DOCUMENT RESUME

ED 426 097 TM 029 327

AUTHOR Lancaster, Brian P.

TITLE Defining and Interpreting Suppressor Effects: Advantages and Limitations.

PUB DATE 1999-01-00

NOTE 21p.; Paper presented at the Annual Meeting of the Southwest Educational Research Association (San Antonio, TX, January 21-23, 1999).

PUB TYPE Information Analyses (070) -- Reports - Descriptive (141) -- Speeches/Meeting Papers (150)

EDRS PRICE MF01/PC01 Plus Postage.

DESCRIPTORS Correlation; Definitions; Heuristics; *Identification; *Predictor Variables; *Statistical Analysis; *Suppressor Variables; Validity

ABSTRACT

Suppressor effects are considered one of the most elusive dynamics in the interpretation of statistical data. A suppressor variable has been defined as a predictor that has a zero correlation with the dependent variable while still, paradoxically, contributing to the predictive validity of the test battery (P. Horst, 1941). This paper explores the three definitions of regression suppressor variables by reviewing existing literature about suppressor effects and provides a heuristic example that demonstrates how the different types of suppressor variables can be detected. Special considerations in detecting suppressor effects are discussed, along with possible limitations researchers may encounter when including suppressor variables in a statistical design. (Contains 1 figure, 4 tables, and 14 references.) (SLD)

Defining and Interpreting Suppressor Effects: Advantages and Limitations

Brian P. Lancaster

Texas A&M University

Paper presented at the annual meeting of the Southwest Educational Research Association, San Antonio, January, 1999.

Abstract

Suppressor effects are considered on of the most elusive and difficult-to-grasp dynamics in the interpretation of statistical data. The present paper explores the three definitions of regression suppressor variables by reviewing existing literature about suppressor effects and also provides a heuristic example that demonstrates how the different types of suppressor variables can be detected. Further, special considerations in detecting suppressor effects are given, along with possible limitations researchers may encounter when including suppressor variables in a statistical design.

Defining and Interpreting Suppressor Variables: Advantages and Limitations

With the plethora of different ways to obtain results, researchers have much to consider in analyzing data. Following confirmation that the researcher has found something either through discovery of a large effect size, statistical significance, or replicability, the researcher must then (and only then) determine from where (e.g., which variables generated the noteworthy effect). For example, when using multiple regression as a "tool" for statistical analysis, the researcher must determine which predictor variables are contributing to predicting the variability of the criterion, or dependent variable. It is commonly known that the "usefulness" of a given predictor variable can be measured by the impact it has on explaining the variance in the dependent variable. The problem becomes confounding for researchers when variables behave in unexpected, indirect ways; such is the case of suppressor variables (Henard, 1998).

The concept of *suppression* was first introduced by Horst (1941), who defined a suppressor variable as a predictor that has a zero correlation with the dependent variable while paradoxically still contributing to the predictive validity of the test battery. Suppression is very interesting in that it truly reveals conclusions that would never be reached on the basis of examining only bivariate relationships. Early on, there were only a few cases where suppressor variables were identified. It wasn't until the late 1960's and early 1970's when suppressor variables were more widely recognized and the definition was further expanded (Cohen & Cohen, 1975; Conger, 1974; Darlington, 1968; Horst, 1966). These extensions convinced researchers to become more aware of the potential dynamics that may occur with predictor variables. More importantly, these extensions demonstrated that certain variables that may seem completely unimportant may actually provide substantial indirect contributions to improving the regression effects (e.g., $\underline{R}^2$).

The present paper presents the reader with a clear, easy-to-grasp explanation of suppressor effects. To do this, three areas will be explored. First, the different types of suppressor variables are defined along with a heuristic example that demonstrates to the reader how the different types of suppressor variables are detected. Second, special considerations in detecting suppressor effects are summarized. Finally, limitations of suppressor inclusion are discussed.

Definitions and Types

Thompson (1998) pointed out that the name "suppressor variable" may have a pejorative connotation because "suppression" sounds like "repression." On the contrary, suppressor variables are actually advantageous because they improve the prediction of the criterion. In essence, these variables suppress irrelevant variance in the other predictor variable(s), thus indirectly allowing for a more concise estimate of the predictor-criterion relationship, even though the suppressor variable directly predicts none or almost none of the criterion variable's variance.

