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Methodology Transfer Paper 1

Causal Analysis: A Method To Identify And Test Cause And Effect Relationships In Program Evaluations

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PREFACE

This is one of a series of methodology transfer papers developed by the Institute for Program Evaluation. The purpose of a methodology transfer paper is to provide GAO evaluators with a clear and comprehensive background of the basic concepts of an evaluation methodology. Additionally, general and specific applications and procedures for using the evaluation methodology are provided.

The paper defines and describes an evaluation method--causal analysis. Causal analysis is not a panacea for evaluating programs. Like all evaluation techniques, it has advantages and limitations. Causal analysis is offered, however, as one way to improve the quality of some GAO evaluations.

TO THE READER

This paper is designed to be self-instructional. Through reading it, you should be able to gain (1) an understanding of the basic concepts and techniques for using causal analysis and (2) the ability to recognize appropriate circumstances in a job for using these techniques. The body of the paper contains, for the most part, non-technical information. Appendix I is a glossary of technical terms. Appendix II and appendix III should be valuable to anyone who plans to make or wishes to understand the statistical calculations used in causal analysis. Appendix II provides step-by-step instructions for using the statistical technique of path analysis. Appendix III presents an example of applying causal analysis to the evaluation of prison parole outcomes.

Fortunately, an evaluator has several resources available at GAO to help with any statistical analysis. The Specialized Skills/Technical Assistance Group in the Institute for Program Evaluation can provide direct support to an evaluator. Additionally, the evaluator has access, through any GAO computer terminal, to statistical packages--such as SPSS (Statistical Package for the Social Sciences)--that perform the statistical computations.

We would appreciate comments on the job-related usefulness of this paper. A brief questionnaire is provided for this purpose on a tear-out sheet on the last page.

OVERVIEW

Causal analysis helps an evaluator identify what affects program results and to what extent. Causal analysis helps answer questions such as: What combination of program procedures, components, resources, and constraints causes a particular result? To what extent do economic, social, and political factors affect a program?

Causal analysis is a two-phase process. The first phase--causal modeling--can be used to describe assumed cause and effect relationships between program outcome(s) and certain key factors and activities from within and outside the program. The second phase--path analysis--is used to analyze statistically the assumed causal relations. This second phase may be infeasible because of data or other restrictions. Nevertheless, causal modeling alone enables evaluators to develop a systematic understanding of assumed cause/effect relationships.

This paper describes and illustrates applying causal analysis in program evaluation. It presents a framework for modeling cause and effect relationships, instructions for testing a model's adequacy and for estimating the relative strength of direct and indirect influences, and examples of using the technique.

Chapter 1 discusses the concept of causality and its relevance to program evaluators. It specifies three conditions that should be analyzed before inferring that a causal relationship exists between two phenomena.

Chapter 2 presents an approach for constructing causal models for program evaluation. This approach requires evaluators to:

--establish the evaluation's scope and focus by specifying a finite set of variables,

--make assumptions about the selected variables' causal interrelatedness and about the effects of known variables that are omitted, and

--test the model's adequacy by determining whether it is consistent with data.

Path analysis, described in chapter 3, is a statistical technique that can be used to test a causal model's adequacy based on predetermined criteria. This technique requires constructing a "path diagram" of the major variables and their relationships, calculating the magnitude of the assumed causal associations, analyzing and revising the assumptions, and interpreting the final path diagram. This chapter defines path analysis and discusses data requirements and potential applications in program evaluation.

Chapter 4 discusses potential applications of causal analysis in program evaluation. It examines three general evaluation situations in which the technique can be applied:

--to find out if an observed effect was really due to a program or activity,

--to identify a program's effects, or

--to understand why a program had a consequence
other than what was expected.

Examples and a few variations of these situations are presented to show how causal models could be specified and how path analysis may be used. Finally, some of the limitations of causal analysis are discussed.

Many people contributed to this document via the review process. In particular, we benefited from peer reviews by fourteen staff from the Institute for Program Evaluation and from outside reviews by Hubert Blalock (University of Washington), Saul Gass (University of Maryland), Larry Gordon (University of Maryland), and Michael Scriven (University of San Francisco). We gratefully acknowledge their assistance.

The document was developed in the Methodology Development and Data Assistance Group, under Keith E. Marvin, Associate Director; by Bruce W. Thompson, Group Director; and by Larry Hodges, Team Leader, assisted by Teresa Spisak, Sandra Thibault, and Patrick Dynes. The project also involved the efforts of members of our technical assistance group: Wayne Dow and Steve Langley.

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Director, Institute
for Program Evaluation

Contents

CHAPTER 1

INTRODUCTION

This paper is for anyone who studies cause and effect relations. It describes and illustrates an approach for explaining any phenomenon (effect) as the result of another phenomenon (cause). The paper contains:

--an overview of causal analysis in evaluating programs,

--an approach for modeling presumed cause and effect relations,

--a procedure, path analysis, for testing the adequacy of the model, and

--examples of applying causal modeling and path analysis.

WHAT IS CAUSALITY?

Causality applies whenever one phenomenon appears to imply the occurrence of another. Scriven defines causation as the relation between mosquitos and mosquito bites. The concept is easily understood, although it has never been satisfactorily defined. 1/

Several authors 2/ have specified conditions that should be met to infer the existence of a causal relationship between two phenomena or variables. Generally, a causal relationship can be inferred by analyzing:

1. how the phenomena are ordered in time,

2. whether they are related or associated, and

3. whether the relationship is due to chance or other factors.

In the first condition, one phenomenon may precede the other or the two may occur simultaneously. For example, striking a bell, X, is followed by ringing of the bell, Y. Furthermore, if X causes Y, it does not follow that a change in Y produces a change in X. Thus, a change in rainfall may produce a change in wheat yields, but a change in wheat yields does not produce a change in rainfall. 3/

1/Scriven [8], p. 19.

2/See, for example, Ackoff [1], p. 16 and Asher [2], p. 11.

3/Blalock [3], p. 10.

Additionally, two phenomena may occur simultaneously and still be causally related. 1/ For example, one could study the effect that a student's intelligence quotient (IQ) has on college grade point average (GPA).

Time sequence can indicate a causal relationship among discrete phenomena, such as striking a bell being followed by ringing of the bell. However, many phenomena such as population growth and attitude changes vary continuously. A causal relationship among continuous phenomena may be inferred by analyzing whether they are related or associated.

For the second condition, therefore, an evaluator looks for a concomitant variation or covariation between X and Y: whether changes in one phenomenon are accompanied by changes in the other. For example, correlation analysis might show for some general population that the higher a student's IQ, the higher the GPA, and, conversely, the lower the IQ, the lower the GPA. In this example, IQ may be considered a "weak" cause since many other variables affect GPA. Some of these variables may even act to obscure the association between IQ and GPA.

Finally, the third condition requires an evaluator to demonstrate that the relationship of the phenomena is not due to chance. This exemplifies the well-known slogan that "correlation is no proof of causation." Thus, "spurious correlation"--a relationship between two variables that are not causally interrelated, although they may at first appear to be--must be considered.

Ackoff 2/ gives a good illustration of spurious correlation. He cites the discovery that people who live in neighborhoods having heavy soot-fall are more likely to contract tuberculosis than people who live in neighborhoods having less soot-fall. Based on this correlation, one researcher concluded that soot-fall produced tuberculosis. Subsequent research, however, showed that dietary deficiencies produce tuberculosis. Further, dietary deficiencies are likely to occur most frequently among low-income groups. Low-income groups are likely to live in low-rent districts. Districts have low rent, among other things, because of heavy soot-fall. Thus, soot-fall and tuberculosis are accidentally, not causally related.

Causality has been defined in many ways and has been the subject of considerable philosophical discussion. Some philosophers have objected to causal thinking because: "(1) causality can never be verified empirically and (2) the notion of cause and effect is far too simple to describe reality, with causal

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1/Hicks [5], pp. 21-25.

2/Ackoff [1], p. 18.

laws being much more a property of the observer than of the real world itself." 1/ Nevertheless, others believe the mere questioning of "why" an event occurred implies causality. In addition, as Cooley points out, "most of what is known about people and the universe has not been based on experimentation, but on observation." 2/ Cooley's philosophy is that to understand a process in a way that will allow improvements, attention must be given to "developing methods for conducting explanatory observational studies." Causation in this sense is an important topic to evaluators.

CAUSAL THINKING AND PROGRAM EVALUATION

Generally, evaluators attempt to answer two types of questions. One is descriptive. The evaluator seeks to answer questions such as "What is?" or "How many?" For example, How many clients were seen? What percent of the potential work force is unemployed? How many accidents have occurred in the workplace? The other type of question is explanatory. The evaluator asks not what happened, but why it happened. As Hicks 3/ explains "That is causation...exhibiting the story, so far as we can, as a logical process."

Thus, causal thinking is an integral part of program evaluation. GAO evaluators, for example, focus on cause and effect relationships in developing "findings" and when recommending program improvements. 4/ When one knows why something happened--the cause--one can more readily determine how to prevent (or facilitate) its recurrence. Consequently, the following process is part of all GAO work:

--Identify any deficiency by measuring the condition observed against acceptable criteria or norms.

--Determine the effects or significance of the deficiency.

--Ascertain the causes of the deficiency.

Causal thinking--concluding that X causes Y--has at least two important uses 5/ for consumers of evaluative information.

1/Blalock and Blalock [4], p. 161.

2/Jöreskog and Sörbom [6], p. xvi.

3/Hicks [5], p. ix.

4/U.S. GAO [10], p. 10-12.

5/Nagel and Neef [7], pp. 182-183.

First, a manager can minimize undesirable effects or enhance desirable effects of changes. For example, by knowing that increased pretrial release will decrease guilty pleas and subsequently increase the number of trials, a prosecutor can plan how to offset these costly effects through other activities that influence trial rates. A second use is when it is possible to change X to have Y change in a certain direction. For example, if improving interracial equality of opportunity is preceded by and covaries or relates directly with minority voter registration, efforts to increase minority voter registration should improve racial equality of opportunity.

Establishing that X may cause Y can be difficult. Few events have single causes as implied in the brief examples above. Furthermore, each event has multiple effects. According to Suchman 1/ this concept suggests:

1. evaluating programs within the context of other programs or events which may also affect the desired objective;

2. identifying the factors which influence the initiated program activity and the intervening events that may include effects other than the desired one; and

3. examining the desired effects' own consequences, both short and long-term, desirable and undesirable.

Since complete explanation will never be possible because of many intervening variables, a pragmatic concept of causality needs to be adopted. This requires, first, making reasonable simplifying assumptions and developing models in which causality is only indirectly tested. Second, the model's adequacy can be directly tested by using "path analysis," a statistical technique that allows inadequate models, which are not consistent with the data, to be identified. This two-phase process is referred to in this paper as "causal analysis."

1/Suchman [9], pp. 84-85.

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CHAPTER 2

CONSTRUCTING CAUSAL MODELS

FOR PROGRAM EVALUATION

This chapter presents an approach for postulating cause and effect relationships for evaluating programs. The approach requires formulating cause and effect "theories," which are essentially models of cause and effect sequences within the context of a program.

Causality for evaluative research attempts to explain successive events by formulating a set of assumed relationships, which are then tested for validity or spuriousness. Thus, establishing a model of causal association between variables in a time sequence involves three distinct activities:

1. selecting a finite set of variables,

2. making assumptions about causal interrelations among the variables and the effects of omitted variables, and

3. testing the model's adequacy.

These activities are not discrete stages. In general, all activities go on simultaneously, are interactive, and are completed together. The model, however, is frequently developed in a discrete order.

SELECTING VARIABLES TO STUDY

Usually many variables would be interesting to study during an evaluation. Selecting from among these variables often depends on how well they can be measured, the cost of collecting data, and the evaluator's prior knowledge of the subject. Most evaluations, however, have limited resources, and, as Weiss 1/ says: it may be "more productive to focus on a few relevant variables than to go on a wide-ranging fishing expedition." Nonetheless, one needs to be careful not to rationalize omitting variables according to one's disciplinary biases, ideological biases, or premature pragmatic considerations of research design. How can evaluators balance these factors to determine the most relevant and feasible variables?

Randers 2/ suggests establishing a "reference mode" and some "basic mechanisms" to guide the modeling effort and limit

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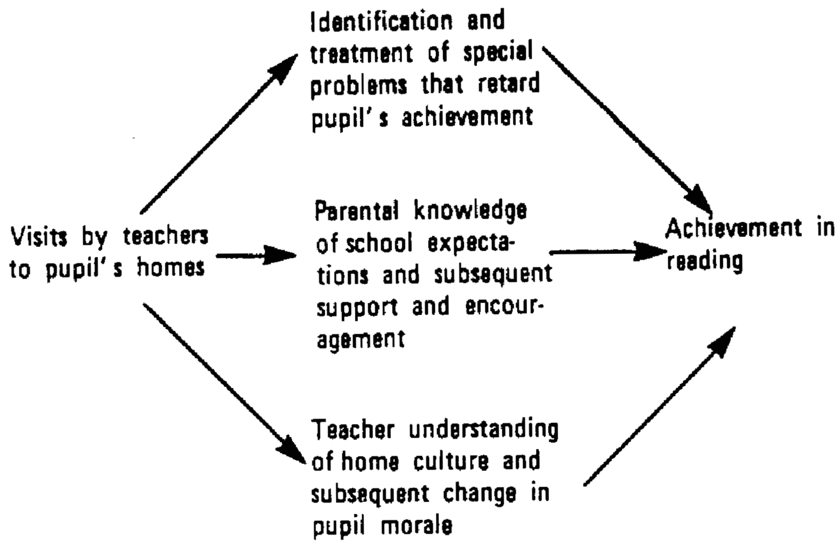
1/Weiss [5], p. 47.

