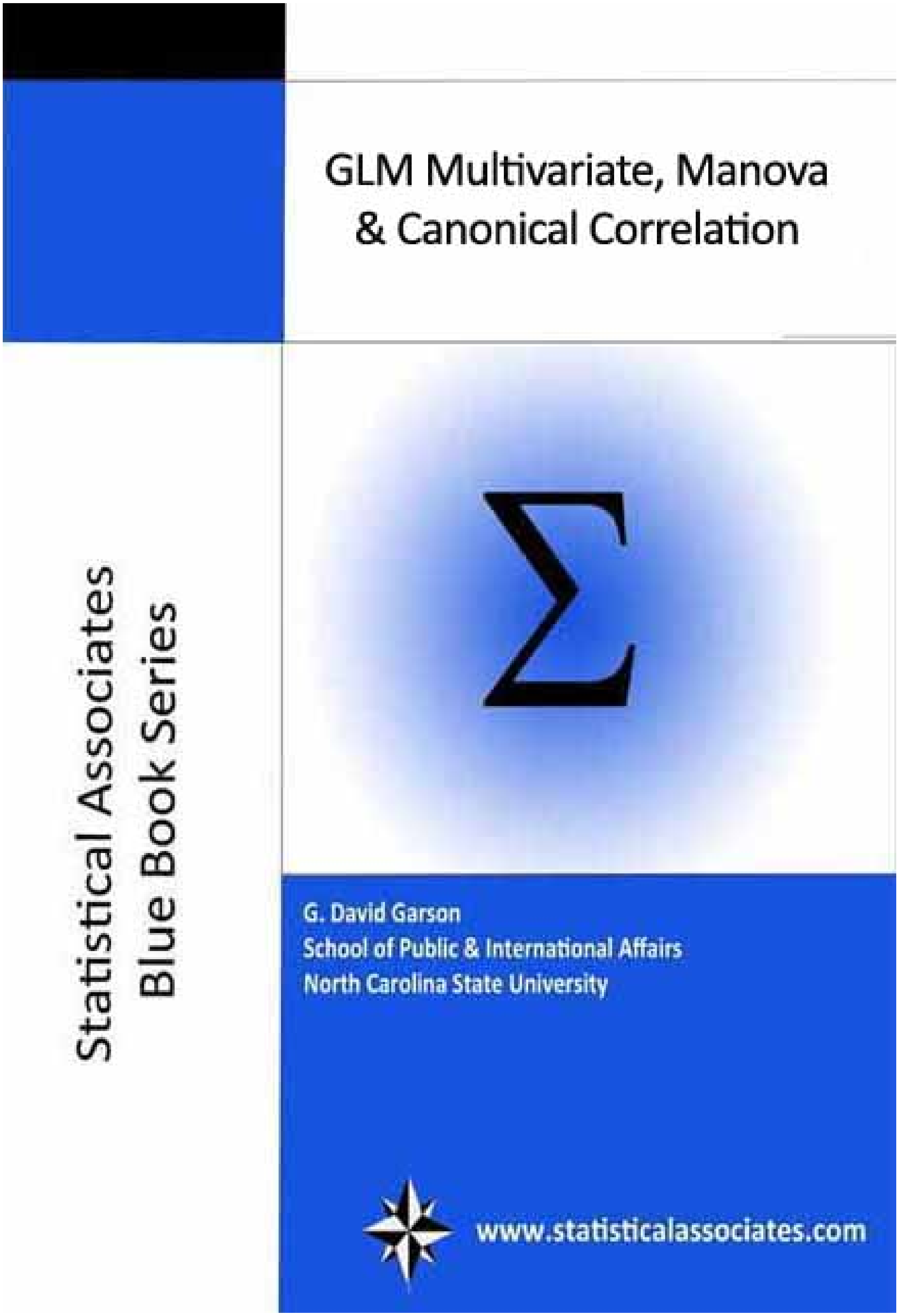
GLM Multivariate, Manova
& Canonical Correlation
Statistical Associates
Blue Book Series
Σ
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ISBN: 978-1-62638-034-9

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GLM MULTIVARIATE, MANOVA, & CANONICAL CORRELATION

Data examples for MANOVA

The example datasets used in this volume are listed below in order of use, with versions for SPSS (.sav), SAS (.sas7bdat), and Stata (.dta).

In most of the illustrations below, two continuous dependent variables (rincome, educ) are predicted from two fixed factors (race, sex) and one covariate (age). Data are drawn from the file "survey_sample", available through the links below.

Variables are coded as follows:
```
rincome: Respondent's income in 12 categories, coded 1 - 12
educ: Highest year of school completed
race: 1=White, 2=Black, 3=Other
sex: 1=Male, 2=Female
age: Age of respondent
```

Download links:

- SPSS: To obtain survey_sample.sav, click here.
- SAS: To obtain survey_sample.sas7bdat, click here.
- Stata: To obtain survey_sample.dta, click here.

MANOVA & MANCOVA

Multivariate GLM is the general linear model now often used to implement two long-established statistical procedures - MANOVA (multiple analysis of variance) and MANCOVA (multiple analysis of covariance). Multivariate GLM, MANOVA, and MANCOVA all deal with analyses where there is more than one outcome variable explained by one or more independent variables. Unlike MANOVA, MANCOVA also supports use of continuous control variables as covariates.

Multiple analysis of variance is used to see the main and interaction effects of categorical variables on multiple dependent interval variables. Dependent variables typically are treated as a set because they are correlated (if they were not correlated, univariate GLM would be appropriate).

MANOVA uses one or more categorical independent variables as predictors, like ANOVA, but unlike ANOVA, there is more than one dependent variable. Where ANOVA tests the differences in means of the interval dependent variable for various categories of the independent variables, MANOVA tests the differences in the centroid (vector) of means of the multiple interval dependents, for various categories of the independent variables. The researcher may also perform planned comparisons or post-hoc comparisons to see which values of a factor contribute most to the explanation of the dependent variables.

There are multiple potential purposes for MANOVA or MANCOVA.

- *Compare group differences.* To compare groups formed by categorical independent variables on group differences in a set of interval dependent variables.
- *Improve model parsimony.* To use lack of difference for a set of dependent variables as a criterion for reducing a set of dependent variables to a smaller, more easily modeled number of variables.
- *Rank predictor variables by discriminant effect.* To identify the independent variables which differentiate values in a set of dependent variables the most.

Multiple analysis of covariance (MANCOVA) is similar to MANOVA but continuous independent variables may be added as covariates. These covariates may be seen as additional predictor variables or may serve as control variables for the independent factors, thereby serving to reduce the error term in the model. Like other control procedures, MANCOVA can be seen as a form of "what if" analysis, asking what would happen if all cases scored equally on the covariates, so that the effect of the factors over and beyond the covariates can be isolated.

