Course Rationale

Assessing the causal effects of educational and social policies and practices is one important aim of educational and social science research. Educational researchers may want to know, for example, what effect a particular teaching practice has on student learning, what effects accountability policies have on teaching practices, or what effect early childhood education programs have on school readiness, and so on. Sociologists may want to know what the effect of certain neighborhood conditions are on child development, or what the effect of social networks are on individual behavior. In such cases, informed policy and practice decisions (including the allocation of resources) should rely on the best-available credible evidence of the causal effects of the policies and practices in question.

Historically, however, much educational and social science research has not been designed in such a way as to allow researchers to make credible causal inferences about the effects of educational and social practices and policies. In part, this is because many quantitative studies in education and 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 most dramatic influence of this model has occurred in economics; the model has more recently begun to influence quantitative work in the fields of sociology, education, and political science as well. 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.
Course Aims

This course, designed for graduate students with some prior training in quantitative research methods (I will assume that students in the course are comfortable with applied regression techniques), will introduce students to a toolkit of quantitative methods to enable them to make valid causal inferences, particularly in the absence of a true randomized experiment. These methods include 1) randomized experiments, 2) instrumental variables; 3) the use of natural and quasi-experiments; 4) longitudinal methods, including interrupted time-series methods and difference-in-differences methods; 5) regression discontinuity; 6) matching estimators, including propensity score matching; and 7) fixed effects estimators. These methods have been historically little used in educational and social science research (other than economics, where some of these methods have a long and rich history), but offer considerable power to researchers interested in generating convincing and credible evidence of casual effects.

The course will introduce students to these topics through weekly methodological lectures and through examples of their use in educational and social science research. 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.

Course Structure

The course will meet for one 2.5-hour lecture/discussion each week in the Spring quarter. Typically, half of each class will be devoted to class discussion and evaluation of one or more articles using these techniques; the other half will introduce students to the rationale, assumptions, and methodology of one of these techniques.

This is an advanced graduate course, suitable for students in a Ph.D program. Consequently, the following should go without saying: I expect that students in the course are motivated by a desire or felt need to learn the course material. Thus, I expect students in this course to come to class each week having carefully read the readings and prepared with questions. Discussion/exegesis of the readings will form the basis of the first half of each class session, so students who have not done the reading will likely benefit little from the course.

Auditors
Auditors are welcome in the course, but I expect that auditors do all readings for the course as well. Auditors need not prepare a final paper for the course. In addition, I will give priority in office hours to students who are enrolled in the course for credit. Auditors should enroll in the course blackboard site so that they will receive emails and announcements for the course.

Readings
Most readings will be available on the course blackboard website (bb.stanford.edu), either as .pdf files or as links to online resources.
Assignment
In addition to the expectation that students do all reading for the course carefully in advance of the class sessions, students enrolled in the course for credit will be required to submit a final paper. This paper may take several forms, as appropriate to individual students’ needs. Some possibilities are:

1) A critical review of the literature in a specific field, focusing particularly on the literature’s 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. Depth, detail, and critical reading are valued here over breadth and vague generalities.

2) 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.

3) 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.

4) Other possibilities are possible subject to discussion/approval of the professor.

Papers will be due on June 9.

A note on academic integrity:

Academic integrity is the pursuit of scholarly activity free from fraud and deception and is an educational objective of this institution. Academic dishonesty includes, but is not limited to, cheating, plagiarizing, fabricating information, facilitating acts of academic dishonesty by others, and submitting the work of another person or work previously used without informing the instructor. The Honor Code, outlining the general expectations pertaining to Academic Integrity applicable to this course are published in the Graduate Student Handbook available at: http://honorcode.stanford.edu. Students are expected to conform to the highest standards of academic integrity in this course — meaning, essentially, don’t lie; don’t cheat; don’t pass off someone else’s work as your own.
Course Outline

Week 1: March 31
Causality and the nature of science. Studying the effects of causes, rather than the causes of effects. The importance of good theory. Causation versus association. The Rubin causal model.

Required Readings:


Supplemental Readings:


Week 2: April 7

Required Readings:


Supplemental Readings:


April 14: No Class

Week 3: April 21

Required Readings:


Supplemental Readings:


**Week 4: April 28**
Quasi-experiments, natural experiments, Difference-in-difference estimators. Leveraging exogenous policy changes, geographical variation, and temporal change to provide unbiased estimates of causal effects.

**Required Readings:**


**Week 5: May 5**
Regression discontinuity estimators.

**Required Readings:**


**Week 6: May 12**
Matching estimators. Propensity score matching. Assumptions, limitations, and strategies.

**Required Readings:**


**Supplemental Readings:**


**Week 7: May 19**

Fixed effects as an identification strategy.

**Required Readings:**


**May 26: No Class**
Week 8: June 2

Required Readings:

