COMPARISON OF METHODS OF ANALYSIS FOR PRETEST AND POSTTEST DATA

by

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(Under the Direction of Jaxk Reeves)

ABSTRACT

In this thesis I compare methods of statistical analyses for Pretest and Posttest Control Group Designs and Non-equivalent Group Designs. I compare the strengths and weaknesses of different methods of analyses, including ANOVA for the difference, ANCOVA, and Repeated Measures ANOVA. Four different data sets are analyzed and compared based on fit statistics and LS mean estimates.

INDEX WORDS: Pretest Posttest Control Group Design, Non-equivalent Group Design, Experimental Validity, ANOVA, ANCOVA, Repeated Measures ANOVA, Longitudinal Study, Mixed Model, Quasi-Experiment

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CHAPTER 1

INTRODUCTION

Pretest-Posttest designs are very common in scientific study. A characteristic common to true Pretest-Posttest designs is that two or more measurements are taken on each experimental unit. Subjects within each group receive a treatment of interest, no treatment, or a neutral treatment. Ideally, these experiments have a completely randomized design, whereby subjects are randomly assigned to the different levels of treatment. Through randomization, the effects of extraneous variables should be removed. Once the subjects are assigned to the groups, but before the actual treatment (if any) begins, each subject is measured on some characteristic to obtain his or her “Pretest” score. After the experiment has commenced, each subject is measured again one or more times to obtain his or her “Posttest” score or scores. When there are a number of such measurements taken at set periods of times for each subject, this is called a longitudinal or repeated measures study. In this thesis, we are primarily interested in the special case where there is only one final Posttest score. For a Pretest-Posttest Group Design (PPGD), the effect of the treatment is assessed by comparing the results for the treatment group to that of the control. When random assignment is used, differences should be primarily attributable to the treatment.

In many settings, however, the ability to randomize may be limited, or the groups may not have been identical at the start of the experiment. This is referred to as Non-equivalent Group Design (NEGD), as the experiment lacks randomization, which is a necessary requirement for the PPGD. NEGDs are a subset of quasi-experimental designs, which are quite common in social science research. For instance, educational studies are often limited due to restrictions on human subjects, and randomization is nearly impossible. Additionally, even if random assignment is possible, groups can potentially become non-equivalent if records for subjects cannot be obtained throughout the study. This can occur if there is a loss of subjects between Pretest and Posttest sessions.

In addition to a lack of randomization, other common issues can arise with this type of design. These issues may include intervention between tests—an event can occur after the Pretest, creating a difference in scores between groups, though the event is not directly related to the treatment itself. Testing effects may occur from prior exposure to the test; subjects tend to score higher simply from receiving an identical test. Maturation is possible, where the two groups change naturally between the tests, unrelated to treatment. Regression toward the mean can also occur between Pretest and Posttest scores. That is, for more extreme Pretest scores, a subject's corresponding Posttest score may appear to have a larger relative gain/loss simply because the original (Pretest) score differed significantly from the average.

There are multiple methods that can be used to analyze PPGDs. If the two groups were truly equivalent at Pretest, one-way analysis of variance (ANOVA) on Posttest scores should be a sufficient method to evaluate differences between the control and treatment groups. Alternatively, an ANOVA on the difference in scores (Posttest – Pretest) could be used to analyze whether the changes in scores from pretest to posttest were different for the groups. Thirdly, analysis of covariance (ANCOVA), using Pretest scores as a covariate, can be used to remove the effect of Pretest scores and fairly compare Posttest scores between groups. Finally, Mixed Modeling can also be used to analyze differences between groups, where treatment type and time are fixed effects and each subject has a random effect. These methods may give similar results, but depending on what a researcher is hoping to infer or how the data fit, some methods may be more appropriate than others.

CHAPTER 2

LITERATURE REVIEW

The purpose of many group design experiments is to allow conclusions to be drawn about cause and effect. This cause and effect relationship is subject to alternative explanations; before a researcher can infer a causal relationship exists between variables, he or she must rule out rival hypotheses. If alternative explanations are ruled out, an experiment is said to possess validity. Experimental validity is an important consideration in both educational and psychological testing, as the interpretations of analyses are dependent on the validity of tests. For a valid PPGD experiment, the results of analyses can be used to determine if there is a difference between groups after a treatment has been imposed. A review of the literature confirms that this design is widely used in scientific investigation, and that a variety of statistical tests exist to analyze this particular design. There is not, however, any consensus on what statistical methods are most appropriate for these analyses. These sources illustrate that more than one statistical method may be used for analyses, but the results of such methods are valid only when the assumptions are met. Additionally, much debate exists about how to treat the baseline (Pretest) information, when it is included. This lack of consensus in the literature stems largely from violations of model assumptions, threats to experimental validity, and lack of guidance on how to best present the analyses.

2.1 EXPERIMENTAL VALIDITY

Experimental validity is a common topic discussed within PPGD research, and this section will discuss two of the main components of experimental validity: internal and external validity. It should be mentioned here that the field of Psychometrics is also concerned with an entirely different concept of validity, known as test validity (including construct, criterion, and content validity). Test validity tends to be more emphasized in social sciences than natural sciences, as variables used in social sciences are typically less subjective or more difficult to quantify. This is often the case with survey data and educational testing. Such validity is not the focus of this research, but more about **test validity** can be found in references such as *Construct Validity in Psychological Tests* (Cronbach and Meehl, 1955).

A seminal piece of literature on experimental validity for both true and quasi-experiments is *Experimental and Quasi-Experimental Designs for Research*, by Campbell, Stanley, and Gage (1963). In this text, the PPGD and NEGD are both noted for their strong control over most threats to experimental validity—one of the causes of its popular usage in research. The text also notes the many factors that jeopardize the experimental validity of an experimental design and the design weakness of the PPGD and NEGD. If not corrected, these factors could lead to erroneous conclusions about the treatment effect. **Experimental validity** can be decomposed into two main categories: internal and external. **Internal validity** is the property of a scientific study necessary to infer a causal relationship between two variables; **external validity** is the property such that causal inference from a study may be extended to the population. Many of these threats to validity are often overlooked or are unavoidable. If the experimental design is not valid, scientific conclusions or relational causation cannot necessarily be inferred.

2.1.1 Internal Validity

When a relationship can be established between two variables, it is necessary to account for potential third variable alternative explanations; this is the essence of internal validity (Cook, 1979). An experiment with high internal validity has control over potential threats, which may become confounded with the treatment, if they are present. Threats to an experiment's internal validity may involve history, maturation, testing, selection bias, experimental mortality, and the interaction of these effects with selection (Campbell, 1963). Because the PPGD requires randomization, these experiments should have high internal validity and guard against the majority of these threats. The NEGD, more commonly used in Education, is susceptible to internal validity threats. *History* and *selection-maturation interactions* are the primary factors affecting internal validity (Cook, 1979).

History effects can be thought of as an event, such as a newsworthy happening, occurring between the Pretest and Posttest measurement, independent of the treatment. A true PPGD controls for the *history* effect, as general events that may produce a difference between Pretest and Posttest scores in the Treatment group should also produce a similar difference between Pretest and Posttest scores for the Control group. An example of a history effect on an experiment would be the occurrence of a natural disaster during the study. Since testing for both groups occurs at the same time, the groups should be affected similarly by the disaster. It is more difficult, however, to control for *intrasession history* or *local history*. For instance, if it is required that treatment interventions occur simultaneously with control interventions, so that different experimenters are used for the two groups, the experimenter difference becomes confounded with the treatment (Campbell, 1963). A visual example of *intrasession history* can be seen in Figure 2.1.

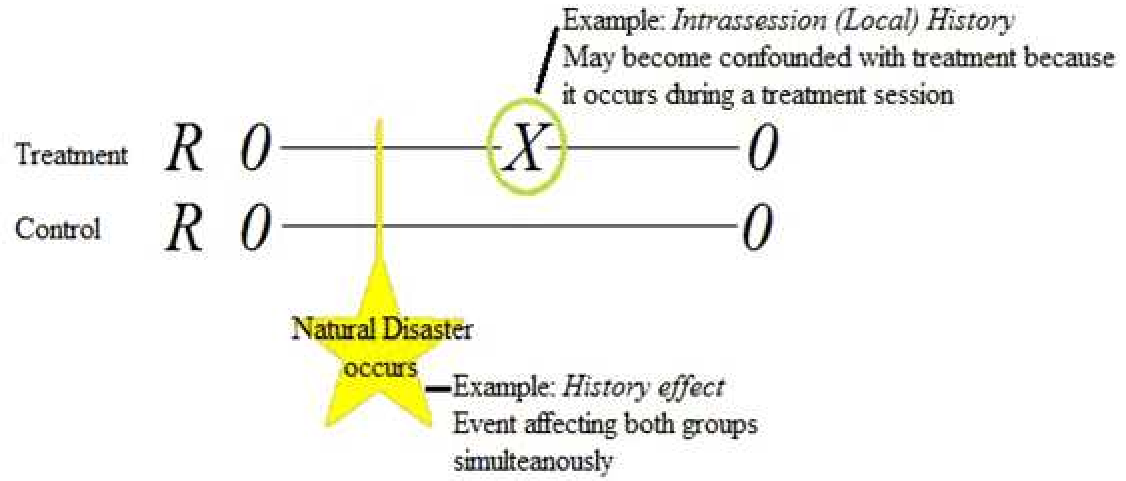

Example: *Intrassession (Local) History*
May become confounded with treatment because
it occurs during a treatment session
Treatment
R
0
X
0
Control
R
0
0
Natural Disaster
occurs
Example: *History effect*
Event affecting both groups
simulteanously

Figure 2.1 Illustration of Intrasession and History Effects
For this illustration, 'R' represents the randomization of subjects to group, 'O' is a test occurence, and 'X' denotes a treatment. The separation indicates that two different groups are being compared across time. The lines are parallel to illustrate events (testing and randomization) occuring at the same time.

Maturation can be thought of as biological and psychological characteristics of subjects that change during the experiment, thus affecting the Posttest scores (Dimitrov, 2003). While maturation is generally accounted for in a PPGD, *selection-maturation interaction* may arise in the NEGD case. For instance, in Education, where classes are a natural way to group, students may mature at different rates during the experiment, resulting from the way that students were assigned to classes, and not necessarily from the treatment. It is particularly common to see differences in growth rates between treatment groups when subjects self-select themselves into receiving a treatment (Cook, 1979). Changes in within-group variances between tests for both Treatment and Control groups may indicate that *maturation* has occurred (an example of this can be seen in Table 5.1). Additionally, if the change in score variances from Pretest to Posttest is significantly different between the Control and Treatment groups, this may indicate that there is a *selection-maturation interaction*.

When subjects are randomly assigned to treatment groups, each group experiences the same testing conditions and the same patterns of global history, so that many of the threats to internal validity may be ruled out. In NEGD studies, however, it is imperative that a researcher examine the data and investigate how these threats may have possibly influenced the study. Further, though randomization should makes causal inference easier, inequities may still exist between groups. For the purpose of this thesis, it was assumed that administering a Pretest is a reasonable way to measure prior differences between groups. This is a major assumption about the validity of the Pretest; while the inclusion of a Pretest is one potential way to measure differences between groups, it is not the only way. One may not conclude a causal relationship exists until all threats to internal validity have been eliminated.

2.1.2 External Validity

The central idea behind sampling for research is to obtain a representative subset of the population of interest, from which to estimate characteristics about the population. If the sampling frame is not representative of its intended population, then an experiment's external validity is compromised. Often in experimentation, aspects of the environment may make the exact experiment unreplicable. An experiment with high internal validity and high control over experimental factors may actually reduce external validity; control factors may not be reproducible in a natural setting. Sources of external invalidity stem from uncertainty as to which factors truly interact with the treatment and which factors can be disregarded (Campbell, 1963). Factors that Campbell references as threats to external validity include interactions of the treatment with: *testing*, *selection bias*, and *reactive effects of experimental arrangements*. If these factors are confounded with the treatment, results of analysis will not be generalizable to the population.

For the PPGD, the most likely threat to external validity is *treatment* and *testing interaction*. An example of *interaction* of *testing* and *treatment* may be seen in attitude-change studies. The introduction of a Pretest may redirect a subject's focus or create changes in behavior, influencing a subject's response at Posttest. If the Pretest sensitizes the subjects to a problem addressed within the Pretest, it may actually increase or decrease the effect of the treatment (Campbell, 1963). If the effect of testing and treatment interaction occurs in the study, the results may not necessarily be extended to the population as a whole, as the introduction of Pretest itself changed behavior.

While the randomization of the PPGD controls for selection within a study, it does not necessarily control for the *interaction* of the *treatment* and *selection* within a population. This becomes more likely as it becomes increasingly difficult to recruit subjects for an experiment. Say, for instance, there is resistance from particular groups or entities, such as schools in high socio-economic neighborhoods, to being included in an experiment. If only schools in lower socio-economic neighborhoods are willing to participate in the experiment, the results of that experiment cannot necessarily be extended to the population of all schools, even if the experiment is internally valid (Campbell, 1963).

A common source of non-representativeness in experimentation comes from *reactive arrangements*. This is somewhat unavoidable for well-designed experiments. The threat of this effect can come from artificial experimental settings (such as a laboratory), a subject's awareness that he or she is participating in an experiment, or any aspect of the experimental procedure. In research on teaching methods, it may be easier to disguise aspects of experimentation, such as including a Pretest or Posttest as part of the typical academic curriculum (Campbell, 1963). The NEGD, though said to have generally weaker internal validity, may in some cases have greater external validity, since it allows the assignment to treatment groups to occur naturally. This reduces the *reactive effects* of experimental procedure and improves the overall external validity of the design, relative to the randomized design (Dimitrov, 2003).

2.2 METHODS OF DATA ANALYSIS

The most appropriate method to analyze Pretest-Posttest data is highly debated. According to Bonate (2000), a method sensitive to the validity of its assumptions may result in inaccurate P-values and false conclusions, while a test with low power is likely to result in a Type II error, with the researcher coming to no conclusions about a study. The ideal method for analysis should maximize power, while minimizing the probability of a making a Type I error.

2.2.1 ANOVA Method

Ambiguity concerning how to analyze or interpret PPGD experiments is prevalent in the literature. In general analyses for the difference between groups (where there isn't necessarily a Pretest score), analysis of variance (ANOVA, which is equivalent to the two-sample t-test if there are only two groups) on Posttest scores is the most commonly used method. For NEGD, this method may not be appropriate, due to possible violations of the assumptions needed for the ANOVA approach to be correct. Bonate (2000) emphasizes the importance of utilizing the Pretest data, although he notes the lack of consensus concerning the precise way in which such Pretest information should be incorporated.

For both the t-test and ANOVA, a primary assumption is that the groups are statistically equivalent at the baseline (i.e. the time at which the Pretest is conducted). Analyzing only the Posttest data does not take into account within-subject variation. Analyses using only Posttest data may provide insufficient power for detecting differences between groups; ignoring the baseline information can potentially lead either to no conclusion or to an incorrect conclusion. Further, even if the Pretest results are statistically equivalent (as they should be under PPGD), applying the t-test or ANOVA to Posttest scores alone may not be the most powerful test for detecting differences between treatment effects. Using Pretest information in the statistical analysis of the Posttest measurements should account for differences between subjects, and allows each subject to act as its own control. By including the Pretest data in the analysis, a researcher can increase the probability of detecting a significant difference between groups, thereby increasing the power of the statistical test.

2.2.2 Difference Method

One of the most commonly used methods in analyzing Pretest-Posttest data is the difference method, or gain in scores. In this analysis, the data are simplified by transforming the bivariate (Pretest, Posttest) into univariate via the relationship, *Difference=Posttest–Pretest* (Equation 1, Table 2.1). The response variable is calculated as either Posttest minus Pretest, or vice-versa, and ANOVA is performed on the differences. A major advantage of this method is ease of interpretation of the transformed variable, either a net gain or loss in score (Bonate, 2000). This method also assumes that each subject's score is independent of the other subjects' scores.

Other methods involving transformations similar to the difference method have also been used in analysis of Pretest-Posttest data. Normalized learning gains (Equation 2, Table 2.1) were developed in Education to offset the effect of large learning gains; they attempt to compare learning or gains fairly. For example, subjects who scored extremely low on the Pretest may appear to gain more between testing sessions (Weber, 2005). For Pretest scorers near 100% of the maximum possible score, these normalized learning gains may be exaggerated. Another transformation is the relative change. Relative change transforms Pretest and Posttest scores into a proportional change of the scores (Equation 3, Table 2.1). Relative change and normalized learning gains may be analyzed in the same manner as the difference in score, but encounter similar problems in analysis. A particular drawback of relative change scores is that they are often not normally distributed (Bonate, 2000). The difference between scores is generally preferred to these methods for its ease in interpretation. A fourth method, overcoming some of the difficulties of both normalized learning gain and relative change, is the logit transform (Equation 4, Table 2.1).

