Part I: Introduction to Econometrics

Causal Inference

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Cause and Effect

The first order priority of today's empirical work: **Causal Inference**

- In other words: **Ceteris Paribus**, does A cause B?
- Definition of "Ceteris Paribus": all other things remaining constant.
- e.g., All else equal, does your attendance to today's lecture increase your final grade on this course?

A **causal relationship** is useful for making predictions about the consequences of changing circumstances or policies.

- It tells us what would happen in alternative worlds $\Rightarrow$ **Counterfactual**.

Counterfactual

We can only observe the path you have taken:

- i.e., attending today's lecture and your final outcome.

But we can't observe the counterfactual (alternative scenarios) at the same time:

- In this case, what would happen, if you skip today's lecture.

We'll come back to this when introducing **potential outcome framework**.

A Motivating Example

Does your attendance to today's lecture increase your final grade on this course?

- To answer this question, we need a group of students that are enrolled in this course.
- Suppose half of the class decided to attend today's lecture, and the other half skipped today's lecture.
- Then after the final evaluation: we can compare the average final grade for those who attended today's lecture to those who did not.

Q: Can we claim the difference of average final grade between two groups is the **causal effect** of attending today's lecture on the final grade of this course?

Ceteris Paribus

The answer is **No**.

- We need to ensure all other things remaining constant
- We are unsure about whether two groups follow the same learning trajectory: e.g., completing homework assignments, effort invested in studying the course materials, attendance to the subsequent lecture...

Q: What if we know after today's lecture, two groups followed the same learning trajectory, can we claim the difference as **causal effect**?

Selection Problem

The answer is still **No**.

- Because students may come from different academic background
- More able students may do well regardless of their attendance to one particular lecture.
- On the other hand, more motivated students may be more willing to attend lecture and invest more in course materials and do better in the final evaluation.

We are comparing **oranges** to **apples**: students are **not identical**!

A Video Explanation

- MRU: Ceteris Paribus
- MRU: Selection Bias

Does Hospital Make You Sicker?

Imagine we're studying a poor elderly population that uses hospital emergency rooms for primary care.

- This sort of care is expensive and crowds hospital facilities
- Essentially, we want to know whether this sort of care is **effective**?

What's your thought on the effectiveness of hospitals?

Pros and Cons of Admitted to Hospitals

- Exposure to other patients by make those who are already vulnerable may have a net **negative** health effect.
- Well, admission to hospitals make get them many valuable services, and timely health monitoring.

So what does the data tell us?

Pulling Data from National Health Interview Survey 2024

- We extract all adult population.
- Create a variable called **hospital**: if emergency room visit during the past 12 months is more than once.
- Health Status is coded from 1 to 5.
- With 1 for Excellent; 2 for very good; 3 for good; 4 for fair; 5 for poor $\Rightarrow$ The higher number, the worse health status
- Then we tabulate the mean and standard error of health status for both groups: who visited hospital in the past 12 months vs those who did not.

Does Hospital Make You Sicker?

- The mean health status of hospital visit group is worse than those who did not visit the hospital

Group	Sample Size	Mean Health Status	Standard Error
Hospital	6946	2.94	1.12
No Hospital	25387	2.35	1.00

Can we claim that hospitals make you sicker?

- **People who go to the hospital are probably less healthy to begin with**!

Does Hospital Make You Sicker Redux?

Consider a group of people,



They make a choice for either receiving hospital treatment or not.

Potential Outcomes

They can two potential outcomes:

- health status of hospital visit (blue):



- health status of no hospital visit (green):

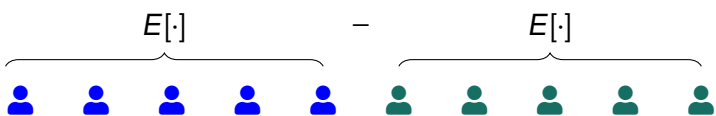


Observed Outcomes

But in reality we only observe one potential outcome for every individual, such as



So the raw difference of mean health status between two groups are:



Mean health status of hospital visit **minus** mean health status of no hospital visit.

