

### Example 3a: Fixed Effects in General Multilevel Models for Two-Level Nested Outcomes (as estimated using restricted maximum likelihood in SAS MIXED and STATA MIXED)

The data for this example come from Snijders and Bosker (2012). In a sample of 3,305 students from 178 schools, we will be examining the extent to which student language at post-test can be predicted from school-level variables of homework amount, denomination (three types), and use of mixed-grade classes, as well as student-level predictors of verbal IQ and performance IQ. Note that this example makes use of three custom SAS macros I wrote (available in the SAS syntax file online) by which to compute total- $R^2$ , pseudo- $R^2$ , and regions of significance for interactions.

#### SAS Syntax and Output for Data Import, Manipulation, and Description:

```
* Define global variable for file location to be replaced in code below;
* \\Client\ precedes actual path when using UIowa Virtual Desktop;
%LET filesave=C:\Dropbox\19_PSQF7375_Clustered\PSQF7375_Clustered_Example3a;

* Import example data excel data file into SAS;
PROC IMPORT DATAFILE="%filesave.\Multilevel_Analysis_Missing.xlsx"
  OUT=work.Students DBMS=XLSX REPLACE;
  SHEET="book_data";
  GETNAMES=YES; RUN;

* Data processing;
DATA work.Students; SET work.Students;
* Label variables;
  LABEL schoolID= "School ID"
         studentID= "Student ID"
         langpost= "Student Language"
         IQverb= "Student Verbal IQ"
         IQperf= "Student Performance IQ"
         denomina= "School Denomination"
         homework= "School Homework"
         mixedgra= "School Mixed Grade";
* Select variables to keep;
  KEEP schoolID studentID langpost IQverb IQperf denomina homework mixedgra;
* Select complete cases;
  IF NMISS(schoolID,studentID,langpost,IQverb,IQperf,denomina,homeework,mixedgra)>0 THEN
DELETE;
* Remove denomina=4,5 for small sample sizes;
  IF denomina IN(4,5) THEN DELETE; RUN;

* Z-score IQ variables for comparability as predictors;
PROC STANDARD DATA=work.Students OUT=work.StudentsZ MEAN=0 STD=1;
  VAR IQverb IQperf; RUN;
* Rename z-scored variables;
DATA work.StudentsZ; SET work.StudentsZ;
  RENAME IQverb=IQverbz IQperf=IQperfz; RUN;

* Create school-level dataset;
PROC MEANS NOPRINT DATA=work.StudentsZ; BY schoolID;
  VAR langpost IQverbz IQperfz homework mixedgra;
  OUTPUT OUT=work.Schools N(langpost)=Nperschool
  MEAN(langpost IQverbz IQperfz denomina homework mixedgra)=
  Smlangpost SMIQverbz SMIQperfz denomina homework mixedgra; RUN;
* Label new school variables;
DATA work.Schools; SET work.Schools;
  LABEL Smlangpost= "School Mean Language"
         SMIQverbz= "School Mean Verbal IQ Z"
         SMIQperfz= "School Mean Performance IQ Z";
  DROP _TYPE_ _FREQ_; * Remove unneeded vars; RUN;
* Merge school-level data back into student data;
DATA work.StudentsSchools; MERGE StudentsZ Schools; BY schoolID;
```

```

* Contrasts for school denomination -- initialize to missing;
denlv2=.; denlv3=.;
IF denomina=1 THEN DO; denlv2=0; denlv3=0; END;
IF denomina=2 THEN DO; denlv2=1; denlv3=0; END;
IF denomina=3 THEN DO; denlv2=0; denlv3=1; END;
LABEL denlv2= "Denom 1 vs 2"
      denlv3= "Denom 1 vs 3";
* Center school predictors near sample mean;
hw2=homework-2;
SMIQverbz0=SMIQverbz-0; * Reminder to center all L2 predictors;
SMIQperfz0=SMIQperfz-0;
LABEL hw2= "School Homework (0=2)";
* Create group-MC student-level variables using original L2 means;
WSlangpost=langpost-SMlangpost;
WSIQverbz=IQverbz-SMIQverbz;
WSIQperfz=IQperfz-SMIQperfz;
LABEL WSlangpost= "Student Language (0=School Mean)"
      WSIQverbz= "Student Verbal IQ Z (0=School Mean)"
      WSIQperfz= "Student Performance IQ Z (0=School Mean)";
RUN;

TITLE "SAS School-Level Descriptives";
PROC FREQ DATA=work.Schools;
    TABLE denomina mixedgra; RUN;
PROC MEANS NDEC=2 DATA=work.Schools;
    VAR SSlangpost SMIQverbz SMIQperfz homework Nperschool; RUN; TITLE;

TITLE "SAS Student-Level Descriptives";
PROC MEANS NDEC=2 DATA=work.StudentsSchools;
    VAR langpost WSlangpost IQverbz WSIQverbz IQperfz WSIQperfz; RUN; TITLE;

```

## STATA Syntax and Output for Data Import, Manipulation, and Description:

```

// Define global variable for file location to be replaced in code below
// \\Client\ precedes actual path when using UIowa Virtual Desktop
global filesave "C:\Dropbox\19_PSQF7375_Clustered\PSQF7375_Clustered_Example3a"

// Import example data excel data file into STATA
clear // clear memory in case a dataset is already open
import excel "$filesave\Multilevel_Analysis_Missing.xlsx", ///
    sheet("book_data") firstrow case(preserve)

// Label variables
label variable schoolID "School ID"
label variable studentID "Student ID"
label variable langpost "Student Language"
label variable IQverb "Student Verbal IQ"
label variable IQperf "Student Performance IQ"
label variable denomina "School Denomination"
label variable homework "School Homework Amount"
label variable mixedgra "School Mixed Grade"

// Select variables to keep
keep schoolID studentID langpost IQverb IQperf denomina homework mixedgra
// Select complete cases
egen nummiss = rowmiss(schoolID studentID langpost IQverb IQperf ///
    denomina homework mixedgra)
drop if nummiss>0
// Remove denomina=4,5 for small sample sizes
drop if denomina==4
drop if denomina==5

// Z-score IQ variables for comparability as predictors
egen IQverbz=std(IQverb)
egen IQperfz=std(IQperf)

```

```

// Create school-level variables
egen Nperschool=count(langpost), by(schoolID)
egen SMLangpost=mean(langpost), by(schoolID)
egen SMIQverbz=mean(IQverbz), by(schoolID)
egen SMIQperfz=mean(IQperfz), by(schoolID)
// Label school-level variables
label variable SMLangpost "School Mean Language"
label variable SMIQverbz "School Mean Verbal IQ Z"
label variable SMIQperfz "School Mean Performance IQ Z"

// Contrasts for school denomination -- initialize to missing
gen denlv2=.
gen denlv3=.
replace denlv2=0 if denomina==1
replace denlv3=0 if denomina==1
replace denlv2=1 if denomina==2
replace denlv3=0 if denomina==2
replace denlv2=0 if denomina==3
replace denlv3=1 if denomina==3
label variable denlv2 "Denom 1 vs 2"
label variable denlv3 "Denom 1 vs 3"

// Center school predictors near sample mean
gen hw2=homework-2
gen SMIQverbz0=SMIQverbz-0 // Reminder to center all L2 predictors
gen SMIQperfz0=SMIQperfz-0
label variable hw2 "School Homework (0=2)"

// Create group-MC student-level variables using original L2 means
gen WSlangpost=langpost-SMLangpost
gen WSIQverbz=IQverbz-SMIQverbz
gen WSIQperfz=IQperfz-SMIQperfz
label variable WSlangpost "Student Language (0=School Mean)"
label variable WSIQverbz "Student Verbal IQ Z (0=School Mean)"
label variable WSIQperfz "Student Performance IQ Z (0=School Mean)"

display as result "STATA School-Level Descriptives"
preserve // Save for later use, then compute school-level dataset
collapse SMLangpost SMIQverbz SMIQperfz homework denomina mixedgra Nperschool, ///
by(schoolID)
tabulate denomina
tabulate mixedgra
format SMLangpost SMIQverbz SMIQperfz homework Nperschool %4.2f
summarize SMLangpost SMIQverbz SMIQperfz homework Nperschool, format
restore // Go back to student-level dataset

display as result "STATA Student-Level Descriptives"
format langpost WSlangpost IQverbz WSIQverbz IQperfz WSIQperfz %4.2f
summarize langpost WSlangpost IQverbz WSIQverbz IQperfz WSIQperfz, format

