

# 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(readstata13) # For importing data
library(ggplot2) # Plotting
library(faraway) # for ilogit function
library(pscl) # For pseudo R squared (pR2)
library(DAMisc) # For pre function
library(MASS) # For murnorm
```

## Study of Social Protest and Immigration Attitudes

Check the 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/27113", server=serverset))

# Get Stata Do File
writeBin(get_file("ajps_replication.do", "doi:10.7910/DVN/27113",
                  server=serverset), "ajps_replication.do")

# Get Data
writeBin(get_file("ajps2_replication.tab", "doi:10.7910/DVN/27113",
                  server=serverset), "ajps2_replication.dta")

# Import Data
d <- read.dta13("ajps2_replication.dta", convert.factors = FALSE)
# Variables
summary(d)
```

##	age	edu	latcomm	knowledge
##	Min. :18.00	Min. :0.000	Min. :1.000	Min. :0.000
##	1st Qu.:28.00	1st Qu.:2.000	1st Qu.:3.000	1st Qu.:0.000
##	Median :38.00	Median :4.000	Median :3.000	Median :1.000
##	Mean :40.16	Mean :3.521	Mean :3.202	Mean :1.162
##	3rd Qu.:50.00	3rd Qu.:5.000	3rd Qu.:4.000	3rd Qu.:2.000
##	Max. :97.00	Max. :7.000	Max. :4.000	Max. :3.000

##	NA's :814	NA's :349	NA's :904	NA's :349
##	female	wt_nation_rev	catholic	pprhisp
##	Min. :0.0000	Min. :0.3181	Min. :0.0000	Min. : 0.00
##	1st Qu.:0.0000	1st Qu.:0.5125	1st Qu.:0.0000	1st Qu.: 14.70
##	Median :1.0000	Median :0.6695	Median :1.0000	Median : 37.80
##	Mean :0.5458	Mean :1.0034	Mean :0.7161	Mean : 42.89
##	3rd Qu.:1.0000	3rd Qu.:1.1042	3rd Qu.:1.0000	3rd Qu.: 69.22
##	Max. :1.0000	Max. :4.3450	Max. :1.0000	Max. :100.00
##	NA's :349	NA's :349	NA's :349	NA's :352
##	ppehhscx	national_origin	american	cuba
##	Min. : 0.00	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.: 19.72	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000
##	Median : 22.87	Median :0.0000	Median :0.0000	Median :0.0000
##	Mean : 22.94	Mean :0.3848	Mean :0.2336	Mean :0.0304
##	3rd Qu.: 24.86	3rd Qu.:1.0000	3rd Qu.:0.0000	3rd Qu.:0.0000
##	Max. :100.00	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	NA's :471	NA's :349	NA's :349	NA's :349
##	pr	dr	south	central
##	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000
##	Median :0.0000	Median :0.0000	Median :0.0000	Median :0.0000
##	Mean :0.0968	Mean :0.0335	Mean :0.0339	Mean :0.0938
##	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	NA's :349	NA's :349	NA's :349	NA's :349
##	incomeq_dummy1	incomeq_dummy3	incomeq_dummy4	incomeq_dummy5
##	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000
##	Median :0.0000	Median :0.0000	Median :0.0000	Median :0.0000
##	Mean :0.2075	Mean :0.1388	Mean :0.1635	Mean :0.1651
##	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	NA's :349	NA's :349	NA's :349	NA's :349
##	perfin	samplestate1	samplestate2	samplestate3
##	Min. :1.000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:2.000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000
##	Median :2.000	Median :0.0000	Median :0.0000	Median :0.0000
##	Mean :2.032	Mean :0.0488	Mean :0.0487	Mean :0.1466
##	3rd Qu.:3.000	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000
##	Max. :3.000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	NA's :561	NA's :349	NA's :349	NA's :349
##	samplestate4	samplestate5	samplestate6	samplestate7
##	Min. :0.000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000
##	Median :0.000	Median :0.0000	Median :0.0000	Median :0.0000
##	Mean :0.049	Mean :0.0539	Mean :0.0487	Mean :0.0487
##	3rd Qu.:0.000	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000
##	Max. :1.000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	NA's :349	NA's :349	NA's :349	NA's :349
##	samplestate8	samplestate9	samplestate10	samplestate11
##	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000
##	Median :0.0000	Median :0.0000	Median :0.0000	Median :0.0000
##	Mean :0.0731	Mean :0.0202	Mean :0.0487	Mean :0.0491

```
## 3rd Qu.:0.0000 3rd Qu.:0.0000 3rd Qu.:0.0000 3rd Qu.:0.0000
## Max. :1.0000 Max. :1.0000 Max. :1.0000 Max. :1.0000
## NA's :349 NA's :349 NA's :349 NA's :349
## samplestate12 samplestate13 samplestate14 samplestate15
## Min. :0.0000 Min. :0.0000 Min. :0.0000 Min. :0.0000
## 1st Qu.:0.0000 1st Qu.:0.0000 1st Qu.:0.0000 1st Qu.:0.0000
## Median :0.0000 Median :0.0000 Median :0.0000 Median :0.0000
## Mean :0.0487 Mean :0.0491 Mean :0.0974 Mean :0.0988
## 3rd Qu.:0.0000 3rd Qu.:0.0000 3rd Qu.:0.0000 3rd Qu.:0.0000
## Max. :1.0000 Max. :1.0000 Max. :1.0000 Max. :1.0000
## NA's :349 NA's :349 NA's :349 NA's :349
## samplestate16 protest_period language_skills metro_county_code
## Min. :0.0000 Min. :0.0000 Min. :1.000 Min. : 4003
## 1st Qu.:0.0000 1st Qu.:0.0000 1st Qu.:1.000 1st Qu.:16980
## Median :0.0000 Median :1.0000 Median :2.000 Median :31100
## Mean :0.0214 Mean :0.6659 Mean :2.029 Mean :28981
## 3rd Qu.:0.0000 3rd Qu.:1.0000 3rd Qu.:3.000 3rd Qu.:38060
## Max. :1.0000 Max. :1.0000 Max. :4.000 Max. :53073
## NA's :349 NA's :349 NA's :369 NA's :349
## metro_county_protest co_met_num_protest generation
## Min. :0.0000 Min. : 0.000 Min. :0.000
## 1st Qu.:0.0000 1st Qu.: 0.000 1st Qu.:0.000
## Median :0.0000 Median : 0.000 Median :1.000
## Mean :0.4189 Mean : 2.137 Mean :1.119
## 3rd Qu.:1.0000 3rd Qu.: 4.000 3rd Qu.:2.000
## Max. :1.0000 Max. :13.000 Max. :4.000
## NA's :349 NA's :349 NA's :392
## protest_generation metco_generation comet_numprot_generation
## Min. :0.0000 Min. :0.0000 Min. : 0.000
## 1st Qu.:0.0000 1st Qu.:0.0000 1st Qu.: 0.000
## Median :0.0000 Median :0.0000 Median : 0.000
## Mean :0.8471 Mean :0.5233 Mean : 2.491
## 3rd Qu.:1.0000 3rd Qu.:1.0000 3rd Qu.: 2.000
## Max. :4.0000 Max. :4.0000 Max. :52.000
## NA's :392 NA's :392 NA's :392
## immopolnew community_participate attend_church
## Min. :1.000 Min. :1.000 Min. :0.000
## 1st Qu.:1.000 1st Qu.:2.000 1st Qu.:1.000
## Median :2.000 Median :2.000 Median :3.000
## Mean :2.077 Mean :1.802 Mean :2.356
## 3rd Qu.:3.000 3rd Qu.:2.000 3rd Qu.:3.000
## Max. :5.000 Max. :2.000 Max. :4.000
## NA's :349 NA's :500 NA's :456
```

#### *# Description of Variables*

```
paste(names(d), attr(d, "var.labels"), sep=": ")
```

```
## [1] "age: Age"
## [2] "edu: Education"
## [3] "latcomm: Perceived commonalities"
## [4] "knowledge: summed political knowledge, knowcong+knowwin+knowideo"
## [5] "female: Female"
## [6] "wt_nation_rev: "
## [7] "catholic: "
## [8] "pprhisp: Pct. Hispanic population by GEOFIPS"
```

```
## [9] "ppehhscx: Pct. of 25+ year olds with high school diploma (or equivalency) by GEOFIPS"
## [10] "national_origin: ID with National Origin"
## [11] "american: ID with Americans"
## [12] "cuba: Cuba"
## [13] "pr: Puerto Rico"
## [14] "dr: Dominican Republic"
## [15] "south: South America"
## [16] "central: Central America"
## [17] "incomeq_dummy1: Income: no report"
## [18] "incomeq_dummy3: Income: second quartile"
## [19] "incomeq_dummy4: Income: third quartile"
## [20] "incomeq_dummy5: Income: fourth quartile"
## [21] "perfin: Financial situation"
## [22] "samplestate1: rstate==AR"
## [23] "samplestate2: rstate==AZ"
## [24] "samplestate3: rstate==CA"
## [25] "samplestate4: rstate==CO"
## [26] "samplestate5: rstate==FL"
## [27] "samplestate6: rstate==GA"
## [28] "samplestate7: rstate==IA"
## [29] "samplestate8: rstate==IL"
## [30] "samplestate9: rstate==MD"
## [31] "samplestate10: rstate==NC"
## [32] "samplestate11: rstate==NJ"
## [33] "samplestate12: rstate==NM"
## [34] "samplestate13: rstate==NV"
## [35] "samplestate14: rstate==NY"
## [36] "samplestate15: rstate==TX"
## [37] "samplestate16: rstate==VA"
## [38] "protest_period: "
## [39] "language_skills: "
## [40] "metro_county_code: "
## [41] "metro_county_protest: "
## [42] "co_met_num_protest: "
## [43] "generation: "
## [44] "protest_generation: "
## [45] "metco_generation: "
## [46] "comet_numprot_generation: "
## [47] "immpolinew: "
## [48] "community_participate: "
## [49] "attend_church: "
```

