Data_Analysis.calm

Three Factor Completely Randomized Design with One Continuous Factor: Using SPSS GLM UNIVARIATE

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This article considers a three factor completely randomized design in which one of the factors is a continuous variable. The example to be considered would derive from an experiment where individuals are randomly assigned to one level of a factor (B) and one level of another factor (C). In addition, there would be a continuous (centred) individual difference variable (A), and the objective is to assess the effects of these three factors and their interactions on the dependent variable (X). Although it is possible instead to perform an analysis of covariance, it may well be that the researcher is not interested in simply controlling for variation in A, but rather in studying the effects of all sources of variance in this three factor experiment.

Table 1 presents the data to be used in this demonstration. There are three levels of B and three levels of C, and each respondent provides a dependent measure as well as a score on a centred continuous variable. Recall, that it is necessary to center the continuous variable by subtracting the grand mean from each individual's score. Thus, the mean of the centred variable (A) is 0. Examination of Table 1 will reveal that sample sizes are unequal, to demonstrate the generality of the procedure.

Table 1
Sample Data

	C1		C2		C3	
	A	X	A	X	A	X
B1	-11.07	17	-13.07	25	-13.07	19
	-10.07	21	-8.07	35	-10.07	20
	-4.07	24	6.93	28	-7.07	27
	9.93	17	7.93	28	-7.07	21
	13.93	11	16.93	24	16.93	26
					-3.07	28
B2	13.93	31	-14.07	21	-10.07	14
	7.93	32	-10.07	18	-3.07	17
	-7.07	18	-1.07	29	16.93	24
	-4.07	27	2.93	17	6.93	21
	-11.07	25			-1.07	19
	5.93	34				
B3	-10.07	28	-8.07	19	15.93	16
	-13.07	28	5.93	10	16.93	21
	16.93	19	6.93	11	-10.07	25
	17.93	31	-9.07	13	-7.07	18
	-8.07	20			5.93	15

Performing the Analysis Using SPSS GLM Univariate.

The analysis of variance can be conducted using multiple regression and/or SPSS GLM Univariate. This article considers the latter case. In this example, the factors B and C each take values from 1 to 3, and the centred continuous variable (A) is read in as a covariate. Before running the analysis, it is necessary to paste the file into the syntax editor so that it can be modified by making additions to the Design statement.[1] These additions are A*B, A*C, and A*B*C. The modified syntax file is as follows (with the additions shown in capitals):

```
UNIANOVA
  x  BY b c  WITH a
  /METHOD = SSTYPE(3)
  /INTERCEPT = INCLUDE
  /CRITERIA = ALPHA(.05)
  /DESIGN = a b c b*c A*B A*C A*B*C.
```

This will produce the summary table for the analysis of variance presented in Table 2. It should also be noted that if the Estimated cell and marginal means were requested in the Options section when setting up the run (not shown here), the resulting values would correspond to the cell intercepts (for BC) and their marginal values (the main effects of B and C). We will see how to compute both the cell intercepts and cell slopes later.

Table 2

Tests of Between-Subjects Effects

Dependent Variable: X

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1203.594[a]	17	70.800	3.688	.001
Intercept	18395.217	1	18395.217	958.237	.000
A	1.200	1	1.200	.063	.804
B	134.631	2	67.315	3.507	.044
C	69.629	2	34.815	1.814	.182
B * C	758.145	4	189.536	9.873	.000
B * A	129.169	2	64.585	3.364	.050
C * A	39.630	2	19.815	1.032	.370
B * C * A	74.533	4	18.633	.971	.440
Error	518.317	27	19.197		
Total	23590.000	45			
Corrected Total	1721.911	44			

a. R Squared = .699 (Adjusted R Squared = .509)

If the modifications were not made to the Syntax file, the output would consist of an analysis of covariance. Except for the total and corrected total Sums of Squares, the various sums of squares values would be different, of course, and the output would be missing the AxB

[1] Alternatively, one could simply set up the run to do an analysis of covariance, select Model, click on Custom, then add the main effects, two way interactions and three way interaction to the model. This has the same effect as making the alteration in the Syntax file.

AxC, and AxBxC interactions (since these sources of variation would all form part of the Sums of Squares for Error). Furthermore, the estimated cell and marginal means would also differ. In short, the results of the analysis using the centred continuous variable as a factor are different from an analysis of covariance using the centered continuous variable as a covariate.