```

### STATA Old-School Listing Output (which I still use because it's easier to paste and annotate):

denomina	Freq.	Percent	Cum.
1	56	31.46	31.46
2	68	38.20	69.66
3	54	30.34	100.00
Total	178	100.00	

mixedgra	Freq.	Percent	Cum.
0.00	116	65.17	65.17
1.00	62	34.83	100.00
<hr/>			
Total	178	100.00	

  

Variable	Obs	Mean	Std. Dev.	Min	Max
SMLangpost	178	40.75	4.95	23.71	50.33
SMIQverbz	178	-0.04	0.46	-2.07	1.22
SMIQperfz	178	-0.03	0.35	-1.19	0.96
homework	178	2.41	0.53	1.33	3.67

  

Variable	Obs	Mean	Std. Dev.	Min	Max
langpost	3,305	41.30	8.87	9.00	58.00
WSlangpost	3,305	-0.00	7.69	-33.55	22.70
IQverbz	3,305	0.00	1.00	-3.85	3.25
WSIQverbz	3,305	-0.00	0.92	-3.54	3.34
IQperfz	3,305	0.00	1.00	-2.91	2.99
WSIQperfz	3,305	-0.00	0.95	-2.77	2.85
Nperschool	178	18.57	7.37	4.00	34.00

**Model 1a for Language: Single-Level Empty Means, No Random Intercept**

$$\text{Language}_{pg} = \beta_0 + e_{pg}$$

```
TITLE "SAS Model 1a for Language: Single-Level Empty Means, Random Intercept";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
CLASS schoolID studentID;
MODEL langpost = / SOLUTION DDFM=BW; RUN; TITLE;
```

Dimensions

Covariance Parameters	1
Columns in X	1
Columns in Z	0
Subjects	1
Max Obs per Subject	3305

This model is treating these cases as independent—one group of 3,305 students.

Number of Observations

Number of Observations Read	3305
Number of Observations Used	3305
Number of Observations Not Used	0

This table tells you how many cases were removed due to incomplete data—make sure you pay attention to this if you are doing any model comparisons (which will need to be based on the exact same cases to be valid).

Covariance Parameter Estimates

Cov Parm	Estimate	Standard Error	Z	Pr >  Z
Residual	78.7355	1.9372	40.64	<.0001

This is the variance of the  $e_{pg}$  residuals assuming independent observations.

Information Criteria

Neg2LogLike	Parms	AIC	AICC	HQIC	BIC	CAIC
23810.0	1	23812.0	23812.0	23814.2	23818.1	23819.1

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	41.3047	0.1543	3304	267.61	<.0001

This is the grand mean for language, pooling over all of the observations.

```
display as result "STATA Model 1a for Language: Empty Means, Random Intercept"
mixed langpost , ///
variance reml dfmethod(residual)
```

```
Mixed-effects REML regression          Number of obs    =    3,305
DF method: Residual                    DF:              min =    3,304.00
                                          avg =    3,304.00
                                          max =    3,304.00
                                          F(0, 3304.00)   =    .
                                          Prob > F        =    .
```

Log restricted-likelihood = -11905.013

langpost	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
_cons	41.30469	.1543475	267.61	0.000	41.00206	41.60732
-----+-----						
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]			
-----+-----						
var(Residual)	78.73553	1.936868	75.0294	82.62472		
-----+-----						

This is the grand mean for language, pooling over all of the observations.

This is the variance of the  $e_{pg}$  residuals assuming independent observations.

**Model 1b for Language: Single-Level Empty Means, Random Intercept**

Level-1: Language  $e_{pg} = \beta_{0g} + e_{pg}$

Level-2:  $\beta_{0g} = \gamma_{00} + U_{0g}$

```
TITLE "SAS Model 1b for Language: Two-Level Empty Means, Random Intercept";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
CLASS schoolID studentID; * OUTPM=Save predicted outcomes;
MODEL langpost = / SOLUTION DDFM=Satterthwaite OUTPM=PredEmpty;
RANDOM INTERCEPT / VCORR TYPE=UN SUBJECT=schoolID; * VCORR gives ICC;
ODS OUTPUT CovParms=CovEmpty; * Save variances; RUN; TITLE;
```

Changes to the syntax: **RANDOM** lists all effects to have random variances across the unit of analysis provided by SUBJECT. TYPE=UN means unstructured—this should be left alone. On MODEL, denominator degrees of freedom (DDFM) now uses **Satterthwaite**, a good general MLM option (Kenward-Roger is better for small samples).

OUTPM requested a dataset called “PredEmpty” that will contain a column “pred” as the model-predicted outcome. Right now, this will be a constant (the mean), but we will eventually use this to compute total- $R^2$ . ODS OUTPUT saves the variance parameters to a dataset called “CovEmpty” that will be used to compute pseudo- $R^2$  later.

```
Covariance Parameters          2
Columns in X                    1
Columns in Z per Subject       1
Subjects                        178
Max Obs per Subject            34
```

Covariance parameters refers to the total number of parameters in the model for the variance. Columns in X refers to the number of fixed effects in the design matrix (i.e., including redundant columns for categorical predictors. Columns in Z refers to the number of random effects.

This model is now treating these cases as nested within schools: 178 schools with up 34 students each (mean ~19, range = 4 to 34).

Iteration History				
Iteration	Evaluations	-2 Res Log Like	Criterion	
0	1	23810.02512060		
1	2	23373.80532705	0.00005932	
2	1	23373.24829101	0.00000122	
3	1	<b>23373.23762514</b>	0.00000000	

For your homework, report the last -2LL value from this table to obtain two digits past the decimal for enough precision.

Estimated V Correlation Matrix for schoolID 1 (truncated to save space)

Row	Col1	Col2
1	1.0000	0.2282
2	<b>0.2282</b>	1.0000

Intraclass Correlation as provided by VCORR:

$$ICC = \frac{\tau_{U_0}^2}{\tau_{U_0}^2 + \sigma_e^2} = \frac{18.5134}{18.5134 + 92.6200} = .2282$$

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr >  Z
UN(1,1)	schoolID	18.5134	2.4694	7.50	<.0001 → L2 random intercept variance
Residual		62.6200	1.5866	39.47	<.0001 → L1 residual variance

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
1	436.79	<.0001

This Null Model LRT is the difference in  $-2LL$  ( $-2\Delta LL$ ) between this model and the same model without any additional parameters in the model for the variance besides residual variance. Here, this is the significance test of the ICC, which in turn provides an effect size for the amount of dependency attributed to school mean differences in language.

Information Criteria

Neg2LogLike	Parms	AIC	AICC	HQIC	BIC	CAIC
<b>23373.2</b>	<b>2</b>	23377.2	23377.2	23379.8	23383.6	23385.6

REML's parm count (2) excludes the fixed effects.

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	40.8960	0.3553	164	115.11	<.0001

The intercept is now the grand mean of the school means, which will differ from the overall grand mean whenever level-2 units have different level-1 sizes (unbalanced).

```
display as result "STATA Model 1b for Language: Empty Means, Random Intercept"
mixed langpost , ///
  || schoolID: , variance reml covariance(unstructured) dfmethod(satterthwaite),
  estat icc // Compute Intraclass Correlation
```

Changes to the syntax: || denotes the random part of the model, which currently includes just an intercept variance across schools (included by default). Covariance(unstructured) is the analog to TYPE=UN means unstructured—this should be left alone (although it doesn't matter here). On MODEL, denominator degrees of freedom (DDFM) now uses **Satterthwaite**, a good general MLM option (Kenward-Roger is better for small samples).

```
Mixed-effects REML regression          Number of obs   =      3,305
Group variable: schoolID              Number of groups =       178

Obs per group:
   min =          4
   avg =         18.6
   max =          34

DF method: Satterthwaite              DF:
   min =        175.69
   avg =        175.69
   max =        175.69
```

```
F(0, 0.00) = .
Log restricted-likelihood = -11686.619  Prob > F = .
```

langpost	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----					
_cons	40.89593	.3553269	115.09	0.000	40.19467 41.59718
-----+-----					

The intercept is now the grand mean of the school means, which will differ from the overall grand mean whenever level-2 units have different level-1 sizes (are unbalanced).

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
schoolID: Identity				
var(_cons)	18.5189	2.470581	14.25797	24.0532 → L2 random int var
var(Residual)	62.61918	1.586618	59.58542	65.80741 → L1 residual var
LR test vs. linear model: chibar2(01) = 436.79      Prob >= chibar2 = 0.0000				

This Null Model LRT is the difference in  $-2LL$  between this model and the same model without any additional parameters in the model for the variance besides residual variance. Here, this is the significance test of the ICC, which in turn provides an effect size for the amount of dependency attributed to school mean differences in language.