2/Randers [3], pp. 247-248.

the variables. First, identify the on-going process during a particular time period (the reference mode) and focus the evaluation on this process. For example, the "reference mode" could be a change in student reading abilities after beginning a program of home visits by teachers. Second, describe the behavior of certain key variables (the basic mechanisms of the process) and diagram them, as depicted in figure 2.1.

Figure 2.1 Basic Mechanisms of a Home Visit Program



Source: Adapted from Weiss [5], p. 50.

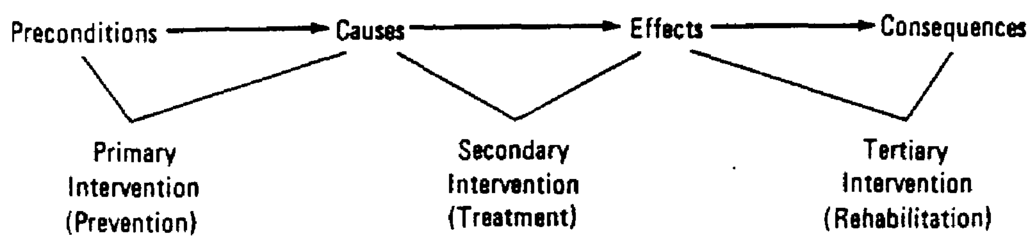
This section discusses points to consider when (1) establishing the evaluation's focus or reference mode and (2) specifying the relevant variables that are basic to the reference mode.

Establishing the Evaluation's Focus

An evaluation often begins with some statement of a "causal" relationship hypothesized between a program's activity and some effect, such as "reassigning police to locations known to have a high incidence of drunk drivers has decreased the number of accidents, deaths, and injuries resulting from drunken driving." The evaluator proceeds to verify the existence of the relationship. It may be sufficient to conclude the effort at this juncture if the evaluator needs only to know that the desired or undesired effect is more likely to occur in the presence of the program being evaluated than in its absence. However, there is likely to be a need to know how or why a program works (or does not work); where improvements in a program can be made (especially when it is not achieving the expected results); or whether program activities are more effective under certain conditions, such as with particular kinds of clients. To gain this information, the evaluator looks for "causal connections" and determines how the program intervenes with and possibly alters the causal chain.

Many programs may be viewed as interventions which attempt to prevent certain undesirable effects or encourage desirable ones. In this sense, programs are established to intervene in a chain of events. Within this chain, Suchman 1/ describes three major cause and effect subgroupings: (1) the relationship between the precondition and causal variables, (2) the relationship between the cause and effect variables, and (3) the relationship between the effect and the consequence variables as shown in figure 2.2.

Figure 2.2 Suchman's Model of Intervening Variable Analysis



Source: Suchman [4], p. 173.

To illustrate, many educational programs emphasize secondary intervention, such as teaching and training programs aimed at decreasing the effects of ignorance or a lack of skill. Additionally, there is increasing emphasis upon both tertiary and primary intervention. Adult education and training programs, tertiary intervention, are designed to reduce the consequences of a lack of education, such as the inability to obtain a job. Preschool programs, emphasizing primary intervention, aim at environmental obstacles, such as lack of good nutrition, which may cause interference with educational achievements.

What the evaluator calls the independent (cause) or dependent (effect) variable is largely a matter of which segment of this causal chain is selected for study. The choice is influenced by the purpose of the study, particularly by considering the study's intended users. In this regard, there are at least three situations in which the question of a causal connection

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1/Suchman [4], p. 173.

between an activity X and an event Y could arise:

1. Activity X occurred and then event Y occurred. Did X cause Y? How? Why?

2. Activity X occurred. What resulted? Did event Y result?

3. Activity X caused event Y. What are the consequences?

The first situation is part of a classic evaluative activity in which the evaluator tries to answer the question "How do we know that the effect was really due to the program or activity?" For example, returning to the police assignment example cited above, how does an evaluator know that the decrease in accidents, etc., was due to reassigning police and was not the result of some other factor? Perhaps, a sudden increase in the price of fuel or a major plant closing reduced the number of drivers on the road, thereby decreasing the probability of an accident. Consequently, the evaluator tries to establish that a relationship exists between the program activity and an observed result and also looks for other factors outside the program that may have influenced the result.

The second situation exists when an evaluator is asked to find a program's effects. This is a "program results" review where the evaluator identifies what the program is causing. For example, the Agriculture Department's Farmers Home Administration provides credit to rural Americans who are unable to obtain credit from other sources at reasonable rates and terms. The evaluator may attempt to find the number of eligible individuals who received credit. This information helps establish a level of program effectiveness and possibly identify areas for improved program performance.

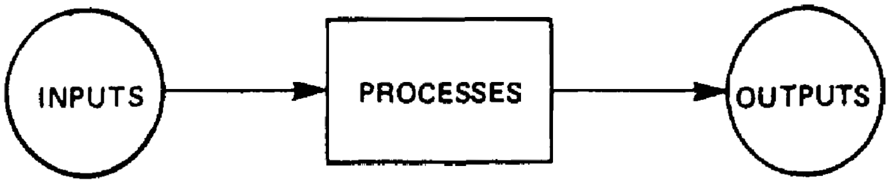
In the third situation, it is presumed that the program or activity has had an unexpected impact. For example, driver education programs are found to improve driving skills, but they lead to teenagers driving at an earlier age, thereby increasing the number of accidents. In this case, an evaluator must take into account the interrelationships between program efforts and the system in which people function. Therefore, not only the program effects, but, also the consequences of those effects must be analyzed.

In summary, defining the situation establishes the evaluation's scope, dictates the time frame, and indicates which variables and relationships to evaluate.

Specifying the Important Variables

Some thought and research is necessary prior to deciding on which variables to include in the causal analysis. The general systems model, figure 2.3, is a good technique for focusing on the important variables. This model concentrates on three types of variables: inputs, processes, and outputs.

Figure 2.3 The General Systems Model



Program inputs may include factors from within the program that can be administratively controlled (internal factors), as well as factors that may impinge on program activities and that are outside the control of program administrators (external factors). The processes include program activities: formal and planned functions, and informal and unplanned functions. The outputs may be unitary or multiple, intended and unintended, positive and negative, and short-term and long-term (see figure 2.4).

Figure 2.4 Components of a Typical Program

Inputs

Internal Factors

- Budgeting
- Staffing
- Legal or regulatory requirements
- Clients
-
-

External Factors

- Political
- Economic
- Social
- Physical
-
-

Processes

Program Activities

- Formal and planned
- Informal and unplanned
-
-

Outputs

Program Results

- Unitary/multiple
- Intended/unintended
- Short-term/long-term
- Positive/negative
-
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After considering a wide range of possible variables, evaluators often select relevant variables on the basis of whatever data are available at the moment. According to Blalock 1/ the obvious starting point is a "careful reading of the literature, combined with a systematic listing of all important concepts or variables and theoretical propositions linking these variables." The following sources of information are also useful starting points for finding variables.

1. Program Personnel. Program personnel may be interviewed to learn whether anything about the program has changed or whether anything unusual has happened recently that might explain the program outcome. Frequently, the occurrence of some event that has been attributed to a program may be at least partially the result of some new development, such as a change in program funding or staffing, new legislation or regulatory requirements, or a change in the mix of program participants.

2. Progress Reports. An analysis of a program's performance trend may show that the effectiveness level is changing over time. Likewise, the analysis may indicate periodic deviations that can be related to changes in the program's operating environment. For example, weather conditions may affect participation in an outdoor recreational program.

3. Previous Evaluation Studies. Previous evaluation studies or audit reports may have already identified many relevant variables. These documents may be obtained from program personnel or from the group that conducted the study. If program evaluations or audits have been performed, the evaluation team should ascertain the status and examine the relevance of the prior findings. Parallels can be drawn reliably only by identifying the essential characteristics of the present outcome and seeking past program outcomes that contain the same features. Unfortunately, it is easy to conclude that a present situation is the same as one in the past when that is not the case, so extreme care should be exercised in observation, examination, and measurement.

4. Causes of Similar Effects From Elsewhere. Where relevant, looking at similar programs or outcomes may help to identify variables. For example, in studying the potential impact of

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1/Blalock [2], p. 28.

national health insurance legislation, it may be useful to examine the experiences of countries with similar programs. Such cases should be examined carefully, however. Similar programs may not be directly transferable, although some may point to unanticipated variables.

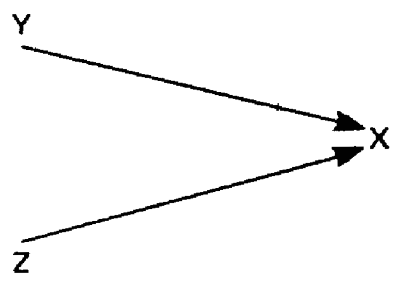
There are no foolproof procedures for deciding which variables to use; nor will the evaluator know for sure whether or not all the relevant variables have been located. Some advise 1/ emphasizing those aspects that are more or less manipulable, and if feasible, those that the evaluator may deliberately change for evaluation purposes. Often, however, nonmanipulable variables are also needed to explain thoroughly the effect. Additionally, limit the relevant variables to those that have immediate bearing upon the current program. One should not, however, prematurely close the search for variables. Modified and more complex models may later be introduced if data do not fit the initial model.

MAKING ASSUMPTIONS ABOUT CAUSAL RELATIONSHIPS

The next step is to identify the significant relationships among the possible causes and effect(s) being studied and construct arrow diagrams. This step occurs concurrently while selecting the relevant variables.

As variables and propositions are collected and consolidated, a useful procedure is to construct an arrow diagram of the major variables which also indicates the presumed links among them. Arrow diagrams (also called path diagrams and flow graphs) provide a bridge between verbal theories and algebraic or structural equations. With arrow diagrams, the causal model literally begins to take shape and the evaluator's assumptions become visible.

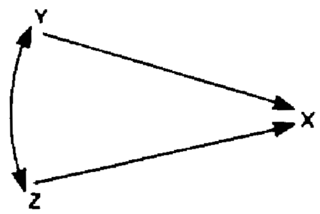
Constructing an arrow diagram involves graphically representing a cause and effect hypothesis by drawing arrows from variables assumed to be causes to variables assumed to be effects. For example, if X is caused by both Y and Z, which are independent of each other, the arrow diagram is:



1/See, for example, Suchman [4], p. 108 and Weiss [5], p. 47.

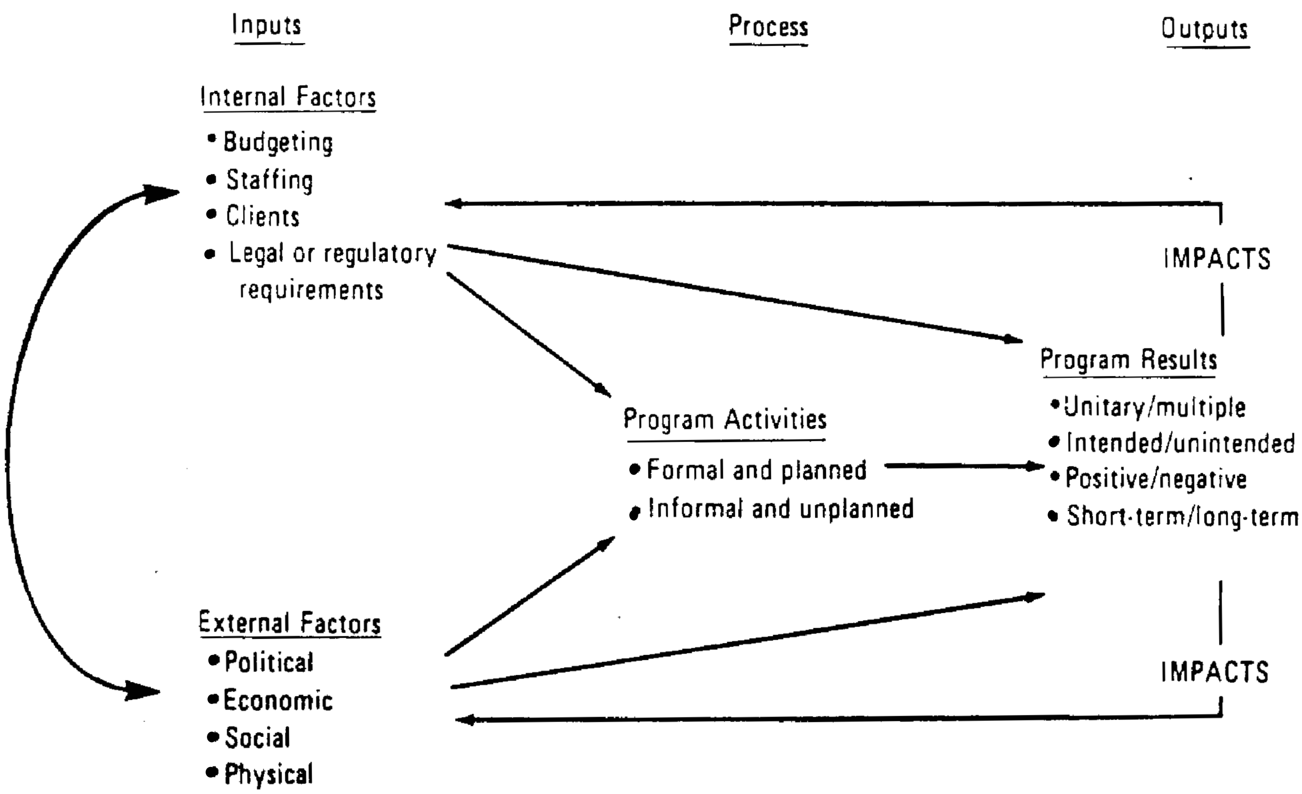
An arrow shows that one variable is thought to affect the other; the direction of the arrow shows the presumed direction of influence. Such diagrams are read from left to right.

