State Electorate Law: Testing Voter Deterrence

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```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.0 --
```

```
## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.0.4     v dplyr   1.0.2
## v tidyr   1.1.2     v stringr 1.4.0
## v readr   1.4.0     v forcats 0.5.0
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(here)
```

```
## here() starts at C:/Users/jhrab/cl_dir
```

```
library(haven)
library(ggplot2)
library(jtools)
library(kableExtra)
```

```
##
## Attaching package: 'kableExtra'
```

```
## The following object is masked from 'package:dplyr':
##
##     group_rows
```

```
library(huxtable)
```

```
##
## Attaching package: 'huxtable'
```

```
## The following object is masked from 'package:kableExtra':
##
##     add_footnote
```

```
## The following object is masked from 'package:dplyr':
##
##     add_rownames

## The following object is masked from 'package:ggplot2':
##
##     theme_grey
```

```r
library(sandwich)
library(flextable)
```

```
##
## Attaching package: 'flextable'

## The following objects are masked from 'package:huxtable':
##
##     align, as_flextable, bold, font, height, italic, set_caption,
##     valign, width

## The following objects are masked from 'package:kableExtra':
##
##     as_image, footnote

## The following object is masked from 'package:purrr':
##
##     compose
```

```r
library(ggstance)
```

```
##
## Attaching package: 'ggstance'

## The following objects are masked from 'package:ggplot2':
##
##     geom_errorbarh, GeomErrorbarh
```

```r
library(stargazer)
```

```
##
## Please cite as:

##  Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables.

##  R package version 5.2.2. https://CRAN.R-project.org/package=stargazer
```

```r
#loading in data
path <- here("data", "anes_voting_law_data_statePolLean.csv")
anes_voting_law_data_statePolLean <- read.csv(path)

path2 <- here("data", "anes16_with_laws.csv")
anes16_with_laws <- read.csv(path2)

path3 <- here("data", "anes_voting_law_data_with_pol_variables.csv")
anes16_new <- read.csv(path3)

path4 <- here("data", "anes_timeseries_2016.dta")
anes_OG <- read_dta(path4)
```

```r
#combining datasets
anes <- cbind(anes16_new, intent_vote = anes16_with_laws$V161030,
              intent_vote_reg = anes16_with_laws$V161024x,
              age_grp = anes16_with_laws$V161267x,
             voted16 =  anes_OG$V161026,
             live_comm = anes_OG$V161331x,
             race_new = anes_OG$V161310x,
             income = anes_OG$V161361x,
             education = anes_OG$V161270)


#renaming variables
anes <- rename(anes, id_law = Check..Photo.ID.vs..No.Photo,
               alt_party = Party.Alignment,
               poverty = Poverty..Over.Under,
               pol_lean = Political.Leaning,
               case_id = V160001...2016.Case.ID,
               state = V161010e...State,
               party_reg = V161019...Party.of.Registration,
               therm_dem = V161086...FT.Dem.Cand,
               therm_rep = V161087...FT.Rep.Cand,
               party_strength = V161156...Strong.Party.Affiliation,
               race = V161310....calc..Race...All,
               gender = V165723...Gender,
               age = V168254..Age..observed.)
```

```r
# 1 = Alternate Party, 0 = Primary Party, NA = Party Not Known
anes$alt_party <- recode(anes$alt_party,
                         'Alternate Party' = 1,
                         'Primary Party' = 0)
```

```
## Warning: Unreplaced values treated as NA as .x is not compatible. Please specify
## replacements exhaustively or supply .default
```

```r
# alternative party as factor
anes$alt_party <- factor(anes$alt_party)

# 1 = Democratic, 0 = Republican
anes$pol_lean <- recode(anes$pol_lean,
```

```r
                        "Democratic" = 1,
                        "Republican" = 0)
anes$pol_lean <- factor(anes$pol_lean)

# 1 = Under Poverty Line, 0 = Over Poverty Line
anes$poverty <- recode(anes$poverty,
                       "Under Poverty Line" = 1,
                       "Over Poverty Line" = 0)
# poverty as factor
anes$poverty <- factor(anes$poverty)

# NA = -1: Missing
anes$party_reg <- na_if(anes$party_reg, "-1:Missing")
anes$race_new <- na_if(anes$race_new, -2)


anes$gender <- recode(anes$gender,
                      "1: Male" = 0,
                      "2: Female" = 1)
```

```
## Warning: Unreplaced values treated as NA as .x is not compatible. Please specify
## replacements exhaustively or supply .default
```

```r
anes$gender <- na_if(anes$gender, "-2: Missing")

# ID law as factor
anes$id_law <- factor(anes$id_law)

# recoding the DV, Counting R's that are not registered to vote/ does not intend to register as a NO(2)
anes$intent_vote[anes$intent_vote_reg == 1] <-  0

# recoding the DV, Counting R's that registered and voted early as a YES(1) for intent_vote
anes$intent_vote[anes$intent_vote_reg == 4] <-  1


# recoding the NO to a 0
anes$intent_vote <- recode(anes$intent_vote, "2" = 0)


# setting the Don't Knows/ Refuse to NA's
anes$intent_vote <- na_if(anes$intent_vote, "-8")
anes$intent_vote <- na_if(anes$intent_vote, "-9")

anes$id_lawW <- ifelse(anes$id_law == "No Photo ID Req", 0, 1)

#subset(anes, select = c(id_law,id_lawW)) %>% View()

# recoding the id laws: 1 = No Photo ID Req, 2 = Gov Photo ID Req, 3 = Any Photo ID Req
#anes$id_law <- recode(anes$id_law,
                   #   "No Photo ID Req" = 1,
                    #  "Gov Photo ID Req" = 2,
                   #   "Any Photo ID Req" = 3)
```

```r
anes$id_law <- factor(anes$id_law)
# race as factor
anes$race_new <- factor(anes$race_new)

# party_reg: 1 = 1: Democratic, 2 = 2: Republican, 3 = 4: None or Independent, 4 = 5: Other
# anes$party_reg <- recode(anes$party_reg,
                        # "1: Democratic" = 1,
                        # "2: Republican" = 2,
                        # "4: None or Independent" = 3,
                        # "5: Other" = 4)
# anes$party_reg <- factor(anes$party_reg)

