Spatial Voting in US Presidential Election

Quantitative Methods 2020: Final Data Essay

Marie-Lou Sohnius

22 December, 2020

Abstract

The text of your abstract. 150-250 words.

1 adds new page after title

Contents

| 1 | adds new page after title | 2 |
|--------------|---------------------------------------------------|----|
| 2 | Introduction | 14 |
| 3 | Research Design | 14 |
| | 3.1 Data | 14 |
| | 3.2 Methods | 14 |
| 4 | Results | 14 |
| | 4.1 Partisanship under the Spatial Voting Theorem | 14 |
| | 4.2 The Independent Voter Equilibrium | 14 |
| 5 | Robustness | 14 |
| 6 | Conclusion | 14 |
| 7 | Appendix | 15 |
| # | adds table of contents | |
| \mathbf{L} | ist of Figures | |
| | 1 A caption | 4 |
| | 2 FDs | 4 |
| | 3 FDs | 5 |
| | 4 Cap | 5 |
| | 5 FDs | 6 |

| 6 | Model fit | 6 |
|-----------------|-------------------------------------|----|
| 7 | FDs | 7 |
| 8 | cap | 14 |
| \mathbf{List} | of Tables | |
| 1 | Logit equations predicting the vote | 13 |

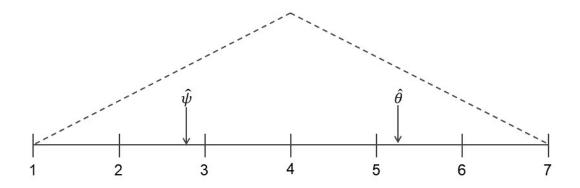


Figure 1: A caption

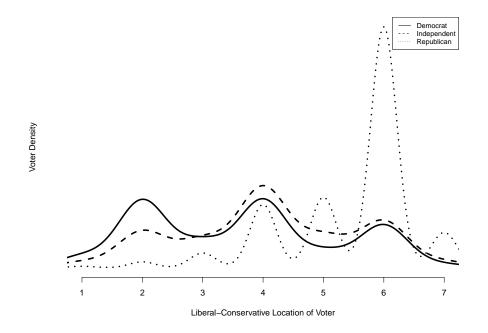


Figure 2: FDs

```
# Scenario (Black)
scenario_ind_hi_r1 <- cbind(1, # Intercept

lr_seq2, # LR Scale

0, # Race = Black

1, # Race = Other/Mixed

1, # Gender = Male</pre>
```