Intraclass correlation

Level	ICC	Std. Err.	[95% Conf. Interval]	
schoolID	.2282393	.0241629	.1843516	.2790014

**Design effect** using mean #students per school:  $= 1 + ((n - 1) * ICC) \rightarrow 1 + [(18-1)*.228] = 4.876$

**Effective sample size:**  $N_{\text{effective}} = (\# \text{Total Obs}) / \text{Design Effect} \rightarrow 3,305 / 4.876 = 677!!!$

**This means that our power to detect level-1 effects will be approximately that of an independent sample of 677 students—only if the ICC were 0 would we have power for level-1 effects based on the actual number of students. Power for level-2 effects is based on the number of schools (178).**

### Model 2a: Add 3 School Predictors

Level-1: Language<sub>pg</sub> =  $\beta_{0g} + e_{pg}$

Level-2:  $\beta_{0g} = \gamma_{00} + \gamma_{01}(\text{Homework}_g - 2) + \gamma_{02}(\text{MixedGrade}_g) + \gamma_{03}(\text{Denomlv2}_g) + \gamma_{04}(\text{Denomlv3}_g) + U_{0g}$

```
TITLE "SAS Model 2a: Add 3 School Predictors";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
  CLASS schoolID studentID;
  MODEL langpost = hw2 mixedgra denlv2 denlv3
    / SOLUTION DDFM=Satterthwaite OUTPM=PredHMD;
  RANDOM INTERCEPT / TYPE=UN SUBJECT=schoolID;
  ESTIMATE "Denomination 2 vs 3"          denlv2 -1 denlv3 1;
  CONTRAST "Test of Model Total-R2" hw2 1, mixedgra 1, denlv2 1, denlv3 1;
  CONTRAST "Test of Change in R2 after HW" mixedgra 1, denlv2 1, denlv3 1;
  CONTRAST "Test of Omnibus Denomination" denlv2 1, denlv3 1;
  ODS OUTPUT CovParms=CovHMD; RUN; TITLE;
```

```
display as result "STATA Model 2a: Add 3 School Predictors"
mixed langpost c.hw2 c.mixedgra c.denlv2 c.denlv3, ///
  || schoolID: , variance reml covariance(unstructured) dfmethod(satterthwaite),
  test (c.mixedgra=0) (c.denlv2=0) (c.denlv3=0), small // Test Change in R2 after HW
  test (c.denlv2=0) (c.denlv3=0), small // Test Omnibus Denomination
  lincom c.denlv2*-1 + c.denlv3*1, small // Denomination 2 vs 3
  predict PredHMD, xb
  corr langpost PredHMD
  display as result r(rho)^2 // total R2
```

**SAS Results:**

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
UN(1,1)	schoolID	15.9505	2.2126	7.21	<.0001
Residual		62.6202	1.5866	39.47	<.0001

Information Criteria

Neg2LogLike	Parms	AIC	AICC	HQIC	BIC	CAIC
<b>23343.0</b>	2	23347.0	23347.0	23349.6	23353.4	23355.4

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	40.0024	0.7248	157	55.19	<.0001
hw2	0.8307	0.6403	156	1.30	0.1964
mixedgra	-2.0141	0.7336	174	-2.75	0.0067
den1v2	2.7418	0.8142	158	3.37	0.0010
den1v3	0.4717	0.8584	162	0.55	0.5834

**Interpret each fixed effect:**

Intercept  $\gamma_{00}$  =

HW2  $\gamma_{01}$  =

MixedGra  $\gamma_{02}$  =

Den1v2  $\gamma_{03}$  =

Den1v3  $\gamma_{04}$  =

Estimates

Label	Estimate	Standard Error	DF	t Value	Pr >  t
Denomination 2 vs 3	-2.2701	0.8265	159	-2.75	0.0067

Contrasts

Label	Num DF	Den DF	F Value	Pr > F
Test of Model Total-R2	4	162	6.68	<.0001
Test of Change in R2 after HW	3	164	8.28	<.0001
Test of Omnibus Denomination	2	159	6.61	0.0017

\* Calculate PseudoR2 relative to two-level empty means model 1b;

`%PseudoR2(NCov=2, CovFewer=CovEmpty, CovMore=CovHMD);`

PseudoR2 (% Reduction) for CovEmpty vs. CovHMD

Name	CovParm	Subject	Estimate	StdErr	ZValue	ProbZ	PseudoR2
CovEmpty	UN(1,1)	schoolID	18.5134	2.4694	7.50	<.0001	.
CovEmpty	Residual		62.6200	1.5866	39.47	<.0001	.
CovHMD	UN(1,1)	schoolID	15.9505	2.2126	7.21	<.0001	0.13843
CovHMD	Residual		62.6202	1.5866	39.47	<.0001	-0.00000

\* Calculate TotalR2 relative to two-level empty means model 1b;

`%TotalR2(DV=langpost, PredFewer=PredEmpty, PredMore=PredHMD);`

Total R2 (% Reduction) for PredEmpty vs. PredHMD

Name	Pred Corr	TotalR2	Total R2Diff
PredEmpty	0.00000	0.000000	.
PredHMD	0.17925	0.032132	0.032132

**R<sup>2</sup> Results:** The four fixed effects of our three level-2 predictors accounted for 13.84% of the level-2 random intercept variance, which was 3.231% of the total language variance (which can be approximated by .1384\*. 2283 = 3.159% using the ICC from the empty model).



**Model 2a: Add Interaction of Mixed Grade by Denomination**

$$\text{Level-1: Language}_{pg} = \beta_{0g} + e_{pg}$$

$$\text{Level-2: } \beta_{0g} = \gamma_{00} + \gamma_{01}(\text{Homework}_g - 2) + \gamma_{02}(\text{MixedGrade}_g) + \gamma_{03}(\text{Denomlv2}_g) + \gamma_{04}(\text{Denomlv3}_g) \\ + \gamma_{04}(\text{MixedGrade}_g)(\text{Denomlv2}_g) + \gamma_{05}(\text{MixedGrade}_g)(\text{Denomlv3}_g) + U_{0g}$$

```

TITLE "SAS Model 2b: Add Interaction of Mixed Grade by Denomination";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
CLASS schoolID studentID;
MODEL langpost = hw2 mixedgra denlv2 denlv3 mixedgra*denlv2 mixedgra*denlv3
      / SOLUTION DDFM=Satterthwaite OUTPM=PredMGxD;
RANDOM INTERCEPT / TYPE=UN SUBJECT=schoolID;
CONTRAST "Omnibus Test of MixedGra by Den Interaction (Change in R2)"
      mixedgra*denlv2 1, mixedgra*denlv3 1;
ESTIMATE "Denomination 2 vs 3" denlv2 -1 denlv3 1;
* Simple effects of mixed grade per denomination;
ESTIMATE "MixedGra Effect for Den=1" mixedgra 1 mixedgra*denlv2 0 mixedgra*denlv3 0;
ESTIMATE "MixedGra Effect for Den=2" mixedgra 1 mixedgra*denlv2 1 mixedgra*denlv3 0;
ESTIMATE "MixedGra Effect for Den=3" mixedgra 1 mixedgra*denlv2 0 mixedgra*denlv3 1;
* Simple effects of denomination per MixedGra;
ESTIMATE "Den lv2 for MixedGra=0" denlv2 1 denlv3 0 mixedgra*denlv2 0 mixedgra*denlv3 0;
ESTIMATE "Den lv3 for MixedGra=0" denlv2 0 denlv3 1 mixedgra*denlv2 0 mixedgra*denlv3 0;
ESTIMATE "Den 2v3 for MixedGra=0" denlv2 -1 denlv3 1 mixedgra*denlv2 0 mixedgra*denlv3 0;
ESTIMATE "Den lv2 for MixedGra=1" denlv2 1 denlv3 0 mixedgra*denlv2 0 mixedgra*denlv3 0;
ESTIMATE "Den lv3 for MixedGra=1" denlv2 0 denlv3 1 mixedgra*denlv2 0 mixedgra*denlv3 1;
ESTIMATE "Den 2v3 for MixedGra=1" denlv2 -1 denlv3 1 mixedgra*denlv2 -1 mixedgra*denlv3 1;
* Differences in simple effects -- interaction contrasts;
ESTIMATE "MixedGra Effect for Den=1 vs 2" mixedgra*denlv2 1 mixedgra*denlv3 0;
ESTIMATE "MixedGra Effect for Den=1 vs 3" mixedgra*denlv2 0 mixedgra*denlv3 1;
ESTIMATE "MixedGra Effect for Den=2 vs 3" mixedgra*denlv2 -1 mixedgra*denlv3 1;
ODS OUTPUT CovParms=CovMGbxD; RUN; TITLE;

display as result "STATA Model 2b: Add Interaction of Mixed Grade by Denomination"
mixed langpost c.hw2 c.mixedgra c.denlv2 c.denlv3 c.mixedgra#c.denlv2 c.mixedgra#c.denlv3, ///
|| schoolID: , variance reml covariance(unstructured) dfmethod(satterthwaite),
test (c.mixedgra#c.denlv2=0) (c.mixedgra#c.denlv3=0), small // Test Omnibus Interaction
// Simple effects of mixed grade per denomination
lincom c.mixedgra*1 + c.mixedgra#c.denlv2*0 + c.mixedgra#c.denlv3*0, small // MG:Den=1
lincom c.mixedgra*1 + c.mixedgra#c.denlv2*1 + c.mixedgra#c.denlv3*0, small // MG:Den=2
lincom c.mixedgra*1 + c.mixedgra#c.denlv2*0 + c.mixedgra#c.denlv3*1, small // MG:Den=3
// Simple effects of denomination per mixed grade
lincom c.denlv2*1 + c.denlv3*0 + c.mixedgra#c.denlv2*0 + c.mixedgra#c.denlv3*0, small // D1v2: MG=0
lincom c.denlv2*0 + c.denlv3*1 + c.mixedgra#c.denlv2*0 + c.mixedgra#c.denlv3*0, small // D1v3: MG=0
lincom c.denlv2*-1 + c.denlv3*1 + c.mixedgra#c.denlv2*0 + c.mixedgra#c.denlv3*0, small // D2v3: MG=0
lincom c.denlv2*1 + c.denlv3*0 + c.mixedgra#c.denlv2*1 + c.mixedgra#c.denlv3*0, small // D1v2: MG=1
lincom c.denlv2*0 + c.denlv3*1 + c.mixedgra#c.denlv2*0 + c.mixedgra#c.denlv3*1, small // D1v3: MG=1
lincom c.denlv2*-1 + c.denlv3*1 + c.mixedgra#c.denlv2*-1 + c.mixedgra#c.denlv3*1, small // D2v3: MG=1
// Differences in simple effects -- interaction contrasts
lincom c.mixedgra#c.denlv2*1 + c.mixedgra#c.denlv3*0, small // MG:Den=1v2
lincom c.mixedgra#c.denlv2*0 + c.mixedgra#c.denlv3*1, small // MG:Den=1v3
lincom c.mixedgra#c.denlv2*-1 + c.mixedgra#c.denlv3*1, small // MG:Den=2v3
predict PredMGxD, xb
corr langpost PredMGxD
display as result r(rho)^2 // total R2