All four of these transformations assume that Pretest and Posttest scores are in the same scale. Equations 2 and 4 further assume that Pretest and Posttest scores are expressed as % correct on a 0 to 100 scale. Note that Equation 2's transform (nlg) becomes undefined if Pretest is 100%, while Equation 3's transform (relative change) becomes undefined if pretest is zero (or 0%). Equation 4's transform (logit) is undefined if either Pretest or Posttest is exactly 0% or 100%. In practice, one adjusts equations 2, 3, or 4, if necessary, so that undefined values don't occur, typically by replacing zero scores by a value that is half-way between zero and the lowest observed non-zero score, and similarly on the high end. Of course, if one finds that such definability adjustments need to be made for more than a few subjects, this might be an indication that the transform being contemplated is not appropriate for the data set under consideration. In that sense, Equation 1's difference transform (which is always defined and is easy to understand), might be preferable to others, but one shouldn't necessarily conclude that it is always the best transformation to use.

Table 2.1

Transformation Equations for Posttest-Pretest Differences

Equation 1. Difference in Scores	$Difference = (Posttest - Pretest)$
Equation 2. Normalized Learning Gains	$nlg = \dfrac{(Posttest - Pretest)}{(100\% - Pretest)}$
Equation 3. Relative Change	$relative\ change = \dfrac{(Posttest - Pretest)}{Pretest}$
Equation 4. Logit Transformation	$logit = \ ln\left[\dfrac{Posttest}{Pretest} \times \dfrac{(100\% - Pretest)}{(100\% - Posttest)}\right]$

2.2.3 ANCOVA Method

The method that has received the most positive remarks in PPGD literature is the analysis of covariance (ANCOVA), using Pretest as a covariate and Posttest as the response. In using the Pretest scores as a covariate, ANCOVA treats the Pretest score as a source of variation uncontrolled for in the experiment. ANCOVA is shown to be more powerful and more versatile in situations where basic ANOVA assumptions, particularly randomization, are violated. ANCOVA has all of the same functions as the Difference method; in fact, the Difference method is actually a specific case of ANCOVA where the regression coefficient for Posttest scores onto Pretest scores is set equal to one (Brogan, 1980). The general ANCOVA model, for the PPGD or NEGD is:

$$Posttest = \ \beta_0 + \beta_1 \times I(Treatment) + \ \beta_2 \times Pretest + error$$

For this model, *I(Treatment)* is an indicator variable. The indicator takes on values of either ‘0’ or ‘1’ for Pretest-Posttest data with only one treatment. For this model, a value of ‘1’ indicates that a subject belongs to the Treatment group and ‘0’ that the subject belongs to the Control group. In non-randomized designs, ANCOVA may be used to adjust for differences that exist between groups at the Pretest, which is likely to occur with intact groups [if treatment groups are formed naturally, for example, through self-selection or assignment of treatment to existing groups (such as a classroom), prior differences unrelated to the treatment are more likely to exist, than if subjects were randomized].The basic questions answered by ANCOVA and ANOVA are similar. While ANOVA tests the overall effect of the treatment at Posttest, ANCOVA tests the effect of the treatment for a specified score at Pretest. If the regression coefficient for Posttest scores onto Pretest scores is close to 1.0, ANOVA for the difference in scores will tend to produce similar results to ANCOVA. Since the ANCOVA requires loss of an additional degree of freedom compared to ANOVA on the differences, ANOVA on the differences will tend to be the more powerful test when the slope for Pretest is near one (Dimitrov, 2003). If the slope is near zero, then simple ANOVA on the Posttest scores will be more efficient than ANCOVA. If this slope is not near either zero or one, then ANCOVA is a more powerful method for analysis than either ANOVA on Posttest scores (β_2=0) or ANOVA on differences (β_2=1). Additionally, unlike the Difference method, which requires that Pretest and Posttest scores be in the same units, the ANCOVA method does not require that covariates (in this case, Pretest) be in the same units as the response (Posttest) (Bonate, 2000).

Though ANCOVA has received much positive acknowledgment from researchers for analysis of Pretest-Posttest data, it has a few shortcomings. ANCOVA assumes that the slopes are equal for the Treatment and the Control group (i.e. that the linear relationship between Pretest and Posttest scores is the same for both groups). This assumption is often violated in practice. For self-selecting treatment groups, ANCOVA may result in biased treatment effects.

When groups are self-selected, estimation of the true treatment effect cannot necessarily be separated from an individuals' preference for that particular method. An example of this occurs when groups have similar Pretest scores, but the two groups mature at different rates over time. Say, for instance, eighth grade students had the option of taking college preparatory (Control) or honors (Treatment) courses in high school, and also take a middle school exit exam (Pretest). Say, then, that the mean Pretest scores are the same for students who took college prep and honors courses. Assume further that the students take a high school exit exam (Posttest), and the mean score for the honors students is higher. Here, the treatment cannot necessarily be separated from the fact that the honors students (or their parents) desired more challenges, and thus may have responded differently to their high school education, compared to their college prep classmates.

2.2.4 Repeated Measures Method (Mixed Model)

Repeated Measures ANOVA has become very popular in research for PPGD. This design is also referred to as a Split-Plot analysis (Agricultural origin), within-subjects ANOVA, or treatment-by-subjects ANOVA (Vogt, 1999). For this design, an experimental unit is one subject, where each subject is treated as a block, and measurements are taken repeatedly (in Pretest-Posttest Design, only twice). For a Repeated Measures design with 'I' between-subjects effects (treatment types), the linear model is:

$$Score_{ijk} = \mu_0 + \alpha_i + T_{j(i)} + \beta_k + \alpha\beta_{ik} + e_{ijk}$$

The variable, *Score* represents the score for the i^{th} treatment, the j^{th} subject and the k^{th} trial for:

i=1,2,..., I (Treatment Groups)

j=1,2,..., n_i (Subjects in Group i)

k=1,2. ..., K (Trials, or Time-points at which each subject is measured)

where

μ_0 is the baseline score

α_i is the treatment or main effect, a fixed effect,

$T_{j(i)}$ is the subject effect nested within treatment, a random effect,

β_k is the time effect, a fixed effect,

$\alpha\beta_{ik}$ is the treatment x time interaction

and e_{ijk} is the error corresponding to the score for the k^{th} test taken by subject j in group i , which remains unexplained by the other terms within the model.

For the PPGD, the within-subjects effect can have only two levels (K = 2), either Pretest or Posttest. The number of groups, I, is usually small; I=2 in the most common case where there is one Control and one Treatment group. The number of subjects within a group, n_i, depends on the experiment; more power accrues as n_i becomes large. Although it is not necessary for $n_1 = n_2 = ... = n_I$ =J, most researchers attempt to keep the n_i relatively balanced in order to maximize power. The summary table for Repeated Measures Analysis provides three F-tests: a main effect for the Groups, a main effect for Time or Trial, and an effect for the Groups-by-Time interaction. See Table 2.2 below for the general format in the case of complete balance, where N=I*J*K represents the total number of scores observed in the data set. This last test (Groups-by-Time interaction) is the one of primary interest when using Repeated Measures Analysis on PPGD.

Table 2.2

Repeated Measures ANOVA Table

Effect	Numerator DF	Denom. DF	F Value
Group	$I-1$	$I*(J-1)$	MSG/MSE_G
Time	$K-1$	$I*(J-1)*(K-1)$	MST/MSE_T
Group*Time	$(I-1)(K-1)$	$I*(J-1)*(K-1)$	$MSTG/MSE_{G*T}$

If applied naively, Repeated Measures ANOVA is misleading because the between-subjects main effect (Group effect) F is too small (Huck, 1975). While Huck makes valid points about potential misinterpretations of the fixed effects, the F value being too small may be a specific case where it is assumed there is little difference between groups at the Pretest, and a significant difference at Posttest. Repeated Measures ANOVA has also been criticized, as its linear model assumes that randomization and treatment intervention occurs prior to the Pretest;

in reality the treatment affects only the Posttest. Repeated Measures Analysis may therefore result in biased estimation of the treatment effect. Because the model assumes that treatment occurs at the Pretest, the actual treatment effect is "spread across" the Pretest and the Posttest in computation for the main effect (Huck, 1975). Similarly, the Time effect is the average of Posttest-Pretest improvement over the two groups, and may not be easily interpretable when these two improvements are dissimilar. Dimitrov (2003) also notes that using the F value from the between subjects factor (Treatment) would be a common mistake. Using the F-test for the main effect of Treatment can be too conservative and increase the probability of making a Type II error, though this too may be a special case. The F-test for the Group-by-Time interaction, however, is an unbiased estimate of the treatment effect (Brogan, 1980).

For Repeated Measures ANOVA, the assumptions are similar to typical ANOVA, but it requires more assumptions than other suggested methods. One additional assumption concerns the structure of the Variance-Covariance matrix for observations on the same individual. The classical assumption is that the error terms are assumed to be independently and identically distributed (iid), and have the same variance for both the Pretest and Posttest scores (Kutner, 2005). Furthermore, it is assumed that the Pretest and Posttest Variance-Covariance matrix is the same for both (or all) treatment groups. While sphericity (which assumes the correlations across repeated measures are the same) is an assumption necessary for Repeated Measures ANOVA, it is not relevant to the PPGD since there is only one pair of measurements (i.e. the Variance-Covariance matrix is 2*2).

Additional criticisms have arisen from the use of Repeated Measures ANOVA for the Pretest-Posttest design. Other methods of analysis provide the same results, but are less complicated. The F-statistic for single-factor repeated measures with only two treatments is equivalent to a two-sided t-test for paired observations (Kutner, 2005). The F-statistic for the Time (trials) does not necessarily reveal anything about the treatments; since the scores are averaged across groups, it indicates only that scores, on average, changed from Pretest to Posttest.

Repeated Measures ANOVA, as it has been referenced in PPGD literature, is a special form of the Mixed Model which assumes the Variance-Covariance matrix has compound symmetry, or that the variance for the Pretest is equal to that of the Posttest. The F-test for the Group-by-Time interaction of Repeated Measures ANOVA and the F-test of an analysis of difference scores will always be the same, as a result of this assumption (Brogan, 1980).

Deviations from the compound symmetry assumption are less examined in PPGD literature. Mixed Models may, however, prove to be useful for analysis in situations where the variances differ between Pretest and Posttest. A benefit of the Mixed Model is that the variance structure of this method can be altered. Of course, for a 2*2 Variance-Covariance matrix, there are only three possible parameters [VAR(Pre), Var(Post), and COV(Pre,Post) = ρ*SD(Pre)*SD(Post)], and the compound symmetry assumption reduces this to two by requiring that the Pretest and Posttest variances be equal. If the additional parameters do not dramatically improve the model's estimate of the treatment effect, it may be better to make the simpler compound-symmetry assumption of the classical repeated measures design. On the other hand, it may be the case that an even more complex structure, such as separate variance-covariance matrices for each group (requiring up to I*K*(K+1)/2 Variance-Covariance parameters in the most general case) may be needed. This goes beyond the level of complexity desired for this thesis, but such complex structure might be needed for proper analysis of some Pretest-Posttest designs.

CHAPTER 3

THE DATA SETS

Four different data sets were analyzed for the purpose of comparing the methods of analysis. Each set involves one Pretest score and one Posttest score (only two within-subject measurements; K=2). Each set also has one Control group and one Treatment group (I=2), used in its final analysis. The sampling frame, for each data set, was taken from an academic setting; all subjects were enrolled in a graduate or undergraduate program at a university at the time of study. Two data sets are NEGDs, lacking randomization in one form or another; two are completely randomized, or PPGDs.

The Nursing (PPGD) data are from an assessment of junior-year undergraduate Nursing students of the Medical College of Georgia. There were 33 total students, combined from two separate campuses. The 33 students took an assessment, called the Self-Directed Learning Readiness Scale (SDLRS or Learning Preference Assessment, LPA), which is intended to measure an individual's readiness to manage his or her own learning. The assessment was given to all 33 students in order to obtain Pretest scores, and then 16 students were randomly selected to receive an "intervention", which consisted of watching an online self-directed learning module. These 16 individuals became the Treatment group; the remaining 17 students who received no intervention were considered the Control group. The 33 students were given the same assessment (the Posttest) again after the "intervention".

The ICA data set is an NEGD that involves an assessment called Intercultural Communication Apprehension (ICA). The ICA was intended to measure, over time, students' fears and attitudes of other cultures. All students who participated in the study were enrolled in a Global Design course at UGA. The students self-selected themselves into treatment groups (the non-equivalent component), students who studied abroad (Treatment) and those who did not (Control). There were three levels of treatment for this study, as study abroad was segmented into two groups based on the duration of travel (Short or Long). For purposes of comparability, and after preliminary analyses indicated no differences between them, the 'Short' and 'Long' groups were combined into one 'Treatment' group, so that the analysis of the ICA data set in Chapter 5 uses I=2 groups. The Control group consisted of students that did not choose to travel. The Pretests were given to all students at the beginning of the Global Design course. The Posttests were given after students had completed the course (for those in the Control group) and studied abroad (if they belonged to the Short or Long Treatment groups). The data originally consisted of 145 records [111 students who did not study abroad, 15 students who studied abroad for an extended period (Long), and 29 students who studied abroad for a shorter period (Short)]. Seventeen of these students had incomplete records for either the Pretest or the Posttest. These seventeen students' records were removed from the data set, so that final data for ICA assessment contains 128 records (87 students for Control, 15 students for Long, and 26 students for Short).

The Econ (NEGD) data set contains records for 200 students (subjects) enrolled in an Introductory Economics course at a large state university. The 200 students took a lecture-style class together, with a co-requisite lab. Two different teaching methods were used for the lab classes: a new more statistical teaching method (Treatment), and the traditional teaching method

(Control). The 200 students were divided into eight different lab classes (25 in each), which were taught by four Teaching Assistants (TAs). Each TA was assigned one Treatment lab and one Control lab to prevent the confounding of method with lab instructor, so the final Econ data set consists of records for 100 students each in Control and Treatment groups. Students chose the lab section to which lab section they were assigned (the non-equivalent component), although they did not know at the time of selection which type of lab they had chosen. All students took a Pretest at the beginning of the semester, and prior to any lab instruction. The Pretest was actually a copy of the previous year's final exam, so the scores on this Pretest tended to be rather low (mean score = 30% correct). The Posttest exam was the course's actual final exam, different from the Pretest. The data set for the study contains, for each student, the teaching method received, the Pretest score, and the Posttest score. Additional demographic information about the students or which of the four TAs instructed them is not available in the data set. The primary objective of this study is to determine if the newer, more statistical method (Treatment) is more effective than the traditional (Control) method, for helping students to learn Introductory Economics.

The final data set examined in this thesis is an example from Bonate (2000) and is referred to as the Sexual Harassment Inventory (SHI) data set (PPGD). The study was intended to measure male college students' attitudes toward sexual harassment. The researchers tested 96 college freshmen at a Midwestern university. After the Pretest, students were randomized into one of three treatment groups: Educational Literature, Video, or Control. For each group, students reviewed literature on sexual harassment, watched a video on sexual harassment, or were given a "neutral control task involving attitudes toward male and female names" (Bonate, 2000, p. 64), respectively. Students' attitudes toward sexual harassment were tested again (using the same SHI instrument), one week after intervention (Posttest). Higher scores on the assessments indicate higher sensitivity toward sexual harassment. As with the ICA study, the SHI study originally contained I=3 treatment groups (30 subjects in Control, 33 in the Educational Literature Group, and 33 in the Video group), but the latter two groups are combined to form the Treatment group used in the analysis performed in Chapter 5. The goal of this study is to determine if the students in the Treatment group improved their SHI scores significantly more than the students in the Control group did.

Table 3.1 below summarizes the key characteristics of the four studies described in this chapter. Note that the four studies contain both large and small sample sizes and contain two PPGDs and two NEGDs. Also, note that the (pooled data) correlations (r) between Pretest and Posttest scores range from a relatively low r=+0.236 for the Econ data set to a relatively high r=+0.785 for the Nursing data set. Also note that for the Nursing and Econ data sets, the correlations between Pretest and Posttest scores within the two groups are rather similar, and are somewhat higher than the overall pooled correlation. However, for the ICA and SHI data sets, the within-group correlations are quitet different (especially for SHI), so that the pooled correlation falls between the two separate group correlations.

Table 3.1

Summary of Characteristics of Four Data Sets

Study	Name	N	$n_{control}$	$n_{treatment}$	Design	r (pre/post)	r_C (pre/post)	r_T (pre/post)
1	Nursing	33	17	16	PPGD	0.785	0.816	0.825
2	ICA	128	87	41	NEGD	0.531	0.497	0.703
3	Econ	200	100	100	NEGD	0.236	0.389	0.397
4	SHI	96	30	66	PPGD	0.430	0.908	0.216

CHAPTER 4

METHODS

A goal of this thesis is to determine which methods of analyses are optimal for PPGDs and NEGDs under different scenarios.hoped The two fundamental models used for analysis are the General Linear Model (GLM) and the Mixed Model. Note that all analyses were performed using SAS 9.2 and 9.3.

The GLM may be written in matrix notation as:

$$Y = X\beta + e$$

Where Y and e are (n*1) vectors, β is an ((k+1)*1) vector, X is a (n * (k+1)) matrix. Here, ‘k’ is the number of predictor variables and ‘n’ is the number of observations. For the PPGD, Y represents a vector of Posttest scores, X is the design matrix, β is a vector containing the parameter estimates for the linear model, and e is the random error that remains unexplained by the model.

