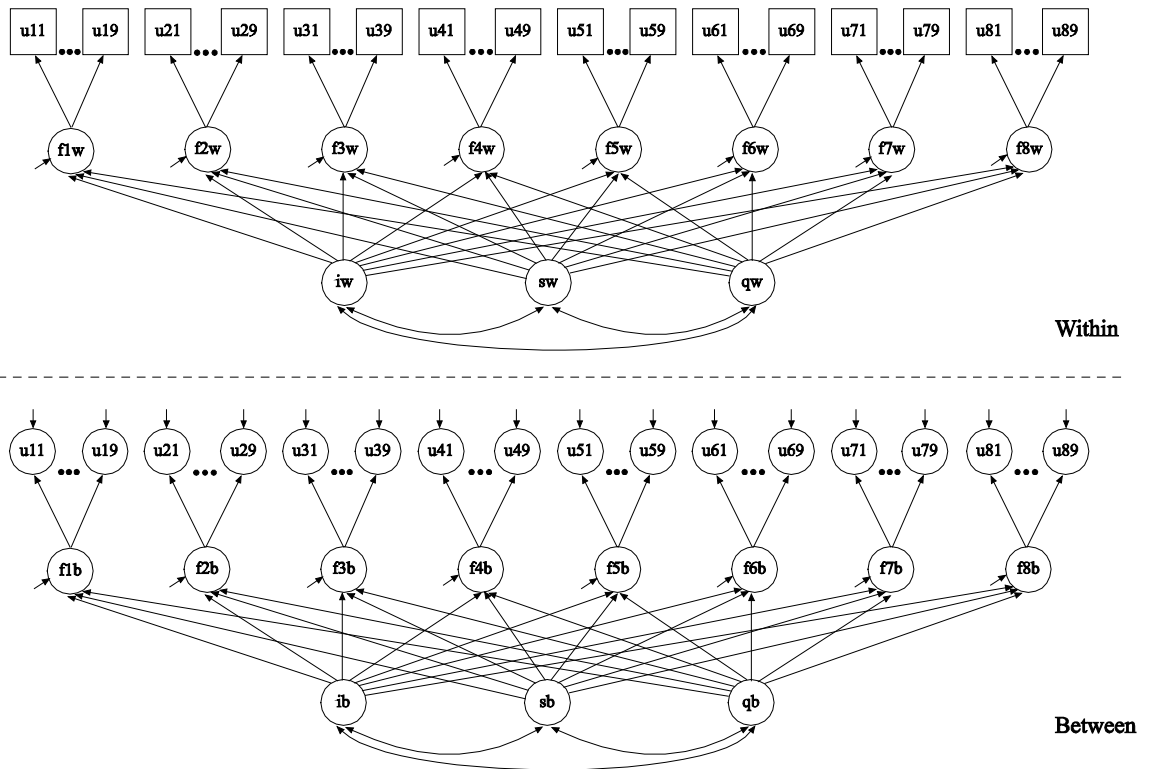


Figure 15: Polytomous multiple-indicator, two-level growth modeling of aggressive behavior over eight time points





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Table 1: Input for Bayes analysis of the Atlas example

---

TITLE:	ATLAS, Step 1
DATA:	FILE = mbr2004atlas.txt;
VARIABLE:	NAMES = obs group severity nutrit; USEV = group - nutrit;
ANALYSIS:	ESTIMATOR = BAYES; PROCESS = 2;
MODEL:	severity ON group (a); nutrit ON severity (b) group;
MODEL CONSTRAINT:	NEW (indirect); indirect = a*b;
OUTPUT:	TECH1 TECH8 STANDARDIZED;
PLOT:	TYPE = PLOT2;

---

Table 2: Output excerpts for Bayes analysis of the Atlas example

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%
severity ON					
group	0.282	0.106	0.010	0.095	0.486
nutrit ON					
severity	0.067	0.031	0.000	0.015	0.125
group	-0.011	0.089	0.440	-0.180	0.155
Intercepts					
severity	5.641	0.072	0.000	5.513	5.779
nutrit	3.698	0.191	0.000	3.309	4.108
Residual Variances					
severity	1.722	0.072	0.000	1.614	1.868
nutrit	1.331	0.070	0.000	1.198	1.468
New/Additional Parameters					
indirect	0.016	0.013	0.010	0.002	0.052

Table 3: TECH8 iterations with PSR for the first 1000 iterations of the 10,000 iterations analysis of the ATLAS example

Iteration	Potential Scale Reduction	Parameter With Highest PSR
100	1.037	2
200	1.014	4
300	1.002	2
400	1.003	3
500	1.002	7
600	1.002	6
700	1.000	6
800	1.003	1
900	1.002	1
1000	1.002	1

Table 4: Output excerpts from Bayesian analysis using 10,000 iterations for the ATLAS example

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
severity ON					
group	0.272	0.089	0.001	0.098	0.448
nutrit ON					
severity	0.074	0.030	0.008	0.014	0.133
group	-0.018	0.080	0.408	-0.177	0.140
Intercepts					
severity	5.648	0.062	0.000	5.525	5.768
nutrit	3.663	0.177	0.000	3.313	4.014
Residual Variances					
severity	1.719	0.083	0.000	1.566	1.895
nutrit	1.333	0.065	0.000	1.215	1.467
New/Additional Parameters					
indirect	0.019	0.011	0.009	0.003	0.045

