**Detailed Simulation Methods**

**Data generation.** Data was generated using flexMIRT 3.0 (Cai, 2015). A total of 40 graded response model (Samejima, 1969) items, with 5 response categories each, were constructed through random number generation – slopes/discrimination parameters/a’s were drawn from a normal distribution with a mean of 2.2 and a standard deviation of 0.20. Severity/b parameter values came from an iterative process. The first (least severe) threshold parameter was drawn from a truncated normal distribution with a mean of -1.5, a standard deviation of 0.50, and a lower bound of -3.0. The remaining severity parameters were found by drawing random positive deviation values from a normal distribution with a mean of 1.0 and a standard deviation of 0.20. This deviation value was then added to the previous severity parameter to obtain the value of the next severity parameter. For instance, if the first severity parameter was a random draw value -1.7 and the first deviation was 0.8, then the second severity parameter was -1.7 + 0.8 = -0.90. If the second deviation value was 0.2 then the third severity parameter would be -0.90 + 0.2 = -0.70. This iterative process continued until all 4 severity parameters were established for each item of the 40 items. The generating item parameters may be found in Table 1.

A unidimensional model was used within each time point and an independent clusters-type solution was specified for the multidimensional aspect, used to model the 5 time points. For the multidimensional aspect of the model, the first time point was specified to have a mean of 0 and standard deviation/variance of 1 to identify the model. Later time point generating mean values were drawn from a normal distribution with a mean of 0.0 and a standard deviation of 0.2; variance values were drawn form a normal distribution with a mean of 1.0 and a standard deviation of 0.20. The correlational structure was specified among variables took on three different generating values, depending on the set value of a 1-lag correlation which could be either 0.3, 0.6, or 0.9. An autoregressive (AR) structure was specified for the correlation matrix and reasonable and functional generating AR correlation values among the factors were found by simulating data (N = 3000) in R from an ARIMA(1,0,0) model with the autoregressive component set to the one of the above-mentioned values. This data was examined (via the acf() function) to obtain lag-correlation values used as generating values in the simulation. Conversions were performed to combine the randomly generated variance values with the AR correlations, in order to submit to flexMIRT a proper variance-covariance matrix from which to generate data. The mean values and variance-covariance matrices used in the generating model for each level of lag-1 factor correlation are provided in Table 2. Item responses for a total of 5000 simulated observations were created within each level of the generating correlation level values, using all 5 time points and all 40 items

**Model estimation.** In each design cell of the simulation study, 100 datasets were drawn from the larger data detailed above and analyses were run. For each analysis, observations were randomly sampled without replacement from the generated N = 5000 datasets previously mentioned. For the cells of the simulation, the following variables were manipulated at the specified levels.

* N = 25, 50, 125, 250, 500
* k = 10, 20, 40 items
* j = 1,2,3,5 time points

These design variables were fully crossed resulting in 60 cells within each level of lag-1 correlation strength; across the 3 levels of generating correlation values, a total of (60\*3=) 180 conditions were investigated. The single time point analyses were repeated using data from each of the lag-1 correlation generating models – with a single time point, these analyses were theoretically redundant as the specified level of correlation should not affect a single time point with a fixed mean and variance – but were conducted for completeness and to verify that the correlation among later time points did not noticeable affect the Time 1 data.

All analyses were conducted in flexMIRT 3.0 (Cai, 2015). All models were fit using Metropolis Hastings – Robbin Monro (MH-RM; e.g., Cai, 2010) estimation – this estimation method was slower than typical Bock-Aitken estimation for single and limited time point cells but was necessary to be able to compare across all simulation cells as the larger (more time point) models were most efficiently fit with MH-RM due to their dimensionality. MH-RM estimation, as with all Monte Carlo – Markov Chain estimation procedures, requires the adjustment of technical estimation settings to ensure precise estimation (such as burn-in length, overall acceptance rates, etc. to ensure the target distributions are accurately modeled by the draws from the chains). Within each cell, an initial MH-RM analysis was manually run and adjustments were made to the proposal standard deviation value to obtain a desirable acceptance rate (e.g., Roberts & Rosenthal, 2001) given the analysis characteristics (number of items, number of dimensions, etc.); this manually optimized proposal standard deviation value was then used for all replications in the cell.

Due to the complexity of the model, requiring both the estimation of item parameters and the latent variable (time point) means and covariance structure, an iterative estimation process was automated that was developed to stabilize the final analysis step by providing improved start values (relative to naïve default values) to the estimation process; example IRTPRO syntax for each step in this process is provided at the end of this supplement. First, the longitudinal aspect of the was ignored (all time points were combined) and item parameters were estimated for a unidimensional model from this restructured data (Syntax A1). Second, the longitudinal feature of the data was maintained, the item parameters were fixed at the estimated values from the previous step and the latent variable means and variance-covariance structure was estimated (Syntax A2). Finally, a full analysis freely estimating both the item parameters and the latent variable parameters was conducted (Syntax A3). This analysis was supplied the parameter estimates from the previous step (both the item parameters originating from step 1 and the latent variable parameter estimated in step 2) as starting values. Parameter estimates from this third step are what were summarized in the Results section of the main manuscript and below.

**Supplemental Simulation Results**

A complete summary of all non-converged replications by simulation cell is provided in Table 3 and a summary of replications requiring collapsing/recoding due to missing response categories is provided in Table 4.

Summary recovery values for both the group mean values (Table 5) and the variances and factors intercorrelations (Tables 6) are reported. As with the item parameter and score results, the estimates of the factor means (Table 5) tended to exhibit small but negative bias while the RMSE values indicated that the generating values were recovered with reasonable accuracy. The correlations among factors were recovered extremely well (Table 6) with the largest observed bias being only 0.03 and the largest RMSE being 0.15, with an average RMSE over all cells of 0.07. Higher correlation RMSE values were generally found in cells with low N. The variances were generally recovered at an acceptable level (Table 5) and expected patterns (higher N or more items= better recovery) were observed. Recovery (both bias and RMSE) for the variances was noticeably poorer for r = 0.6 cells with 20 or 40 items when 5 timepoints were employed in the analysis. This finding is something of an anomaly which we attribute to the generating variance value of Factor 3 (middle portion of Table 2), which was noticeably different from the four other variance values included in the model.

Table 1. Generating item parameters for the simulation study

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Item | a | b1 | b2 | b3 | b4 |
| 1 | 2.28 | -1.91 | -1.13 | -0.11 | 0.56 |
| 2 | 1.71 | -2.00 | -0.90 | 0.11 | 1.46 |
| 3 | 2.23 | -1.20 | -0.19 | 0.88 | 1.79 |
| 4 | 2.10 | -2.20 | -1.12 | 0.11 | 1.04 |
| 5 | 2.41 | -1.89 | -1.06 | -0.14 | 1.00 |
| 6 | 2.23 | -1.81 | -0.77 | 0.24 | 1.11 |
| 7 | 2.14 | -1.51 | -0.81 | 0.50 | 1.19 |
| 8 | 2.74 | -1.47 | -0.35 | 0.42 | 1.34 |
| 9 | 1.80 | -1.71 | -1.07 | -0.35 | 0.61 |
| 10 | 1.71 | -0.64 | 0.43 | 1.62 | 2.80 |
| 11 | 2.05 | -2.32 | -1.42 | -0.07 | 0.97 |
| 12 | 2.07 | -1.31 | -0.52 | 0.50 | 1.35 |
| 13 | 2.46 | -2.27 | -1.77 | -0.99 | -0.18 |
| 14 | 2.44 | -1.68 | -1.01 | 0.17 | 0.78 |
| 15 | 2.29 | -1.16 | 0.04 | 0.94 | 2.01 |
| 16 | 2.22 | -1.39 | -0.12 | 0.88 | 2.03 |
| 17 | 2.58 | -1.02 | -0.26 | 0.78 | 1.55 |
| 18 | 1.99 | -2.37 | -1.41 | -0.56 | 0.36 |
| 19 | 2.24 | -1.36 | -0.35 | 0.94 | 1.83 |
| 20 | 2.27 | -1.19 | -0.39 | 0.72 | 1.49 |
| 21 | 1.80 | -1.82 | -0.93 | 0.16 | 1.42 |
| 22 | 1.80 | -1.07 | -0.14 | 0.64 | 1.82 |
| 23 | 2.07 | -2.70 | -1.65 | -0.37 | 0.40 |
| 24 | 1.97 | -1.76 | -1.05 | -0.20 | 0.89 |
| 25 | 1.90 | -1.92 | -1.29 | -0.18 | 0.99 |
| 26 | 2.20 | -2.14 | -1.25 | -0.36 | 0.82 |
| 27 | 2.04 | -1.82 | -0.93 | 0.17 | 0.87 |
| 28 | 2.29 | -1.79 | -1.11 | 0.00 | 1.13 |
| 29 | 2.33 | -2.11 | -0.92 | -0.22 | 0.31 |
| 30 | 2.36 | -1.46 | -0.64 | 0.27 | 1.25 |
| 31 | 2.15 | -1.85 | -0.68 | 0.42 | 1.34 |
| 32 | 2.29 | -1.72 | -0.68 | 0.47 | 1.47 |
| 33 | 2.29 | -1.00 | 0.18 | 1.29 | 2.61 |
| 34 | 2.08 | -2.24 | -1.12 | -0.17 | 0.89 |
| 35 | 1.94 | -1.46 | -0.87 | 0.23 | 1.28 |
| 36 | 2.15 | -1.72 | -0.87 | 0.15 | 1.00 |
| 37 | 2.18 | -2.35 | -1.33 | 0.09 | 1.09 |
| 38 | 2.54 | -1.98 | -1.06 | 0.13 | 1.21 |
| 39 | 2.30 | -1.73 | 0.00 | 0.81 | 1.87 |
| 40 | 2.36 | -1.78 | -0.53 | 0.52 | 1.39 |

