



## HCM3 model for Growth data

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### 1. Introduction to HCM3 models

In a HCM2 models data that display structures in which the lower-units are cross-classified by two higher-level factors are used. Suppose, however, that one of the higher-level factors is itself nested within a yet-higher level factor. The three-level hierarchical and cross-classified random effects models (HCM3) represent this case, where level-1 units are cross-classified by two higher-level factors, with units from *one* of the higher-level factors nested within a next higher-level unit.

Hong and Raudenbush (2008) used three-level hierarchical and cross-classified random effects models to investigate how schools and their teachers may contribute to student growth, taking into account also the student-level variables. In their study, students were moving over time across teachers and the teachers were nested within schools. We can say that the repeated measures (level-1) were cross-classified by students (rows) and teachers (columns) with teachers nested within schools (clusters). The model is sufficiently flexible to allow the students also to change schools over the course of the study. In general, we may say that level-1 observations are crossed by *rows* and *columns* and the columns are nested within *clusters*.

### 2. Description of the model

A general three-level hierarchical and cross-classified model consists of three sub-models: level-1 or within-cell, level-2 or between-cell, and a level-3 or between-cluster model. As in HCM2, the cells refer to the cross-classifications by rows and columns. The columns, however, are nested within clusters.

For example, if the research problem consists of repeated developmental data on students cross-

classified by student and teachers, with teachers clustered within schools, the level-1 or within-cell model will represent the relationship between time and development for each child. The level-2 or between-cell model will capture the influences of student- and teacher-level predictors, and the level-3 or between-cluster model will examine the effects of school-level variables. Formally, there are  $i=1,2,\dots, n_{jkl}$  level-1 units (*e.g.*, repeated measurement of student achievement) nested within cells cross-classified by  $j = 1,\dots, J$  rows (*e.g.*, students) and  $k = 1,\dots, K$  columns, with columns with cluster  $l = 1, \dots, L$ .

Here is an example of a data layout for three waves of developmental data ( $n_{jkl} = 3$ ) for  $J = 4$  students crossed by  $K = 9$  teachers, with the teachers nested within  $L = 3$  schools:

### Organization of data of the HCM3 example

	School <sub>1</sub>			School <sub>2</sub>			School <sub>3</sub>		
	Teacher 11	Teacher 21	Teacher 31	Teacher 12	Teacher 22	Teacher 32	Teacher 13	Teacher 23	Teacher 33
Stud 1	$Y_{1111}$	$Y_{2121}$	$Y_{3131}$						
Stud 2				$Y_{1212}$	$Y_{2222}$	$Y_{3232}$			
Stud 3							$Y_{1313}$		$Y_{3333}$
Stud 4	$Y_{1411}$				$Y_{2422}$				$Y_{3433}$

The table indicates that the repeated assessments are cross-classified by students and teachers, with teachers clustered within schools. Student 1 stayed in school 1 over three years of observation, changing teachers each year. Similarly, Student 2 stayed in school 2 while changing teachers each year. Student 3 stayed in the same school but was not observed during year 2. Student 4 had all three observations but changed schools after year 1 and year 2.

HCM3 can handle continuously distributed as well as binary outcomes. We use the continuous outcome models in the following discussion. The logic of HGLM, as described and illustrated in Chapter 7, applies and extends to analyses with binary outcomes with HCM3.

### Level-1 or “within-cell” model

We represent in the level-1 or within-cell model the outcome for case  $i$  in individual cells cross-classified by level-2 units  $j$  and  $k$ , with unit  $k$  nested within cluster  $l$ .

$$\begin{aligned}
 Y_{ijkl} &= \pi_{0jkl} + \pi_{1jkl}a_{1ijkl} + \pi_{2jkl}a_{2ijkl} + \dots + \pi_{pjkl}a_{pijkl} + e_{ijkl} \\
 &= \pi_{0jkl} + \sum_{p=1}^P \pi_{pjkl}a_{pijkl} + e_{ijkl}
 \end{aligned}$$

where

$\pi_{0jkl}$  is the intercept, the expected value of  $Y_{ijkl}$  when all explanatory variables are set to zero;

$\pi_{pjkl}$  are level-1 coefficients of predictors  $a_{pijkl}$  ( $p=1, 2, \dots, P$ ) for case  $i$  in cell  $jkl$ ;

$e_{ijkl}$  is the level-1 or within-cell random effect, and;

$\sigma^2$  is the variance of  $e_{ijkl}$ , that is the level-1 or within-cell variance. Here we assume that the random term  $e_{ijkl} \sim N(0, \sigma^2)$ .