Note: “Multivariate” in this context means multiple dependent variables. If the focus is on multiple independent variables with a single outcome variable, the reader is referred to the Statistical Associates “Blue Book” volume on *GLM: Univariate & Repeated Measures*. MANOVA for repeated measures is also discussed in this volume. See also the “Blue Book” volume on *Discriminant Function Analysis*, which yields results equivalent to one-way MANOVA.

GLM in statistics packages

SPSS

MANOVA and MANCOVA are found under Analyze > General linear model > Multivariate in the SPSS menu system. Output is similar to SPSS's old stand-alone MANOVA and MANCOVA programs but under GLM, parameters (coefficients) are created for every category of every factor and this "full parameterization" approach handles the problem of empty cells better than traditional approaches. GLM also accepts categorical variables without the need to manually enter dummy variables. That is, GLM automatically transforms declared categorical variables into sets of indicator variables. GLM calculates parameters using iterative weighted least squares (IWLS). The seminal article on GLM is Nelder and Wedderburn (1972) and an overview is Gill (2001).

Starting with SPSS 7.0, SPSS replaced the MANOVA procedure with the GLM procedure in the menu system. Note, however, that the MANOVA procedure remains available in syntax and has some features not available in GLM, such as correction for violation of sphericity. GLM and MANOVA syntax are listed in the FAQ section below.

SAS

In SAS, PROC GLM's MODEL statement supports multiple dependent variables and its MANOVA statement supports a variety of GLM multivariate tests. The CONTRAST statement is also available to support custom contrasts.

Stata

Multivariate GLM is supported by Stata's `manova` command, which supports MANCOVA as well as MANOVA models. Additionally, the `mvreg` command may be used post-estimation to display the coefficients associated with the multivariate regression model underlying the last run of the `MANOVA` command. Also, a user-written add-on module called `omega2` is available to compute omega-square (type `findit omega2`).

Key coefficients in multivariate GLM

F tests

The significance of the model as a whole and of each predictor variable are tested using F tests, discussed below in sections on the significance of between-subjects effects in univariate analysis.

The value of F is the ratio of mean-square between groups (the numerator in the equation for F) to mean square within groups (the denominator), where groups are formed by the factors. For example, for three levels of race and two levels of sex, there are six groups. Computation of F takes the following into account:

- *Total sum of squares:* Take the deviation of each score from the grand mean of all scores, square the deviations, and sum the squared deviations.
- *Between group sum of squares:* Take the deviation of each group mean from the total mean, square theses deviations, multiply each squared deviation by the corresponding group size, and sum for all groups.
- *Within group sum of squares:* Total sum of squares minus between sum of squares yields the within sum of squares.
- *Between and within group sum of squares:* Divide the sum of squares by its degrees of freedom (df). The means squares reflect population variance.
- *Between group df*: The number of groups minus 1.
- *Within group df*: For each group, its df component is its size minus 1. Within group df is the sum of components for all groups.

The F statistic is also incorporated in multivariate tests of the model. The four major multivariate tests are Pillai's trace, Wilks' lambda, Hotelling's trace, and Roy's largest root, all , discussed below. Customarily, univariate F tests are investigated only after multivariate tests uphold the MANOVA model.

t tests

The parameter estimates tables discussed below use t-tests of the b coefficients, much as in OLS regression, to provide a different test of the significance of each predictor variable.

Partial eta-square

Partial eta-square is the main effect size measure in many of the tables discussed below, including tables of between-subject effects. Partial eta-square indicates maximum effect when it is 1.0. No effect is indicated when partial eta-square is 0.0. That is, the closer to 0.0, the less the variable is contributing to the model. Partial eta-square a nonlinear analog to R-square in regression, similarly interpreted as percent of variance explained.

Partial eta-square is a function of variation accounted for by the given effect divided by the sum of between-group variation accounted for by the effect plus residual within-group variation (error). The SPSS manual notes that "partial eta squared is the matrix product of the hypothesis SSCP matrix and the inverse of the sum of the hypothesis and error SSCP matrices."

In SPSS, partial eta-square is not part of default output but is output when the research checks "Estimates of effect size" in the Options button dialog. What SPSS reports in some tables as “eta-square” is in fact partial eta-square. In SAS and Stata, partial eta-square is part of default output.

R-Square

R-square and adjusted R-square for the model are not the values one would get from OLS regression nor are they an average of OLS estimates for each dependent variable. Rather R-square is usually redundant with partial eta-square, but if nonlinearities are present, partial eta-square will be higher. Adjusted R-squared penalizes for the number of predictors.

Omega-square

Omega-square, also called Hays' omega-square or the "coefficient of determination", is the proportion of variance in the dependent variable accounted for by the independent variable, adjusted for bias and interpreted analogously to adjusted R-square. Adjusted effect size attempts to correct bias which may arise from small sample size, having a large number of variables, and/or estimating a small population effect size. Omega-squared is available in SPSS in syntax using the MANOVA procedure but is not available in the GLM

Multivariate menu module. In SAS, Omega-square is part of default output. In Stata, omega-square is not directly supported but is available in the third-party user-written program, `omega2`.

