Bush 631-607: Quantitative Methods

Lecture 3 (09.14.2021): Causality vol. II

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What is today's plan?

- Causality and deriving cause-effect relationship.
- Limitations of RCTs.
- Alternative designs: observational studies.
- Descriptive statistics: explore our data.
- R work: sub-setting data, spread of the data, quartiles, .

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:

$$\text{Cause} \rightarrow \text{Effect}$$

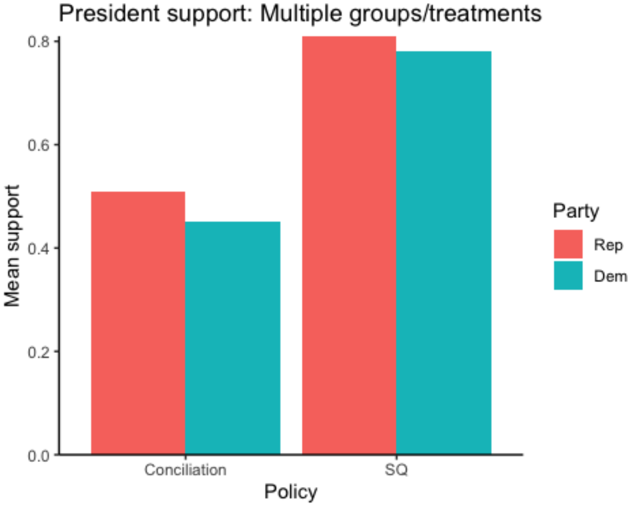
Experimental Research Designs

Mattes and Weeks (2019): FP actions and public opinion

- Elements of experiment:
  - Hypothetical scenario.
  - Adversary: China.
  - Important FP issue - access to arctic.
  - Outcome measured: approval of president's actions.
- Treatments:
  - Description of factors: leader type, party, policy enacted.
  - Vary between groups.
  - Comapre outcome variables: approval (1-5 scale), proportion of support

Experimental Research Designs: RCTs

- Grouping treatments by president party and policy choice



RCTs: Limitations

Ethical:

- Problematic treatments: manipulate police officers behavior.
- Deceit.

Logistical:

- Limited samples: students == elites ?? recruit world leaders ??

The alternative

Observational studies

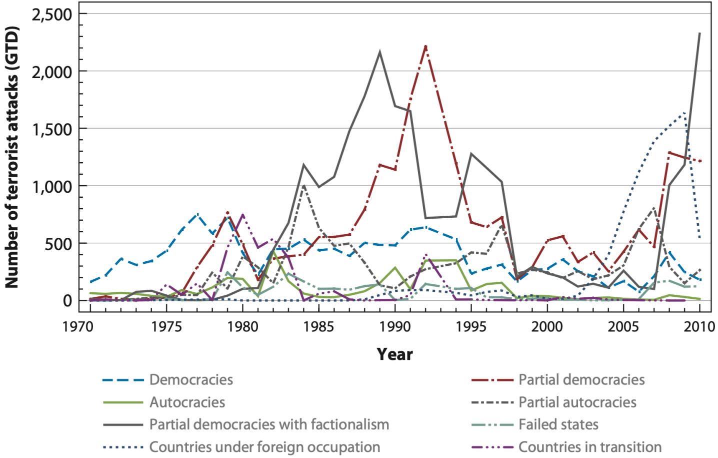
Do democracies experience more terror attacks than other regimes?

How to study?

- Observe actual events: record terror incidents.
- Treatment is 'assigned naturally' - countries are either a democracy or non-democracy.
- Study our collected data: does regime type matter for the frequency of terrorism?

Terrorism and regimes type

The answer?



Observational studies

Internal validity $\rightarrow$ weak:

- Pre-treatment variables.
- Can we show the effect of 'our' treatment?

External validity $\rightarrow$ strong:

- Larger samples.
- Time series data.
- Elites, politicians can be easily collected.
- Results can be generalized.

Observational studies: INTA

Study leaders

Studying leaders

Fuhrmann and Horowitz (2015):

- Personal background and military technology.
- Nuclear weapons.

Rebel background $\rightarrow$ pursue nuclear weapons?

