857-0102-00L

Methods III: Causal Inference

Course Syllabus

Lecturer:
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Tutorial Instructor:
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"Nothing can be more ludicrous than the sort of parodies on experimental reasoning which one is accustomed to meet with, not in popular discussion only, but in grave treatises, when the affairs of nations are the theme... How can such or such causes have contributed to the prosperity of one country, when another has prospered without them? Whoever makes use of an argument of this kind, not intending to deceive, should be sent back to learn the elements of some one of the more easy physical sciences."

John Stuart Mill (1872)

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Course Information:

Lectures: Mondays, 14.00–16.00 in IFW B 42
Tutorials: Tuesdays, 14:00–16:00 in IFW D 42.

Course Description

This course provides an introduction to statistical methods used for causal inference in the social sciences. Using the potential outcomes framework of causality, we discuss designs and methods for data from randomized experiments and observational studies. In particular, designs and methods covered include randomization, matching, instrumental variables, difference-in-difference, synthetic control, and regression discontinuity. Examples are drawn from different social sciences.

Organization

Many problems of causal inference from observational studies revolve around the concept of confounders, i.e. true causes of an effect that may render the impact of a putative cause spurious. There are different ways of handling confounders, depending on whether they are observed or not. After providing a general introduction to causation and causal inference (week 1), we begin by considering research designs in which the confounders are unobserved but rendered impotent through randomization (week 2). Since randomization is not always feasible, we may have to rely on other methods of controlling for confounders. In weeks 3 and 4, we consider designs in which the confounders are observed and can be controlled statistically. In weeks 5-12, we focus on cases in which at least some of the confounders are unobserved.

Prerequisites

Prerequisites and assessment: Knowledge of multiple linear regression and some familiarity with generalized linear models, to the level of Methods III: Regression Models or equivalent. Familiarity with notions of research design in the social sciences, to the level of Methods II: Quantitative Methods or equivalent.

If you need to review material on regression models, please consult this excellent textbook:

- Freedman, David. 2005. *Statistical Models: Theory and Practice.* Cambridge University Press.

If you need to review some `R` basics, you may want to have a look at

- Fox, John. 2002. *An R and S-PLUS Companion to Applied Regression.* Sage Publications.

- Grolemund, Garrett. 2014. *Hands on with R Programming.* O'Reilly Media. URL:`https://rstudio-education.github.io/hopr/`

- Wickham, Hadley and Garrett Grolemund. 2017. *R for Data Science.* O'Reilly Median. URL: `https://r4ds.had.co.nz/`

Software

`R` will be used in tutorials.

Materials

The main course texts will be:

- Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics.* Princeton University Press.

- Rosenbaum, Paul R. 2010. *Design of Observational Studies.* Springer.

Course materials (syllabus, tutorials, slides) are available on the course Dropbox folder:

- `goo.gl/qWMUPG`

Assessment

- **In-Class Exam (35%)**: This will be a two-hour, in class examination held at the end of the semester. It will cover material from the entire semester.

- **Group Research Project (30%)**: The group research project will give students the chance to apply the methods covered by the course to a research question of their choice. Students will work together in groups of 2-3 to design and implement their project. The final products of the group research project are a pre-analysis plan and a poster. Projects will be assessed on the quality of their research design, the implementation of causal inference techniques, the clarity with which empirical results are presented; whether projects uncover significant results and/or find support for research hypotheses will not impact grades. There are multiple deadlines for this project; detailed instructions will be distributed later in the semester:

  - Week 7: Students should submit a one-page proposal that includes a description of the research question and a brief plan for the research, including the data source(s) and identification strategy. The proposal counts **5%** toward the total of the final grade.
  - Week 11: Students will submit a pre-analysis plan for their research project. The pre-analysis plan must specify the hypotheses to be tested, the variables to be used in analyses, and the empirical methods to be used. The pre-analysis plan counts **10%** toward the total of the final grade.
  - Week 15: Poster session where students present the results of their projects with classmates. The poster counts **15%** toward the total of the final grade.

- **Problem Sets (25%)**: There will be seven problem sets throughout the semester. Students' lowest scoring problem set will be dropped from their final grade. All remaining problem sets contribute equally to the final grade.

  All problem sets are due one week after they are assigned. Problem sets must be submitted **both** physically and electronically to `teaching-pp@gess.ethz.ch` at the start of **lecture**. Problem sets should be created using R markdown. The electronic submissions should include a single PDF using your last name as a file name.

- **Tutorial Participation (10%)**: During the tutorials, students will participate in guided activities that reinforce concepts covered in the lecture, introduce additional material, and cover implementation of causal inference methods in R. Students can miss one of tutorial per semester without it negatively impacting their grade. Participation in tutorials marked "optional" is not graded.

Grades will be calculated based on ETH's grading scale from 1.0 to 6.0 and using quarter grade (0.25) steps.

E-mail Correspondence

The Tutorial Instructor (Dalston) will answer emails containing questions about upcoming problem sets/poster deadlines at 16:00 on Fridays before problem sets/poster elements are due. Questions received before this time will be answered; questions sent afterward will not be. Emails concerning other aspects of the course (including problem sets and poster elements that have already been submitted) will be answered normally, and can be directed to either the Lecturer or Tutorial Instructor.

