

Bush 631-607: Quantitative Methods

Lecture 8 (10.19.2021): Prediction vol. III

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What is today's plan?

- ▶ Predictions: Linear model and causal inference.
- ▶ Binary predictors and randomized experiments.
- ▶ Multiple predictors, heterogeneous treatment effects
- ▶ R work: `lm()`, `levels()`, `coef()`.

Least squared

THE LINEAR MODEL

$$Y = \alpha + \beta * X_i + \epsilon$$

Elements of model:

- ▶ *Intercept* (α): the average value of Y when X is zero.
- ▶ *Slope* (β): the average increase in Y when X increases by 1 unit.
- ▶ *Error/disturbance term* (ϵ): the deviation of an observation from a perfect linear relationship.

Minimize the prediction error

Confused by data?

Regression to the mean - its everywhere



How sure are we?

- ▶ What does our model tell us?
- ▶ Do the results mean anything?
- ▶ **Causal inference:**
 - ▶ Predicting the counter-factual.
 - ▶ Assumptions → use regression models for prediction.

Causal inference

Randomized experiments: women politicians and policy outcomes



Causal inference

QSS example: West Bengal (1990's)

```
dim(women)
```

```
## [1] 322 6
```

```
head(women)
```

```
##   GP village reserved female irrigation water
## 1  1      2         1      1           0     10
## 2  1      1         1      1           5      0
## 3  2      2         1      1           2      2
## 4  2      1         1      1           4     31
## 5  3      2         0      0           0      0
## 6  3      1         0      0           0      0
```

Causal inference

Promoting women's issues

```
## drinking-water facilities
```

```
mean(women$water[women$reserved == 1]) -  
  mean(women$water[women$reserved == 0])
```

```
## [1] 9.252423
```

```
## Irrigation facilities
```

```
mean(women$irrigation[women$reserved == 1]) -  
  mean(women$irrigation[women$reserved == 0])
```

```
## [1] -0.3693319
```


Causal inference

Promoting women's issues: regression analysis

```
# Drinking water model
```

```
lm(water ~ reserved, data = women)
```

```
##
```

```
## Call:
```

```
## lm(formula = water ~ reserved, data = women)
```

```
##
```

```
## Coefficients:
```

```
## (Intercept)      reserved
```

```
##      14.738          9.252
```

```
# Irrigation facilities model
```

```
lm(irrigation ~ reserved, data = women)
```

```
##
```

```
## Call:
```

```
## lm(formula = irrigation ~ reserved, data = women)
```

```
##
```

```
## Coefficients:
```

```
## (Intercept)      reserved
```

```
##      3.3879        -0.3693
```

Causal inference

Binary dependent variable:

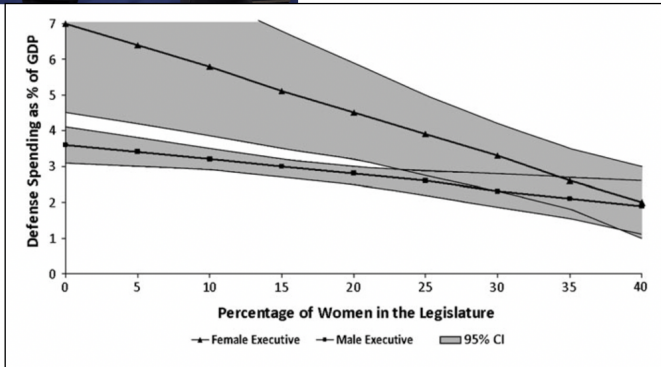
- ▶ slope coefficient (β) = diff-in-means estimator
- ▶ $\hat{\beta}$: estimated average treatment effect
- ▶ Effect with/without women leaders.

