

Multi-level intervention study data and PROC MIXED

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Section 1: Introduction

One of the prominent goals of early intervention research is to identify programs that help young people cope with problems they are likely to encounter, as they grow older. This paper focuses on how to analyze data that is often collected in these studies although the principles apply to many other studies. One of the most frequent locations for early intervention studies is in schools. In these studies, students are recruited from schools and/or classrooms within schools. One way to describe this data structure is to describe the students as being “nested” with classrooms which are in turn, nested within schools. The “nesting” can also be described as a hierarchical (or multilevel) dataset and the statistical model used to analyze such data is described as a hierarchical linear model (HLM). These types of models are also described as Mixed models that contain fixed and random factors. In the SAS system®, Proc Mixed is capable of analyzing these types of data structures. Singer (1999) notes that Proc Mixed follows the language of the physical and biological sciences more than the HLM terminology, which originated in the social and behavioral sciences, especially for education researchers. The key issue with the hierarchical levels of data is that measurements on students (or observation units) within each hierarchical level are not independent from other students that belong to their particular random or nested effect (e.g., classroom or school).

In a simple case, where we have one school and a set of randomly selected classrooms, students nested within particular classrooms are more likely to be similar to each other than with students selected from other classrooms. As a result, using the standard ANOVA model would be problematic because one of the key assumptions would be violated: the assumption that the residuals are independent of each other. To resolve this issue, the HLM or Mixed statistical model has been developed and SAS has implemented it in Proc Mixed.

Section 2: Several Key Issues for Intervention Study

Study Design

The basic design for most intervention studies is to measure one group receiving the intervention and another group which doesn't receive the intervention at pre-test (prior to the intervention) and then again at post-test (after the intervention is complete). In the example used in this study, The Intervention and Reference groups are assessed at three timepoints. In Table 1, the design of the example is shown with 'X' showing that a Group receives the assessment or intervention and 'O' showing that the intervention was not received. Lipsey (1990) identifies several factors that can increase the statistical power to detect the intervention effect.

Table 1: Experimental Design

<u>Group</u>	<u>Pre-test Assessment</u>	<u>Intervention</u>	<u>Mid-point Assessment</u>	<u>Intervention</u>	<u>Post-test Assessment</u>
Intervention	X	X	X	X	X
Reference	X	O	X	O	X

Power Analysis

One of the key issues for intervention research is to make sure that the study design will be sensitive enough to detect the expected difference. The SAS system® does not contain a power analysis module for the Mixed model. However, there is a web site that has this capability. The URL is:

<http://yates.coph.usf.edu/research/psmg/web.htm>

Level of Analysis

Another key aspect of the Mixed model is that predictors can exist at the different “levels” of the data (Kreft & de Leeuw, 1998). For example, a predictor could relate to the individual in the study such as whether they receive a free lunch due to family income versus not receiving a free lunch. In addition, there can be predictors related to one of the higher levels of the data. For example, the percentage of students receiving a free lunch could be calculated for each classroom or school.

Section 3: Expect Respect Project Example

The dataset being used for this paper was collected as part of the Expect Respect Project which was developed by SafePlace: Domestic Violence & Sexual Assault Survival Center and funded by Centers for Disease Control and Prevention. The data were collected from 5th graders from six schools in the intervention group and six schools in the reference group. The key question is: Do students in the Expect/Respect intervention show increased awareness of sexual harassment relative to students in the reference?

Data:

The following SAS code illustrates how to print out the data to illustrate values associated with each variable to be used in this analysis (there were several hundred variables in the study). The new output delivery system (ODS) is used to directly create a file in RTF format containing a table that can be directly read by MS Word.

```
ods rtf file='u:\personal\scsug\data\rtf';
proc print data = csur.newnlm2 (obs=9) noobs split=
  label sxhrs= Sexual Harassment Knowledge Score
  label ntime= Measurement Point
  label type= Intervention versus Reference Group
  label id= Student ID
  label school= School number
  label classrm= Classroom number
  var id school CLASSRM type ntime sxhrs;
run;
ods rtf close;
```

Table 2 shows the values for the first nine observations in the dataset. There are up to three observations for each unique value of Student Id. The three different levels for this dataset are: student, classroom and school. The Sexual Harassment Knowledge scores can vary from 0 to 9 although most scores ranged from 5 to 9.