## Descriptives

```
# DV
table(d$immpolinew)
```

```
##
##      1      2      3      4      5
## 3463 2601  976  394  778
```

```
# (1) immediate legalization of current undocumented immigrants,
# (2) a guest worker program leading to legalization eventually,
# (3) a guest worker program permitting immigrants to be in the country, but only temporarily,
```

```
# (4) an effort to seal or close off the border to stop illegal immigration, and
# (5) none of the above
```

```
# IV
```

```
table(d$protest_period)
```

```
##
```

```
##      0      1
```

```
## 2744 5468
```

```
# coded 1 if the respondent is surveyed after the protests began and 0 otherwise
```

```
# Controls
```

```
summary(d$pprhisp)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##      0.00  14.70   37.80   42.89  69.22  100.00    352
```

```
#Pct. Hispanic population by GEOFIPS
```

```
summary(d$ppehscx)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##      0.00  19.72   22.87   22.94  24.86  100.00    471
```

```
#Pct. of 25+ year olds with high school diploma (or equivalency) by GEOFIP
```

```
d$latcomm <- as.numeric(as.factor(d$latcomm))
table(d$latcomm)
```

```
##
```

```
##      1      2      3      4
```

```
## 373 1178 2636 3470
```

```
# Perceived Commonality with Latino
# 1 Nothing, 2 Little, 3 Some, 4 Lot
```

```
table(d$generation)
```

```
##
```

```
##      0      1      2      3      4
```

```
## 3626 2092  975  809  667
```

```
# ranges from 0 to 4, where 0 reflects noncitizen,
# 1 reflects foreign-born citizen,
# 2 reflects second generation,
# 3 reflects third generation, and
# 4 reflects fourth-plus generation.
```

```
table(d$american, d$national_origin)
```

```
##
```

```
##           0      1
```

```
##      0 3134 3160
```

```
##      1 1918      0
```

```
# Identify as American / National Origin
# Both 0 implies that identifying as Latino
```

```
table(d$language_skills)
```

```
##
##      1      2      3      4
## 3583 1438 2525  646
```

```
# Higher score indicates higher skill
```

```
table(d$knowledge)
```

```
##
##      0      1      2      3
## 2945 2283 1691 1293
```

```
# Higher score indicates higher knowledge
```

```
table(d$catholic)
```

```
##
##      0      1
## 2331 5881
```

```
# Catholic
```

```
table(d$attend_church)
```

```
##
##      0      1      2      3      4
##   981 1082 1476 3200 1366
```

```
# Church Attendance (Not Clear How It's Coded)
```

```
table(d$community_participate)
```

```
##
##      1      2
## 1598 6463
```

```
# a respondent is involved in a civic organization#
```

```
table(d$cuba)
```

```
##
##      0      1
## 7962  250
```

```
# Cuba Origin
```

```
table(d$pr)
```

```
##
##      0      1
## 7417  795
```

```
# Puerto Rico Origin
```

```
table(d$dr)
```

```
##
```

```
##      0      1
```

```
## 7937  275
```

```
# Dominican Republic Origin
```

```
table(d$south)
```

```
##
```

```
##      0      1
```

```
## 7934  278
```

```
# South America Origin
```

```
table(d$central)
```

```
##
```

```
##      0      1
```

```
## 7442  770
```

```
# Central America Origin
```

```
table(d$age)
```

```
##
```

```
##  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35
```

```
## 223 180 170 149 160 185 141 222 198 209 202 183 204 204 187 232 175 237
```

```
##  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53
```

```
## 209 196 164 184 171 197 177 132 132 186 143 117 134 120 116 113 110 111
```

```
##  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
```

```
## 102 132 100  98  81  80 102  69  58  63  61  72  56  50  29  46  47  40
```

```
##  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  89  90
```

```
##  39  23  35  24  25  26  25  19  17  11   9   9   4   6   5   5   2   2
```

```
##  94  97
```

```
##    1    1
```

```
# Age
```

```
table(d$female)
```

```
##
```

```
##      0      1
```

```
## 3730 4482
```

```
# Female
```

```
d$edu <- as.numeric(as.factor(d$edu))
```

```
table(d$edu)
```

```
##
```

```
##      1      2      3      4      5      6      7      8
```

```
## 218 1660 1215  277 2024 1540  753  525
```

```
# Education
```

```
# 1= None to 8=graduate or professional degree
```

```
# Income Variables
```

```
table(d$incomeq_dummy1) # No Report
```

```
##  
##      0      1  
## 6508 1704
```

```
table(d$incomeq_dummy3) # Second Quartile
```

```
##  
##      0      1  
## 7072 1140
```

```
table(d$incomeq_dummy4) # Third Quartile
```

```
##  
##      0      1  
## 6869 1343
```

```
table(d$incomeq_dummy5) # Fourth Quartile
```

```
##  
##      0      1  
## 6856 1356
```

```
# First Quartile is the Reference Category
```

```
table(d$perfin)
```

```
##  
##      1      2      3  
## 1950 3843 2207
```

```
# Financial Situation  
# (1) gotten worse, (2) stays about the same, and (3) gotten better.
```

```
table(d$samplestate1) # AR
```

```
##  
##      0      1  
## 7811  401
```

```
table(d$samplestate2) # AZ
```

```
##  
##      0      1  
## 7812  400
```

```
table(d$samplestate3) # CA
```

```
##  
##      0      1  
## 7008 1204
```

```
table(d$samplestate4) # CO
```

```
##  
##      0      1  
## 7810  402
```



```
table(d$samplestate5) # FL
```

```
##  
##      0      1  
## 7769  443
```

```
table(d$samplestate6) # GA
```

```
##  
##      0      1  
## 7812  400
```

```
table(d$samplestate7) # IA
```

```
##  
##      0      1  
## 7812  400
```

```
table(d$samplestate8) # IL
```

```
##  
##      0      1  
## 7612  600
```

```
table(d$samplestate9) # MD
```

```
##  
##      0      1  
## 8046  166
```

```
table(d$samplestate10) # NC
```

```
##  
##      0      1  
## 7812  400
```

```
table(d$samplestate11) # NJ
```

```
##  
##      0      1  
## 7809  403
```

```
table(d$samplestate12) # NM
```

```
##  
##      0      1  
## 7812  400
```

```
table(d$samplestate13) # NV
```

```
##  
##      0      1  
## 7809  403
```

```
table(d$samplestate14) # NY
```

```
##  
##      0      1  
## 7412  800
```

```
table(d$samplestate15) # TX
```

```
##
##      0      1
## 7401  811
```

```
table(d$samplestate16) # VA
```

```
##
##      0      1
## 8036  176
```

```
# Residing States
```

```
# Other Variables
```

```
# Weight Variable
```

```
summary(d$wt_nation_rev)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
## 0.3181  0.5125  0.6695  1.0034  1.1042  4.3450   349
```

```
# County Code
```

```
summary(d$metro_county_code)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
##      4003  16980   31100   28981   38060   53073   349
```

## Use multinom function

```
library(nnet)
```

### 1.1. Use multinom function (in nnet package) to estimate multinomial logit model

with immigration preference as DV and protest exposure as IV.

```
# Make DV a factor (to make pre function work)
```

```
d$immpolinew <- as.factor(d$immpolinew)
```

```
m1 <- multinom(immpolinew ~ protest_period, data=d, Hess=TRUE)
```

```
## # weights:  15 (8 variable)
## initial  value 13216.704137
## iter   10 value 11178.821466
## final   value 11070.429235
## converged
```

```
summary(m1)
```

```
## Call:
```

```
## multinom(formula = immpolinew ~ protest_period, data = d, Hess = TRUE)
```

```
##
```

```
## Coefficients:
```

```
##      (Intercept) protest_period
```

```
## 2  -0.4191415      0.19799192
```

```
## 3 -1.1998843 -0.10445987
## 4 -2.5592557 0.54521063
## 5 -1.5040864 0.01675964
##
## Std. Errors:
## (Intercept) protest_period
## 2 0.04554779 0.05544707
## 3 0.05962646 0.07509659
## 4 0.10705988 0.12345070
## 5 0.06728117 0.08330732
##
## Residual Deviance: 22140.86
## AIC: 22156.86
```

### 1.1.1. Find Odds Ratio for the exposure variables estimated in 1.1.

Make interpretation

```
exp(coef(m1))
```

```
## (Intercept) protest_period
## 2 0.6576111 1.2189525
## 3 0.3012290 0.9008109
## 4 0.0773623 1.7249717
## 5 0.2222202 1.0169009
```

The odds ratio explanation of the first coefficient implies that those who are exposed to protest makes the choice of 2 (lenient guest worker program) over 1 (full legalization) 1.2 times more likely than those who are not exposed.

### 1.1.2. Calculate Wald Statistics (z-score) for the coefficients in 1.1. and

generate p-values. Are the coefficients significantly different from zero?

```
z <- summary(m1)$coefficients / summary(m1)$standard.errors
round(z, 3)
```

```
## (Intercept) protest_period
## 2 -9.202 3.571
## 3 -20.123 -1.391
## 4 -23.905 4.416
## 5 -22.355 0.201
```

```
p <- (1 - pnorm(abs(z), 0, 1))*2
round(p, 3)
```

```
## (Intercept) protest_period
## 2 0 0.000
## 3 0 0.164
## 4 0 0.000
## 5 0 0.841
```

Only the first and fourth coefficients for exposure variable are significantly different from zero.

## 1.2. Obtain Fitted Values (Predicted Probabilities) from the model estimated in 1.1

```
yhat.m1 <- predict(m1, typ = "prob")
summary(yhat.m1)
```

```
##           1           2           3           4
## Min.      :0.4111   Min.      :0.2912   Min.      :0.1116   Min.      :0.03426
## 1st Qu.:0.4111   1st Qu.:0.2912   1st Qu.:0.1116   1st Qu.:0.03426
## Median :0.4111   Median :0.3296   Median :0.1116   Median :0.05486
## Mean      :0.4217   Mean      :0.3167   Mean      :0.1188   Mean      :0.04798
## 3rd Qu.:0.4428   3rd Qu.:0.3296   3rd Qu.:0.1334   3rd Qu.:0.05486
## Max.      :0.4428   Max.      :0.3296   Max.      :0.1334   Max.      :0.05486
##           5
## Min.      :0.09290
## 1st Qu.:0.09290
## Median :0.09290
## Mean      :0.09474
## 3rd Qu.:0.09840
## Max.      :0.09840
```

## 1.3. Manually calculate predicted probabilities of each preference for

those who are exposed to protest and those who are not.

```
# Not Exposed (all + coef(m1)[?,?]*0 parts can be omitted)
(p1_0 <- 1 / (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*0))))
```

```
## [1] 0.4427869
```

```
(p2_0 <- exp(coef(m1)[1,1] + coef(m1)[1,2]*0) /
  (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*0))))
```

```
## [1] 0.2911816
```

```
(p3_0 <- exp(coef(m1)[2,1] + coef(m1)[2,2]*0) /
  (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*0))))
```

```
## [1] 0.1333803
```

```
(p4_0 <- exp(coef(m1)[3,1] + coef(m1)[3,2]*0) /
  (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*0))))
```

```
## [1] 0.03425501
```

```
(p5_0 <- exp(coef(m1)[4,1] + coef(m1)[4,2]*0) /
  (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*0))))
```

```
## [1] 0.0983962
```

```
# Check that probability sums to 1
p1_0 + p2_0 + p3_0 + p4_0 + p5_0
```

