# STA610 Case Study 2 Report

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## Introduction

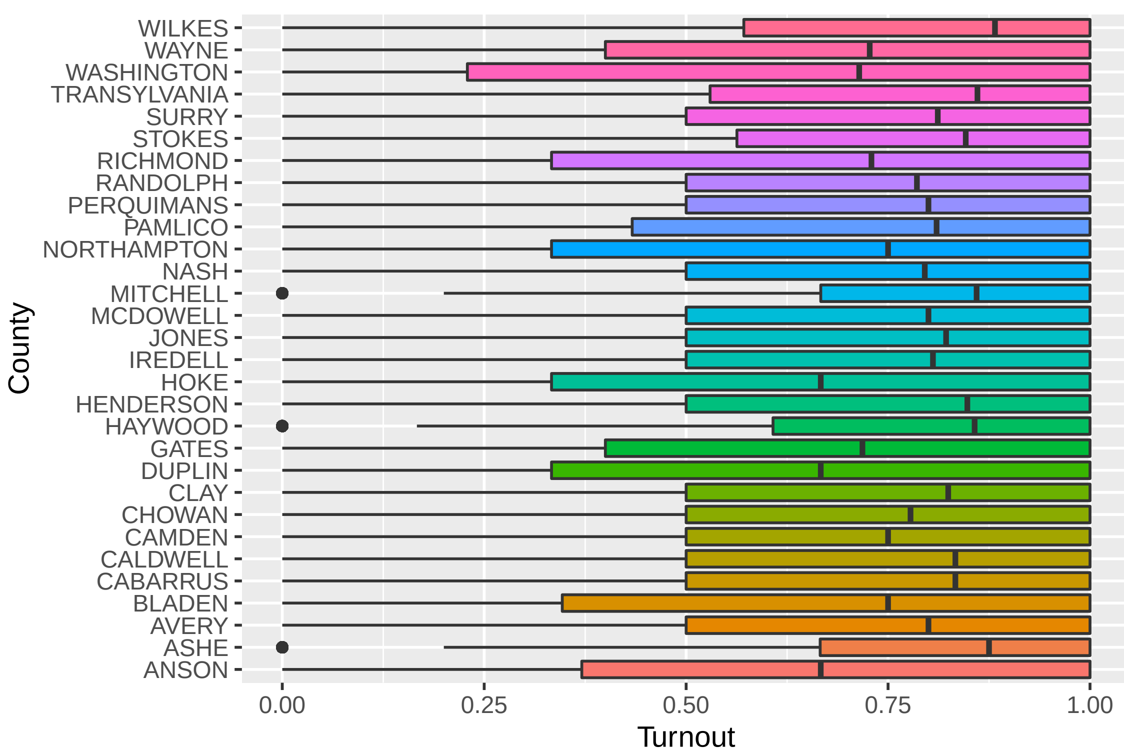
The United States have record-high turnout rates in 2020 over a century. So in this case study, we have built a Bayesian hierarchical model for the 2020 Presidential Election to investigate how different demographic variables lead to different turnout rates and the evidence of heterogeneity across counties. Our data sets come from the North Carolina State Board of Elections (NCSBE), which provides data on both the aggregate counts of registered voters and voters who actually voted by the demographic variables.

Our question of interests is the turn out rate, which is calculated as dividing the total counts of voters who actually voted by the total counts of voters who registered, aggregating all other demographic variables. The potential predictors include the the county, voter tabulation district, age, sex, race, ethnicity and party of the voters. There variables present a natural grouping structure for the turnout rate. Therefore, a Bayesian hierarchical model in this case has the advantages of "borrowing information" from the data set as a whole to stabilize estimates of the turnout rate in groups with relatively small sample size as well as fitting a large amount of random variance in a complex model.

To reduce the computational complexity and get better estimates, we randomly sampled 30 counties from our datasets. We also cleaned the datasets by removing those observations with 'NA's in their total counts of registered voters as well as the cases where the total counts of voters who actually voted exeeded the total counts of registered voters. Those abnormalities are most likely due to measurement errors.

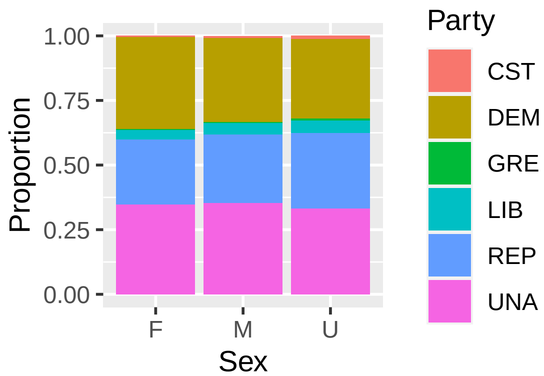
## EDA

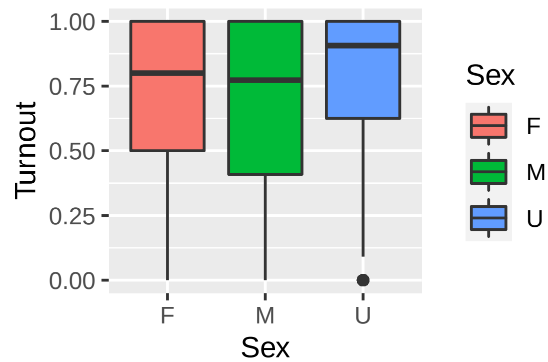
### County



From the boxplot we can see that the median turnout rates do differ by county, which justifies the random intercepts by county in our model.

