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ABSTRACT

The present paper suggests that multivariate techniques are very important in social science research, and that canonical correlation analysis may be particularly useful. The logic of canonical analysis is explained and discussed. The necessity of using replicability/generalizability analyses is argued. It is suggested that cross-validation procedures should be used to examine the replicability of results obtained by canonical analyses and should be implemented to augment interpretation. These analyses are illustrated using a small heuristic data set. (An appendix gives the Statistical Package for the Social Sciences commands for canonical correlation.) Two tables are included. (Contains 21 references.) (Author)

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## CROSS-VALIDATION ANALYSIS FOR THE CANONICAL CASE

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## ABSTRACT

The present paper suggests that multivariate techniques are very important in social science research, and that canonical correlation analysis may be particularly useful. The logic of canonical analysis is explained and discussed. The necessity of using replicability/generalizability analyses is argued. It is suggested that cross-validation procedures should be used to examine the replicability of results obtained by canonical analysis, and should be implemented to augment interpretation. These analyses are illustrated using a small heuristic data set.

## CROSS-VALIDATION ANALYSIS FOR THE CANONICAL CASE

There are two important reasons why multivariate methods are so important, especially in the social sciences (Fish, 1988). First, multivariate methods limit the inflation of Type I "experimentwise" error rates. This refers to the probability of making a Type I error anywhere within the study. Second, "multivariate methods best honor the reality to which the researcher is reportedly trying to generalize" (Thompson, 1991, p. 80). Most researchers live in a reality "in which the researcher cares about multiple outcomes, in which most outcomes have multiple causes, and in which most causes have multiple effects" (Thompson, 1986, p. 9).

Several statistical techniques available for the analysis of multivariate data include multivariate analysis of variance (MANOVA), factor analysis, discriminant analysis, and canonical correlation analysis. These types of analyses are used in studies that involve more than one dependent variable, because only multivariate statistical procedures simultaneously consider all the relationships among the variables being investigated and therefore honor the reality in which all variables interact and influence each other. The most powerful and potentially useful of the multivariate designs is the canonical correlation analysis.

### Canonical Correlation Analysis

Canonical correlation analysis (Thompson, 1984; 1991) is a multivariate analytic method for investigating the relationship between two sets of variables, a set of dependent variables and a set of independent variables, where each set contains two or more variables. This analysis allows for variables of any level of measurement and was developed to examine relationships among all the variables simultaneously (Thompson, 1984). Researchers have for some time recognized that canonical correlation analysis is the most general linear model that subsumes all other parametric procedures (e.g., t-tests, ANOVA, ANCOVA, regression, discriminant analysis, MANOVA) as special cases (Baggaley, 1981; Fornell, 1978; Knapp, 1978).

The degree of relationship, labeled the canonical correlation coefficient, is determined by a correlation between scores on linear predictor composite variables and scores on linear criterion composite variables. An indepth discussion of how these composite scores are created can be found in articles by Eason, Daniel and Thompson (1990) and by Thompson (1984, 1988a).

The canonical composite scores maximize the correlation between the two variables sets. One reason that canonical correlation analysis is such a powerful analytical technique is because it considers all the relationships among all the variables and does not require that variables be converted to nominally-scaled variables, which discards information or distorts reality. Discarding variance by categorizing variables amounts to "squandering of information" (Cohen, 1968, p. 441). As Pedhazur (1982, pp. 452-453) notes,

Categorization of attribute variables is all too frequently resorted to in the social sciences . . . It is possible that some of the conflicting evidence in the research literature of a given area may be attributed to the practice of categorization of continuous variables . . . Categorization leads to a loss of information, and consequently to a less sensitive analysis.

Some time ago, Cohen (1968) noted that univariate procedures, such as ANOVA and ANCOVA, are special cases of multiple regression analysis, therefore multiple regression is a general analytic procedure encompassing all univariate procedures. Similarly, Knapp (1978) suggested that this same relationship exists between canonical correlation analysis and virtually all univariate and multivariate tests of significance. In multiple regression, the optimal linear combination of predictor variables is derived to estimate a criterion variable. An analogous relationship is found in canonical correlation analysis where the maximum linear relationships between sets of variables are isolated.

Canonical correlation analysis is employed when at least two criterion variables and two predictor variables are involved. The number of functions, i.e., linear relationships, that can be computed in a canonical analysis is equal to the number of variables in the smaller of the two variable sets (Thompson, 1991). Canonical functions are derived by the extraction of principle components from a matrix,  $A$ , derived from the bivariate correlation matrix ( $R$ ) involving all the variables in the analysis (Thompson, 1984, p. 13).

The largest amount of common variance across the variable sets is explained by the first canonical function. The remaining canonical

functions are orthogonal to (perfectly uncorrelated with) all other and previous functions. This method allows for the interrelationships shared by the variables to be fully considered, because the predictor variables and the criterion variables are analyzed as sets. Complex relationships between the variable sets are accounted for in determining the variance explained (Eason, 1990). Since the relationship between variables in the social sciences is complex, this statistical method more closely mirrors the reality to which the researcher wishes to generalize.

Canonical correlation analysis computes several types of coefficients which allow for greater insight and more accurate interpretations. Two of the more noteworthy coefficients are standardized function coefficients and canonical structure coefficients. Standardized function coefficients are analogous to beta weights in a regression analysis or pattern coefficients in a factor analysis. The weights which are calculated are used to create the canonical composite scores correlated in the analysis.

Standardized function coefficients are affected by multicollinearity, and can provide incomplete information as to a variable's contribution to a given set of results (Thompson & Borello, 1985). Therefore canonical structure coefficients are calculated to fully understand the nature of the canonical correlation relationship. Canonical structure coefficients are correlations between observed variables and the synthetic or latent canonical score composites. Squaring the structure coefficients tell the researcher the amount of variance a variable shares with a function. The sum of the squared structure coefficients for a particular variable across each function

yields the amount of total variance that the variable contributes to the overall solution.

The amount of variance that a variable contributes to the overall solution is called a communality coefficient ( $h^2$ ). Previously, researchers commonly concluded their analyses after interpreting the standardized function coefficients prior to investigating the canonical structure coefficients (Thompson, 1988a). This practice fails to take into consideration the amount of variance explained by the variables. If only function coefficients are used, a true picture of a variable's importance is unavailable (Thompson & Borrello, 1985).

#### Replicability/Generalizability of Results

Morrison and Henkel (1970) and Carver (1978) provide important and incisive explanations of the limits of significance testing as an aid to interpretation. The Summer, 1993, issue of the Journal of Experimental Education is devoted entirely to an in-depth exploration of these limits.