# dropping all variables not needed
anes <- anes %>% select(-party_reg, -race, -pol_lean, -party_strength, -voted16)

# removing NAs from the data
anes_noNA <- na.omit(anes)
```

```r
# binomial logistic model fit with ID law and minority party interaction
glm_new <- glm(intent_vote ~ id_law * alt_party + race_new + education + gender + poverty + age_grp + li

# binomial logistic model fit with no interaction
glm_new1 <- glm(intent_vote ~ id_lawW + alt_party + education + gender + race_new + poverty + age_grp +

# binomial logistic model fit ID law and race interaction
glm_new2 <- glm(intent_vote ~ id_law + alt_party + id_law * race_new + education + gender + poverty + ag


glm_new4 <- glm(intent_vote ~ id_law : state + race_new + education + gender + age_grp + live_comm + al
```

```r
# summary table results
summary(glm_new1)
```

```
##
## Call:
## glm(formula = intent_vote ~ id_lawW + alt_party + education +
##     gender + race_new + poverty + age_grp + live_comm, family = binomial(link = logit),
##     data = anes_noNA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.6374   0.3652   0.4714   0.5831   1.5437
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.145254   0.390048   0.372 0.709595
## id_lawW     -0.242691   0.167325  -1.450 0.146941
## alt_party1  -0.106997   0.156915  -0.682 0.495315
## education    0.095366   0.028055   3.399 0.000676 ***
## gender      -0.173631   0.157033  -1.106 0.268859
```

```
## race_new2    1.038587   0.347995   2.984 0.002841 **
## race_new3   -0.507966   0.399486  -1.272 0.203533
## race_new4   -2.643955   0.839100  -3.151 0.001627 **
## race_new5   -0.200513   0.226215  -0.886 0.375412
## race_new6   -0.030912   0.403537  -0.077 0.938939
## poverty1     0.059123   0.207494   0.285 0.775693
## age_grp      0.097567   0.022029   4.429 9.46e-06 ***
## live_comm    0.011320   0.006237   1.815 0.069528 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1219.7  on 1491  degrees of freedom
## Residual deviance: 1139.4  on 1479  degrees of freedom
## AIC: 1165.4
##
## Number of Fisher Scoring iterations: 6
```

```r
# final regression results
export_summs(glm_new)
```

```r
# CI's
confint.default(glm_new)
```

```
##                                           2.5 %        97.5 %
## (Intercept)                        -1.393631e+03 1419.82561128
## id_lawAny Photo ID Req             -1.420261e+03 1393.19470436
## id_lawGov Photo ID Req             -1.418836e+03 1394.62126077
## id_lawNo Photo ID Req              -1.419847e+03 1393.60900609
## alt_party1                         -2.065902e+03 2069.75369023
## race_new2                           3.785020e-01    1.75123017
## race_new3                          -1.348459e+00    0.22838344
## race_new4                          -4.261902e+00   -0.96933159
## race_new5                          -6.413419e-01    0.24617076
## race_new6                          -8.108369e-01    0.78363303
## education                           4.712228e-02    0.16110997
## gender                             -4.781913e-01    0.13953353
## poverty1                           -3.068240e-01    0.51183660
## age_grp                             5.346979e-02    0.14013896
## live_comm                          -6.423530e-04    0.02383154
## id_lawAny Photo ID Req:alt_party1 -2.069772e+03 2065.88322927
## id_lawGov Photo ID Req:alt_party1 -2.071156e+03 2064.50042713
## id_lawNo Photo ID Req:alt_party1  -2.069745e+03 2065.91054805
```

```r
summary(glm_new2)
```

```
##
## Call:
## glm(formula = intent_vote ~ id_law + alt_party + id_law * race_new +
##     education + gender + poverty + age_grp + live_comm, family = binomial(link = logit),
##     data = anes_noNA)
```

```
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.7946   0.3573   0.4667   0.5788   1.6100
##
## Coefficients: (4 not defined because of singularities)
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      1.445e+01  1.039e+03   0.014 0.988904
## id_lawAny Photo ID Req          -1.485e+01  1.039e+03  -0.014 0.988595
## id_lawGov Photo ID Req          -1.455e+01  1.039e+03  -0.014 0.988825
## id_lawNo Photo ID Req           -1.439e+01  1.039e+03  -0.014 0.988950
## alt_party1                      -1.148e-01  1.576e-01  -0.729 0.466292
## race_new2                        8.239e-01  3.930e-01   2.097 0.036022 *
## race_new3                       -7.178e-01  4.359e-01  -1.647 0.099588 .
## race_new4                       -2.554e+00  8.605e-01  -2.968 0.002993 **
## race_new5                        2.540e+00  2.615e+03   0.001 0.999225
## race_new6                       -9.356e-02  2.615e+03   0.000 0.999971
## education                        1.037e-01  2.908e-02   3.564 0.000365 ***
## gender                          -1.615e-01  1.588e-01  -1.017 0.309113
## poverty1                         5.791e-02  2.084e-01   0.278 0.781125
## age_grp                          9.931e-02  2.211e-02   4.492 7.06e-06 ***
## live_comm                        1.144e-02  6.262e-03   1.826 0.067789 .
## id_lawAny Photo ID Req:race_new2  6.429e-01  8.617e-01   0.746 0.455614
## id_lawGov Photo ID Req:race_new2  1.442e+01  7.460e+02   0.019 0.984576
## id_lawNo Photo ID Req:race_new2          NA         NA      NA       NA
## id_lawAny Photo ID Req:race_new3  1.584e+01  1.380e+03   0.011 0.990841
## id_lawGov Photo ID Req:race_new3  4.166e-01  1.232e+00   0.338 0.735297
## id_lawNo Photo ID Req:race_new3          NA         NA      NA       NA
## id_lawAny Photo ID Req:race_new4 -1.464e+01  2.400e+03  -0.006 0.995131
## id_lawGov Photo ID Req:race_new4         NA         NA      NA       NA
## id_lawNo Photo ID Req:race_new4          NA         NA      NA       NA
## id_lawAny Photo ID Req:race_new5 -2.867e+00  2.615e+03  -0.001 0.999125
## id_lawGov Photo ID Req:race_new5 -2.321e+00  2.615e+03  -0.001 0.999292
## id_lawNo Photo ID Req:race_new5  -2.741e+00  2.615e+03  -0.001 0.999164
## id_lawAny Photo ID Req:race_new6 -1.406e-01  2.615e+03   0.000 0.999957
## id_lawGov Photo ID Req:race_new6  6.427e+00  3.549e+03   0.002 0.998555
## id_lawNo Photo ID Req:race_new6   1.273e-01  2.615e+03   0.000 0.999961
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1219.7  on 1491  degrees of freedom
## Residual deviance: 1128.4  on 1466  degrees of freedom
## AIC: 1180.4
##
## Number of Fisher Scoring iterations: 15
```