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

```
# Exposed
(p1_1 <- 1 / (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*1))))
```

```
## [1] 0.4111215
```

```
(p2_1 <- exp(coef(m1)[1,1] + coef(m1)[1,2]*1) /
  (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*1))))
```

```
## [1] 0.3295537
```

```
(p3_1 <- exp(coef(m1)[2,1] + coef(m1)[2,2]*1) /
  (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*1))))
```

```
## [1] 0.111558
```

```
(p4_1 <- exp(coef(m1)[3,1] + coef(m1)[3,2]*1) /
  (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*1))))
```

```
## [1] 0.05486325
```

```
(p5_1 <- exp(coef(m1)[4,1] + coef(m1)[4,2]*1) /
  (1 + sum(exp(coef(m1)[,1] + coef(m1)[,2]*1))))
```

```
## [1] 0.09290357
```

```
# Check that probability sums to 1
```

```
p1_1 + p2_1 + p3_1 + p4_1 + p5_1
```

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

#### 1.4. Add as many control variables as you want to the model in 1.1 and

estimate a new model. Does the addition of control variables change results?

```
m2 <- multinom(impolinelw ~ protest_period + pprhispx + ppehhscx +
  latcomm + generation + american + national_origin +
  language_skills + knowledge + catholic + community_participate +
  attend_church + cuba + pr + dr + south + central +
  age + female + edu + incomeq_dummy1 + incomeq_dummy3 +
  incomeq_dummy4 + incomeq_dummy5 + perfin,
  data=d, Hess=TRUE)
```

```
## # weights: 135 (104 variable)
```

```
## initial value 10937.740053
```

```
## iter 10 value 9233.237322
```

```
## iter 20 value 8618.616438
```

```
## iter 30 value 8539.939102
```

```
## iter 40 value 8345.033877
```

```
## iter 50 value 8218.167074
```

```
## iter 60 value 8147.078211
```

```
## iter 70 value 8127.096473
```

```
## iter 80 value 8118.894325
```

```
## iter 90 value 8115.289880
```

```
## iter 100 value 8114.717497
```

```
## final value 8114.717497
```

```
## stopped after 100 iterations
```

```
summary(m2)
```

```
## Call:
```

```
## multinom(formula = impolinelw ~ protest_period + pprhispx + ppehhscx +
## latcomm + generation + american + national_origin + language_skills +
## knowledge + catholic + community_participate + attend_church +
```

```

##      cuba + pr + dr + south + central + age + female + edu + incomeq_dummy1 +
##      incomeq_dummy3 + incomeq_dummy4 + incomeq_dummy5 + perfin,
##      data = d, Hess = TRUE)
##
## Coefficients:
##      (Intercept) protest_period      pprhispx      ppehhscx      latcomm
## 2      -1.980849      -0.3145734 -0.001819638  0.008719747 -0.07516146
## 3      -2.289829      -0.5574759  0.001447268 -0.000140095 -0.18221542
## 4      -6.496172      -0.2408084  0.000401087  0.031402998 -0.37218407
## 5      -1.928831      -0.6025018 -0.001739601  0.012819196 -0.20774430
##      generation american national_origin language_skills      knowledge
## 2  0.2363121 0.2486612      -0.03682604      0.5490361  0.10443008
## 3  0.2256023 0.2935543      -0.07999753      0.5365686 -0.01617441
## 4  0.4705438 0.4440989      -0.19311043      0.9404192  0.18780952
## 5  0.2990625 0.2961504      -0.15062260      0.6186174 -0.21112773
##      catholic community_participate attend_church      cuba      pr
## 2 -0.10993977      -0.001407805 -0.049507405  0.14559429  0.4609621
## 3 -0.07369959      0.002386948 -0.007433073  0.03800353  0.5250377
## 4 -0.34504212      0.399505445 -0.098949522  0.98019574  1.2488778
## 5 -0.24790369      -0.044674751 -0.049991340  0.53504204  0.9506709
##      dr      south      central      age      female
## 2  0.27494085  0.09417254 -0.02229572  0.0009480826  0.0001025442
## 3  0.05120636 -0.10166234 -0.13560593  0.0088062014 -0.2294443370
## 4  1.42738898  1.15355247  0.62472357  0.0232499418 -0.1488301982
## 5  0.22649917  0.07386000  0.48735791  0.0022158239 -0.0635976637
##      edu incomeq_dummy1 incomeq_dummy3 incomeq_dummy4 incomeq_dummy5
## 2  0.09572544      -0.15580327      0.08369169      0.14889850      0.3505930
## 3  0.04001387      -0.06245362      0.06213934      0.20954262      0.1731829
## 4 -0.05959066      -0.09829582      0.02940786      0.04191706      0.4434065
## 5 -0.06718861      0.33025349      -0.19704103      0.07263051      0.1063028
##      perfin
## 2  0.1025742
## 3  0.1405235
## 4  0.2823628
## 5  0.1241964
##
## Std. Errors:
##      (Intercept) protest_period      pprhispx      ppehhscx      latcomm generation
## 2  0.3360917      0.06947625 0.001047184  0.006672226  0.03703024  0.03641859
## 3  0.4402317      0.09048909 0.001371107  0.008930121  0.04745724  0.04684527
## 4  0.6800305      0.15028010 0.002160780  0.011925099  0.06795012  0.06589258
## 5  0.5115395      0.10703686 0.001643882  0.009904887  0.05508401  0.05408065
##      american national_origin language_skills      knowledge      catholic
## 2  0.09314403      0.06987319      0.04779868  0.03341480  0.07132972
## 3  0.11791126      0.09436149      0.06300874  0.04431605  0.09367507
## 4  0.15957774      0.16569058      0.09732622  0.06630097  0.13206745
## 5  0.13576373      0.11235397      0.07297662  0.05377820  0.10659267
##      community_participate attend_church      cuba      pr      dr
## 2      0.08412637      0.02604122  0.1882895  0.1209879  0.1715445
## 3      0.10985348      0.03431243  0.2553712  0.1501885  0.2488871
## 4      0.15581628      0.04810748  0.2977051  0.1834057  0.3134579
## 5      0.13090042      0.03925599  0.2882512  0.1626442  0.3002037
##      south      central      age      female      edu incomeq_dummy1
## 2  0.1668887  0.1106567  0.002321575  0.06468827  0.01979653      0.09610863

```

```
## 3 0.2418580 0.1525378 0.002955715 0.08499700 0.02623240 0.12652930
## 4 0.3229719 0.2665972 0.004113905 0.12802661 0.04254798 0.21552300
## 5 0.3046139 0.1580480 0.003463787 0.10031240 0.03134317 0.13349926
## incomeq_dummy3 incomeq_dummy4 incomeq_dummy5 perfin
## 2 0.09604863 0.09557435 0.1097946 0.04417182
## 3 0.12896967 0.12413920 0.1452679 0.05842463
## 4 0.21999389 0.20040106 0.2041324 0.08974947
## 5 0.16404895 0.15076214 0.1740688 0.06871372
##
## Residual Deviance: 16229.43
## AIC: 16437.43
```

## 1.5. Find Pseudo R Squares, Proportional Reduction in Error (PRE) and

information measures (i.e., AIC, BIC) for BOTH models estimated in 1.1 and 1.4. Compare results. Which model explains DV better?

```
# Pseudo-R2
m1_pR2 <- pR2(m1)
```

```
## fitting null model for pseudo-r2
## # weights: 10 (4 variable)
## initial value 13216.704137
## iter 10 value 11089.341938
## iter 10 value 11089.341930
## final value 11089.341930
## converged
```

```
m2_pR2 <- pR2(m2)
```

```
## fitting null model for pseudo-r2
## # weights: 10 (4 variable)
## initial value 13216.704137
## iter 10 value 11089.341938
## iter 10 value 11089.341930
## final value 11089.341930
## converged
```

```
rbind(m1=round(m1_pR2, 5),
      m2=round(m2_pR2, 5))
```

```
##          llh    llhNull      G2 McFadden   r2ML   r2CU
## m1 -11070.429 -11089.34   37.82539  0.00171 0.00460 0.00493
## m2  -8114.717 -11089.34  5949.24887  0.26824 0.58331 0.60651
```

```
# PRE (Getting Errors)
# Taking Too Much Time, so reducing iteration here
pre(m1, sim=TRUE, R=100)
```

```
## mod1: immpolinelw ~ protest_period
## mod2: immpolinelw ~ 1
##
## Analytical Results
## PMC = 0.422
## PCP = 0.422
## PRE = 0.000
## ePMC = 0.304
```

```
## ePCP = 0.304
## ePRE = 0.001
##
## Simulated Results
##      median lower upper
## PRE 0.000 0.000 0.000
## ePRE 0.001 -0.005 0.005

pre(m2, sim=TRUE, R=100)

## mod1: immopolinew ~ protest_period + pprhispx + ppehhscx + latcomm + generation + american + national
## mod2: immopolinew ~ 1
##
## Analytical Results
## PMC = 0.415
## PCP = 0.543
## PRE = 0.218
## ePMC = 0.306
## ePCP = 0.384
## ePRE = 0.112
##
## Simulated Results
##      median lower upper
## PRE 0.214 0.209 0.219
## ePRE 0.110 0.103 0.118

# Information Measures
AIC(m1)

## [1] 22156.86

AIC(m2)

## [1] 16437.43

BIC(m1)

## [1] 22212.97

BIC(m2)

## [1] 17147.14
```

Model 2 obviously performs better than the model 1.

