Causal Inference in Observational Settings

Peter Davis, University of Auckland
Seminar Series, LSHTM
Thursday, 12 April 2012
CSM Agenda Today

• **Canvass**
  – Sage Handbook/Reader
    • “Inference by Design”: outline, ideas, amendments

• **Share**
  – Intellectual excitement
    • Philosophy, statistics, public health, econometrics

• **Methodological caveat**
Presentation Outline

• Rationale, motivation

• Four “key” papers

• The Handbook
  – Volume I – Background
  – Volume II – Comparing like with like
  – Volume III – Panel data and instruments
  – Volume IV – Experimental analogues

• Concluding thoughts
What’s at Issue

• **Fundamental issue of policy science**
  – how to draw “credible” (causal?) inferences from observational data

• **Causal identification via data analysis**
  – often a form of speculative post-mortem

• **Basic conundrum of causal reasoning**
  – impossible to observe unit response under alternative conditions
Rationale of Proposal

1. Traditional statistical theory
   mainly about representation not causation (i.e. sampling)

2. Statistical inference => causal inference
   random assignment and manipulation of treatment conditions

3. Counterfactual/potential outcomes
   conceptually bridges experimental/observational settings

4. Forward causation only
   cause-to-effect (e.g. impact of policy intervention)

5. Econometrics
   a parallel community of policy practice
Four “Key” Papers

• **Counterfactual thinking**

• **Using panel data**
  – *Does marriage reduce crime?* Sampson et al. *Criminology* 2006

• **Statistical reasoning**

• **The econometric paradigm**
  – *How better research design is taking the con out of econometrics.* Angrist/Pischke, *J Econ Persp* 2010
Ahern et al.

Practice of Epidemiology


Jennifer Ahern, Alan Hubbard, and Sandro Galea

Initially submitted March 26, 2008; accepted for publication January 13, 2009

Causal inference methods allow estimation of the effects of potential public health interventions on the population burden of disease. Motivated by needs for epidemiologic research to be presented in ways that are more interpretable for intervention, the authors present a didactic discussion of the steps required to estimate the population effect of a potential intervention using an importation-based causal inference method and discuss the assumptions of and limitations to its use. An analysis of neighborhood smoking rates and individual smoking behavior is used as an illustration. The implementation steps include the following: 1) modeling the adjusted exposure and outcome association, 2) imputing the outcome probability for each individual while manipulating the exposure by "cutting" it to different values, 3) averaging those probabilities across the population, and 4) obtaining confidence intervals. Imputed probabilities represent counterfactual estimates of the population smoking prevalence if neighborhood smoking norms could be manipulated through intervention. The degree to which temporal ordering, co-morbidity, stability, and sequential treatment assignment assumptions are satisfied in the illustrative example is discussed, along with ways that future studies could be designed to better meet the assumptions. With the approach, the potential effects of an intervention targeting neighborhoods, individuals, or other units can be estimated.

Causality; intervention studies; methods; population; residence characteristics; smoking; social environment

Abbreviations: OEE, generalized estimating equation; OR, odds ratio.

Most analyses of epidemiologic data apply a regression model such as linear or logistic regression. These models have coefficients that estimate differences (relative or absolute) between outcomes (in terms of rates, risks, odds, or prevalence) associated with variation in exposure, while holding constant a set of covariates (1–3). These models estimate differences in outcomes that are stratum specific, because they are estimated within strata of the covariates specified in the model. Although such methods constitute the backbone of modern epidemiologic research (4), they represent only 1 approach to capturing the association between an exposure and an outcome. This approach tells us little about population disease burden or about how the disease burden might change if the exposure were modified. One alternative approach, which can be more informative, would assess how a particular potential intervention on the exposure being studied might modify disease burdens across the population (2, 4). Several methods can estimate population parameters under hypothetical interventions. In simple situations, standardization can estimate a population-based causal effect (5, 6). Certain causal inference methods generalize standardization to situations with covariates that are continuous as well as categorical, covariates that are time dependent, models that include multiple interactions, and nonlinear model forms (5–10). Although many causal inference methods were developed to control time-dependent confounding, the machinery allows the estimation of population parameters under hypothetical interventions for cross-sectional studies. Causal inference analyses of epidemiologic data start with the specification of a causal effect that is of interest. The population average causal effect is specified as the difference in the outcome (e.g., the
Counterfactual – Neighbourhood Norms

