



Latent variable analysis using HMLM for the NYS data

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1. Introduction to HMLM models

Researchers may be interested in studying the randomly varying coefficients not only as outcomes, but as predictors as well. For instance, in a two-level repeated measures study of adolescents' tolerance of deviant behaviors, a user may choose to use the level-1 coefficient capturing the level of tolerance at the beginning of the study to predict the coefficient tapping the linear growth rate.

Treating these coefficients as latent variables, the HLM2, HLM3, HMLM, HMLM2 modules allow researchers to study direct as well as indirect effects among them and to assess their impacts on coefficients associated with observed covariates in the model. Furthermore, using HMLM with unrestricted covariance structures, one may use latent variable analysis to run regressions with missing data.

2. Description of the model

This example employs the National Youth Survey data sets. The MDM file is NYS.MDM, the level-1 data file is NYS1.SAV, and the level-2 file is NYS2.SAV. Figure 11.1 displays a linear growth model with gender as a covariate. The command file that contains the model specification information is NYS2.MLM.

We use π_0 , the level of tolerance at age 11, to predict π_1 , the linear growth rate, controlling for gender. Note that FEMALE must be in the model for both π_0 and π_1 to control for gender fully. Note also that π_0 and π_1 are latent variables, that is, they are free of measurement error, which is contained in e . Furthermore, we assess whether the effect of gender on the linear growth rate may change after controlling for the initial status at age 11. We select the

homogeneous level-1 variance option for this model. Thus, using HLM2 will yield identical results in this case.

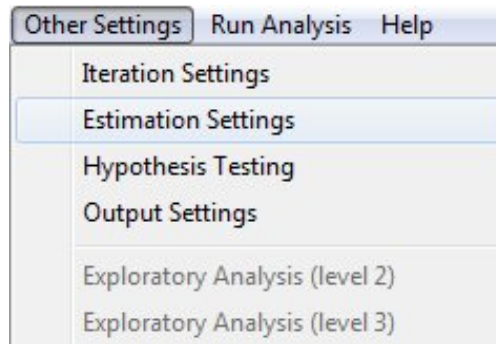
3. Creating the command file

Start by selecting the **Edit/Run old command (.hlm/.mlm) file** option from the **File** menu and open the MLM file **NYS2.MLM**.

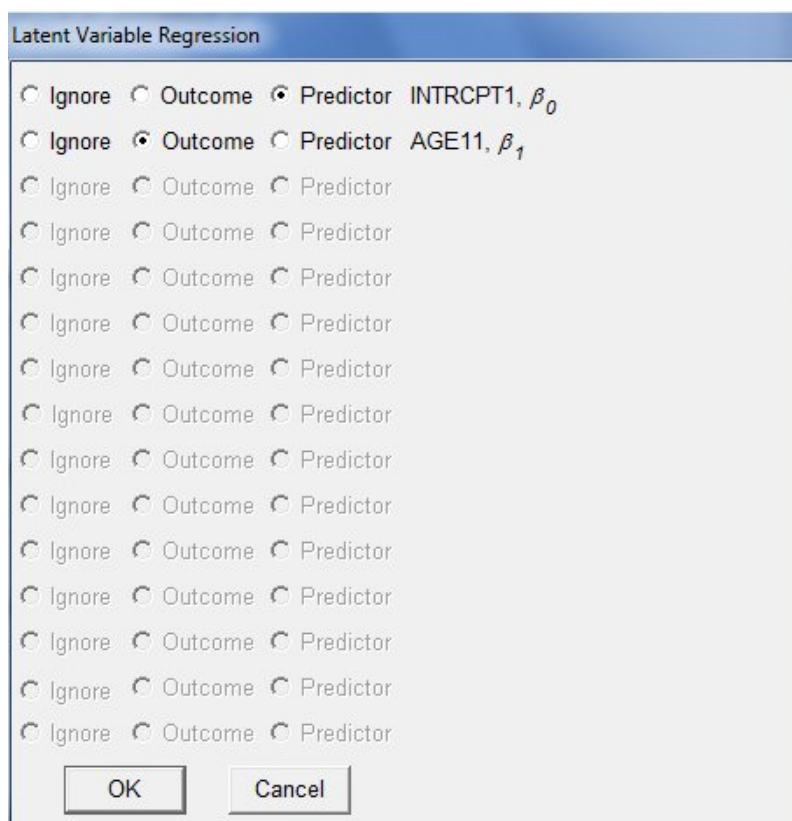
The screenshot shows the HLM2 software interface with the following content:

Outcome	UNRESTRICTED MODEL
>> Level-1 <<	LEVEL 1 MODEL
Level-2	$ATTIT_{mi} = (IND1_{mi}) * ATTIT_{1i}^* + (IND2_{mi}) * ATTIT_{2i}^* + (IND3_{mi}) * ATTIT_{3i}^* + (IND4_{mi}) * ATTIT_{4i}^* + (IND5_{mi}) * ATTIT_{5i}^*$ $ATTIT_{ti}^* = \pi_{0i} + \pi_{1i}(AGE11_{ti}) + \epsilon_{ti}$
INTRCPT1	LEVEL 2 MODEL
ATTIT	$\pi_{0i} = \beta_{00} + \beta_{01}(FEMALE_i)$ $\pi_{1i} = \beta_{10} + \beta_{11}(FEMALE_i)$
EXPO	Combined Model
AGE	$ATTIT_{ti}^* = \beta_{00} + \beta_{01} * FEMALE_i + \beta_{10} * AGE11_i + \beta_{11} * FEMALE_i * AGE11_i + \epsilon_{ti}$ $Var(\epsilon_{ti}) = \Delta$
AGE11	
AGE13	HOMOGENEOUS MODEL
AGE11S	LEVEL 1 MODEL
AGE13S	$ATTIT_{mi} = (IND1_{mi}) * ATTIT_{1i}^* + (IND2_{mi}) * ATTIT_{2i}^* + (IND3_{mi}) * ATTIT_{3i}^* + (IND4_{mi}) * ATTIT_{4i}^* + (IND5_{mi}) * ATTIT_{5i}^*$ $ATTIT_{ti}^* = \pi_{0i} + \pi_{1i}(AGE11_{ti}) + \epsilon_{ti}$
IND1	LEVEL 2 MODEL
IND2	$\pi_{0i} = \beta_{00} + \beta_{01}(FEMALE_i) + r_{0i}$ $\pi_{1i} = \beta_{10} + \beta_{11}(FEMALE_i) + r_{1i}$
IND3	Combined Model
IND4	$ATTIT_{ti}^* = \beta_{00} + \beta_{01} * FEMALE_i + \beta_{10} * AGE11_i + \beta_{11} * FEMALE_i * AGE11_i + \epsilon_{ti}$ $\epsilon_{ti} = r_{0i} + r_{1i} * AGE11_{ti} + e_{ti}$ $Var(\epsilon_{ti}) = Var(Ar_i + e_{ti}) = \Delta = A_1 A_1' + \sigma^2 I$
IND5	

Next, click on the **Estimation Settings** option from the **Other Settings** menu on the main menu bar to open the **Latent Variable Regression** box.



Select the predictor(s) and outcome(s) by clicking the selection buttons in front of them (for our example, select INTRCPT1 as the predictor and AGE11 as the outcome).



Click **OK** to return to the **Estimation Settings** dialog box, and again to return to the main modeling window. Remember to save the command file prior to running the analysis.

4. Interpreting the output

Select HMLM output to illustrate latent variable regression follows.

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, π_0					
INTRCPT2, β_{00}	0.221755	0.015961	13.894	237	<0.001
FEMALE, β_{01}	-0.048274	0.022926	-2.106	237	0.035
For AGE11 slope, π_1					
INTRCPT2, β_{10}	0.070432	0.006781	10.386	237	<0.001
FEMALE, β_{11}	-0.012003	0.009826	-1.222	237	0.222

The results indicate that there is a significant linear growth rate in the attitude toward deviant behaviors (coefficient = 0.070432, s.e. = 0.006781) for males. Also, there is no gender effect on the linear growth rate.

Latent Variable Regression Results

The model specified (in equation format)

$$\pi_1 = \beta_{10}^* + \beta_{11}^* (\text{FEMALE}) + \beta_{12}^* (\pi_0) + r_1^*$$

Outcome	Predictor	Estimated Coefficient	Standard Error	t-ratio	p-value
AGE11, r_1,π_1	INTRCPT2, β_{10}^*	0.024765	0.024807	0.998	0.319
	FEMALE, β_{11}^*	-0.002062	0.013058	-0.158	0.875
	π_0, β_{12}^*	0.205934	0.105410	1.954	0.050

The results indicate that, controlling for gender, the initial status at age 11 has a marginally significant effect on the linear growth rate (coefficient = 0.205934, s.e. = 0.105410). There is no statistically significant partial gender effect, however. Indeed, the gender effect on π_1 appears somewhat reduced after controlling π_0 .

Latent Variable Regression: Comparison of Original and Adjusted Coefficients

Outcome	Predictor	Original Coefficient	Adjusted Coefficient	Difference	Standard Error of Difference
AGE11, r_1,π_1	INTRCPT2	0.07043	0.02477	0.045667	0.024311
	FEMALE	-0.01200	-0.00206	-0.009941	0.006941

This table lists the original coefficients, the adjusted coefficients, and the difference between the two for the intercept and the gender effect. For the variable FEMALE, the “original coefficient” describes the total association, the “adjusted coefficient” describes the direct association, and the “difference” is the indirect association between gender and the linear growth rate, respectively.

Var(r^*)
AGE11, r_1 0.00196

An estimate of the variance of r_1^* , the residual variance in π_1 , controlling both FEMALE and π_0 , is also given.

As mentioned earlier, a latent variable analysis using HLM2 will reproduce identical results. The same procedures generalize to three-level applications (HMLM2, HLM3, & HGLM) to model randomly varying level-2 coefficients as outcome variables. See Raudenbush and Sampson (1999) for an example that implemented a latent variable analysis with a three-level model. In the study, they investigated the extent to which neighborhood social control mediated the association between neighborhood social composition and violence in Chicago.