Program Evaluation(a): Intro and Notation

Chris Conlon

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Applied Econometrics

Overview

This set of lectures will cover (roughly) the following papers:
Theory:

- Angrist and Imbens (1994)
- Heckman Vytlacil (2005/2007)
- Abadie and Imbens (2006)

And draw heavily upon notes by

- Guido Imbens
- Richard Blundell and Costas Meghir

The Evaluation Problem

- The issue we are concerned about is identifying the effect of a policy or an investment or some individual action on one or more outcomes of interest
- This has become the workhorse approach of the applied microeconomics fields (Public, Labor, etc.)
- Examples may include:
  - The effect of taxes on labor supply
  - The effect of education on wages
  - The effect of incarceration on recidivism
  - The effect of competition between schools on schooling quality
  - The effect of price cap regulation on consumer welfare
  - The effect of indirect taxes on demand
  - The effects of environmental regulation on incomes
  - The effects of labor market regulation and minimum wages on wages and employment

Potential Outcomes

- Consider a binary treatment $T_i \in \{0, 1\}$.
  - Some people use $D_i \in \{0, 1\}$ instead.
- We observe the outcome Y_i. But there are two potential outcomes
  - $Y_i(1)$ the outcome for i if they are treated.
  - $Y_i(0)$ the outcome for i if they are not treated (control).
- We are generally interested in $\beta_i \equiv Y_i(1) - Y_i(0)$ which we call the treatment effect.
  - Individuals have heterogeneous treatment effects.
  - In an ideal world we could fully characterize $f(\beta_i)$

Some Challenges

Stable unit treatment value assumption (SUTVA)

- We assume a *ceteris paribus* version of treatment effects
- We need β_i to be a policy invariant (structural) parameter.
- Your β_i doesn't respond to whether or not another individual is treated.
- Two common limitations:
  - Peer effects: Whether you respond to job training program depends on whether your spouse is also treated.
  - Equilibrium effects: if we sent everyone to college, returns to college would be quite different.

Some Challenges

Fundamental Problem of Causal Inference

- We don't observe the counterfactual $Y_i(T_i)$.
- For a single individual we either observe $Y_i(1)$ or $Y_i(0)$ but never both!
  - ex: We don't see what your wage would have been if you didn't attend college.
  - ex: We might know your cholesterol before you took Lipitor, but we don't know what it would be today if you didn't take Lipitor.

$$Y_i = T_i Y_i(1) + (1 - T_i) Y_i(0)$$

i	$Y_i(1)$	$Y_i(0)$	T_i	Y_i
1	1	?	1	1
2	0	?	1	0
3	?	0	0	0
		$\vdots$		
n	?	1	0	1

Structural vs. Reduced Form

- Usually we are interested in one or two parameters of the distribution of β_i (such as the average treatment effect or average treatment on the treated).
- Most program evaluation approaches seek to identify one effect or the other effect. This leads to these as being described as reduced form or quasi-experimental.
- The structural approach attempts to recover the entire joint $f(\beta_i, u_i)$ distribution but generally requires more assumptions, but then we can calculate whatever we need.

Treatment Effects Parameters

Most approaches to estimating treatment effects will recover some moments of $f(\beta_i)$ instead of the entire distribution

Average Treatment Effect (ATE) corresponds to $\mathbb{E}[\beta_i]$.

Average Treatment on Treated (ATT) corresponds to $\mathbb{E}[\beta_i | T_i = 1]$.

Average Treatment on Control/Untreated (ATUT) corresponds to $\mathbb{E}[\beta_i | T_i = 0]$.

We also have that if the probability of treatment $Pr(T_i = 1) = \pi$

$$ATE = \pi \cdot ATT + (1 - \pi) \cdot ATUT$$

Local Average Treatment Effects

Another important object is the Wald Estimator

$$Wald = \frac{\mathbb{E}[Y_i|Z_i = 1] - \mathbb{E}[Y_i|Z_i = 0]}{\mathbb{E}[T_i|Z_i = 1] - \mathbb{E}[T_i|Z_i = 0]}$$

This is useful because under some conditions it corresponds to the 2SLS estimate of Y_i on T_i with binary instrument Z_i.

$$Y_i = \alpha + \beta_i \cdot T_i + u_i$$

$$T_i = \lambda + \pi_i \cdot Z_i + e_i$$

Intent to Treat

We can decompose the numerator and the denominator of the Wald Estimator

$$Wald = \frac{\mathbb{E}[Y_i|Z_i = 1] - \mathbb{E}[Y_i|Z_i = 0]}{\mathbb{E}[T_i|Z_i = 1] - \mathbb{E}[T_i|Z_i = 0]} = \frac{ITT}{ITT_d}$$

- Intent to Treat (numerator) tells us how outcome responds directly to the instrument.
- Intent to Treat "D" (denominator) tells us how treatment probability responds directly to the instrument.

Often people we report the numerator in addition to other parameters.

Local Average Treatment Effects

Under conditions we will explore later in detail 2SLS delivers the local average treatment effect (LATE):

$$\widehat{\beta}_1^{TSLS} \to^p \frac{\mathbb{E}[\beta_i \pi_i]}{\mathbb{E}[\pi_i]} = LATE$$

$$LATE = ATE + \frac{Cov(\beta_i, \pi_i)}{\mathbb{E}[\pi_i]}$$

- Weighted average for individuals for whom Z_i pushes them into treatment (compliers).
- Places more weight on individuals with larger π_i
- Relationship to ATE depends on correlation between (β_i, π_i).

The Selection Problem

- Let's start with the easy cases: run OLS and see what happens.

$$Y_i = \alpha + \beta_i \cdot T_i + u_i$$

- OLS compares mean of treatment group with mean of control group (possibly controlling for other X)

$$\begin{aligned} \beta^{OLS} &= E(Y_i|T_i = 1) - E(Y_i|T_i = 0) \\ &= \underbrace{E[\beta_i|T_i = 1]}_{\text{ATT}} + \left(\underbrace{E[u_i|T_i = 1] - E[u_i|T_i = 0]}_{\text{selection bias}} \right) \end{aligned}$$

- Even in absence of heterogeneity $\beta_i = \beta$ we can still have selection bias.
- $Y_i^0 = \alpha + u_i$ may vary within the population (this is quite common).

Why worry about selection?

Unless we have random assignment...

$$Y_i = \alpha + \beta_i T_i + u_i$$

- People often choose T_i with β_i in mind.
- The problem: $T_i \perp u_i$ and/or $T_i \perp \beta_i$ are likely violated.
- We can get positive or negative selection bias:
  - e.g. Who goes to college? those likely to benefit more than most!
  - e.g. who gets risky surgeries/drugs? people who are very sick.

What's next?

Even the simple cases here are pretty tough (Binary treatment, binary (or no) instrument).
How do we construct counterfactuals that we don't observe?

- Matching
- Regression Adjustment
- Instrumental Variables
- Panel Data