Sometimes Y and Z are assumed to be influencing each other, but the specific direction is either unknown or inconsequential for the analysis. In this case, they are connected by a two-headed curved arrow.



In figure 2.5 the previously discussed program components are arranged in an arrow diagram to show their causal relationships. Using this model as a starting point, evaluators arrange their program variables in a similar causal order: the internal and external factors are assumed to be direct causes of program activities, which, in turn, are assumed direct causes of program results. Furthermore, the program results have future impacts on the original input factors at a later time. Impacts on internal factors are likely to be short-term (occurr'ng within a year or two). Impacts on external factors are likely to be long-term (occurring after 5-10 years). Evaluators need to be alert for these possible feedbacks.

Figure 2.5 Causal Relationships Within the Context of a Program

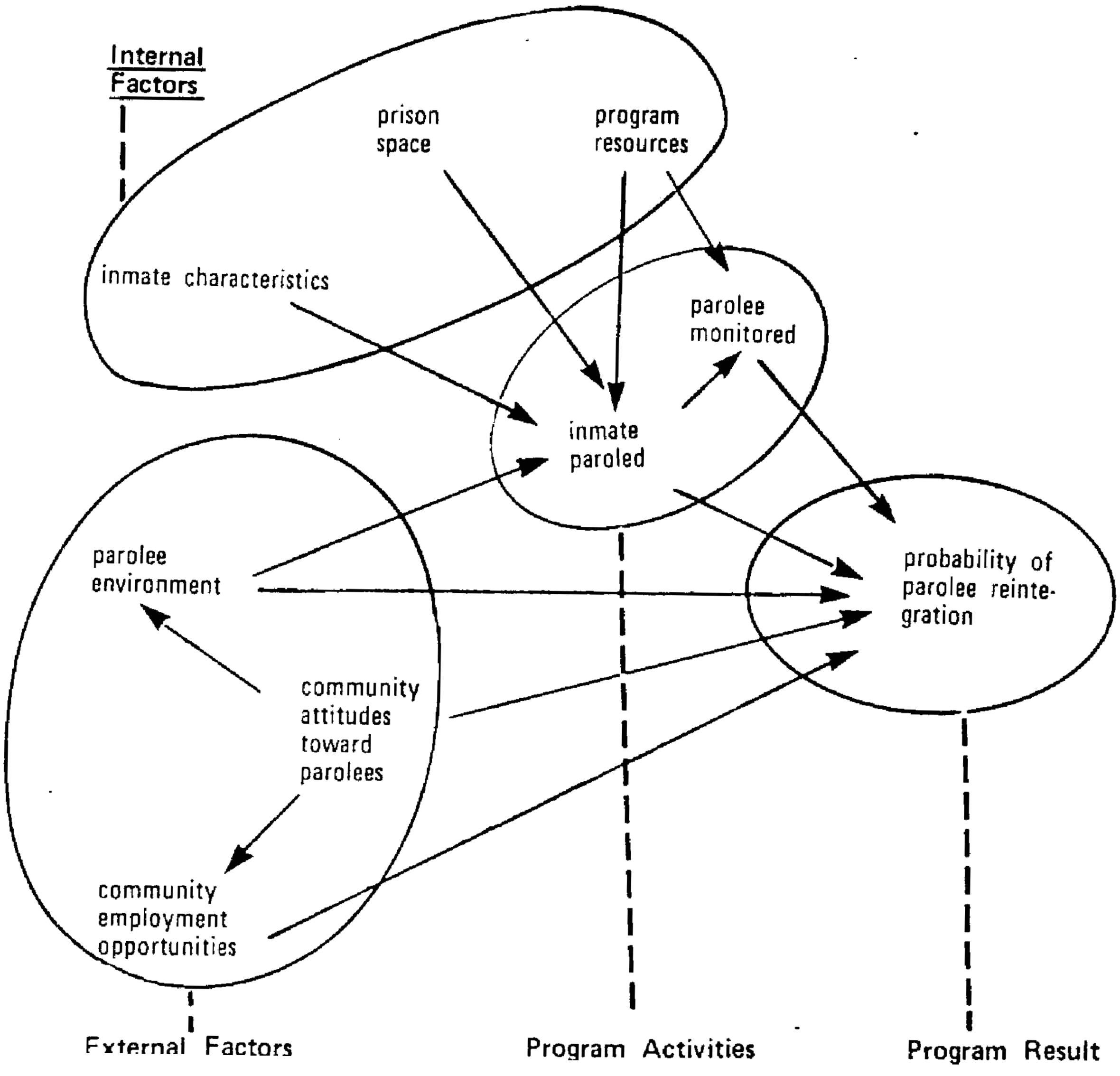


When diagramming causal relationships, include all reasonable direct paths. For example, an internal factor may have a direct effect on the program result in addition to an indirect effect through some program activity. Later, as the theory is tested and revised (using path analysis), certain links may be deleted.

Figure 2.6 is a causal model of a hypothetical prison parole program. Although incomplete, it depicts the key factors being considered and the assumptions being made. This figure shows what is being hypothesized: parolee reintegration into society may be influenced by community employment opportunities, the parolee's environment, community attitudes towards parolees, as well as the parolee monitoring program itself.

When each set of events or factors is measured, it is possible to see what works and what doesn't, for whom it works and for whom it doesn't. If the predicted sequence of events does not work out, further investigation is needed.

Figure 2.6 Model of a Hypothetical Prison Parole Process



In summary, an arrow diagram is a simple, systematic approach for conceptualizing causality. If properly used, it can furnish the evaluator with a logical way to consider the full range of variables that should be included in an explanation and to map out a presumed causal process.

TESTING A MODEL'S ADEQUACY

The "search for causes" now becomes largely one of testing hypothesized associations between the selected causes and effect(s). As stated in chapter 1, three conditions need to be examined before concluding that X causes Y:

1. how X and Y are ordered in time,

2. whether X and Y are related or associated, and

3. whether the relationship between X and Y is due to chance or to other factors.

In testing a causal model, these conditions must be scrutinized. The first two conditions may not be troublesome, but how can an evaluator know that all X's that affect Y directly or indirectly have been found? One never knows for sure. Thus, the third condition requires the evaluator to make certain simplifying assumptions and, in effect, admit that had another set of variables been selected and different assumptions made, the causal model might have looked quite different. According to Blalock:

> ... there is nothing absolute about any particular model, nor is it true that if two models make use of different variables, either one or the other must in some sense be "wrong." 1/

Consequently, causality cannot be demonstrated from any type of empirical information. Furthermore, establishing a statistical relationship (correlation) between two variables does not necessarily mean that one variable caused the other. Correlation is not causation. Nevertheless, accumulated correlation evidence can sometimes build a credible case for a causal relationship. Inferences concerning the inadequacy of causal models, if they are not consistent with the data, can be made, thereby requiring the analyst to modify the model. A technique called path analysis is a tool for doing this.

SUMMARY

This chapter presented a procedure for analyzing cause and effect situations which focuses on building a "causal model" of

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1/Blalock [1], p. 15.

an evaluator's cause and effect assumptions. The evaluator specifies a finite set of variables, makes assumptions about causal interrelatedness, and tests their adequacy. If the resultant model is inadequate, the evaluator modifies it until confidence is attained in the model.

The models of causality that evaluators build are assertions about the presence and the direction of some influence for relationships between pairs of variables. Even with supportive data, however, models cannot be "proved." Empirical evidence can disprove theories, but can never "prove" anything. There may be alternative models that would provide equally plausible or better interpretations of the available facts. For an evaluation's findings to be useful in policy making, it may be important to demonstrate that the most obvious alternative models are not supported better than the model in question.

Even though causal explanations can never be absolutely demonstrated empirically, they are thus still valuable. They force an evaluator to think about the complexity of a task and the difficulty of understanding the inner workings of programs. Most importantly, they help develop the habit of establishing a chain of logical assumptions. This can be of great use in pursuing the rational arguments which form the basis for evaluation. In fact, if an analysis is conducted without a model, many implicit assumptions are likely to remain hidden. Further, without a diagram, the interrelationships among the various causes are likely to be ignored.

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CHAPTER 3

PATH ANALYSIS

Path analysis is a statistical technique for estimating the magnitude of links between variables in a causal model. It can be used with causal modeling, although it is not always necessary or feasible. It provides evaluators with information for possibly revising and better understanding the hypothesized relationships. This chapter defines path analysis and discusses data requirements and potential applications in program evaluation. 1/

WHAT IS PATH ANALYSIS?

Path analysis is a set of procedures for determining the strength of direct and indirect causal associations. It involves (1) constructing a diagram--usually part of a larger causal model, (2) calculating the magnitude of the assumed causal associations, (3) analyzing and revising assumptions, and (4) interpreting the final path diagram.

It uses regression analysis to estimate the strength of postulated causal relationships 2/ and provides an overall estimate of a model's explanatory power. More importantly, path analysis helps to identify spurious relationships that may need revising, and it permits estimating the magnitude of indirect causal paths. Decisions can be made on whether one variable in a model influences another directly, through mediating variables, or both. Additionally, the relative influence of direct and indirect causal paths can be compared. 3/

Path analysis results in an arrow diagram (model) that includes numbers (path coefficients) measuring the relative strength of the paths. Higher numbers indicate stronger "causes." Figure 3.1 shows the result of using path analysis to evaluate a teacher training program. According to this figure, teacher orientation toward task accomplishment had the greatest effect on democratic classroom control (.49), while the training program had the least effect (-.02). A minus sign indicates that as one variable increases in value, the other decreases. For example,

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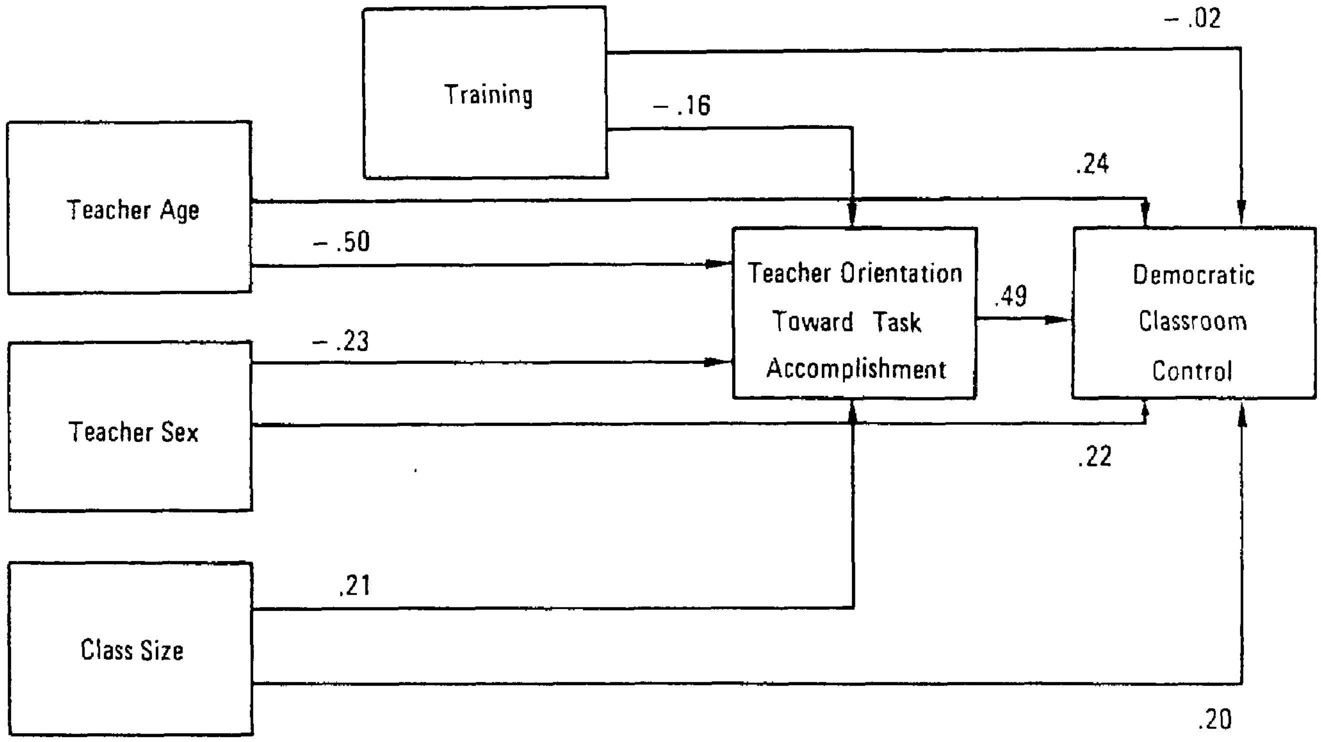
1/For additional information on using quantitative techniques in GAO's work, see U.S. GAO [19], chapter 11.

2/Readers unfamiliar with the fundamental concepts of regression analysis may want to read Kerlinger and Pedhazur [8], pp. 1-100. Appendix I is a glossary for readers unfamiliar with the few statistical terms used in this chapter. The first time these terms appear in the text they are underlined.

