Bush 631-603: Quantitative Methods

Lecture 2 (01.25.2022): Causality vol. I

Rotem Dvir

The Bush school of Government and Public Policy

Texas A&M University

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What is today's plan?

- Causality and deriving cause-effect relationship.
- Research designs to assess causality.
- Randomized controlled experiments (RCTs).
- ▶ R work: more ways to learn of our data, sub-setting data, factor variables.

Causality

- ▶ Identify causes for outcomes of interest:
 - 1. Universal health care and better health status among poor.
 - 2. Drop in president approval during war.
- Establish causality:

Cause \rightarrow Effect

Establish causality

2016 turnout: 59.2% of VEP 2020 turnout: 62% of VEP





ightharpoonup Candidate gender ightarrow election turnout ?

Experiments

- Test causal effects using hypothetical scenario.
- ► Some use actual setting (natural experiment).
- ► Candidate gender and public support? use an experiment. . .

Experiments

President party \rightarrow foreign policy?



Experiments, how?

- ► Test causal effects using a *treatment*.
- ► Treatment(s) represents the proposed causal factor(s).
- Manipulate treatments assign different values.
- Measure and compare outcome across treatments.

Experiments in FP



Mattes and Weeks (2019)

Hawks – Doves and Foreign Policy Reconciliation



The design

- Elements of experiment:
 - Hypothetical scenario.
 - Adversary: China.
 - Important FP issue access to arctic.
 - Outcome measured: approval of president's actions.
- Treatments:
 - Description of factors.
 - Vary between groups.

-Background information:

"The year is 2027. The U.S. President is John Richards. President Richards took office in 2025 after serving in the U.S. Senate for six years."

► The leader's type (variable name = hawk_t):

Hawk/Dove

Hawk

... has a reputation for favoring military solutions over diplomatic ones. He has repeatedly emphasized that military force is essential to protecting American national security. President Richards says that he will not shy away from using force where necessary. He has long said that "the only way to achieve peace is to be ready for war."

Dove

... has a reputation for favoring diplomatic solutions over military ones. He has repeatedly emphasized that military force is not the answer to protecting American national security. President Richards says that he believes in diplomacy and negotiations and will use military force only as a last resort. He has long said that "the only way to achieve peace is to act peacefully."

- ► The setting (all respondents):
 - China: distrusted adversary.
 - ► Tense relations.
 - Specific issue access to arctic.

"One very tense issue is access to the Arctic. The Arctic contains up to 40 percent of the world's oil and gas resources and provides vital shipping routes between continents. In 2027, the U.S. and China both have a major military presence in the Arctic. Each country has thousands of troops in the area and holds frequent military exercises in the region."

President Richards and China:

"In his 2027 State of the Union speech, President Richards declares that getting China to cooperate is important for achieving U.S. foreign policy goals."

Policy choice (variable name = rapproche_t)

Policy Choice Conciliatory Status Quo ... announces that he is sharply reducing the U.S. military presence in the Arctic. He is withdrawing a third of the U.S. forces currently in the Arctic and is calling off planned military exercises in the region.

- Measuring outcomes:
 - President approval (variable name = hddv1): rate on a 1-5 scale.
 - 2. Trust: level of international trust in other nations (yes/no).
 - 3. Internationalism: US involvement in world affairs (1-4 scale).
- Respondents' characteristics:
 - 1. Gender.
 - 2. Voted in 2016?