The data sets were modeled using six different parameterizations or combinations of explanatory variables. The general linear models used for analyses (in terms of the i^{th} individual) are displayed in Table 4.1 below.

Table 4.1

The General Linear Model for Predicting Posttest scores

MODEL	EQUATION
Null	$Y_i = \beta_0 + e_i$
Regression	$Y_i = \beta_0 + \ \beta_2 X_{2i} + e_i$
ANOVA*	$Y_i = \beta_0 + \ \beta_1 X_{1i} + \ \beta_2 X_{2i} + e_i$
DIFF*	$Y_i = \beta_0 + \beta_1 X_{1i} + \ \beta_2 X_{2i} + e_i$
ANCOVA*	$Y_i = \beta_0 + \beta_1 X_{1i} + \ \beta_2 X_{2i} + e_i$
Full (Interaction)	$Y_i = \beta_0 + \beta_1 X_{1i} + \ \beta_2 X_{2i} + \ \beta_3 X_{1i} X_{2i} + e_i$

*Note. For the ANOVA Model, B_2=0 by definition; For the DIFFERENCE Model, B_2=1 by definition.

Where Yi is the Posttest score for the i^{th} individual,

β_0 is the intercept or baseline,

β_1 is the estimate for the treatment effect,

β_2 is the slope estimate for Pretest scores,

β_3 is the estimate for the interaction of Pretest score with the treatment,

X_{1i} is an indicator for group (1 if subject 'i' belongs to Treatment, 0 if Control).

X_{2i} is the Pretest score for the i^{th} individual,

and e is the random error (assumed i.i.d., with mean 0 and unknown but constant variance σ^2).

For the Null model, the mean Posttest score, for all subjects, is used to predict all Posttest scores, without using any other information ($\hat{\beta}_0$ is the mean Posttest score). The Regression model utilizes Pretest as an explanatory variable for predicting Posttest scores. The ANOVA model is equivalent to a 2-sample t-test, and attempts to predict Posttest scores from group membership. The DIFF model uses treatment type to explain changes in score from Pretest to Posttest, and is equivalent to the model where the response variable is the change in score (Difference=Posttest – Pretest).

The ANCOVA model utilizes both treatment type and Pretest scores as explanatory variables for predicting Posttest scores. The ANOVA model and DIFF model are actually special cases of the ANCOVA model. For the ANOVA model, the value for the Pretest coefficient (β_2) is '0'; for the DIFF model, the value for β_2 is '1'. The Full(Interaction) model is a further extension of the ANCOVA model, where there is an additional term for the interaction of Pretest score and Treatment, if such an interaction exists. If the interaction effect for Pretest and Treatment is significant, the predictor variables are dependent upon one another. In other words, an interaction would indicate for the PPGD that the effect of the treatment is dependent upon how a subject scored on the Pretest. Unlike the ANCOVA model, the treatment effect is not constant across groups; an estimate for the treatment effect cannot be isolated without considering Pretest.

To construct these models, each was run individually using SAS's PROC REG with requests for 'Solutions', 'AIC', and 'BIC' (called 'SBC' within SAS's PROC REG). Since Treatment is a dichotomous variable for each data set, an indicator variable (IT) was created for each ('1' for a subject belonging to the Treatment group, '0' for a subject in the Control group). To compare the results of these linear models, Posttest scores were regressed onto the selected explanatory variables (if any). Although the response variable for the DIFF model is (Difference = Posttest – Pretest), the DIFF model was regressed using Posttest as the response variable, with a restriction placed on the parameter estimate for Pretest such that the β_2 parameter was set equal to one. This ensured that the fit statistics and parameter estimates for the six General Linear

Models, shown in Table 4.1, were directly comparable. The best model was selected using AIC or BIC. While R-square and RMSE are important considerations, one must remember that when comparing two hierarchical models with different numbers of parameters, R-square will always be larger for the more complex model (and RMSE will typically be smaller), so neither of these two are useful model selection criteria. It should also be noted that these tests are being performed at a nominal 0.05 level, as if the test/model under examination were the only one which the researcher were considering. If, in fact, a researcher were considering many possible models before selecting one under which to conduct the analyses of interest, then, of course, the researcher would need to make some sort of suitable adjustment for multiple tests being conducted.

A Mixed Model was analyzed separately for each data set, as well. In the PPGD literature, the particular Mixed Model used is more commonly referred to as Repeated Measures ANOVA. A benefit of analyzing the data sets using the Mixed Model is that this formulation allows the repeated measures on the same individual to exhibit correlation, rather than assuming that they are independent of one another. Also, the Variance-Covariance structure can be changed, so that the Pretest and Posttest variances need not be assumed to be constant. Parameter estimates for the covariance are what distinguish the Mixed Model from the GLM. When analyzing each data set, each subject was treated as one cluster, with two observations per cluster (Pretest and Posttest).

The general notation for the mixed model in matrix form is:

$$Y = X\beta + Z\gamma + e \,,$$

where Y is a vector of observed scores,

β is a vector of fixed-effects parameters, X is the design matrix of fixed factors,

γ is a vector of random-effects parameters,

Z is the design matrix of random factors,

and e is a vector of residual errors (whose elements need not necessarily be homogenous nor independent).

The Mixed Model analysis for each data set was run using SAS's PROC MIXED. For each analysis, the response variable was 'Score', and the fixed effects tested for were Group (Control or Treatment), Time (Pretest or Posttest), and Group*Time. The PROC MIXED RANDOM statement (with intercept) was used to determine estimates for the γ vector. The estimates for the Variance-Covariance parameters were computed via Restricted Maximum Likelihood (REML), the denominator degrees freedom specified were estimated via the Kenward-Roger procedure, and the subject effect specified was subject, within group. SAS's default Variance-Covariance structure was used, which assumes the Pretest and Posttest variance are equal. The same procedures and same specifications were used for each data set.

SAS's LS means, for all Group-by-Time effects, were requested for each analysis, with P-values for all pairs of differences specified as an option [(PDIFF = "pairs of differences"). For an example, see Table 5.4 of the Nursing Data Set]. This provided estimates for the difference in scores at all possible levels of Group and Time, along with the corresponding P-values. The 'Estimate' coefficient shown in these tables is such that Group='C' and/or Time='Pretest' is used as the baseline, so that the estimates are for the expected change in score from Pretest to Posttest or from Control to Treatment (or both, if applicable). For an example, see Table Table 5.16 of the Econ data set.

Since the Mixed Model and the GLM have different parameterizations, SAS’s LS Means option was used to compare the results of the two analyses directly. Joint tables were created to show the relationship between the SAS LS Mean estimates (actually a Maximum Likelihood estimate) for the Mixed Model, and LS mean estimates from the GLM. Only the LS means for the best fit GLM were computed (where 'best' was determined by finding the GLM with the lowest AIC or BIC). The LS means estimates for the GLM were computed using two different specifications. The first estimate was found specifying BY LEVEL, which uses the conditional mean for each group, at Pretest, in the linear model, for the Posttest estimates (for an example, see Table 5.17). The second estimate used SAS’s default mean, which is the overall Pretest mean (for an example, see Table 5.18). Standard errors and P-values were requested for both of these methods.

CHAPTER 5

THE ANALYSES

5.1 THE NURSING DATA SET

Descriptive statistics for the Nursing data set are presented in Table 5.1, with illustrative histograms in Figures 5.1-5.3. Although the students assigned to the treatment were randomly selected, the mean score of the Treatment group was nearly seven points lower than the mean score of the Control group, prior to intervention. The Control group took the same test twice and received no form of intervention, and the overall Posttest score did not significantly change for this group. As shown in Figure 5.4, the mean Posttest scores for the Treatment group exceeded the mean Posttest scores for the Control group, despite the lower Pretest scores for the Treatment group. Although these groups were randomized, it appears that they may be non-equivalent, prior to intervention. This is an interesting case where there appears to be no significant difference in Posttest scores, but if one controls for initial (Pretest) differences, then, perhaps there will be a significant Treatment effect. There were no apparent threats to internal validity for the Nursing data set. A potential threat to external validity is *reactive effects of experimental arrangements*. This may have occured because these were opinion-based survey questions which did not measure a gain in knowledge. Here, students who belonged to the Treatment group could have potentially changed the perceptions of their own learning after reviewing the intervention presentation.

Table 5.1

Summary Statistics for Nursing Data Set

Group	N	Trial	Mean	Std Dev	Min	Max
Control	17	Pretest	232.24	18.56	186	259
		Posttest	232.88	17.25	203	263
Treatment	16	Pretest	225.25	21.53	200	270
		Posttest	235.81	26.97	195	286

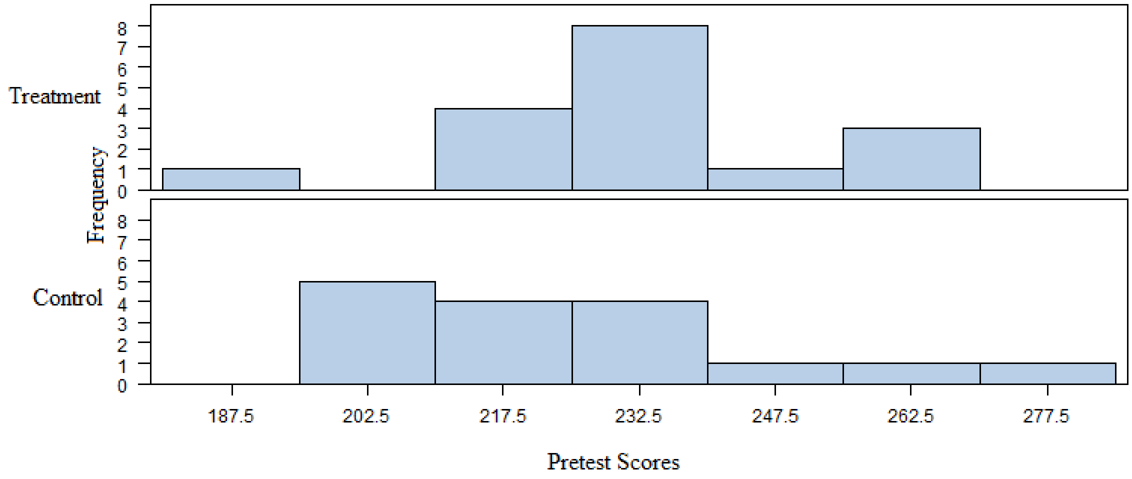


Figure 5.1 Histogram of Nursing Pretest Scores

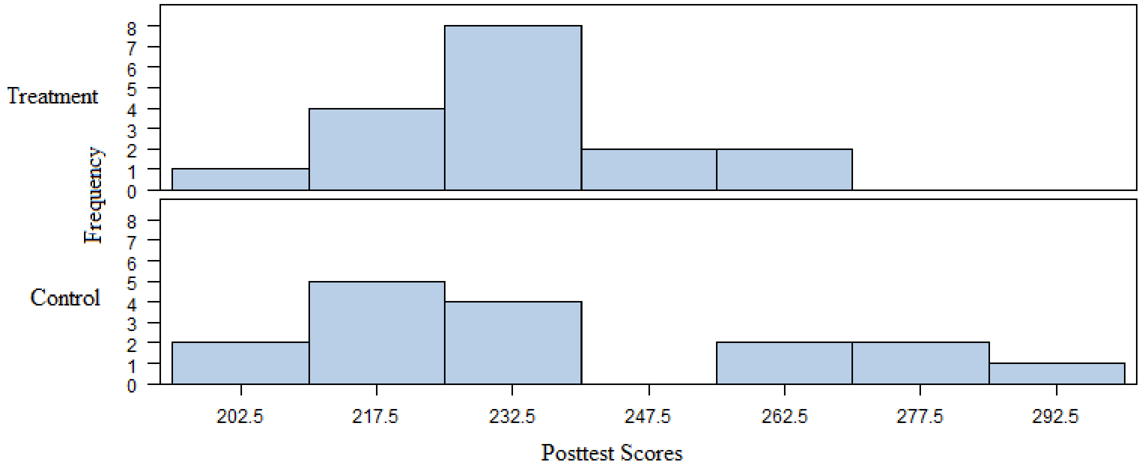


Figure 5.2 Histogram of Nursing Posttest Scores

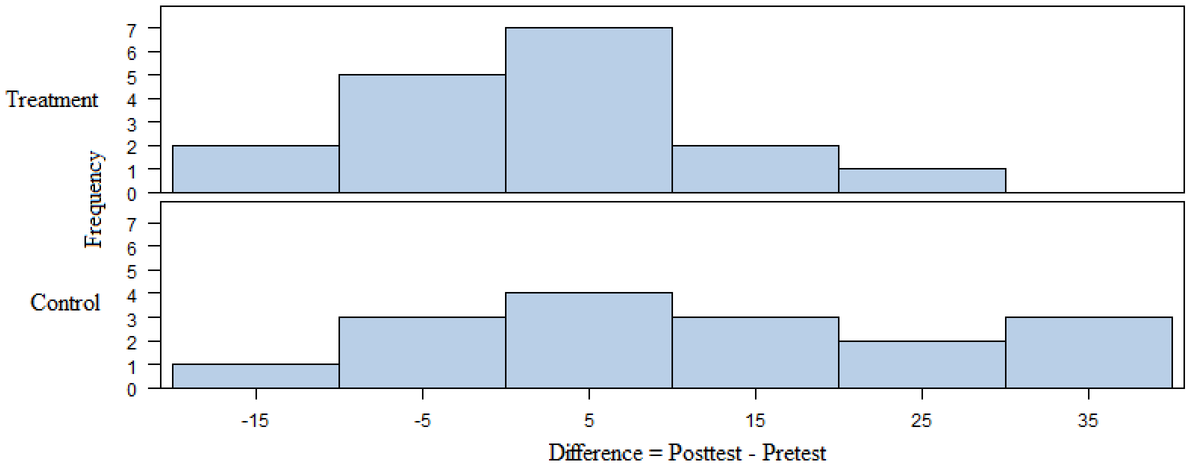


Figure 5.3 Histogram for Nursing Difference Scores

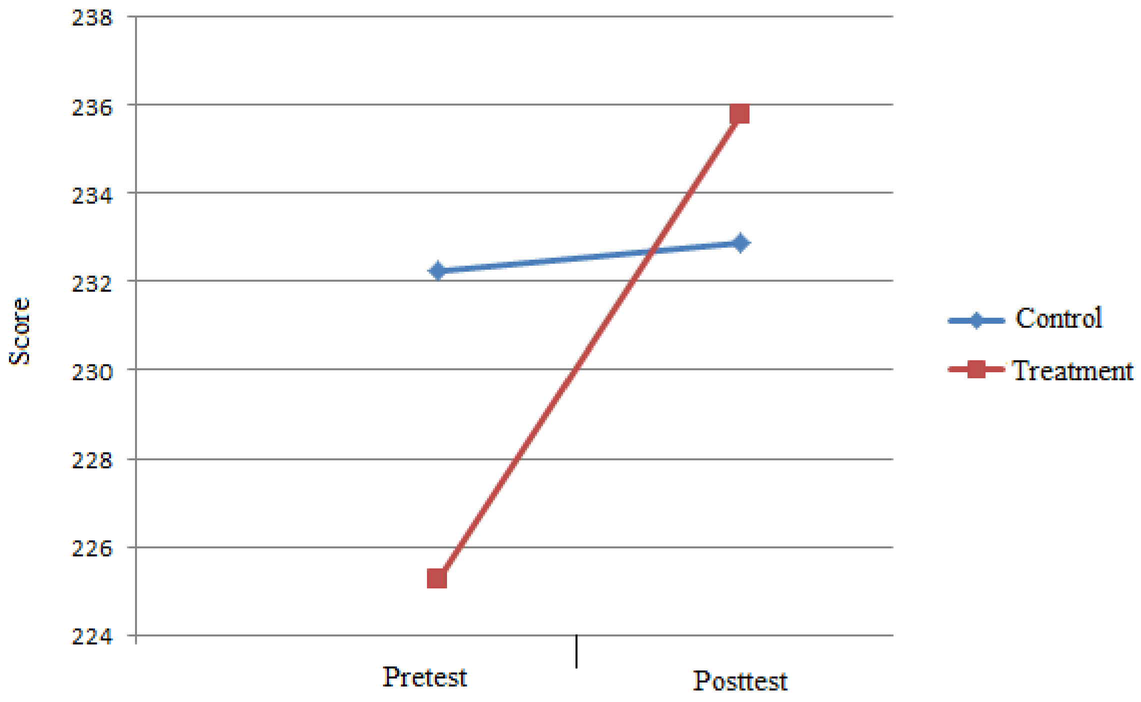


Figure 5.4 Trend Plot for Nursing Scores

The trend plot in Figure 5.4 shows that the Treatment and Control group changed at different rates between testing sessions. Each point represents the mean test score for that group at the indicated time. The line indicates the trend between sessions. The Treatment group improved by more than 10 points; the Control group improved by less than one point.

5.1.1 GLMs for Nursing Data Set

Table 5.2 shows the fit statistics and parameter estimates for the GLMs for the Nursing data set. The ANOVA model illustrates that the Treatment group outperformed the Control group at Posttest, since the β_1 coefficient is 2.93, but the Treatment effect is not statistically significant ($P = 0.7108$). The R-square for the ANOVA table indicates that treatment accounts for only about 0. 5% of the variability in Posttest scores. The predictive power of the GLM for the Nursing data set is significantly improved when Pretest scores are included. In comparing the ANOVA model to the Regression model, it would appear that a nurse's Pretest score is much more informative of his or her Posttest score than the group to which he or she was assigned (Treatment vs. Control), illustrated by all the improved fit statistics (R-square, RMSE, AIC, and BIC).

