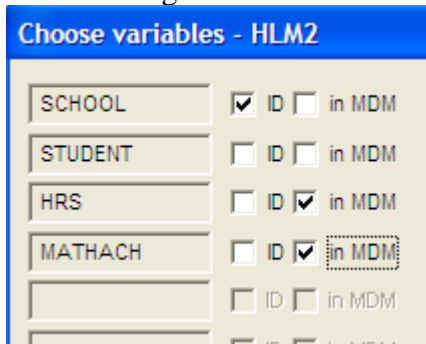


Dataset 2 – Fixed versus Random Coefficients and Level-2 Predictors.

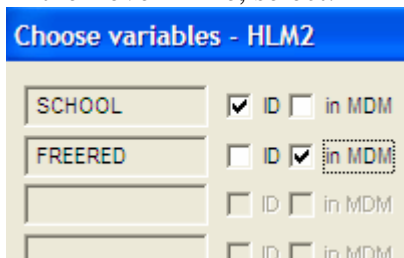
For use with HLM

The design of this dataset is to show how adding a random coefficient to a model dramatically increases data fit even though the coefficients to the slope coefficient are not statistically significant. A level-2 predictor is also added to show the mediation of this effect. The level-1 and level-2 datasets that will be used in this analysis are called “fixrand_L1.sav” and “fixrand_L2.sav” respectively.

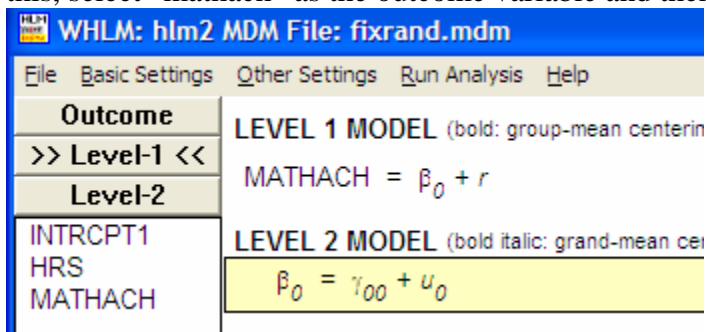
First, we will setup the .MDM file so that we can run the null model. In the Level-1 file, select the following to be in the MDM file:



In the Level-2 file, select:



We will first fit the null/unconditional model in which only the intercept is estimated. To do this, select “mathach” as the outcome variable and then run this model:



In viewing the output we can see the following (abridged);

Summary of the model specified (in equation format)

Level-1 Model

$$Y = B_0 + R$$

Level-2 Model

$$B_0 = G_{00} + U_0$$

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0 INTRCPT2, G00	77.540000	1.134920	68.322	9	0.000

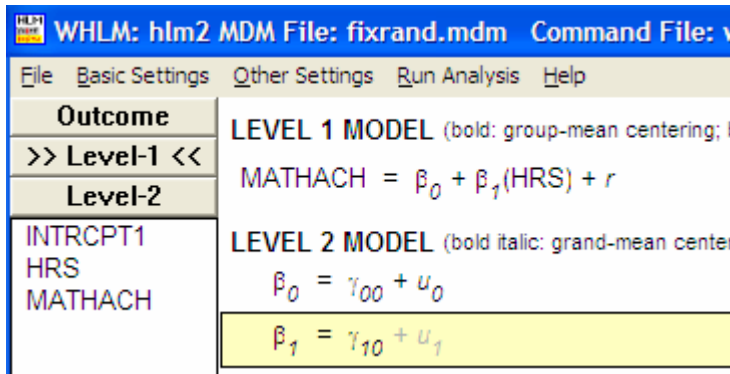
Final estimation of variance components:

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1, U0	2.70982	7.34311	9	20.93499	0.013
level-1, R	7.44133	55.37333			

Statistics for current covariance components model

Deviance = 688.710612
 Number of estimated parameters = 2

Next we will add a fixed effect that has hours of homework that a student has completed each week. We do this by specifying “hrs” as an uncentered level-1 predictor. We do not center hours because it has a meaningful zero (no hours of homework completed each week). Specifying this will produce the following:



with results (abridged):

Summary of the model specified (in equation format)