## 1.6. Using model estimated in 1.4, create several profiles of interests and

simulate the Predicted Probability with Confidence Interval. Plot Results.

```
# Create Profiles
# 1. Treated
profile1 <- c(1, 1, median(d$pprhisp, na.rm=TRUE),
              median(d$ppehhsc, na.rm=TRUE),
              median(d$latcomm, na.rm=TRUE),
              median(d$generation, na.rm=TRUE), 0, 0,
              median(d$language_skills, na.rm=TRUE),
              median(d$knowledge, na.rm=TRUE),
              median(d$catholic, na.rm=TRUE),
              median(d$community_participate, na.rm=TRUE),
```



```

        median(d$attend_church,na.rm=TRUE), 0, 0, 0, 0, 0,
        median(d$age,na.rm=TRUE), median(d$female,na.rm=TRUE),
        median(d$edu,na.rm=TRUE), 0, 0, 0, 0, median(d$perfin,na.rm=TRUE))
# Not Treated
profile0 <- c(1, 0, median(d$pprhispx,na.rm=TRUE),
             median(d$ppehhsx,na.rm=TRUE),
             median(d$latcomm,na.rm=TRUE),
             median(d$generation,na.rm=TRUE), 0, 0,
             median(d$language_skills,na.rm=TRUE),
             median(d$knowledge,na.rm=TRUE),
             median(d$catholic,na.rm=TRUE), median(d$community_participate,na.rm=TRUE),
             median(d$attend_church,na.rm=TRUE), 0, 0, 0, 0, 0,
             median(d$age,na.rm=TRUE), median(d$female,na.rm=TRUE),
             median(d$edu,na.rm=TRUE), 0, 0, 0, 0, median(d$perfin,na.rm=TRUE))

# Function for Prediction
predictmlogit <- function(m2, profile) {

  coeffs1 <- summary(m2)$coefficients
  coeffs <- cbind(t(coeffs1[1, ]), t(coeffs1[2, ]),
                 t(coeffs1[3, ]), t(coeffs1[4, ]))
  covmat <- solve(m2$Hessian)

  ndraws <- 1000
  betadraw <- mvrnorm(ndraws, coeffs, covmat)

  nvars <- ncol(coeffs1)

  xb2 <- betadraw[,1:nvars]%%profile
  xb3 <- betadraw[, (nvars+1):(2*nvars)]%%profile
  xb4 <- betadraw[, (2*nvars+1):(3*nvars)]%%profile
  xb5 <- betadraw[, (3*nvars+1):ncol(betadraw)]%%profile

  prob1 <- exp(0) / (exp(0) + exp(xb2) + exp(xb3) + exp(xb4) + exp(xb5))
  prob2 <- exp(xb2) / (exp(0) + exp(xb2) + exp(xb3) + exp(xb4) + exp(xb5))
  prob3 <- exp(xb3) / (exp(0) + exp(xb2) + exp(xb3) + exp(xb4) + exp(xb5))
  prob4 <- exp(xb4) / (exp(0) + exp(xb2) + exp(xb3) + exp(xb4) + exp(xb5))
  prob5 <- exp(xb5) / (exp(0) + exp(xb2) + exp(xb3) + exp(xb4) + exp(xb5))

  means <- cbind(mean(prob1), mean(prob2), mean(prob3),
                 mean(prob4), mean(prob5))
  sds <- cbind(apply(prob1, 2, sd), apply(prob2, 2, sd), apply(prob3, 2, sd),
              apply(prob4, 2, sd), apply(prob5, 2, sd))
  lci <- cbind(quantile(prob1, probs=0.025),quantile(prob2, probs=0.025),
              quantile(prob3, probs=0.025),quantile(prob4, probs=0.025),
              quantile(prob5, probs=0.025))
  uci <- cbind(quantile(prob1, probs=0.975),quantile(prob2, probs=0.975),
              quantile(prob3, probs=0.975),quantile(prob4, probs=0.975),
              quantile(prob5, probs=0.975))
  zs <- means / sds
  ps <- 2 * (1 - pnorm(abs(zs)))
  results <- t(rbind(means, sds, lci, uci, zs, ps))
  results <- as.data.frame(results)

```

```

colnames(results) <- c("mean", "sd", "lci", "uci", "z", "p")
results$choice <- c("Full \nLegalization",
                    "Lenient Guest \nWorker Program",
                    "Temporal Guest \nWorker Program",
                    "Not Allow", "None of \nthe Above")
results$choice <- factor(results$choice, levels=results$choice)
return(results)
}

# Make Prediction
(pred1 <- predictmlogit(m2, profile1))

##          mean          sd          lci          uci          z          p
## 1 0.50812617 0.018895754 0.47018216 0.54246584 26.891024 0.000000e+00
## 2 0.30981977 0.016382352 0.28107919 0.34335159 18.911801 0.000000e+00
## 3 0.10645658 0.010607467 0.08688638 0.12820404 10.036003 0.000000e+00
## 4 0.01666962 0.003297176 0.01101428 0.02362412  5.055728 4.287525e-07
## 5 0.05892786 0.007266666 0.04601839 0.07464650  8.109339 4.440892e-16
##
##          choice
## 1          Full \nLegalization
## 2  Lenient Guest \nWorker Program
## 3 Temporal Guest \nWorker Program
## 4                Not Allow
## 5          None of \nthe Above

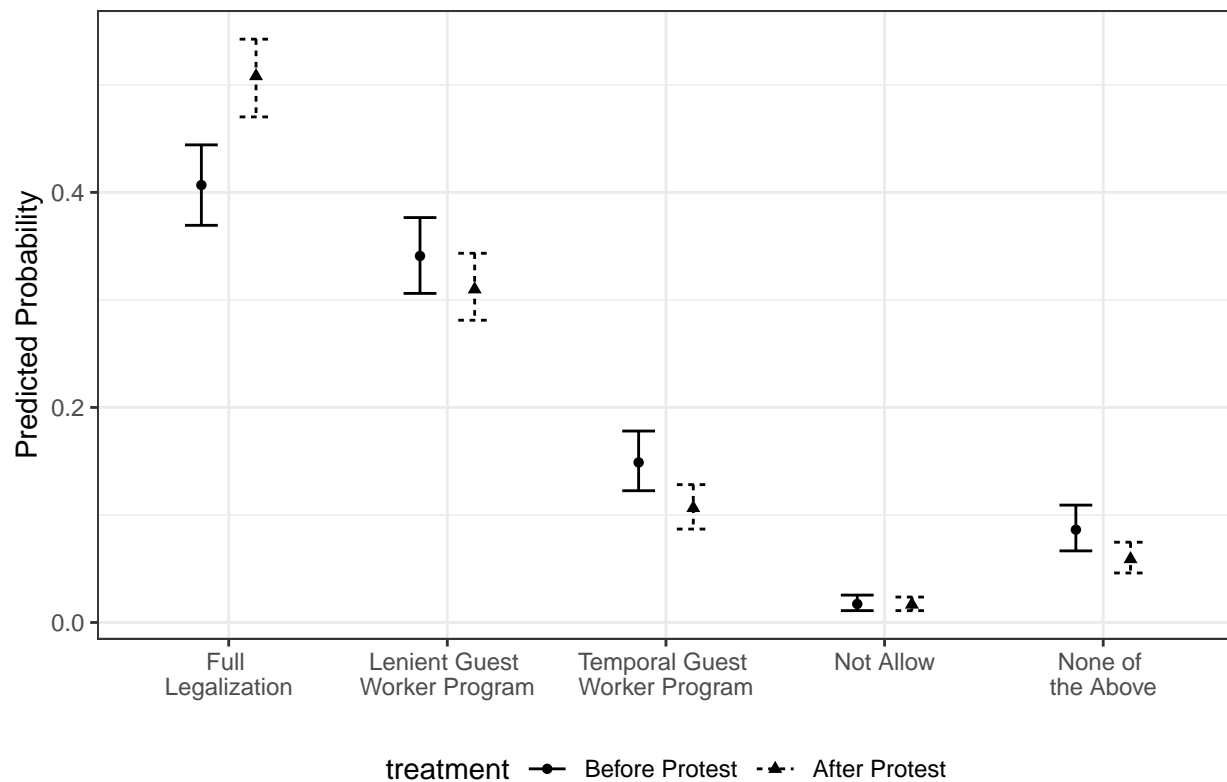
(pred0 <- predictmlogit(m2, profile0))

##          mean          sd          lci          uci          z          p
## 1 0.40679028 0.019790014 0.36933768 0.44418002 20.555331 0.000000e+00
## 2 0.34085218 0.018575625 0.30603913 0.37655784 18.349433 0.000000e+00
## 3 0.14884339 0.014601358 0.12253280 0.17805089 10.193804 0.000000e+00
## 4 0.01719770 0.003727022 0.01101390 0.02546713  4.614327 3.943717e-06
## 5 0.08631646 0.010778700 0.06658862 0.10914557  8.008058 1.110223e-15
##
##          choice
## 1          Full \nLegalization
## 2  Lenient Guest \nWorker Program
## 3 Temporal Guest \nWorker Program
## 4                Not Allow
## 5          None of \nthe Above

# Plot Prediction
predtdt <- rbind(pred1, pred0)
predtdt$treatment <- rep(c("After Protest", "Before Protest"), each=5)
predtdt$treatment <- factor(predtdt$treatment, levels=c("Before Protest",
                                                         "After Protest"))

# Plot
ggplot(predtdt, aes(x=choice, y=mean)) +
  geom_point(aes(shape=treatment), position=position_dodge(width=0.5)) +
  geom_errorbar(aes(ymin=lci, ymax=uci, linetype=treatment),
               position=position_dodge(width=0.5), width=0.3) +
  theme_bw() + xlab(NULL) + ylab("Predicted Probability") +
  labs(caption="Other variables are fixed at median.") +
  theme(legend.position="bottom")

```



Other variables are fixed at median.

## 2. Use mlogit function

```
library(mlogit)
```

### 2.1. Use mlogit function from mlogit package to estimate the same model

as in 1.4. Does it yield the same results?

```
# Create Long Data
d.mlogit <- mlogit.data(d, shape = "wide", choice = "immpolinew")
head(d.mlogit[,1:5],10)
```

```
##      age edu latcomm knowledge female
## 1.1  37   1     4         0         0
## 1.2  37   1     4         0         0
## 1.3  37   1     4         0         0
## 1.4  37   1     4         0         0
## 1.5  37   1     4         0         0
## 2.1  60   2     3         0         1
## 2.2  60   2     3         0         1
## 2.3  60   2     3         0         1
## 2.4  60   2     3         0         1
## 2.5  60   2     3         0         1
```

```
# Replicate Mlogit Model of Immigration Policy Preference
m3 <- mlogit(immpolinew ~ 0 | protest_period + pprhispx + ppehscx +
```

```

latcomm + generation + american + national_origin +
language_skills + knowledge + catholic + community_participate +
attend_church + cuba + pr + dr + south + central +
age + female + edu + incomeq_dummy1 + incomeq_dummy3 +
incomeq_dummy4 + incomeq_dummy5 + perfin, data=d.mlogit)
summary(m3)