Counterfactual

Define the counterfactual health status of those seek hospital visit:

- What we observe for hospital visit group:



- Their counterfactual health status is:



Counterfactual, cont

Similarly for no hospital visit group:

- What we observe for no hospital visit group:



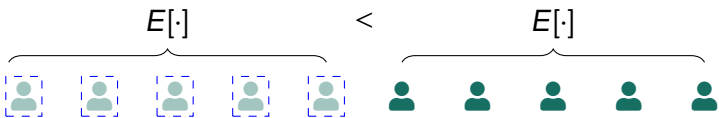
- Their counterfactual health status is:



Causal Effect and Selection Bias

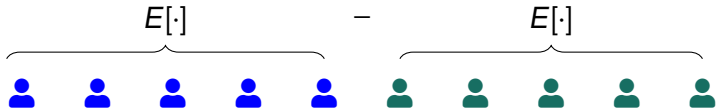
The raw mean health status difference masks the true causal effect due to selection bias:

- Selection bias: hospital visit group may have a worse health status to begin with:

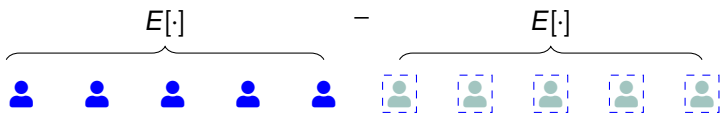


Raw Difference Decomposition

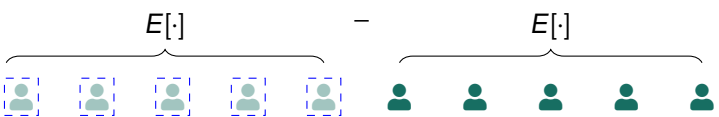
- The raw difference:



- Can be decomposed into two parts:
  - **Average treatment effect on treated**:

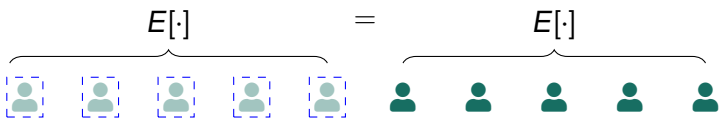


  - **Selection bias**:



Random Assignments Solves the Selection Problem

- If we can randomly assign people to hospital treatment:



- Thus, raw difference of mean health status is the true causal effect.

Potential Outcome Framework

- Let's define hospital treatment as a binary random variable D_i.
- Binary means it can only take two values: $D_i = \{0, 1\}$, either you go to hospital or not.
- The outcome of our interest is a measure of health status, Y_i.
- The question is whether Y_i is affected by hospital care D_i. And in which direction?

Potential Outcome

- Now, assume that we can imagine what might have happened to someone who went to hospital if they had not gone, and vice versa.
- In other words, we can imagine the health status of hospital visit and no hospital visit, regardless an individual who actually went.

$$\text{Potential Outcome} = \begin{cases} Y_{1i}, & \text{if } D_i = 1, \\ Y_{0i}, & \text{if } D_i = 0. \end{cases}$$

- If we take the difference between Y_{1i} and Y_{0i}, we get the causal effect of hospital visit on health status.

Observed Outcome

- However, in reality, we only observe **one** potential outcome: either the outcome of you visit hospital, or the one of no visit.
- The potential outcome that we didn't observe is the **counterfactual**.
- Observed outcome can be written in terms of potential outcome:

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

Expressing Raw Differences in Conditional Means

- So, if we compare the mean observed outcome between two groups, we are comparing two conditional means:

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0]$$

- When $D_i = 1$, we observe the potential outcome of hospital visit Y_{1i}
- When $D_i = 0$, we observe the potential outcome of no hospital visit Y_{0i}
- Thus,

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0]$$

Causal Effect and Selection Bias

- We add and subtract $E[Y_{0i}|D_i = 1]$ on the right hand side, we get

$$\begin{aligned} E[Y_i|D_i = 1] - E[Y_i|D_i = 0] &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0] \\ &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1] \\ &+ E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0] \end{aligned}$$

- We can $E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1]$ **average treatment effect on treated**
- And $E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]$ as **selection bias**

Treatment vs Control

- Remember we define hospital treatment, thus we call hospital visit as a **treatment**.
- Those who visited hospital are called **treatment group**, because they received treatment.
- And we call those who did not go to hospital as **control group**.

Causal Effect and Selection Bias

- Note that we don't observe $E[Y_{0i}|D_i = 1]$ in reality.
- And the sick are more likely to seek treatment, which results in a negative selection bias $E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]$.
- Thus, the observed negative mean difference between two groups masked the **true causal effect** of hospital treatment.

So what could we do?

Random Assignment

- Random assignment solves the selection problem.
- (Actually, we also need law of large number for this to work).
- If we randomly assign people into hospital treatment, then D_i is independent of Y_i

$$\begin{aligned} E[Y_i|D_i = 1] - E[Y_i|D_i = 0] &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0] \\ &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1] \\ &= E[Y_{1i} - Y_{0i}|D_i = 1] \end{aligned}$$

More on Randomized Control Trials (RCT)

- It is important to use RCT to test the effectiveness of a treatment (e.g., drug, vaccine, etc.).
- MRU: RCT