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AUTHOR Barcikowski, Robert; Robey, Randall R.
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ABSTRACT

Use of "special" orthonormal mean contrasts and mean contrast variances can help educational researchers interpret a wide variety of repeated measures data. Most statistical packages allow educational researchers to test for differences across repeated measures using both the univariate mixed model F test and a multivariate test. Numerous researchers have suggested using both tests. The "special" orthonormal mean contrasts can be used to provide researchers with insights into why one or the other or both of these modes of analysis provide significant or non-significant results. Results of the analyses indicate that reporting the per group "special" mean contrasts and contrast variances is useful to understanding what is causing statistical significance (or non-significance) in simple and complex repeated measures designs. Analysis of single groups found in real (and some fabricated) repeated measures data supported the recommendation to use both the univariate and the multivariate tests when considering such designs in exploratory analyses. In more complex designs, it is recommended that the patterns of mean contrasts and contrast variances be observed in each of the groups across each variable. Such patterns would be expected to remain stable when no interaction is present, but to differ when an interaction is found. Seven data tables and one graph are included. An example of a Statistical Analysis System program that performs the needed computations is provided. (TJH)

Interpreting Repeated Measures Data Through "Special" Mean Contrasts

Robert Barcikowski
Ohio University
and
Randall R. Robey
Southern Illinois University

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Interpreting Repeated Measures Data Through "Special" Mean Contrasts

Objectives

The purpose of this paper is to indicate how educational researchers can use "special" mean contrasts and mean contrast variances to help interpret a wide variety of repeated measures data.

Perspectives

Most statistics packages, e.g., BMDP4V (Dixon, 1985), SAS (GLM) (SAS Institute, 1985a), SPSS[x] (MANOVA) (SPSS Inc, 1986), allow educational researchers to test for differences across repeated measures using both the univariate mixed model F test and a multivariate test. Davidson (1972) and Barcikowski and Robey (1984) have shown that for a given data set it is possible for one or the other or both of these tests to be significant (or nonsignificant). Therefore, in single group exploratory repeated measures analysis Barcikowski and Robey advocated the routine use of both of these tests (where possible) to help discern differences among the repeated measures means. Looney and Stanley (1989) also emphasized using both tests in discussing exploratory repeated measures analyses for two or more groups.

What is missing from the output provided by the latter statistical packages is a means of providing researchers with insights into why one or the other or both of these modes of analysis provide significant or nonsignificant results. One means of doing this is to provide researchers with further information on "special" orthonormal mean contrasts, the variances of these mean contrasts, and the relationships of these statistics to estimates of the univariate and multivariate noncentrality parameters.

Methods

Given *any* matrix $\boldsymbol{Q}$ of (K-1) rows of contrast coefficients (developed for repeated measures means), it can be shown (Green and Carroll, 1976, Chapter 5) that the rows of $\boldsymbol{Q}$ can be transformed into *the same* rows of orthonormal contrast coefficients in a matrix $\boldsymbol{C}$, such that $\boldsymbol{C\Sigma C'}$ is a diagonal matrix. Here, Σ is the matrix of variances and covariances among a given repeated measures data set. Furthermore, it can be shown that the diagonal elements of $\boldsymbol{C\Sigma C'}$ will be the variances of the mean contrasts in $\boldsymbol{\Psi}$, where $\boldsymbol{\Psi}$ is a vector of orthonormal mean contrasts. These properties of the contrasts is why they are described as "special" above.

Barcikowski and Robey (1984) have shown that the mixed model (univariate) repeated measures noncentrality parameter for the single group case can be written as:

$$\delta_U^2 = \frac{n(K-1)\sum_{i=1}^{k-1}\psi_i^2}{\sum_{i=1}^{k-1}\sigma_{\psi_i}^2} \qquad (1)$$

Where δ_u is the univariate noncentrality parameter, n is the number of units, K is the number of measures, ψ_i is the ith mean contrast ($i = 1, 2, ..., K$), and $\sigma^2\psi_i$ is the variance of the ith mean contrast. Barcikowski and Robey (1984) have also shown that the multivariate noncentrality parameter δ_M for the single group case can be written as:

$$\delta_M^2 = n\sum_{i-1}^{K-1}\frac{\psi_i^2}{\sigma_{\psi_i}^2} \qquad (2)$$

The relationship between the noncentrality parameter and Cohen's (1988) effect size for power analysis is:

$$f = \sqrt{\frac{\delta^2}{nK}} \qquad (3)$$

where δ^2_U or δ^2_M can be substituted for δ^2.