```

**SAS Results:**

Covariance Parameter Estimates					
			Standard	Z	
Cov Parm	Subject	Estimate	Error	Value	Pr > Z
UN(1,1)	schoolID	15.8630	2.2178	7.15	<.0001
Residual		62.6251	1.5869	39.46	<.0001

Neg2LogLike	Parms	Information Criteria				
		AIC	AICC	HQIC	BIC	CAIC
<b>23334.8</b>	2	23338.8	23338.8	23341.4	23345.2	23347.2

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	39.9590	0.8373	146	47.73	<.0001
hw2	0.7927	0.6433	154	1.23	0.2197
mixedgra	-1.8665	1.2383	168	-1.51	0.1336
den1v2	2.4937	0.9861	145	2.53	0.0125
den1v3	1.0693	1.0788	145	0.99	0.3233
mixedgra*den1v2	1.1955	1.7797	171	0.67	0.5027
mixedgra*den1v3	-1.6545	1.7676	171	-0.94	0.3506

**Interpret each fixed effect:**

MixedGra  $\gamma_{02}$  =

Den1v2  $\gamma_{03}$  =

Den1v3  $\gamma_{04}$  =

MixedGra\*Den1v2  $\gamma_{05}$  =

MixedGra\*Den1v2  $\gamma_{06}$  =

Estimates

Label	Estimate	Standard Error	DF	t Value	Pr >  t
Denomination 2 vs 3	-1.4244	0.9818	145	-1.45	0.1490
MixedGra Effect for Den=1	-1.8665	1.2383	168	-1.51	0.1336
MixedGra Effect for Den=2	-0.6710	1.2779	173	-0.53	0.6002
MixedGra Effect for Den=3	-3.5209	1.2751	174	-2.76	0.0064
Den 1v2 for MixedGra=0	2.4937	0.9861	145	2.53	0.0125
Den 1v3 for MixedGra=0	1.0693	1.0788	145	0.99	0.3233
Den 2v3 for MixedGra=0	-1.4244	0.9818	145	-1.45	0.1490
Den 1v2 for MixedGra=1	2.4937	0.9861	145	2.53	0.0125
Den 1v3 for MixedGra=1	-0.5852	1.4036	191	-0.42	0.6772
Den 2v3 for MixedGra=1	-4.2744	1.5198	188	-2.81	0.0054
MixedGra Effect for Den=1 vs 2	1.1955	1.7797	171	0.67	0.5027
MixedGra Effect for Den=1 vs 3	-1.6545	1.7676	171	-0.94	0.3506
MixedGra Effect for Den=2 vs 3	-2.8500	1.8054	174	-1.58	0.1162

Contrasts

Label	Num DF	Den DF	F Value	Pr > F
Omnibus Test of MixedGra by Den Interaction (Change in R2)	2	172	1.26	0.2865

\* Calculate PseudoR2 relative to two-level empty means model 1b;  
 %PseudoR2(NCov=2, CovFewer=CovEmpty, CovMore=CovMGbxD);

PseudoR2 (% Reduction) for CovEmpty vs. CovMGbxD

Name	CovParm	Subject	Estimate	StdErr	ZValue	ProbZ	PseudoR2
CovEmpty	UN(1,1)	schoolID	18.5134	2.4694	7.50	<.0001	.
CovEmpty	Residual		62.6200	1.5866	39.47	<.0001	.
CovMGbxD	UN(1,1)	schoolID	15.8630	2.2178	7.15	<.0001	0.14316
CovMGbxD	Residual		62.6251	1.5869	39.46	<.0001	-0.00008

\* Calculate PseudoR2 relative to L2 main effects model 2a;  
 %PseudoR2(NCov=2, CovFewer=CovHMD, CovMore=CovMGbxD);

PseudoR2 (% Reduction) for CovHMD vs. CovMGbxD

Name	CovParm	Subject	Estimate	StdErr	ZValue	ProbZ	PseudoR2
CovHMD	UN(1,1)	schoolID	15.9505	2.2126	7.21	<.0001	.
CovHMD	Residual		62.6202	1.5866	39.47	<.0001	.
CovMGbxD	UN(1,1)	schoolID	15.8630	2.2178	7.15	<.0001	0.005487836
CovMGbxD	Residual		62.6251	1.5869	39.46	<.0001	-.000077981

\* Calculate TotalR2 relative to L2 main effects model 2a;  
 %TotalR2(DV=langpost, PredFewer=PredHMD, PredMore=PredMGxD);

Total R2 (% Reduction) for PredHMD vs. PredMGxD

Name	Pred Corr	TotalR2	Total R2Diff
PredHMD	0.17925	0.032132	.
PredMGxD	0.18830	0.035458	.003326123

**Interpret the results for pseudo-R<sup>2</sup> and total-R<sup>2</sup>:**

### Model 1b (Empty Means, Random Intercept) for Student-Level IQverb and IQperf to Get ICCs

```
TITLE "SAS Model 1b for IQverb: Two-Level Empty Means, Random Intercept";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
  CLASS schoolID studentID;
  MODEL IQverbz = / SOLUTION DDFM=Satterthwaite;
  RANDOM INTERCEPT / VCORR TYPE=UN SUBJECT=schoolID; RUN; TITLE;

display as result "STATA Model 1b for IQverb: Empty Means, Random Intercept"
mixed IQverbz , ///
  || schoolID: , variance reml covariance(unstructured) dfmethod(satterthwaite),
  estat icc // Compute Intraclass Correlation
```

### SAS Results:

Estimated V Correlation Matrix for schoolID 1 (truncated to save space)

Row	Col1	Col2
1	1.0000	0.2282
2	<b>0.1201</b>	1.0000

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
UN(1,1)	schoolID	0.1221	0.02002	6.10	<.0001
Residual		0.8941	0.02269	39.40	<.0001

Intraclass Correlation as provided by VCORR:

$$ICC = \frac{\tau_{U_0}^2}{\tau_{U_0}^2 + \sigma_e^2} = \frac{0.1221}{0.1221 + 0.8941} = .1201$$

The LRT indicated the ICC was significant,  $-2\Delta LL(1) = 154.28, p < .0001$ .

```

TITLE "SAS Model 1b for IQperf: Two-Level Empty Means, Random Intercept";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
CLASS schoolID studentID;
MODEL IQperfz = / SOLUTION DDFM=Satterthwaite;
RANDOM INTERCEPT / VCORR TYPE=UN SUBJECT=schoolID; RUN; TITLE;
display as result "STATA Model 1b for IQperf: Empty Means, Random Intercept"
mixed IQperfz , ///
  || schoolID: , variance reml covariance(unstructured) dfmethod(satterthwaite),
  estat icc // Compute Intraclass Correlation

```

## SAS Results:

Estimated V Correlation Matrix for schoolID 1 (truncated to save space)

Row	Col1	Col2
1	1.0000	0.2282
2	<b>0.04847</b>	1.0000

Intraclass Correlation as provided by VCORR:

$$ICC = \frac{\tau_{U_0}^2}{\tau_{U_0}^2 + \sigma_e^2} = \frac{0.04854}{0.04854 + 0.9528} = .04847$$

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z	Pr > Z
UN(1,1)	schoolID	0.04854	0.01124	4.32	<.0001
Residual		0.9528	0.02411	39.53	<.0001

The LRT indicated the ICC was significant,  $-2\Delta LL(1) = 45.20, p < .0001$ .

