# MY457/MY557

## Causal Inference for Experimental and Observational Studies

## Course Syllabus

**Convenor:**
**David Hendry**

**Class instructor:**
**Krisztián (Chris) Pósch**

**Graduate Teaching Assistants:**
**Ginevra Floridi, Yan Wang**

Lent Term 2019

> *"If an instance in which the phenomenon...occurs and an instance in which it does not...have every circumstance save one in common...[then] the circumstance [in] which alone the two instances differ is the...cause..."*
>
> *John Stuart Mill (1864)*

**Contact Information:**


- *David Hendry*, Department of Methodology, London School of Economics and Political Science. Email: `d.hendry@lse.ac.uk`. Office hours: Tuesdays, 10:00-12:00. COL7.05; Sign-up via LSE for You.
- *Chris Pósch*, Department of Methodology, London School of Economics and Political Science. Email: `k.p.posch@lse.ac.uk`. Office hours: Wednesdays, 9:00-11:00. COL.2.03; Sign-up via LSE for You.
- *Ginevera Floridi*, Department of Social Policy, London School of Economics and Political Science. Email: `g.floridi@lse.ac.uk`.
- *Yan Wang*, Department of Sociology, London School of Economics and Political Science. Email: `y.wang149@lse.ac.uk`


**Course Information:**
Meeting times: There will be ten two-hour lectures, Wednesday 12.00-14.00 in PAN.G.01 and five two-hour computer classes in weeks 2, 4, 7, 9 and 11, offered on Wednesday 14.00-16.00, 16.00-18.00, and 18.00-20.00 in FAW.4.01. No classes or seminars will take place during School Reading Week 6.

## 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, causal mediation, and regression discontinuity. Examples are drawn from different social science disciplines.

## Organization

Many problems of causal inference from observational studies revolve around the concept of confounders, i.e., variables that are extraneous to the relationship of interest and that may make it appear (sometimes incorrectly) that a putative cause is associated with an effect. There are a variety of 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 unproblematic through randomization (weeks 2 and 3). Since randomization is not always feasible, we may have to rely on other methods of eliminating the potential pernicious effects of confounders. In week 4, we consider designs in which the confounders are observed and can be controlled statistically. In weeks 5-10, we focus on designs for making valid causal inferences in situations in which at least some of the confounders are unobserved. In week 11, we recap what we have covered and introduce a few extensions.

## Prerequisites

Knowledge of multiple linear regression and some familiarity with generalised linear models, to the level of MY452/MY552 or equivalent. Familiarity with notions of research design in the social sciences, to the level of MY400 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, there are a plethora books and online resources. A good book is:

- Field, Andy, Jeremy Miles, and Zoë Field. 2012. *Discovering Statistics Using R.* New York: Sage.

And a good online resource is hosted by the UCLA Department of Statistics:

- https://stats.idre.ucla.edu/r/

Google and YouTube will probably also prove very useful.

## Software

R will be used in class sessions. You are welcome to use Stata, but there will be less support and a few of the techniques we learn in R may not be achievable (at least easily) in Stata.

## 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.

**Important:** To take full advantage of the course, it is essential that you do all of the readings before the lectures, turn in everything on time, ask questions when you don't understand things (chances are you are not alone), and don't miss lecture or class. Also, the course materials and readings will likely not be perfect, so please let the instructor know if you believe you have found a mistake.

## Assessment

Assessment for MY457 (MSc) will be a two-hour written examination in the ST (100%). Assessment for MY557 (PhD) will be a research paper (of approximately 4,000 words) applying methods from the course to a research question chosen by the student. PhD students are strongly encouraged to discuss their research paper ideas with the instructor(s).

## Schedule

***Week 1***
**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." *Journal of the American Statistical Association* 81: 945-970.

- Freedman, David A. 1991. "Statistical Models and Shoe Leather." *Sociological Methodology* 2: 291-313.

*Further readings:*

- Morgan, Stephen L., and Christopher Winship. 2014. *Counterfactuals and Causal Effect: Methods and Principles for Social Research* 2nd ed. Cambridge: Cambridge University Press, Chapter 1.

*For the truly dedicated:*

- 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.

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

***Week 2***

**Randomized Experiments I**

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:*

- Nagin, Daniel S., and David Weisburd. 2013. "Evidence and Public Policy: The Example of Evaluation Research in Policing." *Criminology & Public Policy* 12: 651-679.

- Gerber, Alan S., and Donald P. Green. 2000. "The Effects of Canvassing, Telephone Calls, and Direct Mail on Voter Turnout: A Field Experiment." *American Political Science Review* 94(3): 653-663.

- Gerber, Alan S., and Donald P. Green. 2012. *Field Experiments: Design, Analysis, and Interpretation.* New York: W.W. Norton & Co., Chapters 1-2.

***Class 1:***

- Re-analysis of Sesame Street experiment.

