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ABSTRACT

The relationship between analysis of variance (ANOVA) methods and their analogs (analysis of covariance and multiple analyses of variance and covariance--collectively referred to as OVA methods) and the more general analytic case is explored. A small heuristic data set is used, with a hypothetical sample of 20 subjects, randomly assigned to five conditions of exposure to an experimental instructional method. Students were also grouped into high or low ability levels. The data illustrate that: (1) regression approaches to ANOVA can be superior to classical ANOVA with respect to statistical power against Type II error; and (2) classical regression analysis can be used to test hypotheses typically but incorrectly associated only with ANOVA, such as polynomial trend and interaction hypotheses. Unlike OVA methods, which require that the researcher discard information by converting all dependent variables to the nominal level of scale, classical regression methods do not require that predictors be nominally scaled. Thus, when researchers have data including higher than normally scaled predictors, regression can yield results that more accurately reflect the reality that the researcher purportedly wishes to study. Nine tables and one graph illustrate the data. Control cards for a computer program are appended. (Author/SLD)

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HEURISTICS FOR UNDERSTANDING THE CONCEPTS OF INTERACTION, POLYNOMIAL TREND, AND THE GENERAL LINEAR MODEL

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ABSTRACT

A small heuristic data set is employed to demonstrate that (a) regression approaches to ANOVA can be superior to classical ANOVA with respect to statistical power against Type II error, and that (b) classical regression analysis can be employed to test hypotheses typically but incorrectly associated only with ANOVA, i.e., polynomial trend and interaction hypotheses. Unlike OVA methods, which require that the researcher discard information by converting all independent variables to the nominal level of scale, classical regression methods do not require that predictors be nominally scaled. Thus, when researchers have data including higher than nominally scaled predictors, regression can yield results that more accurately reflect the reality that the researcher purportedly wishes to study.

Empirical studies of research practice in published articles suggest that ANOVA methods and their analogs (ANOVA, ANCOVA, MANOVA and MANCOVA--here collectively labelled OVA methods) are among the most frequently employed techniques in educational research, although the use of these methods does appear to be consistently declining (Elmore & Woehlke, 1988; Goodwin & Goodwin, 1985, Willson, 1980). This may be most fortunate, because it can be argued that there are serious problems associated with many OVA applications (Cohen, 1968; Thompson, 1986, 1988b).

The primary difficulty with OVA methods is the requirement that independent variables must all be nominally scaled. Since many variables (e.g., aptitude) other than experimental condition assignment and sex are higher than nominally scaled, and since sex is not usually of much interest as a research variable, researchers frequently discard variance of other predictor variables in order to implement OVA analyses. This "squandering of information" can have serious consequences for the integrity of research conclusions (Cohen, 1968; Thompson, 1988b). Even when OVA analyses are appropriate, regression approaches to OVA using planned contrasts offer important advantages over conventional OVA methods (Thompson, 1985, 1988d).

Although for various reasons (Thompson, 1981) some researchers unconsciously resist the realization, it has been increasingly recognized by more and more researchers that all parametric methods are subsumed under the umbrella of what has come to be called the "general linear model." All univariate parametric methods (e.g., ANOVA, *t*-tests) are actually cases of multiple regression analysis, and can be implemented using regression (Cohen, 1968). However, the converse is not true--that is, regression cannot be implemented using its own special cases, such as ANOVA or ANCOVA. This realization has important implications for practice, explored in some readable recent textbooks (cf. Edwards, 1985; Pedhazur, 1982).

Similarly, more and more researchers have come to realize that canonical correlation analysis subsumes all parametric methods, both univariate and multivariate (e.g., MANOVA, discriminant function analysis) (Knapp, 1978). Thompson (1988a) employs a small example data set to illustrate how canonical analysis can be employed to conduct the univariate and multivariate parametric methods that the technique subsumes as special cases. Again, the generality of the general linear model suggests the important implication for practice that the more general analytic methods might beneficially be employed in more research situations than is currently the case (Thompson, 1984).

The purpose of the present paper is to explore the relationship between OVA methods and the more general analytic case. Some researchers incorrectly presume that OVA methods provide access to hypotheses that cannot be tested with regression methods. For example, some researchers believe that polynomial trends (i.e., linear and curvilinear prediction by predictor variables) and interaction effects cannot be tested using regression analysis. A small univariate (i.e., single dependent variable) data set is employed to illustrate how these hypotheses can be tested using multiple regression analysis.

A Classical Factorial ANOVA Design

Table 1 presents scores on several variables for a hypothetical sample of 20 subjects. The subjects are randomly assigned to either one, two, three, four, or five minutes of exposure to an experimental instructional method, the variable labelled "LEV5" in Table 1. The subjects have also been grouped into high or low ability or aptitude levels ("LEV2"). Table 1 also presents the dependent variable scores ("DV") of the 20 subjects. And the table presents scores on other variables, to be discussed subsequently.

