The Use of Structural Equation Models in Interpreting Regression Equations Including Suppressor and Enhancer Variables

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It is shown that the usual interpretation of "suppressor" effects in a multiple regression equation assumes that the correlations among variables have been generated by a particular structural (causal) model, namely, Conger's (1974) two-factor model. A distinction is drawn between the technical definition of "suppression," which is more fittingly labelled *enhancement*, and suppression as the appropriate interpretation of a regression equation exhibiting enhancement when that equation has been generated by the two-factor model. It is demonstrated that a number of models can generate enhancement but cannot sensibly be interpreted in terms of the measuring, removing, or suppressing of irrelevant or invalid variance. How a regression equation is interpreted thus depends critically on the structural model deemed appropriate.

The occurrence of what has loosely been termed "suppression" is frequently a source of dismay and/or confusion among researchers using some form of regression analysis to analyze their data. It has been called "quasi-paradoxical," "ambiguous," "uninterpretable," and probably other more colorful names as well. This paper will show that the usual interpretation of "suppressor" effects in the simple two-predictor case implicitly assumes a unique causal model—namely, the two-factor model explicated by Conger (1974) and discussed below as Model I; however, the pattern of relationships among correlations and regression weights which are used to *technically* define and diagnose "suppression" can be generated by a large number of causal structures for which the notion of suppression as the measuring, removing, or subtracting of irrelevant variance is inappropriate and misleading. Thus, the interpretation of any obtained "suppressor" effects (and, in fact, any regression equation) depends critically upon the causal structural model that is at least implicitly assumed to underlie the data. In most cases, successful interpretation of the regression situation involves estimating and interpreting the parameters of this structural model (see Duncan, 1975; Heise, 1975; or Johnston, 1972, for introductory treatments).

It will be very helpful in the following discussion to distinguish between the technical definition of "suppression" (provided by several authors, e.g., Cohen & Cohen, 1975; Conger, 1974), referring to a pattern of relationships among correlations and regression weights, and the way variables operate in the particular causal model which is usually assumed in discussions of suppression. For reasons which should become apparent, all variables which conform to the more general technical criteria will

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be called *enhancers*, while the terms *suppressors* and *suppression* will be reserved for those particular enhancers which also conform to the two-factor model. Much of the difficulty in interpreting "suppressor" effects stems from the failure to make this distinction or to consider alternative models which might give rise to what will be called *enhancement* phenomena.

This paper will explore some of the variety of models which can and cannot lead to enhancement in the simple two-predictor case and, in so doing, will attempt to clarify how the occurrence of enhancement can be helpful in interpreting a regression equation.

Three Types of Enhancement

There are a number of slightly varying technical definitions of "suppression" (e.g., Cohen & Cohen, 1975; Conger, 1974; Darlington, 1968; Lord & Novick, 1968); however, the variations are relatively minor and in no way affect the argument of this paper. Since Conger's (1974) definition is the most general, it will be used for the definition of *enhancer* variables:

> An . . . [enhancer] variable is defined to be a variable which increases the predictive validity of another variable (or set of variables) by its inclusion in a regression equation. This variable is an . . . [enhancer] only for those variables whose regression weights are increased. (pp. 36–37)

In the two-predictor case, let X_0 be the criterion with predictors X_1 and X_2, reflected if necessary so as to make all correlations with X_0 positive. If X_2 is arbitrarily designated as an enhancer, the above definition holds in the population if and only if the following condition holds:

$$|\beta_{01\cdot 2}| > \rho_{01} \qquad [1]$$

where $\beta_{01.2}$ is the standardized regression coefficient for X_1 and ϱ_{01} is the correlation between X_0 and X_1. Henceforth, $\beta_{01.2}$ and $\beta_{02.1}$ will be abbreviated as β_{01} and β_{02}. There are three distinct types of enhancement which can be derived from Condition 1 by substituting the equation for β_{01},

$$\beta_{01} = \frac{\rho_{01} - \rho_{02}\rho_{12}}{1 - \rho_{12}^2} , \qquad [2]$$

into Condition 1:

$$|\beta_{01}| = \left| \frac{\rho_{01} - \rho_{02}\rho_{12}}{1 - \rho_{12}^2} \right| > \rho_{01} . \qquad [3]$$

The defining characteristics of the three varieties are summarized below, following Cohen and Cohen (1975).