Using the SPSS GLM Output to Compute Intercepts and Slopes.

Of course, if one were to perform the analysis using SPSS GLM UNIVARIATE, it would be necessary to compute the intercepts and slopes using the output from the program. By selecting "Parameter Estimates" in Options, one obtains the regression coefficients, obtained using Dummy Coding. Table 3 presents the regression coefficients produced by SPSS GLM UNIVARIATE. In this case, the two B vectors are defined as 1,0,0 and 0,1,0 for groups B1, B2, and B3 respectively, while the two C vectors have comparable codes for the groups C1, C2, and C3.

We can use the information in Table 3 to calculate the intercept and slope for each cell. Thus, for the B1C1 cell, B1 and C1 both equal 1, while both B2 and C2 equal 0. Thus, for this cell, the regression equation would be:

$$X' = (19.62228 + 4.65929 + 5.59614 - 11.95423) + (-.14371 + .34395 + .11847 - .60211)A$$
$$X' = 17.92348 - .28340A$$

where 17.92348 is the intercept for the B1C1 group and -.28340 is the slope.

We could compute each of these values by hand, but an easier way is to perform the calculations in SPSS. To do this, we would need to create a Data file containing the six columns for the Dummy coding. Then, it would be necessary to enter the Syntax Editor and create the following two equations, one for the intercept and one for the slope for each of the BC cells:

INTERCEPT = 19.62228 + 4.65929*B1 + (-1.32123)*B2 + 5.59614*C1 + (-6.74631)*C2 +
(-11.95423)*B1*C1 + 10.76116 * B1 * C2 + 3.51021 * B2 * C1 + 10.16193 * B2 * C2.

and

SLOPE = (-1.4371) + .34395*B1 + .50586*B2 + .11847*C1 + (-.20584)*C2 + (-.60211)
*B1*C1 + (-.13355)*B1*C2 + (-.02264)*B2*C1 + (-.07252)*B2*C2.

Running these two equations from the Syntax file would produce the values for the cell intercepts and slopes in the data file that you had created. For these data, these values are shown in Tables 4 and 5. Although, not readily apparent, it should be emphasized that these values are exactly the same values that would be obtained if you were to perform bivariate regression analyses for each BC group separately. You might wish to verify this with your own data.

Table 3
Regression Coefficients

Parameter Estimates

Dependent Variable: X

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	19.62228	2.09948	9.34627	.00000	15.31451	23.93005
A	-.14371	.17412	-.82538	.41639	-.50098	.21355
[B=1.00]	4.65929	2.84857	1.63566	.11352	-1.18550	10.50407
[B=2.00]	-1.32123	2.90073	-.45548	.65240	-7.27305	4.63058
[B=3.00]	0[a]	.	.	.	.	.
[C=1.00]	5.59614	2.87368	1.94738	.06196	-.30016	11.49245
[C=2.00]	-6.74631	3.05029	-2.21169	.03564	-13.00499	-.48763
[C=3.00]	0[a]	.	.	.	.	.
[B=1.00] * [C=1.00]	-11.95423	3.97575	-3.00679	.00565	-20.11180	-3.79667
[B=1.00] * [C=2.00]	10.76116	4.12223	2.61052	.01457	2.30303	19.21928
[B=1.00] * [C=3.00]	0[a]	.	.	.	.	.
[B=2.00] * [C=1.00]	3.51021	3.93686	.89163	.38047	-4.56756	11.58798
[B=2.00] * [C=2.00]	10.16193	4.61837	2.20033	.03652	.68582	19.63805
[B=2.00] * [C=3.00]	0[a]	.	.	.	.	.
[B=3.00] * [C=1.00]	0[a]	.	.	.	.	.
[B=3.00] * [C=2.00]	0[a]	.	.	.	.	.
[B=3.00] * [C=3.00]	0[a]	.	.	.	.	.
[B=1.00] * A	.34395	.25218	1.36386	.18387	-.17349	.86139
[B=2.00] * A	.50586	.27417	1.84506	.07602	-.05669	1.06842
[B=3.00] * A	0[a]	.	.	.	.	.
[C=1.00] * A	.11847	.22512	.52626	.60301	-.34344	.58038
[C=2.00] * A	-.20584	.33950	-.60631	.54937	-.90244	.49075
[C=3.00] * A	0[a]	.	.	.	.	.
[B=1.00] * [C=1.00] * A	-.60211	.34639	-1.73822	.09357	-1.31285	.10863
[B=1.00] * [C=2.00] * A	-.13355	.42423	-.31481	.75533	-1.00399	.73689
[B=1.00] * [C=3.00] * A	0[a]	.	.	.	.	.
[B=2.00] * [C=1.00] * A	-.02264	.36859	-.06141	.95148	-.77893	.73365
[B=2.00] * [C=2.00] * A	-.07252	.51369	-.14118	.88878	-1.12653	.98149
[B=2.00] * [C=3.00] * A	0[a]	.	.	.	.	.
[B=3.00] * [C=1.00] * A	0[a]	.	.	.	.	.
[B=3.00] * [C=2.00] * A	0[a]	.	.	.	.	.
[B=3.00] * [C=3.00] * A	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Table 4
Intercepts