As shown in Table 5.2 and Figure 5.5 below, the interaction between Pretest and Treatment (PRE*IT) does not appear to be significant, so the Full (Interaction) model can be reduced to the ANCOVA model. This may be a situation where the DIFF model is superior to the ANCOVA model. In comparing the ANCOVA model to the DIFF model, the ANCOVA has a slightly higher R-square. This difference is marginal and is due solely to the ANCOVA model's extra parameter. The DIFF model has a lower RMSE, AIC, and BIC than the ANCOVA model. The ANCOVA estimate for the Pretest slope (β_2) is 0.91. Since this is close to 1.0, the additional parameter for Pretest in the ANCOVA model does not does not appear to significantly improve the model. The DIFF and ANCOVA models both provide positive estimates for the effect of the Treatment (β_1= 9.92 for DIFFERENCE and β_1= 9.28 for ANCOVA).

As for interpreting the DIFF model with the Nursing data set, for students who did not receive the intervention, one would expect a 0.65 gain in score from Pretest to Posttest. For a student who was in the Treatment group, one would expect a (0.65+9.92=10.57) point gain from Pretest to Posttest (the β_2 coefficient for the DIFF model indicates that a student belonging to the Treatment group will on average improve by 9.92 points from Pretest to Posttest). If one used the ANCOVA model, the estimate for the change from Pretest to Posttest for a student in the Control group is [21.73-(.09*Pretest)], while it is [30.01-(.09*Pretest)] for a student in the Treatment group, or an expected 9.28 point difference between the groups, after accounting for Pretest scores. Both estimates, however, for the effect of treatment, for the DIFF and ANCOVA models, are only marginally significant (P-values= 0.0400 and 0.0592, respectively).

Further, while the DIFF model shows that the Treatment group had greater improvement in scores, it does not convey that the Treatment group was 6.99 points lower, prior to intervention. In fact, none of the linear models directly conveys this information, an aspect of GLMs which is viewed as a weakness by those who prefer Mixed Model (Repeated Measures) analyses.

Table 5.2

Table of Model Results: Nursing Data Set

Model	Par	β_0	β_1	β_2	β_3	P-val	R-sq	RMSE	AIC	BIC
		Int	IT	Pre	Pre(IT)	β_1				
Null	1	234.30					0	22.18	240.5	242.0
Regression	2	35.73		0.87			0.616	13.97	211.0	214.0
ANOVA	2	232.88	2.93	0^*		0.7108	0.005	22.48	207.4	210.4
DIFF	2	0.65	9.92	1^*		0.0400	0.653	13.28	**172.6**	**175.6**
ANCOVA	3	21.73	9.28	0.91		0.0592	0.659	13.37	174.0	178.5
Full	4	54.80	-49.22	0.77	0.26	0.3812	0.672	13.35	209.8	215.7

Note.* These are the β_2 values for the ANOVA model and DIFFERENCE model that make these models statistically comparable to the ANCOVA model. Par—number of estimated explanatory parameters for the given model.

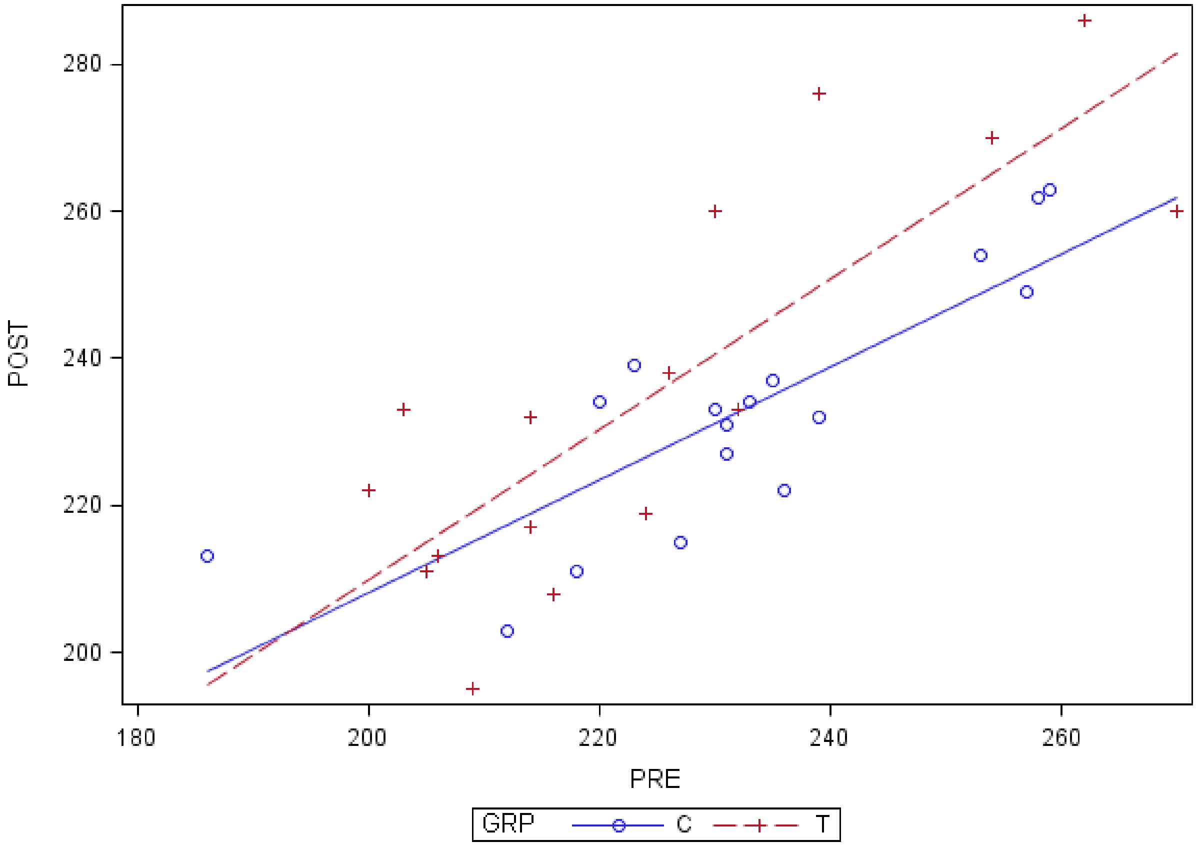


Figure 5.5 ANCOVA with Interaction Plot for Nursing Data Set

The intersection of the two lines in Figure 5.5 is somewhat misleading. One student in the control group received a lower (relative to the mean) Pretest and Posttest score; this one point is highly influential for the Control group regression line. The two lines intersect here, but the interaction term (β_3) is not significant, so that the data can be adequately modeled by parallel lines with slopes of 0.91, separated by a constant distance of 9.28 points.

5.1.2 Mixed Model for Nursing Data Set

Table 5.3 shows the Type 3 Tests of Fixed Effects for the Nursing Data set. If one were to view these results naively, one might conclude that the treatment was not effective, based on the results in Table 5.3. While the F-statistic for Group effect is not significant (P=.7756), this is **not** the statistic of relevance for determining if the intervention is effective. The F-value for the interaction of Group-by-Time indicates that the change in score from Pretest to Posttest is marginally significantly different (P=0.0400) between the Treatment group and the Control group. As is always the case with P-values based on an F-statistic, the F-statistic alone does not indicate the direction of the difference, although the afore-mentioned equivalence between the test of the Group-by-Time effect under the Mixed Model (see Table 5.3) and the test for Treatment effect in the DIFF model (see Table 5.2) does show that it **is** the Treatment group which improves significantly more than the Control group The F-value for Time is also significant (P=.0214), which indicates that the overall change in scores (when averaged over Group) is significantly different from 0 over the time period from Pretest to Posttest.

This data set is somewhat unusual in that the groups were randomized (PPGD), and the Pretest scores are not significantly different from one another (P=.3528 from row 3 of Table 5.4), but if the Pretest scores are ignored (as the ANOVA model assumes), no significant effect due to Treatment is found (P=.7108). On the other hand, if Posttest-Pretest differences are used (either directly or through the Mixed Model), a marginally significant Treatment effect is found. The ANCOVA model shows that the DIFF model perhaps slightly overstates the effect of Pretest score (β_2=0.91 vs. β_2=1.00), but it (ANCOVA) still estimates a Treatment effect of +9.28 points, which is not quite significant at the 5% level (P=.0592). Overall, it appears that this is a case where, even though PPGD was used, examination via ANCOVA, ANOVA on differences (i.e. DIFF model), or Mixed Models all find borderline significant results which would not have been apparent in the absence of Pretest information.

Table 5.3

Type 3 Tests of Fixed Effects for Nursing Data Set

Effect	Numerator DF	Denom. DF	F Value	Pr > F
Group	1	31	0.08	0.7756
Time	1	31	5.87	0.0214
Group*Time	1	31	4.59	0.0400

Table 5.4 shows the LS Means for the differences between-groups and within-groups, for the effect of Group-by-Time. The P-values are for a two-sided significance test, comparing pairs of the i^{th} Group at the j^{th} Time (where *i*= 'C' or 'T' and *j*= 'Pre' or 'Post'). This model estimates that the Control group scored 6.99 points higher than the Treatment group at Pretest, and that the Treatment scored 2.93 points higher than the Control group at Posttest. Neither difference is significantly different from 0 (P=.3538 and .6956, respectively). For the Control group, the mean change in scores is 0.65 (Posttest – Pretest); the mean change for the Treatment group was 10.56. This latter effect (for the Pretest to Posttest change in the Treatment group), is the only one of the four Group-by-Time effects that is significantly different from zero (P=.0033).

While the general conclusions are the same for the Mixed Model analysis and the DIFF model, the DIFF model does not provide estimates for the Pretest, which may or may not be of interest to a researcher. The results from the Mixed Model, demonstrate that the two groups differed prior to intervention by 6.99 points (as seen in line 3 of Table 5.4).

Table 5.4

Differences for Least Square Means for Nursing Data Set

Effect	GRP	TIME	GRP	TIME	Estimate	St Error	DF	T	Pr>|t|
Grp*Time	C	POST	C	PRE	0.65	3.22	31	0.20	0.8421
Grp*Time	C	POST	T	POST	2.93	7.42	31	0.39	0.6956
Grp*Time	C	PRE	T	PRE	-6.99	7.42	31	-0.94	0.3538
Grp*Time	T	POST	T	PRE	10.56	3.32	31	3.18	0.0033

Table 5.5 contains the comparison of the best conditional GLM Postetst estimates with those from the Mixed Model. As expected, the DIFF model and the Mixed Model result in identical estimates for both conditional means.

Table 5.5

Comparison of Best GLM with Mixed Model for Nursing Data Set

	DIFFERENCE MODEL		MIXED MODEL	
Group	Estimate	Std Error	Estimate	Std Error
Control	232.88	3.2211	232.88	5.1671
Treatment	235.81	3.3202	235.81	5.3261

5.2 THE ICA DATA SET

Table 5.6 shows the academic year in which students traveled abroad and took the ICA assessment. This table illustrates there is a potential threat to internal validity for this experiment: the *history effect*. Since data were collected over seven years, the thoughts and experiences between subjects could be different. For example, a student's decision to travel abroad in a given year could be impacted by global events during that time period, or the availability of funding for a given year. Further, the overall increase in technology would increase the availability of global information. Students who took the Global Design course in 2009 (as compared to 2003) could potentially have more intercultural awareness simply because of the increase in available information, created by technological advances (example—smart phones and hand-held internet usage became more readily available).

Table 5.6

Frequency Table for Year by Group for ICA Data Set

Frequency	Long	N/A	Short
2003	0	2	3
2004	0	4	3
2005	0	17	4
2006	6	25	6
2007	6	24	4
2008	0	1	3
2009	3	14	3
Total	15	87	26

Table 5.7 shows the summary statistics for the ICA Data Set, with illustrative histograms in Figures 5.6-5.8. The mean Pretest scores for the Control and Treatment group differ by 0.83,

where the Treatment group received a slightly higher score. This indicates that, at the time of the Pretest, those who eventually chose to study abroad reported feeling only slightly less apprehensive about other cultures, on average, than did their classmates, who ultimately did not choose to travel. At Posttest, students who traveled abroad scored 3.56 points higher on the ICA than their peers who did not choose to travel. The ICA scores were slightly more variable for the Control group variable than for the Treatment group at both time-points; the Posttest variance declined for the Treatment group, but increased for the Control group.

Table 5.7

Summary Statistics for ICA Data Set

Group	# Subjects	Variable	Mean	Median	Std Dev	Min	Max
Control	87	Posttest	56.03	55	7.95	30	70
		Pretest	55.24	55	7.61	34	70
Treatment	41	Posttest	59.59	59	5.01	53	70
		Pretest	56.07	56	6.05	43	70

