Causal Econometrics: Syllabus

47-873

Location: TQ 5219, Tuesday and Thursday 9:00-10:55AM
Instructor: David Childers dchilder@andrew.cmu.edu
Office Hours: TQ5140 or Zoom, Wednesday 2:00-3:00PM or by appointment

Course Description

This course will cover models and methods used in contemporary applied economics and related fields to identify, estimate, and evaluate causal effects and design and execute studies that can credibly evaluate policies and economic theories. Topics include potential outcomes and directed acyclic graphs formalisms for causality and recent developments in control, instrumental variables, panel data, and regression discontinuity methods, including via non- and semi-parametric methods for identification and estimation. Additional topics may be selected based on student interest. Students will apply these tools by replicating and extending recent economic research papers, with the target of developing the skills to understand, critique, and extend an empirical research design.

Motivation

A common goal of empirical research in economics and related fields is to determine the impact of realized or hypothetical interventions in order to assess theories and improve policies. Causal inference is the field which builds models of these impacts and provides tools for their estimation from data. This course will provide an overview of the main classes of modeling approaches to causal inference and econometric methods for working with these models applied in contemporary empirical economics. The focus will especially concern "credible" or "quasi-experimental" methods which attempt to isolate and measure sources of variation in the data which mimic direct application of the policies of interest. These methods, when applicable, provide measures relying on minimal and transparent assumptions and so form a *lingua franca* for persuasive scientific communication (and, increasingly, a requirement for publication in top venues). The goal will be to develop understanding of methods popularly used in empirical practice and also emerging developments likely to be useful in students' own research. To facilitate this applied focus, assignments will be based on understanding, replicating, and extending contemporary applied economic research papers, and content may be tailored towards methods useful in students' particular research areas.

Prerequisites

This is an advanced PhD level course and assumes proficiency with probability, regression, maximum likelihood and/or extremum estimation. Have some mathematical maturity: expect calculus, linear algebra, and some deltas and epsilons. If you took 47-811 you'll be fine; sufficiently advanced statistics classes could substitute. You should know how to code in some statistical or data analytic programming language or be willing to learn quickly. Knowing or being willing to learn something about social science, economics, finance, marketing, accounting, or some related field will probably be helpful for motivating the ideas in this class.

Topics

- Research design and methods
- Causality: Theoretical Frameworks
  - Potential outcomes
  - Structural equation models
- Experiments
  - Randomization, design, power, balance
- Control
  - Conditional randomization, overlap, adjustment formula
  - Backdoor criterion, bad control
  - Regression, weighting
- Estimation and Inference
  - Nonparametric or machine learning regression/density estimation
  - Semiparametric functional estimation "Double ML"
- Instrumental variables
  - Wald estimand, 2SLS, conditional Wald
  - Weak IV, overidentification
  - LATE, heterogeneity, Marginal treatment effect curve
- Difference in differences and Panel data
  - Event studies, staggered implementation, conditional trends
  - Unobserved components model, Fixed effects and interpretations
  - Sequential confounding
- Regression discontinuity
  - Identification, bandwidth, inference, manipulation tests, extensions

Possible optional topics

- Distributional outcomes
  - Quantile/distribution regression and treatment effects, conditional density estimators
- Time series
  - Missing intercept problem, VARs, sequential dependence
- Sample selection and external validity
  - Heckit, selection diagrams, selection on observables
- Mechanisms, links to structural models
  - Mediation, scaling, moments for validation and testing
- SUTVA violations
  - Networks, clusters, general equilibrium
- Online methods
  - Bandits, sequential and adaptive data collection, "off-policy-evaluation"
- Learning optimal policies
- Bayes
- More about any of the main methods (could do extra classes on IV, DiD, etc)

Software

Class lecture notes and examples will be written in R via RMarkdown. Due to prevailing norms and practices in empirical economics, papers to be replicated will primarily have code in Stata, while methods papers will primarily provide code in R. Students may use any programming language they like for assignments but should attain sufficient code literacy to be able to follow the main steps in code written in either of these two languages. Resources for language learning will be made available on request.

To interact with R and Rstudio files files, students should install the freely available and open source R programming language from https://www.r-project.org/ and may wish to also use the free RStudio IDE from https://www.rstudio.com/ or the online version at https://www.rstudio.com/products/cloud/. Stata is commercial software; if you are unable to obtain a valid license, you can still interact with stata data files through R libraries such as `readstata13` and `haven` and process .do and .ado files as text.

Assignments

2x: partial paper replication and evaluation

- Read/skim an AER/QJE paper using the technique for its main result
- Get the data and replicate the main specification
- Then evaluate result based on assumptions of method using paper description or own evaluation of
  - Institutional background and theory
  - Data collection and construction
  - Formal tests of properties
- Propose ways it could be done better, if possible

Final option 1: large scale replication - Include all of above, but for full paper, and adding substantial new analysis

Final option 2: research proposal - Propose research question - Describe data sources and identification strategy to answer question - Implement code for method and set of validation checks

Assessment:

- Replications: 30%
- Class Participation: 10%
- Final project: 60%
  - Presentation 10%
  - Paper: 50%
- Grades will be assigned via the standard Tepper graduate grade scale (A/A-/B+/B/B- etc).

