10

Epilogue

Toward a New Approach to the Practice of Structural Equation Modeling

Methodology is a frustrating and rewarding area in which to work. Just as there is no best way to listen to a Tchaikovsky symphony, or to write a book, or to raise a child, there is no best way to investigate social reality. Yet methodology has a role to play in all of this. By showing that science is not the objective, rigorous, intellectual endeavor it was once thought to be, and by demonstrating that this need not lead to anarchy, that critical discourse still has a place, the hope is held out that a true picture of the strengths and limitations of scientific practice will emerge. And with luck, this insight may lead to a better and certainly more honest, science.

—Caldwell (1982), as cited in Spanos, (1986)

The only immediate utility of all sciences is to teach us how to control and regulate future events by their causes.

—Hume (1739)

As stated in the Preface, one goal of this book was to provide the reader with an understanding of the foundations of structural equation modeling and hopefully to stimulate the use of the methodology through examples that show how structural modeling can illuminate our understanding of social reality—with problems in the field of education serving as motivating examples. At this point, we revisit the question of whether structural equation modeling can illuminate our understanding of social reality. I argue in this chapter that the answer to this question rests not so much on the specific statistical details of the method, but rather on the approach taken to the application of the method. However, as we will see, the approach taken to the application of the method is intimately connected to the statistical underpinnings of the method itself.

Taking the position that the application of the method, and not the method itself, is linked to what we can learn about social reality, this chapter reconsiders the conventional approach to structural equation modeling as represented in most textbooks and substantive applications wherein structural modeling has been employed. The conventional approach to structural equation modeling is considered in light of recent work in the practice of econometric methodology—particularly simultaneous equation modeling.

It is not the intention of this chapter to argue that the econometric approach is the "gold standard" of structural equation modeling practice in the social sciences. Rather, the purpose of this chapter is to examine an alternative formulation of modeling practice in econometrics and to argue that the current discourse on econometric practice may have value when considered in light of the conventional practice of structural equation modeling found in other social sciences. In doing so, one goal of this chapter is to remind the reader of the econometric history underlying structural equation modeling and to outline how that history might have influenced the history of the methodology in the other social sciences.

In addition to outlining an alternative approach to the practice of structural equation modeling, I argue that developments in our understanding of causal inference in the social and behavioral sciences must be brought into current practice to exploit the utility of structural equation modeling. These developments include recent thinking on the counterfactual theory and related manipulationist theory of causation.

The organization of this chapter is as follows. In the next section, we summarize the conventional practice of structural equation modeling to set the framework for the ensuing critique. This is followed by a sketch of the so-called "textbook" practice of simultaneous equation modeling in econometrics. Following this, we outline of the history and components of an alternative methodology proposed by Spanos (1986, 1990, 1995) referred to as the *probabilistic reduction approach.* Following the outline of Spanos's methodology, we discuss the implications of the probabilistic reduction approach to the practice of structural equation modeling. The chapter then turns to the problem of causal inference. Here, we focus attention on philosophical and methodological work on the counterfactual and manipulationist theories of causal inference that has informed econometric practice and may be useful to the practice of structural equation modeling in the other social science disciplines. Finally, we close with a summary.

10.1 Revisiting the Conventional Approach to Structural Equation Modeling

The conventional approach to structural equation modeling was represented in Chapter 1. Throughout this book, reference was made to how various statistical and nonstatistical techniques within structural equation modeling were used in conventional practice. The conventional approach can be reiterated as follows. First, the investigator postulates a theoretical framework to set the stage for the specification of the model. In some cases, attempts are made to relate the theoretical framework directly to the specification of the model as typically portrayed in a path diagram. It is common to find an implicitly articulated one-to-one relationship between the theory and the path diagram—implying that the theory and the diagram correspond to each other up to the inclusion of disturbance terms.

Next, a set of measures are selected to be incorporated into the model. In cases where multiple measures of hypothesized underlying constructs are desired, investigators may digress into a study of the measurement properties of the data before incorporating the variables into a full latent variable model. It can be inferred from a reading of the extant literature that there is very close relationship assumed between the theoretical variables and the empirical latent variables.

In the next phase, the specified model as portrayed in the diagram is estimated. Rarely is the choice of the estimator based on an explicit assessment of its underlying assumptions. Even if such a thorough assessment of the assumptions were made, in many cases, analysts are limited in their choice of estimators due to such real constraints as sample size requirements. In other words, investigators may very well understand the limitations of, say, maximum likelihood estimation to categorical and other nonnormal variables, but the sample size requirements for successful implementation of, say, weighted least squares estimators may be prohibitive.[1]

After the model parameters have been estimated, the fit of the model is almost always assessed. It is quite common to find the presentation of alternative fit indices alongside the standard likelihood ratio chi-square statistic. These indices are presented despite the fact that they are based on conceptually different notions of model fit. For example, displaying the likelihood ratio chi-square test of exact fit with the nonnormed fit index which assesses fit against a baseline model of independence is conceptually dubious insofar as the "alternative hypotheses" being evaluated are entirely different.

As we noted in earlier chapters, it is often the case that a model is determined not to fit the data on a number of criteria. The lack of model fit could be the result of the violation of one or more of the assumptions underlying the chosen estimator. But regardless of the reasons for model misfit, the conventional approach to structural equation modeling takes the next step of model modification. The modification of the model typically proceeds using the modification index in conjunction with the expected change statistic. By necessity, post hoc model modification is typically supplemented with post hoc justification of how the modification fits into the theoretical framework. In any case, at some point in the cycle, model modification stops.

Once the model is deemed to fit the data, it is common to relate the findings back to the original substantive question being posed. However, the results of the model are often related back to the original question in a cursory manner. Seldom is it the case that specific parameter estimates are directly interpreted. Nor do we find a discussion of how the parameter estimates, their signs, and statistical significance support theoretical propositions. Rarer still do we find examples of comparisons of structural models representing different theoretical positions, with models being selected on the basis of, say, the Akaike information criterion statistic.[2] Finally, it is rarely the case that models are used for policy or clinically relevant prediction studies.

To summarize, the conventional approach to structural equation modeling in the social sciences can be described in five steps: (1) a model is specified and considered to be a relatively close instantiation of a theory, (2) measures are gathered, (3) the model is estimated, (4) then typically modified, and finally (5) the results are related back to the original question. Interestingly, the approach to structural equation modeling in the social sciences parallels the conventional approach to econometric modeling described by Pagan (1984), who wrote

> Four steps almost completely describe it: a model is postulated, data gathered, a regression run, some *t*-statistics or simulation performance provided and another empirical regularity was forged.