Statistical "significance is not the end-all and be-all of research" (Thompson, 1988b, p. 18). Researchers often confuse statistical significance with the importance of the effect or with the likelihood that the result is replicable, but significance testing actually evaluates neither of these two concerns (Thompson, 1994).

Researchers who wish to estimate the likelihood that a result is replicable should employ a replicability analysis. Use of a replicability procedure not only gives the researcher information about the likelihood of producing the same result in future research, but also information about the generalizability of the results. Three



types of replicability analyses are available, the jackknife method, developed by Tukey and his colleagues, bootstrap methods, developed by Efron and his associates, and cross-validation methods. Cross-validation methods are computationally simpler estimates of result replicability (Thompson, 1989).

Because statistical significance testing is essentially useless, evaluating the replicability/generalizability (Carver, 1978, 1993) of results is critical in interpreting canonical results. The purpose of the present paper is to describe one strategy for evaluating the replicability of canonical results using cross-validation. SPSS, a computer program, was used to provide a concrete heuristic example of this procedure.

#### Cross-Validation

Cross-validation procedures can provide the researcher with an estimate of the stability of the results across samples (Thompson, in press). Cross-validation is recommended as an appropriate invariance procedure for canonical correlation analysis (Fish, 1986; Thompson, 1984). The method involves splitting a sample randomly into two subgroups (usually of unequal size) and performing separate canonical correlation analyses on each subgroup. In addition, new predictor and criterion composite scores for one group are derived from standardized function coefficients of the second group. Similarly, predictor and criterion composite scores for the second group are derived from standardized function coefficients of the first group. The new composite scores are correlated and compared to derive an invariance estimate.

### Heuristic Example of the Method

To illustrate the technique a data set involving a university study will be presented. The study involved 480 subjects participating in a research project investigating sexual aggression and date rape. The objectives of the study were to discover what types of personality and socio-cultural factors predicted involvement in sexually aggressive behavior. The 13 predictor variables consisted of personality and socio-cultural factors and four criterion variables assessed varying degrees of sexual aggression. SPSS was used to compute the canonical correlation analysis. Appendix A presents the SPSS computer program used to analyze the data in the study.

Table 1 displays the canonical correlation coefficients, structure coefficients, squared structure coefficients, variegate adequacy coefficients, communality coefficients, and redundancy coefficients for each of the four functions derived (Thompson, 1991). The squared canonical correlation coefficient for Function I indicates that 26.83% of the variance was linearly shared by these two variable sets after optimal weighting by the standardized function coefficients that are analogous to regression beta weights. The squared canonical correlation coefficient for Function II indicates that 10.25% of the variance was linearly shared by the two variable sets after optimal weighting by the Function II standardized function coefficients. Only the replicability of these two noteworthy functions are used in the illustrative cross-validation.

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INSERT TABLE 1 ABOUT HERE

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After calculating the canonical correlation analysis, the sample is randomly split into two subgroups (usually of unequal size). Random splitting of the subsample can be performed by using a coin and assigning subjects to subsample one or two based on the result of each coin toss. Separate canonical correlation analyses are performed on each subgroup. New predictor and criterion composite scores for one subgroup are then derived from standardized function coefficients of the second subgroup.

Table 2 presents the invariance statistics for the cross-validation. First, the table displays the Rc's for Functions I-IV, in subsample 1 (n=244) and subsample 2 (n=256). For the predictor variables and the criterion variables the numerals indicate the function, the subsample and the weights used in that particular calculation. The Rc for Function I, subsample 1, using the weights from subsample 1 was .538. The Rc for Function I, subsample two using the weights from subsample 2 was .594. The Rc for Function II, subsample 1, using the weights from subsample 1 was .392. The Rc for Function II, subsample 2, using the weights from subsample 2 is .342. Therefore, for Function I the squared canonical correlation coefficient for group one was .29 and for group two it was .35. For Function II the squared canonical correlation coefficient for group one was .15 and for group two it was .12.

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INSERT TABLE 2 ABOUT HERE

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Secondly, the table displays the shrunken  $R_c$ 's or the invariance check of the squared canonical coefficients for Function I-IV. The invariance check is calculated by using the weights of the other subsample in the analysis. For Function I, the shrunken  $R_c$  for subsample 1 was .288, and the shrunken  $R_c$  for subsample 2 was .313. For Function II, the shrunken  $R_c$  for subsample 1 was .244, and the shrunken  $R_c$  for subsample 2 was .096. These invariance coefficients indicate the amount of shrinkage in the correlation coefficient when the standardized function coefficients from the other subsample are used. The amount of shrinkage indicates the stability of the results.

The shrinkage found in the comparison of the "shrunken" coefficients for the two subsamples, for Functions I and II, may be due the slight difference in which variables contributed to Functions I & II in the two subsamples. The invariance estimates obtained from this analysis indicated that the results were generally replicable.

#### Summary

The present paper suggests that multivariate techniques are very important in social science research, and that canonical correlation analysis may be particularly useful. The logic of canonical analysis was explained and discussed. The necessity of using replicability/generalizability analyses was argued. It was suggested that cross-

validation procedures should be used to examine the replicability of results obtained by canonical analysis, and should be implemented to augment interpretation. These analyses were illustrated using a small heuristic data set.

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Table 1  
Canonical Correlation Analysis Results for Sexual Aggression Study