INSERT TABLE 1 ABOUT HERE.

The data represent a classic 5x2 factor ANOVA problem, and the design is balanced with two subjects in each of the design's 10 cells. Table 2 presents the ANOVA keyout for this problem generated by the SPSS-X package.

INSERT TABLE 2 ABOUT HERE.

Regression Approach to ANOVA, Using Only Creation of a Variable Expressing Interaction

If the researcher desired to implement a GLM approach to analyzing the Table 1 data, the first thing the researcher might wish to do is to isolate some way of testing interaction effects. Afterall, this is one benefit from factorial OVA methods, which some researcher incorrectly believe is unavailable in the regression case. The researcher may be aware that interaction effects can be represented by what Kerlinger and Pedhazur (1973, p. 414) have termed "product variables." Main effects are first translated into Z-score form, as has been done for "LEV5" and "LEV2" in Table 1 (respectively, "ZLEV5" and "ZLEV2"). The results are then simply multiplied times each other to create a new variable ("ZINTER") for each person. For example, as reported in Table 1, the first subject's score on "ZINTER" is 1.34350, i.e., -1.3784 x -.97468.

The researcher then conducts a conventional regression analysis, using "LEV5", "LEV2", and "ZINTER" to predict "DV". The partial SPSS-X printout for this analysis is presented in Table 3. Table 4 illustrates the researcher's effort to recreate the Table 2 keyout using the regression results. The researcher examines the Table 3 printout only to find the sums of squares (SOS) at each step of the analysis. These values are then subtracted from each other in the manner illustrated in Table 4, and the remainder of the keyout is computed by the researcher by hand.

INSERT TABLES 3 AND 4 ABOUT HERE.

Regrettably, the researcher finds these results rather troubling, because the Table 2 and Table 4 results do not match, as they should if a factorial ANOVA can indeed be implemented using regression analysis. For example, the sums of squares for the "LEV5" main effect in the Table 2 classical ANOVA is 6.800, while the SOS for the same effect reported in Table 4 is only 4.225. Similarly, the SOS for the two-way interaction effect in Table 2 is 18.200, while the regression approach yields an SOS for this effect of only 13.225.

Regression Approach to ANOVA, Using a Variable Expressing Interaction and Orthogonal Polynomial Contrast Coding

The researcher, upon reflection, notes that the Table 4 keyout only invests one degree of freedom (df) to probe for the "LEV5" main effect, while four degrees of freedom were spent to produce the larger SOS for "LEV5" reported in the Table 2 classical ANOVA keyout. It seems reasonable that using more degrees of freedom in the ANOVA to explain "DV" may have caused the discrepancy between the effects reported in the two analyses.

The researcher consults several texts, fortunately including Edwards (1985) and Pedhazur (1982). The researcher learns that degrees of freedom are indeed like the probes used to explore a "black box", and that in ANOVA each probe will explain a unique, non-overlapping portion of the variance of "DV" when the probes are perfectly uncorrelated with each other (sometimes called "orthogonal"). The researcher decides to perform trend contrasts using what is called polynomial coding. While this sounds awesome, the probes are actually listed in several books for various research situations (e.g., Hicks, 1973).

The four main effect codes for "LEV5" are listed in Table 1, i.e., "LINEAR", "QUADRATC", "CUBIC", and "QUARTIC". These are the four correct trend codes for a design way with five levels, such as "LEV5" (Hicks, 1973). Following the instructions of Edwards (1985) and Pedhazur (1982), as reported in Table 1, the 10 subjects in the low ability group ("LEV2" = 1) receive a "-1" for the contrast variable for this way ("L2"), while the remaining subjects receive a "+1". The interaction effect contrasts are created by multiplying columns together. For example, "L2LIN" is created by multiplying the "LINEAR" contrast for each subject times the "L2" contrast.

Table 5 presents the partial SPSS-X printout when "DV" is predicted with variables "LINEAR" through "L2QUAR". The correlation matrix indicates that the contrasts or probes are uncorrelated, as desired. The researcher uses the remainder of the printout only for the purpose of determining SOS's for various steps of analysis, as before. The resulting keyout for this research situation is computed by hand from the Table 5 results, and is reported in Table 6.

INSERT TABLES 5 AND 6 ABOUT HERE.

The Table 6 result is much more satisfying for the researcher, since it appears comparable to the Table 2 classical ANOVA outcome. For example, the omnibus effect size for explaining "DV" with all predictors is identical (25.05 / 48.55 = squared _R_ = 51.6%). The results associated with "LEV2" and the two-way interaction effect are both the same.