Table 2: First 9 Observations from Safe Place/CSWR Expect Respect Project Data 1999-2000 School Year

Student ID	School number	Classroom number	Intervention versus Reference Group 1=Intervent 0=Reference	Measurement Point 1=Pre-test 2=Midpoint 3=Post-test	Sexual Harassment Knowledge Score
70887	21	1	0	1	6
70887	21	1	0	2	8
70887	21	1	0	3	8
70890	21	1	0	1	6
70890	21	1	0	2	8
70890	21	1	0	3	6
70895	21	1	0	1	7
70895	21	1	0	2	8
70895	21	1	0	3	8

Data Visualization

One recommended strategy before conducting the analysis is to try to visualize the pattern of change across time. In this data set with several hundred observations, plotting all individual student data on one plot may conceal any patterns. One solution would be to randomly select of subset of the individual observations, and plot those. In this example, another strategy is used which was to calculate the mean sexual harassment score by classroom and plot the means scores across the three measurement points. The following SAS code illustrates how to summarize and plot the data.

```
proc sort data = cswr.newhlm2;
  by classrm ntime ;
run;
**Summarize scores by classroom and assessment time**
proc means data = cswr.newhlm2 noprint ;
  where type ^= . and classrm ^= . ;
  var sxhrs ;
  output out = sxhrs_class mean= ;
  by classrm ntime ;
run;

options reset=all rotate=landscape transparency cback=white;
symbol1 r=40 value = square line=1 color = blue i=join ;
axis1 order=(4 to 9 by 1) label=(angle=90 height=1.5 font=swiss );
axis2 order=(1 to 3) offset=(8,8) minor=none label=(height=1.25 font=swiss );
```

```

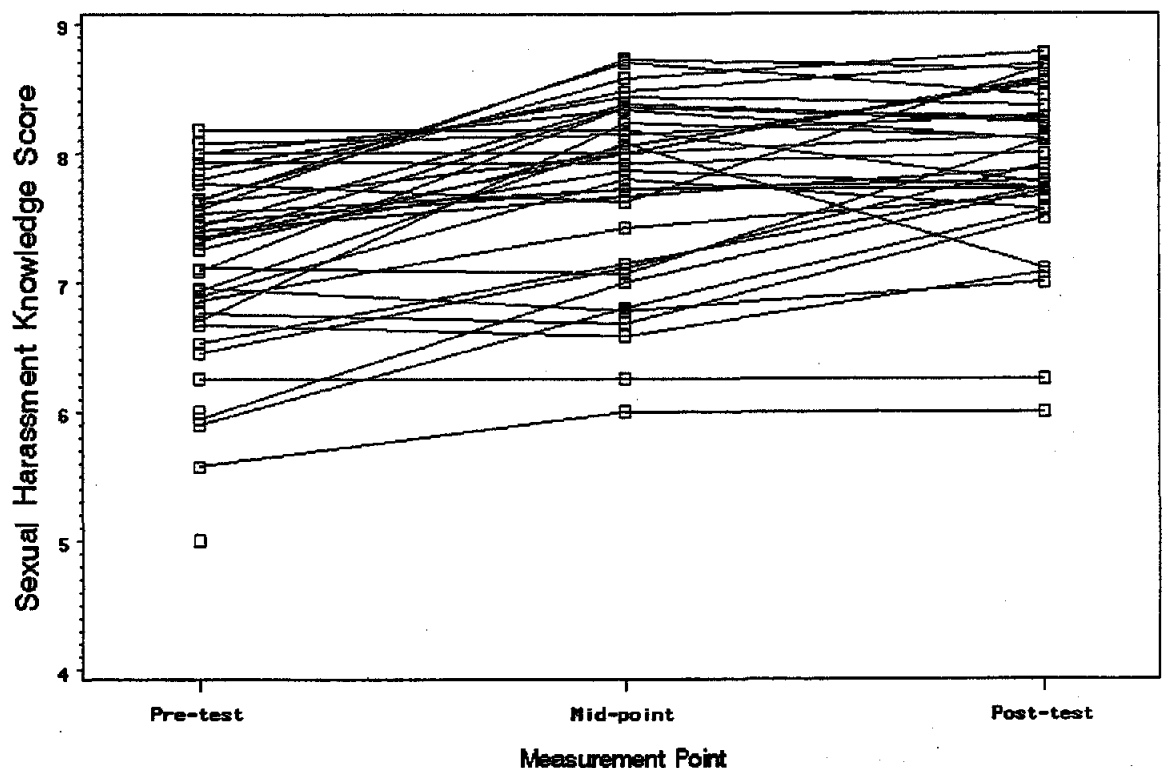
proc gplot data = sxhrs_class ;
  label sxhrs='Sexual Harassment Knowledge Score';
  label ntime='Measurement Point';
  label type='Intervention versus Reference Group';
  format type ftype. ntime fntime. ;
  plot sxhrs*ntime=classrm / vaxis=axis1 haxis=axis2 nolegend ;
  title1 font=swiss height=1.5
  'CSWR Project: Analyzing Safe Place Project Data for YEAR 2';
  title2 font=swiss height=1.5
  'Plot of Mean Sexual Harassment Knowledge by Classroom across Time';
run;

