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ABSTRACT

The paper stresses the importance of consulting beta weights and structure coefficients in the interpretation of regression results. The effects of multilinearity and suppressors and their effects on interpretation of beta weights are discussed. It is concluded that interpretations based on beta weights only can lead the unwary researcher to inaccurate conclusions. Despite warnings, though, researchers are still using only beta weights in the interpretation of regression analyses. A review of the techniques used to interpret regression results in articles from the "Journal of School Psychology" was conducted. Three examples are presented of cases in which interpretation of both beta weights and structure coefficients may have led to alternative conclusions. (Contains 2 tables and 30 references.) (Author/SLD)

The Importance of Structure Coefficients In Interpreting Regression Research

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Abstract

The present article stresses the importance of consulting both beta weights and structure coefficients in the interpretation of regression results. The effects of multicollinearity and suppressors and their effects on interpretation of beta weights is discussed. It is concluded that interpretations based on beta weights only can lead the unwary researcher to inaccurate conclusions. Despite warnings, though, researchers are still using only beta weights in the interpretation of regression analyses. A review of the techniques used to interpret regression results in articles from the Journal of School Psychology years was conducted. Presented are three examples of cases in which interpretation of both beta weights and structure coefficients may have lead to alternative conclusions.

The Importance of Structure

Coefficients In Interpreting Regression Research

Past literature has established that all classical parametric analyses are correlational in nature (Thompson, 1991) and are therefore special cases of multiple regression analysis (Cohen, 1968) at the univariate level. It has been further suggested that MANCOVA, ANCOVA, discriminant analysis, and multiple regression are all special cases of canonical correlation analysis (Baggaley, 1981; Knapp, 1978), all of which in turn fall under the most general case of the general linear model (Bagozzi, Fornell, & Larcker, 1981). Since they are all a part of the same general linear model, all classical parametric analyses employ least squares weights to optimize and improve prediction (Thompson, 1994). As noted elsewhere, these weights in different analyses

> ...are all analogous, but are given different names in different analyses (eg., beta weights in regression, pattern coefficients in factor analysis, discriminant function coefficients in discriminant analysis, and canonical function coefficients in canonical correlation analysis), mainly to obfuscate the commonalties of [all] parametric methods, and to confuse graduate students (Thompson, 1992a, pp. 906-907).

With the recognition that both ANOVA and multiple regression analysis are part of the same general linear system, there has been an increased use of regression in research in the social sciences (Elmore & Woehlke, 1998; Goodwin & Goodwin, 1985; Willson, 1980). There is a growing awareness that multiple regression is a general and

exceedingly flexible technique that can be used whenever the desire is to study the relationship between a set of one or more predictors and one dependent variable (Cohen, 1988; Cohen & Cohen, 1983). In multiple regression, there are no constraints placed on the relationship between variables, factors, or on types of possible comparisons. Multiple regression can be used when factors are correlated or uncorrelated, continuous or categorical. It allows for analysis of main effects, interactions effects, and effects of covariates (Cohen & Cohen, 1983). Essentially, multiple regression techniques can perform all the same functions that ANOVA or its variants can (Kerlinger & Pedhazur, 1973).

One major advantage of the use of multiple regression techniques is that it eliminates the detrimental practice of having to categorize continuous variables to fit into an ANOVA design. This reduces the distortion of the variance inherent in categorizing continuous variables. As noted by Kerlinger and Pedhazur (1973), multiple regression may be the only appropriate method of analysis when (a) using a continuous predictor variable, (b) when predictor variables are both continuous and categorical, (c) when cell frequencies in the design are unbalanced, (d) when conducting trend analysis.

As stated earlier, all classical univariate and multivariate methods use a system of weights as a part of their analysis (Thompson, 1994). The multiplicative weights applied to the standardized predictor variables in regression (sometimes call standardized weights—an oxymoron because a constant such as a weight cannot be standardized) are called beta weights; the weights applied to the unstandardized predictor variables are called "b" weights. Interpretation of regression results sometimes includes an evaluation of the weights; these interpretations usually focus on the beta weights (rather than the b

weights), because the beta weights (unlike the b weights) are not influenced by the variances of the measured variables. As beta deviates from zero, the predictive power of its respective predictor increases (Thompson, 1990). However, as we shall see, even predictors with zero or near-zero weights may be deemed noteworthy.