Next, we outline the history that led to the conventional approach to econometric practice characterized by Pagan to serve as a comparison the conventional practice of structural equation modeling in the social sciences.

10.2 The Conventional Approach to Econometric Practice

In his historical account of econometric practice, Spanos (1989) argues that the Harvard monograph by Haavelmo (1944) formally launched econometrics as a distinct discipline. Moreover, Spanos laments the fact that this monograph, although heavily cited, was rarely read and that there were many key aspects of the work that have been neglected in practice. Neglect of these key aspects of Haavelmo's work may have contributed to the conventional practice of econometric modeling and the difficulties it generated.

A central aspect of Haavelmo's approach was the notion of the joint distribution of the process underlying the available data as being of most importance to identification, estimation, and hypothesis testing. The joint distribution of the observed random variables over the time period of collection is referred to by Spanos (1989) as the *Haavelmo distribution.* We consider the Haavelmo distribution in more detail in Section 10.3.

The second aspect of Haavelmo's contribution, which was arguably ignored in the conventional practice of econometrics, concerned the notion of *statistical adequacy*. Statistical adequacy was a concept introduced by R. A. Fisher and brought to econometrics by Koopmans (1950) and is a property of a statistical model applied to the observed data when the underlying assumptions of the model are met. In cases where a statistical model is not statistically adequate, inferences drawn from the statistical model are suspect at best. Of central importance to the argument presented in this chapter is that statistical adequacy must be established *before* testing theoretical suppositions because the validity of these tests depends on the validity of the statistical model.

A third aspect of Haavelmo's approach concerns his view of data mining. Specifically, this issue concerns the distinction between the statistical model and the estimable econometric model used for testing specific theoretical questions of interest. The statistical model carries with it aspects of the underlying theory insofar as the theory dictates which variables to collect and, possibly, how to measure them. However, the statistical model is designed to capture the probabilistic structure of the data only and is, in an important sense, theory neutral. The relationship between the statistical model and the theoretical parameters of interest is handled by Haavelmo through the process of identification—which in Haavelmo's methodology is intimately linked with the probabilistic structure of the observed data.

The final element of Haavelmo's methodology, which seems to have been neglected in the conventional practice of econometrics, concerns the error term. Specifically, in Haavelmo's methodology, the statistical model is specified in consideration of the probabilistic structure of the observed random variables—not the error term. Spanos (1989) notes that this distinction separates the post-Haavelmo paradigm in econometric methodology from the pre-Haavelmo paradigm that rested on the Gaussian theory of errors.

10.2.1 COMPONENTS OF THE TEXTBOOK APPROACH TO ECONOMETRICS

As Spanos (1989) noted, a lack of careful reading of Haavelmo resulted in what came to be called the "textbook" practice of econometrics (Spanos, 1986). The textbook practice was perhaps best exemplified by two important early econometric textbooks: Goldberger (1964) and Johnston (1972). It is interesting to point out that Goldberger was influential in the application of structural equation modeling to social sciences other than economics. Indeed, Goldberger collaborated with the sociologist O. D. Duncan producing a classic edited volume on structural equation modeling in the social science (Goldberger & Duncan, 1972; Jöreskog, 1973). Goldberger also collaborated with Karl Jöreskog on important applications to structural equation modeling—including the MIMIC model discussed in Chapter 4 (Jöreskog & Goldberger, 1975).[3]

The textbook approach to econometrics as represented by Johnston's and Goldberger's texts incorporated aspects of Haavelmo's probabilistic approach only through the assumed structure of the error term. Moreover, Haavelmo's notions of obtaining a statistically adequate model did not influence the practice of simultaneous equation modeling because there was a prevailing view that the use of sample information without underlying theory was inappropriate (Spanos, 1989).[4] Clearly, under this viewpoint, there is no incentive to consider the underlying probabilistic structure of the data. By default, data mining is also discouraged.

The response to the textbook practice of econometrics was a series of sustained critiques from a variety of perspectives. A discussion of these critiques can be found in Spanos (1990). Suffice to say here that the critiques of the textbook practice of econometrics centered on the validity of employing experimental design reasoning to purely observational data and on the role of statistically adequate models. A specific critique offered by Spanos (1989, 1990) had its origins in the London School of Economics tradition (see, e.g., Hendry, 1983) and focused on the importance of the probabilistic structure of the data and is based on a rereading and adaptation of Haavelmo's original contributions. This approach is described next.

10.3 The Probabilistic Reduction Approach

In Chapter 1, we noted that econometric simultaneous equation modeling could not compete with Box-Jenkins time-series models in terms of predictive performance. One problem with simultaneous equation modeling centered on the distinction between dynamic and static models. However, regardless of the specific problem, econometricians were beginning to realize that simultaneous equation models were not producing the kind of reliable predictions of the behavior of the economy that the Cowles Commission had envisioned. The problem, it seemed, lied in a conventional practice of econometric modeling that deviated from what was originally intended by founders such as Haavelmo (Haavelmo, 1943, 1944; see also Spanos, 1989). The result was that from the mid-1970s to the present, there has been a sustained critique of the conventional approach to econometric modeling.

I argue that one response to this critique offered by Spanos (1986, 1990, 1995) may provide an alternative to the conventional practice of structural equation modeling in the social sciences. Spanos refers to this alternative approach as the *probabilistic reduction approach.*

10.3.1 THE HISTORICAL BACKGROUND OF THE PROBABILISTIC REDUCTION APPROACH

In the development of the probabilistic reduction approach, Spanos (1995) traces the general problem of simultaneous equation modeling to two historical paradigms in statistics: (1) Fisher's experimental design paradigm and (2) the Gaussian theory of errors paradigm. The conventional practice of simultaneous equation modeling in econometrics resulted from a combination of the influence of these paradigms and a lack of careful reading of Haavelmo's (1943, 1944) original work.

Fisher's Experimental Design Paradigm. In the case of Fisher's paradigm, the experimental design represents the theory and the statistical model is chosen before the data are collected. Indeed, the correspondence between the statistical model and the experimental design as representing the theory are nearly identical, with the statistical model differing from the design by the incorporation of an error term.

The major contributions of Fisher's paradigm notwithstanding,[5] the conventional approach to simultaneous equation modeling borrowed certain features of the paradigm that are problematic in light of the reality of economic and social science phenomena. Specifically, as noted by Spanos (1995) the social theory under investigation (e.g., input-process-output theory in education) replaces the experimental designer. Moreover, the theory is required to lead to a theoretical model that does not differ in any substantial way from the statistical model. In other words, adapting the Fisher paradigm to economics and social science applications of structural modeling assumes that the theory and the designer are one and the same and that the statistical model and the theoretical model as derived from the theory differ only up to the inclusion of a white-noise disturbance term.