### Level-2 or “between-cell” model

Each of the  $\pi_{pjkl}$  coefficients in the level-1 or within-cell model becomes an outcome variable in the level-2 or between-cell model:

$$\begin{aligned}\pi_{pjkl} &= \theta_{pl} + (\beta_{p1l} + b_{p1j})X_{1kl} + (\beta_{p2l} + b_{p2j})X_{2kl} + \cdots + (\beta_{pQ_p l} + b_{pQ_p j})X_{Q_p kl} + \\ &\quad (\gamma_{p1l} + c_{p1kl})W_{1jl} + (\gamma_{p2l} + c_{p2kl})W_{2jl} + \cdots + (\gamma_{pR_p l} + c_{pR_p kl})W_{R_p jl} + \\ &\quad b_{p0j} + c_{p0kl} \\ &= \theta_{pl} + \sum_{q=1}^{Q_p} (\beta_{pq l} + b_{pqj})X_{qkl} + \sum_{r=1}^{R_p} (\gamma_{pr l} + c_{prkl})W_{rjl} + b_{p0j} + c_{p0kl}\end{aligned}\tag{14.2}$$

where

$\theta_{pl}$  is the level-2 model intercept, the expected value of  $\pi_{pjkl}$  when all explanatory variables are set to zero;

$\beta_{pq l}$  are the level-2 coefficients of column-specific predictors  $X_{qkl}$ ,  $q = 1, \dots, Q_p$ ,

$b_{pqj}$  are the random effects associated with column-specific predictors  $X_{qk}$ . They vary randomly over rows  $j = 1, \dots, J$ ;

$\gamma_{pr l}$  are the level-2 coefficients of row-specific predictors  $W_{rjl}$ ,  $r = 1, \dots, R_p$ ;

$c_{prkl}$  are the random effects associated with row-specific predictors  $W_{rjl}$ . They vary randomly over columns  $k = 1, \dots, K_l$  and clusters  $l = 1, \dots, L$ ; and

$b_{p0j}$  and  $c_{p0kl}$  are residual row- and column-specific random effects, respectively, on  $\pi_{pjkl}$ , after taking into account  $X_{qkl}$  and  $W_{rjl}$ .

The vector of row random effects, containing  $b_{p0j}, \dots, b_{pQ_p j}$  is assumed multivariate normal with a mean zero and a full covariance matrix  $\tau$ . Similarly the vector with elements  $c_{p0kl}, \dots, c_{pR_p kl}$  is assumed multivariate normal with mean vector zero and full covariance matrix  $\Delta$ .

### Level-3 model

Each of the level-2 coefficients become an outcome variable at level 3:

$$\begin{aligned}
\theta_{pl} &= \delta_{p00} + (\delta_{p01} + b_{p01j})Z_{1l} + (\delta_{p02} + b_{p02j})Z_{2l} + \cdots + (\delta_{p0S_{p0}} + b_{p0S_{p0}j})Z_{S_{p0}l} + d_{p0l} \\
&= \delta_{p00} + \sum_{s=1}^{S_{p0}} (\delta_{p0s} + b_{p0sj})Z_{sl} + d_{p0l} \\
\beta_{pql} &= \delta_{pq0} + (\delta_{pq1} + b_{pq1j})Z_{1l} + (\delta_{pq2} + b_{pq2j})Z_{2l} + \cdots + (\delta_{pqS_{pq}} + b_{pqS_{pq}j})Z_{S_{pq}l} + d_{pql} \\
&= \delta_{pq0} + \sum_{s=1}^{S_{pq}} (\delta_{pqs} + b_{pqsj})Z_{sl} + d_{pql} \\
\gamma_{prl} &= \delta_{pr0} + (\delta_{pr1} + b_{pr1j})Z_{1l} + (\delta_{pr2} + b_{pr2j})Z_{2l} + \cdots + (\delta_{prS_{pr}} + b_{prS_{pr}j})Z_{S_{pr}l} + d_{prl} \\
&= \delta_{pr0} + \sum_{s=1}^{S_{pr}} (\delta_{prs} + b_{prsj})Z_{sl} + d_{prl}
\end{aligned}$$

where

$\delta_{p00}$  is the intercept, the expected value of  $\theta_{pl}$  when all explanatory variables are set to zero;

$\delta_{p0s}$  are the coefficients of cluster-specific predictors  $Z_{sl}$  for  $\theta_{pl}$ ;

$\delta_{pq0}$  is the intercept, the expected value of  $\beta_{pql}$  when all explanatory variables are set to zero;

$\delta_{pqs}$  are the coefficients of cluster-specific predictors  $Z_{sl}$ ,  $s = 1, \dots, S_{pq}$  for  $\beta_{pql}$ ;

$b_{pqsj}$  are the random effects associated with cluster-specific predictors  $Z_{sl}$ . They vary randomly over rows  $j = 1, \dots, J$ ;

$\delta_{pr0}$  is the intercept, the expected value of  $\gamma_{prl}$  when all explanatory variables are set to zero;

$\delta_{prs}$  are the coefficients of cluster-specific predictors  $Z_{sl}$  for  $\gamma_{prl}$ ;

$b_{prsj}$  are the random effects associated with cluster-specific predictors  $Z_{sl}$ . They vary randomly over rows  $j = 1, \dots, J$ ; and

$d_{p0l}$ ,  $d_{pql}$ , and  $d_{prl}$  are residual random effects. We assume these to be multivariate normal in distribution with zero means and variances  $\tau_{p0}$ ,  $\tau_{pq}$ ,  $\tau_{pr}$ , respectively.

