Gov 50: 19. Estimation: Experiments

Matthew Blackwell

Harvard University

Fall 2018

1. Today's agenda

2. Treatment effects with binary outcomes

3. Treatment effects with non-binary outcomes

1/ Today's agenda

Logistics

- Congrats on Midterm 2!

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  - Final report due 12/10.

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- Last time: estimation and inference for surveys.

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- Now: estimation and inference for comparisons between groups.

2/ Treatment effects with binary outcomes

Comparison between groups

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  - Difference between treatment and control groups.
- Bedrock of causal inference!

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    - Primary election in MI 2006
- Treatment group: postcards showing their own and their neighbors' voting records.
    - Sample size of treated group, $n_T = 360$
- Control group: received nothing.
    - Sample size of the control group, $n_C = 1890$

Outcomes

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- Turnout rate (sample mean) in treated group, $\overline{X}_T = 0.37$
- Turnout rate (sample mean) in control group, $\overline{X}_C = 0.30$
- Estimated **average treatment effect**

$$\widehat{\text{ATE}} = \overline{X}_T - \overline{X}_C = 0.07$$

Inference for the difference

- Parameter: **population ATE** $\mu_T - \mu_C$

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- $\rightsquigarrow$ $\overline{X}_T - \overline{X}_C$ is a r.v. with mean $\mu_T - \mu_C$
  - Sample difference in means is on average equal to the population difference in means.

Simulation

- What if these were the true population means? We would still expect some **variation** in our estimates:

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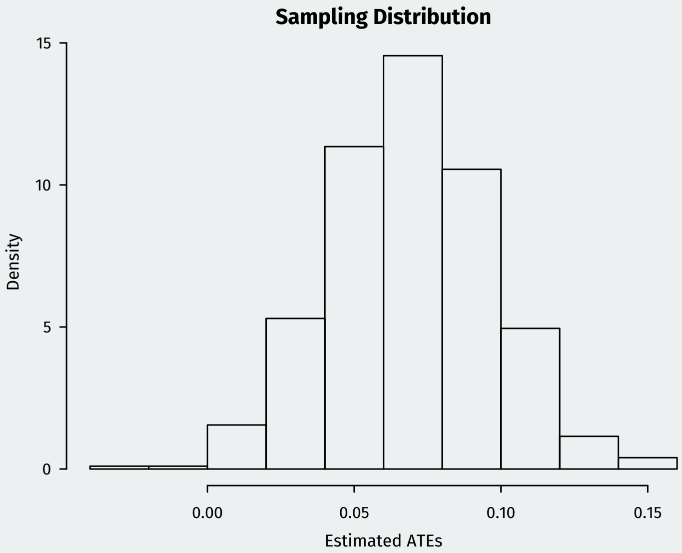
```
xt.sims <- rbinom(1000, size = 360, prob = 0.37) / 360
xc.sims <- rbinom(1000, size = 1890, prob = 0.30) / 1890

hist(xt.sims - xc.sims, freq = FALSE, xlab = "Estimated ATEs",
     main = "Sampling Distribution")
```

Simulations



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$$= \frac{\mu_T(1-\mu_T)}{n_T} + \frac{\mu_C(1-\mu_C)}{n_C}$$

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- **Standard error** is the square root of this variance:

$$\widehat{\text{SE}}_{\widehat{\text{ATE}}} = \sqrt{\frac{\overline{X}_T(1-\overline{X}_T)}{n_T} + \frac{\overline{X}_C(1-\overline{X}_C)}{n_C}} = 0.028$$

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- SE represents how far, on average, $\overline{X}_T - \overline{X}_C$ will be from $\mu_T - \mu_C$.

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- Range of possibilities taking into account plausible chance errors.
- 0 not included in this CI $\rightsquigarrow$ chance error as big as the estimated effect unlikely.