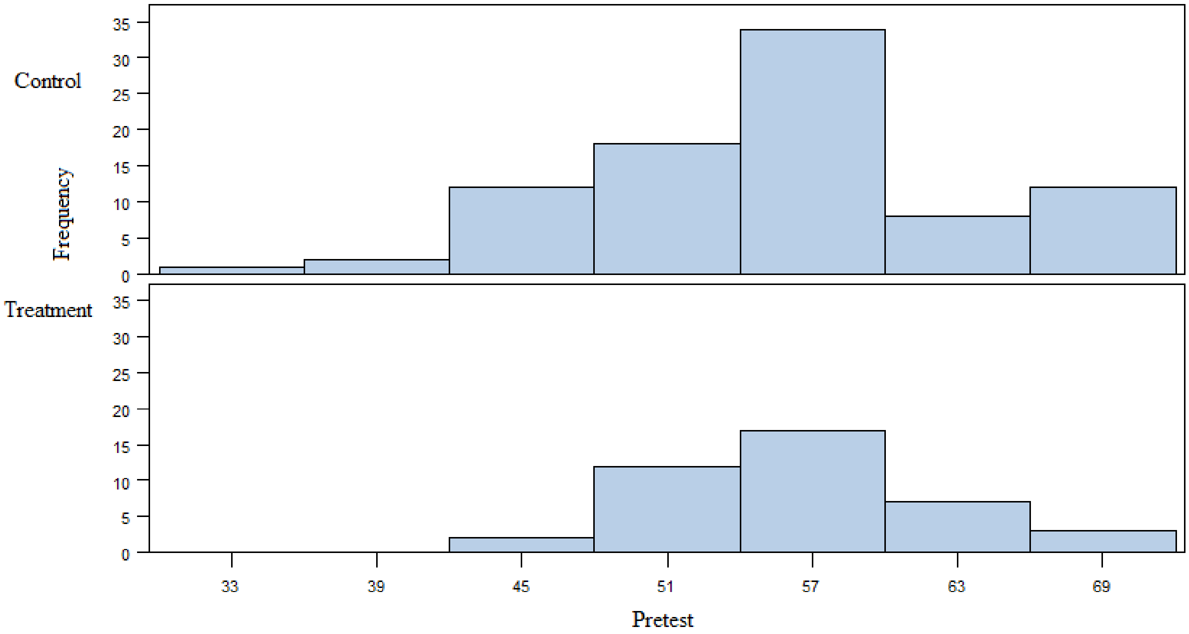


Figure 5.6 Histogram of ICA Pretest Scores

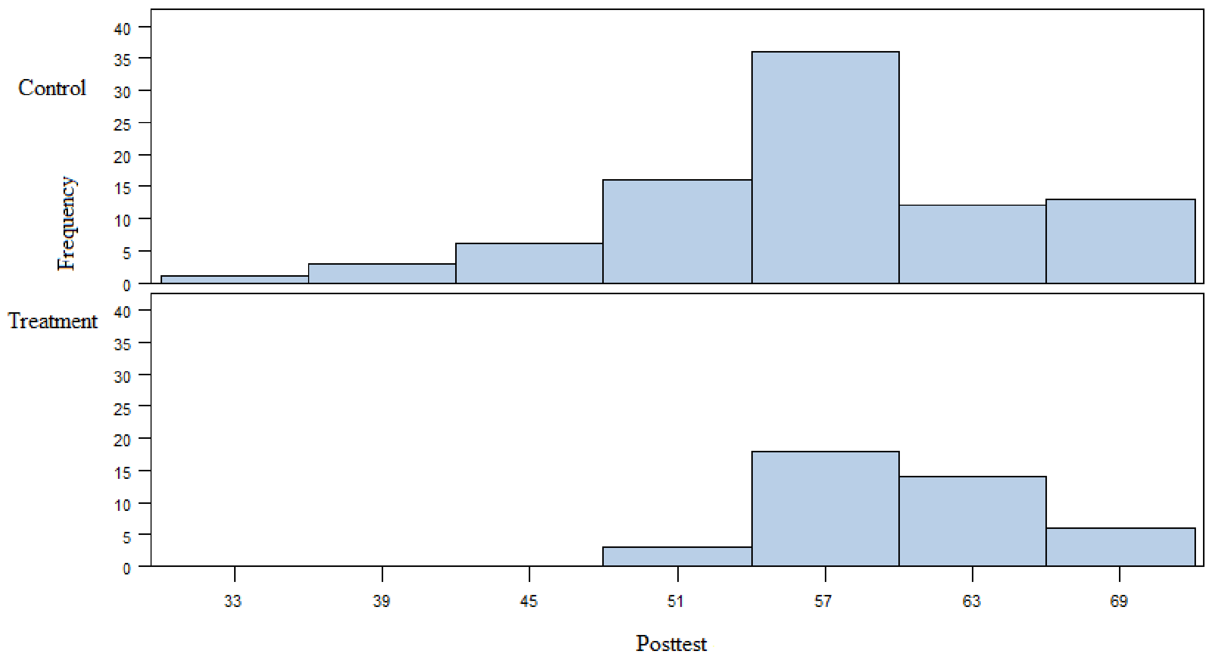


Figure 5.7 Histogram of ICA Posttest Scores

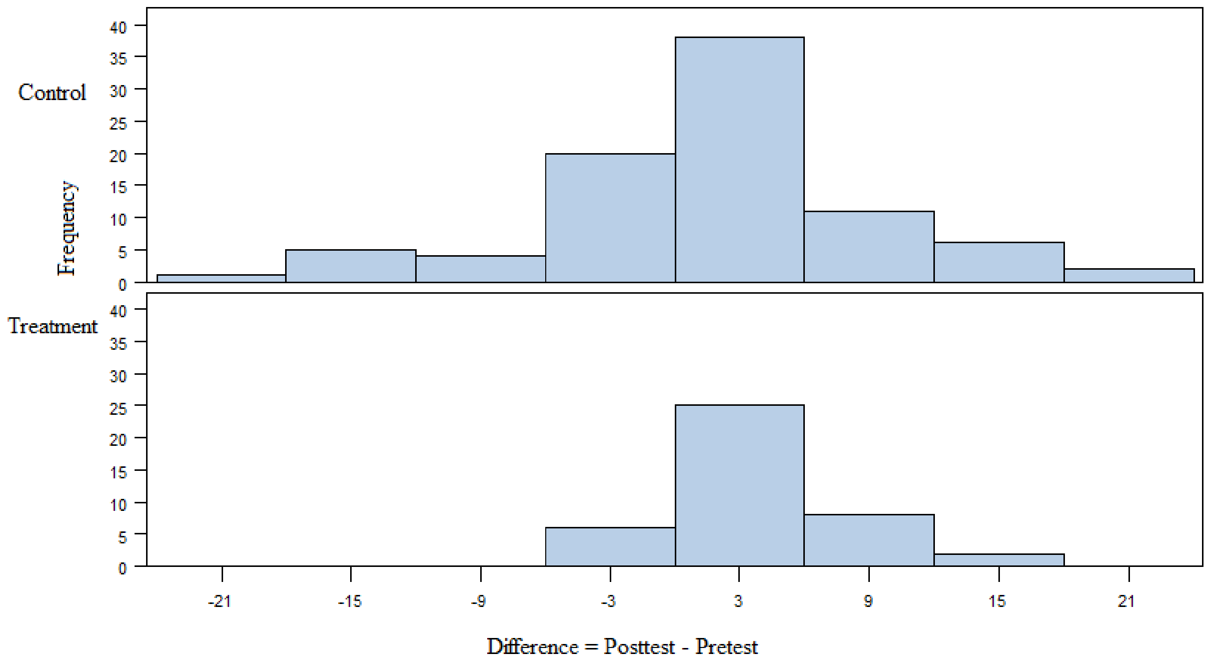


Figure 5.8 Histogram of ICA Difference Scores

Figure 5.9 below shows a trend plot for the ICA data. This figure illustrates that the Treatment and Control groups had similar mean Pretest scores, but that the change in score from Pretest to Posttest was not equivalent between the two groups. The Treatment group scored an average of 3.56 points higher at Posttest.

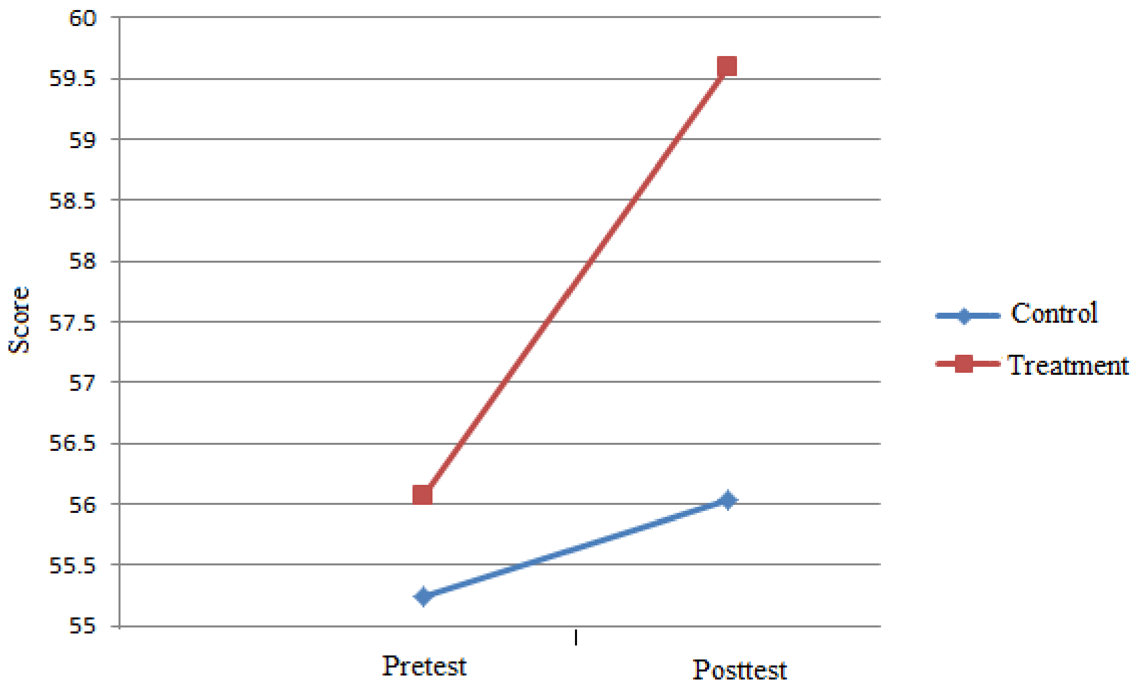


Figure 5.9 Trend Plot for ICA Scores
This plot illustrates that the two groups began with similar Pretest scores. The two groups changed at different rates, with the Treatment group starting both higher at the Pretest and having higher Posttest scores as well (as measured by the means for both groups).

5.1.1 GLMs for ICA Data Set

Table 5.8 shows the fit statistics and parameter estimates for the GLM for the ICA Data set. For the ICA data set, the ANOVA model using only Posttest again appears to be inferior to the other models (0.83 points higher for the Treatment group; P =0.5397). From examining the Full model, one sees that the interaction term isn’t significant, so the model is simplified to the

ANCOVA model. Since the slope estimate for the Pretest is very different from either 0 or 1 (β_2 = 0.53 for the ANCOVA model), neither the DIFF model nor the ANOVA model yield as good fits for this data set as the ANCOVA model does.

Upon considering AIC and BIC, one observes that the ANCOVA model best predicts Posttest scores for the ICA data. Although the R-square is lower for the ANCOVA model than for the Full model, the difference is primarily due to the extra parameter for the interaction (Pretest*IT) term. The ANCOVA model for the ICA data set predicts that for students with the same Pretest score, on average, a student who studied abroad would score 3.11 points higher on the Posttest than a student who did not travel. For example, a student who scored a 55 on the ICA at Pretest but did not study abroad would be predicted to score 55.7 at Posttest; a similar scoring student who did travel abroad would be predicted to score 58.81 at Posttest.

There is, of course, selection bias for this study. The treatment criteria, which was whether a student participated in study abroad, was self-selected. Since students self-selected themselves to be part of the treatment, their true apprehensions about intercultural communication could potentially be confounded with the treatment. Did students who traveled abroad really feel less apprehensive after international travel? Or, are students who want to pursue international travel less apprehensive about other cultures in the first place? If the latter were the only reason, one would have expected a larger difference in Pretest scores between groups.

Table 5.8

Table of Model Results: ICA Data Set

Model	Par	β_0 Int	β_1 IT	β_2 Pre	β_3 Pre(IT)	P-val β_1	R-sq	RMSE	AIC	BIC
Null	1	57.17					0	7.32	510.4	513.3
Regression	2	26.93		0.54			0.282	6.22	470.0	475.7
ANOVA	2	56.03	3.55	0^*		0.0098	0.052	7.15	505.6	511.3
DIFF	2	0.79	2.72	1^*		0.0397	0.116	6.91	496.7	502.4
ANCOVA	3	26.55	3.11	0.53		0.0080	0.322	6.07	**464.8**	**473.3**
Full	4	27.34	-0.43	0.52	0.06	0.9665	0.322	6.09	466.6	478.1

Note. * These are the β_2 values for the ANOVA model and DIFFERENCE model that make these models statistically comparable to the ANCOVA model. Par—number of estimated explanatory parameters for the given model.

Figure 5.10 shows an interaction plot for the ICA data. Based on the lines in the plot, for lower Pretest scores, the effect of the treatment appears to be less pronounced. For higher Pretest scores, the treatment effect appears have a greater impact on intercultural awareness, as measured by this assessment. However, since the interaction term in the Full model isn't significant, the data in Figure 5.10 can be just as well modeled by parallel lines with slopes of +0.53, separated by 3.11 points (i.e. the ANCOVA model).

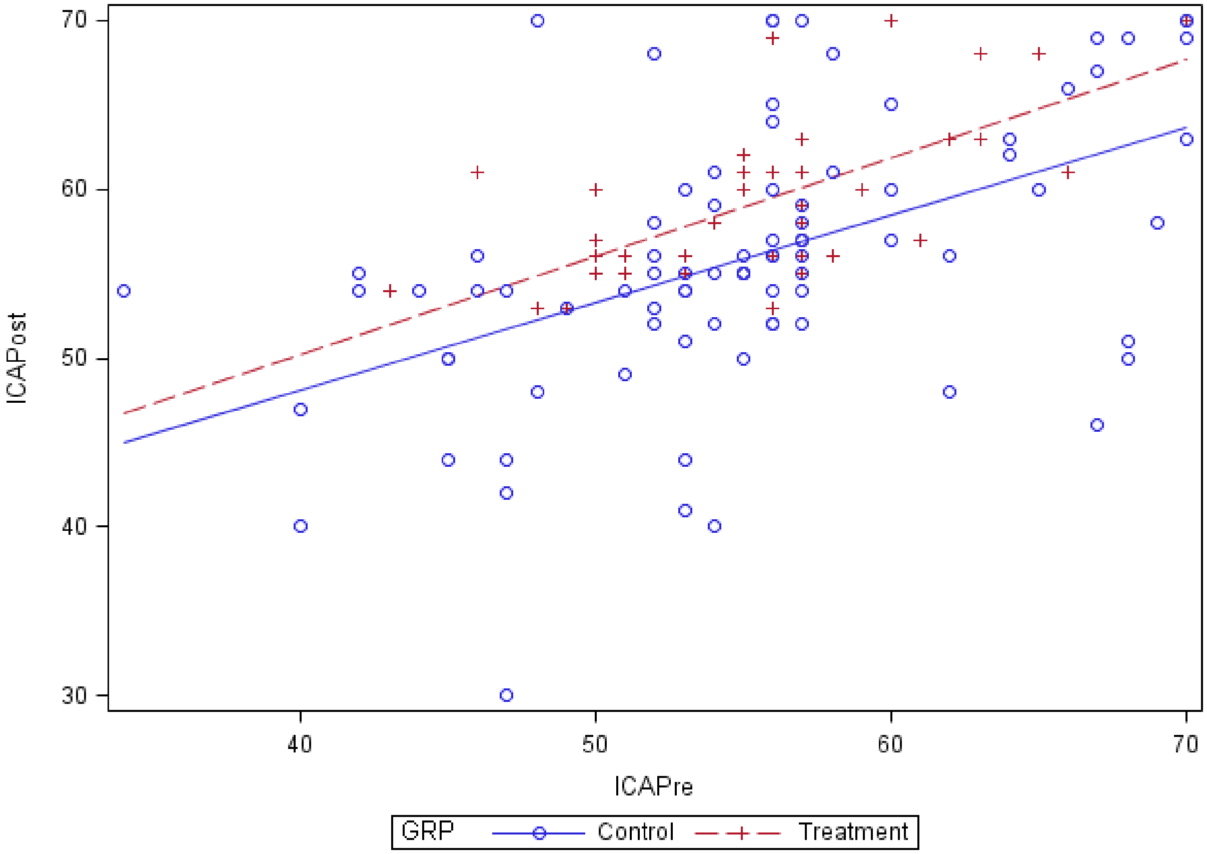


Figure 5.10 ANCOVA with Interaction Plot for ICA Data Set
This figure illustrates that there is no interaction between Pretest and Group. The upward trend for both groups indicates there exists a positive linear relationship between Pretest and Posttest.

5.2.2 Mixed Model for ICA Data Set

Table 5.9 shows the Type 3 Fixed Effect F-values for the ICA data. By comparison of the F-tests for the three effects, this is another scenario where a naïve application of Repeated Measures ANOVA can lead to misinterpretations. The Group effect is marginally insignificant at the 5% level (P = .0670). This effect is of lesser interest since it compares the average of the Pretest and Posttest scores, between groups. The Group-by-Time effect is significant, which indicates that that the two groups changed by different amounts between tests, although this significance is also marginal (P = .0397). The Time effect is very significant (P=.0013), indicating that scores (averaged over groups) changed from Pretest to Posttest.

Table 5.9

Type 3 Tests of Fixed Effects for ICA Data Set

Effect	Numerator DF	Denom. DF	F Value	Pr > F
Group	1	126	3.41	0.0670
Time	1	126	10.83	0.0013
Group*Time	1	126	4.32	0.0397

Table 5.10 shows the differences for the least square mean estimates for the ICA data set, using the Mixed Model. In comparing the differences for the mean estimates for the Control Group, the change of +0.79 points from Pretest to Posttest does not appear to be significantly different from zero (P =.2862). Also, the 0.83 point difference between Pretest scores for the two groups does not appear to be significantly different from zero. Although the mean ICA Pretest scores were similar between the two groups, this does not necessarily mean that the two groups were statistically equivalent. This merely shows that the two groups happened to scored similarly at Pretest. The change from Pretest to Posttest for the Treatment group was significant (P = .0010), with a mean gain in score for treatment group of 3.51 points (Posttest – Pretest). The difference between scores between the Treatment and Control groups at Posttest was also significantly different from zero (P = .0094 from Table 5.10 or P=.0098 from the ANOVA model of Table 5.8), with an estimated effect of +3.55 points.

Table 5.10

Differences for Least Squares Means for ICA Data Set

Effect	GRP	TIME	GRP	TIME	Estimate	St Error	DF	t	Pr>|t|
Grp*Time	C	POST	C	PRE	0.79	0.74	126	1.07	0.2862
Grp*Time	C	POST	T	POST	3.55	1.35	196	2.62	0.0094
Grp*Time	C	PRE	T	PRE	0.83	1.35	196	0.61	0.5399
Grp*Time	T	POST	T	PRE	3.51	1.08	126	3.26	0.0010

In Table 5.1,1 the LS mean from the ANCOVA model is calculated using the conditional Pretest mean by group (55.24 for Control and 56.07 for Treatment). When the estimates from SAS's LS Means are compared for the best GLM and the Mixed Model, the results are identical. The standard error for both of these estimates is lower for the ANCOVA model than for the Mixed Model. In both cases, the formula used for the Standard Error is S*$\frac{1}{\sqrt{n_i}}$, where n_i is the number of subjects in the group (n_T = 41, n_C = 87). The differences in SEs reported above arise because the 'S' used by the ANCOVA model is its RMSE of 6.07 (see Table 5.8), while the Mixed Model uses the pooled SD calculated from the four (Pre,Post)*(C,T) groups shown in Table 5.7, namely S=7.150 .

Table 5.11

Comparison of Best GLM with Mixed Model for ICA Data Set

	ANCOVA MODEL		MIXED MODEL	
Group	Estimate	Std Error	Estimate	Std Error
Treatment	59.59	0.9485	59.59	1.1167
Control	56.03	0.6511	56.03	0.7666

Table 5.12 shows the LS means using the ANCOVA model with a common Pretest score for both groups. When the estimates are calculated using the same Pretest mean (55.5078), the means estimates are less similar to the Mixed Model results shown in Table 5.11. The discrepancy between the different ANCOVA estimates is due to the Pretest means differing by 0.83 between groups. The standard error is higher for each estimate when the overall mean is used, when compared to the conditional mean estimates given in Table 5.11 above .