Variable	Function I		Function II		Function III		Function IV		h <sup>2</sup>
	Func.	Struc.	Func.	Struc.	Func.	Struc.	Func.	Struc.	
Use Phys	0.374	0.374	0.303	0.303	0.593	0.593	0.646	0.646	100.00%
Threat Phys	0.460	0.460	-0.606	-0.606	0.487	0.486	-0.430	-0.430	100.00%
Insistence	0.442	0.442	-0.478	-0.478	-0.575	-0.575	0.496	0.496	100.00%
Ambiguous C	0.673	0.673	0.560	0.560	-0.285	-0.285	-0.391	-0.391	100.00%
Adequacy									
Rd	25.00%	25.00%	25.00%	25.00%	25.00%	25.00%	25.00%	25.00%	25.00%
Rc <sup>2</sup>	6.71%	6.71%	2.56%	2.56%	1.05%	1.05%	0.55%	0.55%	0.55%
Rd	26.83%	26.83%	10.25%	10.25%	4.18%	4.18%	2.19%	2.19%	2.19%
Rd	6.55%	6.55%	0.65%	0.65%	0.37%	0.37%	0.21%	0.21%	0.21%
Adequacy	24.42%	24.42%	6.32%	6.32%	8.77%	8.77%	9.74%	9.74%	9.74%
Hostil.	-0.036	-0.447	0.361	0.019	6.018	0.212	0.209	-0.032	0.10%
Impulsi.	-0.266	-0.526	-0.082	0.121	-0.064	0.179	0.593	0.345	11.90%
Ang.-Stat	0.005	-0.394	0.400	0.319	-0.241	0.079	0.109	-0.158	2.51%
Ang.-Trail	-0.054	-0.496	-1.418	-0.024	2.519	0.472	0.325	-0.561	31.48%
Ang.-Temp	-0.129	-0.447	0.385	-0.049	-1.559	0.223	-1.029	-0.607	36.87%
Ang.-Reac	-0.025	-0.354	0.484	0.038	-0.881	0.419	-0.570	-0.446	19.86%
Anger-In	-0.011	-0.299	0.560	0.518	-0.301	0.090	0.126	-0.204	4.16%
Anger-Out	0.126	-0.424	0.651	0.252	0.644	0.558	0.287	-0.173	2.98%
Ang.-Cont	-0.034	0.405	-0.030	0.053	0.427	-0.043	0.167	0.363	13.18%
Psycho.	-0.273	-0.579	-0.115	0.153	0.263	0.379	0.283	0.030	0.09%
Schiz.	0.030	-0.522	0.484	0.429	0.145	0.280	0.536	-0.158	2.48%
Peer	0.159	0.464	0.536	0.395	-0.022	-0.119	-0.226	-0.091	0.83%
Porno.	0.708	0.848	-0.015	-0.047	0.432	0.230	0.033	0.047	77.60%

Table 2

Invariance Statistics for the Cross-Validation of the Canonical Correlation Analysis

	C111	C112	C121	C122	C211	C212	C221	C222	C311	C312	C321	C322	C411	C412	C421	C422
P111	.538 <sup>a</sup>															
P112		.288 <sup>b</sup>														
P121			.313 <sup>d</sup>													
P122				.594 <sup>c</sup>												
P211					.392 <sup>a</sup>											
P212						.244 <sup>b</sup>										
P221							.096 <sup>d</sup>									
P222								.342 <sup>c</sup>								
P311									.293 <sup>a</sup>							
P312										.128 <sup>b</sup>						
P321											.013 <sup>d</sup>					
P322												.240 <sup>c</sup>				
P411													.261 <sup>a</sup>			
P412														-.038 <sup>b</sup>		
P421															-.025 <sup>d</sup>	
P422																.147 <sup>c</sup>

a The Rc's for Functions I-IV, respectively, in subsample 1 (n=244).

b The shrunken Rc's for Functions I-IV, respectively, in subsample 1 (n=244), based on use of subsample 2's weights.

c The Rc's for Functions I-IV, respectively, in subsample 2 (n=256).

d The shrunken Rc's for Functions I-IV, respectively, in subsample 2 (n=256), based on use of subsample 1's weights.