Leaders and nuclear tech

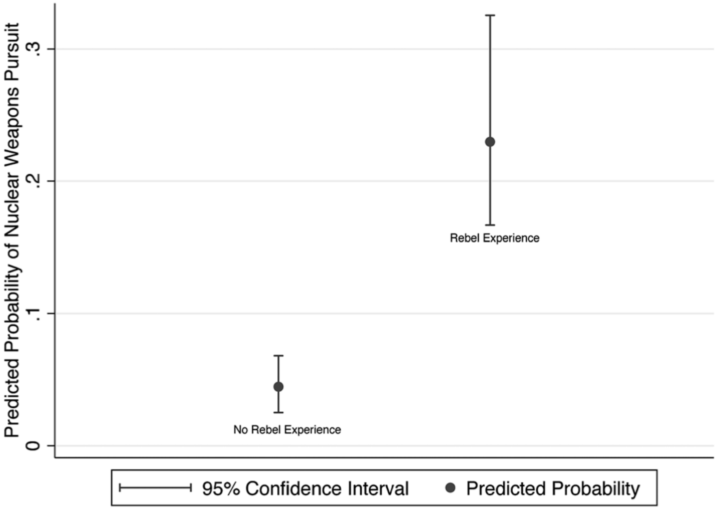
Why?

- Life experiences shape perceptions.
- Ensure national independence, discount allies.
- Underestimate financial and political costs.
- High risk tolerance.

How?

- Data on global leaders (1945-2000).
- 1342 leaders.
- Data on nuclear proliferation programs.
- Indicator for rebel participation.

Leaders and nuclear tech



Working with observational data

Large-n data:

```
dim(mydata)
```

```
## [1] 8852   76
```

Time-series cross-sectional data (TSCS)

code COW numeric country code	idacr COW alpha country code	year Year	leadid30 LEAD Leader ID	leadername Leader Name	startdate LEAD Start Date	inday Leader Entry Day
2	USA	1995	A2.9-73	Clinton	1993-01-20	20
2	USA	1996	A2.9-73	Clinton	1993-01-20	20
2	USA	1997	A2.9-73	Clinton	1993-01-20	20
2	USA	1998	A2.9-73	Clinton	1993-01-20	20
2	USA	1999	A2.9-73	Clinton	1993-01-20	20
2	USA	2000	A2.9-73	Clinton	1993-01-20	20
20	CAN	1945	A2.9-118	King	1935-10-23	23
20	CAN	1946	A2.9-118	King	1935-10-23	23
20	CAN	1947	A2.9-118	King	1935-10-23	23
20	CAN	1948	A2.9-118	King	1935-10-23	23

Leaders data

Main variables we'll use:

```r
# rebel experience: yes/no (coded 1/0)
table(rebels = mydata$rebel)
```

```
## rebels
##    0    1
## 5089 3743
```

```r
# revolutionary leader: yes/no (coded 1/0)
table(rev_leaders = mydata$revolutionaryleader)
```

```
## rev_leaders
##    0    1
## 6816 1041
```

```r
# pursue nuclear tech: yes/no (coded 1/0)
table(pursue_nukes = mydata$pursuit, exclude = NULL)
```

```
## pursue_nukes
##    0    1 <NA>
## 8257  225  370
```

Creating treatment & control groups

```r
# subsets: rebel experience yes/no
lead_rebels <- subset(mydata, subset = (rebel == 1))
lead_norebels <- subset(mydata, subset = (rebel == 0))

dim(lead_rebels)
```

```
## [1] 3743   76
```

```r
# subsets: revolutionary leaders yes/no
rev_leader <- subset(mydata, subset = (revolutionaryleader == 1))
rev_noleader <- subset(mydata, subset = (revolutionaryleader == 0))

dim(rev_leader)
```

```
## [1] 1041   76
```

Differnce-in-means

Does rebel experience matter?

```r
# pursuit of nukes tech: diff-in-means (rebels - no rebels)
mean(lead_rebels$pursuit, na.rm = TRUE) -
  mean(lead_norebels$pursuit, na.rm = TRUE)
```

```
## [1] 0.0376728
```

```r
# pursuit of nukes tech: diff-in-means (rev. leaders - no rev. leaders)
mean(rev_leader$pursuit, na.rm = TRUE) -
  mean(rev_noleader$pursuit, na.rm = TRUE)
```

```
## [1] 0.06781106
```

