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The Interpretation of the Beta Weights in Path Analysis

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Path analysis is a method for determining "the direct and indirect effects of variables taken as causes of variables taken as effects" (Pedhazur, 1982, p. 580). Researchers who use path analysis attempt to arrive at models, often called causal models, showing the relationships between exogenous variables, those with variability explained by causes outside the model, and endogenous variables, those whose variability is explained by some constellation of exogenous and/or other endogenous variables in the model. Regosa (1987) calls path analysis "simple multiple regression with pictures" (p. 186).

Causality

It is worthy of note that there is a heated debate concerning what actually constitutes causality. The consensus is that three criteria must be met:

1) a temporal sequence of variables (X precedes Y),
2) an association or relatedness among variables ($r_{xy}>0$), and
3) control ($X \rightarrow Y$).

While some authors (Biddle & Marlin, 1987; Kenny, 1979) believe that causal relationships can be established with regression and other related techniques, others believe such conclusions are unwarranted (Freedman, 1987; Regosa, 1987) and are the result of faulty logic (Games, 1990). To underscore the fervor researchers exhibit on this issue, Ling (1982) in a review of a book entitled Correlation and Causation (Kenney, 1979) writes, "the serious limitations of this book lie not in its lack of mathematical rigor, but in its faulty logic as well as its faulty presentation and interpretation of certain statistical methodology.... I feel obligated to register my strongest protest against the type of malpractice fostered and promoted by the title and content of this book" (p. 491).

Despite the often repeated admonition that correlation does not imply causation (Games, 1990; Pedhazur, 1982), the literature is filled with examples of interpretations and conclusions erroneously made more broadly than was appropriate. As Hayduk (1987) noted, "causation may not be in the real world or in the equations, but it is definitely in our thinking" (p. XV).

Control

As a criterion in the definition of causality, control means that variation in Y is the direct result of X. Biddle and Marlin (1987) say that it is possible to control statistically for possible confounding effects of variables using partial correlations. Games (1990), on the other hand, believes that random assignment of subjects to groups provides control. He emphasizes that, "the experiment provides control; the correlation study does not" (p. 244). Pedhazur (1982) agrees with Games saying, "one of the most powerful methods of control is randomization. Being in a position to manipulate and randomize, the experimenter may feel reasonably confident in making statements about the kinds of action that need to be taken in order to produce desired changes in the dependent variables" (p. 578).

Thus, there is a distinction drawn between experimental research and correlational research. In the former the independent variables can be manipulated so that instead of simply observing what occurs, researchers can effect change. In correlational research, this is not the case. This distinction has important implications for policy makers. While there are numerous examples of the mistaken belief that manipulating independent variables in correlational studies will change outcomes, the classic example is the Coleman Report. On the basis of correlational information the Coleman Report concluded that "if a minority pupil from a home without much educational strength is put with schoolmates with strong educational backgrounds, his achievement is likely to increase" (Coleman, Campbell, Hobson, McPartland, Mood, Weinfeld & York, 1966, p. 22). Many large scale busing programs were initiated on the basis of the Coleman Report, but increases in minority students' achievement never materialized.

Further, the widespread belief that a model is "'confirmed' if the correlations in the matrix correspond to those we would have predicted from our model" (Biddle & Marlin, 1987, p. 5) does not mean that there is proof for that model. "Consistency of the model with the data, however, does not constitute proof of a theory; at best it only lends support to it" (Pedhazur, 1982, p. 579).

Path Analysis

Numerous authors (Cliff, 1983; Freedman, 1987; Mulaik, 1987; Regosa, 1987) complain that path analytic techniques are often misused and that this misuse is fostered by the availability of computer programs. To further complicate the issue and to underscore why causal modeling is unlikely to determine actual causes, it is possible that "very different causal structures may fit the same set of data equally well" (Stelzl, 1986, p. 309).

Misuse of a technique, however, does not mean that the technique is inappropriate, invalid or incorrect. Mulaik (1987), who states that "the rule of a causal connection is that of functional relation" (p. 23), also argues that the "concept of causality may be modified to have causes determine not specific outcomes but the probabilities of outcomes" (p. 18).