```r
glm_new <- glm(intent_vote ~ id_lawW * alt_party + race_new + education + gender + poverty + age_grp + l


glm_new_no_bin <- glm(intent_vote ~ id_law * alt_party + race_new + education + gender + poverty + age_g

summary(glm_new)
```

```
##
## Call:
## glm(formula = intent_vote ~ id_lawW * alt_party + race_new +
##     education + gender + poverty + age_grp + live_comm, family = binomial(link = logit),
##     data = anes_noNA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.6052   0.3670   0.4687   0.5860   1.5628
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         0.094717   0.392247   0.241 0.809190
## id_lawW             0.014313   0.285085   0.050 0.959958
## alt_party1          0.007776   0.185730   0.042 0.966605
## race_new2           1.034458   0.347953   2.973 0.002949 **
## race_new3          -0.520228   0.400044  -1.300 0.193454
## race_new4          -2.623196   0.838158  -3.130 0.001750 **
## race_new5          -0.205128   0.226351  -0.906 0.364808
## race_new6          -0.038171   0.403432  -0.095 0.924620
## education           0.094395   0.028115   3.357 0.000787 ***
## gender             -0.177697   0.157206  -1.130 0.258329
## poverty1            0.078272   0.208451   0.375 0.707294
## age_grp             0.096911   0.022049   4.395 1.11e-05 ***
## live_comm           0.011493   0.006238   1.842 0.065409 .
## id_lawW:alt_party1 -0.403618   0.353708  -1.141 0.253827
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1219.7  on 1491  degrees of freedom
## Residual deviance: 1138.1  on 1478  degrees of freedom
## AIC: 1166.1
##
## Number of Fisher Scoring iterations: 6
```

```r
summary(glm_new)
```

```
##
## Call:
## glm(formula = intent_vote ~ id_lawW * alt_party + race_new +
##     education + gender + poverty + age_grp + live_comm, family = binomial(link = logit),
##     data = anes_noNA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.6052   0.3670   0.4687   0.5860   1.5628
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         0.094717   0.392247   0.241 0.809190
## id_lawW             0.014313   0.285085   0.050 0.959958
## alt_party1          0.007776   0.185730   0.042 0.966605
```

```
## race_new2           1.034458   0.347953   2.973 0.002949 **
## race_new3          -0.520228   0.400044  -1.300 0.193454
## race_new4          -2.623196   0.838158  -3.130 0.001750 **
## race_new5          -0.205128   0.226351  -0.906 0.364808
## race_new6          -0.038171   0.403432  -0.095 0.924620
## education           0.094395   0.028115   3.357 0.000787 ***
## gender             -0.177697   0.157206  -1.130 0.258329
## poverty1            0.078272   0.208451   0.375 0.707294
## age_grp             0.096911   0.022049   4.395 1.11e-05 ***
## live_comm           0.011493   0.006238   1.842 0.065409 .
## id_lawW:alt_party1 -0.403618   0.353708  -1.141 0.253827
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1219.7  on 1491  degrees of freedom
## Residual deviance: 1138.1  on 1478  degrees of freedom
## AIC: 1166.1
##
## Number of Fisher Scoring iterations: 6
```

