Syllabus: Causal Inference and Program Evaluation

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In most of economics we are interested in causal relations between variables, rather than mere correlations. For example, it is not the correlation between earnings and education that is of interest, but the effect of increasing someone's education by one year on that same person's earnings. In this five lecture course we study methods for estimating and identifying such causal effects. We discuss theoretical and practical issues arising in causal inference as well as applications in the economics literature where these or other methods have been employed.

1. Lecture I: Introduction and Randomized Experiments

   In the first lecture I will introduce some general notation for causal modelling, based on potential outcomes, some of which are ex post observed and some of which are not. Comparisons of these potential outcomes give us the causal effects we are interested in.

   In the second part of the first lecture we look at the analysis of various types of randomized experiments. Although it is rare that we have randomized experiments in economics, understanding how to analyze randomized experiments is an important step towards understanding the analysis of data from observational studies. Most methods for analyzing data from observational studies involve rearranging the data in a way that techniques appropriate for analyzing randomized experiments are appropriate. We shall look at Fisher's tests, Neyman's repeated sampling inference and more model based methods. We shall look at the role of covariates, and look at some applications.

(a) Cox, D. R., (1992), "Causality: Some Statistical Aspects," *Journal of the Royal Statistical Society*, Series A, 155, part 2, 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) Neyman, J., (1923), "On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9," translated in *Statistical Science*, (with discussion), Vol 5, No 4, 465–480, 1990.

(e) Fisher, R. A., (1935), *The Design of Experiments*, chapter 2, "The principles of experimentation, illustrated by a psycho–phisical experiment".

(f) Heckman, J., and J. Smith, (1995), "Assessing the Case for Social Experiments", *Journal of Economic Perspectives*, Vol. 9, 85-110.

(g) Lalonde, R. (1986), "Evaluating the Econometric Evaluations of Training Programs", *American Economic Review*, Vol. 76, No. 4, 604-620.

2. Lecture II: Observational Studies with Unconfounded Treatment Assignment

In the second lecture we look at observational studies where assignment does not depend on the potential outcomes conditional on observed covariates. This assumption is known as unconfoundedness or selection on observables. We look at inference first with a single covariate, using matching, subclassification or blocking, weighting, and regression adjustment, as well as the relationships between all four methods. Then we study the case with multiple covariates and show how the propensity score, the conditional probability of receiving the treatment of interest, can be used to reduce the dimension of the problem. We also discuss how to estimate the propensity score as well as a number of applications.

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

(b) Rosenbaum, P., and D. Rubin, (1983), "The central role of the propensity score in observational studies for causal effects", *Biometrika*, 70, 1, 41–55.

(c) Dehejia, R., and S. Wahba, (1999), "Causal Effects in Non–experimental Studies: Re–evaluating the Evaluation of Training Programs", *Journal of the American Statistical Association*, Vol. 94, No. 448, 1053-1062.

3. Lecture III: Deviations from Unconfoundedness, Sensitivity Analyses and Bounds

Next we discuss how we can assess the validity of the unconfoundedness assumption and assess the sensitivity of the results to violations of the assumptions. An extreme version of this sensitivity analysis is the bounds approach.

(a) Rosenbaum, P., and D. Rubin, (1983), "Assessing Sensitivity to an Unobserved Binary Covariate in an Observational Study with Binary Outcome," *Journal of the Royal Statistical Society, Series B*, 45, 212-218.

(b) Heckman, J., and J. Hotz, (1989) "Alternative Methods for Evaluating the Impact of Training Programs", (with discussion), *Journal of the American Statistical Association*.

(c) Rosenbaum, P., (1987), "The role of a second control group in an observational study", *Statistical Science*, (with discussion), Vol 2., No. 3, 292–316.

(d) Manski, C., G. Sandefur, S. McLanahan, and D. Powers (1992), "Alternative Estimates of the Effect of Family Structure During Adolescence on High School," *Journal of the American Statistical Association*, Vol 87, no. 417, 25–37.

(e) Card, D., and Sullivan "Measuring the Effect of Subsidized Training Programs on Movements In and Out of Employment", *Econometrica*, vol. 56, no. 3 497–530.

4. Lecture IV: Deviations from Unconfoundedness: Instrumental Variables

In the fourth lecture we discuss models where selection is not solely on observables. We look at instrumental variables techniques as a possible alternative set of assumptions and present some general results and applications and the relation to standard selection models.

(a) Angrist, J., G. W. Imbens and D. Rubin, (1996), "Identification of Causal Effects Using Instrumental Variables", (with discussion) *Journal of the American Statistical Association*, Vol. 91. No. 434, 444-472.

(b) Angrist, J., (1990), "Lifetime Earnings and the Vietnam Era Draft Lottery: Evidence from Social Security Administrative Records," *American Economic Review*, Vol. 80, 313-335.

(c) Imbens, G., and D. Rubin, (1998), "Bayesian Inference for Causal Effects in Randomized Experiments with Noncompliance", *Annals of Statistics*, Vol. 25, No. 1, 305–327.

(d) Vytlacil, E., (1999), "Nonparametric Selection Models and the Evaluation of Treatment Parameters", unpublished manuscript, Department of Economics, University of Chicago.

Lecture V: Multivalued Treatments: Counfounded and Unconfounded Assignment

In the fifth lecture we discuss extensions of the methods discussed so far to the case where the treatment takes on more than two values. We look both at methods for unconfounded assignment and at instrumental variables models.

(a) Imbens, G., "The Role of the Propensity Score in Estimating Dose Response Functions", *Biometrika*, Vol. 87, No. 3.

(b) Angrist, J., and G. Imbens, (1995), "Two-stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity", *Journal of the American Statistical Assocation*, Vol. 90, No. 430, 431-442.

(c) Angrist, J., and A. Krueger, (1991), "Does Compulsory School Attendance Affect Schooling and Earnings", *Quarterly Journal of Economics*, Vol. 106, 979-1014.

(d) J. Tinbergen, "Determination and Interpretation of Supply Curves: An Example" *Zeitschrift fur Nationalokonomie*, reprinted in: *The Foundations of Econometrics*, Hendry and Morgan (eds), 233-245..

(e) Angrist, J., K. Graddy and G. Imbens, (1995), "Nonparametric Demand Analysis with an Application to the Demand for Fresh Fish", *Review of Economic Studies*, Vol. 67, 499-527.