The experiment data

```
dim(mydata)
## [1] 1199 32
head(mydata)
## # A tibble: 6 x 32
##
                      caseid hawk_t party_t rapproche_t success_t hawk intl trust vo
                        <dbl> <dbl+1> <dbl+1> <dbl+1> <dbl+1> <dbl+1> <dbl+1> <dbl+2 <dbl+3 <dbl+4 <dbl-4 <dbl>4 <dbl+4 <dbl>4 <dbl-4 <dbl>4 <dbl-4 <dbl>4 <dbl-4 <dbr-4 <dbl-4 <dbr-4 <dbr-4 <dbl-4 <dbr-4 <dbr-4 <dbr-4 <dbr-4 <dbr-4 <dbr-4 <dbr-4 <dbr-4 <dbr
##
## 1 329144398 2 [Dip~ 1 [Rep~ 1 [Reducin~ 1 [Pulls~ 4 [Agr~ 4 [Agr~ 2 [The~ 4
## 2 329105048 1 [Mil~ 1 [Rep~ 1 [Reducin~ 1 [Pulls~ 2 [Dis~ 4 [Agr~ 2 [The~ 4
## 3 328964530 1 [Mil~ 2 [Dem~ 1 [Reducin~ 1 [Pulls~ 2 [Dis~ 2 [Dis~ 2 [The~ 4
## 4 329130310 1 [Mil~ 2 [Dem~ 2 [Maintai~ 2 [Addit~ 4 [Agr~ 5 [Agr~ 1 [The~ 4
## 5 328809639 1 [Mil~ 2 [Dem~ 2 [Maintai~ 1 [Pulls~ 3 [Nei~ 2 [Dis~ 2 [The~ 1
## 6 329124511 2 [Dip~ 1 [Rep~ 2 [Maintai~ 2 [Addit~ 3 [Nei~ 4 [Agr~ 2 [The~ 4
## # ... with 23 more variables: polact 1 <dbl+lbl>, polact 2 <dbl+lbl>,
                   polact_3 <dbl+lbl>, polact_4 <dbl+lbl>, hddv1 <dbl+lbl>,
## #
## #
                   hdmed1_strat <dbl+lbl>, hdmed1_pacifist <dbl+lbl>,
## #
                   hdmed1 warmonger <dbl+lbl>, hddv2 <dbl+lbl>, hdmed2 strat <dbl+lbl>,
## #
                   hdmed2_pacifist <dbl+lbl>, hdmed2_warmonger <dbl+lbl>, birthyr <dbl>,
## #
                   gender <dbl+lbl>, educ <dbl+lbl>, pid3 <dbl+lbl>, pid7 <dbl+lbl>,
## #
                   ideo5 <dbl+lbl>, newsint <dbl+lbl>, pew religimp <dbl+lbl>, ...
```

The experiment data

summary(mydata)

hddv2	hdmed2_strat	hdmed2_pacifist	hdmed2_warmong	er birthyr	gender	educ	pid3
Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000	Min. :1925	Min. :1.000	Min. :1.000	Min. :1.000
1st Qu.:2.000	1st Qu.:2.000	1st Qu.:2.000	1st Qu.:1.000	1st Qu.:1956	1st Qu.:1.000	1st Qu.:2.000	1st Qu.:1.000
Median :4.000	Median :4.000	Median :3.000	Median :2.000	Median :1971	Median :2.000	Median :3.000	Median :2.000
Mean :3.505	Mean :3.403	Mean :2.716	Mean :2.304	Mean :1970	Mean :1.549	Mean :3.355	Mean :2.108
3rd Qu.:5.000	3rd Qu.:5.000	3rd Qu.:4.000	3rd Qu.:3.000	3rd Qu.:1984	3rd Qu.:2.000	3rd Qu.:5.000	3rd Qu.:3.000
Max. :5.000	Max. :5.000	Max. :5.000	Max. :5.000	Max. :1998	Max. :2.000	Max. :6.000	Max. :5.000
pid7	ideo5	newsint	pew_religimp	approve_b		internatioli	sm ally_trust
Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.00	Min. :0.0000	Agree Somewhat	:450	Min. :0.08
1st Qu.:1.000	1st Qu.:2.000	1st Qu.:1.000	1st Qu.:1.00	1st Qu.:0.0000	Agree Strongly		1st Qu.:1.00
Median :4.000	Median :3.000	Median :1.000	Median :2.00	Median :1.0000	Disagree Somewh	at :288	Median :1.00
Mean :3.642	Mean :3.069	Mean :1.753	Mean :2.32	Mean :0.6415	Disagree Strong	ly :105	Mean :0.79
3rd Qu.:6.000	3rd Qu.:4.000	3rd Qu.:2.000	3rd Qu.:4.00	3rd Qu.:1.0000	Neither Agree n	or Disagree:244	3rd Qu.:1.00
Max. :8.000	Max. :6.000	Max. :7.000	Max. :4.00	Max. :1.0000			Max. :1.00
				NA's :231			NA's :1

Exploring the data: cross-tabs

```
# Cross-tabs
table(type = mydata$hawk_t, support = mydata$hddv1)

## support
## type 1 2 3 4 5
## 1 59 132 148 187 74
## 2 73 83 83 217 143
tab2 <- table(support = mydata$hddv1, party = mydata$party_t)
addmargins(tab2)</pre>
```

```
##
       party
## support 1
           2 Sum
##
     1 55 77 132
     2 100 115 215
##
##
     3 115
            116 231
     4 209 195 404
##
     5 120 97 217
##
##
     Sum 599
            600 1199
```