Table 5: Input for Bayesian analysis of Firefighter example

---

TITLE:	Yuan and MacKinnon firefighters mediation using Bayesian analysis Elliot DL, Goldberg L, Kuehl KS, et al. The PHLAME Study: process and outcomes of 2 models of behavior change. J Occup Environ Med. 2007; 49(2): 204-213.
DATA:	FILE = fire.dat;
VARIABLE:	NAMES = y m x;
MODEL:	m ON x (a); y ON m (b) x;
ANALYSIS:	ESTIMATOR = BAYES; PROCESS = 2 ; FBITER = 10000;
MODEL CONSTRAINT:	NEW(indirect); indirect = a*b;
OUTPUT:	TECH1 TECH8;
PLOT:	TYPE = PLOT2;

---

Table 6: Output excerpts for Bayesian analysis of Firefighter example

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
m ON					
x	0.395	0.121	0.000	0.160	0.634
y ON					
m	0.142	0.052	0.003	0.040	0.243
x	0.108	0.117	0.176	-0.127	0.339
Intercepts					
y	0.418	0.057	0.000	0.308	0.530
m	0.000	0.059	0.499	-0.115	0.116
Residual Variances					
y	1.144	0.089	0.000	0.987	1.338
m	1.218	0.093	0.000	1.054	1.419
New/Additional Parameters					
indirect	0.053	0.028	0.004	0.011	0.117



Table 7: Input for Bayesian analysis with priors for Firefighter example

---

TITLE:	Yuan and MacKinnon firefighters mediation using Bayesian analysis Elliot DL, Goldberg L, Kuehl KS, et al. The PHLAME Study: process and outcomes of 2 models of behavior change. J Occup Environ Med. 2007; 49(2): 204-213.
DATA:	FILE = fire.dat;
VARIABLE:	NAMES = y m x;
MODEL:	m ON x (a); y ON m (b) x;
ANALYSIS:	ESTIMATOR = BAYES; PROCESS = 2; FBITER = 10000;
<b>MODEL PRIORS:</b>	<b>a ~ N (0.35, 0.04);</b> <b>b ~ N (0.1, 0.01);</b>
MODEL CONSTRAINT:	NEW(indirect); indirect = a*b;
OUTPUT:	TECH1 TECH8;
PLOT:	TYPE = PLOT2;

---

Table 8: Output excerpts for Bayesian analysis with priors for Firefighter example

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
m ON					
x	0.383	0.104	0.000	0.182	0.588
y ON					
m	0.133	0.046	0.003	0.042	0.223
x	0.112	0.117	0.169	-0.124	0.341
Intercepts					
y	0.418	0.056	0.000	0.308	0.530
m	0.000	0.059	0.499	-0.115	0.116
Residual Variances					
y	1.143	0.089	0.000	0.986	1.338
m	1.218	0.093	0.000	1.053	1.418
New/Additional Parameters					
indirect	0.049	0.023	0.003	0.012	0.102

Table 9: Holzinger-Swineford's hypothesized four domains measured by 19 tests

Factor loading pattern				
	Spatial	Verbal	Speed	Memory
visual	X	0	0	0
cubes	X	0	0	0
paper	X	0	0	0
flags	X	0	0	0
general	0	X	0	0
paragrap	0	X	0	0
sentence	0	X	0	0
wordc	0	X	0	0
wordm	0	X	0	0
addition	0	0	X	0
code	0	0	X	0
counting	0	0	X	0
straight	0	0	X	0
wordr	0	0	0	X
numberr	0	0	0	X
figurer	0	0	0	X
object	0	0	0	X
numberf	0	0	0	X
figurew	0	0	0	X

Table 10: Input for Bayes CFA

---

```

TITLE:      Bayes CFA on 19 variables from Holzinger-Swineford
DATA:      FILE = holzingr.dat;
           FORMAT = f3,2f2,f3,2f2/3x,13(1x,f3)/3x,13(1x,f3);
VARIABLE  NAMES = id female grade agey agem school visual
           cubes paper flags general paragrap sentence wordc wordm
           addition code counting straight wordr numberr figurer
           object numberf figurew deduct numeric problemr series
           arithmet paperrev flagssub; ! flags = lozenges
           USEV = visual cubes paper flags general paragrap sentence
           wordc wordm addition code counting straight wordr
           numberr figurer object numberf figurew;
           USEOBS = school EQ 0;
DEFINE:    visual = visual/sqrt(47.471);
           cubes = cubes/sqrt (19.622);
           paper = paper/sqrt(7.908);
           flags = flags/sqrt(68.695);
           general = general/sqrt(134.970);
           paragrap = paragrap/sqrt(11.315);
           sentence = sentence/sqrt(21.467);
           wordc = wordc/sqrt(28.505);
           wordm = wordm/sqrt(62.727);
           addition = addition/sqrt(561.692);
           code = code/sqrt(275.759);
           counting = counting/sqrt(437.752);
           straight = straight/sqrt(1362.158);
           wordr = wordr/sqrt(116.448);
           numberr = numberr/sqrt(56.496);
           figurer = figurer/sqrt(45.937);
           object = object/sqrt(20.730);
           numberf = numberf/sqrt(20.150);
           figurew = figurew/sqrt(12.845);
ANALYSIS:  ESTIMATOR = BAYES;
           PROCESS = 2;
           FBITER = 20000;
           STVAL = ML;
MODEL:     spatial BY visual* cubes paper flags;
           verbal BY general* paragrap sentence wordc wordm;
           speed BY addition* code counting straight;
           memory BY wordr* numberr figurer object numberf
           figurew;
           spatial-memory@1;
OUTPUT:    TECH1 TECH8 STDYX;
PLOT:      TYPE = PLOT2;