At first glance the results for "LEV5" appear to be different. But in reality the SOS for the effect (6.800) in both tables is the same. In the Table 2 classical ANOVA the omnibus SOS for this main effect is 6.800 and the result is not statistically significant (F = .583, _df_ = 4/10, p>.05). In the Table 6 regression analysis using polynomial orthogonal contrasts, this main effect SOS has been split into four separate components (4.225 + 2.161 + 0.400 + 0.014), each with 1/10 degrees of freedom.

However, one effect associated with "LEV5" is now statistically significant! The linear contrast has an effect size of 8.7%, i.e., explains 8.7% of the variance in the dependent variable, and *F* = 1.798 ($p<.05$). This, of course, is one advantage of regression approaches to ANOVA. Regression approaches to ANOVA using *a priori* contrasts have more statistical power against Type II error (Thompson, 1985). Thus, regression approaches to ANOVA are usually superior to classical ANOVA.

Another important insight can be acquired by comparing the Table 6 results with the Table 4 results reporting the classical regression analysis. The SOS (4.225) and the effect size (8.7%) for the "LINEAR" contrast in Table 6 is identical to the result for "LEV5" reported for the Table 4 regression analysis.

Upon reflection, this should be sensible. Classical regression analysis is based on correlation coefficients that are sensitive only to linear relationship, as every elementary statistics textbook repeatedly and emphatically emphasizes. The linear component of "LEV5" that is common with "DV" involves an effect size of 8.7%. This component is the only component evaluated by classical regression analysis or by the "LINEAR" contrast in the regression approach to ANOVA. The classical ANOVA reported in Table 2, on the other hand, measures *curvilinear* relationship between an effect and the dependent variable. This is also part of the reason why the effect sizes are larger for the classical ANOVA results than for the classical regression results, since the classical ANOVA results are sensitive to more types of relationship among the variables. Of course, polynomial contrasts can be employed to make regression sensitive to curvilinear relationships.

<u>Classical Regression Analysis Testing Interaction and Polynomial Trend, without Orthogonal Contrasts</u>

But classical regression analysis can be employed to test interaction and polynomial trends, without utilizing orthogonal contrasts. In any regression analysis curvilinear effects of predictors can be explored simply by raising predictors to selected exponential powers. The computations reported in Table 7 explored linear (predictor raised to power "1"), quadratic (power "2"), cubic (power "3"), and quartic (power "4") effects.

INSERT TABLE 7 ABOUT HERE.

In Table 7 "LEV5" already tests linear effects, since raising a variable to power "1" has no effect. "QUADLEV5" represents "LEV5" raised to the second power. "CUBLEV5" and "QUARLEV5" represent, respectively, "LEV5" raised to the third and fourth powers. Interaction effects are evaluated by multiplying "LEV2" times each of the four exponential expressions of "LEV5". Table 8 presents the partial SPSS-X printout reporting an analysis of the Table 7 data.

INSERT TABLE 8 ABOUT HERE.

Table 9 presents the keyout computed by hand from the Table 8 results. As expected, the Table 9 results from this classical regression analysis are directly comparable to those from the classical ANOVA presented in Table 2. Figure 1 presents the scattergram of "LEV5" and "DV", and the both the linear and the curvilinear prediction equations for these data. The improved fit of the curvilinear prediction using four exponential expressions of "LEV5" can be seen in the figure.

INSERT TABLE 9 AND FIGURE 1 ABOUT HERE.

Conclusion

It has been demonstrated here that (a) regression approaches to ANOVA can be superior to classical ANOVA with respect to statistical power against Type II error, and that (b) classical regression analysis can be employed to test hypotheses typically but incorrectly associated only with ANOVA, i.e., polynomial trend and interaction hypotheses. The real advantage of classical regression analysis has not been illustrated here.

Unlike OVA methods, which require that the researcher discard information by converting all independent variables to the nominal level of scale, classical regression methods do not require that predictors be nominally scaled. Thus, when researchers have data including higher than nominally scaled predictors, regression can yield results that more accurately reflect the reality that the researcher purportedly wishes to study. In short, classical regression analysis warrants more attention from educational researchers.

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Table 1
Scores on Various Variables for 20 Subjects

LEV5	LEV2	DV	ZLEV5	ZLEV2	LINEAR	QUADRATC	CUBIC	QUARTIC	L2	L2LIN	L2QUAD	L2CUB	L2QUAR	ZINTER
1	1	0	-1.3784	-.97468	-2	2	-1	1	-1	2	-2	1	-1	1.34350
1	1	2	-1.3784	-.97468	-2	2	-1	1	-1	2	-2	1	-1	1.34350
1	2	3	-1.3784	.97468	-2	2	-1	1	1	-2	2	-1	1	-1.34350
1	2	5	-1.3784	.97468	-2	2	-1	1	1	-2	2	-1	1	-1.34350
2	1	1	-.6892	-.97468	-1	-1	2	-4	-1	1	1	-2	4	.67175
2	1	3	-.6892	-.97468	-1	-1	2	-4	-1	1	1	-2	4	.67175
2	2	2	-.6892	.97468	-1	-1	2	-4	1	-1	-1	2	-4	-.67175
2	2	4	-.6892	.97468	-1	-1	2	-4	1	-1	-1	2	-4	-.67175
3	1	2	.0000	-.97468	0	-2	0	6	-1	0	2	0	-6	.00000
3	1	4	.0000	-.97468	0	-2	0	6	-1	0	2	0	-6	.00000
3	2	1	.0000	.97468	0	-2	0	6	1	0	-2	0	6	.00000
3	2	3	.0000	.97468	0	-2	0	6	1	0	-2	0	6	.00000
4	1	3	.6892	-.97468	1	-1	-2	-4	-1	-1	1	2	4	-.67175
4	1	5	.6892	-.97468	1	-1	-2	-4	-1	-1	1	2	4	-.67175
4	2	0	.6892	.97468	1	-1	-2	-4	1	1	-1	-2	-4	.67175
4	2	3	.6892	.97468	1	-1	-2	-4	1	1	-1	-2	-4	.67175
5	1	4	1.3784	-.97468	2	2	1	1	-1	-2	-2	-1	-1	-1.34350
5	1	5	1.3784	-.97468	2	2	1	1	-1	-2	-2	-1	-1	-1.34350
5	2	2	1.3784	.97468	2	2	1	1	1	2	2	1	1	1.34350
5	2	5	1.3784	.97468	2	2	1	1	1	2	2	1	1	1.34350

Table 2
ANOVA Keyout for 5x2 Factorial Balanced ANOVA

Source of Variation	Sum of Squares	DF	Mean Square	F	Sig of F	EFFECT SIZE
Main Effects	6.850	5	1.370	.583	.713	
LEV5	6.800	4	1.700	.723	.596	14.0%
LEV2	.050	1	.050	.021	.887	.1%
2-Way Interactions	18.200	4	4.550	1.936	.181	
LEV5 LEV2	18.200	4	4.550	1.936	.181	.4%
Explained	25.050	9	2.783	1.184	.395	
Residual	23.500	10	2.350			
Total	48.550	19	2.555			

Note. EFFECT SIZEs were computed by hand, and are not routinely provided by SPSS-X.

Table 3
Partial SPSS-X Output Testing Only Linear Effects

```
* * * *   M U L T I P L E   R E G R E S S I O N   * * * *
Equation Number 1    Dependent Variable..   DV

Beginning Block Number  1.  Method:  Enter       LEV5
Variable(s) Entered on Step Number  1..    LEV5

Multiple R            .29500           Analysis of Variance
R Square              .08702
                     DF       Sum of Squares       Mean Square
Regression            1              4.22500           4.22500
Residual             18             44.32500           2.46250
F =        1.71574       Signif F =  .2067
. . .
Beginning Block Number  2.  Method:  Enter       LEV2
Variable(s) Entered on Step Number  2..    LEV2

Multiple R            .29674           Analysis of Variance
R Square              .08805
                     DF       Sum of Squares       Mean Square
Regression            2              4.27500           2.13750
Residual             17             44.27500           2.60441
F =         .82072       Signif F =  .4568
. . .
Beginning Block Number  3.  Method:  Enter        ZINTER
Variable(s) Entered on Step Number  3..    ZINTER

Multiple R            .60038           Analysis of Variance
R Square              .36045
                     DF       Sum of Squares       Mean Square
Regression            3             17.50000           5.83333
Residual             16             31.05000           1.94063
F =        3.00590       Signif F =  .0612
```

Table 4
Keyout Computed by Hand from Table 3 Results

	Previous - SOS Reg	Effect = SOS Reg	SOS	df	Mean Square	F	Effect Size
LEV5		4.225	4.225	1	4.225	2.177	8.7%
LEV2	4.225	4.275	0.050	1	0.050	0.026	0.1%
Inter	4.275	17.500	13.225	1	13.225	6.815	27.2%
Error		31.050	31.050	16	1.941		
Total			48.550	19	2.555		

Table 5
Partial SPSS-X Printouts for Predicting "DV" with Contrasts

	Mean	Std Dev	Variance
DV	2.850	1.599	2.555
LINEAR	.000	1.451	2.105
QUADRATC	.000	1.717	2.947
CUBIC	.000	1.451	2.105
QUARTIC	.000	3.839	14.737
L2	.000	1.026	1.053
L2LIN	.000	1.451	2.105
L2QUAD	.000	1.717	2.947
L2CUB	.000	1.451	2.105
L2QUAR	.000	3.839	14.737

Correlation Matrix:

	DV	LINEAR	QUADRATC	CUBIC	QUARTIC	L2	L2LIN	L2QUAD	L2CUB
LINEAR	.295								
QUADRATC	.211	.000							
CUBIC	.091	.000	.000						
QUARTIC	.017	.000	.000	.000					
L2	-.032	.000	.000	.000	.000				
L2LIN	-.522	.000	.000	.000	.000	.000			
L2QUAD	.288	.000	.000	.000	.000	.000	.000		
L2CUB	.136	.000	.000	.000	.000	.000	.000	.000	
L2QUAR	.034	.000	.000	.000	.000	.000	.000	.000	.000

```
* * * *   M U L T I P L E   R E G R E S S I O N   * * * *
Equation Number 1    Dependent Variable..   DV

 Beginning Block Number  1.  Method:  Enter      LINEAR
 Variable(s) Entered on Step Number  1..    LINEAR

 Multiple R           .29500  Analysis of Variance
 R Square             .08702
                    DF   Sum of Squares      Mean Square
 Regression          1        4.22500            4.22500
 Residual           18       44.32500            2.46250
 F =        1.71574       Signif F =  .2067
 . . .
 Beginning Block Number  2.  Method:  Enter      QUADRATC
 Variable(s) Entered on Step Number  2..    QUADRATC

 Multiple R           .36267          Analysis of Variance
 R Square             .13153
                    DF       Sum of Squares      Mean Square
 Regression          2            6.38571            3.19286
 Residual           17           42.16429            2.48025
 F =        1.28731       Signif F =  .3016
 . . .
 Beginning Block Number  3.  Method:  Enter      CUBIC
 Variable(s) Entered on Step Number  3..    CUBIC

 Multiple R           .37385          Analysis of Variance
 R Square             .13977
```

```
                        DF       Sum of Squares       Mean Square
Regression               3              6.78571           2.26190
Residual                16             41.76429           2.61027
F =         .86654         Signif F =  .4787
. . .
Beginning Block Number  4.  Method:  Enter      QUARTIC
Variable(s) Entered on Step Number  4..    QUARTIC

Multiple R              .37425          Analysis of Variance
R Square                .14006
                        DF       Sum of Squares       Mean Square
Regression               4              6.80000           1.70000
Residual                15             41.75000           2.78333
F =         .61078         Signif F =  .6612
. . .
Beginning Block Number  5.  Method:  Enter      L2
Variable(s) Entered on Step Number  5..    L2

Multiple R              .37562          Analysis of Variance
R Square                .14109
                        DF       Sum of Squares       Mean Square
Regression               5              6.85000           1.37000
Residual                14             41.70000           2.97857
F =         .45995         Signif F =  .7995
. . .
Beginning Block Number  6.  Method:  Enter L2LIN L2QUAD L2CUB L2QUAR
Variable(s) Entered on Step Number  6..    L2QUAR
                                    7..    L2CUB
                                    8..    L2QUAD
                                    9..    L2LIN

Multiple R              .71831          Analysis of Variance
R Square                .51596
                        DF       Sum of Squares       Mean Square
Regression               9             25.05000           2.78333
Residual                10             23.50000           2.35000
F =        1.18440         Signif F =  .3953
```

Table 6
Keyout from Regression Analysis Using Contrasts

	Previous SOS Reg	- Effect = SOS Reg	SOS	df	Mean Square	F	Effect Size
LINEAR		4.225	4.225	1	4.225	1.798	8.7%
QUADRATC	4.225	6.386	2.161	1	2.161	0.919	4.5%
CUBIC	6.386	6.786	0.400	1	0.400	0.170	0.8%
QUARTIC	6.786	6.800	0.014	1	0.014	0.006	.0%
L2	6.800	6.850	0.050	1	0.050	0.021	0.1%
Inter	6.850	25.050	18.200	4	4.550	1.936	37.5%
Error		23.500	23.500	10	2.350		
Total			48.550	19	2.555		

Table 7
Table 1 Predictors Treated as if Intervally Scaled

LEV5	LEV2	DV	QUADLEV5	CUBLEV5	QUARLEV5	ZINTER	ZINTER2	ZINTER3	ZINTER4
1	1	0	1.00	1.00	1.00	1.34350	1.90	-2.62	3.61
1	1	2	1.00	1.00	1.00	1.34350	1.90	-2.62	3.61
1	2	3	1.00	1.00	1.00	-1.34350	3.80	-5.24	7.22
1	2	5	1.00	1.00	1.00	-1.34350	3.80	-5.24	7.22
2	1	1	4.00	8.00	16.00	.67175	.47	-.33	.23
2	1	3	4.00	8.00	16.00	.67175	.47	-.33	.23
2	2	2	4.00	8.00	16.00	-.67175	.95	-.65	.45
2	2	4	4.00	8.00	16.00	-.67175	.95	-.65	.45
3	1	2	9.00	27.00	81.00	.00000	.00	.00	.00
3	1	4	9.00	27.00	81.00	.00000	.00	.00	.00
3	2	1	9.00	27.00	81.00	.00000	.00	.00	.00
3	2	3	9.00	27.00	81.00	.00000	.00	.00	.00
4	1	3	16.00	64.00	256.00	-.67175	.48	.33	.23
4	1	5	16.00	64.00	256.00	-.67175	.48	.33	.23
4	2	0	16.00	64.00	256.00	.67175	.95	.65	.45
4	2	3	16.00	64.00	256.00	.67175	.95	.65	.45
5	1	4	25.00	125.00	625.00	-1.34350	1.90	2.62	3.61
5	1	5	25.00	125.00	625.00	-1.34350	1.90	2.62	3.61
5	2	2	25.00	125.00	625.00	1.34350	3.80	5.24	7.22
5	2	5	25.00	125.00	625.00	1.34350	3.80	5.24	7.22