Table 2. Mean values and variance-covariance matrices used in the generating model for each level of lag-1 factor correlation

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|   | t1 | t2 | t3 | t4 | t5 |
|   | lag-1 correlation = 0.3 |
| Means | 0.00 | 0.13 | -0.53 | -0.09 | -0.07 |
|   |   |   |   |   |   |
| t1 | 1.000 |   |   |   |   |
| t2 | 0.288 | 0.863 |   |   |   |
| t3 | 0.098 | 0.284 | 0.969 |   |   |
| t4 | 0.019 | 0.090 | 0.295 | 0.936 |   |
| t5 | 0.011 | 0.021 | 0.112 | 0.341 | 1.290 |
| lag-1 correlation = 0.6 |
| Means | 0.00 | 0.05 | -0.34 | 0.11 | -0.52 |
|   |   |   |   |   |   |
| t1 | 1.000 |   |   |   |   |
| t2 | 0.690 | 1.240 |   |   |   |
| t3 | 0.305 | 0.554 | 0.644 |   |   |
| t4 | 0.272 | 0.480 | 0.564 | 1.286 |   |
| t5 | 0.138 | 0.284 | 0.324 | 0.748 | 1.131 |
| lag-1 correlation = 0.9 |
| Means | 0.00 | 0.16 | -0.01 | -0.36 | -0.20 |
|   |   |   |   |   |   |
| t1 | 1.000 |   |   |   |   |
| t2 | 1.034 | 1.319 |   |   |   |
| t3 | 0.913 | 1.165 | 1.270 |   |   |
| t4 | 0.708 | 0.915 | 0.998 | 0.968 |   |
| t5 | 0.728 | 0.926 | 1.022 | 0.991 | 1.254 |

 Note. Values on diagonals are variances, values on off-diagonals are covariances (not correlations)

Table 3. Full summary of non-converged or non-stable analyses by design variables.

|  |  |  |  |
| --- | --- | --- | --- |
|  Time-lag 1 Factor Correlation |  Number of Timepoints (j) |  Number of items (k) | Number of initially unconverged replications |
| N = 25 | N = 50 | N = 125 |
| 0.3 | 1 | 10 | 3 |   |   |
|   |   | 20 | 7 |   |   |
|   |   | 40 | 7 | 1 |   |
|   | 2 | 10 | 1 |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |
|   | 3 | 10 |   |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |
|   | 5 | 10 |   |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |
| 0.6 | 1 | 10 |   |   |   |
|   |   | 20 | 6 |   |   |
|   |   | 40 | 4 |   |   |
|   | 2 | 10 |   |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |
|   | 3 | 10 |   |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |
|   | 5 | 10 |   |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |
| 0.9 | 1 | 10 | 3 |   |   |
|   |   | 20 | 8 | 4 |   |
|   |   | 40 | 6 |   | 2 |
|   | 2 | 10 | 1 |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |
|   | 3 | 10 |   |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |
|   | 5 | 10 |   |   |   |
|   |   | 20 |   |   |   |
|   |   | 40 |   |   |   |

Note. Unconverged replication as indicated by failed first- or second-order convergence/stability tests in the flexMIRT general output file. No replications in N = 250 or N = 500 cells were initially unconverged.

Table 4. Number of analyses (out of 100) requiring collapsing of response categories in at least 1 item due to insufficient observations, by simulation design cell

|  |  |  |  |
| --- | --- | --- | --- |
| Time-lag 1 Factor Correlation  | Number of Timepoints (j)  | Number of items (k)  | Number of analyses requiring collapsing |
| N = 25 | N = 50 | N = 125 | N = 250 |
| 0.3 | 1 | 10 | 86 | 42 | 6 | 0 |
|   |   | 20 | 97 | 75 | 7 | 0 |
|   |   | 40 | 100 | 91 | 13 | 0 |
|   | 2 | 10 | 49 | 13 | 0 | 0 |
|   |   | 20 | 77 | 17 | 0 | 0 |
|   |   | 40 | 92 | 0 | 0 | 0 |
|   | 3 | 10 | 18 | 8 | 0 | 0 |
|   |   | 20 | 32 | 0 | 0 | 0 |
|   |   | 40 | 58 | 0 | 0 | 0 |
|   | 5 | 10 | 1 | 0 | 0 | 0 |
|   |   | 20 | 4 | 0 | 0 | 0 |
|   |   | 40 | 18 | 1 | 0 | 0 |
| 0.6 | 1 | 10 | 84 | 41 | 5 | 0 |
|   |   | 20 | 99 | 69 | 11 | 0 |
|   |   | 40 | 98 | 92 | 18 | 0 |
|   | 2 | 10 | 41 | 5 | 0 | 0 |
|   |   | 20 | 63 | 10 | 0 | 0 |
|   |   | 40 | 75 | 30 | 0 | 0 |
|   | 3 | 10 | 20 | 6 | 0 | 0 |
|   |   | 20 | 34 | 5 | 0 | 0 |
|   |   | 40 | 60 | 12 | 0 | 0 |
|   | 5 | 10 | 6 | 0 | 0 | 0 |
|   |   | 20 | 7 | 0 | 0 | 0 |
|   |   | 40 | 14 | 1 | 0 | 0 |
| 0.9 | 1 | 10 | 95 | 39 | 4 | 0 |
|   |   | 20 | 100 | 71 | 8 | 0 |
|   |   | 40 | 100 | 86 | 34 | 1 |
|   | 2 | 10 | 37 | 7 | 0 | 0 |
|   |   | 20 | 67 | 15 | 0 | 0 |
|   |   | 40 | 78 | 26 | 0 | 0 |
|   | 3 | 10 | 12 | 1 | 0 | 0 |
|   |   | 20 | 34 | 2 | 0 | 0 |
|   |   | 40 | 50 | 11 | 0 | 0 |
|   | 5 | 10 | 6 | 0 | 0 | 0 |
|   |   | 20 | 13 | 1 | 0 | 0 |
|   |   | 40 | 19 | 2 | 0 | 0 |

 Note. No analyses required collapsing in any N = 500 simulation cells.

 Table 5. Latent factor mean value recovery values for select cells of the longitudinal IRT simulation