bruce.sps

APPENDIX A  
SPSS Commands to Execute Canonical Crossvalidation

```
TITLE 'MALES ONLY FILE=BRUCE.SPS DISSERTATION (N=480)'  
DATA LIST FILE=SEX FIXED RECORDS=4  
  / ID 1-4 AGE 6-7 ETHNIC 9 GENDER 11 GRADE 13-14 ANGER1 TO ANGER44  
    16-59 HOSTTW1 TO HOSTTW19 61-79  
  / HOSTTW20 TO HOSTTW30 1-11 IMPUL1 TO IMPUL34 13-46 PORN1 TO PORN17  
    48-64 PD1 TO PD13 66-78  
  / PD14 TO PD57 1-44 PEER1 TO PEER4 46-49 SCHIZ1 TO SCHIZ27 51-77  
  / SCHIZ28 TO SCHIZ82 1-55 SEXEXP1 TO SEXEXP13 57-69 RELATION 71  
    LIKELI 72 INV 74  
ASSIGN BLANKS -99999  
VALUE LABELS GENDER 1 'MALE' 2 'FEMALE'/  
  ETHNIC 1 'WHITE' 2 'AFR AMER' 3 'HISPANIC' 4 'ASIAN' 5 'OTHER'/  
SELECT IF (GENDER EQ 1)  
RECODE ANGER1 TO ANGER44 IMPUL1 TO IMPUL34 (5=4)  
RECODE HOSTTW1 TO HOSTTW30 PD1 TO PD57 SCHIZ1 TO SEXEXP13  
  (3=2) (4=2) (5=2)  
EXECUTE
```

```
LIST VARIABLES=ID IMPUL1 TO IMPUL13/CASES=40/FORMAT=NUMBERED  
RECODE IMPUL1 IMPUL7 IMPUL10 IMPUL13 IMPUL19 IMPUL34  
  IMPUL5 IMPUL8 IMPUL9 IMPUL12 IMPUL15 IMPUL21 (1=4) (2=3) (3=2) (4=1)  
EXECUTE
```

```
LIST VARIABLES=ID IMPUL1 TO IMPUL13/CASES=40/FORMAT=NUMBERED
```

```
LIST VARIABLES=HOSTTW1 TO HOSTTW12/CASES=40/FORMAT=NUMBERED  
RECODE HOSTTW1 TO HOSTTW30 (2=0)  
LIST VARIABLES=HOSTTW1 TO HOSTTW12/CASES=40/FORMAT=NUMBERED  
RECODE HOSTTW3 HOSTTW5 TO HOSTTW8 HOSTTW10 HOSTTW12 HOSTTW16  
  HOSTTW19 HOSTTW21 HOSTTW24 HOSTTW26 TO HOSTTW29 (0=1) (1=0)  
EXECUTE
```

```
LIST VARIABLES=HOSTTW1 TO HOSTTW12/CASES=40/FORMAT=NUMBERED
```

```
LIST VARIABLES=PD1 PD3 PD5 PD7 PD9 PD11 PD13 PD15 TO PD30/CASES=40  
  /FORMAT=NUMBERED  
RECODE PD1 TO PD57 (2=0)  
LIST VARIABLES=PD1 PD3 PD5 PD7 PD9 PD11 PD13 PD15 TO PD30/CASES=40  
  /FORMAT=NUMBERED  
RECODE PD1 PD3 PD15 PD21 PD23 PD25 PD28 PD32 TO PD42 PD44 TO PD46  
  PD49 PD50 PD52 PD53 PD55 PD56 (0=1) (1=0)  
EXECUTE  
LIST VARIABLES=PD1 PD3 PD5 PD7 PD9 PD11 PD13 PD15 TO PD30/CASES=40  
  /FORMAT=NUMBERED
```

```
LIST VARIABLES=SCHIZ1 SCHIZ3 SCHIZ5 SCHIZ7 SCHIZ9 SCHIZ11 SCHIZ13  
  SCHIZ15 SCHIZ17 TO SCHIZ30/CASES=40/FORMAT=NUMBERED  
RECODE SCHIZ1 TO SCHIZ82 (2=0)  
LIST VARIABLES=SCHIZ1 SCHIZ3 SCHIZ5 SCHIZ7 SCHIZ9 SCHIZ11 SCHIZ13  
  SCHIZ15 SCHIZ17 TO SCHIZ30/CASES=40/FORMAT=NUMBERED  
RECODE SCHIZ1 SCHIZ3 SCHIZ5 SCHIZ19 SCHIZ28 SCHIZ29 SCHIZ31 SCHIZ35  
  SCHIZ39 SCHIZ40 SCHIZ44 SCHIZ45 SCHIZ53 SCHIZ57 SCHIZ58 SCHIZ60  
  SCHIZ63 SCHIZ65 SCHIZ81 (0=1) (1=0)  
EXECUTE
```

```
LIST VARIABLES= SCHIZ1 SCHIZ3 SCHIZ5 SCHIZ7 SCHIZ9 SCHIZ11 SCHIZ13  
  SCHIZ15 SCHIZ17 TO SCHIZ30/CASES=40/FORMAT=NUMBERED
```

```
LIST VARIABLES=PD2 PD4 PD6 PD8 PD10 PD12 PD14 SCHIZ2 SCHIZ4 SCHIZ6  
  SCHIZ8 SCHIZ10 SCHIZ12 SCHIZ14 SCHIZ16/CASES=40/FORMAT=NUMBERED  
RECODE PD2 PD4 PD6 PD8 PD10 PD12 PD14 SCHIZ2 SCHIZ4 SCHIZ6 SCHIZ8  
  SCHIZ10 SCHIZ12 SCHIZ14 SCHIZ16 (0=1) (1=0)
```

```
EXECUTE
LIST VARIABLES=PD2 PD4 PD6 PD8 PD10 PD12 PD14 SCHIZ2 SCHIZ4 SCHIZ6
SCHIZ8 SCHIZ10 SCHIZ12 SCHIZ14 SCHIZ16/CASES=40/FORMAT=NUMBERED
```

```
LIST VARIABLES=ID PEER1 TO PEER4/CASES=40/FORMAT=NUMBERED
RECODE PEER3 (1=5)(2=4)(4=2)(5=1)
RECODE PEER4 (2=1)(3=1)(4=5)
```

```
EXECUTE
LIST VARIABLES=PEER1 TO PEER4/CASES=40/FORMAT NUMBERED
```

```
LIST VARIABLES=ID PORN1 TO PORN17/CASES=40/FORMAT=NUMBERED
