Introduction to Causal Inference for Educational Research (EDUC 7665-001)
Fall 2022

Instructor: Dr. Wendy Chan
Email: wechan@upenn.edu
Phone: 215-573-2038
Office: GSE Room 342
Office Hours: By appointment (Virtual)

Course Logistics: This class will meet once per week on Tuesdays from 11:30 AM - 1:30 PM in GSE 121.

Course Description: This course offers an applied introduction to methods of causal inference for evaluation research. The course will be organized into three sections: (i) methods for analyzing simple randomized and cluster randomized experiments; (ii) analysis techniques for quasi-experimental and observational studies and; (iii) advanced topics in causal inference methods.

Course Objectives:
At the completion of this course, students should be able to:

- Identify the appropriate methods, study designs, and estimators to use in addressing research problems in causal inference
- Conduct independent statistical analyses using experimental or observational study techniques
- Interpret and discuss methods used in applied studies found in journals such as *Evaluation Review*, the *Journal of Research on Educational Effectiveness*, and *Educational Evaluation and Policy Analysis*

Academic Prerequisites

EDUC 667 or equivalent graduate level introductory statistics course. Knowledge of applied regression is preferred, but not required. Familiarity with the statistical software program R is preferred, but not required.

Textbooks and Other Course Material: All class sessions will focus on methodological articles posted on Canvas. However, the following texts are excellent resources for additional readings on causal inference methods:

- Hernan, Miguel A. & Robins, James M. (2020). *Causal Inference: what if.* Boca Raton: Chapman & Hill/CRC.
- Imbens, Guido. & Rubin, Donald B. (2015). *Causal Inference in Statistics, Social, and Biomedical Sciences.* Cambridge University Press.
- Morgan, Stephen L. & Winship, Christopher (2007). *Counterfactuals and causal inference: Methods and principles for social research.* New York, NY: Cambridge University Press.
- Murnane, Richard J. & Willett, John B. (2010). *Methods Matter: Improving causal inference in educational and social science research.* Boston, MA: Oxford University Press.
- Rosenbaum, Paul. R. (2010). *Design of Observational Studies.* New York, NY: Springer

Software

We will use R and R Studio in this class, which are free and available for download at https://www.r-project.org/ and https://www.rstudio.com/, respectively. You are welcome to use other programs such as Stata, SAS, or SPSS, but please be aware that I will not be able to troubleshoot issues related to any other software program other than R. However, many software programs, including R, have useful help forums online. If you run into computing issues, I encourage you to try searching for solutions online first as another person may have already solved it.

Course Evaluation:

Response to Readings (30%)
Prior to class each week, you will be asked to respond to the readings. All submissions will be uploaded to the "Discussions" forum on the Canvas page for the course. These responses serve two purposes. One, they allow students to raise questions related to the frameworks and methods in each study. Two, they will be used to stimulate discussion of the readings during class.

Course Project (40%)
The final course project will consist of a working paper based on one or more of the causal inference methods discussed in this course. For this project, find either an experimental or observational data set, develop a research question(s) that evaluates the causal impact of an intervention, treatment, policy, or event on some outcome, and submit a paper presenting the results of the study. The working paper should include a brief background, the research question(s), a description of the data, the empirical strategy, results and conclusions. The data analysis code should be submitted as an appendix. You may choose whatever topic you want, as long as the research question(s) is clearly defined and the study is focused on causal inference. The paper should be of publication quality (as might appear in journals such as *Evaluation Review* or the *Journal of Research on Educational Effectiveness*).

The following is a list of websites where students may access various types of data sets.

1. National Center for Education Statistics (https://nces.ed.gov/)
2. Institute for Social Science Research at the University of Michigan (https://www.icpsr.umich.edu/icpsrweb/index.jsp)
3. New York City Clearinghouse (https://opendata.cityofnewyork.us/)
4. Chicago Data Portal (https://data.cityofchicago.org/)
5. Harvard Dataverse (https://dataverse.harvard.edu/dataverse/socialsciencercts)
6. Kaggle (https://www.kaggle.com)
7. Austin Data Clearinghouse (https://data.austintexas.gov/)
8. San Francisco Data Clearinghouse (https://datasf.org/opendata/)
9. Open Baltimore (https://data.baltimorecity.gov)

Article Presentation (30%)
During the last week of class, students (in groups of $2 - 3$ people) will present a methodological article of their choosing and give a 20 - 25 minute presentation. Each presentation should (1) describe the study's main research question(s) and the methods used; (2) explain and interpret the causal estimand(s); (3) discuss the assumptions necessary to identify the estimand(s) and; (4) explain the method/approach proposed in the article.

Other Information:

Attendance: Students are responsible for all of the readings covered during class meetings. If you miss a class, you are responsible for obtaining any notes or summaries of the material that you missed from a classmate.

Academic Honesty: Please consult the GSE Student Handbook on the following webpage for details on expected student conduct: `http://www.gse.upenn.edu/policies/academicintegrity`. Please be sure to read the material in this document. Plagiarism or cheating of any kind will be dealt with according to University policy, which can be found at: `http://www.upenn.edu/academicintegrity`.

Communicating with me: Email is the best way to reach me. If I do not respond within 48 hours, feel free to send a follow up email.

Topic Schedule (Fall 2022)

Week	Date	Readings and Topics
1	08/30	**Readings** Holland, P.W. (1986). Statistics and Causal Inference. *Journal of the American Statistical Association, 81*(396), 945 - 960. Rubin, D.B. (1986). What Ifs Have Causal Answers. *Journal of the American Statistical Association, 81*(396), 961 - 962. **Topics** • Course Introduction • Potential Outcomes Framework • Fundamental Problem of Causal Inference
2	09/06	**Readings** Rubin, D.B. (1974). Estimating Causal Effects of Treatments in Randomized and Non-randomized Studies. *Journal of Educational Psychology, 66*(5), 688 - 701. Rubin, D.B. (1990). Formal Modes of Statistical Inference for Causal Effects. *Journal of Statistical Planning and Inference,* 25, 279 - 292. **Topics** • Simple Randomized Experiments • SUTVA
3	09/13	**Readings** Boruch, R. May, H., ..., & Foley, E. (2004). Estimating the effects of interventions that are deployed in many places: Place-randomized trials. *American Behavioral Scientist, 47*(5), 608 - 633. **Topics** • Cluster randomized experiments • Block randomized experiments
4	09/20	**Readings** Dong, N. & Maynard, R. A. (2013). PowerUp!: A tool for calculating minimum detectable effect sizes and minimum required sample sizes for experimental and quasi-experimental design studies. *Journal of Research on Educational Effectiveness, 6*(1), 24 - 67. Hedges, L.V. & Hedberg, E.C. (2007). Intraclass correlation values for planning group-randomized trials in education. *Educational Evaluation and Policy Analysis, 29*(1), 60 - 87. **Topics** • Statistical power for RCTs and clustered study designs

Week	Date	Readings and Topics
5	09/27	**Readings** Spybrook, J. & Hedberg, E.C. A framework for designing cluster randomized trials with binary outcomes. Working paper. **Topics** • Statistical power (continued) • Statistical power for clustered designs with binary outcomes
6	10/04	**Readings** Angrist, J.D., Imbens, G.W., & Rubin, D.B. (1996). Identification of causal effects using instrumental variables. *Journal of the American Statistical Association,* 91, 444 - 472. Kim, D., Baum, C.F., ..., & Ichiro, K. (2011). The contextual effects of social capital on health: A cross-national instrumental variable analysis. *Social Science & Medicine,* 73, 1689 - 1697. **Topics** • Instrumental variables
7	10/11	**Readings** Angrist, J.D. & Krueger, A.B. (2001). Instrumental variables and the search for identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives, 15* (4), 69 - 85. **Topics** • Instrumental variables (continued)
8	10/18	**Readings** Bloom, H.S. (2012). Modern regression discontinuity analysis. *Journal of Research on Educational Effectiveness, 5* (1), 43 - 82. Skovron, C. & Titiunik, R. (2015). A practical guide to regression discontinuity designs in political science. *American Journal of Political Science,* 2015, 1 - 36. **Topics** • Regression discontinuity
9	10/25	**Readings** Wong, V.C., Steiner, P.M., & Cook, T.D. (2013). Analyzing regression discontinuity designs with multiple assignment variables: A comparative study of four estimation methods. *Journal of Educational and Behavioral Statistics, 38*(2), 107 - 141. **Topics** • Regression discontinuity (continued)

Week	Date	Readings and Topics
10	11/01	**Readings** Cochran, W.G., & Rubin, D.B. (1973). Controlling bias in observational studies: A review. *Sankhya: The Indian Journal of Statistics, Series A, 35* (4), 417 - 466. Rubin, D.B. (1977). Assignment to treatment groups on the basis of a covariate. *Journal of Educational Statistics*, 2, 1 - 26. **Topics** • Matching by a single covariate • Matching on multiple covariates
11	11/08	**Readings** Ho, D.E., Imai, K., King, G., & Stuart, E.A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis, 15*(3), 199 - 236. Rosenbaum, P.R. & Rubin, D.B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41 - 55. **Topics** • Matching by propensity scores • Stratification by propensity scores
12	11/15	**Readings** Austin, P.C. & Stuart, E.A. (2015). Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in Medicine,* 34, 3661 - 3679. Schafer, J.L. & Kang, J. (2008). Average causal effects from nonrandomized studies: A practical guide and simulated example. *Psychological Methods, 13* (4), 279 - 313. **Topics** • Weighting by propensity scores • Balance assessment
13	11/29	**Readings** McCaffrey, D.F., Ridgeway, G., & Morral, A.R. (2004). Propensity score estimation with boosted regression for evaluating causal effects in observational studies. *Psychological Methods, 9*(4), 403 - 425. **Topics** • Machine learning methods for propensity score estimation

Week	Date	Readings and Topics
14	12/06	**Readings** Stuart, E.A., Cole, S.R., Bradshaw, C.P., & Leaf, P.J. (2011). The use of propensity scores to assess the generalizability of results from randomized trials. *The Journal of the Royal Statistical Society, Series A, 174*(2), 369 - 386. Tipton, E. (2013). Improving generalizations from experiments using propensity score subclassification: Assumptions, properties, and contexts. *Journal of Educational and Behavioral Statistics,* 38, 239 - 266. Hedges, L.V. (2017). Challenges in building usable knowledge in education. *Journal of Research on Educational Effectiveness*, 1 - 21. Ioannidis, J.P. (2005). Why most published research findings are false. *PLoS Medicine, 2*(8), e124. **Topics** • External validity and generalization • Replication and reproducibility
15	12/13	Student presentations