```

Figure 1 shows the results of the **Proc Gplot** code illustrated above. The plot does show a fair amount of variation by classroom across time which indicates that classrooms are likely to contribute an important amount of unique variation.

Figure 1: Variation by classroom across time.

CSWR Project: Analyzing Safe Place Project Data for YEAR 2
 Plot of Mean Sexual Harassment Knowledge by Classroom across Time



Proc Mixed Models

The model building strategy described by Singer (1999) was used to first estimate the unconditional means model with no fixed effects and then the conditional means model to test the fixed effects of *Group* (Intervention versus Reference group), *Ntime* (Pre-test, Mid-point, and Post-test), and the *Group*Ntime interaction*. These fixed effects will be specified on the **Model** statement in the Proc Mixed syntax. The random effects will be specified

with a **Random** statement and will include the *School* effect and the Classroom effect (*Classrm*). The specification of the within subject effect (*Ntime*) can be treated using a **Repeated** statement or a **Random** statement. Both examples will be illustrated below.

Repeated Measures Model

Within **Proc Mixed**, the repeated measures model can be used to account for the within-subject correlation of scores. The repeated measures model employs the **Repeated** statement to specify this type of model.

Model 1: Unconditional Means Model

In the following example, there are no fixed effects so that the variance and covariance estimates are not conditioned on any fixed effects. In addition, there are separate **Random** statements for the *School* and *Classrm* random variables. For each of the **Random** statements, a separate **Subject** is specified corresponding to the effect that is being tested. In addition, there is an *intercept* specified on these statements indicating that the random deviation from the grand mean is to be estimated for each level of the respective random effect. This is the key issue to specify a three-level model within SAS (Singer, 1999).

The **covtest** keyword requests a Z test for the variance and covariance components. The **noclprint** keyword requests that the class level information be suppressed in the output. Finally, the **method=ml** request that Maximum Likelihood estimation be used (the REML method is the default). The ML method allows comparisons of nested models with different fixed effects by using a log-likelihood difference test (see Littell et al., 1996 for more information).

```
proc mixed data=cswr.NEWHLM2 covtest noclprint method = ml ;
  class id school classrm ;
  model sxhrs = / solution ;
  random intercept / subject = school;
  random intercept / subject = classrm(SCHOOL);
  repeated ntime / subject = id(classrm*school) type=un ;
  title1 'Safe Place/CSWR Expect Respect Project Data 1999-2000 School Year';
  title2 'Repeated Measures Model 1: Unconditional Means Model ';
run;
```

Selected Proc Mixed results are described below. It is useful to note that each of these pieces of output constitute a separate table in the ODS system. An illustration will be provided below on how to use this method to compare different error terms for the variance-covariance matrix of the residuals. The "Model Information" and "Dimensions" tables which provide information on the basic inputs into the model are not shown.

The covariance parameter estimates are important in evaluating the magnitude of the different variance components. The first two estimates and associated statistical significance tests show that there doesn't appear to be statistically significant variance for schools (although this test has low power to detect this difference due to the small number of schools). By contrast, the test for the classrooms within schools in the table below shows that the variation in Figure 1 does appear to be statistically significant. The variance parameters UN(1,1), UN(2,2), and UN(3,3) reflect the estimates for Time 1, Time 2, and Time 3 variances respectively. The UN(2,1), UN(3,1), and

UN(3,2) reflect the covariance estimates between Time 1, Time 2, and Time 3 respectively. All of these were statistically significant. It appears that the variance increased from Times 1 and 2 to Time 3.