RECODE PORN5 TO PORN17 (2=5)
EXECUTE
```

```
LIST VARIABLES=PGRN5 TO PORN17/CASES=40/FORMAT NUMBERED
```

```
IF (ETHNIC EQ 1)XTHNIC=1
IF (ETHNIC EQ 3)XTHNIC=2
VALUE LABELS XTHNIC 1 'CAUCASIAN' 2 'HISPANIC'
```

```
IF (AGE GT 50)AGE=-99999
COUNT MISSING=ANGER1 TO LIKELI(-99999)
EXECUTE
```

```
FREQUENCIES VARIABLES=MISSING
SELECT IF (MISSING LE 10)
DESCRIPTIVES VARIABLES=ALL
```

```
IF (ANGER13 LT 0)ANGER13=1.50
IF (ANGER20 LT 0)ANGER20=2.58
IF (ANGER25 LT 0)ANGER25=1.76
IF (ANGER26 LT 0)ANGER26=2.10
IF (ANGER36 LT 0)ANGER36=2.18
IF (HOSTTW1 LT 0)HOSTTW1=.51
IF (HOSTTW5 LT 0)HOSTTW5=.42
IF (HOSTTW7 LT 0)HOSTTW7=.14
IF (HOSTTW9 LT 0)HOSTTW9=.12
IF (HOSTTW17 LT 0)HOSTTW17=.26
IF (HOSTTW18 LT 0)HOSTTW18=.37
IF (HOSTTW20 LT 0)HOSTTW20=.23
IF (HOSTTW21 LT 0)HOSTTW21=.45
IF (HOSTTW24 LT 0)HOSTTW24=.33
IF (HOSTTW25 LT 0)HOSTTW25=.10
IF (HOSTTW27 LT 0)HOSTTW27=.34
IF (HOSTTW28 LT 0)HOSTTW28=.33
IF (HOSTTW29 LT 0)HOSTTW29=.52
IF (IMPUL1 LT 0)IMPUL1=2.39
IF (IMPUL8 LT 0)IMPUL8=1.80
IF (IMPUL9 LT 0)IMPUL9=2.46
IF (IMPUL10 LT 0)IMPUL10=2.60
IF (IMPUL11 LT 0)IMPUL11=2.17
IF (IMPUL12 LT 0)IMPUL12=2.14
IF (IMPUL16 LT 0)IMPUL16=1.67
IF (IMPUL17 LT 0)IMPUL17=2.20
IF (IMPUL20 LT 0)IMPUL20=2.25
IF (IMPUL22 LT 0)IMPUL22=1.64
IF (IMPUL28 LT 0)IMPUL28=1.70
IF (IMPUL30 LT 0)IMPUL30=2.36
IF (IMPUL34 LT 0)IMPUL34=2.30
IF (PORN10 LT 0)PORN10=1.91
IF (PORN11 LT 0)PORN11=2.00
IF (PORN12 LT 0)PORN12=2.00
IF (PORN13 LT 0)PORN13=2.00
IF (PORN14 LT 0)PORN14=1.91
IF (PORN15 LT 0)PORN15=1.97
IF (PORN16 LT 0)PORN16=1.99
IF (PORN17 LT 0)PORN17=1.98
```

```

IF (PD2 LT 0)PD2=.33
IF (PD3 LT 0)PD3=.30
IF (PD7 LT 0)PD7=.48
IF (PD11 LT 0)PD11=.36
IF (PD15 LT 0)PD15=.24
IF (PD17 LT 0)PD17=.07
IF (PD20 LT 0)PD20=.43
IF (PD22 LT 0)PD22=.32
IF (PD27 LT 0)PD27=.16
IF (PD28 LT 0)PD28=.17
IF (PD29 LT 0)PD29=.06
IF (PD30 LT 0)PD30=.37
IF (PD35 LT 0)PD35=.35
IF (PD40 LT 0)PD40=.60
IF (PD41 LT 0)PD41=.41
IF (PD42 LT 0)PD42=.86
IF (PD43 LT 0)PD43=.19
IF (PD44 LT 0)PD44=.37
IF (PD45 LT 0)PD45=.39
IF (PD46 LT 0)PD46=.52
IF (PD47 LT 0)PD47=.61
IF (PD49 LT 0)PD49=.43
IF (PD52 LT 0)PD52=.46
IF (PD53 LT 0)PD53=.23
IF (PEER2 LT 0)PEER2=3.95
IF (PEER3 LT 0)PEER3=2.32
IF (SCHIZ1 LT 0)SCHIZ1=.04
IF (SCHIZ5 LT 0)SCHIZ5=.29
IF (SCHIZ13 LT 0)SCHIZ13=.20
IF (SCHIZ14 LT 0)SCHIZ14=.49
IF (SCHIZ17 LT 0)SCHIZ17=.37
IF (SCHIZ18 LT 0)SCHIZ18=.53
IF (SCHIZ19 LT 0)SCHIZ19=.26
IF (SCHIZ20 LT 0)SCHIZ20=.53
IF (SCHIZ22 LT 0)SCHIZ22=.06
IF (SCHIZ26 LT 0)SCHIZ26=.13
IF (SCHIZ28 LT 0)SCHIZ28=.05
IF (SCHIZ36 LT 0)SCHIZ36=.31
IF (SCHIZ38 LT 0)SCHIZ38=.87
IF (SCHIZ46 LT 0)SCHIZ46=.55
IF (SCHIZ49 LT 0)SCHIZ49=.05
IF (SCHIZ55 LT 0)SCHIZ55=.36
IF (SCHIZ57 LT 0)SCHIZ57=.03
IF (SCHIZ58 LT 0)SCHIZ58=.78
IF (SCHIZ64 LT 0)SCHIZ64=.83
IF (SCHIZ70 LT 0)SCHIZ70=.18
IF (SCHIZ81 LT 0)SCHIZ81=.88
IF (SEXEXP3 LT 0)SEXEXP3=1.92
IF (SEXEXP13 LT 0)SEXEXP13=1.99
IF (RELATION LT 0)RELATION=3.38
IF (LIKELY LT 0)LIKELY=1.24
COMPUTE SEXEXP1=SEXEXP1-1
COMPUTE SEXEXP2=SEXEXP2-1
COMPUTE SEXEXP3=SEXEXP3-1
COMPUTE SEXEXP4=SEXEXP4-1
COMPUTE SEXEXP5=SEXEXP5-1
COMPUTE SEXEXP6=SEXEXP6-1
COMPUTE SEXEXP7=SEXEXP7-1
COMPUTE SEXEXP8=SEXEXP8-1
COMPUTE SEXEXP9=SEXEXP9-1
COMPUTE SEXEXP10=SEXEXP10-1
COMPUTE SEXEXP11=SEXEXP11-1
COMPUTE SEXEXP12=SEXEXP12-1
COMPUTE SEXEXP13=SEXEXP13-1