The Theory of Errors Paradigm. The theory of errors paradigm had its roots in the mathematical theory of approximation and led to the method of least squares proposed by Legendre in 1805. A probabilistic foundation was given to the least squares approach by Gauss in 1809 and developed into a "theory of errors" by Laplace in 1812.

The basic idea originally proposed by Legendre was that a certain function was optimally approximated by another function via the minimization of the sum of the squared deviations about the line. The probabilistic formulation proposed by Gauss and later Laplace was that if the errors were the result of insignificant omitted factors, then the distribution of the sum of the errors would be normal as the number of errors increased. If it could be argued that the omitted variables were essentially unrelated to the systematic part of the model, then the phenomena under study could be treated as if it were a nearly isolated system (as cited in Spanos, 1995; Stigler, 1986).

Arguably, the theory of errors paradigm had a more profound influence on econometric and social science modeling than the Fisher paradigm. Specifically, the theory of errors paradigm led to a tremendous focus on statistical estimation. Indeed, a perusal of most econometric textbooks shows that the dominant discussion is typically around the choice of an estimation method. The choice of an alternative estimator, whether it be two-stage least squares, limited-information maximum likelihood, instrumental variable estimation, or generalized least squares, is the result of viewing ordinary least squares as not living up to its optimal properties in the context of real data.

A Comparison of the Two Approaches. The common denominator between the Fisher paradigm and the theory of errors paradigm is the assumptions made regarding the error term. In both cases, the assumptions made regarding the error term lead to the view that the phenomenon under study exists as a nearly isolated system. Where the two traditions differ however, is in their views of redesign and data mining (Spanos, 1995). Specifically, in the Fisher paradigm it is entirely possible that an experiment can be redesigned. Moreover, given that the design is the de facto reality under study, data mining could lead to "discovering a theory in the data." In the context of the theory of errors paradigm, the data are nonexperimental in nature and thus data mining is nonproblematic. Spanos (1995) cites the example of Kepler. Spanos writes, "Kepler's insight was initially suggested by looking at the data and not by a theory. Indeed, the theory came much later in the form of Newton's theory of universal gravitation" (pp. 195–196). In addition, in nonexperimental research, such "experiments" cannot be redesigned.

Regardless of the similarities and differences between the Fisher and theory of errors paradigms, the conventional approach to econometric modeling, and indeed statistical modeling in the social sciences generally, adopted aspects of both. In particular, econometric modeling historically took a dim view with respect to data mining, and social science applications of structural equation modeling have been somewhat silent on this issue. As noted above, this could be the result of confusion between the theory and the experimental design that arises from the Fisher paradigm. A close look at this bias in the context of nonexperimental data leads to the conclusion that the bias is somewhat irrational. Moreover, as we will see when we outline the probabilistic reduction approach, this negative view toward data mining disappears, and instead, the activity becomes positively encouraged.

10.4 Elements of the Probabilistic Reduction Approach

The probabilistic reduction approach to structural equation modeling is presented in Figure 10.1. A key feature of Figure 10.1 is the separation of the theory from the actual data-generating process, or DGP. In this formulation, a *theory* is a conceptual construct that serves to provide an idealized description of the phenomena under study. For example, the input-process-output "model" discussed in Chapter 1, is actually a theory insofar as it describes, in entirely conceptual terms, the processes that leads to important educational outcomes.[6] The constructs that make up the theory are not observable entities, nor are they latent variables derived from observable data. Yet, the theory should be articulated well enough to suggest what measures to obtain even if it does not directly suggest the scales on which they should be measured. Finally, the theory should be sufficiently detailed to allow for predictions based on a statistical model. That is, the statistical model, to be described below, should be capable of a reparameterization sufficiently detailed to allow tests of predictions suggested by the theory.

10.4.1 THE DATA-GENERATING PROCESS

We next consider a very important component of the probabilistic reduction approach—namely the *actual data-generating process* or *DGP*. In the simplest terms, the DGP is the actual phenomenon that the theory is put forth to explain. In essence, the DGP corresponds to the reality that generated the observed data. It is the reference point for both the theory and the statistical model. In the former case, the theory is put forth to explain the reality under investigation—be it the cyclical behavior of the economy or the organizational structure of schooling that generates student achievement. In the latter case, the statistical model is designed to capture the systematic nature of the observed data as generated by the DGP.

10.4.2 THE THEORETICAL MODEL

A theoretical model, according to Spanos, is a mathematical formulation of the theory. The theoretical model is not necessarily the statistical model with a white-noise term added. In social science applications of structural equation modeling, we tend not to see theoretical models as such. Instead, we view the statistical model with the restrictions added as somehow separate from a theoretical model. It is argued below that the restrictions placed on a statistical model, and indeed the issue of identification, implies an underlying theoretical model even if not directly referred to as such.

10.4.3 THE ESTIMABLE MODEL

In some cases, the theoretical model may not be capable of being estimated. This is because the theoretical model is simply a mathematical formulation of

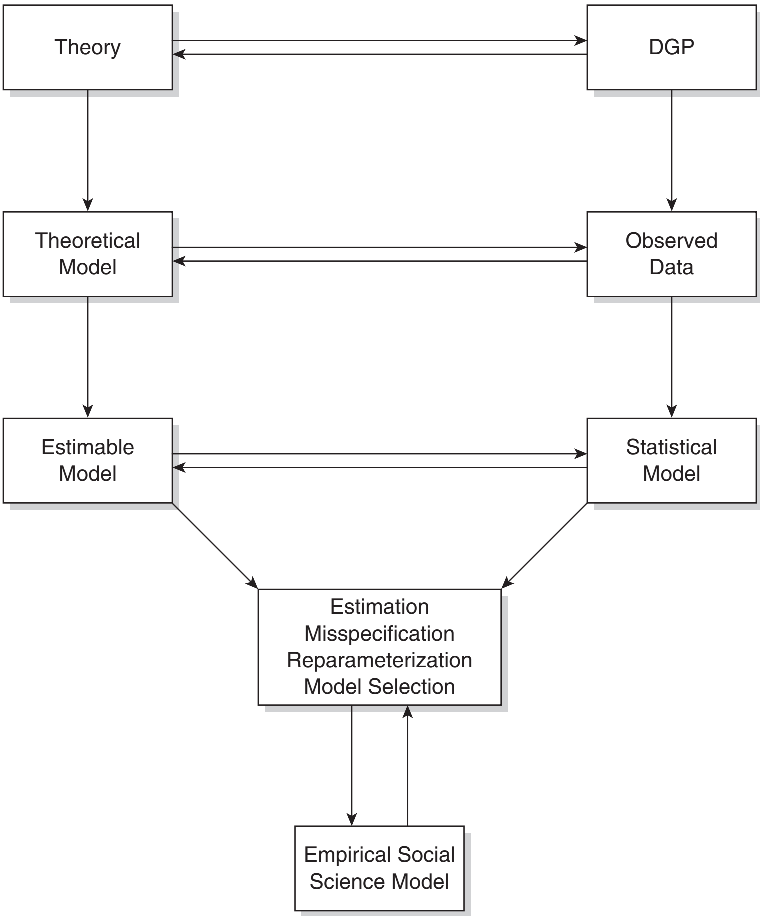

Figure 10.1 Diagram of the Probabilistic Reduction Approach to Structural Equation Modeling