- ▶ Why works?
 - ▶ Randomization \rightarrow causal interpretation

Women leaders of Government

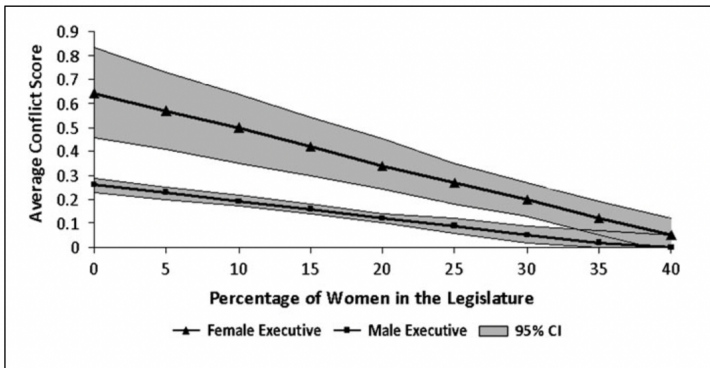


WOMEN LEADERS & FOREIGN POLICY



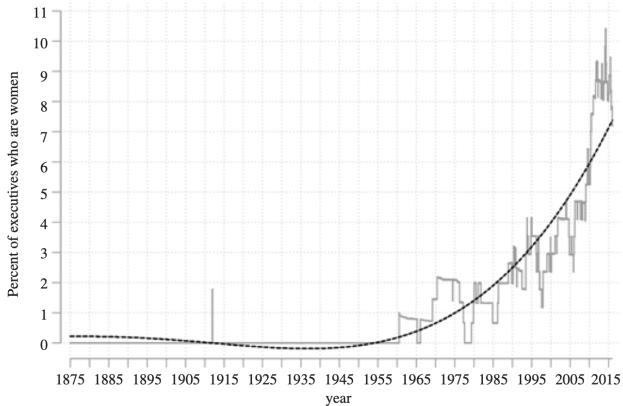
Women leaders in crisis

WOMEN LEADERS IN CONFLICT



Women leaders of Government

Schwartz and Blair (2020)



Women in crisis

Schwartz and Blair (2020)

- ▶ Audience costs → empty threat, inconsistency.
- ▶ Belligerence costs → issue a threat.
- ▶ Gender stereotypes: weak, ill-prepared, emotional.
- ▶ Leader competence: male-female dyads.

Women in crisis

- ▶ Design: experiment
- ▶ Treatments: dyads of conflict interactions.
- ▶ Outcome measures: approval (scale and binary).

```
dim(leader)
```

```
## [1] 2342 58
```

Women leaders

Gender stereotyping: small scale evidence

```
### General: higher disapproval for women
```

```
mean(leader$Disapproval[leader$FemaleUS == 1], na.rm = T) -  
  mean(leader$Disapproval[leader$FemaleUS == 0], na.rm = T)
```

```
## [1] 0.04998737
```

```
mean(leader$DisapprovalBinary[leader$FemaleUS == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$FemaleUS == 0], na.rm = T)
```

```
## [1] 0.01466212
```

```
mean(leader$Disapproval[leader$FemaleOpp == 1], na.rm = T) -  
  mean(leader$Disapproval[leader$FemaleOpp == 0], na.rm = T)
```

```
## [1] 0.131284
```

```
mean(leader$DisapprovalBinary[leader$FemaleOpp == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$FemaleOpp == 0], na.rm = T)
```

```
## [1] 0.0202939
```


Women leaders

```
# Linear model coefficients == diff-in-means estimators
```

```
lm(DisapprovalBinary ~ FemaleUS, data = leader)
```

```
##
```

```
## Call:
```

```
## lm(formula = DisapprovalBinary ~ FemaleUS, data = leader)
```

```
##
```

```
## Coefficients:
```

```
## (Intercept)      FemaleUS
```

```
##      0.49831      0.01466
```

```
lm(DisapprovalBinary ~ FemaleOpp, data = leader)
```

```
##
```

```
## Call:
```

```
## lm(formula = DisapprovalBinary ~ FemaleOpp, data = leader)
```

```
##
```

```
## Coefficients:
```

```
## (Intercept)      FemaleOpp
```

```
##      0.49521      0.02029
```

Gender and conflict approval

Inconsistency in male only vs. mixed dyads

```
# Male dyad <--> Male US, Female foreign
```

```
mean(leader$DisapprovalBinary[leader$MM_NotEngage == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$MF_NotEngage == 1], na.rm = T)
```

```
## [1] -0.05852317
```

```
# Male dyad <--> Female US, Male foreign
```

```
mean(leader$DisapprovalBinary[leader$MM_NotEngage == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$FM_NotEngage == 1], na.rm = T)
```

```
## [1] -0.114592
```

