Quantitative Economics for the Evaluation of the European Policy

Department of economics and management

Co-funded by the Erasmus+ Programme of the European Union

Project funded by
European Commission Erasmus + Programme –Jean Monnet Action
Project number 553280-EPP-1-2015-1-IT-EPPJMO-MODULE

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21/11/2016

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What is causality?

- How does the type of school affect a childs later achievements?
- Do vocational training programs increase trainees' incomes?
- Economic incentives improve occupatioanl safety?

A causal question is a simple question involving the relationship between two theoretical concepts: a cause and an effect.

- Cause $\Longrightarrow$ Effect? or Does X cause Y?

Why is causality so important?

- The primary aim of all sciences.
- Understanding of causal relationships leads to accurate predictions of the future.
- It provides the scientific basis for policy intervention.
- It advances our theoretical knowledge of the world.

Why evaluate?

- Programs and policies are usually designed to change outcomes, for example, to increase incomes, to reduce unemployment, or to raise human capital.
- Understand if these changes are achieved is a crucial question.
- Learn to evaluate the impact of programs/policies helps you to address interesting and policy-relevant questions from many different areas.

Program evaluation

Program evaluation is the systematic process of studying a program, or a policy, to discover how well it is working to achieve intended goals.

The **goal** in program evaluation is to assess the causal effect of public policy interventions.

Examples include effects of:

- Job training programs on earnings and employment.
- Class size on test scores.
- Minimum wage on employment.
- Military service on earnings and employment.

Preliminary questions

To measure the effect of a program/policy is essentially to understand:

- **Effect about what?**: identify the **outcome-variable**.
- **Effect of what?**: specify the **treatment-variable**.
- **Effect for whom?**: identify the **target population**.

Causality with potential outcome

Treatment:
D_i : Indicator of treatment intake for unit i

$$D_i = \begin{cases} 1, & \text{if unit } i \text{ received the treatment} \\ 0, & \text{otherwise} \end{cases}$$

Outcome:
Y_i : Observed outcome variable of interest for unit i.

Potential Outcomes:
Y_{0i} and Y_{1i} : Potential outcomes for unit i.

Y_{1i}: Potential outcome for unit i with treatment;
Y_{0i}: Potential outcome for unit i without treatment (the **counterfactual**).

Causality with potential outcome

Treatment Effect

The treatment effect or causal effect of the treatment on the outcome for unit i is the difference between its two potential outcomes:

$$\Delta_i = Y_{1i} - Y_{0i}$$

Observed Outcomes

Observed outcomes are realized as:

$$Y_i = Y_{1i} D_i + Y_{0i}(1 - D_i) \tag{1}$$

$$\text{or } Y_i = \begin{cases} Y_{1i}, & \text{if } D_i = 1 \\ Y_{0i}, & \text{if } D_i = 0 \end{cases}$$

An example

Imagine a population with 4 units

Table: A numerical example

i	D_i	Y_i	Y_{1i}	Y_{0i}	Δ_i
1	1	3	3	0	3
2	1	1	1	1	0
3	0	0	1	0	1
4	0	1	1	1	0

Connection to linear model

How to estimate the effect of treatment?

- Suppose we wish to measure the impact of treatment on an outcome, Y. For the moment, we abstract from other covariates that may impact on Y.
- D is the treatment indicator: a dummy variable assuming the value 1 if the individual has been treated and 0 otherwise.
- The potential outcomes for individual i at any time t are denoted by Y_{1it} and Y_{0it}.
- These outcomes are specified as:

$$\begin{aligned} Y_{1it} &= \beta + \rho_i + \epsilon_{it} \; if \; D_{it} = 1 \\ Y_{0it} &= \beta + \epsilon_{it} \; if \; D_{it} = 0 \end{aligned} \tag{2}$$

where β is the intercept parameter, ρ_i is the effect of treatment on individual i and ϵ is the unobservable component of Y.