SOURCE: Adapted from Spanos (1986).

a theory, and the latter does not always provide information regarding what *can* be observed or how it should be measured. One only need think of "school quality" as an important theoretical variable of the input-process-output theory to realize how many different ways such a theoretical variable can be measured. Therefore, a distinction needs to be made regarding the theoretical model and an *estimable model*, where the estimable model is specified with an eye toward the DGP (Spanos, 1990).

As an example, let us assume the appropriateness of the input-process-output theory. If interest centers on the measurement of school quality via a survey of school climate, this will have bearing on the form of the estimable model as well as the form of the statistical model (to be described next). If school quality actually referred to the distribution of resources to classrooms, then clearly the estimable model will differ from the theoretical model and auxiliary measurements might need to be added. It may be interesting to note that the theoretical model and estimable model coincides when data are generated from an experimental arrangement. However, we noted that such arrangements are rare in social science applications of structural equation modeling.

10.4.4 THE STATISTICAL MODEL

The statistical model describes an internally consistent set of probabilistic assumptions made about the obtained data series. As Spanos (1990) notes, the statistical model should be an *adequate* and *convenient* summary of the observed data. The term "adequate" is used in the sense that it does not exclude systematic information in the data. The term "convenient" is used to suggest that the statistical model can be used to consider aspects of the theory.

To be clear, the statistical model is not a one-to-one instantiation of the theory. Rather, within the probabilistic reduction approach, the statistical model is chosen to adequately represent the probabilistic information in the data (Spanos, 1990). However, the choice of a statistical model is partly guided by theory insofar as the statistical model must be capable of being used to answer theoretical question of interest.

It is in the context of our discussion of the statistical model that we may wish to revisit the issue of data mining. In the probabilistic reduction approach, the statistical model is specified to capture as much systematic probabilistic information in the data as possible. No theoretical specification is imposed. To take an example from educational research, the lack of independence among observations due to nesting of students in schools is unrelated to the number of plots or other exploratory methods used to detect it. As such, data mining in the form of plots and other methods of exploratory data analysis is not only valid but also strongly encouraged as a means of capturing the systematic information in the data.

Because the notion of the statistical model is unique to the probabilistic reduction approach, it is required that we develop the concept more fully. To begin, consider the joint distribution of the data denoted as $f(\mathbf{y}, \mathbf{x}|\boldsymbol{\theta})$. Generally, statistical models such as regression involve a reduction of the joint distribution of the observed data. Such a reduction can be written as

$$f(\mathbf{y}, \mathbf{x}|\boldsymbol{\theta}) = f(\mathbf{y}|\mathbf{x}; \boldsymbol{\theta}_1) f(\mathbf{x}; \boldsymbol{\theta}_2), \qquad [10.1]$$

where the first term on the right-hand side of Equation [10.1] is the conditional distribution of the endogenous variables given the exogenous variables, and the second term on the right-hand side is the marginal distribution of the exogenous variables. The parameter vectors $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ index the parameters of the conditional distribution and marginal distribution, respectively. To take an example from simple regression, the vector $\boldsymbol{\theta}_1$ contains the intercept, slope, and disturbance variance parameters of the regression model, while the vector $\boldsymbol{\theta}_2$ contains the mean and variance of the marginal distribution of **x**.

Weak Exogeneity. The development of a statistically adequate model proceeds by focusing attention on the conditional distribution of **y** given **x**. However, this immediately raises the question of whether one can ignore the marginal distribution of **x**. This question concerns the problem of *weak exogeneity* (Ericsson & Irons, 1994; Richard, 1982) and represents the first and perhaps most important assumption that needs to be addressed. The problem of weak exogeneity was discussed in Chapter 5. Suffice to say that with regard to the choice of the variables in the model vis-à-vis the theory, the assumption of weak exogeneity requires serious attention.

Continuing with our discussion, if we can assume weak exogeneity, then we can focus our attention on the conditional distribution $f(\mathbf{y}, \mathbf{x}|\boldsymbol{\theta}_1)$. In the context of structural equation modeling, we may write $f(\mathbf{y}, \mathbf{x}|\boldsymbol{\theta}_1)$ as

$$\mathbf{y} = \boldsymbol{\Pi}\mathbf{x} + \boldsymbol{\zeta}^*, \qquad [10.2]$$

which we note is the reduced form specification discussed in Chapter 2 and, in fact, is the multivariate general linear model.

Within the probabilistic reduction approach applied to structural equation modeling, the reduced form specification constitutes the statistical model while the structural form constitutes the theoretical model. Prior to testing restrictions implied by the theory via the structural form, it is necessary to assess the statistical adequacy of the reduced form.

A Note on Identification. It may be interesting to note that the probabilistic reduction approach yields two notions of identification (Spanos, 1990). First, in the context of the statistical model, identification concerns the adequacy of the sample information for estimating the parameters of the joint distribution of the data. It could be the case that there is insufficient information in the form of colinearity that limits the estimation of the statistical model. Colinearity was not explicitly discussed in this book. For a discussion of colinearity in the context of structural equation modeling, see Kaplan (1994).

Second, identification problems in the form of insufficient sample information can be distinguished from identification problems related to insufficient theoretical information—in essence whether structural parameters can be identified from reduced form parameters. However, it must be made clear that the probabilistic reduction approach does not view theoretical identification issues as separate from the statistically adequate model on which it rests.

The two forms of identification are related, but distinction is useful from the view point of the probabilistic reduction approach (see Spanos, 1990).

10.4.5 THE EMPIRICAL SOCIAL SCIENCE MODEL

It is important to note that the statistical model discussed in Section 10.4.4 refers to a model that captures the systematic probabilistic information in the data. Once a convenient and adequate statistical model is formulated, the empirical social science model is reparameterized for purposes of description, explanation, or prediction. The reparameterization that would be easily recognized by practitioners of structural equation modeling is in the form of restricting parameters to zero.[7] In other words, after a statistical model is chosen, the next step is to restrict the model in ways suggested by theory or as a means of testing competing theories.