Timeline

- 10/19: Causal Frameworks
- 10/21: Experiments
- 10/26: Adjustment: estimation
- 10/28: DAGS, do calculus, backdoor
  - Assign replication 1
  - Experimental or adjustment paper: replicate main result, show sensitivity to assumptions, apply DR methods for comparison
  - Due Nov 4?
- 11/2: Semiparametrics: general theory
- 11/4: Instrumental variables
- 11/8: Difference in differences/panel data
- 11/10: Regression Discontinuity
- 11/16: Bonus Topic I
  - Submit idea for topic of research proposal/paper choice for extended replication
- 11/18: Bonus Topic II
  - Assign replication 2
  - IV or DiD paper: replicate main result, show sensitivity to assumptions, apply DR methods for comparison

  - Due Nov 23?
- 11/23: Bonus Topic III
- 11/30: Bonus Topic IV
- 12/2: Present preliminary research proposals/replication results
- Finals period: write up results

Policies

- Be honest, take care of yourselves, be respectful of others (including by following Covid mitigation protocols), ask for help when you need it. CMU policies on all these topics are in effect.
- Group work is fine, encouraged even: just acknowledge your collaborators and cite your sources.

Causal Inference References: General

Monographs

- Angrist and Pischke (2008): Agenda-setting text for applied microeconometric research in past decade. Opinionated, reasonably detailed, but focused on applications rather than mathematics. For better or for worse, you need to be able to think like Josh Angrist to understand and publish empirical work in this area. Focus on potential outcomes approach and methods commonly used in economics.
- Cunningham (2021): Informal introduction to applied methods. Heavy on intuition, lighter on technical material. Provides extensive code and data examples in R and Stata.
- Hernán and Robins (2020): Balanced coverage of potential outcome and DAG methods. Focus is on methods used in biostats and epidemiology. Practically, this means that they are willing to assume selection on observables even in cases where it would get your paper desk rejected from an economics journal. But in the cases you are willing to accept that, they have better estimators.

Class notes

- Goldsmith-Pinkham (2021): Advanced graduate class in applied econometrics. Close in content and style to what's attempted here
- Samii (2021): Advanced graduate class in modern applied causal inference, targeted at political scientists. Up-to-date and fairly comprehensive on topics relevant to applied researchers.
- Petersen and Balzer (2014): Biostatistics approach to causal inference, particularly adjustment methods.
- Wager (2020): Advanced graduate class in statistical methods for causal inference, from a potential outcomes perspective but covering some more frontier topics including machine learning methods.

Readings by Class

Requested and optional readings by class topic. **Bold** text indicates the main suggested reading for the corresponding topic.

Causal inference: Intro

- **Survey of methods economists use in practice: Abadie and Cattaneo (2018): Start here**
- The causal hierarchy and what we can and can't learn from causal models: Bareinboim et al. (2020)
- On "structural" vs "reduced form": Haile (2020)

Experiments

- **Practical guide to designing and analyzing field experiments from JPAL: Glennerster and Takavarasha (2013)**
  - Skim, or read just Ch2 if in a hurry, but read the whole thing on your plane ride to Busia, Kenya or Matlab, Bangladesh if you're actually going to run an experiment

- Analysis of RCT data: Wager (2020) Ch1
- Application: Recht (2021) on data analysis for Bangladesh masking RCT

Adjustment and control

- **Adjustment by control and propensity scores Wager (2020) Ch 2-3**
  - Regression, IPW, Augmented IPW: see also Hernán and Robins (2020) Ch3 on identification, Ch12-13 on estimation
- Assessing and managing overlap: D'Amour et al. (2021), Khan and Tamer (2010)

- Software: Kennedy (2021): *npcausal*

DAGs

- **Intro to DAGs and backdoor criterion: Kelleher (2016)**
- Do-calculus basics: Nielsen (2012), Wager (2020) Ch13
- **Tutorial on backdoor and bad controls Cinelli, Forney, and Pearl (2020)**
- Short book on DAG approach: Pearl, Glymour, and Jewell (2016)
- Monograph from original progenitor: Pearl (2009)
- Software: identification via `dagitty`: Textor et al. (2016), plotting with `ggdag`: Barrett (2021)

