Public Policy Evaluation
Lecture 0: Introduction

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Licence 3 in Economics, ENS Paris-Saclay

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Outline

Who am I ?

Yao Thibaut Kpegli

- Temporary Lecturer and Researcher at ENS Paris Saclay
- Consultant at The World Bank

Research interest

- Decision Science, Health Economics, West Africa, Applied Econometrics

Contact

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Organization

Lectures

- 9 lectures of 3h each
- 9h30 - 12h30 (3h)
- From March 6 to April 10
- No separate tutorial sections:
    - lectures include applications on Python, R, and Stata

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- Final Exam (50 %)

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Materials

- Lecture slides + references
- e-campus or my website

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Public Policy

Public Policy: intervention on a targeted population with the aim of inducing a change in outcomes variables

Examples:

- Politique d'Education Prioritaire (ZEP)
- Active Labor Market Programs (ALMPs)
- Tax Reforms on Tobacco Products (TRTPs)
- Scholarship Program (PACES)

Impact evaluation

Impact evaluation: establishing a causal link between a public policy and changes in outcomes

- Does ZEP improve education outcomes? If so, how much?
- Does PACES improve education outcomes? If so, how much?
- Do the ALMPs improve labor market outcomes? If so, how much?
- Do the TRTPs increase the price and decrease consumption? If so, how much?

Interests of impact evaluation

- To measure the effectiveness of public policies
  - Does the ZEP have intended effects?
- To improve knowledge
  - Specific tax is more effective than ad valorem tax in increasing price and reducing consumption of tobacco
- To help policymakers in designing (or improving) public policies
  - ZEP improved since 1981
  - West African countries learned the importance of introducing specific taxes on tobacco in addition to ad valorem taxes and started doing

Difficulties: selection issues

Participation status in a public policy does not often result from a random process

- Policy placement: policymakers determine beneficiaries of the policy based on socio-demographic characteristics
  - Priority area status of ZEP is determined based on the concentration of disadvantaged populations and low academic results.
- Self-selection: beneficiary status of the intervention is an individual decision (open entry)
  - Unemployed individuals have the freedom to participate in ALMPs

Difficulties: selection issues

Do hospitals make people healthier?

- Health status (assigning 1 to excellent and a 5 to poor)

Group	Sample Size	Mean health status	Std. Error
Hospital	7774	2.79	0.014
No hospital	90049	2.07	0.003

Source: Angrist and Pischke (2008)

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- A simple comparison of means suggests that going to the hospital makes people sicker
  - not impossible: hospitals are full of other sick people who might infect us, and dangerous machines and chemicals that might hurt us.
- Self-selection: people who go to the hospital are probably less healthy to begin with.

The evaluation problem - Rubin's causal model

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- Could we compute Δ_i ?

	Treated ($\mathbf{T}_i = 1$)	Untreated ($\mathbf{T}_i = 0$)
Observed	$\mathbf{Y}_{1i}$	$\mathbf{Y}_{0i}$
Unobserved (counterfactual)	$\mathbf{Y}_{0i}$	$\mathbf{Y}_{1i}$

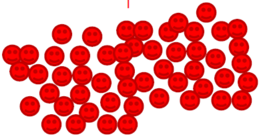
Fundamental problem of causal inference

You could observe either $\mathbf{Y}_{1i}$ or $\mathbf{Y}_{0i}$, but never both.

The evaluation problem - Rubin's causal model

T_i=1

T_i=0



Average of Treated

$E[\mathbf{Y}_i|\mathbf{T}_i = 1] = E[\mathbf{Y}_{1i}|\mathbf{T}_i = 1]$

Average of unreated

$E[\mathbf{Y}_i|\mathbf{T}_i = 0] = E[\mathbf{Y}_{0i}|\mathbf{T}_i = 0]$

- The causal effect of the treatment on the treated is

$$ATT = E[\mathbf{Y}_{1i}|\mathbf{T}_i = 1] - E[\mathbf{Y}_{0i}|\mathbf{T}_i = 1]$$

- We can not compute ATT as $E[\mathbf{Y}_{0i}|\mathbf{T}_i = 1]$ is unobserved

The evaluation problem - Rubin's causal model

- As we do not observe $E[\mathbf{Y}_{0i}|\mathbf{T}_i = 1]$, we could (as in Hospital example) use a naive estimator based on what we observed:

$$NE = E[\mathbf{Y}_{1i}|\mathbf{T}_i = 1] - E[\mathbf{Y}_{0i}|\mathbf{T}_i = 0]$$

- We can rewrite the naive estimator as:

$$NE = \underbrace{E[\mathbf{Y}_{1i}|\mathbf{T}_i = 1] - E[\mathbf{Y}_{0i}|\mathbf{T}_i = 1]}_{ATT} + \underbrace{E[\mathbf{Y}_{0i}|\mathbf{T}_i = 1] - E[\mathbf{Y}_{0i}|\mathbf{T}_i = 0]}_{\text{selection bias}}$$

- Selection bias is null if the potential outcome $\mathbf{Y}_0$ is independent of treatment status $\mathbf{T}$
    - policy placement and self-selection create selection bias.

