

Political Science 209 - Fall 2018

Observational Studies

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What is the fundamental problem of causal inference?

What about randomized control trials allows us to credibly estimate a causal effect?

What can induce citizens to vote?

What was the experiment?

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Letters to randomized households with treatment:

1. Naming and Shaming: your neighbors will know
2. Civic Duty
3. Hawthorne Effect Message
4. Control (no letter)

Let's go to R-studio quick

What is the main problem for observational studies?

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- Confounders: variables that are associated with both treatment and outcome

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- If pre-treatment characteristics are associated with treatment and outcome, we can't disentangle causal effect from confounding bias
- Selection into treatment example: Maybe minimum wage was increased because unemployment was particularly low in NJ, but not PA

Examples of Confounding

- Are incumbents more likely to win elections? Yes, but...

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- Incumbents receive more campaign contributions
- Incumbents have more staff

Examples of Confounding

- Does higher income lead countries to democratize?

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- Does higher income lead countries to democratize?
- Higher income countries have more educated populations

What can we do about confounding in observational studies?

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- Make *Treatment* and *Control* groups as similar to each other as possible
- Especially on variables that might matter for treatment status and outcome
- Analyze subsets or *statistical control*, such that we compare treated and control units that have same value on confounder

Another problem with observational studies:

- Reverse causality

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- Reverse causality
- Example: Does economic growth cause democratization or democratization cause growth?

Why do experiments not suffer from the threat of reverse causality?

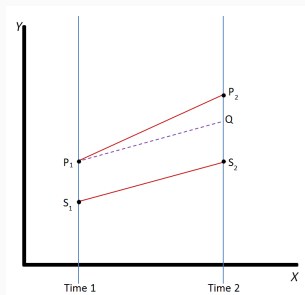
Difference-in-Differences Design

Difference-in-Differences Design

- Compare trends before and after the treatment across the same units
- Takes initial conditions into account

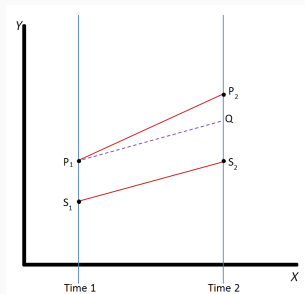
Difference-in-Differences Design

- Need data measured for both treatment and control at two different time periods: before and after treatment



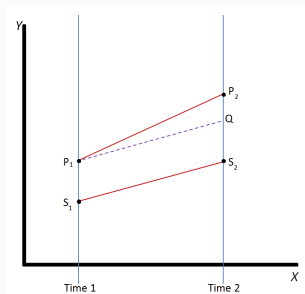
- Total difference between P_2 and S_2 can not be attributed to treatment. Why?

Difference-in-Differences Design



What might be a necessary condition for Diff-in-Diff to work?

Difference-in-Differences Design



What might be a necessary condition for Diff-in-Diff to work?

Parallel Trends Assumptions

Difference-in-Differences Design

The **difference-in-differences** (DiD) design uses the following estimate of the average treatment effect for the treated (ATT),

$$\text{DiD estimate} = \underbrace{\left(\bar{Y}_{\text{treated}}^{\text{after}} - \bar{Y}_{\text{treated}}^{\text{before}} \right)}_{\text{difference for the treatment group}} - \underbrace{\left(\bar{Y}_{\text{control}}^{\text{after}} - \bar{Y}_{\text{control}}^{\text{before}} \right)}_{\text{difference for the control group}}$$

The assumption is that the counterfactual outcome for the treatment group has a time trend parallel to that of the control group.

Describing numeric variables:

- Mean
- Median
- Quantiles

- splitting observations into equally size groups, e.g., quartiles, quantiles
- 75th percentile is the threshold under which 75% of observations lie
- What percentile is the median?

Describing the spread of numeric variables:

- IQR:

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Difference between 75th percentile and 25th percentile

Describing the spread of numeric variables:

Standard Deviation

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$$SD = \sqrt{\frac{1}{n} \sum_{i=1}^N (x_i - \bar{x})^2}$$

Standard Deviation

The sample **standard deviation** measures the average deviation from the mean and is defined as,

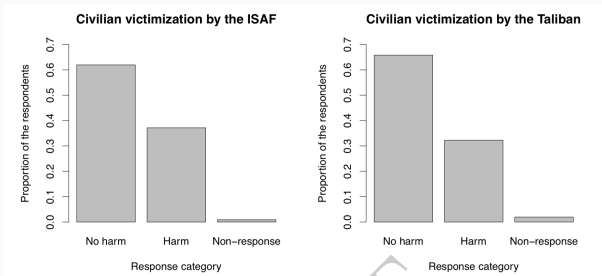
$$\text{standard deviation} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{or} \quad \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

where \bar{x} represents the sample mean, i.e., $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$ and n is the sample size. Few data points lie outside of 2 or 3 standard deviations away from the mean. The square of standard deviation is called **variance**.

Describing single Variables

- Barplots can be used to summarize factor(?) variables
- Proportion of observations in each category as the height of each bar

Barplots



Histograms

- Histograms look similar to barplots
- Used for numeric variables
- Numeric variables are *binned* into groups

Histograms

- Each bar is for one bin
- Height of each bar is the *density* of the bin

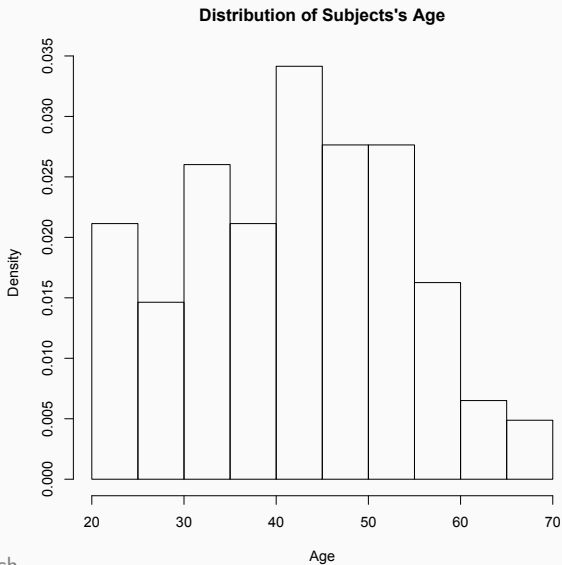
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Histograms

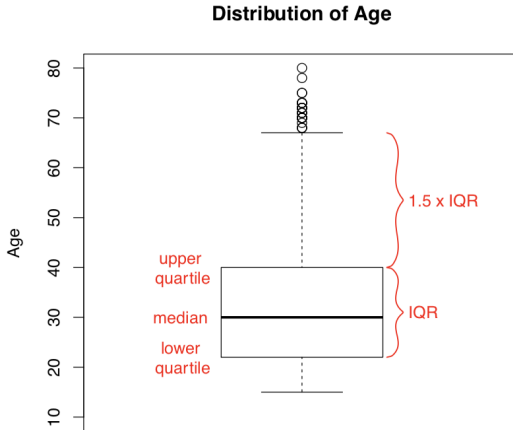
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- Height of each bar is the *density* of the bin
- Important: Height is share of observations in bin divided by bin size
- Unit of vertical axis (y-axis) is interpreted as percentage per horizontal (x-axis) unit

- Area of each bar is the share of observations that fall into that bin
- Area of all bins sum to one



- Boxplots also display the distribution of a numeric variable
- Boxplots show the *median*, *quartiles*, and *IQR*

Boxplots



Boxplots can show how two variables covary