***Week 3***
**Randomized Experiments II**
The prototypical randomized experiment compares one or a small number of experimental treatments to a control group. Randomization is assumed to eliminate confounders, and therefore we can make unproblematic causal inferences. This is an incredibly useful, if somewhat stylized, framework that describes many important applied research settings. However, there are many useful questions that could be answered with an experiment that goes beyond the simple comparison of treatment to control. What if we cannot randomize at the level that is most relevant for the research question? How might we use additional information about the units to counter chance imbalances between experimental groups? What if we are interested in more than one causal variable and the interactions between them? What if the assumption of no interference between units is violated? And what if the average treatment effect is not the most useful or interesting way to summarize a substantive effect? To deal with a small slice of these questions, this week we cover the basics of blocking, clustering, factorial designs, spillover, and treatment effect heterogeneity.

*Readings:*

- Gerber, Alan S., and Donald P. Green. 2012. *Field Experiments: Design, Analysis, and Interpretation.* New York: W.W. Norton & Co., pp. 71-85; 253-273; 289-312.

*Further readings:*

- Boruch, Robert, Henry May, Herbert Turner, Julia Lavenberg, Anthony Petrosino, Dorothy De Moya, Jeremy Grimshaw, and Ellen Foley. 2004. "Estimating the Effects of Interventions That Are Deployed in Many Places: Place-Randomized Trials." *American Behavioral Scientist* 47(5): 608-633.

- Collins, Linda M., John J. Dziak, Kari C. Kugler, and Jessica B. Trail. 2014. "Factorial Experiments: Efficient Tools for Evaluation of Intervention Components." *American Journal of Preventive Medicine* 47(4): 498-504.

- Imai, Kosuke, and Marc Ratkovic. 2013. "Estimating Treatment Effect Heterogeneity in Randomized Program Evaluation." *Annals of Applied Statistics* 7(1): 443-470.

- Na, Chongmin, Thomas A. Loughran, and Raymond Paternoster. 2015. "On the Importance of Treatment Effect Hetorogeneity in Experimentally-Evaluated Criminal Justice Interventions." *Journal of Quantitative Criminology* 31: 289-310.

***Week 4***
**Matching and Weighting on Covariates**
The advantage of randomized experiments is that potential confounders can be safely ignored since they will be 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 that assume that selection into the treatment groups is based on observables. We start by considering a very intuitive method, exact matching, followed by matching techniques based on Euclidean distance and the propensity score. We then move on to some modern developments such as genetic matching and coarsened exact matching. We also consider some practical issues with matching such as matching with and without replacement, common support restrictions, and estimating standard errors. Lastly, we compare OLS regression with matching and weighting estimators.

*Readings:*

- Rosenbaum, Paul. 2009. *Design of Observational Studies.* Heidelberg: Springer, Chapter 7; Chapter 8.1-8.3; Chapter 9.

- Angrist & Pischke. Chapter 3.3.1-3.3.3.

- 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:*

- Bind, Marie-Abele C., and Donald B. Rubin. Forthcoming. "Bridging Observational Studies and Randomized Experiments by Embedding the Former in the Latter." *Statistical Methods in Medical Research*.
- Cochran, W.G. 1968. "The Effectiveness of Adjustment by Subclassification in Removing Bias in Observational Studies." *Biometrics* 24: 295-313.
- Rosenbaum, Paul R., and Donald B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70: 41-55.
- Sekhon, Jasjeet S. 2009. "Opiates for the Matches: Matching Methods for Causal Inference." *Annual Review of Political Science* 12: 487-508.
- Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart. 2017. "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis* 15(3): 199-236.

*For the truly dedicated:*

- Abadie, Alberto, and Guido W. Imbens. 2005. "Large Sample Properties of Matching Estimators for Average Treatment Effects." *Econometrica* 74: 235-267.

***Class 2:***

- Re-analysis of Dehejia and Wahba (1999).

***Week 5***
**Difference-in-Differences**
Confounders cannot always be observed and if they cannot, then we need to find alternative research designs to the ones we have covered thus far in order to make valid causal inferences. 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 compare them 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." *American Economic Review* 84: 772-793.

*Further readings:*

- Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Difference-in-Differences Estimates?" *Quarterly Journal of Political Science* 119(1): 249-275.
- Card, David. 1990. "The Impact of the Mariel Boatlift on the Miami Labor Market." *Industrial and Labor Relations Review* 43: 245-257.
- Di Tella, Rafael, and Ernesto Schargrodsky. 2004. "Do Police Reduce Crime? Estimates Using the Allocation of Police Forces after a Terrorist Attack." *American Economic Review* 94(1): 115-133.
- Galiani, Sebastian, Paul Gertler, and Ernesto Schargrodsky. 2005. "Water for Life: The Impact of the Privatization of Water Services on Child Mortality." *Journal of Political Economy* 113(1): 83-120.
- Hainmueller, Jens, and Dominik Hangartner. Forthcoming. "Does Direct Democracy Hurt Immigrant Minorities? Evidence from Naturalization Decisions in Switzerland." *American Journal of Political Science.*
- Lyall, Jason. 2009. "Does Indiscriminate Violence Incite Insurgent Attacks? Evidence from Chechnya." *Journal of Conflict Resolution* 53(3): 331-362.

