Difference-in-differences

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The Difference-in-Differences Estimator

Foundations of Causal Inference & Basic DiD Setup

Recap: Correlation vs. Causation

The fundamental challenge in empirical work.

- **Correlation:** Two variables move together.
  - *Example:* Ice cream sales are positively correlated with crime rates.
- **Causation:** A change in one variable *causes* a change in another.
  - *Does eating ice cream cause crime?* Unlikely.
- **Confounding Variable:** A third variable affects both.
  - *Hot weather* increases both ice cream sales and the number of people outside (leading to more opportunities for crime).

Our goal is to isolate the causal effect, not just the correlation.

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The Potential Outcomes Framework

Also known as the **Rubin Causal Model**.

Let's think about the effect of a treatment (e.g., a job training program) on an individual *i*.

- **Y_i(1):** The potential outcome for unit *i* **if they receive the treatment**.
  - *Example: Person i's earnings if they attend the program.*
- **Y_i(0):** The potential outcome for unit *i* **if they do NOT receive the treatment**.
  - *Example: Person i's earnings if they do not attend the program.*

The Individual Causal Effect

For any single individual i, the true causal effect of the treatment is the difference between their two potential outcomes:

$$\tau_i = Y_i(1) - Y_i(0)$$

- This is the pure, unadulterated effect of the treatment on that one person.
- *Example:* The increase in Person i's earnings caused *only* by the training program.

The Average Treatment Effect (ATE)

Since we usually can't measure the effect for every single individual, we focus on averages.

The **Average Treatment Effect (ATE)** is the average of the individual causal effects over the entire population.

$$ATE = E[\tau_i] = E[Y(1) - Y(0)]$$

This tells us, "On average, what is the effect of this treatment for a person randomly drawn from the population?"