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Time-lag 1 Factor Correlation | Items (k) | N |   | Bias |   | RMSE |
|  | Timepoints = 3 | Timepoints = 5 |  | Timepoints = 3 | Timepoints = 5 |
|   | time 2  | time 3 | time 2 | time 3 | time 4 | time 5 |  | time 2  | time 3 | time 2 | time 3 | time 4 | time 5 |
| 0.3 | 10 | 25 |  | -0.05 | -0.04 | -0.07 | -0.03 | -0.03 | -0.01 |  | 0.19 | 0.22 | 0.20 | 0.23 | 0.22 | 0.24 |
|  |  | 50 |  | -0.06 | -0.07 | -0.05 | -0.06 | -0.08 | -0.09 |  | 0.15 | 0.17 | 0.14 | 0.16 | 0.18 | 0.18 |
|  |  | 500 |  | -0.05 | -0.04 | -0.06 | -0.06 | -0.05 | -0.06 |  | 0.06 | 0.06 | 0.07 | 0.08 | 0.06 | 0.07 |
|  | 20 | 25 |  | -0.09 | -0.08 | -0.04 | -0.07 | -0.04 | -0.07 |  | 0.19 | 0.19 | 0.17 | 0.19 | 0.16 | 0.21 |
|  |  | 125 |  | -0.08 | -0.08 | -0.07 | -0.10 | -0.07 | -0.09 |  | 0.11 | 0.11 | 0.10 | 0.13 | 0.09 | 0.12 |
|  |  | 250 |  | -0.06 | -0.08 | -0.06 | -0.11 | -0.09 | -0.09 |  | 0.08 | 0.10 | 0.08 | 0.12 | 0.10 | 0.11 |
|  | 40 | 25 |  | -0.08 | -0.13 | -0.09 | -0.13 | -0.05 | -0.10 |  | 0.17 | 0.21 | 0.17 | 0.20 | 0.16 | 0.20 |
|  |  | 50 |  | -0.11 | -0.10 | -0.09 | -0.14 | -0.10 | -0.09 |  | 0.15 | 0.15 | 0.14 | 0.18 | 0.15 | 0.16 |
|  |  | 500 |  | -0.07 | -0.10 | -0.07 | -0.13 | -0.09 | -0.09 |  | 0.08 | 0.10 | 0.07 | 0.13 | 0.09 | 0.10 |
| 0.6 | 10 | 25 |  | -0.05 | 0.01 | -0.03 | -0.04 | -0.05 | -0.03 |  | 0.22 | 0.21 | 0.17 | 0.18 | 0.21 | 0.22 |
|  |  | 50 |  | -0.06 | -0.02 | -0.04 | -0.09 | -0.06 | -0.11 |  | 0.16 | 0.13 | 0.13 | 0.14 | 0.17 | 0.18 |
|  |  | 500 |  | -0.02 | -0.01 | -0.04 | -0.07 | -0.05 | -0.09 |  | 0.05 | 0.04 | 0.05 | 0.08 | 0.07 | 0.10 |
|  | 20 | 25 |  | -0.07 | -0.03 | -0.02 | -0.06 | -0.06 | -0.13 |  | 0.18 | 0.17 | 0.18 | 0.14 | 0.18 | 0.20 |
|  |  | 125 |  | -0.04 | -0.07 | -0.04 | -0.12 | -0.05 | -0.16 |  | 0.08 | 0.10 | 0.08 | 0.13 | 0.09 | 0.18 |
|  |  | 250 |  | -0.03 | -0.05 | -0.03 | -0.12 | -0.06 | -0.16 |  | 0.05 | 0.07 | 0.05 | 0.13 | 0.08 | 0.17 |
|  | 40 | 25 |  | -0.05 | -0.09 | -0.04 | -0.10 | -0.04 | -0.14 |  | 0.19 | 0.16 | 0.16 | 0.16 | 0.17 | 0.23 |
|  |  | 50 |  | -0.02 | -0.08 | -0.06 | -0.12 | -0.05 | -0.14 |  | 0.14 | 0.14 | 0.11 | 0.14 | 0.13 | 0.18 |
|  |  | 500 |  | -0.04 | -0.07 | -0.04 | -0.12 | -0.06 | -0.15 |  | 0.05 | 0.08 | 0.05 | 0.12 | 0.07 | 0.16 |
| 0.9 | 10 | 25 |  | -0.01 | 0.00 | 0.00 | -0.03 | 0.00 | 0.00 |  | 0.15 | 0.19 | 0.13 | 0.17 | 0.17 | 0.18 |
|  |  | 50 |  | 0.00 | 0.03 | 0.01 | 0.00 | -0.03 | -0.02 |  | 0.10 | 0.11 | 0.09 | 0.10 | 0.11 | 0.12 |
|  |  | 500 |  | 0.00 | 0.01 | 0.02 | -0.01 | -0.05 | -0.04 |  | 0.03 | 0.03 | 0.03 | 0.03 | 0.06 | 0.05 |
|  | 20 | 25 |  | -0.01 | -0.01 | 0.01 | 0.01 | -0.02 | -0.01 |  | 0.11 | 0.15 | 0.09 | 0.12 | 0.11 | 0.16 |
|  |  | 125 |  | 0.01 | 0.01 | 0.00 | -0.01 | -0.05 | -0.03 |  | 0.05 | 0.06 | 0.05 | 0.06 | 0.08 | 0.08 |
|  |  | 250 |  | 0.00 | 0.01 | 0.02 | 0.00 | -0.04 | -0.03 |  | 0.04 | 0.04 | 0.03 | 0.04 | 0.06 | 0.06 |
|  | 40 | 25 |  | 0.02 | 0.02 | 0.02 | -0.01 | -0.09 | -0.05 |  | 0.11 | 0.12 | 0.09 | 0.13 | 0.16 | 0.16 |
|  |  | 50 |  | 0.01 | 0.00 | 0.02 | -0.01 | -0.07 | -0.05 |  | 0.06 | 0.08 | 0.06 | 0.07 | 0.11 | 0.12 |
|   |   | 500 |   | 0.02 | 0.00 | 0.02 | -0.01 | -0.07 | -0.04 |   | 0.03 | 0.03 | 0.03 | 0.02 | 0.08 | 0.05 |

Note. Mean of time 1 is always fixed at 0.00, in both the generating and estimated models, for identification.

Table 6. Latent factor variance and correlation value recovery for select cells of the longitudinal IRT simulation

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|   |   |   | Time points = 3 |   | Time points = 5 |
| Time-lag 1 Factor Correlation |  |  | Bias | RMSE |  | Bias | RSME |
| Items (k) | N | Mean of corrs | Mean of variances | Mean of corrs | Mean of variances |   | Mean of corrs | Mean of variances | Mean of corrs | Mean of variances |
| 0.3 | 10 | 25 | 0.00 | -0.19 | 0.20 | 0.50 |  | 0.01 | -0.17 | 0.21 | 0.48 |
|  |  | 50 | 0.02 | -0.12 | 0.14 | 0.30 |  | 0.01 | -0.10 | 0.15 | 0.30 |
|  |  | 500 | 0.01 | -0.05 | 0.04 | 0.09 |  | 0.00 | -0.02 | 0.04 | 0.09 |
|  | 20 | 25 | 0.01 | -0.05 | 0.20 | 0.34 |  | 0.02 | 0.02 | 0.22 | 0.31 |
|  |  | 125 | 0.01 | -0.01 | 0.08 | 0.15 |  | 0.01 | 0.04 | 0.09 | 0.15 |
|  |  | 250 | 0.00 | 0.00 | 0.06 | 0.09 |  | 0.00 | 0.05 | 0.06 | 0.11 |
|  | 40 | 25 | -0.01 | 0.06 | 0.23 | 0.28 |  | -0.01 | 0.16 | 0.22 | 0.29 |
|  |  | 50 | 0.01 | -0.01 | 0.13 | 0.20 |  | -0.01 | 0.10 | 0.14 | 0.21 |
|  |  | 500 | 0.00 | 0.01 | 0.04 | 0.06 |  | -0.01 | 0.13 | 0.05 | 0.14 |
| 0.6 | 10 | 25 | 0.02 | -0.18 | 0.17 | 0.49 |  | 0.02 | -0.19 | 0.18 | 0.47 |
|  |  | 50 | 0.03 | -0.14 | 0.10 | 0.31 |  | -0.01 | -0.01 | 0.13 | 0.26 |
|  |  | 500 | 0.01 | -0.05 | 0.04 | 0.09 |  | -0.01 | 0.04 | 0.04 | 0.08 |
|  | 20 | 25 | 0.02 | -0.05 | 0.15 | 0.33 |  | -0.01 | 0.05 | 0.20 | 0.34 |
|  |  | 125 | 0.01 | -0.03 | 0.07 | 0.14 |  | -0.02 | 0.19 | 0.08 | 0.22 |
|  |  | 250 | 0.01 | -0.02 | 0.05 | 0.09 |  | -0.01 | 0.19 | 0.06 | 0.21 |
|  | 40 | 25 | -0.01 | 0.00 | 0.16 | 0.29 |  | 0.01 | 0.08 | 0.19 | 0.33 |
|  |  | 50 | -0.01 | 0.01 | 0.11 | 0.19 |  | -0.01 | 0.19 | 0.12 | 0.26 |
|  |  | 500 | -0.01 | 0.04 | 0.03 | 0.07 |  | -0.02 | 0.19 | 0.04 | 0.19 |
| 0.9 | 10 | 25 | 0.02 | -0.13 | 0.08 | 0.43 |  | 0.01 | -0.07 | 0.10 | 0.36 |
|  |  | 50 | 0.02 | -0.13 | 0.06 | 0.29 |  | -0.02 | 0.04 | 0.06 | 0.23 |
|  |  | 500 | 0.00 | -0.01 | 0.01 | 0.08 |  | -0.02 | 0.10 | 0.03 | 0.12 |
|  | 20 | 25 | 0.00 | -0.02 | 0.05 | 0.30 |  | -0.01 | 0.03 | 0.08 | 0.30 |
|  |  | 125 | -0.01 | 0.02 | 0.03 | 0.13 |  | -0.01 | 0.06 | 0.04 | 0.13 |
|  |  | 250 | -0.01 | 0.02 | 0.02 | 0.09 |  | -0.02 | 0.05 | 0.03 | 0.09 |
|  | 40 | 25 | -0.02 | 0.00 | 0.06 | 0.32 |  | -0.03 | 0.08 | 0.08 | 0.28 |
|  |  | 50 | -0.02 | 0.08 | 0.04 | 0.20 |  | -0.03 | 0.09 | 0.06 | 0.19 |
|   |   | 500 | -0.03 | 0.07 | 0.03 | 0.09 |   | -0.04 | 0.12 | 0.04 | 0.13 |

Note. Variance of time 1 is always fixed at 1.00, in both the generating and estimated models, for identification.

**SYNTAX**

A1. IRTPRO syntax for initial, time-ignoring 1D analysis of a simulation cell.