Table 5.12

LS Means from Best GLM at Common Pretest Mean for ICA Data Set

	ANCOVA MODEL	
Group	Estimate	Std Error
Treatment	59.28362	0.9495
Control	56.17669	0.6514

5.3 THE ECON DATA SET

This is another example of possible non-equivalent groups prior to intervention. Although the groups selected to receive the treatment were randomized, the groups themselves were self-selected. Thus, it is possible that some sections simply had better or worse students due to factors unrelated to the study. Table 5.13 shows the summary statistics for the Econ data set, with illustrative histograms shown in Figures 5.11-5.13. For this data set, the Treatment group average score was 8.05 points lower than the average score for the Control group, at Pretest. The Treatment Group scored 5.27 points higher than the Control group at Posttest. The standard deviations of scores for the two groups are similar at Pretest and Posttest. Although the SD of scores between testing sessions increases (from Pretest to Posttest) for both groups, the distribution of both Pretest and Posttest scores are somewhat skewed. For this data set, the logit transformation (Equation 4 of Table 2.1) yields slightly better results than untransformed scores, but for ease of comparability with analyses from the other three data sets, we will not examine that transformation here. Trend plots for these data are shown in Figure 5.14.

Table 5.13

Summary Statistics for Econ Data Set

Group	# Subjects	Variable	Mean	Median	Std Dev	Min	Max
Control	100	Posttest	73.87	75	12.64	30	95
		Pretest	34.44	34.5	8.43	14	54
Treatment	100	Posttest	79.14	81	10.21	44	98
		Pretest	26.39	26	7.12	10	48

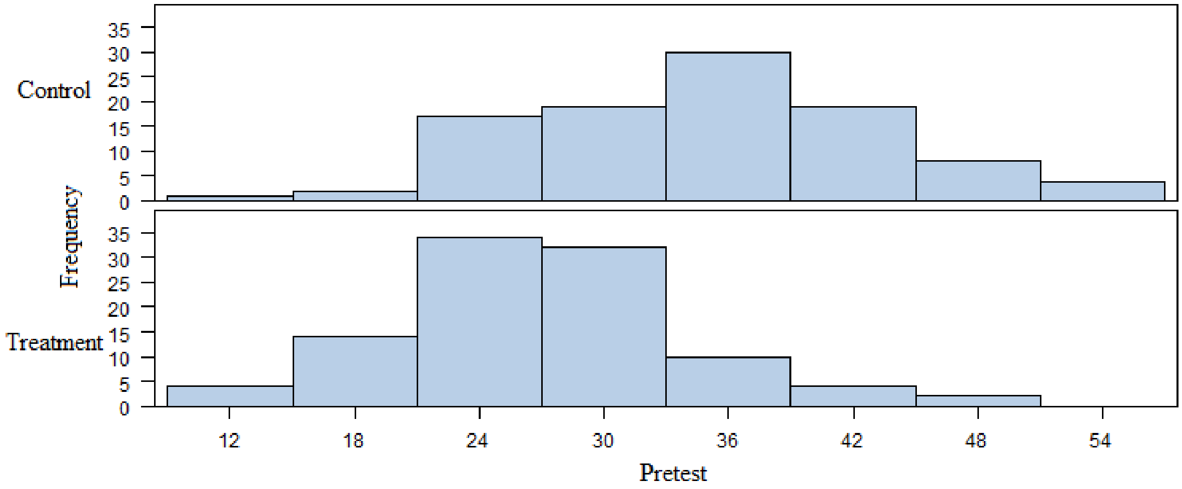


Figure 5.11 Histogram of Econ Pretest Scores

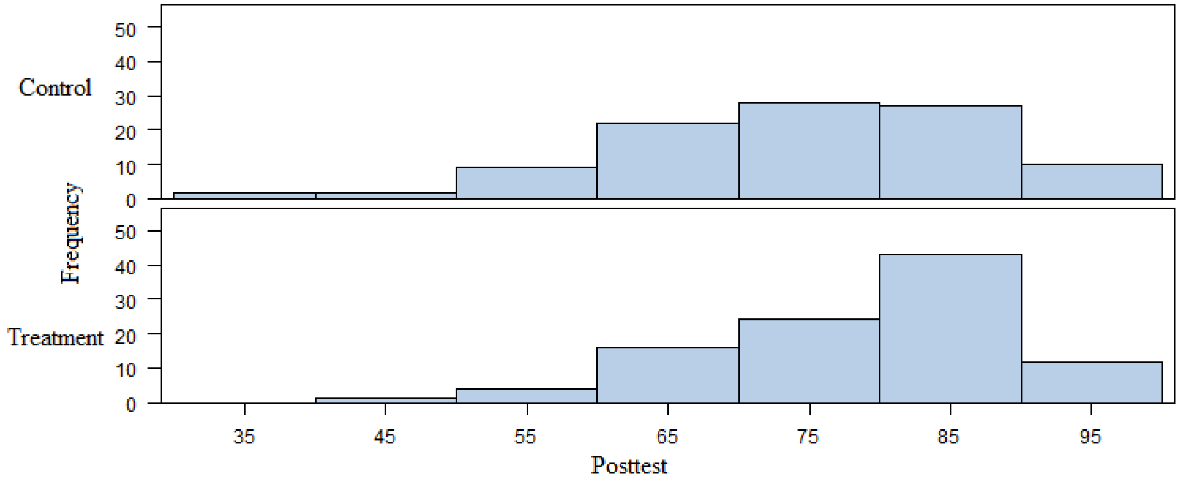


Figure 5.12 Histogram of Econ Posttest Scores

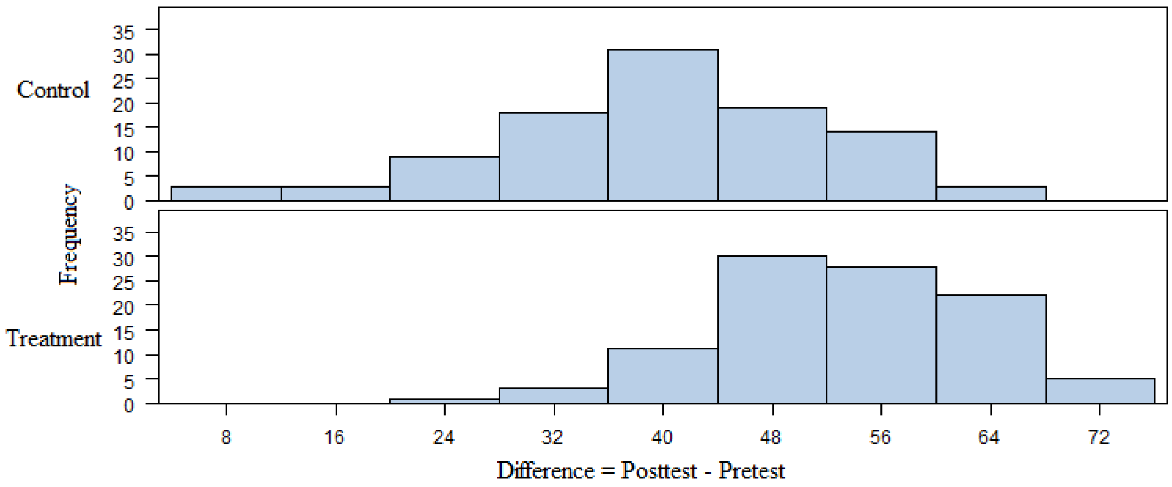
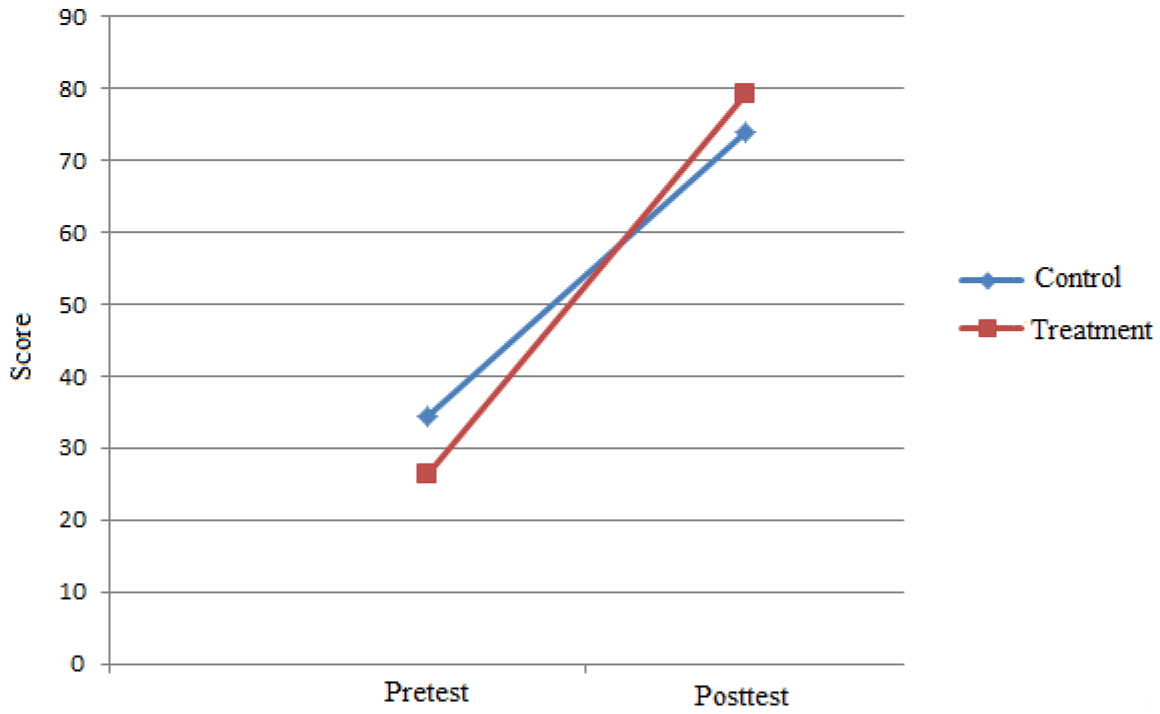


Figure 5.13 Histogram of Econ Difference Scores



5.14 Trend Plot for Econ Scores
This trend plot shows that the Treatment group had a higher mean gain in scores compared to the Control group, as theTreatment line is steeper. Although the two lines intersect, this intersection is different from a significant interaction for the GLM. The plot illustrates that the groups changed at different rates, while the interaction plot (Figure 5.14) illustrates that the linear relationship between Pretest and Posttest is roughly the same for both the Treatment and Control group.

5.3.1 GLMs for Econ Data Set

Table 5.14 shows the fit statistics and parameter estimates for the GLM for the Econ Data set. For the Econ data set, the Regression and ANOVA models produce very similar fit statistics. The R-square is only 5.58% for regression and 5.04% for ANOVA, meaning that Pretest scores or Treatment group alone account for less than 6% of the variation in Posttest scores. The overall correlation between Pretest and Posttest scores is somewhat low (0.2362), particularly when compared to the other data sets (see Table 3.1).

The interaction term included in the Full (Interaction) model is not significant, so the Full Model was reduced to the simpler ANCOVA model. The BIC and AIC values are much lower for the Full and ANCOVA models, compared to the DIFF model. This shows that the estimation of a parameter, for Pretest effect, reduces the overall error in the model (despite the loss in degrees of freedom). Further, the estimated slope for the Pretest effect under the ANCOVA model is 0.58 (not near zero or one), so one would expect that the ANCOVA model would be more appropriate for analysis either the ANOVA or DIFF models. Overall, ANCOVA is probably the most appropriate of these methods for analyzing this data set.

Table 5.14

Table of Model Results: Econ Data Set

Model	Par	β_0 Int	β_1 IT	β_2 Pre	β_3 Pre(IT)	P-val β_1	R-sq	RMSE	AIC	BIC
Null	1	76.51					0	11.76	986.9	990.2
Regression	2	66.87		0.32			0.056	11.46	977.5	984.1
ANOVA	2	73.87	5.27	0^*		0.0014	0.050	11.49	978.6	985.2
DIFF	2	39.43	13.32	1^*		<.0001	0.119	11.07	963.7	970.3
ANCOVA	3	53.97	9.92	0.58		<.0001	0.197	10.59	**947.1**	**957.0**
Full	4	53.78	10.32	0.58	-0.013	0.0912	0.197	10.62	949.1	962.3

Note. * These are the β_2 values for the ANOVA model and DIFFERENCE model that make these models statistically comparable to the ANCOVA model. Par—number of estimated explanatory parameters for the given model.

If one simply compares Posttest scores without accounting for Pretest variability, from the ANOVA model, one would predict Treatment group students to outperform Control group students by about 5.27 points. This difference is significant (P=.0014), but severely underestimates the true difference between the two teaching methods. If one uses difference to measure improvement, one obtains an estimate of 13.32 for the effect of Treatment; definitely an over-estimate. Finally, if one uses the ANCOVA model, one finds the expected difference between two students with the same Pretest score (no matter what that score is) would be +9.92 points, again very significant. Statistical significance of the Treatment effect is not really at issue for the Econ data set: all models agree that the Treatment scores are significantly better than the Control scores. The question of interest is to estimate the size of the difference. Finally, if one uses the Full (Interaction) model, one can see that there is a slight negative interaction between Treatment and Pretest score, so that, in fact, the expected difference in Posttest scores between two students with the same Pretest score (but assigned to different treatment groups) declines as Pretest score increases. This difference is very slight, as shown in Figure 5.15 below, ranging from 10.19 points if Pretest=10 to 9.62 if Pretest=54, fairly close to the constant difference of 9.92 points which would occur if the two lines were exactly parallel (i.e. if the ANCOVA model were used). Hence, as by the AIC and BIC values displayed in Table 5.14, the ANCOVA model is the best GLM for analyzing the Econ data set.

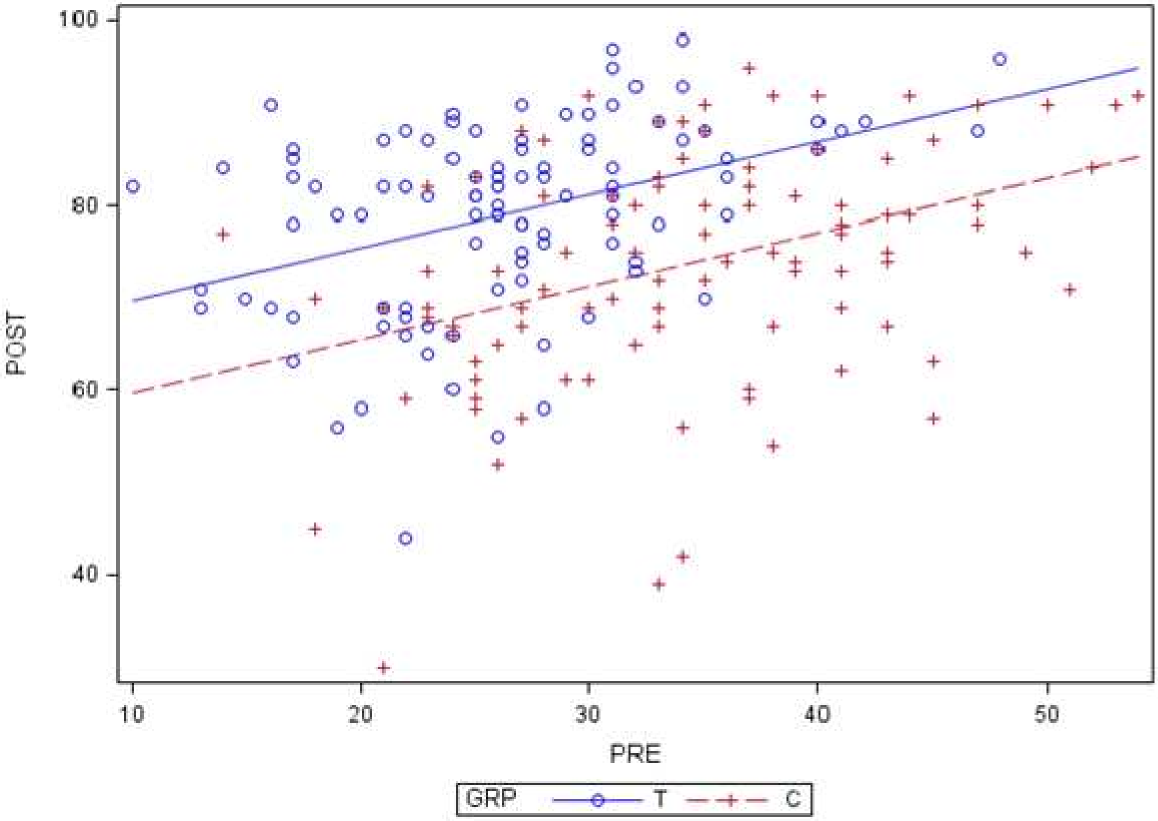


Figure 5.15 ANCOVA with Interaction Plot for Econ Data Set
The interaction plot for the Econ data shows that there is no interaction between Group and Pretest. This data provide a visual example of the well-fitting ANCOVA model.

5.3.2 Mixed Model for Econ Data Set

Table 5.15 displays the F-values for the Econ fixed-effect tests, using the Mixed Model. For the Econ data, while the overall Group effect is not significant (P = .2272), both effects for Time and Group-by-Time are very significant. These significance tests indicate that the average of the two groups improved significantly over time (i.e. from Pretest to Posttest), but that the change was not the same; this is entirely consistent with previous analyses.