As mentioned previously, the classical (or "traditional," Conger, 1974) definition of suppressor variables is one of zero correlation with the dependent variable but, by virtue of a correlation with another predictor, improves the overall effect of the predictor(s) onto the criterion. In practice, variables almost never have an exactly zero correlation with the dependent variable. Therefore, predictors with very small correlations with the dependent variable may also be considered suppressors (Cohen & Cohen, 1975).

Perhaps the best example to demonstrate classical suppression was given by Horst (1966). He describes a study conducted during World War II that attempted to predict pilot success in a pilot training program. Comprising the battery of tests given to the prospective pilots were measures of mechanical ability, numerical ability, spatial ability, and verbal ability. Each of the first three had marked positive correlations with pilot success. Verbal ability, however, had a near-zero correlation with pilot success but fairly high correlations with the other three predictors.

When verbal ability was included into the regression equation, the validity of the overall model increased, not withstanding the fact that verbal ability correlated almost zero with pilot ability. Verbal ability was needed to read the instructions and items on the paper-and-pencil tests. Thus, the measurement method introduced extraneous measurement error variance into the scores on the measures of mechanical, numerical, and spatial ability, i.e., measurement artifact variance (Thompson, 1992). Using the verbal ability scores, which had essentially no relationship with pilot ability, in the prediction nevertheless improved the overall prediction by *effectively removing the measurement artifact variance* from the mechanical, numerical, and spatial ability scores, thereby making them purer and thus more effective predictors of pilot ability. As Horst (1966, p. 355) noted, "To include the verbal score with a negative weight served to suppress or subtract irrelevant ability, and to discount the scores of those who did well on the test simply because of their verbal ability rather than because of abilities required for success in pilot training."

Consider an example involving two predictor variables, X1 and X2. Here r_{yx1} = 0.707106, r_{yx2} = .0, and r_{x1x2} = -0.707106. For these data, the beta weight for the first predictor, X1, will equal:

$$\begin{aligned}\beta &= [\ r_{yx1} - (r_{yx2})\ (r_{x1x2})\ ]\ /\ 1 - r_{x1x2}^2 \\ &= [\ 0.707106 - (.0)\ (-0.707106)\ ]\ /\ 1 - (-0.707106)^2 \\ &= [\ 0.707106 - (.0)\ (-0.707106)\ ]\ /\ 1 - .5 \\ &= [\ 0.707106 - (.0)\ (-0.707106)\ ]\ /\ .5 \\ &= [\ 0.707106 - .0\ ]\ /\ .5 \\ &= 0.707106\ /\ .5 \\ &= 1.414213\ .\end{aligned}$$

The beta weight for the second predictor, X2, will equal:

$$\begin{aligned}\beta &= [\ r_{yx2} - (r_{yx1})\ (r_{x1x2})\ ]\ /\ 1 - r_{x1x2}^2 \\ &= [\ .0 - (0.707106)\ (-0.707106)\ ]\ /\ 1 - (-0.707106)^2 \\ &= [\ .0 - (0.707106)\ (-0.707106)\ ]\ /\ 1 - .5 \\ &= [\ .0 - (0.707106)\ (-0.707106)\ ]\ /\ .5 \\ &= [\ .0 - (-.5)\ ]\ /\ .5 \\ &= .5\ /\ .5 \\ &= 1.0\ .\end{aligned}$$

The R^2 for these data equals:

$$\begin{aligned}R^2 &= (\beta 1)\ (r_{yx1}) + (\beta 2)\ (r_{yx2}) \\ &= (1.414213)\ (0.707106) + (1.0)\ (.0) \\ &= 1.0 + .0 \\ &= 1.0\ .\end{aligned}$$

Thus, in this example, even though X2 has a zero correlation with Y, the use of X2 as part of prediction along with X1 doubles the predictive efficacy of the predictors, yielding perfect prediction!

Using a Venn diagram, Figure 1 graphically illustrates the operation of a classical suppressor variable. Notice that X2, the suppressor variable, has no overlap with the criterion Y. Also notice that the Multiple R is increased due to the inclusion of the suppressor variable.

