PSC7475: Varying Effects by Group

Week 8: Lecture 13

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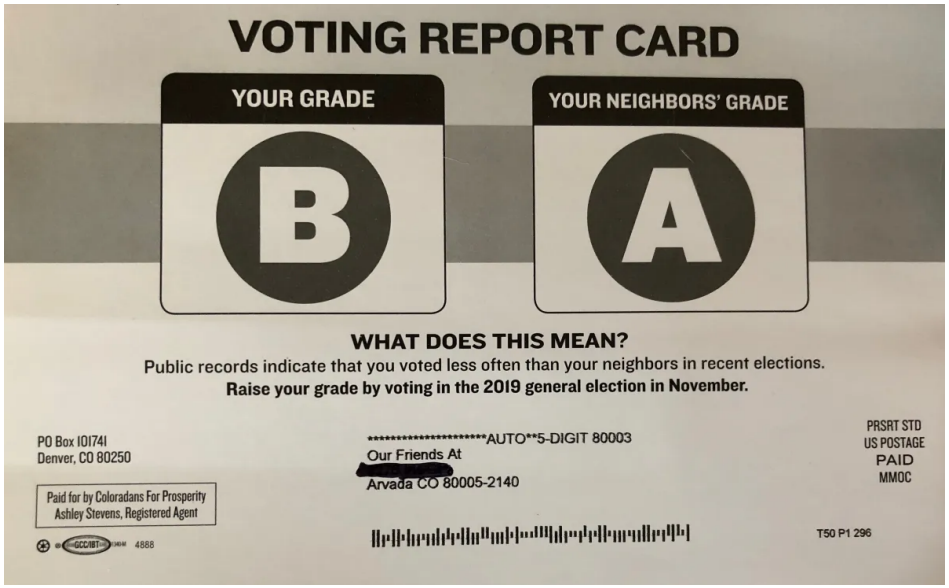
Week 8

- QSS Tidyverse Tutorial 6 due tomorrow
- Proposal for final project due Wednesday by midnight (upload to Blackboard)
  - What is your tentative research question?
  - What data is available to answer this question?
  - Why are you interested in this question?
  - How long? Be brief! Use bullet points. But you must upload a document
- Midterm: will discuss next week
- This week: finishing up regression!

Heterogeneous treatment effects

- **Heterogeneous treatment effects**: effect varies across groups.
  - Average effect of a drug is 0, but + for men and − for women.
  - Important questions for determining who should receive treatment.

Social pressure experiment


VOTING REPORT CARD

YOUR GRADE

B

YOUR NEIGHBORS' GRADE

A

WHAT DOES THIS MEAN?

Public records indicate that you voted less often than your neighbors in recent elections.
Raise your grade by voting in the 2019 general election in November.

PO Box 101741
Denver, CO 80250

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4888

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Our Friends At
[redacted]
Arvada CO 80005-2140

T50 P1 296

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- `primary2004` whether the person voted in 2004, before the experiment.
- Do 2004 voters react differently to social pressure mailer than nonvoters?
- Two approaches:
  - Subsets, subsets, subsets.
  - Interaction terms in regression.

Subset approach

- Easy way to estimate heterogeneous effects: our old friend, `filter()`, `group_by()`, and `summarize()`. Woo!
  - First, get the data

```
data(social, package="qss")
```

Subset approach

- Now, estimate the ATE for the **voters**:

```
VotersATE <- social %>%
  filter(primary2004 == 1,
         messages %in% c("Control","Neighbors")) %>%
  group_by(messages) %>%
  summarize(primary2006_mean = mean(primary2006)) %>%
  pivot_wider(names_from = "messages",
              values_from = "primary2006_mean") %>%
  mutate(ate_v = Neighbors - Control) %>%
  select(ate_v)
VotersATE
```

```
## # A tibble: 1 x 1
##    ate_v
##    <dbl>
## 1 0.0965
```

Filter approach

- Now, estimate the ATE for the **nonvoters**:

```
NonvotersATE <- social %>%
  filter(primary2004 == 0,
         messages %in% c("Control","Neighbors")) %>%
  group_by(messages) %>%
  summarize(primary2006_mean = mean(primary2006)) %>%
  pivot_wider(names_from = "messages",
              values_from = "primary2006_mean") %>%
  mutate(ate_nv = Neighbors - Control) %>%
  select(ate_nv)
NonvotersATE
```

```
## # A tibble: 1 x 1
##   ate_nv
##    <dbl>
## 1 0.0693
```

Difference in effects

- How much does the estimated treatment effect differ between groups?

```
VotersATE$ate_v - NonvotersATE$ate_nv
```

```
## [1] 0.02722908
```

- Any easier way to allow for different effects of treatment by groups?