Gender and audience costs

```
mean(leader$DisapprovalBinary[leader$MM_NotEngage == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$MM_Engage == 1], na.rm = T)
```

```
## [1] 0.3262621
```

```
mean(leader$DisapprovalBinary[leader$FM_NotEngage == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$FM_Engage == 1], na.rm = T)
```

```
## [1] 0.5198552
```

```
mean(leader$DisapprovalBinary[leader$MF_NotEngage == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$MF_Engage == 1], na.rm = T)
```

```
## [1] 0.4359946
```

```
mean(leader$DisapprovalBinary[leader$FF_NotEngage == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$FF_Engage == 1], na.rm = T)
```

```
## [1] 0.4980188
```

Gender and belligerence costs

Make a threat or not...

```
# Belligerence costs by gender
```

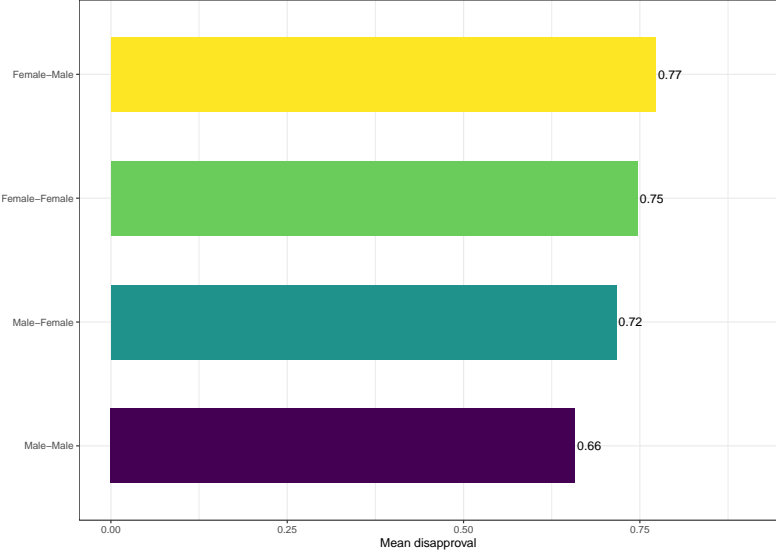
```
mean(leader$DisapprovalBinary[leader$MM_StayOut == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$MM_Engage == 1], na.rm = T)
```

```
## [1] 0.135034
```

```
mean(leader$DisapprovalBinary[leader$FM_StayOut == 1], na.rm = T) -  
  mean(leader$DisapprovalBinary[leader$FM_Engage == 1], na.rm = T)
```

```
## [1] 0.2473684
```

Inconsistency in gender dyads



Binary predictors

Linear model elements:

- ▶ *Slope* (β): the average increase in Y when X increases by 1 unit.

When X is binary:

- ▶ Treatment: yes or no (female leader follow-through or not).
- ▶ X change by 1 unit \rightarrow no to yes.
- ▶ Y (disapproval) changes as well (measured in percentages).

Regression model

Why sanctions fail?

Likelihood of Success Versus Failure

	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>	<i>Model 5</i>	<i>Model 6</i>	<i>Model 7</i>
Hypothesized Variables							
All Busters	-0.24 (0.12)**	-0.46 (0.15)***					
Black Knight Allies			0.05 (0.25)	-0.08 (0.27)			
Black Knight Great Powers					-0.27 (0.24)	-0.44 (0.40)	
HSE Black Knight							0.03 (0.67)
Control Variables							
US Cooperation		-0.99 (0.57)*		-0.93 (0.57)		-0.84 (0.57)	
IO Support		-2.76 (1.41)*		-2.56 (1.46)*		-2.17 (1.49)	
IO × Coop		1.59 (0.60)***		1.54 (0.61)**		1.37 (0.62)**	
US Defensive Alliance		-0.70 (0.76)		-0.59 (0.72)		-0.73 (0.77)	
Target Defense Alliances		0.00 (0.02)		0.00 (0.02)		0.00 (0.02)	
Modest Goal		1.82 (0.68)***		1.77 (0.68)***		1.73 (0.66)***	
Prior Relations		1.38 (0.46)***		1.37 (0.45)***		1.34 (0.46)***	
Democracy		-0.58 (0.71)		-0.46 (0.68)		-0.31 (0.71)	
Post-Cold War		-0.79 (0.64)		-0.79 (0.61)		-0.74 (0.64)	
Time	-0.08 (-0.18)	0.04 (0.77)	-0.01 (0.69)	-0.11 (0.76)	-0.09 (0.18)	-0.08 (0.76)	-0.11 (0.18)
Time ²	0.00 (-0.01)	0.03 (0.14)	0.04 (0.13)	0.05 (0.14)	0.00 (0.01)	0.05 (0.15)	0.00 (0.01)
Time ³	-0.00 (0.00)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.00)	-0.00 (0.01)	0.00 (0.00)
Constant	0.40 (-0.63)	-1.88 (1.59)	-0.77 (1.02)	-3.08 (1.61)*	-1.12 (.51)	-2.79 (1.60)*	-0.25 (0.51)
Prob > X ²	0.02	0.00	0.07	0.00	0.02	0.00	0.01
Observations	840	753	789	753	840	753	840

