Threats to the internal validity of randomized experiments

Fill In Your Name

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Core assumptions

Attrition

Non-compliance

Spillovers

Hawthorne effect

Non-excludability



Key points for this lecture

- Attrition (missing data on outcomes)
- Non-compliance
- Spillovers
- Hawthorne effects
- Differential treatment of treatment arms



Core assumptions



Review of core assumptions

- 1. Excludability
- 2. Non-interference
- 3. Random assignment of subjects treatment



Attrition



Attrition (missing data on outcomes)

- Some units may have missing data on outcomes (= units attrit) when:
 - some respondents can't be found or refuse to participate in endline data collection.
 - some records are lost.
- This is a problem when treatment affects missingness.
 - For example, units in control may be less willing to answer survey questions.
 - For example, treatment may have caused units to migrate and cannot be reached
- If we analyze the data by dropping units with missing outcomes, then we are no longer comparing similar treatment and control groups.



What can we do?

- Check whether attrition rates are similar in treatment and control groups.
- Check whether treatment and control groups have similar covariate profiles.
- Do not drop observations that are missing outcome data from your analysis.
- When outcome data are missing we can sometimes **bound** our estimates of treatment effects.



What can we do?

- But the best approach is to try to anticipate and prevent attrition.
 - Blind people to their treatment status.
 - Promise to deliver the treatment to the control group after the research is completed.
 - Plan ex ante to reach all subjects at endline.
 - Budget for intensive follow-up with a random sample of attriters.



Missing data on covariates is not as problematic

- Missing background covariates (i.e.,variables for which values do not change as a result of treatment) for some observations is less problematic.
 - We can still learn about the causal effect of an experiment without those covariates, as we saw in the Hypothesis Testing and the Estimation modules.
 - We can also use the background covariate as planned by imputing for the missing values.
 - We can also condition on that missingness directly.



Non-compliance



Non-compliance

- Sometimes units assigned to treatment don't take it. They don't comply with their assignment.
 - If all units assigned to control do not take the treatment, but only some units assigned to treatment take the treatment, we have one-sided non-compliance.
- The effect of treatment assignment is not the same as the effect of receiving the treatment.
- The effect of receiving the treatment is often called the "Local Average Treatment Effect" (LATE) or "Complier Average Causal Effect" (CACE).
 - "Local" refers to the idea that the effect only occurs on the people who take the treatment when assigned to treatment (the kinds of people).



$\mathsf{LATE}/\mathsf{CACE}$

- We need two assumptions to hold in order to estimate LATE/CACE from a randomized experiment.
- 1. The exclusion restriction is that the assignment to treatment only has an effect on the outcome through the receipt of treatment and through no other channels.
- The monotonicity assumption is that we do not have any defiers – units that would take the treatment if assigned to control, but not take the treatment if assigned to treatment.



Spillovers



Spillover and interference between units

- Sometimes we suspect that treatment assigned to one unit affects other units' outcomes.
- If the treatment status of a unit affects another unit's outcome, we have a violation of one of the core assumptions for causal inference.
- You might sample units that are far from each other to prevent the "transmission" of treatment across units.



Studying spillover effects

- This is not a problem if you design a study to investigate spillovers in which a unit's outcomes may depend on other units' treatment status.
- To investigate spillovers:
 - You might collect outcome data for units that were never eligible for random assignment to treatment but for which nearby units from which spillovers might occur were eligible for treatment.
 - You might use a two-stage randomization design.
 - You might assign collections of units (e.g., districts) to different levels of intensity of treatment (e.g., different proportions of villages in districts assigned to treatment).



Hawthorne effect



Hawthorne effect

- The Hawthorne effect: knowing that one is being observed/studied can lead subjects to behave differently.
- This could create systematic measurement error in both treatment and control groups.
- It could also result from greater attention given to the treatment group, effectively undoing the creation of equivalent treatment and control groups through randomization.



Good practices

- Collect data as unobtrusively as possible.
- As much as possible, no one other than the subject him/herself should know his/her treatment status.
- Blind enumerators/researchers to subjects' treatment status.
- Don't take extra measurements of the treatment group.



Non-excludability



Differences between treatment and control groups other than the treatment

- Handling the treatment and control groups differently means that observed differences in the outcomes between these groups may be due to the treatment and/or the different handling.
- Examples include using different instruments for data collection or additional rounds of data collection for the treatment group in an effort to obtain data on mechanisms.
- Remember to design your study and your data instruments to treat all treatment arms the same, other than the treatment itself.