Interaction terms

- Can allow for different effects of a variable with an interaction term:

$$\text{turnout}_i = \alpha + \beta_1 \text{primary2004}_i + \beta_2 \text{neighbors}_i + \beta_3(\text{primary2004}_i \times \text{neighbors}_i) + \varepsilon_i$$

- Primary 2004 variable multiplied by the neighbors variable.
  - Equal to 1 if voted in 2004 (primary2004 $==$ 1) and received neighbors mailer (neighbors $==$ 1)
  - Easiest to understand by investigating predicted values.

Predicted values from non-interacted model

- Let $X_i = \text{primary2004}_i$ and $Z_i = \text{neighbors}_i$:

$$\hat{Y}_i = \hat{\alpha} + \hat{\beta}_1 X_i + \hat{\beta}_2 Z_i$$

	Control ($Z_i = 0$)	Neighbors ($Z_i = 1$)
non-voter ($X_i = 0$)	$\hat{\alpha}$	$\hat{\alpha} + \hat{\beta}_2$
voter ($X_i = 1$)	$\hat{\alpha} + \hat{\beta}_1$	$\hat{\alpha} + \hat{\beta}_1 + \hat{\beta}_2$

- Effect of Neighbors for non-voters: $(\hat{\alpha} + \hat{\beta}_2) - (\hat{\alpha}) = \hat{\beta}_2$
- Effect of Neighbors for voters: $(\hat{\alpha} + \hat{\beta}_1 + \hat{\beta}_2) - (\hat{\alpha} + \hat{\beta}_1) = \hat{\beta}_2$

Predicted from interacted model

- Now for the interacted model:

$$\hat{Y}_i = \hat{\alpha} + \hat{\beta}_1 X_i + \hat{\beta}_2 Z_i + \hat{\beta}_3 X_i Z_i$$

	Control ($Z_i = 0$)	Neighbors ($Z_i = 1$)
non-voter ($X_i = 0$)	$\hat{\alpha}$	$\hat{\alpha} + \hat{\beta}_2$
voter ($X_i = 1$)	$\hat{\alpha} + \hat{\beta}_1$	$\hat{\alpha} + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$

Interpreting coefficients

$$\hat{Y}_i = \hat{\alpha} + \hat{\beta}_1 \text{primary2004}_i + \hat{\beta}_2 \text{neighbors}_i$$

$$+ \hat{\beta}_3 (\text{primary2004}_i \times \text{neighbors}_i)$$

	Control Group	Neighbors Group
2004 primary non-voter	$\hat{\alpha}$	$\hat{\alpha} + \hat{\beta}_2$
2004 primary voter	$\hat{\alpha} + \hat{\beta}_1$	$\hat{\alpha} + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$

- $\hat{\alpha}$: turnout rate for 2004 nonvoters in control group.
- $\hat{\beta}_1$: avg difference in turnout between 2004 voters and nonvoters.
- $\hat{\beta}_2$: effect of neighbors for 2004 nonvoters.
- $\hat{\beta}_3$: difference in the effect of neighbors mailer between 2004 voters and nonvoters.

Interactions in R

- You can include an interaction with var1:var2:

```
social.neighbor <- social %>%
  mutate(neighbors = ifelse(messages=="Neighbors",1,
                            ifelse(messages=="Control",0,NA)))
  select(primary2006,primary2004,neighbors) %>%
  drop_na()

fit <- lm(primary2006 ~ primary2004 + neighbors +
          primary2004:neighbors, data = social.neighbor)

coef(fit)
```

```
##           (Intercept)             primary2004
##            0.23710990              0.14869507
##             neighbors primary2004:neighbors
##            0.06929617              0.02722908
```

Interactions in R

```
coef(fit)
```

```
##             (Intercept)             primary2004
##              0.23710990              0.14869507
##               neighbors primary2004:neighbors
##              0.06929617              0.02722908
```

- Compare coefficients to earlier approach:

```
NonvotersATE$ate_nv
```

```
## [1] 0.06929617
```

```
VotersATE$ate_v - NonvotersATE$ate_nv
```

```
## [1] 0.02722908
```