Given "special" mean contrasts and their contrast variances and equations (1) and (2), researchers can better understand what is causing statistical significance or nonsignificance to be found among single group repeated measures means.

An Example: Davidson's Three Cases

The data in Table 1 represent three different possible results. These data were taken from Davidson (1972, p. 450, Cases B, C, and D) with the last measure, X3, in

Table 1
Three Repeated Measures Data Sets Which Yield Different Significance Test Results[a]

Subject	CASE B X1	CASE B X2	CASE B X3[b]	CASE C X1	CASE C X2	CASE C X3	CASE D X1	CASE D X2	CASE D X3
1	49	53	91	52	50	71	51	51	92
2	53	49	111	56	46	91	55	47	112
3	63	65	65	66	62	45	65	63	66
4	37	33	35	40	30	15	39	31	36
5	39	39	59	42	36	39	41	37	60
6	43	51	87	46	48	67	45	49	88
7	43	47	25	46	44	5	45	45	26
8	49	45	47	52	42	27	51	43	48
9	65	65	105	68	62	85	67	63	106
10	59	53	75	62	50	55	61	51	76
Mean	50	50	70	53	47	50	52	48	71

[a]Taken from Davidson (1972, p. 450, Table 4).
[b]Davidson's X3 - 9.

Case B modified here to dramatize the differences between the univariate and multivariate tests. As in Davidson's article these data are treated as population cases.

The population variance-covariance matrix of the measures, and the correlation matrix, is shown in Table 2. These matrices are the same across cases, however, each case has different differences between its repeated measures means. The noncircularity of the variance-covariance matrix could occur in studying persons with some degenerative clinical disorder where the variances become larger across time. That is, as the disorder advances, the subjects become more heterogeneous on the dependent variable. The Greenhouse-Geisser estimate of circularity for each case in the examples is .5247 and the Huynh-Feldt estimate is .5342.

The orthonormalized contrasts for each case, the rows of matrix C, are shown in Table 3. These contrasts remain the same regardless of your initial set of contrasts, e.g., Helmert, polynomial, etc.. From Table 3 we see that the first contrast is basically a comparison between the first two conditions and the last condition, and the second contrast is basically a comparison between the first and second conditions.

Table 2
Population Variance-Covariance Matrix
(Upper Triangle) and Correlation Matrix
(Lower Triangle) For The Cases In Table 1

Condition	1	2	3
1	87.4	80.2	140.2
2	.90	91.4	147.0
3	.54	.55	758.6

Cases B, C and D were analyzed using a computer program that is described in the next section. The results of these analyses are shown in Table 4.

Case B. In Case B we have a large contrast (16.33) coupled with a large contrast variance (412.02) and a small contrast (-0.13) coupled with a small contrast variance (10.20). Given the noncircularity condition, this pattern might occur in studies with an extended baseline. This situation yields a univariate noncentrality parameter, Equation (1), and effect size (.65) which is larger than the multivariate noncentrality parameter, Equation (2), and effect size (.47). These results are reflected in the analysis of Case B, where the Greenhouse-Geisser adjusted univariate test was significant ($F = 6.32$; $p < .0309$) and the multivariate test was not significant ($F = 2.88$; $p < .1140$).

The calculations of the univariate and multivariate noncentrality parameters are considered in more detail below. In these calculations the contributions of the orthonormalized contrasts are placed in brackets. In Case B, it can be seen that the contributions made by the orthonormalized contrasts are similar (.6316 verses .7589) but that the contribution made to the univariate noncentrality parameter is multiplied by the sample size *and the number of contrasts*, whereas the multivariate

Table 3
Orthonormalized Contrast Coefficients Based
On The Variance-Covariance Matrix In Table 2

	Condition		
Contrast	1	2	3
1	-0.413655	-0.402818	0.816473
2	-0.703958	0.710215	-0.006257

Table 4
Power Parameters And F Statistics (With Probabilities) For The Three Example Data Sets In Table 1

Case	Mean Contrasts[a]		Univariate		Multivariate	
			Effect Size	F Statistic (Probability)[b]	Effect Size	F Statistic (Probability)
	Ψ_1	Ψ_2	f_U		f_M	
B	16.33	-0.13	.65	6.32 (.0084) (.0309)	.47	2.88 (.1140)
C	-0.03	-4.24	.17	0.43 (.6593) (.5389)	.77	7.84 (.0130)
D	17.12	-2.96	.69	7.15 (.0052) (.0235)	.72	6.98 (.0176)

Note. The contrast variances were 412.02 and 10.20 for orthonormalized contrasts one and two, respectively.