Project:

 Name = Model 1D;

Data:

 File = .\GRM5\_0.3\_3\_10\_50\_1D\_1.ssig;

Analysis:

 Name = Test1;

 Mode = Calibration;

Title:

Comments:

Estimation:

 Method = BAEM;

 E-Step = 500, 1e-005;

 SE = S-EM;

 M-Step = 50, 1e-006;

 Quadrature = 49, 6;

 SEM = 0.001;

 SS = 1e-005;

Saves:

 PRM, IRT, DBG

Scoring:

 Mean = 0;

 SD = 1;

Miscellaneous:

 Decimal = 2;

 Processors = 4;

 Print P-Nums;

 Min Exp = 1;

Groups:

Group :

 Dimension = 1;

 Items = VAR1, VAR2, VAR3, VAR4, VAR5, VAR6, VAR7, VAR8, VAR9, VAR10;

 Codes(VAR1) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR2) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR3) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR4) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR5) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR6) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR7) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR8) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR9) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(VAR10) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Model(VAR1) = Graded;

 Model(VAR2) = Graded;

 Model(VAR3) = Graded;

 Model(VAR4) = Graded;

 Model(VAR5) = Graded;

 Model(VAR6) = Graded;

 Model(VAR7) = Graded;

 Model(VAR8) = Graded;

 Model(VAR9) = Graded;

 Model(VAR10) = Graded;

 Mean = 0.0;

 Covariance = 1.0;

Constraints:

A2. IRTPRO syntax for analysis using item parameters from 1D model and estimating factor means and variance/covariance matrix

Project:

 Name = test;

Data:

 File = .\wide\_data.ssig;

Analysis:

 Name = Test1;

 Mode = Calibration;

Title:

Comments:

Estimation:

 Method = MHRM;

 Convergence = 3, 0.001;

 Stage1 = 200;

 Stage2 = 100;

 Stage3 = 2000;

 MCsize = 10000;

 Imputation = 1;

 Burnin = 10;

 Thinning = 0;

 GainConst = 0.1;

 Alpha = 1;

 Epsilon = 1;

 Sampler = Spherical;

 ProposalSD = 0.25;

 CovMethod = Accumulation;

Saves:

 PRM, IRT, DBG

Scoring:

 Mean = 0;

 SD = 1;

Miscellaneous:

 Decimal = 2;

 Processors = 4;

 Print P-Nums;

 Min Exp = 1;

Groups:

Group :

 Dimension = 3;

 Items = t1\_v1, t1\_v2, t1\_v3, t1\_v4, t1\_v5, t1\_v6, t1\_v7, t1\_v8, t1\_v9,

 t1\_v10, t2\_v1, t2\_v2, t2\_v3, t2\_v4, t2\_v5, t2\_v6, t2\_v7, t2\_v8, t2\_v9,

 t2\_v10, t3\_v1, t3\_v2, t3\_v3, t3\_v4, t3\_v5, t3\_v6, t3\_v7, t3\_v8, t3\_v9,

 t3\_v10;

 Codes(t1\_v1) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v2) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v3) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v4) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v5) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v6) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v7) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v8) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v9) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v10) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v1) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v2) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v3) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v4) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v5) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v6) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v7) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v8) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v9) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v10) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v1) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v2) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v3) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v4) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v5) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v6) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v7) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v8) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v9) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v10) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Model(t1\_v1) = Graded;

 Model(t1\_v2) = Graded;

 Model(t1\_v3) = Graded;

 Model(t1\_v4) = Graded;

 Model(t1\_v5) = Graded;

 Model(t1\_v6) = Graded;

 Model(t1\_v7) = Graded;

 Model(t1\_v8) = Graded;

 Model(t1\_v9) = Graded;

 Model(t1\_v10) = Graded;

 Model(t2\_v1) = Graded;

 Model(t2\_v2) = Graded;

 Model(t2\_v3) = Graded;

 Model(t2\_v4) = Graded;

 Model(t2\_v5) = Graded;

 Model(t2\_v6) = Graded;

 Model(t2\_v7) = Graded;

 Model(t2\_v8) = Graded;

 Model(t2\_v9) = Graded;

 Model(t2\_v10) = Graded;

 Model(t3\_v1) = Graded;

 Model(t3\_v2) = Graded;

 Model(t3\_v3) = Graded;

 Model(t3\_v4) = Graded;

 Model(t3\_v5) = Graded;

 Model(t3\_v6) = Graded;

 Model(t3\_v7) = Graded;

 Model(t3\_v8) = Graded;

 Model(t3\_v9) = Graded;

 Model(t3\_v10) = Graded;

 Means = 0.0, Free, Free;

 Covariances = 1.0,

 Free, Free,

 Free, Free, Free;

Constraints:

 (t1\_v1, Slope[0]) = 3.3667;

 (t1\_v1, Slope[1]) = 0;

 (t1\_v1, Slope[2]) = 0;

 (t1\_v1, Intercept[0]) = 5.66108;

 (t1\_v1, Intercept[1]) = 3.51352;

 (t1\_v1, Intercept[2]) = 0.1673;

 (t1\_v1, Intercept[3]) = -1.62036;

 (t1\_v2, Slope[0]) = 1.87212;

 (t1\_v2, Slope[1]) = 0;

 (t1\_v2, Slope[2]) = 0;

 (t1\_v2, Intercept[0]) = 2.86868;

 (t1\_v2, Intercept[1]) = 1.69494;

 (t1\_v2, Intercept[2]) = -0.1773;

 (t1\_v2, Intercept[3]) = -2.46353;

 (t1\_v3, Slope[0]) = 2.0172;

 (t1\_v3, Slope[1]) = 0;

 (t1\_v3, Slope[2]) = 0;

 (t1\_v3, Intercept[0]) = 2.03337;

 (t1\_v3, Intercept[1]) = 0.21278;

 (t1\_v3, Intercept[2]) = -1.82284;

 (t1\_v3, Intercept[3]) = -3.44894;

 (t1\_v4, Slope[0]) = 2.34981;

 (t1\_v4, Slope[1]) = 0;

 (t1\_v4, Slope[2]) = 0;

 (t1\_v4, Intercept[0]) = 4.76893;

 (t1\_v4, Intercept[1]) = 2.36463;

 (t1\_v4, Intercept[2]) = -0.44422;

 (t1\_v4, Intercept[3]) = -2.06696;

 (t1\_v5, Slope[0]) = 2.94169;

 (t1\_v5, Slope[1]) = 0;

 (t1\_v5, Slope[2]) = 0;

 (t1\_v5, Intercept[0]) = 4.90171;

 (t1\_v5, Intercept[1]) = 3.25943;

 (t1\_v5, Intercept[2]) = 0.26334;

 (t1\_v5, Intercept[3]) = -2.32187;

 (t1\_v6, Slope[0]) = 2.22076;

 (t1\_v6, Slope[1]) = 0;

 (t1\_v6, Slope[2]) = 0;

 (t1\_v6, Intercept[0]) = 4.26104;

 (t1\_v6, Intercept[1]) = 1.99661;

 (t1\_v6, Intercept[2]) = -0.55463;

 (t1\_v6, Intercept[3]) = -2.21513;

 (t1\_v7, Slope[0]) = 2.4246;

 (t1\_v7, Slope[1]) = 0;

 (t1\_v7, Slope[2]) = 0;

 (t1\_v7, Intercept[0]) = 3.78371;

 (t1\_v7, Intercept[1]) = 1.83485;

 (t1\_v7, Intercept[2]) = -1.15101;

 (t1\_v7, Intercept[3]) = -2.77583;

 (t1\_v8, Slope[0]) = 3.09369;

 (t1\_v8, Slope[1]) = 0;

 (t1\_v8, Slope[2]) = 0;

 (t1\_v8, Intercept[0]) = 4.12462;

 (t1\_v8, Intercept[1]) = 0.74843;

 (t1\_v8, Intercept[2]) = -1.22175;

 (t1\_v8, Intercept[3]) = -3.82692;

 (t1\_v9, Slope[0]) = 2.07782;

 (t1\_v9, Slope[1]) = 0;

 (t1\_v9, Slope[2]) = 0;

 (t1\_v9, Intercept[0]) = 3.7229;

 (t1\_v9, Intercept[1]) = 2.09171;

 (t1\_v9, Intercept[2]) = 0.80411;

 (t1\_v9, Intercept[3]) = -1.28503;

 (t1\_v10, Slope[0]) = 1.56648;

 (t1\_v10, Slope[1]) = 0;

 (t1\_v10, Slope[2]) = 0;

 (t1\_v10, Intercept[0]) = 0.87793;

 (t1\_v10, Intercept[1]) = -0.95438;

 (t1\_v10, Intercept[2]) = -2.26906;

 (t1\_v10, Intercept[3]) = -4.15761;

 (t2\_v1, Slope[0]) = 0;

 (t2\_v1, Slope[1]) = 3.3667;

 (t2\_v1, Slope[2]) = 0;

 (t2\_v1, Intercept[0]) = 5.66108;

 (t2\_v1, Intercept[1]) = 3.51352;

 (t2\_v1, Intercept[2]) = 0.1673;

 (t2\_v1, Intercept[3]) = -1.62036;

 (t2\_v2, Slope[0]) = 0;

 (t2\_v2, Slope[1]) = 1.87212;

 (t2\_v2, Slope[2]) = 0;

 (t2\_v2, Intercept[0]) = 2.86868;

 (t2\_v2, Intercept[1]) = 1.69494;

 (t2\_v2, Intercept[2]) = -0.1773;

 (t2\_v2, Intercept[3]) = -2.46353;

 (t2\_v3, Slope[0]) = 0;

 (t2\_v3, Slope[1]) = 2.0172;

 (t2\_v3, Slope[2]) = 0;

 (t2\_v3, Intercept[0]) = 2.03337;

 (t2\_v3, Intercept[1]) = 0.21278;

 (t2\_v3, Intercept[2]) = -1.82284;

 (t2\_v3, Intercept[3]) = -3.44894;

 (t2\_v4, Slope[0]) = 0;

 (t2\_v4, Slope[1]) = 2.34981;

 (t2\_v4, Slope[2]) = 0;

 (t2\_v4, Intercept[0]) = 4.76893;

 (t2\_v4, Intercept[1]) = 2.36463;

 (t2\_v4, Intercept[2]) = -0.44422;

