Socioeconomic Determinants of 2020 U.S. Presidential Election County-Level Voter Turnout

Exploratory Data Analysis

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Data Description

There are a few different data sources joined together to make this dataset. The turnout rate data is calculating by dividing the voter turnout for the 2020 presidential election in each county (from the MIT Election Lab) by the voting-eligible population (U.S. citizens age 18 and up) according to the 2020 5-year American Community Survey released by the U.S. Census Bureau. The resulting turnout rate should be a proportion between 0 and 1. The exception for the voter turnout data is Alaska, whose voter turnout data is organized by election districts instead of borough and Census areas (Alaska's county equivalents). To have this data be consistent with the predictor variables, I got estimates for Alaska voter turnout data by borough and Census area from a blog post.

The predictors (county-level demographic and socioeconomic characteristics) are from Opportunity Insights, a Harvard-based research lab studying economic opportunity in the United States. Descriptions of the variables can be found here. Datasets for FIPS state and county codes are also used to merge the data sources.

Setup

```
rm(list = ls())
require(readr)
require(tidyr)
require(dplyr)
require(knitr)
```

```
data <- read.csv("../data/processed/data.csv")
head(data)
```

```
##     State         County fips frac_coll_plus2010 foreign_share2010
## 1 Alabama Autauga County 1001         0.22199036       0.020154603
## 2 Alabama Baldwin County 1003         0.26071036       0.037591625
## 3 Alabama Barbour County 1005         0.13349621       0.028143950
## 4 Alabama    Bibb County 1007         0.09924053       0.006859188
## 5 Alabama  Blount County 1009         0.12633450       0.047343444
## 6 Alabama Bullock County 1011         0.10972187       0.013493270
##   med_hhinc2016 poor_share2010 share_white2010 share_black2010 share_hisp2010
## 1      54052.80      0.1059177       0.7724616      0.18134174     0.02400542
## 2      52003.09      0.1229422       0.8350479      0.09752284     0.04384824
## 3      33114.85      0.2506308       0.4675311      0.47190151     0.05051535
## 4      39846.45      0.1268499       0.7502073      0.22282349     0.01771765
## 5      46361.12      0.1331379       0.8888734      0.01500297     0.08070200
## 6      31304.78      0.2804486       0.2191680      0.70221734     0.07119296
```

```
##   share_asian2010 gsmn_math_g3_2013 rent_twobed2015 singleparent_share2010
## 1    0.0078302799          2.759864        739.3654              0.2833759
## 2    0.0059535136          2.792510        816.8452              0.2778664
## 3    0.0036882064          1.600009        527.2908              0.4680706
## 4    0.0007418721          1.531674        604.2776              0.3201363
## 5    0.0018735955          2.815403        567.6959              0.2589052
## 6    0.0017932489          1.039439        266.0000              0.5778636
##   traveltime15_2010   emp2000 ln_wage_growth_hs_grad popdensity2010
## 1         0.2041625 0.6095865            -0.06331379       91.80268
## 2         0.2753262 0.5770263             0.03009291      114.64751
## 3         0.3760492 0.4532710             0.18936642       31.02921
## 4         0.2526830 0.4942406            -0.02007263       36.80634
## 5         0.1943438 0.5778096             0.09646260       88.90219
## 6         0.3921350 0.3746639             0.36383346       17.52395
##   ann_avg_job_growth_2004_2013 job_density_2013 turnout.rate
## 1                  0.010145103        40.719135    0.6618366
## 2                  0.012950056        50.085987    0.6529056
## 3                 -0.020755908         9.230672    0.5402712
## 4                 -0.004644653        12.875392    0.5456975
## 5                 -0.008120399        36.175354    0.6419098
## 6                  0.026254078         6.954023    0.5908043
```

Descriptive Statistics

We have no categorical variables. For each of our continuous variables, we summarize the number of missing values, the mean, median, standard deviation, interquartile range, minimum value, and maximum value.

```
predictors <- names(data)[!(names(data) %in% c('State', 'County', 'fips'))]
summary_table <- data.frame()

for (predictor in predictors) {
  column <- data[[predictor]]
  num_missing <- sum(is.na(column))
  mean_var <- mean(column, na.rm = TRUE)
  median_var <- median(column, na.rm = TRUE)
  sd_var <- sd(column, na.rm = TRUE)
  iqr_var <- IQR(column, na.rm = TRUE)
  min_var <- min(column, na.rm = TRUE)
  max_var <- max(column, na.rm = TRUE)

  summary_table <- rbind(summary_table, data.frame(
    Variable = predictor,
    Missing = num_missing,
    Mean = round(mean_var, 2),
    Median = round(median_var, 2),
    SD = round(sd_var, 2),
    IQR = round(iqr_var, 2),
    Min = round(min_var, 2),
    Max = round(max_var, 2)
  ))
}

kable(summary_table)
```