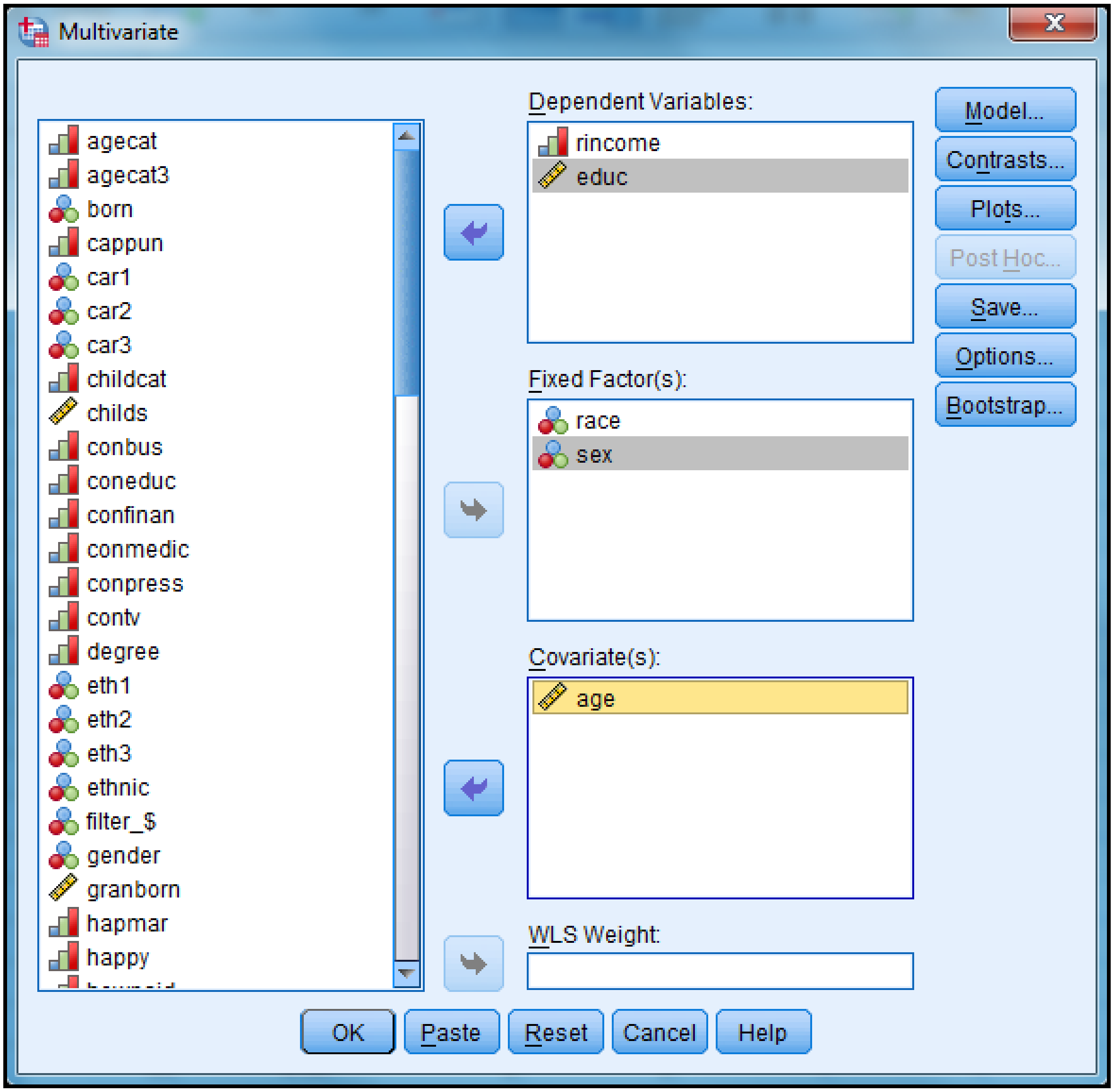
Omega-square is a commonly used measure of the magnitude of the effect of a given independent factor. Cohen (1977) calls omega-square "large" when over .15, "medium" when .06 to .15, and otherwise "small." Note omega-square is not used for random effects designs. While it may be used for one-way repeated measures designs, omega-square is underestimated slightly if there is subject by treatment interaction. Due to sources of variability being large, omega-square is not usually reported for two-way or higher repeated measures designs.

Multivariate GLM in SPSS

SPSS input

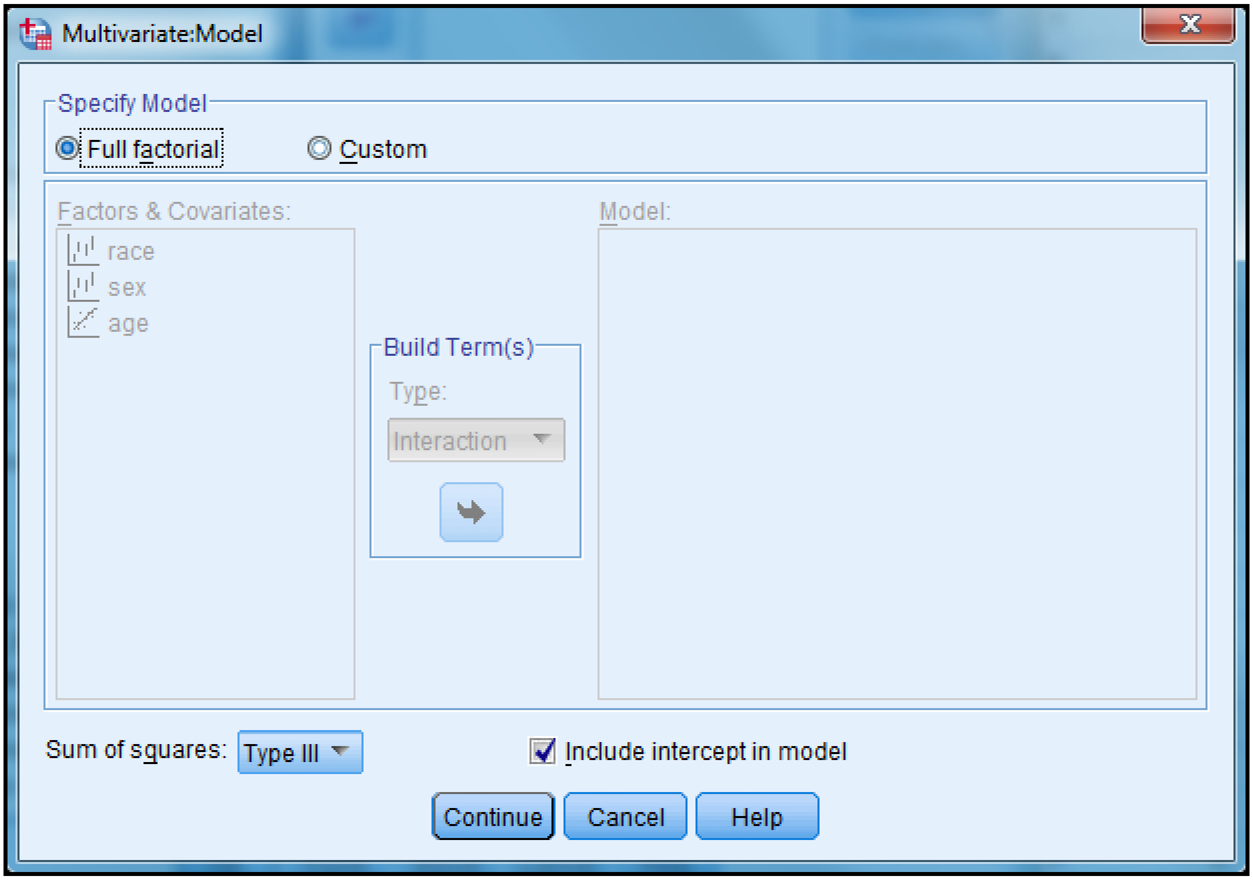
The main multivariate GLM dialog

MANOVA and MANCOVA are requested from the SPSS menu selections Analyze > General Linear Model > Multivariate.
In the figure below, the initial multivariate GLM dialog in SPSS shows that the dependent variables are respondent's income (rincome) and respondent's education (educ). These are predicted by the categorical variables (factors) of respondent's race and sex, and by the continuous variable, respondent's age. While dependent variables should be continuous, it may be noted that in social science it has been common also to use ordinal dependent variables if the number of categories is large (ex., in this example, rincome has 12 categories of dollar income). Fixed factors may be nominal or ordinal. Covariates are continuous-interval.



The Model dialog

Clicking the "Model" button yields the dialog below. Models are entered in SPSS using the Model button dialog illustrated below. The researcher may specify a full factorial model (as here, top right) or custom main and interaction effects. A full factorial model is the default, incorporating the effects of the factors race and sex, the covariate age, and factor interaction race*sex. Covariate by factor interactions are not part of a "full factorial" model. In this dialog, it is also possible to click "Custom" and enter the specific effects desired for a differently specified model and to choose whether to include the intercept (the default) or not.



Multiple and multivariate regression models

A multiple regression model in multivariate GLM is simply one with a single continuous dependent variable, no factors, and multiple covariates. A multivariate regression model is the same, except there are multiple continuous dependent variables. To take a different example using only continuous variables suitable for a regression model, let the dependent variables be tvhours (high = watch television more) and news (low = read newspaper more) . Let the independent variables be mother's education (maeduc), father's education (paeduc), and respondent's education (educ). The SPSS command syntax was "GLM tvhours news WITH maeduc paeduc educ".

Parameter Estimates

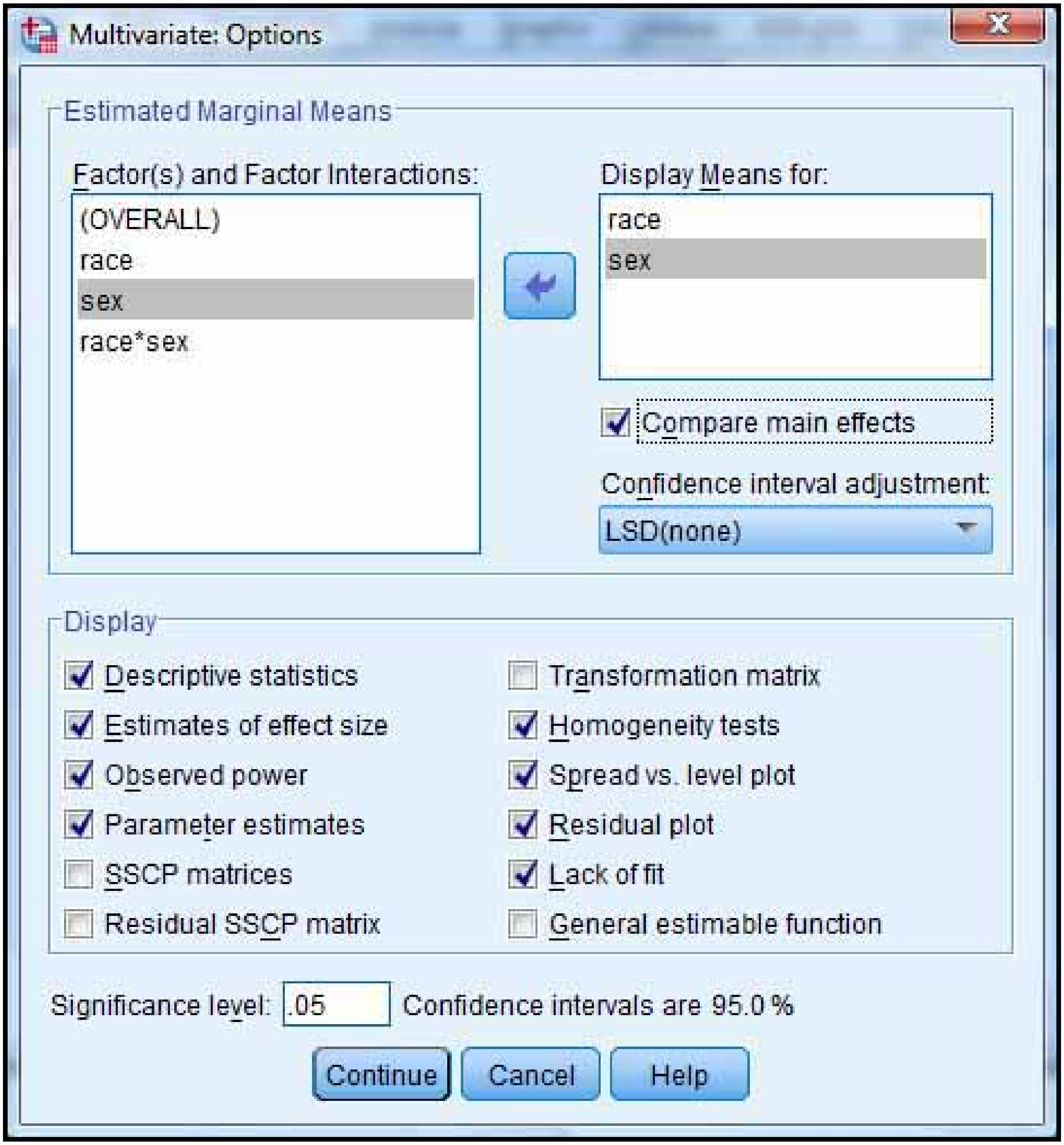
Dependent Variable	Parameter	B	Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared
						Lower Bound	Upper Bound	
Hours per day watching TV	Intercept	5.013	.298	16.824	.000	4.428	5.598	.183
	maeduc	.015	.023	.669	.504	-.029	.059	.000
	paeduc	-.021	.019	-1.090	.276	-.059	.017	.001
	educ	-.165	.023	-7.095	.000	-.210	-.119	.038
How often does respondent read newspaper	Intercept	3.136	.182	17.217	.000	2.779	3.494	.190
	maeduc	.008	.014	.574	.566	-.019	.035	.000
	paeduc	.002	.012	.200	.842	-.021	.025	.000
	educ	-.082	.014	-5.743	.000	-.109	-.054	.025

The b coefficients in this table cannot be assembled into a regression equation directly, as in OLS regression, due to differences in computation. Predicted values of dependent variables can be saved to file under the “Save” button of the SPSS multivariate GLM dialog. The partial eta^2 is an R^2-like effect size measure for each of the two dependent variables.

The television item was a count of hours, so In the output illustrated above, the negative b coefficient for education (educ) indicates that respondent's education (educ) is significantly associated with watching television less. The newspaper item was coded from 1 = “Every day” to 5 = “Never”, so the negative b coefficient for education indicates that education is significantly associated with reading the newspaper more. Both relationships are significant even controlling for parents' education (though parents' education is not significant). By partial eta^2, education explains less than 4% of both media variables so while significant, the relationship is weak in this regression model.