For example, after formulating an adequate representation of the reduced form of the science achievement model, one could test a set of theoretical propositions of the sort implied by the path diagram in Figure 2.1.[8] The path diagram, therefore, represents the empirical model of interest—providing a pictorial representation of the restrictions to be placed on a statistically adequate reduced form model.

10.4.6 RECAP: MODELING STEPS USING THE PROBABILISTIC REDUCTION APPROACH

It is important to be clear regarding the modeling steps that are suggested by the probabilistic reduction approach and to contrast them with the conventional approach described above. The probabilistic reduction approach assumes that there exists a theory (or theories) that the investigator wishes to test. It is assumed that the theory is sufficiently detailed insofar as it is able to suggest the type of measures to be obtained. The theory is assumed to describe some actual phenomenon—referred to as the DGP. In this regard, there is no philosophical difference between the probabilistic reduction approach and the conventional approach.

Assuming that a set of data has been gathered, the next step is to specify a convenient and adequate statistical model of the observed data. Such a statistically adequate model should account for all the systematic probabilistic information in the data. That is, the statistical model is developed on the joint distribution of the data. All means necessary to model the probabilistic nature of the joint distribution should be used because the statistical parameters of the joint distribution have no theoretical interpretation at this point. Indeed, the probabilistic reduction approach advocated by Spanos calls for the free use of data plots and other forms of data summary in an effort to arrive at an adequate and convenient statistical model. Note that model assumptions relate to the conditional distribution of the data, and it may be necessary to put forth numerous statistical models until one is finally chosen. These assumptions include exogeneity, normality, linearity, homogeneity, and independence. Weak exogeneity becomes a very serious assumption at this step because evidence against weak exogeneity implies that conditional estimation is inappropriate—that is, the conditional and marginal distributions must be both taken into consideration during estimation. In any case, a violation of one or more of these assumptions requires respecification and adjustment until a statistically adequate model is obtained.

The next step in the probabilistic reduction approach is to begin testing theoretical propositions of interest via parameter restrictions placed on a statistically adequate model. Note that whereas the resulting statistical model may be based on considerable data mining, this does not present a problem because the parameters of the statistical model do not have a direct interpretation relative to the theoretical parameters. However, the process of parameter restriction of the statistical model is based on theoretical suppositions and should not be data specific. Indeed, as Spanos points out, the more restrictions placed on the model, the less data-specific the theoretical/estimable model becomes. From the point of view of structural equation modeling in the social sciences, this means that we tend to favor models with many degrees of freedom.

In contrast to the probabilistic reduction approach, the conventional approach typically starts with an over-identified model wherein the more overidentifying restrictions the better from a theoretical point of view. However, the process of model modification that characterizes the conventional approach becomes problematic insofar as it does not rest on a statistically adequate and convenient summary of the probabilistic structure of the data.

10.5 Structural Equation Modeling and Causal Inference

In the previous section, a detailed account of an alternative to the conventional application of structural equation modeling was offered. This alternative approach to conventional structural equation modeling focuses almost entirely on the statistical features of the methodology and its common practice. Moreover, in our discussion, attention was paid to the use of the probabilistic reduction approach to improve prediction. Although prediction is critically important in the social and behavioral sciences, an equally important activity is the testing of causal propositions and developing explanations of substantive processes.

It is important to contrast models used for prediction versus models used for causal inference and explanation. In the former case, it is sufficient to have used the probabilistic reduction approach to capture the covariance structure of the data. In the latter case, the logic of causal inference lies outside of the statistical analysis and requires that we examine variables with regard to their potential for manipulation and control.

Historically, developers and practitioners of structural equation modeling have been reluctant to consider it as a tool for assessing causal claims. However, in what is undeniably a classic study of the problem of causality, Pearl (2000) in his book *Causality: Models, Reasoning and Inference* deals directly with, among many other things, the reluctance of practitioners to use structural equation modeling for warranting causal claims. Pearl noted that many of those who have been instrumental in developing structural equation modeling and propagating its use have either explicitly warned against using causal language in regards to its practice (e.g., Muthén, 1987), or have simply not discussed causality at all. However, as Pearl pointed out, the founders of structural equation modeling (especially Haavelmo, 1943; Koopmans et al., 1950; Wright, 1921, 1934) have noted that it can be used to warrant causal claims as long as we understand that certain causal assumptions must be made first.[9] Haavelmo, for instance, believed that structural equations were statements about hypothetical controlled experiments.

Pearl sees the elimination of causal language in structural equation modeling as arising from two distinct sets of issues. First, from the econometric end, Pearl argues that the Lucas's (1976) critique may have led economists to avoid causal language. The Lucas critique centers on the use of econometric models for policy analysis because such models contain information that changes as a function of changes in the phenomenon under study. The following quotation from Lucas (1976; as cited in Hendry, 1995) illustrates the problem.

> Given that the structure of an econometric model consists of optimal decision rules for economic agents, and that optimal decision rules vary systematically with changes in the structure of the series relevant to the decision maker, it follows that any change in policy will systematically alter the structure of econometric models. (Lucas, 1976, as cited in Hendry, 1995, p. 529)

As Hendry (1995) summarizes, "a model cannot be used for policy if implementing the policy would change the model on which that policy was based, since then the outcome of the policy would not be what the model had predicted" (p. 172). From the more modern structural equation modeling perspective, Pearl argues that the reluctance to use of causal language may have been due to practitioners wanting to gain respect from the statistical community who have traditionally eschewed invoking assumptions that they deemed untestable. Finally, Pearl lays some of the blame at the feet of the founders, who, he argues, developed an algebraic language for structural equation modeling that precluded making causal assumptions explicit.

Despite these concerns, a great deal of philosophical and methodological research has developed that, I argue, provides a sensible foundation for testing causal claims within the structural equation modeling context. Specifically, that foundation rests on the *counterfactual model* of causation. Next, I provide a brief review modern philosophical ideas and econometric theory related specifically to the counterfactual theory of causation.

10.6 The Counterfactual Theory of Causation

My focus on the counterfactual theory of causation and the careful formulation of model-based counterfactual claims rests on the argument that properly developed measures that are closely aligned with the data-generating mechanism provides a system for testing counterfactual claims in the context of structural equation models. The probabilistic reduction approach described earlier is, in my view, a more statistically sophisticated approach to developing measures and models that are closely aligned with the DGP than the conventional approach. The counterfactual theory of causation provides a logical overlay to the probabilistic reduction approach and can lead to a sophisticated study of causation within structural equation modeling.