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	SCHOOL	0.2298	0.1446	1.59	0.0560
Intercept	CLASSRM(SCHOOL)	0.08539	0.03879	2.20	0.0139
UN(1,1)	ID(SCHOOL*CLASSRM)	1.3646	0.08671	15.74	<.0001
UN(2,1)	ID(SCHOOL*CLASSRM)	0.4294	0.07056	6.09	<.0001
UN(2,2)	ID(SCHOOL*CLASSRM)	1.3666	0.09213	14.83	<.0001
UN(3,1)	ID(SCHOOL*CLASSRM)	0.3832	0.08033	4.77	<.0001
UN(3,2)	ID(SCHOOL*CLASSRM)	0.2830	0.08008	3.53	0.0004
UN(3,3)	ID(SCHOOL*CLASSRM)	2.1755	0.1287	16.90	<.0001

The following **Fit Statistics** information provides a method of comparing non-nested models and will be used when we look at the best error structure for the **Repeated** statement.

Fit Statistics	
-2 Log Likelihood	5621.8
AIC (smaller is better)	5639.8
AICC (smaller is better)	5639.9
BIC (smaller is better)	5641.6

The **Solution for Fixed Effects** table shows the estimate for the overall grand mean. The estimate is 7.52 which indicates that most students were getting about 7.5 out of 9 questions correct.

Solution for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	7.5173	0.1779	8	42.25	<.0001

Model 2: Test of Intervention Effect

In Model 2, we test the fixed effects: *Group*, *Ntime*, and the *Group X Ntime* interaction. In addition, this model also includes the use of the **Lsmeans** statement to provide a test of the simple main effects and the expected values for each group at each timepoint.

```
proc mixed data=cswr.NEWHLM2 covtest noclprint method = ml ;
  format group fgroup. ntime fntime. ;
  class id school classrm group ntime ;
  model sxhrs = group|ntime / solution ;
  random intercept / subject = school type=vc ;
  random intercept / subject = classrm(SCHOOL) type=vc ;
  repeated ntime / subject = id(classrm*school) type=un ;
  lsmeans group|ntime / diff adjust = tukey ; /* Test of simple effects */
  lsmeans ntime*group ; /* Estimate least squares means for interaction */
  title1 'Safe Place/CSWR Expect Respect Project Data 1999-2000 School Year';
  title2 'Repeated Measures Model 2: Test of Intervention Effect ' ;
run;
```

The following covariance parameter estimates can be compared to those from Model 1 to examine if the addition of the fixed effects explains either the variances or covariances (Singer, 1999). For example, the variance estimate for school was 0.2298 for Model 1 (unconditional means model) and 0.1984 for Model 2 containing the fixed effects. The fixed effects explained 14% of the explainable variation between schools $[(0.2298 - 0.1984) / 0.2298]$.

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	SCHOOL	0.1984	0.1209	1.64	0.0504
Intercept	CLASSRM(SCHOOL)	0.07794	0.03668	2.12	0.0168
UN(1,1)	ID(SCHOOL*CLASSRM)	1.9626	0.1108	17.72	<.0001
UN(2,1)	ID(SCHOOL*CLASSRM)	0.4425	0.07508	5.89	<.0001
UN(2,2)	ID(SCHOOL*CLASSRM)	1.3453	0.08481	15.86	<.0001
UN(3,1)	ID(SCHOOL*CLASSRM)	0.4342	0.07498	5.79	<.0001
UN(3,2)	ID(SCHOOL*CLASSRM)	0.4094	0.06626	6.18	<.0001
UN(3,3)	ID(SCHOOL*CLASSRM)	1.2854	0.08370	15.36	<.0001

The **Solution for Fixed Effects** table shows no statistically significant effect for *Group*, Time 1 and Time 2 do statistically significantly differ from Time 3, and there was a statistically significant interaction effect for the Intervention group indicating there was statistically significantly lower at Time 1 compared to Time 3.