```

```

EXECUTE
COUNT MISSNEW=ID TO LIKELI(-99999)
EXECUTE
MISSING VALUES ID TO LIKELI(-99999)

COMPUTE HOSTLIT=SUM(HOSTTW1 TO HOSTTW30)
COMPUTE IMPULSIT=SUM(IMPUL1 TO IMPUL34)
COMPUTE IMPULSIC=SUM(IMPUL3,IMPUL6,IMPUL9,IMPUL12,IMPUL15,IMPUL18,
    IMPUL21,IMPUL24,IMPUL27,IMPUL30,IMPUL33)
COMPUTE IMPULSIM=SUM(IMPUL2,IMPUL5,IMPUL8,IMPUL11,IMPUL14,IMPUL17,IMPUL20,
    IMPUL23,IMPUL26,IMPUL29,IMPUL32)
COMPUTE IMPULINP=SUM(IMPUL1,IMPUL4,IMPUL7,IMPUL10,IMPUL13,IMPUL16,
    IMPUL19,IMPUL22,IMPUL25,IMPUL28,IMPUL31,IMPUL34)
COMPUTE ANGERSTA=SUM(ANGER1 TO ANGER10)
COMPUTE ANGERTRA=SUM(ANGER11 TO ANGER20)
COMPUTE ANGERTEM=SUM(ANGER11,ANGER12,ANGER13,ANGER16)
COMPUTE ANGERREA=SUM(ANGER14,ANGER15,ANGER18,ANGER20)
COMPUTE ANGERINN=SUM(ANGER23,ANGER25,ANGER26,ANGER30,ANGER33,ANGER36,
    ANGER37,ANGER41)
COMPUTE ANGEROUT=SUM(ANGER22,ANGER27,ANGER29,ANGER32,ANGER34,ANGER39,
    ANGER42,ANGER43)
COMPUTE ANGERCON=SUM(ANGER21,ANGER24,ANGER28,ANGER31,ANGER35,ANGER38,
    ANGER40,ANGER44)
COMPUTE ANGEREXP=(ANGERINN+ANGEROUT-ANGERCON+16)
COMPUTE LIESCALE=SUM(PD2,PD4,PD6,PD8,PD10,PD12,PD14,SCHIZ2,SCHIZ4,
    SCHIZ6,SCHIZ8,SCHIZ10,SCHIZ12,SCHIZ14,SCHIZ16)
COMPUTE PSDSCALE=SUM(PD1,PD3,PD5,PD7,PD9,PD11,PD13,PD15 TO PD57)
COMPUTE SCHIZSCA=SUM(SCHIZ1,SCHIZ3,SCHIZ5,SCHIZ7,SCHIZ9,SCHIZ11,SCHIZ13,
    SCHIZ15,SCHIZ17 TO SCHIZ82)
COMPUTE PEERSCAL=SUM(PEER1 TO PEER2)
COMPUTE PORNSCAL=SUM(PORN1 TO PORN17)
COMPUTE SEXEXTOT=SUM(SEXEXP1 TO SEXEXP13)
SUBTITLE '0 DESCRIPTIVES #####'
FREQUENCIES VARIABLES=MISSING MISSNEW ETHNIC XTHNIC GENDER GRADE
DESCRIPTIVES VARIABLES=ALL

