Gov 50: 4. Randomized Experiments

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Fall 2018

1. Today's agenda

2. Introduction to randomized experiments

3. Gay marriage example

4. Wrapping up

1/ Today's agenda

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   - Conditional statements, subsetting, factor variables

2/ Introduction to randomized experiments

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- **Fundamental problem of causal inference**: only one of the two potential outcomes is observable.

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- Suppose we surveyed 6 people and 3 supported gay marriage:

$$\overline{Y} = \frac{1}{6}(1+1+1+0+0+0) = 0.5$$

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- How do we ensure that the difference-in-means is a good estimate of the SATE?

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  - $\rightsquigarrow$ outcome in control group $\approx$ what would have happened to treatment group if they had control.

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- **Hawthorne effects**:
  - Respondents act differently just knowing that they are under study.

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  - Under randomization, $\overline{X}_{\text{treated}} - \overline{X}_{\text{control}} \approx 0$

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3/ Gay marriage example

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- LaCour & Green (2015). “When contact changes minds: An experiment of transmission of support for gay equality.” *Science*.

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- Why use an "unrelated" survey? $\rightsquigarrow$ **Hawthorne effect**

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```
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##          1    2    3    4    5    6    7
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##   2 2441 2132 2113 2171    0    0 1528
```

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prop.table(table(study1.wave1$treatment))
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```

- Examine the distribution of treatments:

```
prop.table(table(study1.wave1$treatment))
```

```
##
##                                           No Contact
##                                                0.551
##                      Recycling Script by Gay Canvasser
##                                                0.110
##                 Recycling Script by Straight Canvasser
##                                                0.109
##              Same-Sex Marriage Script by Gay Canvasser
##                                                0.121
## Same-Sex Marriage Script by Straight Canvasser
##                                                0.109
```

What do we expect if randomization is done correctly?

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```
tapply(study1.wave1$ssm, study1.wave1$treatment, mean)
```

What do we expect if randomization is done correctly?

```r
tapply(study1.wave1$ssm, study1.wave1$treatment, mean)
```

```
##                                No Contact
##                                      3.04
##            Recycling Script by Gay Canvasser
##                                      3.13
##       Recycling Script by Straight Canvasser
##                                      3.01
##    Same-Sex Marriage Script by Gay Canvasser
##                                      3.03
## Same-Sex Marriage Script by Straight Canvasser
##                                      3.10
```

Estimating SATEs 3 days later (Wave 2)

- What is the effect of gay vs no canvasser?

Estimating SATEs 3 days later (Wave 2)

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```
study1.wave2 <- subset(gay, (study == 1) & (wave == 2))
none.ssm.w2 <- subset(study1.wave2,
                     treatment == "No Contact")
gay.ssm.w2 <- subset(study1.wave2,
   treatment == "Same-Sex Marriage Script by Gay Canvasser")
## estimated SATEs
mean(gay.ssm.w2$ssm) - mean(none.ssm.w2$ssm)
```

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study1.wave2 <- subset(gay, (study == 1) & (wave == 2))
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                     treatment == "No Contact")
gay.ssm.w2 <- subset(study1.wave2,
   treatment == "Same-Sex Marriage Script by Gay Canvasser")
## estimated SATEs
mean(gay.ssm.w2$ssm) - mean(none.ssm.w2$ssm)
```

```
## [1] 0.0999
```

Estimating SATEs 3 days later (Wave 2)

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study1.wave2 <- subset(gay, (study == 1) & (wave == 2))
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## estimated SATEs
mean(gay.ssm.w2$ssm) - mean(none.ssm.w2$ssm)
```

```
## [1] 0.0999
```

- What is the effect of straight vs no canvasser?

Estimating SATEs 3 days later (Wave 2)

- What is the effect of gay vs no canvasser?

```
study1.wave2 <- subset(gay, (study == 1) & (wave == 2))
none.ssm.w2 <- subset(study1.wave2,
                      treatment == "No Contact")
gay.ssm.w2 <- subset(study1.wave2,
   treatment == "Same-Sex Marriage Script by Gay Canvasser")
## estimated SATEs
mean(gay.ssm.w2$ssm) - mean(none.ssm.w2$ssm)
```

```
## [1] 0.0999
```

- What is the effect of straight vs no canvasser?

```
straight.ssm.w2 <- subset(study1.wave2,
    treatment == "Same-Sex Marriage Script by Straight Canvasser")
mean(straight.ssm.w2$ssm) - mean(none.ssm.w2$ssm)
```

Estimating SATEs 3 days later (Wave 2)

- What is the effect of gay vs no canvasser?