 (t2\_v4, Intercept[3]) = -2.06696;

 (t2\_v5, Slope[0]) = 0;

 (t2\_v5, Slope[1]) = 2.94169;

 (t2\_v5, Slope[2]) = 0;

 (t2\_v5, Intercept[0]) = 4.90171;

 (t2\_v5, Intercept[1]) = 3.25943;

 (t2\_v5, Intercept[2]) = 0.26334;

 (t2\_v5, Intercept[3]) = -2.32187;

 (t2\_v6, Slope[0]) = 0;

 (t2\_v6, Slope[1]) = 2.22076;

 (t2\_v6, Slope[2]) = 0;

 (t2\_v6, Intercept[0]) = 4.26104;

 (t2\_v6, Intercept[1]) = 1.99661;

 (t2\_v6, Intercept[2]) = -0.55463;

 (t2\_v6, Intercept[3]) = -2.21513;

 (t2\_v7, Slope[0]) = 0;

 (t2\_v7, Slope[1]) = 2.4246;

 (t2\_v7, Slope[2]) = 0;

 (t2\_v7, Intercept[0]) = 3.78371;

 (t2\_v7, Intercept[1]) = 1.83485;

 (t2\_v7, Intercept[2]) = -1.15101;

 (t2\_v7, Intercept[3]) = -2.77583;

 (t2\_v8, Slope[0]) = 0;

 (t2\_v8, Slope[1]) = 3.09369;

 (t2\_v8, Slope[2]) = 0;

 (t2\_v8, Intercept[0]) = 4.12462;

 (t2\_v8, Intercept[1]) = 0.74843;

 (t2\_v8, Intercept[2]) = -1.22175;

 (t2\_v8, Intercept[3]) = -3.82692;

 (t2\_v9, Slope[0]) = 0;

 (t2\_v9, Slope[1]) = 2.07782;

 (t2\_v9, Slope[2]) = 0;

 (t2\_v9, Intercept[0]) = 3.7229;

 (t2\_v9, Intercept[1]) = 2.09171;

 (t2\_v9, Intercept[2]) = 0.80411;

 (t2\_v9, Intercept[3]) = -1.28503;

 (t2\_v10, Slope[0]) = 0;

 (t2\_v10, Slope[1]) = 1.56648;

 (t2\_v10, Slope[2]) = 0;

 (t2\_v10, Intercept[0]) = 0.87793;

 (t2\_v10, Intercept[1]) = -0.95438;

 (t2\_v10, Intercept[2]) = -2.26906;

 (t2\_v10, Intercept[3]) = -4.15761;

 (t3\_v1, Slope[0]) = 0;

 (t3\_v1, Slope[1]) = 0;

 (t3\_v1, Slope[2]) = 3.3667;

 (t3\_v1, Intercept[0]) = 5.66108;

 (t3\_v1, Intercept[1]) = 3.51352;

 (t3\_v1, Intercept[2]) = 0.1673;

 (t3\_v1, Intercept[3]) = -1.62036;

 (t3\_v2, Slope[0]) = 0;

 (t3\_v2, Slope[1]) = 0;

 (t3\_v2, Slope[2]) = 1.87212;

 (t3\_v2, Intercept[0]) = 2.86868;

 (t3\_v2, Intercept[1]) = 1.69494;

 (t3\_v2, Intercept[2]) = -0.1773;

 (t3\_v2, Intercept[3]) = -2.46353;

 (t3\_v3, Slope[0]) = 0;

 (t3\_v3, Slope[1]) = 0;

 (t3\_v3, Slope[2]) = 2.0172;

 (t3\_v3, Intercept[0]) = 2.03337;

 (t3\_v3, Intercept[1]) = 0.21278;

 (t3\_v3, Intercept[2]) = -1.82284;

 (t3\_v3, Intercept[3]) = -3.44894;

 (t3\_v4, Slope[0]) = 0;

 (t3\_v4, Slope[1]) = 0;

 (t3\_v4, Slope[2]) = 2.34981;

 (t3\_v4, Intercept[0]) = 4.76893;

 (t3\_v4, Intercept[1]) = 2.36463;

 (t3\_v4, Intercept[2]) = -0.44422;

 (t3\_v4, Intercept[3]) = -2.06696;

 (t3\_v5, Slope[0]) = 0;

 (t3\_v5, Slope[1]) = 0;

 (t3\_v5, Slope[2]) = 2.94169;

 (t3\_v5, Intercept[0]) = 4.90171;

 (t3\_v5, Intercept[1]) = 3.25943;

 (t3\_v5, Intercept[2]) = 0.26334;

 (t3\_v5, Intercept[3]) = -2.32187;

 (t3\_v6, Slope[0]) = 0;

 (t3\_v6, Slope[1]) = 0;

 (t3\_v6, Slope[2]) = 2.22076;

 (t3\_v6, Intercept[0]) = 4.26104;

 (t3\_v6, Intercept[1]) = 1.99661;

 (t3\_v6, Intercept[2]) = -0.55463;

 (t3\_v6, Intercept[3]) = -2.21513;

 (t3\_v7, Slope[0]) = 0;

 (t3\_v7, Slope[1]) = 0;

 (t3\_v7, Slope[2]) = 2.4246;

 (t3\_v7, Intercept[0]) = 3.78371;

 (t3\_v7, Intercept[1]) = 1.83485;

 (t3\_v7, Intercept[2]) = -1.15101;

 (t3\_v7, Intercept[3]) = -2.77583;

 (t3\_v8, Slope[0]) = 0;

 (t3\_v8, Slope[1]) = 0;

 (t3\_v8, Slope[2]) = 3.09369;

 (t3\_v8, Intercept[0]) = 4.12462;

 (t3\_v8, Intercept[1]) = 0.74843;

 (t3\_v8, Intercept[2]) = -1.22175;

 (t3\_v8, Intercept[3]) = -3.82692;

 (t3\_v9, Slope[0]) = 0;

 (t3\_v9, Slope[1]) = 0;

 (t3\_v9, Slope[2]) = 2.07782;

 (t3\_v9, Intercept[0]) = 3.7229;

 (t3\_v9, Intercept[1]) = 2.09171;

 (t3\_v9, Intercept[2]) = 0.80411;

 (t3\_v9, Intercept[3]) = -1.28503;

 (t3\_v10, Slope[0]) = 0;

 (t3\_v10, Slope[1]) = 0;

 (t3\_v10, Slope[2]) = 1.56648;

 (t3\_v10, Intercept[0]) = 0.87793;

 (t3\_v10, Intercept[1]) = -0.95438;

 (t3\_v10, Intercept[2]) = -2.26906;

 (t3\_v10, Intercept[3]) = -4.15761;

A3. IRTPTO syntax for final analysis, using previous item and group parameters estimates as start values.

Project:

 Name = IRTPRO\_final\_run;

Data:

 File = .\wide\_data.ssig;

Analysis:

 Name = Test1;

 Mode = Calibration;

Title:

Comments:

Estimation:

 Method = MHRM;

 Convergence = 3, 0.001;

 Stage1 = 200;

 Stage2 = 100;

 Stage3 = 2000;

 MCsize = 10000;

 Imputation = 1;

 Burnin = 10;

 Thinning = 0;

 GainConst = 0.1;

 Alpha = 1;

 Epsilon = 1;

 Sampler = Spherical;

 ProposalSD = 0.19;

 CovMethod = Accumulation;

Saves:

 PRM, IRT, DBG

Scoring:

 Mean = 0;

 SD = 1;

Miscellaneous:

 Decimal = 2;

 Processors = 4;

 Print P-Nums;

 Min Exp = 1;

Groups:

Group :

 Dimension = 3;

 Items = t1\_v1, t1\_v2, t1\_v3, t1\_v4, t1\_v5, t1\_v6, t1\_v7, t1\_v8, t1\_v9,

 t1\_v10, t2\_v1, t2\_v2, t2\_v3, t2\_v4, t2\_v5, t2\_v6, t2\_v7, t2\_v8, t2\_v9,

 t2\_v10, t3\_v1, t3\_v2, t3\_v3, t3\_v4, t3\_v5, t3\_v6, t3\_v7, t3\_v8, t3\_v9,

 t3\_v10;

 Codes(t1\_v1) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v2) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v3) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v4) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v5) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v6) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v7) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v8) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v9) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t1\_v10) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v1) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v2) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v3) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v4) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v5) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v6) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v7) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v8) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v9) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t2\_v10) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v1) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v2) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v3) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v4) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v5) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v6) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v7) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v8) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v9) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Codes(t3\_v10) = 0(0), 1(1), 2(2), 3(3), 4(4);

 Model(t1\_v1) = Graded;

 Model(t1\_v2) = Graded;

 Model(t1\_v3) = Graded;

 Model(t1\_v4) = Graded;

 Model(t1\_v5) = Graded;

 Model(t1\_v6) = Graded;

 Model(t1\_v7) = Graded;

 Model(t1\_v8) = Graded;

 Model(t1\_v9) = Graded;

 Model(t1\_v10) = Graded;

 Model(t2\_v1) = Graded;

 Model(t2\_v2) = Graded;

 Model(t2\_v3) = Graded;

 Model(t2\_v4) = Graded;

 Model(t2\_v5) = Graded;

 Model(t2\_v6) = Graded;

 Model(t2\_v7) = Graded;

 Model(t2\_v8) = Graded;

