

# Causality and observational studies

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## Agenda

- What is causality
- Randomized experiments
- Calculating effects
- Observational studies

Causal: relationship between things where one causes the other

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**Causal inference** is the attempt to derive causal connection based on the conditions of the occurrence of an effect

Think of the causal effect as the difference between what happened and what could have happened with/without a treatment (or change in  $X$ )

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- If two things happen together a lot, we say they are correlated

Does correlation imply causation?

## Ice Cream Sales VS Drowning Deaths

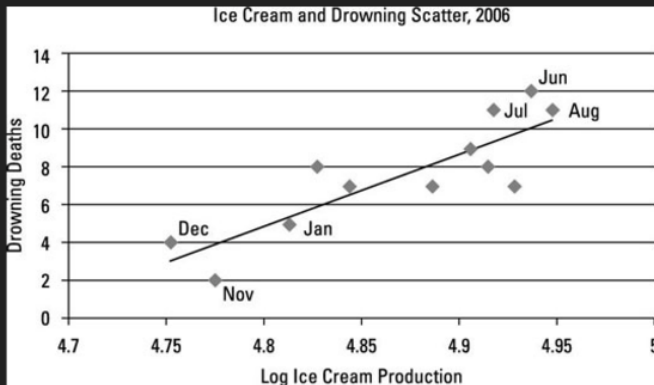


Figure 1: Ice cream sales and drowning incidents

# Correlation not causation

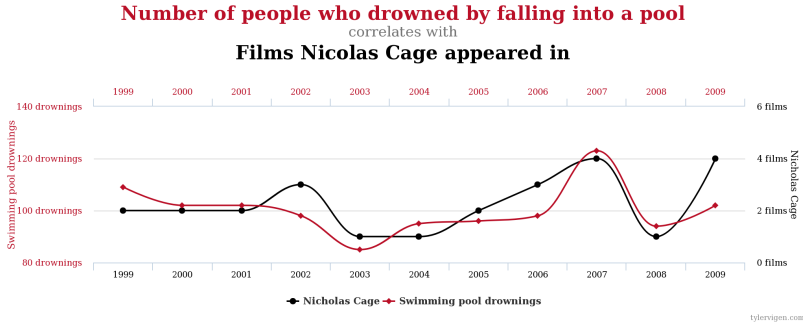


Figure 2: Cage films and pool incidents

Factual: What happened

Counterfactual: What would have happened

**Fundamental problem of causal inference:** We can never observe counterfactuals, must be inferred

Fundamental problem of causal inference in a movie: Sliding Doors (1998) <https://www.youtube.com/watch?v=BvUbv4iwbDs>

## Causal questions in social science research

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- A judge with a daughter gave a pro-choice ruling
- Would she/he have done that if she/he had a son instead?



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  - Randomly assign canvassers to have a conversation about transgender right or a conversation about recycling
  - Trans rights conversations focused on “perspective taking”
- **Outcome of interest:** support for trans rights policies

## A tale of two respondents

	Conversation script (T)	Support for Nondiscrimination law (Y)
Respondent 1	Recycling	No
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- Key interest: Did the second respondent support the law **because** of the perspective-taking conversation?

Useful to have **compact** notation for referring to **treatment variable**

$$T_i = \begin{cases} 1, & \text{if respondent } i \text{ had trans rights conversation} \\ 0, & \text{if respondent } i \text{ had recycling conversation} \end{cases}$$

Similar notation for the **outcome variable**:

$$Y_i = \begin{cases} 1, & \text{if respondent } i \text{ supports trans nondiscrimination laws} \\ 0, & \text{if respondent } i \text{ doesn't support nondiscrimination laws} \end{cases}$$

$i$  is a placeholder to refer to a generic unit/respondent:  $Y_{12}$  is the outcome for the 12th unit

## A tale of two respondents (redux)

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becomes...

$i$	$T_i$	$Y_i$
Respondent 1	0	0
Respondent 2	1	1



## Causal effects & Counterfactuals

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Two **potential outcomes**:

- $Y_i(1)$ : would respondent  $i$  support ND laws if they had trans rights script?
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- $Y_i(1) - Y_i(0) = 0 \rightsquigarrow$

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- To infer causal effect, we need to infer the missing counterfactuals!

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- $\rightsquigarrow$  find a state similar to NJ that didn't increase minimum wage

The problem: we cannot match on everything (imperfect matches)

- Say we match  $i$  (treated) and  $j$  (control)
- $Y_i(1) \neq Y_j(1)$  due to **selection bias**
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- How can we correct for that? **Randomization!**

## **2. Randomized experiments**

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- Treatment and control group are identical **on average**
- Similar on both observable and unobservable characteristics

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How many in our sample support nondiscrimination laws?

$$Y_1 + Y_2 + Y_3 + \dots + Y_n$$

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$\sum_{i=1}^n Y_i$  simply means sum each value from  $Y_1$  to  $Y_n$

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Suppose we surveyed 6 people and 3 supported gay marriage:

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

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

$$\begin{aligned}\text{Sample Average Treatment Effect (SATE)} &= \frac{1}{n} \sum_{i=1}^n [Y_i(1) - Y_i(0)] \\ &= \frac{1}{n} \sum_{i=1}^n Y_i(1) - \frac{1}{n} \sum_{i=1}^n Y_i(0)\end{aligned}$$

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When will the difference-in-means is a good estimate of the SATE?

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$$\bar{Y}_{treated} - \bar{Y}_{control} \approx \frac{1}{n} \sum_{i=1}^n Y_i(1) - \frac{1}{n} \sum_{i=1}^n Y_i(0) = \frac{1}{n} \sum_{i=1}^n [Y_i(1) - Y_i(0)] = \text{SATE}$$

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- Respondents act differently just knowing that they are under study

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- $\bar{X}_{treated}$ : average value of variable for treated group
- $\bar{X}_{control}$ : average value of variable for control group
- Under randomization,  $\bar{X}_{treated} - \bar{X}_{control} \approx 0$

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**Treatment:** officers who are randomly assigned to take a year long statistic course

**Control group:** officers who are randomly assigned and not taking a year-long stat course



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These could be gender, age, race, tenure, income, marital status, education, or any other characteristics

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  - $\bar{Y}_{treated,A} - \bar{Y}_{control}$
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  - $\bar{Y}_{treated,A} - \bar{Y}_{treated,B}$
  - $\bar{Y}_{treated,A} - \bar{Y}_{treated,C}$
  - $\bar{Y}_{treated,B} - \bar{Y}_{treated,C}$ , etc

- 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:
  - $\bar{Y}_{treated,A} - \bar{Y}_{control}$
  - $\bar{Y}_{treated,B} - \bar{Y}_{control}$
  - $\bar{Y}_{treated,A} - \bar{Y}_{treated,B}$
  - $\bar{Y}_{treated,A} - \bar{Y}_{treated,C}$
  - $\bar{Y}_{treated,B} - \bar{Y}_{treated,C}$ , etc
- If treatment arms are randomly assigned, these differences will be good estimators for each causal contrast

# Randomized Experiments from Blacklist

- Blacklist Season 6 Episode 20 (19:39)

### **3. Calculating effects**



Now we Return to R to illustrate how to calculate the effects!

```
## reinstall TPDdata if necessary  
library(TPDdata)
```

Variable	Description
age	Age of the Respondent (R) in years
female	1=R marked "Female" on voter reg., 0 otherwise
voted_gen_14	1 if R voted in the 2014 general election
voted_gen_12	1 if R voted in the 2012 general election
treat_ind	1 if R assigned to trans rights script, 0 for recycling
racename	name of racial identity indicated on voter file
democrat	1 if R is a registered Democrat
nondiscrim_pre	1 if R supports nondiscrim. law at baseline
nondiscrim_post	1 if R supports nondiscrim. law after 3 months

```
trans
```

```
## # A tibble: 565 x 9
##   age female voted_gen_14 voted_gen_1 treat_2 racen-3 democ-4 nondi-5 nondi-6
##   <dbl> <dbl>         <dbl>         <dbl> <dbl> <chr>         <dbl> <dbl> <dbl>
## 1    29      0           0           1    0 Africa-         1      1      1
## 2    59      1           1           0    1 Africa-         1      1      1
## 3    35      1           1           1    1 Africa-         1      0      1
## 4    63      1           1           1    1 Africa-         1      0      0
## 5    65      0           1           1    1 Africa-         0      1      0
## 6    51      1           1           1    0 Caucas-         0      1      1
## 7    26      1           1           1    0 Africa-         1      1      0
## 8    62      1           1           1    1 Africa-         1      1      1
## 9    37      0           1           1    0 Caucas-         0      1      0
## 10   51      1           1           1    0 Caucas-         0      0      0
## # ... with 555 more rows, and abbreviated variable names 1: voted_gen_12,
## # 2: treat_ind, 3: racename, 4: democrat, 5: nondiscrim_pre,
## # 6: nondiscrim_post
```

