Causal Inference for Political Science
POLS 531
Spring 2026
University of Illinois at Urbana-Champaign

Course Information

Meeting Time:	Tuesday, 9:00 AM – 11:50 AM
Location:	David Kinley Hall 314
Instructor:	Jake Bowers
Instructor Email:	jwbowers@illinois.edu
Office Hours:	by appointment at Calendly
Office:	432 David Kinley Hall
Methods Preceptor:	Liliana Brock
Methods Preceptor Email:	lcbrock2@illinois.edu

Overview

We infer what we cannot observe. Last term you engaged with the problems of choosing better or worse descriptions of what we actually observe in data, and also with the problems of statistical inference — where we discussed better and worse ways to learn about descriptions of phenomenon that we cannot directly observe using tools like estimators and tests. Whether an estimator or a test was a good one or bad one depended on assumptions that we had to make about the process of observation. For example, we learned that a randomized experiment and/or a random sample allows us to trust that our estimators are unbiased and tests have controlled false positive error rates.

This term we dive deeper in the different approaches that statisticians and methodologists have developed to make causal inferences.[1] When we say "causal inference" in this course we are really talking about making statistical inferences that we feel comfortable interpreting as reflecting counterfactual causal effects.[2]

What we will see is that "statistical inference for counterfactual causal quantities" aka "causal inference" requires more assumptions than statistical inference alone. The fact that we have to make assumptions is not in and of itself a problem. However, more assumptions require more scrutiny. By the end of the course, I hope that you feel confident choosing, using and scrutinizing assumptions to enable you to make causal inferences from data and designs that help you advance understanding of politics and society in your substantive work.

Learning Objectives

By the end of this course, students will be able to:

[1] I encourage you to check out classes on sampling in order to go deeper into population inference and classes on measurement and psychometrics in order to go deeper into measurement inference.

[2] We recommend you checkout David Waldner (Aug. 2026). *Qualitative Causal Inference & Explanation*. Cambridge University Press to learn more about causal inference that does not involve statistical inference directly.

- Articulate the fundamental problem of causal inference and distinguish causal from descriptive research questions
- Design and analyze basic randomized experiments, including power analysis.
- Understand, implement, interpret, and evaluate causal inferences that depend on adjusting for confounders (including matching and parametric adjustment)
- Understand, implement, interpret, and evaluate causal inferences that depend on instrumental variables and other discontinuities (RDD)
- Understand, implement, interpret, and evaluate causal inferences that depend on assumptions about how outcomes change over time in panel data.

To these ends I have designed a series of activities that should (1) give you opportunities to practice working with data and reasoning about statistics and (2) raise questions for discussion each week.

I do not lecture. Rather, each week we will meet to engage with the questions that you have.

Explorations

Every week or so, I will ask you to complete a short assignment that encourages you to engage creatively with the topics of that section of the course. I anticipate that you will work on most of these assignments in groups and a few alone and that each of you will come to class prepared to discuss them. I don't think that the groups should have more than 3 people in them. However, I'm willing to have larger groups if you talk with me about it. The point of the explorations is for you to (1) practice learning on your own (making mistakes, confronting confusing error messages, finding help online and elsewhere) and in a group (this is how you will learn about statistics for the rest of your career, so these explorations are supposed to help you to practice it now), (2) engage with the topic of the week so that you are prepared to come to class with questions and ideas, (3) practice coding and confronting coding errors.

Final projects

The final project for this class allows you to apply one or more of the specific approaches from the class to a paper that is substantively interesting to you. You may also propose a different final project. The point of the final project is for you to show (to yourself and to the instructor) that you are on the path of mastery of this material.

You are allowed to do this work with a co-author or alone as you see fit.

I will be providing more detailed guidance about this assignment as the term goes on. At the moment I envision this project as a kind of **detailed pedagogical appendix to a paper** that you are writing and/or a **chapter in a methods book** in which you **teach** a reader about a given technique of causal inference and apply this technique to data and interpret the substantive meaning of the results of the analysis. This would involve (1) explaining the abstract assumptions about research design and outcomes and relationships among units and causal mechanisms that underly the statistical inference and the causal effects (ex. "identification conditions"), (2) presenting evidence that helps the reader reason about the credibility of each and every assumption, (3) discussing how departures / failures of assumptions might encourage misleading interpretations of the results, (4) (maybe) propose, implement, and diagnose alternative approaches with different assumptions, (5) explain the version of sensitivity analysis that might help with questions about assumptions that cannot be easily addressed with data and implement and interpret that sensitivity analysis, (6) provide an overarching summary of the causal effect as far as you can tell given your work.