Regression model

MULTIPLE PREDICTORS

$$Y = \alpha + \beta_1 * X_1 + \beta_2 * X_2 + \dots + \beta_p * X_p + \epsilon$$

How to interpret β_j ?

- ▶ Change in Y with 1-unit increase in X_j ...
- ▶ As all other predictors are **held constant**.
- ▶ Independent effect of each β .

Least squared: Multiple predictors

Sum of Squared Residuals (SSR)

$$SSR = \sum_{i=1}^n \hat{\epsilon}^2 = \sum_{i=1}^n (Y_i - \hat{\alpha} - \hat{\beta}_1 * X_{1i} - \hat{\beta}_2 * X_{2i} - \dots - \hat{\beta}_p * X_{pi})^2$$

- ▶ Estimate parameters: $\hat{\alpha}, \hat{\beta}_p$.
- ▶ Minimize SSR.

Women in crisis data

- ▶ Multiple predictors for leader's approval
- ▶ Using factor variables: binary outcome

```
### Generate a Factor variable
leader$inconsis_cond <- NA
leader$inconsis_cond[leader$MM_NotEngage == 1] <-"MM"
leader$inconsis_cond[leader$MF_NotEngage == 1] <-"MF"
leader$inconsis_cond[leader$FM_NotEngage == 1] <-"FM"
leader$inconsis_cond[leader$FF_NotEngage == 1] <-"FF"

# levels of factor
levels(factor(leader$inconsis_cond))

## [1] "FF" "FM" "MF" "MM"
```

Multiple binary predictors

$$Y(\text{Disapproval}) = \alpha + \beta_1 * MM + \beta_2 * MF + \beta_3 * FM + \beta_4 * FF + \epsilon$$

```
fit <- lm(DisapprovalBinary ~ factor(inconsis_cond), data = leader)
fit
```

```
##
## Call:
## lm(formula = DisapprovalBinary ~ factor(inconsis_cond), data = leader)
##
## Coefficients:
##           (Intercept)  factor(inconsis_cond)FM  factor(inconsis_cond)MF
##           0.74661           0.02588           -0.03019
## factor(inconsis_cond)MM
##           -0.08871
```

Multiple binary predictors

Coefficients = diff-in-means??

```
# Regression w/o the intercepts
fit3 <- lm(DisapprovalBinary ~ -1 + inconsis_cond, data = leader)
fit3

##
## Call:
## lm(formula = DisapprovalBinary ~ -1 + inconsis_cond, data = leader)
##
## Coefficients:
## inconsis_condFF  inconsis_condFM  inconsis_condMF  inconsis_condMM
##           0.7466           0.7725           0.7164           0.6579
```

Multiple binary predictors

Same with `tapply()`

```
tapply(leader$DisapprovalBinary, leader$inconsis_cond, mean)
```

```
##           FF           FM           MF           MM  
## 0.7466063 0.7724868 0.7164179 0.6578947
```

Average treatment effect versus control (MM dyad)

```
# Using coef() function  
coef(fit3)["inconsis_condFM"] - coef(fit3)["inconsis_condMM"]
```

```
## inconsis_condFM  
##           0.114592
```

```
coef(fit3)["inconsis_condFF"] - coef(fit3)["inconsis_condMM"]
```

```
## inconsis_condFF  
##           0.0887116
```