Table 8
Partial SPSS-X Printout for True Regression Analysis for Table 7 Data

	DV	LEV5	LEV2	ZINTER	QUADLEV5	CUBLEV5	QUARLEV5	ZINTER2	ZINTER3
LEV5	.295								
LEV2	-.032	.000							
ZINTER	-.522	.000	.000						
QUADLEV5	.330	.981	.000	.000					
CUBLEV5	.351	.943	.000	.000	.989				
QUARLEV5	.363	.903	.000	.000	.968	.994			
ZINTER2	.261	.000	.354	.000	.172	.293	.372		
ZINTER3	.151	.895	.000	.298	.878	.855	.836	.000	
ZINTER4	.271	.000	.275	.000	.174	.297	.378	.983	.000

```
* * * *   M U L T I P L E   R E G R E S S I O N   * * * *
Equation Number 1    Dependent Variable..   DV

Beginning Block Number  1.  Method:  Enter       LEV5
Variable(s) Entered on Step Number  1..    LEV5

Multiple R              .29500          Analysis of Variance
R Square                .08702
                       DF       Sum of Squares       Mean Square
Regression              1              4.22500           4.22500
Residual               18             44.32500           2.46250
F =        1.71574        Signif F =   .2067
```

```
. . .
Beginning Block Number  2.  Method:  Enter      QUADLEV5
Variable(s) Entered on Step Number  2..    QUADLEV5

Multiple R             .36267          Analysis of Variance
R Square               .13153
                     DF       Sum of Squares      Mean Square
Regression            2              6.38571          3.19286
Residual             17             42.16429          2.48025
F =        1.28731       Signif F =  .3016
. . .
Beginning Block Number  3.  Method:  Enter      CUBLEV5
Variable(s) Entered on Step Number  3..    CUBLEV5

Multiple R             .37385          Analysis of Variance
R Square               .13977
                     DF       Sum of Squares      Mean Square
Regression            3              6.78571          2.26190
Residual             16             41.76429          2.61027
F =         .86654       Signif F =  .4787
. . .
Beginning Block Number  4.  Method:  Enter      QUARLEV5
Variable(s) Entered on Step Number  4..    QUARLEV5

Multiple R             .37425          Analysis of Variance
R Square               .14006
                     DF       Sum of Squares      Mean Square
Regression            4              6.80000          1.70000
Residual             15             41.75000          2.78333
F =         .61078       Signif F =  .6612
. . .
Beginning Block Number  5.  Method:  Enter      LEV2
Variable(s) Entered on Step Number  5..    LEV2

Multiple R             .37562          Analysis of Variance
R Square               .14109
                     DF       Sum of Squares      Mean Square
Regression            5              6.85000          1.37000
Residual             14             41.70000          2.97857
F =         .45995       Signif F =  .7995
. . .
Beginning Block Number  6.  Method:  Enter      ZINTER
Variable(s) Entered on Step Number  6..    ZINTER

Multiple R             .64303          Analysis of Variance
R Square               .41349
                     DF       Sum of Squares      Mean Square
Regression            6             20.07500          3.34583
Residual             13             28.47500          2.19038
F =        1.52751       Signif F =  .2449
. . .
Beginning Block Number  7.  Method:  Enter ZINTER2  ZINTER3  ZINTER4
Variable(s) Entered on Step Number  7..    ZINTER4
                                    8..    ZINTER3
                                    9..    ZINTER2
```