The Options dialog

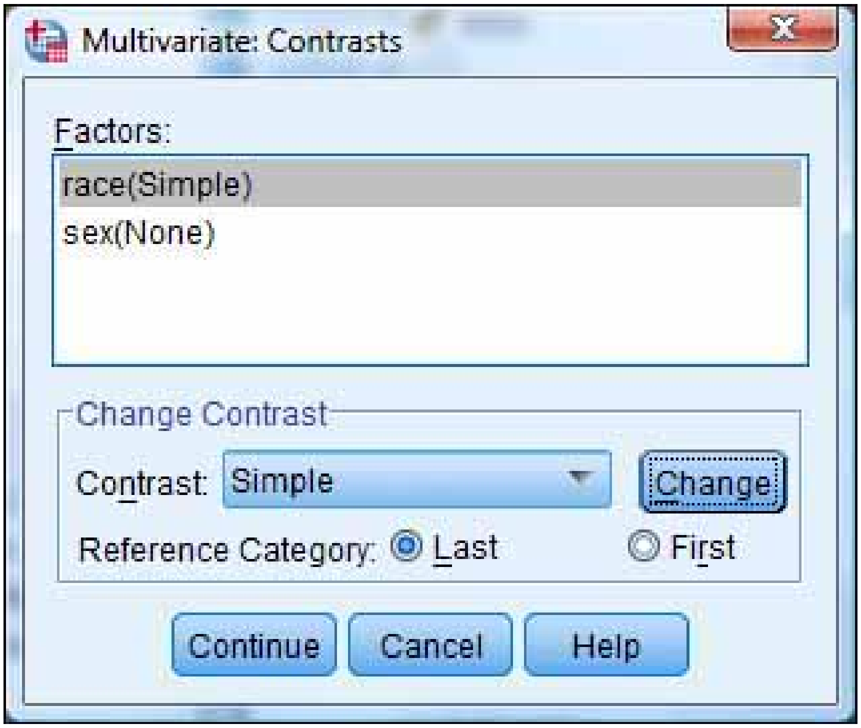
The “Options” button dialog is where desired statistical output may be selected, illustrated below. Here, marginal means tests are requested in the upper portion of the dialog and a variety of statistics in the lower. These output options are illustrated in the “SPSS output” section.



The Contrasts dialog

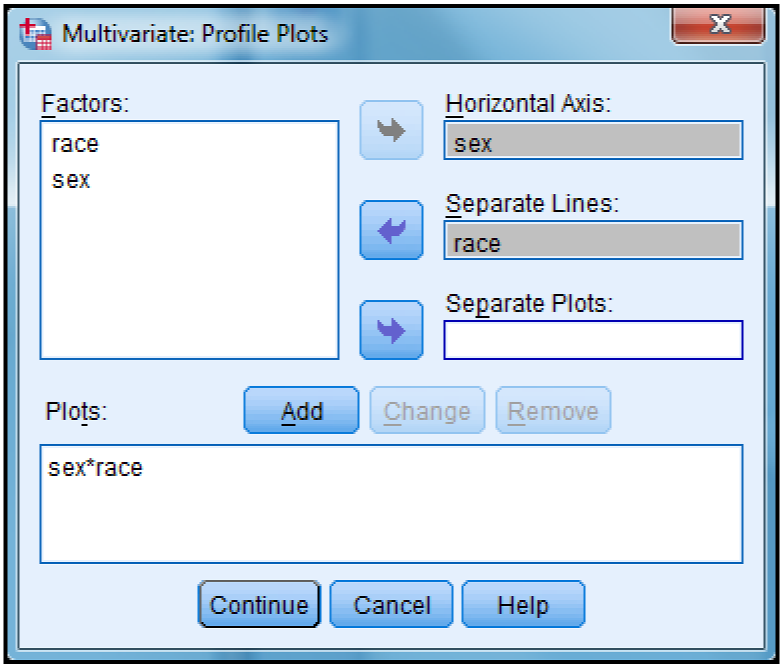
In multivariate GLM, contrast tests show how levels of the multiple dependent variables (here rincome and educ) relate to levels of the factor variables (here race and sex). Below, simple contrasts (comparing a given level with the highest-coded level) were requested for the race variable, whose highest-coded level is 3=Other race. Output tables are discussed further below.

Other types of contrasts than simple are available, described in the FAQ section below.



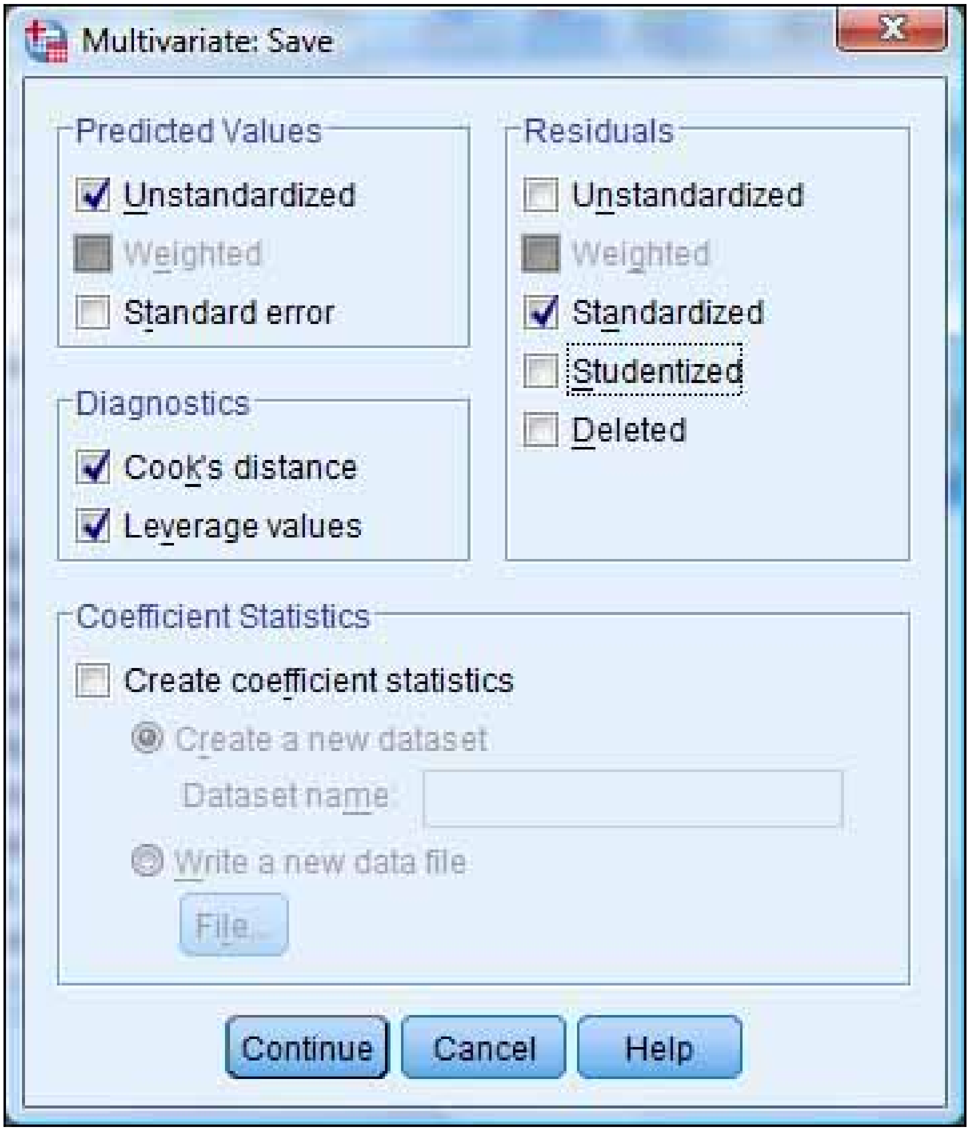
The Plots dialog

The Plots button allows the researcher to request various "profile plots" discussed below. Here sex is entered as the horizontal axis and separate lines are requested for race, then the "Add" button is clicked, then "Continue". Profile plots are illustrated below in the output section.