### 3. Creating the MDM file

In constructing the MDM file, there is the same range of options for data input as for HCM2. HCM3 requires three IDs, one for each of two level-2 factors, and one for the level-3 clusters. The two level-2 factors in our examples are student and teacher. As teachers ( $N = 498$ ) were clustered within schools ( $N = 67$ ) and the model allows students ( $N = 4216$ ) to change schools, we will designate teacher as the column factor and student as the row factor.

**Note:** The level-1 file is to be sorted on ascending row (student) IDs, and, in this file, sorting by column IDs within clusters. The level-2 row file is to be sorted on ascending row (student) IDs. The

level-2 column file is to sorted by column IDs within clusters. The cluster file is to be sorted by cluster IDs.

Data input requires a level-1 file (a time-series student achievement data file in our example), a level-2 row-factor (student-level) file, a level-2 column-factor (teacher-level) file, and a level-3 cluster-level (neighborhood-level) file. Our illustration uses SPSS file input, but the procedure for all other statistical packages is analogous.

**Level-1 file.** The level-1 or within-cell file, GROWTH.SAV has 7342 repeated measures collected on 4216 students. The time series data for the first four students are shown below. Following the school, student, and teacher ID fields are students' values on six variables:

- **MATH**  
A Stanford Achievement Test math test score.
- **YEAR** (year of the study minus 2)  
This variable can take on values of -1, 0, and 1 for the three years of data collection from grade 3 to grade 5.
- **G4D1** is an indicator that that takes on a value of 1 if a child receives intensive math instruction in grade 4 and if the outcome is observed at grade 4. This will be used to assess the effect of grade-4 intensive math instruction on grade-4 outcome.
- **G4D21** is an indicator that a child receives intensive math instruction in grade 4 and if the outcome is observed at grade 5. This will be used to test the effect of grade-4 intensive math instruction on grade-5 outcome for those who do not receive intensive math instruction in grade 5.
- **G5D22**  
An indicator that a child receives intensive math instruction in grade 5 and if the outcome is observed at grade 5. This will be used to test the effect of intensive math instruction in grade 5 on grade 5 outcome for those who did not have intensive math instruction in grade 4.
- **TWOWAY**  
A product term of a two-way interaction between G4D21 with G5D22. It will thus be an indicator that the child received intensive math instruction in both grades 4 and 5 and if the outcome is observed at grade 5. This will test whether having intensive math instruction in both years has an effect that exceeds the sum of the separate effects.

	schid	studid	tchrid	math	year	g4d1	g4d21	g5d22	twoway
1	15	1	83	609.00	-1.00	0.00	0.00	0.00	0.00
2	15	1	104	592.00	0.00	0.00	0.00	0.00	0.00
3	15	1	135	638.00	1.00	0.00	0.00	0.00	0.00
4	15	2	83	586.00	-1.00	0.00	0.00	0.00	0.00
5	15	2	104	592.00	0.00	0.00	0.00	0.00	0.00
6	15	2	185	629.00	1.00	0.00	0.00	1.00	0.00
7	15	3	114	561.00	0.00	0.00	0.00	0.00	0.00
8	15	3	135	584.00	1.00	0.00	0.00	0.00	0.00
9	15	4	83	593.00	-1.00	0.00	0.00	0.00	0.00
10	15	4	114	621.00	0.00	0.00	0.00	0.00	0.00

We see that student 1 attended school 15 and was taught by teachers 83, 104, and 135. None of the teachers adopted intensive math instruction. In addition, student 3 had data for the second and third year only.

**Level-2 row-factor file.** The level-2 row-factor units in the illustration are 4216 students. The data are stored in the file STUDENT.SAV. The level-2 data for the first ten children are shown below. The file has one dummy variable.

	studid	dummy
1	1	0.00
2	2	0.00
3	3	0.00
4	4	0.00
5	5	0.00
6	6	0.00
7	7	0.00
8	8	0.00
9	9	0.00
10	10	0.00