	C1	C2	C3	Mean (B)
B1	17.923	28.296	24.282	23.500
B2	27.407	21.717	18.301	22.475
B3	25.218	12.876	19.622	19.239
Mean (C)	23.516	20.963	20.735	G = 21.738

Table 5
Slopes

	C1	C2	C3	Mean (AB)
B1	-.283	-.139	.200	-.074
B2	.458	.084	.362	.301
B3	-.025	-.350	-.144	-.173
Mean (AC)	.050.	-.135	.139	G = .018

Understanding the Relationship Between these Values and the F-ratios Reported in Table 2.

Each F-ratio refers to these values as follows:

F_A (1,27) = .063. This tests whether the mean slope (.018) varies significantly from 0. In this case, it does not, suggesting that there is no main effect of the continuous independent variable on the dependent variable.

F_B(2,27) = 3.507, p < .044. This tests whether the variation in the mean intercepts for the three levels of B (23.500, 22.475, and 19.239) differ more than could be reasonably expected by chance. Since the F-ratio is significant, we can conclude that they do. We could thus do post hoc tests of these differences.

F_C(2,27) = 1.814. This tests whether the mean intercepts for the three levels of C (23.516, 20.963, and 20.735) differ more than expected on the basis of chance. The F-ratio is not significant, so we can conclude that they do not.

F_{BC}(4,27) = 9.873, p < .001. This is a test that the interaction between B and C is significant. This interaction is reflected in the cell intercepts, and because it is significant, we can conclude that the cell intercepts vary among them selves in ways that are not consistent with the marginal restrictions as indicated by the row and column intercepts. This interaction could be illustrated by plotting the cell intercepts as one would plot the cell means (by selecting plot in the analysis of variance run, one could produce this plot). Post hoc tests of simple main effects could be conducted if desired, and this is demonstrated in a following section.

$F_{AB}(2,27) = 3.364, p<.050.$ This test of the AB interaction evaluates whether the mean slopes of the dependent variable against the centred continuous variable (-.074, .301, -.173) vary more than can be reasonably attributed to chance. Typically, if this interaction is significant, it would not be plotted directly. Instead, three regression lines, one for each level of B might be plotted on the same graph.

$F_{AC}(2,27) = 1.032.$ This is a test of the AC interaction which evaluates whether the three mean slopes (.050, -.135, .139) vary more than expected by chance.

$F_{ABC}(4,27) = .971.$ This is a test of the three way interaction, which assesses whether the cell slopes vary more among themselves than can be expected based on the marginal restrictions defined by the mean slopes.

On the basis of these results, we can conclude that we have significant variation attributed to the main effect of B, as well as the BC and the AB interaction. Before considering relevant post hoc tests, it is instructive to contrast the generalizations based on the results of the F-ratios with those that might be made on the basis of the regression coefficients and their associated tests of significance.

Meaning of the Regression Coefficients for Dummy Coding.

Using the intercepts and slopes in Tables 4 and 5, we can demonstrate precisely what the regression coefficients describe, and hence what their test of significance implies. The meaning and the arithmetic value of each regression coefficient (with some slight rounding error for some values) are shown in Table 6. Note, for example, that although the F-ratio for the main effect of B is significant, neither of the regression coefficients for B (i.e., 4.659 and -1.321) are significant in Table 3. This is not an anomaly. It appears that often individuals would interpret these regression coefficients as tests of the main effect of B, but this is not correct. With Dummy coding, the regression coefficients for the full model do not refer to main effects, but instead to specific simple main effects. That is, the regression coefficient for B1 is the difference between the intercept for the B1C3 cell and the B3C3 cell. Similarly, the regression coefficient for B2 is the difference between the B2C2 cell and the B3C3 cell.