Classical Enhancement

If $\varrho_{02} = 0$ and ϱ_{01} and ϱ_{12} are greater than zero, then $\beta_{01} > \varrho_{01}$, satisfying Condition 1; and classical enhancement is said to obtain. Notice that under classical enhancement, β_{02} is negative even though ϱ_{02} is zero, since

$$\beta_{02} = \frac{\rho_{02} - \rho_{01}\rho_{12}}{1 - \rho^2_{12}} = \frac{-\rho_{01}\rho_{12}}{1 - \rho^2_{12}} . \quad [4]$$

Net Enhancement

When all correlations are positive and yet β_{02} is negative (implying that $\varrho_{02} - \varrho_{01}\varrho_{12} < 0$), then again, $\beta_{01} > \varrho_{01}$, satisfying Condition 1; and net enhancement is said to obtain.

Cooperative Enhancement

When ϱ_{01} and ϱ_{02} are both positive and yet ϱ_{12} is negative, then once again, $\beta_{01} > \varrho_{01}$, satisfying Condition 1; and cooperative enhancement is said to obtain. Notice that under cooperative enhancement, both β_{01} and β_{02} must be positive.

Interpretation of Enhancement

Lord and Novick's (1968) account of suppression expresses implicitly the model usually applied in interpreting enhancement phenomena. They write, "In effect, they [suppressor variables] represent some aspect of the predictor variables that is not related to the criterion but that functions to 'suppress' or subtract out this invalid component and thus to make the original predictor more valid" (pp. 271–272). Notice that in this account, variation in a predictor, say X_1, is presumed to arise from two sources—one relevant to the criterion and the other irrelevant or invalid. Furthermore, variation in the suppressor, X_2, arises mainly from that source which is irrelevant to the criterion; thus, X_2 contributes indirectly to prediction by removing or suppressing the irrelevant variation in X_1.

Conger (1974) expresses this two-factor suppression model formally and shows how variation in the parameters of the model lead to the three types of enhancement defined above. What he and others fail to point out is that although enhancement phenomena which are generated by the two-factor model can be sensibly interpreted in terms of the suppression of irrelevant or invalid variance, there are a number of other models which can be expected to generate data which exhibit all three kinds of enhancement but which cannot be interpreted in terms of suppression or even relevant and irrelevant variance. Moreover, there is nothing about enhancement in general, or one of the three types in particular, which invariably signals some underlying structure. This fact can be made more apparent by examining Conger's two-factor model as well as some other models which can give rise to enhancement, but it is important to understand at the outset the rationale and strategy for examining how differing structural equation (causal) models can generate the same multiple regression equation and that the interpretation of the regression equation depends critically upon which model is believed to be appropriate.

Briefly, it is well known that simply knowing the correlation matrix (and hence the regression coefficients) among three variables—X_0, X_1, and X_2—is not sufficient to allow inference of the causal relationships among the variables. Correlations and regression coefficients are, in this sense, causally uninformative. If, however, one is willing to postulate or hypothesize a causal model in the form of a set of structural equations, each of which represents a causal rather than a mere empirical association, that model can then be shown to impose a very definite structure on the correlation (or covariance) matrix of variables in the model. If this structure is restrictive enough, it will be possible to estimate the parameters of the model from the values in the correlation matrix. However, a large number of models will always be consistent with the actual values in the correlation matrix and the regression equation derived from it, so that how the regression equation is interpreted depends on which model is deemed appropriate.

Since enhancement has been defined above in terms of patterns in the correlation matrix, our strategy will be to postulate some structural models along with content examples to see the kinds of models which can and cannot generate enhancement and how they might be interpreted.

Model I—The Two-Factor Model

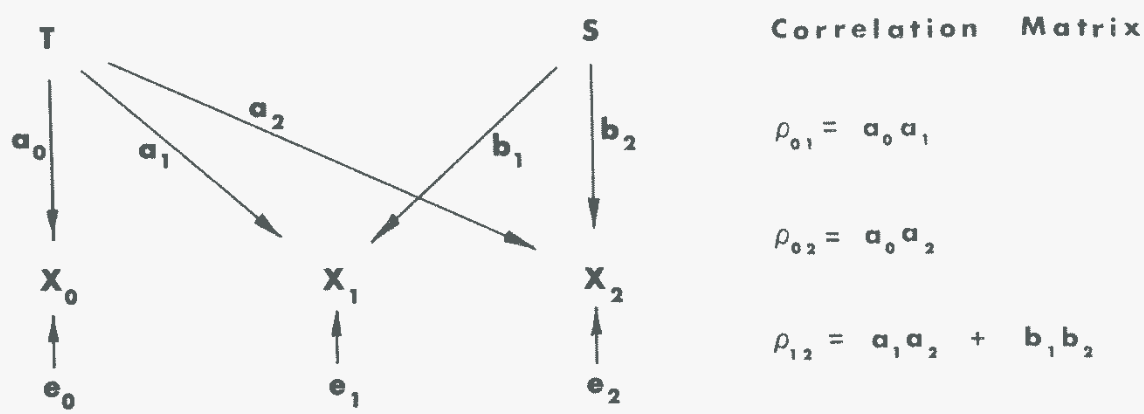
Figure 1 shows Conger's two-factor model, but in the form of a path diagram. T and S are uncorrelated latent variables which are measured by X_0, X_1, and X_2 with measurement errors e_0, e_1, and e_2, respectively, where $E(e_i) = E(e_i e_j) = 0$; $i, j = 0, 1, 2$; and $i \neq j$. The observed criterion, X_0, is assumed to measure only T, while X_1 and X_2 measure both T and S. T and S are assumed to be uncorrelated with each other; hence X_0 and S are uncorrelated. It will be assumed, for convenience, that all variables including S and T have been standardized to mean and variance of 0 and 1.[1] The structural equations which correspond to Figure 1 are

$$X_0 = a_0 T + e_0 \quad [5]$$

$$X_1 = a_1 T + b_1 S + e_1$$

$$X_2 = a_2 T + b_2 S + e_2 \; .$$

Figure 1
Path diagram for Model I



[1]Standardizing all variables except measurement errors and disturbance terms will be done routinely throughout this paper. It simplifies the algebra considerably, but does not affect the fundamental arguments made.

The a's and b's represent structural parameters and have the properties of orthogonal factor loadings or standardized regression coefficients in Equation Set 5. If the factor model of Equation Set 5 is assumed, the unique entries in the correlation matrix of the observed variables X_0, X_1, and X_2 are

$$\rho_{01} = a_0 a_1 \qquad [6]$$

$$\rho_{02} = a_0 a_2$$

$$\rho_{12} = a_1 a_2 + b_1 b_2 .$$

Maintaining the earlier convention requiring ϱ_{01} and ϱ_{02} to be positive, the direction of T is chosen so as to make a_0, and hence a_1, positive. It should be clear from an examination of the correlation matrix that classical enhancement occurs only when $a_2 = 0$ and $b_1 b_2 > 0$. In Figure 1 this simply means there is no arrow connecting T to X_2.

Conger (1974) analyzes the other two types of enhancement from the standpoint of the two-factor model to show that net enhancement will occur whenever $a_2 < a_1 (a_1 a_2 + b_1 b_2)$; and cooperative enhancement, whenever $a_1 a_2 + b_1 b_2 < 0$, which implies that b_1 and b_2 are of opposite sign.

Example. Most discussions of suppression supply an example similar to Darlington's (1968):

> A typical example in which prediction is improved by [suppression] . . . might be a situation in which a test of reading speed is used in conjunction with a speeded history achievement test to predict some external criterion of knowledge of history. Since the history test is contaminated by reading speed, assigning a negative weight to the reading speed test would help to correct for the disadvantage suffered by a student with low reading speed who is competing with faster readers. (p. 163)

In Darlington's example, T and S become, respectively, the latent variables true knowledge of history and true reading speed; and X_0, X_1, and X_2 are, respectively, "some external criterion of knowledge of history," history achievement score, and reading speed score. The "contamination" Darlington refers to is represented by the arrow from S to X_1 in Figure 1 or the structural parameter, b_1, in Equation Set 5. While the specification of no correlation between T and S is somewhat questionable in Darlington's example, it appears that the basic structure is that of Conger's two-factor model.

It should also be apparent that the notion that enhancers can remove or suppress irrelevant variance is quite consistent with the two-factor model. That is, variation in S has no effect whatever on T or X_0 and is therefore a source of variation in X_1 which is irrelevant to T or X_0. Consequently, a negative regression weight attached to X_2 may be thought of as removing or suppressing irrelevant variance in X_1. There are, however, structural models other than the two-factor model which can give rise to enhancement, but for which the notions of irrelevant variance and suppression are inappropriate.