```
study1.wave2 <- subset(gay, (study == 1) & (wave == 2))
none.ssm.w2 <- subset(study1.wave2,
                      treatment == "No Contact")
gay.ssm.w2 <- subset(study1.wave2,
   treatment == "Same-Sex Marriage Script by Gay Canvasser")
## estimated SATEs
mean(gay.ssm.w2$ssm) - mean(none.ssm.w2$ssm)
```

```
## [1] 0.0999
```

- What is the effect of straight vs no canvasser?

```
straight.ssm.w2 <- subset(study1.wave2,
    treatment == "Same-Sex Marriage Script by Straight Canvasser")
mean(straight.ssm.w2$ssm) - mean(none.ssm.w2$ssm)
```

```
## [1] 0.122
```

Script effect?

- Any effects of scripts for gay canvassers?

Script effect?

- Any effects of scripts for gay canvassers?

```r
gay.rec.w2 <- subset(study1.wave2,
    treatment == "Recycling Script by Gay Canvasser")
mean(gay.ssm.w2$ssm) - mean(gay.rec.w2$ssm)
```

Script effect?

- Any effects of scripts for gay canvassers?

```
gay.rec.w2 <- subset(study1.wave2,
    treatment == "Recycling Script by Gay Canvasser")
mean(gay.ssm.w2$ssm) - mean(gay.rec.w2$ssm)
```

```
## [1] 0.032
```

Script effect?

- Any effects of scripts for gay canvassers?

```
gay.rec.w2 <- subset(study1.wave2,
    treatment == "Recycling Script by Gay Canvasser")
mean(gay.ssm.w2$ssm) - mean(gay.rec.w2$ssm)
```

```
## [1] 0.032
```

- Any effects of scripts for straight canvassers?

Script effect?

- Any effects of scripts for gay canvassers?

```
gay.rec.w2 <- subset(study1.wave2,
    treatment == "Recycling Script by Gay Canvasser")
mean(gay.ssm.w2$ssm) - mean(gay.rec.w2$ssm)
```

```
## [1] 0.032
```

- Any effects of scripts for straight canvassers?

```
straight.rec.w2 <- subset(study1.wave2,
    treatment == "Recycling Script by Straight Canvasser")
mean(straight.ssm.w2$ssm) - mean(straight.rec.w2$ssm)
```

Script effect?

- Any effects of scripts for gay canvassers?

```
gay.rec.w2 <- subset(study1.wave2,
    treatment == "Recycling Script by Gay Canvasser")
mean(gay.ssm.w2$ssm) - mean(gay.rec.w2$ssm)
```

```
## [1] 0.032
```

- Any effects of scripts for straight canvassers?

```
straight.rec.w2 <- subset(study1.wave2,
    treatment == "Recycling Script by Straight Canvasser")
mean(straight.ssm.w2$ssm) - mean(straight.rec.w2$ssm)
```

```
## [1] 0.158
```

After the SCOTUS Decision (Wave 5)

After the SCOTUS Decision (Wave 5)

```r
study1.wave5 <- subset(gay, (study == 1) & (wave == 5))
none.ssm.w5 <- subset(study1.wave5,
                      treatment == "No Contact")
gay.ssm.w5 <- subset(study1.wave5,
   treatment == "Same-Sex Marriage Script by Gay Canvasser")
## estimated SATEs
mean(gay.ssm.w5$ssm) - mean(none.ssm.w5$ssm)
```

```
## [1] 0.148
```

After the SCOTUS Decision (Wave 5)

```r
study1.wave5 <- subset(gay, (study == 1) & (wave == 5))
none.ssm.w5 <- subset(study1.wave5,
                     treatment == "No Contact")
gay.ssm.w5 <- subset(study1.wave5,
   treatment == "Same-Sex Marriage Script by Gay Canvasser")
## estimated SATEs
mean(gay.ssm.w5$ssm) - mean(none.ssm.w5$ssm)
```

```
## [1] 0.148
```

```r
straight.ssm.w5 <- subset(study1.wave5,
    treatment == "Same-Sex Marriage Script by Straight Canvasser")
mean(straight.ssm.w5$ssm) - mean(none.ssm.w5$ssm)
```

```
## [1] 0.0986
```

9 months later (Wave 7)

9 months later (Wave 7)

```r
study1.wave7 <- subset(gay, (study == 1) & (wave == 7))
none.ssm.w7 <- subset(study1.wave7,
                     treatment == "No Contact")
gay.ssm.w7 <- subset(study1.wave7,
   treatment == "Same-Sex Marriage Script by Gay Canvasser")
## estimated SATEs
mean(gay.ssm.w7$ssm) - mean(none.ssm.w7$ssm)
```