Variable	Missing	Mean	Median	SD	IQR	Min	Max
frac_coll_plus2010	0	0.19	0.17	0.09	0.09	0.04	0.71
foreign_share2010	0	0.04	0.02	0.06	0.04	0.00	0.72
med_hhinc2016	1	48980.92	47127.10	13398.03	14687.30	20170.89	129150.34
poor_share2010	0	0.16	0.15	0.06	0.08	0.00	0.53
share_white2010	0	0.78	0.86	0.20	0.27	0.03	0.99
share_black2010	0	0.09	0.02	0.15	0.10	0.00	0.86
share_hisp2010	0	0.08	0.03	0.13	0.07	0.00	0.96
share_asian2010	21	0.01	0.00	0.02	0.01	0.00	0.43
gsmn_math_g3_2013	73	3.21	3.24	0.78	0.98	-0.66	6.58
rent_twobed2015	76	692.34	642.51	205.04	195.93	236.00	2085.23
singleparent_share2010	0	0.31	0.30	0.09	0.10	0.00	0.81
traveltime15_2010	0	0.40	0.38	0.14	0.19	0.10	0.99
emp2000	0	0.57	0.58	0.08	0.10	0.24	0.84
ln_wage_growth_hs_grad	684	0.08	0.07	0.14	0.13	-0.72	0.91
popdensity2010	1	262.67	45.30	1774.99	96.74	0.04	70583.63
ann_avg_job_growth_2004_2013	5	0.00	0.00	0.01	0.02	-0.08	0.12
job_density_2013	2	124.24	18.47	862.85	43.30	0.02	36663.16
turnout.rate	0	0.66	0.66	0.11	0.14	0.19	1.58

```
dim(data)
```

```
## [1] 3141   21
```

Missingness

Most variables have either zero or a small fraction of observations missing. The exception is `ln_wage_growth_hs_grad`, which has 21.8% of its observations missing. To handle the missing data, we drop the `ln_wage_growth_hs_grad` variable altogether and drop the counties that have missing data in at least one of the remaining variables.

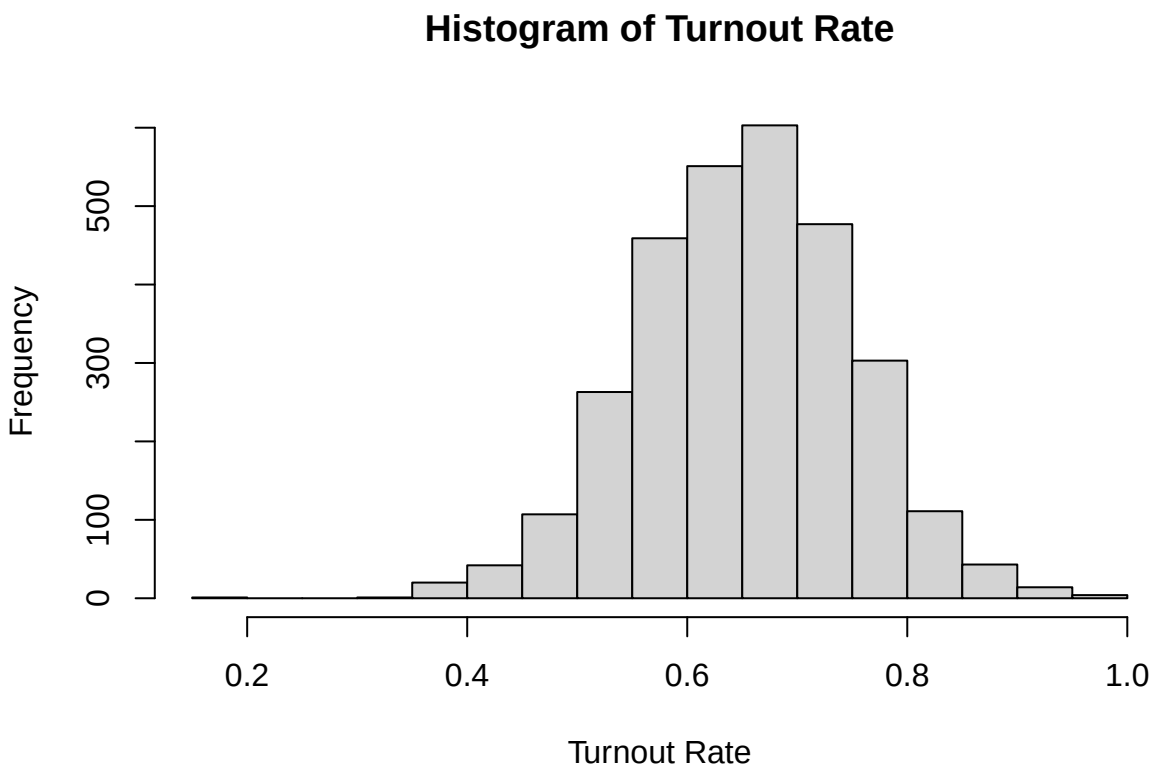
```
data <- select(data, -ln_wage_growth_hs_grad)
data <- subset(data, apply(data, 1, FUN = function(x) {!any(is.na(x))}))
dim(data)
```

```
## [1] 2999   20
```