```r
summary(glm_new_no_bin)
```

```
##
## Call:
## glm(formula = intent_vote ~ id_law * alt_party + race_new + education +
##     gender + poverty + age_grp + live_comm, family = binomial(link = logit),
##     data = anes_noNA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.7796   0.3420   0.4666   0.5877   1.6457
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      1.310e+01  7.177e+02   0.018 0.985441
## id_lawAny Photo ID Req          -1.353e+01  7.177e+02  -0.019 0.984956
## id_lawGov Photo ID Req          -1.211e+01  7.177e+02  -0.017 0.986541
## id_lawNo Photo ID Req           -1.312e+01  7.177e+02  -0.018 0.985417
## alt_party1                       1.926e+00  1.055e+03   0.002 0.998543
## race_new2                        1.065e+00  3.502e-01   3.041 0.002359 **
## race_new3                       -5.600e-01  4.023e-01  -1.392 0.163857
## race_new4                       -2.616e+00  8.400e-01  -3.114 0.001846 **
## race_new5                       -1.976e-01  2.264e-01  -0.873 0.382833
## race_new6                       -1.360e-02  4.068e-01  -0.033 0.973324
## education                        1.041e-01  2.908e-02   3.580 0.000343 ***
## gender                          -1.693e-01  1.576e-01  -1.075 0.282590
## poverty1                         1.025e-01  2.088e-01   0.491 0.623552
## age_grp                          9.680e-02  2.211e-02   4.378  1.2e-05 ***
## live_comm                        1.159e-02  6.243e-03   1.857 0.063300 .
## id_lawAny Photo ID Req:alt_party1 -1.945e+00  1.055e+03  -0.002 0.998529
## id_lawGov Photo ID Req:alt_party1 -3.328e+00  1.055e+03  -0.003 0.997483
## id_lawNo Photo ID Req:alt_party1  -1.917e+00  1.055e+03  -0.002 0.998550
```

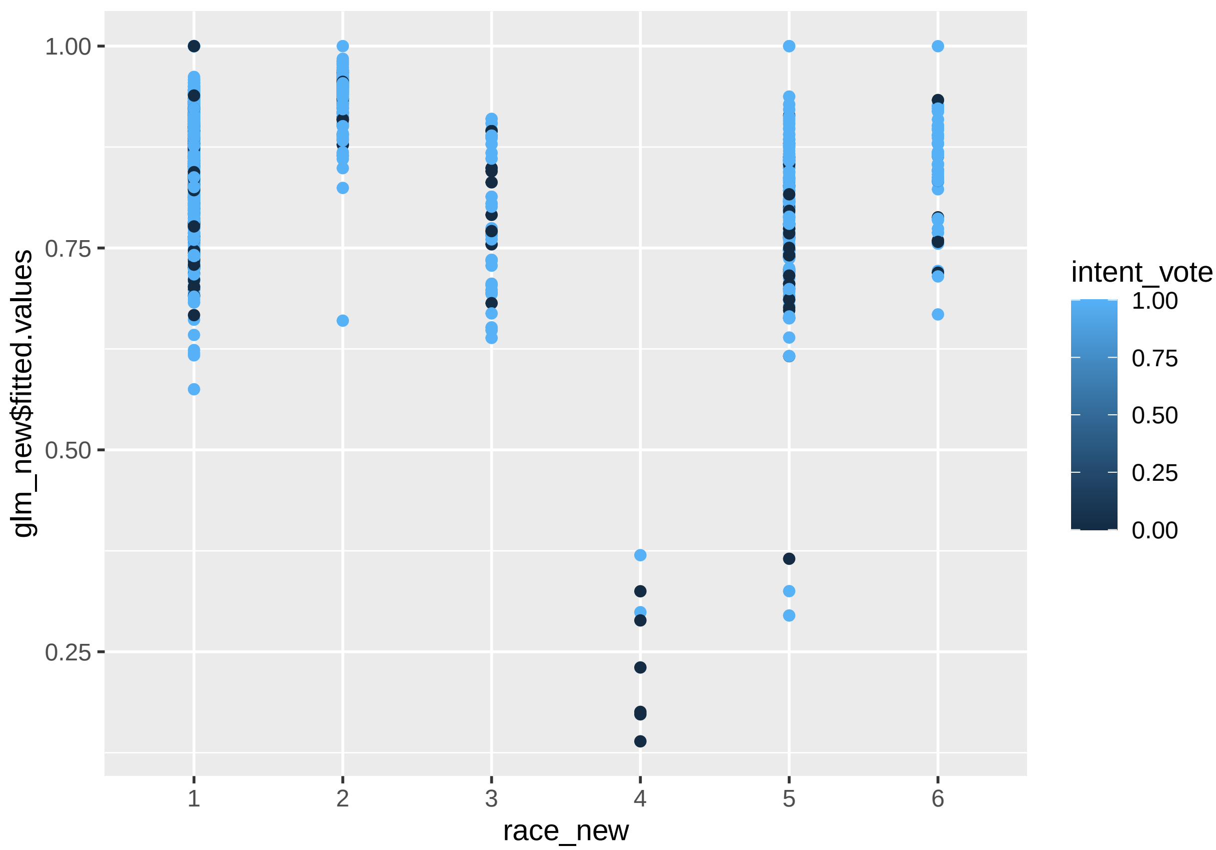
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1219.7  on 1491  degrees of freedom
## Residual deviance: 1128.2  on 1474  degrees of freedom
## AIC: 1164.2
##
## Number of Fisher Scoring iterations: 14
```

```
summary(glm_new1)
```

```
##
## Call:
## glm(formula = intent_vote ~ id_lawW + alt_party + education +
##     gender + race_new + poverty + age_grp + live_comm, family = binomial(link = logit),
##     data = anes_noNA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.6374   0.3652   0.4714   0.5831   1.5437
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.145254   0.390048   0.372 0.709595
## id_lawW     -0.242691   0.167325  -1.450 0.146941
## alt_party1  -0.106997   0.156915  -0.682 0.495315
## education    0.095366   0.028055   3.399 0.000676 ***
## gender      -0.173631   0.157033  -1.106 0.268859
## race_new2    1.038587   0.347995   2.984 0.002841 **
## race_new3   -0.507966   0.399486  -1.272 0.203533
## race_new4   -2.643955   0.839100  -3.151 0.001627 **
## race_new5   -0.200513   0.226215  -0.886 0.375412
## race_new6   -0.030912   0.403537  -0.077 0.938939
## poverty1     0.059123   0.207494   0.285 0.775693
## age_grp      0.097567   0.022029   4.429 9.46e-06 ***
## live_comm    0.011320   0.006237   1.815 0.069528 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1219.7  on 1491  degrees of freedom
## Residual deviance: 1139.4  on 1479  degrees of freedom
## AIC: 1165.4
##
## Number of Fisher Scoring iterations: 6
```

```
# xtab of 0/1 vote and ID law
#xtable(~id_law + state, data = anes_noNA)


anes_noNA %>% count(id_lawW, state)
```

