Paper 260-26

PROC GLM or PROC CALIS?

Diana D. Suhr, Ph.D.
University of Northern Colorado

Abstract

Traditional statistical approaches to data analysis use PROC GLM whereas Structural Equation Modeling (SEM) techniques use PROC CALIS. Similarities and differences between traditional and SEM approaches will be discussed. Regression, analysis of variance (anova), and repeated measures anova are traditional methods using PROC GLM. SEM with PROC CALIS is a comprehensive and flexible approach to multivariate analysis using observed (measured) and unobserved (latent) variables (Hoyle, 1995). Research hypothesis typically tested by traditional methods may be tested using SEM techniques. A repeated measures analysis of variances example illustrates traditional and SEM methodologies. The repeated measures anova tests for differences between the means and for linear trends. The SEM analysis estimates nonlinear trends, variances of measured and latent variables, relationship between latent variable variances, and means of latent variables (initial level and rate of change).

Introduction

PROC GLM is a SAS procedure using the least squares method to fit general linear models. Traditional statistical methods available with PROC GLM are regression, analysis of variance (anova), analysis of covariance (ancova), multivariate anova, and partial correlation.

The PROC CALIS SAS procedure (Covariance Analysis of Linear Structural Equations) estimates parameters and tests the appropriateness of structural equation models using covariance structural analysis. Although PROC CALIS was designed to specify linear relations, structural equation modeling (SEM) techniques have the flexibility to test nonlinear trends.

SEM is a methodology for representing, estimating, and testing a theoretical network of (mostly) linear relations between variables (Rigdon, 1998). A structural equation model is a hypothesized pattern of directional and nondirectional relationships among a set of observed (measured) and unobserved (latent) variables (MacCallum & Austin, 2000). In the most common form of SEM, the purpose of the model is to account for variation and covariation of the measured variables (MVs). Path analysis (e.g., regression) tests models and relationships among MVs. Confirmatory factor analysis tests models of relationships between latent variables (LVs or common factors) and MVs which are indicators of common factors. Latent growth curve models (LGM) estimates initial level (intercept), rate of change (slope), structural slopes, and variance. Repeated measures analysis of variance (anova) is a type of LGM.

Similarities

SEM is similar to traditional methods like correlation, regression and anova in many ways. First, both traditional and SEM are based on linear statistical models. Second, statistical tests associated with both methods are valid if certain assumptions are met. Traditional methods assume a normal distribution and SEM assumes multivariate normality. Third, neither approach offers a test of causality. However, SEM can evaluation a causal hypothesis.

Differences

Traditional approaches differ from the SEM approach in several areas. First, SEM is a highly flexible and comprehensive methodology. This methodology is appropriate for investigating achievement, economic trends, health issues, family and peer dynamics, self-concept, exercise, self-efficacy, depression, psychotherapy, and other phenomenon.

Second, traditional methods specify a default model whereas SEM requires formal specification of a model to be estimated and tested. SEM offers no default model and places few limitations on what types of relations can be specified. SEM model specification requires researchers to support hypothesis with theory and specify relations a priori.

Third, SEM is a multivariate technique incorporating observed (measured) and unobserved variables (latent constructs) while traditional techniques analyze only measured variables. Multiple, related equations are solved simultaneously to determine parameter estimates with SEM methodology.

Fourth, SEM allows researchers to recognize the imperfect nature of their measures. SEM explicitly specifies error while traditional methods assume measurement occurs without error.

Fifth, traditional analysis provides straightforward significance tests to determine group differences, relationships between variables, or the amount of variance explained. SEM provides no straightforward tests to determine model fit. Instead, the best strategy for evaluating a SEM model fit is to use multiple tests (e.g., chi-square, Comparative Fit Index (CFI), Bentler-Bonett Nonnormed Fit Index (NNFI), Root Mean Squared Error of Approximation (RMSEA)).

Sixth, SEM resolves problems of multicollinearity. Multiple measures are required for a latent construct (unobserved variable). Multicollinearity cannot occur because unobserved variables represent distinct latent constructs.

