PUBL0050
Causal Inference

UCL Department of Political Science
School of Public Policy

Term 2 - Academic Year 24-25

Module Name:	Causal Inference
Module Code:	PUBL0050
Lecturer:	Dr Julia de Romémont (j.romemont@ucl.ac.uk)
Student Support & Feedback Hours:	TBD
Teaching:	• 10 x 2h lectures (Wednesdays, 9 – 11am) • 10 x 1h seminars (Fridays, 9am, 10am)
Credits:	15
Assessment Method:	3000 word essay
Assessment Deadlines:	29th April 2025

Course Description

This course provides an introduction to statistical methods used for causal inference in the social sciences. We will be concerned with understanding how and when it is possible to make causal claims in empirical research. In particular, using the potential outcomes framework of causality, we will focus on understanding which assumptions are necessary for giving research a causal interpretation, and on learning a range of approaches that can be used to establish causality empirically. The course will be practical – in that you can expect to learn how to apply a suite of methods in your own research – and theoretical – in that you can expect to think hard about what it means to make claims of causality in the social sciences.

We will address a variety of topics that are currently popular and broadly applied across the social sciences. Topics may include experiments (laboratory, field, and natural); matching; regression; weighting; fixed-effects; difference-in-differences; regression discontinuity designs; instrumental variables; and synthetic control. Examples are drawn from many areas of political science, economics, geography, education, public health, international relations, and public administration.

Pre-requisites

Students should have a working knowledge of the methods covered in typical introductory quantitative methods courses (i.e. to the level of PUBL0055 or equivalent). At a minimum, this should include hypothesis testing and multiple linear regression. You will need to provide me with evidence of having completed at least one prior course that covers this material. There is also an online quiz which you can take to determine whether you are likely to have sufficient knowledge to complete the course.

Students who have not taken PUBL0055 earlier in the year may wish to refresh their knowledge before starting this course. You could consult any of the following textbooks:

- Imai, Kosuke. 2017. *Quantitative Social Science: An Introduction*, Princeton University Press.
- Llaudet, Elena and Imai, Kosuke. 2022. *Data Analysis for Social Science: A Friendly and Practical Introduction*. Princeton University Press.
- Agresti, Alan and Finlay, Barbara. 2009. S*tatistical Methods for the Social Sciences*, Fourth Edition, Pearson International.
- Stock, James and Watson, Mark. 2015. *Introduction to Econometrics*, Updated Third Edition, Pearson.

Learning, Assessment and Feedback

Learning Outcomes

By the end of the course, students should be able to:

1. Understand the concept of causation as it is typically discussed in the social sciences
2. Make distinctions between observational and experimental studies
3. Define the assumptions required to make causal claims from quantitative data
4. Construct research designs that would yield credible causal effects
5. Implement a range of statistical methods which aim to estimate causal effects, including: experiments, matching, regression, weighting, fixed-effects, difference-in-differences, regression discontinuity; and synthetic control
6. Use the R statistical software in applied research
7. Critically evaluate the use of causal inference designs used in published work

These outcomes are indicative of the kinds of knowledge that should be demonstrated on summative assessments.

Teaching Format

Teaching delivery will be split into lectures and seminars. Note that, in addition to the below, office hours will be held by the instructors on the course where you will be able to ask additional questions.

Lectures

All of the main course content will be delivered in 2-hour lectures which will be delivered once a week. You are expected to attend all lectures. The lecture slides will be made available to you to download before the lecture on the website in the tab dedicated to the relevant week.

Seminars

This is a practical module, and a key learning objective is for students to be able to implement the statistical methods we cover during lectures to real data. Each week, you will complete a problem set which involves writing code in the `R` programming language (see below for more details) and interpreting the results.

For each seminar, there is a problem-set with questions for you to work on during your seminar. The goal of these seminars is to provide you with ample time to ask questions about the problem set, and particular issues that relate to coding in 'R'. During your allocated seminar time, you will be able to ask questions of the teacher; speak with other students about the problem set; and watch short live demonstrations from your seminar teacher.

Please note that you are expected to have made some attempt to answer the questions in the seminar tasks (all hosted on the course website) **before** attending the seminar each week. This will make the seminars themselves much more productive. The solutions will be released on the working day after the seminars.

