Pretest-posttest study designs are widely used across a range of scientific disciplines, principally for comparing groups and/or measuring change resulting from experimental treatments. The definitive characteristic of this study design is that (at least) two measurements are made on the same experimental unit: the pretest measurement made prior to the administration of a treatment or intervention and the posttest measurement made at a point in time reasonably afterward. Pretest-posttest studies have been pervasive for many years, however many researchers are still unclear on the statistical methods most appropriate for analyzing such data.

A typical example could be the following: A researcher hypothesizes that literacy skills can be improved by a new reading curriculum. Prior to the delivery of the curriculum, proctors administer a standardized literacy assessment at the start of the school year to 30 students in a school district. Of the 30 students, 15 are then randomly chosen to receive the new curriculum, while the 15 other students receive their districts’ current curriculum. At the end of the school year, all 30 students take the same standardized literacy assessment delivered at baseline again.

There are several common approaches employed to analyze such data, three of which are presented below.

1) ANOVA on Change Scores. The change score ( ) can represent the dependent variable in an ANOVA that compares two or more groups. This is a tempting choice in that it reduces the problem from a multivariate one to a univariate one, with this new variable easily interpreted as net gain or loss. Change scores are often criticized (in many cases unjustly) as being less reliable than the raw scores, however a more serious problem with this approach is that change scores can be greatly biased when regression toward the mean is present. Regression toward the mean is when a first measurement of a variable is an extreme value it will tend to be closer to average on its second measurement (i.e. “averaging out”), and it is a relatively common phenomenon.

2) Repeated Measures ANOVA. Using the data as a mixed factorial design with one between-subjects factor (treatment group) and one within-subjects factor (pretest-posttest) is also a common approach. As explained in a previous newsletter (http://www.cscu.cornell.edu/news/statnews/stnews77.pdf), such data can be analyzed using two different statistical methods. However, regardless of the analysis method chosen, the interaction between the treatment factor and pretest-posttest factor, (i.e. the parameter of interest to detect group differences over time) is equivalent to the treatment main effect within a one-way ANOVA on change scores. Hence this method is subject to all of the previous deficiencies of the ANOVA method.
3) **GLM with covariate.** A General Linear Model framework, with pretest scores as the covariate, is generally the preferred method for analyzing pre-post design data as it eliminates systematic bias and reduces error variance. This method implicitly takes into account regression toward the mean. It has been shown that the outcome in such a GLM may be either the raw posttest scores or change scores, as they will yield exactly equivalent results for the treatment effect. Researchers must keep in mind that though this is likely the appropriate analytic choice, the usual assumptions that underlie GLM still apply: randomization, homogeneity of regression slopes, pretest measurement reliably, and a linear relationship between pretest and posttest scores. Fortunately GLM has potential modifications if such violations are detected (e.g. nonparametric rank-transformations, interaction term between pre-test and treatment).

With regression toward the mean being a common problem, choosing an appropriate method for analyzing pretest-posttest designs should implicitly address this phenomenon, such as GLM with pretest score as the covariate. If you need assistance with a Pretest-Posttest analysis problem, do not hesitate to contact a statistical consultant at the Cornell Statistical Consulting Unit.

**References and Further Reading:**

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