

# Gov 50: 7. Observational Studies

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# Roadmap

1. Calculating effects
2. Observational Studies

# 1/ Calculating effects

# Transphobia study data

```
## reinstall gov50data if necessary  
library(gov50data)
```

Variable Name	Description
age	Age of the 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
vote_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

```
trans
```

```
## # A tibble: 565 x 9
##   age female voted_gen_14 voted_gen_12 treat_ind racename
##   <dbl> <dbl>         <dbl>         <dbl>         <dbl> <chr>
## 1    29      0           0           1           0 African~
## 2    59      1           1           0           1 African~
## 3    35      1           1           1           1 African~
## 4    63      1           1           1           1 African~
## 5    65      0           1           1           1 African~
## 6    51      1           1           1           0 Caucasi~
## 7    26      1           1           1           0 African~
## 8    62      1           1           1           1 African~
## 9    37      0           1           1           0 Caucasi~
## 10   51      1           1           1           0 Caucasi~
## # i 555 more rows
## # i 3 more variables: democrat <dbl>, nondiscrim_pre <dbl>,
## #   nondiscrim_post <dbl>
```

# 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
```

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```
## # 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 0.039
```

We'll 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())
```

```
## # 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

`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
  )
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  )
```

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

`values_from` tell 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
  )
```

```
## # 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
  )
```

```
## # 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
```

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## **2/** Observational Studies



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- Study for today: British newspapers switching their endorsements.
  - Some newspapers 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.



Name	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	Did the respondent's parents vote for Labour (1=Yes, 0=No)?
work_class	Does the respondent identify as working class (1=Yes, 0=No)?

```
library(tidyverse)
library(gov50data)
newspapers
```

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

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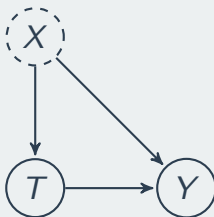
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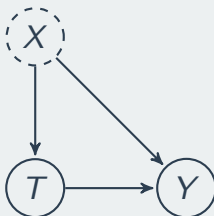
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  - RCTs weaker here because often very expensive to conduct on representative samples.
  - Observational studies often have larger/more representative samples that improve external validity.

# Confounding



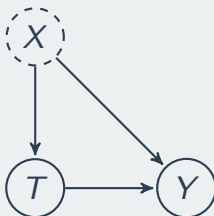
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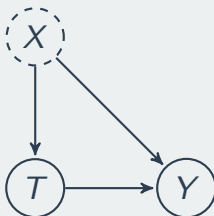
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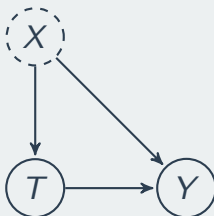
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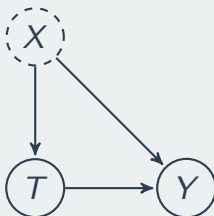
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  - $\bar{Y}_{\text{control}}$  not a good proxy for  $\frac{1}{n} \sum_{i=1}^n Y_i(0)$  in treated group.
  - one type: **selection bias** from self-selection into treatment

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  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.

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- Could there be confounders?

# Cross-sectional design in 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                0.14
```

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- **Statistical control:** adjust for confounders using statistical procedures.
  - Can help to reduce confounding bias.
- 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.
- Threat to inference: we can only control for observed variables  $\rightsquigarrow$  threat of **unmeasured confounding**

# Statistical control in R

```
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`)
```

```
## # 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
```

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- Threat to inference: **time-varying confounders**
  - Time trend: Labour just did better overall in 1997 compared to 1992.

# Before and after in 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
```

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  - 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.

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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.

# Difference-in-differences in 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
```

# Summarizing approaches

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# Causality understanding check

