# Gov 50: 8. Observational Studies

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# Roadmap

1. Observational Studies

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  - **Treated group**: readers of Tory $\to$ Labour papers.

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  - **Treated group**: readers of Tory $\rightarrow$ Labour papers.
  - **Control group**: readers of papers who didn't switch.

# Data

| 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)? |

```r
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_lbll> <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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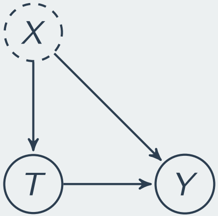
    - Observational studies often have larger/more representative samples that improve external validity.

# Confounding

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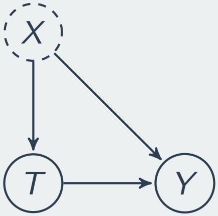


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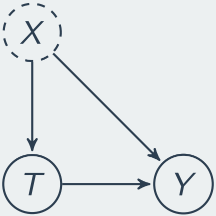


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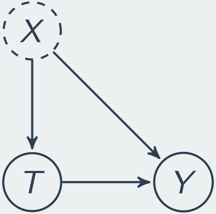


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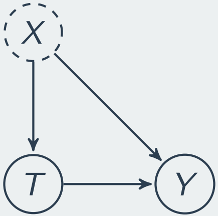


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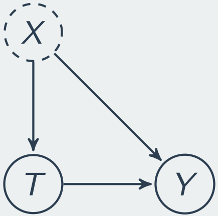


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  - $\overline{Y}_{\text{control}}$ not a good proxy for $\frac{1}{n}\sum_{i=1}^{n} Y_i(0)$ in treated group.
  - one type: **selection bias** from self-selection into treatment

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  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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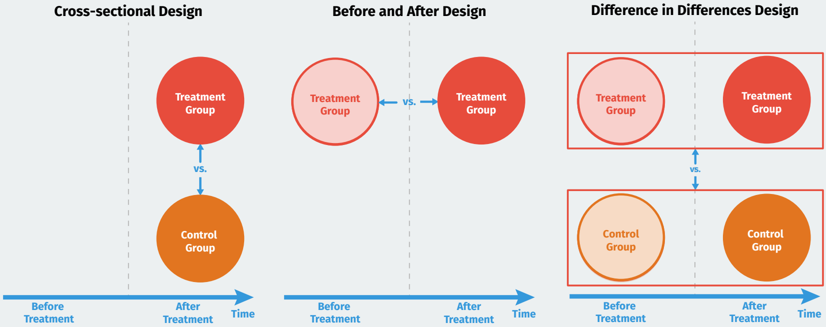

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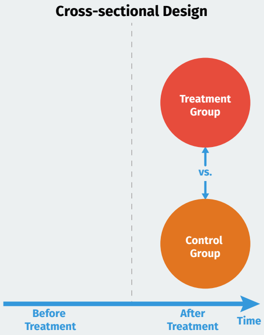
- Compare treated/control groups after treatment happens.



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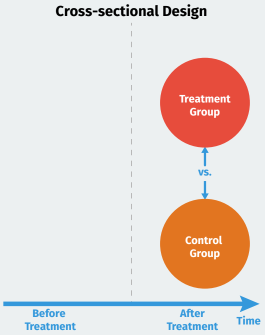


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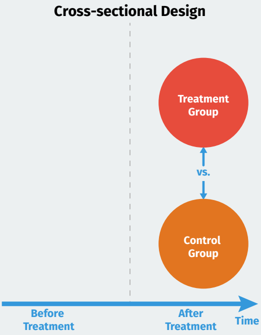


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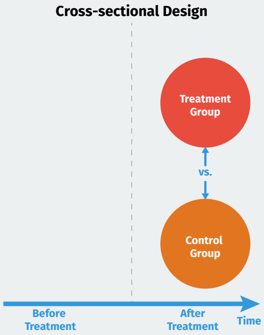


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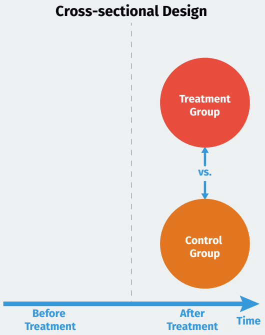


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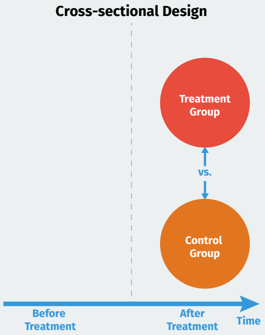


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- Could there be confounders?

# Cross-sectional design in R

```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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    - 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**

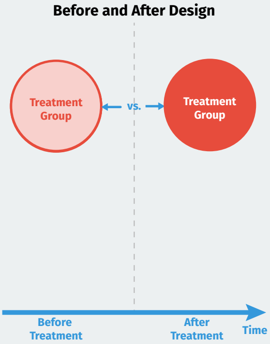
# Statistical control in R

```
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
```

# Before-and-after comparison

- Compare readers of party-switching newspapers before & after switch.