```
## [1] 0.0594
```

9 months later (Wave 7)

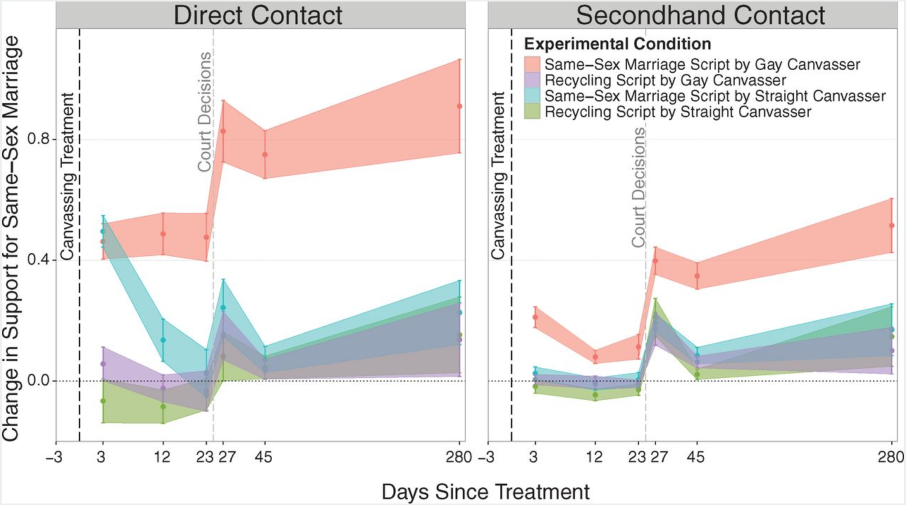
```r
study1.wave7 <- subset(gay, (study == 1) & (wave == 7))
none.ssm.w7 <- subset(study1.wave7,
                      treatment == "No Contact")
gay.ssm.w7 <- subset(study1.wave7,
   treatment == "Same-Sex Marriage Script by Gay Canvasser")
## estimated SATEs
mean(gay.ssm.w7$ssm) - mean(none.ssm.w7$ssm)
```

```
## [1] 0.0594
```

```r
straight.ssm.w7 <- subset(study1.wave7,
    treatment == "Same-Sex Marriage Script by Straight Canvasser")
mean(straight.ssm.w7$ssm) - mean(none.ssm.w7$ssm)
```

```
## [1] -0.0425
```

Big and lasting effects of persuasion



Retraction & media coverage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SCIENCE

359 COMMENTS

Doubts About Study of Gay Canvassers Rattle the Field

By BENEDICT CAREY and PAM BELLUCK MAY 25, 2015

Donald P. Green, left, a co-author of a challenged study by Michael LaCour, right, from Mr. LaCour's Facebook page.

Retraction

APR. 7, 2016 AT 2:00 PM

How Two Grad Students Uncovered An Apparent Fraud — And A Way To Change Opinions On Transgender Rights

By Christie Aschwanden and Maggie Koerth-Baker

Filed under Scientific Method

Hugh Tims, second from left, gives instructions to canvassers before going out in support of same-sex marriage. New research may change the way that political canvassing work is done. ROBERT F. BUKATY / AP

Follow up

POLITICAL SCIENCE

Durably reducing transphobia: A field experiment on door-to-door canvassing

David Broockman[1*] and Joshua Kalla[2]

Existing research depicts intergroup prejudices as deeply ingrained, requiring intense intervention to lastingly reduce. Here, we show that a single approximately 10-minute conversation encouraging actively taking the perspective of others can markedly reduce prejudice for at least 3 months. We illustrate this potential with a door-to-door canvassing intervention in South Florida targeting antitransgender prejudice. Despite declines in homophobia, transphobia remains pervasive. For the intervention, 56 canvassers went door to door encouraging active perspective-taking with 501 voters at voters' doorsteps. A randomized trial found that these conversations substantially reduced transphobia, with decreases greater than Americans' average decrease in homophobia from 1998 to 2012. These effects persisted for 3 months, and both transgender and nontransgender canvassers were effective. The intervention also increased support for a nondiscrimination law, even after exposing voters to counterarguments.

4/ Wrapping up

For next time

- Complete DataCamp Assignment 2

For next time

- Complete DataCamp Assignment 2
- Work on HW 1 (due next Thursday)

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- Go to sections (see website/google calendar for times/locations)

For next time

- Complete DataCamp Assignment 2
- Work on HW 1 (due next Thursday)
- Go to sections (see website/google calendar for times/locations)
- Read QSS 2.5 on Observational Studies for next time.