It has been empathetically argued that in analyzing the results of regression analysis, interpretation of the beta weights in isolation is definitively not sufficient (Pedhazur, 1982; Thompson, 1992b, 1994; Thompson & Borrello, 1985). Beta weights are affected greatly by multicollinearity between variables and the presence of suppressor variables (Cohen & Cohen, 1983; Pedhazur, 1982). Interpretation of analysis by looking at betas only, can result in grossly misleading interpretations (Cohen & Cohen, 1983; Thompson, 1992b).

<u>Multicollinearity</u>

Multicollinearity (sometimes called simply collinearity) exists when two or more predictors are correlated with one another. The presence of multicollinearity between predictors can pose serious threats to the accurate interpretation of regression coefficients and their effects. As stated by Pedhauzer (1982) "high multicollinearity may lead to serious distortions in estimates of the magnitudes of regression coefficients and also may lead to reversals in their signs", (p. 246). However, this problem occurs only if <u>only</u> beta weights are employed in interpreting regression results; multicollinearity is otherwise not a problem.

High correlations between predictor variables can lead to reductions in betas because only one variable is allowed credit for the overlapping variance between the correlated predictors. Since only one variable receives credit for shared variance, it is as

if another variable is robbing the predictor of its proportion of explained variance (Cohen, 1968). Therefore, it is possible for a predictor to be highly correlated with the dependent variable, Y, but have a near zero regression coefficient. A zero or near zero beta weight therefore can indicate either (a) the variable has no predictive value or (b) that the variable has explanatory power but is being denied full credit because another correlated variable is arbitrarily receiving credit for the variable's predictive power (Thompson, 1992b).

Context-specificity of Weights

Thompson and Borrello (1985) correctly emphasize that many predictor variables are commonly correlated to at least some degree. Furthermore, researchers may intentionally select multiple predictors that are highly correlated, so as to multioperationalize constructs that are difficult to measure reliably and validly (e.g., self-concept).

In any case, but especially in the presence of multicollinearity, overinterpretation of GLM weights is a serious threat. The weights can be greatly influenced by which variables are included or are excluded from a given analysis. Furthermore, Cliff (1987, pp. 177-178) noted that weights for a given set of variables may vary widely across samples, and yet consistently still yield the same effect sizes (i.e., be what he called statistically "sensitive").

Any interpretations of weights must be considered context *specific.* Any change (add a new variable, delete a single variable) in the variables in the model can radically alter all of the weights. Too few researchers appreciate the potential magnitudes of these impacts.

These fluctuations are not problematic, if (and only if) the researcher has selected exactly the right model (i.e. , has not made what statisticians call a "model specification error") . As Pedhazur (1982) has noted, though, "The rub, however, is that the true model is seldom, if ever, known" (p. 229). Also as Duncan (1975) has noted, "Indeed it would require no elaborate sophistry to show that we will never have the 'right' model in any absolute sense" (p. 101).

In other words, as a practical matter, the context-specificity of weights is always problematic, and the weights consequently must be interpreted cautiously, and almost never should be the sole basis for interpretation (Thompson & Borrello, 1985). Some researchers acknowledge the vulnerability of the weights to sampling error influences (i.e., the so-called "bouncing beta" problem), but a more obvious concern is the context-specificity of the weights in the real-world context of full or partial model misspecification.

Suppressor Variables

Suppression can be described as a relationship in which the correlation between predictors is “hiding” or “suppressing” their true relationship with the dependent variable (Cohen & Cohen, 1983). Henard (1998) provides an accessible review of suppressor effects.

Variables are termed suppressors because by including them in the analysis, variance is being “subtracted “or “suppressed” (McNemar, 1969). As defined by Pedhauzer (1982), a suppressor variable “has a zero or near zero correlation with the criterion but is correlated with one or more of the predictor variables” (p. 104). A suppressor variable increases the multiple correlation coefficient as a result of the

suppressor predictor variable accounting for "irrelevant variance" or "noise" between two predictor variables which helps to clarify the relationship between the criterion and the other predictor variable.

