In this completely revised and expanded second edition of *Counterfactuals and Causal Inference*, the essential features of the counterfactual approach to observational data analysis are presented with examples from the social, demographic, and health sciences. Alternative estimation techniques are first introduced using both the potential outcome model and causal graphs; after which conditioning techniques, such as matching and regression, are presented from a potential outcomes perspective. For research scenarios in which important determinants of causal exposure are unobserved, alternative techniques, such as instrumental variable estimators, longitudinal methods, and estimation via causal mechanisms, are then presented. The importance of causal effect heterogeneity is stressed throughout the book, and the need for deep causal explanation via mechanisms is discussed.

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Counterfactuals and Causal Inference

Methods and Principles for Social Research

Second Edition

STEPHEN L. MORGAN
Johns Hopkins University

CHRISTOPHER WINSHIP
Harvard University
To my wife, Sydney, my son, Vinny, and my daughter, Beatrix
– Steve Morgan

To my wife, Nancy, and my sons, David and Michael
– Chris Winship
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Without yet knowing it, we began to write this book in 1997 when collaborating on a paper for the 1999 volume of the Annual Review of Sociology, titled “The Estimation of Causal Effects from Observational Data.” We benefited from many helpful comments in the preparation of that manuscript, and we were pleased that many of our colleagues found it to be a useful introduction to a literature that we were, at the time, still working to understand ourselves. Since then, considerable progress in the potential outcomes and counterfactual modeling literature has been achieved, which led us into long discussions of the utility of writing a more comprehensive introduction. In the end, our motivation to learn even more of the literature was the decisive factor.

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