Lecture 8

2024-09-30

Observational Studies

Do newspaper endorsements matter? Can newspaper endorsements change voters' minds? Why not compare vote choice of readers of different papers? Problem: readers choose papers based on their previous beliefs

Study for today: British newspapers switching their endorsements Some newspapers endorsing Tories in 1992 switched to Labour in 1997. Treated group: readers of Tory -> Labour papers. Control group: readers of Tory who didn't switch.

Load dataset:

```
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
## # i 1,583 more rows
```

Example of an observational study: We as researchers observe a naturally assigned treatment. Very common: often can't randomize for ethical/logical reasons.

Internal validity: are the causal assumption satisfied? Can we interpret this as a causal effect? RCTs usually have higher internal validity Observational studies less so because treatment and control groups may differ in ways that are hard to measure

External validity: can the conclusions/estimated effects be generalized beyond this study? RCTs weaker here because often very expensive to conduct on representative samples Observational studies often have larger/more representative samples that improve external validity

Confounder: pre-treatment variable affecting treatment & the outcome.

Confounding bias in the estimated SATE fue to these differences. If our control group is different from our treatment group in terms of confounders, then it's not a good proxy

Research designs

How can we find a good comparison group?

Depends on the data we have available.

Three general types of observational study research designs: 1. Cross-sectional design: compare outcomes treated and control units at one point in time. Assumption: groups identical on average; sometimes called unconfoundedness or as-if randomized 2. Before and after design: compare outcomes before and after a unit has been treated, but need over-time data on treated group Advantage: all person-specific features held fixed Assumption: no time-varying confounders 3. Difference-in-differences design: use the before/after difference of control group to infer what would have happened to treatment group without treatment Change in treated group above and beyond the change in control group Assumption: parallel trends

Let's calculate the cross-sectional estimate:

```
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 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 variable -> treat of unmeasured confounding

Statistical control on 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`)
```

```
## `summarise()` has grouped output by 'parent_labour'. You can override using the
## `.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 in R:

```
newspapers |>
  filter(to_labour == 1) |>
  mutate(
    vote_change = vote_lab_97 - vote_lab_92) |>
  summarize(avg_change = mean(vote_change))
```

```
## # A tibble: 1 x 1
##   avg_change
##        <dbl>
## 1      0.190
```

Differences-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
```