The concept of how suppressors work is often difficult to understand, because the dynamic is somewhat counterintuitive. An example, explained by McNemar (1969) may be helpful to facilitate understanding. Given two correlated predictors, X_1 and X_2, and dependent variable Y, X_1 is highly correlated with Y and X_2 is uncorrelated with Y. There are elements in X_1 that are not related to the dependent variable that serve to decrease the correlation between X_1 and Y. The relationship between the suppressor (X_2) and X_1 accounts for part or all of this irrelevant variance and therefore "suppresses" these elements. Even though X_2 is not directly correlated with Y, it influences the relationship between X_1 and Y, thus adding to the explained variance (Marascuilo & Levin, 1983). The result is an increase in the regression coefficient (beta) for X_1 because the irrelevant variance is subtracted from the correlation between X_1 and Y. The supressor variable itself, X_2, will also have a non-zero beta weight, because it is through the effect of this beta weight that the extraneous variance in the X_1 is removed.

Here is an example. Let's say $r_{YX1} = .7071$, that $r_{YX2} = .0$, and that $r_{X1X2} = .7071$. The beta weight for X1 would be computed as follows.

$$\beta = [r_{YX1} - (r_{YX2})\ (r_{X1X2})]\ /\ [1 - r_{X1X2}^{2}]$$

$$= [0.707106 - (.0)\ (-.070710)]\ /\ [1 - 0.70710^{2}]$$

$$= [0.707106\ - (.0)\ (-0.70710)]\ /\ [1\ -\ .5]$$

$$= [0.707106\ - (.0)\ (-0.70710)]\ /\ .5$$

$$= [0.707106\ - .0]\ /\ .5$$

$= 0.7.106 \; / \; .5$

$= 1.414213$

The beta weight for X_2 would be computed as follows.

$$\beta \quad = [r_{XY2} - (r_{XY2}) \; (r_{X1X2})] \; / \; [1 - r_{X1X2}{}^2]$$

$$= [.0 - (0.707106) - (.0) \; (-0.70710)] \; / \; [1 - 0.70710^2]$$

$$= [.0 - (0.707106) - (.0) \; (-0.70710)] \; / \; [1 - .5]$$

$$= [.0 - (0.707106) - (.0) \; (-0.70710)] \; / \; .5$$

$$= [.0 - (0.707106) - .0] \; / \; .5$$

$$= .5 \; / \; .5$$

$$= 1.0$$

The multiple R^2 can also be computed from these results, as follows.

$$R^2 = (\text{beta1}) \; (r_{YX1}) + (\text{beta2}) \; (r_{YX2})$$

$$= (1.414213) \; (0.707106) + (1.0) \; (.0)$$

$$= 1 + 0$$

$$= 1.0$$

Obviously, the use of the suppressor variable in this case has improved the predictor. Using X1 alone would explain only 50 % of the dependent variable. Using both predictor variables explains 100% of Y, even though X2 directly explains 0% of Y. However, use of the suppressor makes X1 a perfect predictor. Real-world examples of such effects are presented by Horst (1996).

Interpretation Suggestions

It has been suggested that "the thoughtful researcher should always interpret either (a) both the beta weights and the structure coefficients or (b) both the beta weights

and the bivariate correlations of the predictor with Y" (Thompson, 1992b, p.14). Analyses of dissertations (Thompson, 1994) and counseling journals (Bowling, 1993) have demonstrated how failures to interpret structure coefficients have led to inaccurate reporting of results. It has been argued by Pedhazur (1982) that it is redundant to compute structure coefficients because the zero-order correlation provides the same information. Thompson and Borrello (1985, p. 208) make the case, though, that the use of "...only the bivariate correlations seems counterintuitive. It appears inconsistent to first declare interest in an omnibus system of variables and then to consult values taken only two at a time."

The remainder of this article is dedicated to demonstrating the importance of interpreting both beta weights and structure coefficients when conducting regression analysis. Following an explanation of the nature of structure coefficients, three case examples are presented. These examples were extrapolated from a review of a respected school psychology journal, the Journal of School Psychology. Presented are three articles in which interpretation of both beta weights and structure coefficients may have lead to alternative conclusions.