## Model 3a: Remove Mixed Grade by Denomination, Add L2 Group Mean and Group-MC L1

### Student Verbal IQ

$$\text{Level-1: Language}_{pg} = \beta_{0g} + \beta_{1g}(\text{IQverb}_{pg} - \overline{\text{IQverb}}_g) + e_{pg}$$

$$\text{Level-2: } \beta_{0g} = \gamma_{00} + \gamma_{01}(\text{Homework}_g - 2) + \gamma_{02}(\text{MixedGrade}_g) + \gamma_{03}(\text{Denomlv2}_g) + \gamma_{04}(\text{Denomlv3}_g) + \gamma_{05}(\overline{\text{IQverb}}_g) + U_{0g}$$

$$\beta_{1g} = \gamma_{10}$$

```

TITLE "SAS Model 3a: Remove Mixed Grade by Denom, Add L2 and L1 Student Verbal IQ";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
CLASS schoolID studentID;
MODEL langpost = hw2 mixedgra denlv2 denlv3 SMIQverbz0 WSIQverbz
          / SOLUTION DDFM=Satterthwaite OUTPM=PredIQverb;
RANDOM INTERCEPT / TYPE=UN SUBJECT=schoolID;
CONTRAST "Omnibus Test of Verbal IQ (Change in R2)" SMIQverbz0 1, WSIQverbz 1;
ESTIMATE "Denomination 2 vs 3" denlv2 -1 denlv3 1;
ESTIMATE "L2 Contextual Effect of Verbal IQ" SMIQverbz0 1 WSIQverbz -1;
ODS OUTPUT CovParms=CovIQverb; RUN; TITLE;

```

display as result "STATA Model 3a: Remove MixGra by Denom, Add L2 and L1 Student Verbal IQ"

```

mixed langpost c.hw2 c.mixedgra c.denlv2 c.denlv3 c.SMIQverbz0 c.WSIQverbz , ///
  || schoolID: , variance reml covariance(unstructured) dfmethod(satterthwaite),
  test (c.SMIQverbz0=0) (c.WSIQverbz=0), small // Test Omnibus Verbal IQ
  lincom c.denlv2*-1 + c.denlv3*1, small // Denomination 2 vs 3
  lincom c.SMIQverbz0*1 + c.WSIQverbz*-1, small // L1 Contextual Effect of Verbal IQ
predict PredIQverb, xb
corr langpost PredIQverb
display as result r(rho)^2 // total R2

```

**SAS Results:**

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr >  Z
UN(1,1)	schoolID	7.9235	1.1341	6.99	<.0001
Residual		40.5184	1.0252	39.52	<.0001

Information Criteria						
Neg2LogLike	Parms	AIC	AICC	HQIC	BIC	CAIC
21870.4	2	21874.4	21874.4	21877.0	21880.8	21882.8

Solution for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	40.8784	0.5294	164	77.22	<.0001
hw2	0.1425	0.4666	163	0.31	0.7605
mixedgra	-1.0608	0.5390	183	-1.97	0.0506
den1v2	1.6246	0.5965	166	2.72	0.0072
den1v3	-0.3620	0.6263	170	-0.58	0.5640
SMIQverbz0	7.2988	0.5689	192	12.83	<.0001
WSIQverbz	4.9720	0.1206	3124	41.21	<.0001

**Interpret each fixed effect:**

SMIQverbz0  $\gamma_{05} =$

WSIQverbz  $\gamma_{10} =$

Estimates						
Label	Estimate	Standard Error	DF	t Value	Pr >  t	
Denomination 2 vs 3	-1.9866	0.5992	165	-3.32	0.0011	
L2 Contextual Effect of Verbal IQ	2.3268	0.5816	210	4.00	<.0001	

Contrasts				
Label	Num DF	Den DF	F Value	Pr > F
Omnibus Test of Verbal IQ (Change in R2)	2	361	931.48	<.0001

\* Calculate PseudoR2 relative to L2 main effects model 2a;  
`%PseudoR2(NCov=2, CovFewer=CovHMD, CovMore=CovIQverb);`

PseudoR2 (% Reduction) for CovHMD vs. CovIQverb							
Name	CovParm	Subject	Estimate	StdErr	ZValue	ProbZ	PseudoR2
CovHMD	UN(1,1)	schoolID	15.9505	2.2126	7.21	<.0001	.
CovHMD	Residual		62.6202	1.5866	39.47	<.0001	.
CovIQverb	UN(1,1)	schoolID	7.9235	1.1341	6.99	<.0001	0.50324
CovIQverb	Residual		40.5184	1.0252	39.52	<.0001	0.35295

\* Calculate TotalR2 relative to L2 main effects model 2a;  
`%TotalR2(DV=langpost, PredFewer=PredHMD, PredMore=PredIQverb);`

Total R2 (% Reduction) for PredHMD vs. PredIQverb

Name	Pred Corr	TotalR2	R2Diff
PredHMD	0.17925	0.03213	.
PredIQverb	0.62673	0.39279	0.36065

**Interpret the results for pseudo-R<sup>2</sup> and total-R<sup>2</sup>:**

**Model 3b: Add L2 Group Mean and L1 Group-MC Student Performance IQ**

$$\text{Level-1: Language}_{pg} = \beta_{0g} + \beta_{1g}(\text{IQverb}_{pg} - \overline{\text{IQverb}}_g) + \beta_{2g}(\text{IQperf}_{pg} - \overline{\text{IQperf}}_g) + e_{pg}$$

$$\text{Level-2: } \beta_{0g} = \gamma_{00} + \gamma_{01}(\text{Homework}_g - 2) + \gamma_{02}(\text{MixedGrade}_g) + \gamma_{03}(\text{Denomlv2}_g) + \gamma_{04}(\text{Denomlv3}_g) \\ + \gamma_{05}(\overline{\text{IQverb}}_g) + \gamma_{06}(\overline{\text{IQperf}}_g) + U_{0g}$$

$$\beta_{1g} = \gamma_{10}$$

$$\beta_{2g} = \gamma_{20}$$

```
TITLE "SAS Model 3b: Add L2 and L1 Student Performance IQ";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
CLASS schoolID studentID;
MODEL langpost = hw2 mixedgra denlv2 denlv3 SMIQverbz0 WSIQverbz SMIQperfz0 WSIQperfz
  / SOLUTION DDFM=Satterthwaite OUTPM=PredIQperf;
RANDOM INTERCEPT / TYPE=UN SUBJECT=schoolID;
CONTRAST "Omnibus Test of Verbal IQ (Change in R2)" SMIQverbz0 1, WSIQverbz 1;
CONTRAST "Omnibus Test of Performance IQ (Change in R2)" SMIQperfz0 1, WSIQperfz 1;
ESTIMATE "Denomination 2 vs 3" denlv2 -1 denlv3 1;
ESTIMATE "L2 Contextual Effect of Verbal IQ" SMIQverbz0 1 WSIQverbz -1;
ESTIMATE "L2 Contextual Effect of Performance IQ" SMIQperfz0 1 WSIQperfz -1;
ESTIMATE "L2 Verbal vs Performance IQ effects" SMIQverbz0 -1 SMIQperfz0 1;
ESTIMATE "L1 Verbal vs Performance IQ effects" WSIQverbz -1 WSIQperfz 1;
ODS OUTPUT CovParms=CovIQperf; RUN; TITLE;
```

```
display as result "STATA Model 3b: Add L2 and L1 Student Performance IQ"
mixed langpost c.hw2 c.mixedgra c.denlv2 c.denlv3 c.SMIQverbz0 ///
  c.WSIQverbz c.SMIQperfz0 c.WSIQperfz, ///
  || schoolID: , variance reml covariance(unstructured) dfmethod(satterthwaite),
  test (c.SMIQverbz0=0) (c.WSIQverbz=0), small // Test Omnibus Verbal IQ
  test (c.SMIQperfz0=0) (c.WSIQperfz=0), small // Test Omnibus Performance IQ
lincom c.denlv2*-1 + c.denlv3*1, small // Denomination 2 vs 3
lincom c.SMIQverbz0*1 + c.WSIQverbz*-1, small // L1 Contextual Effect of Verbal IQ
lincom c.SMIQperfz0*1 + c.WSIQperfz*-1, small // L1 Contextual Effect of Performance IQ
lincom c.SMIQverbz0*-1 + c.SMIQperfz0*1, small // L2 Verbal vs Performance IQ Effects
lincom c.WSIQverbz*-1 + c.WSIQperfz*1, small // L1 Verbal vs Performance IQ Effects
predict PredIQperf, xb
corr langpost PredIQperf
display as result r(rho)^2 // total R2
```