Model fit: multiple predictors

R^2 with multiple predictors \rightarrow Adjusted R^2

Degrees of freedom (DOF):

- ▶ How many observations vary 'freely'?
- ▶ DOF: $(n - p - 1) = n - (p + 1)$
- ▶ Multiple predictors \rightarrow larger R^2
- ▶ Large sample (data) \rightarrow not much difference b-w R^2 and adjusted R^2

Model fit: multiple predictors

R^2 and adjusted R^2 in regression model

```
# summary() model
summary(lm(DisapprovalBinary ~ MF_NotEngage + FM_NotEngage +
          FF_NotEngage, data = leader))

##
## Call:
## lm(formula = DisapprovalBinary ~ MF_NotEngage + FM_NotEngage +
##     FF_NotEngage, data = leader)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.7725 -0.4211  0.2275  0.5789  0.5789
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.42114    0.01153  36.532 < 2e-16 ***
## MF_NotEngage 0.29527    0.03574   8.262 2.38e-16 ***
## FM_NotEngage 0.35134    0.03674   9.562 < 2e-16 ***
## FF_NotEngage 0.32546    0.03426   9.499 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4796 on 2338 degrees of freedom
## Multiple R-squared:  0.08127,    Adjusted R-squared:  0.08009
## F-statistic: 68.94 on 3 and 2338 DF,  p-value: < 2.2e-16
```

Heterogenous treatment effects

- ▶ Variation in effect of main predictor
- ▶ When?
- ▶ ATE vary among individuals: positive/negative
- ▶ Experiments: differences guide treatment assignment

Women leaders:

- ▶ Respondents' gender and views of leader
- ▶ Do women judge female leaders more harshly?

Heterogenous treatment effects

Leader criticism by respondents gender

```
# Subset of female respondents
```

```
lead.gen <- subset(leader, Gender == 1)
```

```
# Diff-in-means: support for female versus male leader
```

```
mean(lead.gen$Disapproval[lead.gen$FemaleUS == 1], na.rm = T) -  
  mean(lead.gen$Disapproval[lead.gen$FemaleUS == 0], na.rm = T)
```

```
## [1] -0.06103819
```

```
# Subset of male respondents
```

```
lead.gen2 <- subset(leader, Gender == 0)
```

```
# Diff-in-means: support for female versus male leader
```

```
mean(lead.gen2$Disapproval[lead.gen2$FemaleUS == 1], na.rm = T) -  
  mean(lead.gen2$Disapproval[lead.gen2$FemaleUS == 0], na.rm = T)
```

```
## [1] 0.1652623
```

Estimated ATE

```
# Estimated treatment effect for gender  
(mean(lead.gen$Disapproval[lead.gen$FemaleUS == 1], na.rm = T) -  
  mean(lead.gen$Disapproval[lead.gen$FemaleUS == 0], na.rm = T)) -  
(mean(lead.gen2$Disapproval[lead.gen2$FemaleUS == 1], na.rm = T) -  
  mean(lead.gen2$Disapproval[lead.gen2$FemaleUS == 0], na.rm = T))  
  
## [1] -0.2263005
```

- ▶ Women respondents are less critical on female leaders

Regression model: conditional effects

- ▶ Add predictor to the model

$$Y(\text{Disapproval}) = \alpha + \beta_1 * \text{LeaderDyad} + \beta_2 * \text{RespondentGender} + \epsilon$$

- ▶ However, *conditional effect* → Interaction model

$$Y(\text{Disapproval}) = \alpha + \beta_1 * \text{LeaderDyad} + \beta_2 * \text{RespondentGender} + \beta_3 * \text{LeaderDyad} * \text{RespondentGender} + \epsilon$$

Interaction models

$$Y = \alpha + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_1 * X_2 + \epsilon$$

- ▶ Coefficient β_3 : How X_1 depends on X_2 .
- ▶ Average effect of women respondent (and leader): $\beta_2 + \beta_3$.
- ▶ Average effect of men respondent: β_2 .