Structure Coefficients

Structure coefficients are the correlation coefficient between the predictor and the Yhat (Cooley & Lohnes, 1971; Thompson 90). The formula for structure coefficients is as follows:

$$r_{si} = \frac{r_{yi}}{R_{y12\cdots k}}$$

r_{si}= structure coefficient for predictor xi
r_{yi}= correlation between criterion y and xi
$R_{y12\ldots k}$ = multiple correlation of y with k independent variables

As pointed out by Pedhazur (1982) and Thompson (1992b), it is simply the zero-order coefficient expressed in a different metric. As opposed to squared zero-order correlations which express the proportion of Y correlated with X_i, structure coefficients express the proportion of Yhat (the explained variance of Y) that the predictor explains.

Structure coefficients are always correlations. Unlike beta weights, structure coefficients always range between –1 and +1. When predictors are uncorrelated, the structure coefficients provide the same information as do both the zero-order correlations and the beta weights (Thompson, 1992b). As collinearity among predictors increases, the difference between the structure coefficients and the regression coefficients (beta weights) increases (Thompson, 1990). By interpreting betas in conjunction with structure coefficients, inaccurate conclusions can be avoided.

A recent review of regression reporting practices in school psychology was conducted on the Journal of School Psychology years 1963 to 1998. The review of literature shows that many researchers are still erroneously interpreting only beta weights despite warnings that this may lead in inaccurate results. The following are case examples of research articles in which the researchers failed to interpret structure coefficients in conjunction with the beta weights. Through the supplemental analysis reported here, structure coefficients were computed and are used to show how the researchers may have come to alternative conclusions had they used both betas and structure coefficients.

Case 1: Multicollinearity

Kochenderfer and Ladd (1996) provided an example of how the presence of

multicollinearity can lead to alternative conclusions when structure coefficients are analyzed. Beta weights and increases in R^2 were used by the researcher to interpret regression results. The researchers concluded that general, physical and direct verbal victimization made important contributions to loneliness and school avoidance but that indirect verbal victimization did not. Table 1 provides the beta weights as given in the study along with structure coefficients not reported in the article but obtained through supplemental analysis. Had structure coefficients been used in conjunction with the betas, the researchers might have noticed that in relation to the other predictors, indirect verbal victimization was substantially correlated (r_s=.67, r_s=.72) to both the criterion variables as shown by the structure r. The reduced beta weights for both school avoidance and loneliness could therefore be assumed to be the result of multicollinearity between the predictor variables in which the other predictors are <u>arbitrarily</u> receiving credit for the predictive power of indirect verbal victimization, not as a result of a lack of predictability.

Case 2: Suppressors

The study conducted by Denham and Burton (1996) provides examples of almost pure suppressors that went unnoticed due to irresponsible interpretation of only the regression coefficients. For the criterion teacher-rated competence, researchers concluded that the statistically significant contributors were intervention (B = .666) and the interaction between intervention and pretest (B = -.696). Though zero-order correlations were presented in the same table as the regression results in the article, they were not consulted in the interpretation. Had structure coefficients been calculated, the researchers would have realized while both these predictors had very high regression coefficient

(betas), their respective structure coefficients ($r_s = .072$ for intervention, $r_s = .042$ for intervention by pretest) indicate that they were both almost pure suppressors. In subsequent analysis, there were also identified two other possible suppressors of a lesser degree that went unnoticed: intervention for the criterion of peer skills (B = .463, $r_s = .063$) and class for the criterion positive affect (B = .002, $r_s = -.112$).

In interpretation, it can be important to distinguish predictors that directly explain Y from predictors that primarily contribute indirectly, by removing extraneous variance from other predictors. Otherwise, the unwary researcher may inadvertently ascribe effect to the suppressor variable(s). In this example, the fact that the intervention had a noteworthy non-zero beta (.666), but a near zero structure coefficient (.072), means that the intervention alone had essentially no direct impact on outcome. Yet the researchers concluded "children who had the intervention, compared to children who did not experience it, were observed showing decreases in negative emotion, greater involvement, and more initiative in positive peer activity, and were seen as improving socially by their teachers", (p. 225).

Case 3: Multicollinearity and Suppressors

The research article by Teo, Carlson, Mathieu, Egeland, and Sroufe (1996) best demonstrates the importance of consulting both beta weights and structure coefficient and the multitude of effects that multicollinearity can have on accurate data interpretation. As part of their statistical analysis, four different regressions on two criteria (reading and math performance) across four age groups (1st grade, 2nd grade, 3rd grade, 6th grade, and age 16) were conducted. Table 2 provides the beta weights as reported in the study along with structure coefficients in the manner that they should have been presented.

