POL213 TA Session

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```
## Clear Workspace
rm(list = ls())

## Set Working Directory to the File location
## (If using RStudio, can be set automatically)
setwd(dirname(rstudioapi::getActiveDocumentContext()$path))
getwd()
```

```
## [1] "C:/GoogleDrive/Lectures/2019_04to06_UCD/POL213_TA/POL213_TA_resource"
```

```
## Required packages
library(readr) # Reading csv file
library(ggplot2) # Plotting
library(faraway) # for ilogit function
```

Let's Replicate Boudreau and MacKenzie 2014!

Check their paper HERE.

Their Replication Data are HERE.

```
# install.packages("dataverse") # Only Once
library(dataverse)
serverset <- "dataverse.harvard.edu"

(meta <- get_dataset("doi:10.7910/DVN/CNNXPB", server=serverset))

# Get Codebook
writeBin(get_file("boudreau_mackenzie_codebook_ajps.pdf","doi:10.7910/DVN/CNNXPB",
                  server=serverset), "boudreau_mackenzie_codebook_ajps.pdf")
# Get Data
writeBin(get_file("table2_fig1_fig2.tab","doi:10.7910/DVN/CNNXPB",
                  server=serverset), "table2_fig1_fig2.dta")
```

```
# Import Data
d <- read.dta13("table2_fig1_fig2.dta", convert.factors = FALSE)
# Variables
summary(d)
```

```
##      caseid          democrat        pty_strong       know_high
##  Min.   :  17.0   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.: 347.0   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median : 661.0   Median :1.0000   Median :0.0000   Median :1.0000
##  Mean   : 662.6   Mean   :0.5844   Mean   :0.2451   Mean   :0.6077
##  3rd Qu.: 965.0   3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:1.0000
##  Max.   :1365.0   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##
##       init          sup_init       bal_control         bal_party
##  Min.   :19.00   Min.   :0.0000   Min.   :-1.00000   Min.   :-1.00000
##  1st Qu.:20.00   1st Qu.:0.0000   1st Qu.: 0.00000   1st Qu.: 0.00000
##  Median :23.00   Median :1.0000   Median : 0.00000   Median : 0.00000
##  Mean   :22.93   Mean   :0.5148   Mean   :-0.01508   Mean   :-0.01492
##  3rd Qu.:26.00   3rd Qu.:1.0000   3rd Qu.: 0.00000   3rd Qu.: 0.00000
##  Max.   :27.00   Max.   :1.0000   Max.   : 1.00000   Max.   : 1.00000
##                  NA's   :684
##    bal_policy       bal_party_policy   rei_control
##  Min.   :-1.00000   Min.   :-1.0000   Min.   :-1.000000
##  1st Qu.: 0.00000   1st Qu.: 0.0000   1st Qu.: 0.000000
##  Median : 0.00000   Median : 0.0000   Median : 0.000000
##  Mean   :-0.01368   Mean   :-0.0157   Mean   :-0.001865
##  3rd Qu.: 0.00000   3rd Qu.: 0.0000   3rd Qu.: 0.000000
##  Max.   : 1.00000   Max.   : 1.0000   Max.   : 1.000000
##
##    rei_party           rei_policy        rei_party_policy
##  Min.   :-1.000000   Min.   :-1.000000   Min.   :-1.000000
##  1st Qu.: 0.000000   1st Qu.: 0.000000   1st Qu.: 0.000000
##  Median : 0.000000   Median : 0.000000   Median : 0.000000
##  Mean   :-0.003419   Mean   :-0.002798   Mean   :-0.005595
##  3rd Qu.: 0.000000   3rd Qu.: 0.000000   3rd Qu.: 0.000000
##  Max.   : 1.000000   Max.   : 1.000000   Max.   : 1.000000
##
##   con_control          con_party          con_policy
##  Min.   :-1.00000   Min.   :-1.00000   Min.   :-1.00000
##  1st Qu.: 0.00000   1st Qu.: 0.00000   1st Qu.: 0.00000
##  Median : 0.00000   Median : 0.00000   Median : 0.00000
##  Mean   :-0.03202   Mean   :-0.03326   Mean   :-0.03015
##  3rd Qu.: 0.00000   3rd Qu.: 0.00000   3rd Qu.: 0.00000
##  Max.   : 1.00000   Max.   : 1.00000   Max.   : 1.00000
##
##  con_party_policy
##  Min.   :-1.00000
##  1st Qu.: 0.00000
##  Median : 0.00000
##  Mean   :-0.03699
##  3rd Qu.: 0.00000
##  Max.   : 1.00000
##
```

Run Logistic Regression