Solution for Fixed Effects							
Effect	group	ntime	Estimate	Standard Error	DF	t Value	Pr > t
Intercept			7.6356	0.2380	7	32.08	<.0001
group	Intervention		0.3890	0.3404	1655	1.14	0.2533
group	Reference		0	.	.	.	.
ntime		Time 1	-0.5760	0.09737	1655	-5.92	<.0001
ntime		Time 2	-0.2957	0.08968	1655	-3.30	0.0010
ntime		Time 3	0	.	.	.	.
group*ntime	Intervention	Time 1	-0.3084	0.1305	1655	-2.36	0.0182
group*ntime	Intervention	Time 2	0.1661	0.1209	1655	1.37	0.1698
group*ntime	Intervention	Time 3	0	.	.	.	.
group*ntime	Reference	Time 1	0	.	.	.	.
group*ntime	Reference	Time 2	0	.	.	.	.
group*ntime	Reference	Time 3	0	.	.	.	.

The Type 3 tests provide a combined test for those categorical variables with more than two levels (e.g., *Ntime*).

Type 3 Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
group	1	1655	1.05	0.3050
ntime	2	1655	64.76	<.0001
group*ntime	2	1655	6.83	0.0011

The Least Squares Means table shows the estimates for the means for *Group*, *Ntime* at all three timepoints, and the *Group X Ntime* interaction. The biggest change in means appears from Time 1 to Time 2. The separate estimates for means for Intervention versus Reference groups indicates that most change for the intervention group appeared to occur from Time 1 to Time 2 while the Reference group

Least Squares Means							
Effect	group	ntime	Estimate	Standard Error	DF	t Value	Pr > t
group	Intervention		7.6866	0.2388	1655	32.19	<.0001
group	Reference		7.3451	0.2319	1655	31.67	<.0001
ntime		Time 1	7.0999	0.1710	1655	41.52	<.0001
ntime		Time 2	7.6175	0.1700	1655	44.80	<.0001
ntime		Time 3	7.8301	0.1702	1655	46.00	<.0001
group*ntime	Intervention	Time 1	7.1402	0.2447	1655	29.18	<.0001
group*ntime	Intervention	Time 2	7.8950	0.2430	1655	32.49	<.0001
group*ntime	Intervention	Time 3	8.0246	0.2434	1655	32.97	<.0001
group*ntime	Reference	Time 1	7.0597	0.2389	1655	29.55	<.0001
group*ntime	Reference	Time 2	7.3399	0.2379	1655	30.86	<.0001
group*ntime	Reference	Time 3	7.6356	0.2380	1655	32.08	<.0001

The following LSMEANS output give the Tukey post-hoc adjusted pvalues for the comparisons of the main effects.

Effect	group	ntime	_group	_ntime	Adj P
group	Intervention		Reference		0.3050
ntime		Time 1		Time 2	<.0001
ntime		Time 1		Time 3	<.0001
ntime		Time 2		Time 3	0.0013

The test of simple main effects shows that there was a statistically significant change from pre-test to post-test for both Intervention versus the Reference groups. However, it appears that the Intervention group shows a larger gain across time.

Tests of Effect Slices					
Effect	group	Num	Den	F Value	Pr > F
group*ntime	Intervention	2	1655	59.12	<.0001
group*ntime	Reference	2	1655	17.67	<.0001

Model 3: Comparing error terms for Model 2

Proc Mixed offers a flexible array of choices that the data analyst can use to model the within-person variance covariance structure. The choice of the error term can make a significant difference in the test of the fixed effects by correctly modeling the residual error variance (Littell et al., 1996). The six that will be examined for this model are in Table 3 (see Wolfinger, 1993; Hamer & Simpson, 1999 for more detailed advice on when each error type might be most appropriate).

Table 3: Subset of error types available in Proc Mixed on Repeated statement

Error Type	Description
UN	Unstructured—No structure is imposed
CS	Compound Symmetry—Classic repeated measure model
CSH	Compound Symmetry—Same as above except variance can differ across measurement occasions
HF	Same as CSH structure but it constructs the off-diagonal elements by taking arithmetic rather than geometric means.
AR(1)	Auto-regressive (1) specifies a first-order autoregressive structure
ARH(1)	Same as above except variance can differ across measurement occasions.