It should be mentioned at the outset that this section of the chapter neither covers all aspects of a theory of causation that is of relevance to structural equation modeling nor does it overview existing debates between those holding a so-called structural view of causation (e.g., Heckman, 2005) versus those holding a treatment effects view of causation (e.g., Holland, 1986). A more comprehensive review of these issues in general can be found in Kaplan (in press). Instead, this section deals with specific theories of causation that arguably hold great promise in improving the practice of structural equation modeling for advancing the social and behavioral sciences.

10.6.1 MACKIE AND THE INUS CONDITION FOR CAUSATION

A great deal has been written on the counterfactual theory of causation. For the purposes of this chapter, I will focus specifically on the work of Mackie (1980) in his seminal work *The Cement of the Universe* as well as Hoover's (1990, 2001) applications of Mackie's thinking within the econometric framework. A specific extension of the counterfactual theory by Woodward (2003) which advocates a manipulationist view of causation is also discussed. I argue that these works on counterfactual propositions sets the basis for a more nuanced approach to causal inference amenable to structural equation modeling. The seminal work on the counterfactual theory of causation can be found in Lewis (1973). An excellent recent discussion can be found in Morgan and Winship (2007).

To begin, Mackie (1980) situates the issue of causation in the context of a modified form of a counterfactual conditional statement—namely, *if X causes Y, then this means that X occurred and Y occurred, and Y would not have occurred if X had not.* This strict counterfactual proposition is challenging because there are situations were we can conceive of *Y* occurring if *X* had not.[10] Thus, Mackie suggests that a counterfactual statement must be augmented by considering the circumstances or conditions under which the causal event took place—or what Mackie refers to as a *causal field.* To quote Mackie (1980),

> What is said to be caused, then, is not just an event, but an event-in-a-certain-field, and some 'conditions' can be set aside as not causing this-event-in-this-field simply because they are part of the chosen field, though if a different field were chosen, in other words if a different causal question were being asked, one of those conditions might well be said to cause this-event-in-that-other-field. (p. 35)

Contained in a casual field can be a host of factors that could qualify as causes of an event. Following Mackie (1980), let *A*, *B*, *C*, . . . , and so on, be a list of factors within a causal field that lead to some effect whenever some conjunction of the factors occurs. A conjunction of events may be *ABC* or *DEF* or *JKL*, and so on. This allows for the possibility that *ABC* might be a cause or *DEF* might be a cause, and so forth. For simplicity, assume the collection of factors is finite—namely *ABC, DEF,* and *JKL*. Each specific conjunction, such as *ABC* is sufficient but not necessary for the effect. In fact, following Mackie, *ABC* is a "minimal sufficient" condition insofar as none of its constituent parts are redundant. That is, *AB* is not sufficient for the effect, and *A* itself is neither a necessary nor sufficient condition for the effect. However, Mackie states that the single factor, in this case, *A*, is related to the effect in an important fashion—namely, "[I]t is an insufficient but non-redundant part of an unnecessary but sufficient condition: it will be convenient to call this . . . an inus condition" (p. 62).

It may be useful to briefly examine the importance of Mackie's work in the context of a substantive illustration. For example, in testing models that can be used to examine ways of improving reading proficiency in young children, Mackie would have us first specify the causal field or context under which the development of reading proficiency takes place. Clearly, this would be the home and schooling environments. We could envision a large number of factors that could qualify as causes of reading proficiency within this causal field.

In Mackie's analysis, the important step would be to isolate the set of conjunctions, any one of which might be minimally sufficient for improved reading proficiency. A specific conjunction might be phonemic awareness, parental support and involvement, and teacher training in early literacy instruction. This set is the minimal sufficient condition for reading proficiency in that none of the constituent parts are redundant. Any two of these three factors is not sufficient for reading proficiency and one alone—say, focusing on phonemic awareness, is neither necessary nor sufficient. However, phonemic awareness is an inus condition for reading proficiency. That is, the emphasis on phonemic awareness is insufficient as it stands, but it is also a nonredundant part of a set of unnecessary but (minimally) sufficient conditions.

Mackie's analysis, therefore, provides a framework for considering the exogenous and mediating effects in a structural equation model. Specifically, when delineating the exogenous variables and mediating variables in a structural equation model, explicit attention should be paid to the causal field under which the causal variables are assumed to operate. This view encourages the practitioner to provide a rationale for the choice of variables in a particular model and how they might work together as a field within which a select set of causal variables operates. This exercise in providing a deep description of the causal field and the inus conditions for causation should be guided by theory and, in turn, can be used to inform and test theory.

10.6.2 CAUSAL INFERENCE AND COUNTERFACTUALS IN ECONOMETRICS

Because structural equation modeling has its roots in econometrics, it is useful to examine aspects of the problem of causal inference from that disciplinary perspective. Within econometrics, an important paper that synthesized much of Mackie's (1980) notions of inus conditions for causation was Hoover (1990). Hoover's essential point is that causal inference is a logical problem and not a problem whose solution is to be found within a statistical model per se.[11] Moreover, Hoover argues that discussions of causal inference in econometrics are essential and that we should not eschew the discussion because of its seemingly metaphysical content. Rather, as with medicine, but perhaps without the same consequences, the success or failure of economic policy might very well hinge on a logical understanding of causation. A central thesis of the present chapter is that such a logical understanding of causation is equally essential to rigorous studies in the other social and behavioral sciences that use structural equation modeling.

In line with Mackie's analysis, Hoover suggests that the requirement that a cause be necessary and sufficient is too strong, but necessity is crucial in the sense that every consequence must have a cause (Holland, 1986). As such, Hoover views the inus condition as particularly attractive to economists because it focuses attention on some aspect of the causal problem without having to be concerned directly with knowing every minimally sufficient subset of the full cause of the event. In the context the social and behavioral sciences, these ideas should also be particularly attractive. As in the aforementioned example of reading proficiency, we know that it is not possible to enumerate the full cause of reading proficiency, but we may be able isolate an inus condition—say parental involvement in reading activities.

Hoover next draws out the details of the inus condition particularly as it pertains to the econometric perspective. Specifically, in considering a particular substantive problem, such as the causes of reading proficiency, we may divide the universe into antecedents that are relevant to reading proficiency, *C*, and those that are irrelevant, *non-C*. Among the relevant antecedents are those that we can divide into their disjuncts C_i and then further restrict our attention to the conjuncts of particular inus conditions. But what of the remaining relevant causes of reading proficiency in our example? According to Mackie, they are relegated to the causal field. Hoover views the causal field as the standing conditions of the problem that are known not to change, or perhaps to be extremely stable for the purposes at hand. In Hoover's words, they represent the "boundary conditions" of the problem.

