PLSC 30600: Causal Inference.

University of Chicago, Winter 2026.

Location: Cobb Hall 110
Course time: Mon/Wed 16:30–17:50

Instructor: Molly Offer-Westort; mollyow@uchicago.edu
Office hours: Mon 13:20–14:40 and Tue 14:00–15:20; book at https://calendar.app.google/wmSJFvfyxnDHFK5C9
Office: Pick Hall 328

Primary TA: Maggie Wang; mxwang@uchicago.edu; https://maggiexwang.github.io/
Discussion sections: Fri 10:30–11:20 (Regenstein Library 207) or 13:30–14:20 (Cobb Hall 106)

Supplementary math TA: Sophia Lipkin; slipkin@uchicago.edu
Math section: Thu 14:00–15:00 (Pick 407, beginning Week 2)

Course overview. This is the second course in quantitative methods in the Political Science PhD program. The course is an introduction to the theory and practice of causal inference from quantitative data. It will cover the potential outcomes framework, the design and analysis of experiments, matching, weighting, regression adjustment, differences-in-differences, instrumental variables, regression discontinuity designs and more. Students will examine and implement these approaches, considering a variety of examples from across the social sciences. The course will use the R programming language for statistical computing.

Prerequisites. Completing the introductory course in the political science graduate methodology sequence should prepare you for the material in this class. We will rely on background knowledge of core concepts in probability, statistics, and inference as well as experience with statistical programming in R. Familiarity with regression modeling is a plus but not strictly required. Please contact the instructor if you are interested in enrolling but are unsure of the requirements.

Course logistics. We will use a private STACK OVERFLOW forum as a course discussion platform. You will be sent a private invitation to join the forum at the start of the quarter. Lecture materials, problem sets and section code will be posted on the course GitHub page at `https://github.com/UChicago-pol-methods/PLSC30600`. Problem set solutions will be posted after the due date on Canvas. You should attend sections regularly as they comprise a significant element of the course instruction.

Supplementary math section. Beginning in Week 2, we will offer an optional supplementary math section led by Sophia Lipkin. This session is not a formal course component and is not required, nor does it affect your grade. However, we strongly recommend it for doctoral students, as well as for masters students who plan to continue on to Bobby Gulotty's estimation course in the spring. Attendance at this supplementary section is entirely optional, but it is designed to support students who would benefit from additional mathematical foundations for causal inference and estimation.

Course text. The primary textbook for the course is:

- Aronow, P. M. and B. T. Miller (2019). *Foundations of agnostic statistics*. Cambridge University Press

  A free online version of the book is available through the University library: `http://pi.lib.uchicago.edu/1001/cat/bib/12622551`

Additional references:

- Hernán, M. A. and J. M. Robins (2010). *Causal inference: What if?* CRC Boca Raton, FL

A free PDF version of the text is available here: https://miguelhernan.org/whatifbook

- Angrist, J. D. and J.-S. Pischke (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press
- For proofs
  - Hammack, R. (2013). *Book of proof* https://richardhammack.github.io/BookOfProof/
  - Velleman, D. J. (2019). *How to prove it: A structured approach*. Cambridge University Press https://ia800501.us.archive.org/7/items/how-to-prove-it-a-structured-approach-daniel-j.-velleman/How%20to%20Prove%20It%20A%20Structured%20Approach%20%28Daniel%20J.%20Velleman%29.pdf

Computing. This course will use the `R` programming language. If you haven't done so already, you should download and install it from http://www.r-project.org. For this course, I recommend using the free, open source RStudio Desktop IDE; instructions for download and installation here. You can also use any other IDE or editor of your choice, or run R from the command line. Visual Studio Code with the R extension is another good option, although support for interactive R sessions is not as seamless as in RStudio.

Compiling reports. To generate pdf reports, you need to have a version of LaTeX installed. If you don't already use LaTeX, you can install TinyTeX, which is a lightweight, flexible LaTeX installation. To install TinyTeX, you can run the code below in R.

```
install.packages('tinytex', repos = "http://cran.us.r-project.org")
tinytex::install_tinytex()  # install TinyTeX
```

Grading and due dates. There are three homework assignments, an in-class midterm and a take-home midterm, and an in-class final and a take-home final. Homeworks are graded on a 0–3 scale: 0 (not submitted), 1 (check–), 2 (check), 3 (check+). Participation (including sections) is worth 10 points. Homeworks total 30 points (10 each). The midterm totals 30 points (15 in class, 15 take home). The final totals 30 points (15 in class, 15 take home).

Component	Points	Due date
Participation	10	–
Homework 1	10	Fri, January 16 (11:59pm)
Homework 2	10	Fri, January 30 (11:59pm)
Homework 3	10	Fri, February 27 (11:59pm)
Midterm (in class)	15	Wed, February 11
Midterm (take home)	15	Fri, February 13 (11:59pm)
Final (take home)	15	Fri, March 6 (11:59pm)
Final (in class)	15	Exam week: Tue, March 10–Fri, March 13

Course outline.