[a]The contrasts, $\psi = M'C'$ were found such that $C\Sigma C'$ was a diagonal matrix, where M' was a row vector of the three means, C' was the (3 X 2) matrix of orthonormalized contrast coefficients, and Σ was the variance-covariance matrix.

[b]The first probability value is for the unadjusted F test and the second probability value is for the Greenhouse-Geisser adjusted F test. The probability for the Huynh-Feldt adjusted F would be between or equal to the latter probabilities.

contribution to the noncentrality parameter is multiplied by *only* the sample size. This results in the univariate test having a larger noncentrality parameter which combined with the univariate test's larger denominator degrees of freedom yields greater power.

Case B: Univariate

$$\delta_U^2 = 10(2)\left[\frac{(16.33)^2 + (-.13)^2}{412.02 + 10.20}\right]$$

$$\delta_U^2 = 10(2)[.6316]$$

$$\delta_U^2 = 12.63$$

Case B: Multivariate

$$\delta_M^2 = 10\left[\frac{(16.33)^2}{412.02} + \frac{(-0.13)^2}{10.20}\right]$$

$$\delta_M^2 = 10[.6472 + .1117]$$

$$\delta_M^2 = 10[.7589]$$

$$\delta_M^2 = 6.49$$

Case C. In Case C we have a small contrast (-0.03) coupled with a large contrast variance (412.02) and a small contrast (-4.24) coupled with a small contrast variance (10.20). Given the noncircularity condition, this situation might occur with periods of no treatment for baseline and extinction. In this case the change affected by the treatment condition showns only slight deteriorization. Davidson (1972) referred to this case as one where "small but reliable effects are present with effects highly variable but averaging to zero over subjects" (p. 452). Davidson indicated that in such cases the multivariate test is clearly preferable to the univariate test. In the analysis of Case C, the Greenhouse-Geisser adjusted univariate test was not significant ($F = .43$; $p < .5389$) and the multivariate test was significant ($F = 7.84$; $p < .0130$).

The calculations of the univariate and multivariate noncentrality parameters for Case C are considered in more detail below. In these calculations the contributions of the orthonormalized contrasts were again placed in brackets. In Case C, it can be seen that the contributions made by the orthonormalized contrasts are very different (.0426 verses 1.7625). Here the significantly larger contribution made to the multivariate noncentrality parameter causes the multivariate noncentrality parameter to be much larger than its univariate conterpart. This results in the multivariate test having greater power.

Case C: Univariate

$$\delta_U^2 = 10(2)\left[\frac{(-.03)^2 + (-4.24)^2}{412.02 + 10.20}\right]$$

$$\delta_U^2 = 10(2)[.0426]$$

$$\delta_U^2 = .85$$

Case C: Multivariate

$$\delta_M^2 = 10\left[\frac{(.03)^2}{412.02} + \frac{(-4.24)^2}{10.20}\right]$$

$$\delta_M^2 = 10[.0000 + 1.7625]$$

$$\delta_M^2 = 10[1.7625]$$

$$\delta_M^2 = 17.63$$

Case D. In the analysis of Case D, both the Greenhouse-Geisser adjusted univariate (F= 7.15; $p < .0235$) and the multivariate (F= 6.98; $p < .0176$) tests were significant. Given the noncircularity condition, this case might also occur in a baseline-treatment-withdrawl design, but where the criterion measure shows marked deteriorization upon withdrawl of the treatment, perhaps due to the advancing disorder. This case is representative of cases between the extremes represented by cases B and C. In case D the univariate test is sensitive to the large contrast (17.12) and the multivariate test is equally sensitive to both contrasts. Therefore, for different reasons, both tests yield approximately the same effect sizes ($f_U = .69$; $f_M = .72$).

The calculations of the univariate and multivariate noncentrality parameters for Case D are considered in more detail below. In these calculations the contributions of the orthonormalized contrasts were again placed in brackets. In Case D, it can be seen that the contributions made by the orthonormalized contrasts are different (.7149 verses 1.5704). Here the larger contribution made to the multivariate noncentrality parameter causes the multivariate test to overcome the larger number of degrees of freedom of the univariate test and the two test have approximately the same power.