Data analysis: first steps

```
# Calculate mean support for president
# Using the $ sign method
mean1 <- sum(mydata$hddv1) / nrow(mydata)</pre>
mean1
## [1] 3.299416
# Using the indexing method
mean2 <- sum(mydata[,14]) / nrow(mydata)</pre>
mean2
## [1] 3.299416
# Mean proportion of support
mean3 <- mean(mydata$approve_b, na.rm = TRUE)</pre>
mean3
## [1] 0.6415289
```

Logical values



► TRUE / FALSE output.

Logical values

```
class(FALSE)
## [1] "logical"
as.integer(TRUE)
## [1] 1
v1 <- c(FALSE, TRUE, TRUE, FALSE, FALSE)
mean(v1)
## [1] 0.4
sum(v1)
## [1] 2
```

Relational operators

- Evaluate the relationship between two values.
- Results are displayed as logical values

```
12 > 9

## [1] TRUE

"aggies" == "Aggies"

## [1] FALSE

"Aggies" == "Aggies"

## [1] TRUE
```

Relational operators

► Apply to vectors: results are logical values.

```
v3 <- c(4,8,-1,-9,7)
v3 < 0
## [1] FALSE FALSE TRUE TRUE FALSE
v3 >= 4
## [1] TRUE TRUE FALSE TRUE
v3 != 7
## [1] TRUE TRUE TRUE TRUE FALSE
```

Sub-setting data

Partition/split our data for certain calculations.

```
# Proportions of support by party
mean(mydata$approve_b[mydata$party_t == 1], na.rm = TRUE)
## [1] 0.6797521
mean(mydata$approve_b[mydata$party_t == 2], na.rm = TRUE)
## [1] 0.6033058
# Mean approval score by party
mean(mydata$hddv1[mydata$party t == 1], na.rm = TRUE)
## [1] 3.398998
mean(mydata$hddv1[mydata$party_t == 2], na.rm = TRUE)
## [1] 3.2
```

Sub-setting data

- Create subset of one group only.
- Only 'Hawkish' presidents.

```
# Sub-set 'hawks'
mysubdata1 <- mydata[mydata$hawk_t == 1,]</pre>
dim(mysubdata1)
## [1] 600 32
# Calculate mean support/approval
mean(mysubdata1$hddv1)
## [1] 3.141667
mean(mysubdata1$approve_b, na.rm = TRUE)
## [1] 0.5774336
```

Sub-setting data

► Subset function: construct a dataset only for the variables we are interested in.

```
mysubdata2 <- subset(mydata, subset = (hawk_t == 2))</pre>
```

View(mysubdata2)

^	caseid ‡ Case ID	hawk_t ‡ hawk_t	party_t ‡	rapproche_t † rapproche_t	success_t \$ success_t	hawk ‡ hawk	intl ‡ internationalism	trust ‡ trust	voted16 ‡ Voted in 2016
1	329144398								4
2	329124511								4
3	329023155								4
4	329124618								4
5	329011534								4
6	329056352								4
7	328905656								1
8	329147372								4
9	329147427								4
10	329147506								4
11	328849981								4
12	329002390								4
13	328770388								4
14	329231291								1
15	329254548								4

Calculating Group means

 Evaluate difference in support between Republican - Democrat president

```
# Create sub-samples for rep/dem president
mysubdata_rep <- subset(mydata, subset = (party_t == 1))
mysubdata_dem <- subset(mydata, subset = (party_t == 2))</pre>
```

```
# Compute difference in means
mean(mysubdata_rep$approve_b, na.rm = TRUE) -
mean(mysubdata_dem$approve_b, na.rm = TRUE)
```

```
## [1] 0.07644628
```

Compare means within a subset

Hawkish president: sub-sets for respondents' gender

```
# Create sub-samples for gender president
mysubdata4_male <- subset(mydata, subset = (hawk_t == 1 & gender == 1))
mysubdata4_female <- subset(mydata, subset = (hawk_t == 1 & gender == 2)
# Compute difference in means
mean(mysubdata4_female$approve_b, na.rm = TRUE) -
mean(mysubdata4_male$approve_b, na.rm = TRUE)</pre>
```

```
## [1] -0.06519359
```

Conditional Statements

- Useful for creating new variables (columns) in our data.
- Conditional based on values of other variables.
- ▶ Rely on TRUE / FALSE logical statements.