```

---

Table 11: Bayes CFA output excerpts: Model testing

---

Tests of model fit		
Bayesian Posterior Predictive Checking using Chi-Square		
95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values		
	17.221	111.604
Posterior Predictive P-Value		0.006
Information Criterion		
Numbers of Free Parameters		63
Deviance (DIC)		6997.386
Estimated Number of Parameters (pD)		63.641

---

Table 12: Bayes CFA output excerpts: Model results

Parameter	Estimate	Posterior	One-Tailed	95% C.I.	
		S.D.	P-Value	Lower 2.5%	Upper 2.5%
spatial BY					
visual	0.721	0.093	0.000	0.543	0.905
cubes	0.497	0.098	0.000	0.306	0.690
paper	0.568	0.097	0.000	0.382	0.764
flags	0.700	0.096	0.000	0.514	0.892
verbal BY					
general	0.848	0.078	0.000	0.705	1.011
paragrap	0.861	0.078	0.000	0.717	1.021
sentence	0.878	0.077	0.000	0.738	1.039
wordc	0.730	0.082	0.000	0.578	0.900
wordm	0.884	0.077	0.000	0.743	1.043
speed BY					
addition	0.682	0.093	0.000	0.499	0.869
code	0.732	0.088	0.000	0.565	0.912
counting	0.732	0.089	0.000	0.562	0.910
straight	0.785	0.089	0.000	0.617	0.963
memory BY					
wordr	0.538	0.098	0.000	0.349	0.735
numberr	0.541	0.095	0.000	0.362	0.736
figurer	0.629	0.095	0.000	0.447	0.821
object	0.653	0.095	0.000	0.471	0.844
numberf	0.688	0.094	0.000	0.508	0.877
figurew	0.508	0.096	0.000	0.323	0.702
verbal WITH					
spatial	0.635	0.080	0.000	0.461	0.764
speed WITH					
spatial	0.632	0.103	0.000	0.392	0.787
verbal	0.496	0.087	0.000	0.309	0.651
memory WITH					
spatial	0.693	0.095	0.000	0.492	0.868
verbal	0.532	0.086	0.000	0.342	0.675
speed	0.653	0.081	0.000	0.482	0.792

Table 13: Input excerpts for Bayes CFA with informative priors on cross-loadings

---

```

ANALYSIS: ESTIMATOR = BAYES;
           PROCESS = 2;
           FBITER = 10000;
MODEL:    spatial BY visual* cubes paper flags;
           verbal BY general* paragrap sentence wordc wordm;
           speed BY addition* code counting straight;
           memory BY wordr* numberr figurer object numberf
           figurew;
           spatial-memory@1;
           spatial BY general-figurew*0 (a1-a15);
           verbal BY visual-flags*0 (b1-b4);
           verbal BY addition-figurew*0 (b5-b14);
           speed BY visual-wordm*0 (c1-c9);
           speed BY wordr-figurew*0 (c10-c15);
           memory BY visual-straight*0 (d1-d13);
MODEL PRIORS:
           a1-a15 ~ N(0,.01);
           b1-b14 ~ N(0,.01);
           c1-c15 ~ N(0,.01);
           d1-d13 ~ N(0,.01);
OUTPUT:   TECH1 TECH8 STDYX;
PLOT:     TYPE = PLOT2;

```

---

Table 14: Output excerpts for Bayes CFA with informative priors on cross-loadings

---

Tests of model fit		
Bayesian Posterior Predictive Checking using Chi-Square		
95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values		
	-39.871	61.365
Posterior Predictive P-Value		0.353
Information Criterion		
Number of Free Parameters		120
Deviance (DIC)		6966.543
Estimated Number of Parameters (pD)		85.406

---



Table 15: Output excerpts for Bayes CFA with informative priors on cross-loadings

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
spatial BY					
visual	0.668	0.127	0.000	0.436	0.935
cubes	0.542	0.127	0.000	0.300	0.800
paper	0.480	0.125	0.000	0.245	0.731
flags	0.704	0.135	0.000	0.463	0.987
general	0.035	0.076	0.000	0.463	0.987
paragrap	-0.007	0.075	0.464	-0.116	0.183
sentence	-0.052	0.076	0.248	-0.203	0.095
wordc	0.051	0.075	0.252	-0.098	0.199
wordm	-0.018	0.075	0.404	-0.164	0.127
addition	-0.178	0.082	0.014	-0.337	-0.021
code	-0.005	0.078	0.474	-0.158	0.150
counting	0.010	0.082	0.447	-0.154	0.168
straight	0.190	0.079	0.010	0.029	0.339
wordr	-0.045	0.084	0.291	-0.215	0.112
numberr	-0.004	0.083	0.482	-0.169	0.156
figurer	0.123	0.083	0.070	-0.041	0.283
object	-0.151	0.082	0.031	-0.311	0.008
numberf	0.092	0.083	0.133	-0.076	0.252
figurew	0.009	0.083	0.456	-0.157	0.171

Table 16: Output excerpts for Bayes CFA with informative priors on cross-loadings (continued)

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
verbal WITH					
spatial	0.574	0.118	0.001	0.310	0.748
speed WITH					
spatial	0.511	0.132	0.000	0.199	0.704
verbal	0.492	0.107	0.000	0.246	0.662
memory WITH					
spatial	0.577	0.131	0.000	0.290	0.777
verbal	0.562	0.103	0.000	0.314	0.719
speed	0.609	0.098	0.000	0.378	0.766