Interaction model in R

Syntax: use the (*) or (:) between factors

```
# Female leader and respondents gender: Interaction model
summary(lm(Disapproval ~ FemaleUS * Gender, data = leader))

##
## Call:
## lm(formula = Disapproval ~ FemaleUS * Gender, data = leader)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.5809 -1.4157  0.4191  1.4398  2.5843
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.41567    0.06740  65.511 <2e-16 ***
## FemaleUS      0.16526    0.09664   1.710  0.0874 .
## Gender        0.14453    0.09488   1.523  0.1278
## FemaleUS:Gender -0.22630    0.13515  -1.674  0.0942 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.633 on 2334 degrees of freedom
## (4 observations deleted due to missingness)
## Multiple R-squared:  0.001536, Adjusted R-squared:  0.0002522
## F-statistic: 1.197 on 3 and 2334 DF, p-value: 0.3096
```

Interaction model: continuous predictors

- ▶ How the average treatment effect varies along age scale?
- ▶ Linearity assumption: one-unit increase in predictor \rightarrow similar increase in outcome.
- ▶ Data: ICB (observational).
- ▶ Variables:
 - ▶ International crises: 1918-2015.
 - ▶ Y: Crisis management technique (how to respond).
 - ▶ X_1 : Trigger event severity/type
 - ▶ X_2 : Leaders' age.
 - ▶ Model: how response varies based on trigger event (and leader's age).

Interaction model: ICB data

$$\text{CrisisAction} = \alpha + \beta_1 * \text{Trigger} + \beta_2 * \text{Age} + \beta_3 * \text{Trigger} * \text{Age} + \epsilon$$

cracid	actor	sysyrgr	sysyrgda	crisname	leader	cris_date	triggr	crismg	lead_age
1	2 USA	1937	12	PANAY INCIDENT	Roosevelt, F.	12/12/37	9	1	55
2	2 USA	1946	7	TURKISH STRAITS	Truman	8/7/46	2	4	62
3	2 USA	1947	21	TRUMAN DOCTRINE	Truman	2/21/47	2	4	63
4	2 USA	1948	24	BERLIN BLOCKADE	Truman	6/24/48	3	4	64
5	2 USA	1948	23	CHINA CIVIL WAR	Truman	9/23/48	8	1	64
6	2 USA	1950	25	KOREAN WAR I	Truman	6/25/50	8	8	66
7	2 USA	1950	30	KOREAN WAR II	Truman	9/30/50	9	8	66
8	2 USA	1953	16	KOREAN WAR III	Eisenhower	4/16/53	9	7	63
9	2 USA	1953	12	GUATEMALA	Eisenhower	12/12/53	7	4	63
10	2 USA	1954	13	DIEN BIEN PHU	Eisenhower	3/13/54	2	1	64
11	2 USA	1954	3	TAIWAN STRAIT I	Eisenhower	9/3/54	8	4	64
12	2 USA	1956	29	SUEZ NATN.-WAR	Eisenhower	10/29/56	5	6	66
13	2 USA	1957	18	SYRIA/TURKEY CONFRNT.	Eisenhower	8/18/57	2	4	67
14	2 USA	1958	8	IRAQ/LEB. UPHEAVAL	Eisenhower	5/8/58	2	6	68
15	2 USA	1958	17	TAIWAN STRAIT II	Eisenhower	7/17/58	8	1	68
16	2 USA	1958	27	BERLIN DEADLINE	Eisenhower	11/27/58	2	1	68
17	2 USA	1961	9	PATHET LAO OFFENSIVE	Kennedy	3/9/61	8	1	44
18	2 USA	1961	15	BAY OF PIGS	Kennedy	4/15/61	2	5	44

Interaction model: ICB data

Outcome - crisis management method:

- ▶ Negotiation, mediation
- ▶ Non-military pressure (economic)
- ▶ Non-violent military
- ▶ Violence