INSERT FIGURE 1 ABOUT HERE

A more general definition of a suppressor variable was advanced by Darlington (1968), labeled negative suppression (defined by Darlington, (1968) and labeled by Conger (1974)). Cohen and Cohen (1975) named this same category "net" suppression. Negative suppression occurs when a variable receives a negative weight upon inclusion in a regression equation when all variables have positive inter-correlations. McNemar (1945) pointed out the paradoxical quality associated with a suppressor in that it is possible to increase prediction with a variable that has a negative correlation with the criterion, provided there is high correlation with another variable that does have correlation with the criterion.

Figure 1 presents another Venn diagram delineating this definitional extension when compared to the classical definition. Notice that the only basic change is the location of X2, the suppressor variable, which is now overlapping the dependent variable, but is not being given credit for this as signified by $\beta < 0$ even though $r_{yx2} > 0$. Also notice that, as was the case of classical suppression, the inclusion of X2 into the regression equation increases the Multiple R, even though the variable was assigned a negative beta weight. Again, the reason for this phenomenon is because X2 suppresses irrelevant variance in X1, thus allowing for an increased relationship between X1 and the criterion Y.

In both of the previous cases, the focus has been on the beta weights assigned to the suppressors. In the classical definition, the beta weights were unexpectedly nonzero and for the negative definition, the beta weights were unexpectedly negative. It is commonly understood in linear regression that using multiple predictors with high intercorrelations can produce substantially altered results. With the addition of each new intercorrelated predictor variable, all of the existing beta weights will change, sometimes quite remarkably. This phenomenon led to the recognition of an even more general definition of a suppressor, the reciprocal suppressor (Conger, 1974; Lutz, 1983) (or "cooperative," Cohen & Cohen, 1975).

Because beta weights are quite unstable, (i.e., "context specific" – cf. Thompson, 1998), when other variables are applied, any change in the variable(s) in the model can radically alter the value of all other beta weights. Therefore, a suppressor variable is not uniquely defined by its own beta weight but rather generically through its impact on the weights given to all the other predictor variables (Conger, 1974). Suppression occurs when the two independent variables mutually suppress irrelevant variance in each other, hence the term reciprocal suppression (Lutz, 1983). Again using Figure 1, the Venn diagram shows that both X1 and X2 are mutually suppressing each other as evidenced by the inter-correlation between the two and by their beta weights that are larger than their bivariate correlations. It is noteworthy to mention that in this context, any variable can act as both a predictor and as a suppressor (Lord & Novick, 1974).

Choosing a Coefficient

Up to this point, the coefficient of choice has been the bivariate correlation (r_{yx}). Thompson (1992) emphasizes the relevance of interpreting structure coefficients. A structure coefficient is a zero-order correlation of an independent variable with a dependent variable divided by a constant, namely, the multiple correlation coefficient (r_{yx} / Multiple R). Indeed, the structure coefficient and the bivariate correlation will lead to identical interpretations since they are merely expressed in a different metric. Although researchers will generally come to the same conclusions when interpreting either zero-order correlations or structure coefficients, using structure coefficients does have some merit. Thompson and Borrello (1985, p. 208) argued that

> it must be noted that interpretation 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 that consider the variables taken only two at a time.

Heuristic Example

Perhaps the best way to demonstrate the three definitions of suppressor variables is through a simplistic data set. Using a data set constructed by Lutz (1983), Table 2 illustrates suppressor effects using a dependent variable and four variables, the suppressed variable and the three different types of suppressors (classical, negative, and reciprocal).

INSERT TABLE 1 ABOUT HERE

Using Table 2, we can see the inter-variable bivariate correlations and the predictor-criterion bivariate correlations in the upper right diagonal. The structure coefficients are located in the lower left diagonal. Notice that there is virtually no difference between the bivariate correlations and the structure coefficients. The reason for this is because of the exceptionally high Multiple R (> 0.99) that means the division, $r_s = r_{yx} / R$, essentially involves division by one. However, most data sets result in much lower Multiple R's, thus resulting in more noticeable differences between r_{yx} and r_s.

Table 2 shows the criterion variable, Y, the suppressed variable, X_1, and the three definitional suppressor variables, X_{2c}, X_{2n}, and X_{2r}. The classical suppressor, X_{2c}, has a zero correlation with Y and a positive correlation with X_1. The negative suppressor, X_{2n}, has a positive correlation with both Y and X_1, while X_{2r}, the reciprocal suppressor, is negatively correlated with X_1 yet has a relatively high correlation with Y (r_{yx2r}=0.46). Notice that all three of the suppressor variables are correlated with X_1, the suppressed variable.