Finally, a graphical language provides a convenient and powerful way to present complex relationships in SEM. Model approximation involves formulating statements about a set of parameters. A diagram, a pictorial representation of a model, is transformed into a set of equations. The set of equations are solved simultaneously to test model fit and estimate parameters using PROC CALIS.

Repeated Measures ANOVA Example

This example investigates the change in reading achievement for 7- through 13-year old girls. Comparisons of repeated measures anova using PROC GLM and a latent growth curve model using PROC CALIS are shown.

Participants

Participants were part of the National Longitudinal Survey of Youth (NLSY79). The original NLSY79 sample design enabled researchers to study longitudinal experiences of different age groups as well as analyze experiences of women, Hispanics, Blacks, and economically disadvantaged. The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14- to 22-years old when first surveyed in 1979 (Baker, Keck, Mott, & Quinlan, 1993).

As part of the NLSY79, mothers and their children have been surveyed biennially since 1986. Although the NLSY79 initially analyzed labor market behavior and experiences, the child assessments were designed to measure academic achievement as well as psychological behaviors. The child sample consisted of all children born to NLSY79 women respondents participating in the study biennially since 1986.

The number of children interviewed for the NLSY79 from 1988 to 1994 ranged from 4,971 to 7,089. Due to attrition, the number of children who completed four assessments in reading recognition achievement was 1,188. A cohort-sequential design in a previous study permitted estimation of growth curves for 5- through 14-year old boys and girls (Suhr, 1999). For simplicity, the 7-year old girls cohort was used as the example in this paper (n = 135). Assessments were collected at ages 7-, 9-, 11-, and 13-years old for the 7-year old cohort.

Measurement Instrument

The PIAT (Peabody Individual Achievement Test) Reading Recognition Subtest, provided an achievement measure of word recognition and pronunciation ability, essential components of reading (Dunn & Markwardt, 1970). Test-retest reliability of PIAT Reading Recognition ranged between 0.81 for kindergartners to a high of 0.94 for third graders (median = 0.89).

Models

The default model for the repeated measures anova using PROC GLM assumes change is linear, constant across time, and occurs at one unit between each measurement period. In addition, traditional statistical approaches assume measurement occurs without error. Therefore, the PROC GLM model specifies no measurement error. SEM using PROC CALIS explicitly specifies measurement error.

The SEM model shown in Figure 1 specifies latent variables, initial level (intercept) and rate of change (slope). A constant is regressed on the latent variables to determine the mean initial level and mean rate of change across the time period shown. The latent variables are regressed on the measured variables to estimate structural slopes and determine rate of change. The error terms specified indicate the amount of variance in each measured variable (reading achievement). The disturbance terms (error terms of latent variables) estimate the amount of unexplained variance for each latent variable. The correlation between the disturbance terms indicates the relationship between the unexplained variances.

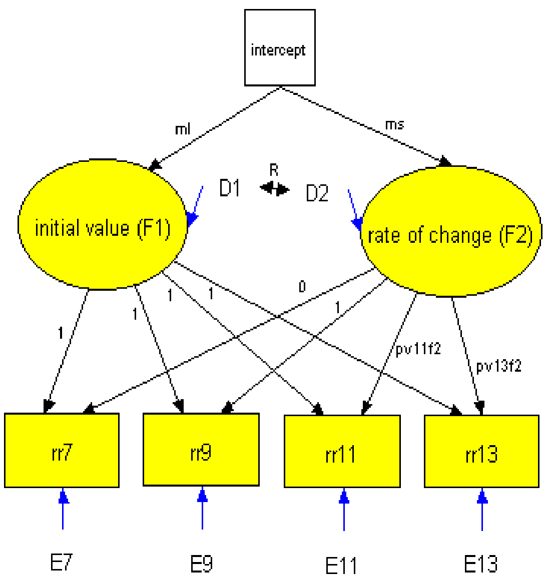

Figure 1. Latent Growth Curve Model

Note: The intercept is a constant equal to 1. Measured variables (reading recognition achievement) are rr7, rr9 rr11, and rr13 measured at ages 7, 9, 11, and 13 respectively. Variances of measured variables are estimated with variances of E7, E9, E11, and E13. Structural slopes are fixed at 0 and 1 for ages 7 and 9 respectively. Structural slopes are estimated by pv11f2 and pv13f2 for ages 11 and 13. Unmeasured variables (latent variables) are initial value (F1) and rate of change (F2). Variances of latent variables are denoted and estimated by D1 and D2. The relationship between latent variable variances is denoted and estimated with R. The intercept is regressed on the latent variables to estimate mean initial value (ml) and mean rate of change (ms).