Case D: Univariate

$$\delta^2_U = 10(2)\left[\frac{(17.12)^2 + (-2.96)^2}{412.02 + 10.20}\right]$$

$$\delta^2_U = 10(2)[.7149]$$

$$\delta^2_U = 14.30$$

Case D: Multivariate

$$\delta^2_M = 10\left[\frac{(17.12)^2}{412.02} + \frac{(-2.96)^2}{10.20}\right]$$

$$\delta^2_M = 10[.7114 + .8590]$$

$$\delta^2_M = 10[1.5704]$$

$$\delta^2_M = 15.70$$

Program: Repeated Analyzer

Using SAS PROC MATRIX (SAS Institute, 1985b) a program, referred to as "Repeated Analyzer" was developed which reports the original contrast coefficients, the original mean contrasts, the orthonormalized contrast coefficients, their mean contrasts, each mean contrast variance, the ratio of each mean contrast to its variance, the univariate and multivariate noncentrality parameters, and Cohen's (1988) univariate and multivariate effect sizes. A copy of Repeated Analyzer is given in appendix A. For more complex designs, the latter results can be examined on a per group basis. The program also reports all of what might be called "traditional" output found in a statistical package such as BMDP4V, e.g., the overall and univariate statistical tests and the Greenhouse-Geisser and Huynh-Feldt estimates of sphericity.

Data

Real data found at Ohio University and textbook data found in the social science literature were analyzed using the preceding program. The data represented the following four types of designs: 1) five designs with one within factor (denoted by the notation [0,1], where the first number refers to the number of between factors and the second number refers to the number of within factors); 2) six designs with one between and one within factor, [1,1]; 3) one design with one between and two within factors, [1,2]; 4) one design with two between and one within factor, [2,1]. Of the [0,1] designs, four had a single repeated measure per occassion and one had four measures per occasion. Of the [1,1] designs one had one measure per occasion, three had two measures, one had three measures and one had six measures. The [1,2] design had one measure and the [2,1] had two measures per occasion. These 13 designs were each analyzed in their original form using BMDP4V and then each cell was analyzed using the Repeated Analyzer Program as a single group design. The final analysis included 70 cells.

Results

Of the 70 cells analyzed, 30 cells (43%) had univariate tests with more power than the multivariate tests; 23 cells (33%) yielded tests of equal power; and 17 cells (24%) had multivariate tests with more power than their univariate tests. Furthermore, 39 cells (56%) had their univariate effect size larger than their multivariate effect size, and 31 cells (44%) had their multivariate effect size larger than their univariate effect size.

In Table 5 are three cases where the univariate test was more powerful than the multivariate test of the omnibus repeated measures mean differences. In Case 1 the univariate effect size is smaller than the multivariate effect size (.65 versus .76). This is caused by the small first contrast (1.27) and its large variance (138.65), but the larger denominator degrees of freedom found with the univariate test make it more powerful (.95 versus .85). In Case 2 the slightly larger effect size of the univariate test assures it (because of its denominator degree of freedom advantage) of having more power than the multivariate test (.85 versus .64). In this case and in Case 3 no unusually small squared contrast to contrast variance ratio is present. In Case 3 the small sample size yielded small power values, but with a larger sample size the univariate test would enjoy a distinct power advantage because of its larger effect size (.42 versus .35).

In Table 6 are three cases where the multivariate test was more powerful than the univariate test. The largest power difference in the data sets occured in Case 1 of Table 6 (.04 versus 1.00). In Case 1 the small squared first contrast (.05) combined with its very large contrast variance (7511.44) caused the univariate test to have little power, however, the multivariate test was able to detect the effect of the second contrast. Small squared contrasts with large contrast variances also allowed the multivariate test to have a power advantage in Cases 2 and 3.

