2K: Causal Inference and Experiments in the Social Sciences

Ryan T. Moore*

2021-07-25 at 16:20 BST

Course Information

Course 2K: Causal Inference and Experiments in the Social Sciences

Essex Summer School in Social Science and Data Analysis

Session 2: 26 July - 6 August 2021

Monday-Friday 14:15-17:45 BST (UTC+01:00)

Instructor Information

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Course Description

This course is an introduction to causal inference and experiments for the social sciences. We will discuss the nature of causal research, how to design research to answer different types of causal questions, how to analyze experimental (and perhaps observational) data, how to implement analysis using the R statistical language, and how to interpret the results of causal analyses. Specific topics will include potential outcomes, experiments, blocked designs, and conjoint, list, and multi-arm bandit survey experiments. We will examine observational matching, sensitivity, instruments, discontinuities, synthetic controls, and other special topics as permitted and as student interest dictates.

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Learning Objectives

By the end of the course, you should be able to

- Identify causal effects using the potential outcomes framework
- Perform design-based inference for randomized experiments
- Create and analyze variety of randomized designs, including for blocked, conjoint, list, and multiarm bandit experiments
- Relate experiments to regression quantities
- Estimate mediation effects and assess their sensitivity

Learning Strategies

Readings

Readings should be completed before the course meeting under which they are listed below. The primary textbook for the course is

Alan S. Gerber and Donald P. Green. Field Experiments: Design, Analysis, and Interpretation. WW Norton, New York, NY, 2012.

Problem Sets

The problem sets will be completed outside of class. You may work with others currently taking the course on the problem sets, but every keystroke of your submission must be your own. You may not copy code or answers from others, but you may develop your code with classmates. You are responsible for understanding every line of code you submit. Academic integrity is a core value of institutions of higher learning; it is your responsibility to avoid and report plagiarism, cheating, and dishonesty.

Software

The primary software for the course is R. See http://j.mp/2swvN0p for help getting started.

Intellectual Property

Course content is the intellectual property of the instructor or student who created it, and may not be recorded or distributed without consent.

Calendar

Day 1: Monday, 26 July

Introduction to causal inference.

The potential outcomes framework. Estimands.

Introduction to computing environments.

Day 2: Tuesday, 27 July
Randomized experiments I: Motivation, selection bias. Exercise in potential outcomes.
Introduction to R.
\Box Submit PS1: Gerber and Green 2.1, 2.10, 2.12
\Box Chapter 2 of
Alan S. Gerber and Donald P. Green. Field Experiments: Design, Analysis, an Interpretation. WW Norton, New York, NY, 2012.
Day 3: Wednesday, 28 July
Randomized experiments II: Inference, testing.
\Box Submit PS2: 3.1, 3.5.a, 3.5.b
\Box Chapter 3 of
Alan S. Gerber and Donald P. Green. Field Experiments: Design, Analysis, an Interpretation. WW Norton, New York, NY, 2012.
Day 4: Thursday, 29 July
Randomized experiments III: Covariates, blocked designs.
\Box Chapter 4 of Gerber and Green
☐ Moore, Ryan T. "Multivariate Continuous Blocking to Improve Political Science Experiments". <i>Political Analysis</i> , 20(4):460–479, Autumn 2012.
☐ Moore, Ryan T. and Sally A. Moore. "Blocking for Sequential Political Experments". <i>Political Analysis</i> , 21(4):507–523, 2013.
Day 5: Friday, 30 July
Regression and Experiments. Heterogeneous treatment effects.
\Box Submit PS3: 3.5.c, 3.5.d, 3.5.e
\Box Chapter 9 of Gerber and Green

Winston Lin. Agnostic notes on regression adjustments to experimental data: Reexamining freedman's critique. The Annals of Applied Statistics, 7(1):295-318,

2013.