Differnce-in-means

Alternative measures: existing nuclear arsenals

```
# existing bomb program: yes/no (coded 1/0)
table(bomb_program = mydata$bombprgm)
```

```
## bomb_program
##    0    1
## 8258  594
```

```
# pursuit of nukes tech: diff-in-means (rebels - no rebels)
mean(lead_rebels$bombprgm, na.rm = TRUE) -
  mean(lead_norebels$bombprgm, na.rm = TRUE)
```

```
## [1] 0.02515995
```

```
# pursuit of nukes tech: diff-in-means (rev. leaders - no rev. leaders)
mean(rev_leader$bombprgm, na.rm = TRUE) -
  mean(rev_noleader$bombprgm, na.rm = TRUE)
```

```
## [1] 0.04400943
```

Why does it matter?

Policy Lessons??

Observational studies

Why study large-N data?

- Policy questions, real (sometime rare) events.
- Japan - Russia war (1905) $\neq$ Gulf war (1991), right?

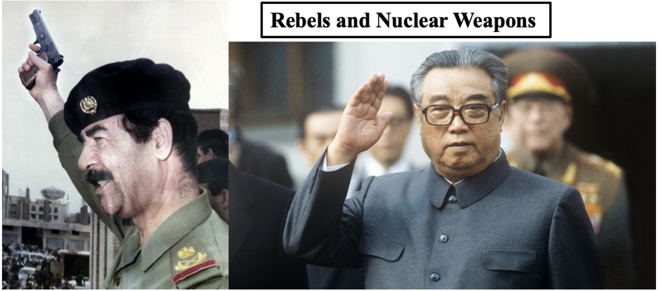
What does studying large-N means?

- Collect lots of observations.
- Apply stats methods to evaluate potential patterns in data.

So, Why?

Universe of cases:

- Better sense of phenomenon.
- Large variation.
- Identify *important cases*.



So, Why?

Construct general theory of state behavior

- Social science overarching goal.
- One case? tough for general argument.
- Theory applies across time and space.

Vietnam (1965) → Afghanistan (2001)

Observational Studies

- Guiding assumption:

Treatment group (rebel leaders) = control group (no rebels)

Is it?

Kadar (Hungary): 1956-1988.
Leader of Hungarian rebellion (1956)

Did not purse Nuclear weapons

Bhutto (Pakistan): 1972-1977.

No rebel background

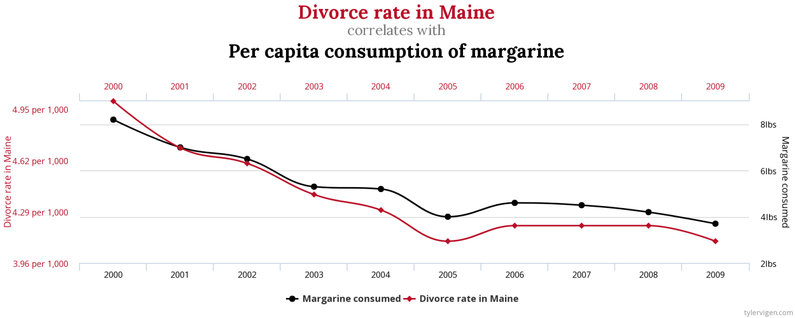
Pursued Nuclear weapons

Confounders

- Pre-treatment variables $\rightarrow$ treatment & outcome.
- Realized 'before' treatment $\rightarrow$ who 'receive' treatment.
- **Selection bias**: cannot assign who gets treatment (assign rebel experience).
- Unobserved differences $\rightarrow$ is it rebel background.
- More examples:
  1. Terrorism and regime type (civil strife).
  2. Economic growth (international trade).
  3. Sanctions effective? (corrupt leader).
  4. Prevail in conflict - democracy (or military capacity).

Inference problems

Association does not imply causation



More? (SpuriousCors_Link)

Our confounders

- **Superpower alliance**: no need to pursue nuclear weapons.

- Hungary & USSR: Kadar did not pursue nuclear weapons.
- UK & US: Churchill and Atlee pursue nuclear weapons.
- West Germany & US: Kohl did not pursue nuclear weapons.

- Both rebels and non-rebels pursue nuclear weapons.

Bias our causal explanation!!!