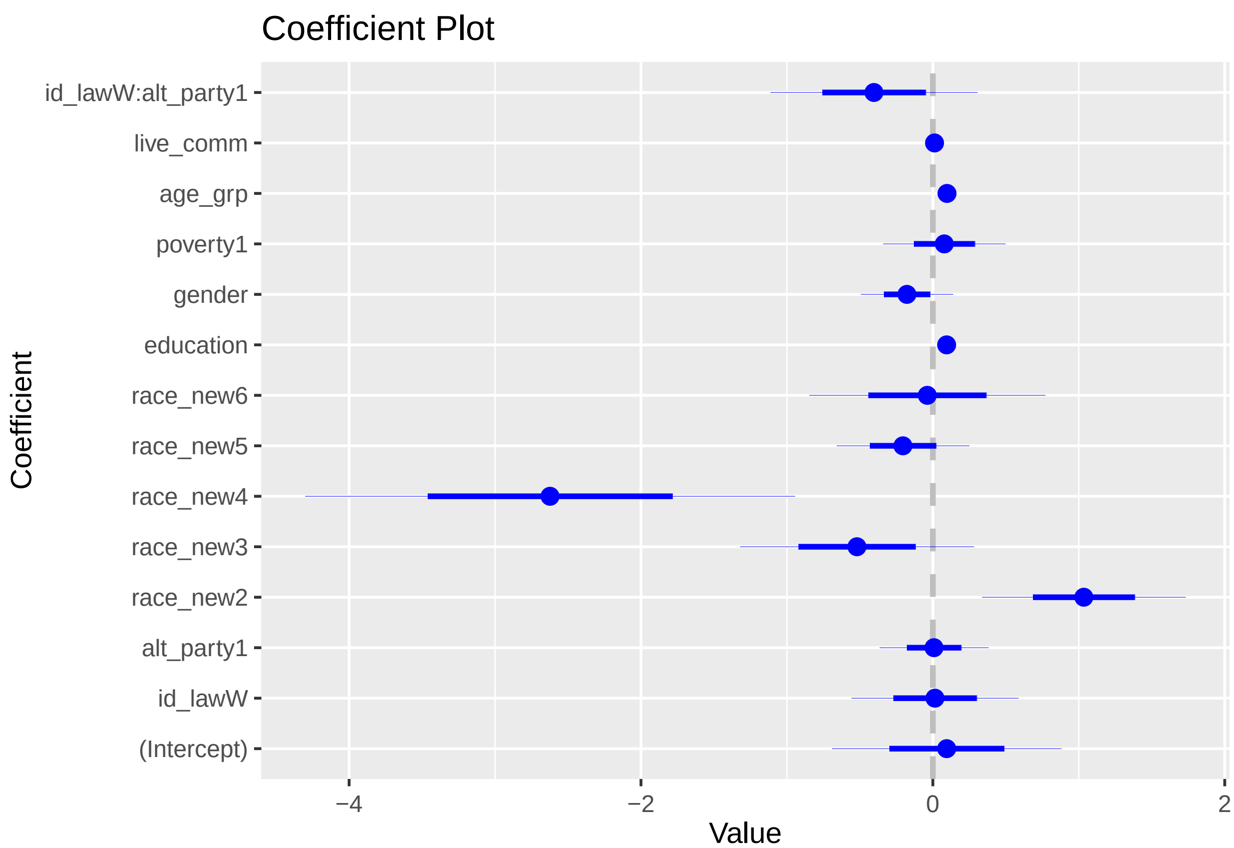
```r
# fitted values across race
ggplot(anes_noNA, aes(race_new, glm_new$fitted.values, color = intent_vote)) +
  geom_point()
```



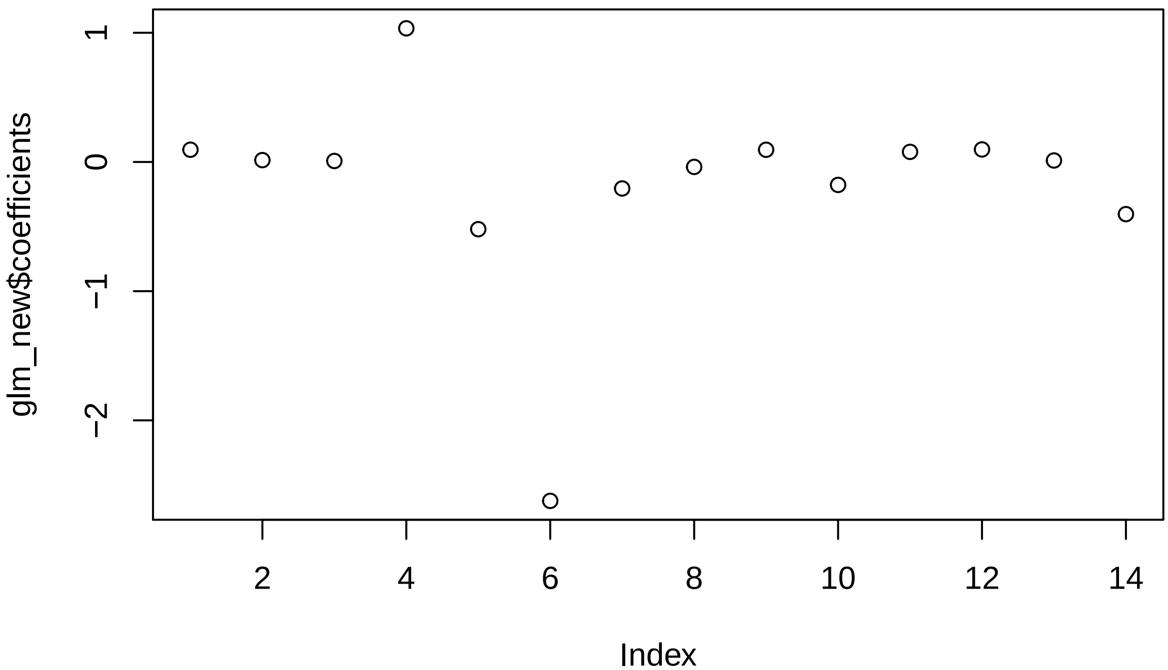

```r
#write.csv(anes_noNA, 'anes_new.csv')



library(coefplot)
```

```
##
## Attaching package: 'coefplot'

## The following object is masked from 'package:ggstance':
##
##     position_dodgev
```