Exploratory Graphs

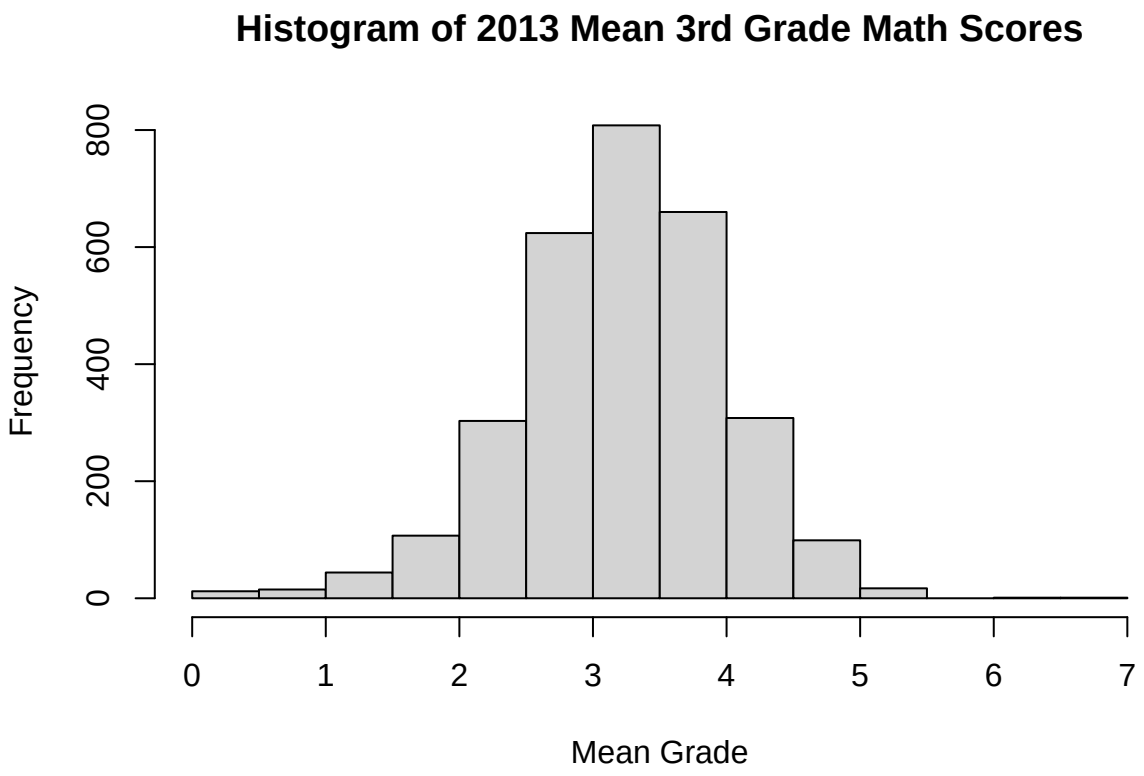
Turnout Rate

```
data <- data %>%
  mutate(turnout.rate = case_when(
    turnout.rate > 1 ~ 1,
    .default = turnout.rate
  ))
hist(data$turnout.rate, main = 'Histogram of Turnout Rate', xlab = 'Turnout Rate')
```