Table 17: Input excerpts for Bayes CFA with three free cross-loadings

---

```
ANALYSIS: ESTIMATOR = BAYES;
           PROCESS = 2;
           FBITER = 20000;
MODEL:    spatial BY visual* cubes paper flags;
           verbal BY general* paragra sentence wordc wordm;
           speed BY addition* code counting straight;
           memory BY wordr* numberr figurer object numberf
           figurew;
           spatial-memory@1;
           spatial BY addition straight object;
OUTPUT:   TECH1 TECH8 STDYX;
PLOT:     TYPE = PLOT2;
```

---

Table 18: Output excerpts for Bayes CFA with three free cross-loadings

---

Tests of model fit		
Bayesian Posterior Predictive Checking using Chi-Square		
95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values		
	-26.253	70.376
Posterior Predictive P-Value		0.173
Information Criterion		
Number of Free Parameters		66
Deviance (DIC)		6957.757
Estimated Number of Parameters (pD)		65.223

---

Table 19: Output excerpts for Bayes CFA with three free cross-loadings (continued)

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
spatial BY					
visual	0.768	0.090	0.000	0.598	0.949
cubes	0.511	0.097	0.000	0.325	0.709
paper	0.583	0.095	0.000	0.398	0.771
flags	0.701	0.091	0.000	0.526	0.886
addition	-0.402	0.171	0.001	-0.834	-0.136
straight	0.349	0.104	0.001	0.138	0.550
object	-0.660	0.272	0.000	-1.317	-0.273
verbal BY					
general	0.851	0.078	0.000	0.707	1.013
paragrap	0.864	0.077	0.000	0.722	1.022
sentence	0.883	0.077	0.000	0.742	1.042
wordc	0.734	0.082	0.000	0.580	0.903
wordm	0.888	0.077	0.000	0.745	1.047
speed BY					
addition	1.024	0.167	0.000	0.757	1.430
code	0.705	0.089	0.000	0.537	0.884
counting	0.748	0.086	0.000	0.588	0.925
straight	0.544	0.102	0.000	0.349	0.750
memory BY					
wordr	0.513	0.095	0.000	0.331	0.703
numberr	0.514	0.095	0.000	0.332	0.705
figurer	0.620	0.093	0.000	0.445	0.807
object	1.208	0.268	0.000	0.829	1.849
numberf	0.682	0.089	0.000	0.515	0.865
figurew	0.499	0.095	0.000	0.316	0.692

Table 20: Output excerpts for Bayes CFA with three free cross-loadings (continued)

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
verbal WITH					
spatial	0.575	0.076	0.000	0.407	0.708
speed WITH					
spatial	0.598	0.101	0.000	0.379	0.769
verbal	0.505	0.087	0.000	0.314	0.657
memory WITH					
spatial	0.752	0.082	0.000	0.559	0.878
verbal	0.586	0.077	0.000	0.414	0.713
speed	0.682	0.074	0.000	0.507	0.800

Table 21: Model testing results for Holzinger-Swineford data ( $n = 145$ )

Model	DIC	PPC 95% CI	PPC p-value	ML p-value
1. CFA	6997	17 - 112	0.006	0.0002
2. CFA + priors	6967	-40 - 61	0.353	-
3. CFA + 3 free	6958	-26 - 70	0.173	0.049
4. CFA + 3 free + priors	6955	-49 - 51	0.478	-

Table 22: Input for Bayes twolevel regression

---

```
TITLE:
DATA:   FILE = c10n50icc1.dat;
VARIABLES: NAMES = y x clus;
          WITHIN = x;
          CLUSTER = clus;
ANALYSIS: TYPE = TWOLEVEL;
          ESTIMATOR = BAYES;
          PROCESS = 2;
          FBITER = 10000;
MODEL:   %WITHIN%
          y ON x;
          y (w);
          %BETWEEN%
          y (b);
MODEL PRIORS:
          b~IG(.001,.001);
MODEL CONSTRAINT:
          NEW(icc);
          icc = b/(b+w);
OUTPUT:  TECH1 TECH8;
PLOT:    TYPE = PLOT2;
```

---



Table 23: Output excerpts for Bayes twolevel regression

Parameter	Estimate	Posterior. S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
Within Level					
y ON					
x	0.909	0.069	0.000	0.777	1.042
Residual variances					
y	2.105	0.135	0.000	1.866	2.394
Between Level					
Means					
y	0.145	0.178	0.191	-0.209	0.493
Variances					
y	0.223	0.205	0.000	0.073	0.805
New/Additional Parameters					
ICC	0.096	0.063	0.000	0.033	0.276

Table 24: Output excerpts for ML twolevel regression

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
y ON				
x	0.909	0.069	13.256	0.000
Residual variances				
y	2.089	0.133	15.653	0.000
Between Level				
Means				
y	0.143	0.152	0.942	0.346
Variances				
y	0.190	0.104	1.828	0.067
New/Additional Parameters				
ICC	0.083	0.042	1.975	0.048

Table 25: Output excerpts for ML in a Monte Carlo study of a twolevel regression model

Parameter	Population	Estimates		S.E.	M.S.E.	95% Cover	% Sig Coeff
		Average	Std.Dev.	Average			
Within Level							
y ON							
x	1.000	0.9957	0.0630	0.0639	0.0040	0.948	1.000
Residual variances							
y	2.000	2.0052	0.1291	0.1281	0.0167	0.946	1.000
Between Level							
Means							
y	0.000	-0.0035	0.1624	0.1485	0.0263	0.892	0.108
Variances							
y	0.222	0.1932	0.1155	0.1045	0.0141	0.808	0.180
New/Additional Parameters							
ICC	0.100	0.0860	0.0458	0.0422	0.0023	0.812	0.498