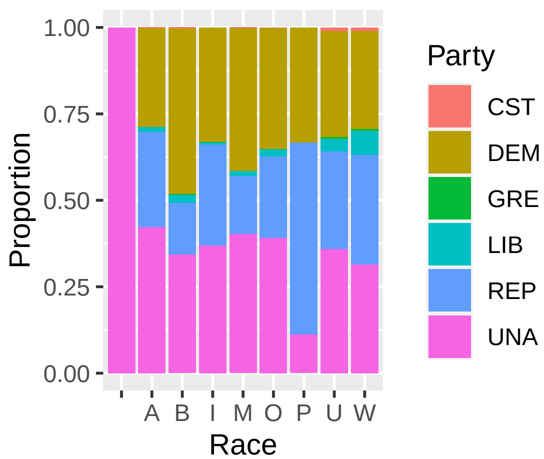
### Sex

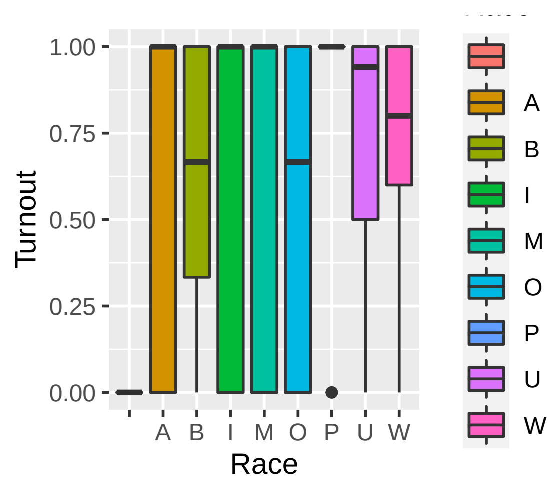



From the boxplot we can see that the median turn out rate in male is the lowest among the genders. There is a higher proportion in female who vote for Democrats than the proportions in other genders.

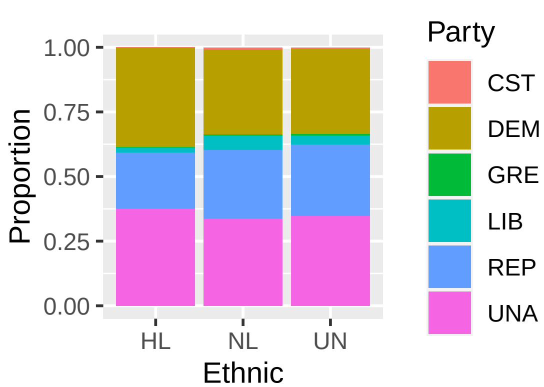
### Race

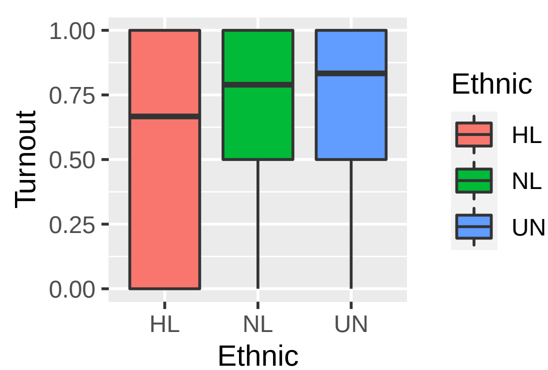



The median turn out rates do differ a lot by race, which necessitates us to include a main effect of race in our model. The proportion of voting for Democrats is the highest in African American than in other race.

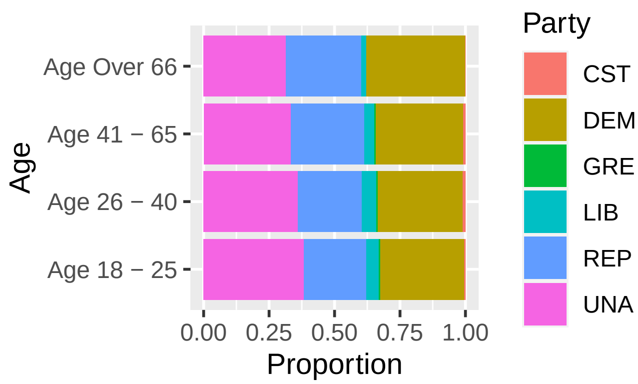
### Ethnic

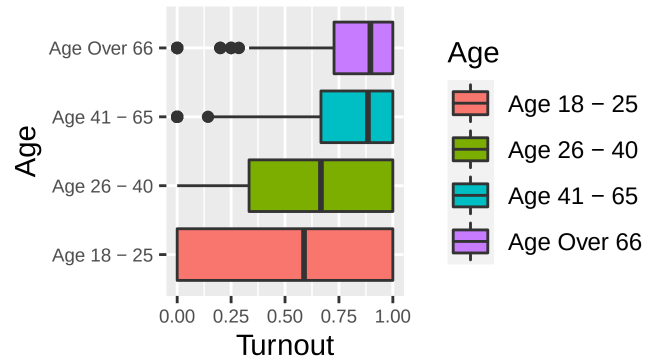



The proportion of voting for Democrats is the highest in Hispanic than in other ethnicity, but the median turn out rate in Hispanic is the lowest.

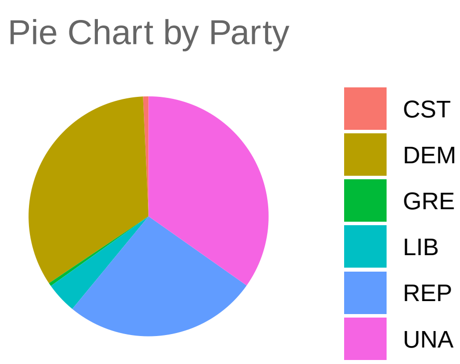
**Age**

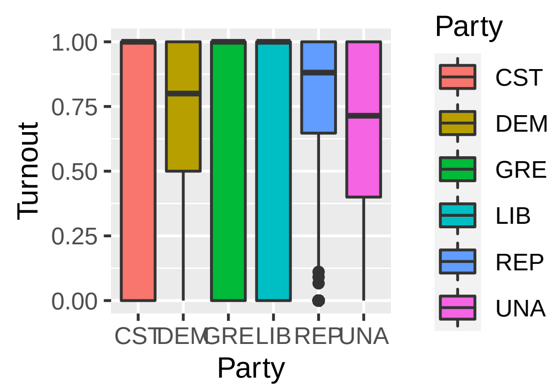



As people grow older, their turn out rates tend to increase and there is a higher proportion of people voting for Republicans. Thus we will incorporate a main effect of age in our model.