 Model(t2\_v9) = Graded;

 Model(t2\_v10) = Graded;

 Model(t3\_v1) = Graded;

 Model(t3\_v2) = Graded;

 Model(t3\_v3) = Graded;

 Model(t3\_v4) = Graded;

 Model(t3\_v5) = Graded;

 Model(t3\_v6) = Graded;

 Model(t3\_v7) = Graded;

 Model(t3\_v8) = Graded;

 Model(t3\_v9) = Graded;

 Model(t3\_v10) = Graded;

 Means = 0.00000, Free, Free;

 Covariances = 1.00000,

 Free, Free,

 Free, Free, Free;

Constraints:

 Equal = (t3\_v1, Slope[2]), (t1\_v1, Slope[0]), (t2\_v1, Slope[1]);

 Equal = (t3\_v2, Slope[2]), (t1\_v2, Slope[0]), (t2\_v2, Slope[1]);

 Equal = (t3\_v3, Slope[2]), (t1\_v3, Slope[0]), (t2\_v3, Slope[1]);

 Equal = (t3\_v4, Slope[2]), (t1\_v4, Slope[0]), (t2\_v4, Slope[1]);

 Equal = (t3\_v5, Slope[2]), (t1\_v5, Slope[0]), (t2\_v5, Slope[1]);

 Equal = (t3\_v6, Slope[2]), (t1\_v6, Slope[0]), (t2\_v6, Slope[1]);

 Equal = (t3\_v7, Slope[2]), (t1\_v7, Slope[0]), (t2\_v7, Slope[1]);

 Equal = (t3\_v8, Slope[2]), (t1\_v8, Slope[0]), (t2\_v8, Slope[1]);

 Equal = (t3\_v9, Slope[2]), (t1\_v9, Slope[0]), (t2\_v9, Slope[1]);

 Equal = (t3\_v10, Slope[2]), (t1\_v10, Slope[0]), (t2\_v10, Slope[1]);

 Equal = (t3\_v1, Intercept[0]), (t1\_v1, Intercept[0]), (t2\_v1,

 Intercept[0]);

 Equal = (t3\_v1, Intercept[1]), (t1\_v1, Intercept[1]), (t2\_v1,

 Intercept[1]);

 Equal = (t3\_v1, Intercept[2]), (t1\_v1, Intercept[2]), (t2\_v1,

 Intercept[2]);

 Equal = (t3\_v1, Intercept[3]), (t1\_v1, Intercept[3]), (t2\_v1,

 Intercept[3]);

 Equal = (t3\_v2, Intercept[0]), (t1\_v2, Intercept[0]), (t2\_v2,

 Intercept[0]);

 Equal = (t3\_v2, Intercept[1]), (t1\_v2, Intercept[1]), (t2\_v2,

 Intercept[1]);

 Equal = (t3\_v2, Intercept[2]), (t1\_v2, Intercept[2]), (t2\_v2,

 Intercept[2]);

 Equal = (t3\_v2, Intercept[3]), (t1\_v2, Intercept[3]), (t2\_v2,

 Intercept[3]);

 Equal = (t3\_v3, Intercept[0]), (t1\_v3, Intercept[0]), (t2\_v3,

 Intercept[0]);

 Equal = (t3\_v3, Intercept[1]), (t1\_v3, Intercept[1]), (t2\_v3,

 Intercept[1]);

 Equal = (t3\_v3, Intercept[2]), (t1\_v3, Intercept[2]), (t2\_v3,

 Intercept[2]);

 Equal = (t3\_v3, Intercept[3]), (t1\_v3, Intercept[3]), (t2\_v3,

 Intercept[3]);

 Equal = (t3\_v4, Intercept[0]), (t1\_v4, Intercept[0]), (t2\_v4,

 Intercept[0]);

 Equal = (t3\_v4, Intercept[1]), (t1\_v4, Intercept[1]), (t2\_v4,

 Intercept[1]);

 Equal = (t3\_v4, Intercept[2]), (t1\_v4, Intercept[2]), (t2\_v4,

 Intercept[2]);

 Equal = (t3\_v4, Intercept[3]), (t1\_v4, Intercept[3]), (t2\_v4,

 Intercept[3]);

 Equal = (t3\_v5, Intercept[0]), (t1\_v5, Intercept[0]), (t2\_v5,

 Intercept[0]);

 Equal = (t3\_v5, Intercept[1]), (t1\_v5, Intercept[1]), (t2\_v5,

 Intercept[1]);

 Equal = (t3\_v5, Intercept[2]), (t1\_v5, Intercept[2]), (t2\_v5,

 Intercept[2]);

 Equal = (t3\_v5, Intercept[3]), (t1\_v5, Intercept[3]), (t2\_v5,

 Intercept[3]);

 Equal = (t3\_v6, Intercept[0]), (t1\_v6, Intercept[0]), (t2\_v6,

 Intercept[0]);

 Equal = (t3\_v6, Intercept[1]), (t1\_v6, Intercept[1]), (t2\_v6,

 Intercept[1]);

 Equal = (t3\_v6, Intercept[2]), (t1\_v6, Intercept[2]), (t2\_v6,

 Intercept[2]);

 Equal = (t3\_v6, Intercept[3]), (t1\_v6, Intercept[3]), (t2\_v6,

 Intercept[3]);

 Equal = (t3\_v7, Intercept[0]), (t1\_v7, Intercept[0]), (t2\_v7,

 Intercept[0]);

 Equal = (t3\_v7, Intercept[1]), (t1\_v7, Intercept[1]), (t2\_v7,

 Intercept[1]);

 Equal = (t3\_v7, Intercept[2]), (t1\_v7, Intercept[2]), (t2\_v7,

 Intercept[2]);

 Equal = (t3\_v7, Intercept[3]), (t1\_v7, Intercept[3]), (t2\_v7,

 Intercept[3]);

 Equal = (t3\_v8, Intercept[0]), (t1\_v8, Intercept[0]), (t2\_v8,

 Intercept[0]);

 Equal = (t3\_v8, Intercept[1]), (t1\_v8, Intercept[1]), (t2\_v8,

 Intercept[1]);

 Equal = (t3\_v8, Intercept[2]), (t1\_v8, Intercept[2]), (t2\_v8,

 Intercept[2]);

 Equal = (t3\_v8, Intercept[3]), (t1\_v8, Intercept[3]), (t2\_v8,

 Intercept[3]);

 Equal = (t3\_v9, Intercept[0]), (t1\_v9, Intercept[0]), (t2\_v9,

 Intercept[0]);

 Equal = (t3\_v9, Intercept[1]), (t1\_v9, Intercept[1]), (t2\_v9,

 Intercept[1]);

 Equal = (t3\_v9, Intercept[2]), (t1\_v9, Intercept[2]), (t2\_v9,

 Intercept[2]);

 Equal = (t3\_v9, Intercept[3]), (t1\_v9, Intercept[3]), (t2\_v9,

 Intercept[3]);

 Equal = (t3\_v10, Intercept[0]), (t1\_v10, Intercept[0]), (t2\_v10,

 Intercept[0]);

 Equal = (t3\_v10, Intercept[1]), (t1\_v10, Intercept[1]), (t2\_v10,

 Intercept[1]);

 Equal = (t3\_v10, Intercept[2]), (t1\_v10, Intercept[2]), (t2\_v10,

 Intercept[2]);

 Equal = (t3\_v10, Intercept[3]), (t1\_v10, Intercept[3]), (t2\_v10,

 Intercept[3]);

 (t1\_v1, Slope[1]) = 0.00000;

 (t1\_v1, Slope[2]) = 0.00000;

 (t1\_v2, Slope[1]) = 0.00000;

 (t1\_v2, Slope[2]) = 0.00000;

 (t1\_v3, Slope[1]) = 0.00000;

 (t1\_v3, Slope[2]) = 0.00000;

 (t1\_v4, Slope[1]) = 0.00000;

 (t1\_v4, Slope[2]) = 0.00000;

 (t1\_v5, Slope[1]) = 0.00000;

 (t1\_v5, Slope[2]) = 0.00000;

 (t1\_v6, Slope[1]) = 0.00000;

 (t1\_v6, Slope[2]) = 0.00000;

 (t1\_v7, Slope[1]) = 0.00000;

 (t1\_v7, Slope[2]) = 0.00000;

 (t1\_v8, Slope[1]) = 0.00000;

 (t1\_v8, Slope[2]) = 0.00000;

 (t1\_v9, Slope[1]) = 0.00000;

 (t1\_v9, Slope[2]) = 0.00000;

 (t1\_v10, Slope[1]) = 0.00000;

 (t1\_v10, Slope[2]) = 0.00000;

 (t2\_v1, Slope[0]) = 0.00000;

 (t2\_v1, Slope[2]) = 0.00000;

 (t2\_v2, Slope[0]) = 0.00000;

 (t2\_v2, Slope[2]) = 0.00000;

 (t2\_v3, Slope[0]) = 0.00000;

 (t2\_v3, Slope[2]) = 0.00000;

 (t2\_v4, Slope[0]) = 0.00000;

 (t2\_v4, Slope[2]) = 0.00000;

 (t2\_v5, Slope[0]) = 0.00000;

 (t2\_v5, Slope[2]) = 0.00000;

 (t2\_v6, Slope[0]) = 0.00000;

 (t2\_v6, Slope[2]) = 0.00000;