```

```

##
## Call:
## mlogit(formula = immppolinew ~ 0 | protest_period + pprhispx +
##       ppehhscx + latcomm + generation + american + national_origin +
##       language_skills + knowledge + catholic + community_participate +
##       attend_church + cuba + pr + dr + south + central + age +
##       female + edu + incomeq_dummy1 + incomeq_dummy3 + incomeq_dummy4 +
##       incomeq_dummy5 + perfin, data = d.mlogit, method = "nr",
##       print.level = 0)
##
## Frequencies of alternatives:
##      1      2      3      4      5
## 0.415391 0.331519 0.122572 0.049588 0.080930
##
## nr method
## 6 iterations, 0h:0m:3s
## g'(-H)^-1g = 0.000769
## successive function values within tolerance limits
##
## Coefficients :
##              Estimate Std. Error z-value Pr(>|z|)
## 2:(intercept)   -1.9863e+00  3.3616e-01 -5.9088 3.445e-09 ***
## 3:(intercept)   -2.2883e+00  4.4012e-01 -5.1994 1.999e-07 ***
## 4:(intercept)   -6.5687e+00  6.8344e-01 -9.6113 < 2.2e-16 ***
## 5:(intercept)   -1.9449e+00  5.1068e-01 -3.8085 0.0001398 ***
## 2:protest_period -3.1269e-01  6.9486e-02 -4.5000 6.795e-06 ***
## 3:protest_period -5.5307e-01  9.0476e-02 -6.1130 9.780e-10 ***
## 4:protest_period -2.3669e-01  1.5097e-01 -1.5678 0.1169394
## 5:protest_period -6.0133e-01  1.0681e-01 -5.6298 1.804e-08 ***
## 2:pprhisp      -1.8125e-03  1.0474e-03 -1.7304 0.0835503 .
## 3:pprhisp       1.4592e-03  1.3709e-03  1.0645 0.2871164
## 4:pprhisp       4.5364e-04  2.1690e-03  0.2091 0.8343351
## 5:pprhisp      -1.6946e-03  1.6406e-03 -1.0329 0.3016342
## 2:ppehhscx      8.7479e-03  6.6736e-03  1.3108 0.1899154
## 3:ppehhscx     -8.6162e-05  8.9288e-03 -0.0096 0.9923006
## 4:ppehhscx      3.1473e-02  1.1968e-02  2.6297 0.0085458 **
## 5:ppehhscx      1.3109e-02  9.8852e-03  1.3262 0.1847857
## 2:latcomm       -7.5320e-02  3.7036e-02 -2.0337 0.0419838 *
## 3:latcomm       -1.8249e-01  4.7444e-02 -3.8464 0.0001199 ***
## 4:latcomm       -3.7294e-01  6.8178e-02 -5.4701 4.499e-08 ***
## 5:latcomm       -2.0672e-01  5.4992e-02 -3.7590 0.0001706 ***
## 2:generation     2.3719e-01  3.6423e-02  6.5121 7.411e-11 ***
## 3:generation     2.2569e-01  4.6842e-02  4.8182 1.449e-06 ***
## 4:generation     4.7553e-01  6.6128e-02  7.1910 6.430e-13 ***
## 5:generation     2.9854e-01  5.4009e-02  5.5275 3.248e-08 ***
## 2:american       2.4962e-01  9.3162e-02  2.6794 0.0073763 **
## 3:american       2.9491e-01  1.1789e-01  2.5017 0.0123603 *

```

## 4:american	4.4786e-01	1.6006e-01	2.7981	0.0051403	**
## 5:american	2.9773e-01	1.3553e-01	2.1967	0.0280398	*
## 2:national_origin	-3.6143e-02	6.9886e-02	-0.5172	0.6050373	
## 3:national_origin	-8.0317e-02	9.4341e-02	-0.8513	0.3945773	
## 4:national_origin	-1.9071e-01	1.6659e-01	-1.1447	0.2523173	
## 5:national_origin	-1.5088e-01	1.1213e-01	-1.3456	0.1784263	
## 2:language_skills	5.4782e-01	4.7800e-02	11.4605	< 2.2e-16	***
## 3:language_skills	5.3507e-01	6.2989e-02	8.4946	< 2.2e-16	***
## 4:language_skills	9.4766e-01	9.7788e-02	9.6910	< 2.2e-16	***
## 5:language_skills	6.1638e-01	7.2847e-02	8.4614	< 2.2e-16	***
## 2:knowledge	1.0468e-01	3.3419e-02	3.1324	0.0017338	**
## 3:knowledge	-1.4907e-02	4.4303e-02	-0.3365	0.7365165	
## 4:knowledge	1.9090e-01	6.6556e-02	2.8684	0.0041262	**
## 5:knowledge	-2.1109e-01	5.3680e-02	-3.9323	8.412e-05	***
## 2:catholic	-1.1103e-01	7.1343e-02	-1.5563	0.1196268	
## 3:catholic	-7.4801e-02	9.3653e-02	-0.7987	0.4244603	
## 4:catholic	-3.4880e-01	1.3247e-01	-2.6330	0.0084643	**
## 5:catholic	-2.4804e-01	1.0640e-01	-2.3311	0.0197473	*
## 2:community_participate	-1.2124e-03	8.4139e-02	-0.0144	0.9885037	
## 3:community_participate	-7.6881e-05	1.0980e-01	-0.0007	0.9994414	
## 4:community_participate	4.0208e-01	1.5623e-01	2.5736	0.0100633	*
## 5:community_participate	-4.3162e-02	1.3071e-01	-0.3302	0.7412448	
## 2:attend_church	-4.9285e-02	2.6045e-02	-1.8923	0.0584496	.
## 3:attend_church	-7.1906e-03	3.4306e-02	-0.2096	0.8339780	
## 4:attend_church	-9.7951e-02	4.8264e-02	-2.0295	0.0424087	*
## 5:attend_church	-4.9940e-02	3.9185e-02	-1.2745	0.2025007	
## 2:cuba	1.4254e-01	1.8832e-01	0.7569	0.4490998	
## 3:cuba	3.2177e-02	2.5560e-01	0.1259	0.8998223	
## 4:cuba	9.8237e-01	2.9885e-01	3.2872	0.0010120	**
## 5:cuba	5.4549e-01	2.8646e-01	1.9042	0.0568804	.
## 2:pr	4.5955e-01	1.2099e-01	3.7981	0.0001458	***
## 3:pr	5.2722e-01	1.5007e-01	3.5131	0.0004428	***
## 4:pr	1.2514e+00	1.8397e-01	6.8024	1.029e-11	***
## 5:pr	9.5001e-01	1.6241e-01	5.8495	4.931e-09	***
## 2:dr	2.7838e-01	1.7148e-01	1.6234	0.1045052	
## 3:dr	4.9134e-02	2.4907e-01	0.1973	0.8436189	
## 4:dr	1.4465e+00	3.1430e-01	4.6022	4.180e-06	***
## 5:dr	2.1822e-01	3.0038e-01	0.7265	0.4675434	
## 2:south	9.7843e-02	1.6688e-01	0.5863	0.5576710	
## 3:south	-9.8875e-02	2.4182e-01	-0.4089	0.6826322	
## 4:south	1.1737e+00	3.2410e-01	3.6213	0.0002931	***
## 5:south	7.2237e-02	3.0422e-01	0.2375	0.8123074	
## 2:central	-2.4483e-02	1.1074e-01	-0.2211	0.8250239	
## 3:central	-1.3290e-01	1.5240e-01	-0.8721	0.3831566	
## 4:central	6.3150e-01	2.6855e-01	2.3515	0.0186957	*
## 5:central	4.9235e-01	1.5755e-01	3.1251	0.0017776	**
## 2:age	9.6097e-04	2.3221e-03	0.4138	0.6789920	
## 3:age	8.8243e-03	2.9552e-03	2.9861	0.0028258	**
## 4:age	2.3568e-02	4.1266e-03	5.7113	1.121e-08	***
## 5:age	2.2922e-03	3.4577e-03	0.6629	0.5073883	
## 2:female	-1.0607e-03	6.4699e-02	-0.0164	0.9869198	
## 3:female	-2.2934e-01	8.4981e-02	-2.6988	0.0069598	**
## 4:female	-1.4484e-01	1.2846e-01	-1.1275	0.2595476	
## 5:female	-6.2416e-02	1.0013e-01	-0.6233	0.5330610	

```
## 2:edu          9.5941e-02  1.9801e-02  4.8454 1.264e-06 ***
## 3:edu          3.9805e-02  2.6227e-02  1.5177 0.1290917
## 4:edu         -6.1934e-02  4.2730e-02 -1.4494 0.1472177
## 5:edu         -6.5405e-02  3.1272e-02 -2.0915 0.0364840 *
## 2:incomeq_dumy1 -1.5422e-01  9.6136e-02 -1.6042 0.1086769
## 3:incomeq_dumy1 -6.4011e-02  1.2651e-01 -0.5060 0.6128688
## 4:incomeq_dumy1 -8.9488e-02  2.1639e-01 -0.4136 0.6791969
## 5:incomeq_dumy1  3.2689e-01  1.3325e-01  2.4532 0.0141593 *
## 2:incomeq_dumy3  8.5018e-02  9.6064e-02  0.8850 0.3761468
## 3:incomeq_dumy3  6.0668e-02  1.2891e-01  0.4706 0.6379121
## 4:incomeq_dumy3  3.2971e-02  2.2115e-01  0.1491 0.8814860
## 5:incomeq_dumy3 -2.0268e-01  1.6384e-01 -1.2371 0.2160638
## 2:incomeq_dumy4  1.5146e-01  9.5589e-02  1.5845 0.1130764
## 3:incomeq_dumy4  2.0727e-01  1.2413e-01  1.6699 0.0949480 .
## 4:incomeq_dumy4  4.6811e-02  2.0131e-01  0.2325 0.8161231
## 5:incomeq_dumy4  7.2618e-02  1.5039e-01  0.4828 0.6292027
## 2:incomeq_dumy5  3.5115e-01  1.0980e-01  3.1983 0.0013826 **
## 3:incomeq_dumy5  1.6985e-01  1.4523e-01  1.1696 0.2421695
## 4:incomeq_dumy5  4.4902e-01  2.0493e-01  2.1911 0.0284477 *
## 5:incomeq_dumy5  1.0155e-01  1.7376e-01  0.5844 0.5589406
## 2:perfin       1.0353e-01  4.4181e-02  2.3433 0.0191153 *
## 3:perfin       1.4177e-01  5.8414e-02  2.4270 0.0152224 *
## 4:perfin       2.8542e-01  9.0086e-02  3.1683 0.0015335 **
## 5:perfin       1.2444e-01  6.8588e-02  1.8144 0.0696211 .
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Log-Likelihood: -8114.7
```

```
## McFadden R^2: 0.10938
```

```
## Likelihood ratio test : chisq = 1993.1 (p.value = < 2.22e-16)
```

```
# Coefficients Look Mostly the Same, but slightly different
```

```
comp <- cbind(as.numeric(coef(m2)), coef(m3),
              abs(as.numeric(coef(m2))-coef(m3)))
colnames(comp) <- c("multinom","mlogit","difference")
round(comp,3)
```

```
##          multinom mlogit difference
## 2:(intercept)    -1.981 -1.986      0.005
## 3:(intercept)    -2.290 -2.288      0.001
## 4:(intercept)    -6.496 -6.569      0.073
## 5:(intercept)    -1.929 -1.945      0.016
## 2:protest_period -0.315 -0.313      0.002
## 3:protest_period -0.557 -0.553      0.004
## 4:protest_period -0.241 -0.237      0.004
## 5:protest_period -0.603 -0.601      0.001
## 2:pprhispix      -0.002 -0.002      0.000
## 3:pprhispix       0.001  0.001      0.000
## 4:pprhispix       0.000  0.000      0.000
## 5:pprhispix      -0.002 -0.002      0.000
## 2:ppehhscx       0.009  0.009      0.000
## 3:ppehhscx       0.000  0.000      0.000
## 4:ppehhscx       0.031  0.031      0.000
## 5:ppehhscx       0.013  0.013      0.000
## 2:latcomm        -0.075 -0.075      0.000
```