The ifelse() function

- ifelse(condition, value if TRUE, value if FALSE).
- Can accept multiple conditions.

```
# Create variable based on conditions
mydata$new1 <- ifelse(mydata$voted16 == 4 &
                         mydata$gender == 2,1,0)
# Cross-tabs: variable values
table(women voters = mydata$new1)
## women voters
##
    0 1
## 683 516
# Cross-tabs: counts of support for new variable
table(newvar = mydata$new1, support = mydata$approve_b)
##
         support
## newvar 0 1
##
       0 186 361
       1 161 260
##
```

The ifelse() function

Respondents' level of 'hawkishness' (survey item):

hawk – hawkishness, measured based on agreement with the statement "The use of military force only makes problems worse." 1 = Disagree strongly, 2 = Disagree somewhat, 3 = Neither agree nor disagree, 4 = Agree somewhat, 5 = Agree strongly

```
# Create variable
mydata$no_hawks <- ifelse(mydata$hawk>3,1,0)

# Cross-tabs: variable values
table(NoHawks = mydata$no_hawks)

## NoHawks
## 0 1
## 757 442
```

Factor Variables

► Categorical variable with finite number of distinct levels/values.

intl – internationalism, measured based on agreement with the statement "The United States needs to play an active role in solving conflicts around the world." 1 = Disagree strongly, 2 = Disagree somewhat, 3 = Neither agree nor disagree, 4 = Agree somewhat, 5 = Agree strongly

Factor Variables

Looking at factor variables

```
mydata$internatiolism <- as.factor(mydata$internatiolism)</pre>
class(mydata$internatiolism)
## [1] "factor"
levels(mydata$internatiolism)
## [1] "Agree Somewhat"
                                      "Agree Strongly"
## [3] "Disagree Somewhat"
                                      "Disagree Strongly"
## [5] "Neither Agree nor Disagree"
table(mydata$internatiolism)
##
               Agree Somewhat
                                            Agree Strongly
##
##
                           450
                                                        112
            Disagree Somewhat
                                         Disagree Strongly
##
##
                           288
                                                       105
## Neither Agree nor Disagree
##
                           244
```

tapply() command

- Apply a function across all levels of factor variable.
- Sort in desired order

```
# tapply: calculate mean approval for all levels
app_int <- tapply(mydata$approve_b, mydata$internatiolism, mean, na.rm = TRUE)
app_int
               Agree Somewhat
##
                                           Agree Strongly
                    0.6544503
##
                                                0.6086957
            Disagree Somewhat
                                        Disagree Strongly
##
                    0.6637555
                                                0.6547619
##
## Neither Agree nor Disagree
##
                    0.5966851
# Sort by value
sort(app int)
## Neither Agree nor Disagree
                                           Agree Strongly
##
                    0.5966851
                                                0.6086957
               Agree Somewhat
##
                                        Disagree Strongly
##
                    0.6544503
                                                0.6547619
            Disagree Somewhat
##
                    0.6637555
##
```

Causal Inference

► The importance of **counterfactual**



Causal Inference

Counterfactual in Foreign policy



May 2000: Israel withdraws from S. Lebanon Prime minister: Ehud Barak



Causal Inference

- Gender / military experience as potential causal factors.
- ► Why maybe?
- ▶ Can we isolate the factors that lead to different outcomes?

Causal Inference: QSS textbook

- ▶ Does an applicant's race affects the chances she/he are offered a job?
- ▶ Race → causal factor for job prospects?
- My name affects my chances of landing a job.
- Is it only my name/race??

Causal Inference: QSS textbook

Résumé	Black-sounding	Callback		Age	Education
i	name T _i	$Y_i(1)$	$Y_i(0)$	- Age	Laucation
1	1	1	?	20	college
2	0	?	0	55	high school
3	0	?	1	40	graduate school
:					
n	1	0	;	62	college

Other factors:

- ► Age.
- ► Education.
- ► Other?

Causal Inference

The fundamental problem of causal inference

- We cannot observe counterfactual outcomes.
- Assume research design helps us infer about our observed counterfactual outcomes.
- Identification process: same situation, one factor changes (president's gender, applicant race).
- ▶ Not possible in reality: *immutable characteristics*.

