Causal Inference in Applied Econometrics

last update: July 17, 2023

Course description
Many of the big questions in the social sciences (and economics) deal with cause and effect. How does immigration affect pay and employment levels? How does a longer education affect someone's future income? These questions are difficult to answer because we have nothing to use as a comparison. We do not know what would have happened if there had been less immigration or if that person had not continued studying.
However, the Laureates of the Nobel Prize in Economics in 2021 - David Card, Joshua Angrist, and Guido Imbens - have shown that it is possible to answer these and similar questions using natural experiments. The key is to use situations in which chance events or policy changes result in groups of people being treated differently, in a way that resembles clinical trials in medicine.
If you are curious about how economists can draw plausible conclusions about cause and effect I invite you to join this course. The course covers core methods and seminal applications dealing with causal inference.
We will work though assumptions, diagnostics, practical examples and code in Stata (and/or R if available). Moreover, students will present and discuss applications or extensions of such designs with practical examples from recent papers.

Syllabus

1. Introduction and Potential Outcome Framework
2. Randomized Controlled Trials
3. Matching and Linear Regression
4. Instrumental Variables
5. Regression Discontinuity Designs
6. Difference-in-Differences
7. Synthetic Control Method

Course Work
Active participation in the course
Presentation (approx. 10 minutes) and discussion of a research paper

Contact Prof. Dr. Mirjam Stockburger (Mirjam.Stockburger@wi.jlu.de)
material accessible via: https://jlubox.uni-giessen.de/getlink/fiVLTs35pQS5CSocnsQn13r2/

Preliminary Schedule
The course will take place from Monday, October 09 to Thursday, October 12; 09:30 to 17:00 at the Justus Liebig University Giessen (room tba).

	time	room	topic
Monday	09:30 – 11:00	tba	intro; PO
(Oct-09)	11:15 – 12:45	tba	RCT
	14:00 – 17:00	tba	Match + Reg
Tuesday	09:30 – 11:00	tba	present + discuss
(Oct-10)	11:15 – 12:45	tba	IV
	14:00 – 17:00	tba	IV + RDD
Wednesday	09:30 – 11:00	tba	present + discuss
(Oct-11)	11:15 – 12:45	tba	RDD + DiD
	14:00 – 17:00	tba	DiD
Thursday	09:30 – 11:00	tba	DiD
(Oct-12)	11:15 – 12:45	tba	SCM
	14:00 – 17:00	tba	present + discuss

Literature (preliminary; to be updated)

Literature to Causal Inference in general:

- Angrist, J. D., and Pischke, J. S. (2014). *Mastering 'Metrics: The Path from Cause to Effect.* Princeton University Press.
  (online material)

- Angrist, J. D., and Pischke, J. S. (2013). *Mostly Harmless Econometrics. An Empiricist's Companion.* Princeton University Press.
  (MHE – online access)

- Cunningham, S. (2021). *Causal inference: The Mixtape.* Yale University Press.
  (The Mixtape – online access)

- Huntington-Klein, N. (2021). *The Effect: An Introduction to Research Design and Causality.* CRC Press.
  (The Effect – online access)

- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data.* MIT press. (Chapter 18: Estimating Average Treatment Effects)
  (Panel-Wooldridge – online access)

Potential Outcome Framework:

- Neyman, J. S. (1923). On the application of probability theory to agricultural experiments. Essay on principles. section 9.(translated and edited by D. M. Dabrowska and T.P. Speed, Statistical Science (1990), 5, 465-480). *Annals of Agricultural Sciences*, 10:1–51

- Fisher, R. A. (1935). The Design of Experiments. *Oliver and Boyd, Edinburgh*
- Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford economic papers*, 3(2):135–146
- Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology*, 66(5):688

Randomized Controlled Trials:

- Baicker, K., Taubman, S. L., Allen, H. L., Bernstein, M., Gruber, J. H., Newhouse, J. P., Schneider, E. C., Wright, B. J., Zaslavsky, A. M., and Finkelstein, A. N. (2013). The oregon experiment-effects of medicaid on clinical outcomes. *New England Journal of Medicine*, 368(18):1713–1722
- Carter, S. P., Greenberg, K., and Walker, M. S. (2017). The impact of computer usage on academic performance: Evidence from a randomized trial at the united states military academy. *Economics of Education Review*, 56:118–132
- Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J. P., Allen, H., Baicker, K., and Group, O. H. S. (2012). The oregon health insurance experiment: evidence from the first year. *The Quarterly journal of economics*, 127(3):1057–1106
- Krueger, A. B. (1999). Experimental estimates of education production functions. *The quarterly journal of economics*, 114(2):497–532
- Taubman, S. L., Allen, H. L., Wright, B. J., Baicker, K., and Finkelstein, A. N. (2014). Medicaid increases emergency-department use: evidence from oregon's health insurance experiment. *Science*, 343(6168):263–268

Matching Methods:

- Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *econometrica*, 74(1):235–267
- Cochran, W. G. (1968). The effectiveness of adjustment by subclassification in removing bias in observational studies. *Biometrics*, pages 295–313
- Crump, R. K., Hotz, V. J., Imbens, G. W., and Mitnik, O. A. (2009). Dealing with limited overlap in estimation of average treatment effects. *Biometrika*, 96(1):187–199
- Diamond, A. and Sekhon, J. S. (2013). Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. *Review of Economics and Statistics*, 95(3):932–945
- Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55

- Shonchoy, A. (2010). Seasonal migration and the effectiveness of micro-credit in the lean period: Evidence from bangladesh. *Institute of Developing Economies Discussion paper No*, 294

Regression and Causality:

-

Instrumental Variables:

-

Regression Discontinuity Designs:

-

Difference-in-Differences:

-

Synthetic Control Method:

-