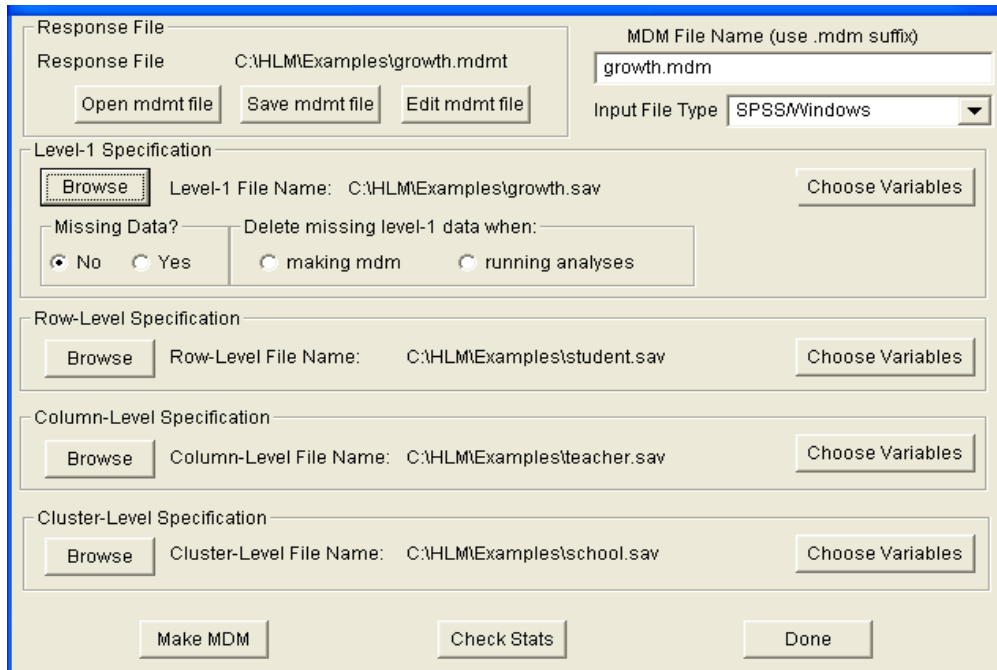
**Level-2 column-factor file.** The level-2 column-factor (teacher) file, TEACHER.SAV, has two IDs and a dummy variable. The first ID is the level-3 (*i.e.*, school) ID and the second ID is the level-2 column factor (*i.e.*, teacher) ID. Figure 15.3 lists the data for the first ten records.

	schid	tchrid	dummy
1	1	3963	0.00
2	1	3974	0.00
3	1	4025	0.00
4	2	9253	0.00
5	2	9263	0.00
6	2	9273	0.00
7	2	9304	0.00
8	2	9315	0.00
9	2	9325	0.00
10	2	9335	0.00

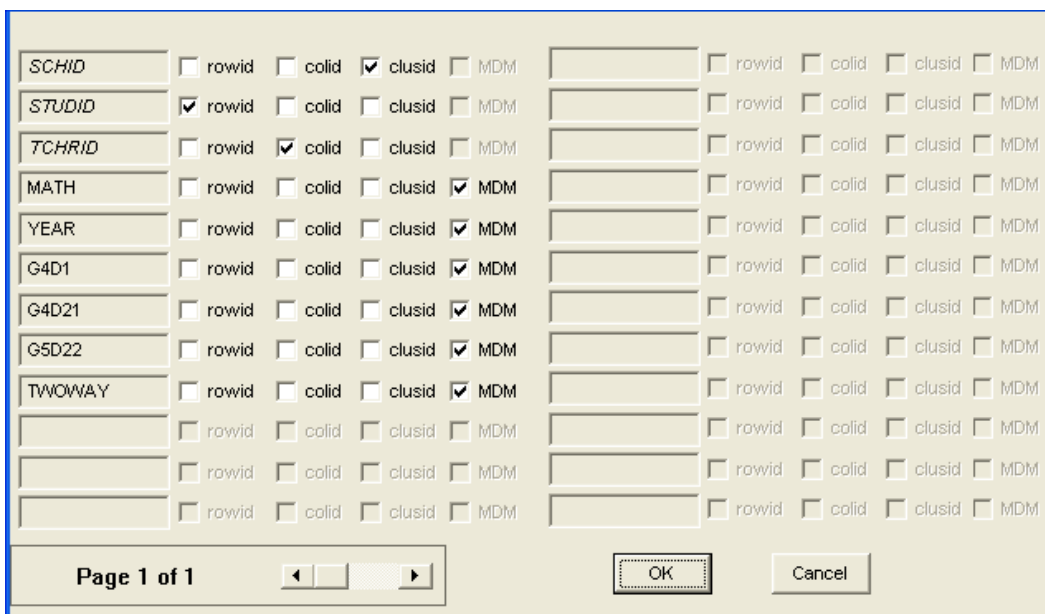
**Level-3 file.** The level-3 (school) level file, SCHOOL.SAV, has the level-3 (school) ID and a dummy variable. Figure 15.4 lists the data for the first ten records.

	schid	dummy
1	1	0.00
2	2	0.00
3	3	0.00
4	4	0.00
5	5	0.00
6	6	0.00
7	7	0.00
8	8	0.00
9	9	0.00
10	10	0.00

In sum, there are six variables at level 1 and one dummy variable for each of the level-2 row- and column-factor files and the level-3 file. The steps for the construction of the MDM for HCM3 are similar to the ones for HCM2. The user will select **HCM3** in the **Select MDM type** dialog box. Note that the program can handle missing data at level 1 or within cell only. The MDM template file, GROWTH.MDMT, contains a log of the input responses used to create the MDM file, GROWTH.MDM, using GROWTH.SAV, STUDENT.SAV, TEACHER.SAV, and SCHOOL.SAV. The completed **Make MDM** dialog box used to create the MDM file is shown below.