3/Dye and Pollack [7], p. 113.

the figure points out that older teachers are less oriented toward task accomplishment than younger teachers (-.50). 1/

Figure 3.1 Evaluation of Teacher Training



Source: Smith and Murray [15], p. 9.

DATA COLLECTION

After constructing a causal model and before performing path analysis, an evaluator collects data. Two basic considerations when collecting data are the information's reliability and validity. Briefly, reliability concerns the extent to which a measuring procedure produces the same results on repeated trials. 2/ All measurements contain some amount of chance error, and "unreliability" is always present to some extent.

1/This interpretation does not apply to "teacher sex" and "training." Since these variables convey information in categories (male/female and the presence/absence of training), they are interpreted as dummy variables. See appendix III, Testing the model's adequacy, and Nie et al. [13], pp. 374-375.

2/Carmines and Zeller [5], p. 11.

"Reliable" measurements, however, tend to be consistent when repeated. Validity, on the other hand, concerns the extent to which an "indicator measures what it is supposed to measure rather than reflecting some other phenomenon." 1/

To obtain data that accurately measure an intended phenomenon requires a well thought out research design. The following planning activities will help an evaluator collect reliable and valid data. 2/

1. Define variables precisely so that they can be measured. For example, "health" is not precisely measurable, but "bed days" may be.

2. Determine what information is already available and what needs to be collected.

3. Decide the costs involved, time required, and degree of precision needed.

4. Define the target population (or universe) and decide whether to collect data from the entire population or a part of it. If necessary, develop a sampling procedure.

5. Determine the frequency and timing of collecting the data.

6. Decide whether the data are to be collected by mail, personal interview, telephone, or other method.

7. Consider and try to control for potential sources of measurement error--such as reporting errors, response variance, interviewer and respondent bias, nonresponse, missing data, and errors in processing the data.

8. Establish uniform procedures for editing, coding, and tabulating the data.

In addition to being reliable and valid, the data for path analysis should meet certain statistical assumptions. These include the standard ones associated with multiple regression analysis as well as some unique to path analysis. In general, these assumptions mean the evaluator should collect data from a representative sample of the population and with minimum

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1/Carmines and Zeller [5], p. 16.

2/U.S. Department of Commerce [18], pp. 5-7.

measurement error. Additionally, the evaluator should specify a model in such a way that (1) there are no variables outside the model that strongly influence any two variables in the model and (2) the causal flow is only in one direction (no feedback loops). 1/ Appendix II describes these assumptions, how they affect the analysis, and what to do when they are not met.

APPLICATIONS IN PROGRAM EVALUATION

Path analysis has specific applications in program evaluation. Models can be specified to compare similar programs or to analyze how a program affects different segments of the population. Models are not restricted to one dependent variable, thereby, enabling multiple goals to be evaluated. In more sophisticated analyses, an evaluator can study reciprocal cause and effect and the joint effect of two or more causes or variables can be combined to represent concepts that are then analyzed.

Program Comparisons

Path analysis can compare program results. For example, an evaluator can examine a program's effect on rural and urban dwellers. To make this comparison, one model is constructed, but the data are gathered from two populations. Then, by examining the differences between specific path coefficients 2/ the evaluator analyzes the differing program results.

Specht and Warren 3/ examined a causal model (see figure 3.2) developed by Bayer 4/ that relates educational aspirations to aptitude, socioeconomic status, and marital plans for men and women.

The path coefficients were compared to determine whether the model's structural parameters--quantities that describe a statistical population--differ between populations--in this case men and women. The research results suggested that differences

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1/The instructions in this chapter are only applicable for models with one-way causal ordering. Path analysis can be used with models having feedback loops; however, the procedures for calculating path coefficients differ. For information on models with two-way causal flow see Asher [1], pp. 52-61.

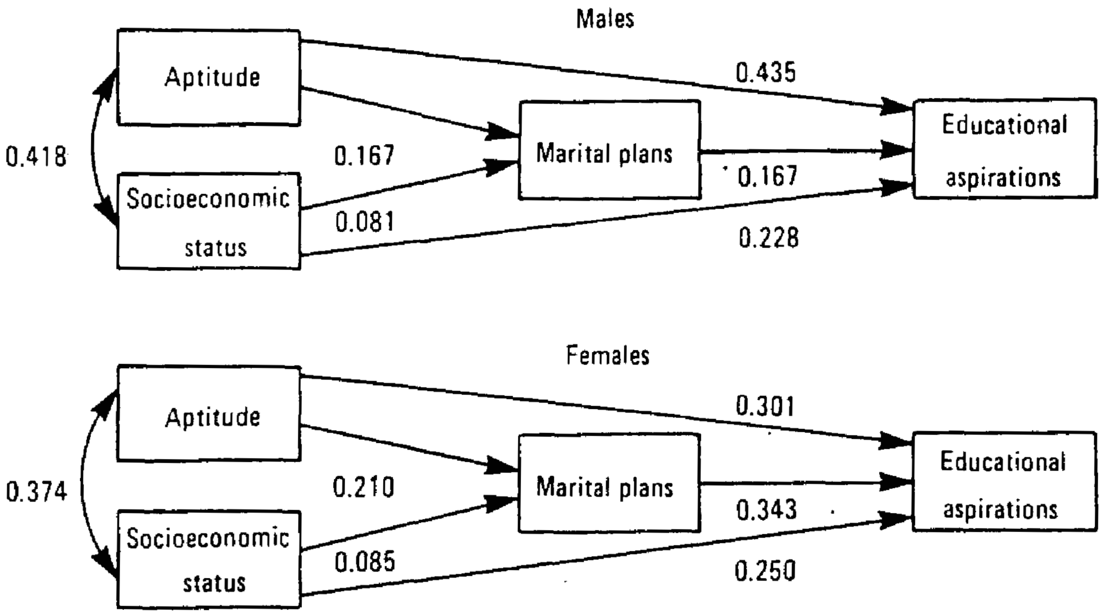
2/Unstandardized path coefficients need to be used because the same variables may have different variances in different populations. Generally, standardized path coefficients are used in other applications. See appendix II, (Step 2. Estimate the path coefficients) for further information.

3/Specht and Warren [16].

4/Bayer [2].

did not exist between groups. For example, as shown in figure 3.2, aptitude has one of the largest relative influences on educational aspirations for both men and women. Specht and Warren were unable to reject the idea that observed differences between the two populations were due to chance.

Figure 3.2 Path Diagram Relating Educational Aspirations to Aptitude, Socioeconomic Status, and Marital Plans, by Sex



Source: Adapted from Specht and Warren [16], p. 49.

Analyzing Multiple Results

One advantage path analysis has over ordinary regression analysis is that more than one dependent variable can be analyzed. A path diagram can be specified with many dependent variables which represent a program's results. However, for simplicity, most causal models have only one or two. By being able to specify more than one result, the evaluator gains a more realistic program model. Using multiple dependent variables does not require special statistical considerations.

An example of this model is Marshall's study of the suburbanization process. He constructed a path diagram to examine two aspects of white suburbanization: the probability that inner city white residents moved to the suburbs between 1965 and 1970 and the probability that white newcomers to metropolitan areas moved to the suburbs. 1/ One hundred twelve metropolitan areas with populations 100,000 or more in 1960 were analyzed to determine whether whites were "pushed" to the

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1/Marshall [11].

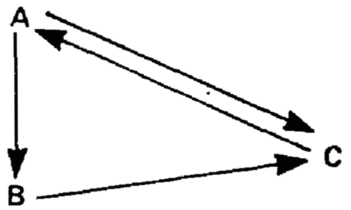
suburbs by inner city problems such as crime and race riots or "pulled" to the suburbs by their need for new homes and jobs.

The research findings indicated that whites were drawn to the suburbs between 1965 and 1970 by their need for homes and jobs rather than that they fled to the suburban areas because of inner city problems. This suggests to policymakers that building new homes and creating jobs in inner cities may significantly change this trend.

Reciprocal Causes and Effects

An evaluator can use path analysis to examine how one variable acts as both a cause and effect of another. In a job training program, for example, unemployment levels affect program results; yet program activities may influence future unemployment in that locality.

These path diagrams have arrows pointing in opposite directions (sometimes called "feedback loops"), as in this example.



They are often more realistic than diagrams with a one-way causal flow. Certain statistical assumptions, however, are no longer valid and may require collecting more data or changing the procedures used to calculate paths. 1/

If measurements are gathered at two points in time for variable A, then ordinary regression analysis can still be used. This means that A_1 (at time one) is a cause of C and C is a cause of A_2 (at time two). By maintaining a distinct temporal order between variables A_1, C, and A_2 the calculating procedures are <u>usually</u> valid. However, if the data have already been

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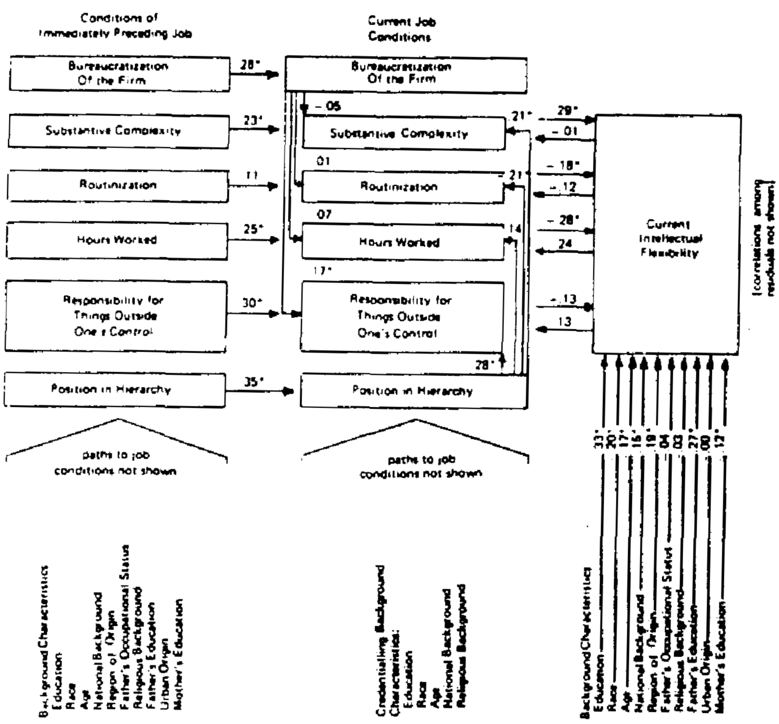
1/See the literature on structural equation modeling for further information. Krishnan Namboodiri *et al.* [9], pp. 492-532; Duncan [6], pp. 67-80.

collected, and only one measurement is available for A, the model can be analyzed with different statistical procedures. 1/

Miller et al. constructed a reciprocal path diagram (see figure 3.3) to measure the degree to which women's psychological functioning both affects and is affected by occupational conditions. 2/ Notice that the psychological and occupational variables function as both independent and dependent variables.

Figure 3.3 The Reciprocal Effects of Occupational Conditions and Intellectual Flexibility



Source: Miller et al. [12], p. 87.
*Coefficients shown are standardized. Those followed by asterisks are statistically significant.

Two-hundred sixty-nine employed wives, aged 26-65, were interviewed to test the following hypotheses.

--Jobs with opportunity for self-direction relate to favorable self-conceptions, flexible social orientations, and effective intellectual functioning.

1/See Asher [1], pp. 52-61, for a general discussion of the statistical procedures. See Krishnan Namboodiri et al. [9], pp. 519-522 for a discussion on using lagged variables.

2/Miller et al. [12].

--Jobs with little opportunity for self-direction relate to unfavorable self-conceptions, more rigid social orientations, and less intellectual functioning.

The research results indicated that work conditions substantially affect women's intellectual flexibility and their psychological functioning. These findings were similar to those derived from longitudinal data for men. But no psychological variables had a statistically significant reciprocal effect on job conditions.

Joint Causes

When analyzed, some variables may have unexpectedly weak direct influences. Even when indirect influences are added to their direct affects, these variables may be statistically much weaker than theory and common sense would lead one to anticipate. In such cases, evaluators can look for other variables that may be interacting and affecting these variables' significance. For example, an evaluator may find only a weak statistical relationship between length of participation in a job training program and obtaining a job. Yet, as education level increases, the relationship between program participation and obtaining a job becomes stronger and stronger. This situation indicates a multiplicative relationship between the two independent variables.

In path analysis, this situation requires creating a new variable by multiplying together education level and program participation. Sometimes these relationships can be anticipated and specified in the initial model. At other times, these nonadditive relationships can be checked by inserting in the model cross-product terms involving all pairs of independent variables. 1/

Identifying Underlying Concepts

Many programs are too complex to be explained adequately by a few variables. One way to include more variables and still retain simplicity, is to combine similar measures. The resulting composite index is then labeled to reflect a concept common to all parts. This composite variable should measure an underlying characteristic of the individual variables. A statistical technique for grouping variables according to underlying concepts is called factor analysis.