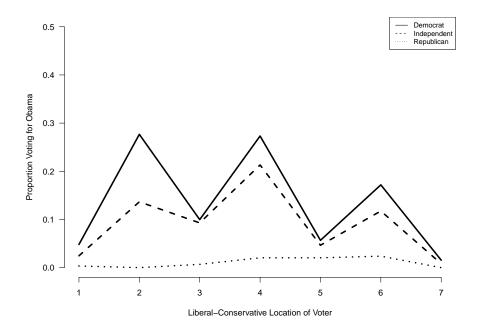


Figure 3: FDs

Party Identification and Spatial Voting

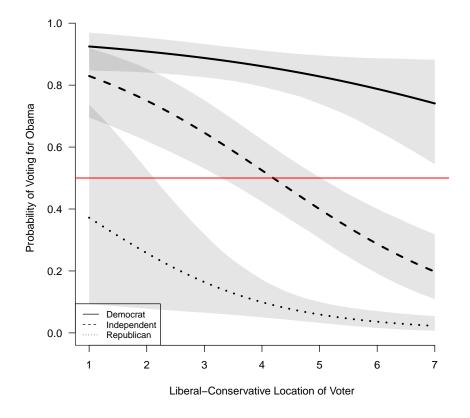


Figure 4: Cap

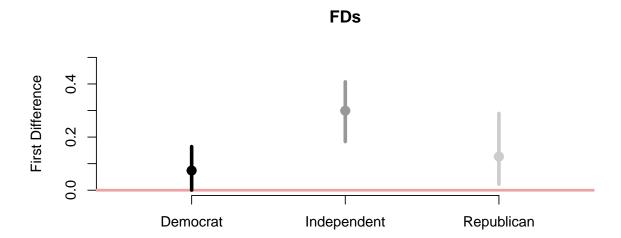


Figure 5: FDs

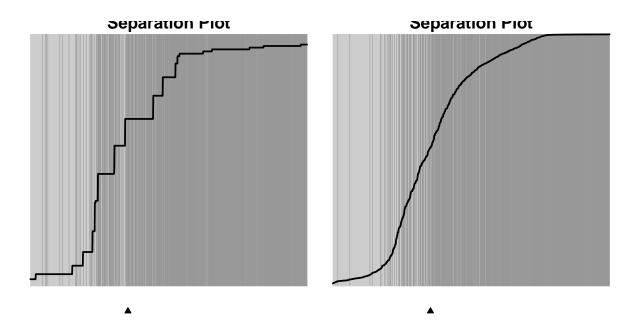


Figure 6: Model fit

Party Identification and Spatial Voting

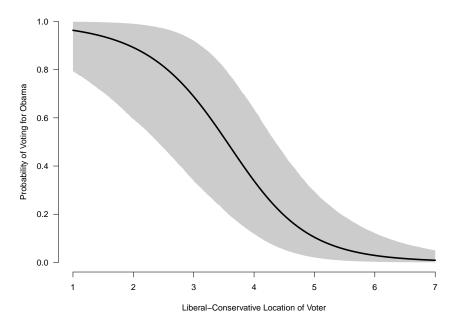


Figure 7: FDs

```
mean(independents_hi*age, na.rm=T), # Age

1, # Religion = Protestant

0, # Religion = Catholic

0, # Religion = Other

1, # Above Median Income

0 # College Degree

)

Xbeta_ind_hi_r1 <- S %*% t(scenario_ind_hi_r1)

p_sim_ind_hi_r1 <- (exp(Xbeta_ind_hi_r1))/ (1 + exp(Xbeta_ind_hi_r1))

p_mean_ind_hi_r1 <- apply(p_sim_ind_hi_r1, 2, mean)

p_qu_ind_hi_r1 <- t(apply(p_sim_ind_hi_r1, 2, quantile, prob = c(0.025, 0.975)))

props_ind_hi_r1 <- as.data.frame(cbind(p_mean_ind_hi_r1, lr_seq2))</pre>
```

```
props_ind_hi_r1$dist <- abs(props_ind_hi_r1$p_mean_ind_hi_r1-0.5)
min_pos <- which.min(props_ind_hi_r1$dist)
props_ind_hi_r1[min_pos,2]</pre>
```

[1] 3.954

```
# Scenario 2 (Female)
scenario_ind_hi_r2 <- cbind(1, # Intercept</pre>
                   lr_seq2, # LR Scale
                   0, # Race = Black
                   0, # Race = Other/Mixed
                   0, # Gender = Male
                   mean(independents_hi$age, na.rm=T), # Age
                   1, # Religion = Protestant
                   0, # Religion = Catholic
                   0, # Religion = Other
                   1, # Above Median Income
                   0 # College Degree
                   )
Xbeta_ind_hi_r2 <- S %*% t(scenario_ind_hi_r2)</pre>
p_sim_ind_hi_r2 <- (exp(Xbeta_ind_hi_r2))/ (1 + exp(Xbeta_ind_hi_r2))</pre>
p_mean_ind_hi_r2 <- apply(p_sim_ind_hi_r2, 2, mean)</pre>
p_qu_ind_hi_r2 \leftarrow t(apply(p_sim_ind_hi_r2, 2, quantile, prob = c(0.025, 0.975)))
props_ind_hi_r2 <- as.data.frame(cbind(p_mean_ind_hi_r2,lr_seq2))</pre>
props_ind_hi_r2$dist <- abs(props_ind_hi_r2$p_mean_ind_hi_r2-0.5)</pre>
min_pos <- which.min(props_ind_hi_r2$dist)</pre>
```

```
props_ind_hi_r2[min_pos,2]
```