In the more complex designs we examined the patterns of mean contrasts and contrast variances across groups and variables. We found similar patterns in the cases of no interaction between the groups and the repeated measures variable and different patterns across groups in the cases of an interaction. Looney and Stanley (1989) present data for a [1,1] design where there is a trial by group interaction,

Table 5
Output From Three Cases Where The Univariate Test Is More Powerful Than The Multivariate Test

Case	Contrast Squared Ψ^2	Contrast Variance σ_Ψ^2	Ratio $\frac{\Psi^2}{\sigma_\Psi^2}$	Effect Size U[a]	Effect Size M	Power U	Power M
1	1.27	138.65	.00	.65	.76	.95	.85
	115.32	76.58	1.51				
	15.12	50.78	.30				
	16.00	14.45	1.11				
2	.19	2.54	.08	.43	.40	.85	.64
	1.04	2.07	.51				
	.18	1.23	.15				
	.03	.52	.05				
3	3.30	12.77	.26	.42	.35	.36	.16
	.65	3.27	.20				
	.03	1.12	.02				

[a]U = value based on the univariate test statistic; M = value based on the multivariate test statistic

Table 6
Output From Three Cases Where The Multivariate Test Is More Powerful Than The Univariate Test

Case	Contrast Squared Ψ^2	Contrast Variance σ_Ψ^2	Ratio $\frac{\Psi^2}{\sigma_\Psi^2}$	Effect Size U[a]	Effect Size M	Power U	Power M
1	.05	7511.44	.00	.04	.38	.09	1.00
	17.43	20.78	.84				
	.01	4.38	.00				
	.00	3.25	.00				
	.01	1.83	.00				
2	3.83	237.98	.02	.27	.43	.32	.53
	16.49	150.85	.11				
	22.82	39.98	.57				
3	3.33	1702.84	.00	.55	1.00	.70	.98
	895.34	301.31	2.97				

[a]U = value based on the univariate test statistic; M = value based on the multivariate test statistic

the results from Repeated Analyzer for these data are shown in Table 7. The results in Table 7 are supported by the graph of the group means over trials shown in Figure 1. Here, the large effect caused by the difference between trials 1 and 2 versus trial 3 in groups 1 and 2 is detected by the first contrast for these groups in Table 7. This effect is most easily detected by the univariate test (but with sufficient sample size both tests would able to discern it). The small but reliable effects found across the means of group two are most easily detected by the multivariate test.

Conclusions

The results indicate the usefulness of reporting the per group "special" mean contrasts and contrast variances to understanding what is causing statistical significance (or nonsignificance) in simple and complex repeated measures designs. Analysis of the single groups found in real (and some fabricated) repeated measures data supported the recommendation to use both the univariate and the multivariate test when considering such designs in exploratory analyses. In more complex designs, such as [1,1] or [2,1], it is recommended that the patterns of mean contrasts and contrast variances be observed in each of the groups across each variable. Such patterns would be expected to remain stable when no interaction is present, but to differ when an interaction is found. It should also be noted that if the orthonomal contrasts that are found are similar to contrasts the researcher is interested in, then the contrast output provides information on whether the contrasts would be worth pursuing in a post hoc testing analysis.

Educational Importance of the Study

In several reviews of social science research journals, it has been found that the use of repeated measures designs has ranged from approximately 25% (Edgington, 1974) to approximately 50% (Robey, 1983). Unfortunately, for an analysis that is used so frequently, the latter review authors also reported that nearly every article they reviewed contained misuses of the repeated measures analysis. Indeed, in recognizing the large use and misuse of repeated measures analyses, the editors of Psychophysiology recently announced an editorial policy (Jennings, Cohen, Ruchkin, and Fridlund, 1987) prohibiting the publication of any paper making use of a repeated measures research design reporting only the traditional uncorrected mixed model analysis. This paper directly addresses a procedure for systematically upgrading the analysis of repeated measures data in the behavioral sciences.

Table 7
Group Output From A Three Groups By Three Trials
Data Set Presented By Looney And Stanley

Case	Contrast Squared Ψ^2	Contrast Variance σ_{Ψ}^2	Ratio $\frac{\Psi^2}{\sigma_{\Psi}^2}$	Effect Size		Power	
				U[a]	M	U	M
1	1942.86 1.14	1580.60 308.59	1.23 .00	.83	.64	.97	.74
2	3.33 895.34	1702.84 301.31	.00 2.97	.55	1.00	.70	.98
3	5635.82 38.84	1648.10 40.79	3.42 .95	1.50	1.21	1.00	1.00

[b]U = value based on the univariate test statistic; M = value based on the multivariate test statistic