 (t2\_v7, Slope[0]) = 0.00000;

 (t2\_v7, Slope[2]) = 0.00000;

 (t2\_v8, Slope[0]) = 0.00000;

 (t2\_v8, Slope[2]) = 0.00000;

 (t2\_v9, Slope[0]) = 0.00000;

 (t2\_v9, Slope[2]) = 0.00000;

 (t2\_v10, Slope[0]) = 0.00000;

 (t2\_v10, Slope[2]) = 0.00000;

 (t3\_v1, Slope[0]) = 0.00000;

 (t3\_v1, Slope[1]) = 0.00000;

 (t3\_v2, Slope[0]) = 0.00000;

 (t3\_v2, Slope[1]) = 0.00000;

 (t3\_v3, Slope[0]) = 0.00000;

 (t3\_v3, Slope[1]) = 0.00000;

 (t3\_v4, Slope[0]) = 0.00000;

 (t3\_v4, Slope[1]) = 0.00000;

 (t3\_v5, Slope[0]) = 0.00000;

 (t3\_v5, Slope[1]) = 0.00000;

 (t3\_v6, Slope[0]) = 0.00000;

 (t3\_v6, Slope[1]) = 0.00000;

 (t3\_v7, Slope[0]) = 0.00000;

 (t3\_v7, Slope[1]) = 0.00000;

 (t3\_v8, Slope[0]) = 0.00000;

 (t3\_v8, Slope[1]) = 0.00000;

 (t3\_v9, Slope[0]) = 0.00000;

 (t3\_v9, Slope[1]) = 0.00000;

 (t3\_v10, Slope[0]) = 0.00000;

 (t3\_v10, Slope[1]) = 0.00000;

StartValues:

 (t3\_v1, Slope[2]) = 3.36670;

 (t3\_v1, Intercept[0]) = 5.66108;

 (t3\_v1, Intercept[1]) = 3.51352;

 (t3\_v1, Intercept[2]) = 0.16730;

 (t3\_v1, Intercept[3]) = -1.62036;

 (t3\_v2, Slope[2]) = 1.87212;

 (t3\_v2, Intercept[0]) = 2.86868;

 (t3\_v2, Intercept[1]) = 1.69494;

 (t3\_v2, Intercept[2]) = -0.17730;

 (t3\_v2, Intercept[3]) = -2.46353;

 (t3\_v3, Slope[2]) = 2.01720;

 (t3\_v3, Intercept[0]) = 2.03337;

 (t3\_v3, Intercept[1]) = 0.21278;

 (t3\_v3, Intercept[2]) = -1.82284;

 (t3\_v3, Intercept[3]) = -3.44894;

 (t3\_v4, Slope[2]) = 2.34981;

 (t3\_v4, Intercept[0]) = 4.76893;

 (t3\_v4, Intercept[1]) = 2.36463;

 (t3\_v4, Intercept[2]) = -0.44422;

 (t3\_v4, Intercept[3]) = -2.06696;

 (t3\_v5, Slope[2]) = 2.94169;

 (t3\_v5, Intercept[0]) = 4.90171;

 (t3\_v5, Intercept[1]) = 3.25943;

 (t3\_v5, Intercept[2]) = 0.26334;

 (t3\_v5, Intercept[3]) = -2.32187;

 (t3\_v6, Slope[2]) = 2.22076;

 (t3\_v6, Intercept[0]) = 4.26104;

 (t3\_v6, Intercept[1]) = 1.99661;

 (t3\_v6, Intercept[2]) = -0.55463;

 (t3\_v6, Intercept[3]) = -2.21513;

 (t3\_v7, Slope[2]) = 2.42460;

 (t3\_v7, Intercept[0]) = 3.78371;

 (t3\_v7, Intercept[1]) = 1.83485;

 (t3\_v7, Intercept[2]) = -1.15101;

 (t3\_v7, Intercept[3]) = -2.77583;

 (t3\_v8, Slope[2]) = 3.09369;

 (t3\_v8, Intercept[0]) = 4.12462;

 (t3\_v8, Intercept[1]) = 0.74843;

 (t3\_v8, Intercept[2]) = -1.22175;

 (t3\_v8, Intercept[3]) = -3.82692;

 (t3\_v9, Slope[2]) = 2.07782;

 (t3\_v9, Intercept[0]) = 3.72290;

 (t3\_v9, Intercept[1]) = 2.09171;

 (t3\_v9, Intercept[2]) = 0.80411;

 (t3\_v9, Intercept[3]) = -1.28503;

 (t3\_v10, Slope[2]) = 1.56648;

 (t3\_v10, Intercept[0]) = 0.87793;

 (t3\_v10, Intercept[1]) = -0.95438;

 (t3\_v10, Intercept[2]) = -2.26906;

 (t3\_v10, Intercept[3]) = -4.15761;

 Mean[1] = 0.19085;

 Mean[2] = -0.28228;

 Covariance[1] = 0.23373;

 Covariance[2] = 0.89897;

 Covariance[3] = 0.25583;

 Covariance[4] = 0.39084;

 Covariance[5] = 0.83691;

A4. flexMIRT syntax for the initial, time-ignoring, 1D analysis using clinical trial data.

<Project>

Title = "itch diary data";

Description = "sleep domain items- all time pts";

<Options>

 Mode = Calibration;

 SavePRM = Yes;

 Etol = 1e-9;

 SaveDBG = Yes;

<Groups>

%Group1%

 File = "C:\Itch\_AM.dat";

 Varnames = usubjid, intfere, diff, early, rested;

 Select = intfere, diff, early, rested;

 Ncats(intfere) = 11;

 Model(intfere) = Graded(11);

 Ncats(diff, early, rested) = 2;

 Model(diff, early, rested) = Graded(2);

<Constraints>

A5. flexMIRT syntax using item parameter estimates from previous analysis to obtain group parameter (means, covariances) estimates.

<Project>

Title = "GSK itch diary Data";

Description = "AM itch long MIRT 8 factors";

<Options>

 Mode = Calibration;

 Algorithm = MHRM;

 RndSeed = 29404;

 Processor = 2;

 ProposalStd = 0.39;

//supply items parameters (rearranged to long. structure) from 1D model

 ReadPRMFile = "AM\_sleep\_8D-prm.txt";

 SavePRM = Yes;

 SaveDBG = Yes;

 Stage1=0;

 Stage2=0;

<Groups>

%G1%

 File = "C:\diary\_wide\_AM.dat";

 Varnames = usubjid, D21\_tx, D28\_tx, D35\_tx, D42\_tx,

D1\_intfere, D1\_dif, D1\_ear, D1\_res,

D7\_intfere, D7\_dif, D7\_ear, D7\_res,

D14\_intfere, D14\_dif, D14\_ear, D14\_res,

D21\_intfere, D21\_dif, D21\_ear, D21\_res,

D28\_intfere, D28\_dif, D28\_ear, D28\_res,

D35\_intfere, D35\_dif, D35\_ear, D35\_res,

D42\_intfere, D42\_dif, D42\_ear, D42\_res,

D49\_intfere, D49\_dif, D49\_ear, D49\_res,

D56\_intfere, D56\_dif, D56\_ear, D56\_res;

 Select =

D7\_intfere, D7\_dif, D7\_ear, D7\_res,

D14\_intfere, D14\_dif, D14\_ear, D14\_res,

D21\_intfere, D21\_dif, D21\_ear, D21\_res,

D28\_intfere, D28\_dif, D28\_ear, D28\_res,

D35\_intfere, D35\_dif, D35\_ear, D35\_res,

D42\_intfere, D42\_dif, D42\_ear, D42\_res,

D49\_intfere, D49\_dif, D49\_ear, D49\_res,

D56\_intfere, D56\_dif, D56\_ear, D56\_res;

 Ncats(

 D7\_dif, D7\_ear, D7\_res,

 D14\_dif, D14\_ear, D14\_res,

 D21\_dif, D21\_ear, D21\_res,

 D28\_dif, D28\_ear, D28\_res,

 D35\_dif, D35\_ear, D35\_res,

 D42\_dif, D42\_ear, D42\_res,

 D49\_dif, D49\_ear, D49\_res,

 D56\_dif, D56\_ear, D56\_res) = 2;

 Ncats(D7\_intfere, D14\_intfere, D21\_intfere, D28\_intfere, D35\_intfere, D42\_intfere, D49\_intfere, D56\_intfere) = 11;

 Model(D7\_intfere, D14\_intfere, D21\_intfere, D28\_intfere, D35\_intfere, D42\_intfere, D49\_intfere, D56\_intfere) = Graded(11);

 Dimensions = 8;

 Covariates = D21\_tx, D28\_tx, D35\_tx, D42\_tx;

 <Constraints>

//fix item prms to previously found values from 1D analysis

Fix (

D7\_intfere, D7\_dif, D7\_ear, D7\_res,

D14\_intfere, D14\_dif, D14\_ear, D14\_res,

D21\_intfere, D21\_dif, D21\_ear, D21\_res,

D28\_intfere, D28\_dif, D28\_ear, D28\_res,

D35\_intfere, D35\_dif, D35\_ear, D35\_res,

D42\_intfere, D42\_dif, D42\_ear, D42\_res,

D49\_intfere, D49\_dif, D49\_ear, D49\_res,

D56\_intfere, D56\_dif, D56\_ear, D56\_res), slope;