However, the causal field is much more than simply the standing conditions of a particular problem. Indeed, from the standpoint linear statistical models generally, those variables that are relegated to the causal field are part of what is typically referred to as the error term. Introducing random error into the discussion allows Mackie's notions to be possibly relevant to indeterministic problems such as those encountered in the social and behavioral sciences. However, according to Hoover, this is only possible if the random error terms are components of Mackie's notion of a causal field.

Hoover argues that the notion of a causal field has to be expanded for Mackie's ideas to be relevant to indeterministic problems. In the first instance, certain parameters of a causal process may not, in fact, be constant. If parameters of a causal question were truly constant, then they can be relegated to the causal field. Parameters that are mostly stable over time can also be relegated to the causal field, but should they in fact change, the consequences for the problem at hand may be profound. In Hoover's analysis, these parameters are part of the boundary conditions of the problem. Hoover argues that most interventions are defined within certain, presumably constant, boundary conditions—although this may be questionable outside of economics.

In addition to parameters, there are also variables that are not of our immediate concern and thus part of the causal field. Random errors, in Hoover's analysis, contain the variables omitted from the problem and are "impounded" in the causal field. "The causal field is a background of standing conditions and, within the boundaries of validity claimed for the causal relation, must be invariant to exercises of controlling the consequent by means of the particular causal relation (INUS condition) of interest" (Hoover, 2001, p. 222).

Hoover points out that for the inus condition to be a sophisticated approach to the problem of causal inference, the antecedents must truly be antecedent. Frequently, this requirement is presumed to be met by appealing to temporal priority. But the assumption of temporal priority is often unsatisfactory. Hoover gives the example of laying one's head on a pillow and the resulting indentation in the pillow as an example of the problem of simultaneity and temporal priority.[12] Mackie, however, sees the issue somewhat more simply—namely the antecedent must be directly controllable. This focus on direct controllability is an important feature Woodward's (2003) manipulability theory of causation described next.

10.7 A Manipulationist Account of Causation Within Structural Equation Modeling

A very important discussion of the problem of manipulability was given by Woodward (2003) who directly dealt with causal interpretation in structural equation modeling. First, Woodward considers the difference between descriptive knowledge versus explanatory knowledge. While not demeaning the usefulness of description for purposes of classification and prediction, Woodward is clear that his focus is on causal explanation. For Woodward, a causal explanation is an explanation that provides information for purposes of manipulation and control. To quote Woodward,

> my idea is that one ought to be able to associate with any successful explanation a hypothetical or counterfactual experiment that shows us that and how manipulation of the factors mentioned in the explanation . . . would be a way of manipulating or altering the phenomenon explained . . . Put in still another way, an explanation ought to be such that it can be used to answer what I call the what-if-things-had-been-different question . . . (p. 11)

We clearly see the importance of the counterfactual proposition in the context of Woodward's manipulability theory of causation. However, unlike Mackie's analysis of the counterfactual theory, Woodward goes a step further by linking the counterfactuals to interventions. For Woodward, the types of counterfactual propositions that matter are those that suggest how one variable would change under an intervention that changes another variable.

10.7.1 INVARIANCE AND MODULARITY

A key aspect of Woodward's theory is the notion of *invariance*. Specifically, it is crucial to the idea of a causal generalization regarding the relationship between two variables (say X and Y) that the relationship remains invariant after an intervention on X. According to Woodward, a necessary and sufficient condition for a generalization to describe a causal relationship is that it be invariant under some appropriate set of interventions. This is central for Woodward insofar as invariance under interventions is what distinguishes causal explanations from accidental association. It should be briefly noted that a stronger version of invariance is *super-exogeneity,* which links the statistical concept of weak exogeneity to the problem of invariance (Ericsson & Irons, 1994; Kaplan, 2004). With regard to causal processes represented by systems of structural equations, another vital issue to the manipulability theory of causation is that of *modularity* (Hausman & Woodward, 1999, 2004). Quoting from Woodward (2003),

> A system of equation is modular if (i) each equation is level invariant under some range of interventions and (ii) for each equation there is a possible intervention on the dependent variable that changes only that equation while the other equations in the system remain unchanged and level invariant. (p. 129)

In the above quote, level-invariance refers to invariance within equations, while modularity refers generally to invariance between equations, so-called equation invariance. In the context of structural equation modeling, level invariance and modularity require very careful consideration. The distinction between the two concepts expands the notion of how counterfactual propositions can be examined. Level-invariance concerns a type of local counterfactual proposition—local in the sense that it refers to invariance to interventions within a particular equation. In other words, the truth of the counterfactual proposition is localized to that particular equation. Modularity, on the other hand, concerns invariance in one equation given interventions occurring in other equations in the system. In the context of the social and behavioral sciences, modularity is, arguably, a more heroic and more serious assumption. For a general critique of modularity, see Cartwright (2007).

10.7.2 OBSERVATIONALLY EQUIVALENT MODELS

A particularly troublesome issue related to level-invariance and modularity concerns the relationship between the reduced form and structural form of a structural model and the attendant issue of observationally equivalent models. We saw in Chapter 2 that the reduced form of a model (essentially equivalent to multivariate regression) can be used to obtain structural parameters provided the parameters are identified. Following Woodward (2003), consider the following structural model

$$y = \beta x + u, \qquad [10.3]$$

$$z = \gamma x + \lambda y + v. \qquad [10.4]$$

The reduced form of this model can be written as

$$y = \beta x + u, \qquad [10.5]$$

$$z = \pi x + w, \qquad [10.6]$$

where $\pi = \gamma + \beta\lambda$, and $w = \lambda u + v$. The problem is that for just-identified models, the reduced form solution provides exactly the same information about the pattern of covariances as the structural form solution. As Woodward points out, although these two sets of equations yield observationally equivalent information, they are distinct causal representations.

To see this, note that Equations [10.3] and [10.4] say that *x* is a direct cause of *y* and *x* and *y* are direct causes of *z*. But, Equations [10.5] and [10.6] say that *x* is a direct cause of *y* and *z* and says nothing about *y* being a direct cause of *z*. If Equations [10.3] and [10.4] represent the true causal system and is assumed to be modular in Woodward's sense, then Equations [10.4] and [10.5] cannot be modular. For example, if *y* is fixed to a particular value due to intervention, then this implies that $\beta = 0$. Nevertheless, despite this intervention, Equation [10.4] will continue to hold. In contrast, given modularity of Equations [10.3] and [10.4], we see that Equation [10.5] will change because π is a function of β.

We see then, that the structural form and reduced form are distinct causal systems, and although they provide identical observational information as well as inform the problem of identification, they do not provide identical causal information. Moreover, given that numerous equivalent models can be formed, the criterion for choosing among them, according to Woodward, is that the model satisfies modularity, because that will be the model that fully represents the causal mechanism and set of relationships (Woodward, 2003, p. 332).