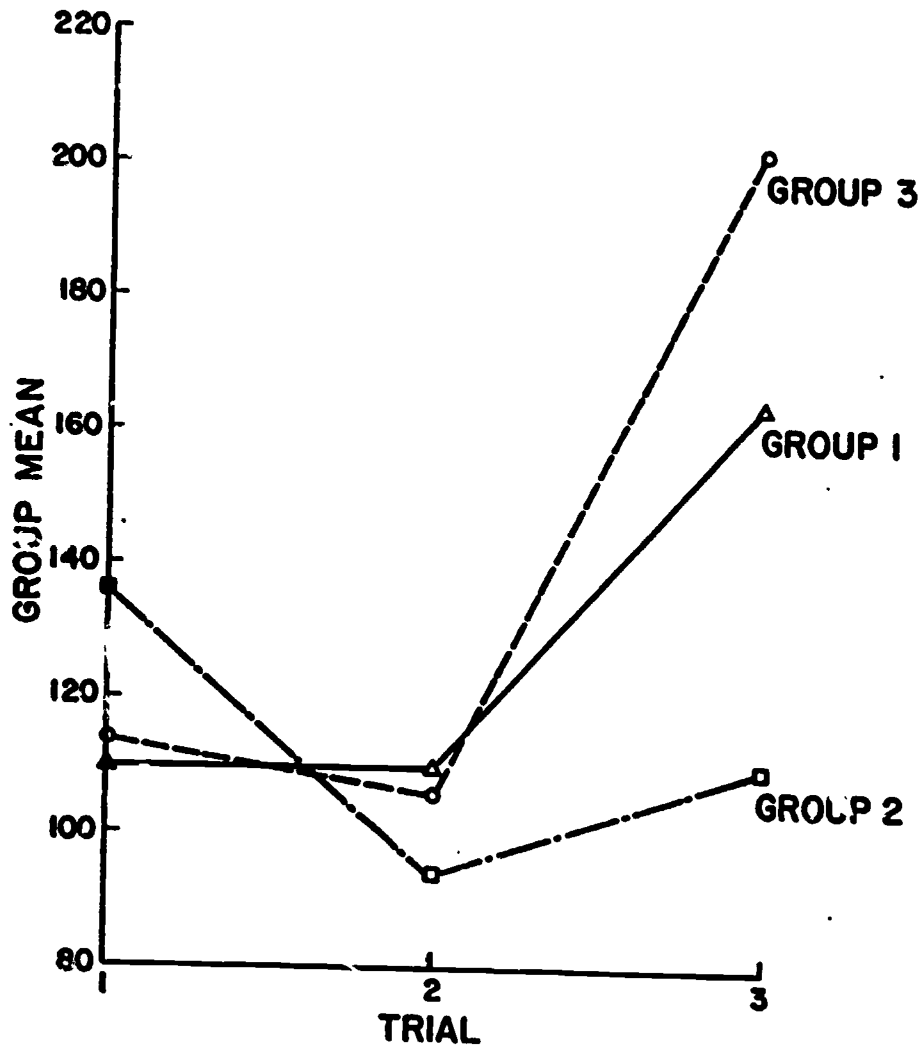

Figure 1. Interaction Plot for the data provided by Looney and Stanley (copied from their article, 1989, Figure 1, p. 223).