Confounders

- Ever present problem of observational studies.
- What do we do?
  - Ensure correct cases identification.
  - Statistical 'control' of confounding factors (we'll get to it).
- **Sub-classification**:
  - Minimize similarities b-w treatment & control groups.
  - subsets of shared pre-treatment values.
  - Comparing main factor within subsets.

Sub-classification in R

- prop.table(): tabulate proportions of different levels of factor variables.

```
# Confounders: alliance with a superpower
# Leaders with rebel experience
prop.table(table(rebel_allies = lead_rebels$spally))
```

```
## rebel_allies
##        0        1
## 0.670247 0.329753
```

```
# Confounders: alliance with a superpower
# Leaders with no rebel experience
prop.table(table(no_rebels_allies = lead_norebels$spally))
```

```
## no_rebels_allies
##         0         1
## 0.5848161 0.4151839
```

Subsetting alliance and rebel leaders

```r
# subsets: rebel/non-rebel leaders and superpower alliance
rebel_ally <- subset(lead_rebels, subset = (spally == 1))
norebel_ally <- subset(lead_norebels, subset = (spally == 1))

# diff-in-means in nuclear weapons pursuit
mean(rebel_ally$pursuit, na.rm = TRUE) -
  mean(norebel_ally$pursuit, na.rm = TRUE)
```

```
## [1] 0.0231065
```

- Fuhrmann and Horowitz (2015):
  - Countries with no superpower alliance $\rightarrow$ 4.6 more likely to pursue nukes.
  - Other confounders for nuclear tech: nuclear cooperation agreement, rivalry, military disputes.

More research designs

Before and After design

- *Longitudinal / Panel data*
- Collecting time series data.
- Time-related information for treatment and control groups.
- Better comparison of groups.

Before and after design: QSS textbook

- Topic: changes to minimum wage and levels of full-time employment.
- Method: compare fast food restaurants (NJ - PA).
- Longitudinal design: compare **within** NJ group
- Before and after (change in minimum wage).
- Result: diff-in-means = 0.023 (2.3% increase in employment).
- Benefit: control all NJ confounders.
- Cost: time trend factor may bias results.

Before and after design: Rebel leaders

- Slight diversion: pursue nuclear weapons over leader tenure
- Compare: year 1 vs. subsequent years

```
# subsets: rebel leaders, first year and subsequent years
reb_one <- subset(lead_rebels, subset = (nonpuryrs == 0))
reb_after <- subset(lead_rebels, subset = (nonpuryrs > 0))

# diff-in-means: nuclear weapons pursuit over time
mean(reb_one$pursuit, na.rm = T) -
  mean(reb_after$pursuit, na.rm = T)
```

```
## [1] 0.2263734
```

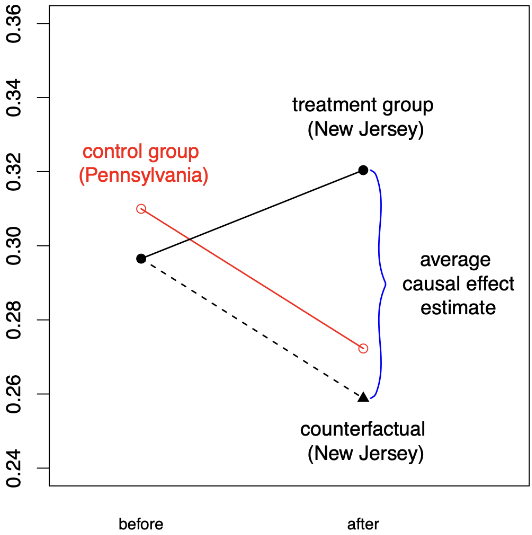
More research designs

Difference in Difference design

- Extends the before-and-after design.
- Control for time trends (effects).
- Using control group before-and-after to infer on treatment group (the counterfactual).

Diff-in-diff design

- Minimum wage and full-time employment



Diff-in-diff design: QSS Textbook

- Quantity of interest:
  - *SATT*: Sample Average Treatment effect for the Treated.
  - Difference b-w observed outcome and counterfactual (no increase in NJ)

$$\text{DiD estimate} = \underbrace{\left(\overline{Y}^{\text{after}}_{\text{treated}} - \overline{Y}^{\text{before}}_{\text{treated}}\right)}_{\text{difference for the treatment group}} - \underbrace{\left(\overline{Y}^{\text{after}}_{\text{control}} - \overline{Y}^{\text{before}}_{\text{control}}\right)}_{\text{difference for the control group}}.$$

Research Designs

- Cross-sectional comparison:
  - Compare treated units with control units after treatment.
  - Assumption: treated and control groups are comparable.
  - Problems of confounders.
- Before-and-after comparison:
  - Compare the same units before and after treatment.
  - Assumption: no time-varying confounding.
- Differences-in-differences comparison:
  - Assumption: similar trend assumptions.
  - Design accounts for unit-specific and time-varying confounders.