These very specific meanings apply to each of the other regression coefficients in Table 3. Consider, for example, the regression coefficients for each of the other “main effect” vectors. The regression coefficient for the Intercept (19.622) is simply the intercept for the B3C3 cell (the one cell coded with all 0's in the Dummy coding used in this analysis by SPSS GLM UNIVARIATE), and the regression coefficient for the continuous variable (-.144) is the slope for the B3C3 cell. Finally, the regression coefficients for the two “main effect” C vectors are deviations of cell values. Thus, for C1 (5.596) it is the difference between B3C1 and B3C3 and for C2 (-6.746) it is the difference between the B3C2 intercept and the B3C3 intercept. Thus, none of these regression coefficients describe the “main effects” that some researchers attribute to them. In each case they describe contrasts involving specific cells in the design. Thus, their tests of significance are tests of the specific contrasts.

Table 6
The Precise Meaning of the Regression Coefficients

Regression Label	Meaning	Value	t-value
Intercept	I33	19.622	9.346 ***
A	S33	-.144	-.825
[B=1]	I13 - I33	24.282 - 19.622 = 4.660 (rounding error)	1.636
[B=2]	I23 - I33	18.301 - 19.622 = -1.321	-.455
[C=1]	I31 - I33	25.218 - 19.622 =5.596	1.947
[C=2]	I32 - I33	12.876 - 19.622 = -6.746	-2.211*
[B=1]*[C=1]	I11 - I13 - I31 + I33	17.923 - 24.282 - 25.218 + 19.622 = -11.955	-3.007**
[B=1]*[C=2]	I12 - I13 - I32 + I33	28.296 - 24.282 - 12.876 + 19.622 = 10.760	2.611*
[B=2]*[C=1]	I21 - I23 - I31 + I33	27.407 - 18.301 - 25.218 + 19.622 = 3.510	.892
[B=2]*[C=2]	I22 - I23 - I32 + I33	21.717 - 18.301 - 12.876 + 19.622 = 10.162	2.200*
[B=1]*A	S13 - S33	.200 - (-.144) = .344	1.364
[B=2]*A	S23 - S33	.362 - (-.144) = .506	1.845
[C=1]*A	S31 - S33	(-.025) - (-.144) =.119	.526
[C=2]*A	S32 - S33	(-.350) - (-.144) = -.206	-.606
[B=1]*[C=1]*A	S11 - S13 - S31 + S33	-.283 - .200 - (-.025) + (-.144) = -.602	-1.738
[B=1]*[C=2]*A	S12 - S13 - S32 + S33	-.139 - .200 - (-.350) + (-.144) = -.133	-.315
[B=2]*[C=1]*A	S21 - S23 - S31 + S33	.458 - .362 - (-.025) + (-.144) = -.023	-.061
[B=2]*[C=2]*A	S22 - S23 - S32 + S33	.084 - .362 - (-.350) + (-.144) = -.072	-.141

* p < .05 ** p < .01

In this example, it was noted that there was no evidence of a significant main effect for C, but in Table 3 it can be seen that the regression coefficient for C2 is significant. Again, this is not an anomaly. Clearly, the variation in the mean intercepts associated with C is not that great. Nonetheless, the intercept for B2C2 is shown to differ significantly from that for B3C3, but in analysis of variance terms this would simply reflect a Type I error. That is, the main effect is not significant, but a specific contrast involved in the definition of that main effect is significant.

Similar observations can be made about the regression coefficients for the various product vectors. The four BC vectors are often viewed as vectors describing the interaction, but in fact they can be shown to be tests of specific contrast/contrast interactions. Thus, the B1C1 regression coefficient is the interaction between the contrast B1C1- B1C3 and that for B3C1 and B3C3which in this example is significant because the first contrast is negative and the second one is positive. It will be noted in Table 6 that two of the other contrast/contrast interactions involving the intercepts in the BC cells are also significant. Because the BC interaction is significant (see Table 3, and above), one might be interested in discussing these contrast/contrast interactions, but it should be stressed exactly what contrasts are involved. Note too that these four contrast/contrast interactions are not mutually orthogonal so that as a unit they do not account for the interaction effect.