Math Scores

```
data <- data %>%
  mutate(gsmn_math_g3_2013 = case_when(
    gsmn_math_g3_2013 < 0 ~ 0,
    .default = gsmn_math_g3_2013
  ))
hist(data$gsmn_math_g3_2013, main = 'Histogram of 2013 Mean 3rd Grade Math Scores', xlab = 'Mean Grade'
```



Preliminary Model

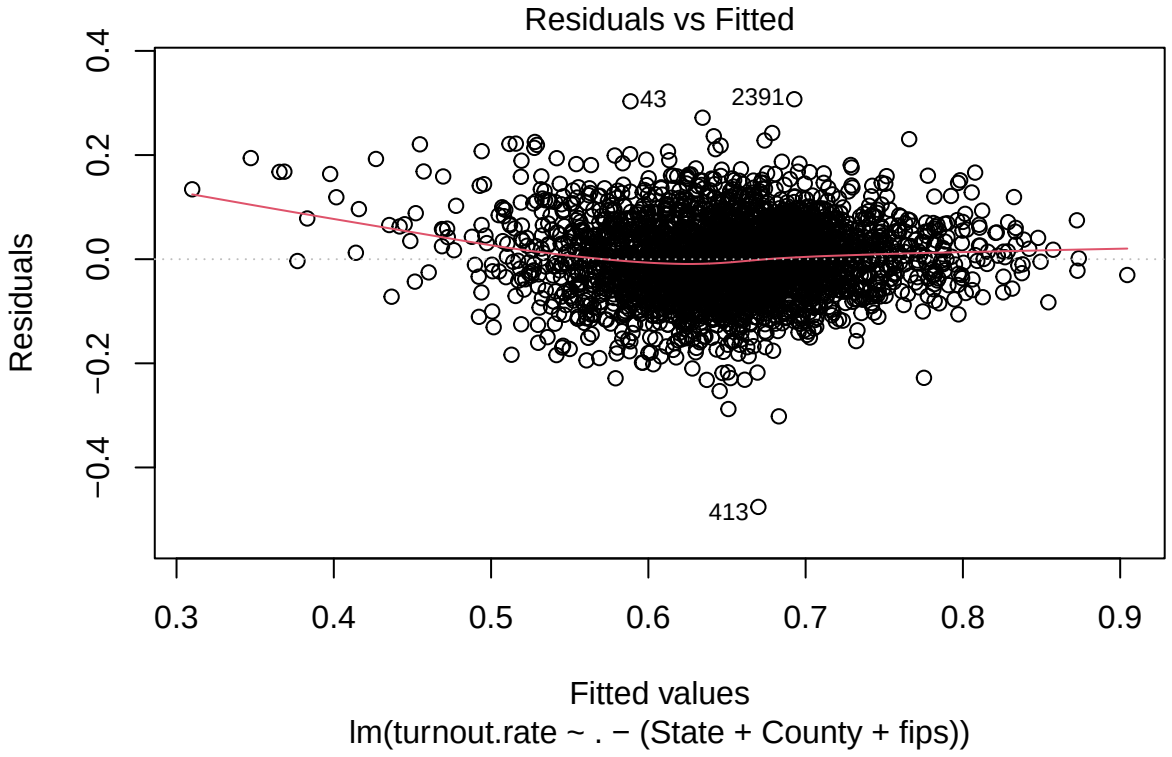
We also check that our hypothesis that the turnout rate can be predicted from county demographics is reasonable by fitting a linear regression model.