Assumptions

In path analysis, the variables are generally expressed as standard scores, and the equation for an endogenous variable is formed by weighting each endogenous and exogenous variable presumed to have a causal effect and summing all these terms plus error. These weights are the path coefficients, and these equations are regression equations. A path analysis arrives at one or more regression equations. In addition, certain assumptions are made when performing such an analysis. A potent criticism of the use of path analysis, however, is that the assumptions required for this technique are frequently not met (Freedman, 1987). Pedhazur (1982) lists the assumptions for nonrecursive models as follows:

1. The relationships among the variables in the model, are linear, additive, and causal.

2. Each residual is not correlated with the variables that precede it in the model.

3. There is a one-way causal flow in the system. That is, reciprocal causation between variables is ruled out.

4. The variables are measured in an interval scale.

5. The variables are measured without error. (p. 582)

Under these assumptions, the path coefficients are the ordinary least squares, regression coefficients. The assumptions have been stated by other authors (Biddle & Marlin, 1987; Freedman, 1987), who also note that newer techniques such as LISREL have all the assumptions of regression plus additional assumptions. These assumptions are seldom tested and would rarely hold if they were tested.

Interpretation of Weights

Another criticism of path analysis is that the weights are not interpreted correctly. Despite the innovations and increasing sophistication of path analysis, including the use of LISREL and hierarchical modeling with their additional assumptions, path analyses generally use regression models for which beta weights are reported. Beta weights as scale-free indices reflecting the increase or decrease in the dependent variable with a unit increase in the independent variable allow for comparisons across variables of different metrics. The magnitude of the beta is a function of the correlation between the independent and dependent variable, the model's variance covariance matrix, and the error term which includes the variances of variables not included in the model. For these reasons, beta weights are highly unstable from sample to sample (Freedman, 1987; Pedhazur, 1982). All the caveats regarding the interpretation of beta weights that apply to multiple regression also apply to path analysis. Problems that arise in explaining phenomena with regression are specification errors, measurement errors and multicollinearity. Consequently these affect the regression weights.

Unfortunately, many researchers believe betas can be interpreted like correlation coefficients. This error is common in published path analyses as well as regression analyses. Although in some cases the magnitude of the beta weights can give an indication of the importance of the variables in the model, the ever present danger of specification errors should lead researchers to be tentative in their interpretations of these weights. When there is high multicolinearity between independent variables in the model, statements about the importance of any one variable based on betas may be very misleading. When choosing variables to be included in or deleted from a path analysis model, theory especially and probably cost, must be considered along with beta weights.

Although, unstandardized regression coefficients depend on the metric of the variable, they tend to be quite stable from sample to sample. Therefore, their use for prediction purposes or making policy decisions is appropriate. However, the variable may not have been reliably measured or may be interval level, and the weights give no information on the relative importance of the variables in the model.

It has been argued that "when the theoretical model refers to one's standing on a variable, not in an absolute sense but relative to others in the group to which one belongs, standardized coefficients are the appropriate indices of the effects of the variables in the model" (Pedhazur, 1982, p. 249). On the other hand, due to their stability across samples, many authors believe "that the unstandardized coefficients come closest to statements of scientific laws" (p. 249).

It is quite possible, if not probable, to reach very different conclusions about the importance of different variables in regression model depending on whether one interprets standardized or unstandardized regression coefficients. Therefore, regression weights should be tested, and both standardized and unstandardized regression coefficients should be reported in all regression analyses. This applies to path analysis as well as to regression analysis.

Conclusions

Scientific laws are statements of cause and effect relationships among variables. If path analysis is to establish causality, a feat which numerous authors view as impossible (Freedman, 1987; Regosa, 1987), then even its appropriate use of beta weights alone will not accomplish that goal. In good path analysis, as in good regression, the following recommendations should be adhered to. First and foremost, a path analysis should be based on sound theory. It is not an exploratory data analysis technique. Second, despite the cost involved, large samples are desired. Third, tests of the assumptions should be conducted.

Fourth, both standardized and unstandardized regression coefficients and a test of those coefficients should be reported. Fifth, replication and cross validation are needed to confirm original conclusions. Finally, regression and path analyses are correlational techniques, and the results of these analyses should not be reported in the "as-if-by-experiment" mode (Freedman, 1987, p. 108).

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