```

```

SUBTITLE '6A INVARIANCE GROUP = 1'
TEMPORARY
SELECT IF (INV EQ 1)
MANOVA FS1 TO FS4 WITH HOSTLIT IMPULSIT ANGERSTA ANGERTRA ANGERTEM
    ANGERREA ANGERINN ANGEROUT ANGERCON PSDSCALE SCHIZSCA PEERSCAL
    PORNSCAL/
PRINT=SIGNIF(EIGEN DIMENR) CELLINFO(MEANS)/
DISCRIM=STAN COR ALPHA(.99)/
DESIGN

```

```

SUBTITLE '6B INVARIANCE GROUP = 2'
TEMPORARY
SELECT IF (INV EQ 2)
MANOVA FS1 TO FS4 WITH HOSTLIT IMPULSIT ANGERSTA ANGERTRA ANGERTEM
    ANGERREA ANGERINN ANGEROUT ANGERCON PSDSCALE SCHIZSCA PEERSCAL
    PORNSCAL/
PRINT=SIGNIF(EIGEN DIMENR) CELLINFO(MEANS)/
DISCRIM=STAN COR ALPHA(.99)/
DESIGN

```

```

SUBTITLE ' '
COMPUTE XEXEXTOT=SEXEXTOT*10000
COMPUTE XS1=FS1*10000
COMPUTE XS2=FS2*10000
COMPUTE XS3=FS3*10000
COMPUTE XS4=FS4*10000
COMPUTE XOSTLIT=HOSTLIT*10000

```

```

COMPUTE XIMPULSIT=IMPULSIT*10000
COMPUTE XNGERSTA=ANGERSTA*10000
COMPUTE XNGERTRA=ANGERTRA*10000
COMPUTE XNGERTEM=ANGERTEM*10000
COMPUTE XNGERREA=ANGERREA*10000
COMPUTE XNGERINN=ANGERINN*10000
COMPUTE XNGEROUT=ANGEROUT*10000
COMPUTE XNGERCON=ANGERCON*10000
COMPUTE XSДСCALE=PSДСCALE*10000
COMPUTE XCHIZSCA=SCHIZSCA*10000
COMPUTE XEERSCAL=PEERSCAL*10000
COMPUTE XORNSCAL=PORNSCAL*10000

```

TEMPORARY

```

SELECT IF (INV EQ 1)
FREQUENCIES VARIABLES=XS1 XS2 XS3 XS4 XOSTILIT XIMPULSIT XNGERSTA
XNGERTRA XNGERTEM XNGERREA XNGERINN XNGEROUT XNGERCON XSДСCALE
XCHIZSCA XEERSCAL XORNSCAL/STATISTICS=DEFAULT/
FORMAT=NOTABLE

```

TEMPORARY

```

SELECT IF (INV EQ 2)
FREQUENCIES VARIABLES=XS1 XS2 XS3 XS4 XOSTILIT XIMPULSIT XNGERSTA
XNGERTRA XNGERTEM XNGERREA XNGERINN XNGEROUT XNGERCON XSДСCALE
XCHIZSCA XEERSCAL XORNSCAL/STATISTICS=DEFAULT/
FORMAT=NOTABLE

```

```

IF (INV EQ 1)FS11=(FS1-(-.0141673))/1.0391149
IF (INV EQ 1)FS21=(FS2-.0820375)/.6114433
IF (INV EQ 1)FS31=(FS3-(-.0998253))/1.1635183
IF (INV EQ 1)FS41=(FS4-.0322112)/1.0094953
IF (INV EQ 1)HOSTILI1=(HOSTILIT-9.4753571)/5.0295050
IF (INV EQ 1)IMPULSI1=(IMPULSIT-76.5417057)/9.2716603
IF (INV EQ 1)ANGERST1=(ANGERSTA-13.4107143)/5.2422115
IF (INV EQ 1)ANGERTR1=(ANGERTRA-19.6320536)/5.5671725
IF (INV EQ 1)ANGERT1=(ANGERTEM-6.8348214)/2.8036558
IF (INV EQ 1)ANGERRE1=(ANGERREA-9.1365179)/2.4346542
IF (INV EQ 1)ANGERIN1=(ANGERINN-16.6277679)/4.2476733
IF (INV EQ 1)ANGEROU1=(ANGEROUT-16.4062500)/3.9507627
IF (INV EQ 1)ANGERCO1=(ANGERCON-23.5312500)/5.5016432
IF (INV EQ 1)PSДСCAL1=(PSДСCALE-19.3142857)/5.1399220
IF (INV EQ 1)SCHIZSC1=(SCHIZSCA-17.1134375)/9.8991294
IF (INV EQ 1)PEERSCA1=(PEERSCAL-6.9506696)/1.9504588
IF (INV EQ 1)PORNSCA1=(PORNSCAL-78.2221429)/8.0740416
IF (INV EQ 2)FS12=(FS1-.0123964)/.9663541
IF (INV EQ 2)FS22=(FS2-(-.0717828))/1.2411284
IF (INV EQ 2)FS32=(FS3-.0873471)/.8234859
IF (INV EQ 2)FS42=(FS4-(-.0281848))/.9927368
IF (INV EQ 2)HOSTILI2=(HOSTILIT-9.5303125)/5.4564703
IF (INV EQ 2)IMPULSI2=(IMPULSIT-76.4235547)/9.3039325
IF (INV EQ 2)ANGERST2=(ANGERSTA-13.4335938)/5.8667796
IF (INV EQ 2)ANGERTR2=(ANGERTRA-19.8730469)/5.9287019
IF (INV EQ 2)ANGERT2=(ANGERTEM-6.6894531)/2.8135258
IF (INV EQ 2)ANGERRE2=(ANGERREA-9.4531250)/2.7263691
IF (INV EQ 2)ANGERIN2=(ANGERINN-17.2936719)/4.1659093
IF (INV EQ 2)ANGEROU2=(ANGEROUT-16.4335938)/4.2087076
IF (INV EQ 2)ANGERCO2=(ANGERCON-24.1210938)/5.3932587
IF (INV EQ 2)PSДСCAL2=(PSДСCALE-19.4310156)/4.7366569
IF (INV EQ 2)SCHIZSC2=(SCHIZSCA-17.4994922)/9.3534248
IF (INV EQ 2)PEERSCA2=(PEERSCAL-6.9492188)/2.0003332
IF (INV EQ 2)PORNSCA2=(PORNSCAL-78.444960)/7.9746172