**Party**




From the pie chart we can see that the winning party is the Democrats and there is approximately same proportion for the unaffiliated party as the Democrats. The distributions of turn out rates do differ a lot by Party, which justifies a main effect of Party in our model.

## Model - Selection / Specification

Model selection was primarily chosen to address the research questions of interest

- Research question 1 is interested in different demographic subgroups. As such, this warrants effects for sex, age, party, ethnicity, and race
- Research question 2 is interested in exploring county-level effects. Because we are taking a random sample out of a larger population of counties, random intercepts are an appropriate choice here
- Research questions 3 and 4 are interested in how the sex/age effect change as a function of party affiliation. As such, interactions between sex/party and age/party are warranted.

Finally, we are asked to prepare a Bayesian hierarchical model - this is why we constructed the Bayesian model.

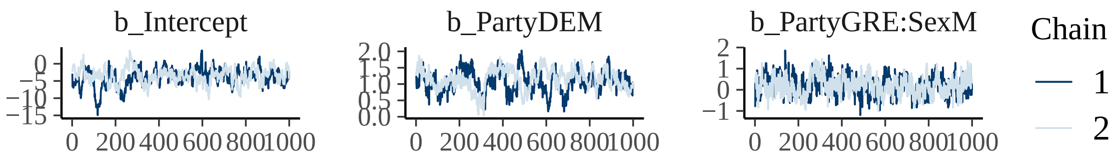
$$y_{ij}|x_{ij} \sim Bin(n_i, \pi_{ij})$$
$$logit(\pi_{ij}) = \beta_0 + \beta_{1a} I(S_i = a) + \beta_{2b} I(A_i = b) + \beta_{3c} I(P_i = c) + \beta_{4d} I(E_i = d) + \beta_{5e} I(R_i = e) +$$
$$\beta_{6bc} I(A_i = b, P_i = c) + \beta_{7ab} I(S_i = a, A_i = b) + b_{0j}$$
$$b_{0j} \sim N(0, \tau^2)$$
$$\beta_0 \sim N(0, 10), \beta \sim MVN(0, 10 * I_{n\beta}), \tau^2 \sim \text{Student-t}(\nu = 3, \mu = 0, \sigma = 1)$$

Where $S_i, A_i, P_i, E_i, R_i$ denote the sex, age range, party affiliation, ethnicity, and race of the group respectively, and where $j$ indexes 1 of 30 counties.

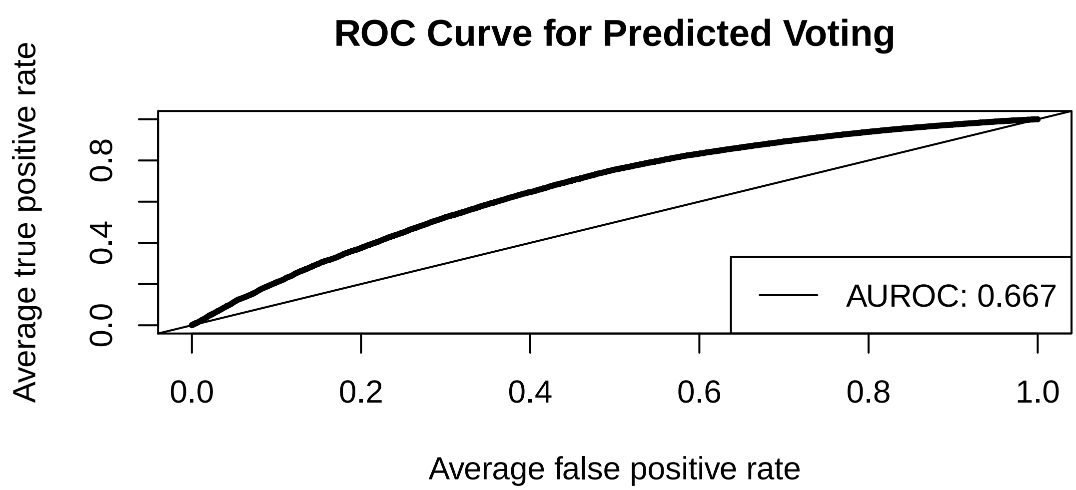
**Prior Specification** As we don't have any particular domain knowledge, priors are chose to be uninformative. We choose flat priors for the fixed effects (intercept included) centered around 0 (no effect) with a relatively large variance.

For the prior on between-group variance $\tau^2$, a student-t distribution is used. This is the result of a recommendation by Gelman for a half-t prior, which under certain assumptions leads us to this Student-t centered around 0.

**Model Diagnostics** To assess whether or not the Markov chain has achieved stationarity, we can investigate trace plots. There are too many parameters to paste *all* of the trace plots, so we will only investigate a subset of the reference intercept, a fixed effect, an interaction term, and a random effect




We can also investigate the ROC curve to assess whether or not the model is performing reasonably from a predictive modeling standpoint:




### Results & Findings

Here are the results of our inference. Fixed effects are given by the `b_` prefix, while random effects are given by the `r_` prefix. Finally, an estimate for the between-county variance can be found under `sd_County__Intercept`.

Coefficients are given on the *log-odds* scale of probability. Thus, we would interpret a fixed effect as the expected change in the log-odds of voting compared to the reference group, holding all else constant. We can exponentiate this coefficient to obtain the regular change in odds, or we can apply the inverse link function (sigmoid) to recover the expected change in probability.

