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BOOK REVIEW

Restoring Causal Analysis to Structural Equation Modeling

Review of **Causality: Models, Reasoning, and Inference** (2nd Edition), by Judea Pearl. New York, NY: Cambridge University Press, 484 pp., $45.00.

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Throughout the 20th century (and well before) causal inference has been an active area of inquiry, with a new burst of activity accompanying the first part of the 21st century. An incomplete list of people who have made important contributions over the past half-century includes scholars in computer science (Judea Pearl), economics (James Heckman), epidemiology (Sander Greenland, Miguel Hernán, James Robbins), philosophy of science (Nancy Cartwright, Clark Glymour, Peter Spirtes), psychology (Donald Campbell, Thomas Cook, Will Shadish), sociology (Ken Bollen, Stephen Morgan, Chris Winship), and statistics (Philip Dawid, Paul Rosenbaum, Donald Rubin). These perspectives overlap, but each has its own unique foci and features.

The occasion for this review is the publication by one of the giants in the area, Judea Pearl, of a second edition of his influential monograph, *Causality: Models, Reasoning, and Inference,* which first appeared in 2000. Pearl offers a broad and evolving framework for causal inference that incorporates many areas of overlap with the perspectives of the scholars just listed, largely ignores the perspectives of other scholars (notably Campbell), and sharpens differences with aspects of other perspectives (e.g., Greenland, Heckman, Rubin). These differences not infrequently have led to spirited exchanges in the literature. The differences reflect in part the different histories, domains of application, and research questions of each scholar's home discipline, as well as different tolerances for specific assumptions that must be made to make progress.

Pearl's book is an intellectual tour de force, providing a framework to answer the full range of questions about causal inference. Although a major contribution, his account will be extremely challenging reading for most social scientists working in structural equation modeling (SEM). Like Campbell, Pearl is a polymath whose breadth of knowledge related to causality spans many disciplines. Unlike Campbell, Pearl's knowledge base includes probability theory, symbolic logic, mathematical statistics, economics, Bayesian ideas and Bayesian networks, law, and computer science. The result is that useful, but unfamiliar concepts are equally likely to be introduced from such areas as philosophy of science, law, symbolic logic, and Bayesian networks, a mixture that can be daunting for those who are not immersed in the scholarship of causal inference. Our review of this broad work is from the standpoint of applied researchers using SEM, the primary audience of this journal.

PEARL'S PERSPECTIVE: AN OVERVIEW

Pearl draws inspiration from the founding fathers of SEM, Sewell Wright in genetics and Trygve Haavelmo in econometrics, each of whom emphasized the importance of causal reasoning. Pearl updates earlier representations by using directed acyclic graphs (DAGs) to represent causal relationships. Like traditional SEM path diagrams, variables are represented as nodes, and nodes are linked by (a) a directed link (causal arrow), (b) a nondirected link (curved double-headed arrow), or (c) no link. Occasionally, Pearl also considers (d) bidirected links to represent mutual influence of the two variables. DAGs are applied throughout the volume to analyze not only the linear models traditionally considered in SEM, but also the binary models considered in Bayesian networks. In this latter application, nodes represent the probability of occurrence of a binary event. A major focus is on blocking paths between antecedent and consequent variables. One key concept is that of d-separation (directional separation) between two nodes. A node X that has no links to Y is assumed to have no causal influence on Y. A path that contains an $X \rightarrow Z \rightarrow Y$ chain (mediated effect) or an $X \leftarrow Z \rightarrow Y$ (spurious effect) are d-separated, if one conditions on Z. In contrast, in the path $X \rightarrow Z \leftarrow Y$, termed an inverted fork (collider), X and Y are d-separated, but become dependent if one conditions on Z. A second key concept is the identification of back-door paths that permit confounding of the key effects (Figure 1). Pearl brings mathematical tools from graph theory and other areas that

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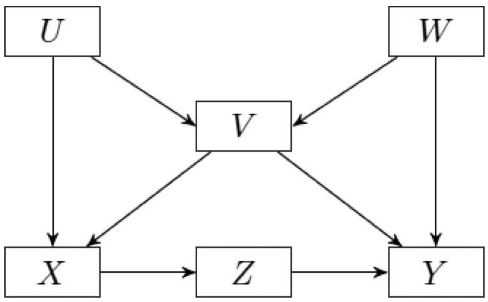

FIGURE 1 Illustration of a causal diagram with a collider variable and back-door paths.

