Policy Evaluation - Estimating Treatment Effects

March 12, 2024

Policy Evaluation - Assessing Evidence

- What criteria should we use to assess existing evidence?
  - Strength of the methodology
    - Does the evidence provide a causal interpretation?
    - Is the evidence rooted in the appropriate historical context?
  - Quality of the data
  - External validity

Policy Evaluation - Assessing Evidence

- Describe the differences between a sample study, and observational study, and an experiment.

Policy Evaluation Outline

- **Steps for conducting a quantitative policy evaluation.**

1. Develop a research question (hypothesis).
   - 1a. Assess the existing evidence.
   - 1b. What is your contribution?
2. Develop a research strategy.
   - 2a. Empirical methodology.
   - 2b. Cost effectiveness/benefit/utility analysis.
3. Identify appropriate data.
   - 3a. Primary vs. secondary data.
   - 3b. Cross-sectional vs. panel (longitudinal) data.
   - 3c. Power analysis?
4. Engage funders/stakeholders.
5. Construct an analytic sample (i.e., data management).
   - 5a. STATA, SAS, R, SQL, Excel, etc.
6. Conduct data analysis.
7. Report findings.

Policy Evaluation - Estimating Treatment Effects

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$$ATE = Avg_n[Y_i^1 - Y_i^0]$$

  Where Y_i^1 is the *potential* outcome for person i with treatment and Y_i^0 is the *potential* outcome for person i without treatment.

Estimating Treatment Effects

- Suppose we're interested in the effect of a new surgical intervention ($D_i = 1$) for cancer on longevity compared to standard chemotherapy ($D_i = 0$).

Outcomes for ten patients receiving surgery (Y^1) or chemotherapy (Y^0)

Patient	Y^1	Y^0
1	7	1
2	5	6
3	5	1
4	7	8
5	4	2
6	10	1
7	1	10
8	5	6
9	3	7
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- Problem: We can never obtain the ATE this way because we don't observe the ***counterfactual***.

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- Estimated Effect of treatment on Y:

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  - Average Treatment Effect for the Untreated:

$$ATU = Avg_n[Y_i^1|D_i = 0] - Avg_n[Y_i^0|D_i = 0]$$

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- With no independence:

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

where π is the share of the sample receiving treatment.

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  - Sometimes called *omitted variable bias*.
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  - To the extent that we can observe and control for these correlates, then our estimates are free from bias (e.g., economy).
  - If these correlates are unobserved, then our estimates will be biased (e.g., risk aversion).

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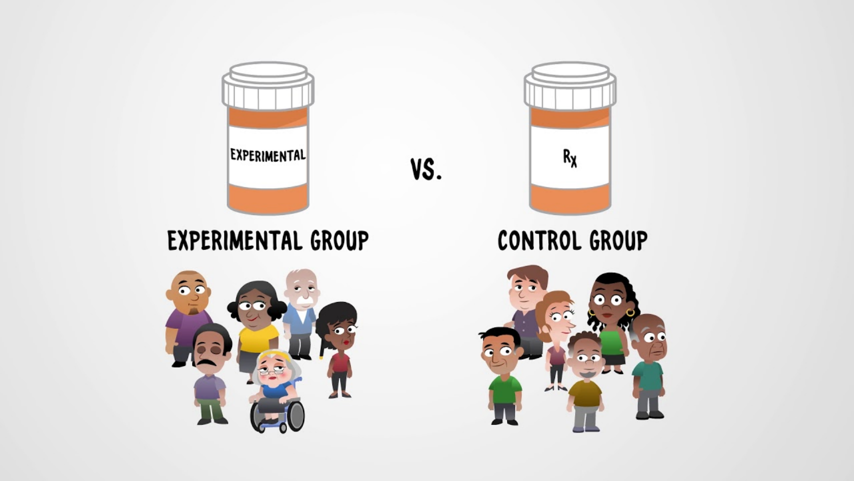

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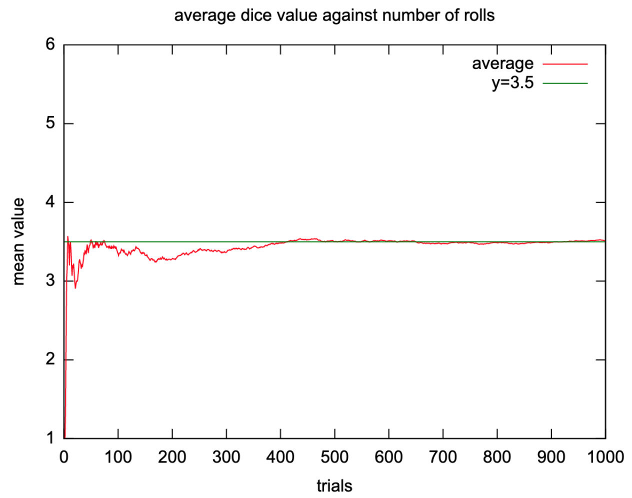
- **IMPORTANT:** This only works when the sample is "sufficiently large".

Policy Evaluation - Randomization

- Law of Large Numbers:



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- Note that "sufficiently large" depends on the population mean and standard deviation of the outcome of interest.

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- But...in policy analysis it's often (though not always) impossible to randomize individuals in our sample into treatment?
- How can we attempt to identify causal effects of policy when randomization is infeasible?