## Research Questions

**1. How did different demographic subgroups vote in the 2020 general elections? For example, how did the turnout for males compare to the turnout for females after controlling for other potential predictors?**

To interpret the coefficients as "turnout", we need to pass them through the `inv_logit_scaled` function

### Race

*Note:* For the race variable, a blank value that we missed appears to be the baseline level. This will make interpretation of race difficult

The expected difference in turnout between a voter with the following race compared to a baseline race voter (holding all else constant) is given in the following table:

| Race | Estimate | Est.Error | Q2.5 | Q97.5 |
|---|---|---|---|---|
| b_RaceA | 0.932 | 0.915 | 0.170 | 1.000 |
| b_RaceB | 0.927 | 0.915 | 0.160 | 1.000 |
| b_RaceI | 0.910 | 0.915 | 0.130 | 0.999 |
| b_RaceM | 0.926 | 0.915 | 0.156 | 1.000 |
| b_RaceO | 0.913 | 0.915 | 0.138 | 0.999 |
| b_RaceP | 0.986 | 0.924 | 0.480 | 1.000 |
| b_RaceU | 0.947 | 0.915 | 0.213 | 1.000 |
| b_RaceW | 0.946 | 0.915 | 0.208 | 1.000 |

Again, interpretation for this variable is difficult due to the erroneous baseline - but an example interpretation is given as follows for reference. An Asian voter has an expected increase in probability of voting of $0.932 - 0.5 = 0.432$ compared to this baseline level, holding all else constant. We observe that all of race effects contain credible intervals of 0, and as such we cannot conclude that race has an impact on voting.

### Ethnicity

| Effect | Estimate | Est.Error | Q2.5 | Q97.5 |
|---|---|---|---|---|
| b_EthnicNL | 0.586 | 0.506 | 0.575 | 0.597 |
| b_EthnicUN | 0.572 | 0.506 | 0.561 | 0.583 |

Holding all else constant:

- A non Hispanic/Latino voter has an expected increase in probability of voting of 0.086
- An undesignated voter has an expected increase in probability of voting of 0.072

compared to the baseline ethnicity (Hispanic / Latino). Both effects appear to be significant, as the coefficient on the log-odds scale does not include 0.

### Age

The remaining effects are slightly trickier to interpret due to the interaction effects. We will explore this more in question 4. For age, we may interpret this effect as the expected change in log odds compared to the baseline age *if* we are working within the baseline party (Constitution Party or CST). Effects given below with interpretation:

| Effect | Estimate | Est.Error | Q2.5 | Q97.5 |
|---|---|---|---|---|
| b_AgeAge26M40 | 0.739 | 0.575 | 0.616 | 0.839 |
| b_AgeAge41M65 | 0.759 | 0.578 | 0.635 | 0.855 |
| b_AgeAgeOver66 | 0.839 | 0.660 | 0.594 | 0.952 |

Holding all else constant,

- An 26-40 year old CST voter has an expected increase in probability of voting of 0.239
- A 41-65 year old CST voter has an expected increase in probability of voting of 0.259
- A 66+ year old CST voter has an expected increase in probability of voting of 0.339

compared to an 18-25 year old CST voter. All age effects are significant, and we observe an increase of voter turnout with age (again, for CST party only).

### Sex

As before, to interpret the marginal effect of the Sex coefficient, we will need to assume 2 voters in the baseline party such that the interaction term does not get introduced. Effects given below with interpretation:

| Effect | Estimate | Est.Error | Q2.5 | Q97.5 |
|---|---|---|---|---|
| b__SexM | 0.553 | 0.572 | 0.405 | 0.680 |
| b__SexU | 0.602 | 0.582 | 0.432 | 0.736 |

Holding all else constant:

- An male voter in the CST party has an expected increase in the probability of voting of 0.053
- An undesignated gender in the CST party has an expected increase in the probability of voting of 0.102

Compared to an female CST voter. However, neither effect is significant (containing 0 on the log-odds scale), and so we fail to reject the hypothesis that gender is significantly associated with voting turnout (for the CST party).

### Party

Finally, party follows the same workflow as before - to obtain the marginal interpretation of the party coefficient, we must assume baseline levels of the terms involved in the party interactions (female voters and 18-25). Effects given below with interpretation:

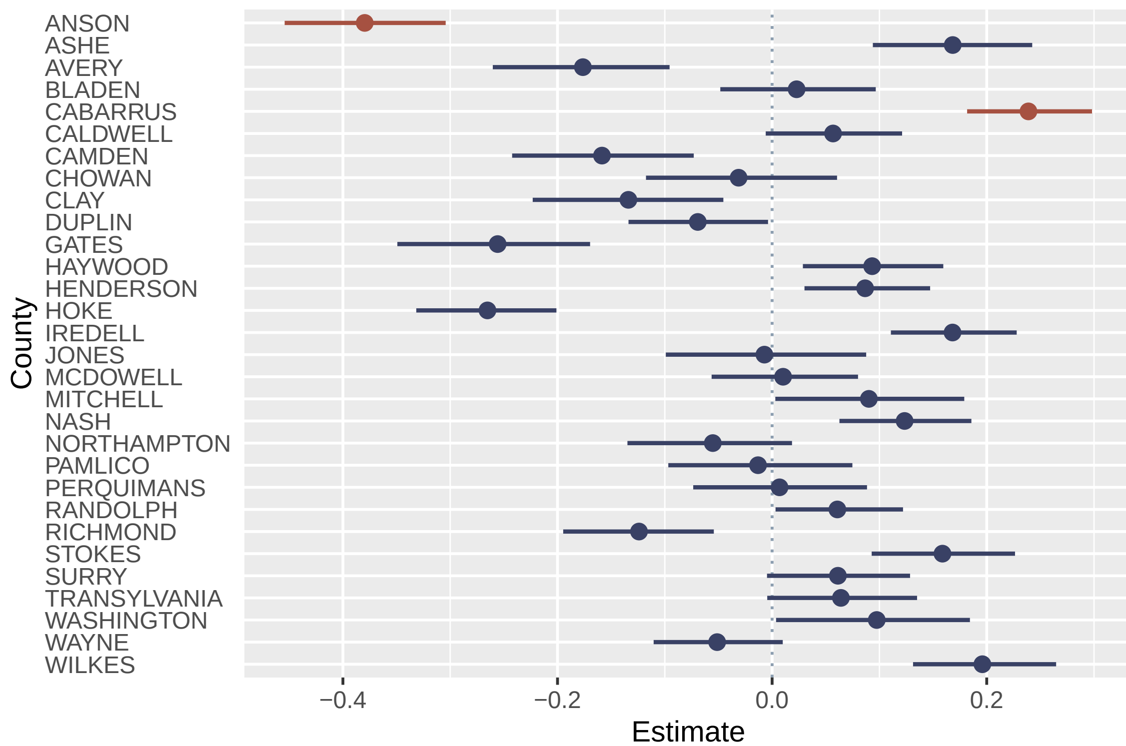
| Effect | Estimate | Est.Error | Q2.5 | Q97.5 |
|---|---|---|---|---|
| b__PartyDEM | 0.753 | 0.580 | 0.606 | 0.843 |
| b__PartyGRE | 0.587 | 0.608 | 0.361 | 0.764 |
| b__PartyLIB | 0.629 | 0.583 | 0.459 | 0.753 |
| b__PartyREP | 0.793 | 0.580 | 0.659 | 0.871 |
| b__PartyUNA | 0.663 | 0.580 | 0.498 | 0.776 |

Holding all else constant,

- 18-25 year old female Democrat voters have an expected increase in the probability of voting of 0.253
- 18-25 year old female GRE voters have an expected increase in the probability of voting of 0.087
- 18-25 year old female Libertarian voters have an expected increase in the probability of voting of 0.127
- 18-25 year old female Democrat voters have an expected increase in the probability of voting of 0.293
- 18-25 year old unaffiliated female voters have an expected increase in the probability of voting of 0.163

compared to 18-25 year old female CST voters. This effect only appears to be significant for Democrat and Republican voters however.

**2. Did the overall probability or odds of voting differ by county in 2020? Which counties differ the most from other counties?**




Based on our dataset and final model with 30 random selected counties, the overall odds of voting differ a lot by county in 2020. The values of the odds of voting range from exp(-0.380) = 0.684 for County Anson to exp(0.239) = 1.270 for County Cabarrus. The estimated average odds of voting is highest for County Cabarrus and lowest for County Anson when all the other variables are the same. Thus, County Cabarrus and County Anson differ the most from other counties.

**3. How did the turnout rates differ between females and males for the different party affiliations?**

Female turnout was higher in the DEM, LIB, REP, and UNA parties, with differences ranging from 0.039 - 0.0382 = 0.001 higher in the LIB party to 0.014 higher in the DEM party. Male turnout was higher in the CST and GRE parties, with the GRE party having the bigger difference at 0.0491 - 0.033 = 0.016.

**4. How did the turnout rates differ between age groups for the different party affiliations?**

For the age groups, the people whose ages range from 18 to 25 belong to the reference group.

For people who voted for the Democrats, the turnout rate is 6.85% for the registered voters who ages range from 18 to 25, 7.85% for the registered voters whose ages range from 26 to 40, 17.80% for the registered voters whose ages range from 41 to 65, and 17.91% for the registered voters whose ages are over 66.

For people who voted for the Republicans, the turnout rate is 8.46% for the registered voters who ages range from 18 to 25, 10.48% for the registered voters whose ages range from 26 to 40, 20.07% for the registered voters whose ages range from 41 to 65, and 19.99% for the registered voters whose ages are over 66.

For people who voted for the Libertarians, the turnout rate is 3.93% for the registered voters who ages range from 18 to 25, 5.26% for the registered voters whose ages range from 26 to 40, 7.72% for the registered voters whose ages range from 41 to 65, and 8.42% for the registered voters whose ages are over 66.

For people who voted for the Green Party, the turnout rate is 3.31% for the registered voters who ages range from 18 to 25, 3.84% for the registered voters whose ages range from 26 to 40, 6.86% for the registered voters whose ages range from 41 to 65, and 4.22% for the registered voters whose ages are over 66.

For people who are unaffiliated with any party, the turnout rate is 4.53% for the registered voters who ages range from 18 to 25, 6.20% for the registered voters whose ages range from 26 to 40, 12.93% for the registered voters whose ages range from 41 to 65, and 16.96% for the registered voters whose ages are over 66.

For people who voted for the Green Party, the turnout rate for the registered voters who ages range from 18 to 25 is 3.31%. The turnout rate for the registered voters whose ages range from 26 to 40 is 3.84%. The turnout rate for the registered voters whose ages range from 41 to 65 is 6.86%. The turnout rate for the registered voters whose ages are over 66 is 4.22%.

For people who are unaffiliated with any party, the turnout rate for the registered voters who ages range from 18 to 25 is 4.53%. The turnout rate for the registered voters whose ages range from 26 to 40 is 6.20%. The turnout rate for the registered voters whose ages range from 41 to 65 is 12.93%. The turnout rate for the registered voters whose ages are over 66 is 16.96%.