**SAS Results:**

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr >  Z
UN(1,1)	schoolID	7.5625	1.0831	6.98	<.0001
Residual		38.5224	0.9748	39.52	<.0001

  

Information Criteria						
Neg2LogLike	Parms	AIC	AICC	HQIC	BIC	CAIC
21703.0	2	21707.0	21707.0	21709.6	21713.3	21715.3

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	40.9319	0.5173	163	79.13	<.0001
hw2	0.1075	0.4558	162	0.24	0.8138
mixedgra	-1.0148	0.5265	182	-1.93	0.0555
den1v2	1.4167	0.5863	166	2.42	0.0168
den1v3	-0.1733	0.6146	169	-0.28	0.7783
SMIQverbz0	5.9262	0.7072	183	8.38	<.0001
WSIQverbz	4.2895	0.1292	3123	33.19	<.0001
SMIQperfz0	2.8834	0.9191	179	3.14	0.0020
WSIQperfz	1.5946	0.1251	3123	12.75	<.0001

**Interpret each fixed effect:**

SMIQperfz0  $\gamma_{06} =$

WSIQperfz  $\gamma_{20} =$

Label	Estimates		DF	t Value	Pr >  t
	Estimate	Standard Error			
Denomination 2 vs 3	-1.5900	0.5986	167	-2.66	0.0087
L2 Contextual Effect of Verbal IQ	1.6367	0.7189	196	2.28	0.0239
L2 Contextual Effect of Performance IQ	1.2888	0.9275	185	1.39	0.1664
L2 Verbal vs Performance IQ effects	-3.0428	1.4660	178	-2.08	0.0394
L1 Verbal vs Performance IQ effects	-2.6949	0.2139	3123	-12.60	<.0001

Contrasts

Label	Num		Den		F Value	Pr > F
	DF		DF			
Omnibus Test of Verbal IQ (Change in R2)	2		345		585.84	<.0001
Omnibus Test of Performance IQ (Change in R2)	2		336		86.17	<.0001

\* Calculate PseudoR2 relative to verbal IQ model 3a;  
`%PseudoR2(NCov=2, CovFewer=CovIQverb, CovMore=CovIQperf);`

PseudoR2 (% Reduction) for CovIQverb vs. CovIQperf

Name	CovParm	Subject	Estimate	StdErr	ZValue	ProbZ	PseudoR2
CovIQverb	UN(1,1)	schoolID	7.9235	1.1341	6.99	<.0001	.
CovIQverb	Residual		40.5184	1.0252	39.52	<.0001	.
CovIQperf	UN(1,1)	schoolID	7.5625	1.0831	6.98	<.0001	0.045564
CovIQperf	Residual		38.5224	0.9748	39.52	<.0001	0.049261

\* Calculate TotalR2 relative to verbal IQ model 3a;  
`%TotalR2(DV=langpost, PredFewer=PredIQverb, PredMore=PredIQperf);`

Total R2 (% Reduction) for PredIQverb vs. PredIQperf

Name	Pred		Total	
	Corr	TotalR2	R2Diff	
PredIQverb	0.62673	0.39279	.	
PredIQperf	0.65037	0.42298	0.030191	

**Interpret the results for pseudo-R<sup>2</sup> and total-R<sup>2</sup>:**

**Model 3c: Add L2 Group Mean and L1 Group-MC IQ Interactions**

$$\text{Level-1: Language}_{pg} = \beta_{0g} + \beta_{1g}(\text{IQverb}_{pg} - \overline{\text{IQverb}}_g) + \beta_{2g}(\text{IQperf}_{pg} - \overline{\text{IQperf}}_g) \\ + \beta_{3g}(\text{IQverb}_{pg} - \overline{\text{IQverb}}_g)(\text{IQperf}_{pg} - \overline{\text{IQperf}}_g) + e_{pg}$$

$$\text{Level-2: } \beta_{0g} = \gamma_{00} + \gamma_{01}(\text{Homework}_g - 2) + \gamma_{02}(\text{MixedGrade}_g) + \gamma_{03}(\text{Denomlv2}_g) + \gamma_{04}(\text{Denomlv3}_g) \\ + \gamma_{05}(\overline{\text{IQverb}}_g) + \gamma_{06}(\overline{\text{IQperf}}_g) + \gamma_{07}(\overline{\text{IQverb}}_g)(\overline{\text{IQperf}}_g) + U_{0g}$$

$$\beta_{1g} = \gamma_{10}$$

$$\beta_{2g} = \gamma_{20}$$

$$\beta_{3g} = \gamma_{30}$$

```
TITLE "SAS Model 3c: Add L2 and L1 IQ Interactions";
PROC MIXED DATA=work.StudentsSchools NOCLPRINT COVTEST NAMELEN=100 IC METHOD=REML;
CLASS schoolID studentID;
MODEL langpost = hw2 mixedgra denlv2 denlv3 SMIQverbz0 WSIQverbz SMIQperfz0 WSIQperfz
              SMIQverbz0*SMIQperfz0 WSIQverbz*WSIQperfz
              / SOLUTION DDFM=Satterthwaite OUTPM=PredIQxIQ COVB;
RANDOM INTERCEPT / TYPE=UN SUBJECT=schoolID; * COVB for regions of significance macro;
CONTRAST "Omnibus Test of IQ Interactions (Change in R2)"
          SMIQverbz0*SMIQperfz0 1, WSIQverbz*WSIQperfz 1;
ESTIMATE "Denomination 2 vs 3" denlv2 -1 denlv3 1;
ESTIMATE "L2 Simple Contextual Effect of Verbal IQ"      SMIQverbz0 1 WSIQverbz -1;
ESTIMATE "L2 Simple Contextual Effect of Performance IQ" SMIQperfz0 1 WSIQperfz -1;
* Get simple slopes of L2 IQ perf at representative values of L2 IQ verb;
ESTIMATE "L2 IQ perf effect at L2 IQ verbz = -1" SMIQperfz0 1 SMIQverbz0*SMIQperfz0 -1;
ESTIMATE "L2 IQ perf effect at L2 IQ verbz = 0" SMIQperfz0 1 SMIQverbz0*SMIQperfz0 0;
ESTIMATE "L2 IQ perf effect at L2 IQ verbz = 1" SMIQperfz0 1 SMIQverbz0*SMIQperfz0 1;
* Get simple slopes of L1 IQ perf at representative values of L1 IQ verb;
ESTIMATE "L1 IQ perf effect at L1 IQ verbz = -1" WSIQperfz 1 WSIQverbz*WSIQperfz -1;
ESTIMATE "L1 IQ perf effect at L1 IQ verbz = 0" WSIQperfz 1 WSIQverbz*WSIQperfz 0;
ESTIMATE "L1 IQ perf effect at L1 IQ verbz = 1" WSIQperfz 1 WSIQverbz*WSIQperfz 1;
* Save info for R2 and regions of significance macro;
ODS OUTPUT CovParms=CovIQxIQ SolutionF=FixIQxIQ CovB=CovBIQxIQ; RUN; TITLE;
```

```
display as result "STATA Model 3c: Add L2 and L1 IQ Interactions"
mixed langpost c.hw2 c.mixedgra c.denlv2 c.denlv3 c.SMIQverbz0 c.WSIQverbz c.SMIQperfz0 c.WSIQperfz ///
              c.SMIQverbz0#c.SMIQperfz0 c.WSIQverbz#c.WSIQperfz, ///
|| schoolID: , variance reml covariance(unstructured) dfmethod(satterthwaite),
test (c.SMIQverbz0#c.SMIQperfz0) (c.WSIQverbz#c.WSIQperfz), small // Test Omnibus Interactions
lincom c.denlv2*-1 + c.denlv3*1, small // Denomination 2 vs 3
// Get simple slopes of L2 IQ perf at representative values of L2 IQ verb
lincom c.SMIQperfz0*1 + c.SMIQperfz0#c.SMIQverbz0*-1, small // L2 IQ perf effect at L2 IQ verbz = -1
lincom c.SMIQperfz0*1 + c.SMIQperfz0#c.SMIQverbz0*0, small // L2 IQ perf effect at L2 IQ verbz = 0
lincom c.SMIQperfz0*1 + c.SMIQperfz0#c.SMIQverbz0*1, small // L2 IQ perf effect at L2 IQ verbz = 1
// Get simple slopes of L1 IQ perf at representative values of L1 IQ verb
lincom c.WSIQperfz*1 + c.WSIQperfz#c.WSIQverbz*-1, small // L1 IQ perf effect at L1 IQ verbz = -1
lincom c.WSIQperfz*1 + c.WSIQperfz#c.WSIQverbz*0, small // L1 IQ perf effect at L1 IQ verbz = 0
lincom c.WSIQperfz*1 + c.WSIQperfz#c.WSIQverbz*1, small // L1 IQ perf effect at L1 IQ verbz = 1
estat vce // Aymptotic covariance matrix of fixed effects for regions
predict PredIQxIQ, xb
corr langpost PredIQxIQ
display as result r(rho)^2 // total R2
```