The images below show the dialog boxes for the level-1 file.



#### 4. Creating the command file

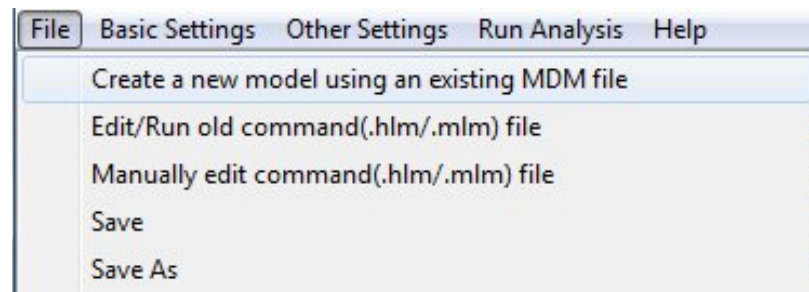
Once the MDM file is constructed, it can be used as input for the analysis. Model specification has five steps:



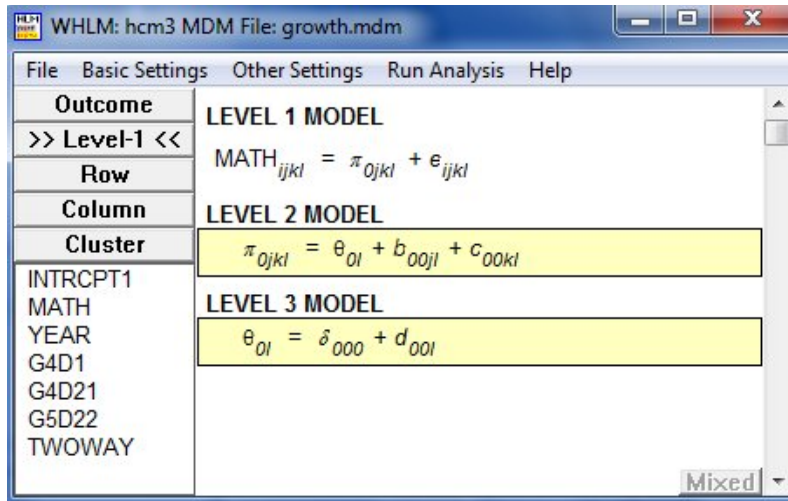
1. Specification of the level-1 model. In our case we shall model mathematics achievement (MATH) as the outcome, to be predicted by YEAR, G4D1, G4D21, G5D22, and TWOWAY. Hence, the level-1 model will have six coefficients for each student: the intercept and the partial slopes for the five variables. For longitudinal analysis, it is possible to select a cumulative effect model to allow carry-over treatment effects by specifying a cumulative Z-structure model (see *Hierarchical Linear Models*, p.390); we use this option in the analysis.
2. Specification of the level-2 row- or column-factor prediction model. Here each level-1 coefficient – the intercept and the five slopes in our example – becomes an outcome variable. One may use variables on student and teacher characteristics (not supplied with the example data files) to predict each of these level-1 coefficients.
3. Specification of row- or column effects as random or non-random. We shall model the intercept and the YEAR slope as varying randomly over rows and columns.
4. Specification of the level-3 prediction model. Here each level-2 coefficient becomes an outcome, and one may select school variables (not included in the example data files) to predict school-to-school in these level-2 coefficients.
5. Specification of the level-2 coefficients as random or non-random. We let two of the six level-2 intercepts vary over schools.

