Causal Inference for Social Science Research

PSCI 7108/SOCY 5601
Fall 2006

Course Description

Time:	Wed 3:30-6:00pm
Location:	Ketchum 116
Instructor:	Ying Lu
Office:	Ketchum 3E
Office hours:	Tues/Thur 4:00-5:30pm

Assessing the causal effects of social and political policies and practices is one important aim of social science research. Historically, however, much sociological and political science research has not been designed in such a way as to allow researchers to make credible causal inferences about the effects of these policies and practices. In part, this is because many quantitative studies in the social sciences are essentially correlational in nature–they may show that there are statistical associations among sets of policy and practice variables and outcomes, but they do not provide strong, convincing evidence of the causal linkages among these variables. In recent decades, however, the so-called counterfactual or potential outcomes model (also called the Rubin Causal Model) and related developments have dramatically changed the way that social scientists have thought of causality. The new causal framework is not so much a set of technical models, but a precise logical framework for thinking about causality-and what constitutes evidence of causality-in the social sciences. In this class, we will cover the approaches to causal inference using potential outcomes framework. In particular, we will look at observational studies with and without ignorable treatment assignment, randomized or quasi-randomized experiments with and without the presence of noncompliance, and various matching methods to estimate the treatment effect under these conditions.

The goals of the class are: 1) to introduce students to these methods for assessing causal effects; 2) to help students understand the assumptions implicit in each of these approaches, so that they can evaluate their appropriateness in a variety of research situations and can critique quantitative research; 3) expose students to examples of social science research that effectively use these techniques; and 4) to help students think about how they might apply these techniques in their own work.

Prerequisites

This course is designed for graduate students with some prior training in quantitative research methods. I will assume that students in the course have solid understanding of the basic yet fundamental statistical concepts and are comfortable with applied regression techniques. If you need to review some of the basic materials, you can refer to class handouts, or books such as

- Fox, J. (1997). *Applied Regression Analysis, Linear Models, and Related Methods*. Thousand Oaks, CA: Sage.
- DeGroot, M. H. (1986). *Probability and Statistics*. 2nd Edition, Addison-Wesley.

Evaluation

Final grades will be calculated based on the following system:

1. There will be no closed-book exams, but occasionally there will be "friendly" pop quizzes so that I know you are with the class [1]. 10%
2. There will be four homework projects which give you a chance to do data analysis using your own program(!)[2] 40%
3. Each student should submit a final term paper[3]. It can be in the following formats, whichever suits you best. 40%
    - A critical review of the literature in a specific field to your interest, focusing particularly on the literatures strengths and weaknesses regarding causal inference. This review should identify a specific causal question and then review the literature (in whatever fields are relevant) that attempts to answer this question.
    - A proposal for a research study that uses one or more of the methods discussed in the course. This proposal should be detailed in specifying the source(s) of data and the analytic strategies to be used. This proposal could be the research design and analysis of a dissertation proposal, for example. No literature review is needed in this proposal.
    - A data analysis paper that uses one or more of the methods discussed in the course to analyze extant data to make valid causal inference. Such a paper would include careful description of the rationale for and methods of analysis used, and a discussion of the assumptions made as well as interpretation of the results.
    - Other possibilities are possible subject to discussion/approval of the professor.
4. finally, class attendance and participation. 10%

Auditing Policies

Auditing is in general not encouraged. If you do choose to audit, you will still have to do all the readings and homework projects. This course needs not to be observed.

[1] Definition of a "friendly" quiz: a quiz that consists of as little technical detail as possible

[2] Teamwork is encouraged since R programming may be challenging to some students. If a team (should be no more than 3 members) is formed, each member's contribution to the final output of each project much be clearly stated.

[3] 10-15 pages double space excluding bibliography, I want you to trade length for quality

Computation

In this course, we use statistical software, called **R**. **R** is available for any platform and without charge at http://www.r-project.org/; it is very similar to commercial software S-plus. Five one-hour **R** sessions will be built into the weekly lectures for students to learn how to implement the methods discussed in the class in **R**.

To get started, you might want to consult the on-line documentation, "Introduction to **R**," available at the **R** project web site. You may also want to refer to a good reference book in **R** or **S**, such as

- Venables, W.N and B. D. Ripley. (2003). *Modern Applied Statistics with S*. 4th Edition, New York: Springer-Verlag.
- Krause, A. and M. Olson. (2002). *The Basics of S-PLUS*. 3rd edition, Springer Verlag.
- Dalgaard, P. (2002). *Introductory Statistics with R*. Springer Verlag.

Tentative course plan

This is just a tentative course plan with an evolving reading list...in particular, more papers applying these methods will be added to the list.

