# 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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T -> Y

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

Does correlation imply causation?

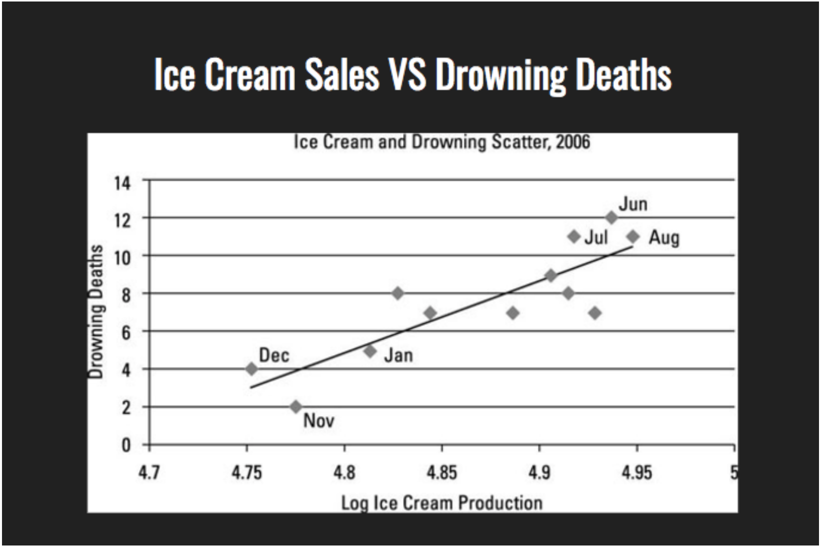


Figure 1: Ice cream sales and drowning incidents

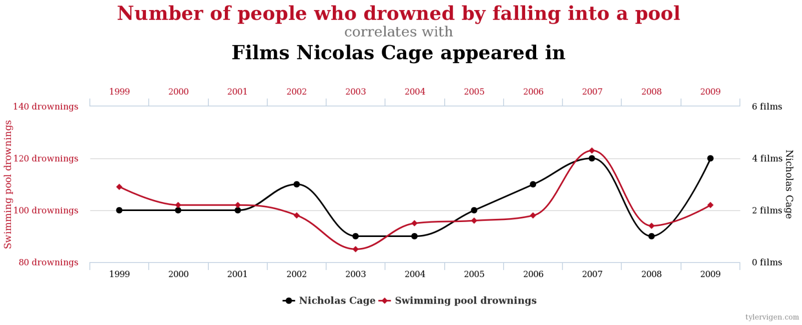


Figure 2: Cage films and pool incidents

## Factual and counterfactual?

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

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- Would she/he have done that if she/he had a son instead?

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  -Trans rights conversations focused on “perspective taking”
- **Outcome of interest**: support for trans rights policies

| | Conversation script (T) | Support for Nondiscrimination law (Y) |
|---|---|---|
| Respondent 1 | Recycling | No |
| Respondent 2 | Trans rights | Yes |

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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...

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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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Causal effect: $Y_i(1) - Y_i(0)$

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- **Fundamental problem of causal inference:**

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- Observe $Y_i(1) - Y_i(0) = 1$ or $Y_i(1) - Y_i(0) = 0$
- 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**
- Those who take treatment may be different that those who take control

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- How can we correct for that? **Randomization!**

# 2. Randomized experiments

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Randomization ensures **balance** between treatment and control groups

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

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$$Y_1 + Y_2 + Y_3 + ... + Y_n$$

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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:

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

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

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\text{Sample Average Treatment Effect (SATE)} &= \frac{1}{n}\sum_{i=1}^{n}[Y_i(1) - Y_i(0)] \\
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When will the difference-in-means is a good estimate of the SATE?

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**Hawthorne effects**:

- Respondents act differently just knowing that they are under study

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

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## An example of balance checking

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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

Balance checking means the differences in pretretment variables should not exist among officers between the two groups on average

What would be examples of pretreatment variables?

# An example of balance checking (cont)

Balance checking means the differences in pretretment variables should not exist among officers between the two groups on average

What would be examples of pretreatment variables?

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

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  - $\overline{Y}_{treated,A} - \overline{Y}_{treated,C}$
  - $\overline{Y}_{treated,B} - \overline{Y}_{treated,C}$, 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 |

# Peak at the data

```r
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

```r
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
```

```r
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
```

```r
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

```r
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

- Can newspaper endorsements change voters' minds?

## Do newspaper endorsements matter

- Can newspaper endorsements change voters' minds?

Why not compare vote choice of readers of different papers?

- Can newspaper endorsements change voters' minds?

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- Problem: readers choose papers based on their previous beliefs

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Our case: British newspapers switching their endorsements

- Some news papers endorsing Tories in 1992 switched to Labour in 1997

- Can newspaper endorsements change voters' minds?

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- Problem: readers choose papers based on their previous beliefs
- 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 -> 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)? |

```r
library(tidyverse)
library(TPDdata)
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_lbll> <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?

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- 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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- 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

- $\overline{Y}_{control}$ 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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Three general types of observational study **research designs**:

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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

# Cross-sectional design

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-sectional design

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:

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

Could there be counfounders?

```r
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: **subclassfication**

- 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
```

# Before-and-after comparison

Compare readers of party-switching newspapers before & after switch

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Advantage: all person-specific features held fixed

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Before-and-after estimate:

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

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

Compare readers of party-switching newspapers before & after switch

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- comparing within a person over time

Before-and-after estimate:

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

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

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

```r
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:

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

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

DiD estimate:

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

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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

```r
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
```

1. **Cross-sectional comparison**
   - Compare treated units with control unites after treatment

# Summarizing approaches

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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)