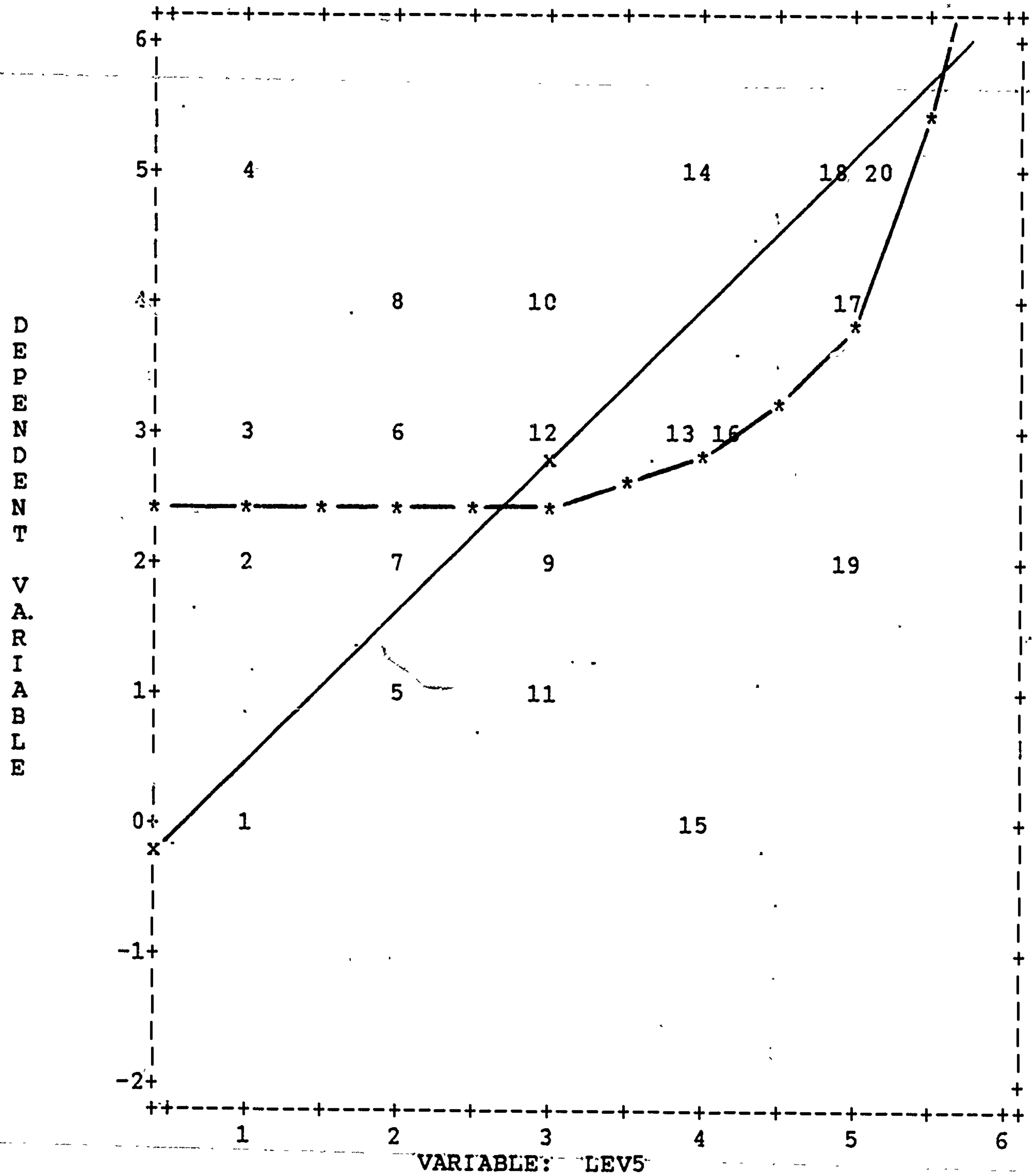
Multiple R	.71831	Analysis of Variance	
R Square	.51596		
	DF	Sum of Squares	Mean Square
Regression	9	25.05000	2.78333
Residual	10	23.50000	2.35000

F = 1.18440 Signif F = .3953

Table 9
Keyout for True Regression Case

	Previous SOS Reg	- Effect = SOS Reg	SOS	df	Mean Square	F	Effect Size
LEV5		4.225	4.225	1	4.225	1.798	8.7%
QUADLEV5	4.225	6.386	2.161	1	2.161	0.919	4.5%
CUBLEV5	6.386	6.786	0.400	1	0.400	0.170	0.8%
QUARLEV5	6.786	6.800	0.014	1	0.014	0.006	.0%
LEV2	6.800	6.850	0.050	1	0.050	0.021	0.1%
ZINTER	6.850	20.075	13.225	1	13.225	5.628	27.2%
Others	20.075	25.050	4.975	3	1.658	0.649	10.2%
Error		23.500	23.500	10	2.350		
Total			48.550	19	2.555		

Figure 1
Plot of Linear and Curvilinear Regression Equations



Note. The case numbers of each of the 20 subjects from Table 1 are presented in the scattergram.