Table 26: Input for for Bayes Monte Carlo twolevel regression using an IG(0.001, 0.001) prior

---

```

TITLE:      Bayes IG (eps,eps)
MONTECARLO:
             NAMES = y x;
             NOBS = 500;
             NREP = 500;
             NCSIZES = 1;
             CSIZES = 10 (50);
             WITHIN = x;
MODEL POPULATION:
             %WITHIN%
             x*1;
             y ON x*1;
             y*2;
             %BETWEEN%
             y*.222; licc = .222/2.222 = 0.1
ANALYSIS:  TYPE = TWOLEVEL;
             ESTIMATOR = BAYES;
             PROCESS = 2;
             FBITER = 1000;
MODEL:     %WITHIN%
             y ON x*1;
             y*2 (w);
             %BETWEEN%
             y*.222 (b); licc = .222/2.222 = 0.1
MODEL PRIORS:
             b~IG(.001,.001);
MODEL CONSTRAINT:
             NEW(icc*.1);
             icc = b/(w+b);
OUTPUT:   TECH9;

```

---

Table 27: Output excerpts for Bayes Monte Carlo twolevel regression using an IG(0.001, 0.001) prior

Parameter	Population	Estimates		S.E.	M.S.E.	95% Cover	% Sig Coeff
		Average	Std.Dev.	Average			
Within Level							
y ON							
x	1.000	1.0051	0.0624	0.0641	0.0039	0.952	1.000
Residual variances							
y	2.000	2.0089	0.1293	0.1297	0.0168	0.948	1.000
Between Level							
Means							
y	0.000	0.0128	0.1646	0.1746	0.0272	0.928	0.072
Variances							
y	0.222	0.2322	0.1373	0.2036	0.0189	0.942	1.000
New/Additional Parameters							
ICC	0.100	0.1011	0.0532	0.0618	0.0028	0.934	1.000

Table 28: Output excerpts for Bayes Monte Carlo twolevel regression using a U(0, 1000) prior

Parameter	Population	Estimates		S.E.	M.S.E.	95% Cover	% Sig Coeff
		Average	Std.Dev.	Average			
Within Level							
y ON							
x	1.000	1.0059	0.0641	0.0640	0.0041	0.954	1.000
Residual variances							
y	2.000	1.9992	0.1314	0.1291	0.0172	0.946	1.000
Between Level							
Means							
y	0.000	0.0190	0.1645	0.2106	0.0277	0.966	0.034
Variances							
y	0.222	0.2304	0.1246	0.3255	0.0156	0.930	1.000
New/Additional Parameters							
ICC	0.100	0.1012	0.0484	0.0841	0.0023	0.928	1.000

Table 29: Output excerpts for Bayes Monte Carlo twolevel regression using a IG(-1,0) prior

Parameter	Population	Estimates		S.E.	M.S.E.	95%	% Sig
		Average	Std.Dev.	Average		Cover	Coeff
Within Level							
y ON							
x	1.000	1.0049	0.0626	0.0640	0.0039	0.946	1.000
Residual variances							
y	2.000	2.0061	0.1286	0.1295	0.0165	0.946	1.000
Between Level							
Means							
y	0.000	0.0123	0.1645	0.2122	0.0272	0.966	0.034
Variances							
y	0.222	0.3348	0.1784	0.3767	0.0445	0.928	1.000
New/Additional Parameters							
ICC	0.100	0.1391	0.0626	0.0876	0.0054	0.928	1.000

Table 30: Input for Bayesian analysis of a two-part growth model

---

```

TITLE:
      nlsy36425x25dep.inp
      cohort 64
      centering at 25
      hd82-hd89 (ages 18 - 25)
      log age scale:  $x_t = a * (\ln(t-b) - \ln(c-b))$ , where t is time,
      a and b are constants to fit the mean curve (chosen as a =
      2 and b = 16), and c is the centering age, here set at 25.
DATA:  FILE = big.dat;
      FORMAT = 2f5, f2, t14, 5f7, t50, f8, t60, 6f1.0, t67, 2f2.0,
      t71, 8f1.0, t79, f2.0, t82, 4f2.0;
DATA TWOPART:
      NAMES = hd82-hd89;
      BINARY = bin1-bin5;
      CONTINUOUS = cont1-cont5;
VARIABLE: NAMES = id houseid cohort weight82 weight83 weight84
      weight88 weight89 weight94 hd82 hd83 hd84 hd88 hd89
      hd94 dep89 dep94 male black hisp es fh1 fh23 fh123 hsdrp
      coll ed89 ed94 cd89 cd94;
      USEOBSERVATIONS = cohort EQ 64 AND (coll GT 0
      AND coll LT 20);
      USEV = male black hisp es fh123hs hsdrp coll bin1-bin5
      cont1-cont5;
      CATEGORICAL = bin1-bin5;
      MISSING = .;
      AUXILIARY = hd82-hd89;
DEFINE:  CUT coll (12.1);
ANALYSIS: ESTIMATOR = BAYES;
      PROCESS = 2;
MODEL:  iu su qu | bin1@-3.008 bin2@-2.197 bin3@-1.621 bin4@-.235
      bin5@.000;
      iy sy qy | cont1@-3.008 cont2@-2.197 cont3@-1.621 cont4@-
      .235 cont5@.000;
      iu-qy ON male black hisp es fh123 hsdrp coll;
OUTPUT:  TECH1 TECH8 STANDARDIZED;
PLOT:   TYPE = PLOT3;
      SERIES = cont1-cont5(sy) | bin1-bin5(su);