Level-1 Model

$$Y = B_0 + B_1*(HRS) + R$$

Level-2 Model

$$B_0 = G_{00} + U_0$$

$$B_1 = G_{10}$$

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	77.441818	1.631933	47.454	9	0.000
For HRS slope, B1					
INTRCPT2, G10	0.021818	0.260511	0.084	98	0.934

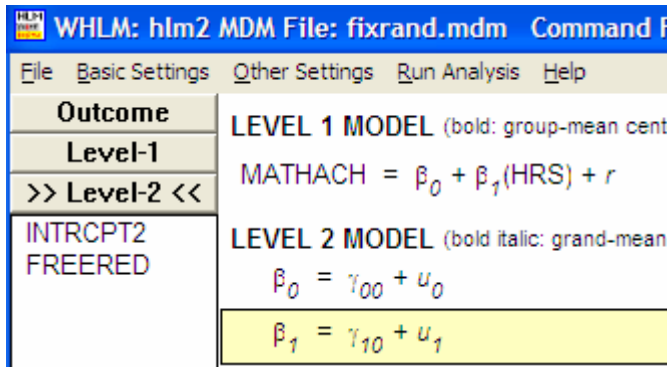
Final estimation of variance components:

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1, U0	2.69958	7.28772	9	20.70465	0.014
level-1, R	7.48260	55.98937			

Statistics for current covariance components model

Deviance = 691.399309
Number of estimated parameters = 2

These results would tell us that on average if a student moves from doing no homework each week to doing one hour of homework each week, their score on the math achievement variable would increase by 0.02 points. This would not seem to be a meaningful outcome, but we may recognize that further analysis is warranted. Because we forced a fixed slope with no random effects, the predicted regression lines are the same for each group. Because of the increase in AIC and BIC, we might be inclined to say that the predictor “hrs” is not a meaningful addition to the model. However if we add the random coefficient for “hrs” we can see that the model fit increases by a dramatic amount. We can do this simply by clicking on the random component associated with the “hrs” variable (u_1) and running the analysis again.



Roberts, J. K. (2005, April). Datasets illustrating specific strengths of hierarchical linear modeling. Paper presented at the annual meeting of the American Educational Research Association, Montreal.

Running this model will produce the following results:

Summary of the model specified (in equation format)

Level-1 Model

$$Y = B0 + B1*(HRS) + R$$

Level-2 Model

$$B0 = G00 + U0$$

$$B1 = G10 + U1$$

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	77.441818	4.783157	16.191	9	0.000
For HRS slope, B1					
INTRCPT2, G10	0.021818	0.818612	0.027	9	0.980

Final estimation of variance components:

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1, U0	15.12460	228.75339	9	63348.04068	0.000
HRS slope, U1	2.58846	6.70011	9	52881.62319	0.000
level-1, R	0.30674	0.09409			

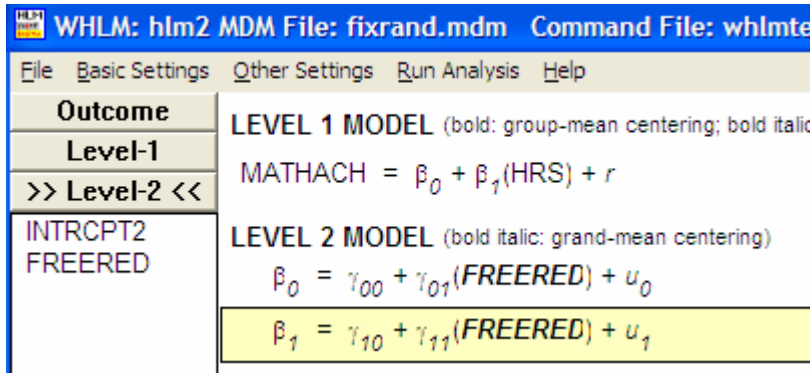
Statistics for current covariance components model

Deviance = 178.171395
Number of estimated parameters = 4

Notice that the fixed effect for “hrs” is not statistically significant if we consider just at the statistical significance of the p-value. Outside of just looking at the amount of reduction in the Deviance statistic (simply the Chi-square), is to consider the AIC (Akaike Information Criteria) and the BIC (Bayesian Information Criteria). The AIC is computed by $AIC = -2 * \ell + 2K$ where K is the number of parameters estimated and $-2 * \ell$ is an estimate of the Chi-Square. The BIC is computed by $BIC = -2 * \ell + K * Ln(N)$ where $Ln(N)$ is the number of people in the study. What is dramatic is to see the amount of reduction in the AIC and BIC which reduced from 699.40 to 190.17 and from 709.74 to 205.68 respectively. This means that we are fitting a much better model in the model with random slopes than in model with only fixed effects for the slopes.