3/ Treatment effects with non-binary outcomes

Minimum wage study revisited

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- What about general outcomes? (continuous, other discrete)
- Setting: study of how minimum wage increase in New Jersey affected employment, using Pennsylvania as a comparison group.

```
minwage <- read.csv("data/minwage.csv")

# proportion of those fully employed before and after
# the increase in the minimum wage
minwage$fullPropBefore <- minwage$fullBefore /
    (minwage$fullBefore + minwage$partBefore)
minwage$fullPropAfter <- minwage$fullAfter /
    (minwage$fullAfter + minwage$partAfter)

# separate NJ and PA
minwageNJ <- subset(minwage, subset = (location != "PA"))
minwagePA <- subset(minwage, subset = (location == "PA"))
```

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```
est <- mean(minwageNJ$fullPropAfter) -
    mean(minwagePA$fullPropAfter)
est
```

```
## [1] 0.0481
```

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- Use this to estimate the SE:

$$\widehat{\text{SE}}_{\widehat{\text{ATE}}} = \sqrt{\widehat{\mathbb{V}}\left(\widehat{\text{ATE}}\right)} = \sqrt{\frac{\widehat{\mathbb{V}}(X_{\text{NJ}})}{n_{\text{NJ}}} + \frac{\widehat{\mathbb{V}}(X_{\text{PA}})}{n_{\text{PA}}}}$$

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```
nNJ <- nrow(minwageNJ)
nPA <- nrow(minwagePA)
se <- sqrt(var(minwageNJ$fullPropAfter) / nNJ +
          var(minwagePA$fullPropAfter) / nPA)
se
```

```
## [1] 0.0336
```

Quick aside on CIs

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- Example: 92% CI

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- Example: 92% CI $\rightsquigarrow \alpha = 0.08$

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- Plug $1 - \alpha/2$ into `qnorm()` function:
- Example: 92% CI $\rightsquigarrow \alpha = 0.08 \rightsquigarrow 1 - \alpha/2 = 0.96$

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- How do we calculate $z_{\alpha/2}$ for any possible CI?
- Plug $1 - \alpha/2$ into qnorm( ) function:
- Example: 92% CI $\rightsquigarrow \alpha = 0.08 \rightsquigarrow 1 - \alpha/2 = 0.96$

```r
# z-values for 92% CI
qnorm(0.96)
```

```
## [1] 1.75
```

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# 90%
c(est - se * qnorm(0.95), est + se * qnorm(0.95))
```

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```
## [1] -0.00715  0.10338
```

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```

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```
# 95%
c(est - se * qnorm(0.975), est + se * qnorm(0.975))
```

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```
## [1] -0.0384  0.1347
```

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- These are large-sample approximations!

Before-and-after comparison

- Assumption: only change over time is the treatment

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- Estimate: $\widehat{\text{ATE}} = \frac{1}{n_{NJ}} \sum_{i=1}^{N} Z_i$

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- Average changes in employment in each store before and after MW change
  - Let $Z_i = X_{i,\text{after}} - X_{i,\text{before}}$
- Estimate: $\widehat{\text{ATE}} = \frac{1}{n_{NJ}} \sum_{i=1}^{N} Z_i$

```
diffs <- minwageNJ$fullPropAfter - minwageNJ$fullPropBefore
est <- mean(diffs)
est
```

```
## [1] 0.0239
```

Standard errors for before-and-after

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```
se <- sqrt(var(diffs) / nNJ)
se
```

```
## [1] 0.0176
```

Standard errors for before-and-after

- Standard error: $\widehat{\text{SE}}_{\widehat{\text{ATE}}} = \sqrt{\widehat{\mathbb{V}}\left(\widehat{\text{ATE}}\right)} = \sqrt{\frac{\widehat{\mathbb{V}}(Z_i)}{n_{NJ}}}$

```
se <- sqrt(var(diffs) / nNJ)
se
```

```
## [1] 0.0176
```

- 95% confidence interval:

Standard errors for before-and-after

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```
se <- sqrt(var(diffs) / nNJ)
se
```

```
## [1] 0.0176
```

- 95% confidence interval:

```
c(est - se * qnorm(0.975), est + se * qnorm(0.975))
```

```
## [1] -0.0107  0.0585
```

Next steps

- Next week: hypothesis testing

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- Next week: hypothesis testing
- Then regression estimation.