**SAS Results (presented in a more convenient order for interpretation):**

Neg2LogLike	Parms	Information Criteria				
		AIC	AICC	HQIC	BIC	CAIC
21692.3	2	21696.3	21696.3	21698.9	21702.7	21704.7



		Contrasts		Num	Den		
Label		DF	DF	F Value	Pr > F		
Omnibus Test of IQ Interactions (Change in R2)		2	380	5.73	0.0035		

Covariance Parameter Estimates				
Cov Parm	Subject	Estimate	Standard Error	Z Value
UN(1,1)	schoolID	7.2581	1.0518	6.90
Residual		38.4731	0.9737	39.51

Intraclass Correlation as provided by VCORR:

$$ICC = \frac{7.2581}{7.2581 + 38.4731} = .1587$$

**Design effect** using mean #students per school:  $= 1 + ((n - 1) * ICC) \rightarrow 1 + [(18-1)*.1587] = 3.698$

**Effective sample size:**  $N_{\text{effective}} = (\# \text{Total Obs}) / \text{Design Effect} \rightarrow 3,305 / 3.698 = 893$

**Our conditional model has reduced the design effect because a greater proportion of level-2 random intercept variance was explained (60.80%) relative to level-1 residual variance (38.56%). This means that our power to detect level-1 effects has improved—it is currently approximately that of an independent sample of 893 students (versus 677 from the empty means model).**

*\* Calculate PseudoR2 relative to empty means model 1b;*  
`%PseudoR2(NCov=2, CovFewer=CovEmpty, CovMore=CovIQxIQ);`

PseudoR2 (% Reduction) for CovEmpty vs. CovIQxIQ

Name	CovParm	Subject	Estimate	StdErr	ZValue	ProbZ	PseudoR2
CovEmpty	UN(1,1)	schoolID	18.5134	2.4694	7.50	<.0001	.
CovEmpty	Residual		62.6200	1.5866	39.47	<.0001	.
CovIQxIQ	UN(1,1)	schoolID	7.2581	1.0518	6.90	<.0001	0.60795
CovIQxIQ	Residual		38.4731	0.9737	39.51	<.0001	0.38561

*\* Calculate PseudoR2 relative to main effects IQ model 3b;*  
`%PseudoR2(NCov=2, CovFewer=CovIQperf, CovMore=CovIQxIQ);`

PseudoR2 (% Reduction) for CovIQperf vs. CovIQxIQ

Name	CovParm	Subject	Estimate	StdErr	ZValue	ProbZ	PseudoR2
CovIQperf	UN(1,1)	schoolID	7.5625	1.0831	6.98	<.0001	.
CovIQperf	Residual		38.5224	0.9748	39.52	<.0001	.
CovIQxIQ	UN(1,1)	schoolID	7.2581	1.0518	6.90	<.0001	0.040248
CovIQxIQ	Residual		38.4731	0.9737	39.51	<.0001	0.001282

*\* Calculate TotalR2 relative to main effects IQ model 3b;*  
`%TotalR2(DV=langpost, PredFewer=PredIQperf, PredMore=PredIQxIQ);`

Total R2 (% Reduction) for PredIQperf vs. PredIQxIQ

Name	Pred Corr	TotalR2	Total R2Diff
PredIQperf	0.65037	0.42298	.
PredIQxIQ	0.65393	0.42762	.004646174

**Interpret the results for pseudo-R<sup>2</sup> and total-R<sup>2</sup>:**

Solution for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	41.0988	0.5120	166	80.27	<.0001
hw2	0.1549	0.4491	161	0.34	0.7306
mixedgra	-0.8030	0.5265	183	-1.53	0.1289
den1v2	1.4829	0.5784	165	2.56	0.0112
den1v3	-0.09376	0.6059	168	-0.15	0.8772
SMIQverbz0	5.3809	0.7269	177	7.40	<.0001
WSIQverbz	4.2784	0.1293	3123	33.10	<.0001
SMIQperfz0	2.8136	0.9058	177	3.11	0.0022
WSIQperfz	1.6068	0.1251	3123	12.84	<.0001
SMIQverbz0*SMIQperfz0	-2.2914	0.9280	203	-2.47	0.0144
WSIQverbz*WSIQperfz	-0.2806	0.1197	3205	-2.34	0.0192

**Interpret each fixed effect:**

SMIQverbz0  $\gamma_{05} =$

SMIQperfz0  $\gamma_{06} =$

SMIQverbz0 \*SMIQperfz0  $\gamma_{07} =$

WSIQverbz  $\gamma_{10} =$

WSIQperfz  $\gamma_{20} =$

WSIQverbz\*WSIQperfz  $\gamma_{30} =$

Label	Estimates		DF	t Value	Pr >  t
	Estimate	Standard Error			
Denomination 2 vs 3	-1.5766	0.5894	166	-2.68	0.0082
L2 Simple Contextual Effect of Verbal IQ	1.1026	0.7382	188	1.49	0.1370
L2 Simple Contextual Effect of Performance IQ	1.2068	0.9144	184	1.32	0.1885
L2 IQ perf effect at L2 IQ verb z = -1	5.1051	1.2713	198	4.02	<.0001
L2 IQ perf effect at L2 IQ verb z = 0	2.8136	0.9058	177	3.11	0.0022
L2 IQ perf effect at L2 IQ verb z = 1	0.5222	1.3219	183	0.40	0.6933
L1 IQ perf effect at L1 IQ verb z = -1	1.8874	0.1767	3167	10.68	<.0001
L1 IQ perf effect at L1 IQ verb z = 0	1.6068	0.1251	3123	12.84	<.0001
L1 IQ perf effect at L1 IQ verb z = 1	1.3262	0.1696	3163	7.82	<.0001

Covariance Matrix for Fixed Effects needed for Regions goes here, omitted to save space

**\* Calculate regions of significance for effect of L2 IQperf;**

```
%Regions(FixData=FixIQxIQ,CovBData=CovBIQxIQ,Pred=SMIQperfz0,
Mod=SMIQverbz0,ModCenter=0,Interact=SMIQverbz0*SMIQperfz0,Order=9);
```

**Regions of significance for SMIQverbz0\*SMIQperfz0 interaction:**

The effect of SMIQperfz0 will be significant at centered values of SMIQverbz0 BELOW the lower bound and ABOVE the upper bound, which translate to these uncentered lower and upper bounds.

Centered Lower	Centered Upper	Uncentered Lower	Uncentered Upper
0.38421	6.38428	0.38421	6.38428

**Level-2 Regions of Significance Result:** This means that the school-level effect of performance IQ will be significantly positive for school mean verbal IQ  $z \leq 0.38$ , nonsignificant for schools between  $z = 0.38$  and  $z = 6.38$ , and significantly negative for school mean verbal IQ  $z \geq 6.38$ . Thus, for a little over half of the schools (school mean verbal IQ  $z \leq 0.38$ ), having greater mean performance IQ than other schools is predicted to help their mean language. For the rest of the schools (school mean verbal IQ  $z > 0.38$ ), greater school mean performance IQ than other schools is not predicted to help their mean language.

```
* Calculate regions of significance for effect of L1 IQperf;
%Regions(FixData=FixIQxIQ,CovBData=CovBIQxIQ,Pred=WSIQperfz,
Mod=WSIQverbz,ModCenter=0,Interact= WSIQverbz*WSIQperfz,Order=10);
```

**Regions of significance for WSIQverbz\*WSIQperfz interaction:**

The effect of WSIQperfz will be significant at centered values of WSIQverbz BELOW the lower bound and ABOVE the upper bound, which translate to these uncentered lower and upper bounds.