INSERT TABLE 2 ABOUT HERE

Finally, Table 3 shows the standardized regression coefficients (beta weights) of the three defined suppressor effects. Each of the beta weights for the suppressed variable

(X_1) is substantially increased by the inclusion of X_2 (β_2). Notice that each of these β_1 weights extend beyond the bounds set forth by the r_{yx1} limit. For example, the structure coefficient for Y and X_1 is 0.70. Thus, it would be expected that the beta weight for this variable would be between 0.00 and 0.70. However, including each of the suppressor variables increases the beta to well over 0.70 for each one. Finally, notice that the inclusion of the reciprocal suppressor increases not only β_1(0.94), but β_2 (0.75) as well.

INSERT TABLE 3 ABOUT HERE

Detection of Suppressor Data

Because researchers are in a perpetual search for substantive relationships between variables, they usually try to use predictors that they believe will be highly correlated with the predictor. For this reason, suppressor variables are usually not consciously sought out to be included in a regression equation. Fortunately, suppressor variables can be incorporated into a study unbeknownst to the researcher. In these situations, even variables that would not be considered theoretically reasonable as direct predictors are possibilities for suppressor effects.

Another complication in detecting suppressor variables is that they may simply be overlooked because of their low zero-order correlations (Velicer, 1978). The definitions above pay particular attention to two indicators of a suppressor effect: beta weights *and* correlations between the predictors. However, many researchers neglect either one or the other. Thompson (1992) and Thompson and Borrello (1985) point out that researchers who interpret only beta weights seriously risk neglecting information about critical relationships between the variables. Thompson (1992) suggested that, "Interpreting only beta weights is not sufficient, except in the one variable case, since then r = beta and (the structure coefficient) = 1.0 (unless R=0.0)" (p. 16).

The emphasis here is that interpretation of either beta weights alone or correlation coefficients alone may lead to major oversights in data analysis. Thompson (1992, p. 14) says it best by stating 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 predictors with Y."

One final problem in detecting suppressor variables is the type of statistical analysis employed. The only analysis that has been discussed to this point is that of linear regression where the predictors are inter-correlated. Knowledgeable researchers understand that all least squares analyses are in fact forms of the General Linear Model and that methodology dynamics illustrated for one heuristic example generalize to other related cases (Thompson, 1998). For example, Cohen (1968) demonstrated that multiple regression subsumes all univariate parametric methods as special cases and that a univariate general linear model can be used for all univariate analyses. Ten years later, Knapp (1978) demonstrated that canonical correlation analysis subsumes all parametric analyses, both univariate and multivariate, as special cases. Thus, it is not surprising that there is the possibility to obtain a suppressor effect in other forms of analysis.

Limitations of Suppressor Effects

It is always a pleasant surprise to discover the addition of a suppressor effect in one's data analysis. It may also be surprising to recognize the limited increase in validity due to the inclusion of the suppressor variable. Conger and Jackson (1972) warned that researchers should not expect to find suppressor-predictor r's to be much larger than the criterion-predictor r.

INSERT TABLE 2 ABOUT HERE

Table 4 shows the incremental increase of validity due to the inclusion of a classical suppressor variable. For example, using Table 4 as a guide, suppose a researcher is using worker satisfaction (Y) as the criterion variable and job salary (X1) and skill level (X2) as the predictor variables. The correlation for Y and X1 is r=.40 and Y and X2 is r=0. Let's also say that X2 is a suppressor variable because it increases the validity of the equation even though there is a zero correlation between Y and X2. Now, in order for skill level, our suppressor variable, to increase the validity of the equation from .40 to .50 (an increase of .10), the relationship between X1 and X2 must be .60. Conceptually, this would not be difficult due to the obvious relationship between job salary and skill level. However, this is typically not the case. Most suppressor-predictor relationships do not exceed r=.40. On top of that, the improvement is not linearly related to the suppressor-predictor correlation (Conger & Jackson, 1972). It is instead curvilenear, suggesting that the increment in improvement is considerably less for lower correlations than for larger ones.