Learn from data

Descriptive Statistics

- Cross-sectional comparison $\rightarrow$ average outcome of interest.
- General findings: 4.8% of all rebel leaders (1945-2000) pursue nuclear weapons.
- More? other numerical summaries (min, max values, range).
- *Quantiles*: divide data to groups based on magnitude.
- **Median**: the middle value when the data is divided to two groups.

The **median** of a variable x is defined as:

$$\text{median} = \begin{cases} x_{((n+1)/2)} & \text{if } n \text{ is odd,} \\ \frac{1}{2}\left(x_{(n/2)} + x_{(n/2+1)}\right) & \text{if } n \text{ is even,} \end{cases}$$

Rebel leaders data

```
# pursuit of nuclear weapons: all leaders
median(mydata$pursuit, na.rm = TRUE)
```

```
## [1] 0
```

```
# pursuit of nuclear weapons: rebel leaders
median(lead_rebels$pursuit, na.rm = TRUE)
```

```
## [1] 0
```

```
# Economic growth measures: GDP per capita
median(mydata$gdpcap, na.rm = TRUE)
```

```
## [1] 3612
```

```
# Involvement in MID: 5 year average
range(mydata$disputes, na.rm = TRUE)
```

```
## [1]  0.00 17.75
```

Descriptive Stats

The mean - median debate

- Both describe center of distribution (data spread).
- Not always equal.

```r
# Economic growth measures: GDP per capita
median(mydata$gdpcap, na.rm = TRUE)
```

```
## [1] 3612
```

```r
# Economic growth measures: GDP per capita
mean(mydata$gdpcap, na.rm = TRUE)
```

```
## [1] 5808.161
```

The mean - median debate

- Why not equal?

```r
v1 <- c(100,200,300)
mean(v1)
```

```
## [1] 200
```

```r
median(v1)
```

```
## [1] 200
```

- mean $\rightarrow$ sensitive to *outliers* - extreme values.

```r
v2<- c(100,200,4000)
mean(v2)
```

```
## [1] 1433.333
```

```r
median(v2)
```

```
## [1] 200
```

Descriptive Stats

- **Quartiles**: more complete description of data.

```
# Quartiles and summary function
summary(lead_rebels$gdpcap)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##     281    1197    2476    3937    5026   41762     454
```

- **IQR**: range that contains 50% of the data (spread of distribution)

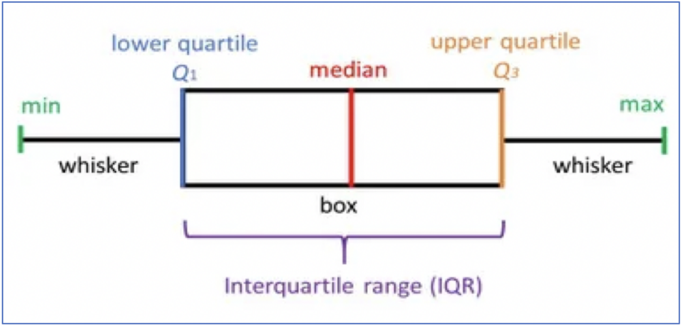
```
# IQR function: openness (economic measure)
IQR(lead_rebels$openness, na.rm = TRUE)
```

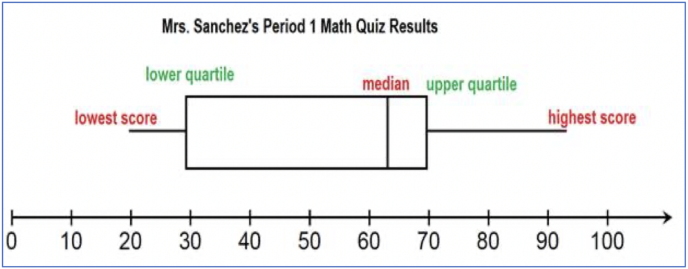
```
## [1] 38.01
```

```
IQR(lead_norebels$openness, na.rm = T)
```

```
## [1] 50.2475
```