Connection to linear model

The observable outcome is then:

$$Y_i = Y_{1i} D_i + Y_{0i}(1 - D_i)$$

so that

$$Y_{it} = \beta + \rho_i D_{it} + \epsilon_{it} \tag{3}$$

where $\mathbf{E}(\epsilon) = 0$ and $cov(\epsilon, D) = 0$. Estimating Eq.(3) by OLS we obtain the estimate of the causal effect of D.

Identification problem for causal inference

Fundamental Problem of Causal Inference
Cannot observe both potential outcomes (Y_{1i}, Y_{0i}) $\Longrightarrow$ How can we find $Y_{1i} - Y_{0i}$?

A large amount of homogeneity would solve this problem:

- (Y_{1i}, Y_{0i}) constant across individuals;
- (Y_{1i}, Y_{0i}) constant across time.

- Unfortunately, often there is a large degree of heterogeneity in the individual responses to participation in public programs/policy.

Quantities of interest

Instead of the individual treatment effect, we might be interested in the **average treatment effect** (ATE):

$$\begin{aligned}\alpha_{ATE} &= \mathbf{E}[Y_{1i} - Y_{0i}] \\ &= \mathbf{E}[Y_{1i}] - \mathbf{E}[Y_{0i}]\end{aligned} \tag{4}$$

- If $ATE > 0 \Longrightarrow \mathbf{E}[Y_{1i}] > \mathbf{E}[Y_{0i}] \Longrightarrow$ The policy is good;
- if $ATE < 0 \Longrightarrow \mathbf{E}[Y_{1i}] < \mathbf{E}[Y_{0i}] \Longrightarrow$ The policy is bad;
- if $ATE = 0 \Longrightarrow \mathbf{E}[Y_{1i}] = \mathbf{E}[Y_{0i}] \Longrightarrow$ The policy has no impact

BUT we can not find the ATE because of the unobserved potential outcomes.

Average Treatment Effect (ATE)

Imagine a population with 4 units:

Table: A numerical example

i	D_i	Y_i	Y_{1i}	Y_{0i}	Δ_i
1	1	3	3	0	3
2	1	1	1	1	0
3	0	0	1	0	1
4	0	1	1	1	0
$\mathbf{E}[Y_1]$			1.5		
$\mathbf{E}[Y_0]$				0.5	
$\mathbf{E}[\Delta]$					1

$$\alpha_{ATE} = \mathbf{E}[\Delta] = 3 * (1/4) + 0 * (1/4) + 1 * (1/4) + 0 * (1/4) = 1$$

Quantities of interest

We might also be interested in the **average treatment effect on the treated** (ATET):

$$\begin{aligned} \alpha_{ATET} &= \mathbf{E}[Y_1 - Y_0 | D = 1] \\ &= \mathbf{E}[Y_{1i} | D = 1] - \mathbf{E}[Y_{0i} | D = 1] \end{aligned} \tag{5}$$

BUT we can not find the ATET because of unobserved potential outcomes.

Average Treatment Effect on the Treated (ATET)

Imagine a population with 4 units:

Table: A numerical example

i	D_i	Y_i	Y_{1i}	Y_{0i}	Δ_i
1	1	3	3	0	3
2	1	1	1	1	0
3	0	0	1	0	1
4	0	1	1	1	0
$\mathbf{E}[Y_1 \vert D = 1]$			2		
$\mathbf{E}[Y_0 \vert D = 1]$				0.5	
$\mathbf{E}[\Delta \vert 1]$					1.5

$$\alpha_{ATET} = \mathbf{E}[\Delta|D = 1] = 3 * (1/2) + 0 * (1/2) = 1.5$$

ATE vs ATET

- ATE is relevant when the treatment has universal applicability.
- ATET is relevant when we want to consider the average gain treatment for the treated.

Estimating ATE

Both Y_{0i} and $(Y_{0i}|D = 1)$ are unobserved $\Longrightarrow$ we can estimate the ATE as:

$$\begin{aligned} A\hat{T}E &= E[Y_{1t} - Y_{0c}] \\ &= E[Y_{1t}] - E[Y_{0c}] \end{aligned} \tag{6}$$

where Y_{1t} is the outcome of treated and Y_{0c} is the outcome of untreated (the **control group**). Both **quantities are observed**.