Day 6: Monday, 2 August

Survey ex	periments. Conjoints, item counts, lists.
□ Sub	mit PS4: Two exercises in /ps/ps4/
	Paul M. Sniderman. Some advances in the design of survey experiments. <i>Annual Review of Political Science</i> , 21:259–275, May 2018.
	Jens Hainmueller, Daniel J. Hopkins, and Teppei Yamamoto. Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments. <i>Political Analysis</i> , 22(1):1–30, 2014.
	Scott F. Abramson, Korhan Koçak, and Asya Magazinnik. What do we learn about voter preferences from conjoint experiments? $Manuscript.\ https://j.mp/2VaIk7p$, August 2019.
	Kirk Bansak, Jens Hainmueller, Daniel J Hopkins, and Teppei Yamamoto. Using conjoint experiments to analyze elections: The essential role of the average marginal component effect (AMCE). SSRN Working Paper, 2020.
	Yusaku Horiuchi, Daniel M Smith, and Teppei Yamamoto. Measuring voters' multidimensional policy preferences with conjoint analysis: Application to japan's 2014 election. <i>Political Analysis</i> , 26(2):190–209, 2018.
	Graeme Blair and Kosuke Imai. Statistical analysis of list experiments. $Political$ $Analysis, 20(1):47-77$, Winter 2012.
	Graeme Blair, Kosuke Imai, and Jason Lyall. Comparing and combining list and endorsement experiments: Evidence from afghanistan. <i>American Journal of Political Science</i> , 58(4):1043–1063, 2014.
Day 7: '	Tuesday, 3 August
Multiarm Catch-up,	bandits. Review, and Agenda Setting
	Molly Offer-Westort, Alexander Coppock, and Donald P Green. Adaptive experimental design: Prospects and applications in political science. $Manuscript.$, 2018. http://j.mp/2FsHlKr.
	Volodymyr Kuleshov and Doina Precup. Algorithms for multi-armed bandit problems. $CoRR$, abs/1402.6028, 2014.
	Neha Gupta, Ole-Christoffer Granmo, and Ashok Agrawala. Thompson sampling for dynamic multi-armed bandits. In 2011 10th International Conference on Machine Learning and Applications Workshops, pages 484–489. IEEE, 2011.

Day 8: Wednesday, 4 August ☐ Submit PS5: Exercises in /ps/ps5/ Mediation. ☐ Chapter 10 of Gerber and Green 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, November 2011. John G. Bullock, Donald P. Green, and Shang E. Ha. Yes, but what's the mechanism? (don't expect an easy answer). Journal of Personality and Social Psychology, 98(4):550–558, 2010. Avidit Acharya, Matthew Blackwell, and Maya Sen. Analyzing causal mechanisms in survey experiments. Political Analysis, 26(4):357–378, 2018. Graeme Blair, Alexander Coppock, and Margaret Moor. When to worry about sensitivity bias: A social reference theory and evidence from 30 years of list experiments. American Political Science Review, 114(4):1297–1315, 2020. Kosuke Imai, Luke Keele, and Teppei Yamamoto. Identification, Inference, and Sensitivity Analysis for Causal Mediation Effects. Statistical Science, 25(1):51-71, February 2010. Interference. Time-varying treatments and covariates. ☐ Chapter 8 of Gerber and Green Michael G. Hudgens and M. Elizabeth Halloran. Toward Causal Inference With Interference. Journal of the American Statistical Association, 103(482):832–842, June 2008. Paul R. Rosenbaum. Interference Between Units in Randomized Experiments. Journal of the American Statistical Association, 102(477):191–200, 2007. Michael E. Sobel. What do randomized studies of housing mobility demonstrate?: Causal inference in the face of interference. Journal of the American Statistical Association, 101(476):1398–1407, 2006. Matthew Blackwell. A framework for dynamic causal inference in political science. American Journal of Political Science, 57(2):504–520, 2013. Day 9: Thursday, 5 August □ "In-class" timed exam, 19:00 BST tonight ☐ For Saturday at 12:00 BST, submit PS6: Exercises in /ps/ps6/ Observational Designs for Causal Inference: Matching, Matching + Regression, Regression

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Discontinuity Designs, Difference-in-Differences, Synthetic Controls