All seminars are held on Fridays. Please stick with your assigned seminar slot, such as to keep an even numbers distribution across the groups. If this is not possible, you can ask the Political Science postgraduate admin team (polsci.pg@ucl.ac.uk) for help. **Attendance during these seminar hours is mandatory and we will take a register at the beginning of the session.** *Note that the course convenor cannot help you with timetabling issues.*

Assessment

Students will be evaluated through a 3000-word research paper applying the methods from the course to a research question chosen by the student.

The research paper should follow the basic elements of a novel research project. The paper should address a specific research question, identify the theoretical contribution, provide testable hypotheses, and implement a suitable design based on one of the methods that we study in the course. The paper should focus narrowly on a topic of the student's choice and display a depth of understanding of one of the approaches discussed on the course, rather than a survey of all methods. The research paper accounts for 100% of the grade for this module and will be submitted online via Moodle.

Please remember that plagiarism is taken extremely seriously and can disqualify you from the module. If you are in doubt about any of this, ask the tutor.

Resources

- **Course website**: The main source of information for lecture recordings, lecture notes, quizzes, problem sets, and readings will be the course website, accessible here.
- **Moodle page**: Other material relevant to the course, such as the lecture recordings and assessment (submission) formalities, will be accessible via the course Moodle site

Readings

We primarily use the following textbook on this course:

- Joshua D. Angrist and Jörn-Steffen Pischke. *Mastering 'Metrics: The Path from Cause to Effect*. Princeton University Press, 2014. Available here.

This book provides an excellent introduction to the potential outcomes framework which forms the conceptual core of this course. It also covers the majority of the methodological approaches that we will study. That said, we will often focus on readings from other books/papers when necessary. The reason that we do not always follow a single textbook is that the field of causal inference is rapidly evolving, and there is no single canonical volume that would cover of all the interesting topics we focus on in this course.

In addition to the textbook treatments, students should read the articles set as "required" reading each week, and it is worth familiarising yourself also with at least some of the "recommended" reading. The required reading will often contain material that is not covered in the textbooks, partly because the methods on this course are at the cutting edge of the discipline and so are (sometimes) too new to have received coverage in textbooks and (often) it is more interesting to read the papers than the book.

The "recommended" readings will typically cover recent or important implementations of the methods we will learn about, and will be helpful in (at least) two regards. First, reading these articles will provide you with an understanding of when the methods we study can provide interesting answers to previously thorny empirical questions. Second, these articles will be helpful templates for the research paper you will write at the conclusion of the course.

Finally, for students who wish to receive a more detailed mathematical exposition of the approaches we will cover on the course, the following books are highly recommended:

- Joshua D Angrist and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, 2008. Available here.
- Stephen L Morgan and Christopher Winship. *Counterfactuals and Causal Inference*. Cambridge University Press, 2015.

Note, however, that these books presents the material in a somewhat less accessible fashion than the 2014 Angrist and Pischke volume, and it is perfectly possible to do well on this module without consulting these more advanced texts. Nevertheless, the relevant chapters are included in the list of "recommended" readings each week.

Software

Throughout the course we will use the free and open source statistical analysis software `R`.

Before the course starts, you can and should download and install (the latest version of) `R` on your personal computer. You should also also download and install `RStudio`, which is a user-interface to `R`. **Please ensure that both `R` and `RStudio` are installed on your personal computers before the first lecture.** UCL machines, either virtual via Desktop@UCL or on campus, will already have this software installed.

Students are not expected to have programming knowledge before starting class, and the computer labs will be centered around bite-size assignments which will help build knowledge of and intuition for coding in `R`. You will be provided with all the relevant code necessary for completing the class assignments and problem sets each week (you will also be provided with solution code for the problem sets).

That said, what you get out of your experience with `R` in this course really will be a function of what you put into learning it. With that in mind, I'd recommend that everyone who is serious about doing well on the course spend at least a little time familiarising yourself with `R` in advance. If you have never used R before, or if you have forgotten everything about it since you last used it, you can work through the R Refresher page of the course website before the course begins.

Academic Freedom and Intellectual Property

Academic freedom is the cornerstone of university research and teaching, so that all university staff, speakers, and students can freely explore questions and ideas and challenge perceived views and opinions, without being censored or harassed by a government, any state authorities, the University, other students, or external pressure groups. As part of the UCL academic community, all staff, speakers, and students share these responsibilities:

- **Everyone must respect freedom of thought and freedom of expression.** Your lecturer will not limit what can be discussed in the seminar, as long as it is relevant to the subject. They will not censor

any topics, and they will expose you to controversial issues, questions, facts, views, and debates.
  - You may disagree with some facts or views that you read or hear in the classroom. You are encouraged to engage with these facts and views in a respectful manner.
  - Your lecturer will not penalise you merely for expressing views they or other students disagree with. However, they will expect you to present logical arguments supported by evidence.
- **You are explicitly prohibited from recording, publishing, distributing or transferring any class material/content**, in whole or in part, in any format, to any individual or entity outside the module, linking to or posting it online (including social media), or making it otherwise available to any person or entity outside the module, unless you have received prior specific written approval from the module leader. You are also explicitly prohibited from aiding or abetting in any of these actions. Similarly, your lecturer will not record, publish or distribute seminar sessions without the explicit consent of the participants.
- **By agreeing to take this module, you agree to abide by these terms.** If you do not comply with these terms, you will potentially be subject to disciplinary actions similar to those under violations of the university Student Code of Conduct.

Schedule

The general schedule for the course is as follows. Details on topics covered and the readings for each week are provided on the following pages. Note that the order or focus of some of the topics may still be slightly altered ahead of the beginning of term.

Week 1 Causal Inference and Potential Outcomes

Week 2 Randomised Experiments

Week 3 Selection on Observables I

Week 4 Selection on Observables II

Week 5 Panel Data and Difference-in-Differences

Week 6 Synthetic Control

Week 7 Instrumental Variables I

Week 8 Unsupervised Scale Measurement I: Interval-Level Indicators

Week 9 Regression Discontinuity Designs

Week 10 Overview and Review

Week 1 Causal Inference and Potential Outcomes

In the first lecture we will introduce the topic of causal inference. We will outline a specific definition of causality using the potential outcomes framework, and will describe the fundamental problem of causal inference. We will highlight the persistent threat of selection bias in observational data and we will discuss differences between statistical inference and causal inference.

Required reading:

- **Either** Joshua D Angrist and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, 2008. Chapter 1 and 2
- **Or** Joshua D. Angrist and Jörn-Steffen Pischke. Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press, 2014. Introduction, p. xi - xv
- Stephen L Morgan and Christopher Winship. Counterfactuals and Causal Inference. Cambridge University Press, 2015. p. 1 – 24 and Chapter 2
- Paul W Holland. Statistics and Causal Inference. *Journal of the American Statistical Association*, 81(3), 1986. *Link to paper.*

Recommended reading:

- David A Freedman. Statistical models and shoe leather. *Sociological methodology*, pages 291–313, 1991. *Link to paper.*
- Gary Taubes, "Do We Really Know What Makes Us Healthy?", *New York Times Magazine*, 16th September, 2007. *Available here*.

Week 2 Randomised Experiments

In this lecture we will review the logic that underpins a research design that has become a mainstay of political science research: randomised experiments. We will focus on why randomisation is such a powerful force for making causal inferences (spoiler: internal validity), and will discuss the trade-offs implicit in experimental research (spoiler: external validity). In learning how to analyse experimental data, we will review the t-test and also cover regression as a tool for analysing experiments.

Required reading:

- **Either** Joshua D Angrist and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, 2008. Chapter 2
- **Or** Joshua D. Angrist and Jörn-Steffen Pischke. Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press, 2014. Chapter 1
- Alan S Gerber, Donald P Green, and Christopher W Larimer. Social pressure and voter turnout: Evidence from a large-scale field experiment. *American Political Science Review*, 102(1):33–48, 2008. *Link to paper.*

Recommended reading:

- Raghabendra Chattopadhyay and Esther Duflo. Women as policy makers: Evidence from a randomized policy experiment in India. *Econometrica*, 72(5):1409–1443, 2004. *Link to paper.*
- Abhijit Banerjee, Esther Duflo, Nathanael Goldberg, Dean Karlan, Robert Osei, William Parienté, Jeremy Shapiro, Bram Thuysbaert, and Christopher Udry. A multifaceted program causes lasting progress for the very poor: Evidence from six countries. *Science*, 348(6236):1260799, 2015. *Link to paper.*
- Joshua L Kalla and David E Broockman. The minimal persuasive effects of campaign contact in general elections: Evidence from 49 field experiments. *American Political Science Review*, 112(1):148–166, 2018. *Link to paper.*
- Laura Haynes, Ben Goldacre, David Torgerson, et al. Test, Learn, Adapt: Developing Public Policy with Randomised Controlled Trials | Cabinet Office. 2012. *Link to paper.*
- Jason Barabas and Jennifer Jerit. Are survey experiments externally valid? *American Political Science Review*, 104(2):226–242, 2010. *Link to paper.*

Week 3 Selection on Observables I

Randomisation is a powerful tool because it means that confounders can be safely ignored by researchers as, in expectation, they will be balanced across treatment and control groups. Sadly, some of the most interesting social science questions cannot be addressed using randomised experiments (Why? First, because experiments are costly, and second, because it would be bad form to randomly assign, for instance, the institutions that govern a country's electoral system, or whether you get a distinction in your degree). When it is not possible to randomise, how can we make valid causal inferences? In the next two lectures, we discuss methods for non-experimental data which assume that selection into treatment groups is based on observable factors. This week we focus on subclassification and matching.

Required reading:

- **Either** Joshua D Angrist and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, 2008. Chapter 2
- **Or** Joshua D. Angrist and Jörn-Steffen Pischke. Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press, 2014. Chapter 1
- Stephen L Morgan and Christopher Winship. Counterfactuals and Causal Inference. Cambridge University Press, 2015. Chapter 5
- Elizabeth A Stuart. Matching methods for causal inference: A review and a look forward. Statistical science: a review. *Journal of the Institute of Mathematical Statistics*, 25(1):1, 2010. *Link to paper.*

Recommended reading:

- Jason Lyall. Are coethnics more effective counterinsurgents? evidence from the second chechen war. *American Political Science Review*, pages 1–20, 2010. *Link to paper.*
- Gilligan, Michael J and Sergenti, Ernest J. Do UN interventions cause peace? Using matching to improve causal inference. *Quarterly Journal of Political Science*, 3(2):89– 122, 2008. *Link to paper.*
- Andrew C Eggers and Jens Hainmueller. MPs for sale? Returns to office in postwar British politics. *American Political Science Review*, 103(4):513–533, 2009. *Link to paper.*
- Rajeev H Dehejia and Sadek Wahba. Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. J*ournal of the American statistical Association*, 94(448):1053–1062, 1999. *Link to paper.*
- Donald B Rubin. For objective causal inference, design trumps analysis. *The Annals of Applied Statistics*, pages 808–840, 2008. *Link to paper.*

Week 4 Selection on Observables II

This week we continue to consider methods that rely on a selection-on-observables assumption for making causal inferences from non-experimental data. In particular, this week we focus on assessing under which conditions linear regression can be used to make causal statements.

Required reading:

- **Either** Joshua D Angrist and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, 2008. Chapter 3
- **Or** Joshua D. Angrist and Jörn-Steffen Pischke. Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press, 2014. Chapter 2

Recommended reading:

- Stephen L Morgan and Christopher Winship. Counterfactuals and Causal Inference. Cambridge University Press, 2015. Chapter 5
- Daniel E Ho, Kosuke Imai, Gary King, and Elizabeth A Stuart. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, 15(3):199–236, 2007. *Link to paper.*
- Aronow, Peter M and Samii, Cyrus. Does regression produce representative estimates of causal effects? *American Journal of Political Science*, 60(1):250–267, 2016. *Link to paper.*
- Słoczyński, Tymon. Interpreting OLS Estimands When Treatment Effects Are Heterogeneous: Smaller Groups Get Larger Weights. The Review of Economics and Statistics, 2020. *Link to paper.*

Week 5 Panel Data and Difference-in-Differences

When we can observe and measure potentially confounding factors, we can recover causal effects by controlling for these factors. Often, however, confounders may be difficult to measure or impossible to observe. If this is the case, we need alternative strategies for estimating causal effects. One approach is to try to obtain data with a time dimension, where one group receives a treatment at a given point in time but the other group does not. Comparing the differences between pre- and post-treatment periods for these two groups allows us to control for unobserved omitted variables that are fixed over time. Under certain assumptions, this can produce valid estimates of causal effects.

Required reading:

- **Either** Joshua D Angrist and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, 2008. Chapter 5
- **Or** Joshua D. Angrist and Jörn-Steffen Pischke. Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press, 2014. Chapter 5
- Jonathan McDonald Ladd and Gabriel S Lenz. Exploiting a rare communication shift to document the persuasive power of the news media. *American Journal of Political Science*, 53(2):394–410, 2009. *Link to paper.*

Recommended reading:

- Dhaval Dave, Andrew I Friedson, Kyutaro Matsuzawa, and Joseph J Sabia. When do shelter-in-place orders fight covid-19 best? policy heterogeneity across states and adoption time. *Economic Inquiry*, 2020. *Link to paper.*
- Andrew Goodman-Bacon and Jan Marcus. Using difference-in-differences to identify causal effects of covid-19 policies. *Survey Research Methods*, 14(2):153–158, Jun. 2020. *Link to paper.*
- Stephen L Morgan and Christopher Winship. Counterfactuals and Causal Inference. Cambridge University Press, 2015. Chapter 11
- David Card and Alan B Krueger. Minimum wages and employment: A case study of the fast food industry in new jersey and pennsylvania. *Technical report, National Bureau of Economic Research*, 1993. *Link to paper.*
- David Card. The impact of the mariel boatlift on the miami labor market. *ILR Review*, 43(2):245–257, 1990. *Link to paper.*
- Elias Dinas, Konstantinos Matakos, Dimitrios Xefteris, and Dominik Hangartner. Waking up the golden dawn: Does exposure to the refugee crisis increase support for extreme-right parties? *Political Analysis*, 27(2):244–254, 2019. *Link to paper.*

Week 6 Synthetic Control

Don't have a good control unit to use in a difference-in-differences design? Don't panic; just synthesise one. Synthetic control approaches allow for causal inferences based on similar assumptions to difference-in-differences, but are particularly well suited for situations in which the treatment occurs for a single unit. By providing a systematic way to choose comparison units, synthetic control is a good method for application to comparative case studies.

Required reading:

- Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Comparative politics and the synthetic control method. *American Journal of Political Science*, 59(2):495–510, 2015. *Link to paper.*
- Alberto Abadie, Alexis Diamond, and Jens Hainmueller. 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, 2010. *Link to paper.*
- Andrew I Friedson, Drew McNichols, Joseph J Sabia, and Dhaval Dave. Did California's Shelter-in-Place Order Work? Early Coronavirus-Related Public Health Effects. *Technical report, National Bureau of Economic Research*, 2020. *Link to paper.*

Recommended reading:

- David Hope. Estimating the effect of the EMU on current account balances: A synthetic control approach. *European Journal of Political Economy,* 44:20–40, 2016. *Link to paper.*
- Benjamin Born, Gernot Mueller, Moritz Schularick, and Petr Sedláček. The costs of economic nationalism: Evidence from the Brexit experiment. *The Economic Journal*, 129(10):2722–2744, 2019. *Link to paper.*
- Alberto Abadie. Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects. *Journal of Economic Literature*, 59(2): 391-425, 2021. *Link to paper.*
- Ala' Alrababa'h, William Marble, Salma Mousa, and Alexandra A. Siegel. Can Exposure to Celebrities Reduce Prejudice? The Effect of Mohamed Salah on Islamophobic Behaviors and Attitudes. *American Political Science Review*, 115(4):1111-1128, 2021. *Link to paper.*

Week 7 Instrumental Variables I

Aside from experiments, all of the strategies covered up to this point rely on the researcher being able to control for confounding factors when estimating causal effects. For the next two weeks, we focus on a strategy – instrumental variables – which can be used to address unobserved confounding factors in the context of cross-sectional data (i.e. when we can't use the panel data methods discussed in previous weeks). This week, we will motivate instrumental variable (IV) methods, by discussing how this strategy can be useful in the context of experimental data where some units fail to comply with the treatment.