```

---



Table 31: Output excerpts for Bayesian analysis of a two-part growth model: Model testing

---

Tests of model fit		
Number of Free Parameters		74
Bayesian Posterior Predictive Checking using Chi-Square		
95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values		
	-44.832	46.344
Posterior Predictive P-Value		0.473

---

Table 32: Output excerpts for Bayesian analysis of a two-part growth model

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
iu ON					
male	1.649	0.171	0.000	1.324	1.993
black	-0.742	0.193	0.00	-1.136	-0.381
hispanic	-0.390	0.221	0.036	-0.834	0.038
es	0.506	0.204	0.006	0.103	0.903
fh123	0.319	0.244	0.095	-0.158	0.796
hsdrp	-0.196	0.200	0.165	-0.593	0.192
coll	-0.330	0.186	0.035	-0.701	0.026
iy ON					
male	0.357	0.070	0.000	0.222	0.490
black	-0.143	0.067	0.014	-0.274	-0.016
hispanic	-0.162	0.075	0.015	-0.308	-0.015
es	0.106	0.065	0.048	-0.020	0.235
fh123	0.217	0.077	0.002	0.068	0.366
hsdrp	0.099	0.066	0.070	-0.033	0.224
coll	-0.038	0.056	0.254	-0.148	0.072

Table 33: Output excerpts for Bayesian analysis of a two-part growth model, continued

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
Intercepts					
cont1	0.000	0.000	1.000	0.000	0.000
cont2	0.000	0.000	1.000	0.000	0.000
cont3	0.000	0.000	1.000	0.000	0.000
cont4	0.000	0.000	1.000	0.000	0.000
cont5	0.000	0.000	1.000	0.000	0.000
iu	0.000	0.000	1.000	0.000	0.000
su	-0.912	0.279	0.000	-1.486	-0.388
qu	-0.366	0.107	0.000	-0.591	-0.172
iy	0.179	0.104	0.033	-0.010	0.381
sy	-0.268	0.133	0.035	-0.497	0.018
qy	-0.113	0.046	0.013	-0.198	-0.015
Thresholds					
bin1\$1	1.395	0.185	0.000	1.028	1.780
bin2\$1	1.395	0.185	0.000	1.028	1.780
bin3\$1	1.395	0.185	0.000	1.028	1.780
bin4\$1	1.395	0.185	0.000	1.028	1.780
bin5\$1	1.395	0.185	0.000	1.028	1.780
Residual variances					
cont1	0.093	0.043	0.000	0.014	0.169
cont2	0.199	0.020	0.000	0.164	0.241
cont3	0.201	0.021	0.000	0.162	0.244
cont4	0.189	0.019	0.000	0.154	0.228
cont5	0.176	0.022	0.000	0.134	0.222
iu	3.451	0.511	0.000	2.572	4.583
su	3.088	0.690	0.000	1.814	4.480
qu	0.356	0.104	0.000	0.177	0.568
iy	0.215	0.037	0.000	0.147	0.289
sy	0.159	0.050	0.000	0.082	0.281
qy	0.018	0.006	0.000	0.009	0.033

Table 34: Output excerpts for ML analysis of a two-part growth model

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
iu ON				
male	1.533	0.164	9.356	0.000
black	-0.705	0.172	-4.092	0.000
his	-0.385	0.199	-1.934	0.053
es	0.471	0.194	2.430	0.015
fh123	0.287	0.224	1.281	0.200
hsdrp	-0.191	0.183	-1.045	0.296
coll	-0.325	0.161	-2.017	0.044
iy ON				
male	0.329	0.058	5.651	0.000
black	-0.123	0.062	-1.986	0.047
hisp	-0.143	0.069	-2.082	0.037
es	0.096	0.062	1.543	0.123
fh123	0.219	0.076	2.894	0.004
hsdrp	0.093	0.063	1.466	0.143
coll	-0.030	0.056	-0.526	0.599
Intercepts				
cont1	0.000	0.000	999.000	999.000
cont2	0.000	0.000	999.000	999.000
cont3	0.000	0.000	999.000	999.000
cont4	0.000	0.000	999.000	999.000
cont5	0.000	0.000	999.000	999.000
iu	0.000	0.000	999.000	999.000
su	-0.697	0.230	-3.030	0.002
qu	-0.266	0.083	-3.201	0.001
iy	0.223	0.079	2.836	0.005
sy	-0.192	0.127	-1.518	0.129
qy	-0.093	0.045	-2.056	0.040

Table 35: Output excerpts for ML analysis of a two-part growth model, continued

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Thresholds				
bin1\$1	1.273	0.164	7.767	0.000
bin2\$1	1.273	0.164	7.767	0.000
bin3\$1	1.273	0.164	7.767	0.000
bin4\$1	1.273	0.164	7.767	0.000
bin5\$1	1.273	0.164	7.767	0.000
Residual variances				
cont1	0.095	0.052	1.807	0.071
cont2	0.199	0.020	10.112	0.000
cont3	0.203	0.022	9.276	0.000
cont4	0.183	0.018	10.228	0.000
cont5	0.169	0.022	7.740	0.000
iu	2.863	0.459	6.243	0.000
su	1.945	0.489	3.978	0.000
qu	0.184	0.061	3.015	0.003
iy	0.189	0.032	5.998	0.000
sy	0.135	0.058	2.306	0.021
qy	0.015	0.008	1.956	0.050