Predictor - triggering event: Verbal/political act, violent act.

```
summary(mydata$lead_age)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	18.00	48.00	56.00	55.84	64.00	91.00	2

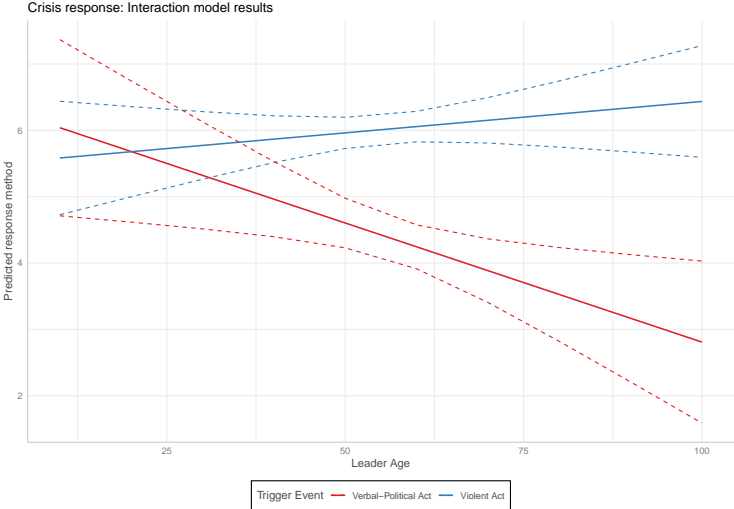
Interaction model: ICB data

```
summary(fit.age <- lm(crismg ~ triggr * lead_age, data = mydata))
```

```
##
## Call:
## lm(formula = crismg ~ triggr * lead_age, data = mydata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.2086 -1.6012  0.9619  1.8246  4.0730
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   6.512835  0.935138  6.965 6.24e-12 ***
## triggr        -0.113761  0.134857  -0.844 0.39913
## lead_age      -0.041579  0.016074  -2.587 0.00984 **
## triggr:lead_age 0.005672  0.002337   2.427 0.01541 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.387 on 927 degrees of freedom
## (2 observations deleted due to missingness)
## Multiple R-squared:  0.06487,    Adjusted R-squared:  0.06184
## F-statistic: 21.44 on 3 and 927 DF,  p-value: 1.984e-13
```

Interaction model: ICB data

Heterogeneous treatment effects: trigger over age



Causality with observational data

Alliance contributions & Leader characteristics



- ▶ The problem of *free riding*

Leaders and alliance contribution

Business experience and military alliances (Fuhrmann 2020):

- ▶ Leader experience explain variations.
- ▶ Business: executive level.
- ▶ Smaller contributions (defense expenditures), Why?
- ▶ Egoistic tendencies.
- ▶ Belief in self-efficacy and power.

Our goals:

1. Evaluate casual effect with linear regression (Δ spending per year).
2. Run *placebo test*: strengthen the proposed causal links.

Alliance contribution

NATO Defense spending data (1949-2020)

```
head(matt1)
```

```
## # A tibble: 6 x 74
##   Country ccode `1949` `1950` `1951` `1952` `1953` `1954` `1955` `19
##   <chr>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <d
## 1 Canada     20      NA  3809.  7718.  12405.  14234.  13242.  13113.  133
## 2 USA         2 147593. 158620. 339387. 478080. 492223. 424699. 402015. 4072
## 3 Czechia   316      NA      NA      NA      NA      NA      NA      NA
## 4 Hungary   310      NA      NA      NA      NA      NA      NA      NA
## 5 Poland    290      NA      NA      NA      NA      NA      NA      NA
## 6 Belgium   211  2074.  2092.  3095.  4574.  4554.  4698.  3891.  37
## # ... with 64 more variables: 1957 <dbl>, 1958 <dbl>, 1959 <dbl>, 1960 <dbl>,
## #   1961 <dbl>, 1962 <dbl>, 1963 <dbl>, 1964 <dbl>, 1965 <dbl>, 1966 <dbl>,
## #   1967 <dbl>, 1968 <dbl>, 1969 <dbl>, 1970 <dbl>, 1971 <dbl>, 1972 <dbl>,
## #   1973 <dbl>, 1974 <dbl>, 1975 <dbl>, 1976 <dbl>, 1977 <dbl>, 1978 <dbl>,
## #   1979 <dbl>, 1980 <dbl>, 1981 <dbl>, 1982 <dbl>, 1983 <dbl>, 1984 <dbl>,
## #   1985 <dbl>, 1986 <dbl>, 1987 <dbl>, 1988 <dbl>, 1989 <dbl>, 1990 <dbl>,
## #   1991 <dbl>, 1992 <dbl>, 1993 <dbl>, 1994 <dbl>, 1995 <dbl>, 1996 <dbl>,
```

Leaders and military alliances expenditures

NATO leaders and defense spending data

cocode (\textsc{COW numeric country code})	year (\textsc{year})	leadername (\textsc{leader name})	business (\textsc{business experience})	Country	def.exp	def.delta
2	2003	G.W. Bush		1 USA	612232.612	13.81651492
2	2004	G.W. Bush		1 USA	667284.639	8.99201159
2	2005	G.W. Bush		1 USA	698019.039	4.60589054
2	2006	G.W. Bush		1 USA	708077.303	1.44097276
2	2007	G.W. Bush		1 USA	726971.529	2.66838457
2	2008	G.W. Bush		1 USA	779854.123	7.27436936
2	2009	Obama		0 USA	841220.473	7.86895241
2	2010	Obama		0 USA	865268.025	2.85865034
2	2011	Obama		0 USA	855022.313	-1.18410840
2	2012	Obama		0 USA	807530.267	-5.55448034
2	2013	Obama		0 USA	745415.975	-7.69188406
2	2014	Obama		0 USA	699563.842	-6.15121420
20	1949	St. Laurent		0 Canada	NA	NA
20	1950	St. Laurent		0 Canada	3808.656	NA
20	1951	St. Laurent		0 Canada	7718.028	102.64439720
20	1952	St. Laurent		0 Canada	12404.681	60.72344453
20	1953	St. Laurent		0 Canada	14234.412	14.75032982

Testing a causal mechanism

Does business experience matter?