	Donald B. Rubin. The design <i>versus</i> the analysis of observational studies for causal effects: Parallels with the design of randomized trials. <i>Statistics in Medicine</i> , 26(1):20–36, 2007.
	Daniel Ho, Kosuke Imai, Gary King, and Elizabeth Stuart. Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. <i>Political Analysis</i> , 15:199–236, 2007.
	Paul R. Rosenbaum and Donald B. Rubin. "The Central Role of the Propensity Score in Observational Studies for Causal Effects". <i>Biometrika</i> , 70(1):41–55, 1983.
	Stefano M. Iacus, Gary King, and Giuseppe Porro. Causal inference without balance checking: Coarsened exact matching. $Political\ Analysis$, $20(1):1-24$, Winter 2012.
	Devin Caughey and Jasjeet S. Sekhon. Elections and the Regression Discontinuity Design: Lessons from Close U.S. House Races, 1942–2008. <i>Political Analysis</i> , 19(4):385–408, 2011.
	Guido W. Imbens and Thomas Lemieux. Regression discontinuity designs: A guide to practice. <i>Journal of Econometrics</i> , 142:615–635, 2008.
	Matthew Blackwell and Anton Strezhnev. Telescope matching for reducing model dependence in the estimation of direct effects: : An application to negative advertising. 2020.
	Brantly Callaway and Pedro H.C. Sant'Anna. Difference-in-differences with multiple time periods. $Journal\ of\ Econometrics,\ 2020.$
Day 10:	Friday, 6 August
Registrati	ion, Replication, Declaration
	Macartan Humphreys, Raul Sanchez de la Sierra, and Peter van der Windt. Fishing, commitment, and communication: A proposal for comprehensive nonbinding research registration. <i>Political Analysis</i> , 21(1):1–20, 2013.
	James E. Monogan. A case for registering studies of political outcomes: An application in the 2010 house elections. <i>Political Analysis</i> , 21(1):21–37, 2013.
	Macartan Humphreys. Reflections on the ethics of social experimentation. Journal of Globalization and Development, $6(1):87-112,\ 2015.$
	Graeme Blair, Jasper Cooper, Alexander Coppock, and Macartan Humphreys. Declaring and diagnosing research designs. <i>American Political Science Review</i> , 113(3):838–859, 2019. See also https://book.declaredesign.org.
	Stefano DellaVigna and Elizabeth Linos. RCTs to scale: Comprehensive evidence from two nudge units. https://eml.berkeley.edu/sdellavi/wp/NudgeToScale2020-05-09.pdf, 2020.

Additional Topic

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Observa	tional studies: Designs for causal inference.
	Kosuke Imai, Gary King, and Elizabeth A. Stuart. Misunderstandings between experimentalists and observationalists about causal inference. <i>Journal of the Royal Statistical Society, Series A</i> , 171(2):481–502, 2008.
Additi	onal Topic
	g for Observational Designs ching on the propensity score. Matching on coarsened measures.
	Paul R. Rosenbaum and Donald B. Rubin. "The Central Role of the Propensity Score in Observational Studies for Causal Effects". <i>Biometrika</i> , 70(1):41–55, 1983.
	Kosuke Imai and Marc Ratkovic. Covariate balancing propensity score. <i>Journal of the Royal Statistical Society: Series B (Statistical Methodology)</i> , 76(1):243–263, 2014.
	Stefano M. Iacus, Gary King, and Giuseppe Porro. Causal inference without balance checking: Coarsened exact matching. <i>Political Analysis</i> , 20(1):1–24, Winter 2012.
Additi	onal Topic
Sensitiv	ity.
Additi	onal Topic
Encoura	gement designs, instrumental variables. "Local" treatment effects.
□ Cł	napters 5 and 6 of Gerber and Green
	Joshua D. Angrist, Guido W. Imbens, and Donald B. Rubin. Identification of causal effects using instrumental variables. <i>Journal of the American Statistical Association</i> , 91 (434):444–455, 1996.
Additi	onal Topic
Syntheti	ic control methods. Interrupted time series.
	Alberto Abadie and Javier Gardeazabal. The Economic Costs of Conflict: A Case Study of the Basque Country. <i>The American Economic Review</i> , 93(1):113–132, 2003.
	Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synthetic Control Methods for Comparative Case Studies: Estimating the Effects of California's Tobacco Control Program. Journal of the American Statistical Association, 105(400):403-

505, June 2010.

 \square Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synth: An r package for synthetic control methods in comparative case studies. *Journal of Statistical Software*, 42(13):1–17, 2011.