Table 36: Input for Bayes multiple-indicator growth modeling

---

```

TITLE:      Hopkins Cohort 1 All time points with Classroom
            Information
DATA:      FILE = Cohort1_classroom_ALL.DAT;
VARIABLE:  NAMES = PRCID stub1F bkRule1F harmO1F bkThin1F
            yell1F takeP1F fight1F lies1F tease1F stub1S bkRule1S
            harmO1S bkThin1S yell1S takeP1S fight1S lies1S tease1S
            stub2S bkRule2S harmO2S bkThin2S yell2S takeP2S
            fight2S lies2S tease2S stub3S bkRule3S harmO3S bk-
            Thin3S yell3S takeP3S fight3S lies3S tease3S stub4S
            bkRule4S harmO4S bkThin4S yell4S takeP4S fight4S
            lies4S tease4S stub5S bkRule5S harmO5S bkThin5S yell5S
            takeP5S fight5S lies5S tease5S stub6S bkRule6S harmO6S
            bkThin6S yell6S takeP6S fight6S lies6S tease6S stub7S
            bkRule7S harmO7S bkThin7S yell7S takeP7S fight7S lies7S
            tease7S gender race des011 sch011 sec011 juv99 violchld
            antisocr conductr athort1F harmP1S athort1S harmP2S
            athort2S harmP3S athort3S harmP4S athort4S harmP5S
            athort5S harmP6S harmP7S athort7S stub2F bkRule2F
            harmO2F bkThin2F yell2F takeP2F fight2F harmP2F
            lies2F athort2F tease2F classrm;
            USEVAR = stub1f-tease7s male;
            CATEGORICAL = categorical = stub1f-tease7s;
            MISSING = ALL (999);
DEFINE:    cut stub1f-tease7s(1.5);
            MALE = 2 - gender;
ANALYSIS:  PROCESS = 2 ;
            ESTIMATOR = BAYES;
            FBITER = 20000;

```

---

Table 37: Input for Bayes multiple-indicator growth modeling, continued

---

```

MODEL:    f1 BY stub1f
          bkrule1f-tease1f (1-8);
          f2 BY stub1s
          bkrule1s-tease1s (1-8);
          f3 BY stub2s
          bkrule2s-tease2s (1-8);
          f4 BY stub3s
          bkrule3s-tease3s (1-8);
          f5 BY stub4s
          bkrule4s-tease4s (1-8);
          f6 BY stub5s
          bkrule5s-tease5s (1-8);
          f7 BY stub6s
          bkrule6s-tease6s (1-8);
          f8 BY stub7s
          bkrule7s-tease7s (1-8);
          [stub1f$1 stub1s$1 stub2s$1 stub3s$1 stub4s$1] (11);
          [stub5s$1 stub6s$1 stub7s$1] (11);
          [bkrule1f$1 bkrule1s$1 bkrule2s$1 bkrule3s$1] (12);
          [bkrule4s$1 bkrule5s$1 bkrule6s$1 bkrule7s$1] (12);
          [harmo1f$1 harmo1s$1 harmo2s$1 harmo3s$1] (13);
          [harmo4s$1 harmo5s$1 harmo6s$1 harmo7s$1] (13);
          [bkthin1f$1 bkthin1s$1 bkthin2s$1 bkthin3s$1] (14);
          [bkthin4s$1 bkthin5s$1 bkthin6s$1 bkthin7s$1] (14);
          [yell1f$1 yell1s$1 yell2s$1 yell3s$1 yell4s$1 yell5s$1] (15);
          [yell6s$1 yell7s$1] (15);
          [takeP1f$1 takeP1s$1 takeP2s$1 takeP3s$1] (16);
          [takeP4s$1 takeP5s$1 takeP6s$1 takeP7s$1] (16);
          [fight1f$1 fight1s$1 fight2s$1 fight3s$1 fight4s$1] (17);
          [fight5s$1 fight6s$1 fight7s$1] (17);
          [lies1f$1 lies1s$1 lies2s$1 lies3s$1 lies4s$1 lies5s$1] (18);
          [lies6s$1 lies7s$1] (18);
          [tease1f$1 tease1s$1 tease2s$1 tease3s$1 tease4s$1] (19);
          [tease5s$1 tease6s$1 tease7s$1] (19);
          [f1-f8@0];
          i s q | f1@0 f2@.5 f3@1.5 f4@2.5 f5@3.5 f6@4.5 f7@5.5
          f8@6.5;
          i-q ON male;
OUTPUT:  TECH1 TECH4 TECH8 TECH10 STANDARDIZED
          SVALUES;
PLOT:    TYPE = PLOT2;

```

---

Table 38: Output excerpts for Bayes multiple-indicator growth modeling

---

Tests of model fit		
Number of Free Parameters		36
Bayesian Posterior Predictive Checking using Chi-Square		
95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values		
	129.488	547.650
Posterior Predictive P-Value		0.002

---



Table 39: Output excerpts for Bayes multiple-indicator growth modeling, continued