So, this project will encourage you to go in-depth into one or perhaps two approaches to causal inference.

In-class quizzes

We will probably begin each class with an ungraded in-class quizz about the material of the **previous week** so that each class reviews the previous week and also engages with new material. This should enable us to talk about each important topic at least twice before moving onto new material.

My Expectations

1. I assume you are eager to learn. Eagerness, curiosity and excitement will impel your energetic engagement with the class throughout the term. If you are bored, not curious, or unhappy about the class you should come and talk with me immediately. Energetic engagement manifests itself in meeting with your classmates outside of the class, in asking questions during the class, and in taking the assignments seriously.
2. I assume you are ready to work. Learning requires work. As much as possible I will encourage you to link practice directly to application rather than merely as a opportunity for me to rank you among your peers. Making work about learning rather than ranking, however, will make our work that much more difficult and time consuming. You will make errors. These errors are opportunities for you to learn — some of your learning will be about how to help yourself and some will be about statistics. If you have too much to do this term consider dropping the course. Graduate school is a place for you to develop and begin to pursue your own intellectual agendas: this course may be important for you this term, or it may not. That is up for you to decide.
3. I assume some previous engagement with high school mathematics.
4. You should ask questions when you don't understand things; chances are you're not alone. **This class is an opportunity to practice courage:** I expect you to make a guess when I ask a question (in writing or in person), I expect that you will ask a question when you have a problem.
5. **Do the work.** This does not mean divide the work up among your classmates so that you only do part of the work. Each person should engage with all of the work even if the people who writes it up changes from week to week.
6. All papers written in this class will assume familiarity with the principles of good writing in **becker:1986**.
7. All final written work will be turned in as pdf files unless we have another specific arrangement.[3] I will not accept Microsoft, Apple, or any other proprietary format.

Late Work

I do not like evaluation for the sake of evaluation. Evaluation should provide opportunities for learning. So, if you'd prefer to spend more time using the final project in this class to learn more, I am happy for you to take that time. I will not, however, entertain late submissions for any subsidiary assignment

[3] For example, if you have some reason why pdf files make your life especially difficult, then of course I will work with you find another format.

that are due throughout the term. If you think that you and/or the rest of the class have a compelling reason to change the due date on one of those assignments, let me know in advance and I will probably just change the due date for the whole class.

Incompletes

Incomplete grades at the end of the term are fine in theory but terrible in practice. I urge you to avoid an incomplete in this class. If you must take an incomplete, you must give me *at least* 2 months from the time of turning in an incomplete before you can expect a grade from me and it may well take me much longer. This means that if your fellowship, immigration status, or job depends on erasing an incomplete in this class, you should not leave this incomplete until the last minute.

Grades are Feedback

Humans need feedback to close the gap between intention and action. They also need feedback to feel good about their progress and to motivate them. In this class I will use grades as feedback. All grades except for the final grade will be satisfactory, unsatisfactory (with the possibility of "outstanding"), and fail. These map roughly onto A+=outstanding, A=satisfactory, C=unsatisfactory, and F=fail (i.e. you didn't try).

I'll calculate your grade for the course this way: 40% explorations (when you turn it in as a group everyone in the group receives the same grade, satisfactory if you are creative and thoughtful and diligent, unsatisfactory if you are not or if you don't seem to be getting the concepts, no late work accepted); 45% final project (graded using a rubric to help you not forget important topics); 15% attendance (satisfactory if you show up, fail if not).

You can miss two classes without grade penalty.

I will drop your lowest exploration grade as well.

Because moments of evaluation are also moments of learning in this class, I do not curve. If you all perform at 100%, then I will give you all As.

You can redo any evaluation or the final paper in order to increase your grade on that assignment. If you want to resubmit something already graded, you need to let me know in advance so that I can make time to grade it again. If you want to resubmit work after the end of the term, that is also ok, but I may take many months to grade that work.