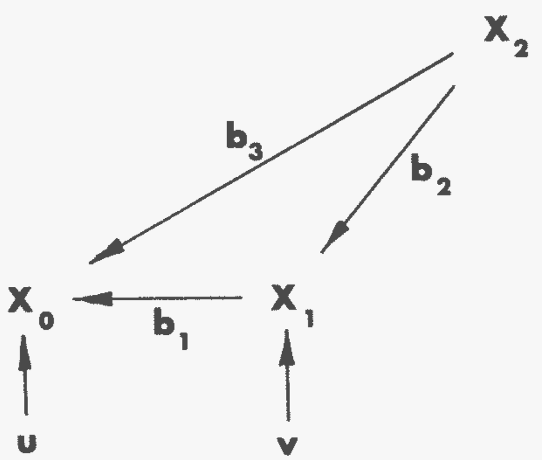
Model II—Enhancers that Do Not Suppress

Another example may prove helpful in thinking about situations where interpreting enhancement as suppression will be quite misleading.

Example. Suppose one were interested in predicting the number of errors made by assembly-line workers as a function of IQ and Intolerance of Boredom scores. Let X_0 be number of errors, X_1 be Intolerance of Boredom score, and X_2 be IQ score. If one obtained sample correlations of $r_{c1} = .3535$, $r_{02} = 0$, and $r_{12} = .707$; noted that this was a case of classical enhancement; and relied on the usual discussions of suppression, one might be tempted to conclude that IQ was totally irrelevant to the number of assembly-line errors made, but did measure precisely that aspect of Intolerance of Boredom which is also irrelevant to the number of errors made. This is the interpretation one would make were the two-factor model the structure underlying these variables. The conclusion does not seem to lead to much insight in this situation, however; and the frustration generated by attempting to interpret cases of enhancement like this as suppression no doubt contributes to a good deal of the confusion and reluctance in interpreting so-called suppression effects.

Model II. Consider the simple case in which no measurement error is allowed; subsequently, this constraint will be relaxed. Suppose that X_0, X_1, and X_2 (all measured without error) are causally related in the population as shown in Figure 2.

Figure 2
Path diagram for Model II



Correlation Matrix

$$\rho_{01} = b_1 + b_2 b_3$$

$$\rho_{02} = b_3 + b_1 b_2$$

$$\rho_{12} = b_2$$

The structural equations which correspond to Model II are (again assuming X_0, X_1, and X_2 are all standardized):

$$X_0 = b_1 X_1 + b_3 X_2 + u \qquad [7]$$

$$X_1 = b_2 X_2 + v$$

where u and v are stochastic disturbance terms representing all sources of variation not otherwise included in the model with $E(u) = E(v) = E(uv) = 0$. The population correlation matrix generated by the structure represented in Equation Set 7 is

$$\rho_{01} = b_1 + b_2 b_3 \qquad [8]$$

$$\rho_{02} = b_3 + b_1 b_2$$

$$\rho_{12} = b_2 \,.$$

Notice first that *all* the variance in X_1 is causally relevant to X_0 and that *all* the variance in X_2 is causally relevant to both X_0 and X_1. Nonetheless, it is easy to show that all three kinds of enhancement can occur in this model.

Classical Enhancement. Fixing $\varrho_{02} = 0$ requires that $b_3 = -b_1 b_2$, while $\varrho_{12} > 0$ implies $b_2 > 0$. Substituting these conditions into the equation for ϱ_{01} yields $\varrho_{01} = b_1(1 - b_2^2)$. Since it is desired that $\varrho_{01} > 0$, then $b_1 > 0$. Thus, when b_1 and b_2 are positive and $b_3 = -b_1 b_2$, classical enhancement will obtain. For example, let $b_1 = b_2 = .707$ and $b_3 = -.50$. The population correlations are then the same as those in our example above, $\varrho_{01} = .3535$, $\varrho_{02} = 0$, and $\varrho_{12} = .707$. Notice that although the correlation between X_0 and X_2 is zero, the standardized regression weight for X_2 will be equal to b_3, which is negative. Moreover, there is no sense in which X_2 can be said to be subtracting or suppressing irrelevant or invalid variance in X_1. The negative weight for X_2 simply represents the fact that X_2 in this model has a direct negative effect on X_0, despite its exactly compensating positive influence on X_0 through X_1.

