

#### COUNTERFACTUALS AND CAUSAL INFERENCE

Second Edition

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

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## **CAMBRIDGE** UNIVERSITY PRESS

32 Avenue of the Americas, New York, NY 10013-2473, USA

Cambridge University Press is part of the University of Cambridge.

It furthers the University's mission by disseminating knowledge in the pursuit of education, learning, and research at the highest international levels of excellence.

www.cambridge.org Information on this title: www.cambridge.org/9781107065079

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First published 2007 Second edition 2015 Reprinted with corrections 2015

Printed in the United States of America

A catalog record for this publication is available from the British Library.

Library of Congress Cataloging in Publication Data Morgan, Stephen L. (Stephen Lawrence), 1971–

Counterfactuals and causal inference : methods and principles for social research / Stephen L. Morgan, Christopher Winship.

pages cm. – (Analytical methods for social research)

Revised edition of the authors' Counterfactuals and causal inference, published in 2007.

Includes bibliographical references and index.

ISBN 978-1-107-06507-9 (hardback) – ISBN 978-1-107-69416-3 (paperback)
1. Social sciences–Research. 2. Social sciences–Methodology.

3. Causation. I. Winship, Christopher. II. Title.

H62.M646 2015 300.72–dc23 2014033205

ISBN 978-1-107-06507-9 Hardback

ISBN 978-1-107-69416-3 Paperback

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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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# **Acknowledgments for First Edition**

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.

We thank Richard Berk, Felix Elwert, George Farkas, Glenn Firebaugh, Jeremy Freese, Andrew Gelman, Gary King, Trond Petersen, David Weakliem, and Kim Weeden for reading some or all of the penultimate draft of the book. We also thank the anonymous reviewer recruited by Cambridge University Press. The insightful comments of all of these readers helped tremendously. We also thank our students at Cornell and Harvard, from whom we have learned much in the course of learning and then presenting this material to them. Their comments and questions were more valuable than they are probably aware.

Finally, we thank Kelly Andronicos and Jenny Todd at Cornell University for assistance with the preparation of the manuscript, as well as Larry Wu and Ed Parsons at Cambridge University Press, Project Manager Peter Katsirubas at Aptara, Inc., and Victoria Danahy at In Other Words.





# **Acknowledgments for Second Edition**

We thank all of the students in our classes at Cornell and at Harvard, as well as those who have attended presentations of the new material in this second edition at other universities. Your excellent questions over the years have shaped this book more than you may realize.

For their generosity and willingness to read and comment on substantial portions of this second edition, we thank Weihua An, Neal Beck, Richard Berk, David Bills, Ken Bollen (and his students), Andy Cherlin, Tom DiPrete, Felix Elwert, Markus Gangl, Guanglei Hong, Mike Hout, Tim Liao, Scott Lynch, Isaac Reed, Matt Salganik, Jasjeet Sekhon, Peter Steiner, Jessica Su, Steve Vaisey, Tyler VanderWeele, David Weakliem, and Hui Zheng. In addition, we thank John Cawley and Dan Lichter for pointing us to relevant literature in health economics and demography.

We also thank Cornell University and Harvard University for the sabbatical support that allowed us to begin the writing of this second edition. Morgan thanks Collegio Carlo Alberto for providing a restful and stimulating environment for work from January through June 2013.

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