• Population average causal effect
  • difference under one intervention vs. another (or none) by estimating counterfactual exposures->outcomes

• Epidemiological association smoking/norms
  • estimate counterfactual - impute new pattern of neighbourhood smoking norms and derive smoking levels

• Prevalence estimates if norms “manipulated”
  • 17% (versus 29%) if all neighbourhoods prohibitive
Ahern et al.

Figure 1. Predicted smoking prevalence corresponding to counterfactually “set” levels of neighborhood smoking norms, New York, New York, 2005.
Sampson et al.

DOES MARRIAGE REDUCE CRIME?
A COUNTERFACTUAL APPROACH TO
WITHIN-INDIVIDUAL CAUSAL EFFECTS

ROBERT J. SAMPSON
Harvard University

JOHN H. LAUR
University of Maryland

CHRISTOPHER WIMER
Harvard University

KEYWORDS: marriage, crime, causality, counterfactual methods, life course

Although marriage is associated with a plethora of adult outcomes, its causal status remains controversial in the absence of experimental evidence. We address this problem by introducing a counterfactual life-course approach that applies inverse probability of treatment weighting (IPTW) to nationally longitudinal data on marriage, crime, and several covariates in a sample of 500 high-risk boys followed prospectively from adolescence to age 32. The data consist of criminal histories and death records for all 500 men plus personal interviews, using a lifetime calendar, with a stratified subsample of 32 men followed to age 70. These data are linked to an extensive battery of individual and family background measures gathered from childhood to age 27—before entry into marriage. Applying IPTW to multiple specifications that also incorporate extensive time-varying covariates in adulthood, being married is associated with an average reduction of approximately 15 percent in the rate of crime compared to unmarried status for the same man. These results are robust, supporting the inference that marriage causally reduces crime over the life course.

We thank the Russell Sage Foundation (Grant 15825-31) for funding support and the following colleagues for advice: Chris Winship, Felix Dresner, David Harding, Steve Raudenbush, Guanglu Hong, Janet Bobo, and the reviewers of Criminology. Direct all correspondence to Robert J. Sampson, Department of Sociology, Harvard University, William James Hall, 22 Oxford St., Cambridge, MA 02138 USA; e-mail: sampson@fas.harvard.edu.

CRIMINOLOGY VOLUME 41 NUMBER 5 2006 405
Using Panel Data - Marriage and Crime

• Does marriage reduce crime?
  • issues of selection and confounding

• Longitudinal data available on “high-risk” men
  • within-individual analysis of role of marriage

• Do states of marriage causally inhibit crime?
  • Yes – average 35% reduction compared to non-married
Sampson et al.

Figure 1. Predicted Crime and Marriage Probabilities by Age (Quadratic Model, N=2,585 Person-Years)
Causal Inference Using Potential Outcomes: Design, Modeling, Decisions

Donald B. Rubin

Journal of the American Statistical Association, Mar 2005, 100, 469, ASLEFOS0001

1. PROLOGUE

In this article, I describe how potential outcomes can be used to provide a general framework for causal inference in observational settings. I also discuss how this approach can be extended to infer causal effects from data collected in randomized experiments. The key idea is to consider the potential outcomes of each individual under all possible values of the treatment variable. These potential outcomes are then used to estimate the causal effect of the treatment on the outcome of interest.