## Calculate the average outcomes in each group

```
treat_mean <- trans |>  
  filter(treat_ind == 1) |>  
  summarize(nondiscrim_mean = mean(nondiscrim_post))  
treat_mean
```

```
## # A tibble: 1 x 1  
##   nondiscrim_mean  
##             <dbl>  
## 1             0.687
```

# Calculate the average outcomes in each group

```
treat_mean <- trans |>
  filter(treat_ind == 1) |>
  summarize(nondiscrim_mean = mean(nondiscrim_post))
treat_mean
```

```
## # A tibble: 1 x 1
##   nondiscrim_mean
##             <dbl>
## 1             0.687
```

```
control_mean <- trans |>
  filter(treat_ind == 0) |>
  summarize(nondiscrim_mean = mean(nondiscrim_post))
control_mean
```

```
## # A tibble: 1 x 1
##   nondiscrim_mean
##             <dbl>
## 1             0.648
```

## Calculating the difference-in means

```
treat_mean - control_mean
```

```
## nondiscrim_mean
```

```
## 1 0.03896674
```

We will see more ways to do this throughout the semester

## Checking balance on numeric covariates

We can use `group_by` to see how the mean of covariates varies by group:

```
trans |>
  group_by(treat_ind) |>
  summarize(age_mean = mean(age))
```

```
## # A tibble: 2 x 2
##   treat_ind age_mean
##       <dbl>   <dbl>
## 1         0     48.2
## 2         1     48.3
```

# Checking balance on categorical covariates

Or we can group by treatment and a categorical control:

```
trans |>
  group_by(treat_ind, racename) |>
  summarize(n = n())
```

## `summarise()` has grouped output by 'treat\_ind'. You can override using the  
## ``.groups` argument.

```
## # A tibble: 9 x 3
## # Groups:   treat_ind [2]
##   treat_ind racename      n
##   <dbl> <chr>      <int>
## 1      0 African American    58
## 2      0 Asian              2
## 3      0 Caucasian         77
## 4      0 Hispanic        150
## 5      1 African American    68
## 6      1 Asian              4
## 7      1 Caucasian         75
## 8      1 Hispanic        130
## 9      1 Native American     1
```

Hard to read!

`pivot_wider()` takes data from a single column and moves it into multiple columns based on a grouping variable:

```
trans |>
  group_by(treat_ind, racename) |>
  summarize(n = n()) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = n
  )
```



`pivot_wider()` takes data from a single column and moves it into multiple columns based on a grouping variable:

```
trans |>
  group_by(treat_ind, racename) |>
  summarize(n = n()) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = n
  )
```

`names_from` tells us what variable will map onto the columns

`values_from` tells us what values should be mapped into those columns

```
trans |>
  group_by(treat_ind, racename) |>
  summarize(n = n()) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = n
  )
```

## `summarise()` has grouped output by 'treat\_ind'. You can override using the  
## `.groups` argument.

```
## # A tibble: 5 x 3
##   racename      `0`    `1`
##   <chr>      <int> <int>
## 1 African American    58    68
## 2 Asian                2     4
## 3 Caucasian          77    75
## 4 Hispanic          150   130
## 5 Native American    NA     1
```

# Calculating diff-in-means by group

```
trans |>
  mutate(
    treat_ind = if_else(treat_ind == 1, "Treated", "Control"),
    party = if_else(democrat == 1, "Democrat", "Non-Democrat")
  ) |>
  group_by(treat_ind, party) |>
  summarize(nondiscrim_mean = mean(nondiscrim_post)) |>
  pivot_wider(
    names_from = treat_ind,
    values_from = nondiscrim_mean
  ) |>
  mutate(
    diff_in_means = Treated - Control
  )
```

## `summarise()` has grouped output by 'treat\_ind'. You can override using the  
## `.groups` argument.

## # A tibble: 2 x 4

	party	Control	Treated	diff_in_means
	<chr>	<dbl>	<dbl>	<dbl>
## 1	Democrat	0.704	0.754	0.0498
## 2	Non-Democrat	0.605	0.628	0.0234

## **4. Observational Studies**

# Do newspaper endorsements matter

- Can newspaper endorsements change voters' minds?