Semiparametric Estimation and Inference

- **General "Double ML" approach: Chernozhukov et al. (2018)**
  - Notes on special cases: ATE/ATT estimation: Chernozhukov et al. (2017), LASSO for linear regression Chernozhukov, Hansen, and Spindler (2015)
  - Software: Bach et al. (2021), Kennedy (2021)
- How to find an influence function: Hines et al. (2021)
- Machine learning methods to use: Athey and Imbens (2019)
- Alternate perspective: TMLE, Super learner, etc Petersen and Balzer (2014)
  - Software: Targeted learning and `tlverse` (Laan et al. 2021)

Instrumental variables

- Binary treatment binary instrument: Wald estimator and LATE theorem: Angrist, Imbens, and Rubin (1996)
  - Covariates: Conditional Wald
- Binary treatment continuous instrument: "Marginal Treatment Effects" Possebom, Wager (2020) Ch 9-10
- Continuous treatment continuous instrument: NPIV Newey and Powell (2003), Bennett, Kallus, and Schnabel (2019)
- Weak IV: Andrews, Stock, and Sun (2019)

Difference-in-Differences and Panel Data

- Tutorials: General: Zeldow (2019), Event Study and Staggered outcome: Baker (2019)
- **Staggered rollout: Outcome, IPW, and DR: Callaway and Sant'Anna (2020b)**
  - Software: `did` (Callaway and Sant'Anna 2020a), for one period DR case: `drdid` (Sant'Anna and Zhao 2020),
- Interpretation of TWFE with heterogeneity: De Chaisemartin and d'Haultfoeuille (2020)
- Parallel trends robustness: Rambachan and Roth (2019)
- Sequential confounding under selection on observables Blackwell and Glynn (2018), Hernán and Robins (2020) section III

Regression discontinuity

- Comprehensive collection of software, surveys, and extensions: Calonico et al. (2021)
  - **Practical guidebook to basics: Matias D. Cattaneo, Idrobo, and Titiunik (2019)**
  - Overview tutorial: Matias D. Cattaneo (2020)
- Related but distinct setup: bunching Kleven (2016)

Selection Bias and external validity

- **Identification across environments Hünermund and Bareinboim (2019)**
- Transportability across environments in DAG framework: Bareinboim and Pearl (2016)
  - Software: https://causalfusion.net/ (must request access)
- Application: metanalysis: Meager (2019)

Time Series

- **Impulse responses, local projections, and VARs: Ramey (2016)**
- Potential outcomes interpretation of IRFs: Rambachan and Shephard (2020)
- IPW estimator: Angrist, Jordà, and Kuersteiner (2018)
- Structural interpretation of IPW: Kocherlakota (2019)
- LP vs VAR: Plagborg-Møller and Wolf (2021)
- Local projection IV Stock and Watson (2018)

Distributional outcomes

- Quantile regression and quantile treatment effects: Koenker (2005)
  - Quantiles *of* treatment effects are not identified Firpo and Ridder (2019)
  - Multiply robust estimators of: Belloni et al. (2017) (maybe also Kallus, Mao, and Uehara (2019))
- Estimation: Distribution regression, Quantile random forests Meinshausen and Ridgeway (2006), etc

- Decomposition of distributions (survey): Fortin, Lemieux, and Firpo (2011)
  - Estimating counterfactual distributions: Chernozhukov, Fernández-Val, and Melly (2013)

Mechanisms and links to structural models

- Validating structural theories with causal evidence Ashworth, Berry, and Mesquita (2021), Andrews, Gentzkow, and Shapiro (2020)
  - Application in macroeconomics Nakamura and Steinsson (2018)
  - Application in labor economics Todd and Wolpin (2021)

- Mediation in DAGs: Direct/indirect effects, frontdoor, etc.

Online methods

- **video Tutorial on Bandits and online experiments for economists: Athey (2021)**
  - Algorithms: UCB, Thompson Sampling Wager (2020) Ch14
- Online and adaptive learning
  - Algorithms: Hedge/Exponential weights/Exp3, FTRL
- Online experiments vs off-policy evaluation
  - Updating from observational data

Learning optimal policies

- **Empirical Welfare Maximization and extensions Wager (2020) Ch11**
  - Based on Kitagawa and Tetenov (2018), Athey and Wager (2021)
  - Software: *policytree* Sverdrup et al. (2020)
- Dynamic Treatment Regimes Wager (2020) Ch12
  - Survey: Chakraborty and Murphy (2014)
- Criteria: Bayes, Minimax regret

Bayes

- Bayesian estimation using classical identification approaches
  - Tutorial on Bayesian adjustment: Oganisian and Roy (2021)
  - Bayesian regression algorithms: BART. Hill (2011)
- Bayes under small samples or weak/partial identification
  - Sharing info via random effects: shrinkage via (empirical) Bayes
  - Bayesian decision theory

SUTVA violations: Interactions and spillovers

- I don't know this area as well as I should but we can learn together
- Networks and local spillovers: Samii (2021) Ch21 and references therein
- General equilibrium and global spillovers
  - Berry and Haile (2021) on simultaneity, some very recent Wager et al papers

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