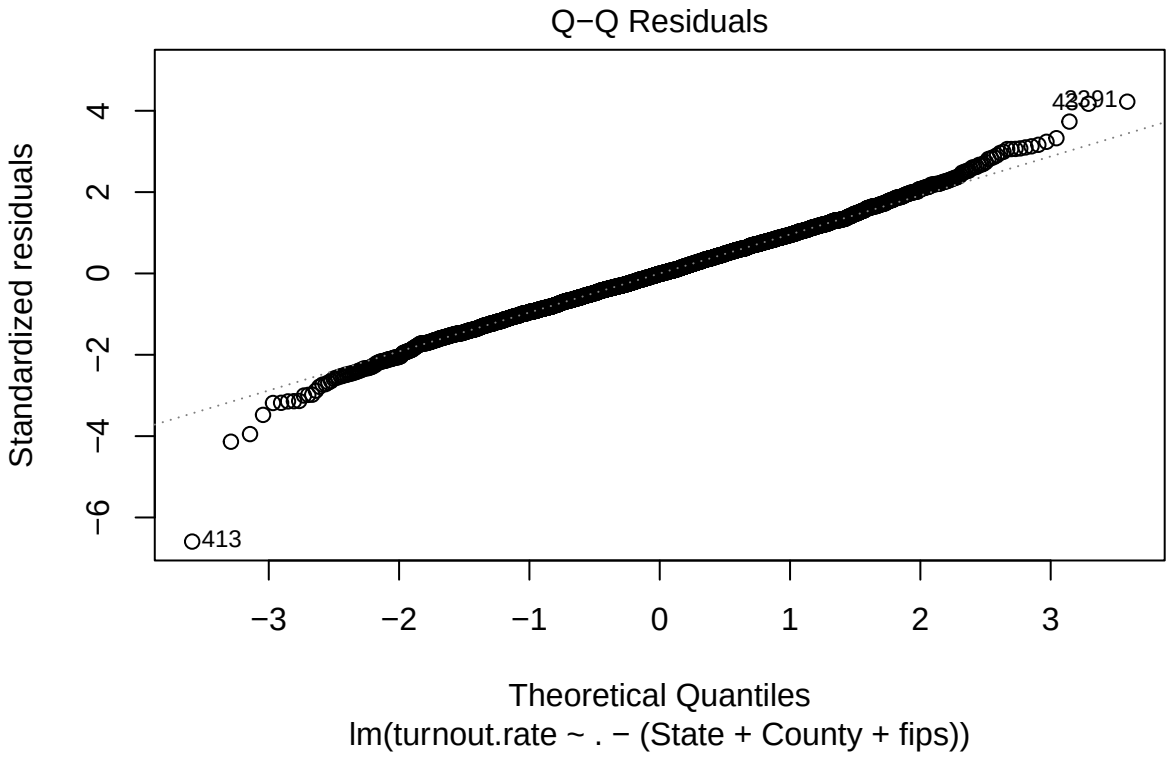
```
lm_model <- lm(turnout.rate ~ . - (State + County + fips), data = data)
summary(lm_model)
```

```
##
## Call:
## lm(formula = turnout.rate ~ . - (State + County + fips), data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.47572 -0.04720 -0.00065  0.04700  0.30720
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  6.083e-01  3.290e-02  18.489  < 2e-16 ***
## frac_coll_plus2010           3.718e-01  2.598e-02  14.313  < 2e-16 ***
## foreign_share2010            1.105e-01  4.960e-02   2.227 0.026033 *
## med_hhinc2016                1.296e-07  2.543e-07   0.510 0.610193
## poor_share2010              -5.756e-01  4.036e-02 -14.262  < 2e-16 ***
## share_white2010              4.233e-02  2.082e-02   2.033 0.042122 *
## share_black2010              5.908e-02  2.084e-02   2.835 0.004615 **
## share_hisp2010              -5.112e-02  2.486e-02  -2.056 0.039840 *
## share_asian2010             -5.062e-01  9.173e-02  -5.519 3.71e-08 ***
## gsmn_math_g3_2013           -9.931e-04  2.142e-03  -0.464 0.642954
## rent_twobed2015             -7.016e-06  1.425e-05  -0.492 0.622587
```

```
## singleparent_share2010       -6.174e-02  2.455e-02  -2.515 0.011971 *
## traveltime15_2010            -4.253e-02  1.170e-02  -3.634 0.000283 ***
## emp2000                       1.137e-01  2.729e-02   4.167 3.17e-05 ***
## popdensity2010               -2.256e-07  5.510e-06  -0.041 0.967336
## ann_avg_job_growth_2004_2013 -7.074e-01  1.068e-01  -6.624 4.12e-11 ***
## job_density_2013             -4.916e-06  1.134e-05  -0.434 0.664669
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07304 on 2982 degrees of freedom
## Multiple R-squared:  0.4416, Adjusted R-squared:  0.4386
## F-statistic: 147.4 on 16 and 2982 DF,  p-value: < 2.2e-16
```

```
plot(lm_model, c(1, 2))
```




Q−Q Residuals
Standardized residuals
4
2
0
−2
−4
−6
2391
413
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(turnout.rate ~ . − (State + County + fips))