[1] 3.173

```
# Scenario 3 (Young)
scenario_ind_hi_r3 <- cbind(1, # Intercept</pre>
                   lr_seq2, # LR Scale
                   0, # Race = Black
                   O, # Race = Other/Mixed
                   1, # Gender = Male
                   quantile(independents_hi$age, na.rm=T, 0.25), # Age
                   1, # Religion = Protestant
                   0, # Religion = Catholic
                   0, # Religion = Other
                   1, # Above Median Income
                   0 # College Degree
                   )
Xbeta_ind_hi_r3 <- S %*% t(scenario_ind_hi_r3)</pre>
p_sim_ind_hi_r3 <- (exp(Xbeta_ind_hi_r3))/ (1 + exp(Xbeta_ind_hi_r3))</pre>
p_mean_ind_hi_r3 <- apply(p_sim_ind_hi_r3, 2, mean)</pre>
p_qu_ind_hi_r3 \leftarrow t(apply(p_sim_ind_hi_r3, 2, quantile, prob = c(0.025, 0.975)))
props_ind_hi_r3 <- as.data.frame(cbind(p_mean_ind_hi_r3,lr_seq2))</pre>
props_ind_hi_r3$dist <- abs(props_ind_hi_r3$p_mean_ind_hi_r3-0.5)</pre>
min_pos <- which.min(props_ind_hi_r3$dist)</pre>
props_ind_hi_r3[min_pos,2]
```

[1] 3.737

```
# Scenario 4 (No Religion)
scenario_ind_hi_r4 <- cbind(1, # Intercept</pre>
                   lr_seq2, # LR Scale
                   0, # Race = Black
                   0, # Race = Other/Mixed
                   1, # Gender = Male
                   mean(independents_hi$age, na.rm=T), # Age
                   0, # Religion = Protestant
                   0, # Religion = Catholic
                   0, # Religion = Other
                   1, # Above Median Income
                   0 # College Degree
                   )
Xbeta_ind_hi_r4 <- S %*% t(scenario_ind_hi_r4)</pre>
p_sim_ind_hi_r4 <- (exp(Xbeta_ind_hi_r4))/ (1 + exp(Xbeta_ind_hi_r4))</pre>
p_mean_ind_hi_r4 <- apply(p_sim_ind_hi_r4, 2, mean)</pre>
p_qu_ind_hi_r4 \leftarrow t(apply(p_sim_ind_hi_r4, 2, quantile, prob = c(0.025, 0.975)))
props_ind_hi_r4 <- as.data.frame(cbind(p_mean_ind_hi_r4,lr_seq2))</pre>
props_ind_hi_r4$dist <- abs(props_ind_hi_r4$p_mean_ind_hi_r4-0.5)</pre>
min_pos <- which.min(props_ind_hi_r4$dist)</pre>
props_ind_hi_r4[min_pos,2]
```

[1] 4.142

```
# Scenario (Low Income)
# scenario_ind_hi_r5 <- cbind(1, # Intercept</pre>
                   lr_seq2, # LR Scale
                   0, # Race = Black
                   O, # Race = Other/Mixed
                   1, # Gender = Male
                   mean(independents_hi$age, na.rm=T), # Age
                   1, # Religion = Protestant
                   O, # Religion = Catholic
                   0, # Religion = Other
                   O, # Above Median Income
                   0 # College Degree
#
\# Xbeta_ind_hi_r5 \leftarrow S \%*\% t(scenario_ind_hi_r5)
# p_mean_ind_hi_r5 <- apply(p_sim_ind_hi_r5, 2, mean)</pre>
\# p_qu_ind_hi_r5 \leftarrow t(apply(p_sim_ind_hi_r5, 2, quantile, prob = c(0.025, 0.975)))
\# props_ind_hi_r5 \leftarrow as.data.frame(cbind(p_mean_ind_hi_r5, lr_seq2))
# props_ind_hi_r5$dist <- abs(props_ind_hi_r5$p_mean_ind_hi_r5-0.5)</pre>
# min_pos <- which.min(props_ind_hi_r5$dist)</pre>
# props_ind_hi_r5[min_pos,2]
# Scenario 6 (College Degree)
# scenario_ind_hi_r6 <- cbind(1, # Intercept</pre>
```

```
#
                      lr_seq2, # LR Scale
                      O, # Race = Black
                      O, # Race = Other/Mixed
                      1, # Gender = Male
                      mean(independents_hi$age, na.rm=T), # Age
                      1, # Religion = Protestant
                      O, # Religion = Catholic
#
                      O, # Religion = Other
                      1, # Above Median Income
                      1 # College Degree
# Xbeta_ind_hi_r6 <- S %*% t(scenario_ind_hi_r6)</pre>
 \# p\_sim\_ind\_hi\_r6 \leftarrow (exp(Xbeta\_ind\_hi\_r6))/ (1 + exp(Xbeta\_ind\_hi\_r6)) 
\# p_{mean_ind_hi_r6} \leftarrow apply(p_sim_ind_hi_r6, 2, mean)
\# p_qu_ind_hi_r6 \leftarrow t(apply(p_sim_ind_hi_r6, 2, quantile, prob = c(0.025, 0.975)))
\# props_ind_hi_r6 \leftarrow as.data.frame(cbind(p_mean_ind_hi_r6, lr_seq2))
 \# \ props\_ind\_hi\_r6\$dist <- \ abs(props\_ind\_hi\_r6\$p\_mean\_ind\_hi\_r6-0.5) 
# min_pos <- which.min(props_ind_hi_r6$dist)</pre>
# props_ind_hi_r6[min_pos,2]
```