## Limitations

Our analysis has several limitations. First, running brm model is quite time consuming, so we narrow down our dataset a lot and run as many iterations as possible on this smaller dataset. This reduction in size of data may be the cause of wide confidence intervals around some our estimates. Next, we don't really try to use poststratification to reweight the estimate by the representation of each county. Thus, our sample could be slightly biased. This could explain why some of our estimates seem unexpectedly low (e.g., <5% turnout among registered voters of some groups. Finally, because of the clear objectives given in research questions, we directly build our model based on questions of interest without diving into model selection too much. Therefore there may be additional predictors that would approve our model's predictive power, but we did not consider them here.

## Appendix

```
knitr::opts_chunk$set(echo = FALSE, cache=TRUE, message = FALSE, warning = FALSE, fig.width = 6, fig
if (!require(pacman)) install.packages("pacman")
pacman::p_load(tidyverse, lme4, gridExtra, grid, ggplot2, lattice, redres, stringr, influence.ME, kn

rstan_options(auto_write=TRUE)
options(mc.cores=parallel::detectCores())
seed <- 149  # Set seed for reproducibility
VS <- read.delim("voter_stats_20201103.txt", header = TRUE)  # Registered voters
HS <- read.delim("history_stats_20201103.txt", header = TRUE)  # Actual voters
# Sum voters across the following relevant categories
VS_aggregated <- aggregate(VS$total_voters,
                           list(County=VS$county_desc,
                                Precinct=VS$precinct_abbrv,
                                Vtd=VS$vtd_abbrv,
                                Age=VS$age,
                                Party=VS$party_cd,
                                Race=VS$race_code,
                                Ethnic=VS$ethnic_code,
                                Sex=VS$sex_code),sum) %>%
  rename(total_voter = x)

HS_aggregated <- aggregate(HS$total_voters,
                           list(County=HS$county_desc,
                                Precinct=HS$precinct_abbrv,
                                Vtd=HS$vtd_abbrv,
                                Age=HS$age,
                                Party=HS$party_cd,
                                Race=HS$race_code,
                                Ethnic=HS$ethnic_code,
                                Sex=HS$sex_code),sum) %>%
  rename(total_voter = x)
# discard election_date,stats_type, and update_date.
county_list <-  unique(HS_aggregated$County)

set.seed(seed)
sample_list <- sample(county_list, size=30, replace=FALSE)

VS_sampled <- VS_aggregated %>%
  filter(County %in% sample_list)

HS_sampled <- HS_aggregated %>%
  filter(County %in% sample_list)
# Merge voter records with registered records
df <-  full_join(VS_sampled, HS_sampled, by = c("County"="County",
                                                 "Precinct"="Precinct",
                                                 "Vtd"="Vtd",
                                                 "Age"="Age",
                                                 "Party"="Party",
                                                 "Race"="Race",
                                                 "Ethnic"="Ethnic",
```

```
                                                "Sex"="Sex")) %>%
  rename(total_registered_voter = total_voter.x,
         total_voted_voter = total_voter.y) %>%
  # Some categories had registered voters that didn't vote - replace with 0
  mutate(total_voted_voter = replace_na(total_voted_voter, 0)) %>%

  # No reason registered voters should be missing - remove these
  filter(!is.na(total_registered_voter)) %>%

  # Voters should not be greater than the number registered - remove these
  filter(total_voted_voter <= total_registered_voter) %>%
  mutate(total_registered_voter = as.numeric(total_registered_voter),
         total_voted_voter = as.numeric(total_voted_voter)) %>%

  # Add in Fan's code for EDA
  mutate(Turnout = total_voted_voter / total_registered_voter)
# Way too many observations to run in a reasonable amount of time - reduce each
# county by half
set.seed(seed)
df <- df %>% group_by(County) %>% sample_frac(0.5, replace = FALSE)
# Party by County
PartybyCounty <- ggplot(df, aes(x = County, fill = Party)) +
  geom_bar(position = "fill") +
  labs(y = "Proportion") +
  coord_flip()
# PartybyCounty

# Turnout by County
# Turnout by County
box_County <- ggplot(df, aes(x = County,
  y= Turnout,
  fill = County)) +
  geom_boxplot() +
  coord_flip() +
  theme(legend.position = "none")
box_County
#### Preccint
# Party by Preccint
ggplot(df, aes(x = Precinct, fill = Party)) +
  geom_bar(position = "fill") +
  labs(y = "Proportion") +
  coord_flip()

# Turnout by Precinct
ggplot(df, aes(x = Precinct, y= Turnout, fill = Precinct)) +
    geom_boxplot()
# Party by Sex
PartybySex <- ggplot(df, aes(x = Sex, fill = Party)) +
  geom_bar(position = "fill") +
  labs(y = "Proportion")
```

```
# Turnout by Sex
box_Sex <- ggplot(df, aes(x = Sex, y= Turnout, fill = Sex)) +
    geom_boxplot()

grid.arrange(PartybySex, box_Sex, ncol = 2)
#### Voter tabulation district
# Party by Voter tabulation district
ggplot(df, aes(x = Vtd, fill = Party)) +
  geom_bar(position = "fill") +
  labs(y = "Proportion")

# Turnout by Vtd
ggplot(df, aes(x = Vtd, y= Turnout, fill = Vtd)) +
    geom_boxplot()
# Party by Race
PartybyRace <- ggplot(df, aes(x = Race, fill = Party)) +
  geom_bar(position = "fill") +
  labs(y = "Proportion")

# Turnout by Race
box_Race <- ggplot(df, aes(x = Race, y= Turnout, fill = Race)) +
    geom_boxplot()

grid.arrange(PartybyRace, box_Race, ncol = 2)
# Party by Ethnic
PartybyEthnic <- ggplot(df, aes(x = Ethnic, fill = Party)) +
  geom_bar(position = "fill") +