```
# subsets by business experience  
no.business <- subset(def.matt, subset = (business == 0))  
business <- subset(def.matt, subset = (business == 1))
```

```
## Diff-in-means estimator  
mean(business$def.delta, na.rm = T) -  
  mean(no.business$def.delta, na.rm = T)
```

```
## [1] -2.134511
```

```
# Regression model  
lm(def.delta ~ business, data = def.matt)
```

```
##
```

```
## Call:
```

```
## lm(formula = def.delta ~ business, data = def.matt)
```

```
##
```

```
## Coefficients:
```

```
## (Intercept)      business
```

```
##          2.847          -2.135
```

The Placebo test

- ▶ Data: non-defense related expenses
- ▶ Business experience matters → not on other issues.

```
## Diff-in-means estimator: non-defense spending  
mean(business$nondefspend_ch, na.rm = T) -  
  mean(no.business$nondefspend_ch, na.rm = T)
```

```
## [1] -0.1239881
```

```
## Regression model  
lm(nondefspend_ch ~ business, data = def.matt)
```

```
##
```

```
## Call:
```

```
## lm(formula = nondefspend_ch ~ business, data = def.matt)
```

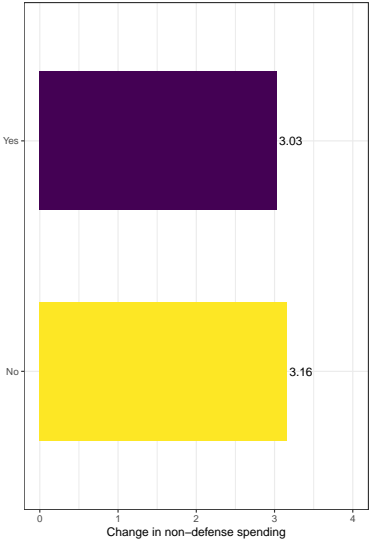
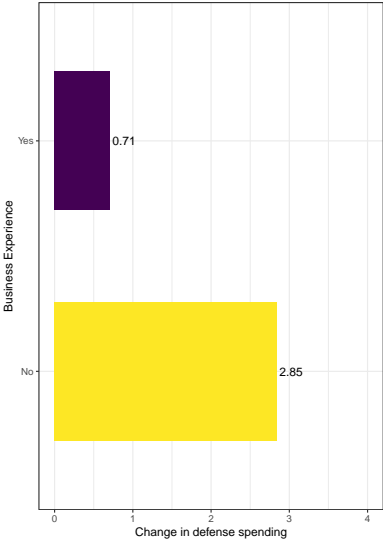
```
##
```

```
## Coefficients:
```

```
## (Intercept)      business
```

```
##          3.164          -0.124
```


Businessmen, politicians and spending



Wrapping up week 8

Summary:

- ▶ Prediction and causal inference.
- ▶ Binary predictors and linear regression models.
- ▶ Multiple predictors.
- ▶ Heterogeneous effects: interaction models.
- ▶ Causal inference with observational data.

Task 3