#### Specification of the level-1 model

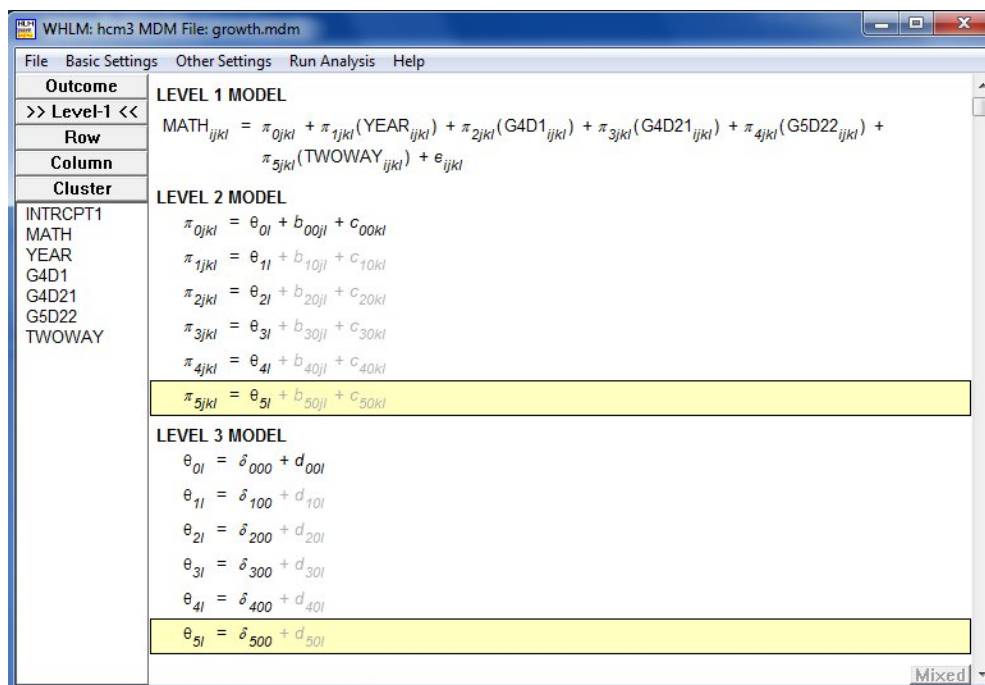
We start by selecting the **Create a new model using an existing MDM file** option from the **File** menu and selecting the MDM file just created (growth.mdm)



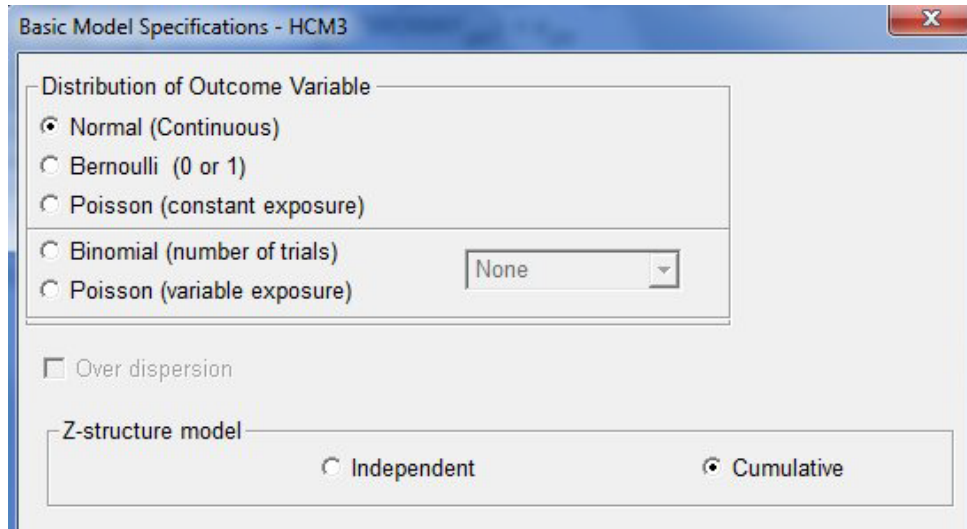
Select MATH as outcome variable. The fully unconditional model is now displayed in the main window.



Add the variables YEAR, G4D1, G4D21, G5D22, and TWOWAY. To the level-1 equation by selecting the **add variable uncentered** from the pop-up menu.



To specify a cumulative z-structure, open the **Basic Settings** dialog box from the main menu and select **Cumulative** instead of the default **Independent** option in the **Z structure model** field.