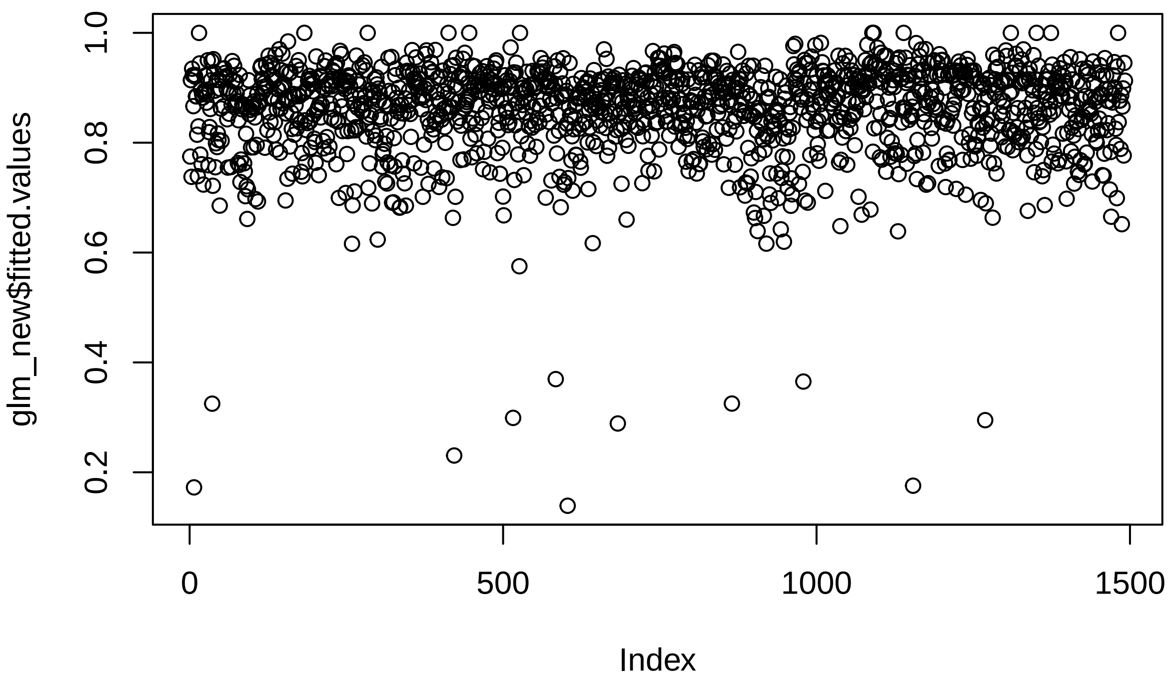
```r
coefplot::coefplot(glm_new)
```




```
plot(glm_new$coefficients)
```

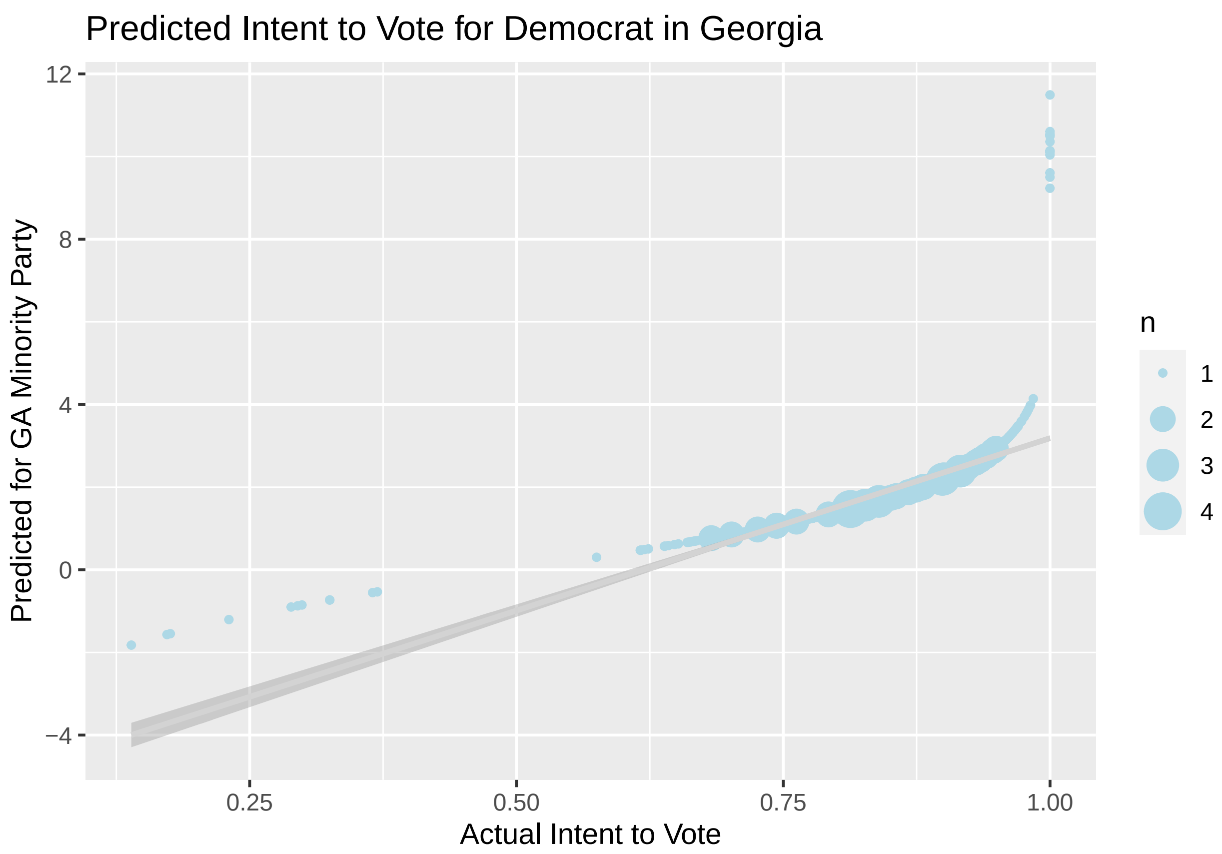



```
plot(glm_new$fitted.values)
```




```
# predicting minority
p_GAminority <- predict.glm(glm_new, interval = "confidence",
                   anes_noNA,
                   se = T,
                   alt_party = 1,
                   state = "GA",
                   race_new = 2)

# predicting majority
p_GAmajority <- predict.glm(glm_new, interval = "confidence",
                            anes_noNA,
                            se = T,
                            alt_party = 0,
                            state = "GA",
                            race_new = 1)



# plotting predicted GA minority values along actual fitted values
ggplot(anes_noNA, mapping = aes(glm_new$fitted.values, p_GAminority$fit)) +
  geom_count(aes(glm_new$fitted.values, p_GAminority$fit), color = "lightblue") +
  geom_smooth(aes(glm_new$fitted.values, p_GAminority$fit), method = "glm", color = "lightgrey") +
  labs(x = "Actual Intent to Vote", y = "Predicted for GA Minority Party", title = "Predicted Intent to
```

```
## `geom_smooth()` using formula 'y ~ x'
```




```r
summ(glm_new)
```

```r
summ(glm_new_no_bin)
```

```r
glm1 <- stargazer(glm_new, type = "text", title = "Regression Results", out = "regression #1", covariat
```

```
##
## Regression Results
## ==================================================
##                              Dependent variable:
##                          ---------------------------
##                                  intent_vote
## --------------------------------------------------
## Photo ID Law                        0.014
##                                    (0.285)
##
## Minority Party                      0.008
##                                    (0.186)
##
## Black                             1.034***
##                                    (0.348)
##
## Asian                              -0.520
```

```
##                                    (0.400)
##
## Native American                  -2.623***
##                                    (0.838)
##
## Hispanic                          -0.205
##                                    (0.226)
##
## Other                             -0.038
##                                    (0.403)
##
## Education                        0.094***
##                                    (0.028)
##
## Gender                            -0.178
##                                    (0.157)
##
## Under Poverty                      0.078
##                                    (0.208)
##
## Age                              0.097***
##                                    (0.022)
##
## Yrs in Comm                       0.011*
##                                    (0.006)
##
## ID Law * Minority Party           -0.404
##                                    (0.354)
##
## Constant                           0.095
##                                    (0.392)
##
## ---------------------------------------------------
## Observations                       1,492
## Log Likelihood                   -569.057
## Akaike Inf. Crit.                1,166.114
## ===================================================
## Note:                   *p<0.1; **p<0.05; ***p<0.01
```

```
glm2 <- stargazer(glm_new1, type = "text", title = "Regression Results", out = "regression #2", covaria
```

```
##
## Regression Results
## =============================================
##                       Dependent variable:
##                   ---------------------------
##                           intent_vote
## ---------------------------------------------
## Photo ID Law                -0.243
##                             (0.167)
##
## Minority Party              -0.107
##                             (0.157)
##
```