Books

No book is perfect for all students. I suggest you ask around, look at other syllabi online, and just browse the shelves at the library and used bookstores to find books that make things clear to you. I will be adding some recommendations here. Let me know now if you have favorites.

If you discover any books or websites that are particularly useful to you, please alert me and the rest of the class about them. Thanks!

Academic Integrity

According to the Student Code, 'It is the responsibility of each student to refrain from infractions of academic integrity, from conduct that may lead to suspicion of such infractions, and from conduct that aids others in such infractions.' Please know that it is my responsibility as an instructor to uphold the academic integrity policy of the University, which can be found here: http://studentcode.illinois.edu/article1_part4_1-401.html.

Accessibility

Students with disabilities who require accommodations should contact Disability Resources and Educational Services (DRES) and provide the instructor with accommodation letters as soon as possible.

Mental Health

The University of Illinois offers a range of mental health services. If you are feeling overwhelmed, anxious, or depressed, please reach out to the Counseling Center (counselingcenter.illinois.edu) or call the Consultation and Crisis Line at 217-333-3704.

Diversity and Inclusion

The Political Science Department is committed to building an inclusive environment where all students feel welcomed and supported. We value diverse perspectives and encourage respectful dialogue.

Course Schedule

Note: This schedule is preliminary and subject to change. If you miss a class make sure you contact me or one of your colleagues to find out about changes.

Data: I'll be bringing in data that I have on hand. This means our units of analysis will often be individual people or perhaps political or geographic units, mostly in the United States. I'd love to use other data, so feel free to suggest and provide it to me — come to office hours and we can talk about how to use your favorite datasets in the class.

Week 1: 20 January 2026 – Introduction to the class, the Fundamental Problem of Causal Inference, Working with Data

- The fundamental problem of causal inference and the potential outcomes framework
- Causal effects as functions of potential outcomes including individual causal effects and average treatment effects (ATE, ATT, ATC)
- Directed Acyclic Graphs (DAGs) to help us reason and communicate about causal relationships: the Backdoor criterion and colliders
- Workflow for credibility
- The **Exploration** for this week focuses on two of the main concepts of causal inference arising from DAGs.

Required:

1. Paul W Holland (1986). "Statistics and Causal Inference". In: *Journal of the American Statistical Association* 81.396, pp. 945–960

2. Paul R Rosenbaum (2017). *Observation and Experiment: An Introduction to Causal Inference*. Cambridge, MA: Harvard University Press, Ch. 1–2
3. Stephen L Morgan and Christopher Winship (2015). *Counterfactuals and Causal Inference: Methods and Principles for Social Research*. 2nd. Analytical Methods for Social Research. New York, NY: Cambridge University Press, Ch. 3.1–3.2, 3.4
4. Scott Cunningham (2021). *Causal inference: The mixtape*. Yale university press. URL: https://mixtape.scunning.com/ Ch. 3–4
5. Jake Bowers and Maarten Voors (2016). "Six Steps to a Better Relationship with Your Future Self, V 2.0". In: *Revista de Ciencia Política* 36.3, pp. 829–848
6. Luke Olson and Jake Bowers (May 2022). "10 Things to Know About Writing Academic Papers in LaTeX". in: *EGAP Methods Guides*. URL: https://egap.org/resource/10-things-to-know-about-hypothesis-testing/ (no need to do the exercises)

Recommended:

1. David Waldner (Aug. 2026). *Qualitative Causal Inference & Explanation*. Cambridge University Press Ch. 1; Ch. 2 up through §2.2.2 on DAGs
2. Marc F. Bellemare et al. (2024). "The Paper of How: Estimating Treatment Effects Using the Front-Door Criterion". In: *Oxford Bulletin of Economics and Statistics* 86.4, pp. 951–993. DOI: https://doi.org/10.1111/obes.12598. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/obes.12598. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/obes.12598 on front-door adjustment
3. Adam N Glynn and Konstantin Kashin (2018). "Front-door versus back-door adjustment with unmeasured confounding: Bias formulas for front-door and hybrid adjustments with application to a job training program". In: *Journal of the American Statistical Association* 113.523, pp. 1040–1049 on front-door adjustment

Week 2: 27 January 2026 – Randomized Experiments: Randomization inference and Identification

- Randomization as the "reasoned basis for [statistical] inference" about causal effects via hypothesis testing and estimation of average causal effects.
- How does randomization **identify** a causal effect? (What do people mean when they say "identification" in the context of causal inference?)

