Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction. Guido W. Imbens and Donald B. Rubin. New York: Cambridge University Press, 2015, xix + 625 pp., $60.00(H), ISBN: 978-0-52-188588-1.

Editor's Note: Following are three reviews of *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction* by Guido W. Imbens and Donald B. Rubin. The reviewers are Matias D. Cattaneo, Cosma Rohilla Shalizi, and Kosuke Imai.

Guido Imbens and Don Rubin present an insightful discussion of the potential outcomes framework for causal inference. In this framework, the goal is to define the effect of a treatment (including, of course, a definition of "treatment" itself), to understand when such an object is identifiable in the population (or, at least, in the superpopulation), and to estimate and conduct statistical inference about this quantity of interest as well as related quantities such as welfare measures or other policy-relevant effects. Despite this goal being fundamental, a final answer is far from settled as many competing and/or complementary approaches have been proposed in the literature (e.g., Heckman and Vytlacil 2007; Manski 2008; Pearl 2009; VanderWeele 2015; Hernán and Robins 2016).

The authors employ the potential outcomes framework to study causal inference in three of the most important settings in applied work: (1) randomized experiments, (2) unconfounded treatment assignment in observational studies (an assumption also known as missing-at-random, conditional independence, selection-on-observables, or ignorability), and (3) experiments with noncompliance (a special case of instrumental variables methods). A key feature of the book is the recurrent use of real empirical examples, and the detailed derivation of the most important calculations needed for implementation, all of which provide much needed guidance on how to go from theory to practice. While these features surely help the reader understand how the different methods work, I suspect the book would be even more effective if the authors provided the data and computer codes used throughout. The authors are also very careful to distinguish between identification, estimation, inference, implementation, and interpretation issues. All these features make the book a must-read for all applied researchers, regardless of their technical background.

Parts I and II (Chapters 1–11) of the book give a brief introduction to causality and the potential outcomes framework, and then present a thorough discussion of the classical analysis of experiments. The part of the book introduces the reader to a variety of interconnected classical ideas, including Fisher's exact testing, Neyman's repeated sampling, regression-based methods and Bayesian model-based methods, which are often encountered in empirical work but treated as fundamentally distinct. Imbens and Rubin elucidated these ideas within a unified methodological framework, while also offering several illustrative empirical applications throughout. Anyone interested in deepening their understanding of the analysis and interpretation of experiments will find these chapters to be an invaluable and timeless reference.

Parts III and IV (Chapters 12–20) focus on settings in which the treatment assignment is unconfounded, that is, where the treatment assignment is independent of the potential outcomes after conditioning on observable characteristics. This type of conditional independence assumption, which is statistical in nature and widely used in empirical work, is the basis for a variety of estimation and inference procedures in causal inference. In this portion of the book, the authors not only review most of their influential work in the area, but also introduce and discuss various new ideas such as model, tuning parameter, and covariate selection methods. Moreover, Part V (Chapters 21–22) presents methods for assessing the plausibility of the underlying key identifying assumptions, as well as approaches based on bounds and other sensitivity analyses that are crucial to understanding the robustness of the results obtained under the selection-on-observables assumption.

The final chapters, Part VI (Chapters 23–25), focus on the analysis of experiments with imperfect compliance. The focus here is mostly on the authors' widely influential work on nonparametric identification of the local average treatment effect (LATE), although an alternative model-based approach to estimation and inference is also presented.

In sum, this book presents a unified framework to causal inference based on the potential outcomes framework, focusing on the classical analysis of experiments, unconfoundedness, and noncompliance. The book has become an instant classic in the causal inference literature, broadly defined, and will certainly guide future research in this area. All researchers will benefit from carefully studying this book, no matter what their specific views are on the subject matter.

Looking ahead, an added benefit of the book is that it lays out the foundations for a systematic and unified statistical analysis of more advanced topics in causal inference such as multivalued, dynamic, and adaptive treatment regimes; difference-in-differences methods; regression discontinuity designs; linear and nonlinear panel or longitudinal data; interference, externalities, spillovers and peer effects; and external validity, meta analysis and counterfactual policy evaluations, just to mention a few examples. One can only hope that the authors can be persuaded to write the second volume.

References

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