  labs(y = "Proportion")

# Turnout by Ethnic
box_Ethnic <- ggplot(df, aes(x = Ethnic, y= Turnout, fill = Ethnic)) +
    geom_boxplot()

grid.arrange(PartybyEthnic, box_Ethnic, ncol = 2)
# Party by Age
PartybyAge <- ggplot(df,
aes(x = Age,
fill = Party)) +
geom_bar(position = "fill") +
labs(y = "Proportion") +
coord_flip() +
theme(axis.text=element_text(size=9))

# Turnout by Age
box_Age <- ggplot(df, aes(x = Age,
y= Turnout,
fill = Age)) +
geom_boxplot() +
coord_flip() +
theme(axis.text=element_text(size=7))
```

```
grid.arrange(PartybyAge, box_Age, ncol = 2)
# Pie Chart by Party
Pie_Party <- ggplot(df, aes(x=factor(1), fill=Party))+
  geom_bar(width = 1) +
  coord_polar("y") +
  labs(x = NULL, y = NULL, fill = NULL, title = "Pie Chart by Party") +
  theme_classic() +
  theme(axis.line = element_blank(),
        axis.text = element_blank(),
        axis.ticks = element_blank(),
        plot.title = element_text(hjust = 0.5, color = "#666666"))

# Turnout by Party
box_Party <- ggplot(df, aes(x = Party, y= Turnout, fill = Party)) +
    geom_boxplot()

grid.arrange(Pie_Party, box_Party, ncol = 2)
formula <- 'total_voted_voter | trials(total_registered_voter) ~
            1 + Age*Party + Sex*Party + Race + Ethnic + (1 | County)'
start_time <- Sys.time()
default_model <- brm(formula=formula, data = df, family = binomial,
                     prior = c(
                       set_prior('normal(0, 10)', class = 'Intercept'),
                       set_prior('normal(0, 10)', class = 'b'),
                       set_prior('student_t(3, 0, 1)', class='sd')
                     ),
                     iter=2000, seed=seed,
                     file = 'final_model',
                     cores=detectCores(),
                     chains=2,
                     silent=0)
end_time <- Sys.time()
#vars <- c('b_Intercept', 'b_AgeAge26M40', 'b_PartyDEM', 'b_SexM', 'b_RaceA', 'b_EthnicNL', #'b_Age
vars <- c('b_Intercept', 'b_PartyDEM', 'b_PartyGRE:SexM')
#plot(default_model, pars=vars, fixed=TRUE, ask=FALSE)
mcmc_plot(default_model, pars=vars, fixed=TRUE, type='trace', ask=FALSE)
fitted_resp <- fitted(default_model)
# Convert from expected counts to probability of success
est_prob <- fitted_resp[, 'Estimate'] / df$total_registered_voter
# Create individual 0's and 1's for each group based off of registered and actual voters
ground_truth_counts <- df$total_voted_voter
ground_truth <- sapply(1:nrow(df), function(i) {
  voters <- rep(1, ground_truth_counts[i])
  non_voters <- rep(0, df[i, 'total_registered_voter'] - ground_truth_counts[i])
  ind_counts <- c(voters, non_voters)
})
ground_truth <- unlist(ground_truth)

# Repeat the predicted group value for every registered voter in the group
predictions <- rep(est_prob, df$total_registered_voter)
pred <- ROCR::prediction(predictions, ground_truth)
```

```r
perf <- performance(pred, "tpr", "fpr")
auc_ROCR <- performance(pred, measure = "auc")
auc_ROCR <- auc_ROCR@y.values[[1]]

# Plot ROC curve
plot(perf, avg= "threshold", lwd=3, main='ROC Curve for Predicted Voting')
abline(coef = c(0,1))
legend('bottomright', legend=paste('AUROC:', auc_ROCR %>% round(3)), col=c('black'), lty=1)
post_summary <- default_model %>% posterior_summary() %>% as_tibble(rownames = 'Effect')
races <- post_summary %>% filter(startsWith(Effect, 'b_Race')) %>% pull(Effect)
post_summary %>%
  filter(Effect %in% races) %>%
  select(-c('Effect')) %>%
  inv_logit_scaled() %>%
  mutate('Race' = races, .before = 'Estimate') %>%
  kable(digits=3) %>%
  kable_styling(position = "center", latex_options = "HOLD_position")
ethnicities <- post_summary %>% filter(startsWith(Effect, 'b_Ethnic')) %>% pull(Effect)
post_summary %>%
  filter(Effect %in% ethnicities) %>%
  select(-c('Effect')) %>%
  inv_logit_scaled() %>%
  mutate('Effect' = ethnicities, .before = 'Estimate') %>%
  kable(digits = 3) %>%
  kable_styling(position = "center", latex_options = "HOLD_position")
ages <- c('b_AgeAge26M40', 'b_AgeAge41M65', 'b_AgeAgeOver66')
post_summary %>%
  filter(Effect %in% ages) %>%
  select(-c('Effect')) %>%
  inv_logit_scaled() %>%
  mutate('Effect' = ages, .before = 'Estimate') %>%
  kable(digits = 3) %>%
  kable_styling(position = "center",latex_options = "HOLD_position")
sexes <- c('b_SexM', 'b_SexU')
post_summary %>%
  filter(Effect %in% sexes) %>%
  select(-c('Effect')) %>%
  inv_logit_scaled() %>%
  mutate('Effect' = sexes, .before = 'Estimate') %>%
  kable(digits=3) %>%
  kable_styling(position = "center", latex_options = "HOLD_position")
parties <- c('b_PartyDEM', 'b_PartyGRE', 'b_PartyLIB', 'b_PartyREP', 'b_PartyUNA')
post_summary %>%
  filter(Effect %in% parties) %>%
  select(-c('Effect')) %>%
  inv_logit_scaled() %>%
  mutate('Effect' = parties, .before = 'Estimate') %>%
  kable(digits=3) %>%
  kable_styling(position = "center", latex_options = "HOLD_position")
#ranef(default_model) %>% kable(digits = 3, align = 'c')
```

```
ranef(default_model)$County[, , 1] %>%
  as_tibble() %>%
  mutate(param = unique(df$County),
  reorder = c(30:1)) %>%
  ggplot(aes(x = reorder(param, reorder))) +
  geom_hline(yintercept = 0, linetype = 3, color = "#8B9DAF") +
  geom_pointrange(aes(ymin = Q2.5, ymax = Q97.5, y = Estimate,
                  color = reorder %in% c(26,30)),
                  shape = 20, size = 3/4) +
  scale_color_manual(values = c("#394165", "#A65141")) +
  labs(x = "County", y = "Estimate") +
  coord_flip() +
  theme(legend.position = "none",
      axis.ticks.y = element_blank(),
      axis.text.y = element_text(hjust = 0))
post_summary_fixed <- post_summary %>% filter(!startsWith(Effect, 'r_'))
#post_summary_random <- post_summary %>% filter(startsWith(Effect, 'r_'))
#post_summary %>% kable(digits = 3, align = 'c')
kable(post_summary_fixed, digits = 3, align = 'c') %>% kable_styling(position = "center", latex_opti
```