 Fix (

 D7\_dif, D7\_ear, D7\_res,

 D14\_dif, D14\_ear, D14\_res,

 D21\_dif, D21\_ear, D21\_res,

 D28\_dif, D28\_ear, D28\_res,

 D35\_dif, D35\_ear, D35\_res,

 D42\_dif, D42\_ear, D42\_res,

 D49\_dif, D49\_ear, D49\_res,

 D56\_dif, D56\_ear, D56\_res), intercept;

 Fix ( D7\_intfere, D14\_intfere, D21\_intfere, D28\_intfere, D35\_intfere, D42\_intfere, D49\_intfere, D56\_intfere), intercept;

//assign TX covariates to predict certain times only

Free beta(3,1);

Free beta(4,2);

Free beta(5,3);

Free beta(6,4);

//Free covariances among factors to be freely estimated

Free COV(1,2);

Free COV(1,3);

Free COV(1,4);

Free COV(1,5);

Free COV(1,6);

Free COV(1,7);

Free COV(1,8);

Free COV(2,3);

Free COV(2,4);

Free COV(2,5);

Free COV(2,6);

Free COV(2,7);

Free COV(2,8);

Free COV(3,4);

Free COV(3,5);

Free COV(3,6);

Free COV(3,7);

Free COV(3,8);

Free COV(4,5);

Free COV(4,6);

Free COV(4,7);

Free COV(4,8);

Free COV(5,6);

Free COV(5,7);

Free COV(5,8);

Free COV(6,7);

Free COV(6,8);

Free COV(7,8);

//impose AR structure to covariances;

Equal G1, COV(1,2): G1, COV(2,3): G1, COV(3,4): G1, COV(4,5): G1, COV(5,6): G1, COV(6,7): G1, COV(7,8);

Equal G1, COV(1,3): G1, COV(2,4): G1, COV(3,5): G1, COV(4,6): G1, COV(5,7): G1, COV(6,8);

Equal G1, COV(1,4): G1, COV(2,5): G1, COV(3,6): G1, COV(4,7): G1, COV(5,8);

Equal G1, COV(1,5): G1, COV(2,6): G1, COV(3,7): G1, COV(4,8);

Equal G1, COV(1,6): G1, COV(2,7): G1, COV(3,8);

Equal G1, COV(1,7): G1, COV(2,8);

//Free means of all later timepoints

Free mean(2,3,4,5,6,7,8);

A6. Fully estimated longitudinal IRT model using previously found item and group parameters from previous steps as start values

<Project>

Title = "GSK itch diary Data";

Description = "AM sleep long MIRT 8 factors";

<Options>

 Mode = Calibration;

 Algorithm = MHRM;

 RndSeed = 9601;

 ProposalStd = 0.25;

 ReadPRMFile = "AM\_sleep\_init-cov\_8D-w\_covars and AR corrs-prm.txt";

 SavePRM = Yes;

 Stage3=10000;

 FactorLoadings = Yes;

 SavePRM = Yes;

 SaveSCO = Yes;

 Score = EAP;

 SaveDBG = Yes;

 WindowSize = 10;

<Groups>

%G1%

 File = "C:\diary\_wide\_AM.dat";

 Varnames = usubjid, D21\_tx, D28\_tx, D35\_tx, D42\_tx,

D1\_intfere, D1\_dif, D1\_ear, D1\_res,

D7\_intfere, D7\_dif, D7\_ear, D7\_res,

D14\_intfere, D14\_dif, D14\_ear, D14\_res,

D21\_intfere, D21\_dif, D21\_ear, D21\_res,

D28\_intfere, D28\_dif, D28\_ear, D28\_res,

D35\_intfere, D35\_dif, D35\_ear, D35\_res,

D42\_intfere, D42\_dif, D42\_ear, D42\_res,

D49\_intfere, D49\_dif, D49\_ear, D49\_res,

D56\_intfere,D56\_dif, D56\_ear, D56\_res;

 Select =

D7\_intfere, D7\_dif, D7\_ear, D7\_res,

D14\_intfere, D14\_dif, D14\_ear, D14\_res,

D21\_intfere, D21\_dif, D21\_ear, D21\_res,

D28\_intfere, D28\_dif, D28\_ear, D28\_res,

D35\_intfere, D35\_dif, D35\_ear, D35\_res,

D42\_intfere, D42\_dif, D42\_ear, D42\_res,

D49\_intfere, D49\_dif, D49\_ear, D49\_res,

D56\_intfere, D56\_dif, D56\_ear, D56\_res;

CaseID = Usubjid;

 Ncats(

 D7\_dif, D7\_ear, D7\_res,

 D14\_dif, D14\_ear, D14\_res,

 D21\_dif, D21\_ear, D21\_res,

 D28\_dif, D28\_ear, D28\_res,

 D35\_dif, D35\_ear, D35\_res,

 D42\_dif, D42\_ear, D42\_res,

 D49\_dif, D49\_ear, D49\_res,

 D56\_dif, D56\_ear, D56\_res) = 2;

 Ncats( D7\_intfere, D14\_intfere, D21\_intfere, D28\_intfere, D35\_intfere, D42\_intfere, D49\_intfere, D56\_intfere) = 11;

 Model( D7\_intfere, D14\_intfere, D21\_intfere, D28\_intfere, D35\_intfere, D42\_intfere, D49\_intfere, D56\_intfere) = Graded(11);

 Dimensions = 8;

 Covariates = D21\_tx, D28\_tx, D35\_tx, D42\_tx;

 <Constraints>

Fix (

D7\_intfere, D7\_dif, D7\_ear, D7\_res,

D14\_intfere, D14\_dif, D14\_ear, D14\_res,

D21\_intfere, D21\_dif, D21\_ear, D21\_res,

D28\_intfere, D28\_dif, D28\_ear, D28\_res,

D35\_intfere, D35\_dif, D35\_ear, D35\_res,

D42\_intfere, D42\_dif, D42\_ear, D42\_res,

D49\_intfere, D49\_dif, D49\_ear, D49\_res,

D56\_intfere, D56\_dif, D56\_ear, D56\_res), slope;

//Assign items to factors/timepoints

Free (D7\_intfere, D7\_dif, D7\_ear, D7\_res), slope(1);

Free (D14\_intfere, D14\_dif, D14\_ear, D14\_res), slope(2);

Free (D21\_intfere, D21\_dif, D21\_ear, D21\_res), slope(3);

Free (D28\_intfere, D28\_dif, D28\_ear, D28\_res), slope(4);

Free (D35\_intfere, D35\_dif, D35\_ear, D35\_res), slope(5);

Free (D42\_intfere, D42\_dif, D42\_ear, D42\_res), slope(6);

Free (D49\_intfere, D49\_dif, D49\_ear, D49\_res), slope(7);

Free (D56\_intfere, D56\_dif, D56\_ear, D56\_res), slope(8);

//Impose equality over time on item parameters

Equal

G1, (D7\_intfere, D7\_dif, D7\_ear, D7\_res), slope(1):

G1, (D14\_intfere, D14\_dif, D14\_ear, D14\_res), slope(2):

G1, (D21\_intfere, D21\_dif, D21\_ear, D21\_res), slope(3):

G1, (D28\_intfere, D28\_dif, D28\_ear, D28\_res), slope(4):

G1, (D35\_intfere, D35\_dif, D35\_ear, D35\_res), slope(5):

G1, (D42\_intfere, D42\_dif, D42\_ear, D42\_res), slope(6):

G1, (D49\_intfere, D49\_dif, D49\_ear, D49\_res), slope(7):

G1, (D56\_intfere, D56\_dif, D56\_ear, D56\_res), slope(8);

Equal

G1, (D7\_dif, D7\_ear, D7\_res), intercept:

G1, (D14\_dif, D14\_ear, D14\_res), intercept:

G1, (D21\_dif, D21\_ear, D21\_res), intercept:

G1, (D28\_dif, D28\_ear, D28\_res), intercept:

G1, (D35\_dif, D35\_ear, D35\_res), intercept:

G1, (D42\_dif, D42\_ear, D42\_res), intercept:

G1, (D49\_dif, D49\_ear, D49\_res), intercept:

G1, (D56\_dif, D56\_ear, D56\_res), intercept;

 Equal

G1, (D7\_intfere), intercept:

G1, (D14\_intfere), intercept:

G1, (D21\_intfere), intercept:

G1, (D28\_intfere), intercept:

G1, (D35\_intfere), intercept:

G1, (D42\_intfere), intercept:

G1, (D49\_intfere), intercept:

G1, (D56\_intfere), intercept;

//Assign covariates to predict only certain time points

Free beta(3,1);

Free beta(4,2);

Free beta(5,3);

Free beta(6,4);

//Free covariances of time points 3 or fewer timepts apart

Free COV(1,2);

Free COV(1,3);

Free COV(1,4);

Free COV(2,3);

Free COV(2,4);

Free COV(2,5);

Free COV(3,4);

Free COV(3,5);

Free COV(3,6);

Free COV(4,5);

Free COV(4,6);

Free COV(4,7);

Free COV(5,6);

Free COV(5,7);

Free COV(5,8);

Free COV(6,7);

Free COV(6,8);

Free COV(7,8);

//impose equality restriction on covariance between times within a TX condition

Equal G1, COV(3,4): G1, COV(5,6);

//free means of later time points

Free mean(2,3,4,5,6,7,8);