## 3:latcomm	-0.182	-0.182	0.000
## 4:latcomm	-0.372	-0.373	0.001
## 5:latcomm	-0.208	-0.207	0.001
## 2:generation	0.236	0.237	0.001
## 3:generation	0.226	0.226	0.000
## 4:generation	0.471	0.476	0.005
## 5:generation	0.299	0.299	0.001
## 2:american	0.249	0.250	0.001
## 3:american	0.294	0.295	0.001
## 4:american	0.444	0.448	0.004
## 5:american	0.296	0.298	0.002
## 2:national_origin	-0.037	-0.036	0.001
## 3:national_origin	-0.080	-0.080	0.000
## 4:national_origin	-0.193	-0.191	0.002
## 5:national_origin	-0.151	-0.151	0.000
## 2:language_skills	0.549	0.548	0.001
## 3:language_skills	0.537	0.535	0.001
## 4:language_skills	0.940	0.948	0.007
## 5:language_skills	0.619	0.616	0.002
## 2:knowledge	0.104	0.105	0.000
## 3:knowledge	-0.016	-0.015	0.001
## 4:knowledge	0.188	0.191	0.003
## 5:knowledge	-0.211	-0.211	0.000
## 2:catholic	-0.110	-0.111	0.001
## 3:catholic	-0.074	-0.075	0.001
## 4:catholic	-0.345	-0.349	0.004
## 5:catholic	-0.248	-0.248	0.000
## 2:community_participate	-0.001	-0.001	0.000
## 3:community_participate	0.002	0.000	0.002
## 4:community_participate	0.400	0.402	0.003
## 5:community_participate	-0.045	-0.043	0.002
## 2:attend_church	-0.050	-0.049	0.000
## 3:attend_church	-0.007	-0.007	0.000
## 4:attend_church	-0.099	-0.098	0.001
## 5:attend_church	-0.050	-0.050	0.000
## 2:cuba	0.146	0.143	0.003
## 3:cuba	0.038	0.032	0.006
## 4:cuba	0.980	0.982	0.002
## 5:cuba	0.535	0.545	0.010
## 2:pr	0.461	0.460	0.001
## 3:pr	0.525	0.527	0.002
## 4:pr	1.249	1.251	0.003
## 5:pr	0.951	0.950	0.001
## 2:dr	0.275	0.278	0.003
## 3:dr	0.051	0.049	0.002
## 4:dr	1.427	1.446	0.019
## 5:dr	0.226	0.218	0.008
## 2:south	0.094	0.098	0.004
## 3:south	-0.102	-0.099	0.003
## 4:south	1.154	1.174	0.020
## 5:south	0.074	0.072	0.002
## 2:central	-0.022	-0.024	0.002
## 3:central	-0.136	-0.133	0.003
## 4:central	0.625	0.632	0.007

## 5:central	0.487	0.492	0.005
## 2:age	0.001	0.001	0.000
## 3:age	0.009	0.009	0.000
## 4:age	0.023	0.024	0.000
## 5:age	0.002	0.002	0.000
## 2:female	0.000	-0.001	0.001
## 3:female	-0.229	-0.229	0.000
## 4:female	-0.149	-0.145	0.004
## 5:female	-0.064	-0.062	0.001
## 2:edu	0.096	0.096	0.000
## 3:edu	0.040	0.040	0.000
## 4:edu	-0.060	-0.062	0.002
## 5:edu	-0.067	-0.065	0.002
## 2:incomeq_dummy1	-0.156	-0.154	0.002
## 3:incomeq_dummy1	-0.062	-0.064	0.002
## 4:incomeq_dummy1	-0.098	-0.089	0.009
## 5:incomeq_dummy1	0.330	0.327	0.003
## 2:incomeq_dummy3	0.084	0.085	0.001
## 3:incomeq_dummy3	0.062	0.061	0.001
## 4:incomeq_dummy3	0.029	0.033	0.004
## 5:incomeq_dummy3	-0.197	-0.203	0.006
## 2:incomeq_dummy4	0.149	0.151	0.003
## 3:incomeq_dummy4	0.210	0.207	0.002
## 4:incomeq_dummy4	0.042	0.047	0.005
## 5:incomeq_dummy4	0.073	0.073	0.000
## 2:incomeq_dummy5	0.351	0.351	0.001
## 3:incomeq_dummy5	0.173	0.170	0.003
## 4:incomeq_dummy5	0.443	0.449	0.006
## 5:incomeq_dummy5	0.106	0.102	0.005
## 2:perfin	0.103	0.104	0.001
## 3:perfin	0.141	0.142	0.001
## 4:perfin	0.282	0.285	0.003
## 5:perfin	0.124	0.124	0.000

## 2.2. Create some choice level variable in the dataset (i.e., some

combination of individual level characteristics and choice characteristics). Run the new model with choice level variable.

```
# commonality high (3,4) * Immigration Yes (1,2,3) as 1
# commonality low (1,2) * Immigration No (4) as 1
# 0 Otherwise
commandimm.1 <- ifelse(d$latcomm%in%c(3,4),1,0)
commandimm.2 <- ifelse(d$latcomm%in%c(3,4),1,0)
commandimm.3 <- ifelse(d$latcomm%in%c(3,4),1,0)
commandimm.4 <- ifelse(d$latcomm%in%c(1,2),1,0)
commandimm.5 <- rep(0, nrow(d))

d2 <- cbind(commandimm.1,commandimm.2,
            commandimm.3,commandimm.4,
            commandimm.5, d)

# Create Long Data
d2.mlogit <- mlogit.data(d2, shape = "wide", varying=1:5, choice = "immpolinew")
```



```
head(d2.mlogit$commandimm,10)
```

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

```
# Replicate Mlogit Model of Immigration Policy Preference
```

```
m4 <- mlogit(impolinew ~ commandimm | protest_period + pprhispx + ppehscx +
  latcomm + generation + american + national_origin +
  language_skills + knowledge + catholic + community_participate +
  attend_church + cuba + pr + dr + south + central +
  age + female + edu + incomeq_dummy1 + incomeq_dummy3 +
  incomeq_dummy4 + incomeq_dummy5 + perfin, data=d2.mlogit)
```

```
summary(m4)
```

```
##
```

```
## Call:
```

```
## mlogit(formula = impolinew ~ commandimm | protest_period + pprhispx +
## ppehscx + latcomm + generation + american + national_origin +
## language_skills + knowledge + catholic + community_participate +
## attend_church + cuba + pr + dr + south + central + age +
## female + edu + incomeq_dummy1 + incomeq_dummy3 + incomeq_dummy4 +
## incomeq_dummy5 + perfin, data = d2.mlogit, method = "nr",
## print.level = 0)
```

```
##
```

```
## Frequencies of alternatives:
```

```
##      1      2      3      4      5
## 0.415391 0.331519 0.122572 0.049588 0.080930
```

```
##
```

```
## nr method
```

```
## 6 iterations, 0h:0m:5s
```

```
## g'(-H)-1g = 0.000769
```

```
## successive function values within tolerance limits
```

```
##
```

```
## Coefficients :
```

	Estimate	Std. Error	z-value	Pr(> z )
## 2:(intercept)	-1.9869e+00	3.3622e-01	-5.9096	3.430e-09 ***
## 3:(intercept)	-2.2873e+00	4.4019e-01	-5.1962	2.034e-07 ***
## 4:(intercept)	-6.8099e+00	7.2013e-01	-9.4564	< 2.2e-16 ***
## 5:(intercept)	-2.0053e+00	5.1360e-01	-3.9045	9.444e-05 ***
## commandimm	1.1819e-01	1.1086e-01	1.0661	0.2863721
## 2:protest_period	-3.1265e-01	6.9486e-02	-4.4994	6.813e-06 ***
## 3:protest_period	-5.5304e-01	9.0475e-02	-6.1126	9.800e-10 ***
## 4:protest_period	-2.3638e-01	1.5104e-01	-1.5651	0.1175630
## 5:protest_period	-6.0200e-01	1.0683e-01	-5.6350	1.750e-08 ***
## 2:pprhispx	-1.8111e-03	1.0474e-03	-1.7291	0.0837912 .
## 3:pprhispx	1.4601e-03	1.3709e-03	1.0651	0.2868355
## 4:pprhispx	4.7536e-04	2.1692e-03	0.2191	0.8265359
## 5:pprhispx	-1.6809e-03	1.6405e-03	-1.0247	0.3055149
## 2:ppehscx	8.7472e-03	6.6750e-03	1.3105	0.1900421
## 3:ppehscx	-9.7943e-05	8.9306e-03	-0.0110	0.9912496
## 4:ppehscx	3.1596e-02	1.1950e-02	2.6440	0.0081932 **
## 5:ppehscx	1.3142e-02	9.8827e-03	1.3298	0.1835867
## 2:latcomm	-7.5354e-02	3.7070e-02	-2.0327	0.0420792 *
## 3:latcomm	-1.8282e-01	4.7492e-02	-3.8495	0.0001184 ***
## 4:latcomm	-2.7678e-01	1.1298e-01	-2.4499	0.0142878 *