If Model II is adopted in interpreting the above example, one does not attempt to sort out some elusive aspect of Intolerance of Boredom that is related to number of errors but not IQ. Instead one concludes that IQ does, as might be expected, negatively influence the number of errors; however, that influence is exactly compensated for by the positive influence of IQ through Intolerance of Boredom on the number of errors made. Given the substantive nature of the example, this conclusion seems more appropriate, although this appropriateness clearly rests both on prior beliefs about what reasonable relationships among the three variables would be and on the inability to construct meaningful latent variables in the two-factor model.

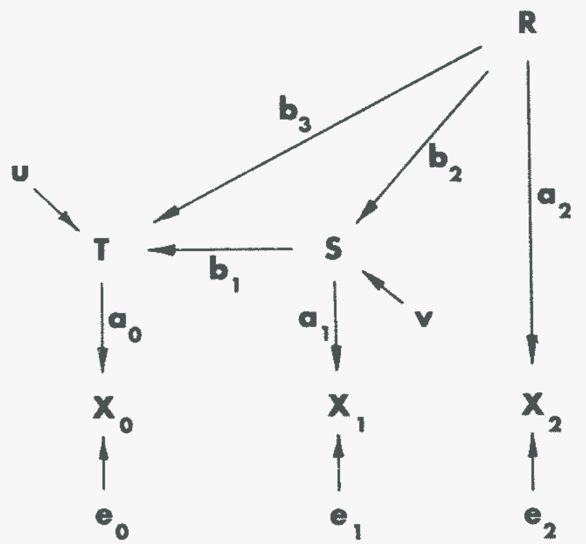
It is important to realize that in the foregoing, no objective criteria have been suggested for deciding between Model I and Model II. Both models could conceivably have generated the correlation matrix which produced classical enhancement. In general, it will always be the case that several alternative models will describe one's data equally well, and considerations above and beyond the data itself must be used to decide among them. The crucial point is that the models are very different, and yet both can generate all three kinds of enhancement. They are *not* superficially different yet formally equivalent ways of saying the same thing. The two models are fundamentally different; and if Model II is the "correct" model, then it is nonsensical to interpret the obtained enhancer effect as suppressing invalid or irrelevant variance as one might do if Model I were appropriate.

Net and Cooperative Enhancement. Consideration of Equation Set 8 shows that both net and cooperative enhancement can also occur when Model II is assumed. A little algebra reveals that the requirements for net enhancement are that $-b_1 b_2 < b_3 < 0$ and $b_1, b_2 < 0$, while those for cooperative enhancement are that $-b_1 b_2 < b_3 < -b_1/b_2$, where $b_2 < 0$ and $b_1, b_3 > 0$.

Model III—Including Measurement Error

It has been assumed so far in Model II that X_0, X_1, and X_2 are measured without error. Allowing measurement error into the model complicates the analysis a bit but does not change the fundamental conclusions about the possibility of enhancement. Figure 3 shows how Model II is changed when X_0, X_1, and X_2 are presumed to be fallible measures of three latent (true) variables, T, S, and R, respectively. Again, for convenience, all variables including T, S, and R are assumed standardized.

Figure 3
Path diagram for Model III



Correlation Matrix

$$\rho_{01} = a_0 a_1 (b_1 + b_2 b_3)$$

$$\rho_{02} = a_0 a_2 (b_3 + b_1 b_2)$$

$$\rho_{12} = a_1 a_2 b_2$$

The structural equations for Model III are

$$X_0 = a_0 T + e_0 \qquad [9]$$

$$X_1 = a_1 S + e_1$$

$$X_2 = a_2 R + e_2$$

$$T = b_1 S + b_3 R + u$$

$$S = b_2 R + v$$

where e_0, e_1, and e_2 are measurement errors with $E(e_i) = E(e_ie_j) = 0$, $i,j = 0, 1, 2$; and $i \neq j$. The disturbances—u and v—have zero means and are uncorrelated with each other and the errors of measurement. Solving Equation Set 9 to eliminate T and S yields

$$X_0 = a_0(b_1b_2 + b_3)R + a_0b_1v + a_0u + e_0 \qquad [10]$$

$$X_1 = a_1b_2R + a_1v + e_1$$

$$X_2 = a_2R + e_2 \ .$$

The population correlation between X_0 and X_1 from this model is $\varrho_{01} = a_0\ [a_1b_2\ (b_1b_2 + b_3) + a_1b_1\sigma_v^2]$. Since S and R are standardized, we have from the last equation in Equation Set 9 that $\sigma_v^2 = 1 - b_2^2$. Thus the equation for ϱ_{01} may be written