The Save dialog

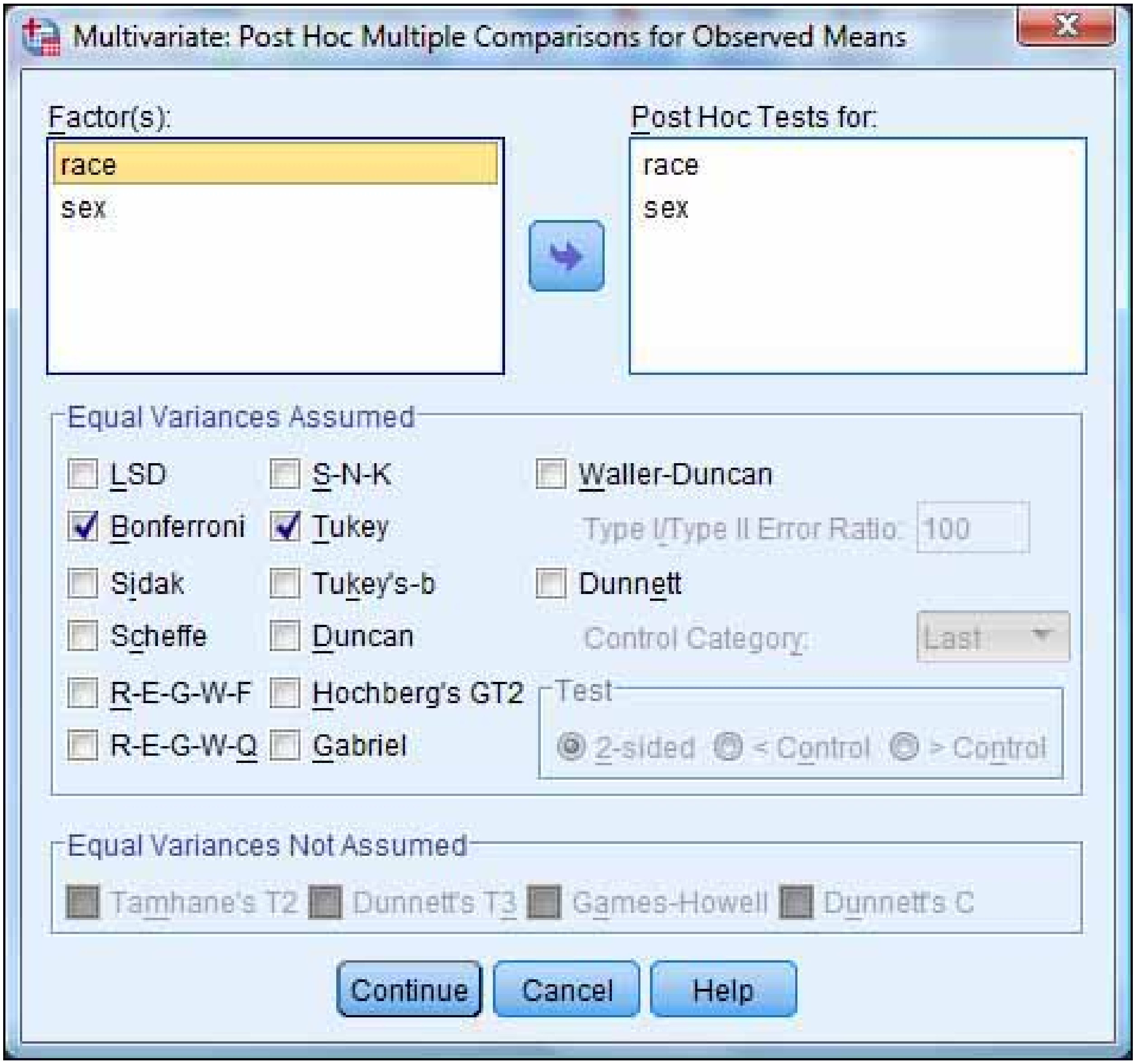
The “Save” button does not generate statistical output but rather allows creation of additional columns in the dataset, to be saved for separate analysis. In the illustration below, the additional columns are those for predicted values, standardized residuals, and the diagnostic coefficients Cook's distance and leverage. That is, after saving, each subject (row) will have a corresponding value on each of these four variables. Use of these values in residual plots is discussed below.