Note. V is a collider variable given that the variables U and W are the direct causes of this variable. Conditioning on a collider variable can introduce an association between U and W leading to a spurious relationship between X and Y. Residual terms (errors in prediction) are not depicted.

simplify the study of potential causal paths between X and Y. Pearl emphasizes that standard tools such as covariance algebra are useful, but are not sufficient for representing causal relationships because $X \rightarrow Y$ is not equivalent to $Y \rightarrow X$, even though the covariance algebra is identical. He introduces the idea of the do(x) operator that mimics the effect of a specific type of manipulation of X. do(x) sets the antecedent variable X equal to a specific value ($X = x$); simultaneously, it deletes all direct causes of X and leaves intact the consequent paths so the effects of $X = x$ can be observed in the causal system. do(x) is not in general equivalent to conditioning on X, which leaves relations to the causes of X intact giving rise to potential backdoor paths. The do(x) operator leads to clear definitions of counterfactuals and many important concepts in SEM. It helps to clearly distinguish between statistical terms and causal terms. For example, the indirect effect in the basic meditational model (Figure 2) "is defined as the expected change in Y affected by holding X constant, at $X = x$, and changing Z to whatever value it would have attained had X been set to $X = x$" (p. 132). Similarly, the do(x) operator leads to a revised definition of total effects in bidirectional models with feedback ($X \rightarrow Y$ and $Y \rightarrow X$) as β_{YX} rather than $\beta_{YX}(1 - \beta_{XY}\ \beta_{YX})^{-1}$ because X is not permitted to change once it is set to its value of x. Pearl's emphasis is on clarifying the causal questions that can and cannot be answered with specific hypothesized causal models that represent our best understanding of the scientific processes that underlie our phenomena of interest. He is interested in providing clear interpretations of those causal effects that can be estimated. In contrast, Pearl argues that SEM research over the past 30 years has focused on topics related to practice—estimation, data structures, measurement, and model fit—topics that Pearl sees as secondary to his key issue of causal inference.

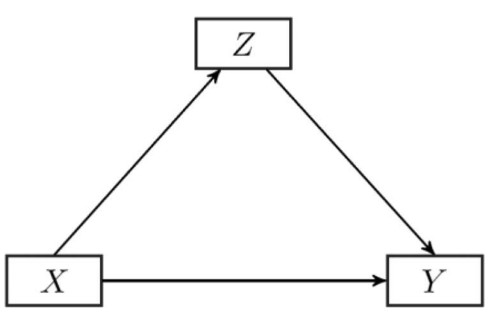

FIGURE 2 Illustration of a basic mediation model.

Note. X is the antecedent variable (often treatment assignment, treatment vs. no treatment), Z is the mediator, and Y is the outcome. Residual terms (errors in prediction) are not depicted.

DETAILED CONTENTS OF THE VOLUME

Causality: Models, Reasoning, and Inference (2nd ed.) begins and ends with an introduction. Chapter 1 opens the book with a brief review of the underlying foundations of the framework. These include basic probability theory with an emphasis on Bayesian ideas, Bayesian networks and their graphical representation, the addition of causal thinking to these networks, and finally the introduction of deterministic functional forms that gives rise to structural causal models. Novel concepts from Pearl's framework are introduced including the do(x) operator and d-separation. The epilogue (Chapter 12) closes the book with a transcript of a 1996 delightful, nontechnical introductory public lecture with copious pictorial illustrations sketching the history of the development of causal ideas from the influence of the deities of the Bible and mythology through contributions by Galileo, Hume, Galton, Pearson, Fisher, and others, ending with an overview of Pearl's own framework. In the preface, Pearl views the epilogue as providing an introduction to causal inference for nonmathematical readers; however, in our view it only presents a terse glimpse of a few key ideas and does not adequately prepare the reader for Chapter 1.