Table 1: Logit equations predicting the vote

| | Dependent variable: | | | |
|--------------------------|---------------------|-------------------------|-------------|--|
| | | Vote for Obama | | |
| | Model 1 (Base) | Model 1 (with controls) | Model 2 | |
| | (1) | (2) | (3) | |
| Left-Right | -0.134 | -0.248^* | -1.628*** | |
| | (0.110) | (0.128) | (0.412) | |
| Independent | -0.810 | -0.692 | | |
| | (0.606) | (0.696) | | |
| Republican | -2.842*** | -2.889** | | |
| | (0.988) | (1.147) | | |
| Black/African-American | | 5.286*** | 21.565 | |
| | | (1.041) | (1,975.579) | |
| Other/Mixed | | 1.523*** | 0.653 | |
| | | (0.354) | (1.181) | |
| Male | | 0.129 | 0.615 | |
| | | (0.201) | (0.682) | |
| $_{ m Age}$ | | -0.017^{***} | -0.022 | |
| | | (0.006) | (0.019) | |
| Protestant | | -0.374 | -0.966 | |
| | | (0.271) | (0.785) | |
| Catholic | | -0.324 | -0.398 | |
| | | (0.298) | (0.969) | |
| Other | | 0.503 | -23.450 | |
| | | (0.752) | (10,754.010 | |
| Above Median Income | | -0.443^{**} | -0.763 | |
| | | (0.209) | (0.648) | |
| College Degree | | 0.239 | 1.175* | |
| | | (0.231) | (0.646) | |
| Left-Right × Independent | -0.316** | -0.263 | | |
| | (0.139) | (0.162) | | |
| Left-Right × Republican | -0.442^{**} | -0.302 | | |
| - | (0.206) | (0.241) | | |
| Constant | 3.291*** | 4.024*** | 7.968*** | |
| | (0.471) | (0.641) | (2.262) | |
| Observations | 1,242 | 1,242 | 104 | |
| Log Likelihood | -424.972 | -339.847 | -34.213 | |
| Akaike Inf. Crit. | 861.943 | 709.693 | 90.427 | |

Note:

*p<0.1; **p<0.05; ***p<0.01

Party Identification and Spatial Voting

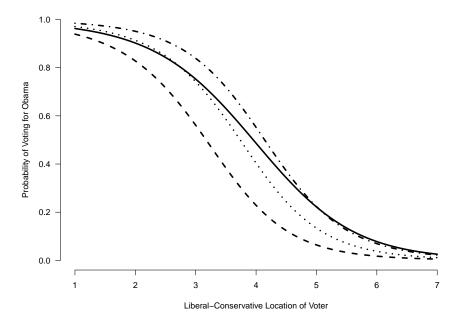


Figure 8: cap

- 2 Introduction
- 3 Research Design
- 3.1 Data
- 3.2 Methods
- 4 Results
- 4.1 Partisanship under the Spatial Voting Theorem
- 4.2 The Independent Voter Equilibrium
- 5 Robustness
- 6 Conclusion

7 Appendix