This policy aims to encourage students to begin problem sets well in advance of the due date and also to work toward answering their own questions. Two great online resources for answering your own questions are Cross Validated (theoretical issues) and Stack Exchange (R issues). Additionally, students will have at least 30 minutes per tutorial to ask questions about problem sets.

Schedule

Week 1 - February 17

Causal Inference Using Potential Outcomes

Today we will introduce the topic of causal inference. We will define causal effects based on the potential outcomes framework of Neyman and Rubin, encounter the fundamental problem of causal inference, and discuss confounding as what separates association from causation, and observational studies from randomized experiments. We introduce examples of well designed observational studies and discuss the foundations and limitations of statistical models.

Readings:

- Holland, Paul W. 1986. Statistics and Causal Inference (with discussion). *Journal of the American Statistical Association* 81: 945-970.
- Freedman, David A. 1991. Statistical Models and Shoe Leather. *Sociological Methodology* 2: 291-313.
- Gerber, Alan S. and Donald P. Green. 2012. *Field Experiments: Design, Analysis, and Interpretation.* W.W. Norton & Company. Chapter 2.

Further readings:

- Splawa-Neyman, Jerzy, [Dabrowska, D. M., and T.P. Speed]. 1923 [1990]. On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9. *Statistical Science* 5: 465-472.
- Rubin, Donald B. 1990. Comment: Neyman (1923) and Causal Inference in Experiments and Observational Studies. *Statistical Science* 5: 472-480.
- Morgan, Stephen L. and Christopher Winship. 2007. Counterfactuals and Causal Inference. Cambridge University Press. Chapter 1: 1-24.

For the truly dedicated:

- Woodward, James. 2003. *Making Things Happen: a Theory of Causal Explanation.* Oxford University Press.

Tutorial 1:

- **Activity**: Refresher to `R` and `R` markdown.
- **Problem set**: None.

Week 2 - February 24

Randomized Experiments

We review the logic of randomized experiments, a research design that is widely believed to maximize internal validity and that is becoming ever more popular in the social sciences. We pay special attention to Fisher's randomization inference, in which randomization is the "sole and reasoned basis for inference". Lastly, we will meet the "Lady tasting tea".

Readings:

- Rosenbaum, Paul. 2009. *Design of Observational Studies.* Heidelberg: Springer, Chapter 2.1-2.3.2: 21-35.
- Fisher, Ronald A. 1935. Design of Experiments. New York: Hafner. Chapter 1-2.

Further readings:

- Gerber, Alan S. and Donald P. Green. 2012. *Field Experiments: Design, Analysis, and Interpretation.* W.W. Norton & Company. Chapter 3.

Tutorial 2:

- **Activity:** No tutorial.
- **Problem set**: Re-analysis of Sesame Street experiment.

Week 3 - March 2

Subclassification and Matching on Covariates

The advantage of randomized experiments is that potential confounders can be safely ignored since they will balanced, at least in expectations. But randomization is not always practical, nor is it always ethical. How can one ensure valid causal inference in a world without randomization? Today, we discuss designs which assume that selection into the treatment groups is based on observables. We start by considering two very intuitive methods, subclassification and exact matching techniques.

Readings:

- Rosenbaum, Paul. 2009. *Design of Observational Studies.* Heidelberg: Springer, Chapter 7: 153-162.

Further readings:

- Cochran, W. G. 1968. The Effectiveness of Adjustment by Subclassification in Removing Bias in Observational Studies. *Biometrics* 24: 295-313.

Tutorial 3:

- **Activity:** Sharp-null hypothesis testing.
- **Problem set**: None.

Week 4 - March 09

Matching and Weighting Using the Propensity Score

Next, we discuss matching techniques that are based the propensity score. For this, students will be introduced to logistic regression with binary outcomes. In addition, we also consider some practical issues with matching such as matching with and without replacement, common support restrictions, and estimating standard errors. Then, we consider weighting as a nifty alternative to matching. Lastly, we compare OLS regression with matching and weighting estimators.

Readings:

- Rosenbaum, Paul. 2009. *Design of Observational Studies.* Heidelberg: Springer, Chapter 8.1-8.3: 163-172 and Chapter 9: 187-194.
- Angrist & Pischke. Chapter 3.3.1-3.3.3, pp.69-91.
- Dehejia, R. H. and S. Wahba. 1999. Causal Effects in Non-Experimental Studies: Re- Evaluating the Evaluation of Training Programs. *Journal of the American Statistical Association* 94: 1053-1062.

Further readings:

- 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.

For the truly dedicated:

- Abadie, A. and G. Imbens. 2005. Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica* 74: 235-267.

Tutorial 4:

- **Activity**: Plotting covariate balance.
- **Problem set:** Re-analysis of Dehejia and Wahba (1999).