Week 1. Getting oriented.

- Course introduction and workflow.
- Potential outcomes framework and links to missing data.
- Identification via bounds and basic framing.

Readings.

- Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association 81*(396), 945–960 (skip Section 5)
- Hernán and Robins, Section 1
- Aronow & Miller, Sections 6.1.1–6.1.3 and 7.1.1–7.1.3
- Manski, C. F. (2003). Identification problems in the social sciences and everyday life. *Southern Economic Journal 70*(1), 11

Reference readings.

- Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology 66*(5), 688–701
- Rubin, D. B. (1976). Inference and missing data. *Biometrika 63*(3), 581–592
- Manski, C. F. (1990). Nonparametric bounds on treatment effects. *The American Economic Review 80*(2), 319–323

- Ding, P. (2023). A first course in causal inference, Appendices A–C

Application.

- Manski, C. F. and D. S. Nagin (1998). Bounding disagreements about treatment effects: A case study of sentencing and recidivism. *Sociological methodology 28*(1), 99–137

Problem Set 1 assigned Mon, January 5; due Fri, January 16 (11:59pm)

Week 2. Fundamentals of identification and the role of the propensity score.

- Random assignment and ignorability.
- Propensity scores for causal inference and missing data.
- Post-treatment variables and non-binary treatments.

Readings.

- Aronow & Miller, Sections 6.1.4 and 7.1.4–7.1.8
- Rosenbaum, P. R. and D. B. Rubin (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika 70*(1), 41–55
  Focus on:
  - The causal framework and motivation (Section 1.1).
  - The definition of the propensity score (Section 1.2).
  - The core theoretical result: balance and ignorability (Theorems 1–3).
  - What adjustment on the propensity score identifies (Theorem 4 and Corollaries 4.1–4.3).

Week 3. Assumptions: Missing at Random and Ignorability.

- **No class Monday (MLK Day).**
- Plug-in and regression estimators under MAR/ignorability.

- Hot deck imputation and practical estimation choices.
- DAGs.

Readings.

- Aronow & Miller, Sections 6.2.1–6.2.3 and 7.2.1–7.2.2

Reference readings.

- Greenland, S., J. Pearl, and J. M. Robins (1999). Causal diagrams for epidemiologic research. *Epidemiology 10*(1), 37–48
- Pearl, J., M. Glymour, and N. P. Jewell (2016). *Causal inference in statistics: A primer*. John Wiley & Sons
- Little, R. J. A. and D. B. Rubin (2002). *Statistical Analysis with Missing Data*. Wiley

Problem Set 2 assigned Mon, January 19; due Fri, January 30 (11:59pm)

Week 4. More approaches to estimation.

- Matching and weighting estimators.
- Propensity score estimation and ML plug-in approaches.
- Causal effect estimation under ignorability.

Readings.

- Aronow & Miller, Sections 6.2.4–6.2.5 and 7.2.3–7.2.6
- https://blogs.worldbank.org/en/impactevaluations/regression-adjustment-in-randomized-experiments-is-the-cure-really-worse-than-the-disease
- https://blogs.worldbank.org/en/impactevaluations/guest-post-by-winston-lin-regression-adjustment-in-randomized-experiments-is-the-cure-really-worse-0

Reference readings.

- Lin, W. (2013). Agnostic notes on regression adjustments to experimental data: Reexamining freedman's critique. *The Annals of Applied Statistics 7*(1), 295–318
- Freedman, D. A. (2008). On regression adjustments in experiments with several treatments. *The Annals of Applied Statistics 2*(1), 176–196
- Dehejia, R. H. and S. Wahba (1998). Propensity score matching methods for non-experimental causal studies. Working Paper 6829, National Bureau of Economic Research
- LaLonde, R. J. (1986). Evaluating the econometric evaluations of training programs with experimental data. *The American Economic Review*, 604–620
- Ho, D. E., K. Imai, G. King, and E. A. Stuart (2007). Matching as nonparametric pre-processing for reducing model dependence in parametric causal inference. *Political Analysis 15*(3), 199–236

Week 5. Overlap and positivity.

- Overlap and positivity, including target population changes.
- Empirical overlap diagnostics and weighting behavior.
- Doubly robust estimation and placebo testing.
- *Tentatively:* Sensitivity analysis.

Readings.

- Aronow & Miller, Sections 6.2.6 and 7.2.7–7.2.8, Section 7.3

Reference readings.

- Bang, H. and J. M. Robins (2005). Doubly robust estimation in missing data and causal inference models. *Biometrics 61*(4), 962–973
- Ding, P. and T. J. VanderWeele (2016). Sensitivity analysis without assumptions. *Epidemiology 27*(3), 368–377
- Rosenbaum, P. R. (1987). Sensitivity analysis for certain permutation inferences in matched observational studies. *Biometrika 74*(1), 13

- Chernozhukov, V., D. Chetverikov, M. Demirer, E. Duflo, C. Hansen, W. Newey, and J. Robins (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal 21*(1), C1–C68
- Hirano, K., G. W. Imbens, and G. Ridder (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica 71*(4), 1161–1189

Midterm exam take-home assigned Mon, February 9, due Fri, February 13 (11:59pm)

Week 6. Design-based inference.