Centered Lower	Centered Upper	Uncentered Lower	Uncentered Upper
3.05751	34.8995	3.05751	34.8995

**Level-1 Regions of Significance Result:** This means that the student-level effect of performance IQ will be significantly positive for within-school verbal IQ  $z \leq 3.06$ , nonsignificant for students between  $z = 3.06$  and  $z = 34.90$ , and significantly negative for within-school verbal IQ  $z \geq 34.90$ . Thus, for the vast majority of students (within-school verbal IQ  $z \leq 3.06$ ), having greater performance IQ than other students in their school is predicted to help their language. Only for very few students (within-school verbal IQ  $z > 3.06$ ) is greater performance IQ than other students in their school not predicted to help their language.

## Sample Results Section [indicates notes about what to customize or also include]

The extent to which the extent to which student language at post-test could be predicted from school-level variables of homework amount, denomination (three types), and use of mixed-grade classes, as well as student-level predictors of verbal IQ and performance IQ, was examined in a series of multilevel models in which the 3,305 students were modeled as nested within their 178 schools. Restricted Maximum likelihood (REML) within SAS [or STATA] MIXED was used in estimating and reporting all model parameters. The significance of fixed effects was evaluated with univariate and multivariate Wald using Satterthwaite denominator degrees of freedom, whereas random effects were evaluated via likelihood ratio tests (i.e.,  $-2\Delta LL$  with degrees of freedom equal to the number of new random effects variances and covariances). Alpha was chosen as .05. Model-implied fixed effects were requested via ESTIMATE [or LINCOM] statements. Effect size for the fixed effects was evaluated via pseudo- $R^2$  values for the proportion reduction in each variance component, as well as with total- $R^2$ , the squared correlation between actual language and language as predicted by the model fixed effects.

As derived from an empty means, random intercept model, student language had an intraclass correlation of  $ICC = .228$ , indicating that 22.8% of the variance in student language was between schools, a significant amount,  $-2\Delta LL(1) = 436.79$ ,  $p < .001$ . We first added the school-level predictors of homework amount (centered at 2), denomination (three types; Type 1 was the reference), and use of mixed-grade classes (none as the reference) to the model predicting the level-2 random intercept. These four fixed effects accounted for significant variance overall,  $F(4, 162) = 6.68$ ,  $p < .001$ , including 13.8% of the level-2 random intercept variance and 3.21% of the total variance. The variance accounted for remained significant after controlling for the effect of homework amount (which was not significant),  $F(3, 164) = 8.28$ ,  $p < .001$ . Schools that used mixed-grade classes had significantly lower average language (Est =  $-2.01$ , SE = 0.73). The effect of denomination was significant as well,  $F(2, 159) = 6.61$ ,  $p < .002$ . Type 2 schools had significantly higher language than both Type 1 schools (Est = 2.74, SE = 0.81) and Type 3 schools (Est = 2.27, SE = 0.83), which did not differ. We then examined an interaction between the use of mixed-grade classes and denomination, but given that none of the interaction contrasts were significant,  $F(2, 172) = 1.26$ ,  $p = .287$ , change in pseudo- $R^2 < .004$ , this interaction was removed.

We then examined the sources of variance in the student-level IQ predictors (which were each z-scored to create comparable scales). An empty means, random intercept model indicated  $ICC = .120$  for verbal IQ and  $ICC = .048$  for performance IQ; both ICCs were significant ( $-2\Delta LL$   $p$ 's  $< .001$ ). Thus, we included IQ predictor effects at both levels—the

school mean of IQ captured the between-school effect at level 2, and student IQ centered at the school mean captured the within-school effect at level 1. We first added effects at both levels for verbal IQ, which contributed significantly to the model overall,  $F(2, 361) = 931.48, p < .001$ , change in total- $R^2 = .361$ ; each effect was significant. At level 2, schools with higher mean student verbal IQ than other schools had higher language on average (Est = 7.30, SE = 0.57), which accounted for an additional 50.3% of the remaining level-2 random intercept variance. At level 1, students with higher verbal IQ than other students in their school also had higher language than other students in their school (Est = 4.97, SE = 0.12), which accounted for 35.3% of the remaining level-1 residual variance. The contextual level-2 effect (Est = 2.33, SE = 0.58) indicated that the level-2 school verbal IQ effect was significantly greater than the level-1 student verbal IQ effect (i.e., a significantly positive incremental effect of school mean verbal IQ after controlling for student verbal IQ). With respect to the previous predictors, the effect of homework amount remained nonsignificant, the advantage for Type 2 schools remained significant, and the effect of using mixed-grade classes became nonsignificant.

We then added effects at both levels for performance IQ, which contributed significantly to the model overall,  $F(2, 336) = 86.17, p < .001$ , change in total- $R^2 = .031$ ; each effect was significant. At level 2, schools with higher mean student performance IQ than other schools had higher language on average (Est = 2.88, SE = 0.92), which accounted for an additional 4.56% of the remaining level-2 random intercept variance. At level 1, students with higher performance IQ than other students in their school also had higher language than other students in their school (Est = 1.59, SE = 0.13), which accounted for 4.93% of the remaining level-1 residual variance. The contextual level-2 effect (Est = 1.29, SE = 0.93) was not significant, indicating equivalent effects of level-2 and level-1 performance IQ (i.e., no significant incremental effect of school mean performance IQ after controlling for student performance IQ). The unique effects of verbal IQ remained significant (level-2: Est = 5.93, SE = 0.71; level-1: Est = 4.29, SE = 0.13) and were also significantly larger than the unique effects of performance IQ (level-2 difference: Est = 3.04, SE = 1.47; level-1 difference: Est = 2.69, SE = 0.21). With respect to the previous predictors, the effect of homework amount remained nonsignificant, the advantage for Type 2 schools remained significant, and the effect of using mixed-grade classes remained nonsignificant.

Finally, we considered the interaction between verbal IQ and performance IQ at each level. This final model is given in [provide Equation for Model 3c] and results are shown in Table X [table should provide estimates, SEs, and  $p$ -values (or stars or bold font) for all model parameters, including variance parameters]. The final model accounted for 60.8% of the level-2 random intercept variance, 38.6% of the level-1 residual variance, and 42.8% of the overall language variance. With respect to the previous predictors, the effect of homework amount remained nonsignificant, the advantage for Type 2 schools remained significant, and the effect of using mixed-grade classes remained nonsignificant. The two new IQ interactions which contributed significantly to the model overall,  $F(2, 380) = 5.73, p < .004$ , change in total- $R^2 = .005$ ; each interaction was significant. Regions of significance were then calculated to describe the range of simple effects of performance IQ implied by these interactions. First, at level 2, the effect of school mean performance IQ (of Est = 2.81, SE = 0.91 for school mean verbal IQ = 0) became significantly weaker (less positive) by 2.29 (SE = 0.93) for every unit higher school mean verbal IQ, which accounted for 4.02% of the remaining level-2 random intercept variance. Regions of significance for the level-2 interaction indicated that the school-level effect of performance IQ will be significantly positive for schools with mean verbal IQ  $z \leq 0.38$ , nonsignificant for schools between  $z = 0.38$  and  $z = 6.38$ , and significantly negative for schools with mean verbal IQ  $z \geq 6.38$ . Thus, for a little over half of the schools (school mean verbal IQ  $z \leq 0.38$ ), having greater mean performance IQ than other schools is predicted to help their mean language. For the rest of the schools (school mean verbal IQ  $z > 0.38$ ), greater school mean performance IQ than other schools is not predicted to help their mean language. Next, at level 1, the effect of student performance IQ (of Est = 1.61, SE = 0.13 at within-school student verbal IQ = 0) also became significantly weaker (less positive) by 0.29 (SE = 0.12) for every unit higher within-school student verbal IQ, which accounted for .001% of the remaining level-1 residual variance. Regions of significance for the level-1 interaction indicated that student-level effect of performance IQ will be significantly positive for within-school verbal IQ  $z \leq 3.06$ , nonsignificant for students between  $z = 3.06$  and  $z = 34.90$ , and significantly negative for within-school verbal IQ  $z \geq 34.90$ . Thus, for the vast majority of students (within-school verbal IQ  $z \leq 3.06$ ), having greater performance IQ than other students in their school is predicted to help their language. Only for very few students (within-school verbal IQ  $z > 3.06$ ) is greater performance IQ than other students in their school not predicted to help their language.