Randomized Controlled Trials (RCT)

USAID MENA Advanced MEL Workshop

2024-06-11

Welcome!

- Who we are
- What we do
- How we hope to help you

Objectives of impact evaluation sessions

- Understand the need for impact estimation of USAID activities
- Understand how impact estimation fits into the Agency performance management framework
- Gain practical knowledge about impact evaluation to help USAID staff better manage and support IEs

Benchmarks for success

By the end of this session, participants will be able to:

- Understand selection bias as a fundemantal difficulty in identifying a valid counterfactual
- Identify randomization as the most effective means of identifying the counterfactual
- Understand the key validity threats to Randomized Controlled Trials (RCTs)
- Identify the key points in the RCT management cycle to identify and mitigate these threats

Benchmarks for success

Bonus content:

- Randomization vs. Optimization
- Longitudinal data

Level Set

Measuring social benefit

We want to know the causal effect of an activity on its beneficiaries

- Job training on earnings and employment
- Teacher qualifications on student outcomes
- Humanitarian assistance on food security

Identifying a treatment assignment

- We established indicators for treatment assignment D_i and an outcome of interest Y_i
- We established the switching equation $Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0$ mapping a potential treatment assignment to a realized outcome
- We re-wrote the switching equation to $Y_i = Y_i^0 + (Y_i^1 - Y_i^0) D_i$ in order to highlight the individual treatment effect term $\delta_i = Y_i^1 - Y_i^0$

The treatment assignment mechanism

- We stressed a distinction between treatment *assignment* and the treatment assignment *mechanism*
- Why is this distinction so important?
- Because many activities we evaluate target specific sub-samples of a broader population
  - The poor
  - The marginalized
  - The conflict-affected
- We can't just compare these participants to a randomly selected member of the population!

Capturing the treatment assignment mechanism

- We start with the individual treatment effect $\delta_i = Y_i^1 - Y_i^0$
- We take the average of all individual treatment effects

$$E[\delta] = E[Y^1 - Y^0]$$

- We take the difference in averages, rather than the average of the differences

$$E[Y^1 - Y^0] = E[Y^1] - E[Y^0]$$

Averages of effects

unit	y0	y1	y1 - y0
1	12	18	6
2	15	13	-2
3	9	22	13
4	20	19	-1
Average	14	18	4

$$E[\delta] = E[Y^1 - Y^0] = E[6, -2, 13, -1] = 4$$

$$E[\delta] = E[Y^1] - E[Y^0] = 18 - 14 = 4$$

Difference-in-means estimator

- Finally, we incorporate the treatment assignment indicator D_i and call it the *difference-in-means estimator*

$$E\big[\delta\big] = E\big[Y^1 - Y^0\big]$$

$$E\big[Y^1 - Y^0\big] = E\big[Y^1\big] - E\big[Y^0\big]$$

$$E\big[Y^1\big] - E\big[Y^0\big] = E\big[Y^1|D=1\big] - E\big[Y^0|D=0\big]$$

Real world data!

unit	y0	y1	y1 - y0
1	?	18	?
2	15	?	?
3	?	22	?
4	20	?	?
Average	17.5	20	2.5

$$E[\delta] = E[Y^1 - Y^0]$$

$$E[Y^1 - Y^0] = E[Y^1] - E[Y^0]$$

$$E[Y^1] - E[Y^0] = E[Y^1|D=1] - E[Y^0|D=0]$$

$$= 20 - 17.5 = 2.5$$

Decomposing the difference in means

What do we know about the treatment assignment mechanism for these groups?

To find out, we decompose the *difference-in-means* estimator into the following:

$$E[Y^1|D=1] - E[Y^0|D=0]$$

$$= E[Y^1] - [Y^0]$$

$$+ E[Y^0|D=1] - E[Y^0|D=0]$$

$$+ (1-\pi)(ATT - ATU)$$

Decomposing the difference-in-means

$E[Y^1] - [Y^0]$ Average Treatment Effect (ATE)

$E[Y^0|D=1] - E[Y^0|D=0]$ Selection bias

$(1-\pi)(ATT - ATU)$ Heterogneous treatment effects

Randomization solves the selection problem