Descriptive Stats





Descriptive Stats

- Other quantiles:
  - terciles (3 groups)
  - quintiles (5 groups)
  - deciles (10 groups)
  - percentiles (100 groups)

```
# deciles (10 groups) for dispute involvement
# compare rebels and non-rebels

quantile(lead_rebels$disputes, probs = seq(from = 0,
                                           to = 1, by = 0.1), na.rm = T)
```

```
##    0%   10%   20%   30%   40%   50%   60%   70%   80%   90%  100%
##  0.00  0.00  0.00  0.00  0.20  0.40  0.60  0.80  1.40  2.20 17.75
```

```
quantile(lead_norebels$disputes, probs = seq(from = 0,
                                             to = 1, by = 0.1), na.rm = T)
```

```
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##  0.0  0.0  0.0  0.0  0.0  0.2  0.4  0.4  0.8  1.4  9.4
```

Spread of data

- **RMS (Root Mean Square)**: magnitude of each observation.

$$RMS = \sqrt{\frac{entry_1^2 + entry_2^2 + entry_3^2 + ...}{\sum entries}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$$

- **SD (Standard Deviation)**: average deviation of each data point from mean ('distance' of points from average).

$$SD = \sqrt{\frac{(entry1 - mean)^2 + (entry2 - mean)^2 + ...}{\sum entries}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

SD manually: NFL Week 1 Winners

```r
# Create vector of top-5 NFL week 1 winners points and the Dolphins
v_win <- c(41,38,37,34,33,17)

# Calculate sample mean
mean(v_win)
```

```
## [1] 33.33333
```

```r
# Create vector of difference of each data point from mean
# Square each resulting differnece
v_diff <- (v_win - mean(v_win))
v_diff_sq <- (v_diff)^2

# Final SD steps: square root of sum of squared differences
#                 divided by sample size
sd_manual <- sqrt((sum(v_diff_sq) / 6))
sd_manual
```

```
## [1] 7.760298
```

Spread of rebel leaders data

```r
# compare mean pursuit of nuclear weapons
sd(lead_rebels$pursuit, na.rm = TRUE)
```

```
## [1] 0.2141889
```

```r
sd(lead_norebels$pursuit, na.rm = TRUE)
```

```
## [1] 0.1020045
```

```r
# compare mean dispute involvement
sd(lead_rebels$disputes, na.rm = TRUE)
```

```
## [1] 1.516794
```

```r
sd(lead_norebels$disputes, na.rm = TRUE)
```

```
## [1] 1.006146
```

Wrapping up week 3

Causality vol. II:

- More methods to assess causal effects.
- Observational studies.
- Large-n data analysis (external validity benefits).
- Confounding bias.
- Designs: before-and-after.
- Designs: diff-in-diff.
- Descriptive stats: median, quartiles, RMS, SD.
- R work: prop.table(), subset(), median, summary, IQR, SD.

Research design task I

- Build your own experiment!
- Submit via Canvas: **September 28, 2021** deadline.

Experiment design: Mattes and Weeks (2019)

Topic	Public opinion and government foreign policy		
My research question	Does the president's party affect public views of foreign policy actions?		
The causal factors tested	1. Party: Republican OR Democrat 2. Policy: Conciliatory OR Status-quo		
Outcome measured	Approval of president's actions in a foreign policy dispute		
The Design	**Value 1**	**Value 2**	**Who reads?**
Treatment 1: Party	[President Richards] is a lifelong member of the Republican party	[President Richards] is a lifelong member of the Democratic party	One for each group
Treatment 2: Policy	[President Richards] 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.	[President Richards] announces that he is maintaining the current U.S. military presence in the Arctic. He will continue to keep U.S. forces in the Arctic and will carry through with planned military exercises in the region.	One for each group
	Text	**Scale (detail categories)**	**Who answers?**
Outcome variable: Approval	How much do you approve of president Richards actions?	1 = Strongly disapprove 2 = Somewhat disapprove 3 = Neither approve nor disapprove 4 = Somewhat approve 5 = Strongly approve	All respondents