```
# For Figure 1
logit.cueexp <- glm(sup_init ~ 0 + rei_party + rei_policy + rei_party_policy + rei_control +
                    con_party + con_policy + con_party_policy + con_control +
                    bal_party + bal_policy + bal_party_policy + bal_control, data=d,
                    family=binomial("logit"))
summary(logit.cueexp)
```

```
##
## Call:
## glm(formula = sup_init ~ 0 + rei_party + rei_policy + rei_party_policy +
##     rei_control + con_party + con_policy + con_party_policy +
##     con_control + bal_party + bal_policy + bal_party_policy +
##     bal_control, family = binomial("logit"), data = d)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6810  -0.9294   0.7469   0.9984   1.6810
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## rei_party         1.10876    0.08237  13.460  < 2e-16 ***
## rei_policy        0.80762    0.08460   9.546  < 2e-16 ***
## rei_party_policy  1.13397    0.07877  14.395  < 2e-16 ***
## rei_control       0.61497    0.07914   7.771 7.80e-15 ***
## con_party         0.80722    0.10978   7.353 1.93e-13 ***
## con_policy        0.33359    0.10733   3.108 0.001882 **
## con_party_policy  0.28344    0.09952   2.848 0.004401 **
## con_control       0.47523    0.10649   4.463 8.10e-06 ***
## bal_party         0.82734    0.12365   6.691 2.22e-11 ***
## bal_policy        0.61576    0.12801   4.810 1.51e-06 ***
## bal_party_policy  0.68401    0.11695   5.849 4.96e-09 ***
## bal_control       0.43685    0.11964   3.651 0.000261 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 7971.2  on 5750  degrees of freedom
## Residual deviance: 7137.6  on 5738  degrees of freedom
##   (684 observations deleted due to missingness)
## AIC: 7161.6
##
## Number of Fisher Scoring iterations: 4
```

```
# Focus on the difference in "conflicting environment"

# Predicted Probability

# (Control in Conflicting Environment / Preferred by Party)
(pi_ctl <- exp(0.47523) / (1 + exp(0.47523)))
```

```
## [1] 0.6166209
```

```
# (Party Cue Received in Conflicting Envionrment / Preferred by Party)
(pi_cue <- exp(0.80722) / (1 + exp(0.80722)))
```

```
## [1] 0.6915168
```

```
# (Party Cue & Opposint Info Received in Conflicting Envionrment / Preferred by Party)
(pi_both <- exp(0.28344) / (1 + exp(0.28344)))
```

```
## [1] 0.5703894
```

```
# Comparing Odds Ratio

# Calculate Odds Ratio
(odds_ctl <- pi_ctl/(1-pi_ctl))
```

```
## [1] 1.608384
```

```r
(odds_cue <- pi_ctl/(1-pi_cue))
```

```
## [1] 1.99888
```

```r
(odds_both <- pi_ctl/(1-pi_both))
```

```
## [1] 1.435302
```

```r
# Control vs. Cue Reception
odds_ctl / odds_cue
```

```
## [1] 0.8046427
```

```r
# Cue + Info vs. Cue Reception
odds_both / odds_cue
```

```
## [1] 0.718053
```

```r
# COntrol vs. Cue + Info
odds_ctl / odds_both
```

```
## [1] 1.120589
```

```r
# Wald statistic and confidence intervals

# Coefficient Table
(cftab <- summary(logit.cueexp)$coefficients)
```

```
##                    Estimate Std. Error   z value     Pr(>|z|)
## rei_party         1.1087647 0.08237433 13.460074 2.686456e-41
## rei_policy        0.8076244 0.08460493  9.545831 1.350204e-21
## rei_party_policy 1.1339734 0.07877436 14.395210 5.545633e-47
## rei_control       0.6149659 0.07913812  7.770792 7.799666e-15
## con_party         0.8072196 0.10977612  7.353327 1.933339e-13
## con_policy        0.3335918 0.10732708  3.108179 1.882440e-03
## con_party_policy 0.2834358 0.09952405  2.847912 4.400703e-03
## con_control       0.4752347 0.10649335  4.462576 8.098009e-06
## bal_party         0.8273432 0.12365050  6.690982 2.216786e-11
## bal_policy        0.6157605 0.12800555  4.810420 1.506132e-06
## bal_party_policy 0.6840147 0.11695324  5.848617 4.956772e-09
## bal_control       0.4368514 0.11963958  3.651395 2.608193e-04
```