1. (8/30) introduction, probability and statistics review
   (a) class handout
2. (9/06) open-book self test,[4] R session I
   (a) R handout
3. (9/13) issues of causality, potential outcome framework
   (a) Cox, D.R. (1992) "Causality: Some Statistical Aspects," *Journal of the Royal Statistical Society, Series A*, 155, 291-301.
   (b) Holland, P. (1986) "Statistics and Causal Inference," (with discussion), *Journal of the American Statistical Association*, 81, 945-970.
   (c) Rubin, D. (1974) "Estimating Causal Effects of Treatments in Randomized and Non-randomized Studies," *Journal of Educational Psychology*, 66, 688-701.
   (d) Rubin, D. (2000) "Statistical Inference for Causal Effects in Epidemiological Studies via Potential Outcomes," *Proceedings of the Societa Italiana di Statistica*, 419-430.
   - Little, R.J.A. and D. B. Rubin. (2000). "Causal Effects in Clinical and Epidemiological Studies via Potential Outcomes: Concepts and Analytical Approaches," *Annual Review of Public Health*, 21, 121145.
   - Maldonado, G. and S. Greenland (2002) "Estimating Causal Effects," *International Journal of Epidemiology*, 31, 422-429.

[4] the grade will not be counted toward final grade, this is mainly for me and you to know how well prepared you are for this course.

4. Biases in OLS when estimating causal effect, some conventional remedies

   (a) Winship, C. and S. L. Morgan. (1999) "The Estimation of Causal Effects from Observational Data", *Annual Review of Sociology*, 25, 659-707.

   (b) Angrist, J. D. (1990), "Lifetime Earnings and the Vietnam Era Draft Lottery: Evidence from Social Security Administrative Records", *American Economic Review*, 80, 313-336.

   (c) Heckman, J.J. (1990) "Varieties of Selection Bias", *American Economic Review*, 80, 313-318.

   (d) Heckman, J.J. (1997) "Instrumental Variables: a Study of Implicit Behavioral Assumptions Used in Making Program Evaluations", *Journal of Human Resources*, 32, 441-462.

5. Inference based on randomized experiments

   (a) Cochran, W.G. (1983) *Planning and Analysis of Observational Studies*, Chapters 1 and 7, Edited posthumously by L.E. Moses and F. Mosteller, New York: John Wiley and Sons.

   (b) Efron, B. and D. Feldman (1991) "Compliance as an Explanantory Variable in Clinical Trials", *Journal of the American Statistical Association*, 86, 9-17.

   (c) Fisher, R.A. (1966) *The Design of Experiments*, 8th Edition, Hafner, New York.

   (d) Neyman, J. (1923) "On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9", translated in *Statistical Science*, (with discussion), 5, 465-1480, 1990.

   (e) Rosenbaum, P.R. (2002) *Observational Studies*, Chapter 2, 2nd Edition, Springer-Verlag.

   (f) Rubin, D. (1990) "Comment: Neyman(1923) and Causal Inference in Experiments and Observational Studies", *Statistical Science*, 5, 472-480.

6. Unconfoundedness and univariate matching

   (a) Smith, H. L. (1997) "Matching with multiple controls to estimate treatment effects in observational studies". *Sociological Methodology*, 27: 325-353.

   (b) Rubin, D.B. (1973) "Matching to Remove Bias in Observational Studies", *Biometrics*, 29, 159-183.

   (c) Rubin, D.B. (1973) "The Use of Matched Sapling and Regression Adjustment to Remove Bias in Observational Studies", *Biometrics*, 29, 185-203.

   (d) Rubin, D.B. (1977) "Assignment to a Treatment Group on the Basis of a Covariate", *Journal of Educational Statistics*, 2, 1-26.

7. multivariate matching

   (a) Rubin, D.B. (1980) "Bias Reduction Using Mahalanobis-Metric Matching", *Biometrics*, 36, 293-298.

   (b) Rubin, D.B. (1979) "Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observational Studies", *Journal of the American Statistical Association*, 74, 318-328.

(c) Smith, H.L. (1997) "Matching with Multiple Controls to Estimate Treatment Effects in Observational Studies", *Sociological Methodology*, 27, 325-353.

(d) Diamond, A. and J.S. Sekhon (2005) "Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies", working paper.

(e) Sekhon, J.S. (2006) "Alternative Balance Metrics for Bias Reduction in Matching Methods for Causal Inference", working paper.

8. Matching via propensity score

   (a) Rosenbaum, P. R. and D. B. Rubin. (1983) "The central role of the propensity score in observational studies for causal effects." *Biometrika*, 70, 41–55.

   (b) Rosenbaum, P. R. and D. B. Rubin. (1984) "Reducing bias in observational studies using subclassification on the propensity score." *Journal of the American Statistical Association* **79**, 516–524.

   (c) Rosenbaum, P. R. and D. B. Rubin. (1985) "Constructing a control group using multivariate matched sampling methods that incorporate the propensity score." *The American Statistician* **39**, 33–38.

   (d) Rosenbaum, P. R. and D. B. Rubin. (1985) "The Bias Due to Incomplete Matching", *Biometrics*, 41, 103-116.

9. R packages implementing matching and propensity score techniques

   (a) Ho, D.E. et. al. (2005) "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference", working paper.

   (b) MatchIt: Nonparametric Preprocessing for Parametric Causal Inference, R Package.

   (c) Matching: Multivariate and Propensity Score Matching Estimator for Causal Inference, R Package.

10. Instrumentral variable revisited

    (a) Angrist, J. D., G. W. Imbens, and D. B. Rubin. (1996) "Identification of causal effects using instrumental variables." (with discussions) *Journal of the American Statistical Association* 90, 431–442.

11. Other topics: TBA