Although the variance for the intercept has actually increased, the random component of the “hrs” variable has effectively reduced our level-1 variance (labeled “Residual”) to almost nil.

Now we can turn our attention to finding a variable to include in our model that explains the additional variance in the intercept and slope coefficients. To do this, we are going to add both the fixed effect and cross-level interaction for a school-level variable that tells the percentage of students on free/reduced lunch at that school. Since “hrs” is a variable that has a meaningful zero, we are not going to center it. We are, however, going to center our free/reduced lunch variable and will therefore grand mean center the variable “freered”. To do this, we would run the following model:



Doing this will produce the following results (abridged):

Summary of the model specified (in equation format)

Level-1 Model

$$Y = B_0 + B_1*(HRS) + R$$

Level-2 Model

$$B_0 = G_{00} + G_{01}*(FREERED) + U_0$$

$$B_1 = G_{10} + G_{11}*(FREERED) + U_1$$

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	77.441818	0.576522	134.326	8	0.000
FREERED, G01	1.636951	0.066197	24.728	8	0.000
For HRS slope, B1					
INTRCPT2, G10	0.021818	0.124513	0.175	8	0.866
FREERED, G11	-0.279068	0.014297	-19.520	8	0.000

Final estimation of variance components:

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1, U0	1.81419	3.29127	8	818.05552	0.000
HRS slope, U1	0.39229	0.15390	8	1087.49710	0.000
level-1, R	0.30674	0.09409			

Statistics for current covariance components model

Deviance = 150.545856
 Number of estimated parameters = 4

Roberts, J. K. (2005, April). Datasets illustrating specific strengths of hierarchical linear modeling. Paper presented at the annual meeting of the American Educational Research Association, Montreal.

Let's now look at the Empirical Bayesian estimated coefficients for the first random effects model and the random effects model with the second-level effect and the cross-level interaction.

Fixed values for the model with just "hrs" having both fixed and random effects.

	ecintrcp	echrs
1	99.853	-3.944
2	94.852	-2.945
3	90.142	-2.055
4	84.849	-.948
5	79.928	-.472
6	74.927	.527
7	69.859	1.057
8	65.150	1.947
9	60.148	2.945
10	54.709	4.107

In order to obtain the values for the Bayesian estimated effects in the model with Free/Reduced Lunch added, we must do a little calculation as HLM does not readily give them to us. The first two columns in the below screen shot from the SPSS residuals file are variables that are generated by HLM. We can then find the actual Bayesian estimate by adding 77.441 (the grand intercept from the output above) to each of the values in the "ebintrcp" column. These are reflected in the computed column "int_new". Likewise, we can find the estimates for the slope of "hrs" by taking our variable "ebhrs" and adding the grand slope estimate (0.022). These corrected values are reflected in the computed column "hrs_new".

	ebintrcp	ebhrs	int_new	hrs_new
1	1.935	-.475	79.38	-.45
2	1.842	-.313	79.28	-.29
3	.419	.017	77.86	.04
4	-3.204	.841	74.24	.86
5	-1.588	.201	75.85	.22
6	-.061	.086	77.38	.11
7	-.210	-.222	77.23	-.20
8	-1.633	.108	75.81	.13
9	1.513	-.283	78.95	-.26
10	.985	.041	78.43	.06

It is easy to see just by “eyeballing” the data that the final model reduces the variance in the intercept and the “hrs” variable by a considerable amount. We can also investigate this effect by looking at the variance components for both models.

As can be seen here, the residual variance associated with the intercept reduced from 228.75 to 3.29 and the residual variance associated with the “hrs” slope reduced from 6.70 to 0.15.

We now have our final model in which the second-level variable is able to mediate much of the variance produced by the level-1 variable “hrs”.

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