Required:

1. Paul R Rosenbaum (2017). *Observation and Experiment: An Introduction to Causal Inference*. Cambridge, MA: Harvard University Press, Ch. 3
2. Ronald Aylmer Fisher (1935). *The Design of Experiments*. Edinburgh, SCT: Oliver and Boyd, Ch. 2
3. Jake Bowers and Thomas Leavitt (2020). "Causality and Design-Based Inference". In: *The SAGE Handbook of Research Methods in Political Science and International Relations*. Ed. by Luigi Curini and Robert Franzese. Vol. 2. Thousand Oaks, CA: SAGE Publications. Chap. 41, pp. 769–804
4. Miguel Ángel Hernán and James M Robins (2020). *Causal Inference: What If*. Boca Raton, FL: Chapman & Hall/CRC. URL: https://miguelhernan.org/whatifbook (the online 2025 version), Ch. 1–3
5. Arthur Lewbel (2019). "The identification zoo: Meanings of identification in econometrics". In: *Journal of Economic Literature* 57.4, pp. 835–903

Recommended:

1. Paul R Rosenbaum (2002b). *Observational Studies*. Second Edition. New York, NY: Springer, Ch. 2
2. Paul R. Rosenbaum (2020b). *Design of Observational Studies*. 2nd. Springer Series in Statistics. Springer, Ch. 2

Week 3: 3 February 2026 – Randomized Experiments: Practicalities and design

- Power analysis and sample size calculations
- Types of random assignment: simple, complete, blocked/stratified, clustered

Required:

1. Alan S Gerber and Donald P Green (2012). *Field Experiments: Design, Analysis, and Interpretation*. New York, NY: W.W. Norton, Ch. 2–4
2. Jake Bowers, Maarten Voors, and Nahomi Ichino (Mar. 2021). *The Theory and Practice of Field Experiments: An Introduction from the EGAP Learning Days*. **Open Source Textbook** (English Edition). Spanish and French Editions released in 2022. Berkeley, CA: Evidence in Governance and Politics. URL: https://egap.github.io/theory_and_practice_of_field_experiments/ Ch. 4 and 7

Recommended:

1. Paul R Rosenbaum (2002a). "Covariance Adjustment in Randomized Experiments and Observational Studies". In: *Statistical Science* 17.3, pp. 286–327
2. David A Freedman (2008b). "On Regression Adjustments to Experimental Data". In: *Advances in Applied Mathematics* 40.2, pp. 180–193
3. David A Freedman (2008c). "Randomization Does Not Justify Logistic Regression". In: *Statistical Science* 23.2, pp. 237–249
4. David A Freedman (2008a). "On Regression Adjustments in Experiments with Several Treatments". In: *The Annals of Applied Statistics* 2.1, pp. 176–196
5. Winston Lin (2013). "Agnostic Notes on Regression Adjustments to Experimental Data: Reexamining Freedman's Critique". In: *The Annals of Applied Statistics* 7.1, pp. 295–318
6. Peter M Aronow and Joel A Middleton (2013). "A Class of Unbiased Estimators of the Average Treatment Effect in Randomized Experiments". In: *Journal of Causal Inference* 1.1, pp. 135–154
7. Joel A Middleton and Peter M Aronow (2015). "Unbiased Estimation of the Average Treatment Effect in Cluster-Randomized Experiments". In: *Statistics, Politics and Policy* 6.1-2, pp. 39–75
8. Luke W Miratrix et al. (2013). "Adjusting Treatment Effect Estimates by Post-Stratification in Randomized Experiments". In: *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 75.2, pp. 369–396

Week 4: 10 February 2026 – Unconfoundedness assumptions and bipartite stratified adjustment

- The conditional independence assumption or "selection on observables"
- Exact matching, Matching on scalars, on scores (propensity and Mahalanobis scores)
- Assessing and justifying stratified designs (balance as assessed by the omnibus test; substantive comparability)
- Sensitivity analysis

Required:

1. Paul R Rosenbaum (2020a). "Modern Algorithms for Matching in Observational Studies". In: *Annual Review of Statistics and Its Application* 7.1, pp. 143–176
2. Paul R Rosenbaum (2020a). "Modern Algorithms for Matching in Observational Studies". In: *Annual Review of Statistics and Its Application* 7.1, pp. 143–176, Ch. 8–10, 14
3. Ben B Hansen and Jake Bowers (2008). "Covariate Balance in Simple, Stratified and Clustered Comparative Studies". In: *Statistical Science* 23.2, pp. 219–236
4. Marie-Abele C Bind and Donald B Rubin (2019). "Bridging Observational Studies and Randomized Experiments by Embedding the Former in the Latter". In: *Statistical Methods in Medical Research* 28.7, pp. 1958–1978
5. TBA Miratrix and Leavitt on Matching

Recommended:

1. Paul R Rosenbaum (2017). *Observation and Experiment: An Introduction to Causal Inference*. Cambridge, MA: Harvard University Press, Ch. 11

Week 5: 17 February 2026 – Unconfoundedness assumptions and non-bipartite stratified adjustment

- Matching on continuous or non-binary "treatments"

Required:

1. Paul R. Rosenbaum (2020b). *Design of Observational Studies*. 2nd. Springer Series in Statistics. Springer, Ch. 12, 14

Recommended:

1. Nathaniel Rabb et al. (July 2022). "The influence of social norms varies with "others" groups: Evidence from COVID-19 vaccination intentions". In: *Proceedings of the National Academy of Sciences* 119.29. DOI: https://doi.org/10.1073/pnas.2118770119
2. Cara Wong et al. (2026). "A Two Path Theory of Context Effects: Pseudoenvironments and Social Cohesion". In: *British Journal of Political Science*

Week 6: 24 February 2026 – No Class — reschedule

Week 7: 3 March 2026 – Unconfoundedness assumptions and parametric adjustment

- Regression as matching
- Parametric vs. non-parametric approaches
- Fixed effects models
- The debate over regression adjustments

Required:

1. Andrew Gelman and Jennifer Hill (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. New York, NY: Cambridge University Press, §9.0–9.2
2. Richard A Berk (2010). "What You Can and Can't Properly Do with Regression". In: *Journal of Quantitative Criminology* 26.4, pp. 481–487

3. Christopher H Achen (2002). “Toward a New Political Methodology: Microfoundations and ART”. in: *Annual Review of Political Science* 5, pp. 423–450
4. Richard A Berk (2004). *Regression Analysis: A Constructive Critique*. Thousand Oaks, CA: SAGE Publications. DOI: https://doi.org/10.4135/9781483348834, Ch. 5

Recommended:

1. Cyrus Samii and Peter M Aronow (2012). “On Equivalencies Between Design-Based and Regression-Based Variance Estimators for Randomized Experiments”. In: *Statistics in Medicine* 31.23, pp. 2726–2740
2. Alberto Abadie, Susan Athey, et al. (2020). “Sampling-Based versus Design-Based Uncertainty in Regression Analysis”. In: *Econometrica* 88.1, pp. 265–296

Week 8: 10 March 2026 – Instrumental Variables designs

- The instrumental variables approach
- Identifying assumptions (ignorable treatment, SUTVA, relevance, monotonicity, exclusion)
- Estimating the LATE using (1) 2SLS, (2) Placebo arms and testing the null hypothesis of no effects effects on compliers.

Required:

1. Joshua D Angrist, Guido W Imbens, et al. (1996). “Identification of Causal Effects Using Instrumental Variables”. In: *Journal of the American Statistical Association* 91.434, pp. 444–455
2. Paul R Rosenbaum (1996). “Identification of Causal Effects Using Instrumental Variables: Comment”. In: *Journal of the American Statistical Association* 91.434, pp. 465–468
3. Alan S Gerber and Donald P Green (2012). *Field Experiments: Design, Analysis, and Interpretation*. New York, NY: W.W. Norton, Ch. 5–6
4. Paul R. Rosenbaum (2020b). *Design of Observational Studies*. 2nd. Springer Series in Statistics. Springer, Ch. 5
5. Paul R Rosenbaum (2017). *Observation and Experiment: An Introduction to Causal Inference*. Cambridge, MA: Harvard University Press, Ch. 13
6. Allison J Sovey and Donald P Green (2011). “Instrumental variables estimation in political science: A readers’ guide”. In: *American Journal of Political Science* 55.1, pp. 188–200