Table 5.15

Type 3 Tests of Fixed Effects for Econ Data Set

Effect	Numerator DF	Denom. DF	F Value	Pr > F
Group	1	198	1.47	0.2272
Time	1	198	3467.04	<.0001
Group*Time	1	198	72.39	<.0001

Table 5.16 shows the LS mean differences for the Econ data set, using the Mixed Model. In the individual comparison for the group-by-time effect, both the Control group and the Treatment group had significant changes from Pretest to Posttest. The first row in Table 5.16 shows the control group improved by 39.43 points from Pretest to Posttest, which is very different from zero (P <0.0001). The bottom row in Table 5.16 shows that the treatment group improved by 52.75 points from Pretest to Posttest, which is also highly significant. The second row in Table 5.16 compares the Treatment and Control group at Posttest, and indicates that the mean score for Treatment group was 5.27 points higher than the Control group. The third row in Table 5.16 is an important one that is not demonstrated by any of the GLMs. This effect shows that the Control group scored 8.05 points higher than the Treatment group at Pretest; the 8.05 point difference is also highly significant (P <0.0001). Although the Treatment group did have an overall 13.32 net gain ($\text{Diff}_{\text{treatment}} - \text{Diff}_{\text{control}}$), it had more room for improvement in score.

Table 5.16

Differences for Least Square Means for Econ Data Set

Effect	GRP	TIME	GRP	TIME	Estimate	St Error	DF	t	Pr>|t|
Grp*Time	C	POST	C	PRE	39.43	1.11	198	35.62	<.0001
Grp*Time	C	POST	T	POST	5.27	1.39	349	3.79	0.0002
Grp*Time	C	PRE	T	PRE	-8.05	1.39	349	-5.80	<.0001
Grp*Time	T	POST	T	PRE	52.75	1.11	198	47.65	<.0001

Table 5.17 shows the comparison of LS mean estimates for ANCOVA and the Mixed Model. The ANCOVA mean estimates, computed with the conditional Pretest scores, are identical to the estimates from the Mixed Model. When comparing the ANCOVA results to that of the Mixed Model, both show that the difference in scores at Posttest was approximately 5.27 points. For the Econ data set, unlike the case with the ICA data set, however, the standard error is less for the Mixed Model estimates than the ANCOVA estimates. In this case, the ANCOVA standard errors are more accurate as they are S*$\frac{1}{\sqrt{n_i}}$= 10.595/10 = 1.0595, where the 'S' is the RMSE estimated from the 200 residual used in fitting the ANCOVA models. The formula for the standard error for the Mixed Model is also S*$\frac{1}{\sqrt{n_i}}$ but the 'S' used is the pooled SD obtained from combining the four SD estimates shown in Table 5.13 (S=9.821). However, that pooling assumes all four SD's are estimating the same thing, whereas it is fairly clear that the two Pretest SDs are much smaller than two Posttest SDs, so this method of pooling used in the Mixed Model artificially deflates the standard error for predicting Posttest scores. This drawback could be

remedied by allowing the variances of the Pretest and Posttest scores to be unequal, rather than forcing equality, as is done under the classical repeated measures design used in this analysis.

Table. 5.17

Comparison of Best GLM with mixed Model for Econ Data Set

	ANCOVA MODEL		MIXED MODEL	
Group	Estimate	Std Error	Estimate	Std Error
Treatment	79.1400	1.0595	79.1400	0.9821
Control	73.8700	1.0595	73.8700	0.9821

Table 5.18 shows the LS mean estimates for the ANCOVA model, when the common Pretest mean is used. When the LS mean is computed using the overall Pretest mean (30.4150), the estimates are quite different from those obtained in Table 5.17. When the conditional Pretest mean is used for estimating the mean Posttest scores for both groups, the difference between the Posttest scores is actually the β_1 ANOVA estimate (5.27). The difference in the estimates for the Table 5.18 is the β_1 estimate for the ANCOVA. Using the average Pretest score, the treatment group is predicted to do 9.92 points higher at Posttest.

Table 5.18

LS Means from Best GLM at Common Pretest Mean for Econ Data Set

	ANCOVA MODEL	
Group	Estimate	Std Error
Treatment	81.4656	1.1284
Control	71.5444	1.1284

5.4 THE SHI DATA SET

Table 5.19 shows the summary statistics for the SHI data set. The mean Pretest score for the Educational Literature group was around 9 or 10 points lower than that of the Video or Control groups, respectively. For the Control group, there was a 0.83 decline in mean SHI scores from Pretest to Posttest. The Educational Literature and the Video groups had mean gains of 20.34 points and 9.52 points, respectively. Although the Educational Literature group had a mean gain more than double the gain of the Video group, the difference in gains between the Educational Literature group and the Video group was not significant. When these groups were compared, pairwise, with the Control group, however, the difference in scores for the Educational Literature and Video groups were both significantly different from the Control group (alpha = 0.05). However, since the Educational Literature group and Video group did not differ significantly from one another, for purposes of analysis, they were combined into one group called "Treatment".

Table 5.19

Summary Statistics for Original SHI Data Set

Group	# Subjects	Variable	Mean	Median	Std Dev	Min	Max
Control	30	Posttest	164.70	167.5	30.21	75	216
		Pretest	165.53	164	22.92	105	211
Educational Literature	33	Posttest	177.64	183	24.99	125	210
		Pretest	157.30	156	24.15	116	200
Video	33	Posttest	176.70	182	24.13	106	207
		Pretest	167.18	170	21.85	116	203

Table 5.20 shows the summary statistics for the SHI data set after combining Educational Literature and Video into one group (Treatment). This is how the data were organized for the analyses in the remainder of this section. Illustrative histograms are displayed in Figures 5.16-5.18, with a trend plot in Figure 5.19.

Table 5.20

Summary Statistics for Condensed SHI Data Set

Group	# Subjects	Variable	Mean	Median	Std Dev	Min	Max
Control	30	Posttest	164.70	167.5	30.21	75	216
		Pretest	165.53	164	22.92	105	211
Treatment	66	Posttest	177.17	182.5	24.38	106	210
		Pretest	162.24	167	23.39	116	203

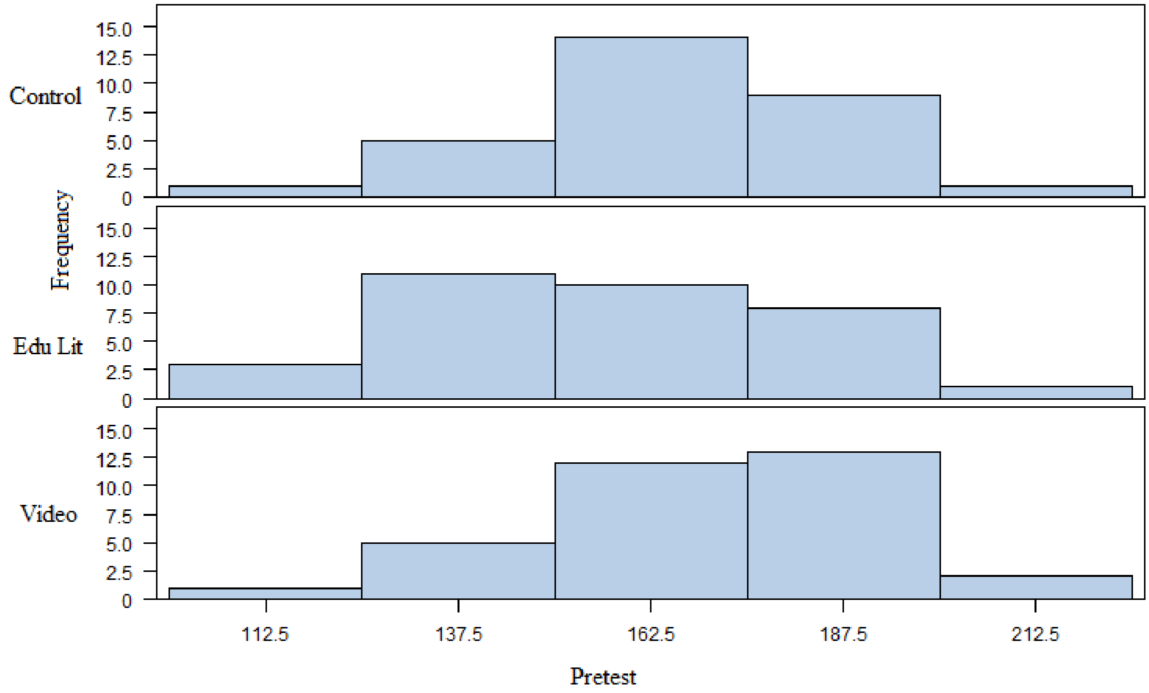


Figure 5.16 Histogram for SHI Pretest Scores

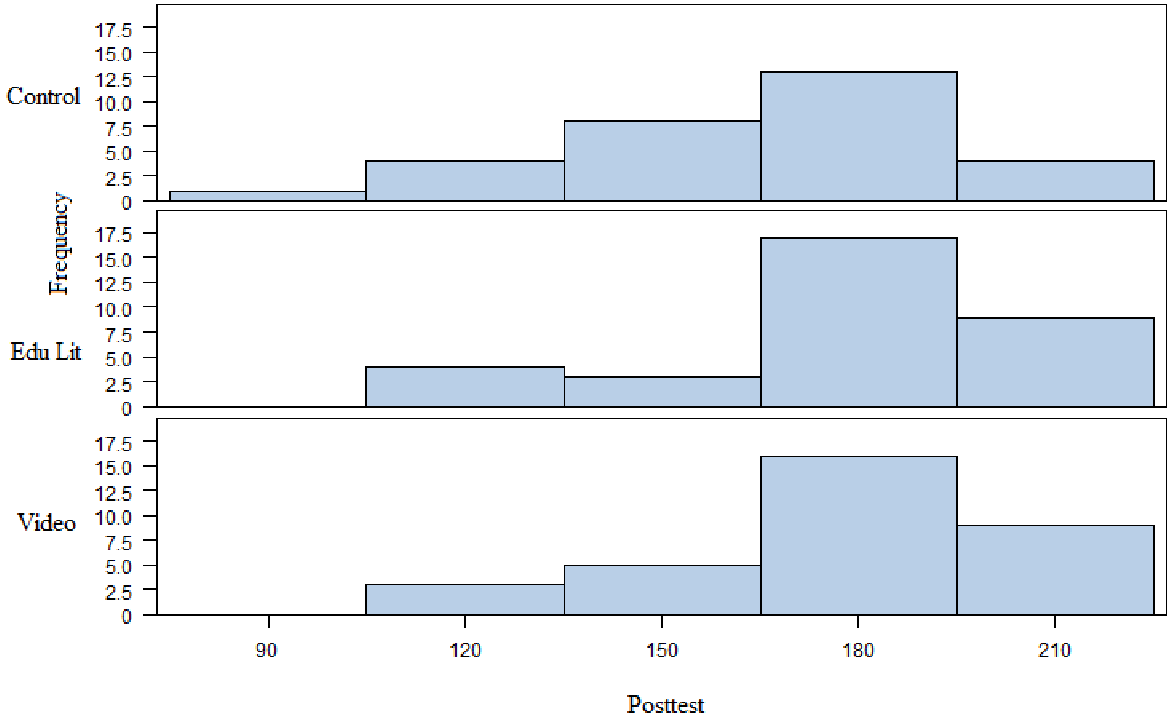


Figure 5.17 Histogram for SHI Posttest Scores

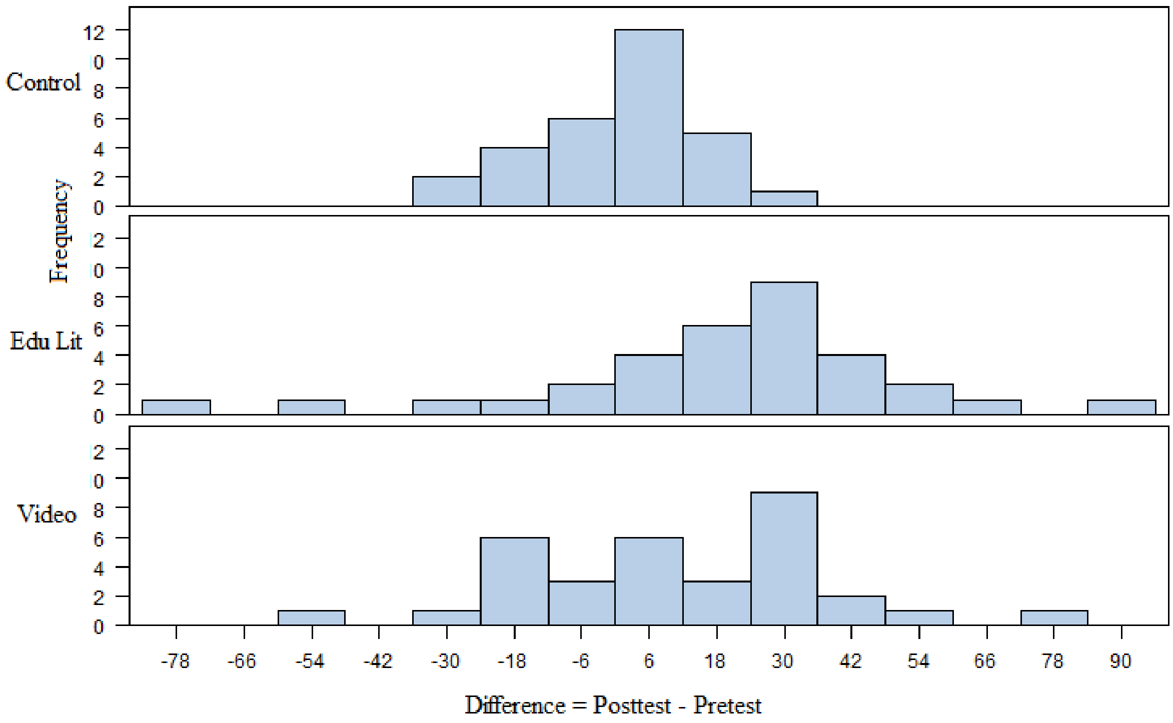


Figure 5.18 Histogram for SHI Difference Scores

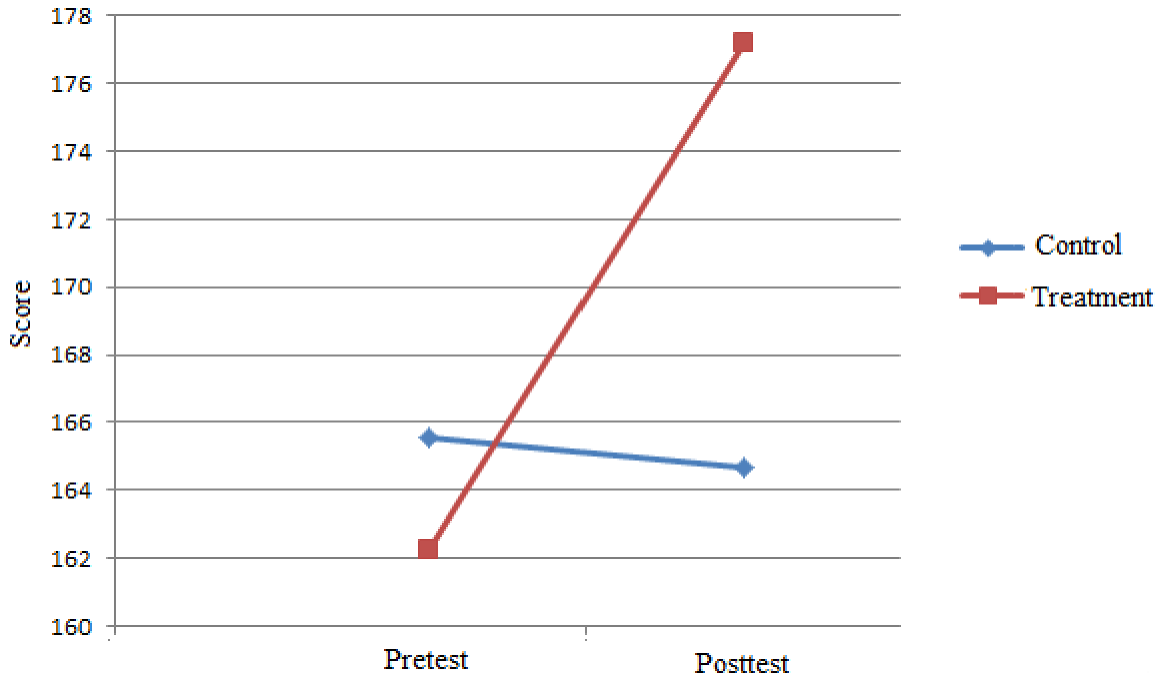


Figure 5.19 Trend Plot for SHI Scores
The trend plot for the SHI data illustrates that the mean score for the Control group actually declined over time. The steeper line for the Treatment group indicates that there was a much larger (and positive) change in score for this group. Since the lines cross, the effect of the Treatment may be exaggerated, as the Treatment mean was initially less than the Control mean.

5.4.1 GLMs for SHI Data Set

Table 5.21 shows the fit statistics and parameter estimates for the GLM for the SHI data set. In comparing the linear models for the SHI data, the Pretest scores explain about 18% of the variation in the Posttest scores, so the Regression model has improved predictive power when compared to the ANOVA model.