Conger and Jackson(1972) demonstrated that much more effort would be spent seeking exceptional suppressor-predictor correlations when that same effort could be spent seeking a new predictor with a low to moderate correlation with the criterion, thereby obtaining the same result. In light of the already difficult time predicting what variables will act as suppressors, and especially as reciprocal suppressors, it seems that suppressor variables should remain what they typically are: a pleasant surprise. When such surprises do occur, however unexpected they may be, it is important for researchers to recognize these effects. It is especially important that researchers do not naively discard predictors with unexpected near-zero correlations with the criterion variable, in cases when such predictors actually improve prediction via suppression effects.

Bibliography

Cohen, J. & Cohen, P. (1975). Applied multiple regression/correlation analysis for the behavioral sciences. New York, NY: Wiley.

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

Conger, A. J. & Jackson, D. N. (1972). Suppressor variables, prediction, and the interpretation of psychological relationships. Educational and Psychological Measurement, 32, 579-599.

Darlington, R. B. (1968). Multiple regression in psychological research and practice. Psychological Bulletin, 69, 161-182.

Henard, D.H. (1998, January). Suppressor variable effects: Toward understanding an elusive data dynamic. Paper presented at the annual meeting of the Southwest Educational Research Association, Houston. (ERIC Document Reproduction Service No. ED 416 215)

Horst, P. (1941). The prediction of personnel adjustment. Social Science Research and Council Bulletin, 48, 431-436.

Horst, P. (1966). Psychological measurement and prediction. Belmont, CA: Wadsworth.

Lord, F. M. & Novick, M. R. (1974). Statistical theories of mental test scores. Reading, MA: Addison-Wesley.

Lutz, J. G. (1983). A method for constructing data which illustrate three types of suppressor variables. Educational and Psychological Measurement, 43, 373-377.

McNemar, J. (1945). The mode of operation of suppressant variables. American Journal of Psychology, 58, 554-555.

Thompson, B. (1992, April). Interpreting regression results: beta weights and structure coefficients are both important. Paper presented at the annyal meeting of the American Educational Research Association, San Francisco. (ERIC Document Reproduction Service No. ED 344 897)

Thompson, B. (1998, April). Five methodology errors in educational research: The pantheon of statistical significance and other faux pas. Paper presented at the annual meeting of the American Educational Research Association, San Diego. (ERIC Document Reproduction Service No. ED forthcoming)

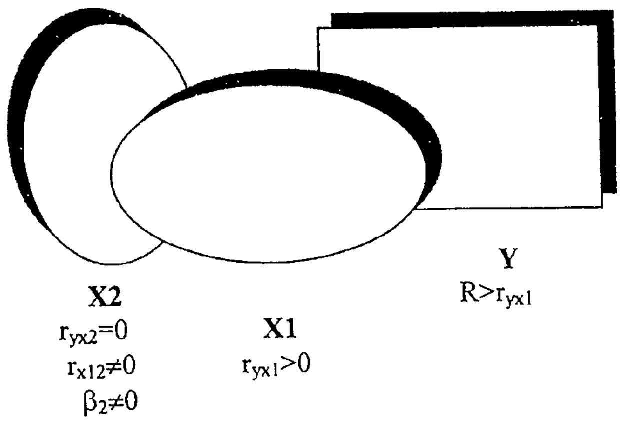
Thompson, B. & Borrello, G. M. (1985). The importance of structure coefficients in regression research. Educational and Psychological Measurement, 45, 203-209.

Velicer, W. F. (1978). Suppressor variables and the semipartial correlation coefficient. Educational and Psychological Measurement, 38, 953-958.