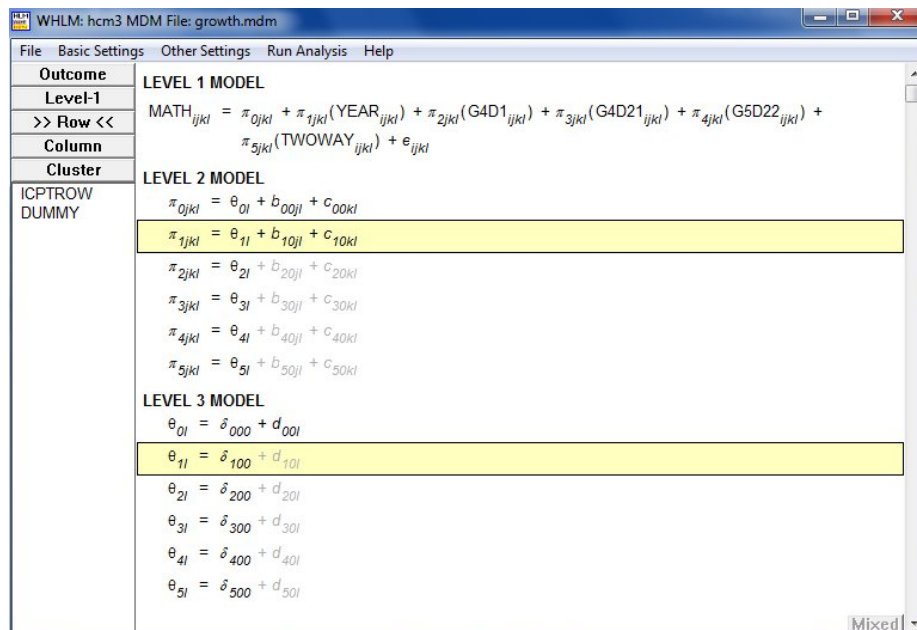


### Specification of the level-2 row- or column-factor prediction model

Here each level-1 coefficient – the intercept and the five slopes in our example – becomes an outcome variable. One may use variables on student and teacher characteristics (not supplied with the example data files) to predict each of these level-1 coefficients.

### Specification of row- or column effects as random or non-random

We now model the intercept and the YEAR slope as varying randomly over rows and columns. To do this, click on the  $\pi_{2,jkl}$  equation and activate both random effects by clicking on them.



Activate the  $d_{10}$  effect in the same way to obtain the final model displayed below.

WHLM: hcm3 MDM File: growth.mdm ...

File Basic Settings Other Settings Run Analysis

Help Outcome Intercept YEAR slope

Outcome  
Level-1  
Row  
Column  
>> Cluster <<  
ICPTCLUS  
DUMMY

**LEVEL 1 MODEL** (bold italic: grand-mean centering)  

$$\text{MATH} = \pi_0 + \pi_1(\text{YEAR}) + \pi_2(\text{G4D1}) + \pi_3(\text{G4D21}) + \pi_4(\text{G5D22}) + \pi_5(\text{TWOWAY}) + e$$

**LEVEL 2 MODEL** (bold italic: grand-mean centering)  

$$\pi_0 = \theta_{0i} + b_{00} + c_{00}$$
  

$$\pi_1 = \theta_{1i} + b_{10} + c_{10}$$
  

$$\pi_2 = \theta_{2i} + b_{20} + c_{20}$$
  

$$\pi_3 = \theta_{3i} + b_{30} + c_{30}$$
  

$$\pi_4 = \theta_{4i} + b_{40} + c_{40}$$
  

$$\pi_5 = \theta_{5i} + b_{50} + c_{50}$$

The level-1 intercept and YEAR slope vary randomly over rows and columns

**LEVEL 3 MODEL** (bold italic: grand-mean centering)  

$$\theta_{0i} = \delta_{000} + d_{00}$$
  

$$\theta_{1i} = \delta_{100} + d_{10}$$
  

$$\theta_{2i} = \delta_{200} + d_{20}$$
  

$$\theta_{3i} = \delta_{300} + d_{30}$$
  

$$\theta_{4i} = \delta_{400} + d_{40}$$
  

$$\theta_{5i} = \delta_{500} + d_{50}$$

These two level-3 coefficients are specified as randomly varying

Mixed

Save the model before running the analysis.

## 5. Interpreting the output

The results of the analysis are given below.

Problem Title: Unweighted model  
 The data source for this run = growth.mdm  
 The command file for this run = growth1.hlm  
 Output file name = growth1.html  
 The maximum number of level-1 units = 7342  
 The maximum number of row units = 4216  
 The maximum number of column units = 498

The maximum number of cluster units = 67  
 The maximum number of iterations = 100  
 Method of estimation: full maximum likelihood  
 Z-structure: cumulative across columns  
 Data design: (row by column) within clusters

The outcome variable is MATH

### Summary of the model specified

#### Level-1 Model

$$\text{MATH}_{ijkl} = \pi_{0jkl} + \pi_{1jkl} * (\text{YEAR}_{ijkl}) + \pi_{2jkl} * (\text{G4D1}_{ijkl}) + \pi_{3jkl} * (\text{G4D21}_{ijkl}) + \pi_{4jkl} * (\text{G5D22}_{ijkl}) \\ + \pi_{5jkl} * (\text{TWO WAY}_{ijkl}) + e_{ijkl}$$

#### Level-2 Model

$$\begin{aligned} \pi_{0jkl} &= \theta_{0l} + b_{00jl} + c_{00kl} \\ \pi_{1jkl} &= \theta_{1l} + b_{10jl} + c_{10kl} \\ \pi_{2jkl} &= \theta_{2l} \\ \pi_{3jkl} &= \theta_{3l} \\ \pi_{4jkl} &= \theta_{4l} \\ \pi_{5jkl} &= \theta_{5l} \end{aligned}$$