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Appendix A
The SAS Program
Repeated Analyzer

```
*

                    DESIGN:  A SPLIT PLOT (2 X 6)  2=BETWEEN 6=WITHIN

                    TEST:    OMNIBUS INTERACTION EFFECT

;
*
     THE DATA SET COLX CONTAINS THE TOTAL NUMBER OF VARIABLES FOUND
     IN THE DATA SET ALLVAR WHICH ARE TO APPEAR IN THE X MATRIX,
     I.E., INDEPENDENT VARIABLE(S) AND COVARIATE(S).
;
DATA COLX;
 INPUT CX;
  CARDS;
1
;
*
     THE DATA SET COLY CONTAINS THE TOTAL NUMBER OF VARIABLES FOUND
     IN THE DATA SET ALLVAR WHICH ARE TO APPEAR IN THE Y MATRIX,
     I.E., DEPENDENT VARIABLE(S).
;
DATA COLY;
 INPUT CY;
  CARDS;
6
;
*
     THE DATA SET ALLVAR CONTAINS ALL OF THE VARIABLES IN THE DESIGN.
     COLUMNS WHICH CONTAIN INFORMATION TO APPEAR IN THE X MATRIX MUST
     PRECEDE THOSE COLUMNS CONTAINING INFORMATION TO APPEAR IN THE
     Y MATRIX.  COLUMNS CONTAINING COVARIATES, IF THERE ARE ANY,
     MUST FOLLOW THE LAST INDEPENDENT VARIABLE AND PRECEDE THE
     FIRST DEPENDENT VARIABLE.  WARNING:  INDEPENDENT AND DEPENDENT
     VARIABLES ARE TESTED IN THE ORDER WHICH THEY APPEAR IN THE
     DATA SET ALLVAR.  THE VARIABLE ORDER CAN BE EASILY MANIPULATED
     BY USING COLUMN INPUT.
;
DATA ALLVAR;
 INPUT CELL OCC1-OCC6;
  CARDS;
1     54.50    46.00    53.91    53.32    54.15    54.98
1     71.90    60.51    56.74    56.03    57.73    58.51
```

```
1      45.45     43.93     52.26     53.62     55.00     56.09
1      44.82     54.22     51.51     52.75     51.07     49.56
1      64.16     57.38     56.33     56.63     53.59     56.52
1      65.55     45.09     53.89     54.58     55.34     54.45
1      54.03     43.93     54.54     54.67     52.07     52.87
1      78.81     65.18     57.32     56.83     54.77     57.36
1      52.50     59.26     55.38     57.34     57.45     55.41
1      42.65     62.39     53.58     53.39     52.33     54.32
1      22.56     50.88     50.65     50.05     52.04     49.90
2      13.35     16.40     47.11     46.64     47.10     47.19
2      56.75     81.68     55.62     58.25     57.07     57.06
2      56.50     25.00     52.77     52.42     54.05     56.32
2      83.12     91.54     61.23     58.80     58.77     61.20
2       8.62     31.91     50.07     49.22     49.15     48.15
2      21.69     41.67     50.98     51.33     50.15     51.00
2      59.90     72.84     57.97     55.42     57.14     57.15
2      58.89     51.30     53.54     54.82     52.11     52.37
2      54.20     66.47     56.49     55.59     57.15     55.58
;
*
     IN REPEATED MEASURES DESIGNS, THE A MATRIX DEFINES THE HYPOTHESIS TO
     BE TESTED FOR GROUP DIFFERENCES.  IT MUST CONFORM TO THE RULES FOR
     CONSTRUCTING AN A MATRIX DESCRIBED IN THE TEXT.
;
DATA A;
 INPUT C1 C2;
  CARDS;
1  -1
;
*
     IN REPEATED MEASURES DESIGNS, THE C MATRIX DEFINES THE HYPOTHESIS
     TO BE TESTED FOR DIFFERENCES AMOUNG THE MEASURES.  CONSTRUCTION
     OF THE C MATRIX MUST FOLLOW THE SAME GENERAL RULES FOR
     CONTSTRUCTING AN A MATRIX.
;
DATA C;
 INPUT OCC1-OCC6;
  CARDS;
1  0  0  0  0  -1