Randomized Controlled Trails (RCTs)

THE GOLD STANDARD OF CAUSAL INFERENCE

Why?

Establish causality by isolating the factor of interest.

How?

Randomization - random assignment to treatments.

RCTs

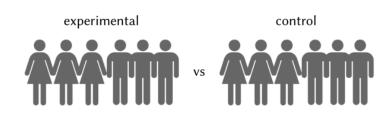
Sample Average Treatment Effect (SATE)

- ► The average individual-level treatment effect.
- Defined as:

$$SATE = 1/n \sum_{i=1}^{n} Y_i(1) - Y_i(0)$$

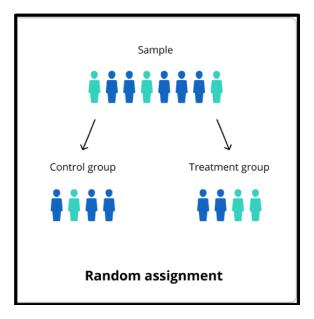
- ightharpoonup n ightharpoonup sample size.
- $lackbox{i} \rightarrow \text{respondent in the sample}.$

RCTs



- ► Compare outcomes between groups.
- ► SATE: average outcome between groups.
- ► Difference-in-means estimator

Random Assignment



Random Assignment

- ▶ Why important?
- Confounding factors similar in sample.
- ▶ Our treatment → Variation in outcomes.
- ▶ Our treatment → Causal factor.

Internal Validity

- Design satisfy causal assumptions?
- ▶ How well does the help us in testing our research question.
- Experiments offer strong internal validity.

External Validity

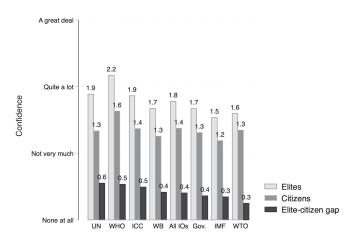
- Can we trust our results beyond the sample?
- Students sample = general public?
- Convenient samples: why?
- ▶ Main problem: sample selection bias
- Other design problems:
 - 1. Setting: lab versus real-world (Hawthorne effect).
 - 2. Unrealistic treatments: missing information.

Reduce external validity

- Replications same design, vary the sample:
 - General public and special samples (students, elites, experts, etc.)
 - Cross-national.
 - Multiple samples of same population.
- ightharpoonup Consistency in results ightharpoonup more confidence in proposed causal factor.

Replications

Public and elite samples: legitimacy of IOs



Causal Inference and president approval

```
# Treatment = president type
# What is proportion of support
tapply(mydata$approve_b, mydata$hawk_t, mean, na.rm = TRUE)
##
## 0.5774336 0.6976744
# Treatment = president party
# What is proportion of support
tapply(mydata$approve_b, mydata$party_t, mean, na.rm = TRUE)
##
## 0.6797521 0.6033058
```

Causal Inference and president approval

Create factorial variable for policy and party

Grouping treatments by president party and policy choice

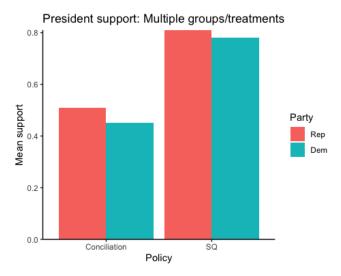
```
mydata$party_policy <- NA
mydata$party_policy[mydata$party_t == 1 & mydata$rapproche_t == 1] <- 1
mydata$party_policy[mydata$party_t == 1 & mydata$rapproche_t == 2] <- 2
mydata$party_policy[mydata$party_t == 2 & mydata$rapproche_t == 1] <- 3
mydata$party_policy[mydata$party_t == 2 & mydata$rapproche_t == 1] <- 3
mydata$party_policy[mydata$party_t == 2 & mydata$rapproche_t == 2] <- 4

# What is proportion of support by group
tapply(mydata$approve_b, mydata$party_policy, mean, na.rm = TRUE)

## 1 2 3 4
## 0.5138889 0.8134328 0.4492188 0.7763158
```

Causal Inference and president approval

- Grouping treatments by president party and policy choice
- Visual:



Wrapping up week 2

Causality vol. I:

- Assessing causal effects.
- Experimental designs (RCTs).
- Counterfactuals.
- Randomization.
- Internal and external validity.
- R work: cross-tabs, relational operations, sub-set data, ifelse(), factor variables.