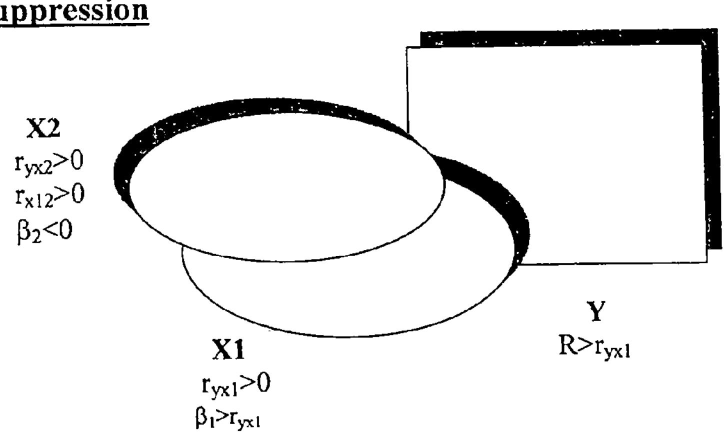
Figure 1

Venn Diagrams Depicting Three Definitions of Suppressor Effects

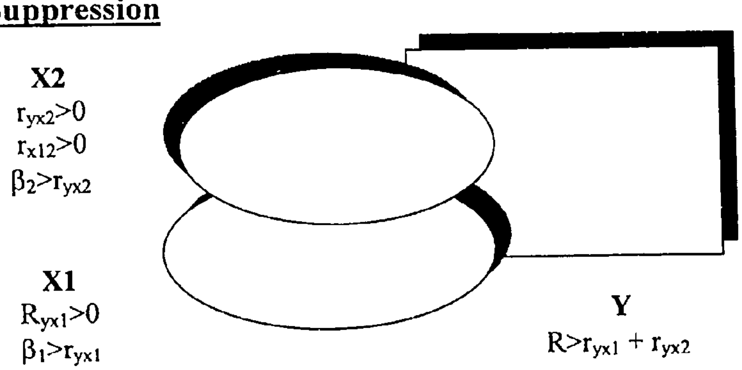
Classical Suppression



Negative Suppression



Reciprocal Suppression



Note. The Venn diagram alone cannot be used to evaluate suppression effects. For example, in the classical suppression diagram, X2 is a suppressor if the coefficients are as presented. However, some such X2 variables corresponding with the diagram might have β weights equal to zero, and the X2 variables would not be considered suppressors.

Table 1
Data Set

Case	Y	X_1	X_{2c}	X_{2n}	X_{2r}
1	-1.50	-0.30	0.90	0.20	-0.30
2	-1.00	-0.80	-0.60	-0.30	0.00
3	-0.50	-0.90	-1.40	-0.60	0.20
4	0.00	-0.30	-0.60	-0.20	0.10
5	0.00	0.30	0.60	0.20	-0.10
6	0.50	0.90	1.40	0.60	-0.20
7	1.00	0.80	0.60	0.30	0.00
8	1.50	0.30	-0.90	-0.20	0.30

Table 2

Correlation Coefficients for Suppressor Variables

	Y	X_1	X_{2c}	X_{2n}	X_{2r}
Y	--	0.70	0.00	0.23	0.46
X_1		--	0.70	0.85	-0.31
X_{2c}	0.00	--	--	--	--
X_{2n}	0.23	--	--	--	--
X_{2r}	0.46	--	--	--	--

Note. Structure coefficients are in the lower left diagonal and bivariate correlations are in the upper right diagonal. Only those coefficients relevant for the discussion of suppressor effects are shown. For all three structure coefficients, Multiple $R > 0.99$.

Table 3

Regression Beta (β) Weights

Suppression Type	β_1	β_2
Classical (X_{2c})	1.40	-1.00
Negative (X_{2n})	1.87	-1.37
Reciprocal (X_{2r})	0.94	0.75

Table 4

Incremental Magnitude Due to Classical Suppression

	Predictor-Criterion Correlation												
	.10	.20	.30	.40	.50	.60	.71	.80	.87	.92	.95	.98	.995
.10	.000	.001	.002	.002	.003	.003	.004	.004	.004	.005	.005	.005	.005
.20	.002	.004	.006	.008	.010	.012	.014	.016	.017	.018	.019	.020	
.30	.005	.010	.015	.021	.026	.031	.037	.042	.045	.048	.050		
.40	.009	.017	.026	.035	.044	.052	.062	.070	.076	.080			
.50	.015	.030	.045	.060	.075	.090	.107	.120	.130				
.60	.025	.050	.075	.100	.125	.150	.175	.200					
.71	.041	.082	.122	.163	.204	.245	.290						
.80	.067	.133	.200	.267	.333	.400							
.87	.100	.200	.300	.400	.500								
.92	.150	.300	.450	.600									
.95	.233	.467	.700										
.98	.400	.800											
.995	.900												

Note. Adapted from Conger and Jackson (1972).