2. POTENTIAL OUTCOMES

In a randomized experiment, each individual is randomly assigned to either the treatment group or the control group. The potential outcomes for an individual are the outcomes they would have received if they had been assigned to each group. The causal effect of the treatment on the outcome of interest is then estimated by comparing the average outcome across all individuals in the treatment group to the average outcome across all individuals in the control group.

3. EXAMPLES

I provide several examples to illustrate the use of potential outcomes in causal inference. These examples include studies in epidemiology, economics, and psychology.

4. DISCUSSION

In this final section, I discuss the limitations and challenges of using potential outcomes in causal inference. I also discuss some ways in which potential outcomes can be used to improve the design and analysis of observational studies.

5. ACKNOWLEDGMENTS

I would like to thank the following individuals for their support and assistance in the development of this article: Dr. John A. Bickel, Dr. Laura D. Bickel, and Dr. David B. Rubin.

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Statistical Reasoning - Design and Decisions

• Science and design vs. analysis and decisions
  • Fisher never related his work on likelihoods and models to his work on experimental design

• Neyman – potential outcomes of treatment
  • defines causal effects for both randomised and non-randomised studies ("Neyman-Rubin" model)

• Causal inference and assignment mechanism
  • assigns treatments to units (randomised in experiments), creating special type of missing data
Rubin

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*Figure 1. “Science”—The Causal Estimand.*
Causal Inference in Observational Settings
Econometrics - “Better” Research Design

• “take the con out of econometrics” (1985)
  • Leamer “Hardly anyone takes data analysis seriously.”

• Better research design – quasi-experimental
  • Instrumental variables, regression discontinuity, differences-in-differences

• Has the design pendulum swung too far?
  • Lack of external validity; ignore the big questions?
Angrist and Pischke

**Figure 1**
Homicide Rates and the Death Penalty in the United States and Canada  
(U.S. and Canada rates on the left and right y-axes, respectively)

Source: Donohue and Wolters (2005).
Sage Handbook Series

• Sage Benchmarks in Social Research Methods
• Four-volume readers
• 75 “readings”
• Previous examples
  – Social Statistics
  – Causality
  – Computational Social Science
• Working title: “Inference by Design”
Current Structure of Proposal

• Volume I – Background
  • Causal inference
  • Potential outcomes
  • “Evaluation research”

• Volume II – Comparing like with like
  • Matching methods
  • Propensity scoring

• Volume III – Panel data and instruments
  • Fixed effects
  • Difference-in-difference
  • Instrumental variables

• Volume IV – Experimental analogues
  • Regression discontinuity
  • Quasi-experiments, natural experiments
  • Field experiments
Volume I - Background

• A. Causal inference from observational data

• B. Potential outcomes and counterfactuals

• C. Programme and policy evaluation
# Causal Inference from Observational Data

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<td>Causal inferences in sociological research</td>
<td>Ann Rev Sociology</td>
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</table>
Causal Inference from Observational Data

• Holland
  » The analysis of causation should begin with studying the effects of causes.
  » No causation without manipulation.

• Sobel
  » Only causal sequences are counterfactually regular.

• Rubin
  » Observational studies can and should be designed to approximate randomized experiments as closely as possible.
## Potential outcomes and counterfactuals

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<td>Causal inference using potential outcomes</td>
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<td>Sampson et al.</td>
<td>Does marriage reduce crime? A counterfactual approach ...</td>
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Potential outcomes and counterfactuals

• Harding
  » This study employs counterfactual models ... to estimate the effects of neighborhood poverty ...

• Sampson et al.
  » Our approach is to extend “counterfactual” methods for time-varying covariates to a within-individual analysis of the role of marriage ...
# Programme and policy evaluation

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<td>Journal of Economic Lit</td>
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<td>2010</td>
<td>Angrist, Pischke</td>
<td>The credibility revolution in empirical economics: how better ...</td>
<td>J Economic Perspectives</td>
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</table>
Programme and policy evaluation

• Ahern et al.
  » Causal inference methods allow estimation of the effects of potential public health interventions ...