$$\rho_{01} = a_0\left[a_1b_2(b_1b_2 + b_3) + a_1b_1(1 - b_2^2)\right] \qquad [11]$$

$$= a_0a_1(b_1 + b_2b_3) \ .$$

The population correlations among X_0, X_1, and X_2 are

$$\rho_{01} = a_0a_1(b_1 + b_2b_3) \qquad [12]$$

$$\rho_{02} = a_0a_2(b_3 + b_1b_2)$$

$$\rho_{12} = a_1a_2b_2 \ .$$

A comparison of the correlations in Equation Set 12 with those in Equation Set 8 reveals the effect of measurement error on the observable correlations. If there is no measurement error, all a's equal unity and the correlations in Equation Set 12 become precisely those of the error-free model. The direction of the latent variables can always be chosen so as to make a_0, a_1, and a_2 positive; and since all variables except the disturbances and measurement errors are standardized, a_0, a_1, and a_2 are equal to the square roots of the reliabilities of X_0, X_1, and X_2. Thus, the correlation matrix for Model III will be exactly the same as that for Model II except that each correlation is attenuated due to the presence of measurement error.

It is apparent from Equation Set 12 that the requirements for classical and cooperative enhancement in Model III are the same as for Model II. Some algebra shows that net enhancement will occur in Model III when

$$-b_1 b_2 < b_3 < -b_1 b_2 (1 - a_1^2)/(1 - a_1^2 b_2^2) < 0 \quad [13]$$

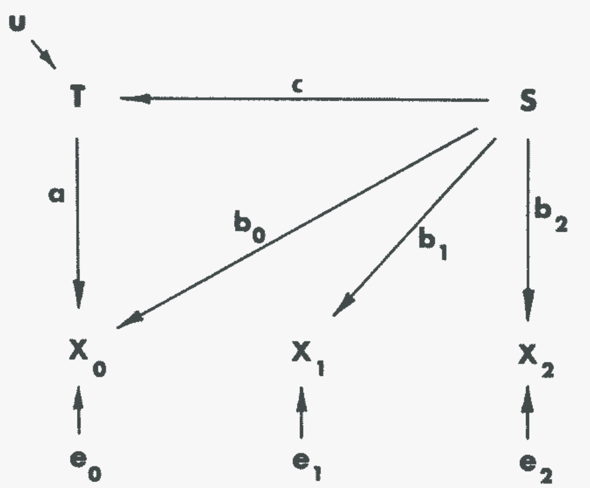
and b_1, $b_2 < 0$. Since the conditions for enhancement in Model III are not substantially different from those of Model II, the interpretation of the two cases is similar. Clearly, the presence or absence of measurement error in a set of variables does not in general affect whether it is reasonable to think about enhancer effects as removing or subtracting irrelevant variance.

There are a number of possible structural models in the two-predictor case, other than the ones discussed so far, which are capable of generating enhancement phenomena. For example, a slight change can be made in the two-factor Model I, and T can be allowed to be influenced by S. This would amount to adding an arrow from S to T and a disturbance to T in Figure 1 and/or simply adding another equation, $T = cS + u$, to the system of Equation Set 5.

It can be shown in the same way as has been shown in Models I to III that all three kinds of enhancement can occur in this revised Model I. However, if T is allowed to be influenced by S, then S is not an irrelevant or invalid component of T and X_1; and once again, it becomes impossible to interpret enhancement as the suppression of irrelevant variance.

These considerations should make it plain that it is only under a very special set of circumstances that enhancement can meaningfully be interpreted as having anything to do with irrelevant or invalid variance, and this conclusion holds a fortiori in the case of more than two predictors. Despite the fact that the presence of enhancement could not help us decide among the foregoing models, its occurrence is not useless information; for there are models which cannot lead to enhancement and could thus be rejected when evidence of enhancement is found. To see this, consider Model IV in Figure 4.