interact.sps

APPENDIX A:
SPSS-X CONTROL CARDS FOR EXAMPLES

```
TITLE 'DEMONSTRATION OF INTERACTION WITH REGRESSION'
FILE HANDLE BT/NAME='INTERACT.DAT'
DATA LIST FILE=BT/LEV5 1 LEV2 3 DV 5
SUBTITLE '#1 CREATE Z-SCORES FOR INTERACTION COMPUTATION'
DESCRIPTIVES VARIABLES=LEV5 TO DV/SAVE/STATISTICS=ALL
SUBTITLE '#2  CLASSICAL 2x4 FACTORIAL ANOVA'
ANOVA DV BY LEV5(1,5) LEV2(1,2)/STATISTICS=ALL
SUBTITLE '#3  CREATE CONTRASTS TO TEST POLYNOMIAL TREND'
COMPUTE LINEAR=0
IF (LEV5 EQ 1)LINEAR=-2
IF (LEV5 EQ 2)LINEAR=-1
IF (LEV5 EQ 4)LINEAR=1
IF (LEV5 EQ 5)LINEAR=2
COMPUTE QUADRATC=LINEAR
IF (LEV5 EQ 1)QUADRATC=2
IF (LEV5 EQ 3)QUADRATC=-2
IF (LEV5 EQ 4)QUADRATC=-1
COMPUTE CUBIC=0
IF (LEV5 EQ 1)CUBIC=-1
IF (LEV5 EQ 2)CUBIC=2
IF (LEV5 EQ 4)CUBIC=-2
IF (LEV5 EQ 5)CUBIC=1
COMPUTE QUARTIC=1
IF (LEV5 EQ 2)QUARTIC=-4
IF (LEV5 EQ 3)QUARTIC=6
IF (LEV5 EQ 4)QUARTIC=-4
IF (LEV2 EQ 1)L2=-1
IF (LEV2 EQ 2)L2=1
COMPUTE L2LIN=L2*LINEAR
COMPUTE L2QUAD=L2*QUADRATC
COMPUTE L2CUB=L2*CUBIC
COMPUTE L2QUAR=L2*QUARTIC
PRINT FORMATS LINEAR TO L2QUAR(F3.0)
LIST VARIABLES=LEV5 TO DV LINEAR TO L2QUAR
SUBTITLE '#4  RUN TREND TEST ANOVA USING REGRESSION'
REGRESSION VARIABLES=DV LINEAR TO L2QUAR/DESCRIPTIVES=ALL/
  DEPENDENT=DV/ENTER LINEAR/ENTER QUADRATC/ENTER CUBIC/
  ENTER QUARTIC/ENTER L2/ENTER L2LIN TO L2QUAR
SUBTITLE '#5  REGRESSION RESULTS  **LINEAR EFFECTS ONLY'
COMPUTE ZINTER=ZLEV5*ZLEV2
PRINT FORMATS ZINTER(F8.5)
LIST VARIABLES=ALL/CASES=50
REGRESSION VARIABLES=LEV5 TO ZINTER/DESCRIPTIVES=ALL/DEPENDENT=DV/
  ENTER LEV5/ENTER LEV2/ENTER ZINTER
SUBTITLE '#6  REGRESSION RESULTS  **CURVILINEAR EFFECTS'
COMPUTE QUADLEV5=LEV5**2
COMPUTE CUBLEV5=LEV5**3
COMPUTE QUARLEV5=LEV5**4
COMPUTE ZINTER2=(ZLEV5**2)*LEV2
COMPUTE ZINTER3=(ZLEV5**3)*LEV2
COMPUTE ZINTER4=(ZLEV5**4)*LEV2
```

```
LIST VARIABLES=LEV5 TO DV QUADLEV5 TO QUARLEV5 ZINTER ZINTER2 TO
  ZINTER4/CASES=50
REGRESSION VARIABLES=DV LEV5 LEV2 ZINTER QUADLEV5 TO ZINTER4/
  DESCRIPTIVES=ALL/
  CRITERIA=TOLERANCE(.00000001)/DEPENDENT=DV/
  ENTER LEV5/ENTER QUADLEV5/ENTER CUBLEV5/ENTER QUARLEV5/
  ENTER LEV2/ENTER ZINTER/ENTER ZINTER2 TO ZINTER4
SUBTITLE '#7  SHOW PREDICTED DV USING EXPONENTIALS'
COMPUTE DVLINEAR=1.875+(.325*LEV5)
COMPUTE DVPOLYNO=2.75-(.583333*LEV5)+(.479167*QUADLEV5)
  -(.166667*CUBLEV5)+(.020833*QUARLEV5)
PRINT FORMATS DVLINEAR DVPOLYNO(F8.5)
LIST VARIABLES=LEV5 DV DVLINEAR DVPOLYNO/CASES=50
PLOT TITLE='DV PREDICTED ONLY LINEARLY'/
  HORIZONTAL='VARIABLE:  LEV5' MIN(1) MAX(8)/
  VERTICAL='DEPENDENT VARIABLE'/PLOT=DV WITH LEV5
```