The Post hoc dialog

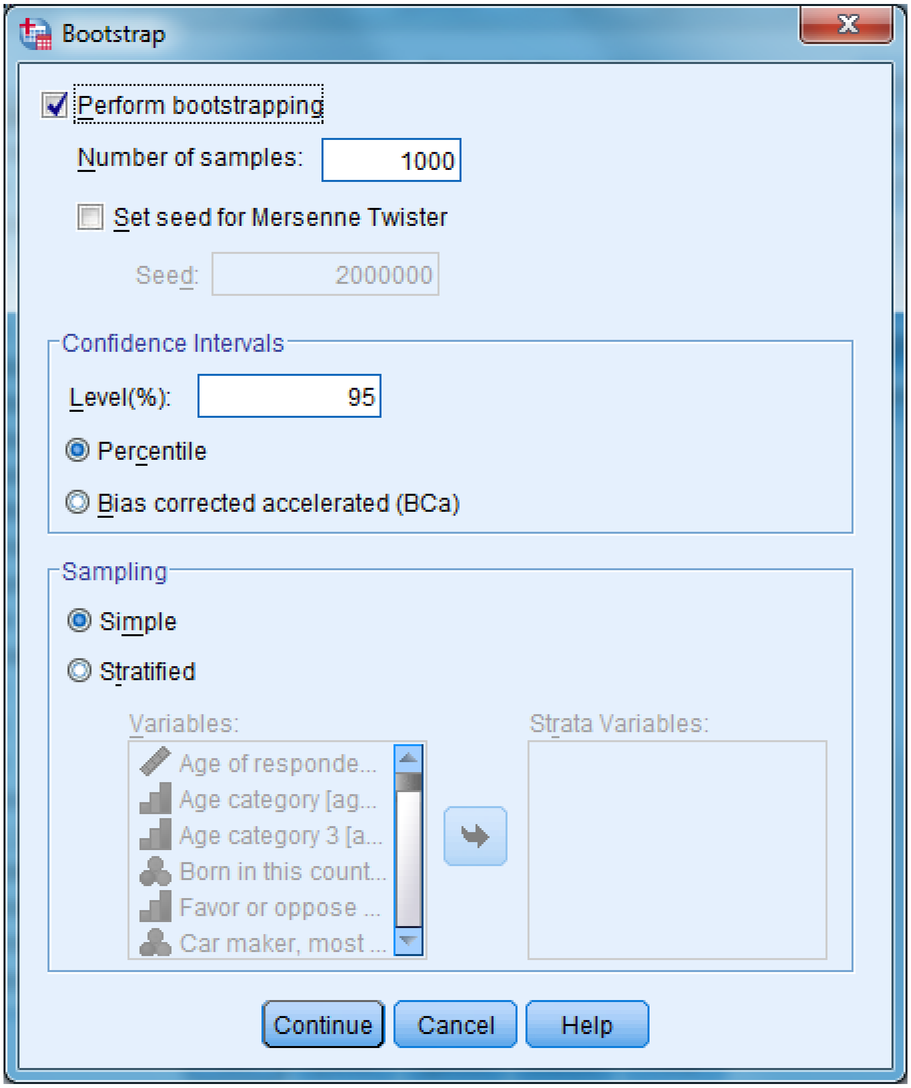
The "Post Hoc" button allows the researcher to request post-hoc tests. *This option will be greyed out if there are any covariates in the model, as for the example in this section.* Post hoc tests show if levels of factors differ significantly on dependent means. They are applied only after the F test shows the model is significant overall. Covariates must be removed before post hoc tests may be calculated. Below the Bonferroni and Tukey post hoc tests are requested for race and sex.

The Bonferroni, Tukey, and other post hoc tests, their purposes and differences, are discussed in the FAQ section further below.



The Bootstrap dialog

If the "Bootstrap" button is pressed and "Perform bootstrapping" is checked, SPSS will perform bootstrapped significance tests, discussed below in the FAQ section. .



Simple versus stratified sampling. SPSS online help notes, "The Simple method is case resampling with replacement from the original dataset. The Stratified method is case resampling with replacement from the original dataset, within the strata defined by the cross-classification of strata variables. Stratified bootstrap sampling can be useful when units within strata are relatively homogeneous while units across strata are very different."

SPSS syntax

Alternative to using the menu system, MANOVA and MANCOVA models may be entered as commands in the syntax window, accessed by clicking the "Paste" button.

For examples in this section, the syntax is that shown below.

```
* Run 1
GLM rincome educ BY race sex WITH age
  /CONTRAST(race)=Simple
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /SAVE=PRED ZRESID COOK LEVER
  /PLOT=PROFILE(sex*race)
  /EMMEANS=TABLES(race) WITH(age=MEAN) COMPARE ADJ(LSD)
  /EMMEANS=TABLES(sex) WITH(age=MEAN) COMPARE ADJ(LSD)
  /PRINT=DESCRIPTIVE ETASQ OPOWER PARAMETER HOMOGENEITY LOF
  /PLOT=SPREADLEVEL RESIDUALS
  /CRITERIA=ALPHA(.05)
  /DESIGN=age race sex race*sex.
```

* Run 2, with the covariate age removed, post hoc tests were requested for race, sex:

```
* Run 2
GLM rincome educ BY race sex
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /POSTHOC=race sex(TUKEY BONFERRONI)
  /CRITERIA=ALPHA(.05)
  /DESIGN= race sex race*sex.
```

SPSS output

Multivariate significance tests

Multivariate tests answer the question, "Which predictor effects are significant?" or more specifically, "Is each effect significant for at least one of the dependent variables?" That is, where the between-subjects F test focuses on the significance of the relationship of each predictor variable to each dependent variable, the multivariate tests focus on relationship of each predictor variables and any interaction effects to the set of dependent variables. These tests appear in the "Multivariate Tests" table of SPSS output. The multivariate formula for F is based not only on the sum of squares between and within groups but also on the sum of crossproducts - that is, it takes covariance into account as well as group means.

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[d]
Intercept	Pillai's Trace	.705	2193.547[b]	2.000	1835.000	.000	.705	4387.094	1.000
	Wilks' Lambda	.295	2193.547[b]	2.000	1835.000	.000	.705	4387.094	1.000
	Hotelling's Trace	2.391	2193.547[b]	2.000	1835.000	.000	.705	4387.094	1.000
	Roy's Largest Root	2.391	2193.547[b]	2.000	1835.000	.000	.705	4387.094	1.000
age	Pillai's Trace	.030	28.385[b]	2.000	1835.000	.000	.030	56.771	1.000
	Wilks' Lambda	.970	28.385[b]	2.000	1835.000	.000	.030	56.771	1.000
	Hotelling's Trace	.031	28.385[b]	2.000	1835.000	.000	.030	56.771	1.000
	Roy's Largest Root	.031	28.385[b]	2.000	1835.000	.000	.030	56.771	1.000
race	Pillai's Trace	.024	11.384	4.000	3672.000	.000	.012	45.536	1.000
	Wilks' Lambda	.976	11.447[b]	4.000	3670.000	.000	.012	45.789	1.000
	Hotelling's Trace	.025	11.510	4.000	3668.000	.000	.012	46.042	1.000
	Roy's Largest Root	.025	22.891[c]	2.000	1836.000	.000	.024	45.783	1.000
sex	Pillai's Trace	.007	6.508[b]	2.000	1835.000	.002	.007	13.016	.908
	Wilks' Lambda	.993	6.508[b]	2.000	1835.000	.002	.007	13.016	.908
	Hotelling's Trace	.007	6.508[b]	2.000	1835.000	.002	.007	13.016	.908
	Roy's Largest Root	.007	6.508[b]	2.000	1835.000	.002	.007	13.016	.908
race * sex	Pillai's Trace	.006	2.776	4.000	3672.000	.026	.003	11.106	.766
	Wilks' Lambda	.994	2.777[b]	4.000	3670.000	.026	.003	11.106	.766
	Hotelling's Trace	.006	2.777	4.000	3668.000	.026	.003	11.106	.766
	Roy's Largest Root	.005	4.472[c]	2.000	1836.000	.012	.005	8.943	.767

a. Design: Intercept + age + race + sex + race * sex

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

d. Computed using alpha = .05

In the figure above, all the main, covariate, and interaction effects are significant at better than the .05 mile by any of the four leading multivariate tests of group differences. This means that each effect is significantly related to at least one of the two dependent variables, rincome and educ.