#### Level-3 Model

$$\begin{aligned} \theta_{0l} &= \bar{\delta}_{000} + d_{00l} \\ \theta_{1l} &= \bar{\delta}_{100} + d_{10l} \\ \theta_{2l} &= \bar{\delta}_{200} \\ \theta_{3l} &= \bar{\delta}_{300} \\ \theta_{4l} &= \bar{\delta}_{400} \\ \theta_{5l} &= \bar{\delta}_{500} \end{aligned}$$

For starting values, data from 5299 level-1 records, 2173 rows, 498 column, and 65 cluster records were used

### Final Results - iteration 485

Iterations stopped due to small change in likelihood function

$$\sigma^2 = 304.82130$$

$\tau_{\pi}$

	YEAR
$\theta_0, b_{00}$	$\theta_1, b_{10}$
769.17514	-18.09880
-18.09880	21.22623

$\tau_{\pi}$  (as correlations)

1.000	-0.142
-0.142	1.000

T<sub>β</sub>

	YEAR
$\theta_{0,C00}$	$\theta_{1,C10}$
133.52764	-24.04565
-24.04565	48.79836

T<sub>β</sub> (as correlations)

1.000	-0.298
-0.298	1.000

T<sub>γ</sub>

	YEAR
$\theta_{0,d00}$	$\theta_{1,d10}$
169.31794	28.10279
28.10279	29.76755

T<sub>γ</sub> (as correlations)

1.000	0.396
0.396	1.000

The value of the log-likelihood function at iteration 485 = -3.536565E+004

**Final estimation of fixed effects:**

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1					
For INTERCEPT					
$\theta_{0,\delta_{000}}$	609.850986	1.962504	310.751	66	<0.001
For YEAR					
For INTERCEPT					
$\theta_{1,\delta_{100}}$	21.064011	1.140716	18.466	66	<0.001
For G4D1					
For INTERCEPT					
$\theta_{2,\delta_{200}}$	2.753381	2.371599	1.161	7338	0.246#
For G4D21					
For INTERCEPT					
$\theta_{3,\delta_{300}}$	0.231710	3.584218	0.065	7338	0.949#
For G5D22					
For INTERCEPT					
$\theta_{4,\delta_{400}}$	7.507799	2.332107	3.219	7338	0.002#
For TWOWAY					
For INTERCEPT					
$\theta_{5,\delta_{500}}$	1.160337	4.322456	0.268	7338	0.788#

The p-val's above marked with a “#” should regarded as a rough approximation.

**Final estimation of fixed effects (with robust standard errors)**

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1					
For INTERCEPT					
$\theta_0, \delta_{000}$	609.850986	1.954775	311.980	66	<0.001
For YEAR					
For INTERCEPT					
$\theta_1, \delta_{100}$	21.064011	1.112653	18.931	66	<0.001
For G4D1					
For INTERCEPT					
$\theta_2, \delta_{200}$	2.753381	2.927131	0.941	7338	0.347#
For G4D21					
For INTERCEPT					
$\theta_3, \delta_{300}$	0.231710	4.389057	0.053	7338	0.958#
For G5D22					
For INTERCEPT					
$\theta_4, \delta_{400}$	7.507799	3.019164	2.487	7338	0.013#
For TWOWAY					
For INTERCEPT					
$\theta_5, \delta_{500}$	1.160337	6.470068	0.179	7338	0.858#

The p-vals above marked with a “#” should be regarded as a rough approximation.

**Final estimation of row and level-1 variance components:**

Random Effect	Standard Deviation	Variance Component	d.f.	$\chi^2$	p-value
$\theta_0, b_{00}$	27.73401	769.17514	2172	11413.58016	<0.001
YEAR/ $\theta_1, b_{10}$	4.60719	21.22623	2172	2177.42726	0.463
level-1, e	17.45913	304.82130			

**Note:** The chi-square statistics reported above are based on only 2173 of 4216 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Final estimation of column level variance components:**

Random Effect	Standard Deviation	Variance Component	d.f.	$\chi^2$	p-value
$\theta_0, c_{00}$	11.55542	133.52764	429	539.50878	<0.001
YEAR/ $\theta_1, c_{10}$	6.98558	48.79836	429	0.01770	>0.500

**Note:** The chi-square statistics reported above are based on only 495 of 498 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

**Final estimation of cluster level variance components:**

Random Effect	Standard Deviation	Variance Component	d.f.	$\chi^2$	p-value
$\theta_0, d_{00}$	13.01222	169.31794	64	256.96222	<0.001
YEAR/ $\theta_1, d_{10}$	5.45596	29.76755	64	136.92770	<0.001

**Note:** The chi-square statistics reported above are based on only 65 of 67 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

As reported by Hong and Raudenbush (2008), no significant causal effect of Grade 4 treatment on Grade 4 outcomes. A positive and significant effect of Grade 5 treatment on Grade 5 outcome,  $\hat{\delta}_{400} = 7.51$  ( $SE = 3.019$ ,  $t = 2.487$ ).

**Statistics for the current model**

Deviance = 70731.304874

Number of estimated parameters = 16