Chapter 2 eschews a priori causal models and focuses on discovering potential causal structures (DAGs) from a set of at least three variables based on the pattern of associations observed in the data. This work is of importance in the SEM context because it can identify alternative models (e.g., using the Tetrad IV program; http://www.phil.cmu.edu/projects/tetrad/current.html) that provide equal or better accounts of the data than the hypothesized model. Familiar principles underlie the algorithms: The causal structure needs to reproduce the data, simpler models are preferred, models that maintain temporal precedence are preferred, and relationships should not depend on specific functions or distributions. Given that the full set of minimal (parsimonious) candidate models have been identified, X has a causal influence on Y if a directed path from X to Y exists in each model in the set.

Chapter 3 presents a formal development of appropriate methods for the adjustment and control of confounding variables, the do(x) operator for describing and identifying causal effects in nonexperimental data sets, as well as a definition of counterfactuals. Pearl provides a formal definition of the causal effect of X on Y, $E(Y|do(x_T)) - E(Y|do(x_{NT}))$, where E is the expectation operator, $X = x_T$ represents the hypothetical treatment, and $X = x_{NT}$ represents no treatment. For Markovian models in which all variables in the model are measured and residuals are independent, causal effects are always identifiable. For non-Markovian models in which there are unobserved variables, Pearl introduces criteria that enable researchers to compute unbiased causal effects of X on Y even if *some* confounders are unmeasured. Finally, Pearl states conditions of causal models in which the causal effects are not identifiable.

Chapter 4 provides several extensions of the analysis of causal effects to more complex designs. First is the situation, of which the regression discontinuity design is a special case, in which a covariate is observed and a treatment is given conditional on a probability function of the covariate and possibly potential confounders. Second is the problem addressed in G-estimation in which multiple treatments could be given based on observed and unobserved covariates: A physician might administer a second treatment based on measures of the patient's (non-)response to the first treatment, and other unobserved covariates. Finally, Pearl brings his graph theoretic approach to bear on mediation analysis in which the effect of a treatment is carried to the outcome through intermediate variables. He provides formal definitions of direct, indirect, and total effects of treatments. Pearl develops theory and algorithms that clarify when such models are identified so that the causal effect of X on Y can be determined. An interesting feature of certain G-estimation problems is that identification can depend on the sequence in which treatments and the measures of the covariates are taken.

Chapter 5 will be of most interest to SEM researchers. Pearl notes that causal models impose restrictions on data providing the only way observational data can be tested. He emphasizes testing these model-implied *local* restrictions rather than overall goodness of fit, an emphasis recently echoed by McDonald (2010). Models with no correlated errors, with correlated errors, and with bidirectional links can all be tested. Pearl also identifies conditions under which models are equivalent. "We never test *a* model but rather a whole *class* of observationally equivalent models from which the hypothesized model can not be distinguished by any statistical means" (p. 148, italics in original). Pearl also considers graphical conditions under which specific direct and total effects can be identified in linear models and proposes an algorithm for recognizing identifiable coefficients. Structural equation models both define a state of equilibrium and predict the effects of interventions through the use of the do(x) operator.

Chapter 6 addresses confounding, which Pearl views as a causal rather than a statistical issue. He considers the classic problem of Simpson's paradox, showing that the paradox can be resolved by using the do(x) operator and assuming *stable unbiasedness* (stable unconfoundedness), namely $P(y|do(x)) = P(y|x)$. That is, Y will have the same value whether X is observed at value x or set to the value x through manipulation. Finally, Pearl relates his analysis of confounding to current analyses of confounding in epidemiology.

Chapter 7 formally defines and presents his theoretical analysis of counterfactual statements. In Pearl's view counterfactual statements "carry as clear an empirical message as any scientific law" (p. 217). They are cast in the language of structural models by setting up equations $\{f_i\}$ corresponding to laws, and background variables (U) corresponding to boundary conditions. Pearl also notes that the predictive value of counterfactuals is received only under two conditions: (a) U is either persistent or (b) potentially observable in the future. The chapter ends by contrasting Pearl's causal model-based conception with that of the Neyman–Rubin potential outcome framework (Holland, 1986) in which the potential outcome variable "is not derived from a causal model or from any formal representation of scientific knowledge, but is taken as a primitive" (p. 243).

