Gov 51: Randomized Experiments

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Changing minds on gay marriage

- Question: can we effectively persuade people to change their minds?
- Hugely important question for political campaigns, companies, etc.
- Psychological studies show it isn't easy.
- **Contact Hypothesis**: outgroup hostility diminished when people from different groups interact with one another.
- Today we'll explore this question the context of support for gay marriage and contact with a member of the LGBT community.
    - Y_i = support for gay marriage (1) or not (0)
    - T_i = contact with member of LGBT community (1) or not (0)

Causal effects & counterfactuals

- What does "T_i causes Y_i" mean? $\rightsquigarrow$ **counterfactuals**, "what if"
- Would citizen i have supported gay marriage if they had contact with a member of the LGBT community?
- Two **potential outcomes**:
  - $Y_i(1)$: would i have supported gay marriage if they **had** contact with a member of the LGBT community?
  - $Y_i(0)$: would i have supported gay marriage if they **didn't have** contact with a member of the LGBT community?
- **Causal effect** for citizen i: $Y_i(1) - Y_i(0)$
- **Fundamental problem of causal inference**: only one of the two potential outcomes is observable.

Sigma notation

- We will often refer to the **sample size** (number of units) as n.
- We often have n measurements of some variable: $(Y_1, Y_2, \dots, Y_n)$
- We often want sums: how many in our sample support gay marriage?

$$Y_1 + Y_2 + Y_3 + \cdots + Y_n$$

- Notation is a bit clunky, so we often use the **Sigma notation**:

$$\sum_{i=1}^{n} Y_i = Y_1 + Y_2 + Y_3 + \cdots + Y_n$$

- $\Sigma_{i=1}^{n}$ means sum each value from Y_1 to Y_n

Averages

- The **sample average** or **sample mean** is simply the sum of all values divided by the number of values.
- Sigma notation allows us to write this in a compact way:

$$\overline{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i$$

- Suppose we surveyed 6 people and 3 supported gay marriage:

$$\overline{Y} = \frac{1}{6}(1 + 1 + 1 + 0 + 0 + 0) = 0.5$$

Quantity of interest

- We want to estimate the average causal effects over all units:

$$\text{Sample Average Treatment Effect (SATE)} = \frac{1}{n}\sum_{i=1}^{n}\{Y_i(1) - Y_i(0)\}$$

- Why can't we just calculate this quantity directly?
- What we can estimate instead:

$$\text{Difference in means} = \overline{Y}_{\text{treated}} - \overline{Y}_{\text{control}}$$

  - $\overline{Y}_{\text{treated}}$: observed average outcome for treated group
  - $\overline{Y}_{\text{control}}$: observed average outcome for control group
- When will the difference-in-means is a good estimate of the SATE?

Randomized control trials (RCT)

- **Randomized control trial**: each unit's treatment assignment is determined by chance.
  - Flip a coin; draw red and blue chips from a hat; etc
- Randomization ensures **balance** between treatment and control group.
  - Treatment and control group are identical **on average**
  - Similar on both observable and unobservable characteristics.
- Control group $\approx$ what would have happened to treatment group if they had taken control.
  - $\overline{Y}_{\text{control}} \approx \frac{1}{n} \sum_{i=1}^{n} Y_i(0)$
  - $\overline{Y}_{\text{treated}} - \overline{Y}_{\text{control}} \approx \text{SATE}$

Some potential problems with RCTs

- **Placebo effects**:
    - Respondents will be affected by any intervention, even if they shouldn't have any effect.
- **Hawthorne effects**:
    - Respondents act differently just knowing that they are under study.

Balance checking

- Can we determine if randomization "worked"?
- If it did, we shouldn't see large differences between treatment and control group on **pretreatment variable**.
  - Pretreatment variable are those that are unaffected by treatment.
- We can check in the actual data for some pretreatment variable X
  - $\overline{X}_{\text{treated}}$: average value of variable for treated group.
  - $\overline{X}_{\text{control}}$: average value of variable for control group.
  - Under randomization, $\overline{X}_{\text{treated}} - \overline{X}_{\text{control}} \approx 0$

Multiple treatments

- Instead of 1 treatment, we might have multiple **treatment arms**:
    - Control condition
    - Treatment A
    - Treatment B
    - Treatment C, etc
- In this case, we will look at multiple comparisons:
    - $\overline{Y}_{\text{treated, A}} - \overline{Y}_{\text{control}}$
    - $\overline{Y}_{\text{treated, B}} - \overline{Y}_{\text{control}}$
    - $\overline{Y}_{\text{treated, A}} - \overline{Y}_{\text{treated, B}}$
- If treatment arms are randomly assigned, these differences will be good estimators for each causal contrast.