Required reading:

- **Either** Joshua D Angrist and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, 2008. Chapter 4
- **Or** Joshua D. Angrist and Jörn-Steffen Pischke. Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press, 2014. Chapter 3
- Joshua D Angrist, Guido W Imbens, and Donald B Rubin. Identification of causal effects using instrumental variables. *Journal of the American statistical Association*, 91(434):444–455, 1996. *Link to paper.*
- Stephen L Morgan and Christopher Winship. Counterfactuals and Causal Inference. Cambridge University Press, 2015. Chapter 9

Recommended reading:

- Allison J Sovey and Donald P Green. Instrumental variables estimation in political science: A readers' guide. *American Journal of Political Science*, 55(1):188–200, 2011. *Link to paper.*
- Moritz Marbach and Dominik Hangartner. Profiling compliers and noncompliers for instrumental-variable analysis. *Political Analysis*, pages 1–10, 2020. *Link to paper.*

Week 8 Unsupervised Scale Measurement I: Interval-Level Indicators

In this lecture we focus on the logic of instrumental variables in the context of observational studies. We will also discuss a number of applied examples that use an IV strategy, paying attention to how they work, and how they can go wrong (which they very often do).

Required reading:

- **Either** Joshua D Angrist and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, 2008. Chapter 4
- **Or** Joshua D. Angrist and Jörn-Steffen Pischke. Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press, 2014. Chapter 3
- Stephen L Morgan and Christopher Winship. Counterfactuals and Causal Inference. Cambridge University Press, 2015. Chapter 9

Recommended reading:

- Holger Lutz Kern and Jens Hainmueller. Opium for the masses: How foreign media can stabilize authoritarian regimes. *Political Analysis*, 17(4):377–399. *Link to paper.*
- Andreas Madestam, Daniel Shoag, Stan Veuger, and David Yanagizawa-Drott. Do political protests matter? Evidence from the tea party movement. *The Quarterly Journal of Economics*, 128(4):1633–1685, 2013. *Link to paper.*
- Daron Acemoglu, Simon Johnson, and James A Robinson. The colonial origins of comparative development: An empirical investigation. *American economic review*, 91(5):1369–1401, 2001. *Link to paper.*
- Elias Dinas, Konstantinos Matakos, Dimitrios Xefteris, and Dominik Hangartner. Waking up the golden dawn: Does exposure to the refugee crisis increase support for extreme-right parties? *Political Analysis*, 27(2):244–254, 2019. *Link to paper.*
- Apoorva Lal, MacKenzie Lockhart, Yiqing Xu, and Ziwen Zu. 2024. How Much Should We Trust Instrumental Variable Estimates in Political Science? Practical Advice Based on 67 Replicated Studies. *Political Analysis* 32(4): 521–40. *Link to paper*

Week 9 Regression Discontinuity Designs

A regression discontinuity design (RDD, for short) arises when the selection of a unit into a treatment group depends on a covariate score that creates some discontinuity in the probability of receiving the treatment. In this lecture we will consider both `sharp' and`fuzzy' RDDs.

Required reading:

- **Either** Joshua D Angrist and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, 2008. Chapter 6
- **Or** Joshua D. Angrist and Jörn-Steffen Pischke. Mastering 'Metrics: The Path from Cause to Effect. Princeton University Press, 2014. Chapter 4
- Stephen L Morgan and Christopher Winship. Counterfactuals and Causal Inference. Cambridge University Press, 2015. Chapter 9

Recommended reading:

- Andrew B. Hall. What happens when extremists win primaries? *American Political Science Review*, 109(1):18–42, 2015. *Link to paper.*
- Andrew C Eggers and Jens Hainmueller. MPs for sale? Returns to office in postwar British politics. *American Political Science Review*, 103(4):513–533, 2009. *Link to paper.*
- Charlotte Cavaillé and John Marshall. Education and anti-immigration attitudes: Evidence from compulsory schooling reforms across western europe. *American Political Science Review*, 113(1), 254-263, 2018. *Link to paper.*
- Erik Meyersson. Islamic rule and the empowerment of the poor and pious. *Econometrica*, 82(1):229–269, 2014. *Link to paper.*

Week 10 Overview and Review

We end with a schematic overview of the course. We will discuss the extent to which the methods we cover on the course sacrifice external validity at the expense of internal validity, and whether this matters. We will also have a Q and A on the final coursework.

Recommended reading:

- Cyrus Samii. Causal empiricism in quantitative research. *The Journal of Politics*, 78(3):941–955, 2016. *Link to paper.*
- Christopher J Ruhm. Shackling the identification police? *Southern Economic Journal*, 85(4):1016–1026, 2019. *Link to paper.*
- Kosuke Imai, Luke Keele, Dustin Tingley, and Teppei Yamamoto. Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational studies. *American Political Science Review*, 105(4):765–789, 2011. *Link to paper.*