Randomization

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Where are we? And what are we at?

We've completed the first part of the course: Congrats!

- Our focus has been on *describing* data: GLMs
- Now, we'll focus on *research design*: causal inference

The goal of the social sciences

Why do we run regressions?

We run regressions to learn about the world, which means...

- To describe data $\rightarrow$ observe the world
  - ... but how do we know if it's not an illusion?
- To make causal claims $\rightarrow$ manipulate the world
  - ... in the social sciences, that's not always possible

$\Rightarrow$ *We design studies to approximate manipulation*

We want to make causal claims

Two (compatible) approaches.

- **Logic of inference:** (King, Keohane and Verba, 1994)
  - We can only imperfectly observe the world
  - ... but we can theorize (causal mechanism)
  - ... and test hypotheses (observable implications)

$\Rightarrow$ *A closer connection between theory and statistics (e.g. EITM).*

We want to make causal claims

Two (compatible) approaches.

- **Logic of inference:** (King, Keohane and Verba, 1994)
- **Potential outcomes** (Donald Rubin)

What is causation?

A sequence of events in which – if the first didn't happend – the second wouldn't occur either.

- We can manipulate the first event $\rightarrow$ what happens then?
- Can we infer what *would have* happened if we did not manipulate?

$\Rightarrow$ *Potential outcomes*

We want to make causal claims

Two (compatible) approaches.

- **Logic of inference:** (King, Keohane and Verba, 1994)
- **Potential outcomes** (Donald Rubin)
  - *causal effect*: difference between what is and could have been

$\Rightarrow$ *a set of methods designed for causal inference with observational data*

The conundrum

The true causal effect

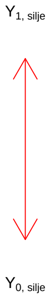
What is causal effect?

Imagine two versions of me.

- I have a headache and I take an aspirine ($Y_{1,Silje}$).
- I have a headache but receive no treatment ($Y_{0,Silje}$).

$\Rightarrow$ *the causal effect is* $Y_1 - Y_0$

True causal effect



A causal effect is the difference between two potential outcomes

- ... but – at best – I can only observe one outcome.

True causal effect is NOT POSSIBLE to observe

A causal effect is the difference between two potential outcomes

- ... but – at best – I can only observe one outcome.

⇒ *We have to compare two different individuals*

Plan B

Plan B: Can we compare across cases?

Let's compare my headache now with Øyvind's current headache ($Y_{1,Silje} - Y_{1,Oyvind}$)

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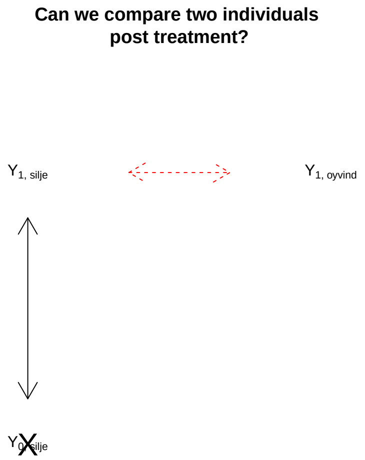
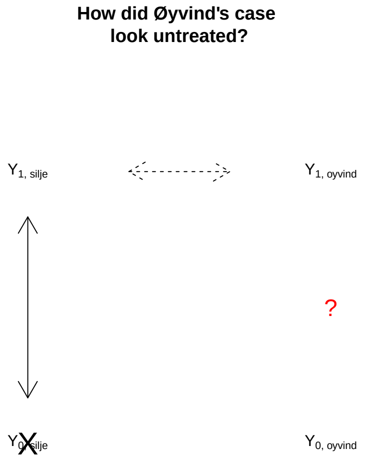


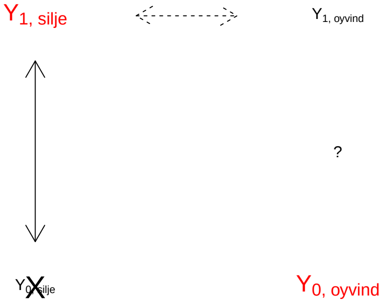
Let's compare my headache now with Øyvind's current headache ($Y_{1,Silje} - Y_{1,Oyvind}$)

- ... but did he even have a headache before?

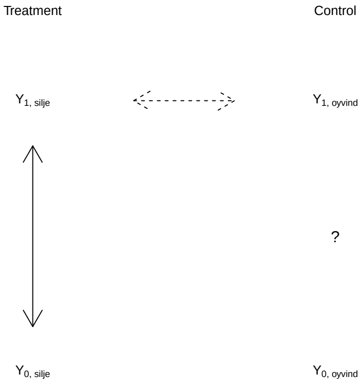
Is there a selection bias?



How did Øyvind's case look untreated?



What do we compare?



Where's the selection bias?

The solution

We have to observe Øyvind's untreated headache ($Y_{0,Oyvind}$) and compare with treated me ($Y_{1,Silje}$)

$$\begin{aligned} Y_{Silje} - Y_{Oyvind} &= Y_{1,Silje} - Y_{0,Oyvind} \\ &= Y_{1,Silje} - Y_{0,Silje} + Y_{0,Silje} - Y_{0,Oyvind} \end{aligned} \tag{1}$$

- **Causal effect**: $Y_{1,Silje} - Y_{0,Silje}$
- **Selection bias**: $Y_{0,Silje} - Y_{0,Oyvind}$

How to do it?

We use statistics

We cannot observe two potential outcomes, but we can rely on the law of large numbers (LLN).

- We use **average** causal effect

Average causal effect = Differences in means - Selection bias

Differences in means

- We create a **dummy** for treated vs. untreated observations:

$$D_i = \begin{cases} 1 & \Leftrightarrow & \mathit{treated} \\ 0 & \Leftrightarrow & \mathit{untreated} \end{cases} \tag{2}$$

- We calculate the **differences in means**

$$= Avg_n[Y_i|D_i = 1] - Avg_n[Y_i|D_i = 0] \tag{3}$$

Differences in means

- We create a **dummy** for treated vs. untreated observations:

$$D_i = \begin{cases} 1 & \Leftrightarrow & treated \\ 0 & \Leftrightarrow & untreated \end{cases} \tag{4}$$

- We calculate the **differences in means**

$$\begin{aligned} &= Avg_n[Y_i|D_i = 1] - Avg_n[Y_i|D_i = 0] \\ &= Avg_n[Y_{1,i}|D_i = 1] - Avg_n[Y_{0,i}|D_i = 0] \end{aligned} \tag{5}$$

Basic assumption

We have to assume that the treatment has the same effect accross all units

- then we can compare across units
- contrast that with the effect of β in OLS vs GLM

Selection bias

Now we have to get rid of the selection bias!

- **A priori** selecting units without bias: randomization
- **A posteriori** assessing the bias and extract it: Rubin's contribution

Why not just compare?

Consider the fate of young mothers

https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(16)31411-8/fulltext

The gold standard

Randomization

Randomization is the gold standard. This requires

- manipulation $\rightarrow$ experiments
- a sufficient number of units (LLN) $\rightarrow$ statistical power

$\Rightarrow$ *Randomization eliminates bias*

Checking on observables

Even when we randomize, we check for signs of selection bias

- we cannot observe the bias
- but we can check the balance of possible correlates (of bias)

$\Rightarrow$ *Here comes the social science theories back in!*

Checking on observables

Even when we randomize, we check for signs of selection bias

$\Rightarrow$ *We verify the balance of pre-treatment variables*

The post hoc fixes