Recommended:

1. Guido W Imbens and Paul R Rosenbaum (2005). “Robust, Accurate Confidence Intervals with a Weak Instrument: Quarter of Birth and Education”. In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 168.1, pp. 109–126
2. Ben B Hansen and Jake Bowers (2009). “Attributing Effects to a Cluster-Randomized Get-Out-the-Vote Campaign”. In: *Journal of the American Statistical Association* 104.487, pp. 873–885

Week 9: 17 March 2026 – No Class — Spring Break

Week 10: 24 March 2026 – Discontinuities as instruments and natural experiments

- Sharp vs. fuzzy RD designs; relationship between “regression discontinuity designs” (RDD) and instrumental variables (IV) and “natural experiments” (unconfoundedness assumptions versus instrumental variables style assumptions)

- Identification assumptions
- Bandwidth selection and specification tests

Required:

1. Matias D Cattaneo et al. (2020). "The Regression Discontinuity Design". In: *Sage Handbook of Research Methods in Political Science & International Relations*. Ed. by Luigi Curini and Robert J Franzese Jr. Washington, D.C.: Sage Publications
2. Devin Caughey and Jasjeet S Sekhon (2011). "Elections and the Regression Discontinuity Design: Lessons from Close US House Races, 1942–2008". In: *Political Analysis* 19.4, pp. 385–408
3. Guido W Imbens and Thomas Lemieux (2008). "Regression Discontinuity Designs: A Guide to Practice". In: *Journal of Econometrics* 142.2, pp. 615–635

Recommended:

1. David S Lee (2008). "Randomized Experiments from Non-Random Selection in US House Elections". In: *Journal of Econometrics* 142.2, pp. 675–697
2. Andrew Gelman and Guido W Imbens (2019). "Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs". In: *Journal of Business & Economic Statistics* 37.3, pp. 447–456
3. Justin McCrary (2008). "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test". In: *Journal of Econometrics* 142.2, pp. 698–714
4. Adam Sales and Ben B Hansen (2020). "Limitless Regression Discontinuity". In: *Journal of Educational and Behavioral Statistics* 45.2, pp. 143–174
5. Joshua D Angrist and Jörn-Steffen Pischke (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press, Ch. 6

Week 11: 31 March 2026 – Panel and Multilevel Data: Using unconfoundedness via risk-set matching and weighting

- Making and strengthening arguments for unconfoundedness using stratification with longitudinal/panel data
- Multilevel matching (when interventions are at one level (like schools) and outcomes are measured at another level (like students))

Required:

1. Paul R. Rosenbaum (2020b). *Design of Observational Studies*. 2nd. Springer Series in Statistics. Springer, Ch. 13
2. Paul R Rosenbaum (2017). *Observation and Experiment: An Introduction to Causal Inference*. Cambridge, MA: Harvard University Press, pp. 227–229
3. José R Zubizarreta and Luke Keele (2017). "Optimal Multilevel Matching in Clustered Observational Studies: A Case Study of the Effectiveness of Private Schools Under a Large-Scale Voucher System". In: *Journal of the American Statistical Association* 112.518, pp. 547–560
4. Samuel D Pimentel et al. (2018). "Optimal Multilevel Matching Using Network Flows: An Application to a Summer Reading Intervention". In: *Annals of Applied Statistics* 12.3, pp. 1479–1505

Recommended:

Week 12: 7 April 2026 – Panel Data 1: Difference-in-Differences using assumptions about outcomes

- The parallel trends assumption
- Panel data methods for causal inference
- Individual and time fixed effects
- First differences and within estimators
- Dynamic panel models
- Event studies and pre-trends testing
- Recent developments: staggered adoption and heterogeneous effects

Required:

1. TBA on difference in differences
2. Kosuke Imai and In Song Kim (2021). "On the Use of Two-way Fixed Effects Regression Models for Causal Inference with Panel Data". In: *Political Analysis* 29.3, pp. 405–415

Recommended:

1. Scott Cunningham (2021). *Causal inference: The mixtape*. Yale university press. URL: https://mixtape.scunning.com/, Ch. 9
2. Adam N Glynn and Konstantin Kashin (2017). "Front-Door Difference-in-Differences Estimators". In: *American Journal of Political Science* 61.4, pp. 989–1002
3. TBA something from Leavitt and/or Laura Hatfield https://diff.healthpolicydatascience.org/