The product vectors involving the centred continuous variable refer to contrasts involving slopes. The regression coefficient for B1A can be seen to be the difference between the B1C3 and the B3C3 cells (i.e., .200 - (-.144) while that for B2A is the difference between the B2C3 cell and the B3C3 cell. Similar observations can be made with respect to the CA vectors. It will be noted here that although the BA interaction was significant (see Table 3), neither of these contrasts are significant, nor would the contrast B1C1 - B2C3 be significant, if tested. Again, this isn't inconsistent with what can happen in analysis of variance, where the effect is significant but contrasts involved in the definition of the effect are not. This is of little help to the researcher who obtains such a result, and might well be indicative of insufficient power for the contrast.

The ABC product vectors identify contrast/contrast effects involving slopes. Thus, as can be seen, the regression coefficient for the B1C1A vector is the interaction between the B1C1 - B1C3 contrast of slopes with the B3C1 - B3C3 contrast of slopes. The other regression coefficients for the ABO product vectors are similarly defined. As before, these four contrast/contrast effects are not orthogonal, and hence are simply four of many contrast/contrast effects that could be identified. In any event, the three way interaction is not significant in this case, so there would be little interest in any specific contrasts.

<u>Post hoc Testsof the Intercepts.</u>

Post hoc tests of the intercepts can be performed directly in SPSS GLM UNIVARIATE, particularly if a small adjustment is made to the EMMEANS statement for the BC interaction. By selecting on Options, moving the two main effects and the interaction effects to the open window, and selecting "Main Effects Tests" produces the following three operations in the Syntax Editor. They are as follows:

```
/EMMEANS = TABLES(b) WITH (A=MEAN) COMPARE (LSD)
/EMMEANS = TABLES(c) WITH (A=MEAN) COMPARE (LSD)
/EMMEANS = TABLES(b*c) WITH (A=MEAN) COMPARE (b) (LSD)
```

This will produce the following two tables for the main effect of B.

Estimates

Dependent Variable: x

b	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1.00	23.501[a]	1.132	21.178	25.823
2.00	22.474[a]	1.302	19.803	25.145
3.00	19.239[a]	1.209	16.759	21.720

a. Covariates appearing in the model are evaluated at the following values: a = -.0033.

Pairwise Comparisons

Dependent Variable: x

(I) b	(J) b	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
1.00	2.00	1.027	1.725	.557	-2.513	4.566
	3.00	4.261*	1.656	.016	.863	7.659
2.00	1.00	-1.027	1.725	.557	-4.566	2.513
	3.00	3.235	1.777	.080	-.411	6.880
3.00	1.00	-4.261*	1.656	.016	-7.659	-.863
	2.00	-3.235	1.777	.080	-6.880	.411

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Note that the intercepts in the first table above are the same (within rounding error) as those reported in Table 4 as the Mean(B) intercepts, and that the pairwise comparisons presented in the above table compare all three intercepts.

The same information is presented for the main effects of C in the following two tables.

Estimates

Dependent Variable: x

c	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1.00	23.516[a]	1.102	21.255	25.777
2.00	20.963[a]	1.370	18.152	23.775
3.00	20.735[a]	1.161	18.353	23.116

a. Covariates appearing in the model are evaluated at the following values: a = -.0033.

Pairwise Comparisons

Dependent Variable: x

(I) c	(J) c	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
1.00	2.00	2.553	1.758	.158	-1.055	6.160
	3.00	2.782	1.600	.094	-.502	6.065
2.00	1.00	-2.553	1.758	.158	-6.160	1.055
	3.00	.229	1.796	.899	-3.455	3.913
3.00	1.00	-2.782	1.600	.094	-6.065	.502
	2.00	-.229	1.796	.899	-3.913	3.455

Based on estimated marginal means

a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

The following two tables present the same information for the BC interaction. Note, in the next table that the intercepts are the same (within rounding error) as the cell values in Table 4. The table of contrasts in the subsequent table then are tests of the simple main effects of B at each level of C. Note too that the tests for the contrasts B1 vs B3 and B2 vs B3 at the level of C3 are the same as the tests of significance of the regression coefficients for the B1 and B2 vectors, confirming the earlier observation that those regression coefficients do not refer to main effect tests.