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Our case: British newspapers switching their endorsements

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- Liberals  $\approx$  New York Times, conservatives  $\approx$  Wall Street Journal

Our case: British newspapers switching their endorsements

- Some news papers endorsing Tories in 1992 switched to Labour in 1997
- **Treated group::** readers of Tory  $\rightarrow$  Labour papers
- **Control group::** readers of papers who didn't switch

## Codebook for newspapers data

Variable	Description
to_labour	Read a newspaper that switched endorsement to Labour between 1992 and 1997 (1=yes, 0=no)
vote_lab_92	Did respondent vote for Labour in 1992 election (1=yes, 0=no)?
vote_lab_97	Did respondent vote for Labour in 1997 election (1=yes, 0=no)?
age	Age of respondent
male	Does the respondent identify as Male (1=yes, 0=no)
parent_labour	Does the respondent' identify as 's parents vote for Labour (1=yes, 0=no)
work_class	Does the responedent identify as working class (1=yes, 0=no)?

```
library(tidyverse)
library(TPDDdata)
newspapers
```

```
## # A tibble: 1,593 x 7
##   to_labour vote_lab_92 vote_lab_97 age male parent_labour work_class
##   <dbl>      <dbl>      <dbl> <hvn_lbl1> <dbl>      <dbl>      <dbl>
## 1         0         1         1     33      0         1         1
## 2         0         1         0     51      0         1         0
## 3         0         0         0     46      0         1         1
## 4         0         1         1     45      1         1         1
## 5         0         1         1     29      0         1         1
## 6         0         1         1     47      1         1         1
## 7         0         1         1     34      1         0         1
## 8         0         1         1     31      0         1         1
## 9         0         1         1     24      1         1         1
## 10        1         1         1     48      0         1         1
## # ... with 1,583 more rows
```

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**External validity**: can the conclusions/estimated effects be generalized beyond this study?

- RCTs weaker here because often very expensive to conduct on representative
- Observational studies often have larger/more representative samples that improve external validity

**Confounder:** pre-treatment variable affecting both treatment & the outcome

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- Leftists (X) more likely to read newspapers switching to Labour (T)
- Leftists (X) also more likely to vote for Labour (Y)

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**Counfounding bias** in the estimated SATE due to these differences



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- Leftists (X) more likely to read newspapers switching to Labour (T)
- Leftists (X) also more likely to vote for Labour (Y)

**Counfounding bias** in the estimated SATE due to these differences

- $\bar{Y}_{control}$  not a good proxy for  $Y_i(0)$  in treated group
- one type: **selection bias** from self-selection into treatment

How can we find a good comparison group?

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Depends on the data we have available

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Three general types of observational study **research designs**:

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- 1 **Cross-sectional design**: compare outcomes treated and control unites at one point in time

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Three general types of observational study **research designs**:

- ① **Cross-sectional design**: compare outcomes treated and control unites at one point in time
- ② **Before-and-after design**: compare outcomes before and after a unit has been treated, but need over-time data on treated group

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Three general types of observational study **research designs**:

- ① **Cross-sectional design**: compare outcomes treated and control unites at one point in time
- ② **Before-and-after design**: compare outcomes before and after a unit has been treated, but need over-time data on treated group
- ③ **Difference-in-differences design**: use before/after information for the treated and control group; need over-time on treated & control group

Compare treatment and control groups after treatment happens

- Readers of switching papers vs. readers of non-switching papers in 1997



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Treatment & control groups assumed identical on average as in RCT