PROC GLM for Repeated Measures Anova

The SAS Code below provides a repeated measures analysis of variance with four repeated measured variables (rr7, rr9, rr11, rr13). The repeated measures represent the assessment of reading recognition achievement for girls ages 7-, 9-, 11-, and 13-years old.

```
PROC GLM DATA = COH7F;
  CLASS GENDER;
  MODEL RR7 RR9 RR11 RR13 =   /NOUNI;
  REPEATED RR 4 / SUMMARY;
```

The NOUNI command requests no univariate (anova) models be printed. The REPEATED RR 4 command indicates four repeated measurements be renamed RR.

PROC CALIS for Repeated Measures Anova

A graphical representation of the Latent Growth Curve model is shown in Figure 1. Repeated measures analysis of variance is a special case of a latent growth curve model.

The PROC CALIS code specifies the equations that will be solved simultaneously. Measured variables are rr7, rr9, rr11, and rr11 (four measures of reading achievement). Parameters to be estimated are the structural slopes (pv11f2, pv13f2), the mean initial level (ml), the mean rate of change (ms), error and disturbance variances (vare7, vare9, vare11, vare13, varD1, varD2) and covariance of the disturbance terms (CD1D2).

```
PROC CALIS DATA = COH7F UCOV AUG ALL;
  LINEQS
    RR7    =  F1   +                 +  E7,
    RR9    =  F1   +            F2   +  E9,
    RR11   =  F1   +  PV11F2    F2   +  E11,
    RR13   =  F1   +  PV13F2    F2   +  E13,
    F1     =  ML   INTERCEPT         +  D1,
    F2     =  MS   INTERCEPT         +  D2;
  STD
    E7     =  VARE7,
    E9     =  VARE9,
    E11    =  VARE11,
    E13    =  VARE13,
    D1-D2  =  VARD1-VARD2;
  COV
    D1 D2  = CD1D2;
  VAR RR7 RR9 RR11 RR13;
```

Using parameter estimates from PROC CALIS, the repeated measures anova with PROC GLM was respecified.

PROC GLM with Respecified Repeated Measures Anova

Estimates of structural slopes (0 1 1.648 2.172) from PROC CALIS replace the original linear contrasts (1 2 3 4) in PROC GLM code. The repeated measures anova model was respecified using PROC GLM to test for nonlinear change.

```
PROC GLM DATA = COH7F;
  CLASS GENDER;
  MODEL RR7 RR9 RR11 RR13 =     /NOUNI;
  REPEATED RR 4 (0 1 1.648 2.172)
     POLYNOMIAL / SUMMARY PRINTM;
```

Results

Results from PROC GLM and PROC CALIS analyses for the repeated measures anova were similar. However, the SEM analysis using PROC CALIS proved more flexible and provided parameter estimates for rate of change, initial level, and variances that were not included in the PROC GLM analysis.

PROC GLM tested for significant mean differences in reading achievement between repeated measures with a linear default model (levels 1, 2, 3, 4). The SEM model estimated nonlinear growth with PROC CALIS by anchoring the rate of change at 0 and 1 and estimating parameters for the third and fourth measurements. The estimates for the third and fourth levels of change with PROC CALIS were 1.648 and 2.172. The growth steps (0, 1, 1.648, 2.172) estimated by PROC CALIS indicated a nonlinear growth trajectory. The SEM model does not assume change is constant and linear whereas the default PROC GLM repeated measures anova model assumes change is constant and equal at each time interval.

PROC GLM, however, was used to test the respecified anova model for a nonlinear trend. Significant differences between the means were found with the linear trend and with the nonlinear trend ($F(3,132) = 429.38$), $p < 0.0001$).