Week 13: 14 April 2026 – Panel Data 3: Combining weighting and assumptions about outcomes

- When to use Two-way fixed effects and when to avoid them (or when to add weights)
- Dynamic panel models

Required:

1. Zhu Shen et al. (2024). "An Anatomy of Event Studies: Hypothetical Experiments, Exact Decomposition, and Weighting Diagnostics". In: *arXiv preprint arXiv:2410.17399*
2. Kosuke Imai and In Song Kim (2021). "On the Use of Two-way Fixed Effects Regression Models for Causal Inference with Panel Data". In: *Political Analysis* 29.3, pp. 405–415

Recommended: TBA

Week 14: 21 April 2026 – Panel Data 4: Synthetic controls via more assumptions about outcomes

- Synthetic controls with one treated unit.
- More generalized approaches

Required:

1. TBA

Recommended:

1. Alberto Abadie, Alexis Diamond, et al. (2012). "Comparative Politics and the Synthetic Control Method". In: *American Journal of Political Science* 59.2, pp. 495–510
2. Alberto Abadie (2020). "Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects". In: *Journal of Economic Literature*
3. Eli Ben-Michael et al. (2021). "The Augmented Synthetic Control Method". In: *Journal of the American Statistical Association*
4. Yiqing Xu (2017). "Generalized synthetic control method: Causal inference with interactive fixed effects models". In: *Political Analysis* 25.1, pp. 57–76

Week 15: 28 April 2026 – TBA to discuss with the class

Required:

1. TBA

Recommended:

1. TBA

Week 16: 5 May 2026 – Final Questions

- Each person brings a question
- Course wrap-up and discussion

Other topics

- Contrasting assumptions about different kinds of unconfoundedness using multiple control groups and differential comparisons.
- Combining assumptions about treatment assignment and outcome processes: double robustness
- Techniques based on making arguments in favor of unconfoundedness assumptions: IPW, AIPW, Balancing weights.
- Techniques based on making arguments in favor of DAG structures: Proximal causal inference and Negative controls.
- Other estimands: Mediation and indirect effects, Average interference effects on networks and graphs
- Other hypotheses: About maximum effects, median effects; About patterns of interference effects on networks and graphs
    1. Devin Caughey, Allan Dafoe, et al. (2023). "Randomisation inference beyond the sharp null: bounded null hypotheses and quantiles of individual treatment effects". In: *Journal of the Royal Statistical Society Series B: Statistical Methodology* 85.5, pp. 1471–1491

2. David Kim et al. (n.d.). "Randomization Tests for Distributions of Individual Treatment Effects Combining Multiple Rank Statistics"
3. Jake Bowers, Mark Fredrickson, et al. (2013). "Reasoning about Interference Between Units: A General Framework". In: *Political Analysis* 21.1, pp. 97–124
4. Jake Bowers, Mark M Fredrickson, et al. (2016). "Research Note: A More Powerful Test Statistic for Reasoning about Interference between Units". In: *Political Analysis* 24.3, pp. 395–403

- Predictive Bayesian causal inference and machine learning.
  Required:

  1. Susan Athey and Guido W Imbens (2017). "The State of Applied Econometrics: Causality and Policy Evaluation". In: *The Journal of Economic Perspectives* 32.2, pp. 3–32
  2. Victor Chernozhukov et al. (2018). "Double/Debiased Machine Learning for Treatment and Structural Parameters". In: *The Econometrics Journal* 21.1, pp. C1–C68

  Recommended:

  1. Stefan Wager and Susan Athey (2018). "Estimation and Inference of Heterogeneous Treatment Effects Using Random Forests". In: *Journal of the American Statistical Association* 113.523, pp. 1228–1242
  2. Naoki Egami et al. (Feb. 2018). "How to Make Causal Inferences Using Texts". Working Paper, https://arxiv.org/pdf/1802.02163.pdf
  3. Amir Feder et al. (2022). "Causal Inference in Natural Language Processing: Estimation, Prediction, Interpretation and Beyond". In: *Transactions of the Association for Computational Linguistics* 10, pp. 590–611

- Causal inference via process tracing

This syllabus is subject to change. Any modifications will be announced in class and posted on Canvas.

References

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