## 5:latcomm	-1.6035e-01	7.0003e-02	-2.2907	0.0219820	*
## 2:generation	2.3717e-01	3.6424e-02	6.5115	7.440e-11	***
## 3:generation	2.2572e-01	4.6843e-02	4.8188	1.444e-06	***
## 4:generation	4.7508e-01	6.6128e-02	7.1843	6.755e-13	***
## 5:generation	2.9814e-01	5.4014e-02	5.5197	3.396e-08	***
## 2:american	2.5009e-01	9.3159e-02	2.6845	0.0072633	**
## 3:american	2.9522e-01	1.1788e-01	2.5045	0.0122617	*
## 4:american	4.4293e-01	1.6022e-01	2.7645	0.0057007	**
## 5:american	2.9597e-01	1.3557e-01	2.1832	0.0290218	*
## 2:national_origin	-3.5976e-02	6.9887e-02	-0.5148	0.6067145	
## 3:national_origin	-8.0201e-02	9.4341e-02	-0.8501	0.3952632	
## 4:national_origin	-1.9474e-01	1.6667e-01	-1.1684	0.2426352	
## 5:national_origin	-1.5201e-01	1.1214e-01	-1.3556	0.1752236	
## 2:language_skills	5.4783e-01	4.7802e-02	11.4604	< 2.2e-16	***
## 3:language_skills	5.3502e-01	6.2993e-02	8.4934	< 2.2e-16	***
## 4:language_skills	9.5214e-01	9.7833e-02	9.7324	< 2.2e-16	***
## 5:language_skills	6.1886e-01	7.2892e-02	8.4901	< 2.2e-16	***
## 2:knowledge	1.0470e-01	3.3418e-02	3.1329	0.0017308	**
## 3:knowledge	-1.4923e-02	4.4300e-02	-0.3369	0.7362255	
## 4:knowledge	1.9137e-01	6.6597e-02	2.8736	0.0040583	**
## 5:knowledge	-2.1123e-01	5.3686e-02	-3.9345	8.338e-05	***
## 2:catholic	-1.1096e-01	7.1345e-02	-1.5552	0.1198908	
## 3:catholic	-7.4706e-02	9.3656e-02	-0.7977	0.4250691	
## 4:catholic	-3.4903e-01	1.3248e-01	-2.6347	0.0084223	**
## 5:catholic	-2.4785e-01	1.0640e-01	-2.3295	0.0198336	*
## 2:community_participate	-9.3056e-04	8.4142e-02	-0.0111	0.9911760	
## 3:community_participate	4.3054e-05	1.0981e-01	0.0004	0.9996872	
## 4:community_participate	3.9983e-01	1.5625e-01	2.5590	0.0104980	*
## 5:community_participate	-4.3347e-02	1.3070e-01	-0.3317	0.7401530	
## 2:attend_church	-4.9367e-02	2.6046e-02	-1.8954	0.0580373	.
## 3:attend_church	-7.2550e-03	3.4307e-02	-0.2115	0.8325173	
## 4:attend_church	-9.6657e-02	4.8274e-02	-2.0023	0.0452566	*
## 5:attend_church	-4.9529e-02	3.9191e-02	-1.2638	0.2062996	
## 2:cuba	1.4242e-01	1.8832e-01	0.7562	0.4495164	
## 3:cuba	3.2390e-02	2.5559e-01	0.1267	0.8991577	
## 4:cuba	9.8380e-01	2.9884e-01	3.2920	0.0009947	***
## 5:cuba	5.4508e-01	2.8650e-01	1.9025	0.0571005	.
## 2:pr	4.5895e-01	1.2099e-01	3.7931	0.0001488	***
## 3:pr	5.2694e-01	1.5007e-01	3.5114	0.0004458	***
## 4:pr	1.2570e+00	1.8404e-01	6.8297	8.507e-12	***
## 5:pr	9.5173e-01	1.6241e-01	5.8600	4.630e-09	***
## 2:dr	2.7926e-01	1.7148e-01	1.6285	0.1034236	
## 3:dr	4.9731e-02	2.4908e-01	0.1997	0.8417447	
## 4:dr	1.4408e+00	3.1452e-01	4.5811	4.626e-06	***
## 5:dr	2.1821e-01	3.0041e-01	0.7264	0.4676128	
## 2:south	9.7718e-02	1.6689e-01	0.5855	0.5581900	
## 3:south	-9.8626e-02	2.4182e-01	-0.4078	0.6833884	
## 4:south	1.1790e+00	3.2403e-01	3.6384	0.0002743	***
## 5:south	7.3167e-02	3.0424e-01	0.2405	0.8099477	
## 2:central	-2.4464e-02	1.1074e-01	-0.2209	0.8251550	
## 3:central	-1.3278e-01	1.5240e-01	-0.8713	0.3835868	
## 4:central	6.2200e-01	2.6873e-01	2.3146	0.0206358	*
## 5:central	4.8774e-01	1.5763e-01	3.0943	0.0019727	**
## 2:age	9.5699e-04	2.3221e-03	0.4121	0.6802478	

```
## 3:age      8.8221e-03  2.9552e-03  2.9853 0.0028332 **
## 4:age      2.3536e-02  4.1256e-03  5.7049 1.164e-08 ***
## 5:age      2.2673e-03  3.4578e-03  0.6557 0.5120102
## 2:female   -9.4525e-04  6.4700e-02 -0.0146 0.9883435
## 3:female   -2.2925e-01  8.4982e-02 -2.6976 0.0069846 **
## 4:female   -1.4499e-01  1.2847e-01 -1.1285 0.2590877
## 5:female   -6.2489e-02  1.0013e-01 -0.6241 0.5325875
## 2:edu      9.5943e-02  1.9802e-02  4.8451 1.265e-06 ***
## 3:edu      3.9793e-02  2.6229e-02  1.5171 0.1292331
## 4:edu      -6.1557e-02  4.2717e-02 -1.4410 0.1495740
## 5:edu      -6.4907e-02  3.1271e-02 -2.0756 0.0379313 *
## 2:incomeq_dummy1 -1.5399e-01  9.6136e-02 -1.6018 0.1092048
## 3:incomeq_dummy1 -6.3796e-02  1.2651e-01 -0.5043 0.6140596
## 4:incomeq_dummy1 -9.6875e-02  2.1649e-01 -0.4475 0.6545280
## 5:incomeq_dummy1  3.2531e-01  1.3327e-01  2.4410 0.0146456 *
## 2:incomeq_dummy3  8.5288e-02  9.6066e-02  0.8878 0.3746445
## 3:incomeq_dummy3  6.1017e-02  1.2891e-01  0.4733 0.6359812
## 4:incomeq_dummy3  2.6440e-02  2.2129e-01  0.1195 0.9048952
## 5:incomeq_dummy3 -2.0380e-01  1.6384e-01 -1.2439 0.2135538
## 2:incomeq_dummy4  1.5166e-01  9.5589e-02  1.5865 0.1126152
## 3:incomeq_dummy4  2.0746e-01  1.2413e-01  1.6713 0.0946547 .
## 4:incomeq_dummy4  4.3367e-02  2.0136e-01  0.2154 0.8294795
## 5:incomeq_dummy4  7.2085e-02  1.5040e-01  0.4793 0.6317318
## 2:incomeq_dummy5  3.5129e-01  1.0980e-01  3.1994 0.0013769 **
## 3:incomeq_dummy5  1.6996e-01  1.4523e-01  1.1703 0.2418859
## 4:incomeq_dummy5  4.4471e-01  2.0498e-01  2.1695 0.0300417 *
## 5:incomeq_dummy5  1.0111e-01  1.7375e-01  0.5819 0.5606346
## 2:perfin    1.0355e-01  4.4184e-02  2.3435 0.0191034 *
## 3:perfin    1.4176e-01  5.8419e-02  2.4267 0.0152378 *
## 4:perfin    2.8451e-01  9.0039e-02  3.1598 0.0015786 **
## 5:perfin    1.2480e-01  6.8570e-02  1.8201 0.0687411 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log-Likelihood: -8114.1
## McFadden R^2:  0.10944
## Likelihood ratio test : chisq = 1994.3 (p.value = < 2.22e-16)
```

### 3. Use Zelig function

```
library(Zelig) # zelig function
library(ZeligChoice) # zelig function to do multinomial logit
```

#### 3.1. Use Zelig function to estimate the same model as in 1.4.

```
m5 <- zelig(as.factor(imppolinelw) ~ protest_period + pprhispx + ppehhscx +
  latcomm + generation + american + national_origin +
  language_skills + knowledge + catholic + community_participate +
  attend_church + cuba + pr + dr + south + central +
  age + female + edu + incomeq_dummy1 + incomeq_dummy3 +
  incomeq_dummy4 + incomeq_dummy5 + perfin,
  model="mlogit", data=d)
```

```
## How to cite this model in Zelig:
##   Thomas W. Yee. 2007.
##   mlogit: Multinomial Logistic Regression for Dependent Variables with Unordered Categorical Values
##   in Christine Choirat, Christopher Gandrud, James Honaker, Kosuke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligproject.org/
```

```
# Reference Group is Level 5 (Not Level 1)
summary(m5)
```

```
## Model:
##
## Call:
## z5$zelig(formula = as.factor(impoline) ~ protest_period + pprhispx +
##   ppehhscx + latcomm + generation + american + national_origin +
##   language_skills + knowledge + catholic + community_participate +
##   attend_church + cuba + pr + dr + south + central + age +
##   female + edu + incomeq_dummy1 + incomeq_dummy3 + incomeq_dummy4 +
##   incomeq_dummy5 + perfin, data = d)
##
##
## Pearson residuals:
##               Min         1Q      Median         3Q        Max
## log(mu[,1]/mu[,5]) -4.869 -0.5695 -0.19777  0.70928  7.529
## log(mu[,2]/mu[,5]) -4.152 -0.5552 -0.26625  0.91327  2.693
## log(mu[,3]/mu[,5]) -3.423 -0.2685 -0.20368 -0.14179  4.223
## log(mu[,4]/mu[,5]) -2.454 -0.1609 -0.06972 -0.02748 19.826
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept):1      1.9449394   0.5106821    3.809 0.000140
## (Intercept):2     -0.0413890   0.5063320   -0.082 0.934851
## (Intercept):3     -0.3434067   0.5814711   -0.591 0.554800
## (Intercept):4     -4.6238135   0.7685775   -6.016 1.79e-09
## protest_period:1      0.6013335   0.1068126    5.630 1.80e-08
## protest_period:2      0.2886480   0.1078512    2.676 0.007443
## protest_period:3      0.0482604   0.1225835    0.394 0.693807
## protest_period:4      0.3646482   0.1690050    2.158 0.030958
## pprhispx:1           0.0016946   0.0016406    1.033 0.301634
## pprhispx:2          -0.0001178   0.0016530   -0.071 0.943170
## pprhispx:3           0.0031539   0.0018766    1.681 0.092835
## pprhispx:4           0.0021483   0.0024763    0.868 0.385652
## ppehhscx:1          -0.0131094   0.0098852   -1.326 0.184786
## ppehhscx:2          -0.0043615   0.0096298   -0.453 0.650613
## ppehhscx:3          -0.0131955   0.0113756   -1.160 0.246054
## ppehhscx:4           0.0183637   0.0134484    1.365 0.172099
## latcomm:1           0.2067177   0.0549925    3.759 0.000171
## latcomm:2           0.1313976   0.0551143    2.384 0.017121
## latcomm:3           0.0242295   0.0627460    0.386 0.699384
## latcomm:4          -0.1662224   0.0779307   -2.133 0.032929
## generation:1        -0.2985376   0.0540093   -5.528 3.25e-08
## generation:2        -0.0613481   0.0513312   -1.195 0.232032
## generation:3        -0.0728457   0.0591042   -1.232 0.217764
## generation:4         0.1769916   0.0742907    2.382 0.017199
## american:1          -0.2977279   0.1355324   -2.197 0.028040
## american:2          -0.0481128   0.1296406   -0.371 0.710545
```

