Causal Inference: Methods for Program Evaluation and Policy Research
APSTA-GE 2012.1.001
Spring 2023

Add last day of class "final"
Add four or five in-class quizzes (drop lowest)

Course Time and Location:

Friday 9:15-12:15
Silver 206

Homework support sessions will be held as needed for the computational track in the main room and for the applied track in Silver 406 from 11:30-12:15.

Instructor:	Jennifer Hill, 210 Kimball Hall (246 Greene St) Jennifer.hill@nyu.edu
Course Assistant:	George Perrett, 210 Kimball Hall (246 Greene St), gp77@nyu.edu Will run lab for computational track and hold office hours
Teaching Assistant:	Applied Track: Lauren Magee (lmm8720@nyu.edu) Will run lab and grade for applied track
Grader:	Computational Track: Angela He
Office Hours:	Jennifer Hill: virtual (zoom), Wednesday 2-3 George Perrett: 210 Kimball Hall Wednesday 5-6, Thursday 11-Noon

Course Description and Prerequisites:
The goal of this course is to provide students with a basic knowledge of how to understand and use statistical designs and methods to address policy questions. It will also allow students to more critically review published research that claims to answer causal policy questions. The primary focus of the course is the challenge of answering causal questions, that is, those that take the form "Did A cause B?" using data that do not conform to a perfectly controlled randomized study. Examples from public policy studies will be used throughout the course to illustrate key ideas and methods. First, we will explore how best to design a study to answer causal questions given the logistical and ethical constraints that exist. We then discuss several approaches to drawing causal inferences from observational studies including propensity score methods, instrumental variables, regression discontinuity, difference in differences (and related methods), and fixed effects models. If time allows we will discuss some simple forms of sensitivity analysis and machine learning based approaches to causal inference.

Pre-requisites:
The prerequisite for the course is two semesters of quantitative methods at the level of RESCH-GE.2003, RESCH-GE.2004 (or the equivalent as approved by the instructor). Students should understand how to implement and interpret regression models including those that include indicator (dummy) variables, interactions, and transformations. Some exposure to and comfort with logistic regression is required. Students need to be *extremely comfortable* with either R or Stata (*see more detail below*).

Discussion boards and office hours:
You have several options for asking questions and receiving feedback.

1) Office hours with the professor, Jennifer Hill (see above).
2) Office hours with the course assistant, George Perrett (see above).
3) Discussion board on EdDiscussion tool linked through Brightspace (Jennifer and George will monitor)

All questions about course content need to be asked through one of these three options. If you ask a question via email you will be redirected to these three options. Asking questions in these forums is a great way to start discussions and help your fellow students who have similar queries.

Grading:
Grading will be based on 6 homework assignments (totaling 40%), five in-class quizzes (10%), one final project or take-home final exam (25%) and one in-class final exam (25%). There are two distinct tracks for the homework assignments and the final take-home exam/project and the content will be different in each of the tracks.

We will not announce in advance what day the in-class quizzes will be held. If you miss class on a quiz day you will receive a 0 on that quiz. At the end of the semester your lowest quiz grade will be dropped.

Homework Tracks

Applied Track. Assignments 1-3 reinforce new concepts (potential outcomes, average treatment effects, randomized experiments, simple estimators) through online quizzes that involve algebra and questions about basic concepts. Assignments 4-6 address propensity scores, instrumental variables, regression discontinuity, fixed effects and difference in differences. These will involve both data analyses and a thoughtful description of the assumptions and findings. Students will have a choice between a take-home final exam and a final project (descriptions and guidelines will be available soon on the Brightspace site).

Computational Track. All six assignments require simulating data and analyzing it in R. These simulations will help students gain a deeper understanding of the structural and parametric assumption required for each design or method as well as the properties of the corresponding estimators. *Students who choose to participate in this track should feel comfortable simulating data from distributions, looping, logic statements, and creating functions.* There will be a choice between a final exam and a final project (descriptions and guidelines will be available soon on the Brightspace site).

Class meeting times, organization, deadlines
The class is scheduled each week for 3 hours. The first two hours and 15 minutes will be spent in shared class time (mix of lecture and activities). Typically, the remaining time (from 11:30-12:15) in groups broken out by homework track and will be used for additional Stata/R instruction, help with/feedback on homework or projects, or more general questions as the need arises.

The class will meet every Friday that the university is open during the semester. The last class on Friday May 5th will be reserved for the in-class exam. The take-home final exam/project will be due on Friday May 12th at noon EST.

Class modality
NYU is committed to in-person instruction. Students are expected to participate in person in weekly lectures. If you are unable to participate in person for reasons that are sanctioned by the university please inform me before class and we can determine how you can learn the necessary material. If NYU policies change we will let you know immediately and determine the best option for alternate instruction.