The following SAS code uses a macro structure to run the **Proc Mixed** model six times substituting the different keywords into the **Type=** specification on the **Repeated** statement. The ODS statement tells SAS to output the Fit Statistics (e.g., AIC, BIC) to a file called **Fitdata**, that is subsequently transposed, modified in a data step, and the combined with the results from the other **Proc Mixed** runs.

```

**Define the Macro**
%macro testerr(dep=);
%let alltype= un cs csh hf ar(1) arh(1);
%do j= 1 %to 6;
    %let etype = %scan(&alltype,&j," ");
    **Define an ODS output dataset which will contain the model fit statistics**
    ods output FitStatistics=Fitdata ;
    proc mixed data=cswr NEWHLM2 covtest noprint method = ml ;
        format group ntime ntime ;
        class id school classrm type ntime time ;
        model &dep = group|ntime ;
        random intercept / subject = school;
        random intercept / subject = classrm(SCHOOL);
        repeated ntime / subject = id(classrm*school) type=&etype ;
    title1 Safe Place/CSWR Expect Respect Project Data 1999-2000 School Year ;
    title2 Repeated Measures Model 3: Test of Best Error Structure ;
run;
**Transpose fit statistic values so there is single observation per model**
proc transpose data = fitdata out=ttfdata ;
    var value ;
run;
**Create new variables to index error structure and rename cols**
data newfit ;
    length errortype $ 7 ;
    set ttfdata ;
    errortype=&etype ;
    rename col1-l12 col2=aic col3=aicc col4=bic ;
    drop _name _label ;
run;
**Create single file of all model information**
proc append base=cswr type &dep data = newfit;
run;
%end;
%mend testerr;
run;

%testerr(dep=sxhrs);
run;

```

The following table shows the results of the SAS code above. Based on the choosing the lowest value of the information criterion, the Compound Symmetry model with heterogeneous variances appears to be best. This suggests that we can assume a constant covariance across the three time points with the variances differing. Give that Model 2 used the unstructured error term, we would want to go back and rerun this model with the CSH error structure. You can also use the difference between the any two $-2 \log$ likelihoods and compare it to a chi-square with degrees of freedom equal to the difference in the number of parameters (Hamer & Simpson, 1999). The data analyst should also use their knowledge of the phenomena to guide their choice of error structures to examine and avoid blindly including all possible choices.

Table 3: Comparing results of Proc Mixed models examining different error structures

Error Type	Log-likelihood	Akaike Information Criterion	Corrected Akaike Information Criterion	Bayesian Information Criterion
Un	5482.8	5510.8	5511.1	5513.6
Cs	5519.7	5539.7	5539.8	5541.7
csh	5483.5	5507.5	5507.7	5509.9
Hf	5499.0	5523.0	5523.2	5525.4
ar(1)	5537.9	5557.9	5558.0	5559.9
arh(1)	5503.9	5527.9	5528.1	5530.3

Growth Curve Model

Another important way to view the within student measurement over time is to estimate a model using students as another random factor. In this model, measurement occasion or time is specified as a continuous variable with the values 0 (baseline), 1 (mid-point) and 2 (post-test). This would permit the specification of time as a random variable and would give us an estimate of the variation in deviation around the grand intercept for individuals, the variation in deviation around the grand slope for time for individuals and the covariation between the intercept deviations and slope deviations (Longford, 1995). These models are known as growth curve models (e.g., Singer, 1999) and also as random coefficient models (e.g., Longford, 1995).

Model 1: Unconditional Growth Curve Model

The SAS code below shows the specification of the **Random** statement for the student level. In addition, a key addition is the inclusion of *ntime1* which tells Proc Mixed to treat this as a random factor. By including both of the intercept and *ntime1* on the random statement, Proc Mixed will estimate a separate deviation from the grand mean and the grand slope for *ntime1* for each individual.

```

proc mixed data=cswr.NEWHLM2 covtest noclprint=10 method = ml ;
  format group fgroup. ntime ftime. ;
  class id school classrm group ntime ;
  model sxhrs = ntime1 / solution;
  random intercept / subject = school          type=un ;
  random intercept / subject = classrm(SCHOOL) type=un ;
  random intercept ntime1 / subject = id(classrm*school) type=un ;
  title1 'Safe Place/CSWR Expect Respect Project Data 1999-2000 School Year';
  title2 'Growth Curve Model 1: Unconditional Model ';
run;

```

The results for the covariance parameter estimates show similar estimates for the school and classroom random variables. However, the estimates for the ID(SCHOOL*CLASSRM) effect differ. The UN(1,1) parameter represents the variance for the individual intercepts, the UN(2,2) parameter represents the variance for the individual slopes, and the UN(2,1) parameter represents the covariance between the individual intercepts and slopes. In this case, the negative value indicates that students with higher baseline scores showed lower change across time.