- *Hotelling's T-Square* is the most common, traditional test where there are two groups formed by the independent variables. SPSS prints the related statistic, *Hotelling's Trace* (a.k.a. Lawley-Hotelling or Hotelling-Lawley Trace). To convert from the Trace coefficient to the T-Square coefficient, multiply the Trace coefficient by (N-g), where N is the sample size across all groups and g is the number of groups. The T-Square result will still have the same F value, degrees of freedom, and significance level as the Trace coefficient. The larger the Hotelling's trace, the more the given effect contributes to the model.

- *Wilks' lambda, U*. This is the most common, traditional test where there are more than two groups formed by the independent variables. Wilks' lambda is a multivariate F test, akin to the F test in univariate ANOVA. It is a measure of the difference between groups of the centroid (vector) of means on the independent variables. The smaller the lambda, the greater the differences. The Bartlett's V transformation of lambda is then used to compute the significance of lambda. Wilks's lambda is used, in conjunction with Bartlett's V, as a multivariate significance test of mean differences in MANOVA, for the case of multiple interval dependents and multiple (>2) groups formed by the independent(s). The t-test, Hotelling's T, and the F test are special cases of Wilks's lambda. Wilks' lambda ranges from 0 to 1, and the lower the Wilks' lambda, the more the given effect contributes to the model.

- *Pillai's trace*, also called Pillai-Bartlett trace, V. Multiple discriminant analysis (MDA) is the part of MANOVA where canonical roots are calculated. Each significant root is a dimension on which the vector of group means is differentiated. The Pillai-Bartlett trace is the sum of explained variances on the discriminant variates, which are the variables which are computed based on the canonical coefficients for a given root. Olson (1976) found V to be the most robust of the four tests and is sometimes preferred for this reason, especially if the homogeneity of variance assumption or other assumptions have not been met. Specifically, if Box's M is significant, then Pillai's trace is preferred over the usual Wilks' lambda. The larger the Pillai's trace, the more the given effect contributes to the model. Pillai's trace is always smaller than Hotelling's trace.

- *Roy's greatest characteristic root (GCR)*, called "Roy's largest root" in SPSS, is similar to the Pillai-Bartlett trace but is based only on the first (and hence most important) root. Specifically, let lambda be the largest eigenvalue, then GCR = lambda/(1 + lambda). Note that Roy's largest root is sometimes also equated with the largest eigenvalue, as in SPSS's GLM procedure (however, SPSS reports GCR for MANOVA). GCR is less robust than the other tests in the face of violations of the assumption of multivariate normality. The larger the root, the more that effect contributes to the model. Note, however, that Roy's largest root sets a lower bound for the significance value, tending to make this test more prone to Type 1 error (false positives) than the nominal significance level might suggest -that is, it is a more liberal test, as the example above illustrates.

Significance tests of between-subjects effects (F tests)

In SPSS output, the "Tests of Between Subjects Effects" table provides an F test of the significance of the model overall (the "omnibus test", in the "Corrected Model" row). This test is also called the omnibus F-test and it answers the question, "Is the model significant for at least one of the predictors?" This table also reports the significance of the intercept and of each predictor variable in the model. There is an F significance test for each dependent variable (here, rincome and educ), both for the model and for each predictor variable.

For the example below, the multivariate general linear model is found to be significant overall for both dependent variables, as shown in the highlighted "Corrected Model" row.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[c]
Corrected Model	Respondent's income	1292.148[a]	6	215.358	28.853	.000	.086	173.119	1.000
	Highest year of school completed	213.248[b]	6	35.541	5.106	.000	.016	30.638	.995
Intercept	Respondent's income	10265.328	1	10265.328	1375.322	.000	.428	1375.322	1.000
	Highest year of school completed	27341.405	1	27341.405	3928.254	.000	.681	3928.254	1.000
age	Respondent's income	389.483	1	389.483	52.182	.000	.028	52.182	1.000
	Highest year of school completed	.252	1	.252	.036	.849	.000	.036	.054
race	Respondent's income	219.340	2	109.670	14.693	.000	.016	29.387	.999
	Highest year of school completed	198.838	2	99.419	14.284	.000	.015	28.568	.999
sex	Respondent's income	62.793	1	62.793	8.413	.004	.005	8.413	.826
	Highest year of school completed	12.055	1	12.055	1.732	.188	.001	1.732	.260
race * sex	Respondent's income	60.040	2	30.020	4.022	.018	.004	8.044	.719
	Highest year of school completed	15.699	2	7.850	1.128	.324	.001	2.256	.250
Error	Respondent's income	13703.800	1836	7.464					
	Highest year of school completed	12778.915	1836	6.960					
Total	Respondent's income	200799.000	1843						
	Highest year of school completed	361620.000	1843						
Corrected Total	Respondent's income	14995.948	1842						
	Highest year of school completed	12992.163	1842						

a. R Squared = .086 (Adjusted R Squared = .083)

b. R Squared = .016 (Adjusted R Squared = .013)

c. Computed using alpha = .05

For the example data, rows after the first show that age, race, sex, and the age*race interaction are all significant for the respondent's income (rincome) dependent variable, controlling for other effects in the model. Of these three predictors, using partial eta^2 as a criterion, age is the most important (though still a weak predictor of income). For the highest year of school completed (educ) dependent variable, only race is significant, controlling for other effects in the model.

Note: To get partial eta-square in the table above in SPSS the researcher must check "Estimates of effect size" in the "Options" button dialog. To get power, "Observed power" must be checked. The noncentrality index is used to compute the power level, which by rule of thumb should be equal or greater than .80 to accept with confidence that the chance of Type II error is low enough for a finding of non-significance by the F test (that is, to be confident that the relationship does not exist).

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Creating Simulated Datasets
Crosstabulation
Curve Estimation & Nonlinear Regression
Delphi Method in Quantitative Research
Discriminant Function Analysis
Ethnographic Research
Factor Analysis
Focus Group Research
Game Theory
Generalized Linear Models/Generalized Estimating Equations
GLM Multivariate, MANOVA, and Canonical Correlation
GLM: Univariate & Repeated Measures
Grounded Theory
Life Tables & Kaplan-Meier Survival Analysis
Literature Review in Research and Dissertation Writing

Logistic Regression: Binary & Multinomial
Log-linear Models,
Longitudinal Analysis
Missing Values & Data Imputation
Multidimensional Scaling
Multiple Regression
Narrative Analysis
Network Analysis
Neural Network Models
Ordinal Regression
Parametric Survival Analysis
Partial Correlation
Partial Least Squares Regression & Structural Equation Models
Participant Observation
Path Analysis
Power Analysis
Probability
Probit and Logit Response Models
Research Design
Scales and Measures
Significance Testing
Social Science Theory in Research and Dissertation Writing
Structural Equation Modeling
Survey Research & Sampling
Testing Statistical Assumptions
Two-Stage Least Squares Regression
Validity & Reliability
Variance Components Analysis
Weighted Least Squares Regression

Statistical Associates Publishing
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