Factor analysis can be performed by numerous statistical computer packages, such as SPSS (Statistical Package for the

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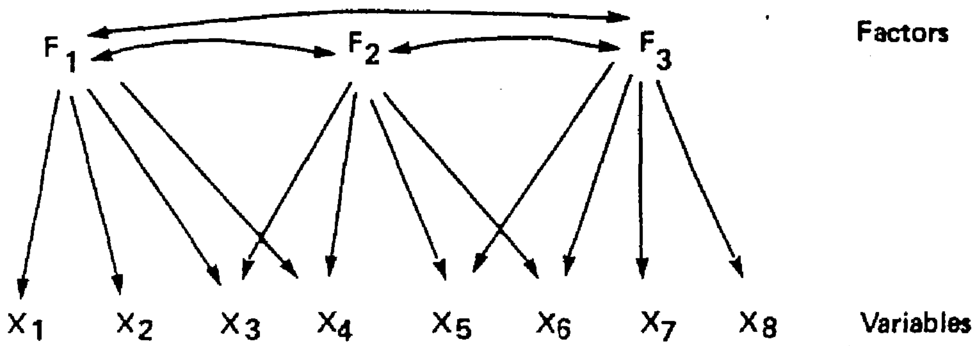
1/For more information on nonadditive models, see Blalock [3], pp. 91-93; Blalock and Blalock [4], pp. 178-186; Krishnan Namboodiri et al. [9], pp. 600-604.

Social Sciences) and SAS (Statistical Analysis System), which are available at GAO. 1/ The program output is lists of factor loadings--numbers that show the extent to which each variable relates to each factor.

This information has two uses in path analysis. First, the variable with the highest factor loading can be considered the "best" measure of its factor. One variable can represent each factor in the path diagram. A second use is to combine variables into composite scales representing the theoretical factors. 2/

Factor analysis should not be used "blindly" as a data reduction technique. Factor analysis assumes a model in which the underlying concepts or factors are postulated causes of the variables. Figure 3.4 illustrates the causal relationships among the variables and factors. In constructing a model using factor analysis, one assumes there are no cause and effect relations among the variables. This means, for example, X_1 does not "cause" X_4 just as X_3 does not "cause" X_6. Depending on the variables, this may not be an accurate assumption. 3/

Figure 3.4 Path Diagram Using Factor Analysis



Miller et. al. included several composite indicators in the previously discussed model (see figure 3.3), which analyzed women's intellectual flexibility. In this model, two variables--substantive complexity of the job and current intellectual flexibility--were measured by multiple indicators. Substantive complexity was measured by seven indicators: hours of work with data, things, and people; complexity of work with data, things,

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1/See U.S. GAO [19], pp. 15-7 to 15-8.

2/These two uses are described in appendix III (Describe the model's components). Methods for combining variables are given in Rummel [14], pp. 440-442 and Nie et al. [13], pp. 487-490.

3/For more information on this topic, see Sullivan and Feldman [17].

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[14] Rummel, R. J., Applied Factor Analysis, Northwestern University Press, Evanston, Illinois, 1970.

[15] Smith, N. L. and S. L. Murray, "The Use of Path Analysis in Program Evaluation," Northwest Regional Educational Laboratory, Portland, Oregon, February 1978.

[16] Specht, D. A. and R. D. Warren, "Comparing Causal Models," Sociological Methodology 1976, D. R. Heise (ed.), Jossey-Bass, San Francisco, California, 1975, pp. 46-82.

[17] Sullivan, J. L. and S. Feldman, Multiple Indicators, Sage Publications, Beverly Hills, California, 1979.

[18] U. S. Department of Commerce, Statistical Policy Handbook, U. S. Government Printing Office, Washington, D.C., May 1978.

[19] U. S. General Accounting Office, "Project Manual," U. S. GAO, Washington, D.C.

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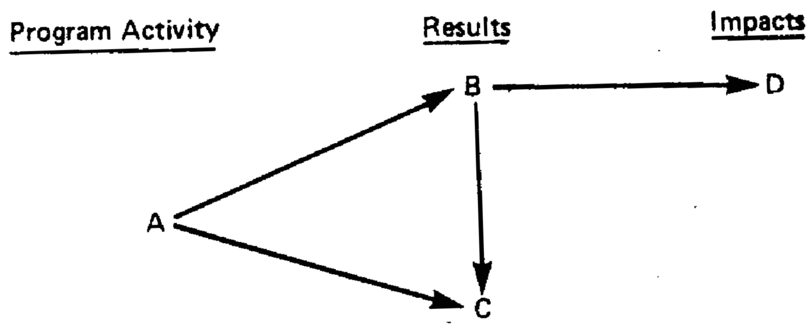
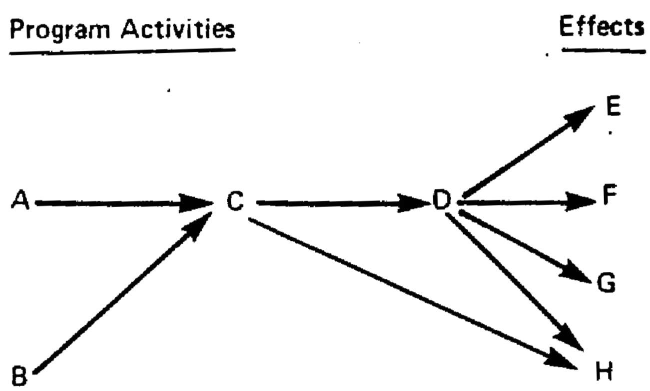
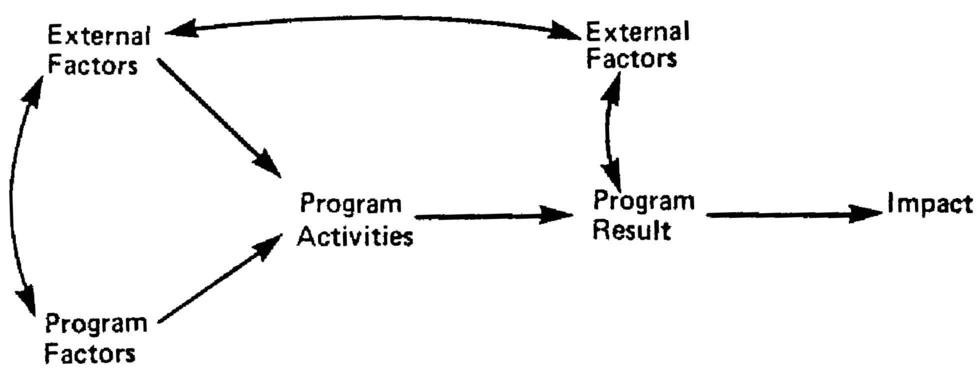
3. An evaluator wants to find the effects of a program. The general approach is to construct a model with multiple effects. The evaluator can emphasize one major program activity and examine its effect on program results and impacts, which are causally linked.



The evaluator can also construct a model with causally linked program activities and multiple, unrelated effects.



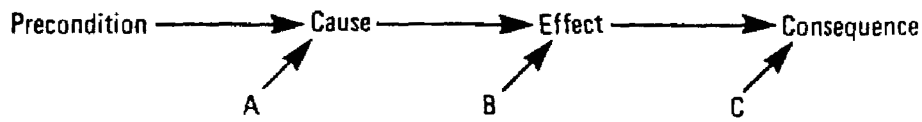
4. The evaluator wants to know why a program had an impact other than what was expected. This could be a complex modeling task requiring the evaluator to identify program and nonprogram processes, their interactions, and their ultimate "impact."



The evaluator could examine associations between external factors and between external factors and program processes for possible indirect or reciprocal influences.

5. An evaluator may also identify a program's impact on an observed causal sequence of events. This involves identifying how and where a program can intervene in the causal chain and alter its consequences. This model may resemble Suchman's intervening variable model (see chapter 2).

External Causal Chain



Program Activities

This situation requires searching for causes--internally and externally--and then analyzing their impact.

6. For a final variation on analyzing impacts, an evaluator identifies a policy's impact. The evaluator identifies programs affected by the policy and analyzes the programs' results. A general model for this situation may have this arrangement:

Environment → Policy → Programs → Impact

LIMITATIONS

Causal analysis can be applied to many evaluation situations. Some causal questions that an evaluator is likely to encounter, however, cannot be answered with causal analysis. For example, an evaluator cannot generally use the technique to predict a program's long-term effects. Causal analysis is not a forecasting technique. Likewise, it cannot find optimal values to minimize costs and maximize benefits as linear programming can.

Additionally, causal modeling does not provide a systematic way of (1) knowing if all relevant variables have been identified and (2) deciding which variables to use, although strong theory in a particular substantive area makes these tasks easier. Further, there is no single, correct model that explains the relations between causes and program results. Statistical techniques, such as path analysis, however, can indicate whether a model is incorrect. Statistics (or science in general) can disprove theories, but can never "prove" them to be true. Because programs are dynamic, a model can only approximate a program's process at a particular time. As new data are gathered and as the program changes, the model will have to be updated.

SUMMARY

Asking causal questions is important in program evaluation. Causal analysis gives evaluators a tool for examining cause and effect relations within and from outside a program. It combines qualitative and quantitative research techniques into a highly flexible and versatile methodology that is applicable in numerous situations.

Causal analysis, however, cannot be used in all situations. We have just presented a few limitations with the technique. Nevertheless, by using the technique carefully and appropriately, an evaluator can gain important understandings of the logical relationships underlying or influencing programs. Finally, causal analysis allows an evaluator to communicate findings fully and clearly to a variety of audiences.

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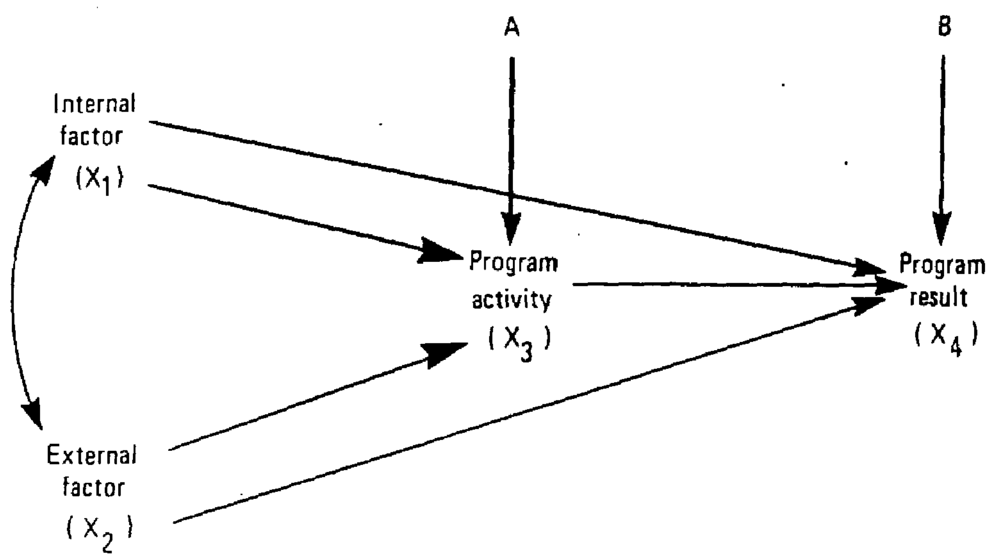
any other variables in the system are placed at the far left. Independent variables that are influenced by others in the system (intervening variables) are placed in the diagram's center. 1/ Residual variables are added to account for unexplained variance in the dependent and intervening independent variables. 2/

c. Draw all theoretically plausible arrows: from each independent variable to the dependent variable, and to each independent variable from each cause. Draw an arrow from each residual to an "effect" variable (that is, any variable that has arrows leading to it). Two-headed curved arrows connect variables at the far left of the diagram that are related, but lack a specific causal order. Whenever possible, specify the causal order. Later, when calculating indirect paths, two-headed curved arrows may present problems. With all the arrows drawn, the model is fully identified.

Figure II. 1 Preliminary Path Diagram



Independent variables: Internal factor, External factor, and Program activity

Dependent variable: Program result

Residual variables: A and B

1/Dye and Pollack [8], pp. 113-114.

2/Land [12], pp. 6-7.

Step 2. Estimate the Path Coefficients

a. Convert the path diagram into a series of regression equations in which first the dependent variable is regressed against all other variables, and then the intervening variables are treated sequentially as dependent variables with their "causes" as independent variables. 1/ Values for the paths (path coefficients) are calculated from these equations.

b. Solve these equations using the regression program from a computer package such as SPSS or SAS. 2/ The output provides the information needed to calculate coefficients for all the paths in the diagram.

--Path coefficients between the independent and dependent variables are usually standardized partial regression coefficients. 3/

--Paths from each residual to its dependent variable have coefficients calculated by: 4/

$$\sqrt{1 - R^2}.$$

R^2 (R-square) is the amount of variance explained by the equation for the particular dependent variable.

1/For example, figure II.1 can be represented by two equations:

$$X_3 = p_{31} X_1 + p_{32} X_2 + p_{3a} A \qquad (1)$$

$$X_4 = p_{41} X_1 + p_{42} X_2 + p_{43} X_3 + p_{4b} B. \qquad (2)$$

Note that program activity (X_3) acts as a dependent variable in equation (1) and as a independent variable in equation (2). Each path coefficient is identified by a symbol in the form p_{ij}, in which "i" indicates where the path is going to (the effect) and "j" indicates where it came from (the cause).

2/See U.S. GAO [15], pp. 15-7 to 15-8.

3/Asher [2], pp. 29-31. Unstandardized partial regression coefficients are used when comparing across samples or time periods, such as when comparing programs.

4/*Ibid.*, p. 31.

--Paths connecting variables that lack a specific causal ordering (two-headed curved arrows) have path coefficients calculated by the Pearson correlation, r. 1/

Each of the three methods represents the best available measure of the relationship between the "cause" and "effect" variables.

Step 3. Analyze the Model

a. Does the model account for a sufficient amount of variance (R-square) in the dependent variable that is the ultimate "effect" being examined? 2/ If not:

--make sure the relationships are linear.