Chapter 8 considers causal effects in randomized experiments in which there is treatment noncompliance or in which participants are only encouraged to receive the treatment (randomized invitation designs). Pearl considers statistical approaches (e.g., Angrist, Imbens, & Rubin, 1996), but prefers to develop large sample bounds for binary or dichotomized outcomes. Linear programming methods help narrow the bounds, and Markov chain Monte Carlo methods can be used to estimate Bayesian credibility intervals in finite samples.

Chapter 9 defines necessary causes and sufficient causes in Pearl's framework. Methods are developed for estimating the probability of sufficiency, defined as the probability of the presence of an active causal process capable of producing the effect, and the probability of necessity, defined as the probability that no alternative process that could also produce the effect is present. Conditions under which bounds of these probabilities can be computed are developed. Applications to epidemiology and legal reasoning are presented.

Chapter 10 presents an analysis of the actual cause, the cause inferred to be responsible for a single event when multiple potential causes are present. This work focuses primarily on identification of the cause of an observed effect (rather than the effect of a cause) and is primarily applicable in legal and epidemiological contexts.

Chapter 11 updates and clarifies many of the key concepts of Pearl's approach. The chapter appears to be an edited version of excerpts from Pearl's causality blog (http://www.mii.ucla.edu/causality/) in which Pearl provides additional insight on his own framework as well as his perspective on other theorists' frameworks for causal inference. Among the topics addressed are (a) the necessity for the distinction between causal and statistical concepts; (b) issues in the estimation of causal effects including the back-door criterion, covariate selection, strong ignorability, and propensity scores; (c) issues with the do(x) operator; (d) linear structural equation models and econometric models; (e) confounding; (f) counterfactuals; and (g) bounds for treatment noncompliance. Many of the clarifications contribute to a deeper intuitive understanding of Pearl's framework. Pearl's approach and his engagement with other perspectives are dynamic and evolving; new developments beyond those contained in Chapter 11 are presented in his causality blog.

A vignette of particular interest and amusement for SEM researchers is a hypothetical dialogue presented in Chapter 11 in a PhD oral of a candidate defending the causal interpretation of SEM against a hostile faculty examiner. The candidate's interpretation of the results nicely summarizes Pearl's perspective:

> Researchers who accept the qualitative [causal] assumptions of model M are compelled to accept the conclusion $c = 0.78$ [the estimate of a key parameter given the candidate's data]. This claim remains logically invincible. Moreover, the claim can be further refined by reporting the conclusions of each contending model, together with the assumptions underlying that model. (p. 373)

Scholars of causal inference having diverse perspectives will agree with this interpretation; they will disagree on whether such an interpretation is sufficient to claim a causal effect. In particular, scholars who accept the randomized experiment as the gold standard for causal inference will deem this interpretation insufficient.

WHAT'S NEW IN THE SECOND EDITION

Readers familiar with the first edition of *Causality* published in 2000 will find little that is new in Chapters 1 to 10 or the epilogue. The table of contents is identical in the two editions; there is a near absence of post-2000 references in these chapters in the second edition. A few small sections have been updated; some chapters end with terse postscripts pointing to citations for new developments. Chapter 11 includes nearly 70 pages of clarifications, extensions, and updates of considerable value to readers. The task of rereading sections and integrating the new and classic material is left to the reader, although careful cross-referencing to specific sections is provided to facilitate this task.