```

DESCRIPTIVES VARIABLES=XEXEXTOT TO PORNSCA2



COMPUTE C111=(.19311\*FS11)+(.15188\*FS21)+(.52995\*FS31)+(.80280\*FS41)  
 COMPUTE C112=(.39931\*FS11)+(.63609\*FS21)+(.26037\*FS31)+(.57420\*FS41)  
 COMPUTE C121=(.19311\*FS12)+(.15188\*FS22)+(.52995\*FS32)+(.80280\*FS42)  
 COMPUTE C122=(.39931\*FS12)+(.63609\*FS22)+(.26037\*FS32)+(.57420\*FS42)  
 COMPUTE C211=(.16819\*FS11)+(.84368\*FS21)+(-.35239\*FS31)+(.28872\*FS41)  
 COMPUTE C212=(.25092\*FS11)+(-.45411\*FS21)+(-.58379\*FS31)+(.61706\*FS41)  
 COMPUTE C221=(.16819\*FS12)+(-.84368\*FS22)+(-.35239\*FS32)+(.28872\*FS42)  
 COMPUTE C222=(.25092\*FS12)+(-.45411\*FS22)+(-.58379\*FS32)+(.61706\*FS42)  
 COMPUTE C311=(.67999\*FS11)+(-.07807\*FS21)+(.51736\*FS31)+(-.49961\*FS41)  
 COMPUTE C312=(.22123\*FS11)+(.47984\*FS21)+(-.71746\*FS31)+(-.44665\*FS41)  
 COMPUTE C321=(.67999\*FS12)+(-.07807\*FS22)+(.51736\*FS32)+(-.49961\*FS42)  
 COMPUTE C322=(.22123\*FS12)+(.47984\*FS22)+(-.71746\*FS32)+(-.44665\*FS42)  
 COMPUTE C411=(.72744\*FS11)+(.56155\*FS21)+(-.57339\*FS31)+(.15409\*FS41)  
 COMPUTE C412=(-.86188\*FS11)+(.41440\*FS21)+(-.28212\*FS31)+(.30199\*FS41)  
 COMPUTE C421=(.72744\*FS12)+(.56155\*FS22)+(-.57339\*FS32)+(.15409\*FS42)  
 COMPUTE C422=(-.86188\*FS12)+(.41440\*FS22)+(-.28212\*FS32)+(.30199\*FS42)  
 COMPUTE P111=(-.27763\*HOSTILI1)+(-.43099\*IMPULSI1)+(.30178\*ANGERST1)+  
 (-.46821\*ANGERTR1)+(-.01434\*ANGERTE1)+(.16058\*ANGERRE1)+  
 (.25305\*ANGERIN1)+(-.02425\*ANGEROU1)+(-.34631\*ANGERCO1)+  
 (-.02587\*PSDSCAL1)+(-.27433\*SCHIZSC1)+(.30461\*PEERSCAL1)+  
 (.36606\*PORNSCAL1)  
 COMPUTE P112=(.08264\*HOSTILI1)+(-.12353\*IMPULSI1)+(-.17083\*ANGERST1)+  
 (-.01091\*ANGERTR1)+(-.00966\*ANGERTE1)+(-.01803\*ANGERRE1)+  
 (-.08692\*ANGERIN1)+(.12772\*ANGEROU1)+(.13046\*ANGERCO1)+  
 (-.30458\*PSDSCAL1)+(.13896\*SCHIZSC1)+(.10073\*PEERSCAL1)+  
 (.79819\*PORNSCAL1)  
 COMPUTE P121=(-.27763\*HOSTILI2)+(-.43099\*IMPULSI2)+(.30178\*ANGERST2)+  
 (-.46821\*ANGERTR2)+(-.01434\*ANGERTE2)+(.16058\*ANGERRE2)+  
 (.25305\*ANGERIN2)+(-.02425\*ANGEROU2)+(-.34631\*ANGERCO2)+  
 (-.02587\*PSDSCAL2)+(-.27433\*SCHIZSC2)+(.30461\*PEERSCAL2)+  
 (.36606\*PORNSCAL2)  
 COMPUTE P122=(.08264\*HOSTILI2)+(-.12353\*IMPULSI2)+(-.17083\*ANGERST2)+  
 (.01091\*ANGERTR2)+(-.00966\*ANGERTE2)+(-.01803\*ANGERRE2)+  
 (-.08692\*ANGERIN2)+(.12772\*ANGEROU2)+(.13046\*ANGERCO2)+  
 (-.30458\*PSDSCAL2)+(.13896\*SCHIZSC2)+(.10073\*PEERSCAL2)+  
 (.80827\*PORNSCAL2)  
 COMPUTE P211=(-.46032\*HOSTILI1)+(.21830\*IMPULSI1)+(.13753\*ANGERST1)+  
 (-.18257\*ANGERTR1)+(-.07228\*ANGERTE1)+(-.05861\*ANGERRE1)+  
 (.28982\*ANGERIN1)+(.19237\*ANGEROU1)+(.26612\*ANGERCO1)+  
 (.07338\*PSDSCAL1)+(.76760\*SCHIZSC1)+(.21395\*PEERSCAL1)+  
 (.35433\*PORNSCAL1)  
 COMPUTE P212=(-.04831\*HOSTILI1)+(-.25602\*IMPULSI1)+(.35202\*ANGERST1)+  
 (-1.91859\*ANGERTR1)+(.42839\*ANGERTE1)+(.79499\*ANGERRE1)+  
 (.44806\*ANGERIN1)+(1.00343\*ANGEROU1)+(-.07647\*ANGERCO1)+  
 (-.21857\*PSDSCAL1)+(.36734\*SCHIZSC1)+(.49528\*PEERSCAL1)+  
 (.12177\*PORNSCAL1)  
 COMPUTE P221=(-.46032\*HOSTILI2)+(.21830\*IMPULSI2)+(.13753\*ANGERST2)+  
 (-.18257\*ANGERTR2)+(-.07228\*ANGERTE2)+(-.05861\*ANGERRE2)+  
 (.28982\*ANGERIN2)+(.19237\*ANGEROU2)+(.26612\*ANGERCO2)+  
 (.07338\*PSDSCAL2)+(.76760\*SCHIZSC2)+(.21395\*PEERSCAL2)+  
 (.35433\*PORNSCAL2)  
 COMPUTE P222=(-.04831\*HOSTILI2)+(-.25602\*IMPULSI2)+(.35202\*ANGERST2)+  
 (-1.91859\*ANGERTR2)+(.42839\*ANGERTE2)+(.79499\*ANGERRE2)+  
 (.44806\*ANGERIN2)+(1.00343\*ANGEROU2)+(-.07647\*ANGERCO2)+  
 (-.21857\*PSDSCAL2)+(.36734\*SCHIZSC2)+(.49528\*PEERSCAL2)+  
 (.12177\*PORNSCAL2)  
 COMPUTE P311=(.67424\*HOSTILI1)+(.37615\*IMPULSI1)+(.10954\*ANGERST1)+  
 (.69421\*ANGERTR1)+(-1.01190\*ANGERTE1)+(-.62232\*ANGERRE1)+  
 (-.17251\*ANGERIN1)+(.37569\*ANGEROU1)+(.45267\*ANGERCO1)+  
 (.00688\*PSDSCAL1)+(-.42082\*SCHIZSC1)+(-.28322\*PEERSCAL1)+  
 (.30413\*PORNSCAL1)  
 COMPUTE P312=(-.06804\*HOSTILI1)+(-.26821\*IMPULSI1)+(.00549\*ANGERST1)+  
 (2.26831\*ANGERTR1)+(-1.54048\*ANGERTE1)+(-.49898\*ANGERRE1)+  
 (-.14692\*ANGERIN1)+(.35408\*ANGEROU1)+(.11597\*ANGERCO1)+



```

( .60283*PSDSCAL1)+(-.29188*SCHIZSC1)+( .09465*PEERSCAL1)+
(.28103*PORNSCAL1)
COMPUTE P321=( .67424*HOSTILI2)+( .37615*IMPULSI2)+( .10954*ANGERST2)+
( .69421*ANGERTR2)+(-1.01190*ANGERTE2)+(-.62232*ANGERRE2)+
(-.17251*ANGERIN2)+( .37569*ANGEROU2)+( .45267*ANGERCO2)+
( .00688*PSDSCAL2)+(-.42082*SCHIZSC2)+(-.28322*PEERSCA2)+
( .30413*PORNSCA2)
COMPUTE P322=(-.06804*HOSTILI2)+(-.26821*IMPULSI2)+( .00549*ANGERST2)+
(2.26831*ANGERTR2)+(-1.54048*ANGERTE2)+(-.49898*ANGERRE2)+
(-.14692*ANGERIN2)+( .35408*ANGEROU2)+( .11597*ANGERCO2)+
( .60283*PSDSCAL2)+(-.29188*SCHIZSC2)+( .09465*PEERSCA2)+
(.28103*PORNSCA2)
COMPUTE P411=(-.01299*HOSTILI1)+(-.23705*IMPULSI1)+( .37519*ANGERST1)+
( .72949*ANGERTR1)+(-.51336*ANGERTE1)+(-.30929*ANGERRE1)+
( .37380*ANGERIN1)+( .80627*ANGEROU1)+( .33600*ANGERCO1)+
(-.12978*PSDSCAL1)+(-.23736*SCHIZSC1)+( .29863*PEERSCAL1)+
(-.24207*PORNSCAL1)
COMPUTE P412=( .60335*HOSTILI1)+(-.20576*IMPULSI1)+( .52459*ANGERST1)+
(-1.26466*ANGERTR1)+(1.25639*ANGERTE1)+( .72763*ANGERRE1)+
(-.05285*ANGERIN1)+(-.05653*ANGEROU1)+( .65559*ANGERCO1)+
(-.23076*PSDSCAL1)+(-.34007*SCHIZSC1)+(-.22526*PEERSCAL1)+
( .18877*PORNSCAL1)
COMPUTE P421=(-.01299*HOSTILI2)+(-.23705*IMPULSI2)+( .37519*ANGERST2)+
( .72949*ANGERTR2)+(-.51336*ANGERTE2)+(-.30929*ANGERRE2)+
( .37380*ANGERIN2)+( .80627*ANGEROU2)+( .33600*ANGERCO2)+
(-.12978*PSDSCAL2)+(-.23736*SCHIZSC2)+( .29863*PEERSCA2)+
(-.24207*PORNSCA2)
COMPUTE P422=( .60335*HOSTILI2)+(-.20576*IMPULSI2)+( .52459*ANGERST2)+
(-1.26466*ANGERTR2)+(1.25639*ANGERTE2)+( .72763*ANGERRE2)+
(-.05285*ANGERIN2)+(-.05653*ANGEROU2)+( .65559*ANGERCO2)+
(-.23076*PSDSCAL2)+(-.34007*SCHIZSC2)+(-.22526*PEERSCA2)+
( .18877*PORNSCA2)
VARIABLE LABELS C111 'CRITERION FUNC 1 GRP 1 DATA GRP 1 WEIGHTS'
C112 'CRITERION FUNC 1 GRP 1 DATA GRP 2 WEIGHTS'
C211 'CRITERION FUNC 2 GRP 1 DATA GRP 1 WEIGHTS'
C212 'CRITERION FUNC 2 GRP 1 DATA GRP 2 WEIGHTS'
C311 'CRITERION FUNC 3 GRP 1 DATA GRP 1 WEIGHTS'
C312 'CRITERION FUNC 3 GRP 1 DATA GRP 2 WEIGHTS'
C411 'CRITERION FUNC 4 GRP 1 DATA GRP 1 WEIGHTS'
C412 'CRITERION FUNC 4 GRP 1 DATA GRP 2 WEIGHTS'
P111 'PREDICTOR FUNC 1 GRP 1 DATA GRP 1 WEIGHTS'
P112 'PREDICTOR FUNC 1 GRP 1 DATA GRP 2 WEIGHTS'
P211 'PREDICTOR FUNC 2 GRP 1 DATA GRP 1 WEIGHTS'
P212 'PREDICTOR FUNC 2 GRP 1 DATA GRP 2 WEIGHTS'
P311 'PREDICTOR FUNC 3 GRP 1 DATA GRP 1 WEIGHTS'
P312 'PREDICTOR FUNC 3 GRP 1 DATA GRP 2 WEIGHTS'
P411 'PREDICTOR FUNC 4 GRP 1 DATA GRP 1 WEIGHTS'
P412 'PREDICTOR FUNC 4 GRP 1 DATA GRP 2 WEIGHTS'

```

```

SUBTITLE '6C CORRELATIONS FOR CROSSVALIDATION'
CORRELATIONS VARIABLES=C111 TO P422/PRINT=SIG/
STATISTICS=DESCRIPTIVES

```

Note. The crossvalidation commands are bolded. First, separate canonical analyses are conducted for the two groups defined by the random assignment to conditions of the variable, INV. Second, z-scores are computed within both of the two groups. Third, the standardized canonical function coefficients analogous to regression beta weights are applied to the standardized variables. Fourth, bivariate correlation coefficients are then computed across all pairs of the synthetic variables, e.g., C111.