Causal Inference

Mixtape Session

Roadmap

- Counterfactuals and causality
  - Causality and models
  - Potential outcomes
  - Randomization and selection bias
  - Randomization inference
- Directed Acyclic Graphs
  - Graph notation
  - Backdoor criterion
  - Collider bias
  - Front door criterion
  - Concluding remarks

References

Material drawn from a number of sources

- Speech by Card on model and design based approaches to empirical micro
- Lewbel (2019), “Identification Zoo”
- Netto (2021), “Experiments in the Armchair: History of Microeconometrics and Program Evaluation”
- Nobel Prize 2021 scientific document, “Answering Causal Questions using Observational Data”

Causality and model

What role, if any, did models come play in causal identification? Empirical micro is split on two philosophical approaches

- **Model**: Causality is model-based. It only exists within the framework of a theory that says “X causes Y” (e.g., Heckman)
- **Design**: Causality is design-based. A claim about causality requires that you design a manipulation in which “X causes Y” (e.g., Rubin)

Models

All models are wrong but some are useful – George Box

- Economists use models to take an otherwise infinitely complex world and place it into something simpler which we hope helps us understand it paradoxically
- Economists believe theirs are useful to understanding market behavior and resource allocation, which leads to public policy

Economist's models

Economics models typically contain the following

- Preferences, choice and objectives
- Constraints
- Endogenous choice variables (e.g., bundles of goods)
- Over what time horizon, the level of aggregation
- Equilibrium

Three economic models within empirical micro

1. **Approximating models**: Consumer demand, labor supply models (e.g., Mincer 1958; 1974)
   - → Theory implies $y_i = f_i(x_i)$ with restrictions on f_i (e.g., concavity)
   - → Researcher estimates a simpler version

$$y_i = \alpha + x_i\beta + \varepsilon_i$$

2. **Exact models**: Models gives us all causes ("complete DGP")
   - → Utility, heterogenous taste, complete demand
   - → Estimate model parameters and distribution of heterogeneity
   - → Functional form, useful for welfare analysis
3. **Working model**: Program evaluation (e.g., Ashenfelter), non-market behavior (e.g., Levitt)
   - → No precise model is used or relied on
   - → Structural outcome model with signed coefficients

Causality and labor economics

- **Mid-century**: Macro and linear systems of equations, identification problems (e.g., Sargan tests, union wage effects)
- **1970s**: Micro data shows up, McFadden's logit, Heckman's selection model, Becker, Mincer
- **1980s**: Econometric critiques like the Lucas critique, Leamer "specification searching", LaLonde (1985) critiques program evaluation, Lewis dismisses IV and Heckit models
- **1980s/1990s**: Design emerges within the Princeton labor group, randomized instruments, natural experiments, "plausibly exogenous", RDD, difference-in-differences

Princeton and design

- Princeton becomes ground zero for design approach (Ashenfelter); Chicago and others model approach (Heckman)
- Rising poverty; Albert Rees brings in micro data; advises Orley Ashenfelter
- Ashenfelter focuses on program evaluation, job trainings program, invents difference-in-differences (though John Snow did it 100 years before)
- Extensive mentoring: David Card, Bob LaLonde, Josh Angrist, Janet Currie, Philip Levine, Pischke, and on and on
- Other faculty: Alan Krueger, Guido Imbens, Don Rubin
- Adoption of potential outcomes (Krueger notes the NEJM and medical concepts)

Credibility revolution wins

- Design approach becomes the dominant causal framework in economics, particularly the “applied micro” fields like labor, health, development
- Nobel Prizes (Vernon Smith, Bannerjee, Duflo, Kremer, Card, Angrist, Imbens)
- Structural wins too though (Deaton) so the debate still rages

2021 Nobel Prize

- David Card (1/2) for empirical labor
- Josh Angrist (1/4) for causal inference (specifically 1990s papers on IV)
- Guido Imbens (1/4) for causal inference (same as Angrist)

Design contributions

What are the broad contributions of the design approach to causal inference?

- Counterfactuals and causality; research design outlines an “explicit counterfactual”, randomization is best, credible instruments are second best
- Substantive specification tests: randomization tests in RCTs like balance across covariates, pre-treatment comparisons, event studies, falsification
- Replication, data warehouses, journal storage of programs, pre-registration

Design limitations

Design approach tends to have limitations though

- Stable Unit Treatment Value Assumption (SUTVA)
- Partial equilibrium and marginal effects only
- Heterogenous treatment effects and LATE
- Short-run (“well-defined counterfactuals” break down)
- Straight-forward predictions disappear (e.g., minimum wage)

Identification

Competing approaches between two schools of econometric thought

- **Design**: Emphasized credible identification with testing and evaluating of assumptions (e.g., pre-trends, smoothness using covariates, McCrary density test)
- **Model**: Functional form, exclusion, calibration

Confidence differs

Schools of thoughts use their models in very different ways

- **Design**: Testable predictions like minimum wage reduces employment
- **Model**: Stipulate complete models where the goal is to estimate parameters, do welfare analysis, maybe out-of-sample predictions

Topics

Reliance (or lack thereof) shapes what topics the two schools select

- **Design**: Anything, “economics is what economists study”, happiness, fringe stuff (e.g., sex work)
- **Model**: Neoclassical topics due to needing models

Design vs Model

- Nowadays, design based approaches tend to be divided into two approaches that confusingly are also called design vs model!
- Design approaches emphasize randomization, includes RCT, IV and matching
- Model approaches place restrictions on potential outcomes like parallel trends (DiD), smoothness (RDD), factor models (synthetic control)
- Both use an underlying causal model called “potential outcomes” which we discuss now