| Effect | Estimate | Est.Error | Q2.5 | Q97.5 |
|---|---|---|---|---|
| b__Intercept | -3.726 | 2.429 | -9.049 | 0.495 |
| b__AgeAge26M40 | 1.042 | 0.303 | 0.473 | 1.652 |
| b__AgeAge41M65 | 1.149 | 0.317 | 0.552 | 1.771 |
| b__AgeAgeOver66 | 1.654 | 0.665 | 0.380 | 2.981 |
| b__PartyDEM | 1.116 | 0.324 | 0.431 | 1.680 |
| b__PartyGRE | 0.351 | 0.439 | -0.569 | 1.177 |
| b__PartyLIB | 0.529 | 0.334 | -0.166 | 1.117 |
| b__PartyREP | 1.345 | 0.325 | 0.657 | 1.914 |
| b__PartyUNA | 0.678 | 0.324 | -0.009 | 1.245 |
| b__SexM | 0.214 | 0.290 | -0.387 | 0.755 |
| b__SexU | 0.414 | 0.332 | -0.274 | 1.025 |
| b__RaceA | 2.623 | 2.381 | -1.584 | 7.739 |
| b__RaceB | 2.539 | 2.380 | -1.661 | 7.681 |
| b__RaceI | 2.310 | 2.381 | -1.901 | 7.454 |
| b__RaceM | 2.521 | 2.380 | -1.685 | 7.659 |
| b__RaceO | 2.348 | 2.379 | -1.830 | 7.497 |
| b__RaceP | 4.284 | 2.505 | -0.078 | 9.985 |
| b__RaceU | 2.887 | 2.380 | -1.310 | 8.035 |
| b__RaceW | 2.857 | 2.380 | -1.338 | 8.007 |
| b__EthnicNL | 0.349 | 0.022 | 0.302 | 0.393 |
| b__EthnicUN | 0.291 | 0.023 | 0.245 | 0.335 |
| b__AgeAge26M40:PartyDEM | -0.895 | 0.304 | -1.510 | -0.325 |
| b__AgeAge41M65:PartyDEM | -0.070 | 0.317 | -0.697 | 0.519 |
| b__AgeAgeOver66:PartyDEM | -0.567 | 0.665 | -1.888 | 0.710 |
| b__AgeAge26M40:PartyGRE | -0.887 | 0.469 | -1.851 | -0.016 |
| b__AgeAge41M65:PartyGRE | -0.382 | 0.501 | -1.367 | 0.544 |
| b__AgeAgeOver66:PartyGRE | -1.401 | 0.900 | -3.100 | 0.388 |
| b__AgeAge26M40:PartyLIB | -0.736 | 0.315 | -1.402 | -0.150 |
| b__AgeAge41M65:PartyLIB | -0.433 | 0.332 | -1.103 | 0.210 |
| b__AgeAgeOver66:PartyLIB | -0.844 | 0.693 | -2.189 | 0.509 |
| b__AgeAge26M40:PartyREP | -0.805 | 0.303 | -1.414 | -0.238 |
| b__AgeAge41M65:PartyREP | -0.150 | 0.318 | -0.768 | 0.461 |
| b__AgeAgeOver66:PartyREP | -0.660 | 0.666 | -1.979 | 0.619 |
| b__AgeAge26M40:PartyUNA | -0.710 | 0.303 | -1.321 | -0.143 |
| b__AgeAge41M65:PartyUNA | -0.008 | 0.317 | -0.630 | 0.585 |
| b__AgeAgeOver66:PartyUNA | -0.195 | 0.666 | -1.526 | 1.085 |
| b__PartyDEM:SexM | -0.454 | 0.290 | -0.997 | 0.142 |
| b__PartyGRE:SexM | 0.199 | 0.446 | -0.631 | 1.145 |
| b__PartyLIB:SexM | -0.242 | 0.302 | -0.799 | 0.363 |
| b__PartyREP:SexM | -0.252 | 0.291 | -0.792 | 0.349 |
| b__PartyUNA:SexM | -0.287 | 0.291 | -0.828 | 0.314 |
| b__PartyDEM:SexU | -0.252 | 0.332 | -0.865 | 0.430 |
| b__PartyGRE:SexU | 0.517 | 0.504 | -0.458 | 1.490 |
| b__PartyLIB:SexU | 0.294 | 0.356 | -0.388 | 1.009 |
| b__PartyREP:SexU | -0.078 | 0.331 | -0.709 | 0.600 |
| b__PartyUNA:SexU | -0.299 | 0.332 | -0.916 | 0.390 |
| sd__County___Intercept | 0.154 | 0.022 | 0.120 | 0.203 |
| lp___ | -62283.898 | 7.649 | -62300.398 | -62269.952 |