Figure 4
Path diagram for Model IV



Correlation Matrix

$$\rho_{01} = (ac + b_0) b_1$$

$$\rho_{02} = (ac + b_0) b_2$$

$$\rho_{12} = b_1 b_2$$

Model IV—No Enhancement Is Possible Here

This model is similar in some respects to Model I and the revised Model I mentioned earlier. The structural equations of the model are

$$X_0 = aT + b_0 S + e_0 \qquad [14]$$

$$X_1 = b_1 S + e_1$$

$$X_2 = b_2 S + e_2$$

$$T = cS + u$$

with $E(u) = E(e_i) = 0$ and all covariances among measurement errors and the disturbance equal to zero. Solving Equation Set 14 to end up with only observables on the left side, we have

$$X_0 = (ac + b_0)S + au + e_0 \qquad [15]$$

$$X_1 = b_1 S + e_1$$

$$X_2 = b_2 S + e_2 \ .$$

The population correlations among X_0, X_1, and X_2 that would be generated by Model IV are

$$\rho_{01} = (ac + b_0)b_1 \qquad [16]$$

$$\rho_{02} = (ac + b_0)b_2$$

$$\rho_{12} = b_1 b_2 \ .$$

It is impossible for any form of enhancement to occur in this model. It is easiest to show this for all kinds of enhancement by using the necessary and sufficient Condition 1,

$$|\beta_{01}| > \rho_{01} \qquad [17]$$

where the directions of X_1 and X_2 are always chosen so as to make ϱ_{01} and ϱ_{02} positive. From this condition we have that

$$|\beta_{01}| = \left|\frac{\rho_{01} - \rho_{02}\rho_{12}}{1 - \rho_{12}^2}\right| > \rho_{01} \qquad [18]$$

$$\left|\frac{(ac + b_0)b_1 - (ac + b_0)b_2 b_1 b_2}{1 - b_1^2 b_2^2}\right| > (ac + b_0)b_1$$

$$\left|(ac + b_0)b_1 \left[\frac{1 - b_2^2}{1 - b_1^2 b_2^2}\right]\right| > (ac + b_0)b_1 \; .$$

Since the quantity in brackets is always positive and less than 1 and $(ac + b_0)b_1$ is always positive and less than 1, the inequality can never hold and enhancement cannot occur.

Conclusions

The foregoing analysis may be considered as an argument to the effect that the numbers obtained by calculating regression and correlation coefficients are substantively uninterpretable apart from at least an implicit structural model. A negative regression weight for X_2 means very different things, depending on whether Model I, II, or some other model is appropriate. Consequently, it is often more informative to specify explicitly a structural model and to attempt to estimate its parameters. Note that while we have analyzed how various structural models can or cannot generate a particular pattern of correlations and regression weights (i.e., enhancement), the same kind of analysis could be applied to any pattern of obtained coefficients.

It sometimes happens that it is impossible to estimate the parameters of the structural model believed to underlie the observed data because there is not enough information in the observed covariances among variables to provide unique estimates of all the structural parameters. When this is the case, the model is said to be underidentified. All of the models examined except Model II fall into this category. This fact, however, suggests the possibility of a situation in which the simple knowledge that enhancement was occurring could be helpful information despite the multiplicity of models that could generate it. Model IV, like Models I and III, is underidentified as it stands. The fact that it can be shown to disallow any kind of enhancement indicates, however, that even underidentified models may sometimes be profitably examined in light of one's data. If, for example, one had reason to believe that either a structure like Model I (or the revised Model I mentioned earlier or Model IV) underlay one's data, then the occurrence of enhancement (over and above what might be attributed to sampling fluctuations) could allow one to reject the latter model. The situations in which the general concept of enhancement could be helpful in this manner would perhaps be rather rare; nonetheless, with underidentified models, any help at all is unusual.

References

Cohen, J., & Cohen, P. *Applied multiple regression/correlation analysis for the behavioral sciences*. New York: Halsted Press, 1975.

Conger, A. J. A revised definition for suppressor variables: A guide to their identification and interpretation. *Educational and Psychological Measurement*, 1974, *34*, 35–46.

Darlington, R. B. Multiple regression in psychological research and practice. *Psychological Bulletin*, 1968, *69*, 161–182.

Duncan, O. D. *Introduction to structural equation models*. New York: Academic Press, 1975.

Heise, D. R. *Causal analysis*. New York: Wiley-Interscience, 1975.

Johnston, J. J. *Econometric methods* (2nd Ed.). New York: McGraw-Hill, 1972.

Lord, F. M., & Novick, M. R. *Statistical theories of mental test scores*. Reading, MA: Addison-Wesley, 1968.

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