Reading materials
There is no required textbook for the course. The required readings are either available through e-journals through the library or will be posted on the Brightspace website. In addition, however, the following books are *recommended*:

Gelman, Andrew, Hill, Jennifer, and Vehtari, Aki (2020) *Regression and Other Stories,* Cambridge University Press.

Guo, Shenyang and Fraser, Mark W. (2010) *Propensity Score Analysis*, Sage Publications.

Morgan, S. and Winship, C. (2007) *Counterfactuals and Causal Inference: Methods and Principles for Social Research,* Cambridge University Press

Angrist and Pischke (2009) *Mostly Harmless Econometrics*, Princeton University Press.

Imbens and Rubin (2015) *Causal Inference for Statistics, Social, and Biomedical Sciences,* Cambridge University Press.

Outline of course Lessons and readings:
The following outline describes the Lessons that will be covered along with anticipated associated readings. It corresponds roughly to the course weeks though we may end up adjusting time spent on each Lesson as we go. Readings highlighted with an * are recommended, not required. All readings will be available on Brightspace (under the appropriate section of Lessons or Resources).

READINGS ARE SUBJECT TO CHANGE WITH APPROPRIATE WARNING.

1) Motivation: What's all the observational vs. randomized fuss about?
Simple randomized experiments (theory and practice) and the Rubin Causal Model

*Winship & Morgan, Chapter 2 (posted on Brightspace under Lesson 1)

*Leamer, Edward (1983) "Let's take the con out of econometrics", *American Economic Review*, 73(1): 31-43 [Available at www.jstor.org]

*Hill, J., Reiter, J., and Zanutto, E. (2004) "A comparison of experimental and observational data analyses" *Applied Bayesian Modeling and Causal Inference from an Incomplete-Data Perspective.* Edited by Andrew Gelman and Xiao-Li Meng. West Sussex, England: Wiley.
[Available on Brightspace under Lesson 1]

*Holland, Paul W. (1986), ``Statistics and causal inference (with discussion)'', *Journal of the American Statistical Association*, 81: 945-970 [Available at www.jstor.org]

*Gelman, Andrew and Hill, Jennifer (2007) Chapters 3 and 4, of *Data Analysis Using Regression and Multilevel/Hierarchical Models,* Cambridge University Press

2) Randomized experiments (including Randomized Block and Matched Pairs Designs) and complications that make them look like observational studies

Gelman, A., Hill, J. and Vehtari, A. (2020) Chapter 18 "Causal Inference Theory and Randomized Experiments," *Regression and Other Stories*, Cambridge University Press
available as RAOS_Ch18 on Brightspace under Topic 1 and 2

Gelman, A., Hill, J. and Vehtari, A. (2020) Chapter 19 "Causal inference using regression on the treatment variable," *Regression and Other Stories*, Cambridge University Press
available as RAOS_Ch19 on Brightspace under Topic 2

Guo and Fraser, Chapter 2, pp 21-36
available on Brightspace under Topic 2

Aubry, T., Bourque, J., Goering, P. *et al.* (2019) A randomized controlled trial of the effectiveness of Housing First in a small Canadian City. *BMC Public Health* 19, 1154. available on Brightspace under Topic 2

*Katz, L.F., Kling, J.R., and Liebman, J.B. (2001) "Moving to Opportunity in Boston: Early Results of a Randomized Mobility Experiment" *The Quarterly Journal of Economics*, 116: 607-654.

*Imbens, G., Rubin, D., and Sacerdote, B. (2001) "Estimating the Effect of Unearned Income on Labor Earnings, Savings and Consumption: Evidence from a Survey of Lottery Players" *American Economic Review* 91(4): 778 (available through e-journals)

*Rubin, D. (1990) "Formal modes of statistical inference for causal effects" *Journal of Statistical Planning and Inference* 25: 279-292. (available through e-journals)

*Sobel, Michael E. (1996), "An introduction to causal inference", *Sociological Methods and Research*, Vol. 24, Iss. 3; p. 353-379 (LL) (available through e-journals)

*Rosenbaum, P. (2002) *Observational Studies*, *2nd ed.*, New York: Springer, Chapter 2

3) Observational Studies and simple ways of adjusting for covariates

Gelman, A., Hill, J. and Vehtari, A. (2020) Chapter 20 from *Regression and Other Stories*, Cambridge University Press, everything but sections on matching
available as RAOS_Ch20

Rosenbaum, P. (2002) *Observational Studies*, *2nd ed.*, New York: Springer, Chapter 1
[available on Brightspace under Lesson 3]

Donohue, J. J., and S.D. Levitt (2001) "The impact of legalized abortion on crime" *The Quarterly Journal of Economics,* 116(2): 379-420
[Available through e-journals]

*Winship, Christopher and Michael Sobel (2004) "Causal Inference in Sociological Studies" in Handbook of Data Analysis edited by Melissa Hardy and Alan Bryman, London: Sage Publications, 36-38

*Rubin, D. (1977) "Assignment to Treatment Groups on the Basis of a Covariate" *Journal of Educational Statistics*, 2: 1-26

*LaLonde, R. (1986) Evaluating the Econometric Evaluations of Training Programs, *American Economic Review*, 76: 604-620 [Available at www.jstor.org]

*Rosenbaum, P. (2002) "Covariance adjustment in randomized experiments and observational studies", *Statistical Science,* 17(3): 286-327

4) Propensity Score Approaches – Introduction

Gelman, A., Hill, J. and Vehtari, A. (2020) Chapter 20 from *Regression and Other Stories*, Cambridge University Press, sections on matching
available as RAOS_Ch20 under Topic 4

Chen, S. and Mallory, A.B. (2021) "The effect of racial discrimination on mental and physical health: A propensity score weighting approach," *Social Science & Medicine*, 285

*Bingenheimer, J.B., Brennan, R.T., and Earls, F.J. (2005) "Firearm violence exposure and serious violent behavior," *Science* 308: 1323-1326 [Available on Brightspace under Lesson 4]

*Schafer, J. and Kang, J. (2008) "Average Causal Effects from Nonrandomized Studies: A Practical Guide and Simulated Example" *Psychological Methods* [Available on Brightspace under Lesson 4]

*Harder, V. S., Stuart, E. A., & Anthony, J. C. (2010). Propensity score techniques and the assessment of measured covariate balance to test causal associations in psychological research. *Psychological methods*, *15*(3), 234–249. https://doi.org/10.1037/a0019623

*Rosenbaum, Paul R. and Rubin, Donald B. (1984) "Reducing Bias in Observational Studies Using Subclassification on the Propensity Score" *Journal of the American Statistical Association*, 79: 516—524 [Available at www.jstor.org]

*Hill, J. (2008) "Discussion of research using propensity-score matching: Comments on 'A critical appraisal of propensity-score matching in the medical literature between 1996 and 2003' by Peter Austin," *Statistics in Medicine*, 27: 2055-2061.

*Guo and Fraser, Chapter 5, pp 127-149, 154-158, 161-162, 167-186

*Hill, J., Weiss, C. and F. Zhai (2011) "Challenges with propensity score matching in a high-dimensional setting and a potential alternative," *Multivariate and Behavioral Research*, 46(3): 477-513.

*Dehejia, Rajeev H. and Wahba, Sadek (1999) "Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs", *Journal of the American Statistical Association*, 94: 1053—1062 [Available at www.jstor.org]

5) Instrumental Variables Models – Introduction and Theory

Gelman, A., Hill, J. and Vehtari, A. (2020) Chapter 21 from *Regression and Other Stories*, Cambridge University Press, section on IV
available as RAOS_Ch21

Gennetian, L., Bos, J., Morris, P. (2002) "Using Instrumental Variables Analysis to Learn More from Social Policy Experiments" Manpower Demonstration Research Corp. working paper [available on Brightspace]

Angrist, J D., Imbens, G W. and D B. Rubin, (1996) "Identification of Causal Effects Using Instrumental Variables," *Journal of the American Statistical Association*, 91: 444-472 [Available at www.jstor.org]

*Labrecque, J., & Swanson, S. A. (2018). Understanding the Assumptions Underlying Instrumental Variable Analyses: a Brief Review of Falsification Strategies and Related Tools. *Current epidemiology reports*, *5*(3), 214–220. https://doi.org/10.1007/s40471-018-0152-1

*Angrist, J D. (1990) "Lifetime Earnings and the Vietnam Era Draft Lottery: Evidence from Social Security Administrative Records," *American Economic Review,* 80: 313-336 [Available at www.jstor.org]

*Angrist JD, Evans WN (1998), "Children and their parents' labor supply: Evidence from exogenous variation in family size", *American Economic Review* 88(3): 450-77 [available at www.jstor.org]

*E. Michael Foster. (2000) "Is more better than less? An analysis of children's mental health services" *Health Services Research.* Chicago: Vol. 35, Iss. 5; p. 1135

6) Regression Discontinuity

Gelman, A., Hill, J. and Vehtari, A. (2020) Chapter 21 from *Regression and Other Stories*, Cambridge University Press, section on RDD
available as RAOS_Ch21

Shadish, Cook & Campbell (2002) "Regression Discontinuity Designs" Chapter 7 in *Experimental and Quasi-Experimental Designs* Boston: Houghton Mifflin Co. (posted on Brightspace with lecture)

Pierson, E., Simoiu, C., Overgoor, J. et al. (2020) "A large-scale analysis of racial disparities in police stops across the United States," *Nature Human Behavior* 4: 736–745.

Brian A. Jacob, Lars Lefgren (2004) "Remedial Education and Student Achievement: A Regression-Discontinuity Analysis" *Review of Economics and Statistics* 86(1)

7) Difference in Differences/ Fixed Effects/ Synthetic Controls

Gelman, A., Hill, J. and Vehtari, A. (2020) Chapter 21 from *Regression and Other Stories*, Cambridge University Press, section on DID/FE available as RAOS_Ch21

Chapter 18 on Panel Data Model in Ashenfelter book *Statistics and Econometrics* (published by Wiley, 2003), pp. 262-273 (available on Brightspace under Lesson 6)

Angrist, J. D., and Krueger, A. (1999), "Empirical Strategies in Labor Economics," in Orley Ashenfelter and David Card (eds), *Handbook of Labor Economics*, Vol. 3A, Amsterdam: Horth-Holland (available on Brightspace under Lesson 6) **pp 16-24**

Hatzenbuehler, M. L., McKetta, S., Kim, R., Leung, S., Prins, S. J., & Russell, S. T. (2022). Evaluating Litigation as a Structural Strategy for Addressing Bias-Based Bullying among Youth. JAMA Pediatrics, 176(1), 52-58. https://doi.org/10.1001/jamapediatrics.2021.3660

*Raifman, J., Moscoe, E., Austin, S.B., Hatzenbuehler, M.L., & Galea, S. (2018). State laws permitting denial of services to same-sex couples and mental distress among sexual minority adults: A difference-in-difference-in-differences analysis. *JAMA Psychiatry, 75,* 671-677

*Bogart & Cromwell. "How much is a neighborhood school worth?" *J. Urban Economics* 47 [Available through e-journals]

*Aaronson, Daniel. (1998) "Using Sibling Data to Estimate the Impact of Neighborhoods on Children's Educational Outcomes," *The Journal of Human Resources*, 33(4): 915-946 [Available through e-journals]

*Card, D. and A. Krueger (1994) "Minimum Wages and Employment: A Case Study of the Fast-food Industry in New Jersey and Pennsylvania," *American Economic Review*, 84(4): 772-784. [Available at www.jstor.org]

*Meyer, B. (1995) “Natural and Quasi-Experiments in Economics,” *Journal of Business and Economic Statistics*, 13(2): 151-161
[Available through e-journals]

*Korenman and Neumark (1991) "Does Marriage Really Make Men More Productive?" Journal of Human Resources, 26(2): 282-307
[available through e-journals]

8) Bonus material: Sensitivity, Machine Learning, and Evaluation Racial Discrimination using Causal Inference

Dorie, V., Harada, M., Carnegie, N., and J. Hill (2016) “A flexible, interpretable framework for assessing sensitivity to unmeasured confounding,” *Statistics in Medicine*, 35(20): 3453-70.

Hill, J. (2011) “Bayesian nonparametric modeling for causal inference,” *Journal of Computational and Graphical Statistics*, 20(1): 217-240.

Pierson, E., Simoiu, C., Overgoor, J. *et al.* A large-scale analysis of racial disparities in police stops across the United States. *Nat Hum Behav* **4,** 736–745 (2020).

Rosenbaum, P. R. (2002). Covariance Adjustment in Randomized Experiments and Observational Studies. *Statistical Science, 17* (3), 286-327

Academic Integrity
All students are responsible for understanding and complying with the New York University Steinhardt School Statement on Academic Integrity. A copy of this statement is available at: http://steinhardt.nyu.edu/policies/academic_integrity.

Students with Disabilities
Students with physical or learning disabilities are required to register with the Moses Center for Students with Disabilities, 726 Broadway, 2nd Floor, (212-998-4980 and online at http://www.nyu.edu/csd) and are required to present a letter from the Center to the instructor at the start of the semester in order to be considered for appropriate accommodation.

Inclusion
NYU values an inclusive and equitable environment for all our students. I hope to foster a sense of community in this class and consider it a place where individuals of all backgrounds, beliefs, ethnicities, national origins, gender identities, sexual orientations, religious and political affiliations, and abilities will be treated with respect. It is my intent that all students’ learning needs be addressed both in and out of class, and that the diversity that students bring to this class be viewed as a resource and strength. If this standard is not being upheld, please feel free to speak with me.

Grading Rubric:
Letter grades will be assigned using the following criteria:

A= Excellent [90-100% of points available in a given assignment category/ 93.66 required for an A versus an A-]

B=Good [80-89.9% of points available in a given assignment category/ 83.3 and below is a B- and 86.7 and above is a B+]

C=Average [70-79.9% of points available in a given assignment category/ 73.3 and below is a B- and 76.7 and above is a B+]

D= Unsatisfactory [60-69.9% of points available in a given assignment category/ 63.3 and below is a B- and 66.7 and above is a B+]

F=Fail