PROC CALIS has no specific tests of significance. The chi-square probability indicated an unacceptable model fit (chi-square = 9.101, df = 3, p = 0.028). The chi-square value is a measure of the difference between the observed and expected covariance matrices. Acceptable model fit is determined by a chi-square value close to zero and a probability value greater than 0.05. RMSEA indicated unacceptable model fit (RMSEA = 0.123). RMSEA is a measure similar to a residual indicating error. An RMSEA less than 0.06 indicates acceptable model fit (Hu and Bentler, 1999). However, CFI (0.997) and NNFI (0.989) indicated acceptable model fit (values greater than 0.90, Hu and Bentler, 1999). Table 1 illustrates the parameter estimates and statistical tests (z-values) included in the PROC CALIS procedure.

Table 1. Estimates for 7-year old girls cohort (n = 135)

	Estimate	SE	z-value
Mean Initial Value (F1)	29.671	0.862	34.410
Mean Growth Rate(F2)	14.156	0.641	22.103
Variance of Initial Value (D1)	78.836	12.832	6.140
Variance of Growth Rate (D2)	10.912	3.387	3.220
Covariance of Initial Value and Growth Rate (R)	8.298	4.972	1.670
Growth Scores			
Age 7	0.000*	---	---
Age 9	1.000*	---	---
Age 11 (pv11f2)	1.648	0.057	28.862
Age 13 (pv13f2)	2.172	0.083	26.259
Variances			
Age 7 (e7)	21.618	6.957	3.110
Age 9 (e9)	23.695	3.898	6.080
Age 11 (e11)	16.902	3.956	4.270
Age 13 (e13)	47.935	8.204	5.840

*indicates fixed value

Conclusion

Repeated measures anova using PROC GLM tested a default model to find significant differences between the means of the repeated measures. The SEM method, using PROC CALIS, estimated rates of change, variances of measured variables and latent variables, mean initial value and mean rate of change. The SEM analysis with PROC CALIS proved flexible, allowed for explicit representation of measurement error, and provided more information than the repeated measures anova with PROC GLM.

References

Baker, P. C., Keck, C. K., Mott, F. L. & Quinlan, S. V. (1993). NLSY79 child handbook. A guide to the 1986-1990 National Longitudinal Survey of Youth Child Data (rev. ed.) Columbus, OH: Center for Human Resource Research, Ohio State University.

Duncan, T. E., Duncan, S. C., Strycker, L. A., Li, F., & Alpert, A. (1999). An introduction to latent variable modeling: Concepts, issues, and applications. Mahwah, NJ: Lawrence Erlbaum Associates, Publishers.

Dunn, L. M. & Markwardt, J. C. (1970). Peabody individual achievement test manual. Circle Pines, MN: American Guidance Service.

Hoyle, R. H. (1995). The structural equation modeling approach: Basic concepts and fundamental issues. In Structural equation modeling: Concepts, issues, and applications, R. H. Hoyle (editor). Thousand Oaks, CA: Sage Publications, Inc., pp. 1-15.

Hu, L. & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1-55.

MacCallum, R. C. & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. Annual Review of Psychology, 51, 201-226.

Rigdon, E. E. (1998). Structural equation modeling. In Modern methods for business research, G. A. Marcoulides (editor). Mahwah, NJ: Lawrence Erlbaum Associates, Publishers, pp. 251-294.

SAS® STAT, Version 6. Cary, N.C.: SAS Institute.

Suhr, D. D. (1999). An investigation of mathematics and reading achievement of 5- through 14-year olds using latent growth curve methodology. Published Doctor of Philosophy dissertation, University of Northern Colorado.

Appendix

Covariance Matrix

	rr7	rr9	rr11	rr13
rr7	984.448	1399.224	1673.709	1900.612
rr9	1399.224	2071.716	2463.462	2796.142
rr11	1673.709	2463.463	2981.679	3372.478
rr13	1900.612	2796.142	3372.478	3888.306
intercept*	29.956	44.045	53.366	61.037

*the intercept row displays mean values

Contact Information

Diana D. Suhr, Ph.D.
University of Northern Colorado
Institutional Research
Greeley, CO 80639
Phone: 970-351-2193
FAX: 970-351-3340
Email: diana.suhr@unco.edu