0  1  0  0  0  -1
0  0  1  0  0  -1
0  0  0  1  0  -1
0  0  0  0  1  -1
PROC SORT DATA=ALLVAR;
 BY CELL;
PROC PRINT DATA=ALLVAR;
 BY CELL;
  TITLE5 'RAW SCORES';
PROC PRINT DATA=A;
 TITLE5 'THE MATRIX A';
PROC PRINT DATA=C;
 TITLE5 'THE MATRIX C';
PROC MEANS MAXDEC=3;
 VAR OCC1-OCC6;
```

```
  TITLE5 'DESCRIPTIVE STATISTICS';
PROC STANDARD DATA=ALLVAR MEAN=0.0 STD=1.0 OUT=ZTAB;
PROC PRINT DATA=ZTAB;
 TITLE5 'Z SCORES';
PROC CORR NOSIMPLE DATA=ALLVAR;
 VAR OCC1-OCC6;
  TITLE5 'CORRELATION MATRIX';
PROC MATRIX PRINT FLOW FUZZ;
TITLE5 ' ';
*
    FETCH MATRICES
;
FETCH CX DATA=COLX;
FETCH CY DATA=COLY;
FETCH ALL DATA=ALLVAR;
FETCH A DATA=A;
FETCH C DATA=C;
*
    REDEFINE THE TRANSFORMATION MATRIX C BY ORTHONORMALIZING THE
    COEFFICIENTS
;
C = C';
GS CTEMP T LINDEP C;
C = CTEMP';
*
    DEFINE THE X MATRIX
;
GRP = ALL(,CX);
X = DESIGN(GRP);
*
    DEFINE THE Y MATRIX
;
FY = CX+1;
LY = CX+CY;
Y = ALL(,FY:LY);
*
    DEFINE N, Q, AND QH
;
N = NROW(X);
Q = NCOL(X)-1;
QH = NROW(A);
*
    CALCULATE THE SUM OF SQUARES DUE TO ERROR
;
B = INV(X'*X)*(X'*Y);
YHAT = X*B;
E = Y-YHAT;
VARCOV = (E'*E) #/ (N-Q-1);
SIGMA = C*VARCOV*C';
EIGEN EVALS EVECS SIGMA;
C = EVECS' * C;
SSE = C*(E'*E)*C';
SIGMA = C*VARCOV*C';
*
```

```
     CALCULATE THE SUM OF SQUARES DUE TO THE HYPOTHESIS
;
G = A*B*C';
V = A*INV(X'*X)*A';
SSH = G'*INV(V)*G;
H = (G'*INV(V)*G) #/ QH;
*
     DECISION REGARDING A UNIVARIATE ONLY ANALYSIS IF P=1
;
P = NCOL(SIGMA);
IF P = 1 THEN GO TO UNIVAR;
*
     CALCULATE WILKS' LAMBDA
;
LAMBDA = DET(SSE)#/DET(SSE+SSH);
LAM_DF1 = P;
LAM_DF2 = QH;
LAM_DF3 = N-Q-1;
*
     CALCULATE THE MULTIVARIATE F TEST
;
M = (N-Q-1)-((P+1-QH)#/2);
IF P*QH > 2 THEN S = SQRT(((P**2)*(QH**2)-4)#/((P**2)+(QH**2)-5));
ELSE S = 1;
EXP = 1#/S;
MULTI_F = ((1-(LAMBDA##EXP))#/(LAMBDA##EXP))*(((M*S)+1-(QH*(P#/2)))#/(QH*P));
MF_DF1 = QH*P;
MF_DF2 = (M*S)+1-(QH*P#/2);
SIG_MF = 1-PROBF(MULTI_F,MF_DF1,MF_DF2);
*
     CALCULATE THE F TEST(S) ON EACH OF THE CONTRASTS
;
UNIVAR: MSH = VECDIAG(H);
MSE = VECDIAG(SIGMA);
UNI_F = MSH#/MSE;
UF_DF1 = QH;
UF_DF2 = N-Q-1;
SIG_UF = 1-PROBF(UNI_F,UF_DF1,UF_DF2);
*
     CALCULATE DELTA SQUARES AND EFFECT SIZS
;
UDELT = (N*P*G*G') #/ TRACE(SIGMA);
UESIZE = SQRT(UDELT) #/ SQRT(N*(QH*P+1));
IF P = 1 THEN GO TO MIXMOD;
MDELT = N * G * INV(SIGMA) * G';
MESIZE = SQRT(MDELT) #/ SQRT(N*(QH*P+1));
*
     CALCULATE THE MIXED MODEL F STATISTIC
;
MIXMOD: MMSSE = TRACE(SSE);
MMMSE = MMSSE #/ ((N-Q-1)*P);
MMSSH = TRACE(SSH);
MMMSH = MMSSH #/ (QH*P);
MMF = MMMSH#/MMMSE;
```

```
MMDF1 = QH*P;
MMDF2 = (N-Q-1)*P;
SIG_MMF = 1-PROBF(MMF,MMDF1,MMDF2);
*
     CALCULATE THE GREENHOUSE-GEISSER-IMHOF EPSILON ANS ITS ADJUSTED
     DEGREES OF FREEDOM AND CALCULATED PROBABILITY
;
GGI = (SUM(EVALS)**2)#/(P*(SUM(EVALS##2)));
GGIMMDF1 = MMDF1*GGI;
GGIMMDF2 = MMDF2*GGI;
GGISIG = 1-PROBF(MMF,GGIMMDF1,GGIMMDF2);
*
     CALCULATE THE HUYNH-FELDT EPSILON AND ITS ADJUSTED DEGREES OF
     FREEDOM AND CALCULATED PROBABILITY
;
HF = (N*P*GGI-2)#/(P*(N-(Q+1)-P*GGI));
IF HF GT 1.00 THEN HF = 1.00;
HFMMDF1 = MMDF1*HF;
HFMMDF2 = MMDF2*HF;
HFSIG = 1-PROBF(MMF,HFMMDF1,HFMMDF2);
```