3. b * c

Dependent Variable: x

b	c	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
1.00	1.00	17.924[a]	1.960	13.903	21.946
	2.00	28.297[a]	1.996	24.202	32.392
	3.00	24.281[a]	1.925	20.331	28.231
2.00	1.00	27.406[a]	1.799	23.716	31.096
	2.00	21.716[a]	2.831	15.908	27.525
	3.00	18.300[a]	2.002	14.193	22.407
3.00	1.00	25.219[a]	1.962	21.192	29.245
	2.00	12.877[a]	2.213	8.337	17.417
	3.00	19.623[a]	2.100	15.315	23.931

a. Covariates appearing in the model are evaluated at the following values: a = -.0033.

Pairwise Comparisons

Dependent Variable: x

c	(I) b	(J) b	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
						Lower Bound	Upper Bound
1.00	1.00	2.00	-9.481*	2.660	.001	-14.940	-4.023
		3.00	-7.294*	2.773	.014	-12.985	-1.603
	2.00	1.00	9.481*	2.660	.001	4.023	14.940
		3.00	2.187	2.662	.418	-3.274	7.649
	3.00	1.00	7.294*	2.773	.014	1.603	12.985
		2.00	-2.187	2.662	.418	-7.649	3.274
2.00	1.00	2.00	6.580	3.464	.068	-.526	13.687
		3.00	15.420*	2.980	.000	9.306	21.533
	2.00	1.00	-6.580	3.464	.068	-13.687	.526
		3.00	8.839*	3.593	.021	1.467	16.212
	3.00	1.00	-15.420*	2.980	.000	-21.533	-9.306
		2.00	-8.839*	3.593	.021	-16.212	-1.467
3.00	1.00	2.00	5.981*	2.777	.040	.283	11.679
		3.00	4.658	2.849	.114	-1.187	10.503
	2.00	1.00	-5.981*	2.777	.040	-11.679	-.283
		3.00	-1.323	2.901	.652	-7.275	4.629
	3.00	1.00	-4.658	2.849	.114	-10.503	1.187
		2.00	1.323	2.901	.652	-4.629	7.275

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Post hoc Tests of the Slopes.

Post hoc Tests of the AB Interaction.

The significant AB interaction indicates that the slopes vary more than expected on the basis of chance across the three levels of B, collapsing across C. These are identified as the marginal values, Mean(AB), in Table 5, and take the values of -.074, .301, and -.173. The most direct way of comparing these slopes two at a time using SPSS GLM UNIVARIATE is to perform the same analysis as above contrasting two levels of B at a time. Thus, to compare the slopes of B2 vs B3, one would select these two levels, and retain all three levels of C. The F-ratio for the AB interaction in the resulting analysis of variance would be a test of the difference between the two mean slopes, i.e., .301 vs -.173. For this example, the F-ratio would be 5.836 at 1 and 17 degrees of freedom if the error term from this reduced analysis was used, and 6.234 at 1 and 27 degrees of freedom if the error term from the original analysis was used.

Post hoc Tests of the ABC Interaction.

The ABC interaction was $F(4,27) = .971$, but if it had been significant, a researcher would probably want to investigate it further. As we noted above, when discussing the regression coefficients for the BA and CA vectors, four simple contrasts involving the B3C3 cell are represented in Table 6. Thus, one way to obtain some contrasts is to perform the analysis of variance a number of times, varying which group is identified as B3C3. Alternatively, as noted earlier, the cell slopes are in fact the slopes that one would obtain if they were to compute the regression of the dependent variable on the centred continuous variable for each group separately. Doing this would present both the slope and the standard error of the slope based on each group, and with this information one could perform a test of the difference between any two slopes, estimating the standard error from the two cells concerned. The degrees of freedom would, of course be the sum of the degrees of freedom for the two tests, and thus would be less than that for the full analysis of variance.

General Observation.

This example has made use of SPSS GLM UNIVARIATE, but it should be emphasized that if instead someone had Dummy coded the data and used multiple regression where all the effects were entered in one step, the regression coefficients obtained would be identical to those in Table 3. If one then attempted to determine the main and interaction effects using the unique sums of squares approach, they would discover that all of the F-ratios with the exception of that for ABC would be different from those reported in Table 2. On the other hand, if someone had effect coded the data and run the multiple regression analysis in one step, they would find that the regression coefficients would not be the same as those in Table 3. Finally, if one attempted to determine the main and interaction effects using the unique sums of squares approach, they would find that the F-ratios are identical to those in Table 2. Confusing, what? Of course, there are obvious explanations, some of which I have tried to offer here. The researcher who ventures into the multiple regression waters without a clear map is in a dangerous situation.