```r
# Z Score
(z_ctl <- (cftab[8,1] - 0) / cftab[8,2])
```

```
## [1] 4.462576
```

```r
(z_cue <- (cftab[5,1] - 0) / cftab[5,2])
```

```
## [1] 7.353327
```

```r
(z_both <- (cftab[7,1] - 0) / cftab[7,2])
```

```
## [1] 2.847912
```

```r
# Confidence Interval
(ci_ctl <- c(cftab[8,1]-1.96*cftab[8,2],cftab[8,1]+1.96*cftab[8,2]))
```

```
## [1] 0.2665077 0.6839616
```

```r
(ci_cue <- c(cftab[5,1]-1.96*cftab[5,2],cftab[5,1]+1.96*cftab[5,2]))
```

```
## [1] 0.5920584 1.0223808
```

```r
(ci_both <- c(cftab[7,1]-1.96*cftab[7,2],cftab[7,1]+1.96*cftab[7,2]))
```

```
## [1] 0.08836864 0.47850292
```

```r
# or Just
(citab <- confint(logit.cueexp))
```

```
## Waiting for profiling to be done...
```

```
##                       2.5 %    97.5 %
## rei_party        0.94941190 1.2725044
## rei_policy       0.64346186 0.9753073
## rei_party_policy 0.98153776 1.2904951
## rei_control      0.46097573 0.7713522
## con_party        0.59480704 1.0255587
## con_policy       0.12426005 0.5453677
## con_party_policy 0.08911084 0.4795508
## con_control      0.26801587 0.6858497
## bal_party        0.58852428 1.0738513
## bal_policy       0.36767526 0.8701283
## bal_party_policy 0.45742117 0.9163917
## bal_control      0.20406438 0.6735910
```

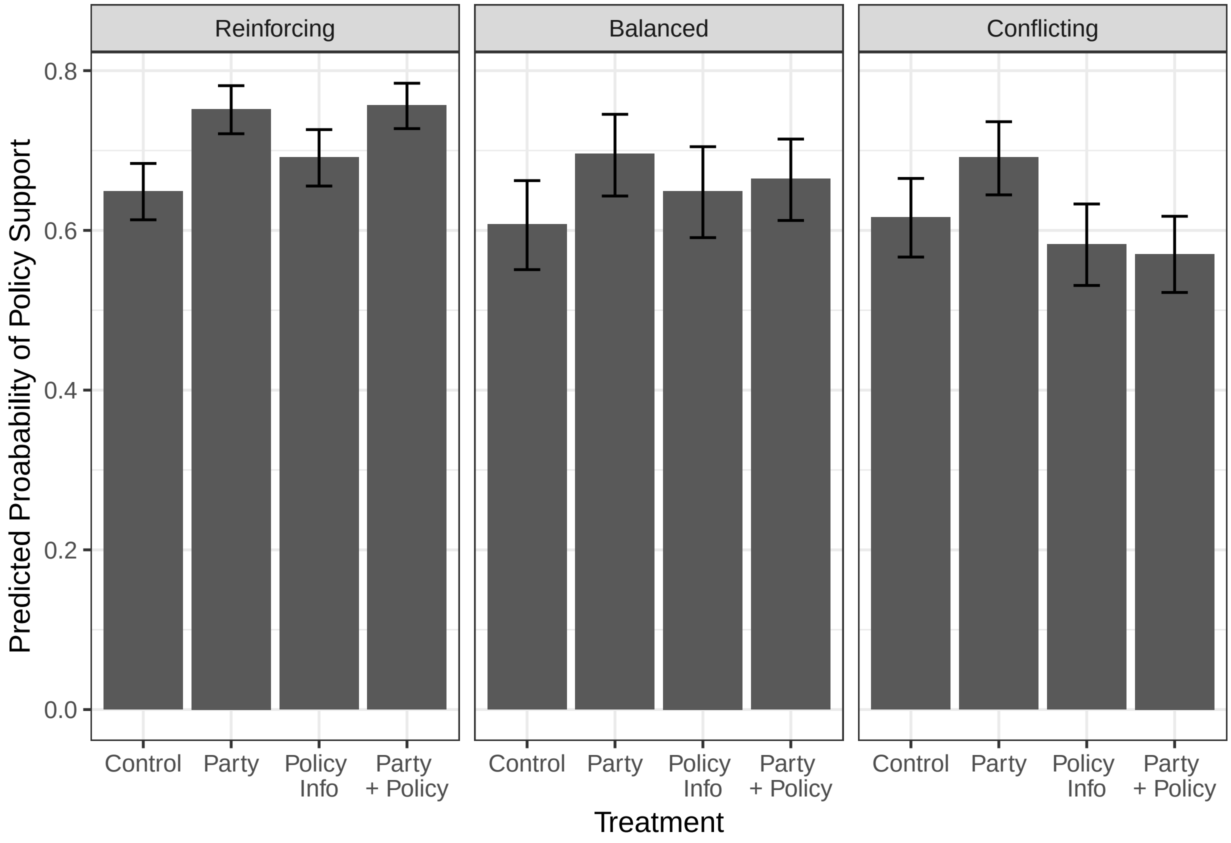
```r
# Replicate Figure 1 in the paper
# Assuming that all other conditions are 0,
# predicted probabilities are just the inverse logit of estimates