## american:3	-0.0028165	0.1487572	-0.019	0.984894
## american:4	0.1501279	0.1810467	0.829	0.406979
## national_origin:1	0.1508781	0.1121257	1.346	0.178426
## national_origin:2	0.1147350	0.1151502	0.996	0.319058
## national_origin:3	0.0705612	0.1316171	0.536	0.591883
## national_origin:4	-0.0398302	0.1878140	-0.212	0.832050
## language_skills:1	-0.6163833	0.0728469	-8.461	< 2e-16
## language_skills:2	-0.0685666	0.0719223	-0.953	0.340417
## language_skills:3	-0.0813146	0.0825621	-0.985	0.324678
## language_skills:4	0.3312824	0.1097468	3.019	0.002539
## knowledge:1	0.2110868	0.0536796	3.932	8.41e-05
## knowledge:2	0.3157691	0.0528210	5.978	2.26e-09
## knowledge:3	0.1961801	0.0603307	3.252	0.001147
## knowledge:4	0.4019916	0.0766625	5.244	1.57e-07
## catholic:1	0.2480358	0.1064022	2.331	0.019747
## catholic:2	0.1370015	0.1051435	1.303	0.192577
## catholic:3	0.1732344	0.1216097	1.425	0.154299
## catholic:4	-0.1007632	0.1507335	-0.668	0.503824
## community_participate:1	0.0431622	0.1307131	0.330	0.741245
## community_participate:2	0.0419498	0.1251666	0.335	0.737510
## community_participate:3	0.0430853	0.1437379	0.300	0.764369
## community_participate:4	0.4452444	0.1784237	2.495	0.012580
## attend_church:1	0.0499395	0.0391849	1.274	0.202501
## attend_church:2	0.0006540	0.0387190	0.017	0.986523
## attend_church:3	0.0427489	0.0447725	0.955	0.339677
## attend_church:4	-0.0480113	0.0551224	-0.871	0.383758
## cuba:1	-0.5454854	0.2864600	-1.904	0.056880
## cuba:2	-0.4029457	0.2811971	-1.433	0.151868
## cuba:3	-0.5133088	0.3308591	-1.551	0.120796
## cuba:4	0.4368825	0.3596984	1.215	0.224526
## pr:1	-0.9500069	0.1624085	-5.849	4.93e-09
## pr:2	-0.4904576	0.1485695	-3.301	0.000963
## pr:3	-0.4227898	0.1732545	-2.440	0.014676
## pr:4	0.3014304	0.2003968	1.504	0.132538
## dr:1	-0.2182197	0.3003787	-0.726	0.467543
## dr:2	0.0601645	0.3044077	0.198	0.843323
## dr:3	-0.1690857	0.3537414	-0.478	0.632656
## dr:4	1.2282770	0.3985668	3.082	0.002058
## south:1	-0.0722368	0.3042184	-0.237	0.812307
## south:2	0.0256065	0.3041924	0.084	0.932914
## south:3	-0.1711113	0.3508467	-0.488	0.625756
## south:4	1.1014461	0.4077424	2.701	0.006906
## central:1	-0.4923461	0.1575470	-3.125	0.001778
## central:2	-0.5168289	0.1666736	-3.101	0.001930
## central:3	-0.6252504	0.1968962	-3.176	0.001496
## central:4	0.1391594	0.2938204	0.474	0.635771
## age:1	-0.0022922	0.0034577	-0.663	0.507388
## age:2	-0.0013312	0.0033941	-0.392	0.694903
## age:3	0.0065321	0.0038617	1.692	0.090738
## age:4	0.0212760	0.0047244	4.503	6.69e-06
## female:1	0.0624163	0.1001320	0.623	0.533061
## female:2	0.0613556	0.1001738	0.612	0.540213
## female:3	-0.1669275	0.1145734	-1.457	0.145131
## female:4	-0.0824192	0.1468509	-0.561	0.574631

```
## edu:1          0.0654052  0.0312720   2.091 0.036484
## edu:2          0.1613463  0.0317145   5.087 3.63e-07
## edu:3          0.1052100  0.0360670   2.917 0.003533
## edu:4          0.0034707  0.0484648   0.072 0.942909
## incomeq_dummy1:1 -0.3268933  0.1332520  -2.453 0.014159
## incomeq_dummy1:2 -0.4811116  0.1399079  -3.439 0.000584
## incomeq_dummy1:3 -0.3909040  0.1624293  -2.407 0.016101
## incomeq_dummy1:4 -0.4163810  0.2350626  -1.771 0.076500
## incomeq_dummy3:1  0.2026763  0.1638367   1.237 0.216064
## incomeq_dummy3:2  0.2876946  0.1667976   1.725 0.084561
## incomeq_dummy3:3  0.2633445  0.1878411   1.402 0.160929
## incomeq_dummy3:4  0.2356476  0.2558336   0.921 0.357000
## incomeq_dummy4:1 -0.0726177  0.1503942  -0.483 0.629203
## incomeq_dummy4:2  0.0788444  0.1496435   0.527 0.598276
## incomeq_dummy4:3  0.1346556  0.1694524   0.795 0.426816
## incomeq_dummy4:4 -0.0258059  0.2280990  -0.113 0.909924
## incomeq_dummy5:1 -0.1015484  0.1737605  -0.584 0.558941
## incomeq_dummy5:2  0.2496064  0.1661857   1.502 0.133104
## incomeq_dummy5:3  0.0683063  0.1912634   0.357 0.720993
## incomeq_dummy5:4  0.3474743  0.2359439   1.473 0.140832
## perfin:1        -0.1244434  0.0685877  -1.814 0.069621
## perfin:2        -0.0209157  0.0688061  -0.304 0.761143
## perfin:3         0.0173296  0.0788768   0.220 0.826101
## perfin:4         0.1609742  0.1026685   1.568 0.116904
##
## Number of linear predictors: 4
##
## Names of linear predictors:
## log(mu[,1]/mu[,5]), log(mu[,2]/mu[,5]), log(mu[,3]/mu[,5]), log(mu[,4]/mu[,5])
##
## Residual deviance: 16229.33 on 27080 degrees of freedom
##
## Log-likelihood: -8114.663 on 27080 degrees of freedom
##
## Number of iterations: 6
##
## Warning: Hauck-Donner effect detected in the following estimate(s):
## '(Intercept):4'
##
## Reference group is level 5 of the response
## Next step: Use 'setx' method
```

### 3.2. Export predicted probabilities for several profiles.

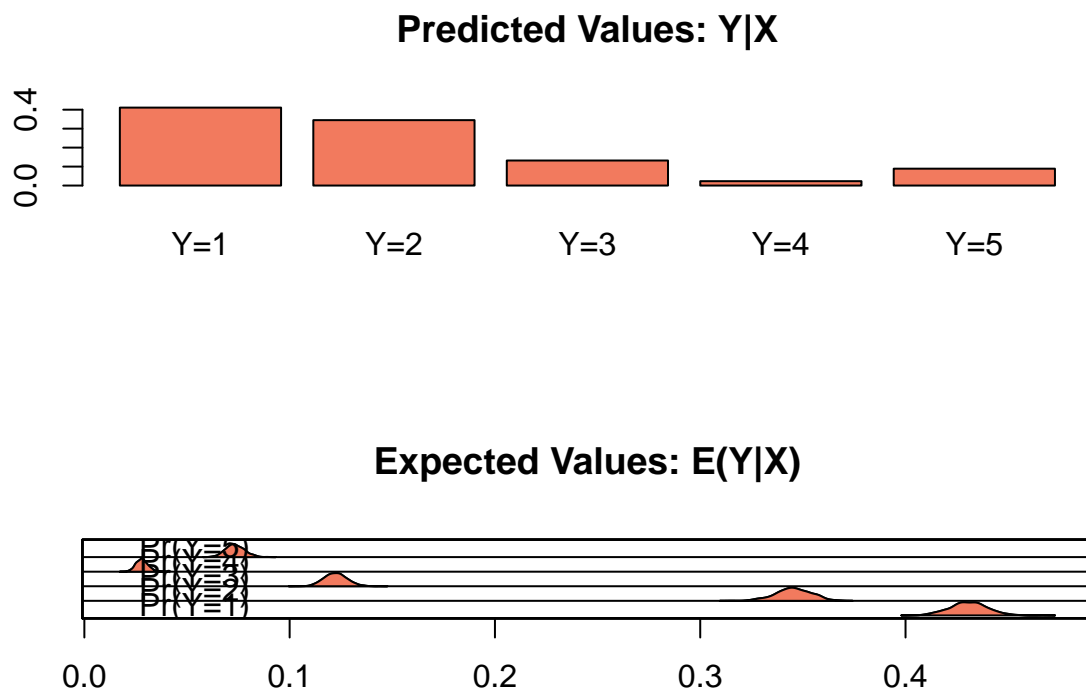
```
# Other Variables are unspecified (Set to Default)
```

```
# Treated
x1 <- setx(m5, protest_period=1)
s1.out <- sim(m5, x = x1)
summary(s1.out)
```

```
##
## sim x :
## -----
```

```
## ev
##           mean          sd        50%        2.5%        97.5%
## Pr(Y=1) 0.43069148 0.008993160 0.43070299 0.41332598 0.44865821
## Pr(Y=2) 0.34544599 0.008493510 0.34539388 0.32786255 0.36101497
## Pr(Y=3) 0.12237738 0.005504209 0.12224897 0.11211233 0.13310216
## Pr(Y=4) 0.02805445 0.002907411 0.02795682 0.02245889 0.03411686
## Pr(Y=5) 0.07343070 0.004525967 0.07310424 0.06512984 0.08277386
## pv
##           1          2          3          4          5
## [1,] 0.411 0.345 0.132 0.023 0.089
```

```
plot(s1.out)
```



```
# Untreated
x2 <- setx(m5, protest_period=0)
s2.out <- sim(m5, x = x2)
summary(s2.out)
```

```
##
## sim x :
## -----
## ev
##           mean          sd        50%        2.5%        97.5%
## Pr(Y=1) 0.33515423 0.011203415 0.3345141 0.31406377 0.35669411
## Pr(Y=2) 0.36733404 0.011832268 0.3672372 0.34553932 0.39167555
## Pr(Y=3) 0.16567038 0.008515186 0.1654406 0.14937051 0.18186875
## Pr(Y=4) 0.02773911 0.003792730 0.0274616 0.02144953 0.03558315
```

```
## Pr(Y=5) 0.10410225 0.007437746 0.1038652 0.08974467 0.11861043
## pv
##      1      2      3      4      5
## [1,] 0.339 0.357 0.166 0.029 0.109
```

```
plot(s2.out)
```