For this data set, the interaction term for Pretest and Treatment (Pretest * IT) is very significant. This model should therefore **not** be reduced to the ANCOVA or DIFF models. This significant interaction indicates that the slope (the effect of Pretest on Posttest) is not the same for two groups. Indeed, as the plot in Figure 5.20 below shows, unlike the case with the Econ data in Figure 5.15 (where the predicting lines were practically parallel), these prediction lines intersect. If the Pretest score is below 179, the Treatment Posttest score is expected to exceed the Control Posttest score, but the opposite is predicted to happen if the Pretest score is above 179. This is a very strange data set, perhaps overly influenced by the outlier (Pretest=105, Posttest=75) in the Control group displayed in the lower left corner of Figure 5.20.

Table 5.21

Table of Model Results: SHI Data Set

Model	Par	β_0 Int	β_1 IT	β_2 Pre	β_3 Pre(IT)	P-val β_1	R-sq	RMSE	AIC	BIC
Null	1	173.27					0	26.82	632.5	635.0
Regression	2	92.01		0.50			0.185	24.34	614.8	620.0
ANOVA	2	164.7	12.47	0^*		0.0340	0.047	26.32	629.9	635.0
DIFF	2	-0.83	15.76	1^*		0.0070	0.072	25.98	627.4	632.5
ANCOVA	3	79.20	14.17	0.52		0.0076	0.245	23.54	609.5	617.2
Full	4	-33.36	174	1.20	-0.97	<.001	0.393	21.24	**590.6**	**600.9**

Note. * These are the β_2 values for the ANOVA model and DIFFERENCE model that make these models statistically comparable to the ANCOVA model. Par—number of estimated explanatory parameters for the given model.

Based on the interaction plot (Figure 5.20) and summary statistics (Table 5.21), it would appear that there was substantially less variability in Posttest scores for the Treatment group than for the Control group. Posttest scores appear to be skewed left, with 75% of students in the Treatment group scored above 168 (Q1) at Posttest. The slope of the line for the Control group is much steeper than the slope for the Treatment. It appears from the interaction plot that Pretest scores were more useful in predicting Control group Posttest scores, compared to the Treatment group, although, as noted above, the outlier is affecting this. If one believes the treatment changed the subjects' perspective on sexual harassment, it appears that students with moderate to low Pretest scores who watched either the video or read literature on the topic became more sensitive to sexual harassment at Posttest, than those in the Control group with a similar low or moderate score. However, this improvement (relative to the Control group) was not found for those who had high Pretest SHI scores.

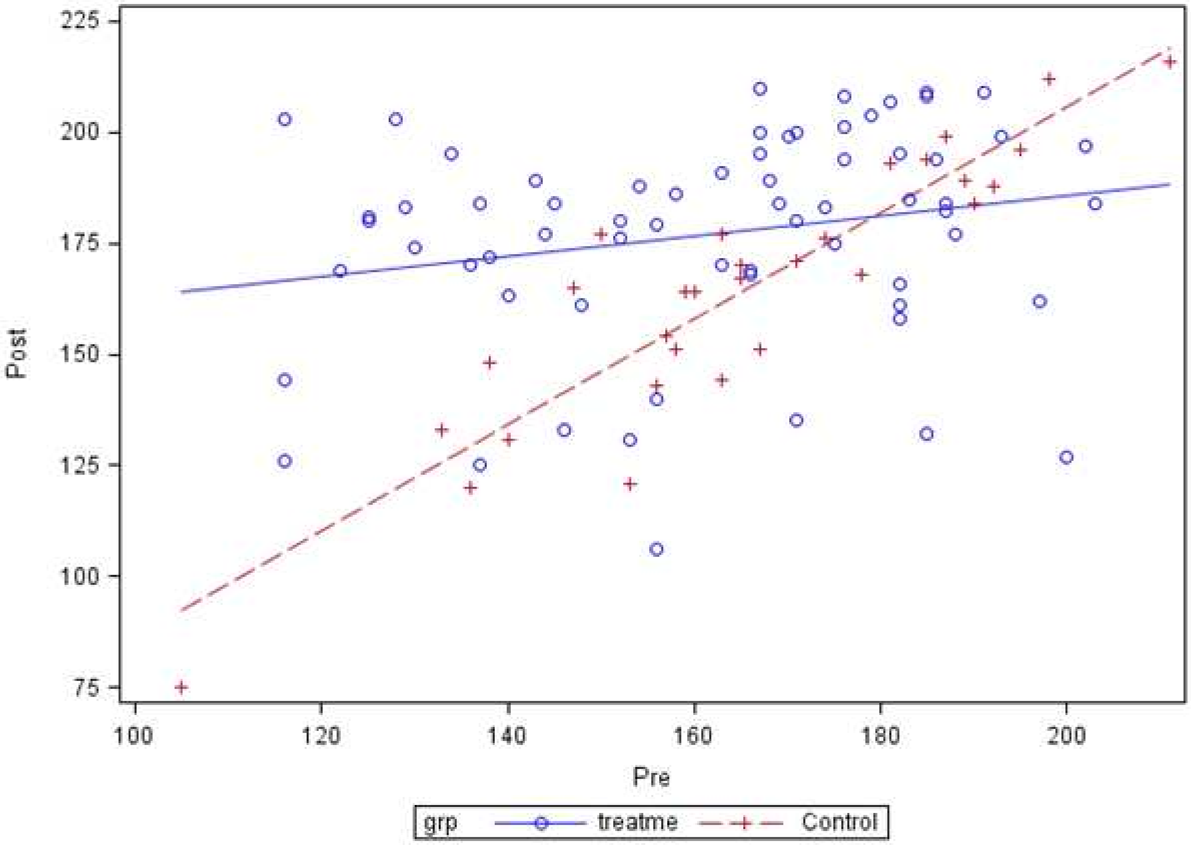


Figure 5.20 ANCOVA with interaction plot for SHI Data Set
The SHI data illustrate a clear interaction between Pretest and Group. The interaction means that Pretest and Posttest scores for the two are not linearly related in the same fashion.

5.4.2 Mixed Model for SHI Data Set

Table 5.22 shows the tests for fixed effects for the SHI data set. In comparing the tests for fixed effects, it appears that the overall Group effect is not significant (P=.3273). The Time effect is significant (P=.0156), which indicates that overall, the subjects' scores changed significantly from Pretest to Posttest. The Group-by-Time effect is also significant (P = .0070), which indicates that the change in score, from Pretest to Posttest, was not the same for both groups (i.e. one group had a greater change in score). This F-test statistic does not illustrate which group had a higher gain, although as noted for the previous data sets, this Group*Time test is equivalent to the test of the IT effect in the DIFF model, which from Table 5.21, shows that the Treatment score is expected to be 15.76 higher than the Control score.

Table 5.22

Type 3 Tests of Fixed Effects for the SHI Data Set

Effect	Numerator DF	Denom. DF	F Value	Pr > F
Group	1	94	0.97	0.3273
Time	1	94	6.07	0.0156
Group*Time	1	94	7.59	0.0070

Table 5.23 shows the differences for the LS means for the SHI data. In comparing the difference estimates, the change in score from Pretest to Posttest for the Control group does not appear to be significantly different from 0. Similarly, in the comparison of Pretest scores between the Treatment group and the Control group, the two groups are not significantly different. This indicates that the two groups, prior to intervention, did not respond significantly differently to the sexual harassment assessment. The estimate for the difference between Pretest and Posttest scores for the Treatment group is highly significant (P = <.0001). The associated coefficient estimate indicates that the mean change from Pretest to Posttest (or Posttest – Pretest) was 14.92 points, and that the Treatment group had a significant positive change in score over time. Also significant was the LS mean difference for the comparison of the Control and the Treatment group, at Posttest. The estimate for the mean difference was 12.47 points, or the Treatment group scored an average of 12.47 points higher on the SHI assessment at Posttest than

the Control group. This is exactly the same estimate as obtained by the ANOVA model of Table 5.21; the minor discrepancies in P-values (.0430 vs. .0239) are due to the slightly different procedures for estimating residual variances under the two procedures.

For this data set, the Mixed Model illustrates that the two groups did not significantly differ at Pretest, but did differ significantly at Posttest. Also, it shows that the Control group did not significantly change from Pretest to Posttest, but the Treatment group did.

Table 5.23

Differences for Least Squares Means for SHI Data Set

Effect	GRP	TIME	GRP	TIME	Estimate	St Error	DF	t	Pr>|t|
Grp*Time	C	POST	C	PRE	-0.83	4.74	94	-0.18	0.8609
Grp*Time	C	POST	T	POST	12.47	5.47	156	2.28	0.0239
Grp*Time	C	PRE	T	PRE	-3.29	5.47	156	-0.60	0.5481
Grp*Time	T	POST	T	PRE	14.92	3.20	94	4.67	<.0001

Table 5.24 shows the LS mean estimates for the best GLM (Full model) with conditional means and the Mixed Model. As seen in the other data sets, the SHI data also provides identical LS mean estimates for the best GLM (the Full(INTERACTION) model), using the conditional mean, and the Mixed Model. The standard error for the SHI data is lower for the Full model.

Table. 5.24

Comparison of Best GLM with Mixed Model for SHI Data Set

	INTERACTION MODEL		MIXED MODEL	
Group	Estimate	Std Error	Estimate	Std Error
Treatment	177.1667	2.6141	177.1700	3.0561
Control	164.7000	3.8774	164.7000	4.5329

Table 5.25 shows the LS mean estimate for the Full (interaction) model, using a common mean Pretest score. Again, when the overall mean (163.2708) is used to compute the LS mean for this GLM, there are differences between the estimates for the interaction model. If one uses the ANCOVA model to predict the difference in scores between the two groups, it appears that Treatment group’s students' mean Posttest score is expected to exceed the Control student's Posttest score by 177.3982-161.9929=15.41 points if both students start with a Pretest score of around 163. While the observed mean difference is 12.96, determining which estimate is ‘correct’ is dependent upon the question the researcher intends to answer. If a researcher is interested in estimating how a ‘typical’ student from each group might score, then estimates from Table 5.24 may be more appropriate. If a researcher is interested in estimating the score for an ‘average’ male freshman of the study, estimates from Table 5.25 may be more appropriate.

Table 5.25

LS Means from Best GLM at Common Pretest Mean for SHI Data Set

	INTERACTION MODEL	
Group	Estimate	Std Error
Treatment	177.3982	2.6167
Control	161.9929	3.8969

CHAPTER 6

CONCLUSIONS

A purpose of this thesis is to find optimal ways to analyze Pretest-Posttest designed studies. Whether it is a true experiment (PPGD) or quasi-experiment (NEGD), a researcher should attempt, prior to experimentation and analysis, to rule out all rival hypotheses to those being tested. Causation between two variables cannot be accurately inferred if the experimental design is not valid. Despite the lack of randomization, the NEGD can still be a beneficial design, as samples are generally easier to form than in true randomized experiments, and there is relative ease in creating a single-blind study (thus minimizing *reactive arrangements*).

There are numerous methods, beyond those presented in this thesis, that exist for analyzing PPGD and NEGD. The best GLM for data analysis is dependent upon the data. For each data set, utilizing the Pretest data in the analyses improved the fit statistics and reduced the proportion of unexplained variance compared to using the ANOVA model, which completely ignores Pretest information. From these examples, neither the Pretest nor the Group alone is most powerful in predicting Posttest scores; a form of the ANCOVA model usually provides the best analysis for the GLM. In building a GLM for these studies, one should probably start with the Full Model (including an interaction term) and reduce to the ANCOVA if the interaction is not significant. When the slope estimate for the Pretest is near ‘1’ or ‘0’, the ANCOVA model may be further reduced to the DIFF model or the ANOVA model, respectively. In these two scenarios, the DIFF model and ANOVA model will generally provide better fit statistics than the

ANCOVA, as the additional parameter estimate for Pretest slope does not significantly reduce the SSE.   In cases where groups are non-equivalent prior to treatment intervention, LS means predictions using the overall Pretest mean may distort the true gains or losses between groups at Posttest. On the other hand, this method may give a truer estimate of the difference between groups at Posttest if they had been equivalent at Pretest. This is a philosophical battle that can't really be answered with certainty if the design is NEGD.

While the Mixed Model may be more difficult to understand, it is more flexible in scenarios where the assumption of constant variability may be violated (though these examples are not shown for simplicity of comparison). Further, the Mixed Model provides estimates for both the Posttest and Pretest scores. Estimation of the Pretest may or may not be of interest to the researcher. If LS means are computed using the conditional group means for the best GLM, the GLM and Mixed Model will yield identical estimates for the Posttest means.

If a researcher prefers the analysis of the GLM and chooses to apply the same mean for both groups, discrepancies between Pretest scores should be taken into account, if they exist. If a researcher prefers the Mixed Model or Repeated Measures ANOVA, it is important to utilize 'Group-by-Time' effect rather than the 'Group' effect. A significant 'Group' effect will tend to show if the groups were different at Pretest and Posttest, which may be due to a lack of equivalence, rather than a treatment intervention. A significant 'Group-by-Time' effect will tend to show if the groups experienced significantly different gains or losses from Pretest to Posttest, which should be the case if the treatment method caused the change in scores. If a researcher is interested in analysis of the difference where the ANCOVA slope is near one and is interested in interested in modeling Pretest scores, the Mixed Model is an ideal fit.

An original goal of this thesis was to provide statistical consultants with some advice concerning how to best explain analyses of Pretest-Posttest designs to clients. Although the preceding discussion has demonstrated that there is generally not one method of analysis which is always best, this investigation has provided data summaries which would be useful no matter what form of analysis is later pursued. These will be illustrated below by referring to the appropriate tables and figures from the Econ data set analysis, although what is said is applicable to all four data sets. First, almost obviously, a consultant should display the summary statistics for the Group*Time samples, as shown in a table such as Table 5.13. One can then simultaneously examine the distribution of Pretest and Posttest scores by Group, as shown in Figures such as 5.12 and 5.13. One could also take the four Group*Time means reported in the original data summary (Table 5.13) and plot them graphically as shown in Figure 5.14 (ignoring, for now, the connecting lines). Alternatively, one could plot (Pretest,Posttest) scores for all subjects in the population, using color coding to represent group membership, as done in Figure 5.15 (again ignoring the plotted lines).

All of the above-mentioned tables and plots are not really analyses at all – they simply display the data in various formats that may be useful. It is recommended that statistical consultants show clients all of these representations of the data before performing any analyses. Many of the ‘mistakes’ made in performing analyses of Pretest-Posttest designs occur because clients and/or consultants rush into analyses without carefully understanding their data. Once all of the has been done, one can begin performing various analyses. One could perform statistical tests to compare any of the pairs of means shown in the original data summary. These are the four tests shown in tables such as Table 5.16 (between Posttest and Pretest scores for Control group, between Treatment and Control groups for Posttest scores, between Treatment and

Control groups for Pretest scores, and between Posttest and Pretest scores for the Treatment group, respectively). The first and fourth of these tests are equivalent to testing that the slopes of the two lines given in the trend plot (Figure 5.14) are zero. The second of these tests is roughly equivalent to the ANOVA model performed on the Posttest scores. The third of these is the test for equality of Treatment and Control means at Pretest, an often ignored, but rather useful, test.

Finally, after examining all of the above, one might conduct what many consider to be the ‘real’ test of interest. If one believes that Posttest-Pretest difference (i.e. ‘gain’) is the relevant measure of success, then one is interested in testing whether the means of difference histograms (such as those plotted in Figure 5.13) are significantly different from one another. This is exactly equivalent to testing that the slopes of the two trend lines plotted in Figure 5.14 are equal to one another. The test statistic for performing this test is given by the Group*Time interaction test shown as the last line of Table 5.15.

Alternatively, if one isn’t certain that ‘gain’ is the appropriate measure, one can consider various linear models that incorporate Pretest score into the analysis. In such cases, one would want to consider plots like those shown in Figure 5.15. The data are the points displayed in the figure, and the only question is which pair of lines should be superimposed as lines of best fit. The pair which are actually drawn in Figure 5.15 (and in analogous figures for other data sets in this thesis) are the Full model lines, which allow the lines to have separate slopes and intercepts. If one constrains oneself to the two parallel lines which best fit the data, this would correspond to the ANCOVA model. If one constrained the best-fitting lines to not only be parallel but also to be flat (zero slope), this would correspond to the ANOVA model. If one searched for the best-fitting pair of lines such that both had slope=1.0, this would correspond to the DIFF model.

While all of the above may seem obvious, it appears that even experienced statisticians can become confused (or confuse clients!) when explaining such results. Presenting graphical displays of the type mentioned above would definitely help consultants to clarify many of the analyses explored in this thesis.

One final caution must be delivered. An underlying assumption within this thesis is that the Pretest score is a valid measurement for determining whether two groups are equivalent. While the Pretest addresses some aspects of validity, the two groups can potentially differ (and likely do differ, particularly for cases of self-selection) in many aspects that the Pretest cannot measure or detect. Additionally, the mere idea of prior exposure to a test may affect how subjects respond at Posttest (*test effects*). If a Pretest is administered for a study, and the mean scores across groups are similar, it does not necessarily indicate that two groups are equivalent. While the ANCOVA adjusts for Pretest scores, it can potentially be a false sense of adjustment in the case where the testing cannot capture the existing differences between groups (likely to occur in the non-randomized case).

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