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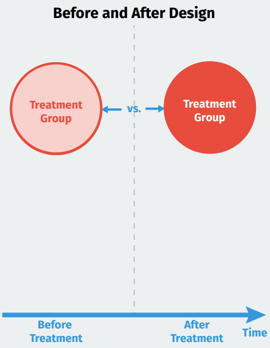

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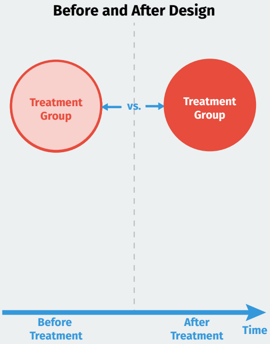


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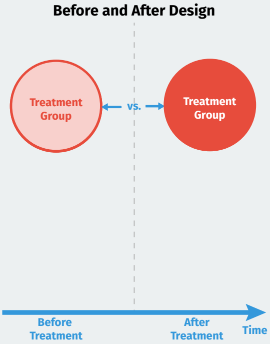


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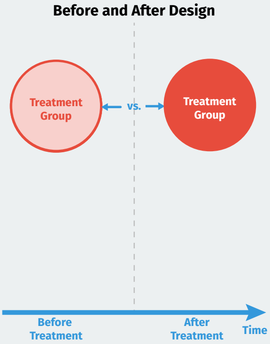


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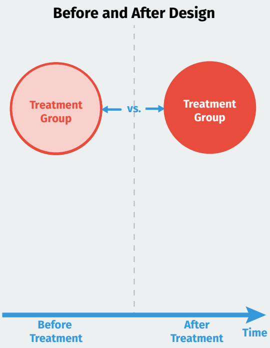


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- **Assumption**: no time-varying confounders
  - Time trend: Labour just did better overall in 1997 compared to 1992.

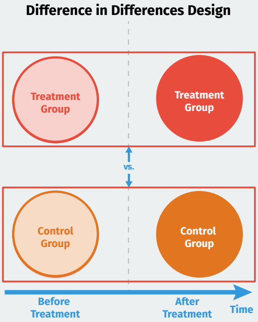
# Before and after in R

```
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
```

# Differences in differences

- Use the before/after difference of **control group** to infer what would have happened to **treatment group** without treatment.



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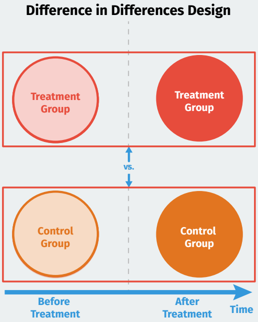


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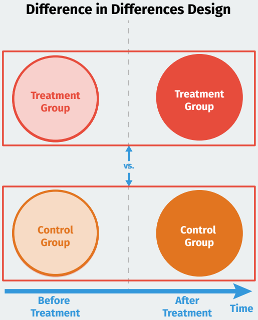


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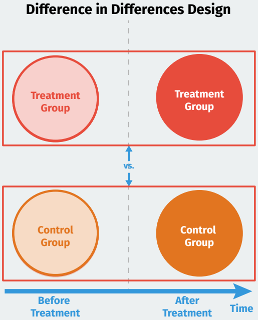


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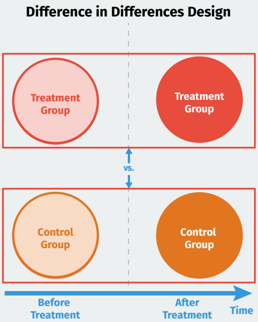


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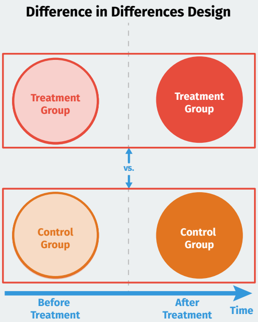


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- **Assumption**: parallel trends
    - Changes in vote of readers of non-switching papers roughly the same as changes that readers of switching papers would have been if they read non-switching papers.
    - Threat to inference: non-parallel trends.

# Difference-in-differences in R

```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
```

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- RCTs handle confounding by design.

# Causality understanding check