Week 5 - March 16

Difference-in-Differences

Confounders cannot always be observed and if they cannot, then alternative research designs have to be found. One such alternative arises in the context of panel data or repeated cross-sections. Here one can take the difference between pre- and post-tests and then compare those across groups. To the extent that the differences in the confounders have remained constant over time, then this estimator can produce valid causal inferences.

Readings:

- Angrist & Pischke. Chapter 5, pp. 221-246.
- Card, David and Alan B. Krueger. 1994. Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania. *The American Economic Review* 84: 772-793.

Further readings:

- Card, David. 1990. The Impact of the Mariel Boatlift on the Miami Labor Market. *Industrial and Labor Relations Review* 43: 245-257.

Tutorial 5:

- **Activity**: Fixed-effects regression.

- **Problem Set**: Re-Analysis of Golden Dawn Voting.

Week 6 - March 23
Instrumental variables: LATE
Instrumental variable (IV) methods can be used to address unobserved confounders in the context of cross-sectional data. Today, we discuss the basic logic of IV-techniques, focusing in particular on randomized encouragement designs and the LATE estimator.

Readings:

- Angrist & Pischke. Chapter 4.1-4.4.3
- Gerber, Alan S. and Donald P. Green. 2012. *Field Experiments: Design, Analysis, and Interpretation.* W.W. Norton & Company. Chapter 5: 131-160 and Chapter 6: 173-191.

Further readings:

- Angrist, Joshua D., Guido W. Imbens and Donald B. Rubin. 1996. Identification of Causal Effects Using Instrumental Variables. *Journal of the American Statistical Association* 9: 444-455.

Tutorial 6:

- **Activity**: Extended analysis of LATE.
- **Problem set**: Re-assessing the effects of watching more Sesame Street on child cognitive development using ITT and LATE estimates.

Week 7 - March 30
Instrumental variables: LATE II
In many observational settings, an instrument is only valid conditional on some covariates. The second session on LATE discusses the assumptions needed to make causal inferences with non-randomized instruments. In addition, we cover recent advances in profiling compliers and non-compliers.

Readings:

- Angrist & Pischke. Chapter 4.4.4-4.6.1

Tutorial 7:

- **Activity**: SUTVA.
- **Problem set**: IV estimates of refugee arrivals on voting in Greece. Profiling compliers and non-compliers in *Washington* Post experiment.
- **Poster**: Project proposal DUE.

Week 8 - April 06
Mock Exam
Students will have the chance to complete a mock exam covering materials from weeks 1–8.

No Tutorial

Week 9 - April 13
No class (Easter Break)

Week 10 - April 20
No lecture (Sechseläuten)

Tutorial 10:

- **Activity (optional)**: PAP help session.
- **Problem Set**: None.

Week 11 - April 27
Regression Discontinuity Designs
RDDs arise when selection into the treatment group depends on a covariate score that creates some discontinuity in the probability of receiving the treatment. We discuss both sharp and fuzzy RDDs.

Readings:

- Angrist & Pischke. Chapter 6.
- Cattaneo, Matias D., Nicolás Idrobo, and Rocío Titiunik. 2019. *A Practical Introduction to Regression Discontinuity Designs: Foundations.* Pages 1–16. Available at `https://doi.org/10.1017/9781108684606` (access provided by ETH Library).

Further readings:

- Pettersson-Lidbom, Per and Björn Tyrefors. 2009. The Policy Consequences of Direct versus Representative Democracy: A Regression-Discontinuity Approach. *Working Paper*.
  (available at: http://people.su.se/ pepet/directdem.pdf)

- Lee, David S. 2008. Randomized Experiments from Non-random Selection in U.S. House Elections. *Journal of Econometrics* 142 (2): 675–697.

For the truly dedicated:

- Hahn, Jinyong, Petra Todd and Wilbert Van der Klaauw. 2001. Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design. *Econometrica* 69: 201-209.

Tutorial 11:

- **Tutorial:** Coefficient plots.
- **Problem set:** Re-analysis of Eggers and Hainmueller (2009).
- **Poster**: Pre-analysis plan DUE.

Week 12 - May 4
Synthetic Control Method
If you would like to use Difference-in-Difference but don't have a good control unit: synthesize one. This estimator is a simple but potentially widely applicable generalization of the Difference-in-Differences estimator.

Readings:

- Abadie, Alberto, Diamond, Alexis and Jens Hainmueller. 2009. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association.*

Further readings:

- Abadie, Alberto and Javier Gardeazabal. 2003. The Economic Costs of Conflict: a Case-Control Study for the Basque Country. *American Economic Review* 92 (1).

Tutorial 12:

- **Activity**: `Synth` in `R`.
- **Problem set**: Re-analysis of Bechtel, Hangartner and Schmid (2018).

Week 13 - May 11
Overview and review
Schematic overview of class: maximizing internal validity of local estimates and the price of sacrificing external validity. Q & A session.

Tutorial 13:

- **Activity (optional)**: Poster help session.
- **Problem set**: None.

Week 14 - May 18
No class

Tutorial 14:

- **Activity (optional)**: Poster help session.
- **Problem set:** None.

Week 15 - May 25
Poster Session
Details TBA.

June XX
In-Class Final Exam
Two hour written exam covering material from the entire semester.