--decide whether to use different or additional independent variables.

--check the data for measurement error.

Convert non-linear relationships to linear ones by making appropriate variable transformations, such as log transformation or higher degree terms. 3/ A decision to remove or add variables should be guided by knowledge about the program. Either converting, removing, or adding variables requires respecifying the model and recalculating the path coefficients. If these revisions fail to increase R-square, then check the data for measurement error, such as reporting errors, response variance, and errors in processing the data.

b. Does the model violate any other statistical assumptions? (See figure II.2)

c. Are the path coefficients directionally correct? For example, if the internal factor is payroll staff size and the program activity is number of checks processed, then we expect the path coefficient to be positive (the number of checks processed increases when staff size increases). If the direction is unexpected, make sure the input data are accurate and that the program is processing them correctly before interpreting the results. Don't automatically reject counter-intuitive results, since they may indicate variables that are incorrectly placed in the model or omitted. For example, increasing staff size may not increase output if it causes overcrowding.

1/Nie et al. [14], p. 390.

2/At the beginning of the evaluation, the evaluator should determine an acceptable value for R-square.

3/For a discussion on identifying appropriate variable transformations see Hanushek and Jackson [9], pp. 96-101.

Figure II.2 Statistical Assumptions and Implications for Data Analysis

Assumption	Implications and Actions
Interval level measurement	Variables are measured on an interval level scale. Including nominal and ordinal data in the model probably will not introduce large errors in estimating the path coefficients unless one collapses the categories too much. 1/ Simply treat the data as dummy variables in the regression analysis. 2/
Homoscedasticity	The prediction errors are equally distributed at all points on the regression line (homoscedasticity). This condition is identified by examining scatter diagrams of each independent variable plotted against the residuals. When the assumption is not met (called heteroscedasticity), a pattern emerges, such as the one in figure II.4. 3/ This is not a critical assumption since heteroscedastic residuals do not bias the estimates of the regression coefficients. They do, however, bias estimates of the standard errors for the coefficients. If this is a problem, then another procedure (generalized least-squares) can be used for the regression computations. 4/
Linear and additive relationships	Relationship between variables is linear and additive in the parameters. This relationship is identified by examining scatter diagrams of the dependent variable plotted against each independent variable. If the relationships do not appear reasonably linear, make the appropriate variable transformations (for example, log transformations or adding interaction terms). 5/ The violation of this assumption can produce a low R-square.

1/Land [12], p. 34.

2/Lyons [13]; Nie et al. [14], pp. 273-383.

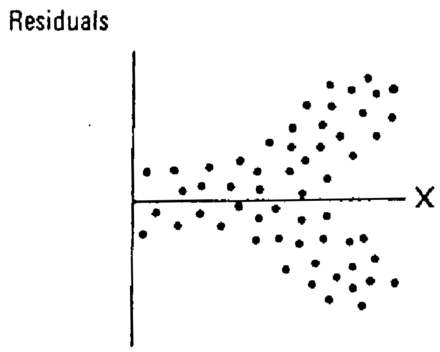
3/Beals [3], p. 344.

4/Chiswick and Chiswick [6], p. 142.

5/Asher [2], p. 27; Blalock [5], p. 44; Wright [16], p. 190.

Uncorrelated residuals	Each residual is uncorrelated with any independent variable directly affecting the dependent variable upon which it acts. Pairs of residuals are uncorrelated. Reduce the likelihood of having correlated residuals by including in the model as specific variables as many potentially disturbing influences as possible. Too many variables, however, will make the model unwieldy. 1/ This assumption can be relaxed when handled as in simultaneous equation procedures. 2/
Multicollinearity	The correlations among variables are not so close to 1.0 that it is difficult to separate the effects of one variable from another (lack of multicollinearity). Multicollinearity may occur between independent variables in the same regression equation. When the correlation between a pair of variables is very high (greater than .85) retain only one in the model or use a combined index. 3/
Measurement errors	Measurements reflect the true value of each variable (low measurement error). Measurement errors produce biased estimates of the path coefficients. 4/ Rigorous quality control standards applied throughout the data collection phase will reduce the amount of measurement error.

Figure II.3 Heteroscedastic Residuals



1/Dye and Pollack [8], p. 116.

2/Krishnan Namboodiri et al. [11], pp. 522-526.

3/Althauser [1], p. 453.

4/Asher [2], p. 63.

Step 4. Revise the Model

a. Delete paths that are neither logical nor statistically significant. Two criteria are generally used to retain paths: 1/

--an arbitrary minimum path coefficient value, usually .05, and/or

--statistical significance at the .05 level (determined by the F-test). 2/

No path should be deleted only because its value is insignificant. If there are sound theoretical reasons for retaining a path, then it should be retained.

b. Compute new path coefficients for the revised model following the procedures in step 2.

c. Identify direct influences by the single path connecting two variables. A direct influence is measured by the path coefficient of that single path (see figure II.4).

d. Identify indirect paths between all pairs of variables using these rules: 3/

1. No path may pass through the same variable more than once.

2. No path may go backward on (against the direction of) an arrow after the path has gone forward on a different arrow.

3. No path may pass through a double-headed curved arrow more than once in a single path.

An easy way to apply these rules is to imagine trying to move from one variable to another in a path diagram without violating any rule.

The indirect paths are either causal (going in the direction of all arrows) or spurious (they begin by going against the direction of an arrow). In figure II.4, note that $p_{42}\ p_{43}$ is not an indirect influence between X_2 and X_3 because it violates rule 2.

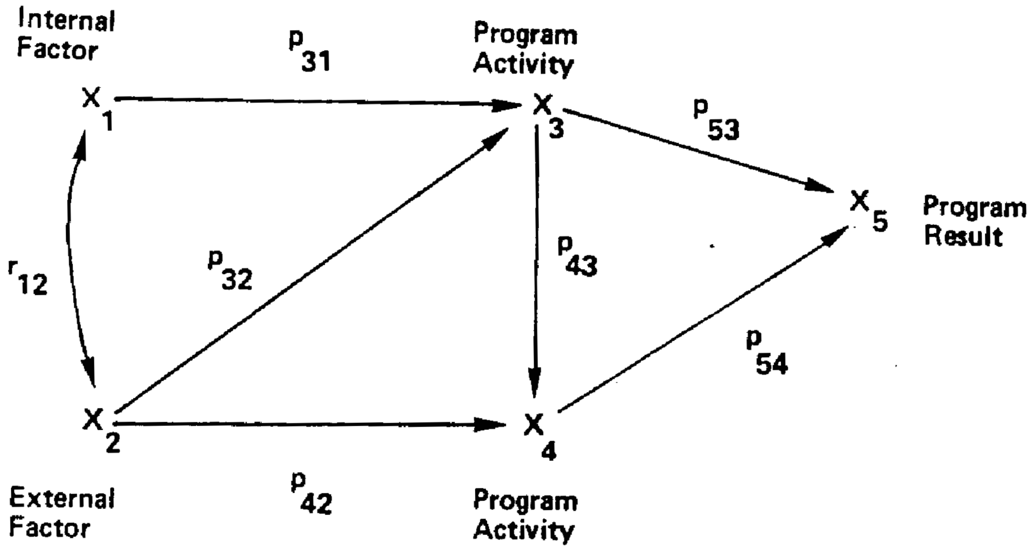
1/Land [12], p. 34; Kerlinger and Pedhazur [10], p. 318.

2/Consult a table of critical F-values to determine the significance level. For an explanation of F-values, consult an introductory statistics text or Nie et al. [14], pp. 334-340.

3/Wright [16], p. 17.

APPENDIX II

Figure II . 4 Calculating Direct and Indirect Paths



Variables	Direct Path	Indirect Path: Causal	Indirect Path: Spurious
$X_1 X_2$	r_{12}		
$X_1 X_3$	p_{31}	$r_{12} p_{32}$	
$X_1 X_4$		$p_{31} p_{43}$ + $r_{12} p_{32} p_{43}$ + $r_{12} p_{42}$	
$X_1 X_5$		$p_{31} p_{53}$ + $p_{31} p_{43} p_{54}$ + $r_{12} p_{32} p_{53}$ + $r_{12} p_{32} p_{43} p_{54}$ + $r_{12} p_{42} p_{54}$	
$X_2 X_3$ . . .	p_{32} . . .	$r_{12} p_{31}$ . . .	
$X_4 X_5$	p_{54}		$p_{43} p_{53}$ + $p_{42} p_{32} p_{53}$ + $p_{42} r_{12} p_{31} p_{53}$

e. Calculate indirect influences between all pairs of variables by multiplying the path coefficients for each indirect path segment. The sum of the indirect paths equals the total indirect influence between two variables. In figure II.4, the total indirect influence of X_1 on X_4 is the sum of three indirect paths: $p_{31} p_{43} + r_{12} p_{32} p_{43} + r_{12} p_{42}$. 1/

With a complex model it is easy to miss paths. Indirect influences, in particular, should be checked either by reapplying these rules or by using different procedures, such as Blalock's algorithm. 2/

f. For each pair of variables, add together the direct and indirect path coefficients. This sum should approximate the Pearson correlation (r) between the variables. As a rule of thumb, the two values should differ by less than .05. 3/ If they differ by more than .05, then too many paths may have been deleted or a significant variable may be missing from the model 4/ and it should be revised.

High spurious values (indicating paths that begin by going against the direction of the arrow) may also indicate that the model is specified incorrectly. 5/

g. Keep revising the model until the sum of direct and indirect influences between most pairs of variables equals or is close in value to their correlation.

h. Compute path coefficients for the final model following the procedures in step 2.

1/This example points to a disadvantage of using curved arrows. The latter two path segments are through the two-headed curved arrow (r_{12}). By including these segments, evaluators may be overestimating the indirect effect of X_1 on X_4, if X_2 is actually causing a change in X_1 (in which case these two path segments would be spurious). Hence, it is preferable, where possible, to specify the direction of causation, especially among variables that can be manipulated.

2/Krishnan Namboodiri et al. [11], pp. 461-462.

3/Kerlinger and Pedhazur [10], p. 318.

4/Billings and Wroten [4], p. 684.

5/Ibid.

Step 5. Interpret the Path Diagram

a. Examine the information contained in the final path diagram. In addition to relative values for direct and indirect influences, 1/ path analysis provides:

--the proportion of total variation in the dependent variable (explained by the regression output, R-square).

--the portion of the dependent variable for which the independent variable is directly responsible (measured by the squared path coefficient). 2/

b. Evaluators can use this information to help to determine if they have included a sufficient number of causes in the model (indicated by R-square); if they have included the "best" causes 3/ (by examining the squared path coefficient); and if the causal ordering is appropriate (indicated by low spurious influences). Additionally, by examining the influence of intervening variables, they may discover high indirect effects that were not evident in the causal model.

1/The strength of direct and indirect paths is relative to what variables have been included, and is, therefore, a function of the model's completeness.

2/Wright [16], p. 164.

3/Peculiarities of the sample drawn may have determined the "best" variables. With a different sample, other variables may explain more variance in the dependent variable.

APPENDIX II

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CAUSAL ANALYSIS OF PAROLE OUTCOMES

This appendix presents an example of applying causal modeling to evaluate parole outcomes. First, a sequence of behavior that might explain parole outcomes and could be altered by a parole program are hypothesized. Then a causal model using previously collected data is developed. 1/ Finally, path analysis is used to test the model's validity.

SELECTING VARIABLES TO STUDY

Establish the Evaluation's Focus

The first step in developing a causal model was to establish the evaluation's focus. This effort was constrained by two factors. First, the lack of a single, strong theory to explain criminal activity or to predict parole outcomes left us without a sound theoretical base. Second, the available data was limited to information on 277 inmates in a maximum security penitentiary. 2/ This data base did not include program information such as funding, staff, activities, or explicit goals. Therefore, a general causal model (see figure III.1) that focussed on parolee's behavior and background was specified.

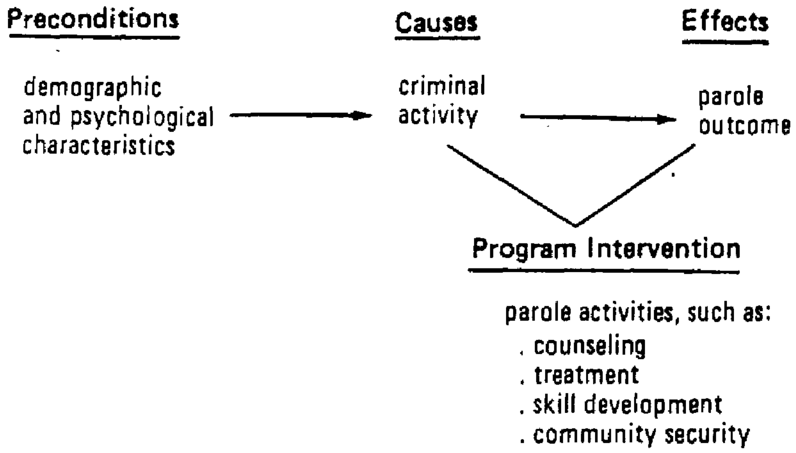
This general causal model, based on Suchman's model of intervening variable analysis, 3/ hypothesizes a social condition that parole programs can attempt to alter. Suchman views programs as a form of intervention trying to prevent undesirable effects by manipulating intervening variables in a known causal sequence. The hypothesis is that an individual's demographic and psychological characteristics influence criminal activity, which, in turn, influences parole outcome. Criminal activity certainly precedes parole. Does it, however, directly influence parole outcomes? Testing this hypothesis is the focus.

1/The data base used in this chapter was collected on actual parolees; however, the parole program is hypothetical. The causal models depicted in this appendix, although realistic, do not portray a specific program.

2/The inmates (all male) were consecutively admitted to the Ohio Penitentiary from October to December 1967. At that time, demographic, psychological, and criminal history information about the inmates was gathered. In 1978, the information was updated from parole and criminal records. See Dynes [2] and Allen [1] for additional information.

3/Suchman [8], pp. 173-176.

Figure III. 1 General Causal Model Explaining Parole Outcome



Specify the Important Variables

The next step was to replace the general model with a few variables from the data base. In theory, we could have constructed a model that included all variables. In practice, however, path analysis assumptions (such as multicollinearity) prevented us from including many variables.

Selecting the "effect" (dependent variable) was easy; number of parole violations was the only available measure of parole outcome. Reducing fifty-nine potential causes or preconditions to a few, however, was difficult. Interviewing government and academic experts and reviewing literature on assessing parole outcomes 1/ provided little help in solving the problem, since they revealed numerous theories and variables. Therefore, three statistical techniques were used to reduce the data set, each producing a list of similar causes.

First, correlations between all potential independent variables and the dependent variable were computed. After identifying 34 variables most highly correlated with the dependent variable, the intercorrelations between all pairs of these variables were examined. High intercorrelations (above .85) indicated that the effects of the two variables could not be separated (called multicollinearity) and, therefore, only one of the pair or a composite index could be used in path analysis. The four independent variables chosen had both high correlations with parole violations (the dependent variable) and low correlations with

---

1/Gottfredson et al. [3], pp. 43-47, conducted an extensive literature review.

each other, and covered the three general categories (demographic and psychological characteristics and criminal activity). These independent variables were:

--socioeconomic status,

--months in military service,

--sociopathic classification, 1/ and

--months incarcerated.

Using another statistical technique, factor analysis, 2/ variables with high factor loadings were combined into indices 3/ to use as independent variables. Ten factors were selected as a first cut-off because they accounted for 60 percent of the variance in all the data. Those are listed in figure III.2. The number of factors was further reduced based on the following criteria:

--Factors 2 and 3 included similar variables pertaining to criminal record from different time periods. Factor 2 was kept because it included lifetime data and it accounted for more variance.

--Factor 4 represented the dependent variable, parole violations. It was, therefore, deleted from the list of causes.

--Factors 7, 9, and 10 were deleted because two criminal justice factors had been already identified (1 and 2) that accounted for more variance.

This left the following five factors:

--institutionalization (measured by four incarceration variables),

--criminal record (arrest and conviction data),

1/Sociopathic classification is a scale ranging from normal individual to hostile sociopath. The scale combines three psychological scales, number of arrests since age 18, percentage of life incarcerated since age 18, and number of escapes. Dynes [2], p. 46.

2/Chapter 3 (Identifying underlying concepts) defines factor analysis and shows a brief example.

3/We used the procedure described by Rummel [7], pp. 440-442.

Figure III.2 The First 10 Factors and Salient Variables

Factor 1. Institutionalization

Incarcerations (pre 67)
Months Incarcerated (pre 67)
Months Incarcerated Since Age 18 (pre 67)
Months Incarcerated (lifetime)

Factor 2. Criminal Record (pre 67 and lifetime)

Arrests (pre 67)
Convictions (pre 67)
Arrests (lifetime)
Convictions (lifetime)

Factor 3. Criminal Record (68-78)

Arrests (68-78)
Convictions (68-78)
Incarcerations (68-78)
Paroles (68-78)

Factor 4. Reintegration

Parole Violations (pre 67)
Parole and Probation Violations (pre 67)
Parole Violations (lifetime)

Factor 5. Marriage

Marital Status
Times Wed

Factor 6. Age

Age
Age at First Conviction

Factor 7. Probations

Probations (pre 67)
Probations (lifetime)

Factor 8. Alienation

Anomie scale
Criminality Level Index

Factor 9. Supervision

Supervision Level

Factor 10. Probations (68-78)

Probations (68-78)

--marriage (marital status and times wed),

--age, and

--alienation (psychological and criminality level test scores).

Finally, for each factor between two and four variables with the highest factor loadings were identified. These were considered to be the "best" measures for the respective factors. This initial list of 14 variables was reduced to five by selecting variables with low intercorrelations and by selecting only one variable from each factor. The third and final list of independent variables was:

--months incarcerated,

--number of arrests,

--marital status,

--age at first conviction, and

--alienation. 1/

One causal model from each of the three lists of causes was constructed. The third list produced a model that accounted for slightly more variance (22%) in the dependent variable than the others (15% and 20%, respectively). The model produced by the third list is used in the remainder of the discussion.

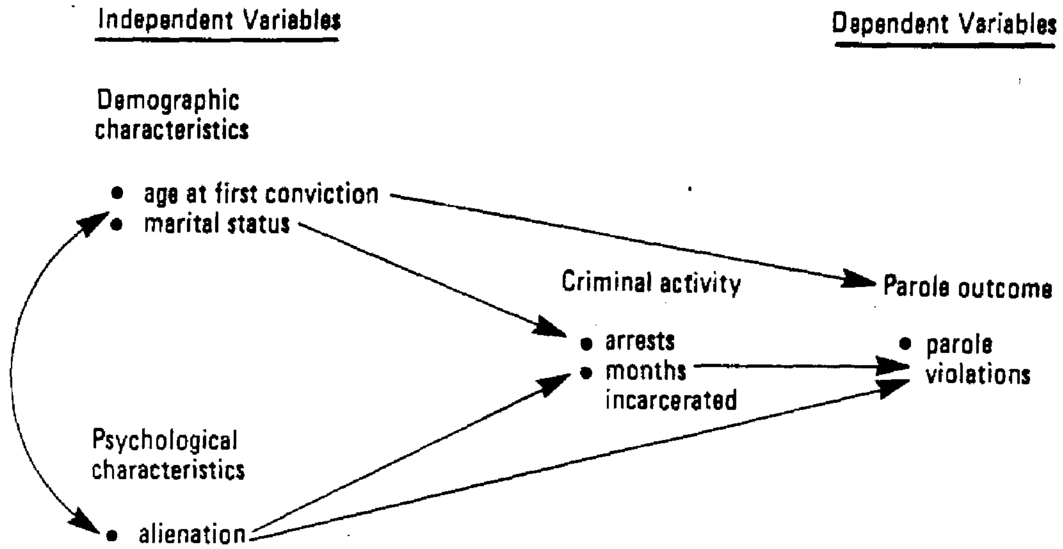
MAKING ASSUMPTIONS ABOUT CAUSAL RELATIONSHIPS

The five independent variables and the dependent variable were arranged in the causal sequence in figure III.3. The demographic and psychological characteristics were assumed to be related; however, the causal order between them was not specified.

This model hypothesizes that changes in age, marital status, and alienation lead to changes in the number of lifetime arrests and months incarcerated, which "causes" changes in the number of parole violations. For example, this model assumes that people who are young when first convicted, divorced or separated, and alienated would have more lifetime arrests, spend more time incarcerated, and have more parole violations than those who lacked these initial characteristics. In addition, the model hypothesizes that the demographic and psychological variables are affecting each other. For example, people who are alienated may be younger when first convicted or *vice versa*.

1/Measured by the Anomie psychological test score.

Figure III.3 Initial Causal Model For Determining Parole Outcomes



One limitation to this model is that the relationships may be due to other factors. Because of numerous and sometimes conflicting theories of criminal behavior, we cannot identify, much less include in the model, all causes of parole outcome.

Furthermore, the model does not include intervening program variables. Because we lacked data, we did not include program processes that could intervene in this sequence. Program activities (such as counseling, drug and alcohol treatment, skill development, and community security) and resources (including funding and staff size) could form a sub-model influencing parole outcome.

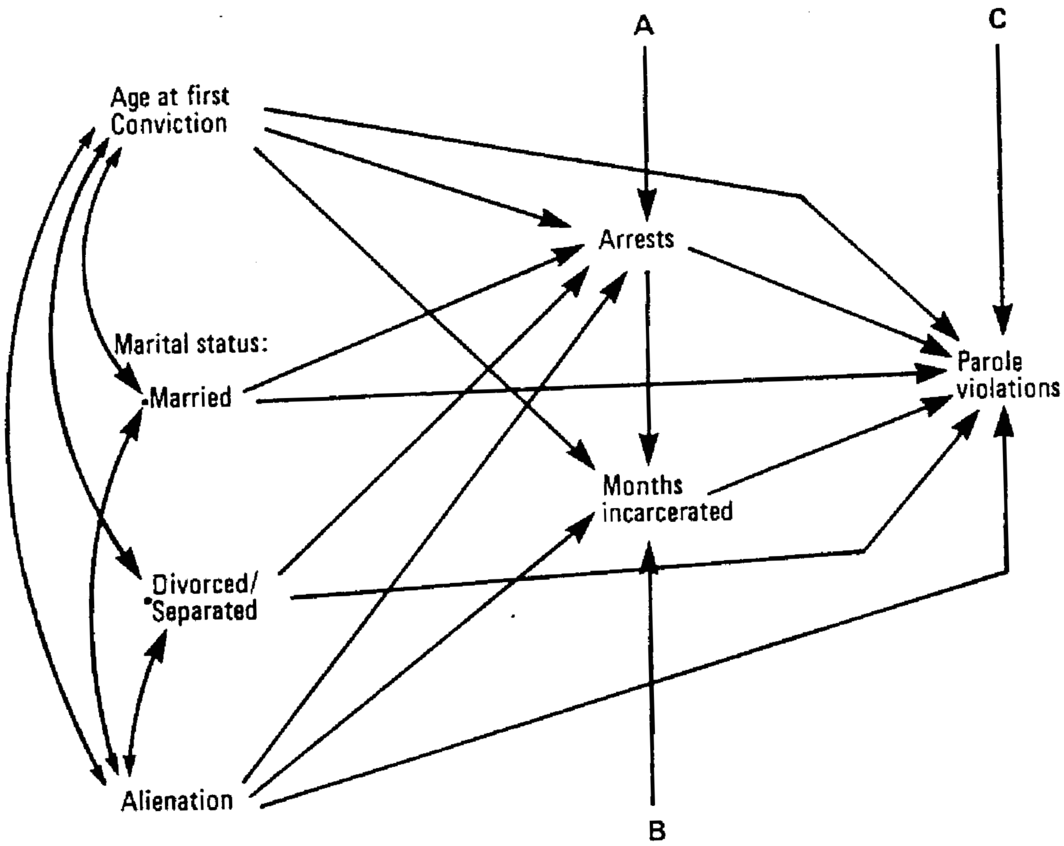
TESTING THE MODEL'S ADEQUACY

Path analysis tests the model's validity and determines the relative strength of the assumed causal relationships. First, a path diagram of the causal model was developed (see figure III.4). Residual terms (A, B, and C) were added to account for outside influences. Marital status was treated as a dummy

APPENDIX III

variable--married and divorced/separated. 1/ Since all likely arrows were drawn, 2/ the diagram was fully identified.

Figure III.4 Preliminary Path Diagram



Calculate the Path Coefficients

To compute path coefficients, each "effect" variable--arrests, months incarcerated, and parole violations--was

---

1/An individual who fell into neither of these categories was single. Single can be considered a reference category by which the effects of the other dummy categories should be interpreted. For more information on creating and interpreting dummy variables see Nie et al. [5], pp. 374-375.

2/It was assumed that marital status had no direct affect on months incarcerated.

regressed against its "causes." 1/ A partial listing of computer output from the SPSS regression subprogram is displayed in figure III.5.

To calculate the path coefficients, three procedures were used. First, the values for direct paths between variables were read from the computer output (the "beta" 2/ values in figure III.5). For example, it was determined that the path from age at first conviction to arrests had a value of -.30. 3/

Second, the paths from residual terms were calculated as:

$$\sqrt{1 - R^2},$$

where R^2 is the amount of variance explained by the equation. Thus, the path between the residual A and arrests was:

$$\sqrt{1 - R^2} = \sqrt{1 - .13} = .93$$

Third, when a relationship between two variables lacked a specified causal ordering, the association was described by the Pearson correlation, r. The computer generated this statistic for all pairs of variables. For example, the path between age at first conviction and married equaled the correlation between the two (.07).

The preliminary path diagram, with path coefficients, is illustrated in figure III.6.

Analyzing the Model

The preliminary model was examined to determine if it accounted for a reasonable amount of variance in the dependent variable (R-square) and to decide whether any statistical assumptions were being violated.

1/Three regression equations were specified. First, regressing arrests against age at first conviction, married, divorced/ separated, and alienation. Second, regressing months incarcerated against age at first conviction, alienation, and arrests. Third, regressing parole violations against all other variables.

2/Standardized partial regression coefficients.

3/The minus sign indicates that the value of one variable increases as the other decreases. The older a person is when first convicted, the fewer lifetime arrests likely.