In interpreting the grade 1 results, the researchers concluded that early history and socioemotional adjustment were the only statistically significant predictors for math and reading performance. In a second look, consulting structure coefficients, it is revealed that maternal life stress, while having a near zero beta weight (B = -.002, B = -.025), is substantially correlated with Y hat (r_s = .50, r_s = .45). It is uncertain whether this is "significant" but the result does suggest that maternal life stress might be <u>arbitrarily</u> denied full credit in this equation due to overlap with other predictors.

Analysis conducted for age 16 provided a more extreme case of undetected multicollinearity. Interpretation of betas only led the researchers to conclude that only socioemotional adjustment was a noteworthy predictor. By consulting structure coefficients in conjunction with the beta weights, it is apparent that early history (B = .186, r_s = .82) is being denied full credit and also should be considered as a substantial contributor to explained variance.

Possible suppressors were identified in the grade 3 regression analysis. When consulting structure coefficients, it was discovered that while maternal life stress had a low structure coefficient (r_s =-.15, r_s =-.15), it had a substantial beta (B = .141, B = .173) in relation to the other reported regression coefficients. As defined earlier, when a beta weight is larger than its respective structure coefficient and they are of the opposite sign, it is an indication that one or more of the predictors are in a suppressor relationship. Given this definition, maternal life stress acts as a suppressor in the 3rd grade.

Conclusion

The disastrous effects that multicollinearity can have on the accurate interpretation of multiple regression results has been well documented (Bowling, 1993;

Thompson, 1994; Thompson & Borrello, 1985). Interrelations between predictor variables can lead to inflation of regression coefficients, reductions in regression coefficients, and even reversal in their signs (Pedhazur, 1982). It is unrealistic to assume that a given set of predictors are naturally going to be uncorrelated (Bowling, 1995), and many times it is optimal to have many intercorrelated variables in order to best define a hard to operationalize construct. Rather than avoiding multicollinearity, it has been suggested that regression coefficients always be interpreted with either zero-order correlation coefficients (Pedhazur, 1982) or structure coefficients (Thompson, 1990, 1992b, 1994).

A review of the Journal of School Psychology, a leading journal in school psychology research, demonstrated that despite warnings of the hazards of erroneous interpretations resulting from analysis of betas in isolation, many current researchers are still failing to consult structure coefficients. The Journal of School Psychology encompasses research on testing, intervention development and implementation, and evaluation of programs. Given the paramount importance of the data analyzed in these journals and the impact of the results on interventions for children, it is essential that sound methodology be used in interpretation of results. It is important that researchers be aware of possible pitfalls in data analysis and take the steps to avoid the reporting of inaccurate results.

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Table 1

Regression Coefficients and Structure Coefficients

For Kochenderfer and Ladd (1996)

	Criteria			
	Loneliness		School avoidance	
Predictors	r_s	B	r_s	B
General	.46	.16	.63	.21
Physical	.81	.25	.69	.17
Direct Verbal	.89	.23	.93	.23
Indirect Verbal	.67	.08	.72	.09

Table 2

Regression Coefficients and Structure

Coefficients for Denham and Burton (1996)

	Outcome			
	Math		Reading	
Variable	r_s	B	r_s	B
Grade 1				
Early history	.88	.394	.82	.343
Home environment	.50	-.002	.45	-.025
Maternal Life Stress	-.12	.059	-.20	.067
Socioemotional Adj	.71	.201	.76	.280
Grade 3				
Early history	.83	.182	.83	.320
Home environment	.65	.095	.63	.074
Maternal Life Stress	-.15	.141	-.15	.173
Socioemotional Adj	.90	.259	.74	.193
Grade 6				
Early history	.86	.369	.97	.281
Home environment	.46	.107	.49	-.021
Maternal Life Stress	-.37	-.021	.03	.158
Socioemotional Adj	.70	.205	.86	.154
Age 16				
Early history	.82	.186	.98	.252
Home environment	.50	.073	.67	.130
Socioemotional Adj	.88	.349	.72	.169

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