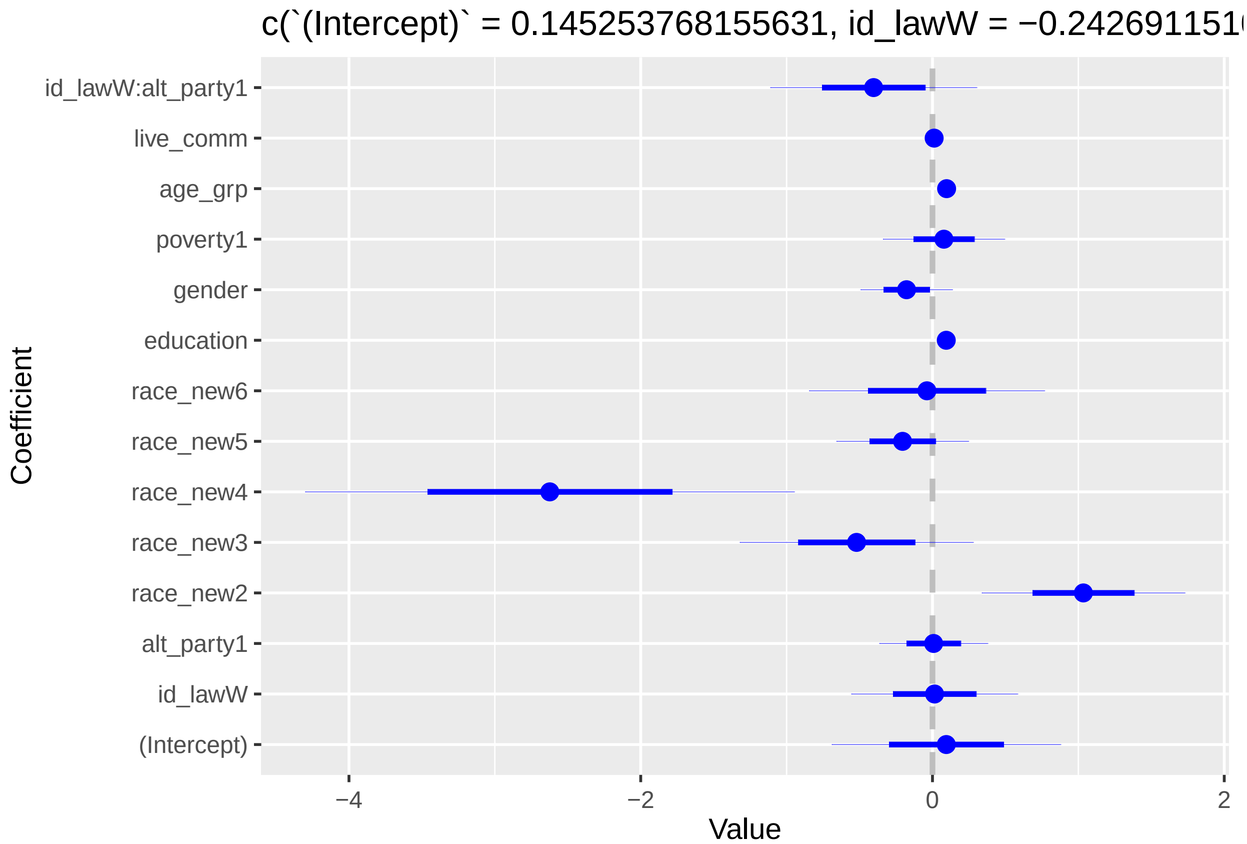
```
## Education                  0.095***
##                             (0.028)
##
## Gender                      -0.174
##                             (0.157)
##
## Black                       1.039***
##                             (0.348)
##
## Asian                       -0.508
##                             (0.399)
##
## Native American            -2.644***
##                             (0.839)
##
## Hispanic                    -0.201
##                             (0.226)
##
## Other                       -0.031
##                             (0.404)
##
## Under Poverty                0.059
##                             (0.207)
##
## Age                         0.098***
##                             (0.022)
##
## Yrs in Comm                 0.011*
##                             (0.006)
##
## Constant                     0.145
##                             (0.390)
##
## ---------------------------------------------
## Observations                 1,492
## Log Likelihood              -569.719
## Akaike Inf. Crit.           1,165.439
## =============================================
## Note:             *p<0.1; **p<0.05; ***p<0.01
```

```
glm2
```

```
##  [1] ""
##  [2] "Regression Results"
##  [3] "============================================="
##  [4] "                      Dependent variable:    "
##  [5] "                  ---------------------------"
##  [6] "                          intent_vote        "
##  [7] "---------------------------------------------"
##  [8] "Photo ID Law                -0.243           "
##  [9] "                            (0.167)          "
## [10] "                                             "
## [11] "Minority Party              -0.107           "
## [12] "                            (0.157)          "
```

```
## [13] "                                              "
## [14] "Education                    0.095***         "
## [15] "                              (0.028)         "
## [16] "                                              "
## [17] "Gender                       -0.174           "
## [18] "                              (0.157)         "
## [19] "                                              "
## [20] "Black                        1.039***         "
## [21] "                              (0.348)         "
## [22] "                                              "
## [23] "Asian                        -0.508           "
## [24] "                              (0.399)         "
## [25] "                                              "
## [26] "Native American              -2.644***        "
## [27] "                              (0.839)         "
## [28] "                                              "
## [29] "Hispanic                     -0.201           "
## [30] "                              (0.226)         "
## [31] "                                              "
## [32] "Other                        -0.031           "
## [33] "                              (0.404)         "
## [34] "                                              "
## [35] "Under Poverty                 0.059           "
## [36] "                              (0.207)         "
## [37] "                                              "
## [38] "Age                          0.098***         "
## [39] "                              (0.022)         "
## [40] "                                              "
## [41] "Yrs in Comm                  0.011*           "
## [42] "                              (0.006)         "
## [43] "                                              "
## [44] "Constant                      0.145           "
## [45] "                              (0.390)         "
## [46] "                                              "
## [47] "----------------------------------------------"
## [48] "Observations                  1,492           "
## [49] "Log Likelihood               -569.719         "
## [50] "Akaike Inf. Crit.            1,165.439        "
## [51] "=============================================="
## [52] "Note:              *p<0.1; **p<0.05; ***p<0.01"
```

```
plot_coef <- coefplot::coefplot.glm(glm_new, glm_new1)

plot_coef
```