(cfcitab <- as.data.frame(cbind(as.numeric(cftab[,1]),citab)))
```

```
##                         V1      2.5 %    97.5 %
## rei_party        1.1087647 0.94941190 1.2725044
## rei_policy       0.8076244 0.64346186 0.9753073
## rei_party_policy 1.1339734 0.98153776 1.2904951
## rei_control      0.6149659 0.46097573 0.7713522
## con_party        0.8072196 0.59480704 1.0255587
## con_policy       0.3335918 0.12426005 0.5453677
## con_party_policy 0.2834358 0.08911084 0.4795508
## con_control      0.4752347 0.26801587 0.6858497
## bal_party        0.8273432 0.58852428 1.0738513
## bal_policy       0.6157605 0.36767526 0.8701283
## bal_party_policy 0.6840147 0.45742117 0.9163917
## bal_control      0.4368514 0.20406438 0.6735910
```

```r
colnames(cfcitab) <- c("est","lb","ub")
cfcitab$est <- ilogit(cfcitab$est)
cfcitab$lb <- ilogit(cfcitab$lb)
cfcitab$ub <- ilogit(cfcitab$ub)
# Add Environment Identifier
cfcitab$env <- factor(rep(c("Reinforcing","Conflicting","Balanced"),each=4),
                      levels=c("Reinforcing","Balanced","Conflicting"))
# Add Treatment Identifier
cfcitab$trt <- factor(rep(c("Party","Policy \nInfo","Party \n+ Policy","Control"),3),
                      levels=c("Control","Party","Policy \nInfo","Party \n+ Policy"))
```

```
ggplot(cfcitab, aes(x=trt,y=est)) +
  geom_bar(stat="identity") +
  geom_errorbar(aes(ymin=lb,ymax=ub), width=0.3) +
  facet_grid(.~env) + xlab("Treatment") +
  ylab("Predicted Proabability of Policy Support") +
  theme_bw()
```



```
# Likelihood ratio test

logit.null <- glm(sup_init ~ 1, d, family=binomial("logit"))
summary(logit.null)
```

```
##
## Call:
## glm(formula = sup_init ~ 1, family = binomial("logit"), data = d)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.203  -1.203   1.152   1.152   1.152
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.05915    0.02639   2.242    0.025 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 7966.2  on 5749  degrees of freedom
## Residual deviance: 7966.2  on 5749  degrees of freedom
##   (684 observations deleted due to missingness)
## AIC: 7968.2
## 
## Number of Fisher Scoring iterations: 3
```

```
(ll1 <- logLik(logit.cueexp))
```

```
## 'log Lik.' -3568.824 (df=12)
```

```
(ll0 <- logLik(logit.null))
```

```
## 'log Lik.' -3983.083 (df=1)
```

```
(g_statusquo <- 2*(ll1[[1]] - ll0[[1]]))
```

```
## [1] 828.5168
```

```
# Or, use the lrtest function to conduct this test
library(lmtest)
lrtest(logit.cueexp, logit.null)
```

```
## Likelihood ratio test
## 
## Model 1: sup_init ~ 0 + rei_party + rei_policy + rei_party_policy + rei_control + 
##     con_party + con_policy + con_party_policy + con_control + 
##     bal_party + bal_policy + bal_party_policy + bal_control
## Model 2: sup_init ~ 1
##   #Df  LogLik  Df  Chisq Pr(>Chisq)    
## 1  12 -3568.8                          
## 2   1 -3983.1 -11 828.52  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Workshop (Choose Either One of Them)

- In the same dataset, know_high is the indicator for knowledge level (1=high, 0=low) and pty_strong is the indicator for partisanship strength (1=high, 0=low). Construct the logistic regression model with interaction and replicate figure 2 in Boudreau and MacKenzie 2014.
- Run probit with the same model as above. Any difference?