- Sometimes called **unconfoundedness** or **as-if randomized**

Compare treatment and control groups after treatment happens

- Readers of switching papers vs. readers of non-switching papers in 1997

Treatment & control groups assumed identical on average as in RCT

- Sometimes called **unconfoundedness** or **as-if randomized**

Cross-section comparison estimate:

$$\bar{Y}_{treated}^{after} - \bar{Y}_{control}^{after}$$

Could there be confounders?

```
switched <- newspapers |>  
  filter(to_labour == 1) |>  
  summarize(mean(vote_lab_97))
```

```
no_change <- newspapers |>  
  filter(to_labour == 0) |>  
  summarize(mean(vote_lab_97))
```

```
switched - no_change
```

```
##   mean(vote_lab_97)  
## 1           0.1404826
```

**Statistical control:** adjust for confounders using statistical procedures

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- Compare treated and control groups within levels of a confounder
- Remaining effect can't be due to the confounder

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One type of statistical control: **subclassification**

- Compare treated and control groups within levels of a confounder
- Remaining effect can't be due to the confounder

Treat to inference: we can only control for observed variables  $\approx$  threat of **unmeasured confounding**



```
newspapers |>
  group_by(parent_labour, to_labour) |>
  summarize(avg_vote = mean(vote_lab_97)) |>
  pivot_wider(
    names_from = to_labour,
    values_from = avg_vote
  ) |>
  mutate(diff_by_parent = `1` - `0`)
```

## `summarise()` has grouped output by 'parent\_labour'. You  
## `.groups` argument.

```
## # A tibble: 2 x 4
## # Groups:   parent_labour [2]
##   parent_labour `0`   `1` diff_by_parent
##           <dbl> <dbl> <dbl>         <dbl>
## 1             0 0.279 0.434         0.155
## 2             1 0.597 0.698         0.101
```

Compare readers of party-switching newspapers before & after switch

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Advantage: all person-specific features held fixed

- comparing within a person over time

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Before-and-after estimate:

$$\overline{Y}_{treated}^{after} - \overline{Y}_{treated}^{before}$$

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Threat to inference: **time-varying confounders**

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Advantage: all person-specific features held fixed

- comparing within a person over time

Before-and-after estimate:

$$\overline{Y}_{treated}^{after} - \overline{Y}_{treated}^{before}$$

Threat to inference: **time-varying confounders**

- time trend: Labour just did better overall in 1997 compared to 1992

```
newspapers |>
  mutate(
    vote_change = vote_lab_97 - vote_lab_92
  ) |>
  summarize(avg_change = mean(vote_change))
```

```
## # A tibble: 1 x 1
##   avg_change
##       <dbl>
## 1      0.119
```

Key idea: use the before-and-after difference of **control group** to infer what would have happened to **treatment group** without treatment



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DiD estimate:

$$\underbrace{(\bar{Y}_{treated}^{after} - \bar{Y}_{treated}^{before})}_{\text{trend in treated group}} - \underbrace{(\bar{Y}_{control}^{after} - \bar{Y}_{control}^{before})}_{\text{trend in control group}}$$

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$$\underbrace{(\bar{Y}_{treated}^{after} - \bar{Y}_{treated}^{before})}_{\text{trend in treated group}} - \underbrace{(\bar{Y}_{control}^{after} - \bar{Y}_{control}^{before})}_{\text{trend in control group}}$$

Change in treated group above and beyond the change in control group

### Parallel time trend assumption

- Changes in vote of readers of non-switching papers roughly the same as changes that readers of switching papers would have been if they read non-switching papers
- Threat to inference: non-parallel trends

```
newspapers |>
  mutate(
    vote_change = vote_lab_97 - vote_lab_92,
    to_labour = if_else(to_labour == 1, "switched", "unswitched")
  ) |>
  group_by(to_labour) |>
  summarize(avg_change = mean(vote_change)) |>
  pivot_wider(
    names_from = to_labour,
    values_from = avg_change
  ) |>
  mutate(DID = switched - unswitched)
```

```
## # A tibble: 1 x 3
##   switched unswitched   DID
##   <dbl>      <dbl> <dbl>
## 1     0.190      0.110 0.0796
```

# Summarizing approaches

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- Compare treated units with control unites after treatment

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## 3. **Differences-in-differences**

- Assumption: parallel trends assumptions

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- Under this assumption, it accounts for unit-specific and time-varying confounding

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All rely on assumptions that can't be verified to handle confounding

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All rely on assumptions that can't be verified to handle confounding

RCTs handle confounding by design (gold standard)