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
UN(1,1)	SCHOOL	0.2074	0.1270	1.63	0.0513
UN(1,1)	CLASSRM(SCHOOL)	0.08205	0.03768	2.18	0.0147
UN(1,1)	ID(SCHOOL*CLASSRM)	0.7931	0.1131	7.01	<.0001
UN(2,1)	ID(SCHOOL*CLASSRM)	-0.2163	0.06308	-3.43	0.0006
UN(2,2)	ID(SCHOOL*CLASSRM)	0.08601	0.05067	1.70	0.0448
Residual		1.0550	0.06609	15.96	<.0001

The Solution for fixed effects shows that the average score at baseline was 7.1216 and there was approximately a .38 increase in correct responses at each subsequent timepoint.

Solution for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > t
Intercept	7.1216	0.1731	8	41.15	<.0001
ntime1	0.3817	0.03293	1686	11.59	<.0001

Model 2: Test of Intervention Effect

The SAS code below shows the **Model** statement now includes *Group*, *Ntime1*, and their interaction to test the differential effect of the interaction. We will also be able to compare the covariance parameter estimates between the different models.

```

proc mixed data=cswr.NEWHLM2 covtest noclprint=10 method = ml ;
  format group fgroup. ntime fntime. ;
  class id school classrm group ntime ;
  model sxhrs = group ntime1 group*ntime1 / solution ddfm=betwithin;
  random intercept / subject = school type=un ;
  random intercept / subject = classrm(SCHOOL) type=un ;
  random intercept ntime1 / subject = id(classrm*school) type=un ;
  lsmeans group ;
  title1 'Safe Place/CSWR Expect Respect Project Data 1999-2000 School Year';
  title2 'Growth Curve Model 2: Test of Intervention Effect ';
run;

```

The covariance parameter estimates show that the slope variance that was statistically significant in Model 1, is no longer statistically significant. This change is due to the variation explained by the fixed effects.

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
UN(1,1)	SCHOOL	0.1941	0.1196	1.62	0.0523
UN(1,1)	CLASSRM(SCHOOL)	0.08208	0.03785	2.17	0.0150
UN(1,1)	ID(SCHOOL*CLASSRM)	0.7879	0.1124	7.01	<.0001
UN(2,1)	ID(SCHOOL*CLASSRM)	-0.2112	0.06256	-3.38	0.0007
UN(2,2)	ID(SCHOOL*CLASSRM)	0.08107	0.05029	1.61	0.0535
Residual		1.0528	0.06592	15.97	<.0001

The solution for the fixed effects indicates that there is no direct effect of the Intervention as shown with the repeated measures model. However, the same interaction effect appears which indicates that the Intervention group is showing increased knowledge across-time relative to the Reference group.

Solution for Fixed Effects						
Effect	group	Estimate	Standard Error	DF	t Value	Pr > t
Intercept		7.0556	0.2353	7	29.98	<.0001
group	Intervention	0.1638	0.3372	7	0.49	0.6419
group	Reference	0	.	.	.	.
ntime1		0.2868	0.04925	1685	5.82	<.0001
ntime1*group	Intervention	0.1700	0.06598	1685	2.58	0.0101
ntime1*group	Reference	0	.	.	.	.

Conclusion

Proc Mixed offers a powerful, flexible procedure for analyzing data collected from early intervention studies and other similar types of designs. In the example above, using the repeated measures model and random effect model for the within-subject variation lead to similar results. Based on these analyses, it appears that the Expect Respect Project was successful in increased students knowledge about sexual harassment. Although a very useful tool, specifying your model correctly in Proc Mixed can be challenging. The researcher employing Proc Mixed will want to think through her or his model carefully in order to make the best choices possible.

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Disclaimer

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Author Notes

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