- Randomization inference vs. asymptotic inference (permutation tests, Fisher vs. Neyman views).
- Blocked/stratified randomization and analysis.
- Cluster-randomized designs (and why SEs change).
- *Tentatively:* Power / MDE and design tradeoffs.
- *Tentatively:* Interference/spillovers (exposure mappings, spillover-robust estimands).

Readings.

- Gerber, A. S. and D. P. Green (2012). *Field Experiments: Design, Analysis, and Interpretation*. W. W. Norton, Chapter 3 (Sections 3.1–3.5), pp. 51–70
- Fisher, R. A. (1935). *The Design of Experiments* (1 ed.). Edinburgh: Oliver and Boyd Ltd, Chapters 1–2.

Reference readings.

- Neyman, J. S. (1990 [1923]). On the application of probability theory to agricultural experiments. Essay on principles. Section 9 (reprint). *Statistical Science 5*(4), 465–472
- Särndal, C. E., B. Swensson, and J. Wretman (1992). *Model Assisted Survey Sampling*. New York: Springer, Chapters 1–3.3
- Hudgens, M. G. and M. E. Halloran (2008). Toward causal inference with interference. *Journal of the American Statistical Association 103*(482), 832–842

- Miguel, E. and M. Kremer (2004). Worms: identifying impacts on education and health in the presence of treatment externalities. *Econometrica 72*(1), 159–217
- Aronow, P. M., A. Jang, and M. Offer-Westort (2025). On the foundations of the design-based approach

Week 7. Research designs: Instrumental variables and regression discontinuity.

- IV: complier LATE framework. Weak instruments and diagnostics.
- How LATE interpretation depends on design and compliance behavior.
- *Tentatively:* Multiple instruments / overidentification logic.
- RD. Sharp vs. fuzzy RD.
- Bandwidth choice and sensitivity.

Readings.

- Imbens, G. W. and J. D. Angrist (1994). Identification and estimation of local average treatment effects. *Econometrica 62*(2), 467–475
- Imbens, G. W. and T. Lemieux (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics 142*(2), 615–635
- Angrist, J. D., G. W. Imbens, and D. B. Rubin (1996). Identification of causal effects using instrumental variables. *Journal of the American Statistical Association 91*(434), 444–472
- McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics 142*(2), 698–714

Reference readings.

- Cattaneo, M. D., N. Idrobo, and R. Titiunik (2019). *A Practical Introduction to Regression Discontinuity Designs: Foundations*. Cambridge University Press
- Staiger, D. and J. H. Stock (1997). Instrumental variables regression with weak instruments. *Econometrica 65*(3), 557–586
- Lee, D. S. (2008). Randomized experiments from non-random selection in u.s. house elections. *Journal of Econometrics 142*(2), 675–697

Problem Set 3 assigned Mon, February 2; due Fri, February 27 (11:59pm)

Week 8. Research designs: Differences in differences and approaches with panel data.

- Modern DiD/event studies
- Staggered adoption problems for TWFE.
- Group-time ATT estimators and event-study plots.
- Parallel trends diagnostics + sensitivity/robustness checks.
- Synthetic control family.

Readings.

- Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics 119*(1), 249–275
- Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230

Reference readings.

- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*(2), 254–277
- Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of econometrics 225*(2), 175–199
- Abadie, A., A. Diamond, and J. Hainmueller (2010). 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
- Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the basque country. *American Economic Review 93*(1), 113–132
- Card, D. and A. B. Krueger (1994). Minimum wages and employment: A case study of the fast food industry in new jersey and pennsylvania. *American Economic Review 84*(4), 772–793

Take-home final assigned Mon, March 2; due Fri, March 6 (11:59pm)

Week 9. External validity.

- Generalizability/transportability: from sample to target population.
- Multi-site experiments and heterogeneity.
- Design-based external validity: sampling frames + weighting for representativeness (with connections to week 6).

Readings.

- Cole, S. R. and E. A. Stuart (2010). Generalizing evidence from randomized clinical trials to target populations: The actg 320 trial. *American Journal of Epidemiology 172*(1), 107–115
- Deaton, A. and N. Cartwright (2018). Understanding and misunderstanding randomized controlled trials. *Social Science & Medicine 210*, 2–21

Reference readings.

- Tipton, E. (2013). Improving generalizations from experiments using propensity score subclassification: Assumptions, properties, and contexts. *Journal of Educational and Behavioral Statistics 38*(3), 239–266
- Pearl, J. and E. Bareinboim (2014). External validity: From do-calculus to transportability across populations. *Statistical Science 29*(4)

In-class final exam during exam week (March 10 – March 13)