SOURCES ON CAUSAL INFERENCE FOR THE SEM RESEARCHER

We believe that Pearl's book is an excellent comprehensive reference book and presentation of Pearl's perspective for readers who are already immersed in the literature of causal inference. The only other full-length source of which we are aware that presents a high-level treatment of the graphical approach to causality is Spirtes, Glymour, and Scheines (2001), a text that might be an even more difficult read for SEM researchers, yet is not as comprehensive. Recent edited collections of chapters by leading contributors to causal inference from several perspectives are offered by Berzuini, Dawid, and Bernardinell (2012) in statistics and Morgan (2013) in the social sciences. Pearl's book is by no means a text. The chapters do not map well onto the topics of an SEM or research methods course. Topics are presented in multiple chapters of the book, requiring backward and forward referencing to achieve understanding. Fortunately, the index is well done, facilitating this process. SEM researchers wishing an initial accessible introduction to many of the key ideas presented by Pearl would do well to consult Bollen and Pearl (2013), followed by more challenging, but accessible papers by Pearl (2009, 2012). Readers wishing a text providing broader treatment of Pearl's and other frameworks for causal inference in research settings should consider Morgan and Winship (2007), a moderate-length, accessible text focused on issues of particular relevance to SEM researchers.

WHAT DOES *CAUSALITY: MODELS, REASONING, AND INFERENCE* OFFER SEM RESEARCHERS?

The volume helps reinvigorate causal thinking in SEM, which fell out favor following criticisms by statisticians of the limits on causal inference imposed by SEM's foundation in covariance algebra. It deemphasizes model evaluation through the use of global fit indexes, and emphasizes the role of a priori theory and substantive knowledge, conditional independence, and evaluation of local fit. It provides graphical tools that greatly simplify analyses of causal effects, identification of models, and detection of equivalent models that provide equally good accounts of identical data. Researchers familiar with Duncan (1966) will recognize many of the same theoretical results for linear structural equation models, but Pearl overcomes many of the shortcomings of the earlier work by interpreting causal effects as what would occur as the result of hypothetical interventions. With the introduction of graph theory and the do(x) operator, Pearl substantially improves the tools with which researchers can make causal queries of their models, adds to our understanding of causal inference with his distinction between causal and statistical relationships, and clarifies the definition of many causal concepts. He also extends the earlier analysis to the consideration of relationships involving binary variables.

COMPARISON WITH OTHER PERSPECTIVES

Pearl believes that he has presented the fundamental approach to causal inference and implies that other approaches are unnecessary. "With all due respect to multiculturalism, all approaches to causation are variants or abstractions of the structural theory presented in this book" (p. 353). We value Pearl's framework and his efforts to show that other frameworks can be translated into his approach. Nevertheless we believe that there is much to be gained by also considering the other major approaches to causal inference. The emphases of Pearl's framework reflect his background in engineering. Causal systems tend to be well understood and can be written as equations or represented as DAGs, there are relatively few unknown causal influences in the system, the units tend to be homogenous, causal effects are assumed to be stable across settings and time, and levels of treatments can be set to specified values as reflected in the do(x) operator. These emphases reflect assumptions underlying control engineering principles. Exactly how one moves from these perspectives to specific applied research problems in clinical, health, social, or education science is less clear. Some promising attempts (e.g., Rivera, Pew, & Collins, 2007) are beginning to be made to apply control engineering principles to the design and evaluation of interventions in the health sciences, but they are in an early stage of development and so far have been used for adaptive rather than standard interventions. Mapping the results from the do(x) operator onto standard interventions in which individual cases vary in their natural (untreated) level of X and in which the intervention itself might produce a different effect on each participant is unclear. The challenging problem of identifying the key construct that is being manipulated (the construct validity of the treatment in Campbell's terms) is bypassed. In response to a challenging problem posed by a reader of determining the effective treatment component in a randomized experiment, Pearl replies "Mathematics deals with ideal situations, and it is the experimenter's job to make sure that the experimental conditions approximate the mathematical ideal as closely as possible" (p. 358). Little guidance is presented on how to think about problems involving the potential causal effects of time-invariant (e.g., gender) versus time-varying (e.g., mother's level of depression or socioeconomic status) variables on outcomes. For many research problems it is unclear how even a talented investigator could approximate the do(x) operator of fixing a variable to a specific value.

Unlike typical situations in control engineering, social science problems can include many potential unmeasured causes. This feature can make it difficult to propose and test a limited set of specific competing models that can be statistically identified. Issues of measurement error and the construct validity of the dependent variable are not addressed. Finally, how to think about causal inference when variables are measured repeatedly over time, problems in which between-subjects and within-subjects analyses will often produce different results (Molenaar, 2004), receives only brief attention. Without a roadmap to help researchers map the ideal results of his framework onto the key research questions that arise in practice, there is an unfortunate risk that the influence of Pearl's framework will be diminished.