• Alwyn, Sullivan
  » The principal inferential device whereby the effects of various policies are made known involves the incorporation of valid comparison into research design ...
Volume II – Comparing like with like

• D. Matching methods

• E. Propensity scoring
## Matching methods

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Matching methods

• Morgan, Harding
  » ... matching techniques can be used effectively to strengthen the prosecution of causal questions in sociology

• Stuart
  » When estimating causal effects using observational data, it is desirable to replicate a randomized experiment as closely as possible by obtaining treated and control groups with similar covariate distributions.
## Propensity scoring

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Volume III – Panel data and instruments

- F. Fixed effects
- G. Difference-in-difference
- H. Instrumental variables.
## Fixed effects

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<td>Change in income and change in self-rated health: Systematic review</td>
<td>SSM</td>
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Fixed effects

• Halaby
  » The fundamental structure of panel data provides the analytical leverage for ... the estimation of causal effects

• Duncan et al.
  » We use whole-childhood data from the PSID to relate children’s completed schooling and nonmarital fertility to parental income ...

• Gunsekara et al.
  » ... the true causal short-term relationship between income and health ... may be much smaller than that suggested by previous, mostly cross-sectional research.
## Difference-in-difference

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Instrumental variables

• Denny

  » Using Instrumental Variables estimation, which allows one to isolate exogenous variation in prayer, leads to the conclusion ... there may be some benefit to prayer ...
Volume IV – Experimental analogues

• I. Regression discontinuity

• J. Quasi-experiments and natural experiments

• K. Field experiments.
Regression discontinuity

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Quasi-experiments and natural experiments

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# Field experiments

<table>
<thead>
<tr>
<th>DATE</th>
<th>AUTHOR(S)</th>
<th>TITLE</th>
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<tr>
<td>2008</td>
<td>Clampet-Lundquist, Massey</td>
<td>Neighborhood effects on economic self-sufficiency: a reconsideration of the MTO experiment</td>
<td>American Journal of Sociology</td>
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<td>2008</td>
<td>Ludwig et al.</td>
<td>What can we learn from neighbourhood effects from MTO?</td>
<td>American Journal of Sociology</td>
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<td>2008</td>
<td>Sampson</td>
<td>Moving to inequality: neighborhoods and experiments meet social structure</td>
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Concluding Thoughts

• Can insistence on causal purity go too far?
  – Smoking and lung cancer; climate change
  – Status of predictive and descriptive work?

• Still plenty of “wriggle room” in clinical trials
  – Major investment in flu vaccine despite doubts

• But still a worthwhile criterion
  – Lack of clinical trial scrutiny for hip replacement

• The policy sciences need this credibility
"...the most urgent call of all is to remove the cloak of invisibility from the shoulders of Indigenous peoples—not only to reveal their diversity and heritage, but also to reflect on their cultural fragility and to protect and strengthen their essential, foundational place in human society."

Indigenous Health
Causal Inference in Observational Settings

Do Hospital Bed Reduction and Multiple System Reform Affect Patient Mortality? A Trend and Multilevel Analysis in New Zealand Over the Period 1988–2001

Peter Davis, PhD.* Roy Lay-Yee, MA,† Alastair Scott, PhD,‡ and Robin Goudie, PhD

Objectives: To assess the effect of changes in patient and hospital conditions on short-term use of hospital beds and hospital stay in New Zealand through the 1990s. Methods: Trend analysis using both univariate and multivariate techniques.

Results: Access to discharge data, accounting for 6,038,177 hospitalizations, was secured for all 31 major public hospitals in New Zealand over the period 1988–2001.

Conclusions: Although the number of hospital beds in New Zealand decreased steadily from 1988 to 2001, the number of hospitalizations remained stable. The trend of hospital admissions was not affected by the reduction in hospital beds. The study found that the reduction in hospital beds did not lead to an increase in hospital stay.

Key Words: health system reform, patient outcomes, multilevel analysis

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