



# PUBLIC POLICY EVALUATION

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Licence 3 in Economics, ENS Paris-Saclay  
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# Outline

- 1 Organization
- 2 Intro
- 3 Lectures
- 4 Overview of lectures
- 5 Application

# 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:
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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      |
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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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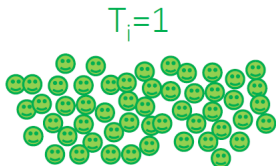
- Could we compute  $\Delta_i$  ?

|                                      | Treated ( $\mathbf{T}_i = 1$ ) | Untreated ( $\mathbf{T}_i = 0$ ) |
|--------------------------------------|--------------------------------|----------------------------------|
| Observed                             | $\mathbf{Y}_{1i}$              | $\mathbf{Y}_{0i}$                |
| Unobserved ( <b>counterfactual</b> ) | $\mathbf{Y}_{0i}$              | $\mathbf{Y}_{1i}$                |

Fundamental problem of causal inference

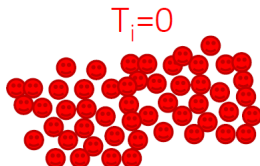
You could observe either  $\mathbf{Y}_{1i}$  or  $\mathbf{Y}_{0i}$ , but never both.

# The evaluation problem - Rubin's causal model



Average of Treated

$$E[Y_i | T_i = 1] = E[Y_{1i} | T_i = 1]$$



Average of untreated

$$E[Y_i | T_i = 0] = E[Y_{0i} | T_i = 0]$$

- The causal effect of the treatment on the treated is

$$ATT = E[Y_{1i} | T_i = 1] - E[Y_{0i} | T_i = 1]$$

- We can not compute ATT as  $E[Y_{0i} | T_i = 1]$  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:

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

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- Selection = Endogeneity (not exogenous)

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

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- Hospital example:

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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).

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# 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)



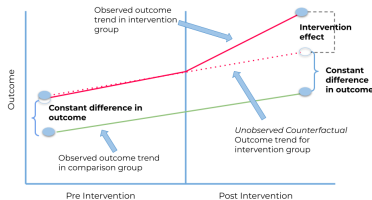


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# Randomized Controlled Trials (RCT)

- 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 independent to treatments
- Estimator: “naive” difference in means between treated and untreated individuals 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  $\epsilon$
- 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.)

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# Application

Understanding the effects of endogeneity on the OLS estimator

Thank you for your attention !