In contrast, the frameworks of Rubin (2005) and Campbell (Shadish, Cook, & Campbell, 2002; see Shadish, 2010; West & Thoemmes, 2010, for comparative reviews) used in the health and social sciences are very concerned about practice and application. Rubin's potential outcomes model defines a causal effect of the difference between the response of a single unit given treatment or control at the same time and in the same context. This ideal is not observable; Rubin develops approximations to this ideal that can be realized in practice and clarifies the assumptions needed for each of the approximations. Rubin does not make homogeneity assumptions about the units or their response to treatment, leading to estimates of average causal effects. Rubin's perspective also offers procedures for addressing situations in which assumptions fail (e.g., treatment noncompliance). Rubin often works in the environment of health research in which causal inferences are desired, but in which there are many unknown variables, randomized experiments are imperfect, the units are not uniform, and the stakes of the research outcome are high.

Similarly, Campbell's perspective developed out of confronting practical issues faced by researchers in psychology and education. His perspective offers researchers lists of plausible threats to internal validity, methods of preventing those threats from occurring, and methods for evaluating the impact of threats when they do occur. It proposes the use of design elements to enhance the information available so that the researcher can rule out potential confounds by consideration of the pattern of results. It takes seriously the issues of construct validity of the independent variable (what aspect of the treatment package is the actual cause), measurement, and generalization of effects to populations of interest. For some designs, Campbell's perspective only permits the researcher to infer the direction, not the magnitude of the causal effect, but in practice such a result might approximate a specific quantitative estimate of an effect with bounds.

Both Rubin and Campbell's frameworks have presented useful analyses of actual research problems (e.g., treatment noncompliance) that appear to have been considered *later* by Pearl. This temporal priority might reflect the ease of conceptualizing different problems within each of the three perspectives. Applied problems exist in which the mathematics of different perspectives are identical (e.g., growth curve modeling, multilevel modeling), but the ease of conceptualizing a problem might flow more naturally from one rather than the other perspective. In contrast, neither Rubin's nor Campbell's perspective is easily applied to the study of causal effects in the systems of variables represented by complex structural equation models (indeed, Rubin has made his position about the lack of clarity of SEM models clear; e.g., Rubin, 2004). Nonetheless, in practice ideas from these perspectives can be applied to limited subsets of variables represented in the model to strengthen causal inference in parts of the model.

From the perspective of researchers who consider the randomized experiment as the gold standard for causal inference, each of the three frameworks must make a strong assumption to address causal inference in the absence of randomization. Pearl assumes that all plausible models (DAGs) have been properly specified and included among the set of models that are considered. Rubin assumes strong ignorability in which all possible covariates that potentially confound the interpretation of the treatment effect have been identified and their effects eliminated. Campbell assumes that all plausible threats to internal validity have been identified and ruled out as potential causes of the observed results. Relative to Pearl, the Rubin and Campbell traditions have more developed practical guidelines to help researchers meet their strong assumptions. We encourage SEM researchers following Pearl's framework to be skeptical and to fiercely confront their preferred models with strong alternative models in the tradition of economics.

We view Pearl's framework as an important alternative to the frameworks of Rubin and Campbell, frameworks that are commonly used in the social sciences. Pearl's framework is particularly attractive to SEM researchers because it allows them to pose causal inquires to complex structural equation models. We also see Rubin and Campbell's frameworks as valuable perspectives for researchers who wish to move from the often abstract answers provided by Pearl's framework to the design and analysis of research in actual settings. In addition, readers might also find useful the perspective of Steyer, Partchev, Kroehne, Nagengast, and Fiege (in press), which includes elements of the perspectives of Pearl, Rubin, and Campbell in a package that is both directly applicable to SEM research and mathematically challenging to the reader. Unlike Pearl, we believe that multiculturalism has its benefits in the causal inference arena. Each perspective offers its own unique insights with the value placed on those insights varying with the research question and domain of application.

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