Figure III.5 Example of Computer Output

Arrests regressed against age at first conviction (AGEFC), married, divorced/separated, and alienation

Dependent variable Arrests

R-Square = .13

Independent variables	Beta	F
AGEFC	-.30	20.41
Married	-.02	.07
Divorced/Separated	.22	6.64
Alienation	-.06	.86

Months incarcerated regressed against AGEFC, alienation, and arrests

Dependent variable Months incarcerated

R-Square = .23

Independent variables	Beta	F
AGEFC	-.31	22.74
Alienation	-.14	4.98
Arrests	.27	18.37

Parole violations regressed against AGEFC, married, divorced/separated, alienation, arrests, months incarcerated

Dependent variable Parole violations

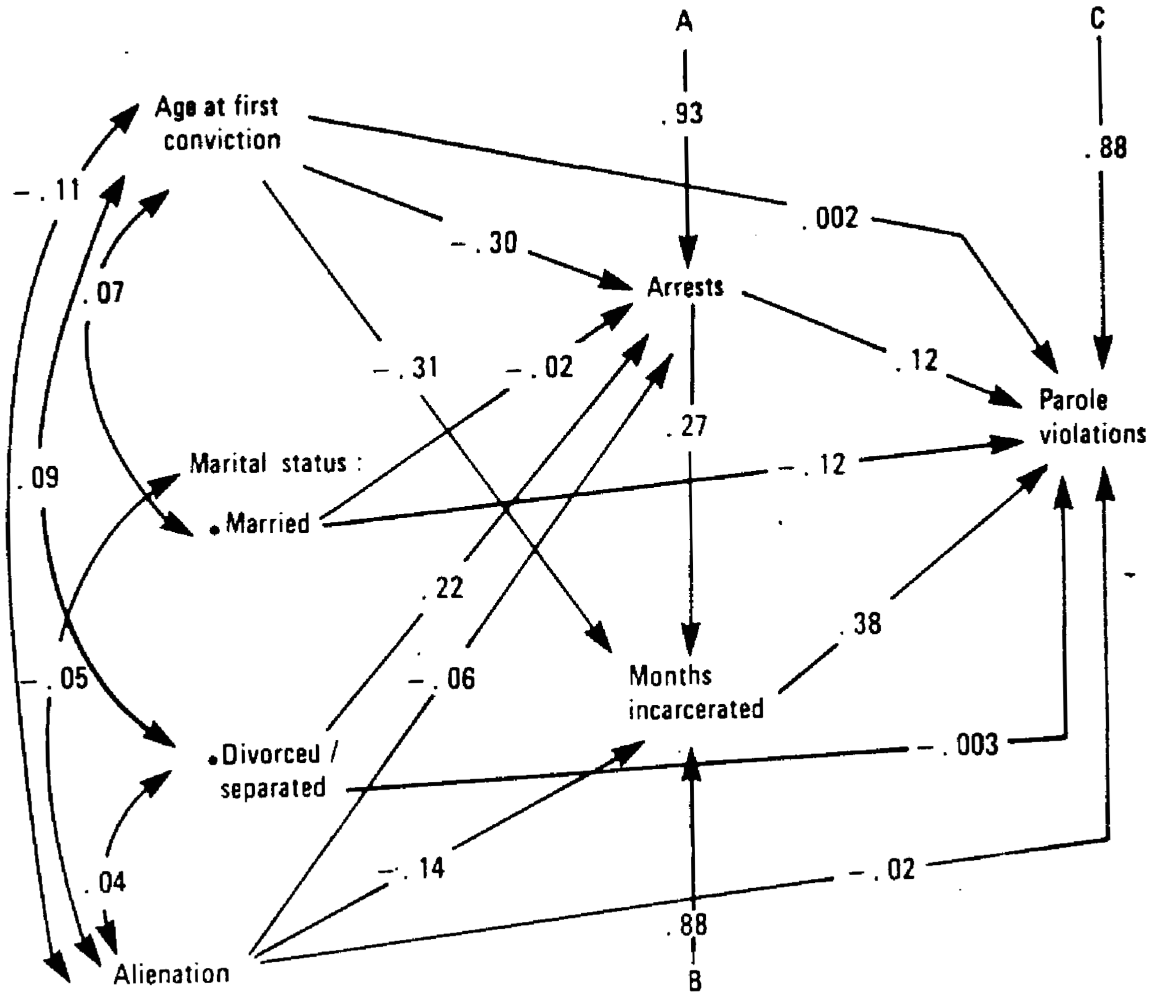
R-Square = .22

Independent variables	Beta	F
AGEFC	.002	.002
Married	-.12	2.37
Divorced/Separated	-.003	.002
Alienation	-.02	.06
Arrests	.12	2.86
Months Incarcerated	.38	28.07

Pearson Correlations (r)

	AGEFC	Mar-ried	Divor-ced/ Sep.	Aliena-tion	Arrests	Months Incar.	Parole Vio.
AGEFC	1.00						
Married	.07	1.00					
Divorced/Sep.	.09	-.61	1.00				
Alienation	-.11	-.05	.04	1.00			
Arrests	-.28	-.17	.20	-.02	1.00		
Months Incar.	-.37	-.11	.06	-.11	.36	1.00	
Parole Vio.	-.18	-.18	.11	-.05	.27	.43	1.00

Figure III.6 Preliminary Model with Path Vaules



This model accounted for 22 percent of the variation in parole violations. This was considered acceptable, since the remaining variance may be accounted for by the many additional causes of criminal behavior identified in the literature 1/ but not included in the model.

At this time, we also reviewed the statistical assumptions. Particularly, we examined scatter diagrams for linear relationships. Generally curvilinear relationships between variables also contributed to the low variance (R-square) explained by the model. Since numerous variable transformations failed to increase the linearity, the original untransformed variables were retained.

1/Pritchard [6], pp. 15-21.

Revise the Model

To make the model as simple as possible, paths that did not explain a significant amount of variation in the dependent variable were eliminated. Two paths with values below .05 were deleted. 1/

New path coefficients for the revised model (shown in figure III.7) were calculated and checked to determine if this model represented the actual relationships in the data (the Pearson correlation, r, between two variables).

The correlation between any two variables in the model can be decomposed into the sum of direct and indirect path coefficients. (An indirect path is the product of the coefficients for the direct paths comprising it. 2/) The sum of the direct and indirect paths should approximate the Pearson correlation (r) between the variables. As a rule of thumb, if the sum of the paths is within .05 of the correlation value, the model is viable. 3/ If not, too many paths may have been deleted or the model may contain too many intervening variables. (Because indirect paths are calculated by multiplying values less than one, the more intervening variables located along a path, the lower the indirect path's value.)

For example, the Pearson correlation between arrests and parole violations was .27 (read from the computer output in figure III.5). This should approximate the sum of direct and indirect paths between the two variables. The direct path was .12. The indirect path was through months incarcerated (.27 x .38 = .10).

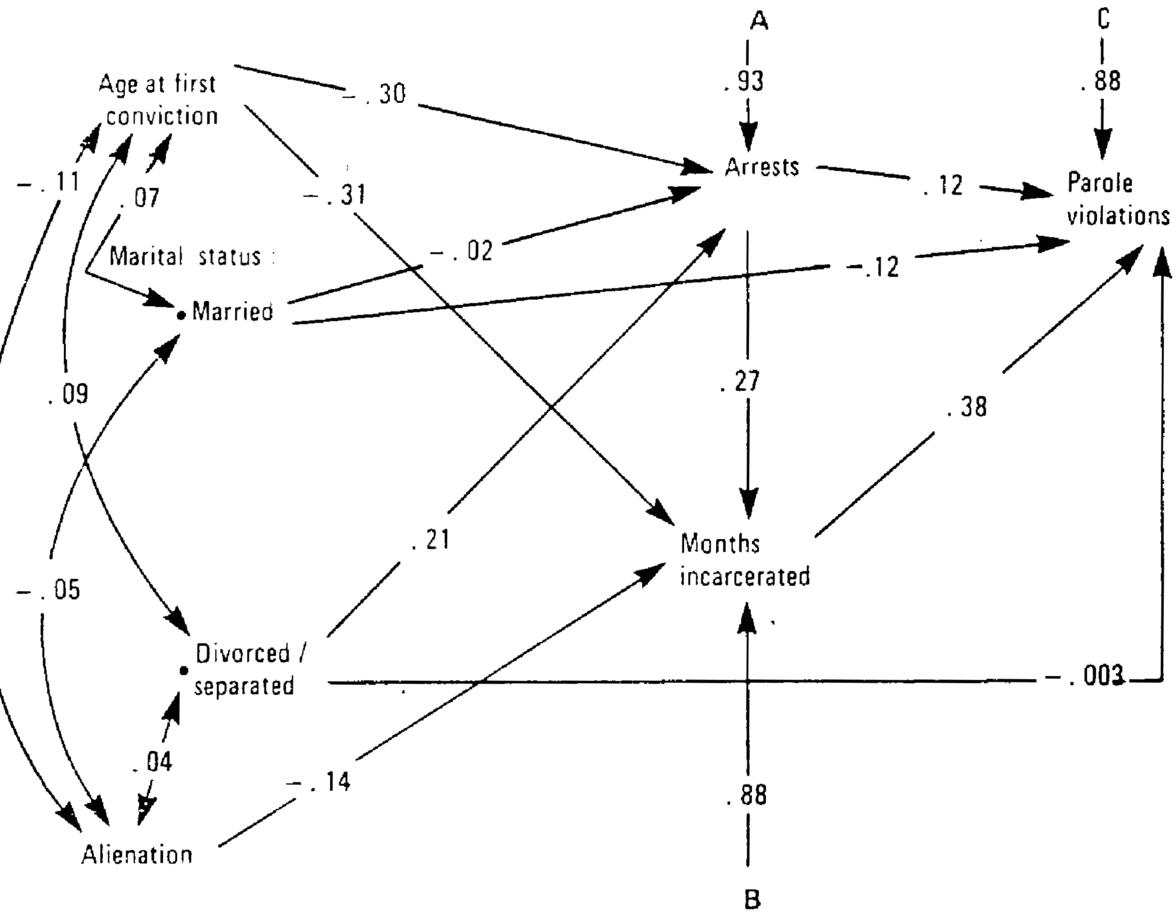
The total effect was the sum of the direct and indirect paths (.12 + .10 = .22). In this case, the observed correlation (.27) and the computed correlation (.22) differed by .05, indicating that the model reasonably represented the actual relationships between these two variables.

1/These two paths were from age at first conviction and alienation to parole violations. The two variables that formed marital status were treated as a unit--when the path from only one variable was significant, both paths were retained. For this reason, the paths from married to arrests and from divorced/separated to parole violations were kept.

2/The specific rules for computing values for indirect paths are in appendix II (Step 4. Revise the Model).

3/Kerlinger and Pedhazur [4], p. 318.

Figure III.7 Revised Model For Determining Parole Outcomes Using Path Analysis



In figure III.8, the entire model was decomposed into direct, indirect, and spurious paths. (A spurious path begins by going against the causal flow.) A high spurious value may indicate that the causal order is specified incorrectly. For example, the spurious relationship between months incarcerated and arrests (.09) was produced by paths through age at first conviction and alienation. By reversing the causal order between age at first conviction and arrests, the spurious relationship would become indirect. Of course, this change would be illogical and was not made. Decisions to reverse arrows should be based on theory or knowledge of time sequences; it should not be based on coefficient size.

Interpret the Path Diagram

By examining the final path diagram and the decomposition into direct and indirect paths, knowledge about the assumed causal relationships was gained. First, it was learned that the model accounted for 22 percent of the variance in parole violations, which was considered acceptable. Second, by examining spurious influences, one could be reasonably confident that the hypothesized causal order was correct. Third, the relative strength of direct and indirect paths could be compared. For

Figure III.8 Direct and Indirect Paths

Variables	Correlations	Direct Causal Paths	Indirect Causal Paths	Total Causal Paths	Indirect Spurious Paths
Arrests & Age	-.28	-.30	.02	-.28	-
Arrests & Married	-.17	-.02	-.02	-.04	-
Arrests & Divorced	.20	.21	-.03	.18	-
Arrests & Alienation	-.02	-	.04	.04	-
Incarcerated & Age	-.37	-.31	-.06	-.37	-
Incarcerated & Married	-.11	-	-.03	-.03	-
Incarcerated & Divorced	.06	-	.02	.02	-
Incarcerated & Alienation	-.11	-.14	.05	-.09	-
Incarcerated & Arrests	.36	.27	-	.27	.09
Parole violations & Age	-.18	-	-.18	-.18	-
Parole violations & Married	-.18	-.12	-.02	-.14	-
Parole violations & Divorced	.11	-.003	.03	.03	-
Parole violations & Alienation	-.05	-	-.04	-.04	-
Parole violations & Arrests	.27	.12	.10	.22	.03
Parole violations & Incarcerated	.43	.38	-	.38	.05

example, nearly half the total influence (.22) of arrests on parole violations was indirect (.10).

SUMMARY

This appendix discussed an example of using causal analysis to evaluate parole outcomes. In developing the parole outcome model, however, limitations of the technique were evident. Causal analysis cannot prove that causal relationships exist nor ensure that all relevant factors are included.

The technique pointed to the interactions among the six variables. We know that the five independent variables do not completely explain parole outcomes. We do not know, however, which variables to add to the model or whether more fundamental causes are responsible for the relationships.

Nevertheless, causal analysis can provide valuable program information. When guided by strong theory, an evaluator can construct a model with most of the significant variables--including manipulable program variables. Such a model would help evaluators and program managers to understand how the program can intervene in a hypothetical social condition and modify the consequences. Further, they could test the model's adequacy and compare the relative strength of program and non-program influences. Causal analysis could, thus, provide program managers with useful insights for program planning and implementation.

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(973354)

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Chap. 3: path analysis	☐	☐	☐	☐	☐
Chap. 4: causal analysis cases	☐	☐	☐	☐	☐
Appendix II: steps in data analysis	☐	☐	☐	☐	☐
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