Parameter	Estimate	Posterior	One-Tailed	95% C.I.	
		S.D.	P-Value	Lower 2.5%	Upper 2.5%
i					
f1	1.000	0.000	0.000	1.000	1.000
f2	1.000	0.000	0.000	1.000	1.000
f3	1.000	0.000	0.000	1.000	1.000
f4	1.000	0.000	0.000	1.000	1.000
f5	1.000	0.000	0.000	1.000	1.000
f6	1.000	0.000	0.000	1.000	1.000
f7	1.000	0.000	0.000	1.000	1.000
f8	1.000	0.000	0.000	1.000	1.000
s					
f1	0.000	0.000	1.000	0.000	0.000
f2	0.500	0.000	0.000	0.500	0.500
f3	1.500	0.000	0.000	1.500	1.500
f4	2.500	0.000	0.000	2.500	2.500
f5	3.500	0.000	0.000	3.500	3.500
f6	4.500	0.000	0.000	4.500	4.500
f7	5.500	0.000	0.000	5.500	5.500
f8	6.500	0.000	0.000	6.500	6.500
q					
f1	0.000	0.000	1.000	0.000	0.000
f2	0.250	0.000	0.000	0.250	0.250
f3	2.250	0.000	0.000	2.250	2.250
f4	6.250	0.000	0.000	6.250	6.250
f5	12.250	0.000	0.000	12.250	12.250
f6	20.250	0.000	0.000	20.250	20.250
f7	30.250	0.000	0.000	30.250	30.250
f8	42.250	0.000	0.000	42.250	42.250

Table 40: Output excerpts for Bayes multiple-indicator growth modeling, continued

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
f1 BY					
stub1f	1.000	0.000	0.000	1.000	1.000
bkrule1f	1.395	0.060	0.000	1.288	1.522
harmo1f	1.858	0.096	0.000	1.695	2.076
bkthin1f	1.335	0.065	0.000	1.221	1.470
yell1f	1.182	0.047	0.000	1.097	1.279
takep1f	1.416	0.063	0.000	1.311	1.553
fight1f	1.416	0.059	0.000	1.308	1.537
lies1f	1.323	0.054	0.000	1.227	1.438
tease1f	1.294	0.052	0.000	1.196	1.402
f8 BY					
stub7s	1.000	0.000	0.000	1.000	1.000
bkrule7s	1.395	0.060	0.000	1.288	1.522
harmo7s	1.858	0.096	0.000	1.695	2.076
bkthin7s	1.335	0.065	0.000	1.221	1.470
yell7s	1.182	0.047	0.000	1.097	1.279
takep7s	1.416	0.063	0.000	1.311	1.553
flight7s	1.416	0.059	0.000	1.308	1.537
lies7s	1.323	0.054	0.000	1.227	1.438
tease7s	1.294	0.052	0.000	1.196	1.402
i ON					
male	0.623	0.092	0.000	0.447	0.803
s ON					
male	0.108	0.049	0.012	0.013	0.205
q ON					
male	-0.015	0.007	0.015	-0.030	-0.001
s WITH					
i	-0.412	0.057	0.000	-0.530	-0.308
q WITH					
i	0.034	0.007	0.000	0.021	0.048
s	-0.028	0.005	0.000	-0.038	-0.019

Table 41: Output excerpts for Bayes multiple-indicator growth modeling, continued

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
Intercepts					
f1	0.000	0.000	1.000	0.000	0.000
f2	0.000	0.000	1.000	0.000	0.000
f3	0.000	0.000	1.000	0.000	0.000
f4	0.000	0.000	1.000	0.000	0.000
f5	0.000	0.000	1.000	0.000	0.000
f6	0.000	0.000	1.000	0.000	0.000
f7	0.000	0.000	1.000	0.000	0.000
f8	0.000	0.000	1.000	0.000	0.000
i	0.000	0.000	1.000	0.000	0.000
s	0.002	0.034	0.479	-0.067	0.068
q	0.002	0.005	0.365	-0.008	0.012
Thresholds					
stub1f\$1	-0.386	0.067	0.000	-0.523	-0.263
bkrule1f\$1	-0.215	0.090	0.007	-0.396	-0.038
harmo1f\$1	1.657	0.142	0.000	1.390	1.951
bkthin1f\$1	1.813	0.098	0.000	1.645	2.035
yell1f\$1	0.389	0.078	0.000	0.236	0.546
takep1f\$1	1.346	0.101	0.000	1.151	1.556
fight1f\$1	0.834	0.096	0.000	0.638	1.016
lies1f\$1	0.667	0.088	0.000	0.487	0.837
teasel1f\$1	0.050	0.084	0.273	-0.120	0.209
stub7s\$1	-0.386	0.067	0.000	-0.523	-0.263
bkrule7s\$1	-0.215	0.090	0.007	-0.396	-0.038
harmo7s\$1	1.657	0.142	0.000	1.390	1.951
bkthin7s\$1	1.813	0.098	0.000	1.645	2.035
yell7s\$1	0.389	0.078	0.000	0.236	0.546
takep7s\$1	1.346	0.101	0.000	1.151	1.556
fight7s\$1	0.834	0.096	0.000	0.638	1.016
lies7s\$1	0.667	0.088	0.000	0.487	0.837
tease7s\$1	0.050	0.084	0.273	-0.120	0.209

Table 42: Output excerpts for Bayes multiple-indicator growth modeling, continued

Parameter	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I.	
				Lower 2.5%	Upper 2.5%
Residual variances					
f1	0.147	0.060	0.000	0.032	0.271
f2	0.489	0.061	0.000	0.371	0.608
f3	1.724	0.170	0.000	1.435	2.099
f4	0.866	0.102	0.000	0.680	1.081
f5	0.686	0.080	0.000	0.543	0.859
f6	0.747	0.087	0.000	0.591	0.933
f7	0.961	0.108	0.000	0.771	1.193
f8	0.527	0.109	0.000	0.321	0.752
i	1.771	0.151	0.000	1.494	2.090
s	0.254	0.034	0.000	0.192	0.327
q	0.004	0.001	0.000	0.002	0.005