In what sense does the manipulability theory of causation inform modeling practice? For Woodward (2003), the problem is that the model possessing the property of modularity cannot be unambiguously determined from among competing observationally equivalent models. Only the facts about causal processes can determine this. For Woodward therefore, the prescription for modeling practice is that researchers should theorize distinct causal mechanisms and hypothesize what would transpire under hypothetical interventions. This information is then mapped into a system of equations wherein each equation represents a clearly specified and distinct causal mechanism. The right-hand side in any given equation contains those variables on which interventions would change the variables on the left-hand side. And, although different systems of equations may be mathematically equivalent, this is only a problem if we are postulating relatively simple associations. As Pearl (2000) points out, mathematically equivalent models are not syntactically equivalent when considered in light of hypothetical interventions. That is, each equation in a system of equations should "encode" counterfactual information necessary for considering hypothetical interventions (Pearl, 2000; Woodward, 2003).

10.7.3 PEARL'S INTERVENTIONAL INTERPRETATION OF STRUCTURAL EQUATION MODELING

Although we have focused mainly on Woodward's treatment of structural equation modeling, it should also be pointed out that Pearl (2000), among other things, offered an interventionist interpretation of structural equation modeling. Briefly, Pearl notes that in practice researchers will often imbue structural parameters with more meaning than they would covariances or other statistical parameters. For example, the interpretation of a purely mediating model

$$y = \beta z + u, \tag{10.7}$$

$$z = \gamma x + v \tag{10.8}$$

is interpreted quite differently from the case where we also allow x to directly influence y—that is,

$$y = \beta z + \lambda x + u, \tag{10.9}$$

$$z = \gamma x + v. \tag{10.10}$$

In the purely mediating model given in Equations [10.7] and [10.8], the effect of intervening on x is to change y by $\beta\gamma$. In the model in Equations [10.9] and [10.10], the effect of intervening on x is to change y by $\beta\gamma + \lambda$.

The difference between the interpretations of these two models is not trivial. They represent important causal information regarding what would obtain after an intervention on x. For Pearl (2000), structural equations are meant to define an equilibrium state, where that state would be violated when there is an outside intervention (p. 157). As such, structural equations encode not only information about the equilibrium state but also information about which equations must be perturbed to explain the new equilibrium state. For the two models just described, an intervention on x would lead to different equilibrium states.

Much more can be said regarding Woodward's (2003) manipulability theory of causation as well as Pearl's (2000) interventional interpretation of structural equation modeling, but a full account of their ideas is simply beyond the scope of this chapter. Suffice to say that in the context of structural equation modeling, Woodward's (2003) as well as Pearl's (2000) expansion of the counterfactual theory of causation to the problem of hypothetical interventions on exogenous variables provides a practical framework for using structural equation modeling to guide causal inference and is line with how its founders (Haavelmo, 1943; Marschak, 1950; Simon, 1953) viewed the utility of the methodology.

10.8 Conclusion

Over the past 10 years, there have been important developments in the methodology of structural equation modeling—particularly in methods such as multilevel structural equation modeling, growth curve modeling, and structural equation models that combine categorical and continuous latent variables. These developments indicate a promising future with respect to statistical and substantive applications. However, it is still the case that the conventional approach to structural equation modeling described earlier in this chapter dominates its applications to substantive problems and it is also still the case that practitioners remain reluctant to fully exploit structural equation modeling for testing causal claims.

How might we reconcile statistical issues with causal issues and at the same time improve the practice of structural equation modeling? In this regard, Pearl (2000) offers a distinction between statistical and causal concepts that I argue is helpful as we attempt to advance the use of structural equation modeling in the social and behavioral sciences. Specifically, Pearl defines a statistical parameter as a quantity determined in terms of a joint probability distribution of observables without regard to any assumptions related to the existence of unobservables. Thus, $E(\mathbf{y}|\mathbf{x})$, the regression coefficient β, and so on are examples of statistical parameters. By contrast, a causal parameter would be defined from a causal model, such as path coefficients, the expected value of y under an intervention, and so on. Furthermore, a statistical assumption is any constraint on the joint distribution of the observables—for example, the assumption of multivariate normality. A causal assumption, by contrast is any constraint on the causal model that is not based on statistical constraints. Causal assumptions may or may not have statistical implications. An example would be identification conditions, which are causal assumptions that can have statistical implications. Finally, in Pearl's view, statistical concepts include: correlation, regression, conditional independence, association, likelihood, and so on. Causal concept, by contrast, include randomization, influence, effect, exogeneity, ignorability, intervention, invariance, explanation, and so forth.

Pearl argues that researchers should not necessarily ignore one set of concepts in favor of the other but to treat each with the proper set of tools. In the context of structural equation modeling, I argue that the probabilistic reduction approach provides an improved set of tools that focus on the statistical side of modeling, whereas the counterfactual and manipulationist views of causation articulated by, for example, Hoover (2001), Mackie (1980), and Woodward (2003) provide the set of tools and concepts for engaging in causal inference. I argue that keeping the distinction between statistical and causal activities clear, but boldly and critically engaging in both, should help us realize the full potential of structural equation modeling as a valuable tool in the array of methodologies for the social and behavioral sciences.

Notes

1. However, with the advent of new estimation methods, such as those discussed in Chapter 5, this may become less of a concern in the future.

2. Except perhaps indirectly when using the Akaike information criterion for nested comparisons.

3. It is beyond the scope of this chapter to conduct a detailed historical analysis, but it is worth speculating whether Goldberger's important influence in structural equation modeling may partially account for the conventional practice observed in the social sciences.

4. As noted in Spanos (1989) this view was based on the perceived outcome of a classic debate between Koopmans (1947) and Vining (1949).

5. Included are such important contributions as randomization, replication, and blocking.

6. A difficulty that arises in the context of this discussion is the confusion of terms such as *theory*, *model*, and *statistical model*. No attempt will be made to resolve this confusion in the context of this chapter and thus it is assumed that the reader will understand the meaning of these terms in context.

7. Of course, nonzero restrictions and equality constraints are also possible.

8. Note that one can also use the multilevel reduced form discussed in Chapter 7 for this purpose as well.

9. Haavelmo, Wright, and Koopmans were referring to simultaneous equation modeling, but the point still holds for structural equation modeling as understood in this book.

10. An example might be a match being lit without it being struck—for example, if it were hit by lightning.

11. In this regard, there does not appear to be any inherent conflict between the probabilistic reduction approach described earlier and the counterfactual model of causal inference.

12. This example was originally put forth by Emanuel Kant in the context of an iron ball depressing a cushion.