We basically find the average Y for observations that received treatment and average Y for observations that received control.

Selection bias

What are we measuring if we compare the outcomes for the treated to the untreated? Is this the causal effect we want (i.e., the effect of treatment on the outcome)? NO

$$\begin{aligned} \mathbf{E}[Y|D=1]-\mathbf{E}[Y|D=0] &= \mathbf{E}[Y_1|D=1]-\mathbf{E}[Y_0|D=0] \\ = \mathbf{E}[Y_1|D=1]-\mathbf{E}[Y_0|D=1] &+ \mathbf{E}[Y_0|D=1]-\mathbf{E}[Y_0|D=0] \\ = \underbrace{\mathbf{E}[Y_1-Y_0|D=1]}_{\text{ATET}} &+ \underbrace{\mathbf{E}[Y_0|D=1]-\mathbf{E}[Y_0|D=0]}_{\text{BIAS}} \end{aligned} \tag{7}$$

where the bias term is the difference between no-treatment outcomes of individuals that are treated and those that are not treated.

- If no selection bias, then we get the ATET. The ATET is of interest but note that it is not the same as the ATE (except in special cases).
- If there is selection bias, estimate of the ATE based on comparing the average outcomes of the treated to the untreated will be misleading (biased).

Selection Bias

Bias term is not likely to be zero for most public policy applications.

The **goal** is to minimize/eliminate it.

Sources of selction bias

- **Self-selection**;
- **Targeting**;
- **Observables** vs. **Unobservables**.

Assumptions for unbiased estimate

What assumptions do we need for the estimate to be unbiased?

- Stable Unit Treatment Value Assumption (SUTVA);
- Unconfoundedness/ignorability.;

Stable Unit Treatment Value Assumption (SUTVA)

The **stable unit treatment value assumption** (SUTVA) assumes that:

- the treatment status of any unit does not affect the potential outcomes of the other units (**non-interference**);
- the treatments for all units are comparable (**no variation in treatment**).

Violations:

- Vaccination (interference);
- Fertilizer A and B on crop yield, but each fertilizer has a lot of versions (variation in treatment).

This assumption may be problematic, so we should choose the units of analysis to minimize interference across units.

Unconfoundedness/Ignorability

Conditional independence assumption:
Given a vector of observable variables **x** (vector of covariates), the assumption states that, conditional on **x**, the outcomes are independent of treatment:

$$(Y_1, Y_0) \perp D|\mathbf{x} \tag{8}$$

Unconfoundedness (strong ignorability):

$$(Y_1, Y_0) \perp D \tag{9}$$

Treatment assignment is **independent** of the outcomes (Y). Technically, unconfoundedness is a stronger assumption. Most people just say ignorability.

Violations:

- Omitted Variable Bias

Assignment mechanism

Assignment Mechanism

Assignment mechanism is the procedure that determines which units are selected for treatment intake. Examples include:

- random assignment;
- selection on observables: **matching, Diff-in-Diff, regression discontinuity**;
- selection on unobservables: **control function approach, instrumental variable estimation**.

Most models of causal inference attain identification of treatment effects by restricting the assignment mechanism in some way.

Key ideas

- Causality is defined by potential outcomes, not by realized (observed) outcomes;
- Estimation of causal effects of a treatment (usually) starts with studying the assignment mechanism.

Readings

- Textbook: J.D. Angrist and J.S. Pischke (2015), *Mastering 'Metrics: The Path from Cause to Effect*; Princeton University Press.
- Imbens, G.W. and J.M. Wooldridge (2009) *Recent Developments in the Econometrics of Program Evaluation*, Journal of Economic Literature, Vol. 47(1), 5-86.
- Holland P.W. (1986) *Statistic and Causal Inference*, Journal of the American Statistical Association, Vol.81(396).

Lectures slides and reading lists are available from the website:
http://qe4policy.ec.unipi.it