***Week 7***
**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, Alexis Diamond, 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* 105(490): 493-505.

*Further readings:*

- Abadie, Alberto and Javier Gardeazabal. 2003. "The Economic Costs of Conflict: A Case-Control Study for the Basque Country." *American Economic Review* 93(1): 113-132.

- Saunders, Jessica, Russell Lundberg, Anthony A. Braga, Greg Ridgeway, and Jeremy Miles. 2015. "A Synthetic Control Approach to Evaluating Place-Based Crime Interventions." *Journal of Quantitative Criminology* 31: 413-434.

***Class 3:***

- Replication of Card and Krueger (1994).

***Week 8***

**Instrumental variables**

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 the local average treatment effects (LATE) estimator. In particular, we contrast the potential-outcomes approach to instrumental-variables estimation with the traditional econometric approach. Finally, because the LATE estimator is only able to identify average treatment effects conditional on covariates under very restrictive assumptions, we introduce a weighting scheme known as a local average response function (LARF) that leads to unbiased treatment effects for the subsample of compliers.

*Readings:*

- Angrist & Pischke. Chapter 4.1-4.4.4.

- 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.

*Further readings:*

- Angrist, Joshua D. 2006. "Instrumental Variables Methods in Experimental Criminological Research: What, Why and How." *Journal of Experimental Criminology* 2: 23-44.

- Angrist, Joshua D., and Alan B. Krueger. 2001. "Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments." *Journal of Economic Perspectives* 15(4): 69-85.

- Gerber, Alan S., and Donald P. Green. 2012. *Field Experiments: Design, Analysis, and Interpretation.* New York: W.W. Norton & Co., pp. 173-192.

- Morgan, Stephen L., and Christopher Winship. 2014. *Counterfactuals and Causal Effect: Methods and Principles for Social Research* 2nd ed. Cambridge: Cambridge University Press, Chapter 9.

***Week 9***
**Causal Mediation**
Even though randomized experiments are commonly understood as the gold standard for causal inference, they are also often criticized as only providing a "black-box" description of a causal process. In other words, the typical randomized experiment can tell us *whether* a treatment has an effect, but not *how* or *why.* This week, we cover a general framework for addressing this limitation that involves identifying an intermediate variable—or "mediator"—on the causal pathway between the implementation of a treatment and the measurement of an outcome.

*Readings:*

- Gerber, Alan S., and Donald P. Green. 2012. *Field Experiments: Design, Analysis, and Interpretation.* New York: W.W. Norton & Co., Chapter 10.

- Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. 2011. "Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies." *American Political Science Review* 105(4): 765-789.

*Further Readings:*

- Pósch, Krisztián. 2018. "Prying Open the Black Box of Causality—A Causal Mediation Analysis Test of Procedural Justice Policing." *Law, Society and Economy Working Paper.*

- Keele, Luke, Dustin Tingley, and Teppei Yamamoto. 2015. "Identifying Mechanisms Behind Policy Interventions via Causal Mediation Analysis." *Journal of Policy Analysis and Management* 34: 937-963.

- Preacher, Kristopher J. 2015. "Advances in Mediation Analysis: A Survey and Synthesis of New Developments." *Annual Review of Psychology* 66: 825-852.

***Class 4:***

- Re-assessing the effect of watching more Sesame Street on child cognitive development; program effect of watching TV vs. program effect of encouragement to watch. ITT, Wald, LATE, and LARF estimators.

***Week 10***
**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 & Piscke. Chapter 6.

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

*Further readings:*

- Cattaneo, Matias D., Nicolás Idrobo, and Rocío Titiunik. Forthcoming. *A Practical Introduction to Regression Discontinuity Designs: Volume I.* Available at: http://www-personal.umich.edu/∼titiunik/books/CattaneoIdroboTitiunik2018-Cambridge-Vol1.pdf.

- Cattaneo, Matias D., Nicolás Idrobo, and Rocío Titiunik. Forthcoming. *A Practical Introduction to Regression Discontinuity Designs: Volume I.* Available at: http://www-personal.umich.edu/~titiunik/books/CattaneoIdroboTitiunik2018-Cambridge-Vol2.pdf.

- Pettersson-Lidbom, Per and Björn Tyrefors. 2009. "The Policy Consequences of Direct versus Representative Democracy: A Regression-Discontinuity Approach." *Working Paper.* Available at: http://www.ne.su.se/polopoly_fs/1.214891.1418657730!/menu/standard/file/directdem.pdf

*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.

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

*Further readings:*

- Keele, Luke. 2015. "The Statistics of Causal Inference: A View from Political Methodology." *Political Analysis* 23: 313-335.

- Imai, Kosuke, Gary King, and Elizabeth A. Stuart. 2008. "Misunderstandings Between Experimentalists and Observationalists About Causal Inference." *Journal of the Royal Statistical Society* 171(2): 481-502.

***Class 5:***

- Exam prep and regression discontinuity exercise.