Selection is an endogeneity issue

- Simple linear regression model:

$$
\begin{aligned}
\mathbf{Y}_i &= \mathbf{Y}_{0i} + \underbrace{(\mathbf{Y}_{1i} - \mathbf{Y}_{0i})}_{\rho}\mathbf{T}_i \\
&= \mathbf{Y}_{0i} + \rho\mathbf{T}_i \\
&= \underbrace{\alpha}_{E[\mathbf{Y}_{0i}]} + \rho\mathbf{T}_i + \underbrace{\epsilon_i}_{\mathbf{Y}_{0i} - E[\mathbf{Y}_{0i}]}
\end{aligned}
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- Naive estimator:

$$\widehat{\rho} = \rho + \underbrace{E[\epsilon_i | \mathbf{T}_i = 1] - E[\epsilon_i | \mathbf{T}_i = 0]}_{\text{endogeneity bias}}$$

Endogeneity bias = correlation between $\mathbf{T}$ and ϵ

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- Selection = Endogeneity (not exogenous)

$$E[\epsilon_i|\mathbf{T}_i = 1] - E[\epsilon_i|\mathbf{T}_i = 0] \neq 0 \Longleftrightarrow E[\mathbf{Y}_{0i}|\mathbf{T}_i = 1] - E[\mathbf{Y}_{0i}|\mathbf{T}_i = 0] \neq 0$$

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$$E[\epsilon_i | \mathbf{T}_i = 1] - E[\epsilon_i | \mathbf{T}_i = 0] \neq 0 \iff E[\mathbf{Y}_{0i} | \mathbf{T}_i = 1] - E[\mathbf{Y}_{0i} | \mathbf{T}_i = 0] \neq 0$$

- Hospital example:

Selection is an endogeneity issue

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- Hospital example: treated had poorer health outcomes in the no-treatment state

To sum up

1. The fundamental problem of impact evaluation is linked to the fact that one cannot simultaneously observe the two potential outcomes of each individual

2. The naive estimator, that is, the simple difference between the average outcomes of treated and untreated, is biased by selection effects (policy placement or self-selection).

Outline

Lectures

The course introduces widely-used impact evaluation methods designed to address selection bias:

1. Experimental methods
    - Lecture 1 - Randomized Controlled Trials (RCT)
2. Quasi-experimental methods
    - Lecture 2 - Difference-in-Differences (DID)
    - Lecture 3 - Instrumental Variables (IV)
    - Lecture 4 - Regression Discontinuity Design (RDD)
3. Non-experimental methods
    - Lecture 5 Propensity Score Matching (PSM)

References

- Angrist, J. D., Pischke, J. S. (2008). Mostly harmless econometrics. Princeton university press.
- Khandker, S. R., Koolwal, G. B., Samad, H. A. (2009). Handbook on impact evaluation: quantitative methods and practices. World Bank Publications.
- Angrist, J. D., Pischke, J. S. (2014). Mastering'metrics: The path from cause to effect. Princeton university press.
- Givord, P.(2014).Méthodes économétriques pour l'évaluation de politiques publiques. Economie prevision, (1), 1-28.
- Online course of Angrist J. Mastering Econometrics

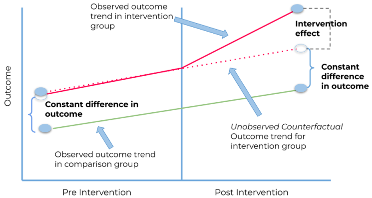
Outline

Randomized Controlled Trials (RCT)

- Randomly split the population in the treated group and untreated group (control group)
- By randomly split, the treated group and untreated group (control group) are identical statistically
- By randomly split, there is no selection issues: any variables, including potential outcomes, are independents to treatments
- Estimator: “naive” difference in means between treated an untreated individuals is an unbiased estimator of the causal effect of interest

Difference-in-Differences (DiD)

- Panel data: observe treated and untreated groups before and after intervention (treatment)
- Common trend assumption: in the absence of treatment, the difference between the two groups would be constant (“fixed”) over time
- Estimator: difference between post-treatment difference and pre-treatment difference is an unbiased estimator of the causal effect of interest



Instrumental Variables (IV)

- Instrument: a variable $\mathbf{Z}$ that satisfies two conditions
  - Relevance: $\mathbf{Z}$ affects the treatment $\mathbf{T}$
  - Exclusion: $\mathbf{Z}$ is independent of the unobserved component of the potential outcomes ϵ
- Variations in the treatment $\mathbf{T}$ caused by $\mathbf{Z}$ are independent to unobserved component of the potential outcomes
- Estimator: instrumented difference in means between treated and untreated individuals is an unbiased estimator of the causal effect of interest

Regression Discontinuity Design

- Several assignment to treatment are based on cutoffs
  - excellence scholarships are based on cutoff
- Treated and untreated individuals around the cutoff are considered to be similar (identical) in characteristics
- Being treated or untreated is independent to characteristics of individuals
- Estimator: difference in means around the cutoff between treated and untreated individuals is an unbiased estimator of the causal effect of interest

Propensity Score Matching (PSM)

- Matches each treated individual with a untreated “twin” who is similar in terms of observable characteristics
- Conditional Independence Assumption (CIA): treatment assignment is independent of potential outcomes after conditioning on the set of observed characteristics
- Estimator: difference in means between matched treated and untreated individuals is an unbiased estimator of the causal effect of interest

Validities

- Internal validity: discuss carefully whether identification assumptions are fulfilled when making policy evaluation
- External validity: discuss the capacity of extrapolating results to other contexts (populations, periods, countries, etc.)

Outline

Application

Understanding the effects of endogeneity on the OLS estimator

Thank you for your attention !