c(`(Intercept)` = 0.145253768155631, id_lawW = −0.242691151
id_lawW:alt_party1
live_comm
age_grp
poverty1
gender
education
race_new6
race_new5
race_new4
race_new3
race_new2
alt_party1
id_lawW
(Intercept)
Coefficient
−4
−2
0
2
Value

	Model 1
(Intercept)	13.10
	(717.73)
id_lawAny Photo ID Req	-13.53
	(717.73)
id_lawGov Photo ID Req	-12.11
	(717.73)
id_lawNo Photo ID Req	-13.12
	(717.73)
alt_party1	1.93
	(1055.03)
race_new2	1.06 **
	(0.35)
race_new3	-0.56
	(0.40)
race_new4	-2.62 **
	(0.84)
race_new5	-0.20
	(0.23)
race_new6	-0.01
	(0.41)
education	0.10 ***
	(0.03)
gender	-0.17
	(0.16)
poverty1	0.10
	(0.21)
age_grp	0.10 ***
	(0.02)
live_comm	0.01
	(0.01)
id_lawAny Photo ID Req:alt_party1	-1.94
	(1055.03)
id_lawGov Photo ID Req:alt_party1	3.33

id__lawW	state	n
0	AK	2
0	AZ	62
0	CA	268
0	CO	43
0	CT	29
0	DE	9
0	IA	32
0	IL	2
0	KY	55
0	MA	60
0	MD	57
0	ME	8
0	NE	18
0	NJ	65
0	NM	16
0	NV	24
0	NY	129
0	OH	1
0	OR	38
0	PA	120
0	UT	21
0	WV	15
0	WY	5
1	AR	18
1	DC	7
1	FL	152
1	GA	2
1	ID	15
1	KS	22
1	LA	34
1	MO	1
1	NC	102
1	NH	13

Observations	1492
Dependent variable	intent_vote
Type	Generalized linear model
Family	binomial
Link	logit

$\chi^2(13)$	81.57
Pseudo-R² (Cragg-Uhler)	0.10
Pseudo-R² (McFadden)	0.07
AIC	1166.11
BIC	1240.42

	Est.	S.E.	z val.	p
(Intercept)	0.09	0.39	0.24	0.81
id_lawW	0.01	0.29	0.05	0.96
alt_party1	0.01	0.19	0.04	0.97
race_new2	1.03	0.35	2.97	0.00
race_new3	-0.52	0.40	-1.30	0.19
race_new4	-2.62	0.84	-3.13	0.00
race_new5	-0.21	0.23	-0.91	0.36
race_new6	-0.04	0.40	-0.09	0.92
education	0.09	0.03	3.36	0.00
gender	-0.18	0.16	-1.13	0.26
poverty1	0.08	0.21	0.38	0.71
age_grp	0.10	0.02	4.40	0.00
live_comm	0.01	0.01	1.84	0.07
id_lawW:alt_party1	-0.40	0.35	-1.14	0.25

Standard errors: MLE

Observations	1492
Dependent variable	intent_vote
Type	Generalized linear model
Family	binomial
Link	logit

$\chi^2(17)$	91.50
Pseudo-R² (Cragg-Uhler)	0.11
Pseudo-R² (McFadden)	0.08
AIC	1164.19
BIC	1259.73

	Est.	S.E.	z val.	p
(Intercept)	13.10	717.73	0.02	0.99
id_lawAny Photo ID Req	-13.53	717.73	-0.02	0.98
id_lawGov Photo ID Req	-12.11	717.73	-0.02	0.99
id_lawNo Photo ID Req	-13.12	717.73	-0.02	0.99
alt_party1	1.93	1055.03	0.00	1.00
race_new2	1.06	0.35	3.04	0.00
race_new3	-0.56	0.40	-1.39	0.16
race_new4	-2.62	0.84	-3.11	0.00
race_new5	-0.20	0.23	-0.87	0.38
race_new6	-0.01	0.41	-0.03	0.97
education	0.10	0.03	3.58	0.00
gender	-0.17	0.16	-1.07	0.28
poverty1	0.10	0.21	0.49	0.62
age_grp	0.10	0.02	4.38	0.00
live_comm	0.01	0.01	1.86	0.06
id_lawAny Photo ID Req:alt_party1	-1.94	1055.03	-0.00	1.00
id_lawGov Photo ID Req:alt_party1	-3.33	1055.03	-0.00	1.00
id_lawNo Photo ID Req:alt_party1	-1.92	1055.03	-0.00	1.00

Standard errors: MLE